

The value of additional reviews in reputation systems: Evidence from a car review platform

Xiao Fan ¹

Ao Sun ²

XuDong Liu ^{3,*}

*Corresponding author

¹ Master Student, School of Management, Harbin Institute of Technology, China, fx15776491086@163.com

² Master Student, School of Management, Harbin Institute of Technology, China, sunnyao_98@126.com

³ Lecturer, School of Management, Harbin Institute of Technology, China, cameran@hit.edu.cn

ABSTRACT

Online reviews, especially additional reviews, have become an important channel for consumers to obtain information about product quality. Based on review data obtained from “AutoHome”, which is a most popular car review platform in China, this study explores the influence of additional review function on the initial reviews from both the reader and reviewer levels. At the reader-level, the introduction of the additional review function improves readers’ perceived usefulness of the reviews. At the reviewer-level, it can drive reviewers to write more initial reviews. In general, the introduction of such a function can be regarded as an improvement of the existing review mechanism. The findings of this study can not only enrich the research on online word-of-mouth, but also provide valuable reference for related practitioners.

Keywords: Online reviews, additional reviews, natural experiment, review usefulness.

INTRODUCTION

With the development of E-commerce, online reviews are becoming increasingly more important for both businesses and consumers. For the former, online reviews are an important means for them to influence the consumer decision; and for the latter, they are also an important channel to understand the products (Ho-Dac, Carson, & Moore, 2013). In order to ensure the quality of online reviews, major E-commerce platforms have introduced the function of additional reviews. Different from initial reviews, additional reviews require more effort from reviewers, suggesting that the reviewers are responsible, so readers’ perceived usefulness will be higher (Jonas, Diehl, & Bromer, 1997). Once the additional review was released, it has become a research hotspot.

Previous studies have shown that additional reviews can impact users’ behavior (Akhtar et al., 2019; Chen, Yan, Xie, Zhang, & Chen, 2019). Consumers’ trust is related to the similarity between the additional reviews and the initial reviews (Akhtar et al., 2019). The emotional changes of additional reviews can also affect consumer’s purchase intention (Chen et al., 2019). However, previous studies have not explored the changes of initial reviews after the introduction of additional reviews, and how these changes may affect user behavior. At the reader-level, the introduction of additional reviews may change the perceived usefulness of the initial reviews, and then may change the amount of reading and the amount of reader comments. At the reviewer-level, the additional reviews may change the reviewers’ enthusiasm for the initial reviews. Initial reviews are an important kind of online reviews, and they also have important effects on consumers (Houser & Wooders, 2006). Therefore, this paper will discuss the influence of additional reviews on the initial reviews at these two levels.

“AutoHome” is the most viewed car online word-of-mouth platform in China (www.autohome.com.cn). It introduced the function of additional reviews in July 2014. In order to implement the natural experiment, we collect all of the online reviews on “AutoHome” published in 2014. We organize them into panel data and conduct natural experiments at both the reader-level and the reviewer-level. The results show that the introduction of additional reviews has an impact on the user behavior in terms of initial reviews. At the reader-level, additional reviews can increase the perceived usefulness of the initial reviews. At the reviewer-level, additional reviews can increase reviews’ enthusiasm for the initial reviews and make them more objective.

The remainder of this paper is organized as follows. Section 2 analyzes the research theories and infers the hypotheses according to the existing literature. We introduce the methodology of this study, which includes the process of data collection and the establishment of the models in Section 3. In Section 4, we introduce the research results of this study. At last, we summarize the contributions, limitations and future work directions in Section 5.

THEORETICAL BACKGROUND AND HYPOTHESES

Theoretical Background

Online reviews

Online reviews refer to online consumers who have completed the purchase behavior to exchange information about product quality and experience (Chatterjee, 2001). Previous studies on online reviews have focused on the usefulness of online reviews,

the impact of online reviews on consumer behavior, and the impact on the characteristics of consumers (Lamb, Cai, & McKenna, 2020). Using hotel review data, Huang finds that when the reviews are based on narrative (unstructured), the positive expressions will enhance the usefulness of the reviews; however, when the reviews are based on list (structured), the negative expressions will enhance the usefulness of the reviews (Huang, Chang, Bilgihan, & Okumus, 2020). Ghose found that the subjectivity of review text has a negative impact on the usefulness of review, and the readability has a positive impact on the usefulness of review (Ghose & Ipeiritos, 2011). Based on the theories of “use and satisfaction” (U&G) and “consumer culture” (CCT), Tran verifies the positive impact of online reviews on purchase intention, and confirms the moderating role of cosmopolitanism (Tran, 2020). By using review data of “surprise box”, Xu finds that consumers tend to publish more reviews with extreme emotions, and the impact is more significant for extreme negative emotions (Xu, 2020).

Additional reviews

Additional reviews mean that consumers comment about the same product again on the basis of the initial reviews. Chen finds that the order of contradictory reviews and product participation can significantly affect consumers' purchase intention, and the influence of product participation on consumers' purchase intention is different with diverse contradictory order (Chen et al., 2019). By using the real review data of hotels in China, Akhtar finds that the more similar between the content of the additional reviews and initial reviews, the more reviewers can earn the trust of other consumers (Akhtar et al., 2019). Consistent with the above studies, our study is also focused on additional reviews. We will put forward our hypotheses in the following section.

Hypotheses Development

The effects of additional review function on readers

Chatterjee defines perceived usefulness as the reader's perception that reviews can reduce their own information gap (Chatterjee, 2001). Additional reviews are the supplements and revisions of initial reviews, and need reviewers to make more efforts (Jonas et al., 1997). The more efforts the reviewer makes, the more serious he/she will be while writing a review (Duan, Gu, & Whinston, 2008). Still further, the more serious he/she will be while writing a review, which shows the responsible attitude of the reviewer, so the higher the perceived usefulness of the reader. Accordingly, we propose the following hypothesis.

H1: The perceived usefulness of reviews increases after the additional review function is launched.

According to the Information Adoption Model (IAM), which is the determinant of consumers, adoption of online reviews depend on the perceived usefulness of online reviews, while the main factors influencing the perceived usefulness of online reviews are information quality and source credibility (Sussman & Siegal, 2003). In other words, consumers are more likely to adopt reviews with higher perceived usefulness than the lower ones. The content of additional reviews usually contains more information about the product and the deeper understanding of the product as time goes by, thus, consumers will find additional reviews more useful (Pee, 2016). That is to say, consumers are more inclined to read the additional reviews which are more helpful rather than the initial reviews which are less useful. Therefore, this study argues that the introduction of additional reviews may reduce the view number of initial reviews. Based on the above arguments, we propose H2.

H2: The view number of an initial review decreases after the additional review function is launched.

The Elaboration Likelihood Model (ELM) points out that when consumers purchase products with high involvement, they tend to put more energy into searching for products related information, and will conduct fine evaluation on the information content (Hong, 2015). Relatively, the investment of cars is expensive for most families, so consumers' purchase decision-making about cars is also more serious. Therefore, the car has a high level of involvement in products. Before buying a car, consumers will collect as much information as possible, and process the collected information. Other readers' comments are also a way for users to obtain the information. After the launch of additional review function, reviewers are willing to make more efforts. Then they are more likely to respond to readers' questions. This means that readers are more likely to get the information they truly want through the readers' comments. It will increase the enthusiasm of readers to comment. Therefore, we put forward H3.

H3: The number of readers' comments increases after the additional review function is launched.

The effects of additional review function on reviewers

Previous studies have found that the motivations of comment can be roughly divided into two aspects: (1) the motivation of positive reviews, which includes helping others, producing involvement, self-improvement, helping businesses, sharing the emotional needs; (2) the motivation of negative reviews, which includes helping others and payback (Sundaram, Mitra, & Webster, 1998). Obviously, whether it is a positive review or a negative review, emotion is crucial to motivation, especially for the experiential products, such as cars. Additional review is an important channel to express emotions, and reviewers also aim to write reviews to share their feelings. However, for the platform of “AutoHome”, the prerequisite for making an additional review is to make an initial review. Therefore, with the introduction of additional reviews, the amount of initial reviews may also increase. For this reason, this study puts forward H4.

H4: The number of initial reviews increases after the additional review function is launched.

Nelson divides products into experience products and search products according to whether users need to learn the characteristics of products through experience (Nelson, 1974). The reviews on “AutoHome” are structured, and the reviewers can only comment within a given framework. There are different attributes specified in the framework. Thus, we can also divide the attributes in the framework into observational attributes and experiential attributes according to whether we need

experience to know the attribute. The initial reviews are more about the description of observational attributes, while the additional reviews are more about the description of experiential attributes. Therefore, after the introduction of additional reviews, the initial reviews will reduce the number of words of experiential attributes, however, may improve the user's participation and increase the number of words of observational attributes. Yet it is not clear which of these two changes has a greater impact; that is, how the number of words changes is uncertain. Thus, we put forward the following two opposing hypotheses:

H5a: The length of an initial review increases after the additional review function is launched.

H5b: The length of an initial review decreases after the additional review function is launched.

Self-enhancement Theory is one of the most important motivations affecting word-of-mouth communication (De Angelis, Bonezzi, Peluso, Rucker, & Costabile, 2012). According to the self-enhancement theory, reviewers tend to make consistent attitude on the same product in order to maintain their public reputation (Berger & Schwartz, 2011). Before the introduction of additional reviews, reviewers can only comment once. And they tend to comment immediately after receiving the car. However, the joy when they just received the product and their lack of understanding of the product make them give a high score in the rating. After the introduction of the additional review function, reviewers have the opportunity to comment twice. In order to make the emotional attitudes of the two reviews tend to be the same, at least not in the opposite state, reviewers will try their best to keep objective and neutral when making the initial rating. Therefore, the initial ratings will be lower. For this reason, this study puts forward hypothesis H6.

H6: The rating of an initial review decreases after the additional review function is launched.

Figure 1 summarizes the overall research framework of this paper, covering research objects, theories, hypotheses and variables.

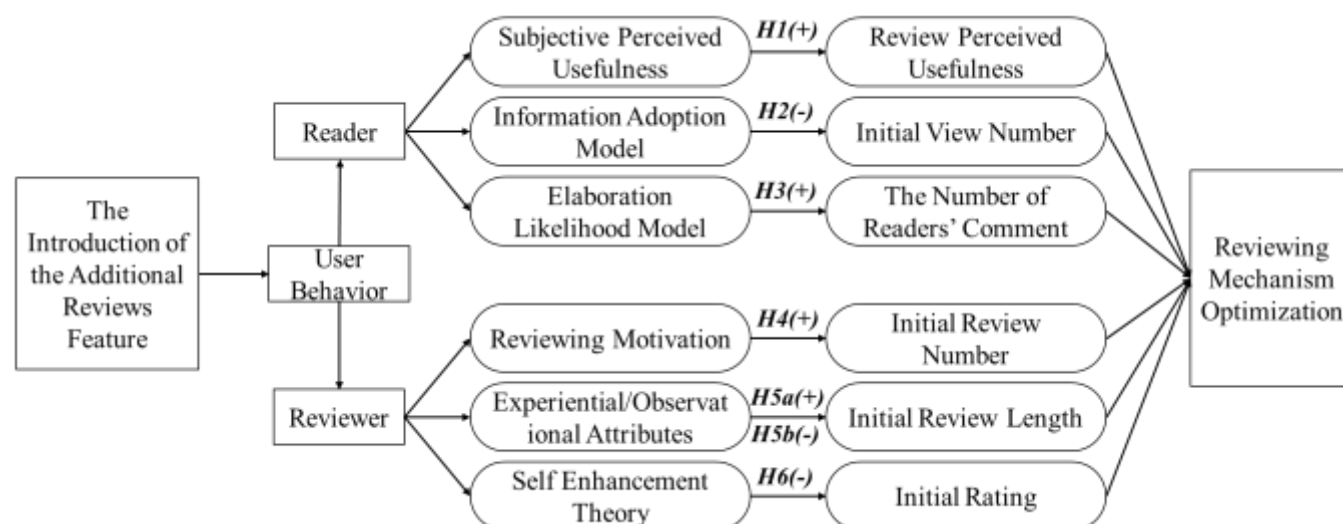


Figure 1: Research Design

METHODOLOGY

Data Collection

“AutoHome” is the most popular auto platform in China. “AutoHome” introduced the function of additional reviews in July 8, 2014. In order to conduct a natural experiment, we collected the reviews and related data posted in 2014 from “AutoHome”. If the time window is too short, the results may not show up; furthermore, if the time window is too long, it will dilute the impact of this event. Therefore, we selected 14 weeks as the time window. Using Python crawler program, we collected the data between 7 weeks before and after the introduction of the function of additional reviews (from May 20 to August 26, 2014). We labelled each car (represented by an ID). All the reviews of the selected cars in the selected time window, as well as the pageview number, review likes count, reader comments count, initial rating, car price, reviewer level and other information are crawled. In order to ensure that the natural experiment can eliminate other interference, we excluded those cars which only have reviews before or after the introduction of the function. Finally, we collected a total of 24,621 reviews involving 392 types of cars. The time window is numbered by week (-7 to 7). Week-7 through week-1 represent the weeks before the introduction of the function, and week1 through week7 represent the weeks after it. Taking “ID” as the i of panel data and “week” as the t of panel data. We averaged the weekly data, and then sorted the data into panel data with $i = 392$ and $t = 14$. After removing the missing values, we finally collected 3,972 panel data.

Variables and Models

In order to facilitate the collation of panel data, we take the week as the dimension of all variables and get the average value of the week. We present all the variables and their measurement in Table 1.

Table 1: Variable Description

Variable Type	Variable	Description	Note
Dependent variable	$useful_visit_{it}$	usefulness (review likes count) \div visits count	the average value of the week
	$comment_visit_{it}$	comments count \div visits count	
	$ln_visitcount_{it}$	the logarithm of pageview number	
Independent variable	$addreview_t$	dummy variable indicates whether period t is after the event	
Control variable	ln_price_{it}	the logarithm of car price	the average value of the week
	$reviewer_level_{it}$	reviewer level	
	$ln_visitcount_{it}$	the logarithm of pageview number	

We use $useful_visit_{it}$ and $comment_visit_{it}$ representing the perceived usefulness (quantify by the likes count) per unit amount of visit and the number of reader comments per unit amount of visit, respectively. $addreview_t$ is a dummy variable, which 0 represents before the introduction of additional reviews and 1 represents after the introduction of additional reviews. ln_price_{it} is the logarithm of car price, and $reviewer_level_{it}$ represents reviewer level. These two variables are used as the control variables to control other factors that may affect dependent variables. $ln_visitcount_{it}$ represents the logarithm of pageview. We believe that, although 1/10 and 100/1000 are both equal to 0.1, the meanings they represent are quite different. In this study, we discuss the absolute, not the relativity. So, Model (1) and (3) add the control variable $ln_visitcount_{it}$ to control the magnitude of the dependent variable.

Then, according to the hypotheses $H1-H3$, the reader-level models are proposed as:

$$useful_visit_{it} = \beta_0 + \beta_1 addreview_t + \beta_2 ln_price_{it} + \beta_3 reviewer_level_{it} + \beta_4 ln_visitcount_{it} + \varepsilon_{it} \quad (1)$$

$$ln_visitcount_{it} = \beta_0 + \beta_1 addreview_t + \beta_2 ln_price_{it} + \beta_3 reviewer_level_{it} + \varepsilon_{it} \quad (2)$$

$$comment_visit_{it} = \beta_0 + \beta_1 addreview_t + \beta_2 ln_price_{it} + \beta_3 reviewer_level_{it} + \beta_4 ln_visitcount_{it} + \varepsilon_{it} \quad (3)$$

Moreover, num_{it} represents the total number of reviews per week. ln_len_{it} is used to measure the number of words, and $star_{it}$ represents the initial rating. The other variables in Model (4) through (6) are consistent with Model (1) through (3).

$$num_{it} = \beta_0 + \beta_1 addreview_t + \beta_2 ln_price_{it} + \beta_3 reviewer_level_{it} + \varepsilon_{it} \quad (4)$$

$$ln_len_{it} = \beta_0 + \beta_1 addreview_t + \beta_2 ln_price_{it} + \beta_3 reviewer_level_{it} + \varepsilon_{it} \quad (5)$$

$$star_{it} = \beta_0 + \beta_1 addreview_t + \beta_2 ln_price_{it} + \beta_3 reviewer_level_{it} + \varepsilon_{it} \quad (6)$$

METHODOLOGY

The Results of the Reader-Level

Table 2 shows the descriptive statistical result of the reader-level variables. There should be 3,972 pieces of panel data in 14 weeks, but the observations are not exactly equal due to the missing value of some models and some variables.

Table 3 shows the correlation test of the variables of the reader-level. It can be found that the correlation coefficients between variables are less than 0.5. And the last row of Table 3 shows the variance inflation factor values (VIF). We can see that all the VIF values are less than 5. Therefore, there is no multicollinearity, so that the selected variables can be further analyzed.

In order to test the hypotheses of reader-level, we conduct the fixed effects regression. The results of regression are shown in Table 4. It can be found that $addreview_t$ is significant ($p < 0.01$) in Model (1) and (2). Furthermore, after the introduction of additional reviews, the perceived usefulness ($useful_visit_{it}$) increases while the pageview ($ln_visitcount_{it}$) decreases. And the regression results of readers' comments are not significant. Therefore, $H1$ and $H2$ are supported, while $H3$ is rejected. The number of readers' comments does not have significant improvement. Thus, additional reviews probably make people lazy, and readers are more willing to wait for additional reviews than to participate in reviews.

Table 2: Descriptive Statistics of Reader-Level

Variable	Obs#	Mean	Std. Dev.	Min	Max
$ln_visitcount_{it}$	3,972	9.006	1.5713	5.2149	14.9800
$useful_visit_{it}$	3,898	0.0009	0.0011	0	0.0173
$comment_visit_{it}$	3,911	0.0001	0.0002	0	0.0054
$addreview_t$	3,972	0.4615	0.4986	0	1
ln_price_{it}	3,972	2.6370	0.8659	0.4054	6.8046
$reviewer_level_{it}$	3,972	0.9775	0.6740	0	3

Table 3: Correlation Matrix and VIF Values of Reader-Level

	(1)	(2)	(3)	(4)	(5)	(6)
(1) <i>useful_visit_{it}</i>	1					
(2) <i>comment_visit_{it}</i>	0.1504	1				
(3) <i>addreview_t</i>	0.0643	0.0239	1			
(4) <i>ln_price_{it}</i>	-0.1489	-0.0887	0.0032	1		
(5) <i>reviewer_level_{it}</i>	-0.0286	-0.0516	-0.0283	0.0385	1	
(6) <i>ln_visitcount_{it}</i>	-0.2094	-0.1376	-0.0420	0.3154	-0.0034	1
VIF	1.0500	1.0700	1.0800	1.0400	1.0800	1.0200

Table 4: Regression Results of Reader-Level

	(1) <i>useful_visit_{it}</i>	(2) <i>ln_visitcount_{it}</i>	(3) <i>comment_visit_{it}</i>
<i>addreview_t</i>	0.0110** (0.0034)	-0.1411*** (0.0392)	0.0548 (0.0665)
<i>ln_price_{it}</i>	0.0047 (0.0087)	0.0372 (0.0793)	-0.1053 (0.0780)
<i>reviewer_level_{it}</i>	-0.0001 (0.0029)	0.0993** (0.0316)	-0.0963 (0.0666)
<i>ln_visitcount_{it}</i>	-0.0152*** (0.0019)		-0.2408*** (0.0451)
<i>_cons</i>	0.2069*** (0.0325)	8.885*** (0.2125)	3.258*** (0.5245)
<i>Obs#</i>	3,898	3,972	3,911
<i>Adj. R²</i>	0.0312	0.0363	0.0393

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The Results of the Reviewer-Level

Table 5 shows the descriptive statistics of the variables of reviewer-level. This study does not fill in the missing value, therefore, in the descriptive statistics, the minimum number of reviews is 1 instead of 0.

Table 6 shows the correlation test results of the variables of the reviewer-level and the VIF values. Obviously, as shown in Table 6, the variables of reviewer-level can be further analyzed.

In order to test the hypotheses of reviewer-level, we conduct the fixed effects regression on Model (4) through (6), and the results are shown in Table 7. It can be seen that *addreview_t* is significant ($p < 0.001$) in Model (4) and (6), in which *num_{it}* is significantly increased and *star_{it}* is significantly decreased, however the regression result of *ln_len_{it}* is not significant. Therefore, the hypotheses *H4* and *H6* are supported and hypotheses *H5a* and *H5b* are rejected. There are two possible explanations for no significant change in the length of reviews. First, according to our hypothesis, the number of words for the observational attribute has increased, and meanwhile, the number of words for the experiential attribute has decreased. On the whole, the changes of the two may offset each other. Second, most users pursue a sense of participation rather than identity, therefore the online additional reviews will not change their efforts, that is to say, the number of words in the two attributes has not changed at all. However, it is not clear which of these explanations is correct.

Table 5: Descriptive Statistics of Reviewer-Level

Variable	Obs#	Mean	Std. Dev.	Min	Max
<i>num_{it}</i>	3,972	5.2181	6.2264	1	79
<i>ln_len_{it}</i>	3,935	5.9301	0.5067	2.8332	7.6353
<i>star_{it}</i>	3,951	4.1741	0.0002	1	5
<i>addreview_t</i>	3,972	0.4615	0.4986	0	1
<i>ln_price_{it}</i>	3,972	2.6370	0.8659	0.4054	6.8046
<i>reviewer_level_{it}</i>	3,972	0.9775	0.6744	0	3

Table 6: Correlation Matrix and VIF Values of Reviewer-Level

	(1)	(2)	(3)	(4)	(5)	(6)
(1) <i>num_{it}</i>	1					
(2) <i>star_{it}</i>	0.1698	1				
(3) <i>ln_len_{it}</i>	0.1864	0.1188	1			
(4) <i>addreview_t</i>	0.0652	-0.0359	0.0072	1		
(5) <i>ln_price_{it}</i>	-0.0026	0.2788	-0.0531	0.0032	1	
(6) <i>reviewer_level_{it}</i>	-0.0218	-0.0322	0.0806	-0.0283	0.0385	1

	(1)	(2)	(3)	(4)	(5)	(6)
VIF	1.0500	1.0200	1.0500	1.0800	1.0400	1.0700

Table 7: Regression Results of Reviewer-Level

	(4) <i>num_{it}</i>	(5) <i>ln_len_{it}</i>	(6) <i>star_{it}</i>
<i>addreview_t</i>	0.8091*** (0.1765)	0.0026 (0.1519)	-0.0363*** (0.0117)
<i>ln_price_{it}</i>	0.3054 (0.2059)	0.0252 (0.0231)	0.0299 (0.0164)
<i>reviewer_level_{it}</i>	-0.1156 (0.0630)	-0.0458** (0.0166)	0.0131 (0.0123)
<i>_cons</i>	4.1386*** (0.5501)	5.8181*** (0.0632)	4.101*** (0.0470)
<i>Obs#</i>	3,939	3,935	3,951
<i>Adj. R²</i>	0.0001	0.0003	0.1734

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ROBUSTNESS CHECK

In order to verify the robustness of this study, the different time windows of 16 weeks and 12 weeks were selected to further test the above variables. The test results of reader-level at 16 weeks and 12 weeks are shown in Table 8. It can be found that the results remain consistent with Table 4. For example, the regression results of 16 weeks and 12 weeks of usefulness are significantly increased, which are consistent with 14 weeks. Therefore, the results of reader-level have passed the robustness check.

Similarly, this paper uses the same time windows to test the robustness of the variables of reviewer-level, and the results are shown in Table 9. It can be seen that, for the same dependent variable, the regression results of 16 weeks and 12 weeks are basically identical, which are consistent with the regression results of 14 weeks.

Table 8: Robustness Check of Different Time Windows at Reader-Level

	(1) <i>useful_visit_{it}</i>		(2) <i>ln_visitcount_{it}</i>		(3) <i>comment_visit_{it}</i>	
	<i>16weeks</i>	<i>12weeks</i>	<i>16weeks</i>	<i>12weeks</i>	<i>16weeks</i>	<i>12weeks</i>
<i>addreview_t</i>	0.1225*** (0.0033)	0.0118*** (0.0035)	-0.1599** (0.0372)	-0.1283** (0.0424)	0.0638 (0.0702)	0.0494 (0.0606)
<i>ln_price_{it}</i>	0.0052 (0.0074)	0.0083 (0.0109)	0.0195 (0.0680)	-0.0119 (0.0690)	-0.0561 (0.0913)	-0.1485 (0.0962)
<i>reviewer_level_{it}</i>	-0.0003 (0.0029)	-0.0005 (0.0030)	0.1047** (0.0304)	0.0998** (0.0351)	-0.0190 (0.0794)	-0.1154 (0.0788)
<i>ln_visitcount_{it}</i>	-0.0152** (0.0017)	-0.0154** (0.0021)			-0.2445*** (0.0451)	-0.2444*** (0.0508)
<i>_cons</i>	0.2057*** (0.0284)	0.1990*** (0.0383)	8.9152*** (0.1833)	9.040*** (0.1877)	3.096*** (0.5229)	3.4225*** (0.5890)
<i>Obs#</i>	4,414	3,339	4,428	3,353	4,427	3,352
<i>Adj. R²</i>	0.0334	0.0122	0.0015	0.0064	0.0465	0.0376

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Robustness Check of Different Time Windows at Reviewer-Level

	(4) <i>num_{it}</i>		(5) <i>ln_len_{it}</i>		(6) <i>star_{it}</i>	
	<i>16weeks</i>	<i>12weeks</i>	<i>16weeks</i>	<i>12weeks</i>	<i>16weeks</i>	<i>12weeks</i>
<i>addreview_t</i>	0.6245*** (0.1775)	0.4256* (0.1668)	0.0025 (0.0148)	0.0195 (0.0166)	-0.0315** (0.0110)	-0.0371** (0.0123)
<i>ln_price_{it}</i>	0.3737 (0.1999)	0.3332 (0.2662)	0.0314 (0.0205)	0.0019 (0.0226)	0.0223 (0.0154)	0.0324 (0.0177)
<i>reviewer_level_{it}</i>	-0.1081 (0.0591)	-0.1061 (0.0673)	0.0549*** (0.0159)	0.0463** (0.0177)	0.0159 (0.0112)	0.0099 (0.0132)
<i>_cons</i>	4.0448*** (0.5400)	4.1618*** (0.7014)	5.7878*** (0.0573)	5.8823*** (0.0621)	4.1153*** (0.0431)	4.1024*** (0.0493)
<i>Obs#</i>	4,462	3,371	4,453	3,368	4,474	3,383
<i>Adj. R²</i>	0.0001	0.0001	0.0001	0.0002	0.1645	0.1698

Notes: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CONCLUSION AND DISCUSSIONS

To some extent, the introduction of additional reviews is the inevitable product of the development of online reviews, which has an impact on the initial reviews. On the basis of previous studies, this study aims to explore the influence of additional review function on initial reviews from the reader- and reviewer-level with the data from “AutoHome”. At the reader-level, additional reviews can improve the perceived usefulness of the initial reviews, and can decrease the view number of initial reviews. At the reviewer-level, additional reviews can increase the number of initial reviews and lower the initial rating, making the initial reviews more objective. However, the length of initial reviews has not changed.

In general, this study enriches the research on online word-of-mouth and provides a new research direction for online reviews. Our study finds that additional reviews can affect user behavior in terms of initial reviews and it can also improve the overall appraisal. The findings of this paper also have some practical implications. Consumers will be advised to read reviews with additional reviews because that's usually more useful. And the platform can introduce the function of additional reviews to improve the comment mechanism.

There are still several limitations in this study. First, due to the reviews' characteristics of “AutoHome” platform, the results of this study are only applicable to E-commerce platforms with structured reviews. Second, it is not clear which of the hypotheses is the reason why the length of reviews has not changed significantly. Third, the research perspective has not been considered comprehensively, and the future research may consider a wider range of the influencing factors.

ACKNOWLEDGMENT

This work was partially supported by the National Natural Science Foundation of China (Grant # 71801063) and the China Postdoctoral Science Foundation (Grant # 2018M640300).

REFERENCES

- Akhtar, N., Kim, W. G., Ahmad, W., Akhtar, M. N., Siddiqi, U. I., & Riaz, M. (2019). Mechanisms of consumers' trust development in reviewers' supplementary reviews: A reviewer-reader similarity perspective. *Tourism Management Perspectives*, 31, 95-108. <https://doi.org/https://doi.org/10.1016/j.tmp.2019.04.001>
- Berger, J., & Schwartz, E. M. (2011). What drives immediate and ongoing word of mouth? *Journal of Marketing Research*, 48(5), 869-880. <https://doi.org/https://doi.org/10.1509/jmkr.48.5.869>
- Chatterjee, P. (2001). Online reviews: Do consumers use them? In M. C. Gilly & J. Meyers-Levy (Eds.), *Advances in Consumer Research* (Vol. 28, pp. 129-133). Provo: Association for Consumer Research.
- Chen, H., Yan, Q., Xie, M., Zhang, D., & Chen, Y. (2019). The sequence effect of supplementary online comments in book sales. *Ieee Access*, 7, 155650-155658. <https://doi.org/https://doi.org/10.1109/access.2019.2948190>
- De Angelis, M., Bonezzi, A., Peluso, A. M., Rucker, D. D., & Costabile, M. (2012). On braggarts and gossips: A self-enhancement account of word-of-mouth generation and transmission. *Journal of Marketing Research*, 49(4), 551-563. <https://doi.org/https://doi.org/10.1509/jmr.11.0136>
- Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? — An empirical investigation of panel data. *Decision Support Systems*, 45(4), 1007-1016. <https://doi.org/https://doi.org/10.1016/j.dss.2008.04.001>
- Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE Transactions on Knowledge and Data Engineering*, 23(10), 1498-1512. <https://doi.org/https://doi.org/10.1109/TKDE.2010.188>
- Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: Do brand strength and category maturity matter? *Journal of Marketing*, 77(6), 37-53. <https://doi.org/https://doi.org/10.1509/jm.11.0011>
- Hong, I. B. (2015). Understanding the consumer' s online merchant selection process: the roles of product involvement, perceived risk, and trust expectation. *International Journal of Information Management*, 35(3), 322-336. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2015.01.003>
- Houser, D., & Wooders, J. (2006). Reputation in auctions : Theory, and evidence from eBay. *Journal of Economics & Management Strategy*, 15(2), 353-369. <https://doi.org/https://doi.org/10.1111/j.1530-9134.2006.00103.x>
- Huang, G.-H., Chang, C.-T., Bilgihan, A., & Okumus, F. (2020). Helpful or harmful? A double-edged sword of emoticons in online review helpfulness. *Tourism Management*, 81, 104135. <https://doi.org/https://doi.org/10.1016/j.tourman.2020.104135>
- Jonas, K., Diehl, M., & Bromer, P. (1997). Effects of attitudinal ambivalence on information processing and attitude intention consistency. *Journal of Experimental Social Psychology*, 33(2), 190-210. <https://doi.org/https://doi.org/10.1006/jesp.1996.1317>
- Lamb, Y., Cai, W., & McKenna, B. (2020). Exploring the complexity of the individualistic culture through social exchange in online reviews. *International Journal of Information Management*, 54, 102198. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2020.102198>
- Nelson, P. (1974). Advertising as information. *Journal of Political Economy*, 82(4), 729-754. <https://doi.org/https://doi.org/10.1086/260231>
- Pee, L. G. (2016). Negative online consumer reviews: Can the impact be mitigated? *International Journal of Market Research*, 58(4), 545-567. <https://doi.org/https://doi.org/10.2501/IJMR-2016-035>

- Sundaram, D. S., Mitra, K., & Webster, C. (1998). Word-of-mouth communications: A motivational analysis. In J. W. Alba & J. W. Hutchinson (Eds.), *Advances in Consumer Research* (Vol. 25, pp. 527-531). Provo: Association for Consumer Research.
- Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, 14(1), 47-65. <https://doi.org/https://doi.org/10.1287/isre.14.1.47.14767>
- Tran, L. T. T. (2020). Online reviews and purchase intention: A cosmopolitanism perspective. *Tourism Management Perspectives*, 35, 100722. <https://doi.org/https://doi.org/10.1016/j.tmp.2020.100722>
- Xu, X. (2020). Examining the role of emotion in online consumer reviews of various attributes in the surprise box shopping model. *Decision Support Systems*, 136, 113344. <https://doi.org/https://doi.org/10.1016/j.dss.2020.113344>