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The Impact of Online Review Content and Linguistic Style Matching on New Product Sales: The Moderating Role of Review Helpfulness

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ABSTRACT

This article investigates the moderating role of review helpfulness on the effects of online review content and linguistic style matching on new product sales. Using data from 105,494 online reviews from a popular website, IMDB.com, following 264 movie releases, the article shows that the impact of review style and content on new product sales is contingent upon review helpfulness. In particular, results suggest that linguistic style matching, positive emotion, and cognitive components of online review content significantly impact new product sales when the reviews are deemed helpful by the readers. These findings collectively suggest that online review research benefits from deeper textual analysis that includes review content and linguistic style compared to traditional methods that rely solely on numerical ratings. Also, review helpfulness plays a critical role in consumer decision-making considering a rapidly increasing amount of online information is now available to consumers. [Submitted: March 31, 2017. Revised: April 1, 2019. Accepted: April 3, 2019.]

Subject Areas: Linguistic Style Matching, LIWC, Online Review Content, and Review Helpfulness.

INTRODUCTION

As the Internet has become ubiquitous, consumers' use of peer-generated online reviews is becoming more prevalent than ever before as a part of the product information search, a key step in the consumer decision-making process (Wang, Guo, Zhang, Wei, & Chen, 2016). From a customer's decision-making perspective, online reviews enhance customer value and increase decision efficiency (Kozinets, De Valck, Wojnicki, & Wilner, 2010), and are considered to be more reliable and less biased than firm-generated product information (Brown, Broderick, & Lee,

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2007). From a firm's standpoint, online reviews are shown to boost online and offline sales (Chintagunta, Gopinath, & Venkataraman, 2010), product awareness (Liu, 2006), and word-of-mouth (Berger & Milkman, 2012). Therefore, as a ubiquitous, peer-to-peer, and mostly text-based communication tool, online reviews are vital for both consumer and firm decision-making, and therefore deserve greater scrutiny of their outcomes.

As online review generation has become mainstream, review websites have started to host a huge number of online reviews, which to an extent creates information overload for users. For instance, in *Amazon.com*, electronics and computer categories average more than 4,000 reviews per product, whereas the beauty products category averages around 400 (Anderson, 2015). Similarly, the books category averages several hundred reviews with some top-selling titles attracting thousands of reviews (Cao, Duan, & Gan, 2011). Therefore, the amount of online information available may be more than what consumers need and, thus lead to inefficiency in decision-making (Jones, Ravid, & Rafaeli, 2004). To help consumers overcome this information overload issue, websites now allow users to rate helpfulness of these reviews and share them with the readers.

Online reviews, therefore, communicate three types of information to the consumers, including a numerical rating, a text content, and a helpfulness rating of the review. Out of these three components, the majority of existing research on the effects of online reviews on consumer purchase behavior has predominantly focused on the effects of numerical review characteristics, which include volume (number of reviews posted), valence (numerical rating) and dispersion (variance in the product rating; e.g., Chen & Xie, 2008; Chintagunta et al., 2010; Liu, 2006). More recently, researchers have started focusing on understanding how the two inseparable components of text content, the review sentiment and the linguistic style (Huffaker, Swaab, & Diermeier, 2011), play a significant role in consumer decision-making (Gundecha & Liu, 2012; Ludwig et al., 2013). As recent studies suggest that consumers go beyond considering numerical ratings of the reviews and examine other review characteristics during the decision-making process (e.g., Hu, Koh, & Reddy, 2014), our understanding on the effects of the text content and helpfulness rating of reviews on consumer decision making (i.e., product sales) is limited. Therefore, to address this literature gap, we focus on two research questions: (i) How do review style and content affect new product sales? and (ii) How does review helpfulness moderate these effects?

In this article, we focus on the effects of online review content and style on new product sales in the motion picture industry. The review content refers to nouns, verbs, and adjectives that communicate emotions and logic; the linguistic style, however, refers to the use of function words such as pronouns (Tausczik & Pennebaker, 2010). In particular, this study examines the moderating role of review helpfulness on the link between content and style of online reviews and new product sales. We posit that because users are likely to undervalue, disregard, or completely miss online reviews deemed unhelpful, effects of reviews on consumers' decision-making will rely heavily upon review helpfulness. We use a dictionary-based, computerized text mining approach to analyze 105,494 online reviews from a popular website, *IMDB.com*, following 264 movie releases. Text analytics is pertinent to the purpose of this study because it allows us to uncover the conceptual content and linguistic style in unstructured textual data (Kulkarni, Apte, & Evangelopoulos, 2014). In addition, the motion picture industry provides an ideal context for this study because movies are experiential products, and thus inability to evaluate movies before purchase leads to heavy reliance on online reviews to make decisions (Chintagunta et al., 2010).

Our study attempts to contribute to the electronic word-of-mouth (eWOM) literature in three ways. First, drawing upon communication accommodation theory (Giles & Smith, 1979), we extend the previous work by studying linguistic style matching (LSM) in conjunction with textual content. Although social psychology research documents the role of content and style in the behavioral outcomes of written communication (Ireland & Pennebaker, 2010), eWOM literature presents a gap in this more comprehensive approach. Similar to the content, style of an online review or the use of function words, including pronouns, prepositions, articles, conjunctions, and auxiliary verbs, conveys meaning, and creates an impact on readers' behavioral reactions to the written communication. Second, most previous work on online reviews focuses on existing product sales and thus uses numerical measurement proxies. We attempt to address this gap by implementing a hierarchical linear model (Singer & Willet, 2003) to study the link between the change in deeper textual characteristics and the change in new product sales with a longitudinal perspective. Deep textual characteristics refer to affective and cognitive components used to communicate a user's positive and negative emotions as well as his or her logic. Third, we contribute to the extant eWOM theory by documenting how review helpfulness as a key variable interacts with review content and style, and leads to changes in new product sales.

The rest of the article is presented as follows. In the next section, we discuss the extant literature on eWOM, linguistic style matching and review helpfulness, and present the related hypotheses. The third section discusses the data and the methodology used to test the hypotheses. Finally, we offer a discussion of the results and a conclusion presenting the contributions, limitations, and future direction of the studies.

LITERATURE REVIEW

Electronic WOM refers to online product or service information generated by users not associated with a company (Brown et al., 2007; Godes et al., 2005). EWOM takes various forms, such as product reviews (Chen & Xie, 2008; Cheng & Ho, 2015; Zhu & Zhang, 2010), virtual communities (Guo, Pathak, & Cheng, 2015), blogs (Kozinets et al., 2010; Senecal & Nantel, 2004), and microblogs (Hennig-Thurau, Wiertz, & Feldhaus, 2015; Topaloglu, Dass, & Kumar, 2017). Extant research suggests that eWOM has a positive impact on both online (Chevalier & Mayzlin, 2006) and offline sales (Chintagunta et al., 2010; Liu, 2006; Srinivasan, Rutz, & Pauwels, 2016) because consumers find it to be more reliable than seller-controlled online information (Brown et al., 2007) and tend to access it right before making a purchase (Chen & Xie, 2008). EWOM also has an effect on product awareness (Liu, 2006) and subsequent eWOM (Berger & Milkman, 2012; Kozinets et al., 2010). EWOM becomes particularly important during new product introductions (Liu, 2006) because it influences firms' marketing communication strategy such that managers use online product reviews as complements or substitutes to seller-created product information (Chen & Xie, 2008). Further, product and consumer characteristics affect the relationship between online product reviews and sales (Zhu & Zhang, 2010). For instance, recommendations for experience products (i.e., movies) are significantly more influential than recommendations for search products (Liu, 2006; Senecal & Nantel, 2004).

Existing studies mostly use quantitative indicators of eWOM, including valence, dispersion, and volume (see Table 1). Valence, described as the degree of attraction or aversion expressed toward a product, may lead to both normative and informative consequences (Filieri, 2015). A positive or negative post can have "a persuasion effect," which leads to behavioral outcomes, whereas a neutral post can have "an informative effect" (Liu, 2006). Dispersion on the other hand, is defined as "the extent to which product-related conversations are taking place across a broad range of communities" (Godes & Mayzlin, 2004). Past studies investigating the behavioral outcomes of these different eWOM metrics present equivocal findings. Srinivasan et al. (2016) find a positive relationship between eWOM valence and sales. Chevalier and Mayzlin (2006) also demonstrate a causal relationship between numerical ratings and sales after a highly anticipated book release. In a similar vein, accounting for the sequential release of new products, Chintagunta et al. (2010) find that valence, not volume, drives sales. Some earlier works, however, find that volume (Duan, Gu, & Whinston, 2008; Liu, 2006) or dispersion (Godes & Mayzlin, 2004), not valence of eWOM, affects sales. One potential explanation for these findings is the undermined role of textual characteristics, including emotion or reason-based word choice and linguistic styles, in eWOM formation (Ludwig et al., 2013).

HYPOTHESES

Linguistic Style Matching

Recent advances in text analytics allow researchers to analyze large volumes of verbatim review data, which creates an opportunity to extend eWOM theory by investigating both review style and content (Gundecha & Liu, 2012). In any social interaction, individuals automatically mimic others' verbal and nonverbal behaviors (Ireland & Pennebaker, 2010). Nonverbal mimicry ranging from aligning postures to matching breathing patterns (LaFrance, 1985; McFarland, 2001) is a way to communicate emotions and attitudes (Ramanathan & McGill, 2007). Verbal mimicry, however, is evident in oral and written communication. Past research on verbal mimicry makes a clear distinction between language style and language content (Ireland & Pennebaker, 2010). Style and content of online reviews provide important decision inputs for users (Huffaker et al., 2011). Text content refers to regular nouns, verbs, or adjectives that communicate internal feelings or objective reasoning. However, because linguistic style permeates content, focusing solely on content is insufficient in text-based communication. Meaning is also conveyed through style or function words, including pronouns, prepositions, articles, conjunctions, and auxiliary verbs (Tausczik & Pennebaker, 2010). For instance, using a formal linguistic style compared to an informal style could lead to vastly

Table 1: Overview of major empirical studies in the literature.

Article	Key Variables					Context	Key Finding
	Online Review Characteristics				Sales		
	Numeric	*Sentiment*	*Linguistic Style*	*Helpfulness*			
Senecal & Nantel, 2004	√	✗	✗	✗	✗	Electronics	Online reviews are more influential than expert reviews in affecting product choice
Chevalier & Mayzlin, 2006	√	✗	✗	✗	✗	Books	Review ratings impact sales-ranking
Liu, 2006	√	√	✗	✗	√	Movies	Volume (not valence) of reviews predicts sales
Duan et al., 2008	√	✗	✗	✗	√	Movies	Valence (not volume) of reviews predicts sales after accounting for endogeneity
Chen & Xie, 2008	√	✗	✗	✗	✗	Electronics	Marketing strategy can be adjusted based on online reviews to increase sales
Zhu & Zhang, 2010	√	✗	✗	✗	√	Video Games	Reviews are less effective for popular games
Cao et al., 2011	√	√	✗	√	✗	Software	Semantic characteristics are more influential than others in affecting review helpfulness
Ludwig et al., 2013	√	√	√	✗	√	Books	Affective content and linguistic style affect sales
Hu et al., 2014	√	√	✗	√	√	Books	Ratings affect sales only through review sentiment
Srinivasan et al., 2016	√	√	✗	✗	√	FMCG	Traditional (not online) marketing is the main driver of sales
Gao et al., 2017	√	✗	✗	✗	✗	Physician Services	Low quality physicians are less likely to be rated online.
This article	√	√	√	√	√	Movies	Review helpfulness moderates the relationship between review characteristics and sales

different interpretation of the same sentiment. In an online setting, where there is a high level of author anonymity, LSM serves as a significant criterion to qualify the source of a message. Thus, the use of similar function words, irrespective of content, influences the message interpretation (Ireland & Pennebaker, 2010). In fact, based on communication accommodation theory (Giles & Smith, 1979), the level of matching between two conversations also leads to behavioral outcomes similar to sales or subsequent online reviews (Ireland & Pennebaker, 2010).

Relying on social psychology theories, communication accommodation theory posits that when interacting with others, people adjust their verbal and nonverbal communication (speech, voice, gestures, etc.) to accommodate social expectations for the conversation (Giles & Smith, 1979). This phenomenon is also valid in written communication. Writers' linguistic styles or use of function words either highlight or reduce the social distance between their readers and themselves (Giles, 2009). LSM is an automatic, trait-like individual difference. Interestingly, writers fail to adjust their degree of style matching even when they are instructed to do so (Ireland & Pennebaker, 2010). The well-known strength-of-the-weak-ties hypothesis purports that weak ties among distant social network members are more influential than the strong ties among close network members (Granovetter, 1973). As the linguistic style diverges from a social norm, readers perceive a diverse social identity. Therefore, when an online product review is written in a style different than what an online user is familiar with, the style itself, that is, the function word usage matching the social norm, irrespective of the content, will have an impact on the reader's evaluation and judgment (Pornpitakpan, 2004). Extending the strength-of-the-weak-ties framework to the eWOM context, Godes and Mayzlin (2004) find that when a broad range of communities generate eWOM, related TV show viewership increases because weak ties across dissimilar communities enable effective and result-oriented information to spread. In other words, the social structure has an impact on the way eWOM is interpreted. Further, past studies find a strong relationship between review content variance and new product sales (Duan et al., 2008). Moviegoers prefer different and diverse information when they make a decision to watch a movie (Phillips, Mannix, Neale, & Gruenfeld, 2004). Therefore, we propose that low LSM, which suggests that online reviews are generated by users from diverse communities, is likely to have a positive impact on new product sales.

H 1: *Low LSM in online reviews will have a positive impact on new product sales.*

The Role of Content

The dual processing theories in the social psychology literature suggest that there are two distinct processes in human cognition that influence consumer attitudes (Chaiken & Trope, 1999). One is a fast and associative information processing based on low-effort heuristics, and the other is a slow rule-based processing based on high-effort systematic reasoning (Cheng & Ho, 2015). On the one hand, valence and arousal of consumer emotions directly influence attitudes (Clore & Storbeck, 2006). For example, altruism, self-enhancement, and reciprocity initiate positive WOM; in contrast, anxiety reduction and vengeance trigger negative WOM (Berger & Milkman, 2012). Similarly, positive affective cues in a website lead to positive behavioral intentions (Li, Browne, & Chau, 2006). On the other hand, a distinct, deliberate, and conscious cognitive process also influences attitude formation (Chaiken & Trope, 1999). Online reviewers diligently considering the true merits of a product and its objective attributes go through a detailed cognitive processing before generating a review. These affective and cognitive processes work together to shape online consumer attitudes (Massey, Khatri, & Montoya-Weiss, 2007; Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2015). Generating an online review about a new product is an expression of such attitudes, and the mental process that users go through when creating it is reflected in their linguistic styles as well as the cognitive and affective cues woven in the content of their message. Using text analytics facilitates capturing positive and negative tone and cognitive content of online reviews, and determining how these cues affect purchasing behavior. It is expected that a text with meager affective and cognitive content does not have the desired impact on behavioral outcomes.

Prior research shows that both emotion-based and reason-based expressions in online reviews trigger similar processes in readers' cognition and lead to behavioral outcomes (Pappas et al., 2015). While firms want customers to disseminate positive or at least neutral information, negative information tends to travel faster (Godes et al., 2005) and is found more credible (Chevalier & Mayzlin, 2006). Negative evaluators are seen as more intelligent and competent than positive ones (Hennig-Thurau et al., 2015), and strongly opinionated information tends to be more viral than neutral information (Berger & Milkman, 2012). Further, Srinivasan et al. (2016)) find that in Facebook posts, the affective component measured in positive and negative dimensions as well as the cognitive component separately impact online sales. Therefore, we conclude that positive and negative sentiments in online reviews should have an impact on new product sales. It is the richness of an online content, its affective and cognitive substance, which creates an impact on purchase behavior. We propose that:

H 2A: *Positive affective content of online reviews will have a positive impact on new product sales.*

H 2B: *Negative affective content of online reviews will have a negative impact on new product sales.*

H 2C: *Cognitive content in online reviews will have a positive impact on new product sales.*

Review Helpfulness

Online information search behavior is a fundamental research stream in the e-commerce literature (Boyer & Hult, 2005; Wang et al., 2016). How web-based information is presented impacts information overload, decision-making, and information usability (Oztekin, 2011; Speier, Vessey, & Valacich, 2003). Users utilize low-effort heuristics or decision-making cues when there are too many options to choose from (Chakravarti, Janiszewski, & Ülkümen, 2006) or the involvement with the choice decision is low (Chaiken & Trope, 1999). Although online reviews contribute to the efficiency of consumer decision-making, large volumes of available online reviews create information overload for consumers (Cao et al., 2011). Product categories, such as books, DVDs, or electronics, average several hundred reviews per product in popular online retailers (Cao et al., 2011), and this trend is projected to grow (Kulkarni et al., 2014). For online retailers, review helpfulness emerges as an attempt to provide value to online users and reduce their cognitive overload. A helpful online review is defined as "a peer-generated product evaluation that facilitates the consumer's purchase decision process" (Mudambi & Schuff, 2010). Therefore, online users are likely to use review helpfulness as a simple decision-making cue.

Review extremity, review depth, and product type affect the perceived helpfulness of online reviews (Mudambi & Schuff, 2010). An online review produced by an expert reviewer makes readers feel that the review is more useful (Cheng & Ho, 2015) and influential (Zhu & Zhang, 2010), and the website is more trustworthy (Fuller, Serva, & Benamati, 2007). Prior research finds that the reviews considered helpful have a stronger impact on book sales than the other reviews do (Chen & Xie, 2008). Helpfulness ratings not only work as a decision-making cue but also help in increasing a review's exposure as websites often rank reviews based on their helpfulness ratings. The majority of users may not even see most reviews with low helpfulness ratings. Therefore, review helpfulness plays a highly critical role in online retailing and has the potential to increase the effects of review style and content on new product sales. Therefore, we propose that:

H 3: *Positive impact of low LSM on new product sales will accentuate when review helpfulness is high.*

H 4A: *Positive impact of positive affective content on new product sales will accentuate when review helpfulness is high.*

H 4B: *Negative impact of negative affective content on new product sales will accentuate when review helpfulness is high.*

H 4C: *Positive impact of cognitive content on new product sales will accentuate when review helpfulness is high.*

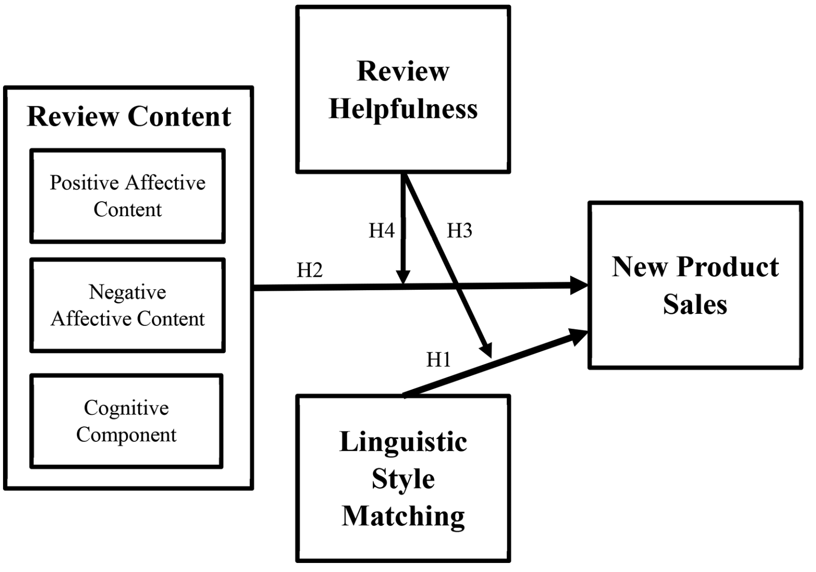
The research framework of our study is presented in Figure 1.

METHOD

Data

This section details our sample, sources, and procedure for data collection. We collect data on 760,175 online reviews from 876 movies during the period June 2005 to December 2009 from IMDB. Apart from the reviews, we also collect information such as the total revenue, budget, launch date, distribution, rating, genre, and award nominations for each movie. Following previous research (Liu, 2006), we use production budget as a proxy for advertising budget, which typically amounts to 50% of the movie production budget (Vogel, 2001, p. 96). We use the genre description from Yahoo! Movies (*Sci-Fi, Thriller, Children, Romance, Comedy, Action, Drama*) and three MPAA ratings (*PG*, *R*, and others). For each review, we extract the date, star rating, total number of views of the review, and number of viewers identifying it as a helpful review.

Figure 1: Research framework of this study.



Below, we explain the specific problems we encountered and the rules we used to resolve them. First, we exclude movies launched before the start of the sample period or in theaters for fewer than 8 weeks (Eliashberg & Shugan, 1997). Second, we exclude movies for which consumer reviews are not available from the day of launch. Third, we exclude movies if information on any of the following characteristics is not available: revenue, budget, launch date, distribution, rating, genre, and award nominations. And finally, we exclude movies if we did not have the helpfulness score. Based on these rules, our final sample reduces to 105,494 reviews from 264 movies.

Dependent Variable

The dependent variable of our study is box office sales. We performed univariate analysis of the variable and found it to be not normally distributed. Therefore, we performed a log transformation of the variable, and use it as the dependent variable in this study.

Text Mining of Reviews

One of the goals of this article is to investigate how the review content and language style affect the sales of new products. Therefore, we use natural language processing tools to text mine online reviews. Our text mining objective faces two challenges. First, movie reviews consist of unstructured semantic analysis of movies. They are written by movie viewers who are expressing their views without following any predetermined specific writing format. This calls for a text mining tool that has a broad data dictionary to uncover the underlying emotions and cognitions of the reviewers. Second, the level of domain knowledge varies across the reviewers. Therefore, it is possible that reviewers have different writing styles while posting their comments. Given these two challenges in our context, we decided to use a text mining software called the Linguistic Inquiry and Word Count (LIWC, 2007 edition) to uncover emotions, cognitions, and linguistic styles in the reviews (Pennebaker, Francis, & Booth, 2001). LIWC uses a broad dictionary of more than 4,500 words to determine 22 standard linguistic dimensions and 32 psychological constructs (Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007), and therefore is suitable enough to explore the movie reviews. The dictionary includes 116 words for its pronoun category (e.g., I, them, itself), which we used to measure linguistic style matching. Nine hundred and fifteen words are classified under the affect category, including regular words (e.g., amazing, disappointing), misspellings, and internet slang (e.g., LOL, ROFL). Out of these affective words, 406 are positive emotion words (e.g., love, nice, sweet), and 499 are negative emotion words (e.g., hurt, ugly, nasty). Similarly, the dictionary has around 730 words for cognitive components such as need, consequence, cause, know, etc. The software reads each review one word at a time. As each word is processed, the dictionary file is searched; if there is a match, the word category score, which is found by dividing the number of matching target words by the number of total words in a review, is incremented. The internal reliability of the subcategories used in our research are shown to be sufficiently high ($\alpha \leq 0.91$; Pennebaker et al., 2007).

The initial purpose of the LIWC system was to identify a group of words that tapped basic affective and cognitive dimensions (Pennebaker et al., 2007). The number of word categories, however, has expanded over time. While developing these categories, researchers have first generated sets of words. For example, the emotion or affective sub-dictionaries were based on words from several sources, including common emotion rating scales, such as the PANAS (Watson, Clark, & Tellegen, 1988), Roget's Thesaurus, and standard English dictionaries. This process was followed by extensive brainstorming sessions. One of the first validity tests of the LIWC scales was conducted by Pennebaker and Francis (1996), who found that LIWC successfully measures positive emotions, negative emotions, and cognitive elements. The validity of LIWC dictionaries has been confirmed in more than 100 studies including textual analyses of online reviews (Goes, Lin, & Au Yeung, 2014), blogs (Cohn, Mehl, & Pennebaker, 2004), social media sentiment (Topaloglu et al., 2017), newspaper articles (Humphreys, 2010), and instant messaging (Slatcher & Pennebaker, 2006). In particular, researchers use LIWC to generate scores for affective and cognitive states based on the count and usage of preselected words. Goes et al. (2014)), for instance, utilize LIWC to extract positive and negative sentiments from online reviews and explore the relationship between the number of viewers and review objectivity.

We measured helpfulness as the sum total number of viewers who rated a review helpful. As the helpfulness information on the websites are given as "15 out of 30 people found this review helpful," we did consider helpfulness as a ratio between the two numbers, that is, 15/30 = 0.50. However, we realized that the ratios are in percentages, and therefore bear limited meaning. For example, our model would have considered "15 out of 30" to have the same level of helpfulness as "5 out of 10." Furthermore, as we are studying the level of helpfulness, it made more sense to use total number of viewers who rated a review helpful as our score, and not just the ratio. Because the helpfulness depends on the number of views of the reviews, we control for "views" in our model with "distribution" covariate.

Controls

In line with prior research, we include the following control variables that may affect online activity—advertising spend, distribution, movie genre and awards.

Advertising Spend (BUDGET): Extant literature suggests that advertising expenditure plays a fundamental role in the box office revenue generation (Elberse & Eliashberg, 2003; Prag & Casavant, 1994; Zufryden, 1996). As consumers rely on movie advertisements as a source of information, it is important that we control movies' total advertising budget in our analysis.

Movie Distribution (DISTRIBUTION): The number of screens on which a movie is released is the most important influence on viewership (Neelamegham & Chintagunta, 1999) as higher distribution increases visibility, driving up box office revenue.

Movie Genre: Some genres are more likely to have higher buzz than others. For example, movies in the action, thriller, or romance genres generally attract more attention. Similarly, movies with R-rating, or movies with stars are more likely to be reviewed by a larger number of critics and to succeed in box office. Therefore, we included MPAA ratings (R_RATED, PG_RATED) and genres (COMEDY, ACTION, DRAMA) in the model.

Movie Awards (AWARDS): Movies that are nominated for awards receive high visibility and greater press coverage, thus resulting in greater box office revenue. Therefore, we included AWARDS as a control in our model. Table 2 includes model variables.

Model

As our dataset is a panel longitudinal data, we used a mixed model to control for the random effects of time, and examine the fixed effects related to our hypotheses. The model is specified as following:

$$
\begin{aligned}
\text{Log}(BO)_{it} = {} & \beta_0 + \beta_1 \times LSM_{i,t-1} + \beta_2 \times VOLUME_{i,t-1} \\
& + \beta_3 \times VALENCE_{i,t-1} + \beta_4 \times DISPERSION_{i,t-1} \\
& + \beta_5 \times BUDGET_i + \beta_6 \times DISTRIBUTION_{i,t-1} \\
& + \beta_7 \times POSITIVE\_EMO_{i,t-1} + \beta_8 \times NEGATIVE\_EMO_{i,t-1} \\
& + \beta_9 \times COGNITION_{i,t-1} + \beta_{10} \times HELPFUL \\
& + \beta_{11} \times R\_RATED + \beta_{12} \times PG\_RATED + \beta_{13} \times COMEDY \\
& + \beta_{14} \times ACTION + \beta_{15} \times DRAMA + \beta_{16} \times AWARDS_{t-1} \\
& + \beta_{17} \times LSM_{i,t-1} \times HELPFUL + \beta_{18} \times VALENCE_{i,t-1} \\
& \times HELPFUL + \beta_{19} \times POSITIVE\_EMO_{i,t-1} \times HELPFUL
\end{aligned}
$$

Table 2: Model variables.

Variable	Operationalization	Source
Dependent Variable		
New Product Sales (BO)	Box office sales at week t	IMDB
Review Characteristics		
Linguistic Style Matching (LSM)	The ratio of the total number of function words in a specific online review to the average number of function words across all reviews for a particular movie (Ireland & Pennebaker, 2010). $LSM_{ij} = \frac{Fij}{\frac{\sum_{i=1}^{N} Fij}{Nj}}$; F_{ij} = number of function words in review i for movie j over number of words in review i for movie j; N_j = number of reviews for movie j.	IMDB
Volume	The total number of reviews for a movie posted at week t	IMDB
Valence	The average rating given by the reviewers for a movie at week t	IMDB
Dispersion	The standard deviation of the ratings given by the reviewers for a movie at week t	IMDB
Helpfulness	The sum total number of viewers who rated a review helpful	IMDB
Positive Emotion (POSITIVE_EMO)	The average positive emotion of the reviews computed by LIWC for a movie at week t	IMDB
Negative Emotion (NEGATIVE_EMO)	The average negative emotion of the reviews computed by LIWC for a movie at week t	IMDB
Cognitive Component (COGNITION)	The average cognitive component of the reviews computed by LIWC for a movie at week t	IMDB
Movie Characteristics		
Budget	An indicator variable created by median split where $BUDGET = 1$ when the advertising budget of the movie is higher than the median, and $BUDGET = 0$ otherwise.	IMDB
Distribution (THEATER)	The number of theaters that showed the movies at week $t - 1$.	IMDB
MPAA rating	The movie rating included in the model as two indicator variables, *PG_RATED* (= 1, else 0) and *R_RATED* (= 1, else 0).	Yahoo! Movies
Movie Genre	The movie genre included in the model as three indicator variables *COMEDY* (= 1, else 0), *ACTION* (= 1, else 0), and *DRAMA* (= 1, else 0).	Yahoo! Movies
Award Nominations (AWARD)	The number of nominations of the movies announced before week t.	Yahoo! Movies

$$+ \beta_{20} \times NEGATIVE\_EMO_{i,t-1} \times HELPFUL$$
$$+\beta_{21} \times COGNITION_{i,t-1} \times HELPFUL + \alpha_1 \times TIME_i + e_i \quad (1)$$

To illustrate the significance of the helpfulness as the moderator, we estimated the model (Equation (1)) with and without the interaction terms. The model without the interactions terms is shown below:

$$\begin{aligned}\text{Log}(BO)_{it} = {} & \beta_0 + \beta_1 \times LSM_{i,t-1} + \beta_2 \times VOLUME_{i,t-1} + \beta_3 \times VALENCE_{i,t-1} \\ & + \beta_4 \times DISPERSION_{i,t-1} + \beta_5 \times BUDGET_i \\ & + \beta_6 \times DISTRIBUTION_{i,t-1} + \beta_7 \times POSITIVE\_EMO_{i,t-1} \\ & + \beta_8 \times NEGATIVE\_EMO_{i,t-1} + \beta_9 \times COGNITION_{i,t-1} \\ & + \beta_{10} \times HELPFUL + \beta_{11} \times R\_RATED \\ & +\beta_{12} \times PG\_RATED + \beta_{13} \times COMEDY + \beta_{14} \times ACTION \\ & + \beta_{15} \times DRAMA + \beta_{16} \times AWARDS_{t-1} + \alpha_1 \times TIME_i + e_i \qquad (2)\end{aligned}$$

The above models are estimated using PROC MIXED in SAS.

RESULTS

In this section, we first discuss our data and then present the findings from our analysis. Table 3 presents the static data description of our data. Overall, we have 2,876 weeks of usable data from 264 movies. The average LSM = 0.76 ($\sigma = 0.11$) suggests that on average, review writing style is 75% similar to the writing style of other reviews. The average helpfulness is 0.15 ($\sigma = 0.59$), suggesting that on average, only a small number of reviews are considered helpful. Next, we illustrate the dynamic data description of our data. Figure 2 presents model variable dynamics with a descriptive purpose using functional data analysis (Dass & Shropshire, 2012). It illustrates how the average values of different variables calculated across all the movies in our sample change over time. The x-axis represents time in weeks after the movie release and ends with the tenure of the movies at the theater. As expected, average sales decreases following a short increase in the early weeks of movies. Average LSM score, however, fluctuates. It increases in the early weeks of a movie release followed by a temporary decrease. This curve shape tells us that linguistic styles and social identities of those who post reviews either early or late during the tenure of a movie in the theaters are similar to each other. In the middle, a more diverse group of reviewers chimes in. This is consistent with the previous research that finds the impact of eWOM dispersion declines over time (Godes & Mayzlin, 2004). Review content displays an insightful evolution. Average positive sentiments in reviews show an S shape decrease. However, negative sentiments and cognitive components of the reviews increase over time, suggesting that as weeks progress, reviews on average become more negative and more rational. Finally, review helpfulness shows a sharp decline after the early weeks of a movie release, suggesting that the earlier reviews are deemed more helpful than later reviews. This

Table 3: Descriptive statistics and correlation matrix.

Variables	*N*	Mean	SD	Max	Min	1	2	3	4	5	6	7	8	9
1. New product sales	3551	5,483,438.64	13,227,266.53	238,615,211	0	1								
2. LSM	2876	.76	.11	.99	0	−.04*	1							
3. Helpfulness	2876	0.155	0.597	1	0	.33**	.04	1						
4. Positive emotion	2876	5.27	1.70	19.02	0	.52**	.12**	.49**	1					
5. Negative emotion	2876	2.19	.99	10.81	0	−.06**	.00	.01	−.29**	1				
6. Cognitive component	2876	16.39	1.97	26.71	8	−.05**	.05*	.02	−.02	.03	1			
7. Volume	2876	14.66	41.77	1,152	1	.40**	.03	.79**	−.06**	.03	.02	1		
8. Valence	2876	6.19	2.05	10	0	.00	.12	.02	.18**	−.24**	−.10**	−.02	1	
9. Dispersion	2876	2.13	1.45	27.09	0	.09**	−.00	.09**	−.11**	.12**	.07**	.15**	−.21**	1

$*p < .1$; $**p < .05$.

Figure 2: Average variable evolution over time.

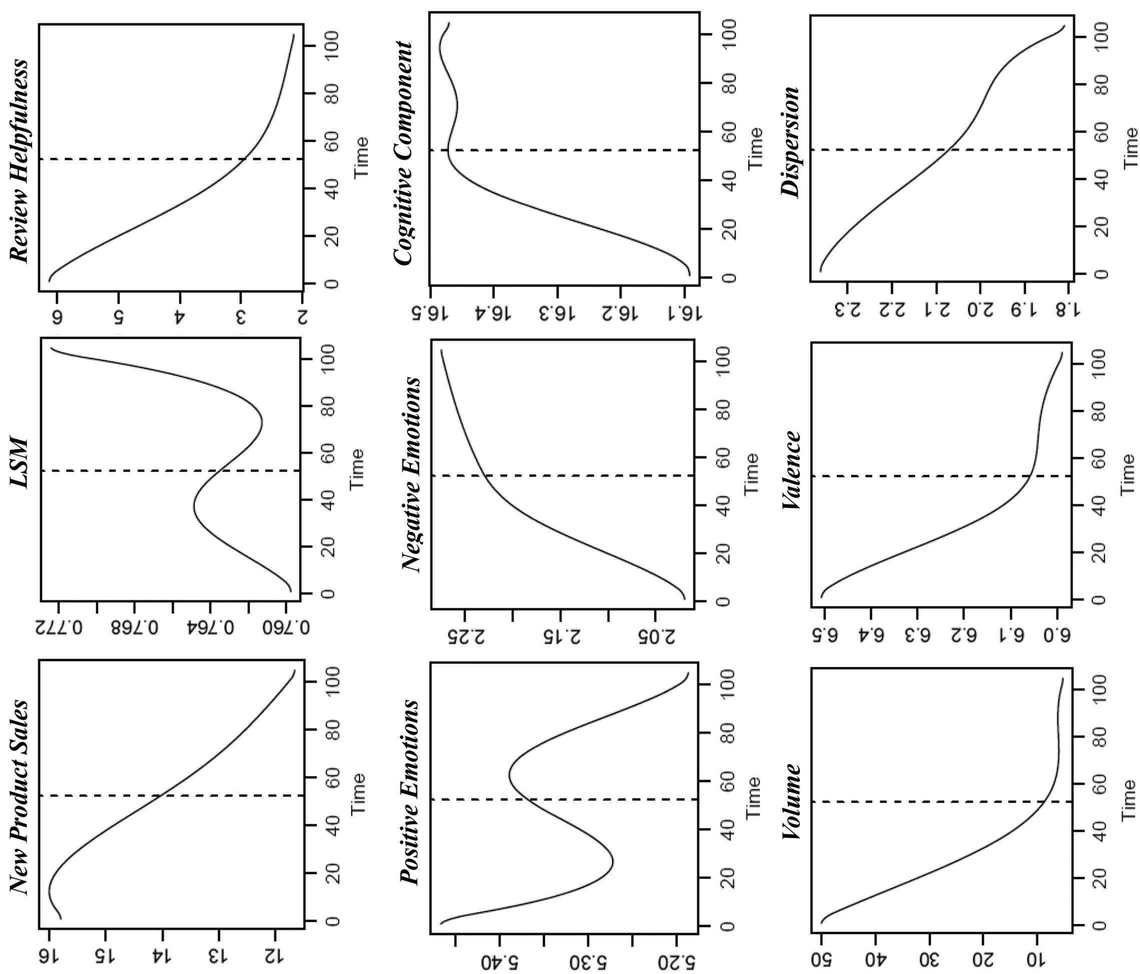


Table 4: Model results.

Variable	Eq. (2) Estimates (no interactions)	Eq. (1) Estimates (with interactions)
Intercept	14.683***	14.594***
LSM	−0.489**	−0.371**
Positive emotion	−0.019	−0.026*
Negative emotion	−0.026	−0.029
Cognitive component	0.004	−0.002
Helpfulness		0.659
LSM*Helpfulness		−4.481**
Valence*Helpfulness		−0.068**
Positive emotion*Helpfulness		0.242***
Negative emotion*Helpfulness		0.181
Cognitive component*Helpfulness		0.102**
Control variables		
Volume	0.003***	0.005***
Valence	0.006	0.009
Dispersion	0.028	0.054**
Budget	0.864***	0.859***
Distribution	0.793***	0.796***
R_Rated	−0.498**	−0.475**
PG_Rated	0.273	0.256
Comedy	0.424**	0.417**
Action	0.149	0.124
Drama	−0.097	−0.079
Award nominations	0.015**	0.016**
Random Effects		
Time	−0.464***	−0.459***

*$p < .1$; **$p < .05$; ***$p < .001$; AIC = 5807.8; AIC = 5781; BIC = 5875.7; BIC = 5869.2.

emphasizes the importance of studying the moderating role of review helpfulness as early rectifications on management strategies may improve sales of lackluster movies. (Appendix A presents dynamic plots of these variables for each movie.)

The results of the two-level mixed model provide partial support for the proposed hypotheses (Table 4). We proposed that when there is a low LSM between a review and all the reviews about a particular movie, readers are more likely to encounter a review by a reviewer similar to themselves. Thus, they feel more comfortable with the purchase decision, and new product sales are positively affected. The results of the analysis show a significant effect in this direction ($\beta = -0.489$, $p < .05$), thus supporting H1. In addition to the impact of review style, the richness of review content is also expected to play a critical role in the behavioral outcomes of online reviews. However, we find that positive emotions ($\beta = -0.019$, n.s.), negative emotions ($\beta = -0.026$, n.s.), and cognitive components ($\beta = -0.004$, n.s.) in the content of online reviews do not have a significant direct effect on box office revenue. Therefore, H2A, H2B, and H2C are not supported. When we look at the interaction between review helpfulness and review style and content, the results show significant differences. We observe a significant interaction effect of linguistic style and review helpfulness on box office revenue ($\beta = -4.481, p <$ .05). The impact of content generated by reviewers from diverse communities on new product sales is accentuated when the reviews are considered helpful. Thus, H3 is supported. Further, a helpful review with high positive emotional content has a significant impact on new product sales ($\beta = 0.242$, $p < .001$). Thus, H4A is supported. Helpful reviews with negative emotional content, however, do not have a significant positive impact on new product sales ($\beta = 0.181$, n.s.). Therefore, H4B is not supported. Finally, helpful reviews with high cognitive content have a positive impact on box office revenue ($\beta = 0.102$, $p < .05$). This finding supports H4C. Collectively, these results provide strong support for the notion that review helpfulness works as a critical decision-making cue and that the effect of review style and content on new product sales largely depends on review helpfulness.

Of the control variables, consistent with prior research (Godes & Mayzlin, 2004), the effects of volume ($\beta = 0.005$, $p < .001$) and dispersion ($\beta = 0.054$, $p < .05$) are positive and significant. However, valence does not have a significant effect on sales ($\beta = -0.009$, n.s.). This finding is consistent with the argument that online product ratings are not an ideal metric to study review characteristics (Liu, 2006), and our results suggest that contextual analysis and linguistic styles are viable alternatives. Finally, various movie characteristics, including budget ($\beta = 0.859$, $p < 0.001$), distribution ($\beta = 0.796$, $p < .001$), award nomination ($\beta = 0.016$, $p < .05$), R rating ($\beta = -0.475$, $p < .05$), comedy genre ($\beta = 0.417$, $p < .05$), and action genre ($\beta = 0.453$, $p < .05$), affect box office revenue.

Robustness Checks

We performed multiple checks on the robustness of the model implemented in the study. First, we address the issue of reverse causality and potential endogeneity issue of movie revenue at week t and movie rating at week $t - 1$. Extant studies suggest that movie distribution plays a significant role on the movie evaluation and its ratings (e.g., Eliashberg & Shugan, 1997). Therefore, movie distribution, in terms of number of movie theaters at week $t - 1$ may be considered as an instrument variable to control for endogeneity. Second, the findings of our analysis suggest that diversity in opinion and different linguistic styles can help increase sales of new products as the diversity can stimulate curiosity among potential consumers. To verify this assertion, we included an interaction between dispersion and LSM in the model, but unfortunately, the term is found to be insignificant.

Third, we tested the U-shaped relationship between review content (positive emotions, negative emotions, and cognitive components) and new product sales. These new variables were found to be insignificant, and the main results unchanged. Fourth, extant literature suggests that the movie reviews affect movie sales differently during the tenure of the movie. For instance, Basuroy, Chatterjee, and Ravid (2003) suggest that positive reviews are positively effective in the early eight weeks, while the effects of negative reviews on movie sales diminish over time. To verify this hypothesis, we split our data set into two sets: (i) movies that ran for eight weeks or less and (ii) movies that ran more than eight weeks, and estimate our model (Equation 1) using each subsample separately. Results suggest that the moderating role of review helpfulness on the effects of valence and cognitive components on sales is significant in the early eight weeks. However, the moderating role on the effects of LSM on sales is significant after eight weeks of movie tenure. Finally, to validate our use of a mixed model to test our hypotheses, we ran the fixed effects model as a single layer multiple regression model without the control variables but with time as a predictor. Results presented in the Appendix B suggest that only volume, dispersion and time are significant. On further testing for multicollinearity on the single layer model, we only found "time" to have a VIF factor higher than 9 (Maruyama, 1998), highlighting the validity of the mixed model to test the hypotheses.

DISCUSSION

This study highlights the impact of online review content and linguistic style matching on new product sales and the key role review helpfulness plays in this relationship in the context of the motion picture industry. Relying on cognitive psychology literature (Chaiken & Trope, 1999), we hypothesize that affective and cognitive elements in review content should have an impact on behavioral outcomes of online reviews. Although prior research investigates online reviews mostly based on quantitative metrics such as volume, valence, or dispersion, recent advances in data collection and text analytics allow researchers to dig deeper into qualitative characteristics of online reviews. For instance, valence mostly measured by online product ratings denotes a degree of attraction or aversion toward a product (Chevalier & Mayzlin, 2006). This approach, however, presents room for improvement for three reasons. First, online ratings suffer from high ceiling effects and low variability; this is evident in the accumulation of scores toward the boundaries of a rating scale (Resnick & Zeckhauser, 2002). Second, looking beyond the numerical ratings and analyzing the content provide a richer understanding of customer opinions (Kozinets et al., 2010). Third, users generating long product reviews usually do so after an extensive elaboration, and their posts may include pros and cons of the product. Analyzing the multidimensional content of large data sets becomes a challenge for researchers (Godes et al., 2005) and leads them to use numerical product ratings (Chevalier & Mayzlin, 2006). After all, valence may take two values, positive or negative, and it is a daunting task to determine whether a long and detailed product review is favorable or critical. In many instances, it can be both. Using a text mining approach, however, enables us to extract both positive and negative emotions woven into the fabric of online reviews.

Social psychology theories purport that style and content are inseparable components in oral and written communication (Huffaker et al., 2011). Communication accommodation theory suggests that when interacting with others, people adjust their communication style to accommodate social expectations (Giles & Smith, 1979) and that readers feel more comfortable when an online review style matches a certain standard they come to expect. When LSM is low, reviews are generated by users from diverse backgrounds. Therefore, we hypothesize a direct negative impact of LSM on new product sales. In addition, we show that review helpfulness, the likelihood that a review facilitates others' decision-making process, moderates the relationship between online reviews and new product sales, considering the difficulty users face in processing the huge amount of available online information. Table 5 provides a summary of the research findings.

Implications for Research

This study provides unique insights into eWOM theory. First, our analysis shows that the impact of online review content on new product sales strongly depends on review helpfulness. This finding also supports the theory that when elaboration likelihood is low, customers opt for a peripheral route that includes low-effort decision-making cues, not a central route that involves careful consideration of the true merits of presented information (Chaiken & Trope, 1999). In other words, when a large amount of online information is available, especially for low-involvement products, customers are unlikely to process most of the information and review helpfulness functions as a critical decision-making cue. Positive emotions and cognitive components in the content of helpful reviews have a significant positive impact on new product sales.

Furthermore, the results reveal that LSM has a significant negative impact on new product sales. Prior research argues that when reviewers' writing styles match an expected norm, readers feel more comfortable and are more likely to take an action (Ireland & Pennebaker, 2010). This is also consistent with the strength of the weak-ties hypothesis that argues that people dissimilar to each other are more influential over each other than people who are similar to each other (Granovetter, 1973). To our knowledge, Ludwig et al.'s study (2013) is the only one to test this phenomenon for online reviews, and they find a positive impact of LSM in online reviews on book sales. Contrary to their work, however, we find that as stylistic match between an online review and all the reviews regarding the same product goes down, sales increase. Social dynamics in an online review setting may differ from the contexts of existing studies, including personal correspondence, academic writing, or poetry (Ireland & Pennebaker, 2010). Style inconsistency possibly hints at the reviewer variety that attracts a wider range of customers, which subsequently brings in more new product sales. In addition, our data show an interaction between LSM and review helpfulness. That is, helpful reviews generated by diverse users exert a significant influence over new product sales.

Implications for Practice

This study also has implications for practitioners and decision makers. Managing the online sentiment after a product launch, encouraging customers to generate online reviews, and running viral marketing campaigns are increasingly popular strategic elements decision makers consider (Gunnec & Raghavan, 2017). In this respect, our results suggest that product managers should encourage their customers to generate helpful online reviews that are also rich in terms of their affective and cognitive content. These types of reviews, especially early in the product life cycle, are shown to be more effective than high product ratings. Mudambi and Schuff (2010) find that extreme ratings are considered less helpful than moderate ratings for experience goods and that the length of a review has a positive impact on helpfulness perceptions. Therefore, when decision makers prompt their

Table 5: Summary of the findings.

Expectations	Results	Implications
H1: Low LSM in online reviews will have a positive impact on new product sales.	Supported	Decision makers should encourage users from diverse backgrounds to post reviews.
H2A: Positive affective content of online reviews will have a positive impact on new product sales.	Not supported	The amount of online information and low elaboration likelihood undermines the impact of review content on sales.
H2B: Negative affective content of online reviews will have a negative impact on new product sales.	Not supported	The amount of online information and low elaboration likelihood undermines the impact of review content on sales.
H2C: Cognitive content in online reviews will have a positive impact on new product sales.	Not supported	The amount of online information and low elaboration likelihood undermines the impact of review content on sales.
Moderating Effects of Review Helpfulness		
H3: Positive impact of low LSM on new product sales will accentuate when review helpfulness is high.	Supported	Decision makers should encourage users from diverse backgrounds to post helpful reviews.
H4A: Positive impact of positive affective content on new product sales will accentuate when review helpfulness is high.	Supported	Decision makers should encourage users to post helpful reviews that include positive affective components.
H4B: Negative impact of negative affective content on new product sales will accentuate when review helpfulness is high.	Not supported	Helpful reviews are preferable even with negative affective content because they do not exert negative influence on new product sales.
H4C: Positive impact of cognitive content on new product sales will accentuate when review helpfulness is high.	Supported	Decision makers should encourage users to post helpful reviews that include logical reasoning.

customers to post an online review following a purchase, they should encourage customers to express their opinions in detail and at length.

In addition, our results show that stylistic inconsistencies in online reviews lead to an increase in new product sales. This finding stands in contrast to conventional understanding in eWOM research that the comments of a select few opinion leaders are most effective in moving the products (Helm, Möller, Mauroner, & Conrad, 2013) because these influential opinion leaders or category experts are expected to have a more consistent linguistic style. On the contrary, our results reveal that reviewers from diverse backgrounds whose linguistic styles are not necessarily consistent with each other prove to be more valuable in viral marketing campaigns.

Limitations and Future Directions

This research presents some limitations. Similar to the results of all dictionary-based text mining studies, the findings of this research depend heavily on the validity and reliability of the dictionary used. Although all of these types of dictionaries present an improvement potential, the number of studies and contexts in which the LIWC dictionary has been successfully tested gives us confidence in our results (Tausczik & Pennebaker, 2010). Further, future text-mining studies in this realm should consider changing writing habits in online communication. In particular, the role of emojis as a new generation of emoticons in online reviews should be investigated. Because emojis are shorthand tools to express emotions and ideas (Novak, Smailović, Sluban, & Mozetič, 2015), they may strengthen the impact of affective and cognitive components on behavioral outcomes. In addition, future research should consider variables other than review helpfulness that may potentially function as an online decision-making cue given the increasingly large amount of online information. One potential alternative for future research is to study the possibility of creating a match between the personal characteristics of reviewers and readers. Customers are becoming less likely to read and heed all product reviews. Similar to the way websites offer different products to their customers based on customers' previous buying habits, they may display matching reviews to their customers and save them time and hassle. Although our study tried to include as many controls as possible (number of screens (DISTRIBUTION), number of awards (AWARDS), marketing budget (BUDGET), MPAA ratings (R_RATED, PG_RATED), and genres (COMEDY, ACTION, DRAMA)), future studies may also consider adding information from third-party endorsements such as articles written in popular press in the analysis to provide another layer of robustness. As the online platforms are constantly evolving, it is possible that the style, content, and type of reviews are changing. Therefore, future studies may consider examining whether such changes are occurring, and if so, how they change the findings reported in this article.

CONCLUSION

In this article, we explore the impact of online review content and style on new product sales and the moderating role of review helpfulness in this relationship.

We collect a large number of online reviews from the motion picture industry and utilize a dictionary-based text mining approach to test the proposed relationships. The results reveal a significant interaction between online review content and review helpfulness. In particular, positive emotions and cognitive components in the content of helpful online reviews impact new product sales. Further, LSM of online reviews exerts a negative impact on new product sales. Overall, these findings highlight the importance of studying textual characteristics of online reviews and the impact of review helpfulness as a decision-making cue in this research realm.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Data Description using Functional Data Analysis
Appendix B: Results from Single level Model

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