

# Temporal Changes in the Impact of Drivers of Online Review Influence

## Vamsi Vallurupalli

Indian Institute of Management Calcutta  
Kolkata, India  
Email: vallurupalliv13@email.iimcal.ac.in

## Indranil Bose

Indian Institute of Management Calcutta  
Kolkata, India  
Email: bose@iimcal.ac.in

## Abstract

Online reviews have become ubiquitous in modern day business environment. They shape consumer perception regarding a product or service, and thereby affect sales and profits. Extant work on online review influence has ignored the possibility of change in impact of drivers of influence over time, as more reviews are posted. This study attempts to bridge the gap. Drawing from elaboration likelihood model (ELM) and Simon's theory of bounded rationality, hypotheses regarding temporal changes in the impact of drivers of influence have been proposed. The hypotheses have been tested based on online review data from Yelp.com. Also, a set of hypotheses have been proposed regarding changes in review content characteristics over time, tested over the same dataset, and compared with the findings on temporal changes in the impact of drivers of review influence. The insights from this study have important implications for both theory and practice and have been discussed.

**Keywords:** Review influence, Temporal variations, ELM, text mining

## 1 Introduction

The advent of web 2.0 has brought significant changes in the purchase behavior of customers. Particularly interesting and important is the rise of Internet enabled word of mouth communication, suitably referred to as Electronic Word of Mouth (E-WOM). With the growing use and popularity of channels supporting E-WOM, it is becoming increasingly important for firms to manage E-WOM.

The current study is based on online consumer reviews, which arguably constitute the most effective channel for consumers' voice. The importance of online reviews for both consumers and businesses is well understood and documented. (Nielsen, 2012) for instance, reported that consumer reviews are the most trusted source of information for consumers, next only to the direct recommendations made by family and friends. Similarly, based on a survey of consumers from USA and Canada, (Anderson, 2014) reported that 88% of consumers have read online reviews to evaluate a local business and about 40% of them do so on a regular basis. Furthermore, the percentage is gradually increasing over the years. This makes it important for firms to recognize the determinants of influence of online reviews.

A rich stream of literature has investigated the antecedents of influence of reviews<sup>1</sup>. It has been found that both characteristics of the content, including the star rating (Mudambi & Schuff, 2010; Pan & Zhang, 2011), information content (Mudambi & Schuff, 2010; Baek, Ahn, & Choi, 2012) and message sentiment (Kuan, Hui, Prasarnphanich, & Lai, 2015) and the characteristics of the reviewer, including reputation (Ghose & Ipeiritis, 2011) and past activity (Ngo-Ye & Sinha, 2014) affect the helpfulness of the review. Besides these, the impact of other factors, such as review age (Otterbacher & Arbor, 2009) and readers' characteristics (Lee & Koo, 2015) on review helpfulness has also been established. In all current studies, however, it has been assumed that the impact of drivers of influence of reviews remain same for all reviews. In this study, we have investigated the possibility of change in impact of drivers of influence over time, as more reviews are posted. Based on elaboration likelihood model (ELM) and Simon's theory of bounded rationality, a model has been proposed for temporal changes in the impact of drivers of influence and tested using review data from Yelp.com. Additionally, in this paper, it has been recognized that the gap between content being created and that needed by consumers for making decisions, is more important than an understanding of the latter alone. Therefore, additional hypotheses have been proposed regarding possible temporal changes in characteristics of reviews and compared with the findings on temporal changes in the impact of drivers of review influence. The comparison yielded interesting insights, which have been discussed.

Rest of the paper is organized as follows. The following section presents an overview of the extant literature in this field. Following this, a model of temporal changes in the impact of drivers of review influence has been proposed. Next, a brief overview of the data used for the study has been presented. The results of hypotheses testing have been presented in the following section. Following this, a discussion of the results and implications of the results is presented. The paper concludes by listing limitations of the study, and the scope for future work in this field.

## 2 Background and Literature Review

There is rich literature in information systems and marketing on the factors affecting the influence of online reviews. Based on a detailed review of the literature, the factors have been classified into three categories: message related characteristics, reviewer related characteristics and user rating related characteristics. Message related characteristics consist of those factors, which may be directly derived from the review message (textual / video component of the review). This includes semantic content, length, subjectivity, sentiment, discrete emotions etc. It may be noted that the primary focus of the extant literature has been on message related characteristics. Reviewer related characteristics are those which relate to the reviewer, who posted the review. Perceived credibility of the reviewer (based on reviewer rank, information disclosure etc.) and reviewer activity are the two most investigated characteristics within this category. User rating related characteristics include the numeric rating given by the reviewer and variables which may directly be derived from the user rating details (such as review extremity and deviation from average rating).

A brief summary of the literature has been presented in Table 1 below.

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<sup>1</sup> The term "influential review" used in this study is the same as the terms "helpful review" or "useful review" used in previous studies, and defined as *a peer-generated product evaluation that facilitates the consumer's purchase decision process* (Mudambi & Schuff, 2010). The term influence has been preferred here, as it is platform neutral.

Paper	Focal point of investigation	Finding
(Mudambi & Schuff, 2010), (Baek et al., 2012)	Review message	Length is associated with review influence
(Baek et al., 2012), (Kuan et al., 2015)	Review message	Review sentiment affects review influence
(Yin, Bond, & Zhang, 2014), (Ahmad & Laroche, 2015)	Review message	Different discrete emotions may impact review influence in different ways.
(Otterbacher & Arbor, 2009), (Ghose & Ipeirotis, 2011), (Scholz & Dorner, 2013)	Review message	Subjectivity / objectivity may impact review influence
(Ghose & Ipeirotis, 2011), (Kuan et al., 2015)	Review message	Readability may impact review influence
(Cao, Duan, & Gan, 2011)	Review message	Semantic factors (words and their usage) impact review influence
(Ghose & Ipeirotis, 2011)	Review message	Language informality affects influence
(Xu, Chen, & Santhanam, 2015)	Review message	Type of review message (video / textual) affects review usefulness
(Weathers, Swain, & Grover, 2015)	Review message	Balanced reviews more influential than less balanced reviews
(Otterbacher & Arbor, 2009), (Ghose & Ipeirotis, 2011), (Baek et al., 2012)	Reviewer	Reviewer's reputation affects review influence
(Forman, Ghose, & Wiesenfeld, 2008), (Ghose & Ipeirotis, 2011)	Reviewer	Information disclosure by a reviewer affects influence of a review
(Ngo-Ye & Sinha, 2014)	Reviewer	Reviewer engagement affects review influence
(Zhang, Craciun, & Shin, 2010), (Baek et al., 2012), (Wu, 2013), (Chen & Lurie, 2013)	User rating	Star rating affects review influence
(Mudambi & Schuff, 2010), (Pan & Zhang, 2011), (Kuan et al., 2015)	User rating	Rating extremity affects review influence
(Baek et al., 2012), (Yin, Mitra, & Zhang, 2016)	User rating	Deviation from average rating affects review influence

**Table 1: Summary of previous studies examining drivers of online review influence**

Despite a rich stream of work, as summarized above, there is an important gap in the literature. The extant studies have investigated the determinants of review influence, assuming that their impact on influence remains the same over time and across all reviews. However, the influence of a review may depend on previous reviews, in which case, there will be a change over time in the impact of various drivers of influence. In this study, we have tried to bridge the gap. Specifically, a research model has been proposed and tested for temporal changes in the impact of drivers of influence of reviews. Additionally, the temporal changes in drivers of influence have been compared with changes in characteristics of content being created, and implications for theory and practice drawn. The proposed research model has been presented in the following section.

### 3 Proposed Model

The research model proposed for the study is grounded in two popular theories: elaboration likelihood model (ELM) (Petty & Cacioppo, 1986), and Simon's theory of bounded rationality (Simon, 1955). A brief overview of the two theories is presented below, followed by a description of how the theories lead to the proposed model.

#### *Elaboration likelihood model (ELM)*

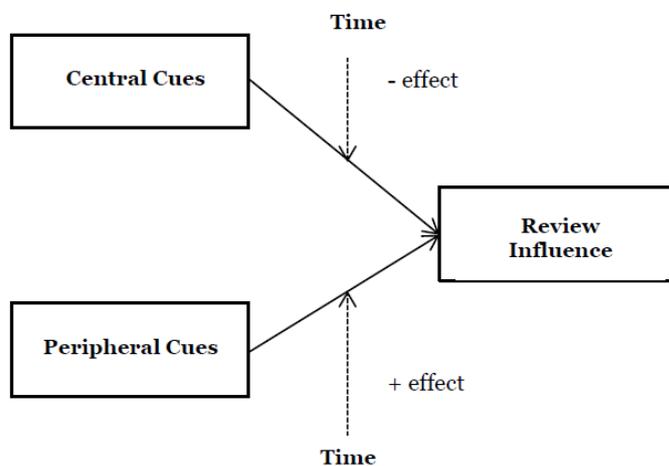
Elaboration Likelihood Model (ELM) is a popular psychological model of persuasion, proposed by Petty & Cacioppo in 1986 (Petty & Cacioppo, 1986). The model proposes that there are two major routes to persuasion: central route and peripheral route. When a person gives a careful thought and consideration of the argument's merits, the persuasion is likely to happen through the central route. The central route, therefore, is more likely to be used when the individual has both the motivation and

ability to process the information being presented. The change in attitude as a result of the processing of the argument is likely to endure, because of the high level of involvement of the individual. On the other hand, when an individual doesn't weigh the logical merits of the argument, and rather uses specific heuristics, peripheral route is likely to be employed. Therefore, when the individual's motivation or ability to process information is low, peripheral route is likely to be employed. The individual cues within a message or argument, which are likely to be processed through central (or peripheral) routes, are called central (or peripheral) cues respectively.

*Simon's theory of bounded rationality*

Simon's theory of bounded rationality suggests that humans are not perfectly rational in their decision making activity, primarily because of two reasons. One is the lack of availability of information, and the other is their inability to process large amounts of information, even when it is available. Due to this, they use specific heuristics to take decisions, and seek information to evaluate these heuristics. Such a decision process, termed "satisficing" is targeted at a satisfactory, rather than an optimal decision.

In the context of online reviews, when only few reviews have been posted, information available to make purchase decisions is low. We propose that at this stage, there is higher motivation to read and understand the available reviews. This triggers central processing of information contained in the reviews, and the impact of central cues is therefore higher in the initial reviews. As more reviews are posted, the motivation of readers to read subsequent reviews is lower, as some part of information need has already been fulfilled by the initial reviews. This may also be explained by Simon's theory of bounded rationality. As discussed, the theory suggests that there are cognitive limitations on the amount of information that can be processed while making decisions. Because of this, a decision maker seeks a satisficing, rather than an optimal decision. While making decisions based on online reviews, we propose that a customer implicitly employs heuristics, related to specific product and delivery characteristics to reach a decision. As information available to evaluate the heuristics becomes available with initial reviews, the need for further information reduces, and the corresponding motivation to read subsequent reviews also decreases. Lower motivation leads to a lesser impact of central cues on purchase decisions in later reviews. Likewise, because of lower motivation, the subsequent reviews may be expected to involve greater peripheral processing, leading to a higher impact of peripheral cues in subsequent reviews. This leads us to the model illustrated in Figure 1.



**Figure 1: Proposed Research Model**

Following the extant literature, we have used length of review, as measured by the count of words and the extent of analytical content in the review as central cues. Reviewer's reputation, review rating, and review rating extremity have been used as peripheral cues. The individual hypotheses based on the model and these variables have been summarized below.

*H1: Length has lesser impact over review influence in later reviews as compared to earlier reviews*

*H2: Analytical content has lesser impact over review influence in later reviews as compared to earlier reviews*

*H3: Reviewer credibility has higher impact over review influence in later reviews as compared to earlier reviews*

*H4: Review rating has higher impact over review influence in later reviews as compared to earlier reviews*

*H5: Review rating extremity has higher impact over review influence in later reviews as compared to earlier reviews*

It may be noted that the primary stated practical implication of the study of determinants of reviews is enabling the e-commerce and other review sites to offer effective suggestions and interventions to write more useful reviews. Such interventions are possible only if the characteristics of the content created are known and how they compare with the impact of content characteristics on review helpfulness is understood. Towards this end, as part of this paper, we attempt to explore the change in characteristics of content created over time, and how these changes compare with the temporal changes in the impact of content characteristics on review influence.

Specifically, we suggest that the readers have an implicit understanding of how central cues may support the decision making activity of the reader, which is not so in case of peripheral cues. Therefore, change in central cues over time follow the same direction as the change in impact of drivers of these cues. The same, however, doesn't hold for peripheral cues. Based on this, the following hypotheses have been proposed.

*H6: Length of reviews is lower in later reviews as compared to earlier reviews*

*H7: Analytical content of reviews is lower in later reviews as compared to earlier reviews*

*H8: Review rating is similar in later reviews as earlier reviews*

It may be noted that the underlying logic stated for the above hypotheses are with respect to review content, and not the reviewer. Therefore, reviewer credibility has not been included in the above hypotheses.

## 4 DATA AND METHOD

To test the proposed model, data from Yelp has been used. The data was made available as a part of Yelp Dataset Challenge (Yelp, 2016). Additionally, textual characteristics of the review content were extracted using a text analysis tool called Linguistic Inquiry and Word Count (LIWC), which is popularly being used in recent years in studies related to online reviews (Goes, Lin, & Yeung, 2014; Yin et al., 2014, 2016).

A brief overview of the final set of variables used in this study is presented in Table 2.

Yelp dataset, as mentioned above, and being used for this study, is a rich dataset, consisting of online review data for multiple services, and not just restaurants. Also, the review data is available for businesses located in both US and Europe. For the purpose of this study, we employed three filters over the data. First, data for restaurants alone was used. Second, data from Arizona, USA alone was used for this study. And third, data for only those businesses (restaurants), for which at least 50 reviews were posted, was used in the study. In future, we plan to extend the study to restaurants across geographies and possibly, different type of businesses.

To test H1 till H5, the following logistic regression model was used.

$$\text{ReviewInfluence} = \beta_1 * \text{Length} + \beta_2 * \text{AnalyticContent} + \beta_3 * \text{Fans} + \beta_4 * \text{StarRating} + \beta_5 * \text{StarRatingSquared} + \beta_6 * \text{LengthTimeInteraction} + \beta_7 * \text{AnalyticContentTimeInteraction} + \beta_8 * \text{FansTimeInteraction} + \beta_9 * \text{StarRatingTimeInteraction} + \beta_{10} * \text{StarRatingSquaredTimeInteraction} + \text{error}$$

Variable	Description
Length	Length of the review
AnalyticContent <sup>2</sup>	Extent of analytical content in the review text
Fans	Number of fans of reviewer (Proxy for reviewer's credibility)
StarRating	Rating given by the reviewer

<sup>2</sup>This variable is computed directly by LIWC, using a machine learning approach. LIWC has been trained on a text corpus, where the extent of analytical content in each text document was marked manually by a set of reviewers. Based on it, it computes the score for this variable for new textual documents.

StarRatingSquared	Square of rating given by the reviewer (Proxy for extremity of rating)
LengthTimeInteraction	Interaction between time and length
AnalyticContentTimeInteraction	Interaction between time and extent of analytical content
FansTimeInteraction	Interaction between time and reviewer's credibility
StarRatingTimeInteraction	Interaction between time and review rating
StarRatingSquaredTimeInteraction	Interaction between time and review rating extremity

**Table 2: Description of variables used in the model**

To test hypotheses H6, H7 and H8, the content characteristics were divided into two separate categories, one which consisted of the first fifty percent of the reviews, and the second, which consisted of the remaining reviews for a business. A comparison of the mean of content characteristics between the two groups was then done using a t-test.

## 5 RESULTS

The results of hypotheses testing have been summarized in Tables 3 and 4 below. The implications of the results have been discussed in the following section.

HYPOTHESES	SUPPORTED / REJECTED*
H1: Length has lesser impact over review influence in later reviews as compared to earlier reviews	Supported
H2: Analytical content has lesser impact over review influence in later reviews as compared to earlier reviews	Partially Supported **
H3: Reviewer credibility has higher impact over review influence in later reviews as compared to earlier reviews	Supported
H4: Review rating has higher impact over review influence in later reviews as compared to earlier reviews	Supported
H5: Review rating extremity has higher impact over review influence in later reviews as compared to earlier reviews	Supported

\* p value  $\leq$  0.05; \*\* p-value  $\leq$  0.10

**Table 3: Results of hypotheses testing (temporal impact of drivers of influence)**

HYPOTHESES	SUPPORTED / REJECTED*
H6: Length of reviews is lower in later reviews as compared to earlier reviews	Supported
H7: Analytical content of reviews is lower in later reviews as compared to earlier reviews	Supported
H8: Review rating is similar in later reviews as earlier reviews	Supported

\* p value  $\leq$  0.05

**Table 4: Results of hypotheses testing (temporal change in review content characteristics)**

It may be noted that for central cues, the temporal change in the impact of drivers of influence and temporal change in the characteristics of content created follow the same direction. But the same doesn't hold for peripheral cues (user rating). Therefore, explicit guidelines may be needed for peripheral cues by the e-commerce and review sites, especially at later stage, to enhance the usability of reviews posted at that stage.

## 6 IMPLICATIONS

The results from the study have important implications for theory and practice. First, it extends our knowledge of the determinants of review influence, by incorporating the effect of time on the impact of characteristics of review content on review influence. Second, the study presents a comparison of temporal change in characteristics of content created with temporal change in the impact of these

characteristics over time. To the best of our knowledge, it is the first study to examine both how the impact of review content characteristics on review influence varies based on when the review has been posted, as well as how these variations compare with change in content characteristics over time. The results from the study could be useful for practitioners in e-commerce industry and review hosting sites to guide the authors in posting more useful reviews. Finally, the results could be useful by individual sellers and manufacturers to understand the impact of reviews on consumers, and make appropriate interventions, if necessary.

## 7 LIMITATIONS AND FUTURE SCOPE

An important limitation of the current study is that the model has been validated by using review data from a single platform. Since reviews across platforms may have different characteristics, future studies may attempt to validate the findings for different platforms. Specifically, it may be noted that this study is based on service reviews, and the validity of propositions in the context of product reviews need to be examined. Second, the hypotheses regarding change in content characteristics over time have been validated simply by using a t-test, without controlling for potentially confounding factors. We suggest the readers to view it as a preliminary testing, and future studies may build on it by incorporating other review and reader characteristics. Notwithstanding any concerns regarding robustness, the approach demonstrates the practical utility of incorporating characteristics of content being created in the study of how content characteristics impact review influence.

## 8 CONCLUSION

The study examined temporal variations in the impact of drivers of influence of online reviews. A research model grounded in relevant theories was proposed, and validated using restaurant review data. Also, the model has been compared with the changes observed in content characteristics over time, and implications for theory and practice drawn. It is hoped that future studies will extend this work and enhance our understanding of this phenomenon.

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