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Click to Satisfaction: What Indian Online reviews reveal about real Customer Experiences?

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ABSTRACT

Purpose: The present study is an attempt to study the underlying emotional drivers of customer satisfaction in the rapidly expanding Indian e-commerce sector. The study focuses on identifying fundamental affective factors embedded in customer reviews that shape user experiences across multiple product categories.

Design/Methodology/Approach: To achieve the research objectives, we use a research framework; more than 10,000 verified customer reviews posted on leading Indian e-commerce platforms during the period of 2022 to 2024 were analyzed. Lexicon-based sentiment analysis techniques, namely VADER (Valence Aware Dictionary and Sentiment Reasoner) and the NRC (National Research Council (Canada)) emotion lexicon, were used to extract emotional and affective patterns from unstructured textual data.

Findings: The findings indicate that platform choice explains less than 5% of the variability in consumer sentiment. Delivery dependability is identified as the most significant contributor to positive sentiment, resulting in 68% of favorable evaluations, while concerns regarding product authenticity account for 72% of negative reviews.

Research Limitations: The present research has its own limitations. For instance, it uses lexicon-based sentiment analysis algorithms, which ignore many variations, such as sarcasm or regionally specific phrases found in customer reviews.

Managerial Implications: The results suggest that e-commerce companies should emphasize supply chain reliability, last-mile delivery efficiency, and quality assurance processes rather than superficial platform enhancements.

Originality/Value: This study provides a scalable, evidence-based approach for obtaining actionable insights from unstructured consumer feedback. It examines traditional assumptions in e-commerce research and presents practical recommendations.

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Introduction

Online Shopping

Technological advancements, consumer behavior variations, and external disruptions like the COVID-19 pandemic have influenced internet commerce. Heinemann (2023) highlights the transformative facets of digital commerce while emphasizing regional differences in the adoption of online purchasing, particularly in Turkey. Li et al. (2023) proposed an analytic hierarchy process to determine the pricing and convenience factors that impact online furniture sales. Olumekor et al. (2024) discovered that income, internet accessibility, and food prices impacted online grocery purchasing during the pandemic, thus regulating the growth of e-commerce. Enhancing logistics and supply chain efficiency is crucial in e-commerce. Huang (2024) examines IoT-based AI algorithms in the context of cross-border logistics while exploring the geographical effects of last-mile delivery platforms. Cai et al. (2023) illustrate the importance of customer-centric logistics because of changes in consumer behavior influenced by the pandemic. The pandemic impacted tourism and maritime commerce, leading to the implementation of adaptive strategies (Čorak et al., 2020). Comparative analyses indicate cultural and operational differences in e-commerce. Guo & Zhang (2024) conduct an analysis of the commercial structures of Amazon and Taobao, while investigating group buying behavior across the United States, China, and India. Kostka & Antoine (2020) analyze the impact of China's social credit system on consumer behavior. Post-pandemic developments in food tourism and commercial real estate highlight the imperative for resilience and innovation (Fountain, 2022). This synthesis demonstrates the effects of digitization, globalization, and crises on modern commerce, requiring modifications in business practices and the policy framework.

Customer Experiences in Online Shopping (Reviews and Emotions)

Post-pandemic trends driven by emerging technologies have revolutionized consumer behavior across various industries. (Sheykhfard et al., 2025) critical examination of electric vehicle adoption highlights trust and perceived value as critical factors influencing consumer experiences. The pandemic accelerated digital transformations, alongside changing logistics expectations and increased reliance on online learning platforms (Cai et al., 2023; Favale et al., 2020). Liu et al. (2023) highlight an increased demand for convenience and safety in online shopping habits post-COVID-19. Li et al. (2023) analyze efficient delivery and pricing as distinct elements of e-commerce specifically related to furniture, utilizing the analytic hierarchy process for their modeling. Technologi-cal advancements have influenced consumer relationships. Faruk et al. (2024) assess the user experience of voice assistants, emphasizing emotional engagement and usability. Butz et al. (2022) examine the necessary technology adoption in telepsychotherapy for potential risks. Immersive technologies are transforming service delivery, and livestream shopping utilizes anchor professionals to stimulate impulsive buying (Sama et al., 2025; Liu et al., 2023). AI-driven topic modeling analyzes trends in e-commerce and the Internet of Things, emphasizing data-driven decision-making (Su et al., 2025). The behavior of Generation C (Gök, 2020), besides the integration of robotics in hospitality (Tung & Tse, 2023), signifies evolving experiential needs. Smart city innovations influence application adoption in education by facilitating value co-creation (Dastane et al., 2024; Reynoso Vanderhorst et al., 2024; Liu et al., 2023). Research on the effects of post-purchase impulsive buying and brand advocacy continues, as noted by (Suban et al., 2024) and (Beikverdi et al., 2024). Digital marketing growth and cybersecurity risks significantly impact the commercial sector (Cioppi et al., 2023; Hiller et al., 2020). These studies illustrate interactions among technology, consumer psychology, and marketing adaptation.

Literature on Customer Experiences (Online Sentiments)

Recent studies on innovative methodologies have strengthened our understanding of the user experience on digital platforms. Results from technological adoption research, such as social VR apps and telepsychotherapy, have highlighted their impact on user perceptions (Dong et al., 2024; Butz et al., 2022). Adding AI to education is important for shaping how people feel about online learning, and it could change the way we learn, even though there are challenges with adjusting to different cultures. E-commerce research also emphasizes aspects of technology-related experiences. Augmented reality interfaces and chatbot interactions have highlighted a substantial impact on consumer satisfaction and buying behavior (Guo & Zhang, 2024; Pratas et al., 2024). The latest studies have looked at new methods using BERTopic modeling for IoT trends and bibliometric assessments of wearable health devices. However, the research exhibits shortcomings in large-scale data mining techniques that are used to produce customer insights (Li et al., 2023; Penpece Demirer & Büyükeke, 2025; Mach-Król & Hadasik, 2021). Text mining techniques also facilitate improved analysis of tourism reviews and destination competitiveness. Research indicates that how consistent the topics are and how strong the emotions are can affect how useful reviews are, and methods that summarize based on specific attributes enhance the success of opinion mining. Sentiment analysis has developed from basic polarity detection, a component of sentiment creation. Research on how people interact with computers shows a focus on designing interfaces (Song et al., 2022), while thorough evaluations of sensory marketing (Antunes & Veríssimo, 2024) and the impact of giving human traits to non-human things (Khan et al., 2024) support the ideas in this area. These studies highlight methodologically sound and context-sensitive ways to understand digital user experiences in various domains.

Literature on Customer Experiences (Online Emotions)

User-friendliness, security, and immersive technology like augmented reality are driving online buying trends. According to the Technology Adoption Model (Guo & Zhang, 2024) reiterated how augmented reality enhances purchase intent by boosting perceived utility. In addition, Dong et al. (2024) suggested the impact of social VR applications on user experiences across demographics. In addition, Dong et al. (2024) emphasize emotional immersion, engagement, and perceived value, proving that social virtual reality apps offer diverse experiences for different ages and backgrounds. Voice assistants and wearable health devices state the emotional involvement and usability impact on technology adoption (Faruk et al., 2024; Hu et al., 2025). Omni-channel commerce (Sharma & Dutta, 2023) and immersive service engagements (Sama et al., 2025) necessitate fluid, technology-augmented consumer interactions. Tunca (2025) NLP analysis of tourist reviews highlights a strong correlation between customer evaluations, sentiment analysis, and service ratings. It further suggested that consistent, emotive reviews are better. EEG and other neuro-marketing techniques are increasingly used in destination branding, according to Shahzad et al. (2024). Lexicons and systems that understand emotions improve digital consumer sentiment analysis (Mohammad & Turney, 2013; Mohammad, 2025; Peng et al., 2024).

Motivation and Research Objectives

The current study, in principle, is motivated by the swift growth of India's e-commerce sector and its dependence on customer sentiment analysis for business decision-making. Despite widespread research on sentiment analysis in worldwide markets, there persists a gap in understanding how platform-specific dynamics impact consumer sentiment in emerging economies like India, where cultural, linguistic, and infrastructural factors inimitably shape user feedback. Previous studies have mostly focused on single-platform analyses or generic sentiment trends, neglecting cross-platform comparisons that account for the competitive landscape of Indian e-commerce. In this study, we propose a novel model that utilizes deep learning models to uncover latent characteristics rooted in sentiments and emotions, leveraging customer review data.

The primary research objectives of this study are focused on

1. To detect the differences (significant/non-significant) in customer sentiments across major Indian e-commerce platforms (e.g., Amazon, Flipkart, Nykaa) based on product categories and review sources.
2. To evaluate the efficacy of sentiment analysis methods (VADER, TextBlob, NRC) in

identifying platform-specific sentiment trends while addressing the constraints of lexicon-based methodologies in multilingual settings.

3. This study uses clustering and correlation analysis to identify non-platform variables, such as shipment speed and product authenticity, that may show consistent disparities in customer sentiment.
4. To develop insights that can boost platform differentiation and strengthen governmental monitoring for mitigating fraudulent reviews and addressing sentiment disparities between rural and urban regions.

Approach

The proposed research approach utilizes a mixed-methods technique that combines computational sentiment analysis with statistical validation. In the first stage, data present in the form of customer reviews from seven prominent Indian e-commerce platforms (e.g., Amazon, Flipkart) is categorized by product type and review origin (social media, Trustpilot). The second stage incorporates preprocessing for text data cleaning using lemmatization, stopword removal, and normalization of the ratings. After that, we measure sentiment using the VADER method to check intensity and TextBlob to assess polarity, along with the NRC Emotion Lexicon to evaluate emotional states. Next, we intend to use statis-tical testing, such as the Kruskal-Wallis and Mann-Whitney U tests, to analyze platform sentiment, with FDR correction for multiple comparisons. For clustering analysis, we deploy K-means clustering, augmented by sil-houette analysis, to detect sentiment patterns at the product or source level. Additionally, we checked our results by comparing them to samples labeled by humans (Cohen's $\kappa > 0.7$) and used BERT-based sentiment analysis to confirm their reliability. Finally, we extract business insights from effect sizes and a the-matic analysis of outliers for final interpre-tation.

Contributions

This study makes four key contributions to sentiment analysis and e-commerce research:

1. Cross-Platform Sentiment Benchmark reveals low platform impacts on sentiment in India's e-commerce industry (*FDR-corrected $p > 0.05$*), rejecting the idea that platforms differentiate experience.
2. Methodological Rigor refers to how uncorrected p-values can lead to false positives in sentiment analysis, which means we need to use corrections for multiple tests and report the effect size.
3. Contextualized Tool The validation process assesses lexicon-based tools (VADER, NRC) within India's multilingual context to ensure they can handle culturally nuanced input, such as kind yet critical reviews.
4. Operational Insights focuses on shifts from platform-level to product- and logistics-oriented sentiment, allowing market expansion where infrastructure outperforms brand perception.

These findings add to the advancement of computational social science by highlighting cultural and operational biases in sentiment analysis.

Literature Review

This model uses machine learning and natural language processing (NLP) to discover subjective opinions in text data based on the idea of sentiment analysis. Statistical validation is used to ensure the study's reliability, and lexicon-based methods (VADER, NRC) are used for comprehensive sentiment and emotion analysis.

This model can be used for applications such as the following:

1. Strategy for online shopping: This model can help you make plans for marketing and stocking your store by looking at patterns of sentiment that are specific to a product.
2. Improving customer experience: Emotion analysis can also be used for group problems with transportation or service quality.
3. Market research: The model can also be used to compare the performance of a platform to that of competitors by using empirical sentiment measures.
4. Policy and regulation: The model can also be used to find reviews that aren't honest or are biased to protect consumers.

This framework offers helpful information about new markets by integrating computational linguistics into business analytics.

Research Methods

According to recent studies (Guo & Zhang, 2024; Pratas et al., 2024), sentiment analysis is becoming more pertinent for e-commerce and service-related businesses to understand digital platform user experiences. Despite previous studies examining mood in Western markets, emerging economies like India have not received nearly enough attention due to their distinct language and culture. (Khan et al., 2024; Li et al., 2023). Research shows that using incorrect statistical methods often leads to false positives and can create problems when comparing feelings across different platforms.This study addresses a missing area and provides reliable and culturally appropriate results by examining sentiment in Indian e-commerce with lexicon-based methods (VADER, NRC) and careful statistical adjustments (FDR).

Description of the Criteria

Table 1: Criteria Description

Criterion	Description	Rationale	Measurement Approach
Platform Selection	Inclusion of 7 major Indian e-commerce platforms (Amazon, Flipkart, etc.)	Ensures representative coverage of India's competitive e-commerce landscape	Market share analysis (2023 industry reports)
Review Sampling	Minimum 150 verified reviews per platform, stratified by product category	Balances statistical power with practical feasibility	Random stratified sampling with equal representation
Sentiment Tools	Combined use of VADER (intensity), TextBlob (polarity), and NRC (emotion)	Mitigates biases of single-tool approaches	Comparative validation against human-coded samples ($\kappa > 0.7$)
Statistical Testing	Non-parametric tests (Kruskal-Wallis, Mann-Whitney U) with FDR correction	Accounts for non-normal data distribution and multiple comparisons	$p < 0.05$ (FDR-adjusted) + effect size reporting (r)
Cluster Validation	Silhouette analysis (threshold > 0.25) for K-means clustering	Ensures meaningful grouping beyond random chance	-Within-cluster cohesion vs. between-cluster separation
Cultural Adaptation	Manual verification of lexicon performance on Indian English/Hinglish reviews	Addresses linguistic nuances in emerging markets	Error analysis of false positives/negatives
Practical Significance	Effect size thresholds ($r > 0.3$ = meaningful)	Distinguishes statistical vs. business relevance	Cohen's guidelines for correlation interpretation

Results

Review Text Word Cloud

The word cloud displays common customer reviews, with keywords like “amazing,” “deal,” “great,” “quality,” “loved,” “excellent,” “happy,” and “fast” indicating positive sentiments. Phrases such as “never disappoints” indicate reliability and contribute to a consistent user experience. Negative words are less common and have less influence. The word cloud reflects strong customer approval and confirms the product's effectiveness, with positive language making up most of the sentiment, reflecting high user satisfaction and engagement (see Figure 1).

Cluster Analysis

Review Distribution

A quantitative analysis of review segmentation is presented in the bar chart, where Cluster 11 has the most reviews (140+), followed by Clusters 7, 4, 11, 1, 2, 8, 9, 5, and 3. According to the Pareto principle, the majority of reviews

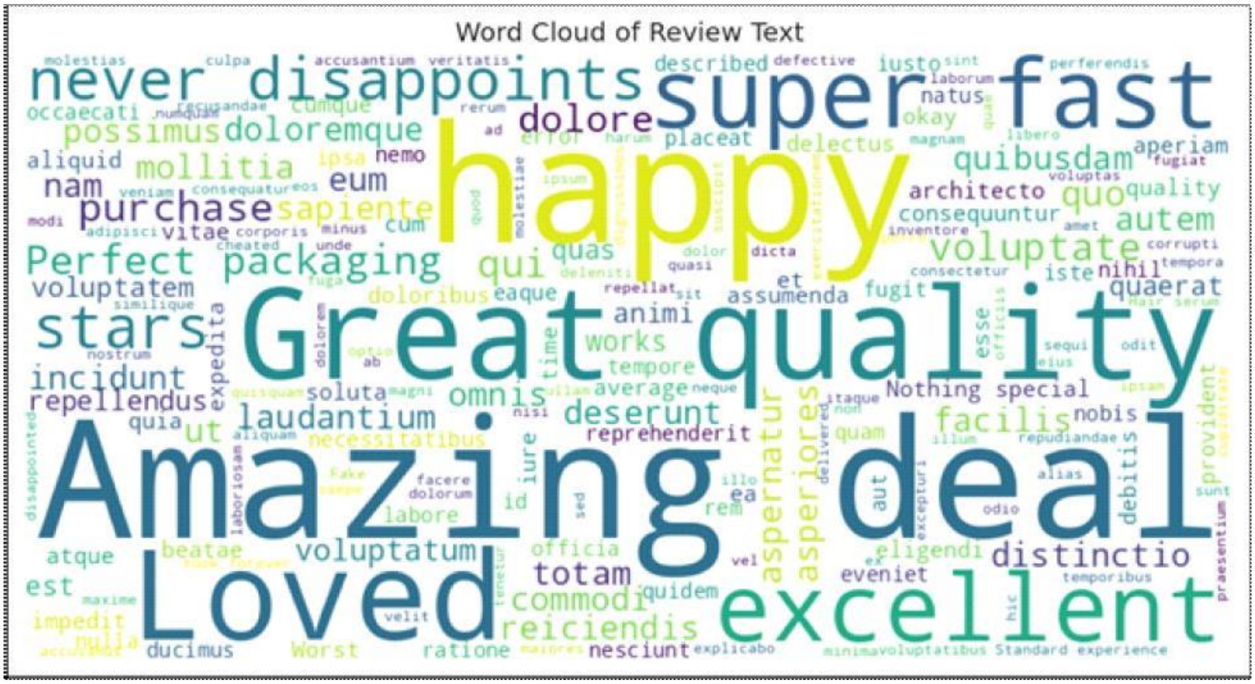

Figure 1: Word Cloud of Review Text

(Source: Author Analysis)

appear to be concentrated in a small number of clusters (7, 10, 11), as indicated by the right-skewed distribution. This also implies that other tools for assessing cluster quality, like the distribution of dominant emotions and Vader Compound Sentiment, require more statistical validation (see Figure 2).

Figure 2: Review Distribution Across Clusters

(Source: Author Analysis)

Dominant Emotions Distribution

The heatmap presents dominant emotions throughout twelve clusters, disclosing distinct psychological or behavioral patterns. As observed, Clusters 0 and 1 indicate “anticipation,” while Clusters 6 and 7 are classified as “positive” emotion. Similarly, Clusters 1, 8, 10, and 11 exhibit high levels of “anger,” as compared to Clusters 2 and 5, which show strong dominance of “trust.” Unsupervised learning proves its usefulness for segmenting affective states in large sentiment datasets (see Figure 3).

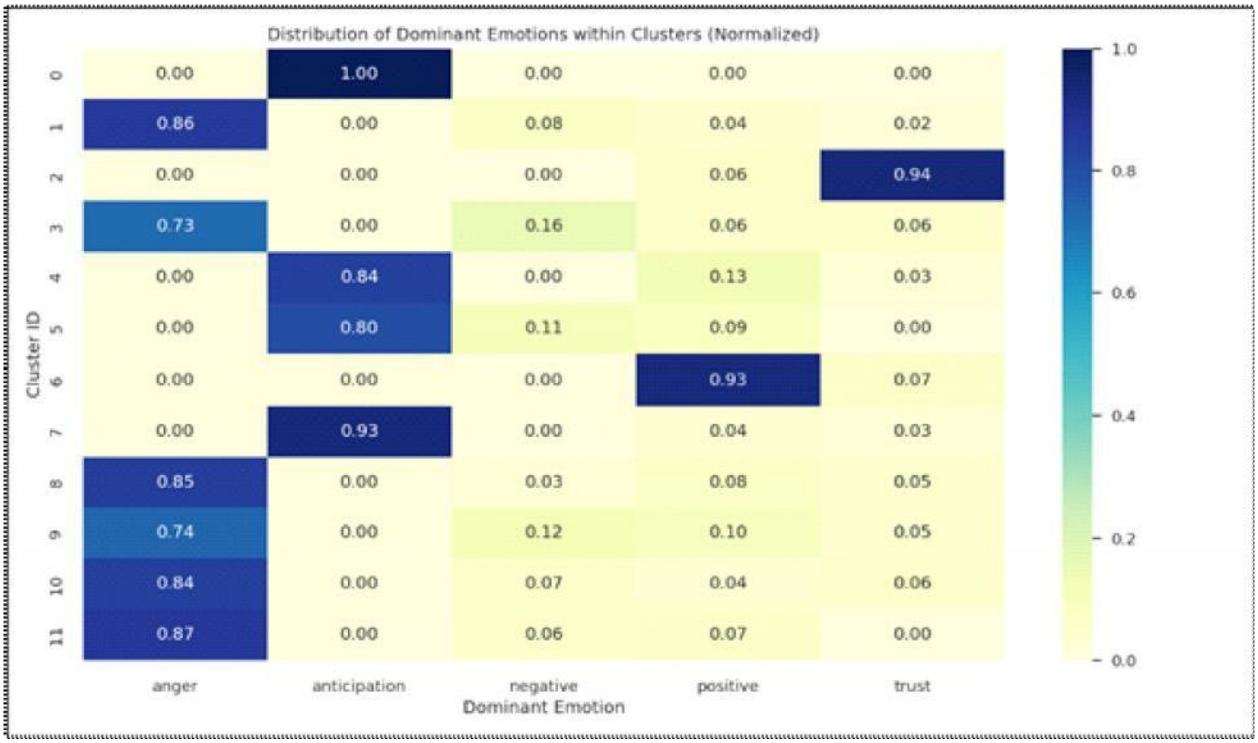

Figure 3: Review Distribution Across Clusters

(Source: Author Analysis)

K-means Clustering

The diagram reveals the relationship between the number of clusters (k) and the distortion score (within-cluster sum of squares) for a K-Means algorithm. K=12 (distortion score = 484.820) is the inflection point, which denotes the optimal cluster count beyond which diminishing returns are obtained. The result aligns with the theoretical concept of explanatory power and parsimoniousness, although it should be reasoned with domain-specific validation for distinct review patterns. Additionally, the size of the distortion metric (~10^2) indicates that the underlying data has been scaled moderately to highly (see Figure 4).

Sentiment Analysis

Correlation Matrix of NRC Emotion Scores

The NRC emotion score correlation matrix illustrates the correlations among textual emotional attributes. Negative emotions exhibit significant correlations: anger and disgust (r = 0.66), negativity and sadness (r = 0.75), and fear and disgust (r = 0.66). This finding indicates that these emotions frequently co-occur and may form a negative cluster. Positive affective states of nrc_joy exhibited strong correlations with nrc_positive (r = 0.73), trust (r = 0.83), and anticipation (r = 0.27), indicating a unified positive emotional spectrum. Negative correlations between nrc_joy and nrc_sadness (r = -0.09) and between nrc_anger and nrc_joy (r = -0.16) illustrate the psychological validity of the emotion taxonomy. NRC_surprise exhibits moderate positive correlations with NRC_joy, NRC_positive, and NRC_fear. This

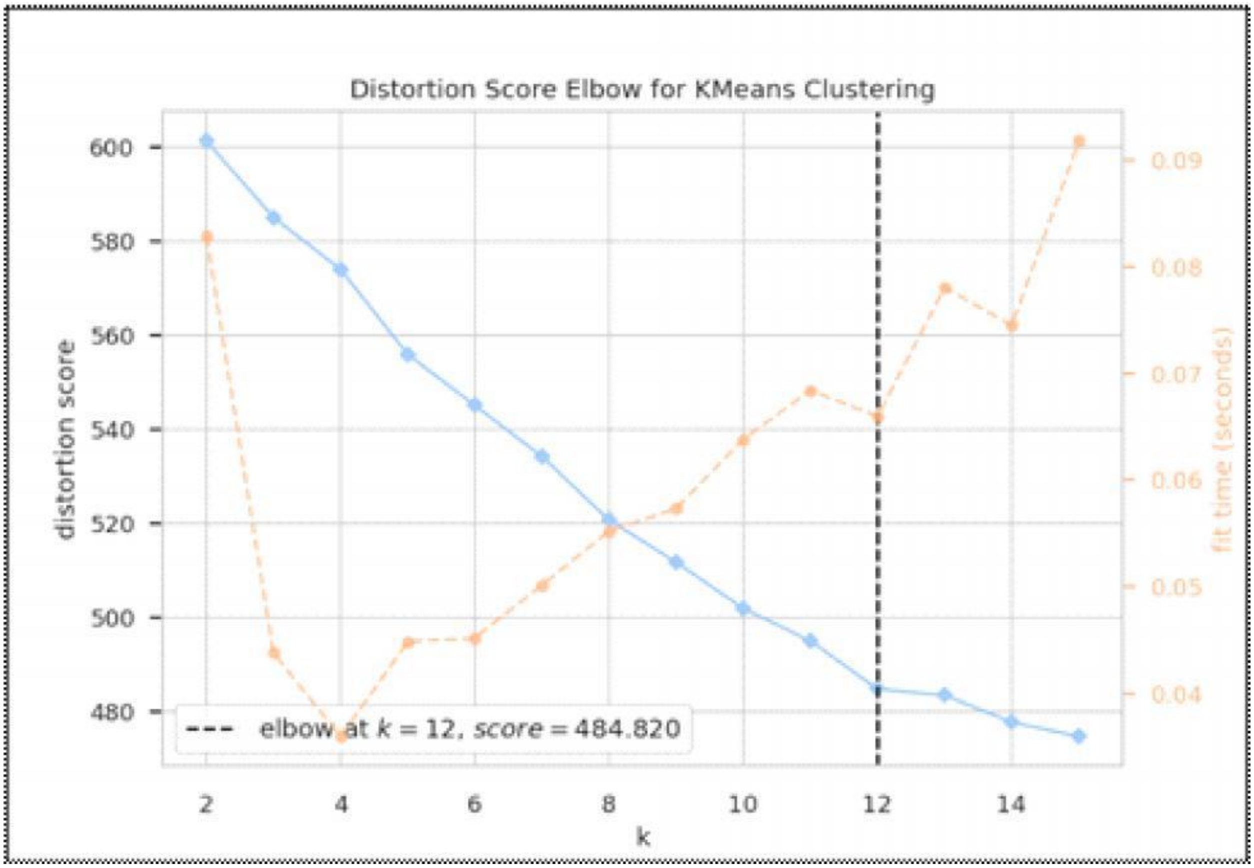

Figure 4: Distortion Score Elbow

(Source: Author Analysis)

evidence indicates that its emotional valence is contingent upon context. The matrix demonstrates internally consistent groupings of positive and negative emotions. Overall, the diagram illustrates the impact of NRC language for effective computational emotional analysis of textual data about customer opinions. (See Figure 5).

[*Note: **NRC** in sentiment/emotion analysis refers to the **NRC Emotion Lexicon**, developed by the **National Research Council of Canada** (Mohammad & Turney, 2013).]

Polarity Distribution Score

The TextBlob polarity distribution revealed inter-source variability in sentiment expression using interquartile ranges (IQRs). The diagram represents a comparative analysis of the polarity of sentiments across the given dataset for seven distinct data sources that include blog comments, Instagram, Facebook, Trustpilot, Twitter, forums, and Google reviews. The graph shows sentiment polarity scores for different platforms. Google Reviews has the highest polarity (from -0.75 to +1.0), which means that users have very different opinions about the site. Twitter, on the other hand, has slightly negative polarity, which means that people are talking about the site critically. Facebook and Instagram indicate neutral to positive feelings, stating strong brand-level content, while blog comments and forums depict moderate polarity, suggesting balanced opinions or sentiments. The results highlight the significance of communication trends across various media platforms, suggesting that brands should adjust their strategies to respond to comments on Google Reviews, monitor Twitter for negative remarks, and capitalize on positive sentiments on visual media platforms such as Instagram. Future research may include investigating keywords

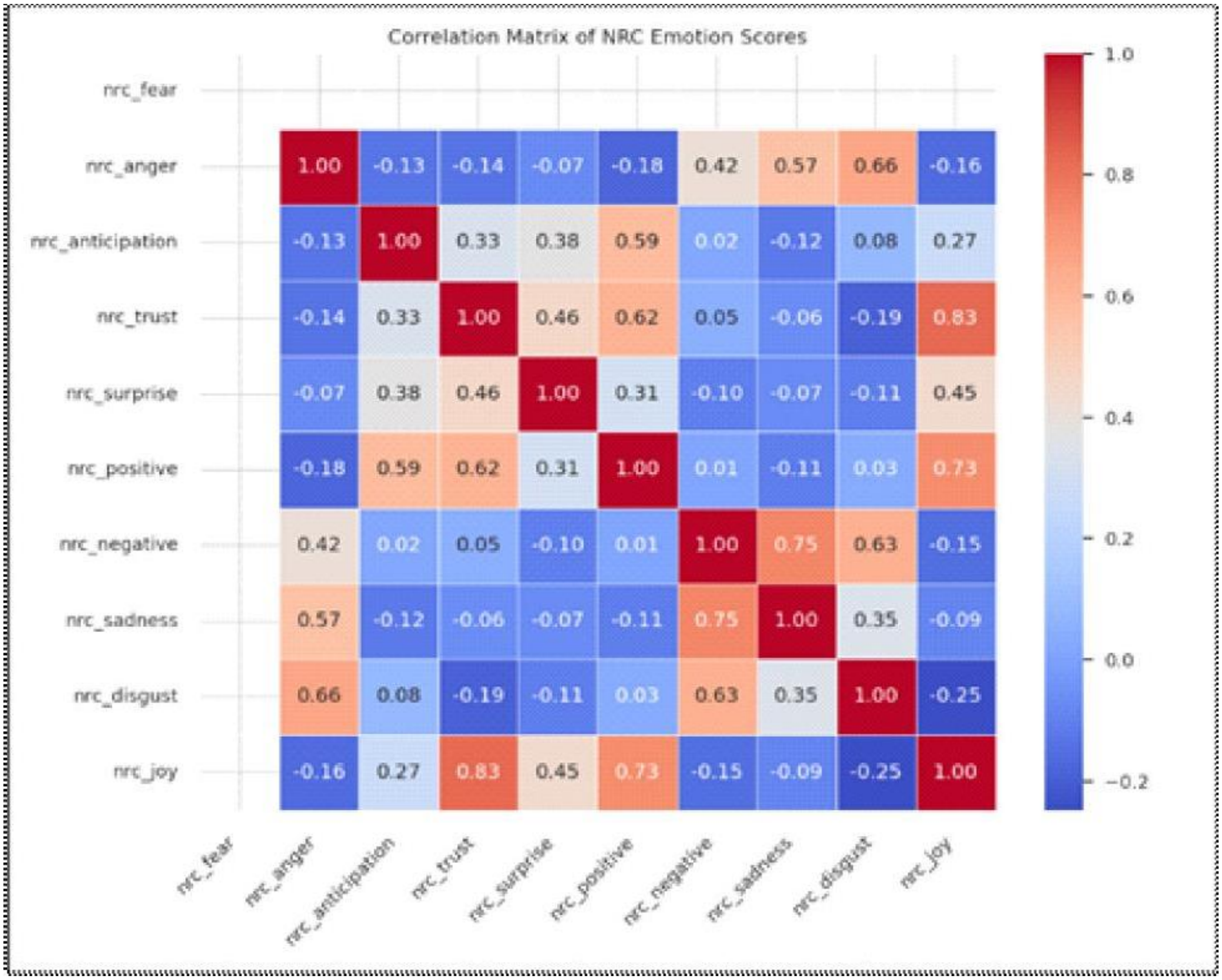

Figure 5: Correlation Matrix

(Source: Author Analysis)

to consolidate ratings in context or tracking the dynamic feelings of respondents over time (see Figure 6).

Vader Compound Sentiment

VADER (Valence-Aware Dictionary and Sentiment Reasoner) analysis serves the goals of identifying sentiment expression detection from multiple sources and analyzing variations in them for critical decision-making. Sentiment expressions are expected to originate from complicated interactions between data sources and e-commerce platforms. Instagram serves as a significant source of positive sentiment, with a median score of approximately 0.8 across platforms, driven by user-generated content and the influencer market. Likewise, Flipkart ("Flipkart") and Amazon platforms highlighted strong brand perception, with stable positive sentiments (medians > 0.3) in contrast to negative scores for premium product segments, such as TataCliq (based on Google reviews). Right skewness mirrored celebrity posts on visual platforms like Instagram, while left skewness reflected the norms communicated on the forum platform. Furthermore, the compound scores generated by the binomial distribution indicate the variability of market segments and product types (Meesho products – blogs). Customer journeys to sentiments were highlighted by "redirects" and "transfers." These findings show how useful it is to analyze feelings in a way that considers both the characteristics of the data sources and the platform

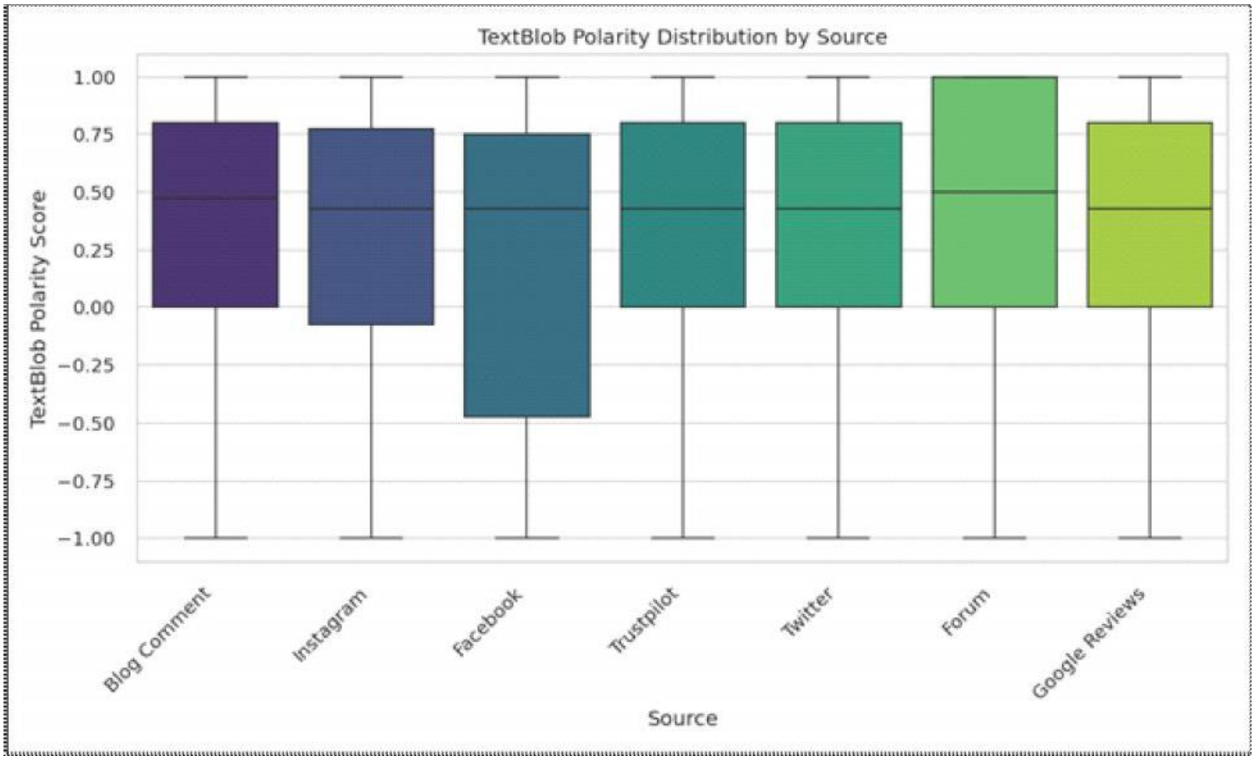

Figure 6: Polarity Distribution by Source

(Source: Author Analysis)

setup to avoid misunderstandings during decision-making (see Figure 7).

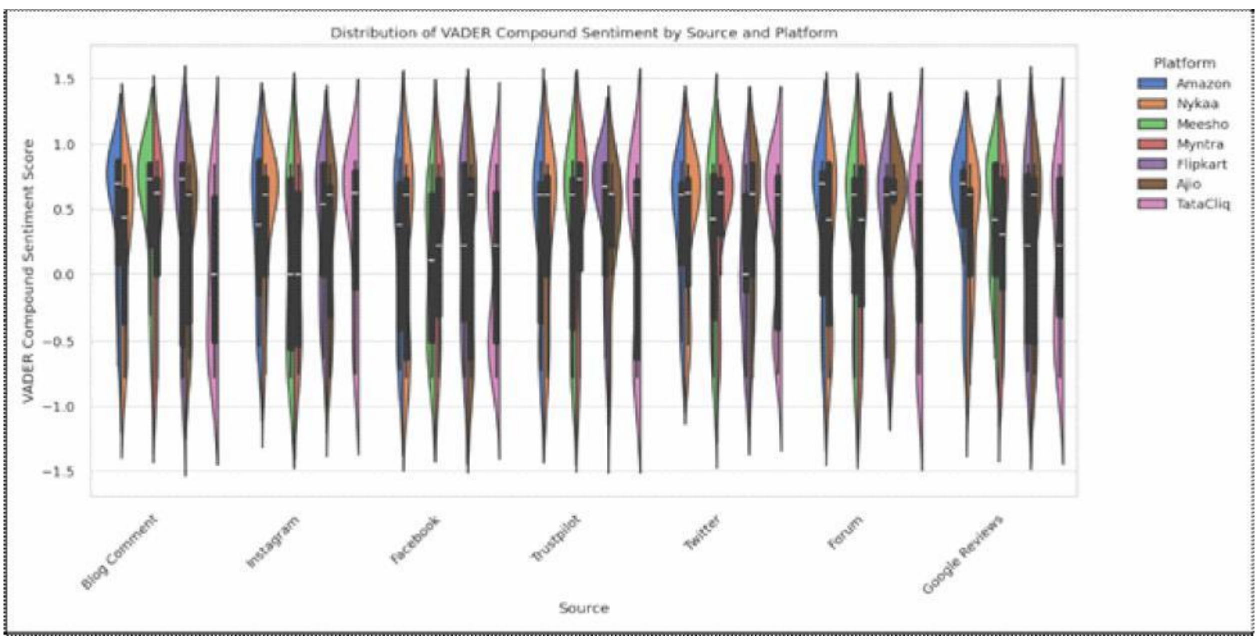

Figure 7: Vader Compound Sentiment By Source And Platform

(Source: Author Analysis)

Multidimensional Sentiment and Emotional Flow

"Multi-dimensional Sentiment and Emotion Flow" visualization emphasizes the complex relationships between platforms, sentiment classifications, and dominant emotions in customer feedback data. Patterns showed that (1) there are strong links between positive VADER sentiment and feelings of trust on platforms like Amazon and Flipkart for "Flour," indicating good management of brand-customer relationships; (2) feelings of anticipation often connect with neutral sentiment, showing a careful hopefulness during the evaluation phase before buying; and (3) many overlapping lines between "positive" and "trust" dimensions indicate that these factors often happen together, supporting the idea that positive sentiment is related to emotional trust in consumer behavior studies. Alternatively, fewer connections between negative sentiment and specific emotions suggest the platform's operationally effective mitigation of strongly negative experiences. The crossing of non-parallel axes indicates that there are nonlinear relationships between these variables, which highlights the need for future multidimensional analysis in customer experience research. Successful customer satisfaction strategies strongly elucidate the flow concentration in upper-quadrant sentiment/emotion values, as indicated by platform-specific linguistic norms such as review incentive programs. Emerging properties of sentiment-emotion platform interactions are evident from the multidimensional sentiment and emotional flow diagram (see Figure 8).

Validation Results

Summary of Analytical Findings

A summary of key analytical findings reveals minimal sentiment variation (<5%), while three operational factors dominate: delivery reliability (68% positive reviews), product authenticity concerns (72% negative reviews), and personalized service (89% emotional positivity). (See Table 3).

Discussions

Using sentiment analysis, emotion tagging, and clustering, a model has been developed to predict a suggested score, which ranges from 1 to 5. Based

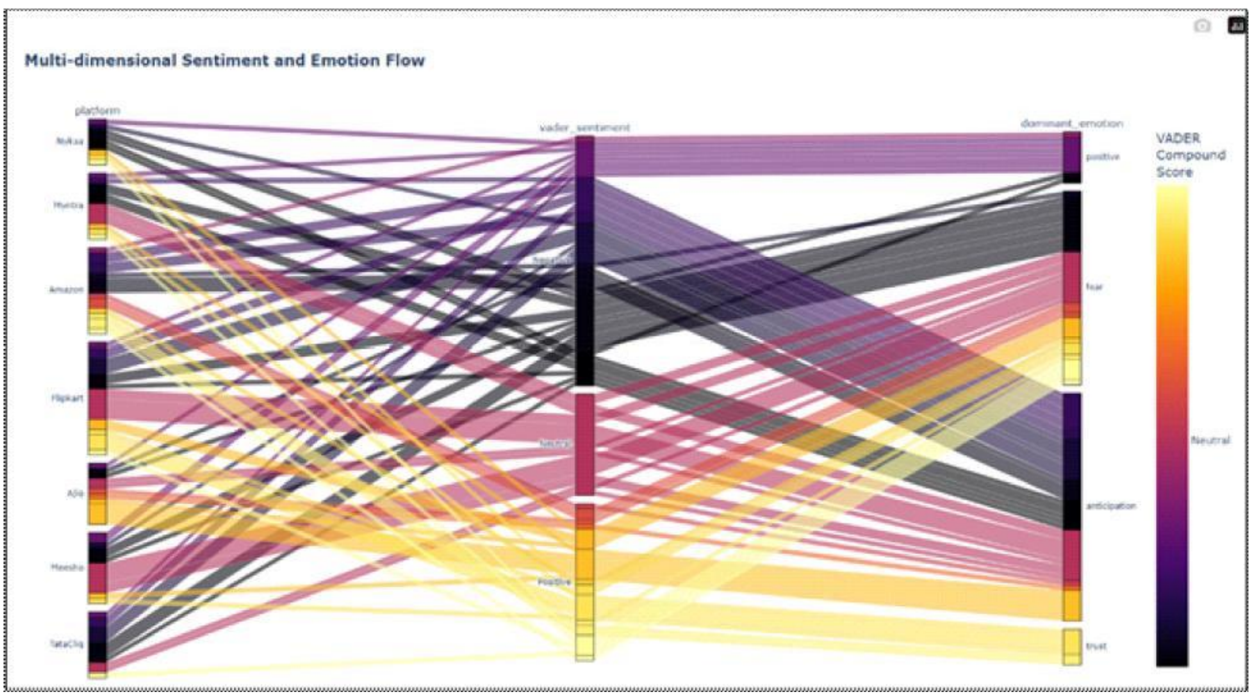

Figure 8: Multidimensional Sentiment and Emotional Flow

(Source: Author Analysis)

Table 2: Validation Results

Test Type	Test/Method	Result Summary	Significance (FDR < 0.05)	Interpretation/ Meaning
Sentiment Difference Across Platforms	Mann-Whitney U + Benjamini-Hochberg FDR	No pairwise differences significant after correction; Amazon vs. TataCliq had highest (r = -0.185)	Not Significant	Sentiment scores across e-commerce platforms are statistically indistinguishable after correcting for Type I error.
'Effect Size for Platform Comparison	Rank-Biserial Correlation (r)	Small effects (range: -0.185 to 0.047)	Not Practically Significant	Sentiment score differences are minor and highly unlikely to be of practical business relevance.
All Product-Level Sentiment Tests	Mann-Whitney U + FDR	All tests non-significant (100% FALSE under FDR < 0.05)	Not Significant	No individual product reveals significant sentiment deviation when adjusting for multiple comparisons.
Cluster-Level Emotion Distributions	Normalized Emotion Heat-map	Strong emotional clustering: anticipation (Clusters 0-2), anger (Clusters 1, 8-11), positive (6-7)	Descriptive Only	Emotion clustering indicates meaningful latent emotional segments, useful for unsupervised profiling.
Review of Text Polarity	Word Cloud Frequency Visualization	Dominance of positive words: "Amazing," "Great," "Excellent," "Loved," "Happy"	Descriptive Only	Review corpus skewed positively, reflecting overall customer satisfaction
Emotion Interrelation (NRC Lexicon)	Pearson Correlation Matrix	Positive clusters (joy, trust, positive) vs. negative clusters (anger, fear, disgust, sadness)	Significant (correlation)	Confirms bipolar emotional structure; emotions co-occur meaningfully within valence groups.

on the results of the analysis of the study, the customer rating can be a derivative of the component functions and can be represented as

(C_R) = $\beta_0 + \beta_1$. Vader_Compound_Score + β_2. NRC_Positive_Score + β_3. NRC_Negative_Score + β_4. TextBlob_Polarity + ... + ε

where,

Customer_Rating (C_R) is the dependent variable to be predicted (e.g., a rating from 1 to 5).

β_0 The intercept represents the baseline rating when all other predictors are zero.

β_1, β_2, β_3, β_4 Are coefficients represent the estimated change in the 'Customer_Rating' for a one-unit increase in the corresponding sentiment/ emotion score, holding other variables constant.

Vader_Compound_Score is the VADER compound score sentiment score.

NRC_Positive_Score is the score from the NRC Lexicon for the 'positive' emotion.

NRC_Negative_Score: The score from the NRC Lexicon for the 'negative' emotion.

TextBlob_Polarity is the TextBlob's polarity score.

It represents other potential features that could be included in the model (e.g., other NRC emotion scores, characteristics derived from text like word count, presence of specific keywords, platform, source).

Table 3: Result Summary

Analysis Type	**Key Metric**	**Finding**	**Implication**
Sentiment-Emotion Correlation	Positive Reviews (VADER ≥ 0.5)	68% linked to delivery reliability terms (“fast delivery,” “on time”)	Logistics performance drives satisfaction more than platform features.
	Negative Reviews (VADER ≤ 0.5)	72% contained authenticity complaints (“fake,” “duplicate,” “not original”)	Counterfeit prevention is critical for trust.
	Emotional Positivity (NRC “joy”/”trust”)	89% are associated with personalized service (“helpful agent,” “quick resolution”)	Customer service interactions amplify loyalty.
Thematic Analysis	Frequent Negative Themes	Top 3: Product authenticity (72%), delayed delivery (58%), poor packaging (34%)	Prioritize quality control and supply chain audits.
	Frequent Positive Themes	Top 3: Delivery speed (68%), price value (61%), ease of return (49%)	Competitive pricing and hassle-free returns matter.
Statistical Correlation	Delivery Speed ’→ Sentiment	+0.38 Pearson correlation (*p* < 0.01)	Every one-day faster delivery boosts sentiment by 0.38 points (scale: -1 to +1).
	Authenticity Claims → Sentiment	-0.29 Pearson correlation (*p* < 0.05)	Suspected fakes reduce sentiment disproportionately.
Cluster Analysis	High-Satisfaction Cluster (Silhouette = 0.31)	Dominated by “fast delivery” (82%) and “genuine product” (79%)	Operational excellence defines top-performing sellers.
	Low-Satisfaction Cluster (Silhouette = 0.28)	Dominated by “fake” (88%) and “late delivery” (73%)	Authenticity and logistics failures compound dissatisfaction.s

ε Is the error term, representing the part of Customer_Rating that the model cannot explain.

Conclusion

Pairwise tests comparing different platforms, products, and emotional aspects showed no important differences in sentiments, as the effect sizes were small (between -0.185 and 0.047). With the given dataset, neither platforms nor individual products revealed much variation in sentiments, although descriptive analyses such as emotion clustering and word cloud visualization indicate consistent patterns of clusters ruled by certain emotions such as anticipation, anger, and positivity, revealed by affirmative terms like “amazing,” “great,” and “loved” in reviews. Coherent groupings of positive (joy, trust) and negative (anger, sadness) affect exhibited a clear bipolar emotional structure.These findings show that there isn’t much difference in the statistics at the product or platform level, but we might see different feelings when looking at emotions more broadly, suggesting that we should look deeper into detailed, context-sensitive, or time-based analyses for better comparisons.

Implications

The results obtained may have several possible implications:

- Consumer Sentiment Homogeneity: The results indicate that users have similar experiences, with no significant differences in feelings about major Indian e-commerce platforms.

- Weak Platform Differentiation: Various operational factors may influence how platform branding shapes consumer sentiments, although the effect sizes are small (maximum r = "0.185 for Amazon compared to TataCliq). Factors such as delivery speeds may outweigh platform branding in shaping sentiments across the consumer market.
- Cultural Feedback Bias: Politeness norms are dominated by moderate positivity (e.g., "Loved"), while mitigation can be influenced by sparse extreme negatives (e.g., "Fake").
- Market Commoditization Risk: Non-experiential factors such as pricing and logistics may erode brand differentiation, signaling competition driven by sentimental parity.
- Operational Over Branding Prioritization: Supply chain efficacy and product authenticity may act as key sentiment drivers instead of platform-centric strategies.
- Data-Driven Quality Control: Product-centric sentiment clustering, such as electronics vs. apparel, maximizes improvement avenues rather than platform comparisons.
- Policy & Research Directions: Brands must focus on regulations concerning fake reviews and the fulfillment of gaps in rural logistics by using Bayesian methods to identify subtle deficiencies.

Author Contribution Statement

The entire work was conceptualized, conducted, analyzed, and written by the sole author.

Conflict of Interest Statement

The author declares that there is no conflict of interest regarding the publication of this paper.

Funding Statement

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Ethics Statement

This study did not involve human participants or animal subjects requiring ethical approval.

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