EXPLORING HEURISTIC CUES FOR CONSUMER PERCEPTIONS OF ONLINE REVIEWS HELPFULNESS: THE CASE OF YELP.COM

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Abstract

With the prevalence of online reviews, consumers are more inclined to be exposed to an unwieldy glut of information. In contrast to the research on the outcomes of online reviews, recent studies have shifted attention to the antecedents of online reviews, particularly investigating what characteristics lead to a review that is perceived more helpful by online consumers. Our research model of online review helpfulness is built upon a rich stream of literatures demonstrating how people are persuaded and influenced by information, especially the dual process theories. In this study, we specifically focus on the effect of heuristic factors: rating deviation with existing reviews’ average rating, and peer recognitions of the reviewer including network centrality and “elite” status. The model is empirically tested based on 16343 reviews of hotels from Yelp.com using zero-inflated negative binomial regression. Empirical results indicated that, in addition to a review’s content attributes, rating deviation and peer recognitions of the reviewer also have significant impacts on consumer perceptions of review helpfulness. These findings add new theoretical insights into the research of online review helpfulness, and offer practical implications for online review providers to have a better prediction of valuable reviews.

Keywords: Review helpfulness, Heuristic cues, Peer recognitions, Rating Deviation.
1 INTRODUCTION

With the emerging of user-generated contents (UGC), online word-of-mouth (WOM) is playing an increasingly important role nowadays in disseminating information, facilitating trust, and promoting commerce in the e-marketplace (Duan et al. 2008). As the prevalence of online reviews, consumers are more inclined to be exposed to an unwieldy glut of information (Godes & Silva 2012). To address this problem, the social voting mechanism has been introduced to many online reviews platform allowing users to give “helpful/useful” votes to the reviews they read in order to signal the credibility of the reviews (Otterbacher 2009). The results of helpful voting can help consumers to search and view the reviews to overcome the information overload (Willemsen et al. 2011).

In contrast to the research on the outcomes of online reviews (for example, Chevalier & Mayzlin 2006; Duan et al. 2008), recent studies have shifted attention to the antecedents of online reviews (Cheung & Thadani 2012; Stephen & Lehmann 2009), particularly investigating what characteristics lead to a review that is perceived more helpful by online consumers (Baek et al. 2013; Ghose & Ipeirotis 2011; Korfiatis et al. 2012; Mudambi & Schuff 2010; Yin et al. 2014).

Although prior studies have many significant findings, some important questions still have not been addressed. First, these studies primarily focused on the review itself, such as the numerical rating and the length of content (Korfiatis et al. 2012; Mudambi & Schuff 2010). The social cues of the reviewer have not been studied thoroughly, only the authorship gets enough attentions (Baek et al. 2013; Forman et al. 2008; Ghose & Ipeirotis 2011). This is partly because of that prior researches were mainly based on e-commerce website, especially Amazon.com where social cues of reviewers were not obviously observed. Second, prior studies have documented mixed findings concerning how review helpfulness is influenced by rating extremity (Forman et al. 2008; Mudambi & Schuff 2010). But, we are aware that almost no study to date has focused on the deviation of the rating with existing reviews’ average rating for a certain product (Baek et al. 2013), that can serve as one important heuristic cue for consumers to evaluate review helpfulness. Third, most existing studies focus on the review helpfulness of physical goods instead of services. Due to the intangible nature of services, consumers rely heavily on other customers’ reviews to assess services quality prior to purchase (Racherla & Friske 2012).

In this paper, we will address the above limitations. The research model of online review helpfulness in this study is built upon a rich stream of literatures demonstrating how people are persuaded and influenced by information (Chaiken 1980; Petty & Cacioppo 1986). Here, we specifically focus on the effect of heuristic factors: rating deviation, and peer recognitions of the reviewer. The model is empirically tested using 16969 reviews of hotels from Yelp.com, a popular third-party review platform dedicated to services businesses and integrating extensive social networking functions.

2 LITERATURE REVIEW

The literatures on review helpfulness center around the question of "what kind of reviews are perceived more helpful to consumer's decision-making" (Korfiatis et al. 2012; Wu et al. 2011), and explore how the characteristics of reviews influence consumer’s perceptions of review helpfulness.

Existing studies mainly investigate two key components of online review: the message (review itself) and the source (reviewer). Most of the studies considered the numerical star or content attributes of the review, including the rating, review length (Mudambi & Schuff 2010), and the two-sidedness of review (Schlosser 2011). In the other hand, a few studies indicated that the review helpfulness is determined by the review itself as well as by ‘who said it’ (e.g., Cheung et al. 2012; Racherla & Friske 2012).

Table 1 provides a summary of prior studies on consumer perceptions of review helpfulness. The attributes of review and reviewer investigated as well as the methods used are highlighted in the table.
<table>
<thead>
<tr>
<th>Prior Studies</th>
<th>Data/Method</th>
<th>Message (review itself)</th>
<th>Source (reviewer)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Rating / Extremity</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Two-Sidedness Length</td>
<td>Identity Information</td>
</tr>
<tr>
<td>Forman et al. (2008)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Mudambi &amp; Schuff (2010)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Zhang et al. (2010)</td>
<td>Survey/SEM</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Connors et al. (2011)</td>
<td>Lab Experiment</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Ghose et al. (2011)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Pan &amp; Zhang (2011)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Wu et al. (2011)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Schlosser (2011)</td>
<td>Lab Experiment</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Korfilatis et. al (2012)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Cheung et al. (2012)</td>
<td>Survey/SEM</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Baek et al. (2013)</td>
<td>Amazon/ Econometrics</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 1: Summary of Prior Studies on the Helpfulness of Online Reviews

3 RESEARCH MODEL

In the persuasion literature, two of the most prevalent dual process theories are elaboration likelihood model (ELM) (Petty & Cacioppo 1986) and heuristic-systematic model (HSM) (Chaiken 1980). ELM and HSM provide similar mechanisms in explaining individuals’ information process and judgment strategies (Cheung et al. 2009). Recently, these two frameworks have been applied to understand how the consumer process the information from reviews and evaluate their helpfulness for purchasing decision (e.g., Baek et al. 2013; Cheung et al. 2012). While the importance of the dual process theories for review helpfulness has been well proved, knowledge about the heuristic cues that affect review helpfulness from a theoretical perspective remains scant.

![Research Model Diagram](image)

Figure 1: Research Model

In this study, we apply HSM as referenced theoretical framework and present a theory-grounded model to understand consumer perceptions of review helpfulness. Choosing HSM is because that
HSM provides broader and more appropriate explanations of individuals’ information processing behavior in the context of online communities as Zhang and Watts (2008) suggested. According to the framework of HSM, the research model (Figure 1) posits that consumers use both systematic as well as heuristic cues to assess whether or not a review is helpful for their purchasing decision.

3.1.1 Rating Deviation

The average star rating for a certain product may be the other consumers’ congruent opinions on the product (Schlosser 2011), so the rating deviation reflects the extent to which the individual’s evaluation is not consistent with other peers’ opinions on the product (Baek et al. 2013). The review that has more deviation with average rating may reflect this reviewer’s particular experience of hotels services, deliver obvious and decisive opinions, and then can be assessed more informative by other review readers (Forman et al. 2008; Pavlou & Dimoka 2006). The great deal of information within the review can help consumers to build the virtual experience and decrease uncertainty in purchasing these services, such as booking the hotel.

Furthermore, most of the people have the tendency to strongly prefer avoiding losses to acquiring gains (Kahneman & Tversky 1979). Some studies also suggest that losses are twice as powerful, psychologically, as gains (Vohs& Luce, 2010, p. 736). Similarly, for online review, negative ratings are perceived more credible and useful in the experiential services (Yang & Mai 2010). Since negative reviews alter us to great risk, we may pay greater attention to reviews with negative deviation compared reviews with positive deviation that highlight the benefits. This leads us to hypothesize,

H1: Review deviation (measured by the difference between the review’s rating and past average rating) has a positive effect on consumer perceptions of review helpfulness, and the effect of negative deviation will be stronger.

3.1.2 Reviewer Elite Badge

Websites can designate prolific reviewers with one badge (e.g., top reviewer in Amazon, elite status in yelp, and so on), which also represent social status and online reputation (Forman et al. 2008). The most important step to becoming an “elite” Yelper is to write as many useful and unbiased reviews as possible (Luca 2011). The badge is visible to website readers, and they can filter to only see reviews by elite Yelper. In the context of UGC websites, the underlying motivation for users to spend time and effort to contribute is that they can gain attention and reputation (Shen 2010; Tang et al. 2012). Therefore, the badge is a crucial signal for the reputation of a reviewer, and then can help reader to differentiate reviews by elite Yelper from others (Baek et al. 2013; Luca 2011). In conclusion, we have reasons to believe the reviews by elite Yelper would be deemed more helpful by readers. This leads us to hypothesize,

H2: The review posted by the reviewer with elite badge will be perceived more helpful by the consumers.

3.1.3 Reviewer Network Centrality

In recent years, many third-party review platforms with extensive social networking features are emerging continually (for examples, Yelp, Epinion and etc.). Thus, online social networks formed by interacting among the reviewers should be considered as the critical antecedents for consumers’ perception of review helpfulness (Lu, et al. 2010; Wang 2010).

Social network studies have indicated that network centrality represent the individual node’s important features, and represent the influencing power of the individual (Smith et al. 2007). In addition, related studies also found that the number of social ties correlating with trustworthiness (Prell 2003; Susarla et al. 2012). Due of information overload in online environments, the reviews posted by reviewers with lower trustworthiness may be ignored by consumers because of higher uncertainty and risk associated with services purchasing-decision. This leads us to hypothesize,
H3: The review posted by the reviewer with higher network centrality (measured by the number of friends in online social network) will be perceived more helpful by the consumers.

3.2 Systematic Cues

Systematic cues are the arguments contained in a message, which require the recipient high cognitive effort in deciding to accept a message’s opinion (Chaiken 1980). Two content cues, review length and easy of understanding mostly investigated by prior studies are identified as systematic cues in our model. So, we can present two following hypotheses,

H4: Review length (measured by word counts) has a positive effect on consumer perceptions of review helpfulness.

H5: Easy of understand of the review (measured by readability index) has a positive effect on consumer perceptions of review helpfulness.

3.3 Control Variables

A series of relevant variables are considered as control variables in order to analyse the influence of independent variables of interest. According to the literature, two types of control variables including individual review level and the hotel level are suggested. In the individual review level, elapsed days of a review since posted is offered (Pan & Zhang 2011), while in the hotel level (Yin et al. 2014), the popularity and the average rating are offered. The detailed definition and operationalization listed in Table 2.

4 Research Methods

4.1 Data and Variables

Data for this research were collected from Yelp.com in September 2012, which is one of the top ratings and review sites with more than 50 million unique visitors a month. Yelp.com was chosen because the website has extensive social networking features and provides the entire history of all reviews posted for restaurants, hotels, and a variety of other local business services. We collected the entire history of review data up to September 2012 for all the hotels in San Francisco. In the end, we collected a total of 16343 reviews across the 307 hotels.

We summarize all variables in Table 2, and also illustrate how the data collected from the Yelp were used to operationalize the variables. For the validity of empirical analysis, the operationalization is based on an extensive survey of the literature (Baek et al. 2012; Korfiatis et al. 2012; Mudambi & Schuff 2010; Yin et al. 2014).

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Variables</th>
<th>Operationalization</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td>Review helpfulness</td>
<td>The number of ‘useful’ votes on each review;</td>
</tr>
<tr>
<td><strong>Heuristic cues</strong></td>
<td>Rating deviation</td>
<td>The deviation of the review rating from the average rating;</td>
</tr>
<tr>
<td><strong>Heuristic cues</strong></td>
<td>Reviewer elite badge</td>
<td>Whether or not a review posted by the “elite” reviewer; (1= yes, 0= no; )</td>
</tr>
<tr>
<td>– Peer recognitions of the</td>
<td>Reviewer network centrality</td>
<td>The number of friends of each reviewer;</td>
</tr>
<tr>
<td>reviewer</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Systemic Cues</strong></td>
<td>Review length</td>
<td>The number of words in a review message;</td>
</tr>
<tr>
<td></td>
<td>Easy of understanding</td>
<td>Coleman-Liau Index of Readability;</td>
</tr>
<tr>
<td><strong>Control Variable</strong></td>
<td>Elapsed days</td>
<td>The difference between the date the</td>
</tr>
</tbody>
</table>
### 4.2 Descriptive statistics

Table 3 presents a summary of descriptive statistics for all the variables in the sample.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.Review Helpfulness</td>
<td>1.37</td>
<td>2.48</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.Deviation(Positive)</td>
<td>0.46</td>
<td>0.68</td>
<td>0.02</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.Deviation(Negative)</td>
<td>0.46</td>
<td>0.78</td>
<td>0.06</td>
<td>-0.39</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.Network Centrality</td>
<td>119.74</td>
<td>404.20</td>
<td>0.42</td>
<td>0.01</td>
<td>-0.06</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.Elite badge</td>
<td>1.04</td>
<td>1.77</td>
<td>0.28</td>
<td>-0.01</td>
<td>-0.11</td>
<td>0.47</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.Length</td>
<td>165.44</td>
<td>130.44</td>
<td>0.25</td>
<td>-0.07</td>
<td>0.13</td>
<td>0.06</td>
<td>0.07</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.Easy of Understanding</td>
<td>5.43</td>
<td>2.64</td>
<td>-0.02</td>
<td>0.07</td>
<td>-0.06</td>
<td>-0.02</td>
<td>-0.02</td>
<td>0.02</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8.Elapsed Days</td>
<td>839.21</td>
<td>613.85</td>
<td>0.08</td>
<td>-0.07</td>
<td>0.10</td>
<td>0.25</td>
<td>-0.03</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.Popularity</td>
<td>176.53</td>
<td>137.05</td>
<td>0.01</td>
<td>-0.07</td>
<td>-0.03</td>
<td>0.15</td>
<td>0.16</td>
<td>0.00</td>
<td>-0.05</td>
<td>0.05</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>10.Average Rating</td>
<td>3.60</td>
<td>0.57</td>
<td>0.01</td>
<td>-0.09</td>
<td>-0.07</td>
<td>0.05</td>
<td>0.07</td>
<td>-0.05</td>
<td>0.05</td>
<td>0.08</td>
<td>0.18</td>
<td>1.00</td>
</tr>
</tbody>
</table>

### 4.3 Econometric model

The data also demonstrates ‘over-dispersion’, because the variance of the ‘useful’ votes is larger than the mean. Furthermore, the phenomenon of excess zeroes is definitely a concern in this dataset because a large proportion of reviews (47.32%) did not receive a single useful vote. Thus, the negative binomial model, one of Poisson model variations, will be more fitted to model this dataset (Sheu et al. 2004).

### 5 Results and Discussions

#### 5.1 Results

The STATA program was used for the empirical analyses. The results of ZINB regression were shown in Table 4, which include a logit and a NB regression. The logit model is to predict whether or not the zero is “certain zero”. The logit results reveal that elapsed days of a review and the popularity of the hotel could decrease the probability of that a review always couldn’t get any useful votes. In addition, the network centrality of a review only gets significant support from the results weakly (p <0.1). The Vuong test suggests that the zero-inflated negative binomial model is a significant improvement over a standard negative binomial model ($z = 3.11$, p<0.01).

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Negative Binomial Coefficient</th>
<th>Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating deviation(Positive)</td>
<td>0.165**</td>
<td></td>
</tr>
</tbody>
</table>
Table 4: Results of Zero-inflated Negative Binomial Regression

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating deviation (Negative)</td>
<td>0.265**</td>
<td></td>
</tr>
<tr>
<td>Reviewer network centrality</td>
<td>0.255**</td>
<td>-0.269*</td>
</tr>
<tr>
<td>Reviewer Elite badge</td>
<td>0.117**</td>
<td>0.197</td>
</tr>
<tr>
<td>Review length</td>
<td>0.519**</td>
<td></td>
</tr>
<tr>
<td>Easy of Understanding</td>
<td>-0.013*</td>
<td></td>
</tr>
<tr>
<td>Review Elapsed Days</td>
<td>0.081*</td>
<td>-1.593**</td>
</tr>
<tr>
<td>Popularity</td>
<td>-0.001**</td>
<td>-0.007*</td>
</tr>
<tr>
<td>Average Rating</td>
<td>0.019</td>
<td>-0.272</td>
</tr>
</tbody>
</table>

Likelihood-ratio test of alpha=0: chibar2(01) = 4582.52 p<0.01;
Vuong test of zinb vs. standard negative binomial: z =3.11 p<0.01;
+, p<0.1; *, p<0.05; **, p<0.01;

As shown Table 4, all the hypotheses were empirically supported. In the aspect of rating deviation, both positive and negative rating deviations have significant effects on review helpfulness. Furthermore, when the rating given by the reviewer is below the average rating (that is negative deviation), the influencing power will be stronger ($\beta=0.265$ vs 0.165). We also conduct post-hoc test to evaluate the differences in two coefficients, which validate the above statement (Chi2(1)=35.43, p<0.01).

Peer recognitions of the reviewer, as one of the important heuristic cues, actually have stronger effects on the helpfulness of online review. Yelp designs a reviewer ranking system, where they formally certify certain reviewers as elite members. The analytical results show the reviews by elite members should get more helpful votes from the consumers ($\beta=0.117$, p<0.01). A second peer recognition is the number of “friends” the reviewer has, which was conceptualized as network centrality in our model. Empirically, we found the reviews posted by the reviewer with higher network centrality also would be deemed as more helpful ($\beta=0.255$, p<0.01).

For content cues, the results state that the helpful votes increase as the length of a review message increases ($\beta=0.519$, p<0.01) and the effort to understand the review decreases ($\beta=-0.013$, p<0.05). According our results concerning control variables in Table 4, the elapsed days of reviews could help to get more useful votes ($\beta=0.081$, p<0.05).

5.2 Discussions

Utilizing real-world reviews data from Yelp.com, the empirical results provided supports for our model and hypotheses. In this section, we discuss how the results address main insights of theoretical hypotheses that heuristic cues have significant effects on review helpfulness.

Recently, Baek et al.(2013) found consumers may judge the review whose rating is congruent with the average rating to be the most trustworthy review, leading them to conclude that kind of reviews is more helpful. However, our research revealed that a review will get more useful votes when its rating is far deviated from the average rating for a hotel. In our opinion, a review with larger rating deviation may represent the added or “surprise” informational value (Yin, Mitra, & Zhang 2012), and then can easily get more attentions and recognitions from consumers. Due to the higher associated risk and the intangible nature of experience services (Bansal & Voyer 2000), the review with higher rating deviation delivered more distinctive and certain information, and thus was perceived more helpful by consumers. Furthermore, the coefficient of negative rating consistency is larger than the coefficient of positive rating consistency ($\beta=0.165$, higher than $\beta=0.051$), so it reveals the negative bias in consumer perceptions of review helpfulness (Luo 2007; Pavlou & Dimoka 2006). This finding can be attributed
to loss aversion of consumers (Kahneman & Tversky 1979) when they are confronted with high uncertainty and taste diversity in hotel booking.

In accord with our hypotheses, empirical results also demonstrate that peer recognitions of the reviewer actually affect consumer perceptions of review helpfulness after controlling content cues. The “elite” badge suggests a strong role for reviewer reputation (Luca 2011), and then reviews by elite members should be voted more helpful by readers (H2a was supported). Furthermore, reviews in Yelp.com are posted by identifiable reviewers who interact with one another to form directed or undirected social ties. The high number of social ties is an indicator that a reviewer holds the most amount of social capital (Ellison, Steinfield, & Lampe 2007), which can arouse the readers’ trust on this reviewer (Hu, Liu, & Zhang 2008; Racherla & Friske 2012). Thus, the consumer can use less cognitive work to judge the helpfulness of a review through processing heuristic cues from social ties quickly.

For content cues, two hypotheses (H3, and H4) were supported by empirical results which are consistent to prior literature (Mudambi & Schuff 2010; Korfiatis et al. 2012). The length has the stronger effect on review helpfulness than other variables in terms of significant level ($\beta=0.519$, $p<0.01$). When consumers are willing to read and compare open-ended reviews, the amount of information could matter and affect review helpfulness.

6 CONCLUSIONS AND LIMITATIONS

In the paper, we present a theory-grounded model which mainly explores the effects of heuristic cues on consumer perceptions of review helpfulness, and test the hypotheses with real-world data from Yelp.com. The present study brings several contributions to the research and practice of online review.

First, we studied the effect of rating deviation of each review on consumer perceptions of review helpfulness, which is one of the first empirical studies. However, our result is opposite to prior literature, such as Baek et al. (2013), which mainly give the theoretical explanation from the perspective of conformity. Our study emphasizes that a clear and unequivocal review may contain enough information to guide purchasing decision-making, especially for the context of experience services.

Second, this is one of the first studies integrating peer recognitions of the reviewer in online environments. The number of friends with direct ties, representing the network centrality of focal reviewer in online social network, will have significant influence on review helpfulness when consumers take less cognitive efforts in information processing on review message. Thus, the paper extends related studies on social network by illuminating the important role of network position in online information communication.

Third, our study use the reviews of hotel services on Yelp.com as the research context, which is opposed to the majority of prior studies using product reviews (e.g., book and electronic products) on e-commerce websites (Baek et.al 2013; Mudambi & Schuff 2010). Consumers may confront with higher uncertainty and risk when choosing experiential services such as a hotel stay (Bansal & Voyer 2000). It is well known that under high uncertainty, consumers are more influenced by the information from socially recognizable sources (Forman et.al 2008). Although a few studies began to validate this opinion using survey method (Cheung et al. 2012; Connors & Mudambi 2011), the present study uses real-world data from Yelp.com which has sufficient amount of social cues of the reviewer and fills the gap to certain extent.

This study also has several limitations. We only focused on one type of business services, the hotel. In future research, we are planning to extend our empirical studies to other types of services. Our sample data are cross-sectional so that they can’t capture the dynamics of the reviewer’s contributions and readers’ voting behaviors. In future, we should design a longitudinal study to obtain more rigorous empirical results. Third, we need to further conceptualize peer recognitions of the reviewer in details.
Acknowledgement

The first author acknowledges the Program for Young Excellent Talents of UIBE for financial supports.

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