# Impact of Social Media Sentiment on Consumer Purchasing Behavior through Online Review

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**Abstract**

With the popularization of the Internet, online shopping has become a kind of shopping that is known to all. The network customers are accustomed to obtaining the related information from the net. Under this circumstance, online reviews can spread at a stupendous speed on the Internet and their influence expand a lot. The purpose of this article is to explore the relationships between the social media sentiment indicators and consumer behaviors with the example of online reviews. This research used natural language processing and statistical analysis methods to explore this question. The result of this work showed that the social media sentiment indicators could impact the consumer behaviors for the demand for rigid goods, after purchasing stage of consumer behaviors and consumers' purchasing behavior on non-fashion products with high discount rates. This paper provided an important opportunity for the relative company to advance their understanding of the importance of social media sentiment indicators and offered a fresh perspective for businesses on how to increase the influence of online reviews on consumers.

***Keywords****-social media; online shopping; sentiment indicators; consumer behavior*

## 1. INTRODUCTION

Over the past few decades, the Internet has become an important trading platform where people could exchange goods and services [1]. In 2021, UNCTAD released a report that shows global e-commerce sales had reached $26.7 trillion globally in 2019, which was 30 percent of global gross domestic product [2]. In China, the domestic internet market has become an important part of the global internet market in recent years [3]. According to "The 47th China Statistical Report on Internet Development", as of December 2020, the number of netizens in China has reached 989 million and the number of online shopping users was 782 million, accounting for one-fifth of the global netizens and 79.1% of the global netizens respectively [4]. Increasing online activities led to great interest in understanding factors that affect consumers' behavior during online shopping [5].

Social media, as an important medium of consumer socialization, has a strong influence on the ways of interaction between businesses and consumers. In this medium, consumers' sentiment and expectations of products are important factors. Managers should consider these factors to make efficient online market strategies [6]. In social media, consumers' online reviews depending on their attitudes and feelings about products, which is defined as social media sentiment [7]. Social media messages with sentiment are highly correlated with consumer confidence that measures consumers' optimism about the economy and both of them identically affect consumer decision-making [8]. Companies nowadays continuously improve the quality of products and strengthen their good reputations to improve consumer confidence in social media [9]. Therefore, understanding how social media sentiment affects consumer purchasing behavior is significant for companies. Meanwhile, consumers who understand this question could make a better strategy than before.


G. Vilas Bhau et al. (Eds.): MSEA 2022, ACSR 101, pp. 462–469, 2023.
https://doi.org/10.2991/978-94-6463-042-8_67

A previous study showed that companies had been expected to observe consumers' loyalty, interests, and sentiment toward products by monitoring social media activities [10]. A positive attitude toward online shopping from innovation or increasing suggestions of products could encourage consumers to make more online purchases [1]. However, the relationship between social media sentiment and online sales is not significant in some cases. In the clothing market, positive sentiment toward clothes showed that they had been fashionable and popular rather than indicating how much people were willing to purchase [11]. These researches roughly introduced the importance of sentiment analysis in social media and how companies changed public sentiment. However, there was a lack of specific influence of social media sentiment through the consumer purchasing process. Therefore, this paper focuses on online reviews of clothing, household appliance products, food, electronic products, and skincare products, exploring how social media sentiments of these affect buying behavior. The results of this research could effectively help companies to push different reviews and make advertising strategies to guide or influence consumers purchasing behavior.

The remainder of this paper is organized as follows: Section 2 introduces the research method and model. Data analysis and research discussion will be shown in Section 3 and Section 4 respectively. Finally, the paper will conclude the finding in Section 5.

## 2. METHODOLOGY

This research used natural language processing, reliability analysis, factorial analysis, and correlational analysis to investigate the relationships between the emotion of social media and consumer behavior. The research included both primary and secondary data. The method in this research consists of two sections, which are data processing and the research model.

### 2.1. Research data and collection process

#### 2.1.1. Social media emotional detection

This part used secondary data to extract and analyze the comments from Taobao and Jingdong shopping platforms, which are the most popular online shopping platforms in China. We chose Clothing, household appliance products, food, electronic products, and skincare products in Taobao and Jingdong as the research subjects in our study. Because these five industries had high transaction volume, a wide range of consumers, and high representativeness. Each industry was chosen two representative products and collected their web page's comments in the past year for analysis. A total of 24,504 comments were collected.

In the data analysis phase, we mainly used the natural language processing method to analyze. Natural Language Processing was a data processing tool based on emotional word sets and textual features to classify the text [11]. Before starting the analysis, emotional word sets were built and classified into positive and negative words such as Table 1. Afterward, ERNIE (Enhanced representation through knowledge integration) model was used in this research to deal with the data and classify the positive and negative emotions of the whole comments. Although many similar models had been proposed, we still chose ERNIE on account of its simplicity and accuracy. So, this research used the same method as Zhang. H did [12]. Finally, we calculated the percentage of each type of emotion from online reviews and formed a monthly indicator. In the questionnaire mentioned below, we set a question that consumers' purchasing behavior happened in which months. The monthly indicators were set in order to build a better corresponding relationship in this questionnaire. The accuracy in ERNIE was 93 percent, which means the results were reliable in this part.

**TABLE 1.** AN EXAMPLE OF AN EMOTION-WORDS SET (EWS)

| *Positive words* | *Negative words* | *Positive words* | *Negative words* |
|---|---|---|---|
| Good | Bad | Surprise | Disappointed |
| Convenient | Disappointed | Safely | Useless |
| High quality | Inconvenient | Useful | Poor attitude |
| Satisfaction | Offensive | Cheap | Ugly |
| Practical | unsatisfied | Economical | Expansive |
| expectant | Disappointed | Great | Extravagant |
| excitement | Unsavory | Safely | Poor rating |
| Effective | Angry | Original | Fake |
| Good service | Provoked | Repurchase | Blacklist |

#### 2.1.2. Online Survey

In order to collect data on consumer purchasing behaviors, this research adopted a questionnaire to get their data. Part of the questionnaire was shown in Figure 1 to 3. This part primarily introduced the collecting data. The survey mainly focused on consumers who have consumption behavior on shopping websites during the past year.

This questionnaire was designed with 23 questions. 5 Likert scales as a tool of measurement were used in the questionnaire, which aimed to quantify the consumers' purchase intention and the degree of influence by emotional indicators in their decision-making process. This approach to sample collection was convenient, cost-effective, and random. The initial sample was composed of 262 participants randomly with a 100 percent response rate. All participants were voluntary. We invited them to fill out the online questionnaire by posting a link address and a short description on social media apps like shopping groups, WeChat, QQ, and so on. In addition, ethical problems in this questionnaire were considered seriously. A short description was provided at the beginning of the questionnaire, which aiming to state the purpose of the research clearly. At the same time, the participants were required to sign a letter of consent so that protecting their privacy. We were committed to analyzing their answers accurately, legally, and securely.

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Dear Madam/Sir, Hello! This is a survey about the impact of the emotional indicators of online reviews on consumer purchasing behavior. (When negetive reviews account for most of reviews , the sentiment indicator is negative; When positive reviews account for most of reviews, the sentiment indicators is positive.) This survey is only for academic research, and the survey results are absolutely confidential. We hope you can answer them according to your actual situation. Thank you very much for taking the time to participate in this survey! Your answers are very important for this study. Thank you for your cooperation!

**Figure 1.** Introduction of questionnaire

*7. Do you read online reviews when you shop online?

- 1. Never
- 2. In a few cases
- 3. Most of the time
- 4. Read reviews of each product

*8. Which of the following purchasing stages will you check for online reviews? 【多选题】

- 1. Before purchase
- 2. Purchasing
- 3. After purchase, before reveiving
- 4. After receiving the goods

**Figure 2.** Question about consuming behavior

*20. When the proportion of positive and negative comments is equal, you will

- 1. Completely terminate the purchase
- 2. Keep the purchase intention, but no purchase action will occur
- 3. Generate purchase behavior

*21. Which of the following factors will affect your shopping decision? 【多选题】

- Price
- Place of dispatch
- Time of delivery
- Commodity evaluation
- Shops scores
- Number of product buyers

**Figure 3.** Question about attitude and factor

## *2.2. Model*

This research used the SPSS to analyze the valid data. We set the percentage of sentiment indicators monthly as an independent variable and the results of the questionnaire as the dependent variable. The research process combined the data and results of two sections to find the relationships between these variables by taking reliability analysis, factorial analysis, and correlational analysis.

In this research, reliability analysis was used to judge the reliability of the questionnaire. The Cronbach's alpha coefficient was used as the discriminant index to compare these results. In addition, in order to find the factors of influence on consumer purchase behaviors, we used factorial analysis to collect and summarize the impact factors. The correlational analysis method was also used in this research to observe the correlation between the social media sentiment indicators and impact factors and further to reveal the impact of different degrees of emotions of reviews on consumers purchasing behaviors.

# 3. Data Analysis:

## *3.1. Reliability Analysis*

The reliability analysis of the questionnaire used Cronbach's alpha coefficient as a discriminating index. When the α coefficient was greater than 0.7, the result could be concluded that the questionnaire has high reliability. In reliability analysis, as shown in Table 2, the overall reliability coefficient of the questionnaire is 0.927. So the questionnaire has high reliability.

**TABLE 2.** RELIABILITY STATISTICS

| *Cronbach Alpha* | *number of items* |
|---|---|
| 0.927 | twenty-two |

### *3.2. Factorial Analysis*

As shown in Table 3, the KMO value of the sample was 0.918, which was suitable for factor analysis. At the same time, the significance probability of the Bartlett sphericity test was almost equal to zero, indicating that there has been a certain correlation between these data and been very suitable for factor analysis.

**TABLE 3.** KMO AND BARTLETT'S TEST

| *KMO Sampling Suitability Quantity* | | *0.918* |
|---|---|---|
| Bartlett's sphericity test | approximate chi-square | 2936.614 |
| | degrees of freedom | 231 |
| | salience | 0 |

It could be seen from Table 4 that the variance of the common factor in all cases was between 0.4 and 0.9, indicating that the comment indicators given by the questionnaire had a significant impact on the overall results.

**TABLE 4.** COMMON FACTOR VARIANCE

| *Common factor variance* | | |
|---|---|---|
| | initial | extract |
| You place great trust in online reviews | 1 | 0.617 |
| You rely heavily on online reviews during online shopping | 1 | 0.747 |
| If there are no online reviews, you will terminate the purchase intent | 1 | 0.369 |
| Online reviews have a big impact on your consumer decision-making behavior | 1 | 0.687 |
| Before you buy, online reviews will influence your purchasing decisions | 1 | 0.621 |
| When you are buying, online reviews will influence your purchasing decisions | 1 | 0.558 |
| Online reviews can influence your purchasing decisions before you receive them after the purchase | 1 | 0.805 |
| After you receive the goods, online reviews will affect your consumption decisions | 1 | 0.805 |
| Positive Reviews Have More Influence on Your Buying Decision | 1 | 0.467 |
| Negative reviews have more impact on your buying decisions | 1 | 0.608 |
| The number of reviews has a greater impact on your buying decision | 1 | 0.472 |
| Review quality has more impact on your buying decision | 1 | 0.603 |
| When it comes to shopping for clothing, review sentiment metrics influence you more | 1 | 0.69 |
| When it comes to buying home appliances, review sentiment indicators influence you more | 1 | 0.649 |
| When it comes to buying groceries, review sentiment indicators influence you more | 1 | 0.711 |
| When it comes to buying skincare and beauty products, review sentiment metrics have a bigger impact on you | 1 | 0.658 |
| When buying electronic products such as mobile phones, the review sentiment indicator has a greater impact on you | 1 | 0.646 |
| When it comes to buying products you know about, review sentiment metrics have a bigger impact on you | 1 | 0.511 |
| When it comes to buying influencer products, review sentiment metrics have a bigger impact on you | 1 | 0.628 |

| Common factor variance | | |
|---|---|---|
| When it comes to buying big-name products, review sentiment metrics influence you more | 1 | 0.643 |
| When you buy products that people around you recommend to you, the review sentiment indicator has a greater impact on you | 1 | 0.656 |
| Review sentiment metrics have a bigger impact when buying a product, you think most people will like | 1 | 0.731 |
| Extraction method: a principal component analysis. | | |

The principal component analysis method was used here to conduct factor analysis on the different influences of the 22 questions in the questionnaire. If the eigenvalue of a factor was greater than or equal to 1, the factor would be meaningful and should be retained. According to the gravel diagram of the eigenvalues of each component, it could be seen that the eigenvalues of the first four factors were greater than 1. So, four common factors were taken. After retaining the factors, four factors were screened out using SPSS and the cumulative variance contribution rate was 63.090%. That could be also understood that these four factors could explain 63.090% of the amount of information in 22 different cases. Subsequently, after using SPSS for factor analysis, rotation was performed by using The Caesar normalized maximum variance method and examining the analysis results. Four factors were extracted from those 22 cases and the component matrix table was shown in Table 5.

**TABLE 5.** COMMON FACTOR VARIANCE

| *Composition matrix* [a] after rotation | | | | |
|---|---|---|---|---|
| | Element | | | |
| | S1 | S2 | S3 | S4 |
| You place great trust in online reviews | 0.010 | 0.248 | 0.160 | 0.728 |
| You rely heavily on online reviews during online shopping | 0.217 | 0.083 | 0.142 | 0.820 |
| If there are no online reviews, you will terminate the purchase intent | 0.342 | 0.166 | 0.152 | 0.448 |
| Online reviews have a big impact on your consumer decision-making behavior | 0.664 | 0.08 0 | 0.065 | 0.486 |
| Before you buy, online reviews will influence your purchasing decisions | 0.681 | 0.123 | 0.030 | 0.375 |
| When you are buying, online reviews will influence your purchasing decisions | 0.515 | 0.045 | 0.441 | 0.311 |
| Online reviews can influence your purchasing decisions before you receive them after the purchase | 0.207 | 0.106 | 0.852 | 0.160 |
| After you receive the goods, online reviews will affect your consumption decisions | 0.142 | 0.159 | 0.852 | 0.185 |
| Positive reviews have more influence on your buying decision | 0.544 | 0.288 | 0.272 | 0.119 |
| Negative reviews have more impact on your buying decisions | 0.707 | 0.211 | - 0.043 | 0.248 |
| The number of reviews has a greater impact on your buying decision | 0.493 | 0.323 | 0.347 | 0.07 0 |
| Review quality has more impact on your buying decision | 0.625 | 0.416 | - 0.088 | 0.178 |
| When it comes to shopping for clothing, review sentiment metrics influence you more | 0.766 | 0.189 | 0.163 | 0.201 |
| When it comes to | 0.765 | 0.199 | 0.146 | 0.055 |

| *Composition matrix* [a] *after rotation* | | | | |
|---|---|---|---|---|
| buying home appliances, review sentiment indicators influence you more | | | | |
| When it comes to buying groceries, review sentiment indicators influence you more | 0.777 | 0.218 | 0.244 | 0.018 |
| When it comes to buying skincare and beauty products, review sentiment metrics have a bigger impact on you | 0.769 | 0.183 | 0.164 | 0.077 |
| When buying electronic products such as mobile phones, the review sentiment indicator has a greater impact on you | 0.675 | 0.233 | 0.368 | -0.037 |
| Review sentiment metrics affect you less when buying products that you know about | 0.310 | 0.578 | 0.053 | 0.279 |
| When it comes to buying influencer products, review sentiment metrics have a bigger impact on you | 0.066 | 0.751 | 0.239 | -0.040 |
| When it comes to buying big-name products, review sentiment metrics influence you more | 0.201 | 0.747 | 0.063 | 0.203 |
| When you buy products that people around you recommend to you, the review sentiment indicator has a greater impact on you | 0.320 | 0.720 | -0.014 | 0.189 |
| Review sentiment metrics influence you more when buying products, you think most people like | 0.253 | 0.795 | 0.154 | 0.100 |
| Extraction method: a principal component analysis. | | | | |
| Rotation method: Caesar's normalized maximum variance method. | | | | |

a. The rotation has converged after 6 iterations.

These four factors were explained and classified by the factor loadings in each case as shown in Table 5. Then we named these factors according to the questionnaire questions.

For the factor S1, online reviews before and during purchases could have an influence on consumers' consumption decisions, especially on their consumption decision-making behavior. Meanwhile, positive, and negative reviews and the quality of these reviews had a greater impact on purchasing decisions. When the consumer wanted to buy something in different product categories, the impact of the comment sentiment indicator would have an impact on the buying behavior. In addition, the proportion of these problem scenarios was high and the load was over 0.5. Therefore, they could be classified together and the factor S1 could be named as rigid demand commodity purchase behavior.

For factor S2, if someone wanted to buy products which they did not know a lot like some popular products on Internet, three kinds of products had a good result. They were the well-known brand products, products recommended by people around and products that most people prefer and the proportion of these problem scenarios. These three kinds of products' loads were over 0.5. They could also be classified and named fashion goods purchase behavior.

For factor S3, online reviews had a large proportion of those two issues. These reviews affected consumer decision-making in many ways, including after purchasing and after receiving products. Therefore, S3 could be named as post-purchase behavior.

For factor S4, there was a factor loading greater than 0.5 in those two issues of great trust in online reviews and great dependence on online reviews in the online shopping process. And then they were classified together and the factor was named trustworthiness.

## 3.3. Correlational Analysis

In order to further explore the relationship between these reviews and consumers' willingness to consume, a correlation analysis was carried out. A two-sided test of significance was performed on each factor to analyze whether there has been a correlation between each factor. The results were shown in Table 6.

**TABLE 6.** CORRELATION

| Correlation | | | | | | |
|---|---|---|---|---|---|---|
| | | S1 | S2 | S3 | S4 | Factor rate |
| S1 | Pearson correlation | 1 | 0 | 0 | 0 | -0.160 * |
| | Sig. (Two-tailed) | | 1 | 1 | 1 | 0.013 |
| | number of cases | 240 | 240 | 240 | 240 | 240 |
| S2 | Pearson correlation | 0 | 1 | 0 | 0 | -0.038 |
| | Sig. (Two-tailed) | 1 | | 1 | 1 | 0.553 |
| | number of cases | 240 | 240 | 240 | 240 | 240 |
| S3 | Pearson correlation | 0 | 0 | 1 | 0 | 0.128 * |
| | Sig. (Two-tailed) | 1 | 1 | | 1 | 0.048 |
| | number of cases | 240 | 240 | 240 | 240 | 240 |
| S4 | Pearson correlation | 0 | 0 | 0 | 1 | -0.065 |
| | Sig. (Two-tailed) | 1 | 1 | 1 | | 0.318 |
| | number of cases | 240 | 240 | 240 | 240 | 240 |

*. At the 0.05 level (two-tailed), the correlation is significant.

It was known from Table 6 that the social media favorable comment rate has been significantly correlated with rigid demand commodity purchase behavior and post-purchase behavior at the confidence level of 0.05. More specifically, it had a significantly negative correlation with rigid demand commodity purchase behavior and a positive correlation with post-purchase behavior. Obviously, the favorable comment rate of the products had a greater impact in the situation corresponding to rigid demand commodity purchase behavior and post-purchase behavior.

### *3.4. Discussion*

Through the factor correlation analysis above, it could be known that social media sentiment and comment indicators had little effect on the fashion goods purchase behavior and trustworthiness. On the whole, consumers could be affected by social media sentiment in the entire purchase process from the generation of purchase demand to the purchase of the product. This work found that a negative correlation existed between rigid demand commodity purchase behavior and the favorable comment rate. In this case, the negative reviews dominated before and during the purchase process. It could be also acknowledged that more negative emotional comments had a more obvious inhibitory effect on consumers' willingness to consume when buying daily necessities. In contrast, in the two stages before and after the purchase, more positive sentiment comments would reduce the generation of consumer returns. In addition, when consumers had a specific demand for a product type for which they might have no specific purchase object, the impact of online reviews would be more useful. It could be understood that when consumers buy a certain kind of goods with a purpose, they would be more affected by the high praise rate of the goods resulting in the impulse to buy. On the contrary, when consumers just followed the trend or got recommended to buy specific goods because of the impact of these external evaluations, the praise rate had less impact on their purchase intention.

## 4. CONCLUSION

This article explored how social media sentiment influenced consumers' buying behavior. The surge in the number of online shoppers and the great interest in understanding the factors that influenced consumers' behavior in online shopping were also been discussed in the article. After packaging and classifying comments through social media sentiment detection and collecting questionnaires to obtain consumer behavior data, this research established a relationship between consumer behavior and the social media sentiment model and conducted data analysis by SPSS. The specific factors which had an impact were found by correlation analysis, which confirmed that both positive and negative social media sentiment would have a significant impact on consumer behavior.

It was concluded that social media emotions had a certain impact on consumers' purchasing behavior. Negative reviews played a leading role in the purchase process of buying rigid demand products or daily necessities. The more negative reviews appear, the lower consumers' desire to buy. The reason for this case might be that consumers pay more attention to negative emotional comments when choosing such products. Favorable comments started to play a bigger role after consumers bought. And the higher the favorable rate was, the less the chance of the products being returned. When buying fashionable products or products had been evaluated by the outside world, the favorable rate of goods was not correlated with the purchase intention. Therefore, this paper had a certain reference for merchants to push comments on the platform. Merchants could use the influence of social media emotions on consumers' purchasing behavior, optimizing the display of comments and guiding consumers' behavior to a certain extent. However, in reality, the platform could not monitor the positive rate of consumers' consumption in real-time. So, the estimated sentiment index had a certain lag. If the platform could obtain the dynamic changes of the sentiment index of the product evaluation more accurately in each time period in the future, it would be significantly more effective for it to play a role in leading consumer behavior.

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