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

Nan Hu [a,2,*], Noi Sian Koh [b,2], Srinivas K. Reddy [c,1,2]

[a] Department of Accounting and Finance, University of Wisconsin Eau Claire, Eau Claire, WI 54702, USA
[b] Nanyang Polytechnic, School of Information Technology, 180 Ang Mo Kio, Ave 8, 569830 Singapore
[c] Center for Marketing Excellence, Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, #05-01, 178899 Singapore

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A B S T R A C T

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.

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.[3] Nielsen, in a large scale (26,000 participants) global study in April 2007, found that 78% of participants trust recommendations from other consumers.[4] 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.[5] 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

* Corresponding author. Tel.: +1 715 836 2196.
E-mail addresses: hun@uwec.edu (N. Hu), Koh_Noi_Sian@nyp.gov.sg (N.S. Koh), sreddy@smu.edu.sg (S.K. Reddy).
[1] Tel.: +65 6828 0742.
[2] All authors contributed equally.
[3] http://www.emarketer.com/Reports/All/Emarketer_2000549.aspx.
[4] http://www.nielsen.com/media/2007/pr_071001.html.
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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

Table 1
Selected work on online user-generated content — interrelationship between ratings, sentiments and sales.

	Rating	Sentiments		Dependent variable	Inter-relationship between ratings, sentiments and sales rank	Sample size (context)
		Manual coding	Text mining			
Archak et al. [1]	√		√	Sales rank		115 (camera & photo); 127 (audio & video)
Berger et al. [2]			√	Sales quantity		234 (books)
Chevalier & Mayzlin [9]	√			Sales rank		2387 (books)
Chintagunta et al. [10]	√		√	Box office sales		148 (movies)
Clemons et al. [6]	√			Beer sales		1159 (beer companies)
Das and Chen [12]			√	Stock prices		145, 110 (stocks)
Dellarocas et al. [13]	√			Box office sales		80 (movies)
Duan et al. [14]	√			Box office sales & total reviews		71 (movies)
Forman et al. [16]	√			Sales rank		786 (books)
Fowdur et al. [17]			√	Market share		982 (movies)
Godesan and Ipeirotis [21]	√		√	Sales rank		144 (audio & video players); 109 (digital cameras): 158 (DVD players)
Godes and Mayzlin [19]	√			Rating		44 (TV shows)
Li and Hitt [30]	√			Sales rank		2651 (books)
Liu [32]	√	√		Box office sales		40 (movies)
Netzer et al. [35]			√	Co-occurrence		135 (car models); 5 (drug forums)
Reddy et al. [40]		√		Box office sales & longevity of show		142 (Broadway shows)
Tsang and Prendergast [46]	√	√		Interestingness, trustworthiness & purchase intention	√ (Only between ratings & sentiments)	24 reviews (controlled experiment)
Zhang and Dellarocas [51]	√			Box office sales		128 (movies)
Our research	√		√	Sales rank, ratings, sentiments	√	Panel: 4405 (books)

to identify positive and negative language in text. Depending on the problem examined, there are different types of sentiment analysis [31]. Archak et al. [1] used *feature-based sentiment analysis* for two electronic product categories, which extracted sentiments relating to the attributes (such as picture quality of cameras) and estimated their impact on sales. Using *subjectivity analysis*, 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.

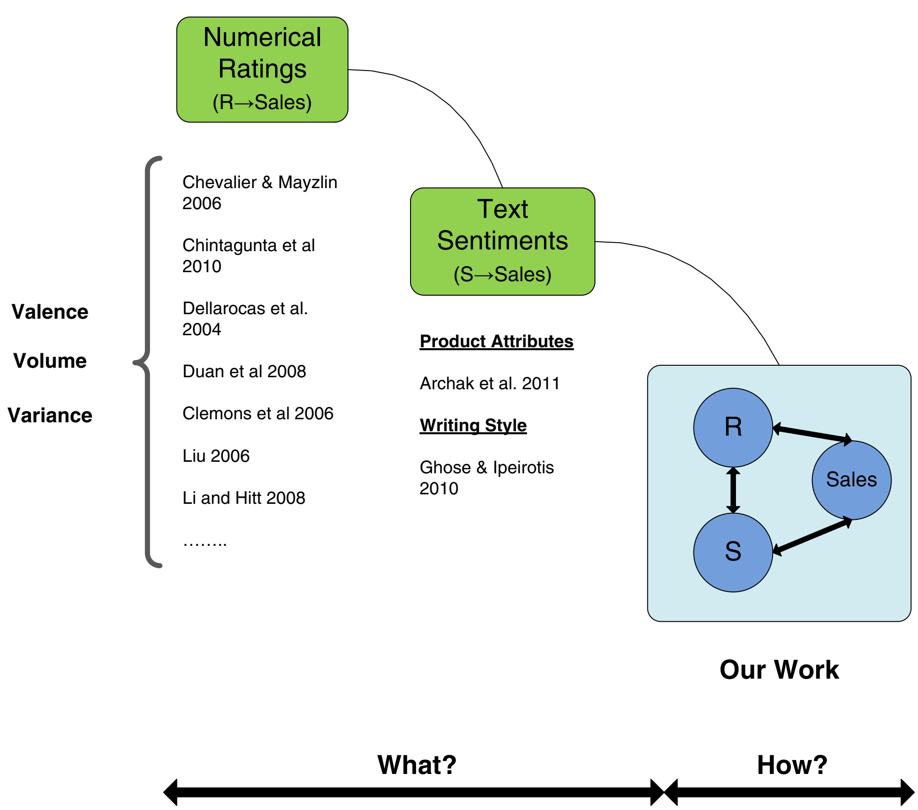

Fig. 1. Contribution of our work in relation to prior research.

For our study on the inter-relationship among ratings, sentiments, and sales rank, we performed sentiment analysis at the review level (i.e. *document-level sentiment classification*, see Liu [31]). Instead of merely determining whether a review is "thumbs up" or not, we attempted to infer the reviewers' implied numerical evaluation from the text sentiments on a multi-point scale. Pang and Lee [37] have addressed the rating-inference problem in determining an author's evaluation with respect to a multi-point scale. Using a labeled dataset, they achieved 66.3% accuracy on a three-point scale and 54.6% accuracy on a four-point scale. Their labeled dataset however, did not include neutral reviews. As the term *frequency approach* in sentiment analysis has shown to be quite effective in sentiment classification [1], we have adopted this in our measure. Fig. 2 presents the system design of our sentiment extraction and mining process. The sequence of tasks was as follows. We wrote a Java crawling code using the Amazon Web Service Application Programming Interface (API) to collect product information and online reviews from Amazon Web Service. The dataset we obtained is from the book category and it comprised two separate tables — book items and book reviews. The first table contained book item information such as the unique ASIN identification number, the average rating, sales rank, and price for each item. The second table contained the customer review information such as customer ID, rating, helpful votes, and total votes for each review. Subsequently, the text contents of each review were hashed for duplicate removal. Three supplementary sentiment databases were used to support the sentiment extraction algorithm.

- First, an electronic General Inquirer Dictionary [45], which provides the base language data where each word has been pre-tagged on its polarity (i.e., positive or negative). The General Inquirer dictionary has been used by Hatzivassiloglou and Mckeown [23], Turney and Littman [47], and several others in their research work.
- Second, a "lexicon" which is a manually-picked collection of strong positive and negative words that were found from the reviews of Amazon.com.[6]
- Third, word expansion was performed by finding the various morphological forms of words from the list of seed words in the dictionary and the lexicon (e.g., like and likes are different forms of the same lexeme).

The list of words from the dictionary formed the list of moderate sentiment terms while those in the lexicon formed the list of strong sentiment terms. Based on these two lists of seed words, we performed word expansion and calculated the number of sentiment terms in each review to obtain the sentiment score. The polarity and strength of an opinion was estimated based on the occurrences of sentiment words within the title and the content. We classified the sentiment terms into strong positive sentiments, strong negative sentiments, moderately positive sentiments, and moderately negative sentiments. The strong positive sentiments commonly seen in the Amazon reviews are terms like *excellent* and *awesome* and strong negative sentiments are terms like *terrible* and *awful*. The moderately positive terms (e.g., *nice*, *satisfactory*) and moderately negative terms (e.g., *redundant*, *dislike*) were collected from a publicly available online dictionary where each word has been pre-tagged as either positive or negative.

We presented a heuristic measurement and gave a weight of 2 and −2 for the strong positive and strong negative terms respectively. The moderately positive term was given a weight of 1 and moderately negative term was given a weight of −1. Each word in the title and content was checked against the sentiment database and assigned a count value (±1 or ±2). For robustness check, we have used a sentiment mining technique in which the weight for each term is determined through training and tuning. As our empirical results did not change qualitatively, we will present the heuristic measurement because of parsimony and strong agreement from our human judges.

For each review, we computed the number of sentiment term occurrences within a review. The polarity of a review was calculated based on the occurrences of the sentiment words times their individual weights within the review. The difference between the positive terms and negative terms were normalized by the total number of sentiment terms to discount the influence of longer reviews. The sentiment score of a customer review i was computed as:

$$Sentiment_i = \frac{(SP_i * wg + MP_i) - (SN_i * wg + MN_i)}{(SP_i + SN_i) * wg + MP_i + MN_i} \quad (1)$$

where:

- SP_i: the number of strong positive terms in review i
- SN_i: the number of strong negative terms in review i
- MP_i: the number of moderately positive terms in review i
- MN_i: the number of moderately negative terms in review i
- wg: the weight of strong terms

From Eq. (1), the minimum and maximum sentiment score obtained from each review was [−1, 1]. For product item j, there are n reviews. The text of each review contains a title and the content (see Fig. 3). To study which components of online reviews impact sales, for the i^{th} review of product j, we estimated the sentiment score for the title and the content separately using Eq. (1) before aggregating them to get the sentiment score for this review.

To facilitate comparisons between the numeric rating and the sentiment score, we converted the sentiment score for each review to a scale of 1 to 5, rounding to one decimal point, which is similar to that of the numeric rating scale in Amazon.com.[7] To validate our method we recruited two judges (doctoral students) who were asked to independently read a sample of 200 reviews. For each review, the judges were asked to gauge if the sentiment score we estimated was accurate and reflected the overall sentiments expressed in the review. The sequences of reviews were randomly selected and both judges rated the reviews in the same order to avoid order biases. We conducted inter-judge reliability tests to determine the extent of agreement shown by the two judges in assessing the proper reflection of the sentiment score in the sample of reviews. Overall, there was significant agreement between the two judges on the sentiment score of all reviews with Cohen's kappa of 0.8521. In addition, we had a third judge read a sample of 100 reviews (without seeing the score derived by our method) and assign a score on a 5-point scale based on their assessment of how positive or negative the review was. The correlation between the judge's scores and the sentiment scores derived by our approach was 0.73. This provides some validation of the sentiment scores derived by our approach.

4. Conceptual framework

As current literature leaves us with a somewhat unclear picture of the inter-relationship between ratings, sentiment, and sales rank, we developed a conceptual framework to seek a clearer understanding of 1) the inter-relationship between ratings, sentiments, and sales and 2) the way ratings and sentiments affect each other. Previous research has studied the impact of product characteristics such as age (elapsed time since the release of the book) and/or retail price on sales. Similarly, researchers have looked at the impact of age on ratings [20,30,33,34]. To the best of our knowledge, there has been no work on the impact of these product characteristics on *sentiments*. The conceptual model (see Fig. 4) also captures the impact of other user-generated review characteristics on sales.

[6] The terms were obtained by Archak et al. [1] from the reviews in Amazon.com. Each term was given a score on the scale of 0 to 100. Among the 2697 terms/phrases they obtained, we extracted 40 strong positive terms (with scores higher than 95) and 30 strong negative terms (with scores less than 30).

[7] Suppose from Eq. (1) we obtain a sentiment score of $x = 0$, the sentiment score on a 1 to 5 scale is: $f(x) = 2x + 3 = 3$.

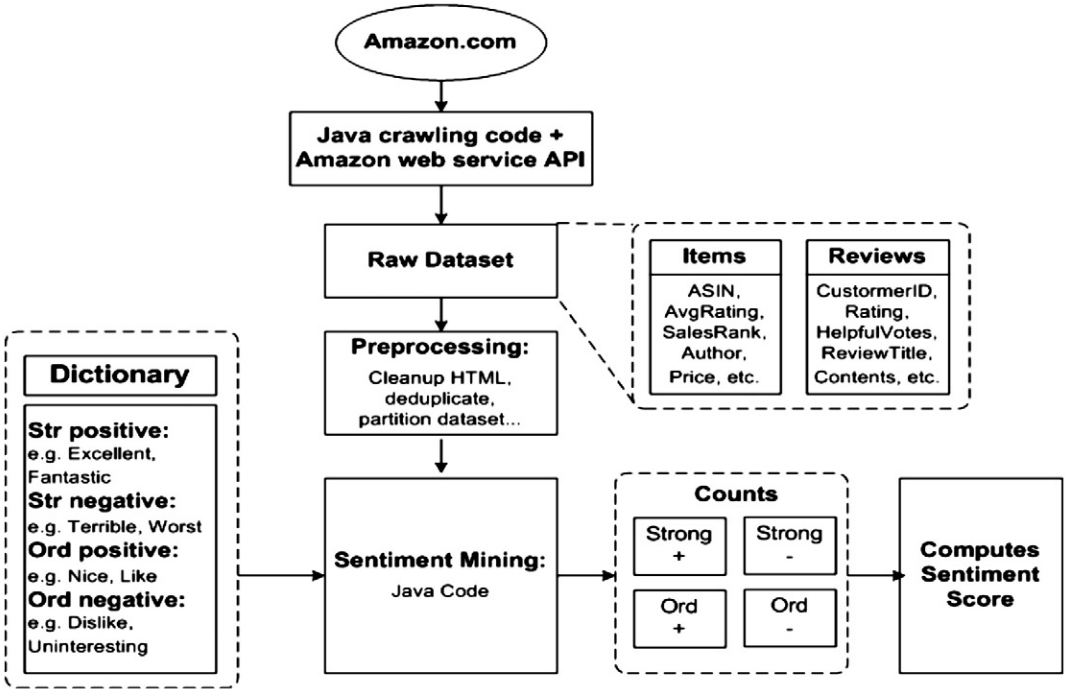

Fig. 2. System design of sentiment extraction and mining process.

Hu et al. [26] argued that the distribution of product reviews is often J-shaped and the simple average ratings may not convey the essence of the review to the reader. They recommended that product review systems should provide other distribution information like variance or mode. On Amazon.com, one could gather not only the average rating information but also the distribution of these ratings. Low variance would suggest a more consistent opinion by users and could be viewed as an important piece of information when evaluating and making a purchase decision. Assessing the variance in sentiments expressed in text reviews may be a bit harder and not as quantifiable as numerical ratings distribution and as such may have less of an impact on sales. Some researchers have incorporated variance into their models [6,10,19] with mixed results. While Chintagunta et al. [10] did not find significant effect of variance on sales, Clemons, Gao and Hitt [6] and Godes and Mayzlin [19] found the effect to be negative and significant. We expect that variance in ratings will have a significant negative impact on sales while variance in sentiments will have a lesser impact on sales.

With each review, Amazon.com provides the helpfulness of the review to its readers. It provides information on how many people who previously read the review found it helpful.[8] We feel that potential customers will be influenced by the helpfulness of the reviews when making choices and the average helpfulness ratio of reviews for the item will have a positive impact on sales. In addition to looking at the helpfulness of all reviews for an item, we also explored the possibility that customers may not be in a position to evaluate the helpfulness of all reviews for the items they are evaluating. Instead they may choose to look at the top five (or ten) most helpful reviews or the most recent reviews. The way that this information is provided by Amazon.com also makes it easy for consumers to view and evaluate. So it will be a useful path to explore.

4.1. Data

To conduct our study, we collected a panel data set of books sold on Amazon.com from September 2005 to January 2006 using its Web Service (AWS). We initially chose 10,000 books randomly to gather sales and review information. Of these 10,000 books, we found that 4405 books had text reviews that we could capture. For each item, we collected the title, when the book was released, Amazon's retail price and sales rank (which we used as a proxy for sales).[9]

In addition, we collected information on reviews, such as total number of reviews (volume), the numerical rating from which average (valence) and variance can be computed, helpfulness of the review, and the original text of reviews from which sentiments can be extracted and scored. We also computed sentiment scores for the title of the review as well as the content of the review. Considering that consumers do not read all reviews, we collected ratings and sentiment information on the most recent reviews and most helpful reviews.[10] The summary statistics and correlation of the variables are provided in Tables 2 and 3.

[8] Forman et al. [16] and Ghose and Ipeirotis [18] attempted to explain what determines the helpfulness ratio (ratio of helpful votes over the total number of votes of a review). Forman et al. [16] found that the disclosure of a reviewer's identity has a positive impact and an equivocal review (review with 3 stars) has a negative impact on helpfulness. Ghose and Ipeirotis [18] found that in general, the writing style (subjectivity, readability, and spelling errors) impact helpfulness of a review.

[9] Researchers that have used data from Amazon.com have used sales rank as a proxy for demand [1,9,18]. They cite the work done by researchers who have found an approximately linear relationship between ln(sales) and ln(sales rank) [8,40,41]. These researchers approximated the relationship for books on Amazon.com to be $\ln(\text{sales}) = 9.61 - .78 * \ln(\text{sales rank})$. While Brynjolfsson, Hu and Smith [5] calibrated the relationship to be $\ln(\text{sales}) = 10.526 - 0.871 * \ln(\text{sales rank})$.

[10] Amazon.com provides this type of information on the first page of each item, with the most helpful reviews provided on the left/center of the page and most recent reviews on the right hand side of the page. We thank one of the reviewers for suggesting that we look at this in addition to the average ratings and sentiments of all reviews. We have looked at the top five and ten most helpful reviews and the five and ten most recent reviews for each item when they are available. The results between the five and ten most helpful and recent reviews did not differ much. We have thus chosen to present the results for five most helpful and recent reviews.

Fig. 3. Segments of online reviews.

4.2. Model

The following three-equation model is a representation of the model in Fig. 4 and captures not only the effects of various product and user-generated characteristics on sales, but also the interrelationships between ratings, sentiments, and sales.

Salesrank :

$$\begin{aligned}\ln(SR)_{jt} &= \alpha_0 + \alpha_1 (AR)_{jt} + \alpha_2 (AS)_{jt} + \alpha_3 \ln(P)_{jt} \\ &+ \alpha_4 \ln(Age)_{jt} + \alpha_5 \ln(TR)_{jt} + \alpha_6 (AH)_{jt} \\ &+ \alpha_7 (VR)_{jt} + \alpha_8 (VS)_{jt} + \mu_j + \varepsilon_{SRjt}\end{aligned}$$

Sentiment :

$$\begin{aligned}AS_{jt} &= \beta_0 + \beta_1 \ln(SR)_{jt} + \beta_2 (AR)_{jt} + \beta_3 \ln(P)_{jt} + \beta_4 \ln(Age)_{jt} \\ &+ \beta_5 \ln(TR)_{jt} + \beta_6 (AS)_{j(t-1)} + \nu_j + \varepsilon_{ASjt}\end{aligned}$$

Rating :

$$\begin{aligned}AR_{jt} &= \gamma_0 + \gamma_1 \ln(SR)_{jt} + \gamma_2 (AS)_{jt} + \gamma_3 \ln(P)_{jt} + \gamma_4 \ln(Age)_{jt} \\ &+ \gamma_5 \ln(TR)_{jt} + \gamma_6 (AR)_{j(t-1)} + \omega_j + \varepsilon_{ARjt}\end{aligned}$$

where,

- j 1,….., N book items.
- P_{jt} price of book j at time t
- Age_{jt} age of book j at time t
- TR_{jt} total number of reviews of book j at time t
- AH_{jt} average helpfulness ratio of book j at time t
- SR_{jt} sales rank of book j at time t
- AR_{jt} average rating of book item j at time t.
- AS_{jt} average sentiment of the book item j at time t.
- VR_{jt} variance of rating for book item j at time t.
- VS_{jt} variance of sentiment for book item j at time t.
- $AR_{j(t-1)}$ average rating of book item j by time $t-1$.
- $AS_{j(t-1)}$ average sentiment of the book item j by time $t-1$.
- μ_j, ν_j and ω_j are the product-level fixed effects for the three equations respectively to control for unobserved heterogeneity across products and ε_{SRjt}, ε_{ASjt}, ε_{ARjt} are the residual error terms.

5. Results and discussion

The three-equation, non-recursive model is estimated using three-stage least squares with fixed effects. The model estimates (standardized) appear in Table 4.

Based on the results in Table 4, we highlight the interrelationship between sales rank, sentiments, and ratings in Fig. 5. Examining the relationships between the three endogenous variables, we find that the impact of average ratings on sales is not significant; whereas, the impact of average sentiments on sales is negative and significant (−0.074). Our results indicate that the impact of ratings on sales rank is mostly indirect, through sentiments, and the impact of sentiments on sales rank is mostly direct. Much of the previous research which looked at just numerical ratings found a direct impact on sales [9,16].[11] Ghose

[11] These are the two pieces of research which looked at Amazon.com books in their analysis and are most relevant for comparison. Other researchers investigating different product categories found mixed impact of ratings on sales. Whereas Liu [32] and Duan et al. [14] found no significant impact of ratings on box-office of movies, Dellarocas et al. [13] and Chintagunta et al. [10] found positive impact. Clemons et al. [6], looking at beer, and Moe and Trusov [33], looking at bath fragrances and beauty products, found a significant effect of ratings on sales.

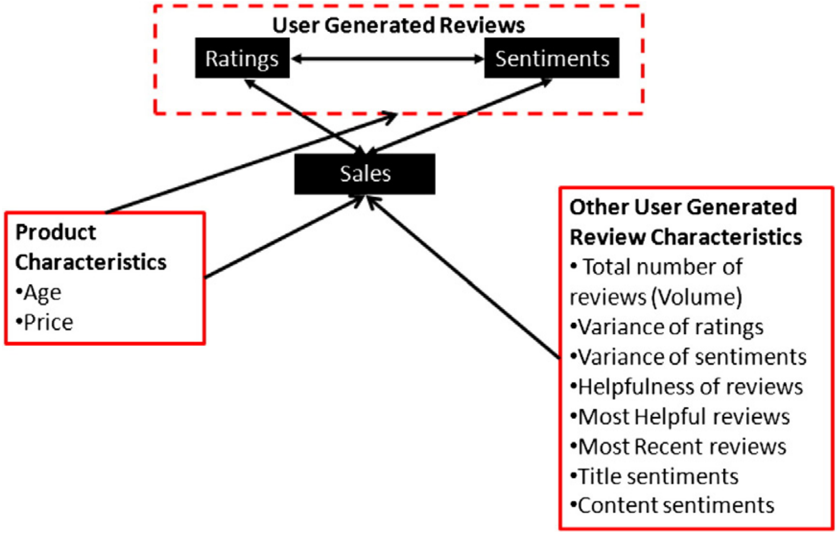

Fig. 4. Conceptual framework.

and Ipeirotis [18], who looked at electronic products in their research and had some measures of sentiments (namely writing style), found that the ratings had a significant effect on sales in only one of the three product categories (in the presence of average subjectivity of reviews). Our finding of the impact of numerical ratings on sales being mostly indirect and through sentiments is an interesting and an important one. This finding suggests a potential sequential nature of consumer decision making. Due to the nature of the complex task of searching and purchasing in an online environment, consumers may use different strategies to lessen the burden of their cognitive effort. The way that they may do this is by using ratings as a way to screen potential items and use text reviews to evaluate the limited set of screened items to make the final choice. However caution should be exercised as this is based on aggregate data and not individual-level data. Future work should explore this further to identify the mechanism and the role played by ratings and sentiments in the online decision-making process.

To study how ratings and sentiments interact with each other in influencing sales, we also introduced an interaction term (Ratings ∗ Sentiments) in our original model for the sales rank equa-

Table 2
Summary statistics of panel dataset from Amazon.com.

	September 2005		January 2006	
Variable	Median	Mean (SD)	Median	Mean (SD)
Price	16.29	18.15 (22.73)	15.72	19.06 (16.60)
Sales rank	3955.00	36,653.31 (98,796.62)	4317.00	53,196.36 (135,516.17)
Age (days)	149.00	421.24 (803.69)	297.00	657.02 (945.03)
Number of reviews	12.00	42.68 (161.36)	12.00	43.85 (168.75)
Average helpful ratio	0.40	0.41 (0.16)	0.17	0.20 (0.22)
Average rating	4.16	3.88 (0.78)	4.00	3.72 (1.21)
Average sentiment score	3.66	3.71 (0.42)	3.78	3.73 (0.72)
Variance of rating	1.29	1.62 (1.13)	1.41	1.70 (1.62)
Variance of sentiments	0.69	0.70 (0.36)	0.58	0.69 (0.65)
Average title sentiment	3.61	3.62 (0.60)	3.67	3.70 (1.08)
Average content sentiment	3.70	3.80 (0.40)	3.84	3.76 (0.62)
Most helpful rating	4.00	3.88 (1.05)	4.00	3.61 (1.39)
Most helpful sentiment score	4.04	3.99 (0.48)	3.63	3.68 (0.54)
Recent rating	4.00	3.85 (0.85)	3.80	3.66 (0.91)
Recent sentiment	3.98	3.77 (0.51)	3.64	3.66 (0.53)
Sample size		4405 books		4405 books

Table 3
Correlation table.

	P	*Age*	*TR*	*AH*	*AR*	*AS*	*ATS*	*ACS*	*VR*	*VS*
Price	1	−0.3	0.23	0.01	0.03	0.01	0.02	0	−0.03	−0.04
Age		1	−0.54	−0.22	−0.13	−0.1	−0.02	−0.17	0.09	0.01
TR (total reviews)			1	0.24	−0.02	−0.17	−0.09	−0.23	0.03	0.06
AH (avg helpful)				1	−0.02	−0.07	−0.03	−0.11	0.02	0
AR (avg rating)					1	0.45	0.38	0.39	−0.61	−0.26
AS (avg sentiment)						1	0.9	0.76	−0.3	−0.37
ATS (avg title score)							1	0.41	−0.25	−0.38
ACS (avg content score)								1	−0.27	−0.24
VR (var of rating)									1	0.28
VS (var of sentiment)										1

Table 4
Model estimates (3SLS fixed effects model).

	SR_{jt}	AS_{jt}	AR_{jt}
ln $(SR)_{jt}$ (sales rank)		−0.2079	0.3959
AR_{jt} (average rating)	−0.0148	0.0693***	
AS_{jt} (average sentiment)	−0.0742**		−0.0421
ln $(P)_{jt}$ (price)	0.3310***	−0.0029	−0.0067
ln $(Age)_{jt}$ (age)	0.1995***	−0.0066	−0.0580***
ln $(TR)_{jt}$ (total review)	−0.8305***	−0.0463***	−0.0345***
AH_{jt} (average helpful)	−0.1068***		
VR_{jt} (variance of rating)	0.0063		
VS_{jt} (variance of sentiment)	0.0013		
$AR_{j(t-1)}$ (average rating at $t-1$)			0.7983***
$AS_{j(t-1)}$ (average sentiment at $t-1$)		0.6986***	
Intercept	0.0230***	0.0367***	0.0324
Max VIF	1.94	2.61	2.61
Adjusted R^2	0.98	0.93	0.87

Standardized coefficients. Significance: ***$p < .001$; **$p < .01$; *$p < .05$.

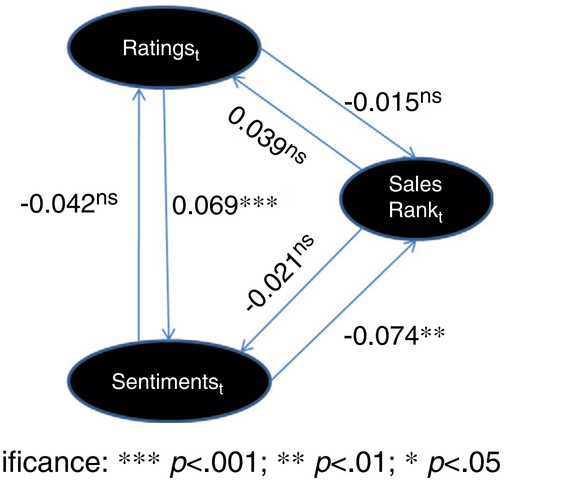

Fig. 5. The results of the inter-relationship between ratings, sentiments, and sales rank.

tion. Since the interaction effect was significant and negative (para = −0.0649 and $p < 0.001$), indicating a moderation impact of ratings and sentiments on sales.

5.1. Alternative models

As mentioned earlier, consumers may sample some reviews of items and not go through all the reviews. As Amazon.com presents the most helpful reviews and the most recent reviews on the first page of an item, consumers may choose to use them when evaluating and making a purchase decision. It would be interesting to see what the impact on sales rank would be if we use valence information (ratings and sentiments) from only the most helpful and the most recent reviews.[12]

Many times, the title of the review presents a summary view of what is in the full text of the review. Customers look at the titles of the reviews to get a feel for what the review might say and then decide whether to read the text of the review. To see if there is a differential impact of the sentiments in the title and the content of the review, we decomposed the total sentiment score into that based on just the title of the online review and one based on the body (or content) of the review. To understand how the sentiments expressed in the title and the body of the review affect sales rank, we estimated a model where we had average sentiments from the title of the review and the body of the review included (instead of the overall average sentiments).

In the computation of the summary sentiment score for each review we gathered information on the number of strong positive, strong negative, moderately positive, and moderately negative sentiments expressed. It will be interesting to see their differential impact on sales. So we estimated models with various combinations of these sentiments.

5.1.1. Impact of most recent and most helpful reviews

Fig. 6 presents the estimates of the interrelations between most helpful/most recent ratings, sentiments, and sales rank. We substituted most helpful/most recent ratings/sentiments for average ratings/sentiments in the original model.[13] The use of the most recent or most helpful reviews does not change the qualitative interpretation of the effects. The ratings (whether most recent or most helpful) still seem to have an indirect impact on sales rank. Likewise, sentiments (whether most recent or most helpful) still seem to have a significant direct impact on sales rank. However, some of the standardized coefficient estimates are larger in these models. For example, the direct effect of most helpful sentiments (−0.101; $p < 0.01$) and most recent sentiments (−0.127; $p < 0.01$) on sales rank is larger than the corresponding impact of average sentiments (−0.074; $p < 0.01$). This is an interesting finding as it indicates that the most evident and accessible set of reviews on Amazon.com (namely the most helpful and most recent) play a significant role in determining sales. The mental effort required by consumers in reading through a large number of reviews is minimized by sampling the most recent and most helpful reviews to make their evaluation and choice. This is an area that requires further research. Researchers attempting to extract sentiments from text reviews may examine whether a subset of reviews that consumers use may just be sufficient to see the impact on sales. Also, from the perspective of Amazon.com or other similar sites, the way and the kind of user-generated information that is presented to the consumers may make a difference. In this case, Amazon.com provides these two types of reviews in an easily viewable way for consumers. Since on Amazon the most helpful and most recent reviews are easily accessible to customers, their impact on sales is much larger than the average impact of all reviews. It seems that customers do rely on the most recent and most helpful reviews to make their evaluation and choice.

From a heuristic perspective, information that is more accessible has a dominant impact on judgment and decision making [25,42] and our results on the most helpful and most recent reviews seem to suggest this. Understanding consumer behavior in the rich, user-generated online environment in terms of search strategies and the heuristics used in evaluating and making choices is going to be important for firms when designing their websites to make them easier and more helpful.

5.1.2. Impact of title and content sentiments

We examined the impact of ratings and sentiments, taking into account the structure of the review. Both the title and content sentiments have significant negative impact on sales rank. We find that the sentiments in the content (body) of the review have a larger impact than the sentiments in the title of the review (para = −0.2304 and $p < .001$; vs. para = −0.0129 and $p < .01$). The title may convey some information that is useful, but the customers seem to be paying more attention to the sentiments expressed in the content of the review. It is likely that in this case, customers are using title sentiments as a screening device but still would validate their choice by digging into the content sentiments. One possible implication for product reviewers here is that they may need to pay attention to the way they title their review. It should be crisp and clearly point to the sentiments expressed in the full text so that it entices potential buyers to look deeper at their review.

[12] The averages were taken for the five most helpful reviews and the five most recent reviews for each book item. We also estimated models using 6–10 most helpful/recent reviews. We obtained similar results. We discuss the results for the five most helpful and the five most recent reviews.

[13] The overall results of these models parallel the results reported earlier for the average ratings/sentiments model. The estimates for the full model for all these alternate models can be obtained from the authors.

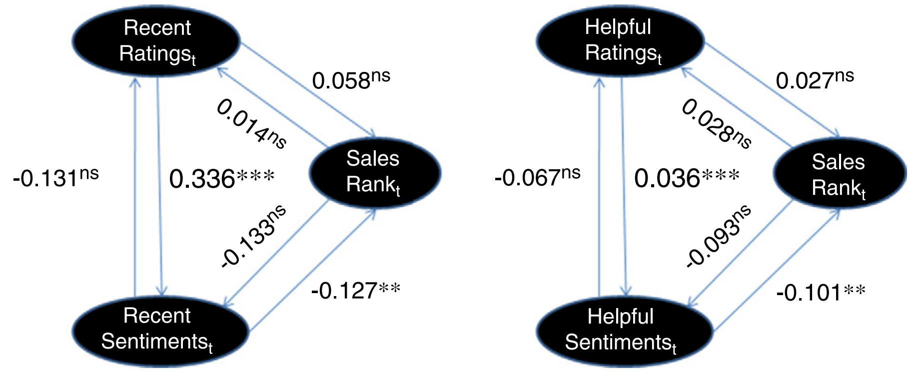

Fig. 6. The results of the interrelationship between most helpful/most recent ratings, sentiments, and sales rank. Significance: ***$p < .001$; **$p < .01$; *$p < .05$.

5.1.3. Impact of strong and moderate sentiments

Next, we examined how sentiments of different strengths may affect sales rank.[14] We estimated two models using the same structure as in the original model, but replacing the average sentiment AS_{jt} with different components of sentiments. We examined the impact of strong sentiments (strong positive and strong negative) and moderate (moderately positive and moderately negative) sentiments. As four sets of sentiments are not linearly independent, we could use only at most three of the sentiments in the model. We chose to use combinations of the sentiments to get a better understanding of the impact on sales rank.

Thus, in the original model presented in Section 4.2, we replaced the AS_{jt} variable in the sales rank equation with three of the sentiments.[15] We estimated models with the following sets of sentiments: 1) ASN_{jt}, AMP_{jt}, AMN_{jt}, *and* 2) *ASPjt*, AMP_{jt}, AMN_{jt}. The coefficients of strong and moderate sentiments are presented in Table 5.[16]

A consistent picture emerges here: moderate sentiments seem to have a stronger impact on sales rank than strong sentiments (Models 1 and 2). The impact of moderately negative sentiments is stronger than strong negative sentiment (Model 1). Similarly, moderately positive sentiments have a stronger impact than strong positive sentiments (Model 2). This is a very interesting result as it appears that contrary to what one would expect strong sentiments are not as impactful as moderate sentiments. Previous research in this area has found that reviews generally tend to be on the positive side. The average numerical rating in our study was 3.72 out of a possible 5. It appears that high numerical ratings and strong sentiments are being discounted. Customers seem to put more value on sentiments in moderately worded reviews and they seem to find the moderately negative and moderately positive sentiments to have the greatest value. An alternative explanation would be customers doubt that the extremely positive sentiments are from real respondents, but may be promotional reviews posted by companies or authors.

6. Implications, limitations and future research

User-generated online reviews are becoming an important source of information for consumers and firms when making purchase or investment decisions. Therefore, there is a need to understand how consumers perceive both quantitative and qualitative information embedded in online reviews and under what circumstances or which aspects of these reviews are likely to impact sales. This paper contributes to the emerging literature on user-generated content, and specifically on online reviews, by addressing these fundamental but largely neglected questions. This study adds to the literature on the user-generated content by examining the direct and indirect effects of ratings and sentiments on sales rank and their inter-relationships.

Our empirical results reveal that the ratings' effect on sales rank is mostly indirect, through sentiments, while sentiments' effect on sales rank is mostly direct. Sales rank, on the other hand, does not impact ratings and sentiments contemporaneously. The results are summarized in Table 6.

The mediating role of sentiments suggests a possible sequential decision-making process where ratings play an important role in the early stages of search and text sentiments play an important role in evaluation and choice. To shed some light on this decision process, we conducted a survey with 156 (100 male, 56 female) Amazon.com users. These were all undergraduate students from a major business school in the United States. Participation was voluntary and no monetary incentive was given. Respondents were given a scenario of buying a travel guide on New Zealand from Amazon.com. Supposing the keywords typed in were "travel guide on New Zealand," respondents were presented with the screen shot of the search results that would appear on Amazon.com. A series of questions were asked as to the relative importance of numerical ratings and text reviews during the search, evaluation and purchase. A majority (58%) of the respondents felt that numerical ratings are important in the early stages of search and awareness, and its importance decreases as consumers move from search stage to final purchase stage; whereas 65% of the respondents felt that text sentiments are important when making a purchase and its importance increases as consumers move from search stage to final purchase stage; (Fig. 7). We summarize our results in Fig. 8. The results in this study suggest the relevance of ratings and sentiments may be different over the course of search, evaluation, and purchase and we hope that these findings will be an impetus for future research on this timely and important topic.

Table 5
Model using different sentiments and their impact on sales rank.

	Model 1	Model 2
AR_{jt} (average rating)	−0.0230*	−0.0038
ASN_{jt} (strong negative)	0.0144**	–
AMP_{jt} (strong positive)	–	−0.0136
AMP_{jt} (moderately positive)	−0.0224***	−0.0391**
AMN_{jt} (moderately negative)	0.1580***	0.0837***
Intercept	0.2422***	0.0243***

Standardized coefficients. Significance: ***$p < .001$; **$p < .01$; *$p < .05$.

[14] The strong positive/negative score or moderately positive/negative score for the i^{th} review was calculated using the following formula: $\frac{senti_{par}t_i}{SP_i+SN_i+MP_i+MN_i}$,where $senti\_part_i \in \{SP_i, SN_i, MP_i, MN_i\}$. The strong positive (SP)/negative (SN) score or moderately positive (MP)/negative (MN) score for each product was obtained from the content of each review. The final strong positive/negative score or moderately positive/negative score of a product is the average of all the strong positive/negative scores or moderately positive/negative scores over all the reviews received by that product item respectively.

[15] We used three of the four possible sentiments to avoid issues of singularity in the model. As the results on other control variables do not change qualitatively, we have presented the key results of the strong and moderate sentiments in Table 4.

[16] The results of the other variables in the model are qualitatively similar to the ones reported earlier in Table 3 and are not presented here for brevity. The full results of all these models are available from the authors.

Table 6
Summary results — inter-relationship between ratings (R), sentiments (S) and sales rank (SR).

	Average reviews	Most recent	Most helpful	Title sentiments	Content sentiments	Strong sentiments	Moderate sentiments
R → SR	×	×	×				
R → S	√	√	√	√	√	√	√
S → R	×	×	×				
S → SR	√	√	√	√	√	√	√

√ Significant × not significant.

The findings from this research provide some important managerial implications. The increased use of text reviews and the strong direct impact of sentiments expressed in text reviews on sales suggest that firms should provide an easy and intuitive mechanism for consumers to provide their text reviews. Amazon.com, Expedia.com and Tripadvisor.com are good examples of firms that do this well. Even these firms can benefit by providing sentiment scores along with the numerical ratings. Our methodology can be implemented in a dynamic way in real-time to extract and present sentiment scores.

Firms managing their sites should take note of the sequential nature of the customer evaluation and decision making process where they potentially use numerical ratings to short list their choices. Firms should design an easy and intuitive architecture to make the experience for customers to make their search, evaluation, and choice easier; this will help gain and retain customers.

Another practical implication of our finding is that if an online retailer wants to nudge customers' attention toward a certain product, the strategic placement of the most recent or most helpful sentiments of the product can be enlarged in a pop up screen when a user mouses over the product. This will essentially reduce the search time and direct customers to the most recent/helpful information based on the movement of the mouse. Online retailers should consider our findings in designing their user interfaces in order to maximize their systems' usability and effectiveness.

Some limitations of the study, however, must be acknowledged. Despite the advances in text mining to capture the essence of sentiments efficiently, one has to be aware of the limits on accuracy. We have provided some validation of the sentiment scores derived by using human judges on a sample of the reviews. However, future work should incorporate such validation to provide greater confidence in the use of text mining tools to extract sentiments.

The work of Forman et al. [16] found a significant effect of reviewer disclosure on sales. As we were unable to collect this information in our study, we could not include this variable in our model. Ghose and Ipeirotis

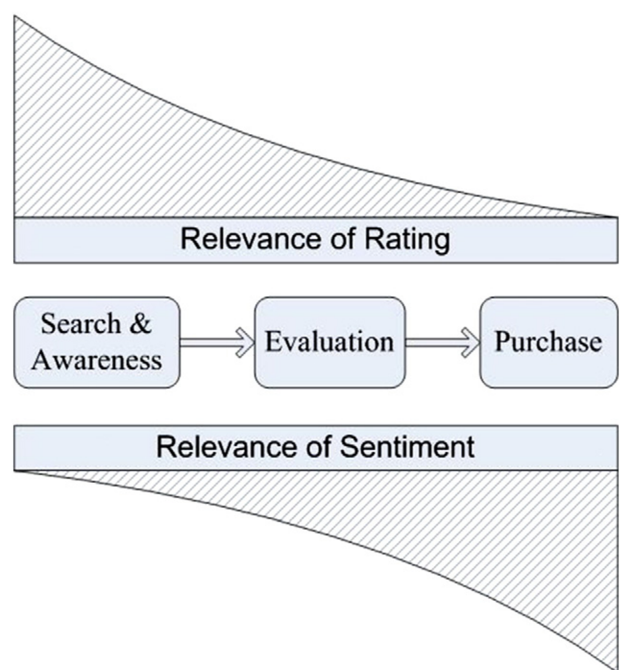

Fig. 8. Ratings and sentiments and their relevance in stages of the decision making process.

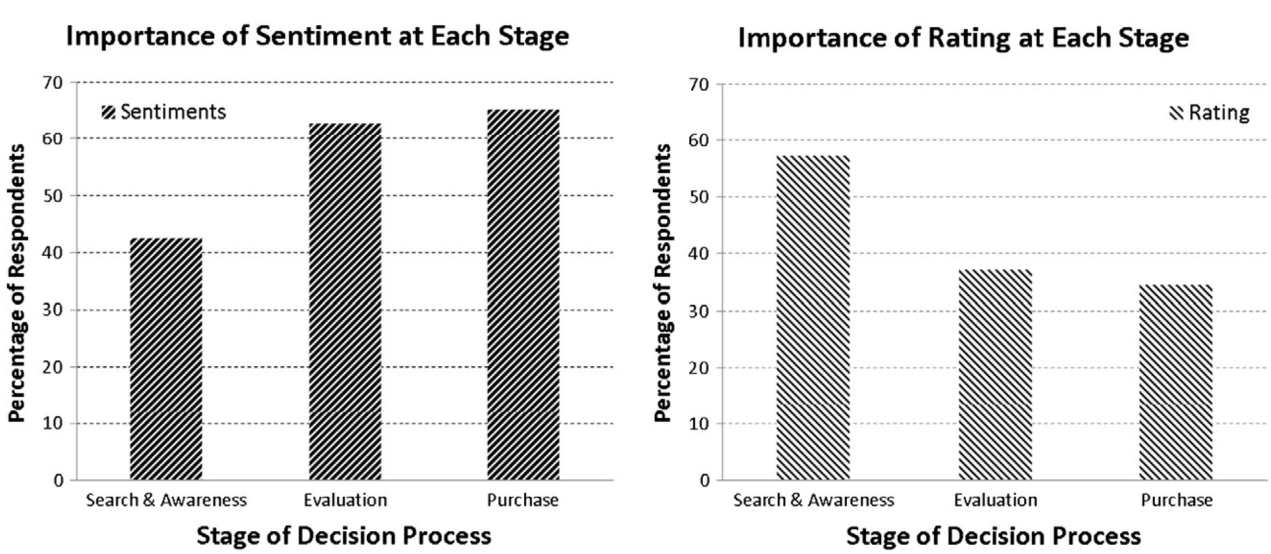

Fig. 7. Importance of numerical ratings and text sentiments in purchase process.

[18] found that average helpfulness of the review was impacted by reviewer disclosure. We have incorporated average helpfulness in our model and believe that some of the disclosure impact may be captured by this variable. However, future work should incorporate this important variable.

Our survey results reveal the different roles played by ratings and sentiments, however, this is just a preliminary look at this issue and is only indicative of the possible role of ratings and sentiments in the purchase process. Further investigations about the order in which people search (do they look for the most positive ratings/comments first, or do they look for lower ratings/negative comments first?) would shed more light on the role played by ratings and sentiments in the purchase process. Future work using experiments, eye-tracking or other related methods [7,49] will help achieve a better understanding of the process suggested in Fig. 8.

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Nan Hu is an Assistant Professor of Accounting & Finance at the University of Wisconsin at Eau Claire. He received his Ph.D. from the University of Texas at Dallas. Nan's research focuses on investigating the value implications and market efficiency of both traditional information and non-traditional information, using a combination of theories from accounting, finance, marketing, information economics, sociology, psychology, and computer science. Nan's research has appeared at JMIS (*Journal of Management Information Systems*), MISQ (*MIS Quarterly*), *IEEE Transactions on Engineering Management*, CACM (*Communications of the ACM*), ACM *Transactions on Management Information Systems*, DSS (*Decision Support Systems*), JCS (*Journal of Computer Security*), JBR (*Journal of Business Research*), JAAF (*Journal of Accounting, Auditing, and Finance*), and IT&M (*Information Technology and Management*).

Noi Sian Koh is a Lecturer at the School of Information Technology, Nanyang Polytechnic. She received her Ph.D. in Information Systems from Singapore Management University. Her research has appeared at *Decision Support Systems* and *Journal of Electronic Commerce Research and Applications* (funded in part by Wharton-SMU Research Centre).

Dr. Srinivas K. Reddy is Professor of Marketing, and Director, Center for Marketing Excellence, Lee Kong Chian School of Business at Singapore Management University. He holds M.Phil and Ph.D. degrees in Business Administration from Columbia University. Reddy taught previously at New York University's Stern School of Business, Columbia University, University of Georgia, the University of California, Los Angeles and Stanford Business School. His research has been published in *Management Science*, *Statistical Science*, *Journal of Probability and Statistics*, *Journal of Marketing Research*, *Journal of Marketing*, *Journal of Business Research* and *Neuroimage*.