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Effects of Sentiment Inconsistency of Online Composite Reviews on Product Sales

-- Based on the Perspective of Cue Diagnosticity Theory

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Abstract

Unlike single reviews, composite reviews encompass the comprehensive experiences and attitudes of consumers after purchasing and using a product. The impact of the sentiment shifts within these composite reviews on potential consumers' purchasing decisions remains unknown. Based on the cue diagnosticity theory, this study investigates the effect of sentiment inconsistency in composite reviews on product sales and further explores the moderating effects of review volume and price discounts. Using a dataset of real transactions and consumer reviews from a leading online apparel retailer in China, this study quantifies the sentiment inconsistency in composite reviews using support vector machine model and empirically tested the hypotheses. The results indicate that sentiment inconsistency in composite reviews has a significant negative impact on product sales. The higher the degree of sentiment inconsistency, the lower the product sales. Furthermore, the product review volume and price discounts rate moderate this effect. Specifically, an increase in the review volume further amplifies the negative impact, whereas an increase in product price discounts rete can effectively mitigate this negative impact.

Keywords

Online Composite Reviews; Sentiment Inconsistency; Cue Diagnosticity Theory; Product Sales.

1. Introduction

According to the market research report by BrightLocal, 98% of online consumers rely on online reviews when making purchasing decisions (Paget, 2023), highlighting the crucial role of online reviews in product sales (Kaur and Singh, 2021). However, traditional single review format (each consumer can only post one review about the product and consumption experience) makes it challenging for consumers to provide comprehensive feedback about the product and post-purchase experience, thereby offering limited information to potential consumers (Wei et al., 2023). In recent years, online review systems in e-commerce platform have evolved from single initial reviews to include additional follow-up reviews (after the initial review, consumers review the product again after they have finished using it), forming what is now known as online composite reviews (henceforth 'OCR'). Unlike single reviews, OCRs encompass the overall experiences and varying attitudes of consumers after purchasing and using a product (Zhao et al., 2020), thus providing greater value for potential consumers' purchasing decisions (Shi et al., 2018). However, changes in consumer attitudes reflected in these reviews can lead to sentiments inconsistency within OCR (The sentiment of two reviews by the same consumer on the same purchase changes), causing confusion for potential consumers' purchasing decisions and eventually influencing retailers' sales. As so far, related

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research on the impact of online reviews on product sales has predominantly focused on treating follow-up reviews and initial reviews as independent entities. These studies examined the effects of review quantity, length, and sentiment on product sales separately (Luo et al., 2022; Shi et al., 2018), thereby overlooking the significant characteristic of sentiment shifts within OCR texts that influence potential consumers' purchasing decisions (Chang et al., 2014).

Furthermore, to mitigate the uncertainty caused by sentiments inconsistency in composite reviews, consumers need to utilize different cues provided by online retailers to aid their purchase (Wang et al., 2024; Gao and Su, 2016; Kakaria et al., 2023; Yan et al., 2019). In the context of online shopping, consumers' main sources of information are company information and other consumers' comments (Floyd et al., 2014; Ahn and Lee, 2024). Price discount is the most significant marketing strategy used by online retail enterprises to stimulate product sales (Carlson and Kukar-Kinney, 2018). Discounts allow consumers to acquire products at lower prices, thus facilitating purchasing decisions and helping e-commerce retailers achieve sales growth (Wang and Chen, 2022). At the same time, as more and more reviews are generated, the number of consumer reviews becomes an important dimension of product evaluation. Product review volume reflects the product's popularity (Yang et al., 2016; Moon et al., 2024), affecting consumer perceptions of the product and subsequently influence their purchasing decisions.

According to cue diagnosticity theory, OCRs contain more consumer experience information and are therefore more influential in altering consumer decisions compared to product price discounts and review volume (Li et al., 2021). Consequently, when price discounts and review volume coexist with OCR, the diagnosticity of these two cues diminishes. Accordingly, when high-diagnosticity cues lead to uncertainty, consumers will further utilize low-diagnosticity cues (Langan et al., 2017). And information provided by low-diagnosticity cues, combined with high-diagnosticity cues, jointly influences consumer decisions. And in this way, product price discount and review volume should moderate the effectiveness of OCRs in influencing consumer behavior (Ba et al., 2020). However, current research has yet to analyze the moderating mechanism of product price discounts and review volume on the relationship between sentiment inconsistency in OCRs and product sales.

To address the knowledge gap discussed above, this study intends to empirically investigate the effects of sentiment inconsistency within OCRs on product sales through a large-scale data analysis of real customer reviews and product sales from an online retailer. To do so, this study firstly employ a support vector machine model to quantify the sentiment shifts within the OCRs of certain product. Grounded in cue diagnosticity theory, this study considers sentiment inconsistency in OCR as high-scope cues and product price discounts and review volume as low-scope cues. We then construct a theoretical model to examine the impact of sentiment inconsistency in OCRs on product sales and further explore the moderating mechanisms of product discount rates and review volume on this impact. The results show that sentiment inconsistency in composite reviews has a significant negative impact on product sales. Furthermore, an increase in the review volume further amplifies the negative impact, whereas an increase in product price discounts rate can effectively mitigate this negative impact.

This study delineates the causal mechanisms linking sentiment shifts observed in online composite reviews to fluctuations in product sales. In doing so, it expands the existing scholarly discourse on the sales implications of online reviews to encompass the nuanced effects of composite review analysis. Meanwhile, this research furnishes a theoretical framework that companies may leverage to strategically optimize the management of composite reviews, with the ultimate aim of bolstering product sales and, by extension, elevating the pragmatic utility of composite reviews in the domain of sales. At the same time, by using machine learning methods to analyze the sentiment of composite comment text, this study further improved the measurement method of review sentiment variation.

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2. Theoretical Background and Hypothesis Development

2.1. Literature Review

Early research on online composite reviews focused on the comparative analysis of the characteristics and usefulness of follow-up reviews versus initial reviews. In terms of statistical indicators of reviews, existing studies have found differences between follow-up reviews and initial reviews in aspects such as review quantity, length, and emotional intensity (Shi et al., 2018). Regarding review usefulness, previous research has discovered that follow-up reviews are relatively more useful compared to initial reviews (Hu and Ning, 2017; Zhang et al., 2019), as follow-up reviews provide deeper insights into the product after its use (Zhang et al., 2019). Potential consumers tend to give greater weight to follow-up reviews during their shopping process. Moreover, potential consumers attribute the formation of follow-up reviews to external product factors rather than the subjective factors of the reviewers (Hu and Ning, 2017), which implies that follow-up reviews are relatively more objective than initial reviews.

The primary difference between single reviews and OCRs is that the latter reflects the attitudes of the same consumer at different post-purchase stages. Consequently, recent scholars have begun to study OCR as an integrated whole, considering both stages of the review. However, current research primarily utilizes questionnaires or experimental methods to analyze the impact of sentiments in OCR on their perceived usefulness. The findings indicate that sentimentally contradictory OCR are considered more useful because readers are more likely to attribute the contradictions to product factors (Li and Ren, 2017; Wang et al., 2015). In recent years, studies on the impact of sentiments in OCR on consumer purchase intentions have emerged. These studies, based on scenario experiments or questionnaires, have found that sentiments inconsistency can lead to conflicting attitudes in potential consumers when reading the reviews (Wang et al., 2021) or skepticism about the authenticity of inconsistent reviews (Zheng and Duan, 2022), thereby reducing consumers' purchase intentions.

The impact of online reviews on product sales has garnered extensive attention in previous research. Online reviews influence consumer perceptions of products by providing relevant information about products and services, making them a decisive factor in the sales performance of products on e-commerce platforms (Wang et al., 2024; Liu et al., 2023; Zhao et al., 2018;). Researchers have conducted numerous analyses on how online reviews affect product sales, primarily focusing on the effects of review valence and volume. Regarding review valence, existing studies have mainly explored the impact of review ratings or sentiment on product sales, but these studies have not reached a consensus. Some researchers argue that critical reviews have a stronger influence on consumer purchases (Chevalier and Mayzlin, 2006; Wang et al., 2022), while others believe that positive reviews effectively boost product sales (Fernandes et al., 2022). As for the review volume, existing studies generally agree that the volume of online reviews reflects product sales. A higher number of reviews indicates that a product is popular among consumers (Yang et al., 2016). Products with fewer reviews are usually not trusted by consumers, as they cannot obtain useful information from a limited number of reviews (Fan et al., 2017). Thus, consumers are more likely to purchase products with a greater review volume. However, only a few studies on OCR have focused on issues related to product sales, and these studies have typically treated additional and initial reviews as independent components, simply comparing their respective impacts on product sales. Shi et al. (2018) analyzed the effects of various dimensions of initial and additional reviews on product sales, finding that the number of initial reviews significantly affects product sales, whereas the number of follow-up reviews does not. In studies on experiential goods, researcher examined the impact of the number of follow-up reviews on the sales of an international pharmaceutical sales platform (Luo et al., 2022).

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In reviewing related literature of this study, we find that existing research has explored the statistical characteristics and usefulness of OCRs and impact of OCRs on consumer perceptions. These studies proved that sentiments shift in OCR significantly affects consumer purchasing behavior. Meanwhile, although previous studies have confirmed the decisive impact of review valence and volume on product sales, research on OCR has been limited to simple comparisons of the effects of initial and follow-up reviews when examining sales issues. Due to data availability constraints, the actual impact of sentiments shift within OCR on product sales has yet to be examined. In this study, we empirically test the impact of sentiment inconsistency in OCR on product sales based on real sales and review data from online retailer.

2.2. Theoretical Background

In the context of online shopping, consumers face temporal and spatial distances from the products they purchase, exacerbating information asymmetry (Srivastava et al., 2021). Online consumers navigate purchase decisions by processing various cues (Wang et al., 2023; Yan et al., 2019), thus the cue diagnosticity theory is widely applied to explain the impact of multiple cues on online consumer decisions (Narwal and Nayak, 2020; Rokonuzzaman et al., 2021). Diagnosticity of cues refers to consumers' perception of the reliability of cues when judging product quality during shopping (Akdeniz et al., 2013). Based on diagnosticity, cues can be classified into high-scope and low-scope cues. High-scope cues are formed over time and have a more enduring impact that is difficult for merchants to manipulate easily, such as reputation. Low-scope cues, on the other hand, can be altered in the short term and are less diagnostic compared to high-scope cues, such as marketing activities (Rokonuzzaman et al., 2021).

Based on existing research, consumers in online shopping rely on various cues from retailers and third-party reviews for decision-making (Ba et al., 2020). Factors such as brand, service assurance, price discounts, and reviews have been analyzed for their effects on consumer decisions and product sales (Rokonuzzaman et al., 2021; Kay Byun et al., 2021; Wen et al., 2021). In this study, because the product quality and service quality of the same business will not have too much fluctuation, consumers primarily make decision based on product reviews and price discounts (Duan et al., 2022; Rokonuzzaman et al., 2020). Among these cues, the review volume is a key factor of research interest, reflecting product popularity and consumer perception, thus influencing purchase decisions and sales (Kim, 2021). While previous studies have examined the impacts of review volume and price discounts on consumer decisions, they have focused predominantly on single initial reviews and have not yet incorporated composite reviews into the cue diagnostic theory framework.

According to cue diagnostic theory, the diagnosticity of cues varies depending on their accessibility (Akdeniz et al., 2013). High-scope cues, which typically have higher diagnosticity, exert stronger influence on purchase decisions when multiple cues are presented (Akdeniz et al., 2013). However, when the diagnosticity of high-scope cues diminishes, the influence of low-scope cues increases, and both types of cues jointly affect consumer purchase decisions (Rokonuzzaman et al., 2021). OCR differs significantly from single reviews by capturing consumers' varied experiences and often exhibit sentiment inconsistency. As cues with higher diagnosticity, OCR sentiment inconsistency directly impacts consumer decisions more profoundly (Luo et al., 2022). When combined with cues like review volume and price discounts, the diagnosticity tends to decrease. Yet, research on how these dynamics unfold in the context of OCR remains scant, particularly regarding changes in key cue diagnosticity and their impact on product sales.

The primary focus of this study is to examine how sentiment inconsistency in OCRs influences product sales. That is, for a product, if the sentiment of the consumer's initial review and the additional review are inconsistent, what impact will it have on product sales? Additionally, the study analyzes the moderating effects of product review volume and price discounts on the

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relationship between OCR sentiment inconsistency and product sales. The specific research model is depicted in Figure 1.

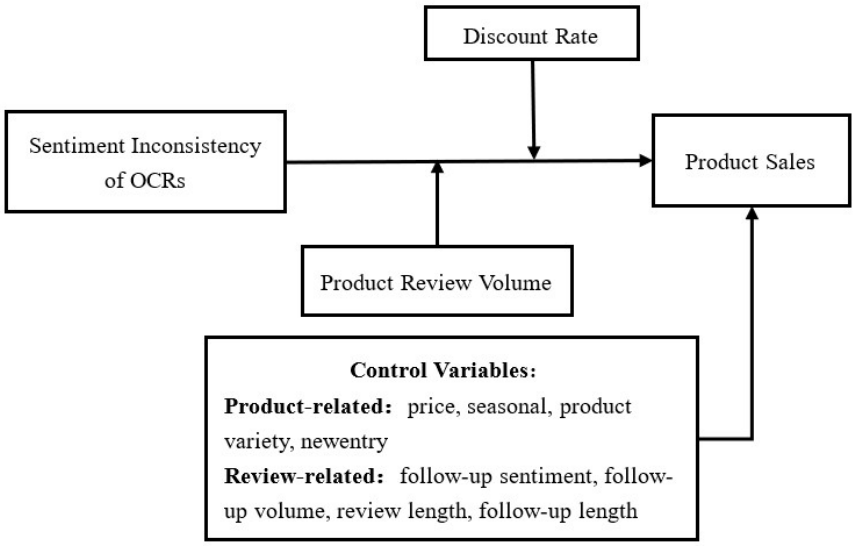


Figure 1. Research Model

2.3. Hypothesis Development

2.3.1. Effects of Sentiment Inconsistency of OCRs on Product Sales

With the explosion of information, product reviews in online retail are increasing, and companies hope to reduce the information processing cost of potential consumers through composite reviews. However, when consumers read composite reviews, they will be affected by sentiment inconsisteny. For OCRs, sentiment inconsistency refers to instances where the follow-up review and initial review posted by the same consumer have different sentiment directions (Li and Ren, 2017; Wang et al., 2021). This study focuses on product sales, therefore, defining the independent variable at the product level as the proportion of sentiment inconsistent OCR, which is the percentage of such reviews within the total OCR of a product.

According to cue diagnosticity theory, sentiment inconsistent OCRs prevent consumers from making effective judgments about product quality (Kay Byun et al., 2021), leading to doubts about the product. Additionally, when cues provide conflicting information, the negativity bias effect causes consumers to be more influenced by negative information, which is considered more useful (Miyazaki et al., 2005). Thus, sentiment inconsistent OCRs make consumers more susceptible to negative emotions, increasing perceived risk. Based on this analysis, sentiment inconsistent OCRs negatively impact consumer product evaluations. The higher the proportion of sentiment inconsistent OCRs, the greater the uncertainty consumers perceive about the product and experience information in the reviews. To avoid risks, consumers prefer to purchase products with stable quality. Based on the above analysis, this study proposes the first hypothesis:

Hypothesis 1: Sentiment inconsistency in OCRs negatively impacts product sales. The higher the proportion of sentiment inconsistency in OCR, the lower the product sales.

2.3.2. Moderating role of Product Review Volume

Rational consumers seek to reduce shopping risks through analyzing various cues. When different sources of cues align, information processing efficiency is enhanced. Conversely, when cues from different sources conflict, their usefulness decreases, negatively affecting consumer decision confidence (van Ooijen et al., 2017). Product review volume indicates popularity (Kim, 2021). A higher number of reviews implies that more users have purchased and reviewed the

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product, enhancing potential consumers' overall perception of it (Luo et al., 2022). However, because the number of reviews does not directly reflect product quality, its cue diagnosticity is lower than that of sentiments expressed in OCRs (Ba et al., 2020).

When composite reviews are sentimentally inconsistent, the effect of the review volume as a cue is enhanced. As previously mentioned, sentiment inconsistency in OCRs increases potential consumers' uncertainty about product quality. A higher review volume suggests greater product popularity, conveying positive signals about product quality despite not directly reflecting it (Kim, 2021). The inconsistency between the cues provided by OCR sentiments and review volume reduces consumer trust among different cues (Akdeniz et al., 2013). Thus, as review volume increases, the contradiction between the information generated by the number of comments and the information generated by inconsistent composite comment sentiment increases. Consumers perceive greater inconsistency between the cues provided by OCR sentiments and review volume, leading to doubts about cue authenticity and negatively impacting purchase decisions.

Additionally, consumers tend to minimize information processing costs by narrowing the information set they need to process（Chong et al., 2016）. As the number of product reviews increases, consumers are more inclined to read composite reviews which contain more useful information, especially if relying solely on tremendous initial reviews for purchase decisions requires significant effort and time. Therefore, as review volume increases, the impact of sentiment inconsistency in OCRs becomes stronger, leading to a more significant negative impact on future product sales. Based on the above analysis, this study proposes the second hypothesis:

Hypothesis 2: Products initial review volume negatively moderates the impact of sentiment inconsistency in OCRs on product sales. The greater the number of product initial reviews, the stronger the negative impact of sentiment inconsistency in OCRs on sales.

2.3.3. Moderating Role of Product Price Discounts

Business managers can develop strategies to provide marketing cues that mitigate the negative effects of high-diagnosticity cues (Kay Byun et al., 2021). These marketing cues ensure that consumers are exposed to information beyond just reviews, thereby influencing how they use reviews (Liu and Ji, 2018). With increasing competition in e-commerce, frequent price discounts have become a popular marketing strategy in online sales (Tan et al., 2019).

When OCRs, as high-scope cues, are sentimentally inconsistent, consumers choose to further process the price discount which is treated as a low-scope cue (Li, 2018; Kay Byun et al., 2021). Price discounts effectively reduce consumers' perceived shopping costs, allowing them to try products without price constraints. Price discounts for the same product do not imply a decline in product quality (Chen et al., 1998) and can enhance shopping pleasure, prompting quicker purchase decisions (Ba et al., 2020). As previously mentioned, consumers use different cues to make decisions to reduce shopping risks and minimize potential losses. When a product's price is reduced due to discounts, the perceived potential risk also decreases, which can reduce the extent to which consumers search for and process product information (Lee and Tsai, 2014). When consumers receive substantial discounts, their evaluation of product information becomes less detailed (Ba et al., 2020). Therefore, higher discount rates diminish the negative impact of sentimentallly inconsistent OCRs on consumers. Based on this, the third hypothesis of this study is proposed:

Hypothesis 3: The discount rate positively moderates the impact of sentiment inconsistency in OCRs on product sales. The greater the discount rate, the smaller the negative impact of sentiment inconsistency in OCRs on sales.

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3. Research Methodology

3.1. Data Collection

The dataset used in this study comes from a leading online apparel retailer in China. Given that apparel is the product category with the highest online sales penetration rate (Statista, 2018), sales data and consumer purchase behavior data in the apparel industry can effectively reflect the realities of the online retail market. Additionally, as a influential and large-scale online retailer in China, the firm used in this study provides an ideal setting for online retail research (Wang and Chen, 2022). The selected brand has been operating on Tmall for over ten years and consistently ranks among the top sellers on the platform, boasting a large user base. This ensures that the study can obtain sufficient data and that the sample data, being from a brand with no offline sales channels, will not be influenced by offline sales, thus ensuring a certain level of representativeness.

In this study, data were collected for all products sold by the brand on Tmall from April 1, 2019, to April 30, 2019, as well as all product reviews up to April 2019. Since the primary focus is on the impact of sentiment inconsistency in composite reviews on product sales, products without composite reviews were excluded from the dataset. Ultimately, the study included sales records for 1,163 products and 578,708 review records, among which 13,608 were composite reviews. The sample data encompassed a wide range of data fields, including (1) order-level information such as order ID, order time, order amount, and order discount; (2) review-level information such as initial review text, follow-up review text, review time, and corresponding order ID; and (3) product-level information such as product SKU count, product price, and product seasonality.

3.2. Variable Description

(1) Definition of Study Variables

Dependent Variable: The dependent variable in this study is product sales (Sales), defined as the sales of the product from April 1, 2019, to April 30, 2019.

Independent Variable: The independent variable is the degree of sentiment inconsistency in OCRs (InconR). Existing research focusing on single initial reviews considers reviews that contain both positive and negative sentiments as inconsistent reviews (Huang and Korfiatis, 2015). In this study, we define sentimentally inconsistent OCRs as those where the sentiment of the follow-up review contradicts the initial one. Previous research measures the overall sentiment of reviews by the percentage of positive or negative reviews out of the total number of reviews (Duan et al., 2022). Accordingly, this study defines the degree of sentiments inconsistency in OCRs of a certain product as the percentage of sentimentally inconsistent OCRs out of the total number of OCRs.

Moderating Variables: Review volume (RevVol) refers to the total number of reviews for each product over the past year (as the Tmall platform displays reviews for one year). Discount rate (DisRate) is the ratio of the actual payment amount to the original price of the product.

Control Variables: This study controls for several potential influencing factors, including product-related and review-related factors. Product Price (Price) refers to the original price of the product. Product variety (ProVar) is the he number of different styles available for a product, represented by the number of SKUs, which influences consumer purchasing behavior (Tu et al., 2016). Seasonal sales (Seasonal) means whether the product is being sold in its intended season. New entry (Newentry) means whether the product is a new release. Overall sentiment of follow-up reviews (FollowSent) refers to the general sentiment expressed in follow-up reviews. Follow-up reviews volume (FollowVol) is the number of follow-up reviews. Length of follow-up reviews (FollowLen) is the average length of follow-up reviews. Length of initial reviews (RevLen) is the average length of initial reviews. Previous studies have shown that the price

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level of a product is a significant moderating factor in online reviews. Depending on the product price, consumers focus on different sources of review information (Ba et al., 2020). The variety of a product, indicated by the number of available styles, impacts consumer purchase behavior (Tu et al., 2016). Whether a product is sold in its intended season and whether it is a new product both affect consumer purchasing decisions (Li et al., 2019). Additionally, the quantity, sentiment, and length of reviews influence consumer purchasing decisions (Aghakhani et al., 2021). Therefore, these variables are controlled in this study.

(2) Calculation of OCR Sentiment Inconsistency

According to the variable definitions, the formula for calculating the degree of sentiment inconsistency in OCRs is as follows:

$$InconR_i = \frac{InconVol_i}{CompoVol_i}$$

Where $CompoVol_i$ represents the total number of composite reviews for product i, $InconVol_i$ denotes the number of composite reviews with inconsistent sentiments for product i. This study employed a machine learning approach to classify the sentiment direction of each composite review, thereby quantifying the sentiment consistency of each composite review and subsequently assessing the degree of sentiment inconsistency in product reviews.

In the sentiment analysis based on machine learning, this study employed a supervised learning approach. Initially, 1680 comments were selected for annotation to form the training and testing sets, following annotation procedures outlined in prior research (Bai et al., 2020). Three research assistants, specialized in research field of this study, participated in the annotation process. The reviews were divided equally among them in three separate rounds, ensuring each assistant annotated distinct sets of comments three times. Each assistant assigned sentiment polarity as either negative (-1) or positive (+1) based on varying emotional tones. The aggregated annotations were then reviewed to identify discrepancies, followed by intensive discussions to achieve consensus on sentiment polarity. Comments posing uncertainty were collectively discussed by the assistants to finalize their sentiment classification. Subsequently, all annotations were compiled to create the training and testing sets. Prior to model training and testing, the reviews underwent tokenization using the Jieba package in Python. Stopwords were removed based on the HowNet corpus provided by the Chinese Knowledge Internet (CNKI). The annotated 1680 comments were then divided into training and testing sets at a 1:3 ratio. Furthermore, TF-IDF was employed to construct feature vectors for the training set. Five different classification models-Logistic Regression, Support Vector Machine (SVM), Decision Tree, Naïve Bayes, and K-Nearest Neighbors (KNN)-were evaluated. Each model was tested using the testing set, and the results are presented in Table 1 as described.

From the results in table 1, it is evident that the Support Vector Machine (SVM) demonstrated the highest accuracy among all models. Therefore, this model was selected for classifying review sentiments. The SVM model was saved and subsequently applied to the cleaned review data for classification. Before classification, the study first tokenized all review data and constructed feature vectors. The model was then used to predict the sentiment polarity of each review, ultimately determining the sentiment consistency of each composite review and the sentiment inconsistency degree of product OCRs.

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Table 1. Results of Model Fitting

		Precision	Recall	F1_score
Logistic Regression	-1	0.92	0.68	0.79
	1	0.84	0.93	0.89
	accuracy			0.84
SVM	-1	0.89	0.74	0.81
	1	0.97	0.95	0.90
	accuracy			0.87
Decision Tree	-1	0.70	0.72	0.71
	1	0.84	0.82	0.83
	accuracy			0.79
Naive Bayes	-1	0.96	0.23	0.37
	1	0.69	1.00	0.82
	accuracy			0.72
KNN	-1	0.38	0.98	0.55
	1	0.89	0.08	0.14
	accuracy			0.41

3.3. Descriptive and Correlation Analysis

(1) Descriptive Summary

The descriptive statistics for the variables in this study are presented in Table 2. Product sales (Sales), initial review quantity (RevVol), product price (Price), initial review length (RevLen), follow-up review volume (FollowVol) and length (FollowLen) are all continuous variables, exhibiting large variances and wide value ranges. Following the approach of previous studies (Yin et al., 2021), the natural logarithms of these continuous variables were taken to linearize their transformations. This approach compresses the variable scales, reduces the impact of outliers, and converts potential nonlinear relationships into linear ones, thereby enhancing the robustness of the regression results.

Table 2. Descriptive Statistics of Variables

Variable Name	Obeservation	Mean	Std. Error	Min	Max
Sales	1163	265.7	1739.2	1	48174
InconR	1163	0.6	1.9	0	1
RevVol	1163	497.9	1732.9	1	35860
DisRate	1163	0.1	0.1	0	0.8
Price	1163	159.4	91.2	28	848
Seasonal	1163	0.59	0.45	0	1
ProVar	1163	8.4	6.6	3	107
NewEntry	1163	0.91	0.05	0	1
FollowSent	1163	0.15	0.73	-1	1
RevLen	1163	18.6	6.3	3	68.4
FollowVol	1163	11.7	41.4	1	798
FollowLen	1163	36.2	34.8	1	343

(2) Variable Correlation Analysis

Table 3 lists the correlation coefficients for all variables in this study. The results indicate that the degree of emotional inconsistency in composite reviews is negatively correlated with product sales, while the quantity of product reviews and the level of product discounts are

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positively correlated with product sales. This provides initial support for the theoretical assumptions of this study. Additionally, the data show that all correlation coefficients between variables are less than 0.8, indicating that there are no significant multicollinearity issues.

Table 3. Correlation Matrix for the study Variables

	1	2	3	4	5	6	7	8	9	10	11	12
Sale	1											
InconR	-0.119	1										
RevAm	0.090	-0.029	1									
DisRate	0.276	0.012	-0.111	1								
Price	-0.360	0.039	0.066	-0.156	1							
Seasonal	0.016	-0.005	-0.069	0.000	-0.030	1						
ProVar	0.293	-0.039	0.499	-0.037	-0.177	-0.056	1					
NewEntry	0.053	-0.011	0.015	0.027	0.057	0.032	0.011	1				
FollowSent	0.153	-0.692	-0.004	-0.002	-0.031	-0.003	0.045	0.006	1			
RevLen	-0.102	-0.007	0.261	-0.020	0.209	0.000	0.056	-0.017	0.006	1		
FollowVol	-0.029	-0.012	0.686	-0.085	0.164	-0.045	0.483	0.026	-0.025	0.285	1	
FollowLen	-0.036	-0.181	0.302	-0.051	0.093	-0.028	0.154	0.009	0.158	0.210	0.350	1

To further verify the absence of multicollinearity, this study conducted a variance inflation factor (VIF) test for all variables, with the results presented in Table 4. All VIF values are less than 10, meeting the standard for collinearity diagnosis (Vittinghoff et al., 2005). The test result confirms that there are no significant multicollinearity issues among the variables, ensuring the reliability of the subsequent regression analysis results.

Table 4. VIF Test Results for The Study Variables

Variables	VIF	1/VIF
FollowVol	5.27	0.189
RevVol	4.96	0.202
ProVar	1.47	0.679
FollowSent	1.36	0.733
FollowLen	1.34	0.747
InconR	1.22	0.820
Price	1.22	0.822
RevLen	1.15	0.872
Disrate	1.05	0.957
Seasonal	1.01	0.989
NewEnrty	1.01	0.991

4. Empirical Analysis

4.1. Results for Hypothesis Tests

This study uses cross-sectional data for regression analysis. According to the descriptive statistics presented in the previous section, the continuous variables in this study exhibit significant variance. Therefore, logarithmic transformations were applied to the continuous variables before conducting the regression to mitigate the influence of potential outliers. To test the first hypothesis, the following regression equation (1) is proposed:

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$$Sale_i = \beta_0 + \beta_1 InconR_i + \beta_2 Controls_i + \varepsilon_i \quad \text{(Equation 1)}$$

Where $Sale_i$ represents the sales of product i in April 2019, $InconR_i$ denotes the degree of emotional inconsistency in composite reviews for one year preceding April 2019, β_1 is the regression coefficient for this variable. β_2 represents the collection of regression coefficients for all control variables, and ε_i is the error term. The regression results based on this equation are presented in Table 5. Model 1-1 includes only the independent variable, while Model 1-2 incorporates both the independent variable and all control variables.

The regression results of Model 1-1 indicate that the degree of sentiment inconsistency in OCRs has a significant negative impact on product sales (β= -0.593, p < 0.01). When control variables are added in Model 1-2, the overall fit of the regression model improves significantly, with R2 increasing to 0.319. Moreover, the sign and significance of the independent variable's coefficient remain consistent with the results from Model 1-1. Thus, based on the above regression analysis, Hypothesis 1 is validated. Specifically, the degree of sentiment inconsistency in OCRs negatively impacts product sales, with higher proportions of sentimentally inconsistent OCRs leading to lower product sales.

Additionally, among the control variables, the initial review volume (β= 0.504, p < 0.01) and the discount rate(β= 0.747, p < 0.01) both have significant positive effects on product sales, consistent with previous research on the impact of review volume and discount rates on sales. The initial review volume reflects the product's popularity, and an increase in initial review volume fosters a positive perception of the product among current consumers. Meanwhile, increased discount rates not only reduce consumers' shopping costs but also enhance shopping pleasure, validating the related hypotheses and implications of this study.

Table 5. OLS Regression Results

Variables	Model 1-1	Model 1-2
InconR	-0.593***	-0.496***
RevAm		0.504***
DisRate		0.747***
Price		-0.858***
ProVar		0.073***
NewEntry		2.117*
Seasonal		0.121
AddSent		0.100***
RevLen		-0.213
AddAm		-0.741***
AddLen		-0.119*
Constant	3.857***	4.442***
R^2	0.01	0.319
N	1163	1163

* p < 0.05, ** p < 0.01, *** p < 0.001.

To further explore the moderating effects of product review volume and discount rates on the impact of emotional inconsistency in composite reviews, this study proposes Equation (2). $Controls_i$ represents all other control variables excluding the moderating variables. To mitigate potential multicollinearity issues arising from interaction effects, both the independent and moderating variables were centered prior to regression analysis. Additionally, variance inflation factor (VIF) tests were conducted to ensure the reliability of the regression

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results, with maximum VIF values for variables in all three models (2-1 to 2-3) being below 10 (7.47, 5.3, 7.51), indicating there is no significant multicollinearity among the variables.

$$Sale_i = \alpha_0 + \alpha_1 InconR_i + \alpha_2 RevVol_i + \alpha_3 DisRate_i + \alpha_4 InconR_i * RevVol_i + \alpha_5 InconR_i * DisRate_i + \alpha_6 Controls_i + \varepsilon_i \quad \text{(Equation 2)}$$

Models 2-1 to 2-3 in Table 6 present the regression results based on Equation (2). Model 2-1 shows that the interaction term between review volume (RevVol) and sentiment inconsistency (InconR) is significantly negative (β = -0.406, p < 0.01), alongside the significant negative coefficient of sentiment inconsistency itself. This suggests that as review quantity increases, the detrimental effect of emotional inconsistency in OCRs on product sales becomes more pronounced. Similarly, Model 2-2 reveals that the interaction term between discount rate (DisRate) and sentiment inconsistency is significantly positive (β = 0.018, p < 0.05), complemented by a significant negative coefficient of sentiment inconsistency itself. Hence, an increase in the discount rate mitigates the negative impact of sentiment inconsistency on product sales. Higher discount rates alleviate the adverse effects of sentiment inconsistency in OCRs. These analyses confirm Hypotheses 2 and 3 of this study.

Table 6. Regression Results for The Moderating Effects

Variables	Model 2-1	Model 2-2	Model 2-3
InconR	-0.386**	-0.256**	-0.452**
RevVol	0.659***	0.503***	0.662***
DisRate	0.698***	0.613***	0.830***
InconR*RevVol	-0.406***		-0.422***
InconR*DisRate		0.018**	0.092**
Price	-0.853***	-0.859***	-0.855***
ProVar	0.071***	0.073***	0.071***
NewEntry	2.068*	2.120*	2.084*
Seasonal	0.138	0.121	0.138
FolllowSent	0.097***	0.100***	0.098***
RevLen	-0.199	-0.214	-0.201
FollowVol	-0.729***	-0.740***	-0.725***
FollowLen	-0.123*	-0.119*	-0.124*
Constant	3.811***	4.438***	3.764***
N	1163	1163	1163

* p < 0.05, ** p < 0.01, *** p < 0.001.

4.2. Robustness Check

In the previous section, the three hypotheses of this study were tested. To ensure the robustness of the research findings, this section conducts robustness analysis through two different methods. First, to address nonlinearity issue caused by variable variance, the variables in the regression were logarithmically transformed in the previous section. To further eliminate the influence of extreme values on the research results, the sample was refined based on the original dataset. Following common practices in previous studies (Wang and Chen, 2022), products with sales exceeding three standard deviations of the sample, i.e., sales over 1739.2*3, were excluded, resulting in a final sample of 1147 products for regression analysis. The regression results based on the refined dataset are shown in Table 7. The results in column (1) show that the coefficient for the independent variable, the degree of sentiment inconsistency in OCRs, is significantly negative (β = -0.255, p < 0.05). The results in column (2) show that the

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interaction term between product review volume and the independent variable is significantly negative (β = -0.378, p < 0.05). The results in column (3) show that the interaction term between product discount rate and the independent variable is significantly positive (β = 0.015, p < 0.1). The coefficient signs and significance levels of the main variables are consistent with those of the main regression, confirming the robustness of the research results.

Table 7. Regression Results for The Subsample

Variables	(1)	(2)	(3)	(4)
InconR	-0.255**	-0.275**	-0.254**	-0.336**
RevVol	0.481***	0.624***	0.480***	0.627***
DisRate	0.681***	0.638***	0.737***	0.740***
InconR*RevVol		-0.378**		-0.392**
InconR*DisRate			0.015*	0.084*
Price	-0.808***	-0.804***	-0.809***	-0.807***
ProVar	0.089***	0.087***	0.089***	0.087***
NewEntry	2.083*	2.038*	2.086*	2.053*
Seasonal	0.134	0.148	0.134	0.149
FollowSent	0.097***	0.096***	0.098***	0.096***
RevLen	-0.196	-0.182	-0.196	-0.184
FollowVol	-0.748***	-0.736***	-0.748***	-0.732***
FollowLen	-0.121*	-0.124*	-0.121*	-0.125*
Constant	4.175***	3.589***	4.171***	3.547**
N	1147	1147	1147	1147

* p < 0.05, ** p < 0.01, *** p < 0.001.

Table 8. Negative Binomial Regression Results

Variables	(1)	(2)	(3)	(4)
InconR	-0.072**	-0.094**	-0.073**	-0.096**
RevVol	0.137***	0.170***	0.137***	0.170***
DisRate	0.999***	0.993***	0.968***	1.003***
InconR*RevVol		-0.089*		-0.089*
InconR*DisRate			0.009**	0.003**
Price	-0.273***	-0.271***	-0.273***	-0.271***
ProVar	0.013***	0.013***	0.013***	0.013***
NewEntry	0.781*	0.769*	0.779*	0.770*
Seasonal	0.038	0.042	0.038	0.042
FollowSent	0.026***	0.025***	0.026***	0.025***
RevLen	-0.073	-0.069	-0.073	-0.069
FollowVol	-0.190***	-0.186***	-0.190***	-0.185***
FollowLen	-0.034	-0.0352	-0.034	-0.0352
Constant	1.567**	1.424**	1.569**	1.422**
N	1163	1163	1163	1163

* p < 0.05, ** p < 0.01, *** p < 0.001.

Furthermore, a negative binomial regression model was employed to analyze the sample data for two reasons. Firstly, dependent variable in this study, product sales, is a non-negative

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continuous variable, and as shown in Table 2. Meanwhile, the mean value of this variable is 265.7 with a standard deviation of 1739.2, which is significantly larger than the mean, indicating a dispersion issue with this variable. The negative binomial regression effectively improves the fit for dispersed data. The results of the negative binomial regression are presented in Table 8. The coefficient signs and significance levels of the main variables in this analysis are consistent with those in the primary regression. These robustness checks further confirm the stability of the findings in this study.

5. Key Findings

Although the great importance of OCRs in consumer purchase behavior has been recognised both in academic research and industry practices (Wang et al., 2021), knowledge on the essential characteristic of the sentiment changes in OCR text remains inadequate. This study is among the first to explore the effects of sentiments variation of OCRs on online retailing sales. Using sales and review data from a leading online apparel retailer on Tmall.com, this study quantifies the degree of sentiment inconsistency in online composite reviews through support vector machine model. Based on cue diagnosticity theory, we further empirically analyzes the impact of sentiment inconsistency in OCRs on product sales, as well as the moderating roles of review volume and discount rate. First, sentiment inconsistency in OCRs significantly exerts negative impact on product sales. An increase in sentimentally inconsistent OCRs suppresses consumer purchasing decisions, resulting in decreased future sales. Second, the quantity of reviews has a negative moderating effect on the impact of emotional inconsistency in composite reviews. An increase in the number of reviews amplifies the negative impact of emotional inconsistency on product sales. Third, the discount rate of products mitigates the negative impact of emotional inconsistency in composite reviews. Higher discount rates reduce the adverse effects of emotional inconsistency on product sales.

6. Conclusion

6.1. Theoretical Implications

This study makes three main theoretical contributions. First, we contribute to online customer review literature by focusing on text sentiment of composite review. Research on online reviews has received extensive attention (Fernandes et al., 2022), but few studies have considered the variation in sentiment expressed by the same consumer in review text. Online composite review has been becoming extremely common in e-commerce platform and the comprehensive text information reflected increases consumers' trust in such reviews (Wang et al., 2021). Therefore, a deeper discussion of the impact of composite reviews is greatly needed. Our study adds to this stream of literature by focusing on the review text and exploring sentiment inconsistency in online composite review.

Second, we propose a mechanism by which sentiment inconsistency in OCRs affects product sales and enhance the understanding of cue diagnosticity theory. As noted above, previous studies have studied composite reviews through questionnaires or experimental methods. However, these studies lack analysis of the real-world scenarios in which consumers use composite reviews to assist in purchasing decisions. In the online shopping, consumer uses different cues to make decisions (Wang et al., 2024). Based on cue diagnosticity theory, this study discuss the relationship between sentiment inconsistency in OCRs and sales, and further explores the moderating role of price discounts and review volume. We provide direct empirical evidence of this mechanism by analyzing real review and transaction data and the results support our proposed influence mechanism. In doing so, this study expands the application situation of cue diagnosticity theory and provides theoretical support for managing OCRs to boost sales.

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Finally, we contribute to the measure of sentiment variation in online review by analyzing the review text using a machine learning approach. Review valence is one of the most important factors influencing consumer decision-making (Tata et al., 2020). Previous research quantified sentiment inconsistency mainly by calculating rating variances without deeply exploring the review text (Wang et al., 2024) . Compared to ratings, review text more accurately reflects consumers' true emotions (Luo et al., 2022) and has a greater impact on potential consumers. This study introduces a new method for measuring review inconsistency using a support vector machine model. And the text-based analysis improves the accuracy of quantifying emotional inconsistency in reviews.

6.2. Practical Implications

Our results also provide useful insights for retailers, especially regarding the innovative use of composite reviews in the online marketing context. First, our findings stress the importance of proper management of online composite reviews. Online composite reviews are widely used in e-commerce-platform nowadays. We find that sentiment inconsistency in OCRs significantly negatively impacts product sales. Therefore, after implementing follow-up review features, online retailers should strengthen the management of composite reviews. Measures such as economic incentives or review responses can help reduce sentimentally inconsistent reviews and enhance the positive effects of composite reviews on sales. Second, our research shows that reducing the quantity of reviews or increasing product discount rate can effectively mitigate the negative impact of sentiment inconsistency in composite reviews. When there is a high proportion of sentiment inconsistency in OCRs, companies can take measures to discourage consumers from posting reviews, thereby reducing the total review volume. Additionally, for products with a high proportion of sentiment inconsistent reviews, companies can increase the discount rate. Third, this study quantifies sentiment inconsistency in composite reviews using machine learning and validates their objective impact. As consumers now pay more attention to textual reviews rather than simple statistical indicators (Topaloglu and Dass, 2021), the proposed quantification method provides a new approach for effective review management. E-commerce companies should utilize their review data to establish effective text analysis systems for real-time monitoring and rapid response to unfavorable reviews.

6.3. Limitations and Future Research

This study also suffers from several limitations. First, apparel is the category with the highest penetration rate in online sales, and the data for this study comes from leading apparel brands on the largest e-commerce platform in China, which lends a certain representativeness to the results. However, whether these findings can be generalized to different product categories and industries requires validation through more diverse datasets, which is a direction for future research. Second, this study selects the magnitude of price discounts as a moderating variable. Price discounts are the most commonly used promotional method by online retail enterprises (Liu et al., 2021)., ensuring the representativeness of this study. However, existing research indicates that other forms of promotions (such as gifts, free shipping, etc.) have different impacts on consumer purchasing behavior. Future research can further explore the effects of different promotional methods based on this study to enrich the findings. Third, the dependent variable in this study focuses on product sales. With the widespread adoption of composite reviews, these reviews may have various impacts on consumer behavior and corporate operations. Future research can further expand on this study to explore these diverse effects.

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