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Mining Pros and Cons of Product Features from Online Reviews: Aspect-Sentiment Analysis on Textual Reviews

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Research-in-Progress

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Extended Abstract

Online reviews have become the modern-day referral, which shapes consumers' perceptions of products and thus influences product sales performance in the digital economy (Blanco, Sarasa, & Sanclemente, 2010). Prior literature suggests that online consumers' textual information significantly affects product performance and has important strategic value for organizations (Zhou et al., 2018). Sentiment analysis is used to identify the positive and negative tone of textual information (Hu, Bose, Koh, & Liu, 2012) and has become a primary application of analytics when researchers investigate how user-generated information influences product performance. However, most existing online review studies conduct sentiment analysis at the review level, which focuses on identifying the valence of an individual message or review (e.g., Hu et al., 2012; Wu, Huang, & Zhao, 2019), rather than the feature-based, which aims to reveal prior customers' evaluation of product features in reviews (e.g., Wang, Lu, & Tan, 2018). Since consumers' fundamental purpose in reading textual reviews is to obtain details about the product attributes' pros and cons (Xu, 2019), conducting sentiment analysis at review-level fails to measure customer satisfaction concerning each attribute of products or services and does not match the mechanism of how online text reviews are consumed. Therefore, feature-based review-level sentiment analysis better reflects the actual value of textual information in the digital economy.

Moreover, although some studies have attempted to simultaneously detect sentiment and product features from text reviews (e.g., Lin & He, 2009; Wang et al., 2018), the review-level analysis neglects the variance of topic sentiments. The variance of topic sentiments is crucial since consumers check out multiple text reviews before buying (Wang, Liu, & Fang, 2015), and the distribution of product evaluation matters in making purchase decisions (Sun, 2012). Most existing studies investigate the effect of aggregated review sentiments on product sales, which discounts the uniqueness of each review. Therefore, neglecting the variance of topic sentiment in review analysis would lead to incorrect conclusions on the effect of textual reviews. Moreover, similar to numerical ratings, the key characteristics (volume, valence, and variance) of textual reviews interact with each other, and their interactions also influence consumer purchase decisions.

This study aims to fill the research gap by proposing a model elaborating the interactions among the three dimensions of text reviews, whereby volume and variance moderate the effects of feature-valence on product sales. Most studies of online reviews in the Information Systems (IS) have applied theories related to information processes and social communication to answer a central question: How do online reviews influence consumer behaviors and thus shape product sales in the digital market? Among the numerous studies, one main research stream elaborates on the phenomenon that people spread their opinions regarding products, brands, or companies and influence other people's perceptions through electronic word-of-mouth (eWOM). This research stream has identified three key metrics widely used to measure the effectiveness of eWOM: volume, valence, and variance (e.g., Dellarocas, Zhang, & Awad, 2007; Duan, Gu, & Whinston, 2008; Liu, 2006). Volume influences consumers' purchase decisions via an awareness effect (Duan et al., 2008). Valence influences product sales through persuasive effects that shape consumers' evaluations of the product and ultimately influence their purchase decisions (Li, Li, & Zhu, 2016). Variance is also essential because it captures the extent to which consumers differ from each other in their enjoyment of a product and attribute this difference to the product's underlying characteristics (Sun, 2012).

To explore the relationship among the three key metrics of textual reviews, we build our research framework (shown in Figure 1) upon information processing theory, which states that people consume all information they receive within the processing system (Miller, 2002). First, consumers post reviews online based on their evaluations of past experiences. Positive reviews may promote future purchases by highlighting product reputation, usage satisfaction, experience enjoyment, and recommendations (Chern, Wei, Shen, & Fan, 2015). Conversely, negative reviews inhibit future purchases because they imply usage dissatisfaction, disappointment, and complaints (Berger, Sorensen, & Rasmussen, 2010). Online reviews' positive or negative orientation can lead to different modes of action in the receivers (Salehan & Kim, 2016). Second, the review valence could be moderated by review volume, which indicates the information intensity. The warranting principle argues that due to a lack of information about online review sources, evaluations of online reviews are more appropriately based on information that cannot be easily manipulated by the information source. High review volume is hard to manipulate and thus is perceived as more reliable. Therefore, review volume enhances the reliability of reviews and moderates the effect of review valence. Third, information effectiveness depends on its observability, cost, and consistency (Amblee & Bui, 2011). The consistency among consumer reviews is expected to increase the credibility of reviews and thus enhance the effect of those reviews on product sales. For a product with negative sentiments, a higher variance would correspond to higher subsequent demand (Sun, 2012).

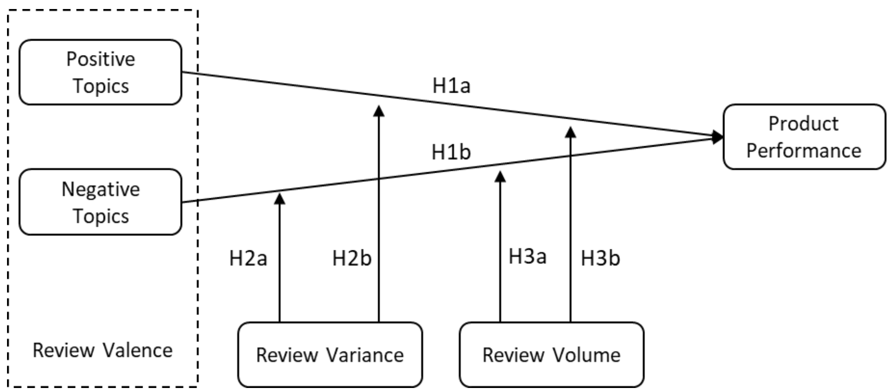

Figure 1: Research Framework

To empirically test our hypotheses, we collected data from Amazon.com related to smartwatch products since it is an emerging category and customers may heavily rely on online reviews when making purchase decisions. To analyze textual reviews, we apply one text mining technique called the Aspect Sentiment Unification Model (ASUM), which is proposed by Jo and Oh (2011) to reveal the weights of aspects and their associated sentiment polarity. After obtaining the aspect and sentiment scores for each review, we applied the latent multilevel regression model to examine the relationship between textual reviews and product sales performance.

Our study systematically examines the interaction of key metrics of textual reviews. There are three advantages of examining the effects of these key metrics of reviews in concert. First, this approach mimics the way in which consumers read and process online reviews. Since consumers' fundamental purpose of reading textual reviews is to obtain details about the product attributes' pros and cons (Xu, 2019), conducting sentiment analysis at the review level fails to measure customer satisfaction concerning each attribute of products or services and does not match the mechanism of how online text reviews are consumed. In addition, averaging reviews with opposite sentiments could generate a moderate evaluation, losing the review extremity and information about the variance of sentiments. Therefore, it is necessary to discuss the variance within one topic, which reflects the mixed nature of reviews. In sum, we contribute to the online review literature by proposing a model elaborating the interactions among the three dimensions of text reviews, whereby volume and variance moderate the effect of valence on product sales.

This study also contributes to IS field from a methodological perspective. We demonstrate that by applying ASUM, we can address three issues related to text review analysis: the variance of sentiments within the topic also matters; one aspect identified in text mining may span various product categories while invoking similar sentiments; a word may invoke different sentiments depending on the context. Our research also has several practical implications. Understanding how online reviews affect customer decision-making is vitally important to sellers that rely on online reviews to disseminate information about their products. Our empirical results provide valuable guidance on information management for sellers in digital markets. We found that the effectiveness of strategies to increase product sales varies across different scenarios. Thus, seller online information management strategies must be adjusted accordingly. For non-popular products that have positive evaluations, increasing review volume is extremely powerful because the higher volume will enhance the positive effect of reviews. For negative topics, significant debates could improve product sales eventually.

Reference

Blanco, C. F., Sarasa, R. G., & Sanclemente, C. O. (2010). Effects of visual and textual information in online product presentations: looking for the best combination in website design. *European Journal of information systems, 19*(6), 668-686.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive marketing, 21*(4), 23-45.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter?—An empirical investigation of panel data. *Decision Support Systems, 45*(4), 1007-1016.

Hu, N., Bose, I., Koh, N. S., & Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems, 52*(3), 674-684.

Jo, Y., & Oh, A. H. (2011). *Aspect and sentiment unification model for online review analysis*. Paper presented at the Proceedings of the fourth ACM international conference on Web search and data mining, Hong Kong, China. https://doi.org/10.1145/1935826.1935932

Li, J., Li, X., & Zhu, B. (2016). User opinion classification in social media: A global consistency maximization approach. *Information & Management, 53*(8), 987-996.

Lin, C., & He, Y. (2009). *Joint sentiment/topic model for sentiment analysis.* Paper presented at the Proceedings of the 18th ACM conference on Information and knowledge management.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of marketing, 70*(3), 74-89.

Miller, P. H. (2002). *Theories of developmental psychology*: Macmillan.

Sun, M. (2012). How does the variance of product ratings matter? *Management Science, 58*(4), 696-707.

Wang, Liu, X., & Fang, E. E. (2015). User reviews variance, critic reviews variance, and product sales: An exploration of customer breadth and depth effects. *Journal of Retailing, 91*(3), 372-389.

Wang, Lu, X., & Tan, Y. (2018). Impact of product attributes on customer satisfaction: An analysis of online reviews for washing machines. *Electronic commerce research and applications, 29*, 1-11.

Wu, J., Huang, L., & Zhao, J. L. (2019). Operationalizing regulatory focus in the digital age: evidence from an e-commerce context. *MIS quarterly, 43*(3), 745-764.

Xu, X. (2019). Examining the relevance of online customer textual reviews on hotels' product and service attributes. *Journal of Hospitality & Tourism Research, 43*(1), 141-163.

Zhou, S., Qiao, Z., Du, Q., Wang, G. A., Fan, W., & Yan, X. (2018). Measuring customer agility from online reviews using big data text analytics. . *Journal of management information systems, 35*(2), 510-539.