01 Nov 2019

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Recommended Citation

Chen, L. (2019). The Impact of the Content of Online Customer Reviews on Customer Satisfaction: Evidence from Yelp Reviews. *Proceedings of the ACM Conference on Computer-Supported Cooperative Work and Social Computing (2019, Austin, TX*, pp. 171-174. Association for Computing Machinery (ACM).
The definitive version is available at https://doi.org/10.1145/3311957.3359448

The Impact of the Content of Online Customer Reviews on Customer Satisfaction: Evidence from Yelp Reviews

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ABSTRACT

As customers are increasingly participating in online product and service reviews, companies can leverage the content of those consumer reviews to improve or retain customer satisfaction. By using a panel data set collected from Yelp, this study empirically tests the effects of voting and sentiment of customer reviews on future customer satisfaction. The results show that cool votes on customer reviews have a positive impact on customer satisfaction in the next month. While average positive sentiment score has a positive effect on customer satisfaction of a restaurant, average negative score has a negative influence. In addition, the diversity of the sentiment scores moderates the effects of positive and negative sentiment scores on customer satisfaction. This research provides a nuanced understanding of how the content of online customer reviews affects customer satisfaction, an important indicator of the quality of service or product.

CSCW '19 Companion, November 9–13, 2019, Austin, TX, USA

ACM ISBN 978-1-4503-6692-2/19/11.
https://doi.org/10.1145/3311957.3359448

KEYWORDS

Online customer reviews; customer satisfaction; voting; sentiment analysis; yelp

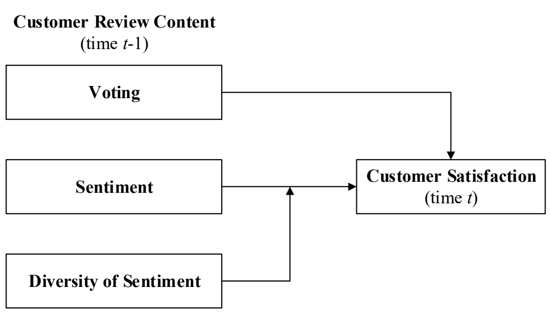

Figure 1: Research framework.

INTRODUCTION

Customer satisfaction is commonly defined as a customer's overall evaluation of the quality of a service or product [13]. Maintaining a high level of customer satisfaction rating is important for any company as such high rating is widely regarded as the best indicator of a company's capability of making profit [8]. Customers who are satisfied with the product or service are more likely to repurchase, be more loyal to the company or brand, and engage in positive word-of-mouth behaviors.

With the advent of the Internet, consumers are increasingly participating in online platforms to review products or services. Companies can benefit from online reviews by integrating customer voices into their product manufacturing or service delivery process. An important challenge for companies is to improve or retain customer satisfaction by leveraging the user-generated content on online review platforms. While previous research on online product review content has intensively addressed factors that impact the usefulness of reviews [7; 10] and how review textual content can be used for product ratings prediction [9], there is limited research on how the online customer review content influences the customer satisfaction of the firm. This study empirically tests the impact of online customer review content on customer satisfaction by applying a fixed-effect regression model on a panel data set collected from Yelp. Specifically, this study focuses on sentiment expressed in customer reviews and voting (including usefulness, funny, and cool voting) of customer reviews.

RESEARCH SETTING AND DATA

Data were collected from Yelp, a leading customer review platform for restaurants. Consumers can post reviews with a satisfaction score on Yelp. Other consumers can vote on a customer review in terms of its usefulness, funny, and cool characteristics. Only businesses that are restaurants and have customer reviews across at least two months were included in the analysis. To extract interesting variables for statistical analysis, a sentiment analysis tool called SentiStrength was used to analyze positive and negative sentiment scores of customer reviews [3; 12]. Other variables such as the usefulness, funny, and cool votes of customer reviews were directly extracted from the raw data set. As the unit of analysis is at company level, sentiment scores and voting were aggregated to company level in each month. Specifically, average and standard deviation of customer review sentiment scores were used to measure the overall customer sentiment and its diversity. As a result, a monthly unbalanced panel data set was constructed containing 48,503 companies and 898,985 observations across 132 months from year 2008 to year 2018. Fig. 1 shows the proposed research framework that provides guidance for the empirical data analysis.

Table 1: Estimation results

	(1)	(2)	(3)
Primary variables			
sat_{it-1}	0.036***	0.031***	0.031***
	(0.001)	(0.002)	(0.002)
$usefulness_{it-1}$		-0.005***	-0.004**
		(0.001)	(0.001)
$funny_{it-1}$		0.001	0.001
		(0.002)	(0.002)
$cool_{it-1}$		0.006***	0.006***
		(0.001)	(0.001)
pos_senti_{it-1}		0.007**	-0.002
		(0.002)	(0.003)
neg_senti_{it-1}		-0.005**	0.003
		(0.002)	(0.002)
$sd\_pos\_senti_{it-1}$		-0.008**	-0.111***
		(0.003)	(0.013)
$sd\_neg\_senti_{it-1}$		-0.009***	0.084***
		(0.002)	(0.008)
Interaction terms			
pos_senti_{it-1}*			0.036***
$sd\_pos\_senti_{it-1}$			(0.004)
neg_senti_{it-1}*			-0.039***
$sd\_neg\_senti_{it-1}$			(0.003)
Control variables			
$elite\_ratio_{it-1}$	0.007†	0.007†	0.006
	(0.004)	(0.004)	(0.004)
$count\_user_{it-1}$	-0.010†	-0.010†	-0.012*
	(0.006)	(0.006)	(0.006)
$count\_review_{it-1}$	0.012*	0.012*	0.013*
	(0.006)	(0.006)	(0.006)
$reviewer\_tenure_{it-1}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
monthly dummies	yes	yes	yes
observations	898,985	898,985	898,985
R-squared	0.315	0.315	0.315
# of companies	48,503	48,503	48,503

Notes: (1) Robust standard errors in parentheses;
(2) *** p<0.001, ** p<0.01, * p<0.05, † p<0.1;
(3) R squared includes fixed effects.

PRELIMINARY RESULTS

The linear panel regression model is specified as:

$$sat_{it} = \gamma sat_{it-1} + \beta_0 + \beta_1 usefulness_{it-1} + \beta_2 funny_{it-1} + \beta_3 cool_{it-1} + \beta_4 pos\_senti_{it-1} + \beta_5 neg\_senti_{it-1} + \beta_6 sd\_pos\_senti_{it-1} + \beta_7 sd\_neg\_senti_{it-1} + \beta_8 pos\_senti_{it-1} * sd\_pos\_senti_{it-1} + \beta_9 neg\_senti_{it-1} * sd\_neg\_senti_{it-1} + W_{t-1}\delta + \mu_i + \varepsilon_{it}$$

where sat_{it} and sat_{it-1} denote the average customer satisfaction of company i in time period t and $t-1$ respectively; $usefulness_{it-1}$, $funny_{it-1}$, and $cool_{it-1}$ are the average number of usefulness, funny, and cool votes of the customer reviews of company i in time period $t-1$, respectively; pos_senti_{it-1} and $sd\_pos\_senti_{it-1}$ represent average and standard deviation of positive sentiment of company i's customer reviews in time period $t-1$; neg_senti_{it-1} and $sd\_neg\_senti_{it-1}$ are average and standard deviation of negative sentiment of company i's customer reviews in time period $t-1$; W_{t-1} denotes all control variables; μ_i is the company-level fixed effects or unobserved heterogeneity; ε_{it} represents the error term; $\beta_0 - \beta_9$, γ, and δ are parameters to estimate.

A fixed-effects linear regression method was used to estimate the above model. Table 1 presents model estimation results. Major findings are explained below.

- Voting on customer reviews has a mixed effect on customer satisfaction. Interestingly, the average number of cool votes on customer reviews is positively associated with customer satisfaction in the next month. While funny votes have no significant impact on customer satisfaction, usefulness votes are found to have a negative effect on customer satisfaction.
- As shown in model 2, positive sentiment expressed in customer reviews has a positive effect on customer satisfaction in the next month. In contrast, negative sentiment in customer reviews is negatively associated with customer satisfaction in the next month. Interestingly, the standard deviations of positive and negative sentiment scores both have a negative impact on customer satisfaction in the next month. In other words, a higher level of consistency of positive/negative sentiment (i.e., a lower level of standard deviation) is positively related with customer satisfaction in the next month. Companies receiving online customer reviews with inconsistent sentiment may find difficult to synthesize diversified or even conflicting customer opinions to improve the quality of their services or products, thus improving customer satisfaction becomes a challenge.
- In terms of the moderation effects, as shown in model 3, standard deviation of positive sentiment moderates the effect of positive sentiment on customer satisfaction such that the effect is more positive if the positive sentiment scores are more diverse. Similarly, standard deviation of negative sentiment moderates the effect of negative sentiment on customer satisfaction such that the effect is more negative if the negative sentiment scores are more diverse. In summary, the diversity of consumer voices boosts the effects of positive and negative sentiment on future customer satisfaction.

Summary of Key Findings

- Compared with usefulness and funny voting, cool voting of online customer reviews is more important to enhance future customer satisfaction.
- A more consistent sentiment (both positive and negative) expressed in online customer reviews leads to a higher level of customer satisfaction in the next month. The consistency of customer opinions matters.
- The diversity of consumer sentiment not only boosts the positive effect of positive sentiment on future customer satisfaction, but also enhances the negative impact of negative sentiment on future customer satisfaction.

CONCLUSION AND FUTURE WORK

In summary, the current study has provided evidence that the content of online customer reviews is important for companies to improve or retain customer satisfaction. Content analysis of online customer reviews can be leveraged in company decision making in order to maintain or improve business performance. To better incorporate online customer voices into the improvement of product/service quality, companies need to differentially model the positive and negative customer sentiments as well as different types of votes on online customer reviews. For the future work, the findings can be further refined by including other aspects of online social interaction such as social network structure and topics of the textual content [2; 3]. An aspect-based sentiment analysis [11] may provide a more in-depth understanding of specific aspects of consumer reviews and their implications for business improvement. The current study can also be extended to other online settings such as those focusing on knowledge sharing [4; 5] and social support exchange [1; 3; 6].

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