



## Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales



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### ARTICLE INFO

#### Article history:

Received 25 February 2012

Received in revised form 23 May 2013

Accepted 29 July 2013

Available online 15 August 2013

#### Keywords:

User-generated content

Online consumer reviews

Sentiments

Ratings

Interplay

Search and choice

### ABSTRACT

It is generally assumed that ratings are a numeric representation of text sentiments and their valences are consistent. This however may not always be true. Using a panel of data on over 4000 books from Amazon.com, we develop a multiple equation model to examine the inter-relationships between ratings, sentiments, and sales. We find that ratings do not have a significant *direct* impact on sales but have an indirect impact through sentiments. Sentiments, however, have a direct significant impact on sales. Our findings also indicate that the two most accessible types of reviews – most helpful and most recent – play a significant role in determining sales. This suggests that information that is easily accessible and cognitive effort-reducing heuristics play a role in online purchase decisions. This study advances our understanding on the inter-relationship between ratings, sentiments, and sales and sheds insight on the *relevance* of ratings and sentiments over a sequential decision making process.

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### 1. Introduction

A recent eMarketer report finds that the number of Internet users that are creating and using user-generated content will shoot up significantly in the next few years. It reports that by 2013, the number of user-generated content creators in the US will grow to 115 million, up from 83 million in 2008. Similarly, the number of US Internet users that consume some form of user-generated content will reach 155 million by 2013, up from 116 million in 2008.<sup>3</sup> Nielsen, in a large scale (26,000 participants) global study in April 2007, found that 78% of participants trust recommendations from other consumers.<sup>4</sup> Power Reviews, in a May 2010 survey, found that 64% of the online shoppers spend 10 min or more reading reviews and 68% of the online shoppers read at least four product reviews before purchasing.<sup>5</sup> Evidently, online reviews are a form of user-generated content that is increasingly becoming an important source of information to consumers in their search, evaluation, and choice of products.

A number of researchers have examined the impact of online consumer reviews on product sales, concentrating on numeric ratings

that accompany the reviews. Typically, researchers have looked at valence [9,14,32,34], variance in ratings [10,19] and volume of reviews [14,32].

Although several researchers have acknowledged the importance of capturing the sentiments expressed in product reviews, they cite the difficulty in doing so. For example, Ghose and Ipeirotis [18] pointed out that numeric ratings might not fully capture the polarity information in the review. Chevalier and Mayzlin [9] found evidence from their analysis of review length (total number of characters in the online review), “that customers read review text rather than relying simply on summary statistics” (p. 345). Godes et al. [21] alluded to the inability to analyze communication content as one of the key problems of analyzing user-generated content. Liu [32], in analyzing 12,000 movie review messages using human judges, reported that it was “an extremely tedious task.”

The development of text mining tools has made this task less tedious, more efficient than manual coding and has increased the ability to analyze large amounts of user-generated content. Despite the limitation of text mining being less accurate than human judges (for informal text like Amazon.com reviews, the accuracy levels tend to be around 80% [35]), its usefulness has prompted its application in marketing and other applied areas [1,2,12,15,17,18,29,35].

While numeric ratings can be viewed as codified assessments on a standardized scale, sentiments expressed in the text provide more tacit, context-specific explanations of the reviewer's feelings, experiences, and emotions about the product or service. They could be framed as highly positive, neutral, or negative statements with varying degrees

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<sup>3</sup> [http://www.emarketer.com/Reports/All/Emarketer\\_2000549.aspx](http://www.emarketer.com/Reports/All/Emarketer_2000549.aspx).

<sup>4</sup> [http://www.nielsen.com/media/2007/pr\\_071001.html](http://www.nielsen.com/media/2007/pr_071001.html).

<sup>5</sup> <http://socialcommercetoday.com/2010-social-shopping-study-top-line-results/>.

of emotion. Such sentiments provide rich information to their readers and are likely to provide them with a tacit feel, beyond the numeric ratings.

Recent pioneering work by Archak et al. [1] and Ghose and Ipeirotis [18] explored the impact of certain elements of text reviews on product sales. Archak et al. [1] who used text mining on reviews for two electronic product categories, extracted sentiments relating to the attributes (such as picture quality of cameras) and estimated their impact on sales. Ghose and Ipeirotis [18] found that the writing style of text reviews (subjectivity levels, readability, and extent of spelling errors) impacted product sales even in the presence of valence and volume of reviews in some of the product categories.

Apart from the numeric ratings not fully capturing the “polarity of information in the text reviews” [18], we feel that sentiments, in fact, might play a different role than ratings in the choice process. As search, evaluation, and choice in an online environment can be quite complex, consumers may utilize different pieces of information during different phases of the choice process to arrive at a final purchase. In the consumer decision-making literature researchers have shown that consumers faced with complexity and abundance of information but limited by their cognitive abilities to process all information in a limited time, often attempt to reduce their cognitive effort and resort to simplifying strategies and heuristics to arrive at a decision [3,4,38,48,49]. Information that requires less effort to process [43] and is easily aligned [52], such as price and numerical ratings, may be used to simplify (reduce) the consideration set. Then, more effortful strategies like using sentiments expressed in the reviews can be used to arrive at the final decision.

What this suggests is that ratings and sentiments may have different proximities to the final choice (sales). If ratings are used to reduce the set of products to be considered and product reviews (sentiments) are used during the final choice, this may reflect the relative impact that these two sources have on sales. This leads to some interesting research questions: What is the differential impact of sentiments and ratings on sales? What is the interplay of ratings, sentiments, and sales? Do ratings and sentiments have only a direct impact on sales or do they impact sales through each other? Do sales impact ratings and sentiments? Which components of ratings and sentiments (for example, most recent or most helpful reviews, sentiments expressed in the title or in the content of text reviews) have an effect on sales?

Using a panel of data on over 4000 books from Amazon.com, we extracted sentiments from product reviews and developed a comprehensive model to explore the above research questions. An interesting finding is the differential impact of ratings and sentiments on sales and the potential sequential nature of this impact. A few aspects of our study distinguish it from previous work in this area (Table 1). While previous work has addressed the issue of whether ratings or sentiments have an impact on sales and *what* that impact is, in this research we address the issue of *how* these two elements of user-generated reviews affect each other *and* product sales (Fig. 1). Specifically, we tease out the relative impact of ratings and sentiments on sales and the different paths in which they affect sales. In addition, we examine how different elements of sentiments impact sales. In particular, we investigate the impact of more accessible online reviews (like most recent and most helpful or the sentiments expressed in the title of the review) on product sales; we also examine the effect of strong versus moderate sentiments on sales.

The rest of the paper is organized as follows. In Section 2, we review some theoretical background to highlight the different roles that numerical ratings and text sentiments play in affecting sales. The research setting and methodology on how we extract sentiments is presented in Section 3. Section 4 provides the conceptual model and describes the data used for estimating the model. The results are presented and discussed in Section 5. In section 6 we

discuss the implications and the limitations and conclude with suggestions for future research.

## 2. Effect of word of mouth information on sales

Research from a variety of perspectives has found that reviews have effects on sales. Behavioral work has examined that negative reviews hurt product evaluations and reduce purchase likelihood and sales [27,50]. Pavlou and Dimoka [39] showed the economic value of text comments through trust in a seller's benevolence and credibility. Quantitative work has investigated how reviews influence purchase (see, for example, [1,9,6]). Although these studies have shown significant effects of ratings and/or sentiments on sales, we are unaware of any research that has examined the inter-relationship of ratings and sentiments with sales.

### 2.1. Routes through which ratings and sentiments affect sales

Due to limited processing capacity, consumers are likely to try to reduce the amount of effort that they expend on making decisions. We suggest that the routes through which ratings and sentiments affect sales may be different due to differences in cognitive processing.

Numerical attributes such as price and ratings are easy to compare, whereas experience attributes (e.g. how interesting the story plot is) are inherently subjective and, thus, difficult to evaluate [11,28]. These differences can change the way consumers process information [22,24]. In particular, attributes and information that can be easily aligned or are numerical in nature such as price, product specifications, or ratings are typically presented in a straightforward format and requires less time to obtain and process. On the other hand, obtaining detailed information about consumers' experiences or sentiments requires the reading of text reviews, which involves more time in evaluating and decision making.

We argue that ratings may have a large indirect effect on sales while sentiments have a more direct effect on sales. Consumers have finite time and attention, and the sheer amount of choices available makes it difficult to read the reviews for every choice available. Research on cognitive effort [36,38,44,48,49] has found that consumers have limited cognitive resources and often fall back on simplifying strategies and heuristics to arrive at decisions. With demands on their time and attention, consumers try to reduce the amount of effort spent on making judgments and decisions. The information that is more accessible will get more attention. In this, the accessibility of information is influenced by its comparability. Information that can be easily aligned [52] or interpreted through numeric values along a standard scale [25] is considered more accessible and less effortful to process [43].

The cost–benefit framework and research on cognitive effort suggest that the information contained in ratings and sentiments are different and the effort required to process such information is different as well. This means that in coping with decision making, consumers may adopt certain heuristic strategies to reduce their consideration set initially and then proceed with more effortful information processing to arrive at a decision. As it requires more effort and time to process text reviews than numeric ratings, consumers may rely on the qualitative information later in the decision-making process after the decision is relatively simplified. This suggests that the proximity of sentiments to the final decision making may be closer than are ratings.

Hence, in this paper we study how consumers use ratings and sentiments of online reviews to make their purchase decisions and which components of online reviews consumers use to make such a decision.

## 3. Methodology

### 3.1. Sentiment mining in online consumer reviews

To conduct our study, we first had to process the text content of each online review. Sentiment (or polarity) analysis was performed

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