A Multi-Modal Text Analytics Framework for eCommerce Customer Reviews: Integrating Emotion Detection, Sentiment Analysis, and Topic Modelling

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Abstract

Understanding customer sentiment and emotional response from eCommerce reviews is critical for businesses seeking to improve product quality, marketing strategy, and customer retention. While prior work has addressed emotion detection, sentiment classification, and topic discovery in isolation, limited research has combined all three modalities into a unified analytical framework applied to eCommerce review data. This paper presents a multi-modal text analytics pipeline integrating transformer-based emotion detection using DistilRoBERTa, lexicon-based sentiment analysis using TextBlob, and unsupervised topic modelling via Latent Dirichlet Allocation (LDA). Applied to a dataset of 23,485 women's clothing eCommerce reviews, the framework reveals that joy dominates customer emotional responses across all product categories, while sizing and fit issues represent the most recurrent negative theme across multiple LDA topics. Cross-modal analysis confirms convergent validity between emotional, sentiment, and topical signals. The proposed framework offers actionable insights for marketing, product development, and inventory management, demonstrating the practical value of combining complementary NLP techniques for business intelligence.

Keywords: emotion classification, sentiment analysis, topic modelling, LDA, eCommerce, NLP, DistilRoBERTa, TextBlob, customer reviews, text analytics

1. Introduction

The rapid growth of eCommerce has generated an unprecedented volume of user-generated text data. Customer reviews represent a rich source of behavioural and experiential signals that businesses can exploit to improve products and services. The global eCommerce market is projected to reach $55.6 trillion by 2027 (Business Wire 2022), and with approximately 2 billion people accessing eCommerce platforms globally, the scale of available review data continues to expand (Munna et al. 2020).

Customer reviews vary widely in length, tone, and linguistic complexity. Customers may express nuanced emotional states — satisfaction, disappointment, or surprise — that require fine-grained classification beyond simple positive or negative polarity (Poria et al. 2017). Additionally, recurring themes such as sizing inconsistency or fabric quality may be embedded across thousands of reviews, requiring topic modelling techniques to surface (Barde & Bainwad 2017).

Prior work has largely addressed these challenges in isolation. Sentiment analysis identifies polarity (Vanaja & Belwal 2018, Taboada et al. 2011), emotion classification captures affective states (Acheampong et al. 2021), and topic modelling discovers latent themes (Blei et al. 2003). However, the combination of all three into a unified business analytics framework remains underexplored in the eCommerce domain.

This paper addresses this gap by presenting a multi-modal text analytics framework that simultaneously applies transformer-based emotion detection, lexicon-based sentiment analysis, and LDA topic modelling to a large dataset of eCommerce clothing reviews. The framework is designed with business applicability in mind, producing insights directly relevant to marketing, product development, and customer experience functions.

2. Related Work

Sentiment analysis of eCommerce reviews has been widely studied. Huang et al. (2023) reviewed current techniques and identified opportunities for deeper semantic understanding beyond polarity classification. Ji et al. (2018) demonstrated the value of sentiment analysis for identifying product quality issues in eCommerce settings. Drus & Khalid (2019) conducted a systematic literature review of sentiment analysis on social media content, providing a comprehensive taxonomy of approaches.

Emotion classification introduces finer granularity, distinguishing states such as joy, sadness, fear, and disgust as defined by Ekman's foundational taxonomy of basic emotions (Ekman 1992). Acheampong et al. (2021) reviewed transformer-based approaches for text emotion detection, demonstrating strong performance of BERT-family models. The DistilRoBERTa model used in this study offers competitive performance with reduced computational overhead, making it well suited to applied classification tasks.

Topic modelling via LDA (Blei et al. 2003) has been applied across multiple review domains. Kwon et al. (2021) applied LDA to airline review data and combined it with sentiment scores to derive actionable service insights. Calheiros et al. (2017) combined topic modelling and sentiment analysis for hotel review analysis, demonstrating that the integration of these two approaches yields richer insight than either alone. The present work extends this combined approach by additionally incorporating emotion detection as a third analytical layer.

3. Dataset

The dataset consists of 23,485 women's clothing eCommerce reviews sourced from Kaggle. Each review is associated with a product category label spanning six departments: Tops, Dresses, Bottoms, Jackets, Intimate, and Trend. The dataset contains no pre-assigned emotion labels, making it representative of real-world unlabelled review corpora. Review lengths vary considerably, from single-sentence ratings to detailed multi-paragraph descriptions of product fit, fabric, and appearance.

4. Methodology

4.1 Text Preprocessing

All reviews underwent a standardised preprocessing pipeline: HTML tag removal, lowercasing, punctuation removal, stopword filtering, and tokenisation. TF-IDF vectorisation (Roelleke & Wang 2008) was applied for feature extraction prior to topic modelling.

4.2 Emotion Detection via DistilRoBERTa

Emotion classification was performed using the pre-trained `j-hartmann/emotion-english-distilrc` model from HuggingFace, fine-tuned for multi-class emotion classification. The model assigns each review one of seven emotion labels — joy, sadness, neutral, surprise, fear, disgust, and anger — corresponding to Ekman's taxonomy of basic emotions (Ekman 1992). This transformer-based approach eliminates the need for labelled training data, making it directly applicable to the unlabelled review corpus.

4.3 Sentiment Analysis via TextBlob

Sentiment polarity was computed using a lexicon-based approach. Each review was classified as positive (polarity > 0), negative (polarity < 0), or neutral (polarity $= 0$). The lexicon-based approach, consistent with methods proposed by Taboada et al. (2011), provides a computationally efficient complement to the transformer-based emotion module.

4.4 Topic Modelling via LDA

Latent Dirichlet Allocation (Blei et al. 2003) was applied to the full review corpus to extract five latent topics. The number of topics was selected based on interpretability of the resulting keyword distributions. Word clouds were generated for each topic to facilitate qualitative interpretation.

4.5 Cross-Modal Analysis

Following individual analyses, cross-modal visualisations were constructed to examine relationships between topics, sentiments, and emotions. A heatmap of topic distribution across sentiment categories and a stacked bar chart of topic distribution across emotion classes enabled integrated interpretation of the three analytical outputs, following the approach of Kwon et al. (2021) and Calheiros et al. (2017).

5. Results

5.1 Emotion Distribution

Joy was the dominant emotion across the full dataset, with over 13,000 instances — far exceeding all other emotion categories combined. Sadness was the second most frequent emotion (approximately 3,500 instances), followed by neutral responses (approximately 2,700) and surprise (approximately 2,500). Fear, disgust, and anger occurred in substantially smaller quantities, each below 700 instances. This distribution indicates an overall positive customer experience with the reviewed products.

Across product categories, joy remained dominant in all six departments. However, the Tops and Dresses categories showed relatively elevated levels of sadness and neutral emotions compared to other categories, suggesting product-specific issues warranting further investigation.

Table 1: Distribution of emotion classes and sentiment categories across the review dataset.

Emotion Class	Count (approx.)	Sentiment	Count (approx.)
Joy	13,500	Positive	$\sim$21,000
Sadness	3,500	Negative	$\sim$1,300
Neutral	2,700	Neutral	$\sim$1,200
Surprise	2,500	—	—
Fear	650	—	—
Disgust	600	—	—
Anger	$<$40	—	—

5.2 Sentiment Analysis Results

Sentiment analysis confirmed the broadly positive nature of the review corpus. Positive reviews accounted for approximately 21,000 instances (approximately 89% of the dataset), while negative and neutral reviews each numbered approximately 1,200–1,400 instances. The Dresses category received both the highest volume of positive reviews and the highest absolute count of negative reviews, consistent with its proportional dominance in the dataset.

5.3 LDA Topic Modelling Results

Five distinct topics were extracted from the review corpus:

- **Topic 1 — Fit and Appearance (Jeans/Pants):** Keywords: *love, fit, great, pant, jean, wear, color, perfect, look, length*. Customers expressed strong positive sentiment regarding fit, colour, and length of trouser-type garments.
- **Topic 2 — Sizing Issues (Shirts/Dresses):** Keywords: *fit, size, small, shirt, dress, little, like, large, arm, look*. A recurring theme of sizing inconsistency, particularly around arm length and overall size guidance.
- **Topic 3 — Sizing and Return Behaviour:** Keywords: *size, small, fit, ordered, like, wear, store, run, tried, medium*. Extends the sizing theme with evidence of customers ordering multiple sizes, suggesting inadequate size guidance prior to purchase.
- **Topic 4 — Fabric and Aesthetic Quality (Dresses/Skirts):** Keywords: *dress, look, fabric, like, color, skirt, love, fit, beautiful, flattering*. Highly positive sentiment around fabric quality, colour selection, and aesthetic appeal.
- **Topic 5 — Comfort and Wearability (Sweaters/Dresses):** Keywords: *love, great, sweater, wear, color, dress, fit, comfortable, look, perfect*. Strong positive endorsement of comfort and wearability across knitwear products.

5.4 Cross-Modal Analysis

The heatmap of topic distribution across sentiment categories confirmed that positive sentiment dominated all five topics. Topic 4 (fabric and aesthetic quality) had the highest volume of positive reviews (4,815), while Topic 2 (sizing issues) had the highest proportion of negative sentiment (380 negative reviews), consistent with its thematic content. Cross-modal analysis of topic distribution across emotion classes revealed that Topic 3 was most strongly associated with joy and surprise, while Topic 0 showed higher proportional alignment with anger and disgust — consistent with the negative sentiment findings for that topic cluster.

6. Business Implications

The integrated framework produces actionable insights across several business functions (Singh et al. 2022, Huang et al. 2023):

- **Marketing and Customer Success:** The high prevalence of joy-classified reviews provides strong material for testimonials and social proof campaigns. Topic 4 and Topic 5 keywords (*beautiful, flattering, comfortable, perfect*) represent authentic language suitable for advertising copy.
- **Product Development:** Topics 2 and 3 reveal a persistent sizing inconsistency problem, particularly for shirts and dresses. The co-occurrence of *tried*, *ordered*, *small*, and *medium* in Topic 3 suggests customers are ordering multiple sizes due to insufficient size guidance. Improved sizing charts or virtual fit tools would directly address this pattern.
- **Inventory Management:** Products associated with high-joy, positive-sentiment topics (Topics 4 and 5) represent strong-demand items. Stock levels can be optimised accordingly, while products generating negative emotional signals warrant review before restocking.
- **Customer Retention:** Negative emotion signals in the Tops and Trend categories represent high-risk churn signals. Proactive customer service outreach to reviewers exhibiting these patterns can reduce attrition (Yang et al. 2020).

7. Discussion

The results demonstrate that combining transformer-based emotion detection, lexicon-based sentiment analysis, and LDA topic modelling produces a richer characterisation of customer experience than any single method provides alone. The convergence of findings across methods — for instance, Topic 2's sizing theme aligning with elevated sadness and negative sentiment — strengthens confidence in the reliability of individual outputs.

The framework's primary strength is its ability to decompose complex review corpora into interpretable layers: what customers feel (emotion), how positively or negatively they evaluate products (sentiment), and what specific themes they discuss (topics). This decomposition is particularly valuable for product managers and marketing teams who require specific, actionable signals rather than aggregate scores.

A notable limitation is the lexicon-based sentiment approach, which may misclassify contextdependent language (Apte & Sri Khetwat 2019). Future work could replace lexicon-based scoring with a fine-tuned transformer classifier to improve contextual accuracy. Additionally, the current framework assigns a single emotion label per review, whereas customers may simultaneously express multiple emotional states. Extending the framework to support multi-label emotion classification would increase fidelity to real emotional expression (Poria et al. 2017).

8. Conclusion

This paper presented a multi-modal text analytics framework integrating transformer-based emotion detection, sentiment analysis, and LDA topic modelling for eCommerce customer review analysis. Applied to 23,485 clothing reviews, the framework identified joy as the dominant customer emotion, revealed persistent sizing issues as the primary negative theme, and demonstrated strong cross-modal consistency between emotional, sentiment, and topical signals.

The framework offers practical value for eCommerce businesses seeking data-driven insights from customer feedback without the prohibitive cost of manual annotation. Future work will extend the approach to multi-label emotion classification, evaluate performance on datasets from other retail domains, and explore time-series sentiment tracking to monitor product performance over time.

Code Availability

The implementation and experimental code used in this study is available at: https://github.com/hasaniftikhar07/multimodal-ecommerce-text-analytics

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