Proceedings of CONF-BPS 2026 Symposium: Innovation, Finance, and Governance for Sustainable Global Growth
DOI: 10.54254/2754-1169/2026.BJ30721

The Relationship Between Emotional Value, Utility Value, and Product Sales—An Empirical Analysis Based on Amazon Electronics Review Data

Jiaran Liu

School of Statistics and Data Science, Capital University of Economics and Business, Beijing, China
32023120075@cueb.edu.cn

Abstract. This research investigates how emotional and utility value in online reviews affect product sales. As e-commerce grows, online reviews are key for consumer decisions, with positive reviews boosting sales. Prior studies mainly cover how review sentiment or usefulness directly impacts purchase intent, but few examine the limits of review value on sales in uniform markets. Based on this, this study selects 500 electronic products from the Amazon platform as the research objects. By scraping relevant review data and employing a multiple linear regression model for systematic analysis, the study finds that, contrary to conventional wisdom, the explanatory power of emotional value and utility value on sales metrics is minimal, and the regression coefficient for emotional value is negative. This result implies that in a highly comparable electronics market concerning functionality and performance, high ratings are no longer the core driver of sales; the traditional logic of 'positive reviews drive sales' is invalid in this context. The study also suggests an urgent necessity to incorporate other potential moderating variables into an overall assessment of the impacts that reviews have on sales-variables such as product category characteristics, price, and brand. It raises questions about the effectiveness of current online rating systems in certain markets.

Keywords: Emotional Value, Utility Value, Multiple Linear Regression Analysis, E-commerce

1. Introduction

In today's rapidly developing social media landscape, people often refer to evaluations of goods or services on social media before making consumption decisions. The traditional view holds that high product ratings and high perceived utility reflected in reviews significantly and positively influence product sales. However, further verification is required to determine whether this conclusion universally applies across all market environments.

This study focuses on the electronics category on the Amazon platform. The electronics market is typically characterized by rapid technological iteration, product homogenization, and a relatively rational component in consumer decision-making. The core research question is: In this specific

DOI: 10.54254/2754-1169/2026.BJ30721

market environment, are the emotional and utility values in reviews still effective predictors of product sales? Does their influence align with traditional expectations?

To answer this question, this study obtained data for 500 Amazon electronic products from the Amazon Reviews dataset, including the average emotional value rating, a utility value score derived from text analysis, and the number of reviews (used as a proxy variable for sales). A multiple linear regression model was used to analyze the relationships between the variables quantitatively. This research can help consumers avoid purchasing useless products due to marketing hype and guide merchants' promotional strategies.

2. Literature review

Existing research on the relationship between online reviews and sales has formed a relatively mature theoretical system. Chevalier and Mayzlin [1] were the first to empirically prove that online book reviews positively influence sales. This finding has been verified later in categories such as movies [2], among others [3]. However, a systematic review by King et al. [4] posits that most of the existing research focuses on experience goods and does not adequately consider high-involvement search goods(e.g., electronics). Methodologically, with the development of text analysis techniques, researchers have begun shifting from simple rating analysis to deeper content mining, such as extracting product features from reviews [5] or estimating the economic impact of reviews [6]. Tirunillai and Tellis [7] demonstrated extracting product feature information from massive reviews using topic modeling. Goh et al. [8] distinguished the different impact mechanisms of user-generated content versus marketing content. Forman et al. [9] found that reviewer identity metadata plays a huge role in building trust and consequently influences product price and sales. Other cross-cultural studies [10] show that the effect of reviews varies significantly across cultures. Although abundant, most existing literature assumes a simple linear promotional effect of emotional value(ratings) and utility value (functional evaluation) on sales [11]. Very few have deeply explored the moderating effects under specific market environments. Therefore, this paper supplements the relative importance of utility value and electronic products as well as the boundary conditions in a highly homogenized market, where emotional and utility value is emphasized.

3. Data collection and processing

This study collected anonymized data for 500 electronic products from the Amazon platform. Each data entry includes a product ID, the average emotional value rating X_1 for all reviews of that product, a utility value score X_2 extracted via natural language processing, and the total number of reviews Y received by the product. Here, $X1$ and $X2$ both range from 1-5 points, and Y is used as a substitute for the product's total sales volume.

3.1. Analysis model

To examine the impact of the two independent variables on the dependent variable, this study established a multiple linear regression model:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\varepsilon$$

Where Y is the sales metric, X_1 is emotional value, X_2 is utility value, β_0 is the intercept, β_1 and β_2 are regression coefficients, and ε is the random error term. The study used Python's

DOI: 10.54254/2754-1169/2026.BJ30721

statsmodels library for regression analysis, with the significance level set at $\alpha=0.05$.

3.2. Data analysis and results

The regression analysis yielded surprising results. The model is summarized as follows:

Regression model: $Y = 3020.05 + -428.33 * X_1 + 8.30 * X_2$

$R^2=0.0076$ Adjusted $R^2= 0.0036$

F-test $p-value= 0.149$

Table 1. OLS regression results

Dep. Variable:		y	R-squared:		0.008
Model:		OLS	Adj. R-squared:		0.004
Method:		Least Squares	F-statistic:		1.913
Date:		Wed, 17 Sep 2025	Prob (F-statistic):		0.149
Time:		18:38:39	Log-Likelihood:		-4548.5
No. Observations:		500	AIC:		9103.
Df Residuals:		497	BIC:		9116.
Df Model:		2			
Covariance Type:		nonrobust			
	coef	std err	t	P>|t|	[0.025	0.975]
const	3020.0470	965.045	3.129	0.002	1123.977	4916.117
x1	-428.3344	396.664	-1.080	0.281	-1207.679	351.010
x2	8.2966	438.058	0.019	0.985	-852.378	868.971
Omnibus:		649.790	Durbin-Watson:		0.855
Prob(Omnibus):		0.000	Jarque-Bera (JB):		90973.270
Skew:		6.382	Prob(JB):		0.00
Kurtosis:		67.837	Cond. No.		59.2

The model $R^2=0.0076$ indicates that the two variables, emotional value and utility value, explain only 0.76% of the variation in the sales metric, demonstrating very weak explanatory power; the model is almost ineffective.

Among them, the coefficient for emotional value (X_1) is -428.33, which is negative. This implies that, controlling for utility value, a one-point increase in rating is associated with an expected decrease of approximately 428 reviews. However, $p=0.281$, far greater than 0.05, and is statistically insignificant. We cannot reject the null hypothesis that "emotional value does not affect sales."

It is particularly noteworthy that the model's intercept is statistically significant ($p=0.002$), suggesting the presence of other, more important factors driving sales.

In response to this result, the initial research hypothesis ($\beta_1 > \beta_2$) was further tested. Calculation results show that $\beta_1 - \beta_2 = -436.63$, with $p=0.7071$, meaning there is no statistical evidence supporting the notion that the influence of emotional value is greater than that of utility value.

DOI: 10.54254/2754-1169/2026.BJ30721

4. Discussion

The findings of this study contradict the conclusions of numerous previous studies, but this does not imply that this study is erroneous; instead, it reveals the context-dependent nature of online review influence.

Regarding this unexpected result, there are three conjectures. First, in the electronics market, extremely high ratings (e.g., above 4.8) may come from niche, enthusiast products with limited target markets. Conversely, due to their large user base, some moderately rated (e.g., 4.0-4.5) bestsellers are more likely to receive negative reviews, pulling down the average score, yet their absolute sales volume is huge. This leads to a weak negative correlation between ratings and sales. Second, electronic products have transparent parameters and converging functionalities, constituting a highly homogenized market. Consumers may rely more on hard indicators like brand, price, and specific specifications for decision-making [12] rather than subjective ratings thus marginalizing the emotional value of reviews. Finally using review count as a proxy for sales introduces noise as the proportion of purchasers who leave reviews is not constant and may vary by product weakening its correlation with actual sales. Furthermore reviewers are not a random sample and suffer from self-selection bias [13] which may lead to systematic errors in measuring emotional value and utility value. Additionally, the method used in this study to measure utility value, based on keyword matching, might be too simplistic to capture the complex and nuanced descriptions of utility within reviews. Future research should employ more advanced NLP models to quantify this construct more accurately.

Moreover, the findings strongly suggest that moderating variables are crucial. Price, brand awareness, marketing intensity, and product lifecycle stage may significantly moderate the relationship between review value and sales. A simple linear main effects model is insufficient to capture the complexity of the real world.

5. Conclusion

By analyzing Amazon electronics review data, this study draws the following core conclusions: First, relying solely on rating and textual utility is insufficient to predict the sales performance of electronic products effectively; their combined explanatory power for the sales proxy variable is minimal. Second, no evidence supported the hypothesis that emotional value has a greater impact on sales than utility value; instead, the data show an insignificant negative relationship.

The significance of this study lies in its methodological warning. One should avoid simplistically generalizing conclusions from specific goods like books and movies to other product categories in consumer behaviour research. For e-commerce platforms and sellers, the research results suggest that in the electronics field, investing in brand building, pricing strategies, or highlighting complex specifications might be more effective sales strategies than solely pursuing higher ratings.

This study has several limitations. The primary limitation is using review count instead of actual sales revenue as the dependent variable. Second, the measurement method for utility value is relatively rudimentary. The model also fails to consider such important control and moderating variables as price and brand. Future researchers may wish to pursue the following avenues: First, acquire actual sales data against which to check the conclusions. Second, employ more advanced NLP techniques that allow for a finer measurement of utility value-providing hints from research related to review helpfulness [14]. Third, and most importantly, variables such as price, brand strength, and product type are introduced as moderators to construct more explanatory moderated models, thereby revealing the complex relationship between online review value and sales.

DOI: 10.54254/2754-1169/2026.BJ30721

References

[1] Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345-354.

[2] Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. Journal of Marketing, 70(3), 74-89.

[3] López-López, I., & Parra, J. F. (2023). The impact of online reviews on consumer purchasing decisions: A meta-analysis of 15 years of research. Journal of Retailing and Consumer Services, 70, 103-115.

[4] King, R. A., Racherla, P., & Bush, V. D. (2014). What we know and don't know about online word-of-mouth: A review and synthesis of the literature. Journal of Interactive Marketing, 28(3), 167-183.

[5] Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. Management Science, 57(8), 1485-1509.

[6] Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. IEEE Transactions on Knowledge and Data Engineering, 23(10), 1498-1512.

[7] Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. Journal of Marketing Research, 51(4), 463-479.

[8] Goh, K. Y., Heng, C. S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user- and marketer-generated content. Information Systems Research, 24(1), 88-107.

[9] Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. Information Systems Research, 19(3), 291-313.

[10] Cheng, X., & Zhou, M. (2019). The effects of online reviews on purchase intention: A comparative study between the United States and China. International Journal of Electronic Commerce, 23(4), 454-478.

[11] Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. Journal of Retailing, 84(2), 233-242.

[12] Pavlou, P. A., & Dimoka, A. (2006). The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation. Information Systems Research, 17(4), 392-414.

[13] Li, X., & Hitt, L. M. (2008). Self-selection and information role of online product reviews. Information Systems Research, 19(4), 456-474.

[14] Baek, H., Ahn, J., & Choi, Y. (2012). Helpfulness of online consumer reviews: Readers' objectives and review cues. International Journal of Electronic Commerce, 17(2), 99-126.