Research on the Mechanism of the Influence of E-WOM Dispersion on Consumers Return Intention

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Abstract. Based on the attribution theory, this paper constructs a conceptual framework for the influence of the dispersion of electronic word of mouth on consumers’ return intentions, focusing on the impact of the interaction between robot review and e-WOM dispersion on consumers’ attribution selection, the study uses situational experiments to collect data and verify hypotheses. The study found that: (1) Consumers are more willing to return goods when faced with high-dispersion electronic word of mouth; (2) When facing high-dispersion electronic word of mouth, consumers tend to attribute it to existing reviewers; (3) The influence of word-of-mouth dispersion on attribution selection is regulated by robot reviews. For the word-of-mouth dispersion of robot reviews, the tendency of word-of-mouth dispersion to be attributed to product reasons becomes greater. The research has laid a theoretical foundation for further exploring the influence of e-WOM dispersion on consumers’ return intentions, and also provides theoretical guidance and reference for enterprises to rationally use Internet robots and reduce return rates.

1 Introduction
In the shopping environment, the evaluation of the same product by existing reviewers is often different, namely e-WOM dispersion. E-WOM dispersion has an important impact on consumer decision-making. Because there is a certain time interval between the two decisions of "buy or not" and "keep or not", important product experience information often appears at the second decision point [1]. Therefore, the influence mechanism of e-WOM dispersion on purchase decision and return decision may be different. Former scholars focused on the impact of word-of-mouth dispersion on consumer behaviour, mainly focusing on the impact of purchase behaviour [2], repurchase intention [2], and subsequent evaluation [3] of consumers, but not return intention.

In addition, the former research only considered the influence mechanism of the dispersion of electronic word-of-mouth from the perspective of human reviews, ignoring the influence of the robot reviews. Based on consumers' negative views of artificial intelligence [4], consumers will have an aversion to the dispersion of electronic word-of-mouth with robot reviews, which will increase the tendency of consumers to attribute aversion to products and lead to more product returns. In
2 Literature review and hypotheses

2.1 The Impact of Discrete Online Reputation on Willingness to Return
Discrete electronic word-of-mouth refers to the degree of difference in the evaluation of a certain product or service by consumers, which is intuitively expressed as the standard deviation of the product star rating [5]. The dispersion of electronic word-of-mouth has a certain impact on consumers' repurchase intentions [2] and returns behaviour [6].

Expectation Confirmation Theory (ECT) believes that consumers will compare their expectations before shopping (Exception) with the performance obtained after shopping (Perceived Performance). The performance gap generated by the comparison will form consumer satisfaction. With the increase in consumer satisfied, consumer’s willingness to keep items increases, and vice versa. Consumers who purchase products under the condition of high dispersal of online reputation may be more likely to make a return decision due to the discrepancy between perceived performance and expected expectations when inspecting the product [6]. Based on the above reasoning, the research puts forward the following hypotheses.

H1. The dispersion of e-WOM has a significantly negative impact on return intention.

2.2 The Mediating Role of Attribution Selection
Attribution Theory believes that people use "common sense psychology" to explain daily life events [7], which embodies the process of individuals determining potential causes or explanations of observable events [8], so the behaviour is usually attributed to internal or external reasons [9]. Some scholars believe that attribution theory can be used to explain the difference in the acceptance of electronic word-of-mouth by consumers. Based on this, a small number of scholars believe that consumers generally attribute inconsistent product reviews to two reasons: one is product cause, the second is the reason for the existing reviewers. If consumers attribute the discrete online reputation to product-related reasons, the perceived credibility and usefulness will increase; conversely, they perceived credibility and usefulness will decrease [9]. Therefore, the study puts forward:

H2. Attribution selection mediates the influence of e-WOM dispersion on the return intention.

2.3 Moderating Role of Robot Reviews
With the development of artificial intelligence, the behaviour of robots tends to be more human, and they can generate fluent and meaningful language through high-level neural language models (NLM), and generate online comments like ordinary consumers [10]. At the same time, some scholars have suggested that many companies manipulate online reviews to influence consumers' perception and judgment of products [11]. When the presence or influence of robots are included in the electronic word-of-mouth information, such word-of-mouth brings consumers a sense of deception and disappointment, which will cause consumers to feel more discomfort and disgust [12].

Prospect theory believes that when people are facing losses, they tend to accept risks; when facing gains, they tend to avoid risks [13]. When consumers are faced with the possibility of false reviews, regardless of whether they can correctly identify false reviews, they will reduce their trust in word-of-mouth information, increase the perceived risk of word-of-mouth information, and take corresponding measures to avoid risks [14]. That is to say, in terms of the discrete network reputation formed by robot reviews, no matter what the discrete state, consumers tend to avoid risks by returning goods. This is true for the high dispersion of electronic word-of-mouth. Therefore, the original tendency to attribute the low dispersion of electronic word of mouth to product reasons will be strengthened, and the tendency to attribute the high dispersion of electronic word of mouth to product reasons will be strengthened. Therefore, the study puts forward:
H3. The impact of discrete electronic word of mouth on the willingness to return is regulated by robot reviews. When consumers inform that there are robot reviews, the willingness to return is greater.

H4. The influence of discrete electronic word of mouth on attribution selections is regulated by robot reviews. For the discrete electronic word of mouth that informs about robot reviews, the tendency of discrete electronic word of mouth to be attributed to product reasons becomes greater.

Based on the above research hypotheses, the research proposed a conceptual framework (Figure 1).

Figure 1. Conceptual framework of research.

3 Study 1: The Impact of e-WOM dispersion on Willingness to Return

3.1 Pre-experiment

The purpose of the pre-experiment is to determine the experimental stimulus, the lowest average star level that participants can accept when buying products, and the lowest average star level that the participants will not have the idea of return after purchase.

87 subjects were collected and then 6 kinds of product introductions were provided in Pre-experiment. The introductions consist of dry goods cover and dry goods product information. After browsing product introductions, the subjects need to answer the 4 questions of product’s emotional love (e.g., “The product in the picture above attracts you (1=very not attracted, 7=very attractive)” [9]. Then choose the dry goods with the greatest difference in emotional affection as the stimulus. Finally, the subjects were required to answer the lowest average star rating (1-5 stars) that may have a purchase behaviour for dry goods and the lowest star rating (1-5 stars) that would not produce returns. The results showed that the reliability of the items on the scale was high (α=0.922), and the “dried apricot” product had the greatest difference in the degree of preference among the subjects (SD_dried_apricot=1.58; SD_dried_cranberry=1.16, SD_raisins=1.47, SD_dried_coconut=1.50, SD_dried_blueberry=1.41, SD_dried_mango=1.34) were selected as the experimental stimulus; the lowest average star rating that subjects can accept when buying dry food is 3.53 stars (SD=0.864); Exclude 13 subjects who are not affected by star level); The lowest average star rating that subjects will not return after buying dry food is 3.97 (SD=0.954; Excluding 18 means that they are not affected by star level Of subjects).

3.2 Experimental Design

Experiment 1 uses a single factor (e-WOM dispersion: high vs. low) experimental design between subjects. According to existing research [15], the standard deviation of the high (low) dispersion of the
3.2 Experimental Process
The experiment conducted online experiments on the subjects through questionnaire surveys. The subjects first entered the context “please imagine you are browsing on an online shopping platform, and then you will see the basic information of related products.” After browsing the information of each word-of-mouth distribution map, the subjects were required to answer questions about their willingness to return. Finally, subjects need to complete questions about demographic indicators. A total of 104 questionnaires were returned in Experiment 1, of which 16 questionnaires were deleted due to incorrect answers to the attitude test questions, and 88 questionnaires were valid. The data shows that 92% of the subjects are below 30 years old, 73% of the subjects whose monthly consumption level is above 1000, and 95.5% of the subjects whose online shopping age is more than one year.

3.4 Measurement
Return willingness. Referring to the existing research, this research will use 2 question item (e.g., “Imagine that you have placed an order for the above product and have not yet shipped it. You have browsed the above product information. Would you like to return the product?”; 1=Not willing to return, 7=Very strong) [16].

3.5 Results and Discussion
Hypothesis testing. The study uses an independent sample T-test to verify H1. The analysis results show that consumers’ willingness to return goods in high e-WOM dispersion (M_{high}= 3.88) is significantly greater than in low e-WOM dispersion (M_{low}= 3.16, T=3.134, P=0.002<0.010), hypothesis H1 is established.

Discussion. Experiment 1 proved the discrete electronic word of mouth influences consumers’ willingness to return. According to the attribution theory, consumers tend to think attributively about the reasons when faced with discrete electronic word of mouth [17]. Therefore, Experiment 2 will measure consumer attribution selection to explore whether they play an intermediary role in the process of discrete electronic word-of-mouth affecting their willingness to return.

4. Study 2: The Mediating Role of Attribution Selection

4.1 Experimental Design
Experiment 1 uses a single factor (e-WOM dispersion: high vs. low) experimental design between subjects. To verify whether H1 is robust, the manipulation of discrete electronic word of mouth in Experiment 2 will be consistent with Experiment 1.

4.2 Experimental Process
The experiment conducted online experiments on the subjects through questionnaire surveys. The subjects first entered the context “please imagine you are browsing on an online shopping platform, and then you will see the basic information of related products”. After browsing the information of each word-of-mouth distribution map, the subjects were required to answer questions about attribution selection and return intention. Finally, subjects need to complete questions about demographic indicators. A total of 95 questionnaires were collected in Experiment 2, of which 16 questionnaires were deleted due to incorrect answers, and 79 questionnaires were valid. The data shows that 89.9% of the subjects are under 30 years old and 79.7% are students, 91.1% of the subjects whose monthly consumption level is above 1000, and 97.5% of the subjects whose online shopping age is more than one year.
4.3 Measurement
Attribution selection. With reference to existing studies, this study uses a single item to measure attribution selection (“Do you think the reason for the above word-of-mouth distribution is the product itself or the Is there a commenter reason?”; 1=product reason, 7=existing commenter reason) [15]. The higher the score, the more likely the participants are to attribute word-of-mouth discreteness to the commenter. The measurement of return willingness is the same as experiment 1.

4.4 Results and Discussion
Hypothesis testing. The model 4 of SPSS20.0 and SPSS PROCESS macro (version 3.3) is used to analyse the mediating effect of attribution selection in the relationship between word-of-mouth dispersion and return intention. The results show that word-of-mouth dispersion has a significant positive predictive effect on the willingness to return (B=1.09, t=4.54, p<0.001), and the H1 is verified again. When the intermediary variable is added, although the significance decreases, the direct predictive effect of word-of-mouth dispersion on the willingness to return is still significant (B=0.71, t=2.61, p<0.01), and the positive predictive effect of e-WOM dispersion on attribution selection It is still significant (B=1.68, t=16.61, p<0.001), and the positive predictive effect of attribution selection on return intention is also significant (B=0.11, t=2.78, p<0.01). In addition, the upper and lower bounds of the bootstrap 95% confidence interval for the direct effect of word-of-mouth dispersion on the intention to return do not contain 0(Table 1), indicating that the willingness to return can be predicted through the intermediary effect of attribution selection. The direct effect (0.71) and the intermediate effect (0.38) accounted for 65.54% and 34.46% of the total effect (1.09), respectively. Therefore, H2 is verified.

Table 1. Decomposition of Total, Direct and Intermediate Effects.

| Effect            | BootSE | BootLLCI | BootULCI | Relative effect value |
|-------------------|--------|----------|----------|-----------------------|
| Total effect      | 1.09   | 0.24     | 0.61     | 1.56                  | --                    |
| Direct effect     | 0.71   | 0.29     | 0.15     | 1.29                  | 65.54%                |
| Intermediate effect | 0.38 | 0.18     | 0.04     | 0.76                  | 34.46%                |

Discussion. Experiment 2 verified H1 again, but neither discussed the boundary conditions of these effects. Studies have found that machine behaviour is one of the important reasons for changing the distribution of product word-of-mouth [18]. When there is a factor of robot reviews in the cause of discrete electronic word-of-mouth, will the influence of discrete electronic word-of-mouth on the willingness to return be affected? How will the mediating role of attribution selection change? To this end, Experiment 3 will manipulate robot reviews to explore its impact.

5. Study 3: The Moderating Role of Robot Reviews

5.1 Experimental Design
Experiment 2 uses 2 (e-WOM dispersion: high vs. low) × 2 (robot reviews: inform yes vs. inform no) inter-group experimental design. The discrete manipulation of electronic word-of-mouth is consistent with Experiment 1. The manipulation of robot reviews refers to existing research methods [19], and directly informs the subjects whether there are robot reviews in the question.

5.2 Experimental Process
The experiment conducted online experiments on the subjects through questionnaire surveys. First enter the context “please imagine you are browsing on an online shopping platform”. After browsing
the stimulus packaging pictures and product information, subjects are required to answer have ever purchased or tasted the products. The product in this study is a fictitious product, after that, the subjects entered the context again “please imagine that you have purchased the above products but have not yet shipped them.” Then subjects will see the word-of-mouth distribution maps in 4 scenarios. The picture includes a distribution map of electronic word-of-mouth, with 47 reviews and a star distribution of 1-5 stars [15]. Scenario 1-2 has five consumer reviews from Amazon (China).com, no special tips; Scenario 3-4 has five consumer reviews from Amazon (China).com, and the subjects were informed that there were robot reviews. After browsing each product's electronic word-of-mouth distribution map, the subjects were required to answer two questions about the attribution selection and return intention. Finally, subjects need to complete questions about demographic indicators. In Experiment 3, 170 subjects were convened to conduct the experiment. The experimental data of 12 subjects who did not meet the experimental requirements due to purchase or tasting experience were removed, and a total of 158 valid data were collected. Analyzing the descriptive statistical results of basic user information in 158 valid questionnaires, 96.8% of the subjects were under 30 years old, and most of the subjects were students (78.5%). The monthly consumption level of the subjects is between 1000-3000, accounting for 91.8%. The data shows that 96.2% of the subjects are online shopping for more than one year, and 98.7% of the subjects are online shopping frequently.

5.3 Measurement
The measurement method of attribution selection in experiment 3 is the same as experiment 2, and the measurement method of return intention in experiment 3 is the same as experiment 1.

5.4 Results and Discussion
Manipulation testing. According to Geuens and Pelsmacker (2017) [20], the robot reviews controlled (informed yes vs. informed no) is to inform the subjects whether there are robot reviews in the experiment, which is an obvious fact, so no manipulation test is required.

Hypothesis testing. Use SPSS20.0 and SPSS PROCESS macro (version 3.3) model 8 (Model8 assumes that the first half of the intermediary model and the direct path are adjusted, consistent with the theoretical model of this study) for analysis, to test the adjusted intermediary model. The results (see Table 2) show that after putting robot reviews into the model, the product of word-of-mouth dispersion and robot reviews has no significant effect on the prediction of return intention (B=-0.21, t=-0.89, p>0.01), and word-of-mouth dispersion The product term with robot reviews has a significant predictive effect on attribution selection (B = -0.73, t=-2.96, p<0.01), indicating that robot reviews cannot play a moderating role in the direct prediction of the willingness to return with discrete word-of-mouth. Adjusting the predictive effect of word-of-mouth dispersion on attribution selection, the research results support H4 but not H3.

Table 2. Intermediary Model Tests with Moderation.

| Variable                      | Attribution | Return intention |
|-------------------------------|-------------|-----------------|
|                               | β    | se | t   | β    | se | t   |
| E-WOM dispersion              | 1.03*** | 0.18 | 5.84 | 0.54** | 0.17 | 3.13 |
| Robot reviews                 | 0.49** | 0.18 | 2.78 | 0.55** | 0.17 | 3.24 |
| E-WOM dispersion x robot      | -0.73** | 0.25 | -2.96 | -0.21 | 0.24 | -0.89 |
| reviews                       |      |      |      | 0.10* | 0.04 | 2.54 |
| Attributions                  | --    | --   | --   | 0.10* | 0.04 | 2.54 |
| R2                            | 0.06  |      |      | 0.06  |      |      |
| F                             | 12.61*** |      |      | 9.96*** |      |      |
5.5 Discussion
Experiment 3 explored the moderating role of robot reviews in the relationship between the dispersion of electronic word-of-mouth and attribution selection and return intention is investigated. It turns out that robot reviews cannot play a moderating role in the relationship between discrete online reputation and willingness to return, but it can play a moderating role in the intermediary chain of “discrete online reputation-attribution selection-willingness to return”.

6. Research Conclusion and Enlightenment

6.1 Theoretical Contribution
Scholars in the past studied the dispersion of word-of-mouth from the perspective of human comments, and less considered the influence of technological factors (machines) on consumers. This study is based on the scenario of the existence of robot reviews in the dispersion of electronic word-of-mouth. It is found that robot reviews work in a complex system coexisting with human reviews, and the combination of human reviews and robot reviews can change human emotions and behaviours.

6.2 Management Significance
In the process of promoting human-machine interaction, enterprises should avoid the conflict between the application of robots and the interests of consumers. At present, the process of putting robots into practical applications will inevitably lead to a variety of consumer resistance and negative attitudes [21]. Compared with real-person reviews, robot reviews are usually less likely to be recognized, and consumers will not accept robots. Recommended products [19], and when the robot involves intuition or emotion, consumers may be more dissatisfied with the robot [4]. Therefore, in the face of many problems of human-machine interaction, enterprises should consider the negative impact of machines on human behavior. Even if robotics has penetrated into the lives of the masses, companies should be cautious about advancing human-machine interaction and should not add robots to applications involving emotions, to avoid triggering consumers' stronger willingness to return.

6.3 Research Limitations and Prospects
In conclusion, this study also has the following limitations. Firstly, in this study, the manipulation of the regulatory variables of robot review (perception with vs. perception without) refers to the existing research methods to directly inform the subjects whether there is robot influence, but in the actual shopping environment, the subjects are more based on their perception. Therefore, future research cannot reveal the existence of robots to the subjects, and make them directly perceive the existence of robots through more detailed situational experimental designs. Secondly, this study can increase the selection of experimental samples, enrich the representativeness of samples, and strengthen the universality of the conclusion. Because the main object of this study is Chinese college students under the age of 30, the whole consumer group has not been considered more broadly.

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