The Impact of Product Review Usefulness on the Digital Market Consumers Distribution*

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Abstract

Purpose: This study is a quantitative study and analyzes the effect of evaluating the extreme and usefulness of product reviews on sales performance by using text mining techniques based on product review big data. We investigate whether the perceived helpfulness of product reviews serves as a mediating factor in the impact of product review extremity on sales performance. **Research design, data and methodology:** The analysis emphasizes customer interaction factors associated with both product review helpfulness and sales performance. Out of the 8.26 million Amazon product reviews in the book category collected by He & McAuley (2016), text mining using natural language processing methodology was performed on 300,000 product reviews, and the hypothesis was verified through hierarchical regression analysis. **Results:** The extremity of product reviews exhibited a negative impact on the evaluation of helpfulness. And the helpfulness played a mediating role between the extremity of product reviews and sales performance. **Conclusion**: Increased inclusion of extreme content in the product review's text correlates with a diminished evaluation of helpfulness. The evaluation of helpfulness exerts a negative mediating effect on sales performance. This study offers empirical insights for digital market distributors and sellers, contributing to the research field related to product reviews based on review ratings.

Keywords: Review Helpfulness, Digital Market Consumer Distribution, Big Data, Text Mining, Natural Language Processing

JEL Classification Code : D12, D83, M15, M21, M31

1. Introduction

1.1. Customer Engagement and Distribution Efficacy

Distribution constitutes an operational endeavor that engenders the utility of place, time, and ownership, facilitating the seamless transfer of goods and services from producers to consumers. As the destination of distribution is directed to consumers, distribution is occasionally explained within the realm of marketing, encompassing facets like brand reputation and consumer engagement (Thabit & Raewf, 2018). The efficacy of distribution is influenced by not solely the direct conveyance of goods (Rao et al., 2009) but also the effectiveness with which consumers make purchasing decisions.

The digital industry is disrupting many existing industries. Machine-oriented cars are transforming into digital devices, and mobile devices are becoming portable computers (Rahmati et al., 2021). Companies are also being asked for an integrated digital perspective that goes beyond

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the existing institutionalized process while introducing innovative digital technology into their products and operations (Svahn et al., 2017). The market is in a similar situation. The influence of the online market is growing especially with COVID-19, and customers in the online market are actively using blogs, online forums, and purchase reviews from digital markets to present their opinions (Shen et al., 2015).

In the online-based digital industry, product reviews are a very influential factor in sales performance, and they have unique characteristics that differ from the seller's information in that customers voluntarily write.

However, it is difficult to say that product reviews only have a positive effect on sales performance, and there is a lack of research on how the product reviews usefulness evaluation affect sales performance. Digital markets frequently place useful product reviews and if a useful product review negatively affects sales performance, such behavior can adversely affect sales performance, so research about this matter should be carried out promptly. The main purpose of this study is to contribute to improving the performance of the digital market and expanding related study through research on how the usefulness evaluation of product reviews affects sales performance.

Amazon, a prominent global digital marketplace, has achieved groundbreaking efficiency in distribution through the implementation of its fulfillment system. However, realizing this accomplishment would have posed challenges without a dedicated emphasis on customer service within Amazon's online platform (Prahalad & Ramaswamy, 2000). These days, the digital market actively endeavors to influence consumers' purchasing decisions by employing the sharing economy, such as the purchase review systems (Nadeem et al., 2021), while sellers cultivate product loyalty through strategic advertising on social media platforms (Rapp et al., 2013) for the efficacy of distribution. Favorable evaluations by consumers of a consumer support system can cultivate a positive reputation in the product purchase performance (Salehan & Kim, 2016).

1.2. Characteristics of the Digital Market

The digital market's share is expanding compared to the offline market, driven by the spatial and temporal convenience for buyers (Taken Smith, 2012; Bala & Verma, 2018; Kannan, 2017). Influenced by the recent COVID-19 pandemic, non-face-to-face technologies rapidly developed (Chakraborty & Maity, 2020; Donthu & Gustafsson, 2020) and are accelerating the shift of consumers toward the digital market (Gu et al., 2021; Hashem, 2020; Akram et al., 2021). Companies venturing into the digital market are confronted with the pressing need to delve into the intricacies of consumers' online purchasing decision-making processes by

formulating innovative strategies that offer a competitive advantage (Kurdi et al., 2022; Gursoy et al., 2022).

Consumers in the digital market actively utilize various online channels for gathering information and assessing the value of products (Ghose & Ipeirotis, 2010; Ryan, 2016; Chaffey & Smith, 2013). In contrast to traditional markets where customers can physically evaluate products by seeing, smelling, and touching them (Degeratu et al., 2000; Levin et al., 2003; Füller et al., 2007), in online markets, limitations arise in comprehending the value of products mainly based on information available online. This limitation emphasizes the importance of the information provided by supplier or external experts, as well as insights by previous buyers (Kannan, 2017; Chaffey & Smith, 2013).

1.2.1. Information Distortion in Digital Market

But ensuring the objectivity of information in online channels poses challenges (Taiminen & Karjaluoto, 2015; Chaffey & Smith, 2013). Sellers in the digital market may selectively emphasize positive aspects while concealing negative information in product descriptions (Dimoka et al., 2012; Pavlou & Gefen, 2005; Granados et al., 2006). Comparison shopping websites such as Google shopping often highlight specific products received advertising fees (Olbrich & Schultz, 2014; Yang & Gose, 2010).

1.2.2. Objectivity of Product Review

In situations of information distortion, consumers actively rely on product reviews (Mudambi & Schuff, 2010; Sen & Lerman, 2007). Previous buyers typically share their experiences by voluntarily writing product reviews without any specific remuneration (Sen & Lerman, 2007; Park & Kim, 2008). Although individual product review may be subjective, product reviews are perceived relatively objective compared to the seller's product description (Ghose & Ipeirotis, 2010). Some potential buyers further enhance objectivity by assessing the helpfulness evaluation of product reviews (Decker & Trusov, 2010).

Researchers have investigated the impact of product reviews on sales performance (Kim et al., 2016). A comprehensive study has been conducted on the influence of product review ratings, representing a numerical evaluation of a product (Hu et al., 2014; Floyd et al., 2014; Moon et al., 2010). Perceived as objective, product review ratings are easily collected and analyzed in this research field (Sutton & Austin, 2015; Miles, 1979; Büschken & Allenby, 2016), and many studies have employed the mean or variance of the rating for main variable (De Langhe et al., 2016; Kopalle et al., 2017).

In this context, product review data from Amazon, the largest global digital market platform, has been used for comprehensive research of digital market, encompassing quantitative analysis of ratings and big data-driven studies,

including emotional analysis (Haque et al., 2018; Fang & Zhan, 2015; Feng et al., 2012; Danescu-Niculescu-Mizil et al., 2019).

This study focuses on the aspect that product reviews with high usefulness ratings, which are often placed in the front of the product review section in the digital market, may negatively affect sales performance. In addition, there is a difference in expanding product review extremity studies based on product review ratings by actively utilizing big data methodologies. To this end, this study introduced a methodology that analyzes Amazon big data through text mining. Since the usefulness evaluation of product reviews will not only be based on ratings, but will read the review text, we judged that text mining will be useful in understanding the characteristics of these review texts.

2. Theoretical Background

2.1. Literature on Product Review

2.1.1. Voluntary Characteristics of Product Reviews

With the proliferation of various social media platforms, many individuals who do not have any partnerships with product sellers provide voluntary meaningful product information on social media platforms such as blogs, YouTube, as well as Instagram, etc. (Flanagin & Metzger, 2008; Chadwick, 2007). The provision of such voluntary information of product has a significant impact on the sales performance of the digital market (Tiago & Veríssimo, 2014; Bala & Verma, 2018). Product reviews are recognized as having a positive impact on product sales (Tiago & Veríssimo, 2014; Ghose & Ipeirotis, 2010; Floyd et al., 2014). So, many digital market platforms seek to influence sales performance by providing opportunities for individuals can voluntarily produce information about their products (Killian & McManus, 2015; Lamberton & Stephen, 2016; Labrecque et al., 2013).

Product reviews containing evaluative comments provided by buyers after purchasing, are recognized as more objective than sellers' information (Park et al., 2007; Reyes & Rosso, 2012).

2.1.2. Composition of Product Reviews

Product reviews in digital markets typically include titles, text, and ratings (Park et al., 2007), and sometimes have voting system to measure the helpfulness of the reviews (Ghose & Ipeirotis, 2007; Ghose & Ipeirotis, 2010). Potential buyers can evaluate product review helpfulness by their volume, average rating, and valuable insights from the content (Flanagin et al., 2014; Kreimeyer et al., 2017).

2.1.3. Research Areas of Product Reviews

Many studies have explored the impact of product reviews on corporate performance. Their main focus was on quantitative dimensions such as mean and standard deviation of ratings, and number of product reviews (Ghose & Ipeirotis, 2010; Hu et al., 2008; Sen & Lerman, 2007; Park et al., 2007; Dellarocas et al., 2007). Previous studies on quantitative aspects of product reviews have shown that higher mean ratings lead to higher sales performance (Chevalier & Mayzlin, 2006; Hu et al., 2008; Ye et al., 2009). Similar effects have been observed with the number of product reviews (Zhou et al., 2022).

Despite the product review text containing meaningful comments from previous buyers, limited research has been conducted due to difficulties in identifying the text contents.

2.2. Limitations of the Product Reviews

2.2.1. The Limitation of a 5-point Scale Rating

Many digital markets, such as Amazon, utilize 5-point scales for assessing product valuation ratings (Coelho & Esteves, 2007; Garland, 1991). Some arguments suggest that accurately identifying differences within these 5 scales may be very challenging (Roche et al., 2004). To address this, adopting a 7 or 10-point scale has been proposed (Finstad, 2010; Tarka, 2017). However, increasing scale size may reduce the proper respondent responses for the increasing response time (Wisner, 2020).

2.2.2. Bias in Ratings

Moreover, product review ratings exhibit a propensity of skewness (Mudambi & Schuff, 2010; Kuan et al., 2015; Croarkin et al., 2004). Review authors, typically buyers who have already made purchase decisions for that product, tend to provide positive reviews, influenced by both their information gathered during the decision-making process and a sense of self-efficacy towards the product (Lee et al., 2008; Sen & Lerman, 2007). Buyers may intentionally submit extreme product review to express their opinions clearly (Filieri et al., 2018; Mudambi & Schuff, 2010). It will also increase the bias of review ratings.

2.3. Analysis of Product Review Content

To enhance the objective evaluation of a product's value, it is essential to comprehensively understand the buyer's opinion by integrating additional information beyond the product review rating. While some product review authors provide only ratings, many of them actively express specific opinions in the review text. Analyzing the textual content of a product review proves highly beneficial evaluating the

product's value (Hu et al., 2014; Fang et al., 2016; Patrick et al., 2011).

This study closely examines the elements of product reviews through big data analysis, and analyzes the impact of these factors on sales performance, which closely identifies interactions between customers.

2.3.1. Using Big Data Analysis Methodology

Advancements in big data analysis techniques including data mining, play a crucial role in overcoming the limitations of product review research centered on quantitative factors (Ghazal et al., 2013; Jeyapriya & Selvi, 2015). Big data analysis facilitates the identification of which products the buyers tend to purchase together, offering insights of their preferences (He & McAuley, 2016; Akter & Wamba, 2016; Chaffey & Smith, 2022). Text mining techniques, one of the prominent big data methodologies (Nadkarni et al., 2011; Hirschberg & Manning, 2015; Yi et al., 2003; Sun et al., 2017), employ natural language processing (NLP) techniques to identify the part of speech and language elements in the text (Nadkarni et al., 2011; Hirschberg & Manning, 2015; Yi et al., 2003; Sun et al., 2017). These big data methodologies enhance the scope of existing product review studies, which were previously constrained on the volume and ratings.

It remains complicated to sort out the content of the product reviews. Examining the extreme expressions in texts aids in comprehending opinion extremity. Recent advances in text mining techniques that can quantify words and parts of speech in a text, provide a means of identifying the effects of extremity in product evaluation (Owoputi et al., 2013). Since extreme expressions often incorporate superlative adjectives and superlative adverbs, scrutinizing the presence of these words in product reviews facilitates a nuanced understanding of extremities (Ravi & Ravi, 2015; Zhao et al., 2021).

2.3.2. Review Extremity and Helpfulness evaluation

Previous research has recognized that the extremity of product reviews influences on sales (Moon et al., 2014). There are varied perspectives among researchers regarding the extremity of product reviews. Some researchers argue that extreme reviews lack utility due to their perceived lack of persuasiveness (Mudambi & Schuff, 2010; Filieri, 2016), with some asserting that extreme product reviews are considered helpful (Filieri et al., 2018; Cao et al., 2011). Additionally, arguments suggest that these results depend on the empirical and exploratory nature of the data and the characteristics of the products (Mudambi & Schuff, 2010).

Studies examining the helpfulness of product reviews commonly analyze standard deviations of ratings (Eslami et al., 2018). Big data analysis can be leveraged to identify whether the text of a product review contains extreme expressions, facilitating a comprehensive understanding of the extreme product reviews impact on usefulness evaluations.

Potential buyers frequently cast votes for helpfulness after reviewing the text of a product review, rather than relying solely on numerical ratings. Extreme opinions on products will be considered unhelpful, as they may be perceived as deviating significantly from the actual value. The perception of extreme content in a product review can lead to a diminished helpfulness vote for the review.

In light of the above considerations, the hypothesis is formulated as follows.

H1: The more extreme terms are used in product review text; the rate of helpfulness will be decreased.

2.3.3. Review Helpfulness and Sales Performance

In assessing the helpfulness of product reviews and their association with sales performance, researchers contend that reviews tend to be more helpful when they are less extreme and contain substantial information (Mudambi & Schuff, 2010), which can negatively impact sales performance. Although longer product reviews may be perceived as helpful, they may also present both negative and positive information about the product, leading to increased uncertainty in purchasing decisions. Therefore, it has a potentially negative impact on sales performance (Chen et al., 2009). The extremity of the product review is known to influence decision-making diagnostically, with a positive effect on sales performance (Skowronski & Carlston, 1989). Given that extreme reviews are considered unhelpful (Mudambi & Schuff, 2010), the perceived helpfulness of reviews may have a relatively negative impact on sales volume.

In light of the above considerations, the hypothesis is formulated as follows.

H2: The rate of helpfulness of product reviews is expected to negatively impact on the sales performance.

2.2.4. Mediating Effects of Product Review Helpfulness

Despite numerous studies exploring the determinants of product review helpfulness, there is limited research on the impact of helpfulness on sales performance (Li et al., 2013; Krishnamoorthy, 2015). Product reviews considered helpful can influence the delay in purchasing decisions (Lee & Choeh, 2020). The substantial number of helpfulness votes can also be attributed to the increased interest of potential buyers. In situations where potential buyers are unable to read all of the product reviews, labeled as helpful reviews can gather more attention, influencing purchasing decisions. Consequently, the results of helpfulness votes, representing the evaluation of potential buyers, will exhibit a mediating

effect on the impact of factors such as product review extremity on sales performance.

Research related to the usefulness of product reviews has mainly focused on the factors influencing the usefulness evaluation and the typical factors include length, readability, extreme rating, when created, and product characteristics (Wang et al., 2019; Kuan et al., 2015) but there are few studies on the relationship between performance and usefulness. In this study, the factors affecting the usefulness evaluation as well as the effect of the usefulness on sales performance were identified.

In light of the above considerations, the hypothesis is formulated as follows.

H3: The helpfulness vote will serve as a mediating factor in the impact of the extremity of the review text on sales performance.

3. Research Methods and Data

3.1. Defining and Measuring Variables

3.2.1. Dependent Variable

A company's performance is assessed through various indicators such as sales, net profit, product sales, and brand recognition (Kapfer, 2008; Murphy et al., 1996). However, many digital markets, including Amazon, do not disclose direct information about a sellers' performance as trade secrets (Easterbrook, 1981; Glaeser, 2018). Amazon facilitates the identification of relative product sales volume by revealing sales rankings of each category, providing insights into sales.

Amazon's sales ranking algorithm is known to depend on both current and cumulative sales (Sharma et al., 2020). Consequently, many studies on Amazon's performance utilize sales ranking as a significant indicator of sales

performance (Mudambi & Schuff, 2010; Amblee & Bui, 2011). Therefore, in this study, the book category sales rankings released by Amazon sales and product review data (He & McAuley, 2016) is designated as the dependent variable.

3.2.2. Independent Variable

The independent variables in this study were defined as the extremity of the product review text. Measurement of the extremity of the product review text was conducted specifically by quantifying the mean presence of superlative adverbs and superlative adjectives in the product review text in accordance with established methodologies from prior research (Sun et al., 2017).

3.2.3. Mediator Variable

The mediating variable in this study was assessed through the evaluation of product review helpfulness. The helpfulness evaluation on Amazon's product review, featuring a voting function, was quantified as the mean percentage of respondents who voted the review helpful to the total number of voters for each product (Danescu-Niculescu-Mizil & Kossinets et al., 2009; Mudambi & Schuff, 2010).

3.2.3. Control Variables

The control variables in this study are defined as the mean and standard deviation (SD) of ratings (Dhanasobhon et al., 2007; Haque et al., 2018), price, review helpfulness vote Mean, review helpfulness yes mean, review helpfulness yes SD (Mudambi & Schuff, 2010; Kaushik et al., 2018), and review title extremity, review text mean, description words, review title mean, review title SD (Zhang et al., 2011; Kaushik et al., 2018) drawing upon prior research in the domain of product reviews.

Table 1: Technical statistics and correlations

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Review Text Extremity	.57	.47	1												
2. Review Helpfulness	.75	.16	-	1											
3. Review Rating Mean	4.15	.52	-.116	.284*	1										
4. Review Rating SD	.97	.38	.076*	-.338	-.694	1									
5. Price	9.79	7.57	.106*	.073*	.120*	-.092	1								
6. Description Words	181.65	139.9	.090*	-.037	-.074	.070*	0.00	1							
7. Review Title Mean	4.91	1.03	.344*	.026*	-.047	.031*	.159*	.084*	1						
8. Review Title SD	2.84	.93	.135*	-.047	-	.047*	.067*	.053*	.599*	1					
9. Review Title Extremity	.03	.05	.101*	-	.052*	-.038	.053*	-.040	.096*	.051*	1				
10. Review Text Mean	178.87	86.69	.688*	-	-.221	.164*	.077*	.151*	.437*	.188*	-.024	1			
11. Review Helpfulness	6.02	15.25	.184*	-.059	-.138	.162*	.135*	0.00	.163*	.041*	0.00	.223*	1		
12. Review Helpfulness Yes	4.54	4.84	.300*	.071*	-.108	.180*	.282*	-	.295*	.116*	0.02	.346*	.468*	1	
13. Review Helpfulness Yes	7.98	9.87	.215*	0.00	-.024	.155*	.232*	-	.217*	.153*	.038*	.229*	.345*	.889*	1
14. Sales Ranking	1,063,6	1,299,	-.114	-	.223*	-.086	.174*	-.055	-.028	.071*	-	-.212	-	.118*	.26

* n=8,588 (Number of products), n=300,000 (Number of product reviews), † p < .10, * p < .05, ** p < .01, *** p < .001, SD: Standard Deviation

3.2. Data

The empirical analysis in this study utilized product review data sourced from Amazon, a prominent global digital marketplace (Statista, 2021). The product review system on Amazon is structured to input ratings, summary, texts and real names. And it allows to vote the helpfulness of each review.

For this empirical study, Amazon product review data collected by He and McAuley (2016) was employed. This dataset includes information on the number of voters who assessed the helpfulness of reviews, a metric not publicly disclosed on Amazon's website these days, facilitating the computation of the helpfulness evaluation rate. The dataset spans 33 product categories, this study focuses specifically on the book category sold on Amazon since 1994.

The analysis covered 300,000 product reviews associated with 8,588 products. The subjects of this study were Amazon's product reviews, reviews, and ratings by 65,536 buyers. All product reviews are disclosed, so there are no restrictions on using them for research. The product reviews included in this study were prepared from November 20, 1996, to July 23, 2014.

It was challenging to confirm the general validity and reliability of using multiple questions by measuring each variable as a single question, but significant correlation was confirmed through correlation and regression analysis. Hypothesis verification of hypotheses such as mediating effects was performed through hierarchical multiple regression analysis.

4. Results

Hypothesis verification was conducted through regression analysis after preliminary examination of descriptive statistics and correlation analysis. The results of the analysis are presented below.

4.1. Descriptive Statistics and Correlation

Before conducting a comprehensive analysis, both descriptive statistics and correlation analysis were performed. In Table 1, the results of the correlation analysis revealed significant associations among the key variables. Review Text Extremities ($\beta = -.114$, $p = .000$) displayed a statistically significant negative correlation with Sales Ranking. However, the correlation between Review Helpfulness and Sales Ranking did not reach statistical significance.

Table 2: Multicollinearity of Variables

Variables	Collinearity statistics	
	Tolerance	VIF
Independent Variable		
Review Text Extremity	.506	1.977
Mediator Variable		
Review helpfulness	.831	1.203
Control Variables		
Review Rating Mean	.472	2.119
Review Rating SD	.467	2.142
Price	.877	1.140
Description Words	.963	1.039
Review Title Mean	.487	2.053
Review Title SD	.597	1.675
Review Title Extremity	.959	1.043
Review Text Mean	.434	2.306
Review Helpfulness Vote Mean	.748	1.338
Review Helpfulness Yes Mean	.144	6.954
Review Helpfulness Yes SD	.178	5.628

* n=7,902(Number of products), R (.490), R^2(.240), Adjusted R^2(.239), F(191.493***), Dependent Variable: Sales Ranking

Prior to conducting the comprehensive analysis, a preliminary assessment was conducted to ascertain the extent of multicollinearity among variables. The evaluation revealed that all tolerances exceeded 0.1, and the variance inflation factor (VIF) consistently remained below 8, indicating an absence of multicollinearity issues. As shown in Table 2, the assessment for multicollinearity revealed that all variables were within an acceptable range. Consequently, all variables were retained for further analysis.

4.2. Review Extremity and Helpfulness: H1

Table 3 below presents the outcomes of the analysis examining the impact of product review text extremity on the evaluation of helpfulness.

In Table 3 Model 1, which exclusively incorporated all control variables exhibited a significant association with the dependent variable, Review Helpfulness.

Model 2 in Table 3, with the inclusion of independent variables, Review Text Extremity exhibited a statistically significant negative correlation with Review Helpfulness ($\beta = -.042$, $p = .004$). Consequently, Hypotheses 1 was supported.

Table 3: Review Text Extremity and Review Helpfulness

Variables	Standardization Coefficient Beta	
	Model 1	Model 2
Independent variable		
Review Text Extremity		-.042**
Control variables		
Review Rating Mean	.122***	.122***

Variables	Standardization Coefficient Beta	
	Model 1	Model 2
Review Rating SD	-.271***	-.272***
Price	-.007	-.006
Description Words	.000	.000
Review Title Mean	.031+	.032+
Review Title SD	-052***	-.053***
Review Title Extremity	-.015	-.011
Review Text Mean	-.011	.017
Review Helpfulness Vote Mean	-.112***	-.112***
Review Helpfulness Yes Mean	.490***	.492***
Review Helpfulness Yes SD	-.342***	-.342***
R^2	.168	.169
Adjusted R^2	.167	.168
F	144.767***	133.533***

* n=7,905 (Number of products), † p < .10, * p < .05, ** p < .01, *** p < .001, Dependent Variables: Review Helpfulness

4.3. Review Helpfulness and Sales Performance: H2

Table 4 presents the findings from the analysis investigating the impact of review helpfulness on sales ranking.

Model 1 in Table 4, incorporating solely control variables, revealed a significant association between all control variables and the dependent variable, Sales Ranking.

Table 4: Review Helpfulness and Sales Ranking

Variables	Standardization Coefficient Beta	
	Model 1	Model 1
Independent variable		
Review Helpfulness		-.035**
Control variables		
Review Rating Mean	.169***	.173***
Review Rating SD	.044**	.035*
Price	.147***	.147***
Description Words	-.019+	-.019+
Review Title Mean	.007	.008
Review Title SD	.050***	.048***
Review Title Extremity	-.049***	-.050***
Review Text Mean	-.202***	-.202***
Review Helpfulness Vote Mean	.013	.009
Review Helpfulness Yes Mean	-.443***	-.426***
Review Helpfulness Yes SD	.664***	.652***
R^2	.238	.239
Adjusted R^2	.237	.238
F	224.549***	206.961***

* n=7,902 (Number of products), † p < .10, * p < .05, ** p < .01, *** p < .001, Dependent variable: Sales ranking

In Model 2, with the inclusion of additional independent variables, Review Helpfulness demonstrated a significant negative relationship with Sales Ranking (β = -.035, p = .001). Consequently, Hypothesis 2 was supported.

4.3. Mediating Effects of Helpfulness: H3

Baron and Kenny's (1986) conditions for assessing mediating effects were employed to validate the mediating role of Review Helpfulness in the influence of Review Extremity on Sales Ranking. The initial condition necessitates a significant impact of the independent variable on the mediator, while the second condition mandates a significant effect of the independent variable on the dependent variable. The third condition requires a significant effect of the mediator on the dependent variable.

Table 5: Mediating Effects of Review Helpfulness

Variables	Standardization Coefficient Beta		
	Model 1	Model 2	Model 2
Independent variable			
Review Text Extremity		-.031*	.030*
Mediator Variable			
Review Helpfulness			-.034**
Control variables			
Review Rating Mean	.169***	.169***	.173***
Review Rating SD	.044**	.045**	.036*
Price	.147***	.146***	.146***
Description Words	-.019+	-.019+	-.019+
Review Title Mean	.007	.006	.007
Review Title SD	.050***	.051***	.049***
Review Title Extremity	-.049***	-.053***	-.053***
Review Text Mean	-.202***	-.222***	-.222***
Review Helpfulness Vote Mean	.013	.012	.009
Review Helpfulness Yes Mean	-.443***	-.445***	-.428***
Review Helpfulness Yes SD	.664***	.664***	.652***
R^2	.238	.239	.240
Adjusted R^2	.237	.238	.239
F	224.549***	206.961***	191.493***

* n=7,902 (Number of products), † p < .10, * p < .05, ** p < .01, *** p < .001, Dependent variable: Sales ranking

The first condition was assessed and supported through Hypothesis 1. For the second condition, Review Text Extremity (β = .031, p = .023) in Model 2 of Table 5 was found to have a statistically significant association with Sales Ranking. Confirming the third condition by inputting all variables in Model 3, all variables were statistically significant, indicating a mediating effect. As evident in Model 2 and Model 3, Review Helpfulness exhibited a partial mediating effect, with Review Text Extremities (from .031, p = .023 → .030, p = .030) maintaining statistical significance.

Sobel-test (Sobel, 1982) results also affirmed the significance of the mediating effect of Review Helpfulness.

Table 6: The Mediating Effect of Helpfulness by Sobel-test

Independent Variables → Dependent Variables	a/(Sa)	b/(Sb)	Test statistics	p-value
Review Text Extremity → Sales Ranking	-.064/.022	-.530/.167	2.909	.0036

In Table 6, 'a' represents the non-standardized coefficient in the regression analysis of independent variables and mediator variables, with 'Sa' denoting the standard error of 'a.' Meanwhile, 'b' signifies the non-standardized coefficient of mediator variables and dependent variables in a full regression model, and 'Sb' denotes the standard error of 'b.'

4.3. Discussion

As a result of empirical research, it was observed that the evaluation of the helpfulness of product reviews was influenced by the extremity of the product review text. The extremity of the product review text was measured by employing text mining techniques to quantify the occurrence of superlative adjectives and superlative adverbs. In the text mining process, the text was tokenized into words, and the count of superlative adjectives and superlative adverbs was identified through natural language processing (NLP) based on part of speech tagging. Due to time constraints, this process utilized a subset of 300,000 reviews from the total product review data for empirical analysis.

As a result of this study, it would be prudent to place the product reviews evaluated as highly useful on the digital market front, as the useful product reviews can negatively affect sales performance. In addition, this study will provide the basis for expanding the rating-oriented purchase review research to the text mining base and provide many implications for research related to the sales performance of the digital market.

Furthermore, an analysis was conducted to examine the relationship between superlative adjectives and adverbs in the text and rating extremity. The standard deviation of rating, commonly used in previous product review studies (Mudambi & Schuff, 2010; DiMaggio et al., 1996), was selected as the measure of rating extremity. As shown in Table 1, the correlation between review text extremity and rating standard deviation has a statistically significant positive relationship.

There was a limit to the variables that could be used in the model using the previously collected big data. In addition, it is necessary to utilize other digital market reviews. Better research results could be obtained if big data suitable for the research model can be actively collected after previous research.

5. Conclusions

This study used big data analysis to analyze the impact of product review factors such as helpfulness on product sales performance that are closely related to the final stage of distribution in the digital market. To verify the impact of the helpfulness of product reviews on sales performance, this study employed part-of-speech tagging, which is a text mining technique widely used in big data analysis. The aim was to examine the influence of product review extremities on helpfulness evaluations and confirm their mediating effect on sales performance. The analysis result revealed that the product reviews evaluated as helpful could exert a negative mediating effect on sales performance.

The limitation of this study was that it could not add more factors to produce better research results because it was based on the previously collected big data. In addition, targeting only the Amazon digital market is another limitation. If sufficient resources are provided in the future, more sophisticated research could be conducted through the collection of big data based on previous studies. This study is meaningful in that it explored a new aspect of product review research based on big data.

This study is meaningful as it integrates rating-focused product review research with big data analysis methodology to identify factors affecting the sales performance of digital markets. It also offers implications suggesting that helpfulness of product reviews might lead to adverse outcomes.

This study is a study on the influence of product reviews, which is of high importance to the digital market. Although rating-oriented research has been mainly conducted, this study is differentiated in that it has attempted to incorporate text mining-based research. In addition, the fact that product reviews evaluated as useful can have a negative mediating effect on sales performance has high implications for managers in the digital market who put useful reviews at the forefront.

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