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Evaluating Quick-Commerce Platforms: A Sentiment and Topic Modeling Analysis of User Reviews

Toshif Khan, and Muhammad Abusaqer

Computer Science Department

Minot State University

Minot, ND, 58707

Toshif.khan@minotstateu.edu, and

Muhammad.abusaqer@minotstateu.edu

Abstract

Quick commerce (q-commerce) platforms have gained popularity in certain markets, particularly India, through services such as BlinkIt, Zepto, and JioMart, which promise the delivery of groceries and essentials in 10–30 minutes. This study analyzes 4,620 user reviews from these platforms to examine user sentiment, platform performance, and dominant topics. After standard text preprocessing and vectorization, a logistic regression classifier was trained on 80% of the data and achieved an accuracy of approximately 86%. Although negative sentiment dominated (roughly 78% of the reviews), platform comparisons revealed that BlinkIt had a comparatively higher average rating of around 2.55, with JioMart and Zepto averaging about 1.50–1.53. Latent Dirichlet Allocation (LDA) topic modeling identified five main themes related to operational issues, customer service, positive experiences, delivery delays, and payment/wallet concerns. These insights underscore critical areas where q-commerce platforms can improve service reliability and customer support to enhance user satisfaction.

1. Introduction

Quick commerce (q-commerce) is an emerging branch of e-commerce focused on delivering groceries and daily essentials within 10–30 minutes [1]. Popular platforms like Zepto and Blinkit prioritize ultra-fast fulfillment as a key competitive advantage, while JioMart has also entered the rapid-delivery space. This crowded marketplace highlights the importance of user experience (UX) factors, such as delivery reliability, refund processing, and customer support, as crucial differentiators among competing platforms.

To assess whether q-commerce platforms truly fulfill their promise of near-instant service, this study analyzes 4,620 user reviews collected from Zepto, Blinkit, and JioMart. These reviews reflect a wide range of user experiences, from significant complaints about late deliveries to praise for exceptional speed. The list below presents a sample of reviews illustrating the diverse sentiments:

Sample Reviews

- *"Delivery was late by 45 minutes and no response from customer care."* (1-star, Zepto)
- *"App experience is smooth. Got my groceries in 12 minutes!"* (5-star, Blinkit)
- *"Refund not processed even after 3 days. Frustrating!"* (2-star, JioMart)

Leveraging both sentiment classification and topic modeling, the study reveals that negative feedback predominates (with approximately 78% of reviews deemed negative), although Blinkit garners a slightly higher average rating of around 2.55 relative to the 1.50–1.53 range of Zepto and JioMart. Furthermore, Latent Dirichlet Allocation (LDA) on the entire corpus identifies five principal themes: operational issues, customer service, positive experiences, delivery delays, and payment/wallet concerns.

These findings emphasize the pivotal nature of on-time delivery, efficient refund practices, and responsive customer support in shaping user perception. Although the focus rests on three major q-commerce platforms, the analytical framework—combining logistic regression for sentiment classification and LDA for topic discovery—can likewise benefit other on-demand services such as DoorDash and UberEats, helping them optimize user satisfaction.

2. Background

2.1 Q-commerce

Q-commerce is a specialized subset of e-commerce that focuses on speed, convenience, and small-basket orders, fulfilled within 10–30 minutes using either local stores or dark stores as depicted in Figure 1 [2]. Its rapid growth is driven by factors such as increasing internet connectivity, widespread smartphone usage, and the expanding ecosystem of digital payments [3]. As consumer expectations shift toward near-instant service, more businesses adopt this model to meet urgent demands and foster competitive advantages.

Despite its advantages in convenience, q-commerce also introduces operational complexities, including managing real-time inventory, optimizing delivery routes, and handling last-mile logistics. Organizations like Blinkit, Zepto, and JioMart handle these challenges differently, affecting both service quality and user perceptions. This evolving marketplace calls for rigorous, data-centric evaluations to understand how effectively q-commerce platforms fulfill their promise of rapid delivery and how users respond when services fall short.

To understand how users perceive and evaluate such time-sensitive services, some researchers often employ sentiment analysis, a computational approach that systematically classifies and interprets users' subjective opinions in textual data [4]. Complementing sentiment analysis, topic modelling, especially methods like Latent Dirichlet Allocation (LDA) groups large volumes of text into coherent clusters (or "topics") to reveal the underlying themes users discuss [5].

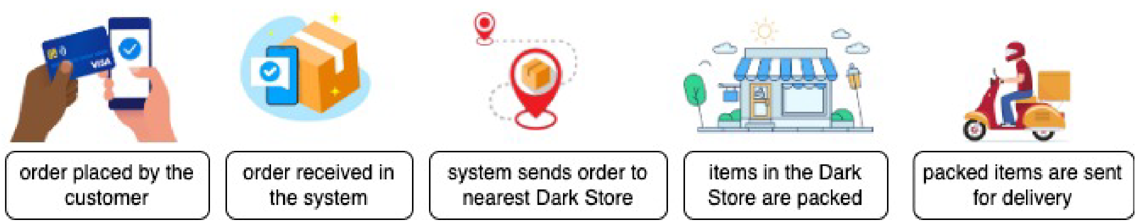

Figure 1: Process flow of grocery products ordered online using the instant delivery app

2.2 Descriptive Statistics

Descriptive statistics provide a summarized view of the dataset, offering quick insights into overall user behavior [6]. In this research, metrics such as average ratings, review counts per platform, and sentiment distribution (e.g., 78% negative) help identify platform-specific performance trends without the need for in-depth modeling.

2.3 Sentiment Analysis

Sentiment analysis is the process of identifying and categorizing opinions expressed in textual data to determine whether the underlying attitude is positive, negative, or neutral [7]. In this study, it is used to quantify user satisfaction across platforms. For example, complaints about delivery delays or refund issues are typically classified as negative, whereas reviews praising fast service are categorized as positive.

2.4 Topic Modeling (LDA)

Topic modeling, particularly through Latent Dirichlet Allocation (LDA), is a machine learning method used to uncover hidden thematic structures within large text corpora [8]. Instead of manually reading thousands of reviews, LDA automatically groups them into coherent topics, such as customer service or payment issues, thereby highlighting the areas that are most important to users.

3. Related Work

Mahajan and Sood [9] explore the operational design of q-commerce ventures in Southeast Asia, focusing on the impact of micro-warehousing strategies on delivery speed and cost efficiency. Mahajan and Sood's findings indicate that small, strategically located warehouses significantly reduce last-mile delivery times but require careful stock management to avoid frequent product stockouts.

Gupta et al. [10] examine how consumer perceptions of quick deliveries evolve over repeated usage, highlighting that customer loyalty tends to increase once a platform demonstrates consistent, on-time service. Gupta et al.'s study also identifies that introducing loyalty-based reward systems such as monthly subscriptions for free deliveries can further boost user retention in q-commerce apps.

Roy and Subramani [11] investigate the role of user experience (UX) design in ultra-fast grocery delivery applications. Roy and Subramani find that clear navigation, transparent order tracking, and proactive customer notifications are key to enhancing consumer trust. Roy and Subramani's research underscores that even minor interface issues lead to negative reviews, given the heightened expectations associated with instantaneous deliveries.

Zhang et al. [12] perform a comparative case study on q-commerce businesses across multiple countries, including India, China, and the United Arab Emirates. Zhang et al.'s cross-cultural analysis reveals that, while rapid delivery is a universal appeal, user satisfaction also depends on localized factors such as payment preferences and cultural norms regarding tipping delivery staff.

Kumar and Banerjee [13] employ sentiment analysis techniques similar to those in the current paper, but apply them specifically to user-generated content on social media platforms discussing hyper-local deliveries. Kumar and Banerjee [14] conclude that complaints related to lost or incorrect orders often escalate quickly on public forums, thereby highlighting the importance of real-time customer service interventions to mitigate reputational damage.

Lastly, Shroff [15] proposes a hybrid approach that integrates topic modeling and network analysis to map user concerns and their interconnections. Applying this framework to a major q-commerce platform, Shroff identifies refund delays and app crashes as critical pain points. By visualizing how these issues co-occur in user discourse, the study provides actionable insights into which areas of the user experience most urgently require optimization.

4. Methodology

This research adopts a structured analytical pipeline to investigate and evaluate user sentiment and thematic concerns regarding quick-commerce (q-commerce) platforms, specifically, BlinkIt, Zepto, and JioMart. The methodology consists of four major phases: data acquiring, data preprocessing, sentiment classification, and topic modeling.

4.1 Data acquiring

The dataset used in this research was publicly sourced from the Kaggle[1]. It contains a total of 4,620 user reviews, each comprising a numeric rating (1-5 scale), the review text, the review date, and the corresponding platform (BlinkIt, Zepto, JioMart).

4.2 Data Preprocessing

Standard text-cleaning procedures were performed on the reviews, including:

- Lowercasing all text.
- Removing punctuation, special characters, and excessive whitespace.
- Eliminating stopwords using the NLTK stopword corpus.

For sentiment labeling, ratings 1–2 were treated as *negative*, rating 3 as *neutral*, and ratings 4–5 as *positive*. Because the distribution of sentiments was imbalanced (negative sentiment was most frequent), a stratified train–test split was employed to maintain class proportions. We then vectorized the cleaned text using TF-IDF (Term Frequency–Inverse Document Frequency), restricting the vocabulary to the top 5,000 terms.

4.3 Sentiment Classification

A logistic regression model (with class_weight='balanced' to mitigate class imbalance) was trained on 80% of the dataset and tested on the remaining 20%. Performance was measured by accuracy, precision, recall, F1-score, and a confusion matrix. The primary goal was to classify each review as negative, neutral, or positive based on the text.

[1] https://www.kaggle.com/datasets/mannacharya/blinkit-vs-zepto-vs-instamart-reviews

4.4 Topic Modeling

Latent Dirichlet Allocation (LDA) was performed to reveal hidden themes in the review corpus. After tokenization and dictionary creation with Gensim, five topics were extracted. Each topic's most salient keywords served as a guide for interpreting underlying themes such as delivery issues, customer service, and operational reliability.

5. Results and Discussion

This section outlines the main findings regarding data distributions, sentiment classification performance, and topic modeling insight.

5.1 Data Distributions

- **Rating Distribution**
  In Figure 2, the distribution of the rating shows that over 72% of the reviews had a rating of 1, indicating a strong negative trend. Ratings of 5 accounted for about 14%, with 2, 3, and 4 comprising the remaining 14%. Consequently, the overall sentiment skew was heavily negative.

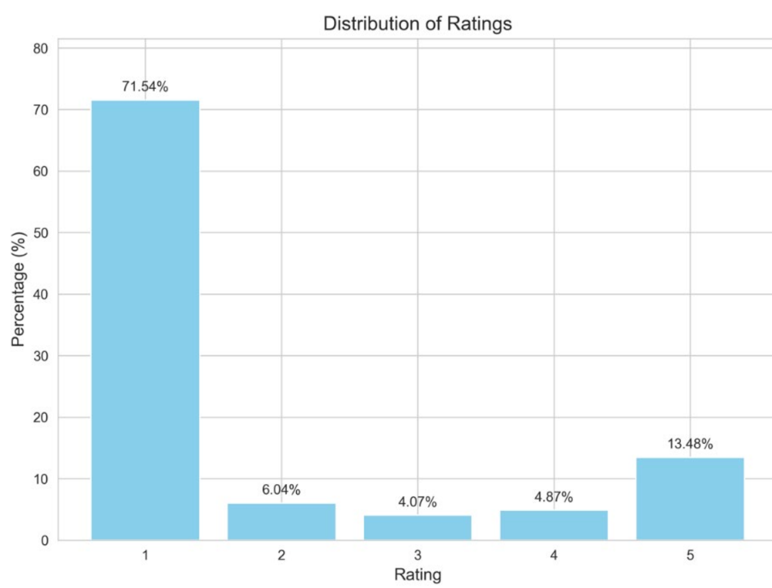

Figure 2. Distribution of Ratings

- **Platform Distribution**
  The dataset was relatively balanced across the three platforms, with Zepto (37.7%) having slightly more reviews than JioMart (32.5%) and BlinkIt (29.9%) as shown in Figure 3.

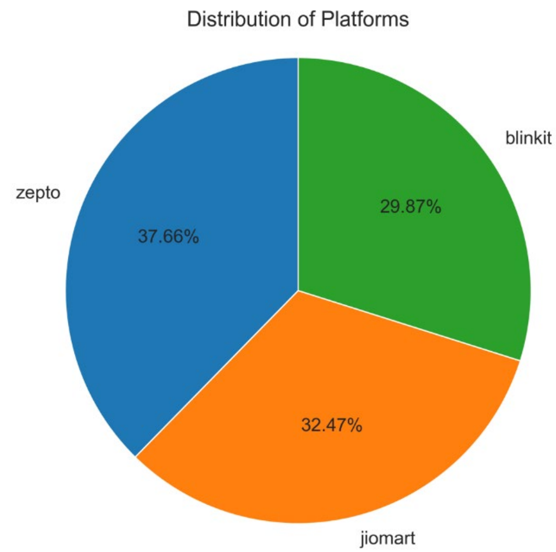

Figure 3. Platform Distribution

- **Review Length**
  On average, user reviews contained about 29 words, with most falling in the 20–40 range. A small portion (about 177 reviews) contained fewer than 10 words.

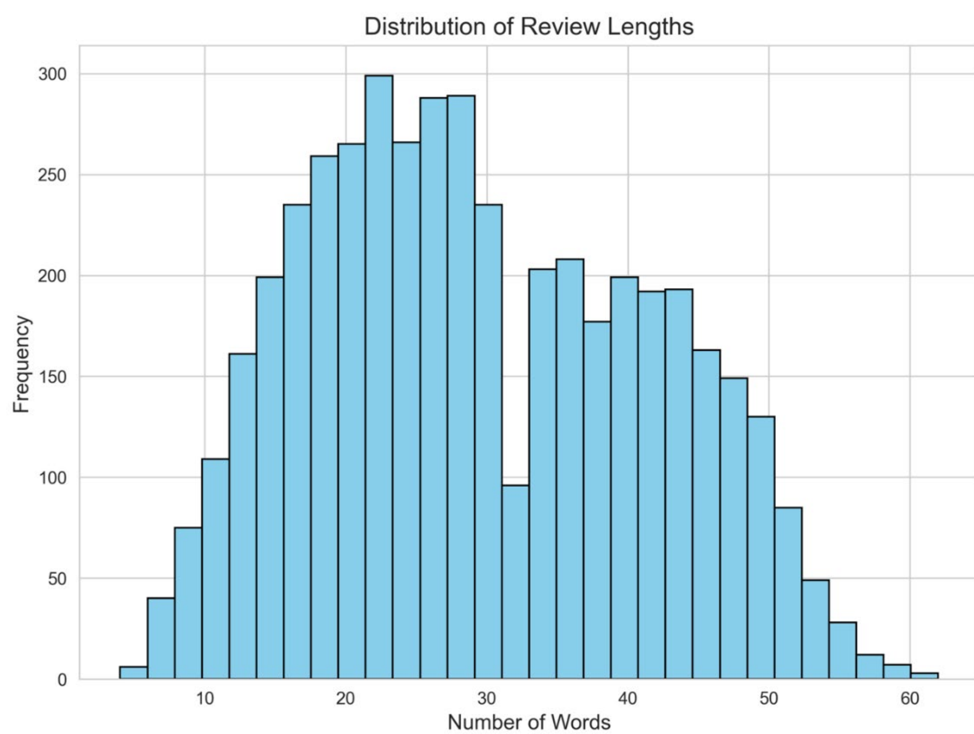

Figure 4. Distribution of Review Lengths

5.2 Sentiment Classification Results

Training a logistic regression classifier on the TF-IDF vectors yielded an overall accuracy of approximately **86%** on the held-out test set. Table 1 provides the precision, recall, and F1-scores for the three sentiment classes.

Sentiment	Precision	Recall	F1-score
Negative	0.95	0.91	0.93
Neutral	0.14	0.18	0.18
Positive	0.72	0.82	0.77
Accuracy	-	-	0.86
macro avg	0.61	0.64	0.62

Table 1. Classification Metrics for Sentiment Analysis

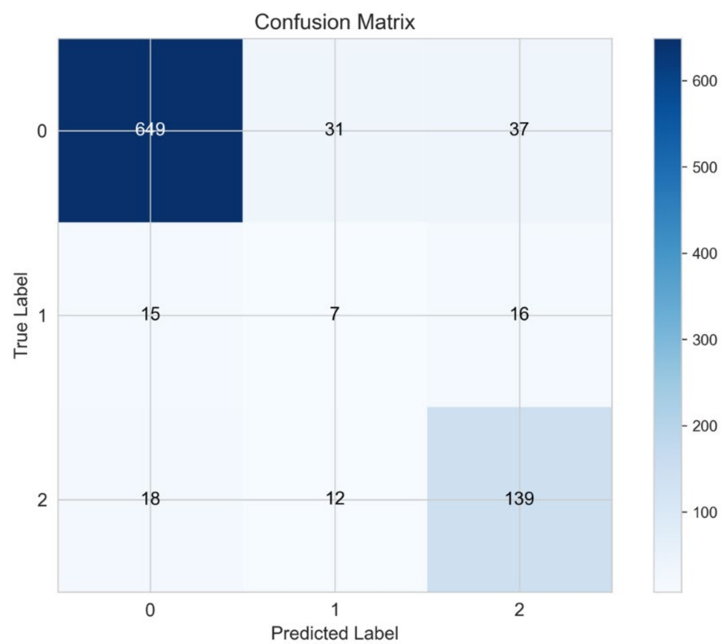

Figure 5. Confusion Matrix for Logistic Regression model to predict reviews' sentiment.

The highly skewed distribution of sentiments affected classification for the neutral category, reflected in lower precision and recall. In contrast, negative and positive sentiments were identified more reliably. These findings suggest that while the logistic regression model can robustly capture polarized feedback, additional techniques (e.g., data augmentation or oversampling) might be needed to improve recognition of neutral sentiment.

5.3 Platform-Specific Insights

A comparison of average ratings by platform showed that:

- BlinkIt had the highest average rating (≈ 2.55).
- JioMart and Zepto trailed with averages near 1.50–1.53.

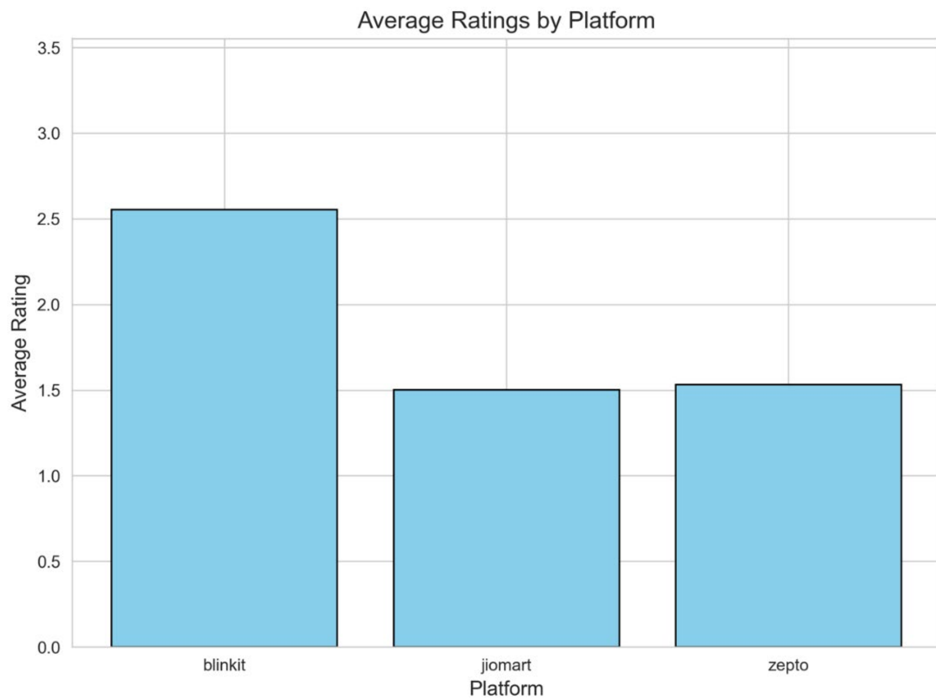

Figure 6. Average Ratings by Platform.

Despite BlinkIt's relatively better performance, it still exhibited a notable proportion of negative feedback. For JioMart and Zepto, the more pronounced dissatisfaction suggests underlying operational or service-related challenges.

5.4 Topic Modeling Results

Five main themes emerged from the LDA analysis:

1. Operational Issues: Emphasizing orders, refunds, out-of-stock items, and app reliability.

2. Customer Service Concerns: Highlighting problems with product quality, complaint handling, and response times.

3. Positive Experiences: Reflecting praise for quick deliveries, application usability, and product freshness.

4. Delivery Issues: Relating to late or incorrect deliveries, poor handling, or packaging problems.

5. Payment and Wallet Issues: Addressing problems with payment gateways, wallet integrations, and transaction inconsistencies.

These topics underscore significant pain points, particularly around refunds, service reliability, and the quality of customer support.

6. Future work

Several avenues exist for enhancing this analysis:

1. Advanced Embeddings
   Incorporate transformer-based models (e.g., BERT, RoBERTa) to capture contextual nuances in user reviews, potentially boosting sentiment classification accuracy.

2. Temporal Analysis
   Investigate trends over time to determine whether user sentiment shifts in response to platform improvements, new feature rollouts, or promotional events.

3. Cross-Lingual Analysis
   Many reviews in emerging markets may mix English with other languages; future research can employ multilingual or transliteration-based approaches.

7. Conclusion

This study provides an examination of user sentiment and topic patterns for BlinkIt, Zepto, and JioMart through logistic regression–based classification and LDA topic modeling. The findings highlight substantial negative sentiment, underscoring frequent complaints about refunds, customer support, and delivery logistics. Although BlinkIt displays relatively higher average ratings, all platforms face consistent user dissatisfaction in certain areas.

Despite achieving an 86% accuracy, the classification struggled with underrepresented neutral sentiments, which justified a 62% F-1 score, suggesting the need for more balanced datasets or advanced modeling. Nevertheless, the identified topics offer concrete directions for platform optimization, from more responsive support systems to improved order handling. The analysis underscores the importance of ongoing monitoring of user feedback and sophisticated text analytics to guide targeted improvements and maintain competitive advantages in the quick-commerce sector.

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