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Does the review deserve more helpfulness when its title resembles the content? Locating helpful reviews by text mining

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ABSTRACT

Online review helpfulness has always sparked a heated discussion among academics and practitioners. Despite the fact that research has extensively examined the impacts of review title and content on perceptions of online review helpfulness, the underlying mechanism of how the similarities between a review' title and content may affect review helpfulness has been rarely explored. Based on mere exposure theory, a research model reflecting the influences of title-content similarity and sentiment consistency on review helpfulness was developed and empirically examined by using data collected from 127,547 product reviews on Amazon.com. The TF-IDF and the cosine of similarity were used for measuring the text similarity between review title and review content, and the Tobit model was used for regression analysis. The results showed that the title-content similarity positively affected review helpfulness. In addition, the positive effect of title-content similarity on review helpfulness is increased when the title-content sentiment consistency is high. The title sentiment also negatively moderates the impact of the title-content similarity on review helpfulness. The present research can help online retailers identify the most helpful reviews and, thus, reduce consumers' search costs as well as assist reviewers in contributing more valuable online reviews.

1. Introduction

Online reviews have become a prevalent information source in consumers' everyday online shopping lives (Eslami, Ghasemaghaei & Hassanein, 2018; Kim, Maslowska & Tamaddoni, 2019). Different from vendor-generated product information, online reviews can provide consumers with information on the first-hand experience of peer consumers and detailed product information, which has the potential to reduce the risk and uncertainty related to their purchase decisions (Eslami et al., 2018; Salehan & Dan, 2016). However, the overwhelming amount of online reviews may cause information overload (Malik & Hussain, 2018a; Sun, Han & Feng, 2019; Zhou & Guo, 2017). To deal with this problem, many online retailers offer consumers the opportunity to vote on whether comments were helpful or not, and organize displayed reviews in order of helpfulness. ' One limitation of this approach is the positive feedback loop (Wan, 2015), in which early reviews attract more online shoppers' attention when compared to the most recently submitted reviews. How to find useful online reviews while avoiding the problem of a positive feedback loop is a question that many online review managers ask.

A growing body of studies, therefore, have sought to understand what factors make a review helpful (Ren & Hong, 2019;

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Yang, Zhou, Yao, Chen & Wei, 2019). Knowing the key factors affecting review helpfulness, merchants can evaluate the helpfulness of online review prior before sharing them with consumers. Previous researches highlighted the impact of compiling digital (codified numerical) information of reviews on review helpfulness (Zhou & Shuiqing, 2019). For example, Wang, Wang and Yao (2019) suggested that review extremity and review length were factors that significantly affected online review helpfulness. Subsequently, some scholars evaluated factors related to online reviews' open-ended textual information, such as review readability (Fang, Ye, Kucukusta & Law, 2016; Wang et al., 2019 and review sentiment (Al-Smadi, Al-Ayyoub, Jararweh & Qawasmeh, 2019; Eslami et al., 2018; Nakayama & Wan, 2019; Ren & Hong, 2019). Even though online reviews include a title and content, most of the literature on online review has concentrated on content (Chua & Banerjee, 2017; Kim & Kang, 2018). Scholars are beginning to realize that simply investigatingcontents without considering title is insufficient for understanding review helpfulness. Among the literature that considers the role of the review title, the focus has been on sentiment (Salehan & Dan, 2016), length and informativeness (Chua & Banerjee, 2017). Salehan and Dan (2016) indicated that reviews with more positive sentiment in the title will receive more readers. Chua and Banerjee (2017) found that title length has a positive effect on review helpfulness. Moreover, title informativeness, which is measured by product aspects (i.e., the degree to which a title highlights product characteristics) and lexical density (i.e., the proportion of nouns in titles), has a positive impact on review helpfulness.

Although previous researches advanced our understanding of how consumers assess review helpfulness, the research treated reivew title and content independently. It may, therefore, overlook the potential effect of similarity between titles and content on perceived helpfulness (Chua & Banerjee, 2017). Specifically, the title of the review is a summary and abbreviation of the content of the review, which determines, to some extent, whether the consumer will read this review (Salehan & Dan, 2016). Therefore, the similarity between title and content may affect a review's perceived value. Using text mining techniques, the title and content were measured to explore whether similarity affects a consumer's perceived review helpfulness. Text similarity can only measure the similarity of two pieces of text, but cannot measure the author's writing style nor the attitudes expressed in the review. Therefore, we also considered the role of reviews' title sentiment and content sentiment. Sentiment is defined as "attitude, thought, or judgment prompted by feeling" (Siering, Muntermann & Rajagopalan, 2018, pp. 3). Previous researches on the textual information contained in reviews highlighted the importance of title sentiment and review content sentiment (Salehan & Dan, 2016). Thus, the present study investigated the following questions: (1) Does review title-content similarity affect review helpfulness? (2) What are the roles of a review's title sentiment, content sentiment, and title-content sentiment consistency in determining review helpfulness?

The present research contributes to the existing literature in following ways. Firstly, different from the previous studies that usually examined the impacts of review title and content on review helpfulness independently (Chua & Banerjee, 2017), the present study explored the influence of the similarities between review title and content on review helpfulness. Secondly, previous studies usually adopted a sentiment mining approach to predict the helpfulness of reviews, but the present study developed a research model that predicts the performance of reviews by combining text mining and sentiment mining methods. Finally, the present study examined the impacts of both review title-content similarity and sentiment consistency on review helpfulness and explored whether the influence of review title-content similarity on review helpfulness varied in different review sentiment contexts.

2. Literature review

2.1. Review helpfulness

Among the many features of online reviews, the helpfulness of a review is the most important. It, therefore, has received extensive attention from scholars (Malik & Hussain, 2018a). Review helpfulness is defined as consumers' perceived value of a review that describes the quality of a product or service in the process of purchase decision-making (Shengli & Fan, 2019; S. Zhou & Guo, 2017). A helpful review can provide great value to potential consumers by reducing their search costs (Eslami et al., 2018; Mudambi & Schuff, 2012). Mudambi and Schuff (2012) defined a helpful review as "a peer-generated product evaluation that facilitates the consumer's purchase decision process"(Mudambi & Schuff, 2012), pp. 186).

Previous literature identified many factors affecting a review's helpfulness (Li, Pham & Chuang, 2019; Ma, Xiang, Du & Fan, 2018). For instance, several studies indicated that review length positively affects reivew helpfulness(Eslami et al., 2018; Mudambi & Schuff, 2012; Salehan & Dan, 2016). Longer reviews contain more information related to the product and more details about the reviewers' experience, thus, consumers perceive them as more helpful (Wang et al., 2019). In addition, several studies investigated the effect of review rating on reivew helpfulness(Filieri, Raguseo & Vitari, 2018; Mudambi & Schuff, 2012; Salehan & Dan, 2016). They found that reviews with an extreme rating (positive or negative review) are perceived as more helpful than neutral review (Mudambi & Schuff, 2012). Recently, ground in social influence theory, Zhou and Guo (2017) indicated that the order of a review is negatively associated with review helpfulness. However, a common shortcoming of these studies is that there is no deeper mining and analysis of the review text. Subsequently, Siering et al. (2018) mined review text and found that both review content-related signals (i.e., review sentiment strength) and reviewer-related signals (i.e., reviewer ranking) affect the helpfulness of online reviews. More recently, Ren and Hong (2019) investigated the differential effects of three discrete emotions (sadness, fear, and anger) on review helpfulness. The results showed that sadness embedded in a review negatively affects review helpfulness while fear embedded in a review positively influences review helpfulness. Moreover, anger embedded in a review has a negative effect on review helpfulness, and this effect is greater for experience products than for search products. Leveraging two web-based experiments, Craciun and Moore (2019) investigated the effects of reviewer reputation, reviewer gender and content sentiment on review helpfulness and reviewer credibility. The results showed that when reviewer reputation cues are present, negative sentiment in the review will lower male reviewers' credibility and the helpfulness of their reviews, yet has no effect on female reviewers. When reputation cues are absent, negative sentiment in the review will lower female reviewers' credibility, yet has no effect on male reviewers. Sun et al. (2019) analyzed the effects of review informativeness on the helpfulness of a review for search products versus experience products and employed machine learning techniques to predict the classification performance based on their proposed model. The results showed the best classification threshold for search products is greater than for experience products. This is because, attributes for a search product are objective. It is easy for consumers to compare search product attributes and reach homogenous conclusions. As a result, consumers may rarely obtain new and useful insight from the review for search products. In contrast, experience product attributes are subjective, and the information in the reviews for experience products are more likely to be unique and valuable. Thus, compared to experience product reviews, search product reviews require a relatively large number of votes to be considered helpful.

Although online reviews mostly comprise both review titles and review content, early literature on review helpfulness rarely paid attention to the role of review titles. In recent years, scholars have investigated the effect of review titles on consumers' perceived review value. For instance, Salehan and Dan (2016) analyzed 2,616 reviews collected from Amazon.com and found that title sentiment negatively influenced review readership. Specially, the negative effect of title sentiment on review readership was larger for positive titles than neutral and negative ones. Chua and Banerjee (2017) analyzed 2,307 Amazon reviews and found that title lexical density positively affected reivew helpfulness. Moreover, the relationship between title lexical density and review helpfulness was positive for novice reviewers, yet non-significant for reputed reviewers. Interestingly, these two studies came to conflicting conclusions regarding the effect of title length on review helpfulness. Salehan and Dan (2016) found that title length was negatively correlated to review readership because longer titles demotivate consumers to read since reading them takes more time. Chua and Banerjee (2017) found the opposite result and speculated that short titles lack detail information. One reason for the conflicting results may be that these studies failed to consider the similarity between review title and review content. If the title of the review is similar to its content, could consumers perceive the review to be more helpful? Inspired by this question, we examined the impact of similarity between review title and review content on consumers' perceived review helpfulness. In addition, prior studies suggested that the objective sentiment embedded in review text affects consumers' attitudes toward reviews. Thus, to obtain a more accurate understanding of the effect of title-content similarity, we take sentiment-side difference into consideration by introducing sentiment-related moderators on the relationship between text similarity and review helpfulness.

2.2. The mere exposure theory

The mere exposure theory explains the phenomenon that "mere repeated exposure of the individual to a stimulus object enhances his attitude toward it" ((Zajonc, 1968), pp. 1). Zajonc (1968) suggested that there are four types of evidence that supports the theory: (1) the relationship between word frequency and affective connotation of words; (2) the impact of exposure frequency which is manipulated experimentally on the affective connotation of nonsense symbols and words; (3) the relationship between word frequency and their referents' attitude; and (4) the impact of exposure frequency which is manipulated experimentally on attitude.

According to this theory, mere repeated exposure of an object (more specifically, stimuli) will improve the perceiving individual's attitude toward it. The stimuli could be words, photographs, drawings and kinds of rating procedures such as liking ratings and preference judgments (Bornstein & D'agostino, 1992). As such, scholars have applied this theory in various research contexts including business intelligence, consumer psychology, and cognitive sciences (Hekkert, Thurgood & Whitfield, 2013; Kouchaki, Smith-Crowe, Brief & Sousa, 2013; Montoya, Horton, Vevea, Citkowicz & Lauber, 2017; Salimpoor, Zald, Zatorre, Dagher & McIntosh, 2015). For instance, Montoya et al. (2017) conducted an analysis of the impact of the mere exposure effect on recognition, familiarity, and liking and revealed that the relationship was characterized by an inverted-U shaped curve and a positive slope which were correlated with visual stimulation. In the context of the present study, when mere repeated exposure of the stimuli to a review reader occurs, the reader's attitude toward the stimuli will improve. In other words, consumers will regard a review as more helpful when they perceive that the title of a review is similar to its content. Following the extant literature, the present study applied the mere exposure theory in an online review context and explored the impacts of review title-content similarity on review helpfulness.

3. Research model and hypotheses

To answer the two questions mentioned above, we use the mere exposure effect theory as the theoretical foundation to derive our hypothesis. The first research objective of our study was to investigate the correlation between textual similarity and review helpfulness as means to detect the potential effect of the mere exposure on the consumers' perceived review value. Our second research objective was to explore whether sentiment characteristics (e.g., title sentiment and review sentiment) will strengthen or weaken this association. The third objective of this study was to extend and test the realtionship between similarity and review helpfulness by considering sentiment consistency between the title and the content of the review. Fig. 1 provides an overview of the proposed model. We first checked the direct effect of text similarity on review helpfulness. Then, weexamined the moderating effects of title sentiment, review sentiment and sentiment consistency on the relationship between text similarity and review helpfulness.

Online reviews are mostly composed of titles and contents, and these two separate textual components play different communicative roles (Chua & Banerjee, 2017). Review titles are written to attract consumers' attention and to offer succinct information to make a decent first impression (De Ascaniis & Gretzel, 2012). Review contents, however, are usually informative and reliable in order to provide a sufficient description of the product functionality including product feature descriptions (Dor, 2003). Both review title and content are utilized to present reviewers' opinions, feeling, and preference towards a particular product. Therefore, the texts of a review title and its content may be similar. Text similarity is introduced to capture the consistency of reivew title and content. We expected that the similarity of title and content will positively associate withperceived reivew helpfulness. According to mere

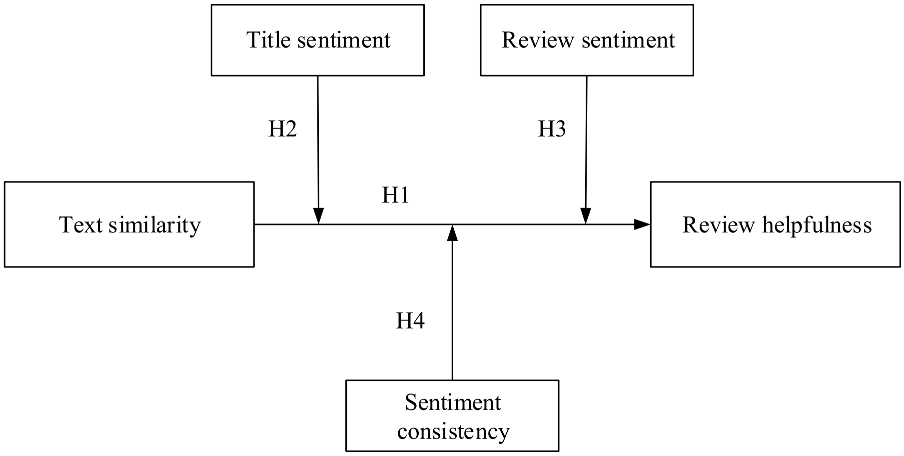

Fig. 1. The conceptual framework of the hypotheses.

exposure effect theory, the repeated exposure of a stimulus will improve the stimulated individual's attitude toward it (Bornstein & D'agostino, 1992). Thus, when review content that is similar to the title appears in the consumer's field of vision, the readers' preference for this review may increase. This increase in preference may be weakened or even disappeare when the title of the review is not similar to the content, since the premise of the mere exposure effect does not occur (Montoya et al., 2017). Hence, we propose that:

Hypothesis 1. The text similarity of title and content will positively affect review helpfulness.

The theory of selective attention suggests that individuals selectively respond to information since their information processing ability is limited (Treisman, 1969). This theory is also applicable to the field of online reviews (Salehan & Dan, 2016). The large number of reviews available online have made it difficult and time-consuming for consumers to identify helpful information (S. Zhou & Guo, 2017). Thus, consumers must pay selective attention to online reviews (Salehan & Dan, 2016). As such, the title of a review plays an important role in summarizing review content. Consumers can guess the content of a review by the title and then decide whether or not to read the review (Hu, Koh & Reddy, 2014). Prior researches have used hordes of experiments to prove the significant influence of title sentiment (Hu et al., 2014; Salehan & Dan, 2016). For example, Hu et al. (2014) proved that the sentiment of review title has a significant negative effect on product sales rank. Salehan and Dan (2016) found that reviews with more positive sentiment in the title will attract more readers. People are more likely to read reviews when the title sentiment of the review is positive. Thus, we predict that the sentiment of a title may weaken the positive relationship between text similarity and review helpfulness. Since consumers prefer reviews with positive title, they may be less affected by the similarity between title and content when there is a higher level of positive sentiment in the review title. Therefore, we hypothesize that:

Hypothesis 2. The positive impact of the text similarity on review helpfulness will be weaker when title sentiment is positive.

Reviews are generally comprised of a comprehensive review rating plus open-ended textual content (Eslami et al., 2018). While some researchers used the digital (numerical) information from review rating to predict review helpfulness (Raffaele Filieri, Raguseo & Vitari, 2019; Lee, Hu & Lu, 2018), other have utilized textual information extracted from content for this objective (Eslami et al., 2018; Malik & Hussain, 2018a; Shin, Chung, Xiang & Koo, 2019). To investigate the influence of textual information in reviews, some scholars have employed sentiment analysis techniques to calculate sentiment scores embodied in reviews (Eslami et al., 2018; Hu et al., 2014; Nakayama & Wan, 2019; Saumya, Singh & Dwivedi, 2019). The review sentiment score measures the extent to which a review is positive or negative (Mafael, 2019; X. Wang, Tang & Kim, 2019). Previous studies have suggested that negative reviews are more diagnostic and, therefore, more helpful than positive ones (Eslami et al., 2018; Hong, Xu, Wang & Fan, 2017). Moreover, the negativity bias theory also suggests that individuals are more likely to be concerned with negative cues than positive ones (Rozin & Royzman, 2001). According to the theory of the mere exposure effect, when an individual prefers the stimuli, the impact of mere repeated exposure will be strengthened. Thus, we hypothesize that:

Hypothesis 3. The positive impact of the text similarity on review helpfulness will be stronger when review sentiment is negative.

As mentioned above, we introduce text similarity to capture the text consistency of the title and content of a review. To further confirm the impact of the repeated exposure effect on the process by which consumers perceive the value of a review, we considered the consistency of title sentiment and review sentiment. Text content refers to the information the review provides while text sentiment reflects the review's style which is defined as reviewer's choice of words to convey the information (Salehan & Dan, 2016; Zhang & Lin, 2018). Text sentiment refers to the extent to which a text is positive, negative or neutral (Zhang & Lin, 2018; Zhou & Yang, 2019). A positive text contains a reviewer's positive feedback, while a negative text contains negativefeedback. Furthermore, a neutral text encompasses both positive and negative feedback (Eslami et al., 2018). According to the repeated exposure effect theory, we expected a positive relationship between title-content text similarity and review helpfulness, such that higher levels of title-content sentiment consistency strengthen review helpfulness. On the one hand, individuals tend to motivate themselves to have a consistent perception of an object (Abelson et al., 1968); therefore, consumers are more likely to achieve a consistent state of mind when title sentiment is consistent with content sentiment. On the other hand, one type of evidence supporting the repeated exposure effect theory is the relationship between word frequency and sentiment word connotation (Zajonc, 1968). Therefore, the premise of the repeated exposure effect will be more robust when considering sentiment consistency. Therefore, we hypothesize that:

Hypothesis 4. The positive impact of the text similarity on review helpfulness will be stronger when the sentiment of review title is consistent with that of review content.

4. Methodology

4.1. Data collection

Amazon.com was selected as the research context. To measure how consumers evaluate a review, Amazon.com asks “Was this review helpful to you?” after each review and shows helpfulness information alongside the review (“15 of 27 people found this review helpful”). In this case, 15 and 27 mean the number of helpful votes and the total votes of the review, respectively. For each review, we obtained review title text, review content, review rating, review date, the number of helpful votes, and the total votes of online reviews. Review helpfulness was calculated by dividing the number of helpful votes by the total votes (Mudambi & Schuff, 2012). Title length and review length were calculated by counting the number of words in the title and the content, respectively. The time distance (TimeD) was measured by the amount of days since the first review was posted for a given product. Title sentiment and review sentiment computation were performed by using TextBlob (Mundra, Dhingra, Kapur & Joshi, 2019), which has been proved to be an effective sentiment analysis tool (Gauba et al., 2017; Mundra et al., 2019). The TextBlob is a Python-based library for performing Natural Language Processing (NLP) functions, and provides a sentiment score for a text based on Naïve Bayes Analyzer (Gauba et al., 2017). The score that ranged from -1 to 1 is the quantitative evaluation for expressed text sentiment. The lower the value, the more negative the sentiment is. According to Han, Pei and Kamber (2011), the dissimilarity of objects characterized by numerical attributes can be measured by Manhattan distance. Therefore, we used $|TitleSentiment - ReviewSentiment|$ to represent the distance between title sentiment and review sentiment. Because both title sentiment and review sentiment range from -1 to 1, $|TitleSentiment - ReviewSentiment|$ are values ranged from 0 to 2. Therefore, we use the Minimum-Maximum (MM) normalization formula (Han et al., 2011) to map it to an interval [0,1], which is shown below. Finally, text similarity was calculated based on our proposed similarity measurement algorithm, which is detailed in the next section.

$$v_i{}' = \frac{v_i - min}{max - min}(new\_max - new\_min) + new\_min$$

The dataset used in the present study was collected from Amazon product data (He & McAuley, 2016), which includes 142.8 million reviews across 24 product types spanning a period of 18 years. The data collection period was from November 27 to November 29, 2018. We chose five representative product types that have been frequently studied by scholars: beauty, grocery, cell phone, clothing, and video (Malik & Hussain, 2018a, 2018b; Shen, Zhang, Yu & Min, 2019). As such, we obtained an original dataset contained 1054,652 reviews. Table 1 shows the composition of the dataset by product and provides some examples of reviews for each set of products. We deleted reviews with less than 10 votes since basing review helpfulness on a small number of votes may be unreliable and biased. Finally, our sample reminds 127,547 reviews. The summary statistics of the sample are presented in Table 2. The average review was positive, with an average review rating of 4.12. Moreover, the average text similarity was 0.18, indicating some reviews demonstrated similarities in title and content. Furthermore, there are relatively low correlations between the variables, indicating that multicollinearity was unlikely to confound our results.

4.2. Text similarity measurement

The similarity measurement of text is an important topic that has been widely studied in the fields of linguistics, psychology and information theory (Bär, Zesch & Gurevych, 2011; Mohammad, Jaradat, Mahmoud & Jararweh, 2017; Nanda et al., 2019). The Text

Table 1
The composition of the dataset and some examples of reviews.

Product types	Proportion	Examples
Beauty	23%	**Love Beauty Junkees Brushes!** This is the perfect brush for powder concealer or precision application of powder. The quality is amazing just like all beauty junkees brushes. Love it!
Grocery	17%	**Yummy** This is my favorite flavor of the Kashi chewy granola bars. It has just enough mocha flavor to make it extra tasty. If you like Kashi bars mocha and almonds you'll like these!
Cell phone	22%	**Great Phone** I purchased this phone a few months ago and can truly say it is one of the best investments I have ever made! I had doubts on how comfortable I'd be lugging around a big phone like this but that was short lived once it was in my hands.
Clothing	32%	**Nice skirt** Nice and puffy tutu skirt. I would recommend this for girls under 10 yr. old. It will be too short and small for older girls.
Video	6%	**Not my Cup of Tea** Watched only a few minutes of this pilot and didn't like any of what I saw. OK if you're into a lot of classical music I guess.

Table 2.
Descriptive statistics ($n = =127,547$).

Variables	Min	Max	Mean	SD	1	2	3	4	5	6	7	8
1.Helpfulness	0	1	0.32	0.43								
2.Similarity	0	1	0.18	0.14	0.02							
3.Rating	1	5	4.12	1.19	0.05	−0.02						
4.TimeD	0	4899	4413	466	0.00	0.01	0.01					
5.Title length	1	29	5.09	2.91	0.01	0.47	−0.04	−0.05				
6.Review length	1	2663	103	102	0.01	0.04	−0.02	−0.16	0.25			
7.Title sentiment	−1	1	0.29	0.39	0.11	0.03	0.36	0.01	0.01	−0.01		
8.Review sentiment	−1	1	0.21	0.19	0.03	0.01	0.37	0.05	−0.08	−0.18	0.23	
9.Sentiment consistency	0	1	0.84	0.12	−0.08	0.09	−0.11	−0.01	0.08	0.03	−0.37	−0.07

similarity measurement method treats text as a set of words (Mohammad et al., 2017). The frequencies of each word in a simple text and in the entire texts set (all occurrences) were calculated first, and then each text was transferred as a vector using the word frequency information. Finally, the cosine of similarity or Jaccard similarity between vectors was calculated to represent the similarity between texts (Gomaa & Fahmy, 2013). In the context of this study, we applied the Term Frequency Inverse Document Frequency (TF-IDF) to determine the relevance of the words in a text on the basis of the set of considered texts. As the term implies, TF-IDF calculates the value of each word in a document using an inverse proportion of word frequency in a specific document to the percentage of documents in which the word appears (Qaiser & Ali, 2018; Yahav, Shehory & Schwartz, 2019). The mathematical definition of the TF-IDF value of a word is as follows:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

$$idf_i = log\frac{|D|}{1 + |\{j: t_i \in d_j\}|}$$

$$TF - IDF_{i,j} = tf_{i,j} \times idf_i$$

Where $n_{i,j}$ is the appearing frequency of $word_i$ in document d_j. $\sum_k n_{k,j}$represents the sum of the frequency of all the words in document d_j. $|D|$ denotes the total amount of files in the corpus. $|\{j: t_i \in d_j\}|$ is the amount of the texts which contain the $word_i$.

This study performs the above analysis on each term in the text set to produce the TF-IDF value of each term in each text. Then we use the TF-IDF value of each term as their respective weights. As such, we mapped each document d to a feature vector of the vector space:

$$d = (t_1, w_1; t_2, w_2; \cdots; t_m, w_m)$$

Where t_i represents the feature item of the document content, and w_i denotes the weight corresponding to the feature item.

Finally, we used the cosine of similarity between vectors to represent the similarity between the title text and the content text of a review since it has been proven to be a robust metric for calculating the similarity between two strings (Tata & Patel, 2007). The mathematical definition of our title-content similarity is as follows:

$$TextSimilarity(d_k{}^{title}, d_k{}^{content}) = \frac{d_k{}^{title} \cdot d_k{}^{content}}{||d_k{}^{title}||\ ||d_k{}^{content}||}$$

Where $d_k{}^{title}$ represent the title text vector of document k, and $d_k{}^{content}$ denote the content text vector of document k.

4.3. Model specification

The potential selection problem and the censored nature of our sample suggest that the dependent variable is a limited variable (Siering et al., 2018). Thus, referring to Mudambi and Schuff (2012), the Tobit regression was applied in our study. A quadratic term of the rating was included to control a possible nonlinear relationship between review' rating and its helpfulness (Mudambi & Schuff, 2012; Zhu, Yin & He, 2014). Square of review ratings was calculated after mean-centering and was standardized to reduce the multicollinearity problem (Chang & Chuang, 2011; Chua & Banerjee, 2017). The resulting regression model is shown below:

$$Helpfulness = Constant + \alpha(TextSimilarity) + \beta(C) + \chi(M) + \delta(TextSimilarity \times M) + \varepsilon$$

in the above equation, Constant is the constant term; α, β, χ, and δ are the coefficient vectors correlated with the vector of variables; C represents a vector of control variables; M denotes a vector of moderating variables; ε indicates the idiosyncratic error.

Table 3.
Tobit regression results for review helpfulness.

	Model 1	Model 2	Model 3	Model 4	Model 5
Text similarity		0.04***	0.04***	0.04***	0.04***
Title sentiment			0.25***	0.25***	0.21***
Title sentiment × Text similarity			−0.04***	−0.04***	−0.03***
Review sentiment				−4.99E-03	−4.60E-03
Review sentiment × Text similarity				−2.54E-03	3.43E-04
Sentiment consistency					−0.09***
Sentiment consistency × Text similarity					0.04***
Rating	0.18***	0.18***	0.10***	0.10***	0.09***
Rating2	0.04***	0.04***	0.05***	0.05***	0.04***
TimeD	3.73E-04	−7.08E-04	−1.64E-03	−1.56E-03	−2.16E-03
Title length	0.02*	−0.01	−0.01	−0.01	−3.92E-03
Review length	0.01	0.01*	0.01*	0.01	0.01*
N	127,547	127,547	127,547	127,547	127,547
Mean VIF	1.73	1.71	1.57	1.52	1.49
Log likelihood	−119,776	−119,759	−119,101	−119,100	−119,002
Pseudo R^2	0.0017	0.0018	0.0073	0.0073	0.0081
P value χ^2	0.000	0.000	0.000	0.000	0.000

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

5. Data analysis and results

5.1. Hypotheses testing

In order to validate our hypotheses, we evaluated our proposed model through a statistical analysis software, Stata. Two underlying objectives were analyzed: a) the effect of title-content text similarity on review helpfulness; and b) whether title sentiment, review sentiment, and title-content sentiment consistency moderate the relationship between text similarity and review helpfulness, and if so, how. The estimation results of the proposed model are presented in Table 3. Model 1 is the base model that contains control variables only. Model 2 correlates with the main effect of the text similarity on the helpfulness of online reviews with other control variables. Model 3, 4, and 5 test the moderating effect of title sentiment, review sentiment, and sentiment consistency by adding the interaction terms of them with text similarity respectively. All variables were mean-centered and standardized to reduce the multicollinearity problem. Moreover, we checked the variance inflation factors (VIFs) for each model. Results show that the VIFs ranged from 1.03 to 2.95, indicating that multicollinearity problem is not serious.

Hypothesis 1 assumes that the text similarity of title and content positively affects review helpfulness. As shown in Model 2, the hypothesized path from text similarity to review helpfulness is significantly positive ($\beta = 0.04$, $p < 0.001$). Besides, this relationship remains stable when we add the moderating effect. Thus, Hypothesis 1 is strongly supported.

Hypothesis 2 proposes that the positive impact of the text similarity on review helpfulness will be weaker when title sentiment is positive. As shown in Model 3, the coefficient for the interaction between text similarity and title sentiment is significantly negative ($\beta = -0.04$, $p < 0.001$). Therefore, Hypothesis 2 is strongly supported.

Hypothesis 3 postulates the positive impact of the text similarity on review helpfulness will be stronger when review sentiment is negative. However, the results in Model 4 indicate that the coefficient for the interaction between text similarity and review sentiment is not significant ($\beta = -2.54\text{E-}03$, $p > 0.05$). Hence, Hypothesis 3 is not supported.

Hypothesis 4 predicts that the positive impact of the text similarity on review helpfulness will be stronger when the sentiment of a review title is consistent with that of review content. As shown in model 5, the coefficient for the interaction between text similarity and sentiment consistency is significantly positive ($\beta = 0.04$, $p < 0.001$). Therefore, Hypothesis 4 is strongly supported.

5.2. Robustness checking

Most preceding studies used Tobit regression (Korfiatis, García-Bariocanal & Sánchez-Alonso, 2012; Mudambi & Schuff, 2012) as model specifications, which we used as well in the above analysis. Here, we verify that our findings are robust to alternative model specifications. Considering the limited nature of our dependent variable, logistic regression was employed to retest our model. Logistic regression requires that the dependent variable is a dichotomous variable while the helpfulness of a review used in our study is a continuous variable which ranges from 0 to 1. Therefore, an appropriate helpfulness threshold value was selected first. For our experiments, 0.6 is chosen for the threshold value since its efficiency has been widely proven by prior studies (Krishnamoorthy, 2015; Malik & Hussain, 2017). This threshold value suggests that reviews with a helpfulness value greater than 0.6 are labeled as helpful reviews and vice versa. Table 4 reports the estimates of our proposed model using the logistic regression, which are almost identical to those from our original regression.

Table 4.
Robustness check results for alternative model specification.

	Tobit regression		Logistic regression	
Text similarity	0.04***	0.0075	0.04***	0.0070
Title sentiment	0.21***	0.0077	0.18***	0.0073
Title sentiment × Text similarity	−0.03***	0.0073	−0.02**	0.0070
Review sentiment	−4.60E-03	0.0072	−1.66E-03	0.0067
Review sentiment × Text similarity	3.43E-04	0.0061	−2.06E-03	0.0057
Sentiment consistency	−0.09***	0.0071	−0.10***	0.0068
Sentiment consistency × Text similarity	0.04***	0.0070	0.03***	0.0066
Rating	0.09***	0.0112	0.09***	0.0105
Rating2	0.04***	0.0067	0.04***	0.0064
TimeD	−2.16E-03	0.0065	−3.44E-03	0.0062
Title length	−3.92E-03	0.0076	0.01	0.0072
Review length	0.01*	0.0068	0.02**	0.0065
N	127,547		127,547	
Log likelihood	−119,002		−78,097	
Pseudo R^2	0.0081		0.0121	
P value χ^2	0.000		0.000	

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

6. Discussion

Based on the mere exposure theory, the present research investigates the impact of similarity between review title and content on online review helpfulness. Our study found that consumers perceive reviews with similar text in title and content as more helpful. This is consistent with the exposure effect theory, which suggests that the repeated appearance of an object will increase the degree of individual preference for it. This suggests that the more similar between a review title and content are, the more helpfulness of the review will be perceived to be. Our study, thus, applied the mere exposure theory in the context of online reviews and validated it as a useful theoretical foundation for explaining online reviews helpfulness.

In addition, this study also investigated how title sentiment and review sentiment affect consumers' assessment of review-shelpfulness. Our study found that title sentiment positively affects review helpfulness and negatively moderates the relationship between text similarity and review helpfulness. Indeed, according to the attribution theory, consumers are likely to attribute positive sentiment to the product but relate negative sentiment to the reviewer. Therefore, consumers are less likely to read reviews with negative titles since negative sentiment is attributed to the reviewer (Salehan & Dan, 2016). Conversely, a review will receive more attention from consumers if the reviewer expresses positive sentiment in the review title (Salehan & Dan, 2016). However, both the impact of review sentiment on review helpfulness and the moderating effect of review sentiment were not significant. These results may be explained by Elaboration Likelihood Model (ELM). ELM assumes that when consumers process information, they may choose to take a central or a peripheral route (Petty, Cacioppo & Schumann, 1983). The central route requires higher cognitive effort and is taken when readers are capable and willing to process information. The peripheral route requires less cognitive effort and is taken when readers are not capable or willing to process information (Angst & Agarwal, 2009; Filieri, Hofacker & Alguezaui, 2017; Petty et al., 1983; Salehan & Dan, 2016). The review content sentiment affects readers' perceptions via the peripheral route, which may be less effective than the central route (Salehan & Dan, 2016).

Finally, the present study also explored the impacts of the consistence of title sentiment and review sentiment on the relationship between text similarity and review helpfulness. Our study found that the positive relationship between title-content similarity and review helpfulness will be strengthened when the sentiments of title and content are consistent. This observation confirms that consumers will improve their attitude towards a review when a review's' title is similar to its content both in objective text and subjective sentiment. This further enhances the role of text similarity and sentiment consistency in forming perceptions of online review helpfulness.

6.1. Implications

6.1.1. Theoretical implications

The present study has several theoretical implications. Firstly, different from the extant studies which usually assumed that review title and content are independent of each other (Akbarabadi & Hosseini, 2018; Chua & Banerjee, 2017; Salehan & Dan, 2016), the present study found that title-content similarity positively affects review helpfulness. This result indicates that the similarity between review title and review content should be taken into consideration in explaining consumers' review evaluation behavior. Our study thus contributes to the online review literature by validating the positive influences of textual similarity on review helpfulness.

Secondly, previous studies usually adopted the mere exposure theory to explain consumer psychology behavior (Montoya et al., 2017). Our study applied the mere exposure theory in the online review environment and regarded a review's title and content as a repeated exposure of a stimulus object to review readers. The results of our empirical study validated the mere exposure theory as a useful theoretical foundation for explaining review helpfulness.

Finally, unlike extant studies which explained review helpfulness by mainly focusing on numerical and textual factors (Ham, Lee, Kim & Koo, 2019; Ren & Hong, 2019; Yang et al., 2019), our study examined the influences of both review title-content similarity and sentiment consistency on review helpfulness. The results of our study show that the repeated exposure effect is enhanced when review title and content are not only textually similar but also affectively consistent. Our study thus further validated the applicability of the mere exposure theory in the online review literature, paving the way for future studies.

6.1.2. Practical implications

This research yields several managerial implications. First, online vendors are encouraged to focus on the significant role of the text similarity between the review's' title and content. Specifically, according to our results, the greater the similarity between a review's' title and its content, the more helpful the review is perceived for consumers' purchase decision-making. Thus, online review aggregators (e.g., Amazon) could employ the text similarity calculation algorithm to screen reviews and then present the most helpful reviews to potential consumers.

Second, the present research also offers an effective method of employing sentiment analysis to predict online review helpfulness. Specifically, the positive effect of title-content similarity will strengthen when the sentiment of the title and the content is consistent. One important implication is that online review aggregators could locate helpful reviews through combining text similarity calculation algorithm and sentiment analysis techniques. Online vendors also can adopt sentiment analysis techniques to identify consumers' attitudes towards their products.

6.2. Limitations and future research

As with all empirical research, this study had some limitations. First, as is the case for many previous studies in the field of online review, the present research focused exclusively on a single online review platform (i.e., Amazon.com). While the findings may be applicable for other online review platforms, such as TripAdvisor.com, future studies are encouraged to retest our research model in different online review platforms. Second, previous studies have found that title-related and content-related characteristics have a significant impact on review readership (Chua & Banerjee, 2017; Salehan & Dan, 2016). Therefore, future researches are encouraged to explore whether reviews with similar text in the title and content will receive more readerships. Third, another limitation is the lack of language and cultural diversity reflected in the review sample. Our sample was collected from Amazon's US website, so all reviews were written in English. Our proposed text similarity algorithm may not apply to non-English text environments. Hence, future studies should investigate the effect of text similarity on online review helpfulness for reviews written in other languages. In addition, sentiment expressing is different in different cultures. For instance, Takahashi, Ohara, Antonucci and Akiyama (2002) indicated that people who live in collectivist cultures express negative sentiments less freely than those living in individualistic cultures. Future studies are encouraged to consider cultural differences when examining the effect of sentiment characteristics on review helpfulness. Fourth, this study did not consider possible irony reflected in the review text, which has received widespread attention from scholars examining online text (Reyes & Rosso, 2012; Reyes, Rosso & Buscaldi, 2012; Zhang, Zhang, Chan & Rosso, 2019). In fact, irony detection is also an important problem for sentiment analysis (Hernández-Farías, Benedí & Rosso, 2015; Reyes & Rosso, 2014; Reyes, Rosso & Veale, 2013). For example, Reyes and Rosso (2011) proposed an irony detection model to mine subjective information from customer reviews. Farías, Patti and Rosso (2016) casted detecting irony in tweets as a classification problem, and the results of classification experiments showed that affective information can help distinguish between ironic and non-ironic tweets. Hence, future research can combine irony detection with sentiment analysis and apply the results to predict review helpfulness.

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Supplementary materials

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