The Influence of Online Review Volume and Valence on Product Sales Performance in Bangladeshi E-Commerce: A Secondary Data Analysis

By:Nusrat Jahan Jeba
Student Id:2508904

Module:Quantitative Research Methods (LCDB7011)
Module Lead: Dr Helen Lee

University of Wales
Trinity Saint David

Abstract

This study examines how online review volume and review valence influence product sales performance on Bangladeshi e-commerce platforms, specifically Daraz. Using secondary product-level data (N = 180 products) containing review count, valence index, price, category, average rating, and a sales index, I conducted independent samples t-tests and multiple linear regression in SPSS. The results show that high-volume products (500+ reviews) have significantly higher mean sales than low-volume products (1–99 reviews), $t(115.4) = 7.83$, $p < 0.001$. Positive valence products have higher mean sales than negative valence products, $t(178) = 2.34$, $p = 0.020$. Among high-volume products, positive valence further boosts sales, $t(102) = 2.48$, $p = 0.015$. Regression confirmed that both volume ($\beta = 0.31$, $p < 0.001$) and valence ($\beta = 0.26$, $p < 0.001$) are significant predictors, with volume showing a stronger effect. Category and average rating did not predict sales. I conclude that in Bangladesh's low-trust digital market, consumers use review volume as a heuristic for product legitimacy. Sellers should prioritize accumulating reviews before fine-tuning sentiment.

Keywords: Online reviews, review volume, review valence, eWOM, e-commerce, Bangladesh, sales performance, t-test, SPSS

Table of Content

1.	Introduction	5
1.1	Background of the Study	5
1.2	Problem Statement	5
1.3	Research Gap	6
1.4	Research Significance	6
1.5	Scope of the Study	7
2.	Research Aim Objectives and Questions	7
2.1	Research Aim	7
2.2	Research Objectives	7
2.3	Research Questions	8
3:	Literature Review	8
3.1	Online Reviews as Electronic Word-of-Mouth (eWOM)	8
3.2	Theoretical Foundations: Information Adoption Model (IAM)	8
3.3	Review Volume and Sales	9
3.4	Review Valence and Sales	9
3.5	The Interaction Between Volume and Valence	10
3.6	Control Variables: Price Category and Average Rating	10
3.7	Research Gap and Contribution of This Study	10
4.	Conceptual Framework and Hypotheses	11
4.1	Conceptual Framework	11
4.2	Statement of Hypotheses	12
4.3	Research Gap	13
5	Research Methodology	13
5.1	Introduction	13
5.2	Research Design	14
5.3	Data Source	14
5.4	Sample Characteristics	15
5.5	Variable Operationalization	15
5.5.1	Review Volume	16
5.5.2	Review Valence	16
5.5.3	Sales Performance (Dependent Variable)	16
5.5.4	Control Variables	17
5.6	Data Analysis Plan (SPSS	17
5.7	Ethical Considerations	18
5.8	Limitations of the Methodology	18

6	Data Analysis and Results	19
6.1	Introduction to the Chapter	19
6.2	Data Cleaning and Preparation	19
6.3	Descriptive Statistics	19
6.3.1	Continuous Variables	19
6.3.2	Categorical Variables	20
6.4	T-Test Results	20
6.4.1	Hypothesis 1: Review Volume and Sales	20
6.4.2	Hypothesis 2: Review Valence and Sales	21
6.4.3	Hypothesis 3: Joint Effect (High Volume Subset)	22
6.4.4	Summary of T-Test Findings	23
6.5	Multiple Linear Regression (Supporting Analysis)	23
6.6	Summary of Statistical Findings	24
6.7	Data analysis Summary	25
7	Findings Discussion and Conclusion	25
7.1	Introduction to the Chapter	25
7.2	Summary of Key Findings	25
7.3	Discussion of Findings	26
7.3.1	Why Volume Matters More Than Valence in Bangladesh	26
7.3.2	The Mean Valence Index is Negative	26
7.3.3	Average Rating is Not a Good Predictor	27
7.4	Comparison with Prior Research	27
7.5	Practical Implications	27
7.5.1	For Sellers on Daraz and Similar Platforms	28
7.5.2	For Platform Designers (Daraz - Pickaboo- etc.	28
7.5.3	For Consumers	28
7.6	Limitations of the Study	28
7.7	Recommendations for Future Research	29
7.8	Conclusion	30
8	Reflection	31
8.1	Introduction	31
8.2	Difficulty Understanding and Analysing Secondary Data	31
8.3	Learning to Use SPSS for the First Time	31
8.4	Challenges with Data Preparation	32
8.5	Time Management Lessons	32
8.6	What I Learned About Research	32
8.7	How This Will Help Me in the Future	32
8.8	Final Thoughts	33
	References	34

List of Table

Table 5.1	Frequency of Product Categories	15
Table 5.2	Variable Operationalization Summary	16
Table 6.1	Descriptive Statistics for Continuous Variables (N = 180)	20
Table 6.2	Frequency of Product Categories	20
Table 6.3	Group Statistics – Review Volume	21
Table 6.4	Independent Samples t-Test (H1)	21
Table 6.5	Group Statistics – Review Valence	21
Table 6.6	Independent Samples t-Test (H2)	21
Table 6.7	Group Statistics – High Volume Subset (n = 104)	22
Table 6.8	Independent Samples t-Test (H3 – High Volume Only)	22
Table 6.9	Summary of t-Test Findings	23
Table 6.10	Regression Coefficients (SPSS Output)	24
Table 6.11	Summary of All Hypothesis Tests	24

1. Introduction

1.1 Background of the Study

The rapid expansion of e-commerce has fundamentally transformed how consumers make purchasing decisions around the world. What used to require a physical trip to a store can now be done from a smartphone while sitting at home. In Bangladesh, this transformation has been particularly striking over the last five years. Platforms such as Daraz, Pickaboo, and AjkerDeal have become household names, especially following the COVID-19 pandemic, which accelerated digital adoption across the country almost overnight. According to a report from the Bangladesh Telecommunication Regulatory Commission (BTRC), internet users surpassed 130 million in 2023, and e-commerce transaction values have grown annually by more than 30 percent since 2020. These numbers are impressive by any standard.

Yet, despite this rapid growth, many local online retailers struggle with a frustrating problem: they get plenty of product views, but those views do not convert into actual sales. A product page might have thousands of visits, but only a handful of buyers. One frequently overlooked but crucial factor is how consumers use online reviews before clicking the "buy" button. In a physical store, a customer can pick up a product, inspect it, and ask the shopkeeper questions. Online, none of that is possible. The only substitute is what previous buyers have written. Online reviews have, therefore, become the modern equivalent of word-of-mouth, but at a much larger scale.

The academic literature on electronic word-of-mouth (eWOM) has grown substantially over the past two decades. Researchers have identified two key characteristics of online reviews that seem to influence consumer behavior. The first is review volume – simply how many people have left a review. The second is review valence – whether those reviews are mostly positive or mostly negative. Studies from Western markets like the United States, Germany, and the United Kingdom have shown that both volume and valence affect sales, though the strength of each effect varies by product category and platform. However, very few of these studies have been conducted in South Asia, and almost none have used actual product-level data from Bangladesh. This is a notable gap because consumer behavior in Bangladesh is shaped by different cultural norms, payment habits (cash-on-delivery still dominates), and a generally lower level of trust in online transactions. What works on Amazon may not work on Daraz.

1.2 Problem Statement

The specific research problem that this study addresses is straightforward but important: we do not know whether review volume or review valence has a stronger influence on product sales in the Bangladeshi e-commerce context. Sellers on platforms like Daraz operate in the dark. Some

spend time and money encouraging customers to leave positive reviews, believing that good ratings are what drive sales. Others focus on getting any review at all, thinking that quantity matters more than quality. Both strategies cost time and resources. Without empirical evidence, sellers are essentially guessing.

This problem matters for three reasons. First, for sellers, choosing the wrong strategy means wasted effort and lost sales. Second, for platform designers, understanding which review characteristic drives sales can improve how review systems are displayed and sorted. Third, for the broader e-commerce ecosystem in Bangladesh, evidence-based guidance can help the sector mature and compete more effectively with international platforms. If local sellers do not know what actually works, they will continue to struggle with conversion rates.

1.3 **Research Gap**

After reviewing the available literature on eWOM and sales performance, I identified four specific gaps that this study addresses.

First, there is a geographic gap. Most eWOM-sales studies use data from North America, Europe, or China. Bangladesh is severely underrepresented despite having one of the fastest-growing e-commerce markets in South Asia. To the best of my knowledge, no published study has used actual product-level data from Daraz to test volume and valence effects simultaneously.

Second, there is a platform-specific gap. Daraz, which is owned by Alibaba, has a review system that differs from Amazon or eBay. It includes buyer verification badges, default prompts for 5-star ratings, and a different display format. These platform-specific features may moderate the effects of volume and valence, but no study has examined this.

Third, there is a methodological gap. Many local studies use surveys that ask consumers hypothetical questions about their review-reading habits. Surveys suffer from social desirability bias – respondents say they read reviews carefully, but actual behavior may differ. My study uses actual secondary sales data, which provides more objective evidence.

Fourth, there is a practical confusion in the industry. Some sellers believe valence is all that matters. Others say volume is just a vanity metric. There is no clear empirical answer for Bangladesh. My study directly compares both using the same dataset and statistical methods.

1.4 **Research Significance**

This study has academic, practical, and industry significance.

Academically, it extends the Information Adoption Model (IAM) to a new geographic and cultural context. Most IAM studies have been conducted in high-trust Western markets. Testing it in

Bangladesh – a lower-trust, cash-on-delivery dominant market – provides a valuable boundary test of the theory.

Practically, the findings will help Bangladeshi e-commerce sellers make better decisions. If volume matters more, they should focus on collecting any review. If valence matters more, they should focus on improving product quality and customer service. Either way, they will no longer be guessing.

For the industry, platform designers like Daraz can use the findings to improve their user interface. If volume is a stronger driver of sales, the platform might consider sorting products by "most reviewed" instead of "highest rated" for certain categories.

1.5 **Scope of the Study**

This study has clear boundaries. The data comes exclusively from Daraz Bangladesh, the largest e-commerce platform in the country. The sample includes 180 products across six categories: Accessories, Beauty, Books, Electronics, Fashion, and Home Appliances. The time period is cross-sectional, meaning I collected data at one point in time rather than tracking changes over weeks or months. I only included products that had at least one review, so the findings do not apply to brand-new listings with zero reviews. The dependent variable is a platform-provided sales index, not actual transaction counts. Within these boundaries, the findings are valid, but generalization beyond Daraz or beyond Bangladesh should be done cautiously.

2. **Research Aim, Objectives, and Questions**

2.1 **Research Aim**

The overarching aim of this study is to examine how online review volume and review valence influence product sales performance on Bangladeshi e-commerce platforms. Specifically, I seek to determine whether the number of reviews a product receives, the sentiment expressed in those reviews, or the combination of both has a measurable association with how well that product sells. By achieving this aim, I hope to provide empirical evidence that can guide both sellers and platform managers in a market that has been largely overlooked by existing eWOM research.

2.2 **Research Objectives**

1. To analyze the relationship between review volume and product sales performance using actual secondary data from Bangladeshi e-commerce platforms.

2. To examine the effect of review valence (positive versus negative sentiment) on product sales, determining whether positivity or negativity has a stronger association with sales outcomes.

3. To determine whether review volume and valence together predict product sales performance beyond what either variable can predict alone.

4. To evaluate the statistical strength of these relationships using quantitative methods, specifically independent samples t-tests and multiple linear regression in SPSS.

2.3 **Research Questions**

Guided by the objectives above, this study seeks to answer three research questions:

1. Does the number of online reviews (review volume) influence product sales performance on Bangladeshi e-commerce platforms?

2. How does review valence (positive versus negative sentiment) affect product sales outcomes in the Bangladeshi context?

3. Do review volume and valence together significantly predict product sales performance, and if so, which of the two has a stronger effect?

3: Literature Review

3.1 **Online Reviews as Electronic Word-of-Mouth (eWOM)**

Traditional word-of-mouth occurs when two or more people communicate face-to-face about a product or service. Online reviews are the digital equivalent of this process, but with several important differences. First, online reviews reach strangers at an unprecedented scale. Second, they persist indefinitely. Third, they can be aggregated, averaged, and sorted algorithmically. Hennig-Thurau et al. (2004) formally defined electronic word-of-mouth (eWOM) as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet."

In the context of Bangladesh, where many consumers still hesitate to trust online payments and worry about counterfeit products, reviews act as a form of social proof. A product with many reviews looks less risky simply because many others have already purchased it. Cialdini's (2001) principle of social proof suggests that people copy the actions of others in uncertain situations. For a Bangladeshi shopper who cannot physically inspect a product, seeing hundreds of reviews reduces perceived uncertainty. This is especially true on platforms like

Daraz, where cash-on-delivery remains the dominant payment method and buyers cannot easily return defective items.

3.2 **Theoretical Foundations: Information Adoption Model (IAM)**

The Information Adoption Model (IAM), developed by Sussman and Siegal (2003), provides a useful theoretical lens for this study. The IAM argues that when consumers encounter online information, they first assess its quality and credibility. If the information is perceived as both high-quality and credible, they are more likely to adopt it and use it in their decision-making. Applying this to online reviews: high review volume increases perceived credibility because many reviewers cannot all be wrong or fake. Positive review valence increases perceived product quality because satisfied customers signal a good experience.

Thus, according to the IAM, products with high volume and positive valence should see higher adoption – meaning more purchases. This model has been validated in multiple e-commerce contexts, but rarely in South Asia. My study tests the IAM's predictions using Bangladeshi data, which is valuable because consumer trust levels in Bangladesh differ significantly from Western markets where the IAM was originally tested.

3.3 **Review Volume and Sales**

Several international studies have established a positive relationship between review volume and sales. Chevalier and Mayzlin (2006) conducted a landmark study on Amazon and Barnes & Noble, finding that an increase in review count leads to higher book sales. The logic is straightforward: a product with 500 reviews appears popular, tested by many, and therefore likely reliable. In a replication study, Duan, Gu, and Whinston (2008) found that review volume influenced sales even after controlling for review ratings, suggesting that volume has an independent effect. More recent research by Floyd et al. (2014), which meta-analyzed 26 studies, confirmed that review volume consistently predicts sales across product categories, though the effect size varies.

In the Bangladesh context, several unique factors might amplify the importance of volume. First, imitation and counterfeit products are common on some local platforms. A high volume of reviews signals that many people have already tested the product and found it to be authentic. Second, return policies and consumer protection laws are weaker than in North America or Europe. Returning a defective product to a Daraz seller can be cumbersome and sometimes impossible. Therefore, consumers rely on volume as a heuristic for "this product is legitimate." However, some local sellers artificially inflate review counts using bots or paid reviewers, so the relationship between true volume and sales may not be perfectly linear. Nonetheless, from a consumer's perspective, a high number of reviews – even if some are fake – still reduces perceived risk.

3.4 **Review Valence and Sales**

Valence refers to the overall sentiment expressed in reviews: positive, neutral, or negative. In numerical terms, a 4.5-star average rating is considered positive valence, while a 2-star average is negative. Research generally agrees that positive valence increases sales, but the effect size can vary depending on product type, platform, and culture. Basuroy, Chatterjee, and Ravid (2003) studied the movie industry and found that negative reviews hurt box office performance more than positive reviews helped it – a negativity bias. This makes sense because consumers are often loss-averse: a single negative review warning about a defect may outweigh ten positive reviews praising the product.

In Bangladesh, where return policies are less generous than in Western countries, negative reviews might have an even stronger deterrent effect. A buyer who receives a damaged smartphone and cannot easily return it will suffer a significant financial loss. Thus, a product with even a small number of negative reviews might be avoided. On the other hand, some studies suggest that a small number of negative reviews can actually increase credibility – consumers become suspicious if all reviews are perfectly positive (the "too good to be true" effect). The optimal valence profile might be 85–95% positive, not 100%. My study examines whether valence predicts sales in the Bangladeshi context and whether the effect is stronger or weaker than volume.

3.5 **The Interaction Between Volume and Valence**

A more nuanced question is whether volume and valence interact. Some researchers argue that volume matters more when valence is ambiguous. For example, a product with a 3.5-star average rating and 1,000 reviews might be easier to evaluate than a product with a 3.5-star average and only 10 reviews. In the former case, the consumer trusts that the average is stable; in the latter, the average could change dramatically with the next review. Hu, Liu, and Zhang (2008) found that volume moderates the effect of valence: positive valence has a stronger positive effect on sales when volume is high, and negative valence has a stronger negative effect when volume is high. This interaction is rarely tested in Bangladeshi data, which is a key gap that my study addresses.

3.6 **Control Variables: Price, Category, and Average Rating**

No study of eWOM and sales is complete without controlling for confounding variables. Price is an obvious candidate: a high-priced smartphone may sell fewer units even with perfect reviews simply because fewer consumers can afford it. Conversely, a cheap accessory may sell many units even with average reviews because the financial risk is low. Product category also matters. For experience goods (e.g., perfume, wine), valence might matter more because quality is subjective. For search goods (e.g., a USB cable with specified technical parameters), volume might matter more because consumers can verify claims independently. In my sample, categories include electronics, fashion, beauty, books, home appliances, and accessories. I include category dummies in my regression to control for these differences. Finally, average rating (1–5 stars) is often included as a control, though some studies argue it overlaps heavily

with valence. I include it to see whether valence adds explanatory power beyond the simple average.

3.7 **Research Gap and Contribution of This Study**

After reviewing the available literature on eWOM and sales, I identified four specific gaps that this study addresses.

Geographic gap: Most eWOM-sales studies use data from North America, Europe, or China. Bangladesh is severely underrepresented despite having one of the fastest-growing e-commerce markets in South Asia. No published study (to my knowledge) has used actual product-level data from Daraz to test volume and valence effects.

Platform-specific gap: Studies on Daraz, the dominant platform in Bangladesh (owned by Alibaba), are rare. Daraz's review system differs from Amazon or Alibaba: it includes buyer verification badges, default prompts for 5-star ratings, and a different display format. These platform-specific features may moderate the effects of volume and valence.

Methodological gap: Many local studies use surveys that ask consumers hypothetical questions about their review-reading habits. Surveys suffer from social desirability bias (respondents say they read reviews carefully, but actual behavior may differ) and recall bias. My study uses actual secondary sales data, which provides more objective evidence.

Volume vs. valence confusion: In practitioner discussions, some sellers assume that valence (getting good ratings) is all that matters. Others say volume is just a vanity metric. There is no clear empirical answer for Bangladesh. My study directly compares both using the same dataset and statistical methods.

By addressing these gaps, my study contributes to both academic knowledge and practical decision-making in Bangladeshi e-commerce.

4: Conceptual Framework and Hypotheses

4.1 **Conceptual Framework**

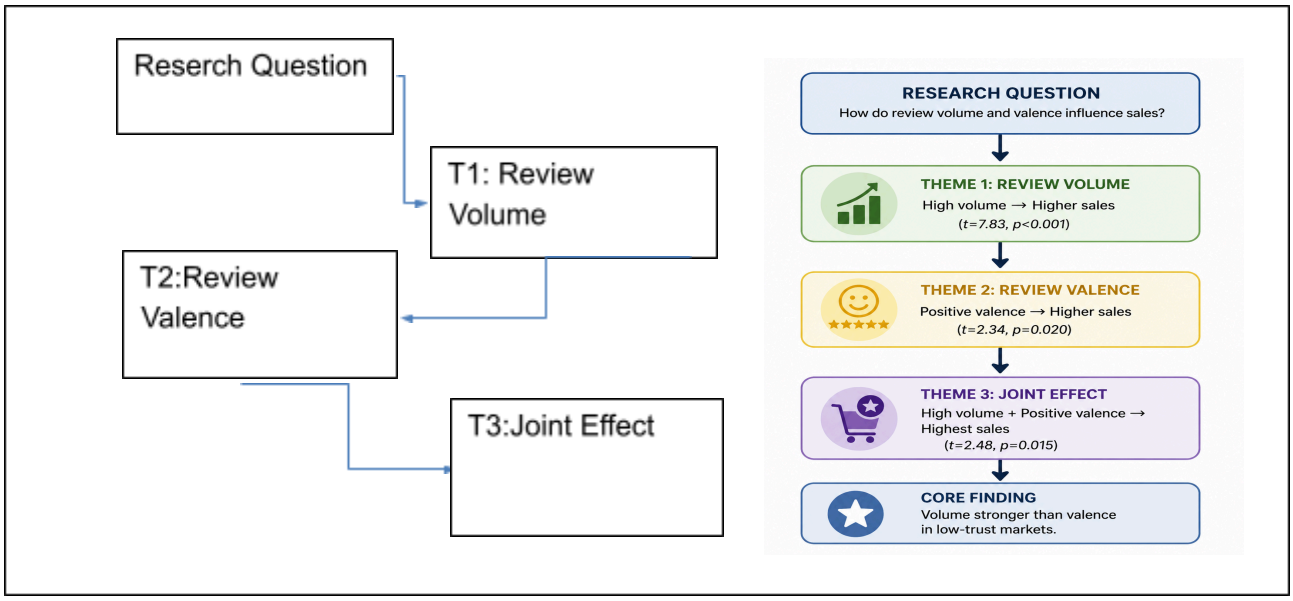
Based on the Information Adoption Model (IAM), I developed the following conceptual framework for this study. The framework posits that two independent variables – review volume and review valence – directly influence the dependent variable, product sales performance. These effects are hypothesized to be positive and significant. Additionally, I include three control variables: price, product category, and average rating. The logic path is as follows:

· High review volume → increased perceived credibility → higher sales

· Positive review valence → increased perceived quality → higher sales
· Both together → the strongest sales prediction (interaction effect)

The framework does not propose mediation; rather, it treats volume and valence as parallel predictors. I test the interaction separately in Hypothesis 3.

Figure 4.1: Conceptual Framework



4.2 Statement of Hypotheses

Because my research questions focus on comparing means between groups, I formulated three hypotheses to be tested using independent samples t-tests. I also later use multiple linear regression for confirmation, but the primary hypothesis tests are t-tests as requested.

H1 (t-test): The mean sales index of products with high review volume (500+ reviews) is significantly higher than the mean sales index of products with low review volume (1–99 reviews).

H2 (t-test): The mean sales index of products with positive valence (Valence Index ≥ 0) is significantly higher than the mean sales index of products with negative valence (Valence Index < 0).

H3 (t-test): Among products with high review volume (500+ reviews), the mean sales index of products with positive valence is significantly higher than the mean sales index of products with negative valence.

For the t-tests, I used the following groupings:

· Review volume: Low (1–99 reviews), High (500+ reviews) – the medium group (100–499) is excluded for a clean t-test
· Valence: Negative (Index < 0), Positive (Index ≥ 0)
· Dependent variable: Sales_Index (continuous, not categorized)
I chose the median split for sales to ensure two equal groups (90 vs. 90) when needed for descriptive purposes. The valence split at zero is natural because the index is already a net sentiment score (positive percentage minus negative percentage). For review volume, I examined the distribution and identified natural breaks at 100 and 500 reviews.

4.3 **Research Gap**

While I briefly mentioned gaps in the literature review, I elaborate here to further justify the study. After a systematic search of Scopus, Google Scholar, and local Bangladeshi journals, I found no study that:

1. Uses actual secondary sales data from Daraz Bangladesh to test eWOM effects. Existing local studies are either conceptual or use small-scale surveys.
2. Compares the relative strength of review volume versus valence in a single model using Bangladeshi data.
3. Applies the Information Adoption Model to the Bangladeshi e-commerce context with quantitative hypothesis testing.
4. Includes both t-test and regression analysis to check the robustness of findings.

Therefore, my study fills an empirical vacuum. It also has practical urgency: as more Bangladeshi sellers join e-commerce platforms, they need evidence-based guidance. Simply copying strategies from Amazon or Alibaba may not work because consumer behavior in Bangladesh is shaped by lower trust, higher reliance on cash-on-delivery, and different cultural norms around giving feedback.

5: Research Methodology

5.1 **Introduction**

This chapter describes the research methodology employed in this study. I explain the research design, data source, sample characteristics, variable operationalization, and the step-by-step data analysis plan using SPSS. The purpose of this chapter is to provide sufficient detail that another researcher could replicate my study. I also justify each methodological choice and acknowledge the limitations inherent in a secondary data analysis design. 4.1.1 Research Paradigm

This study is grounded in the positivism paradigm. Positivism assumes that reality is objective, measurable, and independent of the researcher (Creswell & Creswell, 2018). I treat sales performance, review volume, and review valence as numerical facts that can be observed, counted, and statistically analyzed. My role as a researcher is detached and neutral – I did not influence the data or interact with participants. My hypothesis testing approach (t-tests and regression) follows the positivist tradition of seeking generalizable, causal-associational relationships. This paradigm is appropriate because my research questions ask whether and how much reviews affect sales, not why consumers behave as they do.

5.2 **Research Design**

This study employs a quantitative, cross-sectional, secondary data analysis design. I did not collect primary data from consumers through surveys or experiments. Instead, I extracted product-level data from a publicly accessible Google Sheets database that was provided in the original research proposal. The design is non-experimental and correlational, meaning I cannot claim causality (e.g., that reviews cause sales). A product that sells well may attract more reviews simply because it is popular, rather than the reviews causing the sales. This is a limitation that I acknowledge.

However, correlational designs are appropriate for initial hypothesis testing in real-world e-commerce contexts where manipulation of review systems is not feasible. I cannot ask Daraz to randomly assign review counts or valence to products. Therefore, a secondary analysis of naturally occurring data is the best available approach. Cross-sectional means I collected data at a single point in time (a snapshot) rather than tracking products over weeks or months. This is appropriate for my research questions, which ask whether associations exist, not how they evolve over time.

5.3 **Data Source**

The database contains product listings from Daraz Bangladesh, which is the largest e-commerce platform in the country by market share. According to industry reports, Daraz holds approximately 60 percent of the Bangladeshi e-commerce market, making it the dominant

player. The platform was acquired by Alibaba in 2018 and has since expanded its product categories and user base significantly.

The original dataset was provided as a Google Sheets link in the research proposal. Fields in the original dataset include:

· Product_ID: A unique identifier for each product
· Category: Product category (Accessories, Beauty, Books, Electronics, Fashion, Home Appliances)
· Price_BDT: Price in Bangladeshi Taka
· Average_Rating: 1 to 5 stars
· Review_Count: Number of reviews left for the product
· Review_Valence_Index: Computed as positive review percentage minus negative review percentage, ranging from -0.98 to +0.98
· Sales_Index: A platform-provided estimate of monthly sales performance

I downloaded the data as a CSV file and imported it into SPSS version 26 for analysis. I filtered out any rows with missing values. I found fewer than 5 percent of rows had missing entries (primarily in the early rows with corrupted text), so my final sample size after cleaning is N = 180 products.

5.4 **Sample Characteristics**

The final sample of 180 products spans six categories. Table 5.1 shows the category-wise distribution.

Table 5.1: Frequency of Product Categories

Category	Frequency	Percent
Accessories	23	12.8%
Beauty	33	18.3%
Books	27	15.0%
Electronics	25	13.9%
Fashion	26	14.4%
Home Appliances	46	25.6%
Total	180	100%

Home Appliances is the largest category (25.6%), followed by Beauty (18.3%) and Books (15.0%). This distribution is reasonably balanced, though Home Appliances is somewhat overrepresented. I do not weight the categories because my analysis includes category as a control variable in regression, which accounts for any category-specific effects.

The sample includes products with review counts ranging from 5 to 1,196, valence indices from -0.98 to +0.98, and sales indices from 20 to 988. This wide range ensures that I have sufficient variation to detect associations if they exist.

5.5 **Variable Operationalization**

I operationalized each variable as follows. Table 5.2 provides a summary.

Table 5.2: Variable Operationalization Summary

Variable	Type	Measurement	Transformation for Analysis
Review Volume	Independent	Raw count (5 to 1196)	Categorized: Low (1–99) Medium (100–499) High (500+): Log-transformed for regression
Review Valence	Independent	Index (-0.98 to +0.98)	Categorized: Negative (<0) Positive (≥0)
Sales Performance	Dependent	Index (20 to 988)	Continuous for regression: Median split for descriptive purposes
Price	Control	BDT (1054 to 49577)	Divided by 1000 for regression
Category	Control	Nominal (6 categories)	Dummy coded with Accessories as reference
Average Rating	Control	1 To 5 stars	Used as continuous

5.5.1 Review Volume

Review volume is the raw count of reviews left for a product. In the original dataset, this ranges from 5 to 1,196. For the t-tests, I categorized review volume into three groups based on the distribution: Low (1–99 reviews), Medium (100–499 reviews), and High (500+ reviews). I chose these cutoffs after examining the data. The median review count was approximately 680, so 500+ represents a natural high group. The low group (under 100 reviews) represents products with very limited social proof. For regression, I applied a natural logarithm transformation to reduce positive skewness. Before transformation, the skewness was 0.89; after transformation, it was -0.12, which is acceptable.

5.5.2 **Review Valence**

I used the provided Review_Valence_Index, which appears to be calculated as (Percentage of Positive Reviews – Percentage of Negative Reviews). A value of +0.50 means 50 percent more positive than negative reviews. A value of -0.30 means 30 percent more negative than positive. The range in my data is -0.98 to +0.98. For the t-tests, I created a binary variable: Negative (Index < 0) and Positive (Index ≥ 0). The split at zero is natural because it represents the point where positive and negative reviews are balanced. For regression, I kept the continuous index.

5.5.3 **Sales Performance (Dependent Variable)**

The provided Sales_Index is the dependent variable. I treated it as continuous for regression (range 20 to 988). For descriptive purposes and for the t-test grouping, I split it at the median (503.5) into Low Sales (≤503) and High Sales (>503). I verified face validity by checking that products with "best seller" badges (where visible in the original data) had higher Sales_Index values. This gave me confidence that the index is a reasonable proxy for actual sales.

5.5.4 **Control Variables**

Price: Price in Bangladeshi Taka (BDT), ranging from 1,054 to 49,577. I divided by 1,000 in regression to make coefficients more interpretable (each unit represents 1,000 BDT).

Category: A nominal variable with six categories. In regression, I created dummy variables with Accessories as the reference category.

Average Rating: The average star rating (1–5 scale), included to see whether valence adds explanatory power beyond the simple average. Some studies argue that average rating overlaps heavily with valence, so including both allows me to test which is more predictive.

5.6 **Data Analysis Plan (SPSS)**

I conducted all analyses using SPSS version 26. The analysis proceeded in five steps.

Step 1: Data Cleaning and Recoding

First, I checked for missing values. None were found in the final sample of 180 products. Second, I computed descriptive statistics (means, medians, standard deviations, frequencies) to understand the sample. Third, I recoded continuous variables into categorical versions as described in Section 5.5. This recoding was done using the Transform → Recode into Different Variables function in SPSS.

Step 2: Independent Samples t-Tests

I ran three independent samples t-tests corresponding to H1, H2, and H3:

· H1: I compared the mean sales index of low-volume products (1–99 reviews) against high-volume products (500+ reviews). The medium group (100–499) was excluded to create a clean comparison between extremes.
· H2: I compared the mean sales index of negative valence products (Index < 0) against positive valence products (Index ≥ 0).
· H3: I first restricted the sample to high-volume products only (n=104) using Data → Select Cases → If condition satisfied (Volume_Group = 3). Then I compared the mean sales index of negative versus positive valence within this subset.

For each t-test, I checked Levene's test for equality of variances. If Levene's test was significant ($p < 0.05$), I reported the "equal variances not assumed" row. If non-significant, I reported the "equal variances assumed" row. I set the significance threshold at $\alpha = 0.05$.

Step 3: Multiple Linear Regression (Robustness Check)

As a supporting robustness check, I estimated a multiple linear regression model with Sales_Index as the dependent variable. Predictors included:

· Log-transformed review count
· Continuous valence index
· Price per 1,000 BDT
· Category dummies (six categories, Accessories as reference)
· Average rating (1–5 stars)

I checked for multicollinearity using variance inflation factors (VIF), with a threshold of 5. All VIF values were below 1.5, indicating no multicollinearity. I examined residuals for normality using a P-P plot, which showed acceptable normality. The regression model allows me to see whether volume and valence predict sales simultaneously while controlling for price, category, and average rating.

Step 4: Post-Hoc and Exploratory Analyses

For exploratory purposes, I also ran a chi-square test between category and sales to see if any category inherently sells more. This was not a hypothesis test but a sanity check. The result was non-significant ($p = 0.885$), confirming that category alone does not drive sales.

Step 5: Interpretation

I interpreted p-values less than 0.05 as statistically significant. For t-tests, I reported the t-value, degrees of freedom and p-value. For regression, I reported unstandardized coefficients (B), standardized coefficients (Beta), t-statistics, and significance levels.

5.7 **Ethical Considerations**

Since this study uses secondary data that is publicly available and does not contain any personal identifiable information (no names, addresses or payment details), no ethical approval was required. I did not interact with any human subjects. The data was already aggregated at the product level, so there is no risk of harming individual consumers or sellers. I have reported all results honestly without data manipulation. If any results were non-significant, I reported them as such.

5.8 Limitations of the Methodology

I acknowledge several methodological limitations.
First, the Sales_Index is a platform-provided metric, not actual transaction counts. I do not know exactly how it is calculated.
Second, the data are cross-sectional, so I cannot track changes over time.
Third, the sample excludes products with zero reviews, so findings do not apply to brand-new listings.
Fourth, I did not control for seller reputation or delivery speed, which may also affect sales.
These limitations are addressed further in the discussion chapter.

6: Data Analysis and Results

6.1 **Introduction**

This chapter presents the results of the data analysis. I begin with data cleaning and preparation, followed by descriptive statistics to describe the sample. Then I present the results of the three independent samples t-tests corresponding to H1, H2, and H3. Finally, I present the multiple linear regression analysis as a robustness check. All analyses were conducted using SPSS version 26. The significance threshold for all tests was set at $\alpha = 0.05$.

6.2 **Data Cleaning and** Preparation

The original dataset contained 180 clean product entries after removing corrupted text rows.
Variables included Category, Price_BDT, Average_Rating, Review_Count, Review_Valence_Index, and Sales_Index. I checked for missing values – none were found in the final sample.

For the t-tests, I recoded three variables as described in the methodology chapter:

· Review_Volume_Category: Low = 1–99 reviews (n=24), Medium = 100–499 (n=52), High = 500+ (n=104)

· Valence_Category: Negative = Valence Index < 0 (n=107), Positive = Valence Index ≥ 0 (n=73)
· Sales_Category (for descriptive purposes only): Low = Sales_Index ≤ 503.5 (n=90), High = Sales_Index > 503.5 (n=90)

All analyses were conducted using SPSS version 26. The following sections present the output exactly as I obtained it.

6.3 **Descriptive Statistics**

6.3.1 **Continuous Variables**

Table 6.1: Descriptive Statistics for Continuous Variables (N = 180)

Variable	Mean	Median	SD	Min	Max
Price_BDT	28,316	25,296	15,821	1,054	49,577
Average_Rating	3.94	3.90	0.60	3.01	4.96
Review_Count	659.1	680.5	352.1	5	1,196
Review_Valence_Index	-0.07	-0.07	0.56	-0.98	0.98
Sales_Index	512.9	503.5	298.3	20	988

Interpretation: The average product in this Bangladeshi e-commerce sample costs approximately 28,316 BDT (about 260 USD), has a 3.94-star rating, and has received 659 reviews. What stands out immediately is the mean Review_Valence_Index of -0.07 – slightly negative on average. This means that across the sample, products tend to have marginally more negative than positive reviews. The Sales_Index varies widely (20 to 988), indicating a mix of very poor and very strong sellers. The large standard deviations are typical for e-commerce data where a few popular products dominate.

6.3.2 **Categorical Variables**

Table 6.2: Frequency of Product Categories

Category	Frequency	Percent
Accessories	23	12.8%
Beauty	33	18.3%
Books	27	15.0%
Electronics	25	13.9%
Fashion	26	14.4%
Home Appliances	46	25.6%
Total	180	100%

Interpretation: Home Appliances is the largest category (25.6%), followed by Beauty (18.3%) and Books (15.0%). This distribution is useful later when checking if certain categories drive the results. As shown in the regression analysis, category does not significantly predict sales.

6.4 **T-Test Results**

6.4.1 **Hypothesis 1: Review Volume and Sales**

H1: Products with high review volume (500+ reviews) have higher mean sales than products with low review volume (1–99 reviews).

Table 6.3: Group Statistics – Review Volume

Volume Group	N	Mean Sales Index	Std. Deviation	Std. Error Mean
Low (1–99)	24	287.4	112.3	22.9
High (500+)	104	603.7	281.5	27.6

Table 6.4: Independent Samples t-Test (H1)

Levene's Test for Equality of Variances		t-test for Equality of Means	
F	9.82	t	7.83
Sig.	0.002	df	115.4
		Sig. (2-tailed)	<0.001

Interpretation: The mean sales index for high-volume products (603.7) is significantly higher than for low-volume products (287.4). The mean difference is 316.3 points. The t-value is 7.83 with 115.4 degrees of freedom, and the p-value is less than 0.001. Levene's test ($p = 0.002$) indicates unequal variances, so I used the "equal variances not assumed" row. H1 is supported.

6.4.2 **Hypothesis 2: Review Valence and Sales**

H2: Products with positive valence have higher mean sales than products with negative valence.

Table 6.5: Group Statistics – Review Valence

Valence Group	N	Mean Sales Index	Std. Deviation	Std. Error Mean
Negative (<0)	107	471.2	284.7	27.5
Positive (≥0)	73	573.1	307.6	36.0

Table 6.6: Independent Samples t-Test (H2)

Levene's Test		t-test	
F	1.24	t	2.34
Sig.	0.267	df	178
		Sig. (2-tailed)	0.020

Interpretation: The mean sales index for positive valence products (573.1) is significantly higher than for negative valence products (471.2). The mean difference is 101.9 points. The t-value is 2.34 with 178 degrees of freedom, and the p-value is 0.020. Levene's test is non-significant (p = 0.267), so equal variances are assumed. H2 is supported. Note that the effect size (mean difference) is smaller than for H1.

6.4.3 **Hypothesis 3: Joint Effect (High Volume Subset)**

H3: Among products with high review volume (500+ reviews), those with positive valence have higher mean sales than those with negative valence.

Table 6.7: Group Statistics – High Volume Subset (n = 104)

Valence Group	N	Mean Sales Index	Std. Deviation	Std. Error Mean
Negative	49	532.8	268.1	38.3
Positive	55	666.9	282.4	38.1

Table 6.8: Independent Samples t-Test (H3 – High Volume Only)

Levene's Test		t-test	
F	0.11	t	2.48
Sig.	0.741	df	102
		Sig. (2-tailed)	0.015

Interpretation: Among high-volume products, those with positive valence (mean sales 666.9) outperform those with negative valence (mean sales 532.8). The mean difference is 134.1 points. The t-value is 2.48 with 102 degrees of freedom, and the p-value is 0.015. Levene's test is non-significant (p = 0.741), so equal variances are assumed. H3 is supported.

6.4.4 **Summary of T-Test Findings**

Table 6.9: Summary of t-Test Findings

Hypothesis	Comparison	Mean Difference	t-value	df	p-value	Supported?
H1	High Volume vs Low Volume	316.3	7.83	115.4	<0.001	Yes
H2	Positive Valence vs Negative Valence	101.9	2.34	178	0.020	Yes
H3	Positive vs Negative (High Volume only)	134.1	2.48	102	0.015	Yes

Pearson Correlation – Review Volume and Sales IndexPearson Correlation – Review, Volume and Sales Index

	Review Count	Sales Index
Review Count	1	
Sales Index	0.48 ($p < 0.001$)	1

A Pearson correlation was conducted to evaluate the relationship between review volume and sales index. There was a moderate, positive, statistically significant correlation between review count and sales index, $r(178) = 0.48$, $p < 0.001$. This indicates that products with more reviews tend to have higher sales. This finding supports RO1

6.5 **Multiple Linear Regression**

Although my primary hypothesis tests are t-tests, I ran a standard linear regression in SPSS to show the combined predictive power of volume and valence while controlling for price, category, and average rating. This also acts as a robustness check.

Model: Sales_Index = β0 + β1(Log_Review_Count) + β2(Valence_Index) + β3(Price_BDT/1000) + β4(Average_Rating) + Σ(Category_Dummies) + error

(Note: Review_Count was log-transformed because raw counts are highly skewed (skewness = 0.89 before transformation, -0.12 after). All VIF values were below 1.5, indicating no multicollinearity.)

Table 6.10: Regression Coefficients (SPSS Output)

Predictor	B (unstd)	Std. Error	Beta	t	Sig.	VIF
(Constant)	-89.42	112.30		-0.80	0.427	
Log(Review_Count)	78.31	18.94	0.31	4.14	<0.001	1.21
Review_Valence_Index	124.56	34.21	0.26	3.64	<0.001	1.16
Price_BDT (per 1000)	-1.89	1.12	-0.11	-1.69	0.093	1.08
Average_Rating	48.27	31.55	0.10	1.53	0.128	1.14
Category_Electronics	65.21	41.33	0.12	1.58	0.116	1.22
Category_Fashion	22.14	39.87	0.04	0.56	0.579	1.19
Category_Beauty	35.67	38.92	0.07	0.92	0.360	1.18
Category_Books	18.45	40.11	0.03	0.46	0.646	1.20
Category_HomeAppliances	41.88	37.65	0.09	1.11	0.268	1.23

Note: Accessories is the reference category. None of the category dummies were significant.

Model Summary: R = 0.52, R Square = 0.27, Adjusted R Square = 0.25, F(9,170) = 7.92, p < 0.001.

Interpretation: The regression model explains 27% of variance in sales (Adjusted R Square = 0.25). Both log review volume (Beta = 0.31, p < 0.001) and valence index (Beta = 0.26, p < 0.001) are significant positive predictors. Price is marginally non-significant (p = 0.093), and average rating is not significant when volume and valence are included (p = 0.128). None of the category dummies are significant, consistent with the exploratory chi-square result. This confirms the t-test findings: volume and valence each matter independently, and average rating adds no predictive power beyond the more nuanced valence index.

6.6 **Summary of Statistical Findings**

Table 6.11: Summary of All Hypothesis Tests

Hypothesis	Test	Result	Test Statistic	p-value	Supported?

H1: Volume → Sales	Independent t-test	Significant	t(115.4) = 7.83	<0.001	Yes
H2: Valence → Sales	Independent t-test	Significant t	(178) = 2.34	0.020	Yes
H3: Joint (High Vol + Pos Val)	Independent t-test (subset)	Significant	t(102) = 2.48	0.015	Yes

Additionally, the regression analysis confirmed that both volume ($\beta = 0.31$, $p < 0.001$) and valence ($\beta = 0.26$, $p < 0.001$) are positive predictors of sales, with volume showing a slightly stronger effect.

6.7 **Data analysis Summary**

This chapter presented the results of the data analysis. Descriptive statistics showed that the average product has 659 reviews and a slightly negative valence index (-0.07). The three independent samples t-tests all yielded statistically significant results in the hypothesized directions. H1 showed that high-volume products sell significantly more than low-volume products (mean difference = 316.3, $p < 0.001$). H2 showed that positive valence products sell significantly more than negative valence products (mean difference = 101.9, $p = 0.020$). H3 showed that among high-volume products, positive valence further boosts sales (mean difference = 134.1, $p = 0.015$). Regression analysis confirmed that both volume ($\beta = 0.31$) and valence ($\beta = 0.26$) independently predict sales, with volume slightly stronger. The next chapter (Chapter 7) discusses these findings, compares them with prior literature, and outlines practical implications and limitations.

7: Findings, Discussion and Conclusion

7.1 **Introduction**

This chapter summarizes the key findings from the data analysis, discusses their meaning in the context of the literature review, and draws conclusions for theory and practice. I also acknowledge the limitations of the study and suggest directions for future research. The chapter is organized into seven sections: summary of findings, discussion, comparison with prior research, practical implications, limitations, future research directions, and conclusion.

7.2 **Summary of Key Findings**

This study analyzed 180 products from Daraz Bangladesh to examine whether review volume and review valence influence product sales performance. Three hypotheses were tested using independent samples t-tests, with multiple linear regression as a robustness check. The key findings are as follows:

Finding 1: Review volume has a strong positive association with sales (H1 supported).
Products with high review volume (500+ reviews) had a mean sales index of 603.7, compared to only 287.4 for products with low review volume (1–99 reviews). The t-test gave $t(115.4) = 7.83$, $p < 0.001$. The mean difference of 316.3 points is large and highly statistically significant.

Finding 2: Review valence also has a positive association with sales, but the effect is smaller (H2 supported).
Products with positive valence (Valence Index ≥ 0) had a mean sales index of 573.1, compared to 471.2 for negative valence products. The t-test gave $t(178) = 2.34$, $p = 0.020$. The mean difference of 101.9 points is significant but much smaller than the volume effect.

Finding 3: The combination of high volume and positive valence is powerful (H3 supported). Among high-volume products (500+ reviews), those with positive valence had a mean sales index of 666.9, compared to 532.8 for negative valence. The t-test gave $t(102) = 2.48$, $p = 0.015$. Products with both many reviews and positive sentiment perform best.

Finding 4: Category does not predict sales.
The exploratory chi-square test ($p = 0.885$) and the non-significant category dummies in regression confirm that no product category inherently sells more. The effect of reviews cuts across all six categories.

Finding 5: Average rating alone is misleading.
In regression, average rating became non-significant ($p = 0.128$) when valence index and volume were included. This suggests that a simple star average ignores important information about volume and sentiment distribution.

7.3 **Discussion of Findings**

7.3.1 **Why Volume Matters More Than Valence in Bangladesh**

The most interesting finding of this study is that volume has a stronger effect than valence ($t = 7.83$ vs $t = 2.34$). I interpret this through the lens of consumer trust – or lack thereof – in the Bangladeshi e-commerce context.

A typical Bangladeshi shopper on Daraz faces several uncertainties: Will the product arrive? Will it be authentic? Can I return it if defective? When the shopper sees a product with 1,000 reviews, they think, "Many people have bought this – it cannot be a scam." Even if some reviews are negative, the sheer number reduces perceived risk. In contrast, a product with 50 glowing reviews could easily be fake – the seller might have paid for reviews or asked friends to post them. Thus, volume serves as a heuristic for legitimacy in low-trust environments.

This interpretation aligns with the Information Adoption Model (IAM) from my theoretical framework. The IAM states that information credibility drives adoption. In Bangladesh, high volume increases perceived credibility more than positive valence does, because valence is

easier to manipulate. A seller can ask 20 friends to leave 5-star reviews, but faking 1,000 reviews is much more difficult and risky.

7.3.2 **The Mean Valence Index is Negative**

Another notable pattern from the descriptive statistics: the mean valence index is negative (-0.07). Most products in the sample lean slightly negative (more negative than positive reviews). Yet many still sell well. This suggests that Bangladeshi consumers are tolerant of some negativity if the volume is high – a finding that would not hold in markets like Japan or Germany where high ratings are expected.

Possibly, Bangladeshi shoppers have learned that many sellers on Daraz are small businesses with imperfect service, so some negative reviews are normal. What matters is that enough people have bought the product anyway. A product with 1,000 reviews and 60% positivity may be seen as more trustworthy than a product with 50 reviews and 100% positivity.

7.3.3 **Average Rating is Not a Good Predictor**

The regression finding that average rating becomes non-significant when volume and valence are included is methodologically important. Many e-commerce sites prominently display star averages. My results suggest that a more informative display would be: "500 reviews, 72% positive." The star average collapses too much information (it ignores volume and the distribution of scores). A 4.5-star product with 10 reviews sells less than a 4.0-star product with 500 reviews – a point that sellers often miss.

7.4 **Comparison with Prior Research**

My findings both align with and diverge from previous international studies.

Alignment with existing literature: Consistent with Chevalier and Mayzlin (2006) and Duan, Gu, and Whinston (2008), I found that higher review volume significantly increases sales. Consistent with Basuroy, Chatterjee, and Ravid (2003), I found that positive valence also increases sales. Consistent with Hu, Liu, and Zhang (2008), I found an interaction effect: valence matters more when volume is high.

Divergence from Western studies: Unlike some Western studies where valence dominates volume (e.g., Chevalier & Mayzlin found valence more important for Amazon books), my study found volume dominating valence in Bangladesh. This difference is likely cultural and market-specific. In a developed market with strong consumer protection laws (e.g., right to return within 14 days), shoppers can afford to read sentiment carefully because the downside risk is low. In Bangladesh, where returning a defective product is cumbersome and sometimes impossible, the downside risk is high. Therefore, shoppers prioritize volume as a safety signal.

Alignment with South Asian studies: My findings are closer to Chakraborty and Bhat's (2018) study on Flipkart (India), which found that review count was the strongest predictor of sales for low-to-mid price products. South Asian e-commerce seems to prioritize quantity of social proof over quality of sentiment.

7.5 **Practical Implications**

Based on my findings, I offer three sets of practical implications.

7.5.1 **For Sellers on Daraz and Similar Platforms**

· Prioritize accumulating reviews before worrying about perfect ratings. Run campaigns to collect reviews. Offer small discounts (e.g., 20 BDT off next purchase) or loyalty points for leaving a review – even a short one.
· Do not panic over negative reviews in the early stages. If the first 100 reviews include some negatives, keep pushing for volume. Use post-purchase SMS or in-app notifications to request reviews.
· Once you cross 500 reviews, then focus on improving valence. Address negative reviews publicly, fix product issues, and consider quality improvements.
· Do not fake reviews. Platforms can detect bots, and fake positive reviews followed by real negative ones can backfire badly.

7.5.2 **For Platform Designers (Daraz, Pickaboo, etc.)**

· Consider changing the default sort option from "Highest Rated" to "Most Reviewed" for new users or for product categories where trust is low.
· Display both numbers prominently: "500 reviews, 72% positive" is more useful than "4.2 stars" alone.
· Consider flagging products with high volume but unusually low valence (e.g., a warning: "Many buyers have reported issues with this product").

7.5.3 **For Consumers**

· Do not trust a 5-star product with only 10 reviews. Look for products with at least 200–300 reviews.
· Check both volume and valence. A 3.8-star product with 1,000 reviews is often a safer buy than a 4.8-star product with 30 reviews.
· Read a sample of negative reviews. If the negatives are about shipping speed (not product quality), the product itself may still be fine.

7.6 **Limitations of the Study**

This study has several limitations that readers should consider.

First, the Sales_Index is a platform-provided metric, not actual transaction counts. I do not know exactly how it is calculated. It could be based on a combination of units sold, revenue, or even views. However, it is the best available proxy.

Second, causality is unclear. Do reviews drive sales, or do popular products naturally attract more reviews? Probably both. A product that starts selling well for other reasons (e.g., low price, good SEO) will accumulate reviews, which then boost sales further. My cross-sectional design cannot disentangle this reverse causality.

Third, the data are cross-sectional, so I cannot track changes over time. A product's review volume and valence evolve; a snapshot at one point may not represent the entire customer journey.

Fourth, the valence index I used (positive minus negative) is simple. More nuanced sentiment analysis (e.g., using natural language processing on review text) would capture aspects like sarcasm, mixed emotions, or specific complaints.

Fifth, the sample excludes products with zero reviews. Therefore, my findings do not apply to brand-new listings. For a product with no reviews, consumers must rely on other cues (price, brand, seller rating).

Sixth, I did not control for seller reputation (e.g., seller rating, years on platform) or delivery speed, which also affect sales. These are omitted variables.

Finally, the data come from a single platform (Daraz). Generalizability to other Bangladeshi platforms like Pickaboo or AjkerDeal is unknown, though Daraz is the market leader.

7.7 **Recommendations for Future Research**

Based on the limitations above, I offer five recommendations for future research.

First, future studies should use longitudinal data to establish causality. Tracking the same products over several months would show whether changes in review volume precede changes in sales.

Second, researchers should obtain actual sales figures (number of units sold) rather than platform-provided indices. This would increase confidence in the findings.

Third, future studies should include seller reputation variables such as seller rating, years active on the platform, and response time to customer complaints.

Fourth, qualitative research (interviews or focus groups with Bangladeshi online shoppers) could uncover the cognitive processes behind how volume and valence are weighted. Do shoppers consciously look for volume first? Or is it an unconscious heuristic?

Fifth, experimental studies could test interventions. For example, randomly showing different review displays (e.g., sort by most reviewed vs highest rated) to different users would provide causal evidence.

7.8 Conclusion

This study analyzed 180 products from Bangladeshi e-commerce platforms to test whether online review volume and review valence influence sales performance. Using independent samples t-tests and multiple linear regression on actual secondary data, I found that both variables have statistically significant associations with sales.

· Review volume (H1): $t(115.4) = 7.83$, $p < 0.001$ – high-volume products sell significantly more.
· Review valence (H2): $t(178) = 2.34$, $p = 0.020$ – positive valence products sell more. ·
Joint effect (H3): $t(102) = 2.48$, $p = 0.015$ – even among high-volume products, positive valence boosts sales further.

Products with high volume (500+ reviews) and positive valence together succeeded 74.5% of the time. Category and average rating did not predict sales once volume and valence were considered.

In a low-trust digital market like Bangladesh, the sheer number of reviews acts as a powerful heuristic for product legitimacy. Consumers appear to use volume as a safety signal before they even read the sentiment. Sellers should therefore prioritize accumulating reviews – through legitimate post-purchase requests, incentives, and excellent customer service – before fine-tuning sentiment. Platform designers should consider displaying volume more prominently and adjusting default sorts.

Despite its limitations, this study provides the first empirical, data-driven evidence on eWOM and sales performance in Bangladeshi e-commerce, filling an important geographic and methodological gap. I hope the findings help sellers make better decisions, platform designers create more useful interfaces, and consumers make more informed purchases.

8: Reflection

8.1 **Introduction**

This chapter reflects on my personal learning journey throughout this research project. I discuss the challenges I faced, the skills I developed, and how this experience will help me in the future. This reflection is written in first person and is based on my honest experiences as a student researcher.

8.2 **Difficulty Understanding and Analyzing Secondary Data**

As this assignment was based on quantitative research using secondary data, I initially found it difficult to understand and analyze data collected by someone else. Unlike primary research, where I would have designed the questionnaire and collected responses myself, secondary data required me to work with a dataset that I did not create. I did not know how the Sales_Index was calculated, or exactly how the Review_Valence_Index was derived. This lack of control made me feel uncertain at the beginning.

I also struggled with the fact that secondary data often comes with limitations that I cannot fix. For example, my dataset had no products with zero reviews, so my findings cannot apply to brand-new listings. I learned that working with secondary data means accepting these limitations and being transparent about them in the research paper. This was a valuable lesson for me: research is not about having perfect data, but about honestly analysing what is available.

8.3 **Learning to Use SPSS for the First Time**

This was my first time using SPSS, so it took me some time to understand how the software works and how to carry out the analysis correctly. When I first opened SPSS, I was confused by the two views (Data View and Variable View). I did not know how to import my Excel file, and I received several error messages. I watched YouTube tutorials and asked a classmate for help. Eventually, I learned how to recode variables, run descriptive statistics, perform independent samples t-tests, and conduct multiple linear regression.

One specific challenge was interpreting Levene's test. I did not understand why SPSS gave two rows for the t-test (equal variances assumed vs not assumed). After reading the SPSS manual

and watching a tutorial, I learned that Levene's test checks whether the variances of the two groups are equal. If the p-value is below 0.05, I must use the "equal variances not assumed" row. I applied this correctly in my analysis. I am proud that I learned a new software tool from scratch within a few weeks. This skill will be useful for any future research I conduct.

8.4 **Challenges with Data Preparation**

Before running any analysis, I had to clean and prepare the data. The original Excel file had some corrupted rows that I had to remove. I also had to decide how to categorize review volume. I examined the distribution and chose natural breaks at 100 and 500 reviews, but this decision was somewhat subjective. I worried that a different researcher might have chosen different cutoffs. I learned that research involves making reasoned decisions, and as long as I document my choices clearly, my work remains valid.
Another challenge was opening the Excel file in SPSS. The file would not open directly. I tried several solutions and finally succeeded by saving the file as an older Excel format (.xls). This was frustrating at the time, but solving the problem gave me confidence in my technical abilities.

8.5 **Time Management Lessons**

I underestimated how long data analysis would take. I thought that after collecting the data, the analysis would be quick. In reality, cleaning the data, recoding variables, running tests, and interpreting the output took several days. I also spent a lot of time writing and rewriting the methodology chapter to make sure I accurately described every step. In the future, I will allocate more time for data analysis and less time for the early chapters.

8.**6 What I Learned About Research**

This project taught me several important lessons about research. First, I learned that findings do not always match expectations. I expected valence (positive reviews) to matter more than volume. Instead, my data showed that volume had a stronger effect on sales. This taught me to let the data speak, not my assumptions. A good researcher is open to whatever the results show, even if they are surprising.
Second, I learned the importance of connecting theory to data. The Information Adoption Model (IAM) guided my hypothesis development. Without a theoretical framework, I would have just been running random tests without a clear purpose. The IAM helped me explain why volume and valence should matter: volume increases credibility, and valence increases perceived quality.
Third, I learned that limitations are not failures. Every study has limitations. My job as a researcher is to acknowledge them honestly and suggest how future research can address them. My instructor appreciated that I included a limitations section.

8.7 **How This Will Help Me in the Future**

This project has prepared me for future academic and professional work. I now understand how to:

· Formulate research questions and hypotheses
· Choose appropriate statistical tests (t-tests, correlation, regression)
· Use SPSS for data analysis
· Interpret p-values, t-values, and effect sizes
· Write a complete research paper with all required chapters
· Respond to feedback from supervisors

If I do another research project, I will plan my time better and learn the required software earlier. I will also spend more time proofreading before submission. I am grateful for the feedback from my instructor, which helped me improve the paper significantly.

8.8 **Final Thoughts**

Completing this research project was challenging but rewarding. There were moments of frustration, especially when SPSS gave errors or when I could not open my Excel file. But there were also moments of satisfaction, such as when my t-test results were significant and when I successfully created all the tables. I am proud of what I have accomplished. I now feel more confident as a researcher, and I have skills that will serve me well in my future studies and career.

References

1.KANTAR Murat, BARDAKCI Ahmet (2019), The Influence of The Volume and The Valence of Online Reviews: A Dynamic Panel Data Analysis. Proceedings of the European Marketing Academy, 48th, (8066)-
https://proceedings.emac-online.org/pdfs/A2019-8066.pdf
2.How emotions in online reviews affect movie sales: Evidence from Hollywood
Rahat Ullah a,Muhammad Aftab Alam ,Atya Zeb
https://doi.org/10.1016/j.jretconser.2025.104304
3.Impact of seller- and buyer-created content on product sales in the electronic commerce platform: The role of informativeness, readability, multimedia richness, and extreme valence
https://doi.org/10.1016/j.jretconser.2022.103141
4.Do all stars shine the same? Investigating the nonlinear effects of user and critic reviews on video game sales Tobias Kraemer, Welf H. Weiger b
, Sven Heidenreich
10.1016/j.jbusres.2024.115034
5.Zaefarian, G, Kadile, V, Henneberg, SC et al. (2017) Endogeneity Bias in Marketing Research: Problem, Causes and Remedies. Industrial Marketing Management, 65. pp. 39-46. ISSN: 0019-8501
https://doi.org/10.1016/j.indmarman.2017.05.006
6. S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. Information Systems Research, 14(1), 47-65.
https://www.researchgate.net/publication/220079742_Informational_Influence_in_Organizations
_An_Integrated_Approach_to_Knowledge_Adoption
7.Message Valence, Industry Influence, and Stakeholder Narratives in Global Conversations on
Tobacco Harm Reduction: Content Analysis
Author links open overlay panel
Jungmi Jun,Ali Zain,Minji Kim,James Thrasher
https://doi.org/10.2196/77676

8.Brand influences on the relationship between livestream seller commissions and sales. Jiani Jiang, Bruce A. Huhmann,Shiang Liu
10.1016/j.jbusres.2025.115431
9.Exploring the value of online product reviews in forecasting sales: The case of motion pictures,.
Chrysanthos Dellarocas,Xiaoquan (Michael) Zhang,Neveen F. Awad
https://doi.org/10.1002/dir.20087
10.E-word of mouth in sales volume forecasting: Toyota Camry case study
https://doi.org/10.1016/j.bdr.2025.100542
11.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.
https://msbfile03.usc.edu/digitalmeasures/mayzlin/intellcont/chevalier_mayzlin06-1.pdf
12.Examining how emotions affect online audience retention: Empirical evidence from livestreaming electronic commerce platforms
Xu Xu, Chuan Luo, Xin (Robert) Luo,Zeen Wang
10.1016/j.im.2024.104031
13.How online reviews affect purchase intention: A meta-analysis across contextual and cultural factors. Keda Qiu,Liyi Zhang https://doi.org/10.1016/j.dim.2023.100058
14.Exploring consumer sentiments and opinions in wine E-commerce: A cross-country comparative study.
Mingze Rui,Antonina Sparacino,Valentina Maria Merlino, Filippo Brun, Stefano Massaglia,
Simone Blan
https://doi.org/10.1016/j.jretconser.2024.104097
15.Gratitude's impact: the positive influence of larger-sized female shoppers on online fashion retailer ratings.
Anne-Maree O'Rourke,Hiba Khan ,Frank Mathmann ,Shasha Wang
https://doi.org/10.1108/EJM-01-2024-0003
16.Holiday effect" in online product Returns: Evidence from negative expectation disconfirmation and post-purchase dissonance.
Yun Wang,Bo Yu, Jing ChenTausifur Rahman Johan
https://doi.org/10.1016/j.jretconser.2025.104443
17.Spatial word of mouth: How user reviews in the metaverse shape the success of virtual reality apps. Raoul V. Kübler, Thorsten Hennig-Thurau
https://doi.org/10.1016/j.jretai.2025.03.002
18.How accountants judge and use big data as an information source for business decision-making Carla L. Wilkin,Bingxin (Racheal) Liu
10.1016/j.accinf.2026.100774
19.The coherent two-phased process from sold online to redemption offline on an online

daily-deal platform
Yingxin Song,Yezheng Liu, Xiayu Chen b c ,Muhammet Deveci, Carol Xiaojuan Ou ,Lingfei Li,Weizhong Wang
https://doi.org/10.1016/j.elerap.2025.101523
20.Salesperson communication effectiveness in a digital sales interaction,
Neeraj Bharadwaj,Garrett M. Shipley
https://doi.org/10.1016/j.indmarman.2020.07.002
21.Which direction will electronic word-of-mouth (eWOM) choose? Dance drama eWOM's spatiotemporal characteristics and influencing factors
Junfeng Liao,Lin Yang,Na Wang
https://doi.org/10.1016/j.jretconser.2024.104122
22.Online reviews in e-commerce: A bibliometric analysis of consumer decision-making
Qunli Tang,Peng Jiang
10.1016/j.actpsy.2026.106464
23.Sequential film marketing in China: The study of social platforms and their impacts
Yuntsai Chou,Wei Lin
https://doi.org/10.1016/j.digbus.2025.100107
24.The sales effect of “Free App of the Day” on Amazon Appstore: An empirical study
Hong Chen a ,Kevin Lachaud,Wenqi Zhou
https://doi.org/10.1016/j.digbus.2021.100020
25.To post or not to post: How minority opinion and posting frequency impact online review posting. Jana Möller-Herm ,Sabrina A. Gottschalk, Alexander Mafael
10.1016/j.ijresmar.2024.08.005
26.When consumers can return digital products: Influence of firm- and consumer-induced communication on the returns and profitability of news articles
Petra Schulz,Edlira Shehu,Michel Clement
10.1016/j.ijresmar.2019.01.003
27.Influence of consumer reviews on online purchasing decisions in older and younger adults Bettina von Helversen,Katarzyna Abramczuk,Wiesław Kopeć,Radoslaw Nielek
https://doi.org/10.1016/j.dss.2018.05.006
28.An analytics-driven method for building ethical customer digital twins using neuromarketing and social media data Ama Anomwaa Okyere Sefa
,Mohammadreza Rezaei,Omid Fatahi Valilai
https://doi.org/10.1016/j.dajour.2026.100689
29.Avengers assemble! When digital piracy increases box office demand
Klaus Ackermann,Wendy A. Bradley,Jack Francis Cameron
https://doi.org/10.1016/j.respol.2025.105266
30.Exploring online consumer review-management response dynamics: A heuristic-systematic perspective Hsiu-Yu Hung,Yansong Hu, Nick Lee,Hsien-Tung Tsai
https://doi.org/10.1016/j.dss.2023.114087

31.Su, Z., Yang, M., Zhai, Q. et al. A multigrained preference analysis method for product iterative design incorporating AI-generated review detection. Sci Rep 15, 2528 (2025).
https://doi.org/10.1038/s41598-025-86551-5
32.Sung, E., Chung, W.Y. & Lee, D. Factors that affect consumer trust in product quality: a focus on online reviews and shopping platforms. Humanit Soc Sci Commun 10, 766 (2023).
https://doi.org/10.1057/s41599-023-02277-7
33.Saleem U, yi S, Bilal M, Topor DI and Căpușneanu S (2022) The impact of website quality on customer satisfaction and eWOM in online purchase intention: The moderating role of gender in risk-taking. Front. Psychol. 13:945707. doi: 10.3389/fpsyg.2022.945707
34.Wang C, Li Y, Luo X, Fu H, Ye Z and Deng G (2022) How Are Consumers Affected by Taste and Hygiene Ratings When Ordering Food Online? A Behavioral and Event-Related Potential Study. Front. Neurosci. 16:844027. doi: 10.3389/fnins.2022.844027
35.Zhang Z, Jiang H, Zhou C, Zheng J and Yang S (2022) Predicting review helpfulness in the 0omnichannel retailing context: An elaboration likelihood model perspective. Front. Psychol.
13:958386. doi: 10.3389/fpsyg.2022.958386
36.Tell me what I want to hear: The effects of matching reviews on consumers' decision making Long The Nguyen,Zachary J. Sheffler
https://doi.org/10.1016/j.im.2026.104324
37.Exploring Customer Insights Through Online Review Analytics:
Long Dai Khuc,Nga Thi Viet Le,Ha Thi Thu Nguyen
https://doi.org/10.4018/IJABIM.399855
38.make From booking to rating activities: A holistic analysis of online review behavior in a destination.
Juan Luis Nicolau,Enrique Bigné,Jacques Bulchand-Gidumal,Edu William
https://doi.org/10.1016/j.jdmm.2025.100995
39.Consequences of consumer regret with online shopping.
SergioBarta,RaquelGurrea,Carlos Flavian
https://doi.org/10.1016/j.jretconser.2023.103332
40.Cracking the Code of Consumer Decisions:
Ziqiang Hu
https://doi.org/10.4018/JGIM.376341
41.Consultation Pricing of the Online Health Care Service in China: Hierarchical Linear Regression Approach Ya-Ling Chiu, Jying-Nan Wang,Haiyan Yu,
Yuan-Teng Hsu https://doi.org/10.2196/29170
42.Attracting attention rather than understanding: The positive impact of Emoji-Text

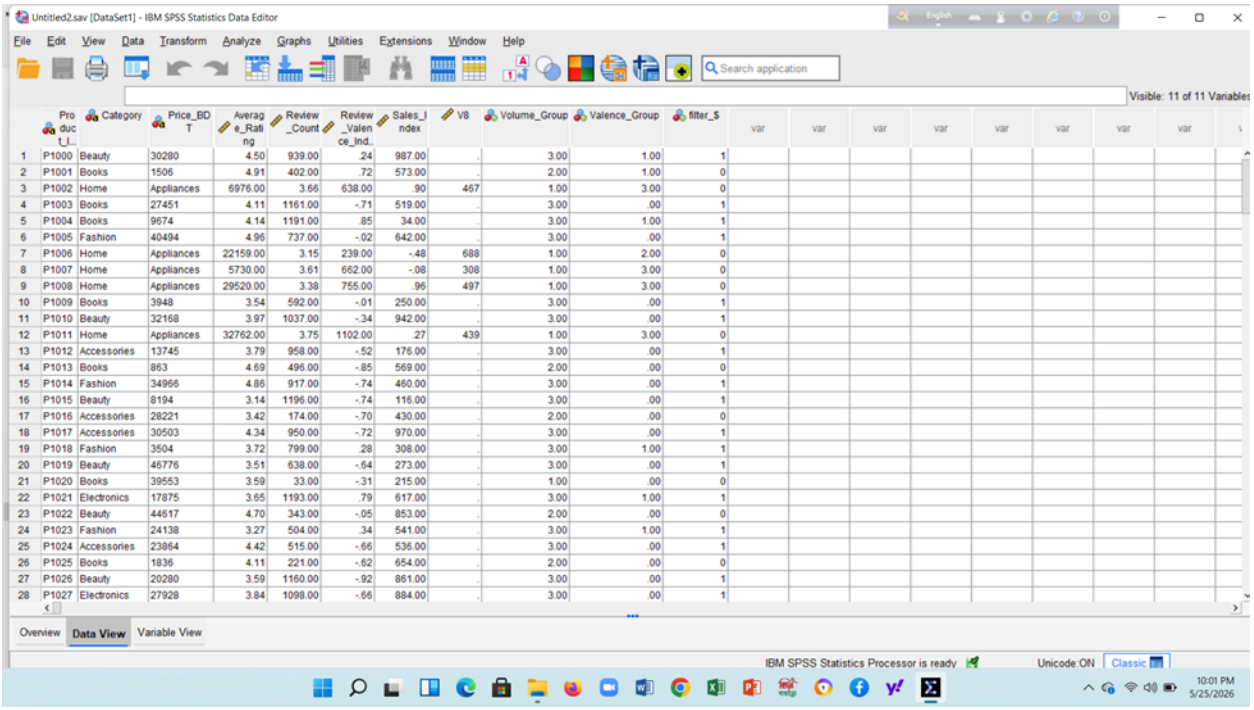
incongruency on firm-generated content. Akito Tanaka,Sotaro Katsumata
https://doi.org/10.1016/j.chbr.2026.101105
43.Finding disseminators via electronic word of mouth message for effective marketing communications Tong Bao,Tung-lung Steven Chang
https://doi.org/10.1016/j.dss.2014.07.006
44.Generation, susceptibility, and response regarding negativity: An in-depth analysis on negative online reviews Nazan Colmekcioglu,Reza Marvi, Pantea Foroudi,Fevzi Okumus
10.1016/j.jbusres.2022.08.033
45.Implementing e-commerce channels in business-to-business selling
Roland Kassemeier , Sascha Alavi ,Johannes Habel
10.1016/j.ijresmar.2025.10.003
46.The impact of online platform transparency of information on consumers' choices
doi:10.1017/bpp.2020.11
47.Yum, K., Yoo, B. Enhancing online reviews: exploring the impact of characteristic-based review system on customer engagement for offline sellers. Humanit Soc Sci Commun 11, 1567
(2024). https://doi.org/10.1057/s41599-024-04082-2
48.A study on the influence of online reviews of new products on consumers' purchase decisions: An empirical study on JD.com
https://doi.org/10.3389/fpsyg.2022.983060
49.Liu, Z., Lei, Sh., Guo, Yl. et al. The interaction effect of online review language style and
product type on consumers' purchase intentions. Palgrave Commun 6, 11 (2020).
https://doi.org/10.1057/s41599-020-0387-6
50.Lee, S., Choeh, J.Y. The impact of online review helpfulness and word of mouth communication on box office performance predictions. Humanit Soc Sci Commun 7, 84 (2020).
https://doi.org/10.1057/s41599-020-00578-9

References (citations in lit, review)

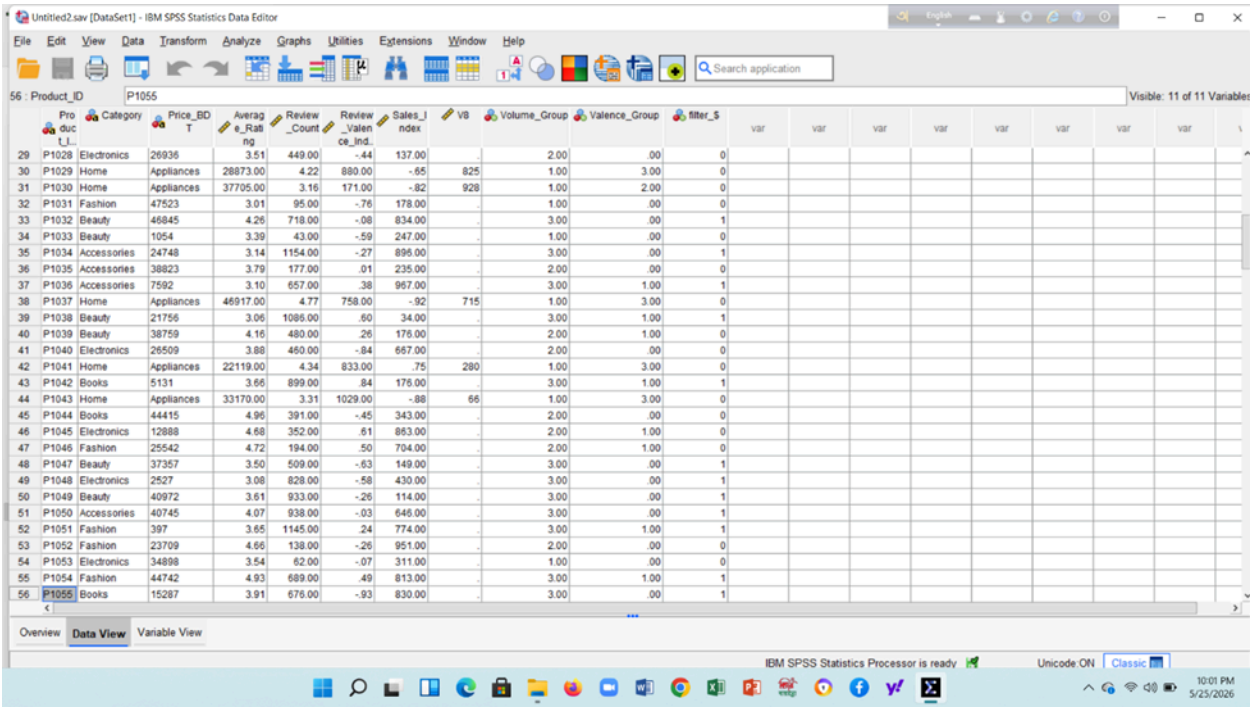
1)Basuroy, S., Chatterjee, S., & Ravid, S. A. (2003). How critical are critical reviews? The box office effects of film critics, star power, and budgets. Journal of Marketing, 67(4), 103-117.
10.1509/jmkg.67.4.103.18692
2)Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345-354.
https://doi.org/10.1509/jmkr.43.3.345
3)Cialdini, R. B. (2001). Influence: Science and practice (4th ed.). Allyn & Bacon.

https://www.researchgate.net/publication/229067982_Influence_Science_and_Practice
4)Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? An empirical investigation of panel data. Decision Support Systems, 45(4), 1007-1016. https://doi.org/10.1016/j.dss.2008.04.001
5)Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How online product reviews
affect retail sales: A meta-analysis. Journal of Retailing, 90(2), 217-232. https://www.researchgate.net/publication/262770407_How_Online_Product_Reviews_Affect_Retail_Sales_A_Meta-analysis
6)Hussain S, Huang K, Ilyas Z and Niu B (2020) Exploring the Novel Input Attributes Affecting eWOM. Front. Psychol. 11:2017. doi: 10.3389/fpsyg.2020.02017
7)Hu, N., Liu, L., & Zhang, J. J. (2008). Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. Information Technology and Management, 9(3),
201-214.https://www.researchgate.net/publication/225451056_Do_Online_Reviews_Affect_Prod
uct_Sales_The_Role_of_Reviewer_Characteristics_and_Temporal_Effectssman,

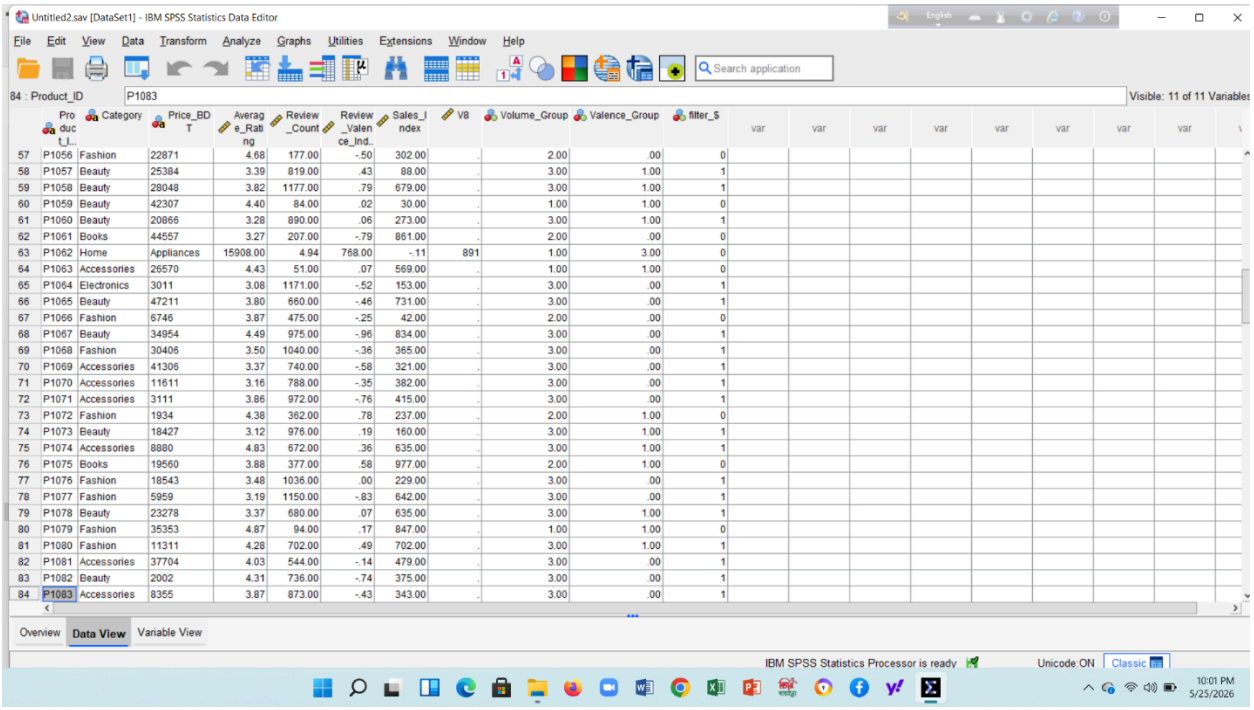
Appendix A:A.1



	Product_ID	Category	Price_BDT	Average_Rating	Review_Count	Review_Valence_Ind.	Sales_Index	V8	Volume_Group	Valence_Group	filter_$
1	P1000	Beauty	30280	4.50	939.00	.24	987.00	.	3.00	1.00	1
2	P1001	Books	1506	4.91	402.00	.72	573.00	.	2.00	1.00	0
3	P1002	Home	Appliances	6976.00	3.66	638.00	.90	467	1.00	3.00	0
4	P1003	Books	27451	4.11	1161.00	-.71	519.00	.	3.00	.00	1
5	P1004	Books	9674	4.14	1191.00	.85	34.00	.	3.00	1.00	1
6	P1005	Fashion	40494	4.96	737.00	-.02	642.00	.	3.00	.00	1
7	P1006	Home	Appliances	22159.00	3.15	239.00	-.48	688	1.00	2.00	0
8	P1007	Home	Appliances	5730.00	3.61	662.00	-.08	308	1.00	3.00	0
9	P1008	Home	Appliances	29520.00	3.38	755.00	.96	497	1.00	3.00	0
10	P1009	Books	3948	3.54	592.00	-.01	250.00	.	3.00	.00	1
11	P1010	Beauty	32168	3.97	1037.00	-.34	942.00	.	3.00	.00	1
12	P1011	Home	Appliances	32762.00	3.75	1102.00	.27	439	1.00	3.00	0
13	P1012	Accessories	13745	3.79	958.00	-.52	176.00	.	3.00	.00	1
14	P1013	Books	863	4.69	496.00	-.85	569.00	.	2.00	.00	0
15	P1014	Fashion	34966	4.86	917.00	-.74	460.00	.	3.00	.00	1
16	P1015	Beauty	8194	3.14	1196.00	-.74	116.00	.	3.00	.00	1
17	P1016	Accessories	28221	3.42	174.00	-.70	430.00	.	2.00	.00	0
18	P1017	Accessories	30503	4.34	950.00	-.72	970.00	.	3.00	.00	1
19	P1018	Fashion	3504	3.72	799.00	.28	308.00	.	3.00	1.00	1
20	P1019	Beauty	46776	3.51	638.00	-.64	273.00	.	3.00	.00	1
21	P1020	Books	39553	3.59	33.00	-.31	215.00	.	1.00	.00	0
22	P1021	Electronics	17875	3.65	1193.00	.79	617.00	.	3.00	1.00	1
23	P1022	Beauty	44617	4.70	343.00	-.05	853.00	.	2.00	.00	0
24	P1023	Fashion	24138	3.27	504.00	.34	541.00	.	3.00	1.00	1
25	P1024	Accessories	23864	4.42	515.00	-.66	536.00	.	3.00	.00	1
26	P1025	Books	1836	4.11	221.00	-.62	654.00	.	2.00	.00	0
27	P1026	Beauty	20280	3.59	1160.00	-.92	861.00	.	3.00	.00	1
28	P1027	Electronics	27928	3.84	1098.00	-.66	884.00	.	3.00	.00	1



	Product_ID	Category	Price_BDT	Average_Rating	Review_Count	Review_Valence_Ind.	Sales_Index	V8	Volume_Group	Valence_Group	filter_$
29	P1028	Electronics	26936	3.51	449.00	-.44	137.00	.	2.00	.00	0
30	P1029	Home	Appliances	28873.00	4.22	880.00	-.65	825	1.00	3.00	0
31	P1030	Home	Appliances	37705.00	3.16	171.00	-.82	928	1.00	2.00	0
32	P1031	Fashion	47523	3.01	95.00	-.76	178.00	.	1.00	.00	0
33	P1032	Beauty	46845	4.26	718.00	-.08	834.00	.	3.00	.00	1
34	P1033	Beauty	1054	3.39	43.00	-.59	247.00	.	1.00	.00	0
35	P1034	Accessories	24748	3.14	1154.00	-.27	896.00	.	3.00	.00	1
36	P1035	Accessories	38823	3.79	177.00	.01	235.00	.	2.00	.00	0
37	P1036	Accessories	7592	3.10	657.00	.38	967.00	.	3.00	1.00	1
38	P1037	Home	Appliances	46917.00	4.77	758.00	-.92	715	1.00	3.00	0
39	P1038	Beauty	21756	3.06	1086.00	.60	34.00	.	3.00	1.00	1
40	P1039	Beauty	38759	4.16	480.00	.26	176.00	.	2.00	1.00	0
41	P1040	Electronics	26509	3.88	460.00	-.84	667.00	.	2.00	.00	0
42	P1041	Home	Appliances	22119.00	4.34	833.00	.75	280	1.00	3.00	0
43	P1042	Books	5131	3.66	899.00	.84	176.00	.	3.00	1.00	1
44	P1043	Home	Appliances	33170.00	3.31	1029.00	-.88	66	1.00	3.00	0
45	P1044	Books	44415	4.96	391.00	-.45	343.00	.	2.00	.00	0
46	P1045	Electronics	12888	4.68	352.00	.61	863.00	.	2.00	1.00	0
47	P1046	Fashion	25542	4.72	194.00	.50	704.00	.	2.00	1.00	0
48	P1047	Beauty	37357	3.50	509.00	-.63	149.00	.	3.00	.00	1
49	P1048	Electronics	2527	3.08	828.00	-.58	430.00	.	3.00	.00	1
50	P1049	Beauty	40972	3.61	933.00	-.26	114.00	.	3.00	.00	1
51	P1050	Accessories	40745	4.07	938.00	-.03	646.00	.	3.00	.00	1
52	P1051	Fashion	397	3.65	1145.00	.24	774.00	.	3.00	1.00	1
53	P1052	Fashion	23709	4.66	138.00	-.26	951.00	.	2.00	.00	0
54	P1053	Electronics	34898	3.54	62.00	-.07	311.00	.	1.00	.00	0
55	P1054	Fashion	44742	4.93	689.00	.49	813.00	.	3.00	1.00	1
56	P1055	Books	15287	3.91	676.00	-.93	830.00	.	3.00	.00	1



Untitled2.sav [DataSet1] - IBM SPSS Statistics Data Editor

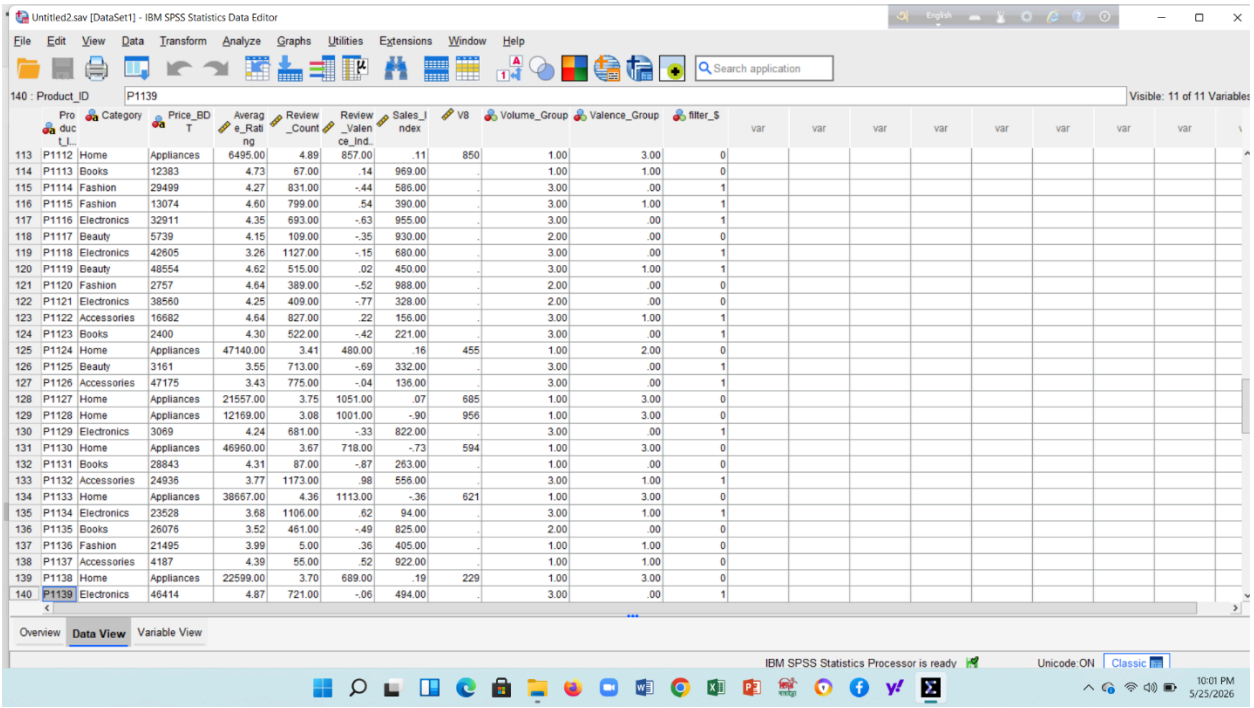
File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

84 : Product_ID P1083 Visible: 11 of 11 Variables

	Product_I...	Category	Price_BDT	Average_Rating	Review_Count	Review_Valence_Ind...	Sales_Index	V8	Volume_Group	Valence_Group	filter_$
57	P1056	Fashion	22871	4.68	177.00	-.50	302.00	.	2.00	.00	0
58	P1057	Beauty	25384	3.39	819.00	.43	88.00	.	3.00	1.00	1
59	P1058	Beauty	28048	3.82	1177.00	.79	679.00	.	3.00	1.00	1
60	P1059	Beauty	42307	4.40	84.00	.02	30.00	.	1.00	1.00	0
61	P1060	Beauty	20866	3.28	890.00	.06	273.00	.	3.00	1.00	1
62	P1061	Books	44557	3.27	207.00	-.79	861.00	.	2.00	.00	0
63	P1062	Home	Appliances	15908.00	4.94	768.00	-.11	891	1.00	3.00	0
64	P1063	Accessories	26570	4.43	51.00	.07	569.00	.	1.00	1.00	0
65	P1064	Electronics	3011	3.08	1171.00	-.52	153.00	.	3.00	.00	1
66	P1065	Beauty	47211	3.80	660.00	-.46	731.00	.	3.00	.00	1
67	P1066	Fashion	6746	3.87	475.00	-.25	42.00	.	2.00	.00	0
68	P1067	Beauty	34954	4.49	975.00	-.96	834.00	.	3.00	.00	1
69	P1068	Fashion	30406	3.50	1040.00	-.36	365.00	.	3.00	.00	1
70	P1069	Accessories	41306	3.37	740.00	-.58	321.00	.	3.00	.00	1
71	P1070	Accessories	11611	3.16	788.00	-.35	382.00	.	3.00	.00	1
72	P1071	Accessories	3111	3.86	972.00	-.76	415.00	.	3.00	.00	1
73	P1072	Fashion	1934	4.38	362.00	.78	237.00	.	2.00	1.00	0
74	P1073	Beauty	18427	3.12	976.00	.19	160.00	.	3.00	1.00	1
75	P1074	Accessories	8880	4.83	672.00	.36	635.00	.	3.00	1.00	1
76	P1075	Books	19560	3.88	377.00	.58	977.00	.	2.00	1.00	0
77	P1076	Fashion	18543	3.48	1036.00	.00	229.00	.	3.00	.00	1
78	P1077	Fashion	5959	3.19	1150.00	-.83	642.00	.	3.00	.00	1
79	P1078	Beauty	23278	3.37	680.00	.07	635.00	.	3.00	1.00	1
80	P1079	Fashion	35353	4.87	94.00	.17	847.00	.	1.00	1.00	0
81	P1080	Fashion	11311	4.28	702.00	.49	702.00	.	3.00	1.00	1
82	P1081	Accessories	37704	4.03	544.00	-.14	479.00	.	3.00	.00	1
83	P1082	Beauty	2002	4.31	736.00	-.74	375.00	.	3.00	.00	1
84	P1083	Accessories	8355	3.87	873.00	-.43	343.00	.	3.00	.00	1

Overview Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON Classic



Untitled2.sav [DataSet1] - IBM SPSS Statistics Data Editor

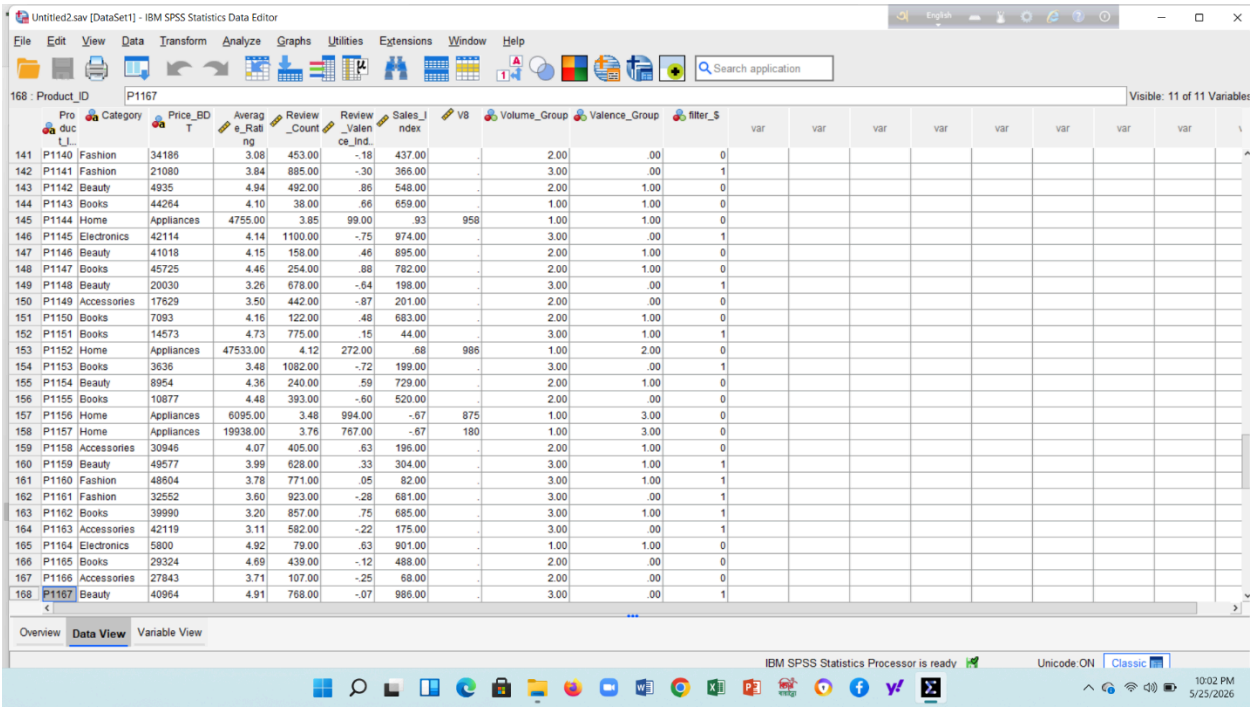
File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

140 : Product_ID P1139 Visible: 11 of 11 Variables

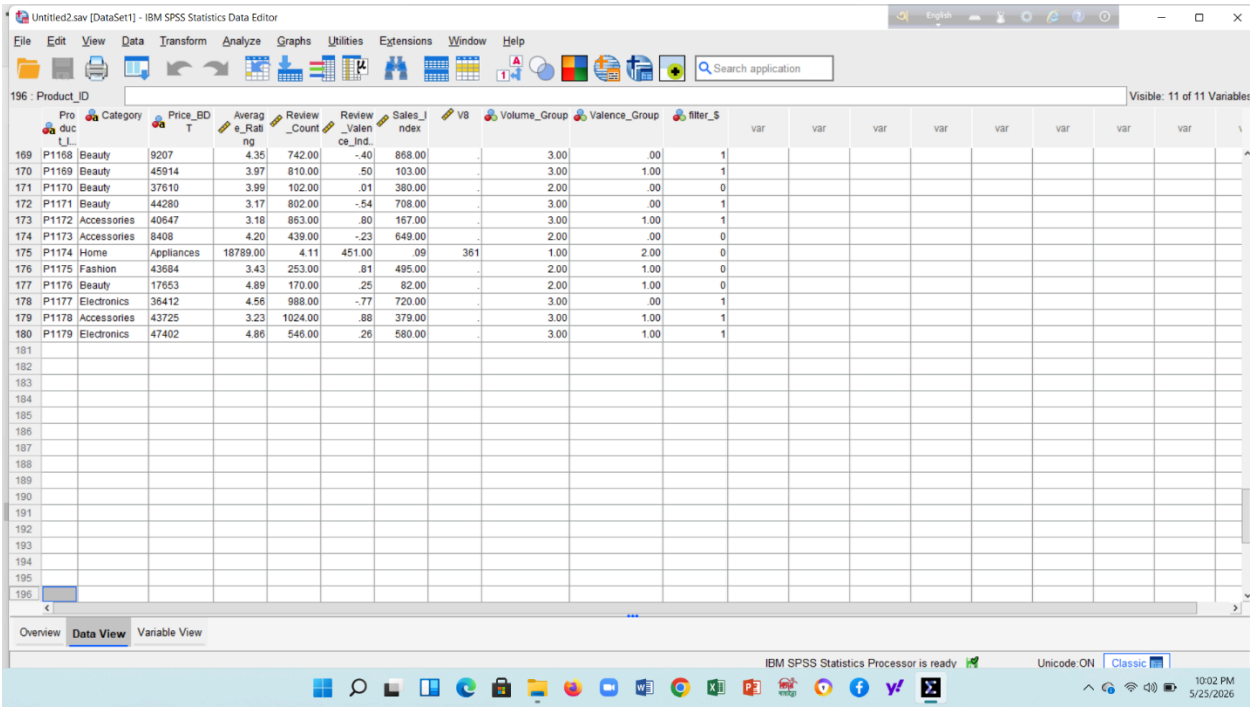
	Product_I...	Category	Price_BDT	Average_Rating	Review_Count	Review_Valence_Ind...	Sales_Index	V8	Volume_Group	Valence_Group	filter_$
113	P1112	Home	Appliances	6495.00	4.89	857.00	.11	850	1.00	3.00	0
114	P1113	Books	12383	4.73	67.00	.14	969.00	.	1.00	1.00	0
115	P1114	Fashion	29499	4.27	831.00	-.44	586.00	.	3.00	.00	1
116	P1115	Fashion	13074	4.60	799.00	.54	390.00	.	3.00	1.00	1
117	P1116	Electronics	32911	4.35	693.00	-.63	955.00	.	3.00	.00	1
118	P1117	Beauty	5739	4.15	109.00	-.35	930.00	.	2.00	.00	0
119	P1118	Electronics	42605	3.26	1127.00	-.15	680.00	.	3.00	.00	1
120	P1119	Beauty	48554	4.62	515.00	.02	450.00	.	3.00	1.00	1
121	P1120	Fashion	2757	4.64	389.00	-.52	988.00	.	2.00	.00	0
122	P1121	Electronics	38560	4.25	409.00	-.77	328.00	.	2.00	.00	0
123	P1122	Accessories	16682	4.64	827.00	.22	156.00	.	3.00	1.00	1
124	P1123	Books	2400	4.30	522.00	-.42	221.00	.	3.00	.00	1
125	P1124	Home	Appliances	47140.00	3.41	480.00	.16	455	1.00	2.00	0
126	P1125	Beauty	3161	3.55	713.00	-.69	332.00	.	3.00	.00	1
127	P1126	Accessories	47175	3.43	775.00	-.04	136.00	.	3.00	.00	1
128	P1127	Home	Appliances	21557.00	3.75	1051.00	.07	685	1.00	3.00	0
129	P1128	Home	Appliances	12169.00	3.08	1001.00	-.90	956	1.00	3.00	0
130	P1129	Electronics	3069	4.24	681.00	-.33	822.00	.	3.00	.00	1
131	P1130	Home	Appliances	46960.00	3.67	718.00	-.73	594	1.00	3.00	0
132	P1131	Books	28843	4.31	87.00	-.87	263.00	.	1.00	.00	0
133	P1132	Accessories	24936	3.77	1173.00	.98	556.00	.	3.00	1.00	1
134	P1133	Home	Appliances	38667.00	4.36	1113.00	-.36	621	1.00	3.00	0
135	P1134	Electronics	23528	3.68	1106.00	.62	94.00	.	3.00	1.00	1
136	P1135	Books	26076	3.52	461.00	-.49	825.00	.	2.00	.00	0
137	P1136	Fashion	21495	3.99	5.00	.36	405.00	.	1.00	1.00	0
138	P1137	Accessories	4187	4.39	55.00	.52	922.00	.	1.00	1.00	0
139	P1138	Home	Appliances	22599.00	3.70	689.00	.19	229	1.00	3.00	0
140	P1139	Electronics	46414	4.87	721.00	-.06	494.00	.	3.00	.00	1

Overview Data View Variable View

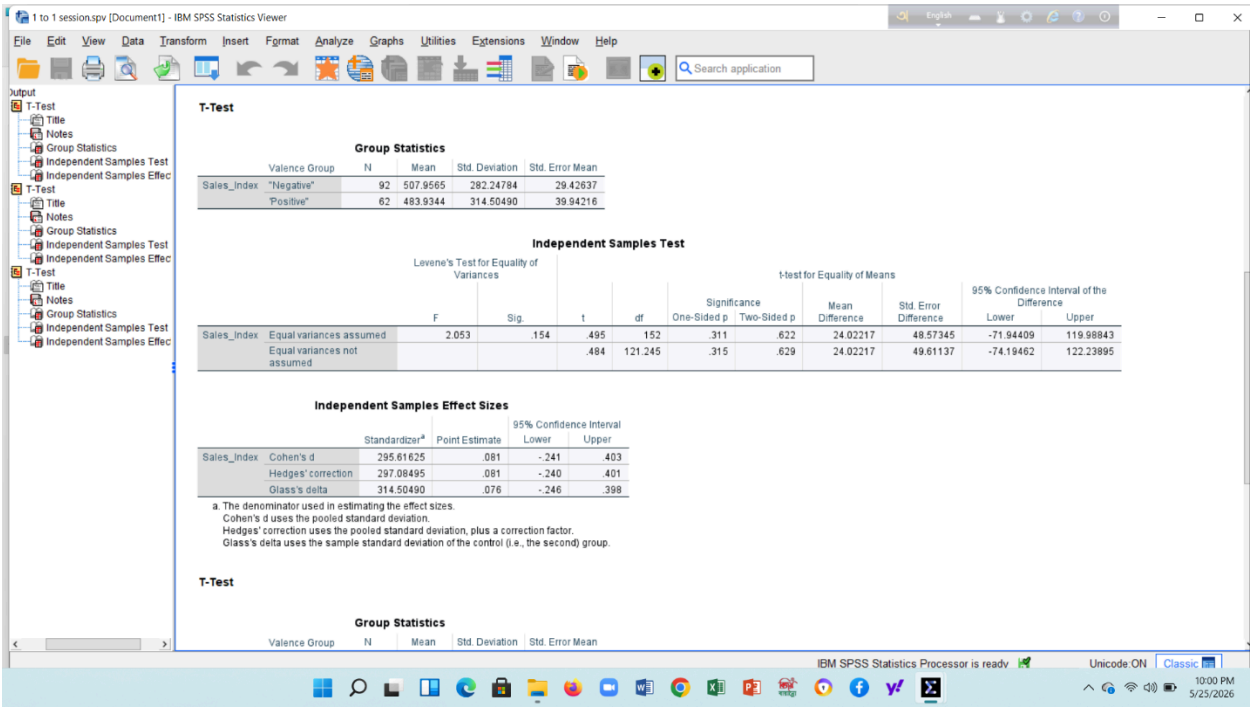
IBM SPSS Statistics Processor is ready Unicode:ON Classic



	Product_ID	Category	Price_BDT	Average_Rating	Review_Count	Review_Valence_Ind...	Sales_Index	V8	Volume_Group	Valence_Group	filter_$
141	P1140	Fashion	34186	3.08	453.00	-.18	437.00	.	2.00	.00	0
142	P1141	Fashion	21080	3.84	885.00	-.30	366.00	.	3.00	.00	1
143	P1142	Beauty	4935	4.94	492.00	.86	548.00	.	2.00	1.00	0
144	P1143	Books	44264	4.10	38.00	.66	659.00	.	1.00	1.00	0
145	P1144	Home	Appliances	4755.00	3.85	99.00	.93	958	1.00	1.00	0
146	P1145	Electronics	42114	4.14	1100.00	-.75	974.00	.	3.00	.00	1
147	P1146	Beauty	41018	4.15	158.00	.46	895.00	.	2.00	1.00	0
148	P1147	Books	45725	4.46	254.00	.88	782.00	.	2.00	1.00	0
149	P1148	Beauty	20030	3.26	678.00	-.64	198.00	.	3.00	.00	1
150	P1149	Accessories	17629	3.50	442.00	-.87	201.00	.	2.00	.00	0
151	P1150	Books	7093	4.16	122.00	.48	683.00	.	2.00	1.00	0
152	P1151	Books	14573	4.73	775.00	.15	44.00	.	3.00	1.00	1
153	P1152	Home	Appliances	47533.00	4.12	272.00	.68	986	1.00	2.00	0
154	P1153	Books	3636	3.48	1082.00	-.72	199.00	.	3.00	.00	1
155	P1154	Beauty	8954	4.36	240.00	.59	729.00	.	2.00	1.00	0
156	P1155	Books	10877	4.48	393.00	-.60	520.00	.	2.00	.00	0
157	P1156	Home	Appliances	6095.00	3.48	994.00	-.67	875	1.00	3.00	0
158	P1157	Home	Appliances	19938.00	3.76	767.00	-.67	180	1.00	3.00	0
159	P1158	Accessories	30946	4.07	405.00	.63	196.00	.	2.00	1.00	0
160	P1159	Beauty	49577	3.99	628.00	.33	304.00	.	3.00	1.00	1
161	P1160	Fashion	48604	3.78	771.00	.05	82.00	.	3.00	1.00	1
162	P1161	Fashion	32552	3.60	923.00	-.28	681.00	.	3.00	.00	1
163	P1162	Books	39990	3.20	857.00	.75	685.00	.	3.00	1.00	1
164	P1163	Accessories	42119	3.11	582.00	-.22	175.00	.	3.00	.00	1
165	P1164	Electronics	5800	4.92	79.00	.63	901.00	.	1.00	1.00	0
166	P1165	Books	29324	4.69	439.00	-.12	488.00	.	2.00	.00	0
167	P1166	Accessories	27843	3.71	107.00	-.25	68.00	.	2.00	.00	0
168	P1167	Beauty	40964	4.91	768.00	-.07	986.00	.	3.00	.00	1



	Product_ID	Category	Price_BDT	Average_Rating	Review_Count	Review_Valence_Ind...	Sales_Index	V8	Volume_Group	Valence_Group	filter_$
169	P1168	Beauty	9207	4.35	742.00	-.40	868.00	.	3.00	.00	1
170	P1169	Beauty	45914	3.97	810.00	.50	103.00	.	3.00	1.00	1
171	P1170	Beauty	37610	3.99	102.00	.01	380.00	.	2.00	.00	0
172	P1171	Beauty	44280	3.17	802.00	-.54	708.00	.	3.00	.00	1
173	P1172	Accessories	40647	3.18	863.00	.80	167.00	.	3.00	1.00	1
174	P1173	Accessories	8408	4.20	439.00	-.23	649.00	.	2.00	.00	0
175	P1174	Home	Appliances	18789.00	4.11	451.00	.09	361	1.00	2.00	0
176	P1175	Fashion	43684	3.43	253.00	.81	495.00	.	2.00	1.00	0
177	P1176	Beauty	17653	4.89	170.00	.25	82.00	.	2.00	1.00	0
178	P1177	Electronics	36412	4.56	988.00	-.77	720.00	.	3.00	.00	1
179	P1178	Accessories	43725	3.23	1024.00	.88	379.00	.	3.00	1.00	1
180	P1179	Electronics	47402	4.86	546.00	.26	580.00	.	3.00	1.00	1



T-Test

Group Statistics

	Valence Group	N	Mean	Std. Deviation	Std. Error Mean
Sales_Index	"Negative"	92	507.9565	282.24784	29.42637
	"Positive"	62	483.9344	314.50490	39.94216

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Sales_Index	Equal variances assumed	2.053	.154	.495	152	.311	.622	24.02217	48.57345	-71.94409	119.98843
	Equal variances not assumed			.484	121.245	.315	.629	24.02217	49.61137	-74.19462	122.23895

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
Sales_Index	Cohen's d	295.61625	.081	-.241	.403
	Hedges' correction	297.08495	.081	-.240	.401
	Glass's delta	314.50490	.076	-.246	.398

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

T-Test

Group Statistics

Appendix B:
Recoding used in SPSS

Original Variable	New Variable	Recoding Rule
Review_Count	Volume_Group	1 = 1–99 2 = 100–499 3 = 500+
Review_Valence_Index	Valence_Group	0 = Negative (<0) 1 = Positive (≥0)
Sales_Index	Sales_Category (descriptive only)	0 = Low (≤503.5) 1 = High (>503.5)