Journal of Business Research 126 (2021) 1–11

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Uncovering the effects of textual features on trustworthiness of online consumer reviews: A computational-experimental approach

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ARTICLE INFO

Keywords:
eWOM
Textual features
Computational text mining
Trustworthiness
Review valence
Content concreteness

ABSTRACT

Online consumer reviews are word-of-mouth exchanges on the Internet that can be harnessed for decision support. Combining computational and experimental methods, the current two-part research uncovered the effects of textual features on trustworthiness of consumer reviews on TripAdvisor. Taking a bottom-up approach, Study 1 employed text mining and human rating methods to explore the salient review topics that impact review trustworthiness. Study 2 took a top-down approach by examining the textual features that drive the effects of review topics identified in Study 1 and testing them across two product categories—hotel and restaurant—in an online experiment. The findings indicate that review trustworthiness has a moderating effect on review adoption in that highly trustworthy reviews are more likely to be adopted by consumers to aid in their judgement formation. This research also explicated the role of three textual features—namely, attribute salience, review valence, and content concreteness—in review trustworthiness.

1. Introduction

Online consumer reviews are word-of-mouth exchanges on the Internet that can be harnessed for decision support (Maslowska, Malthouse, & Bernritter, 2017). Particularly for experiential goods that can only be accurately evaluated after use, such as travel destinations, restaurants, and hotels, it is commonplace for potential consumers to seek more information and read online reviews to aid in their decision-making processes. Accompanying the prevalence of online consumer reviews is a growing concern about fake reviews. Evidence has been discovered of merchants arranging positive reviews on their own products and negative reviews for their competitors on major online retailing websites to manipulate viewers' impressions toward the products (Fortune, 2019; The Wall Street Journal, 2019). As a result, nearly half of American adults surveyed admit that it is difficult to assess the trustworthiness of online reviews (Pew Research Center, 2016).

To address this issue, a growing body of studies have investigated factors that affect consumers' perceptions of the trustworthiness of user-generated reviews. Prior research in this regard has mostly focused on source characteristics, such as platform features (e.g., DeAndrea, Van Der Heide, Vendemia, & Vang, 2018) and reviewer profiles (e.g., Agnihotri & Bhattacharya, 2016; Lim & Van Der Heide, 2015), and examined how these source characteristics serve as cues that aid viewers in forming judgments on trustworthiness. In online review settings, however, the limited quantity of information that consumers can obtain about the source increases the difficulty of assessing trustworthiness based merely on reviewer/platform cues (Metzger & Flanagin, 2013; Reimer & Benkenstein, 2016). Rather, the literature suggests that when evaluating the trustworthiness of the reviews, consumers primarily use cues embedded in the reviews, such as content and writing style (Filieri, 2015, 2016). Hence, consumers form their judgments of trustworthiness based on the textual features of consumer reviews and then decide whether they will adopt the reviews to aid in their decision-making. Table 1 summarizes representative works on content features and review effectiveness.

Following this line of thought, the present study examined what specific textual features affect trustworthiness and the role of trustworthiness in the adoption of online consumer reviews. Review adoption refers to that "consumers who adopt information from online consumer reviews(OCRs) would accept the recommendations contained in OCRs and subsequently take action by following these recommendations" (Filieri, 2015, pp. 1264–1265), which can be reflected by the high similarity between the review writer's rating and the review reader's rating of the product/service. This study identified two textual

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https://doi.org/10.1016/j.jbusres.2020.12.052
Received 20 December 2019; Received in revised form 15 December 2020; Accepted 19 December 2020
Available online 31 December 2020

Table 1
Summary of Representative Works on Textual Features of Online Consumer Reviews.

Article	Textual Features	Whether the Textual Features Were Pre-Selected	Dependent Variable
Agnihotri and Bhattacharya (2016)	Content readability, associated sentiments	Yes	Review helpfulness
Filieri (2016)	Review extremity, review valence, length of the review, type of information, type of detail, writing style	No, used consumer interviews	Review trustworthiness
Folse et al. (2016)	Negatively valenced emotional expressions, language complexity	Yes	Review helpfulness, reviewer rationality and trustworthiness, attitude toward the product
Ketron (2017)	Quality of grammar and mechanics, review length	Yes	Purchase intention
Ludwig et al. (2013)	Affective content, linguistic style match	Yes	Conversion rates
Mudambi and Schuff (2010)	Review extremity, review depth	Yes	Review helpfulness
Moon et al. (2019)	Review extremity, hotel attributes	Yes	Review fakery, review trust
Packard and Berger (2017)	Endorsement style	Yes	Perceptions of the review writer's expertise and attitudes toward the product
Reimer and Benkenstein (2016)	Review valence, review argumentation	Yes	Review trustworthiness, purchase intention
Sparks et al. (2013)	Presence of eco-certification logos, content concreteness	Yes	Attitude toward the resort, purchase intention
Willemsen et al. (2011)	Expertise claims, review valence, argument density and diversity	Yes	Perceived usefulness of reviews
Current Study	Attribute salience, review valence, content concreteness	No, used texting mining and human ratings	Review trustworthiness

features—attribute salience and review valence—that affect consumers' perceptions of the trustworthiness of online consumer reviews. Attribute salience refers to how important a product attribute is in assessing the product and forming evaluations (Kangale, Kumar, Naeem, Williams, & Tiwari, 2016). Attribute salience varies across consumer segments and product categories. For instance, when grocery shopping, some consumers may prioritize price over quality, while quality may be most important to others. As another example, consumers may consider food quality the most important attribute to consider when evaluating a restaurant, but food quality may be less important for hotels. Review valence is defined as "the tone with which products are being discussed in online reviews, with positively valenced reviews emphasizing a product's strengths, and negatively valenced reviews emphasizing its weaknesses" (Ketelaar, Willemsen, Sleven, & Kerkhof, 2015, p. 651). Review valence in this study refers to a textual feature rather than the valence indicated in the overall numerical ratings. The literature has suggested two opposite views pertaining to review valence as a textual feature: "negativity bias" and "positivity bias." The former contends that negative reviews have a stronger effect on consumer decision-making (e.g., Kusumasondjaja, Shanka, & Marchegiani, 2012), and the latter indicates positive reviews have a greater impact (e.g., Wu, 2013; Zhang, Craciun, & Shin, 2010). The current study applied a rigorous mixed-methods approach that combined text mining, human rating, and an online experiment to examine this issue across two product categories. This study helps to resolve the conflicting findings in the literature and, therefore, contributes to the scholarship on consumer reviews.

This study also contributes to the scholarship with the new method we used to extract salient product attributes from consumer reviews. The bulk of relevant studies on consumer behavior have used conjoint analysis to identify product attributes that are important to consumers (e.g., Chen, Hsu, & Lin, 2010). The results from conjoint analysis are based on self-reported data on consumer choices made from among a pre-selected list of product attributes. More recent studies have applied computational methods and machine learning to analyze product attributes discussed in the texts of consumer reviews (e.g., Decker & Trusov, 2010; Moon, Kim, & Bergey, 2019), using "the language of the consumer rather than that of product designers and manufacturers" (Lee & Bradlow, 2007). These computational studies also used a pre-defined list of attributes in their text mining processes. By contrast, our study automatically extracted latent textual features that affect review trustworthiness beyond the constraints of pre-selected attributes. This bottom-up approach has the advantage of identifying previously underexplored textual features (e.g., food and call complaints). From a practical perspective, uncovering these features is useful for pinpointing the aspects that should receive the industry's attention and for developing actionable strategies for improving products and services accordingly. Furthermore, this study endeavored to make theoretical sense of the extracted textual features by linking them to theoretical constructs, such as attribute salience and review valence, and validating the effects of the constructs with experimentation. By doing so, our study translated data-driven insights into meaningful theoretical propositions to contribute to the accumulation of academic knowledge.

This research employed a two-part mixed-methods design. Study 1 followed a bottom-up, inductive approach and used text mining and human rating methods to explore the salient textual features that impact consumers' perceptions of trustworthiness and the effect of trustworthiness on review adoption. Specifically, we selected a representative sample of hotel reviews ($N = 822$) from TripAdvisor following a systematic sampling method and invited participants to rate the trustworthiness of the reviews through an online crowdsourcing platform. Then we applied the text effect model developed by Fong and Grimmer (2016) to automatically extract the most important textual features in relation to trustworthiness. We identified room, food, and call complaints as the key factors that impact trustworthiness. In addition, we found that trustworthiness plays a moderating role such that the more trustworthy participants consider a particular review, the more likely they will adopt the review to aid in their decision-making.

Given that Study 1 was exploratory in nature and the findings on textual features were data-driven, we designed Study 2 to validate the findings from a theory-driven approach. We interpreted the textual features—room, food, and call complaints—by linking them to theoretical constructs. The literature indicates that room is the most frequently mentioned attribute in hotel reviews and that food is less important (Sánchez-Franco, Navarro-García, & Rondán-Cataluña, 2016; Sparks & Browning, 2011). This is understandable as the main function of hotels is providing accommodations. The results of Study 1 revealed that room played a more important role in influencing trustworthiness than food. Taking these findings into account, we hypothesized the differential role of room and food in decision-making stems from their discrepancy in attribute salience. Moreover, call complaints were negatively valenced, so the negative impact of call complaints on trustworthiness discovered in Study 1 could tentatively be explained by the positivity bias (Wu, 2013). Hence, we proposed attribute salience and review valence were the theoretical mechanisms underlying the effects of room, food and call complaints on trustworthiness. The literature also suggests that content concreteness is another factor that may play a role in the evaluation of review trustworthiness (Kronrod, Lee, &

Gordeliy, 2017; Sparks, Perkins, & Buckley, 2013); therefore, we also included this factor in Study 2 to provide a more complete account of the textual effects. We then conducted a 3 (attribute salience: low, medium, high) by 2 (review valence: positive vs. negative) by 2 (product category: hotel vs. restaurant) by 3 (message variation) mixed factorial experiment with content concreteness as a measured variable. The results showed the three constructs could explain about 50% variance in review trustworthiness for hotels and restaurants. This provides evidence of the robustness of the three theoretical constructs as explanations for Study 1 and demonstrates the feasibility of translating data-driven insights into theoretical knowledge and developing practically actionable guidelines from consumer-generated unstructured data.

2. Literature review

2.1. Textual features of online consumer reviews

Consumer reviews generally consist of quantitative and qualitative components. The former refers to numerical ratings (e.g., ranging from 1 star to 5 stars), while the latter refers to reviews submitted mainly in a text format. The bulk of the literature focuses on quantitative ratings and indicates that review ratings are significant predictors of actual purchases (Chua & Banerjee, 2016). The advantage of this approach is that it provides a clear-cut method to predict review effects based on numerical ratings, but it does not consider the impact of review text on consumer purchase decision-making (Packard & Berger, 2017). More importantly, review texts are found to have a stronger impact on review readers' evaluative responses than star ratings (De Pelsmacker, Dens, & Kolomiiets, 2018). Therefore, in the past few years, scholars have turned to exploring the effects of qualitative components above and beyond numerical ratings, particularly of textual features of online consumer reviews, employing various methods, including large-scale computational textual analysis tools. These studies took a top-down approach, with their investigations focusing on a number of pre-selected textual features, such as review sentiments (Agnihotri & Bhattacharya, 2016; Ludwig et al., 2013), linguistic styles (Folse, Porter, Godbole, & Reynolds, 2016; Packard & Berger, 2017), review readability (Agnihotri & Bhattacharya, 2016), and review depth or quality (Mudambi & Schuff, 2010; Willemsen, Neijens, Bronner, & De Ridder, 2011). The current study instead takes a bottom-up approach, which has the advantage of detecting textual features unnoticed in prior studies and expanding the scope of theory development.

Moreover, most prior research concentrated on textual effects on perceived helpfulness/usefulness (Agnihotri & Bhattacharya, 2016; Folse et al., 2016; Mudambi & Schuff, 2010; Willemsen et al., 2011) and purchase/recommendation intention (Packard & Berger, 2017), while giving less attention to review trustworthiness. Nevertheless, we can draw insights from another related stream of research that deals with how to detect fraudulent reviews based on textual features or linguistic styles, as perceived trustworthiness is critical to distinguishing between fraudulent and authentic reviews. For example, Yelp, a third-party review website, has its own algorithm to detect fraudulent or suspicious reviews and filter them out. Luca and Zervas (2016) analyzed a large corpus of filtered reviews and published reviews on Yelp, considered a proxy for fraudulent reviews and a proxy for authenticated reviews, respectively, and compared their language features. They suggested that fraudulent reviews tend to be more extreme than authenticated reviews, regardless of review valence. Using an experimental design, Kronrod et al. (2017) instructed participants to write reviews for a hotel stay that they had or had not actually experienced. They found that fictitious reviews generally used fewer verbs in the past tense, fewer unique words, and more abstract language due to the lack of actual experiences and concrete memories.

2.2. The role of trustworthiness

Message trustworthiness is defined as "the degree of confidence in the validity of the information in terms of objectivity and sincerity" (Reimer & Benkenstein, 2016, p. 5993). The extent to which readers deem the information trustworthy determines their willingness to use the information in their decision-making processes (Nabi & Hendriks, 2003). Compared with offline word-of-mouth that mainly circulates within social circles, the trustworthiness of online consumer reviews is difficult to assess due to the anonymity and lack of prior knowledge of the sources. Therefore, users usually base their judgments on various cognitive heuristics, which mainly fall into two categories: source and content cues (Machackova & Smahel, 2018; Pan & Chiou, 2011). Relevant source cues identified by previous research include reviewer characteristics, such as the number of friends a reviewer has (Lim & Van Der Heide, 2015) and a reviewer's review history (Agnihotri & Bhattacharya, 2016; Lim & Van Der Heide, 2015), as well as platform features (DeAndrea et al., 2018). The general assumption behind these findings is if review readers can verify that the review contributor is a real customer of the product with no connection to the merchant, they tend to believe that the review is trustworthy and truthful.

Nevertheless, additional studies have revealed that in online review settings, source characteristics play a less important role than the quality of the content (Willemsen et al., 2011). As noted, "credibility in e-WOM is not a characteristic inherent to the source per se but is rather an evaluation made by the receiver based on the quality of information provided by a reviewer" (Filieri, 2015, p. 1267). Given the paucity of quantitative investigations on this subject, Filieri (2016) adopted a grounded theory approach and conducted qualitative interviews with 38 review users of TripAdvisor. The study found that content characteristics, including review length, type of information, and type of detail, influence consumers' perceptions of message trustworthiness. More specifically, if a lengthy review provides factual information about product attributes and specific facts related to purchasing and experiencing a product that are relevant to review users, the review users are more likely to consider the review trustworthy.

The current study employed a mixed-methods approach that first inductively inferred salient textual features that affect review trustworthiness by mining a large corpus of review texts and then deductively tested the textual features in an experiment. These endeavors were intended to answer the following research question:

RQ1: What textual features of online consumer reviews affect consumers' perceptions of trustworthiness of the reviews?

Another stream of research has examined the persuasive impact of message trustworthiness in online consumer review settings. Some studies demonstrated that message trustworthiness has a linear positive association with attitude toward the product and with purchase intention (Filieri, 2016; Filieri, Alguezaui, & McLeay, 2015; Pan & Chiou, 2011; Sparks et al., 2013), indicating that higher levels of trustworthiness directly facilitate attitude formation in a positive light. Other studies suggested that trustworthiness moderates the effects of review features on review adoption (Reimer & Benkenstein, 2016). Specifically, positive reviews result in greater purchase intentions than negative appraisals only when consumers consider the reviews trustworthy. In contrast, lower perceived trustworthiness in the reviews reversed the effects, as consumers held skeptical attitudes toward the authenticity of the reviews, which activated reactance to the intended persuasion and caused a boomerang effect. In this situation, trustworthiness was a key factor that determined whether consumers adopted the review. Given the contradictory findings in the literature, a second research question was posed to investigate the role of trustworthiness in the online review setting, as follows:

RQ2: What is the role of review trustworthiness in relation to the adoption of online consumer reviews?

3. Study 1

3.1. Method

To evaluate the effect of textual features on the trustworthiness of the review text, the current study adopted a computational design introduced in Fong and Grimmer (2016). We recruited a group of raters to read randomly assigned hotel reviews, evaluate the trustworthiness of the reviews, and indicate their attitudes toward the hotels reviewed. We employed the text effect model in Fong and Grimmer (2016) to test the influence of the review text on trustworthiness. In addition, the role of trustworthiness to the adoption of the hotel review was assessed using multilevel models. Review adoption was measured by the correlation between the review writer's rating and the review reader's rating of the hotel. A high correlation indicates that the review reader accepts the view in the review and follows the recommendation.

3.1.1. Materials

We needed a sample of reviews to be evaluated by the study participants. We obtained the sample from TripAdvisor using the following steps. First, we selected the top 25 U.S. cities visited by overseas travelers according to a report by the U.S. Department of Commerce in 2017. Second, we developed a computer program to search the hotels on TripAdvisor using the 25 city names as the queries, and then recorded the first 10 pages of hotels from each city that the search produced. Third, for each hotel, we scraped and automatically recorded the first 20 pages of reviews, including the text comments and original ratings by online reviewers. The original ratings ranged from 1 to 5. Ultimately, we obtained 79,265 unique reviews.

Fourth, to select a diverse collection of reviews, we conducted a *K-Mean* clustering based on semantic similarities between the text of the reviews. We executed the procedure for the reviews separately at different rating levels. Our procedure was as follows. (1) We selected all review texts where the rating equaled j, where $j \in [1, 5]$. (2) We then converted the texts into a document-term matrix following standard text mining procedures, such as removing stop words and lemmatization. (3) We performed the *K-Mean* clustering algorithm based on the document-term matrix, as determined by the within group sum of squares. More specifically, we tried different numbers of clusters from $K = 2$ through $K = 15$ and calculated the within-cluster sum of squares for each K. The within-cluster sum of squares is a measure of the variability of the observations within each cluster. In general, a cluster that has a small sum of squares is more compact than a cluster that has a large sum of squares. To determine the optimal number of clusters, we selected the value of K at the "elbow"—the point after which the inertia begins to decrease in a linear fashion (Lantz, 2013). Following the procedure, we picked $K = 5$ as the optimal number of clusters for the subsequent analysis. (4) Finally, from each cluster we selected the top 40 review texts that were closest to the cluster center. In this way, we maximized the diversity of the selected texts in both rating and content variety. Theoretically, the total number of reviews should be 40 (top 40 reviews) $\times$ 5 (5 clusters) $\times$ 5 (rating 1–5) = 1000. Because some clusters had fewer than 40 reviews, we selected all the reviews in those clusters instead. We, thus, obtained 822 reviews to use in the experiment. We also removed the hotel names and indefinable terms to eliminate possible confusion.

3.1.2. Participants, procedure, and measures

The participants were recruited from Amazon Mechanical Turk (MTurk) in exchange for a small payment. In total, there were 5094 participants (female: 63%; Caucasian: 79%; average age: 35). Each participant evaluated 10 randomly assigned hotel reviews. Some of the evaluations were incomplete and therefore in the final tally we had 49,496 evaluations.

The random assignment was implemented through an online survey using Qualtrics. The participants read only one review at a time. Only the review text was displayed, and the original rating by the online reviewer was not presented to the participants. The participants then answered two questions that measured the trustworthiness of the review text ("On a scale from 0 to 10, how trustworthy do you think this review is?") and their attitudes toward the hotel ("On a scale from 0 to 10, how do you rate this hotel?"). The average trustworthiness score was 7.28 ($Mdn = 8$, $SD = 2.16$), and the average hotel rating from the participants was 5.30 ($Mdn = 5$, $SD = 2.54$). The correlation between these two variables is significant ($r = 0.21$, $p < .01$).

3.1.3. Data analysis

One of our goals was to discover the textual features and estimate their effect on the trustworthiness of the review. We used the text effect model developed by Fong and Grimmer (2016) to extract textual features in relation to participants' ratings of review trustworthiness. The model assumes that there are K (binary) latent textual features in the review texts that are predictive of trustworthiness. We tested whether the presence of a word in a review increased the trustworthiness and, thereby, detected the latent textual features based on the presence of a particular cluster of words.

We discovered latent text features using the supervised Indian Buffet Process (sIBP) and implemented the model in the "texteffect" package in R (Fong, 2019). First, we randomly divided the data, placing 70% in the training set and 30% in the test set. In the training set, we applied the sIBP to the review texts and trustworthiness. This enabled us to detect a few clusters of words, known as "topics" in topic models. These topics were the latent text features that may have influenced the trustworthiness of the review. The clusters of words were grouped automatically based on the document-term matrix and the trustworthiness of the review. Second, to avoid overfitting and p-hacking problems,[1] we followed the procedure suggested by Fong and Grimmer (2016); that is, once a model was found to properly fit the data in the training set, we used the model to infer the treatment effects in the test set. More specifically, we employed a regression model and calculated the confidence intervals of the coefficients using a bootstrapping approach. Bootstrap is a statistical method that estimates the parameters multiple times by random resampling with replacement from the original sample. "The bootstrap intervals are an order of magnitude more accurate than the standard intervals" (Efron, 1987, p. 171); the bootstrapping approach is the default setting in the "texteffect" package.

3.2. Results

3.2.1. Text treatment effect

Following the procedure described in 3.1.3, we inferred the latent textual features that increased trustworthiness based on the frequency of particular words and estimated the textual effects on trustworthiness with the text effect model (Fong, 2019). The analysis involved an iterative process. We tried multiple combinations of the model parameters and the number of textual features (i.e., K) and selected the best solution based on both the exclusiveness between the textual features (whether

[1] Overfitting is the circumstance in which a statistical model fits a dataset too well in the sense that the model is unnecessarily complicated and "contains more unknown parameters than can be justified by the data" (Everitt, 2006, p. 290). Overfitted models may extract some residual variance and, thereby, increase the fit of the model for a particular set of data but fail to be generalized to other data, which is problematic for future prediction (Burnham & Anderson, 2002). The practice of p-hacking involves trying out different statistical analyses and/or data eligibility specifications to seek significant results for a dataset (Head, Holman, Lanfear, Kahn, & Jennions, 2015); p-hacking may inflate the probability of the type I error and undermine the robustness of the research (Rytchkov & Zhong, 2020).

any two clusters of words differed significantly from one another) and the interpretability of the textual features (whether the cluster of words could be interpreted in a meaningful way). We finally arrived at a solution with five textual features.

Table 2 provides a summary of top words associated with each latent textual feature discovered from review texts and participants' evaluations of the trustworthiness of the reviews. The words in the second column of Table 2 are the top words most associated with the latent textual features. Higher association indicates a stronger effect such that the latent textual feature was associated with a higher frequency of a particular word.[2] Each latent textual feature was characterized by a cluster of top words that appeared frequently together. We then assigned a manual label to each textual feature based on the literal meaning of the top words associated with the feature, namely, food in hotel (food), miscellaneous (misc.), room condition (room), phone call complaints (call complaint), and check-in stories (check-in).

The text effect model estimated the average marginal component effects (AMCE) and their confidence intervals for each latent textual feature. The AMCE refers to the marginal effect of each underlying textual feature with other textual features being held constant. The estimated coefficients are summarized in Fig. 1. As shown, the descriptions of room condition had a positive effect on trustworthiness, as participants were more likely to trust reviews with descriptions of room conditions (e.g., bathroom). On the contrary, food descriptions (e.g., bread, sausage, and chicken) and expressing complaints had a negative effect on trustworthiness. The ratings by review writers and the ratings by review readers were closer to each other when the reviews contained a description of room conditions, whereas the gap was larger for reviews with food descriptions and call complaints.

3.2.2. Moderation of trustworthiness

Fig. 2 presents the association between the original ratings and the participants' ratings of the hotels. In this study, each participant rated multiple reviews, and each review was rated by multiple participants. Therefore, the ratings are correlated with the participants and review texts. We conducted a multilevel model by including random intercepts at both participant and review levels to retest the relationship between the original ratings and the participants' ratings with considerations of the intra-class correlations, with the results presented in Table 3. Model I indicates that the original ratings of the review texts were positively correlated with the participants' ratings. Model II suggests that the main effect of the original ratings was negatively associated with the participants' ratings when controlling for the interaction effect between original rating and trustworthiness. The significant interaction effect demonstrates that whether an online review influenced others' ratings depended on the perceived trustworthiness of the review. The more trustworthy the review, the stronger the positive correlation between the original ratings and the participants' ratings. The variance of the ratings across different participants (intra-class correlation coefficient—ICC across participants) was 18.5%, and the variance of the ratings across review texts (ICC across texts) was 15.8%. We noticed that the coefficients of original rating and trustworthiness became negative in Model II when the effect size of the interaction effect was larger than those of the main effects. In other words, the positive relationship between the original ratings and the participants' ratings was highly conditional.

Table 2
Top Ten Words for Five Discovered sIBP Treatments.

No.	Keywords	Manual label
1	bread, pool, house, resort, favorite, drive, sausage, chicken, politely, think	Food
2	inform, fact, double, fund, yell, reach, remainder, final, instead, deposit	Misc.
3	room, time, floor, one, bathroom, two, area, can, though, use	Room
4	call, tell, manager, speak, say, check, ask, situation, finally, call-back	Call complaint
5	one, hotel, room, make, offer, see, think, get, check-in, include	Check-in

In summary, Study 1 detected three significant textual features that influenced review trustworthiness: room, food, and call complaint. These textual features we identified are context specific such that they are either hotel attributes or descriptions of specific scenarios of hotel consumption. To enhance the generalizability of the feature commonalities of the review texts, we strove to infer general textual properties that may account for the treatment effects by linking them to theoretical concepts. Based on the patterns identified in Study 1, we hypothesized two possible explanations for the textual treatment effects. The first was attribute salience. Room condition, as a hotel attribute, may play a more important part in consumers' judgment formations of the trustworthiness of a particular review compared to food quality in hotel restaurants, as room condition is key to the quality of the staying experience with a hotel (Sánchez-Franco et al., 2016; Sparks & Browning, 2011). The second explanation was review valence. Reviews in the call complaint cluster were by nature negative since they involved calls in which consumer expressed their dissatisfaction toward the hotels, while reviews in the room and food clusters could be positive or negative. Hence, we proposed that attribute salience and review valence were the underlying mechanisms for the effects of room, food, and call complaint on trustworthiness, subject to further testing. In addition, content concreteness has been identified as a factor that plays a role in the evaluation of review trustworthiness (Kronrod et al., 2017; Sparks et al., 2013). Hotel reviews can be concrete and specific through detailed descriptions of a hotel's attribute(s) and the consumer's own experience; they can also be abstract and general in stating holistic evaluations of the hotel. Given that reviews in the room, food, and call complaint clusters varied in content concreteness, we also included this factor in Study 2 to provide a more complete picture of the textual effects. Moreover, Study 2 tested the three variables across two product categories—hotels and restaurants—to increase the generalizability of the findings.

4. Study 2

4.1. Attribute salience

Economic theory posits that "goods are valued for their utility-bearing attributes or characteristics" (Rosen, 1974, p. 34). When consumers evaluate a product and make relevant purchase decisions, they assess the attributes that the product possesses. These attributes may carry different weight in the evaluation formation and decision making (Kangale et al., 2016).

Online consumer reviews provide a valuable source of information regarding individual attributes of products. Scholars have begun to use large quantities of available review texts to estimate the effects of different product attributes in review texts on consumer choices (Archak, Ghose, & Ipeirotis, 2011; Kangale et al., 2016). The findings have mostly supported that consumers have different tastes in terms of ranking the importance of product features and that review texts containing product features that are important to consumers are more influential in predicting consumer choices and future sales. With regard to experiential goods, Dolnicar and Otter (2003) comprehensively reviewed hotel attributes that attracted the most academic attention and identified several categories, including hotel image (e.g., brand familiarity and star rating), general hotel features (e.g., price of accommodation and free local calls), room attributes (e.g., cleanliness and

[2] The value of the association is the mean parameter for the posterior distribution of phi, where phi is the effect of the topic on the count of word *w*. A larger value indicates that the topic is associated with a higher frequency of the word *w*.

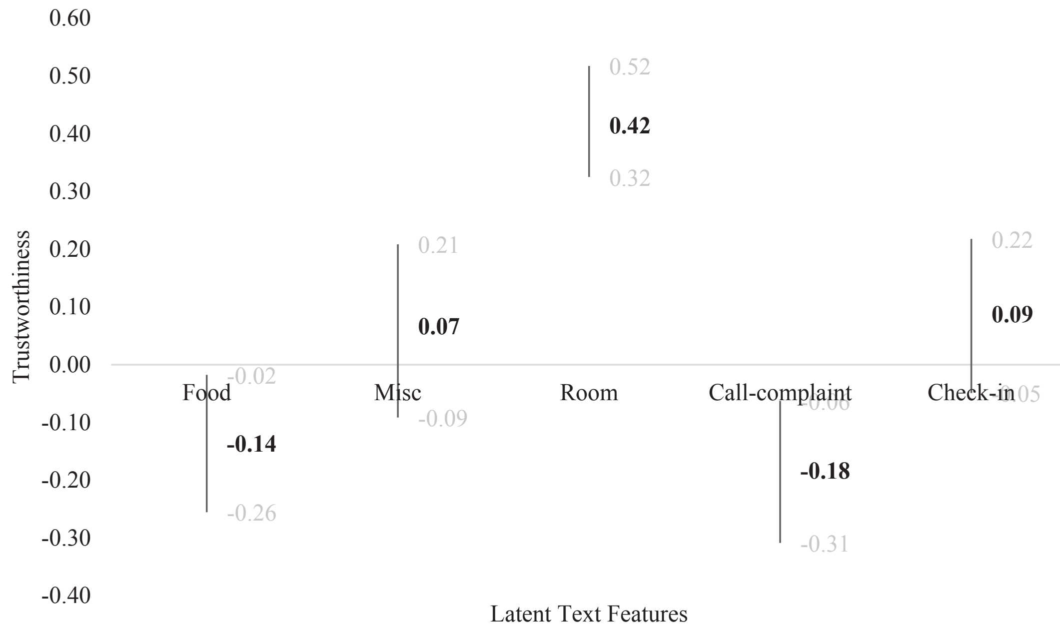

Fig. 1. The Effect of Review Text Features on Trustworthiness. The grey numbers indicate the 95% confidence intervals for effects of discovered treatments. The parameters are the average marginal component effects (AMCE) estimated using Fong and Grimmer (2016) text effect model.

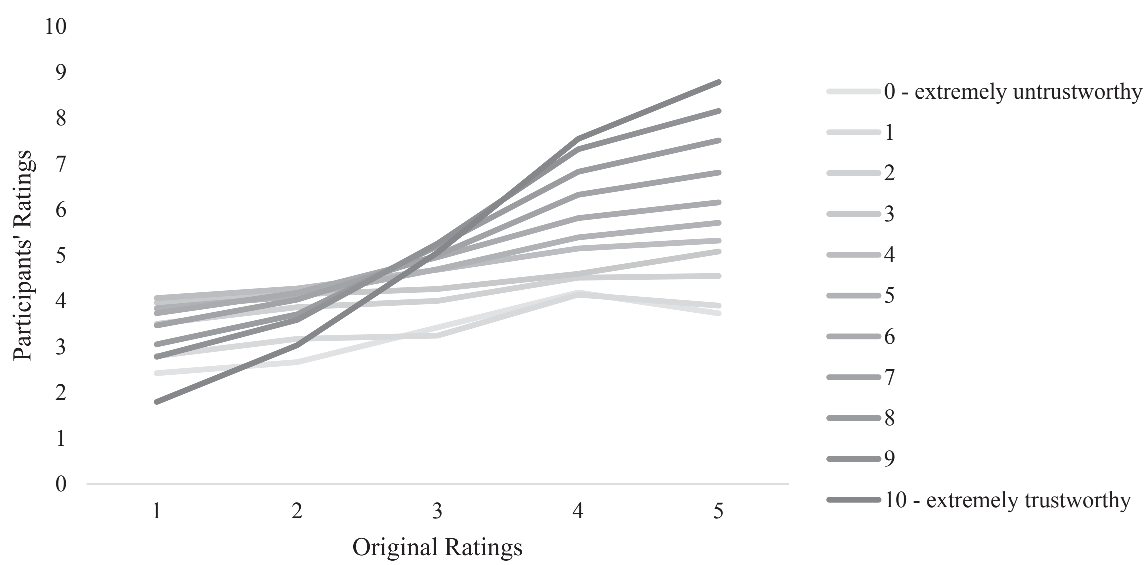

Fig. 2. The Moderation Effect of Trustworthiness on the Correlation Between Original Ratings in Text Reviews and Participants' Hotel Ratings.

comfort), location (e.g., convenient distance to airports and downtown areas), and services (e.g., check-in and -out times and bell service). Sánchez-Franco et al. (2016) analyzed 19,318 reviews for Spanish hotels from Booking.com and found that room was the most frequently mentioned attribute, followed by appearance (associated with staff). This indicates that consumer reviews about hotels mainly involve the core product function—room—as well as service quality with a particular focus on interactions with hotel staff (Sparks & Browning, 2011).

Based on the findings of Study 1, we predicted that the differences in review trustworthiness between the room and food clusters were caused by the differences in attribute salience, in that room is a more important attribute than food to hotel consumers. Therefore, we proposed a hypothesis for this investigation:

H1: Consumer reviews of product attributes of higher salience are considered more trustworthy by consumers than those of product attributes of lower salience.

4.2. Review valence

Review valence has been one of the most studied features of online consumer reviews in relation to review effectiveness (Maslowska et al., 2017). The negativity bias in psychology literature contends that when people evaluate positive versus negative information, they tend to value negative information more (Rozin & Royzman, 2001). In this sense, negative reviews should have a stronger effect on purchase decision-making compared to positive reviews (Chevalier & Mayzlin, 2006). Consistent with the negativity bias, studies have shown that negative consumer reviews are rated as more credible than positive reviews; skeptical consumers consider that negative reviews, which do not seem

Table 3
Multilevel Models Predicting Participants' Hotel Ratings.

	Model I		Model II	
	Estimate (*SE*)	*t* value	Estimate (*SE*)	*t* value
Original rating	1.08** (0.20)	53.23	−0.25** (0.26)	−9.65
Trustworthiness	0.14** (0.00)	32.16	−0.40** (0.01)	−49.26
Original rating × Trustworthiness			0.18** (0.00)	76.14
Intercept	0.93** (0.08)	12.22	4.76** (0.09)	54.18
Variance of intercepts				
Across users	0.71		0.65	
Across reviews	0.63		0.56	
Residual	2.61		2.33	
Marginal R^2	38.9%		44.5%	
Conditional R^2	59.6%		63.5%	
# of ratings	49,404			
# of participants	5094			
# of reviews	822			

Notes: ** indicates $p < .01$.

to be faked by merchants themselves, are truthful and trustworthy (Kusumasondjaja et al., 2012). However, Wu (2013) failed to find support for the negativity bias in three empirical studies using computational and experimental methods; in particular, an analysis of Amazon book reviews revealed that review valence was positively associated with review helpfulness, displaying a pattern of positivity bias. For the absence of a negativity bias, Wu explained that consumers' judgments of review helpfulness mainly depends on the quality of the information contained in the reviews rather than review valence. Moreover, a meta-analysis found that though review valence was not a significant predictor of review usefulness or attitude, the positivity degree in negative reviews (i.e., percentage of positive reviews in a negative review set) was positively related to usefulness and attitude (Purnawirawan, Eisend, De Pelsmacker, & Dens, 2015). In this vein, despite the importance of negative reviews that mitigate consumer skepticism, positive reviews actually influence the judgment formation. In light of the inconsistencies in the earlier studies, Ketelaar et al. (2015) suggested that whether positive or negative reviews have a greater weight in consumer decision-making is contingent upon individual differences in review readers, such as consumer expertise. More specifically, the negativity bias is evident in expert consumers, and novice consumers show a positivity bias. This discrepancy may be attributed to the differential goals of information processing: novice consumers are more motivated by a pre-commitment goal (e.g., making a purchase), and positive reviews are considered to have more diagnostic value, as they support the pre-commitment goal (Ahluwalia, 2002). Expert consumers, meanwhile, are more motivated by accuracy goals and tend to pay more attention to negative reviews to improve their knowledge repertoire.

Based on the above literature, we reached no consensus regarding the role of review valence in predicting trustworthiness. Study 1 found a positive association between review valence and message trustworthiness, indicating a positivity bias. Therefore, we posited a hypothesis to reexamine the effect of review valence on message trustworthiness:

H2: Positive reviews are considered more trustworthy than negative reviews.

4.3. Content concreteness

Content concreteness is a language feature pertaining to the degree to which specific details are provided in a narrative (Li, Huang, Tan, & Wei, 2013). In the context of online consumer reviews, concrete reviews supply specific, detailed descriptions of product attributes and/or the reviewers' own purchase and consumption experiences, while abstract reviews provide overall information and holistic evaluations of the products (Sparks et al., 2013).

From an information processing perspective, consumers find concrete information more useful and trustworthy than abstract information in aiding their decision-making (Herr, Kardes, & Kim, 1991; Li et al., 2013; Sparks et al., 2013). The reason may lie in "a kind of 'eyewitness' principle of the weighing of evidence, such that firsthand, sense-impression data is assigned greater validity and relevance simply because one gathered it oneself: 'I was there,' 'I saw it with my own eyes'" (Borgida & Nisbett, 1977, p. 269). In this view, concrete consumer reviews serve as evidence that the reviewers are authentic consumers of the products and the details given in the reviews are based on their actual experiences. Hence, this language feature has been used to detect fake reviews; researchers found that fake reviews contained significantly fewer concrete nouns and unique words, further corroborating the association between content concreteness and message trustworthiness (Kronrod et al., 2017). Therefore, considering the literature, we proposed content concreteness is another predictor of review trustworthiness. Accordingly, we formulated the following hypothesis:

H3: Content concreteness is positively associated with the trustworthiness of online reviews.

4.4. Method

Study 2 employed a 3 (attribute salience: low, medium, high) by 2 (review valence: positive vs. negative) by 2 (product category: hotel vs. restaurant) by 3 (message variation) mixed factorial design. Attribute salience, review valence, and message variation were between-subject factors, and product category was a within-subject factor. Three varied messages were used to represent each treatment level to enhance "the ability to generalize to message categories" (Thorson, Wicks, & Leshner, 2012, p. 119).[3] Moreover, two product categories—hotels and restaurants—were included to test whether the effects of the general textual features could be generalized to product categories other than hotels. In addition to the four manipulated factors, content concreteness was included as a measured variable in the experiment.

4.4.1. Materials

We conducted a pre-test to select appropriate hotel attributes that corresponded with the three levels of attribute salience: low, medium, and high. Participants ($N = 299$; 49% female; 79% Caucasian; age $M = 35$) were invited to list the five attributes that they consider most important when choosing a hotel/restaurant in the order of importance. Based on the results, the following were chosen for low, medium, and high salience, respectively: hotel gym, parking, and room for hotels, and method of payment, parking, and food for restaurants. Original reviews from TripAdvisor.com were selected as the experimental stimuli. Specifically, positive reviews selected had an original rating of 5, and negative reviews had an original rating of 1 to ensure the variance between the two levels. The selected reviews were modified wherever

[3] Message variation means that we employed three different messages to represent each treatment level. The three messages within each cell share common features in terms of the treatment variables and vary in features except for the treatment. If an experiment involving consumer responses to marketing messages includes only one message to represent each treatment level, "any conclusion that can be made about the effect of the manipulation must be constrained to that particular message" (Thorson et al., 2012, p. 119). By employing three messages for each treatment level, we can conclude that the experimental results were caused by the treatment, which refers to a particular type of message, rather than to a single message.

necessary so that each review only focused on one attribute and all reviews were approximately equal in length. Eighteen reviews were used for hotels and restaurants each. An example of a positive hotel review focusing on room condition was as follows: "The rooms were clean and spacious. Super comfy bed, huge bathroom with tub and stand up shower. Making plans to stay here again soon." Following is an example of a negative restaurant review focusing on method of payment: "They accepted payments in cash only, which is ridiculously inconvenient. The waitress suggested that I could walk two parking lots over to an ATM, which, of course, I was forced to do."

We created mock TripAdvisor webpages displaying the reviews as the experimental stimuli (provided in the Appendix). The names of the hotels were not disclosed on the pages, and we used the pseudo reviewer name "XXXYYY." The format of and all other information on the pages except review content were held constant across all conditions.

4.4.2. Procedure and measures

We recruited participants through MTurk and received 409 valid responses (52% female; 78% Caucasian; age $M = 36$). The participants were randomly assigned to one experimental condition in which they viewed one hotel review and one restaurant review and then indicated their responses regarding content concreteness, review trustworthiness, attitude toward the hotel/restaurant, and manipulation check questions. The order in which the hotel review and the restaurant review showed up was counterbalanced so that half the participants saw one hotel review first and the other half were exposed to one restaurant review first.

We measured the content concreteness of the review with one item: "On a scale of 0–10, how concrete do you think the content of this review is?" This bi-polar item was anchored by two opposite adjectives: abstract = 0 and concrete = 10 ($M = 7.12$, $Mdn = 7.00$, $SD = 2.10$). We assessed the review trustworthiness ($M = 7.27$, $Mdn = 7.00$, $SD = 1.89$) and attitude toward the hotel ($M = 5.51$, $Mdn = 6$, $SD = 2.42$) using the same items as in Study 1.

We then asked a series of follow-up questions for manipulation check. First, we asked the subjects to rate the valence of the displayed reviews. As expected, the subjects rated positive review comments significantly higher than negative comments ($M_{positive} = 6.79$, $M_{negative} = 4.38$, $F = 491.4$, $p < .01$). We measured attribute salience by asking the participants to rate the importance of each attribute on a 0–10 scale: "When you are deciding which hotel you should choose for your next stay, how important is the quality of the hotel room to you?" We then calculated attribute salience for a subject by dividing the rating score of an attribute (e.g., room) by the total rating scores given by that subject (e.g., rating for room + rating for parking + rating for gym = 8 + 3 + 5 = 16). Therefore, the indicator of attribute salience ranged from 0 to 1. As expected, when reviewing hotels, the manipulation was successful for three levels of attribute salience: high (room: $M = 0.47$), medium (parking: $M = 0.34$), and low (gym: $M = 0.23$; $p < .01$). For restaurants, however, the medium level of attribute salience (parking: $M = 0.28$) did not pass the manipulation check, while the participants considered food ($M = 0.44$) more important than method of payment ($M = 0.29$) when choosing restaurants. We, thus, included only two levels of attribute salience (high: food; low: method of payment) for restaurants in the analysis.

4.5. Results

We tested the impacts of attribute salience, review valence, and content concreteness on review trustworthiness using multiple regression models. Table 4 summarizes the results of the regression models for hotel reviews. Given that attribute salience had three levels—high (room), medium (parking), and low (gym)—it was coded as two dummy variables: room (room = 1, gym = 0) and parking (parking = 1, gym = 0) in the analysis. Model I only included the main effects of the three factors as predictors, and Model II added the interaction terms among the factors. The results reported here are mainly based on Model II. In terms of the main effects, attribute salience (room vs. gym) ($b = 1.40$, $SE = 0.61$, $p < .05$), review valence (positive vs. negative) ($b = 1.30$, $SE = 0.59$, $p < .05$), and content concreteness ($b = 0.78$, $SE = 0.06$, $p < .01$) were positively associated with review trustworthiness. In other words, positive, concrete reviews about room conditions were considered highly trustworthy, while negative, abstract reviews commenting on unimportant attributes such as the hotel gym were considered untrustworthy. No significant three-way interaction emerged among the three factors, but significant two-way interactions were observed between attribute salience and content concreteness ($b = -0.24$, $SE = 0.08$, $p < .01$) and between review valence and content concreteness ($b = -0.16$, $SE = 0.08$, $p < .05$). More specifically, the positive effect of content concreteness on review trustworthiness was smaller for reviews about room conditions than for reviews about the hotel gym; content concreteness had a weaker effect on review trustworthiness for positive reviews than for negative reviews. In other words, when reading negative reviews about unimportant attributes, consumers rely more on the extent of content concreteness to evaluate the reviews and whether they should trust the reviews.

Table 4
OLS Regression Models in Predicting Trustworthiness (Study 2: Hotel).

	Model I Coefficient (*SE*)	Model II Coefficient (*SE*)
Attribute salience		
Room vs. gym	−0.06 (0.13)	1.40 (0.61)*
Parking vs. gym	0.04 (0.13)	0.21 (0.69)
Review valence		
Positive vs. negative	0.22 (0.11)*	1.30 (0.59)*
Concreteness	0.64 (0.03)**	0.78 (0.06)**
Attribute salience × Review valence		
Room × Positive		−0.10 (0.87)
Parking × Positive		−0.42 (0.92)
Attribute salience × Concreteness		
Room × Concreteness		−0.24 (0.08)**
Parking × Concreteness		−0.01 (0.09)
Positive × Concreteness		−0.16 (0.08)*
Room × Positive × Concreteness		0.08 (0.12)
Parking × Positive × Concreteness		0.02 (0.12)
Intercept	2.61 (0.21)**	1.63 (0.42)**
Adjusted R^2	49%	51%

Notes: * indicates p < .05. ** indicates p < .01.
Model I:
$Trustworthiness_i = \beta_0 + \beta_1 Room_i + \beta_2 Parking_i + \beta_3 Positive_i + \beta_4 Concreteness_i + \varepsilon_i$
Model II:
$Trustworthiness_i = \beta_0 + \beta_1 Room_i + \beta_2 Parking_i + \beta_3 Positive_i + \beta_4 Concreteness_i + \beta_5 Room_i{*}Positive_i + \beta_6 Parking_i{*}Positive_i + \beta_7 Room_i{*}Concreteness_i + \beta_8 Parking_i{*}Concreteness_i + \beta_9 Positive_i{*}Concreteness_i + \beta_{10} Room_i{*}Positive_i{*}Concreteness_i + \beta_{11} Parking_i{*}Positive_i{*}Concreteness_i + \varepsilon_i$

It is worth noting that the difference in adjusted R^2 between Model I (49%) and Model II (51%) was 2%, which indicates that the addition of the interaction terms into the regression model increased the explanation power of the model by 2%. This suggests that the main effects of attribute salience, review valence, and content concreteness were strong predictors of review trustworthiness in that they accounted for about 50% of the variance, while the interaction terms added small incremental explanatory power. Considering these results, we decided to interpret the findings and discuss the implications mainly focusing on the main effects of the three textual features, which are of highly practical significance based on the large effect sizes.

Table 5 summarizes the results of the regression models predicting the trustworthiness of restaurant reviews. As indicated in Model II, which includes both the main effects and the interaction effects, review valence ($b = 1.78$, $SE = 0.64$, $p < .01$) and content concreteness ($b = 0.66$, $SE = 0.06$, $p < .05$) were positively associated with review trustworthiness. Moreover, significant two-way interactions were found between attribute salience and review valence ($b = -1.87$, $SE = 0.94$, $p < .05$) and between review valence and content concreteness ($b = -0.27$,

Table 5
OLS Regression Models in Predicting Trustworthiness (Study 2: Restaurant).

	Model ICoefficient (*SE*)	Model IICoefficient (*SE*)
Attribute salience		
Food vs. payment	−0.13 (0.14)	−0.10 (0.65)
Review valence		
Positive vs. negative	0.14 (0.12)	1.78 (0.64)**
Concreteness	0.59 (0.03)**	0.66 (0.06)**
Attribute salience × Review valence		
Food × Positive		−1.87 (0.94)*
Attribute salience × Concreteness		
Food × Concreteness		−0.04 (0.09)
Positive × Concreteness		−0.27 (0.09)**
Food × Positive × Concreteness		0.33 (0.13)*
Intercept	3.11 (0.26)**	2.69 (0.46)**
Adjusted R^2	45%	44%

Notes: * indicates p < .05. ** indicates p < .01.
Model I:
$Trustworthiness_i = \beta_0 + \beta_1 Food_i + \beta_2 Positive_i + \beta_3 Concreteness_i + \varepsilon_i$
Model II:
$Trustworthiness_i = \beta_0 + \beta_1 Food_i + \beta_2 Positive_i + \beta_3 Concreteness_i + \beta_4 Food_i{*}Positive_i + \beta_5 Food_i{*}Concreteness_i + \beta_6 Positive_i{*}Concreteness_i + \beta_7 Food_i{*}Positive_i{*}Concreteness_i + \varepsilon_i$

$SE = 0.09$, $p < .01$). A significant three-way interaction effect was observed among the three predictors ($b = 0.33$, $SE = 0.13$, $p < .05$). The inclusion of the interaction terms did not significantly increase the explanatory power of the model as indicated in the difference in adjusted R^2 between Model I (45%) and Model II (44%). Thus, for restaurant reviews, we interpreted the results mainly based on the significant main effects of review valence and content concreteness.

In summary, Study 2 investigated the role of attribute salience, review valence, and content concreteness in predicting review trustworthiness across two categories of experiential goods: hotels and restaurants. We found consistent evidence that positive reviews were considered more trustworthy than negative reviews and concrete reviews were considered more trustworthy than abstract reviews. Attribute salience was a significant factor for predicting the trustworthiness of hotel reviews but not for restaurant reviews.

5. Discussion

Combining computational and experimental methods, this research uncovered the effects of textual features on trustworthiness of online consumer reviews. By mining a large corpus of consumer reviews of hotels on TripAdvisor, Study 1 revealed that review trustworthiness had a moderating effect on review adoption in that highly trustworthy reviews were more likely to be adopted by consumers to aid in their decision-making; their attitudes toward the hotel were highly correlated with the attitudes expressed in trustworthy reviews, and the magnitude of the correlation became smaller for untrustworthy reviews. It also identified that consumer reviews about room condition had a positive impact on trustworthiness, whereas reviews on food and call complaints had negative effects. Based on these findings, we inferred two possible operative mechanisms that could explain these textual effects: attribute salience and review valence. Through an experiment, Study 2 confirmed the effects of the factors on trustworthiness in the context of hotel reviews and extended the investigation into restaurant reviews. Content concreteness was included in Study 2 as a control variable and was found to be a significant factor to trustworthiness. We discuss the implications of these findings in relation to theory and practice as follows.

5.1. Theoretical implications

This research revealed the textual features that influence consumers' perceptions of review trustworthiness, including attribute salience, review valence, and content concreteness. Attribute salience and review valence serve as the underlying mechanisms that explain why reviews on certain topics (e.g., room conditions) are more trustworthy than reviews on other topics (e.g., call complaints). When evaluating online hotel reviews, consumers tend to believe reviews pertaining to attributes that are important to consumer decision-making and, in turn, are more likely to adopt the reviews for judgement formation. Room attributes, representing the core product function of hotels, have been recognized as the most important category of hotel attributes and are predictive of consumer choices (Dolnicar & Otter, 2003; Sánchez-Franco et al., 2016; Sparks & Browning, 2011). The current research further explicates the indirect route of room attributes influencing the effectiveness of consumer reviews via trustworthiness. For restaurant reviews, however, attribute salience is not a significant predictor of review trustworthiness. One possible explanation is that the relationship between attribute salience and review trustworthiness is moderated by product category. It is likely that the interplay among antecedents of review trustworthiness is more complex than suggested by previous studies (e.g., Filieri, 2016; Moon et al., 2019). Future studies are recommended to follow this direction to further elucidate the role of various factors in impacting review trustworthiness.

In terms of review valence, this research finds robust evidence that positive reviews are considered more trustworthy than negative reviews. This is contradictory to the well-documented negativity bias in the literature (Chevalier & Mayzlin, 2006; Kusumasondjaja et al., 2012), indicating, instead, a reversed pattern—positivity bias in the context of online consumer reviews (Ketelaar et al., 2015; Purnawirawan et al., 2015; Wu, 2013). Therefore, although the negativity bias is a common cognitive tendency in information processing and decision-making (Rozin & Royzman, 2001), it may be attenuated or reversed under certain circumstances, such as when message receivers are new and need more information (Ketelaar et al., 2015; Zhang et al., 2010) or when the primary information processing goal is to assess the trustworthiness of the review, as indicated by this study. Nevertheless, different from Wu (2013) conclusion that "the negativity bias documented in the psychology literature may not be so applicable to the context of eWoM" (p. 978), we tend to believe that the effect of review valence is contingent on factors such as individual differences and information processing goals rather than on the eWoM scenario, given that empirical evidence of the negativity bias in this scenario also exists (Kusumasondjaja et al., 2012). In this sense, we suggest future research explore possible moderating factors of the negativity bias in the context of online consumer reviews to further contribute to this research stream.

Regarding content concreteness, the findings of this study in two product categories echo those of prior studies that revealed concrete reviews are more trustworthy than abstract reviews (Filieri, 2016; Herr et al., 1991; Li et al., 2013; Sparks et al., 2013). This indicates that the "eyewitness" principle plays a critical role in the assessment of review trustworthiness in that specific details on purchases and uses of the product can only be obtained through actual experiences (Borgida & Nisbett, 1977). Moreover, the effect of content concreteness on trustworthiness is contingent on attribute salience and review valence; content concreteness plays a more important role for negative reviews about unimportant attributes. The discovery of the interaction effect enhances our understanding of the role of content concreteness in consumer review effectiveness. In this vein, this study contributes to the literature on online consumer reviews by elucidating the role of certain textual features. However, opportunities exist for future studies to continue exploring other textual features that may play a role in information processing and decision-making.

5.2. Managerial implications

This work developed a computational method by which product attributes can be automatically extracted from large amounts of consumer reviews using a bottom-up approach. Prior research used either conjoint analyses through self-report surveys or text mining methods to study product features with a pre-selected list of product attributes (Chen et al., 2010; Decker & Trusov, 2010; Moon et al., 2019). This bottom-up approach is especially useful for identifying previously unreported textual features. From a managerial perspective, the new method can enhance the efficiency of handling vast volumes of textual data, pinpoint the attributes that are important to consumer decision-making, and develop actionable strategies accordingly.

Based on the findings, several suggestions can be made to improve e-commerce practices. Given the critical role of online reviews in aiding consumer decision-making, e-commerce websites should encourage consumers to post reviews after consumption, particularly about experiential goods. More importantly, e-commerce websites and hotels should develop effective mechanisms to detect fake reviews and help review users to evaluate the trustworthiness of reviews. Based on the findings of this research, we offer recommendations as follows. First, as previously mentioned, third-party review websites such as Yelp have started to filter out suspicious reviews using their own algorithms. To improve this practice, the e-commerce industry needs more guidance regarding the language features of fake or suspicious reviews. We suggest that reviews that contain fewer concrete nouns and unique words should be labeled as suspicious. Third-party review websites may develop filtering algorithms accordingly. Second, this research finds that positive reviews are considered more trustworthy than negative reviews and, thereby, play a more important role in consumer decision-making. However, it is common that consumers who are satisfied with the consumption are reluctant to write reviews; on the other hand, consumers who had bad consumption experiences are more prone to writing reviews to express their dissatisfaction. Therefore, both hotel websites and third-party review websites may consider providing incentives to encourage consumers to share their positive experiences. The incentives may be either tangible (e.g., lucky draw) or intangible (e.g., virtual badges). Third, the finding that positive reviews are more trustworthy than negative reviews also indicates that negative reviews might not have a detrimental effect on product sales, as consumers are less likely to adopt negative reviews for decision-making. E-commerce marketers, however, should still handle negative reviews carefully and mitigate the possible influences these reviews may exert. Fourth, hotel websites and third-party review websites should also provide guidelines to review writers regarding how to write effective reviews. In particular, they should encourage review writers to share more specific details about the products rather than providing an overall evaluation if they want their reviews to produce the intended effects. We suggest that review writers should write reviews about the product attributes that are important to consumer decision-making because these reviews are more likely to be trusted and, thereby, adopted to aid judgment formation. For instance, hotel websites and third-party review websites may suggest a review template to review writers that highlights certain hotel attributes, such as room condition, serving as a clear guide on what elements are expected to be included in a good review.

5.3. Limitations and suggestions for future research

Despite its substantial contributions, this study has several limitations that need to be addressed in future research. First, the underlying mechanisms of the detected textual effects were not fully explained by review valence and content concreteness, indicating that the existing theories insufficiently explain the phenomenon. Future studies need to explore additional explanations and mechanisms. Second, content concreteness in the present study was based on consumers' perceptions rather than specific language features that determine the level of concreteness. It is possible that individual differences exist in terms of understanding what comprises a concrete/abstract review. More research efforts are necessary to explore the antecedents of content concreteness, which would offer more actionable guidelines for e-commerce practitioners. It is recommended that future experimental studies manipulate two levels of content concreteness (abstract vs. concrete) rather than including this as a measured variable. Lastly, this study investigated the isolated effects of a single review. However, in a real-world scenario, it is common that consumer reviews show up in bundles along with numerical ratings. Future studies are encouraged to extend this research by examining the joint effects of multiple reviews or review texts and ratings.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2020.12.052.

References

Agnihotri, A., & Bhattacharya, S. (2016). Online review helpfulness: Role of qualitative factors. *Psychology & Marketing, 33*(11), 1006–1017. https://doi.org/10.1002/mar.20934.

Ahluwalia, R. (2002). How prevalent is the negativity effect in consumer environments? *Journal of Consumer Research, 29*(2), 270–279. https://doi.org/10.1086/341576.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science, 57*(8), 1485–1509. https://doi.org/10.1287/mnsc.1110.1370.

Borgida, E., & Nisbett, R. E. (1977). The differential impact of abstract vs. concrete information on decisions. *Journal of Applied Social Psychology, 7*(3), 258–271.

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodal inference* (2nd ed.). Springer-Verlag.

Chen, Y.-H., Hsu, I.-C., & Lin, C.-C. (2010). Website attributes that increase consumer purchase intention: A conjoint analysis. *Journal of Business Research, 63*(9–10), 1007–1014. https://doi.org/10.1016/j.jbusres.2009.01.023.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43*, 345–354, 10.1509%2Fjmkr.43.3.345.

Chua, A. Y., & Banerjee, S. (2016). Helpfulness of user-generated reviews as a function of review sentiment, product type and information quality. *Computers in Human Behavior, 54*, 547–554. https://doi.org/10.1016/j.chb.2015.08.057.

Decker, R., & Trusov, M. (2010). Estimating aggregate consumer preferences from online product reviews. *International Journal of Research in Marketing, 27*, 293–307. https://doi.org/10.1016/j.ijresmar.2010.09.001.

De Pelsmacker, P., Dens, N., & Kolomiiets, A. (2018). The impact of text valence, star rating and rated usefulness in online reviews. *International Journal of Advertising, 37*(3), 340–359. https://doi.org/10.1080/02650487.2018.1424792.

DeAndrea, D. C., Van Der Heide, B., Vendemia, M. A., & Vang, M. H. (2018). How people evaluate online reviews. *Communication Research, 45*(5), 719–736. https://doi.org/10.1177/0093650215573862.

Dolnicar, S., & Otter, T. (2003). Which hotel attributes matter? A review of previous and a framework for future research. In Proceedings of the 9th Annual Conference of the Asia Pacific Tourism Association (pp. 176-188). University of Technology Sydney.

Efron, B. (1987). Better bootstrap confidence intervals. *Journal of the American Statistical Association, 82*, 171–185.

Everitt, B. S. (2006). *The Cambridge dictionary of statistics* (3rd ed.). Cambridge University Press.

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research, 68*, 1261–1270. https://doi.org/10.1016/j.jbusres.2014.11.006.

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research, 58*, 46–64. https://doi.org/10.1016/j.annals.2015.12.019.

Filieri, R., Alguezaui, S., & McLeay, F. (2015). Why do travellers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management, 51*, 174–185. https://doi.org/10.1016/j.tourman.2015.05.007.

Folse, J. A. G., Porter, M., III, Godbole, M. B., & Reynolds, K. E. (2016). The effects of negatively valenced emotional expressions in online reviews on the reviewer, the review, and the product. *Psychology & Marketing, 33*(9), 747–760. https://doi.org/10.1002/mar.20914.

Fong, C. (2019). Texteffect: Discovering latent treatments in text corpora and estimating their causal effects. *R package version*, 3. https://CRAN.R-roject.org/package=texteffect.

Fong, C., & Grimmer, J. (2016, August). Discovery of treatments from text corpora. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Vol. 1: Long Papers, pp. 1600-1609).

Head, M. L., Holman, L., Lanfear, R., Kahn, A. T., & Jennions, M. D. (2015). The extent and consequences of p-hacking in science. PLOS Biology, e1002106. doi: 10.1371.journal.pbio.1002106.

Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research, 17*(4), 454–462. https://doi.org/10.1086/208570.

Kangale, A., Kumar, S. K., Naeem, M. A., Williams, M., & Tiwari, M. K. (2016). Mining consumer reviews to generate ratings of different product attributes while producing feature-based review-summary. *International Journal of System Science, 47*(13), 3272–3286. https://doi.org/10.1080/00207721.2015.1116640.

Ketelaar, P. E., Willemsen, L. M., Sleven, L., & Kerkhof, P. (2015). The good, the bad, and the expert: How consumer expertise affects review valence effects on purchase intentions in online product reviews. *Journal of Computer-Mediated Communication, 20*, 649–666. https://doi.org/10.1111/jcc4.12139.

Ketron, S. (2017). Investigating the effect of quality of grammar and mechanics (QGAM) in online reviews: The mediating role of reviewer credibility. *Journal of Business Research, 81*, 51–59. https://doi.org/10.1016/j.jbusreas.2017.08.008.

Kronrod, A., Lee, J. K., & Gordeliy, I. (2017). Detecting fictitious consumer reviews: A theory-driven approach combining automated text analysis and experimental design (Working Paper No. 17-124). Marketing Science Institute.

Kusumasondjaja, S., Shanka, T., & Marchegiani, C. (2012). Credibility of online reviews and initial trust: The roles of reviewer's identity and review valence. *Journal of Vacation Marketing, 18*(3), 185–195. https://doi.org/10.1177/1356766712449365.

Lantz, B. (2013). *Machine learning with R*. Packt Publishing Ltd.

Fortune. (2019). Fraudulent company reviews are flooding the Internet. Here's what firms can do. Retrieved from http://fortune.com/2019/01/23/online-company-ratings-manipulations/ Accessed September 10, 2019.

Lee, T. Y., & Bradlow, E. T. (2007). *Automatic construction of conjoint attributes and levels from online consumer reviews [Working paper]*. The Wharton School, University of Pennsylvania.

Li, M., Huang, L., Tan, C., & Wei, K. (2013). Helpfulness of online product reviews as seen by consumers: Source and content features. *International Journal of Electronic Commerce, 17*(4), 101–136.

Lim, Y. S., & Van Der Heide, B. (2015). Evaluating the wisdom of strangers: The perceived credibility of online consumer reviews on Yelp. *Journal of Computer-Mediated Communication, 20*, 67–82. https://doi.org/10.1111/jcc4.12093.

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science, 62*(12), 3412–3427. https://doi.org/10.1287/mnsc.2015.2304.

Ludwig, S., de Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing, 77*(1), 87–103, 10.1509%2Fjm.11.0560.

Machackova, H., & Smahel, D. (2018). The perceived importance of credibility cues for the assessment of the trustworthiness of online information by visitors of health-related websites: The role of individual factors. *Telematics & Informatics, 35*, 1534–1541. https://doi.org/10.1016/j.tele.2018.03.021.

Maslowska, E., Malthouse, E. C., & Bernritter, S. F. (2017). Too good to be true: The role of online reviews' features in probability to buy. *International Journal of Advertising, 36*(1), 142–163. https://doi.org/10.1080/02650487.2016.1195622.

Metzger, M. J., & Flanagin, A. J. (2013). Credibility and trust of information in online environments: The use of cognitive heuristics. *Journal of Pragmatics, 59*, 210–220. https://doi.org/10.1016/j.pragma.2013.07.012.

Moon, S., Kim, M.-Y., & Bergey, P. K. (2019). Estimating deception in consumer reviews based on extreme terms: Comparison analysis of open vs. closed hotel reservation platforms. *Journal of Business Research, 102*, 83–96. https://doi.org/10.1016/j.jbusres.2019.05.016.

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly, 34*(1), 185–200.

Nabi, R. L., & Hendriks, A. (2003). The persuasive effect of host and audience reaction shows in television talk shows. *Journal of Communication, 53*(3), 527–543.

Packard, G., & Berger, J. (2017). How language shapes word of mouth's impact. *Journal of Marketing Research, 54*(4), 572–588. https://doi.org/10.1509/jmr.15.0248.

Pan, L. Y., & Chiou, J. S. (2011). How much can you trust online information? Cues for perceived trustworthiness of consumer-generated online information. *Journal of Interactive Marketing, 25*, 67–74. https://doi.org/10.1016/j.intmar.2011.01.002.

Pew Research Center. (2016). Online shopping and e-commerce. Retrieved from https://www.pewinternet.org/2016/12/19/online-shopping-and-e-commerce/. Accessed on November 12, 2019.

Purnawirawan, N., Eisend, M., De Pelsmacker, P., & Dens, N. (2015). A meta-analytic investigation of the role of valence in online reviews. *Journal of Interactive Marketing, 31*, 17–27. https://doi.org/10.1016/j.intmar.2015.05.001.

Reimer, T., & Benkenstein, M. (2016). When good WOM hurts and bad WOM gains: The effect of untrustworthy online reviews. *Journal of Business Research, 69*, 5993–6001. https://doi.org/10.1016/j.jbusres.2016.05.014.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.

Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review, 5*, 296–320, 10.1207%2FS15327957PSPR0504_2.

Rytchkov, O., & Zhong, X. (2020). Information aggregation and p-hacking. *Management Science, 66*(4), 1605–1626. https://doi.org/10.1287/mnsc.2018.3259.

Sánchez-Franco, M., Navarro-García, A., & Rondán-Cataluña, F. J. (2016). Online customer service reviews in urban hotels: A data mining approach. *Psychology & Marketing, 33*(12), 1174–1186. https://doi.org/10.1002/mar.20955.

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management, 32*, 1310–1323. https://doi.org/10.1016/j.tourman.2010.12.011.

Sparks, B. A., Perkins, H. E., & Buckley, R. (2013). Online travel reviews as persuasive communication: The effects of content type, source, and certification logos on consumer behavior. *Tourism Management, 39*, 1–9. https://doi.org/10.1016/j.tourman.2013.03.007.

Thorson, E., Wicks, R., & Leshner, G. (2012). Experimental methodology in journalism and mass communication research. *Journalism & Mass Communication Quarterly, 89*(1), 112–124. https://doi.org/10.1177/1077699011430066.

Willemsen, L. M., Neijens, P. C., Bronner, F., & De Ridder, J. A. (2011). Highly recommended! The content characteristics and perceived usefulness of online consumer reviews. *Journal of Computer-Mediated Communication, 17*(1), 19–38. https://doi.org/10.1111/j.1083-6101.2011.01551.x.

The Wall Street Journal. (2019). How companies secretly boost their Glassdoor ratings. Retrieved from https://www.wsj.com/articles/companies-manipulate-glassdoor-by-inflating-rankings-and-pressuring-employees-11548171977?mod=trending_now_1 Accessed September 10, 2019.

Wu, P. F. (2013). In search of negativity bias: An empirical study of perceived helpfulness of online reviews. *Psychology & Marketing, 30*(11), 971–984. https://doi.org/10.1002/mar.20660.

Zhang, J. Q., Craciun, G., & Shin, D. (2010). When does electronic word-of-mouth matter? A study of consumer product reviews. *Journal of Business Research, 63*, 1336–1341. https://doi.org/10.1016/j.jbusres.2009.12.011.

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