Summer 7-5-2020

Factors Influencing the Perception of Seller Credibility in Online Reputation System: an Eye-Movement Approach

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Abstract: The current online reputation systems for online sellers face great challenges from bad-faith behavior such as malicious negative reviews, click farming, mismatch between images and commodities, and forged commodities. To optimize the design of online reputation systems, explore the consumer utilization of credit clues, and describe the law of mutual trust, this paper puts forth three hypotheses about the influencing factors of consumer perception of online seller credibility and integrates various research methods such as an eye-movement experiment, questionnaire survey, econometric analysis, and empirical research. To evaluate the three hypotheses, the display modes of commodities on a current e-commerce platform were optimized, and eye-movement experiments were conducted on original and optimized webpages. Results show that the display of sales growth, the refinement and tagging of review content significantly impacted consumer perception of seller credibility. Further, designers of online reputation systems were advised to display sales trends, provide personalized sales queries, and tag a variety of reviews for consumers to easily ascertain credible sellers. This advice helped curb bad-faith behavior.

Keywords: e-commerce platform, credit clues, reputation system, eye movement experiment

1. INTRODUCTION

Reputation is the foundation for the trusted trading relationship between the buyer and the seller, and an important guarantee of the orderly development of the market [1, 2]. After years of exploration and innovation, China has made marked progress in the construction of e-commerce credit system. However, bad-faith behaviors are still commonplace in the field of e-commerce, such as malicious negative reviews, click farming, mismatch between image and commodity, forged and fake goods, etc. The rampant spread of such behaviors has disrupted the order of the online market, and violated the legitimate rights and interests of consumers, posing a serious threat to the healthy transactions [3]. Lack of information about the background, especially trustworthiness of participants in these markets, creates suspicion and mistrust among participants. The scarcity of trust has become a significant bottle neck in the development of e-commerce [4, 5].

The online reputation system, a cornerstone of e-commerce platform, maintains the stability of online transactions, laying the basis for good mutual trust and high market efficiency [6, 7]. But every silver lining has a cloud: the traditional online reputation system is prone to malicious attacks and rating fraud, when faced with numerous bad-faith behaviors [8, 9]. To overcome these defects, cement the credit mechanism of e-commerce platform and make up for the lack of good faith in e-commerce, it is necessary to optimize current online reputation system [10, 11].

The remainder of the paper is organized as follows: Section 2 introduces related works on online reputation systems from eye tracking perspective. Section 3 introduces the main process of eye movement experiment and

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the analysis of the simulation results is provided in section 4. In the last section, we present conclusions and directions for future work.

2. RELATED WORKS

With the aid of eye-tracking devices, scholars have been able to analyze information cognition and browsing modalities of subjects using large online shopping platforms. This has enabled researchers to understand shopper intentions and decision-making as affected by information clues on e-commerce platforms [13, 14]. Online reviews, celebrity endorsements, brands, and trademarks have also been evaluated for this purpose [15]. Via experimental analyses, Yan et al. suggested that consumers paid more attention to negative reviews than to positive ones, even when they contradicted. They also found that good brands improved consumers' cognition of online reviews, combating the passive influence of negative reviews [16]. References [17, 18] investigated the advertising effects of celebrity endorsements, revealing that they resulted in more effective advertising, especially when the celebrity image complemented the product's function. Bertarelli discovered a correlation between consumer cognitive needs and the match between celebrity and product. The advertising effect improved with the matching degree for those having high cognitive needs, whereas those with low cognitive needs were insensitive to the matching degree [19]. Beldad et al. examined how the match between the gender of the virtual sales assistant and the product gender affected consumer purchase intentions, concluding that consumers tended to trust an assistant's advice if they were highly matched; they were unaffected by assistant gender or product gender alone [20].

Over the years, fruitful results have been achieved via eye-movement experiments conducted with online reputation systems, leading to new methodological and theoretical insights on advertising research. Unfortunately, several of these studies are marred by significant issues. Relevant studies on online reputation systems have experimentally analyzed the effectiveness of market guarantees and have improved the identification and classification of moral hazards based on a trust model. However, they have failed to discuss the utility of external credit clues provided by the system from the perspective of consumer perception. They have further disregarded the impact on consumer perception of seller credibility. Online reputation systems have been studied via economic experiments, simulations, game-theory applications, and other methods. However, few scholars have extended psychological methods, such as eye-movement experimentation, to studying these systems or to analyzing how credit clues affect consumer perception of seller credibility. Current studies on eye movement experiments have concentrated on application scenarios of products like books, webpages, and toys, highlighting the influence of the numbers, types, and forms of design elements on consumer purchase intentions and transaction behavior. Nevertheless, there is no in-depth report on the selection of credible sellers when multiple sellers offer homogenous commodities. To help resolve these shortfalls, this research starts with the consumer perception of seller credibility and then introduces the eye-movement experiment to help optimize a new design for online reputation systems, aiming to bolster consumer decision-making abilities of selecting credible sellers and boosting the effectiveness of online reputation systems.

3. EXPERIMENT DESIGN

We first conducted a questionnaire survey online, which mainly covered two aspects, namely, demographic characteristics (gender, occupation, age, monthly income/living cost) and online shopping information (online shopping experience, monthly online shopping frequency, commodity search habit and awareness of click farming on Taobao.com). In total, 289 questionnaires were returned. Excluding 8 invalid ones, 281 valid questionnaires were available for analysis. In terms of demographic characteristics, about 60% of the respondents are females, over 90% of them are students, 83.39% are aged between 18 and 25, and 42.91% earn or spend 1,000~1,500 yuan per month (the monthly income/living cost reflects the fact that the respondents are predominantly students). According to the online shopping information we collected, 281 of the respondents have online shopping experience, with only 8 have never shopped online; 79% of them shopped online 1~2 or 3~5 times per month; 85.41% are aware of click farming on Taobao.com. Also, we utilized five-point Likert Scale to explore where consumers usually select items (such as flagship store or Tmall, “Hot Sell”, etc.) and what information they think highly of when shopping on Taobao.com (for example, sales volume, reviews volume, reviews content, etc.). The reliability coefficients of the data matrices were 0.859 and 0.969, respectively, both of which are greater than 0.7, indicating that the data are fully trustworthy and usable.

Questionnaire analysis revealed that consumers were more concerned about the commodity itself than propriet or information of the store. High correlation was found by matching consumer attention to commodity sales, review volumes, review content, and positive and negative review rates. Further analysis revealed that consumers focused the most on three credit clues: review content, negative reviews, and commodity descriptions. Refer to [14, 15, 18], drawing from studies on click farming, we summed the typical features of stores engaging in fake order placements, learning that sales volumes soar over the short term and reputation was high despite new registrants. The volume of reviews rapidly increased over a short period, and the content of reviews was extremely similar and pretentious. On the basis of this, three hypotheses are put forward as follows:

H1: The presentation of sales growth will positively impact consumer perception of seller credibility.

H2: The display of the growth in the number of reviews will positively impact consumer perception of seller credibility.

H3: The tagging of review content will positively impact consumer perception of seller credibility.

3.1 Preparations

In the context of the Internet, there is a new product classification framework called Search, Experience, and Credence. Search products are identified as those for which consumers have the ability to obtain information on product quality prior to purchase, while experience products are those whose relevant attribute information cannot be known until the trial/use of the product/service. And credence products are those whose relevant attribute information is not available prior to and after the use of the product/service for a considerable period of time. We selected an experience-type commodity for the experiment as the purchase of search and credence products is mostly unaffected by external credit clues. In light of the questionnaire survey and relevant studies, pitaya fruit found in a flagship store on Taobao.com was determined as the target of the study.

According to the credit clues (store sales, store credit, number of reviews and tagging of review content) mentioned in the four hypotheses, the original webpage was photoshopped based on the existing webpage of the store. To eliminate the interference of other factors, any content irrelevant to our experiment was removed from the webpage, e.g. “add to the shopping cart” and “price”. The original webpage thus designed is shown in Figure1.

As mentioned before, the typical features of a store engaging in click farming include the sale volumes soars in a short period, the reputation is high despite recent registration, the volume of reviews explodes in a short period, and the reviews are extremely similar in content or bombastic. In light of the three hypotheses, we presented three optimized webpage designs (shown in Figure 2).

• **Sale volume design.** Seller credibility can be well-demonstrated by analyzing long-term historical data. We originally planned to group monthly sales variations annually or semiannually. Unfortunately, accurate sales data were unavailable for these durations. Therefore, we observed daily sales changes of the target commodity, deriving a daily sales measure. After a week, we plotted the data on a line chart to show the sales trend and used this evaluation to verify H1.

• **Review volume design**. Similar to the acquisition of sales data, we observed daily changes in the volumes of reviews, deriving the number of reviews daily for a week. The obtained data were plotted on a line chart to describe the trend and used to verify H2.

Figure 1. Original webpage design

Figure 2. Optimized webpage design

• **Review content design.** The original webpage displayed the content of all reviews at once. Owing to the huge amount of data, consumers often browse only the first few pages of reviews, most of which are positive as selected by sellers. Within this display mode, it is impossible for consumers to fully understand the overall rating. To resolve this issue, we originally planned to mine the content of all reviews using Java programming to extract high-frequency words. However, this was extremely difficult because only 10 reviews could be expanded at once when clicking on the link to a detailed subpage of reviews. Therefore, we extracted 100 reviews, from which high-frequency words were identified. Next, we extrapolated the total number words in all reviews. Finally, the words were tagged to verify H3. After typesetting, the optimized webpage design was improved.

3.2 Experimental process

Forty-one students conversant with online shopping were recruited from a university, with 90.9% of them shopping online at least once or twice per month. Each subject was tested continuously for five minutes. The experimental process was as follows:

Step 1: We instructed the subject to adjust their sitting posture such that the eye tracker could accurately record eye positions.

Step 2: We notified the subject to look at a moving ball appearing on the screen and to perform the fixed-point calibration.

Step 3: We described the shopping scene to the subject with the following verbiage: “Let us say that you want to buy some pitayas, which are currently in season. Please do not consider the price; look carefully at the commodity information and answer the questions. To ensure the experimental effect, please retain the same sitting posture throughout the experiment, so that the eye tracker can record your eye position and related data.”

Step 4: All subjects were shown the original webpage first and their eye position were recorded by the eye tracker. After answering the questions, they then browsed the optimized webpage and repeated the previous process.

4. EXPERIMENTAL ANALYSIS

After 41 subjects completed their tests, the invalid data of 5 subjects were eliminated. Then, the eye movement data collected through our experiment were subjected to regression analysis to verify the four hypotheses separately. According to related references, the eye movement was described by the following variables: time to first fixation (*tff*), first fixation duration (*ffd*), fixation duration (*fd*), fixation count (*fc*), and visit duration (*vd*).

4.1 Analysis of sale volumes

4.1.1 Chart analysis

• Trajectory analysis

The subjects fixed their eyes on monthly sales from the start to the end of the eye-movement recording. After the webpage was optimized, fixation on monthly sales became more prominent and lasted for a longer duration.

• Heat map analysis

After webpage optimization, the subjects’ eye sight covered a wider range of heat points on monthly sales, showing a trend of sales figures from the original webpage, and the highlight values reached their peak levels. This means that the subjects were more interested in the optimized module of store sales (Figure 3, Figure 4).

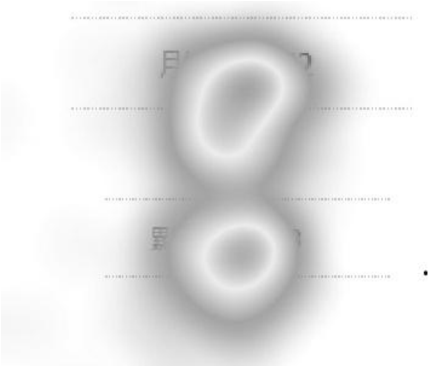

Figure 3. Heat map for sale volumes in the original webpage

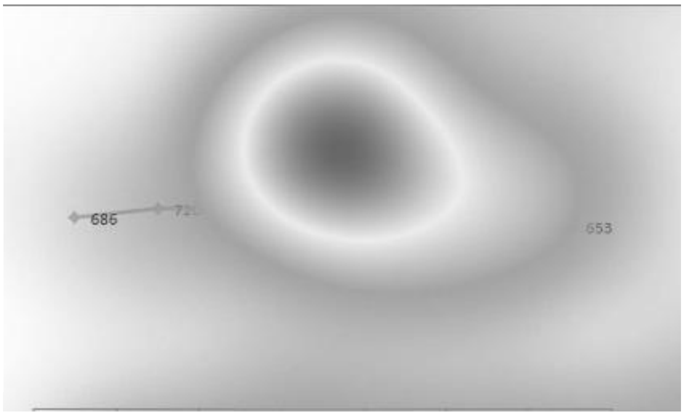

Figure 4. Heat map for sale volumes in the optimized webpage

4.1.2 Data analysis

Using a simple linear regression, significantly effective indices were identified from subjects' visits to the webpage. Finally, a fitting regression was carried out with the commodity credit score rated by subjects using the explained variable and the relevant variables acquired from paired sample t-tests.

Taking the *vd* as the explained variable, two indices with high significance through stepwise regression were selected as the explanatory variables, namely, *ffd* and *fd*. The linear regression was calculated to test which independent variable were significant (Table 1). The results indicate that both first fixation duration and fixation duration are significantly effective ($p<0.05$).

Table 1. stepwise regression analysis results of original webpage (sales volumes)

	Unstandardized Coefficient	Standard error	T statistics	Sig.
Intercept	1.56	0.40	3.87	0.000***
ffd	-6.99	2.89	-2.42	0.021**
fd	8.69	3.15	2.75	0.009*
Adjusted R^2	0.138			
F	3.81			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results indicate that the p-values of both first fixation duration (*ffd*) and fixation duration (*fd*) were smaller than 0.05, indicating that the two explanatory variables were significantly effective.

Results of the linear regression indicate that after webpage optimization, the first fixation duration (*ffd*) comprised the only eye movement index with a p-value smaller than 0.05, indicating that this variable was significantly effective (Table 2).

Table 2. stepwise regression analysis results of optimized webpage (sale volumes)

	Unstandardized Coefficient	Standard error	T statistics	Sig.
Intercept	-0.12	0.61	-0.20	0.841
ffd	3.57	1.66	2.16	0.038*
fd	1.77	3.12	0.56	0.574
Adjusted R^2	0.118			
F	3.33*			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The *vd* to the sale volumes of the original and optimized webpages were considered two independent samples and subjected to paired sample t-tests. The test results ($t(35)=4.22$, $p<0.001$) indicate an obvious difference in the visit durations to store sales in the original and optimized webpages. This means the display of sales trend over a period of time helped prolong the visit duration of the subject.

The *ffd* of the sale volumes in the original and optimized webpages were considered two independent samples and subjected to paired sample t-tests. It can be seen that $t(35)=0.31$, $p=0.763$, where the p-value of the t-test was far greater than 0.05. Thus, there was no significant difference in the first fixation duration of store sales in the original and optimized webpages. The change of display mode did not immediately lengthen the first fixation duration. The credit scores (*Score*) rated by the subjects before and after webpage optimization were considered two independent samples and subjected to paired sample t-tests. The test results show an obvious difference in commodity credit scores rated by subjects before and after webpage optimization ($t(35)=-3.914$, $p<0.001$). The post-optimization score was 0.838 units higher than the original score. The fitting regression equation of the original webpage is expressed as Eq. 1, extrapolated in Table 3:

$$Score = \alpha + \beta \times sales\_vd2 + \gamma \times sales\_ffd + \varepsilon \tag{1}$$

Table 3. Fitting regression analysis results of original webpage (sale volumes)

	Unstandardized Coefficient	Standard error	T statistics	Sig.
Intercept	4.89	0.24	20.29	<2e-16***
sales_vd2	-0.21	0.13	-1.66	0.107
sales_ffd	-2.27	1.07	-2.12	0.041*
Adjusted R^2	0.136			
F	3.75			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The fitting regression equation of the optimized webpage can be expressed as (Table 4):

$$Score\_after = \alpha_1 + \beta_1 \times sales\_vd\_after3 + \gamma_1 \times sales\_ffd\_after3 + \delta \times sales\_ffd\_after + \varepsilon \tag{2}$$

Table 4. Fitting regression analysis results of optimized webpage (sale volumes)

	Unstandardized Coefficient	Standard error	T statistics	Sig.
Intercept	5.51	0.39	14.22	2.23e-15***
sales_vd_after3	-0.01	0.04	-2.38	0.023*
sales_ffd_after3	0.45	17.68	0.03	0.980
sales_ffd_after	-2.31	3.02	-0.77	0.449
Adjusted R^2	0.197			
F	3.86			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results of the fitting regressions and paired sample t-tests on credit scores revealed that the credit score of the commodity was positively correlated with the first fixation duration at the store sales section.

Overall, the subjects generally attached high attention to monthly sales of the commodity during online shopping. After the graphic display of the monthly sales of the commodity over a period, the subjects fixed their eyes at the monthly sales trend for longer durations. Moreover, the first fixation time had a linear positive correlation with the visit duration to the store sales. Additionally, the visit duration was greatly extended after webpage optimization. Thus, the display of sales growth positively impacts consumer perception of seller credibility. Therefore, H1 is supported.

4.2 Analysis of reviews volumes

4.2.1 Chart analysis

After webpage optimization, the subjects' eyesight covered a wider range of heat points on the number of reviews than that on the original webpage. However, the peak level of highlight values remained basically unchanged (Figure5, Figure6).

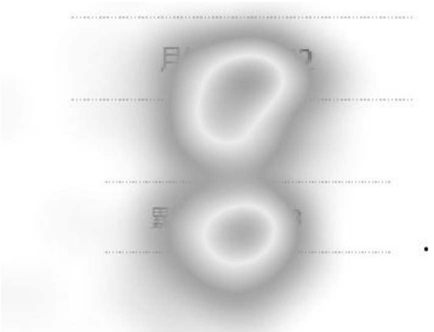

Figure 5. Heat map for reviews volumes in the original webpage

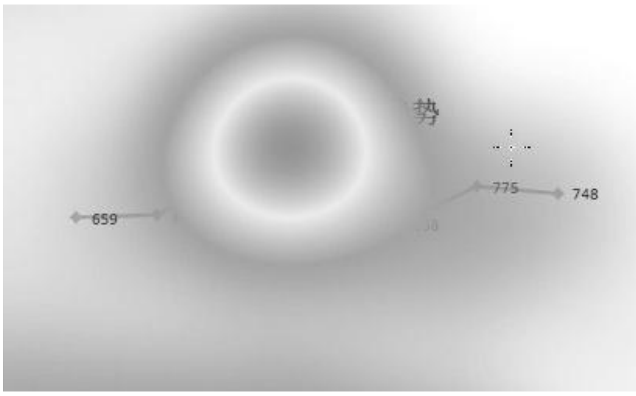

Figure 6. Heat map for reviews volumes in the optimized webpage

4.2.2 Data analysis

Taking the *vd* as the explained variable, an index with high significance (*ffd*) through stepwise regression was selected as the explanatory variable. Results show that the five variables were closely correlated on the number of reviews. Hence, the relevant variables were directly subjected to paired sample t-tests, and the commodity credit of the original webpage was contrasted with that of the optimized webpage. Results of the linear regression indicate that the t-statistic of the first fixation duration was in the effective range, indicating that this explanatory variable is significantly effective (Table 5).

Table 5. stepwise regression analysis results of original webpage (reviews volumes)

	Unstandardized Coefficient	Standard error	T statistics	Sig.
Intercept	0.29	0.13	2.31	0.028*
ffd	1.13	0.49	2.26	0.030*
Adjusted R^2	0.106			
F	5.13			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The linear regression results of the optimized webpage show that this explanatory variable is not significant (Table 6).

Table 6. stepwise regression analysis results of optimized webpage

	Unstandardized Coefficient	Standard error	T statistics	Sig.
Intercept	0.38	0.13	2.85	0.007**
Comment_ffd	0.77	0.51	1.49	0.145*
Adjusted R^2	0.034			
F	2.22			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The visit durations to the number of reviews in the original and optimized webpages were considered two independent samples and subjected to paired sample *t*-test. Because the *p*-value (0.182) of the *t*-test ($t(35)=-1.362$) was far greater than 0.05, and the *t*-statistic fell outside the effective range, there was no significant difference in the visit durations to the number of reviews in the original and optimized webpages. Thus, the number of reviews is not a primary clue for the subjects to perceive seller credit during online shopping.

The first fixation durations on the number of reviews in the original and optimized webpages were considered two independent samples and subjected to paired sample *t*-tests. It can be seen that $t(35)=0.726$ and $p=0.047$. Thus, the first fixation durations on the number of reviews in the original and optimized webpages differed insignificantly.

The commodity credit scores rated by the subject before and after webpage optimization were considered two independent samples and subjected to paired sample *t*-tests ($t(35)=-3.914$, $p<0.001$).

In summary, the subjects had no significant changes in their attention, visit duration, and first fixation duration concerning the number of reviews via webpage optimization. Therefore, the display of the growth in the number of reviews had an insignificant impact on consumer perception of seller credibility.

4.3 Analysis of reviews contents

4.3.1 Chart analysis

Owing to the addition of typical tags following webpage optimization, the subjects' eyesight covered a wider range than on the original webpage, and the highlight values concentrated on all tags (Figure 7, Figure 8).

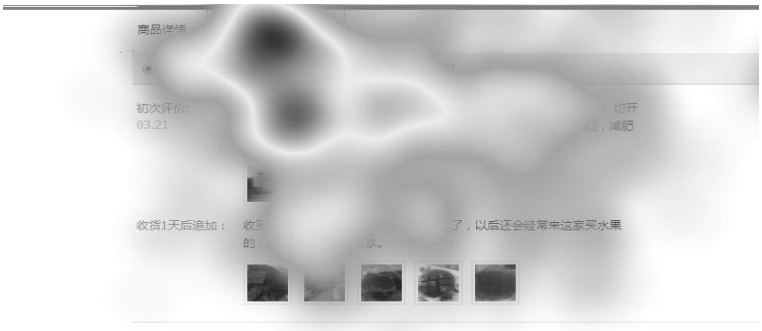

Figure 7. Heat map for reviews contents in the original webpage

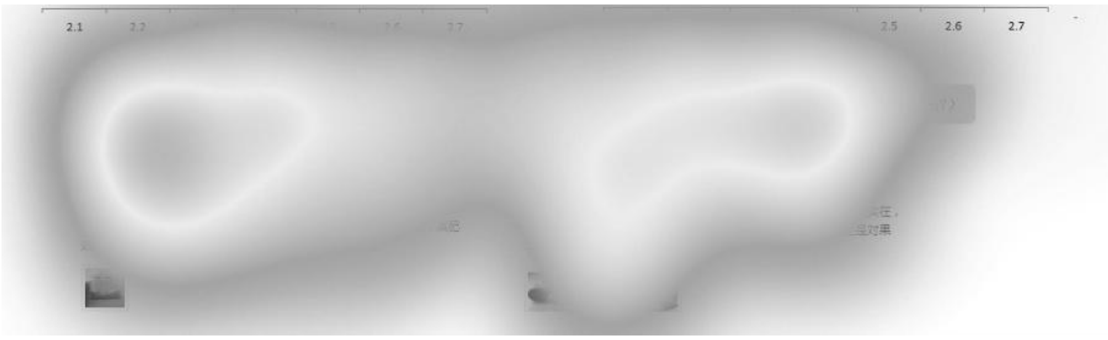

Figure 8. Heat map for reviews contents in the optimized webpage

4.3.2 Data analysis

Taking *vd* as the explained variable, eye movement indicators *ffd*, *fd*, and *fc* were regressed in a stepwise manner. No explanatory variable was found to be significantly effective. Thus, we performed a principal component analysis. All eye movement indices were summed and subjected to a fitting regression with the commodity credit score as the explained variable.

Visit durations vs. the review content in the original and optimized webpages were considered two independent samples and subjected to paired sample t-tests. The test results ($t(35)=-1.532$, $p=0.134$) show insignificant differences between visit durations of review content before and after webpage optimization.

The times to first fixation on the review content in the original and optimized webpages were considered two independent samples and subjected to paired sample t-tests. The test results ($t(35)= -2.857$, $p=0.007$) show that the time to first fixation on the review content changed considerably from the webpage optimization. After more tags were added to highlight the review content, the subjects observed the tagged content more quickly than before.

The first fixation durations on the review content in the original and optimized webpages were considered two independent samples and subjected to paired sample t-tests. The test results ($t(35)=-2.478$, $p=0.018$) show a significant difference in the first fixation duration before and after webpage optimization. The subjects fixed their eyes on the webpage for longer durations after the optimization.

The commodity credit scores rated by the subject before and after webpage optimization were considered two independent samples and subjected to paired sample t-tests. The test results ($t(35)= -3.914$, $p<0.001$) show a significant difference in the commodity rating score before and after webpage optimization.

In summary, the subjects fixed their eyes on tagged content for a long duration, and the trajectory almost covered all tags. There were significant changes to the time to first fixation and the first fixation duration from webpage optimization. Subjects noticed the content having more tags sooner and spent more time reading the review content. Comparing the fitting regression results before and after optimization, it is clear that the commodity credit score was mainly affected by the first fixation duration and that the two factors had a positive correlation. In other words, the addition of highly generalized tags encouraged consumers to spend more time reading reviews, enabling them to make more rational purchase choices. Thus, H3 is supported.

5. CONCLUSIONS

According to the results of the questionnaire survey, consumers pay the most attention to three credit clues in online shopping: review content, negative review rate, and commodity description. Drawing from studies on click farming, we summed the typical features of a store engaging in fake order placement. Those features are indicated by phenomena wherein sales volume soars over a short period, reputation is high despite recent registration, review volumes explodes in a short period, and content of reviews is extremely similar and pretentious. Therefore, three hypotheses were put forward and subjected to econometric analysis.

H1 is supported. The display of sales growth positively impacted the consumer perception of seller credibility. H2 is not supported. The display of growth in the number of reviews did not significantly impact the consumer perception of seller credibility. H3 is supported. The tagging of review content positively impacted consumer perception of seller credibility.

Based on the above empirical results, we put forward the following suggestions for online reputation systems on e-commerce platforms. Rather than displaying only monthly sales and relevant data, sellers should display the changes in daily sales over a recent period and, perhaps, the changes in monthly sales over the past year or so. They could also enable consumers to search for sales in any period. This way, the buyer has more power to judge if the seller is legitimate and can estimate trustworthiness. Trustworthy sellers will then attract more buyers, consumer rights and interests will be safeguarded, and e-commerce platforms will remain fair and safe. Furthermore, sellers should add positive tags to review content so that consumers can easily gain an objective and thorough understanding of the commodity. This measure helps crack down on bad-faith behavior.

ACKNOWLEDGEMENTS

This work was supported by the Beijing Natural Science Foundation (9182016, 9194031), National Natural Science Foundation of China (71874215, 71571191), MOE (Ministry of Education in China) Project of Humanities and Social Sciences (15YJCZH081, 17YJAZH120, 19YJCZH253), Fundamental Research Funds for the Central Universities (SKZZY2015021) and Program for Innovation Research in Central University of Finance and Economics.

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