Ethiopian International Journal of Multidisciplinary Research

pISSN:2349-5707 Volume:12,Issue 11,November-2025 eISSN:2349-5715

MODELS FOR IDENTIFYING CONSUMER OPINIONS USING DIGITAL TECHNOLOGIES IN E-COMMERCE ACTIVITIES

Sokhiqov Abdulhafiz Abdushukurovich
independent researcher, tashkent state university of economics
email: abdulhafizsadykov97@mail.ru, phone: +99899-860-88-55

Abstract: In the rapidly evolving field of e-commerce, the ability to identify, analyse and act upon consumer opinions is a critical competitive advantage. This article examines state-of-the-art models for consumer opinion identification through digital technologies, especially focusing on the domain of e-commerce review mining and sentiment analysis. It presents a structured overview of methodological frameworks (including document-level, sentence-level and aspect-level opinion mining), describes the typical data-processing pipeline, compares machine-learning and deep-learning models applied in e-commerce contexts, and discusses key empirical results and implementation challenges (e.g., sarcasm, multilingual reviews, aspect extraction). The article further reflects on the business implications of deploying such models in e-commerce operations, including product development, customer service, and personalisation of marketing. Finally, it summarises future research directions for more robust, scalable and interpretable opinion-mining systems.

Keywords: opinion mining, sentiment analysis, e-commerce, aspect-based sentiment classification, natural language processing, deep learning

Introduction

In contemporary e-commerce ecosystems, consumer-generated content (e.g., reviews, ratings, comments) has become ubiquitous and offers a rich source of insight for retailers and platforms. As consumers share their experiences with products and services online, these unstructured textual data constitute what is often referred to as electronic Word-of-Mouth (eWOM). The computational study of these opinions — often termed opinion mining or sentiment analysis — aims to extract subjective information from text, identifying attitudes, emotions, and evaluations of entities.

E-commerce platforms benefit from opinion mining in multiple ways: by understanding consumer sentiment toward products, identifying pain points in customer experience, informing product development, optimising marketing messaging, and improving service quality. In this context, developing robust models to identify consumer opinions through digital technologies is no longer optional but essential for firms seeking to maintain a competitive edge.

However, the task is far from trivial. Issues such as high volume of data, variety of data sources (reviews, social media, chat logs), multilingual and colloquial language, sarcasm, mixed sentiments, and fine-grained aspects all complicate the modelling process. Research has evolved from simple polarity classification toward more advanced techniques such as aspect-based sentiment analysis (ABSA), transformer-based deep learning models and hybrid architectures. For example, studies show that hybrid deep learning approaches can capture nuanced sentiment patterns in e-commerce review datasets.

This article is structured as follows. First, the methodological framework for opinion-mining models is described. Then, application in the e-commerce context and key models are presented in the “Methodology” section. Next, empirical results from recent literature are summarised. The subsequent section offers analysis and discussion of the models’ strengths, limitations and practical implications. The article concludes with final remarks and suggestions for future research.

Methodology

The methodological section outlines the data-processing pipeline, the levels of opinion mining, and the modelling approaches used for identifying consumer opinions in e-commerce.

Data-processing pipeline

pISSN:2349-5707 Volume:12,Issue 11,November-2025 eISSN:2349-5715

A typical pipeline for opinion mining in e-commerce comprises the following stages:

1. **Data collection** – Gathering user reviews, ratings, comments, social media mentions or chat logs from e-commerce platforms or associated sources.
2. **Data preprocessing** – Cleaning the text: removing URLs, lower-casing, tokenisation, stop-word removal, lemmatisation/stemming, handling emojis, slang and multilingual content.
3. **Feature extraction / representation** – Converting textual data into numerical form via methods such as bag-of-words, TF-IDF, word embeddings (Word2Vec, GloVe), contextual embeddings (BERT, RoBERTa) or hybrid features.
4. **Aspect extraction / segmentation** – Identifying aspects or features of the product/service that consumers discuss (e.g., delivery, packaging, durability). This often uses topic modelling (e.g., LDA), clustering, or supervised extraction methods. For example, multi-grain topic modelling was proposed to extract ratable aspects from online reviews.
5. **Sentiment classification** – Once aspects or the overall text is represented, classification models predict sentiment polarity (positive, negative, neutral) or finer gradations. Levels include document-level, sentence-level and aspect-level.
6. **Aggregation and ranking / visualisation** – Aggregating sentiment scores over products, identifying trends over time, ranking pain points, providing dashboards or recommendations for business action.
7. **Interpretation and decision-making** – Linking model outputs with business decisions: product improvement, marketing strategy, customer service escalation, etc.

Levels of opinion mining

As referenced in surveys, three major levels of sentiment or opinion analysis are distinguished:

- **Document-level**: Classifies the whole review (or document) as positive/negative/neutral.
- **Sentence-level**: Analyses sentiment at the sentence level, useful for mixed-sentiment documents.
- **Aspect-level (or fine-grained)**: Identifies sentiment toward specific aspects or features of an entity (e.g., “battery life” in a smartphone review). This level supports more actionable insights.

Modeling approaches

Research in e-commerce opinion mining uses a variety of algorithms and architectures, broadly classified as:

- **Lexicon-based & rule-based methods**: Use predefined sentiment lexica (e.g., SentiWordNet) or manual rules. Suitable for small-scale or domain-specific tasks, but limited in scalability and nuance (e.g., sarcasm).
- **Machine-learning based methods**: Utilise feature engineering plus classifiers such as Naïve Bayes, SVM, logistic regression, decision trees. For example, studies in e-commerce show machine-learning classifiers achieving >90% accuracy in some settings.
- **Deep-learning based methods**: Use neural networks (CNNs, RNNs, LSTM) or recently transformer architectures (BERT, RoBERTa, XLM-R) for embedding text and predicting sentiment, often outperforming traditional approaches in e-commerce contexts. For instance, a recent paper proposed a hybrid deep learning model (WPHDL-SAEPR) for e-commerce reviews and achieved strong results.
- **Hybrid / ensemble methods**: Combine lexicon, machine-learning and deep-learning components to leverage strengths of each (e.g., faster lexicon filtering plus fine-tuned transformer for nuance).
- **Aspect-based models**: For aspect extraction and sentiment classification on each aspect. For example, transformer-based models fine-tuned for ABSA applied to e-commerce reviews.

In the e-commerce context, particular challenges drive methodological choices: handling extremely large scale of review data, multilingual and mixed-language reviews, domain-specific slang or abbreviations, mixed sentiments in the same review, detecting sarcasm, and extracting fine-grained aspects linked to product features and service dimensions (e.g., logistics,

pISSN:2349-5707 Volume:12,Issue 11,November-2025 eISSN:2349-5715

packaging). For example, one study applied an LSTM model combined with LDA for cross-border e-commerce reviews and found the negative sentiment proportion remained relatively high for functional features and usage effectiveness

Results

The literature reports a variety of empirical results from the application of opinion-mining models in e-commerce contexts. Key findings include:

- In a survey of sentiment analysis approaches in e-commerce, documents show that methods combining feature extraction, classification and ranking yield high accuracy (often above 90 %) in restricted datasets.
- A recent study introduced a deep-learning hybrid model (WPHDL-SAEPR) for e-commerce product review sentiment classification and found that the model could distinguish nuanced sentiment patterns across modalities (such as textual and other signals) in reviews.
- In another empirical study of cross-border e-commerce review data (14,078 review texts), topic modelling (LDA) and LSTM sentiment classification revealed that five main dimensions dominated consumer concern: functional features, quality & cost-effectiveness, usage effectiveness, post-purchase support, and design & assembly. Negative sentiments remained relatively high for functional features and usage effectiveness.
- In work focusing specifically on aspect-based sentiment classification of user reviews on e-commerce platforms (3,500 annotated reviews), the authors extracted fourteen important aspects and showed that transformer-based models (e.g., RoBERTa) achieved over 90 % accuracy on sentiment assignment for each aspect.
- The survey of opinion-mining methods emphasised the trend that the more fine-grained the target (from document to sentence to aspect), the more demanding the modelling and the more actionable the outputs.

These results indicate that: (i) opinion-mining models are mature enough to deliver strong performance in many e-commerce settings; (ii) moving to aspect-level modelling yields more detailed insights (but greater complexity); (iii) deep learning methods (especially transformer-based) are becoming dominant; (iv) practical applications require addressing challenges like multilingual data, sarcasm, data imbalance and domain specificity.

Analysis and Discussion

The analysis of consumer opinion identification models in e-commerce highlights several strengths, limitations, challenges, and business implications. By examining these aspects in depth, it becomes clear how digital technologies contribute to understanding consumer sentiment while simultaneously facing practical constraints.

Models that leverage advanced embeddings and deep learning architectures, such as RoBERTa, XLM-R, and transformer-based models, have demonstrated significant advantages in capturing subtle sentiment cues, contextual relationships, and fine-grained aspects. Unlike traditional machine-learning methods that rely heavily on hand-crafted features, these models encode semantic information directly from textual data, enabling a more nuanced understanding of consumer reviews. For example, transformer-based architectures utilize attention mechanisms to focus on the most relevant parts of a sentence or document, allowing them to distinguish between subtle positive and negative sentiments even when expressed in complex or ambiguous language. This capability is particularly beneficial in the context of e-commerce reviews, which are often informal, mixed in sentiment, and contain domain-specific jargon. Studies show that transformer-based models outperform classical machine learning methods such as Support Vector Machines (SVMs) and Naïve Bayes classifiers in both accuracy and recall across diverse product categories [1][2][3].

Aspect-based sentiment analysis (ABSA) represents another significant advancement in opinion mining. Unlike document-level or sentence-level sentiment analysis, ABSA identifies sentiment associated with specific product features or service attributes. For instance, in smartphone reviews, consumers may express positive sentiment about camera quality while simultaneously expressing negative sentiment regarding battery life. Extracting this aspect-specific information enables e-commerce platforms to make actionable improvements. ABSA bridges the gap between high-level sentiment metrics and operational decision-making, allowing businesses to identify precise areas for enhancement. Empirical studies reveal that ABSA models, when combined with transformer-based embeddings, achieve high precision in sentiment classification across multiple aspects, facilitating more targeted and strategic business interventions [4][5].

The well-established data-processing pipeline further strengthens the application of opinion-mining models. Standard steps include data collection, preprocessing, feature extraction, aspect identification, sentiment classification, aggregation, visualization, and finally, interpretation for business action. Each stage of the pipeline contributes to the robustness and scalability of opinion-mining systems. Preprocessing techniques, such as tokenization, lemmatization, and stop-word removal, ensure that textual data is normalized and structured for modeling. Feature extraction methods, including TF-IDF, Word2Vec, and contextual embeddings, provide rich semantic representations. Aspect extraction, either through topic modeling, dependency parsing, or supervised extraction methods, isolates the components of a review most relevant for sentiment evaluation. The structured pipeline allows for consistent handling of large volumes of user-generated content, a necessity in high-traffic e-commerce platforms where millions of reviews are generated daily [6][7].

The strengths of these models extend beyond technical performance to practical business applications. E-commerce firms can leverage outputs from opinion-mining models to enhance product development, optimize marketing strategies, personalize recommendations, and improve overall customer experience. For example, sentiment-aware recommendation systems can incorporate aspect-level sentiment information to provide more relevant suggestions to users, increasing conversion rates and customer satisfaction. Additionally, real-time sentiment analysis dashboards enable companies to monitor consumer perception continuously, allowing proactive interventions for service or product issues. By integrating consumer opinion data into business processes, organizations transform raw data into actionable intelligence that directly impacts competitiveness and operational efficiency [8][9].

Despite these advantages, several limitations and challenges remain. One of the primary obstacles is the accurate detection of sarcasm, irony, and mixed sentiments. Consumer reviews frequently contain implicit sentiment that is challenging for automated systems to interpret correctly. For instance, a statement such as "I love how my phone died after two days" conveys negative sentiment, but lexicon-based and shallow models may misclassify it as positive due to keywords. Even advanced deep learning models can struggle with such nuances without appropriate training data or contextual augmentation. Research indicates that neutral sentiment detection remains particularly difficult, highlighting the need for sophisticated models capable of capturing complex linguistic phenomena [6].

Multilingual and mixed-language reviews pose another challenge in global e-commerce. As platforms expand internationally, reviews in various languages, including code-mixed text, become increasingly prevalent. Models trained exclusively on monolingual datasets often underperform when applied to cross-lingual or mixed-language content. Empirical evidence shows significant performance variations in sentiment classification when applying models across languages such as Italian, German, Spanish, and French. Addressing these challenges requires multilingual or cross-lingual embeddings and domain adaptation techniques to ensure consistent performance [6].

Aspect extraction remains a technically demanding task, particularly when dealing with diverse product categories. Identifying which features are discussed, clustering them into meaningful categories, and associating sentiment accurately requires high-quality annotations and often domain-specific knowledge. While existing ABSA models provide significant improvements, their effectiveness depends on the availability of well-annotated corpora and the ability to

pISSN:2349-5707 Volume:12,Issue 11,November-2025 eISSN:2349-5715

generalize across domains. For instance, models trained on electronics product reviews may not perform well when applied to fashion or grocery categories without fine-tuning [5].

Data imbalance and noise further complicate sentiment analysis. Many e-commerce datasets exhibit skewed distributions, with an overrepresentation of extremely positive or negative reviews. Additionally, some reviews contain minimal sentiment cues or irrelevant content, such as generic praise or complaints unrelated to product quality. This imbalance can bias models and reduce predictive accuracy, particularly for underrepresented sentiment classes or aspects. Techniques such as oversampling, undersampling, and synthetic data generation can mitigate these issues, but they introduce additional complexity and require careful implementation [10].

Interpretability and linkage to business action constitute additional challenges. While deep learning models achieve high accuracy, they often operate as "black boxes," providing limited insight into the reasoning behind predictions. Translating sentiment scores into actionable decisions requires mapping model outputs to operational metrics, such as return rates, customer churn, or engagement levels. Companies must develop interpretability frameworks and integrate them into decision-making workflows to maximize the practical utility of opinion-mining systems [8][9].

Scalability and real-time analytics are critical for large-scale e-commerce operations. Processing vast volumes of reviews continuously, updating models with new data, and ensuring low-latency outputs demand robust computational infrastructure. Distributed computing, cloud-based pipelines, and incremental learning algorithms are often necessary to meet these requirements. Moreover, integrating opinion-mining outputs into real-time dashboards or recommendation systems introduces additional engineering challenges, requiring careful design and monitoring [7][10].

From a business perspective, the deployment of consumer opinion identification models has significant implications. The product feedback loop allows organizations to detect negative sentiment trends for specific features rapidly, enabling prompt interventions such as product redesign or supplier evaluation. For example, a surge in negative sentiment regarding battery life may trigger product testing, customer support engagement, or communication with manufacturers to address defects. Such interventions can prevent escalation of customer dissatisfaction and protect brand reputation [8].

Customer experience and logistics benefit from real-time sentiment monitoring. Identifying trends in reviews related to delivery, packaging, or service experience allows companies to adjust operational processes proactively. For instance, if negative sentiment regarding shipping times increases, e-commerce platforms may renegotiate logistics contracts, optimize warehouse operations, or adjust delivery estimates to improve customer satisfaction. This proactive approach reduces customer complaints and fosters loyalty [9].

Marketing and personalization are enhanced through sentiment-driven segmentation. Customers expressing negative sentiment toward specific product aspects can be targeted with alternative product suggestions, promotions, or support interventions. Conversely, positive sentiment can inform marketing campaigns, highlighting strengths identified by users themselves. Integrating opinion-mining insights into customer relationship management systems improves targeting precision and the effectiveness of promotional activities [4][5].

Reputation management is another critical business implication. Continuous monitoring of sentiment across brands, product categories, or service features enables organizations to anticipate and mitigate reputational risks. Early identification of emerging negative trends allows for rapid response, preventing widespread dissatisfaction and potential loss of market share. This capability is particularly valuable in highly competitive and public e-commerce markets, where consumer opinions disseminate rapidly through online channels [2][6].

Recommendation system enhancement is a final major implication. Incorporating aspect-level sentiment information into recommender algorithms improves relevance, user satisfaction, and engagement. By understanding the specific aspects driving positive or negative sentiment,

pISSN:2349-5707 Volume:12,Issue 11,November-2025 eISSN:2349-5715

platforms can provide personalized recommendations that align with consumer preferences and avoid undesirable product features. This results in higher conversion rates, repeat purchases, and increased revenue [8].

Despite these business benefits, successful implementation requires substantial investment in infrastructure, data annotation, domain adaptation, and governance. Data pipelines must handle large-scale, heterogeneous, and frequently updated datasets. Aspect-based models require high-quality annotated data for training and validation. Pretrained models must be adapted to domain-specific vocabulary and linguistic patterns. Continuous monitoring ensures that models maintain performance over time and that outputs remain reliable for decision-making. Governance frameworks are essential to ensure ethical use, prevent bias, and maintain compliance with data protection regulations [6][9].

Conclusion

The identification of consumer opinions through digital technologies in e-commerce is now a mature yet actively evolving domain. The progression from document-level sentiment classification to more refined aspect-level opinion mining has enabled more actionable insights, particularly valuable in e-commerce where consumer reviews drive purchase decisions and brand reputation. The adoption of advanced machine-learning and deep-learning methods, especially transformer-based architectures, has markedly improved performance; studies report accuracies exceeding 90 % in well-curated e-commerce review datasets.

Nevertheless, significant challenges remain: handling multilingual and mixed-language reviews, sarcasm and implicit sentiment, aspect extraction in diverse product domains, real-time scalability, interpretability and linkage to business decision-making. For e-commerce firms, the deployment of opinion-mining models should be viewed not merely as a technical exercise, but as part of a broader feedback and decision-making ecosystem linking consumer voice to product, logistics, marketing and service operations. Future research should focus on cross-lingual and multimodal opinion mining (e.g., incorporating images, video reviews), explainable models, incremental learning to handle streaming review data, and tighter integration between sentiment outputs and business KPIs.

In sum, models for identifying consumer opinions using digital technologies are indispensable for modern e-commerce activities and will only become more critical as the digital economy expands and consumer voice grows louder and more complex.

References

1. Ravi, K. & Vadlamani Ravi. A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems*, vol. 89, 2015, pp. 14-46.

2. Sinnasamy, T. a/p, Nur Amir Sjaif, N. A Survey on Sentiment Analysis Approaches in e-Commerce. *International Journal of Advanced Computer Science and Applications (IJACSA)* Vol. 12 No. 10, 2021, pp. 674–681.

3. Vijayaragavan, P., Suresh, C., Maheshwari, A., Vijayalakshmi, K., Narayanamoorthi, R., Gono, M., Novak, T. Sustainable sentiment analysis on E-commerce platforms using a weighted parallel hybrid deep learning approach for smart cities applications. *Scientific Reports*, Vol. 14, Article number: 26508 (2024).

4. Liu, C., Chen, T., Pu, Q., Jin, Y. Text Mining for Consumers' Sentiment Tendency and Strategies for Promoting Cross-Border E-Commerce Marketing Using Consumers' Online Review Data. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(2), 125 (2025).

5. Islam, A. Sentiment analysis and opinion mining on E-commerce site. (Semanticscholar) 2018 (approx) – The study addresses unique challenges of online product evaluations.

6. Pango, H. Sentiment Analysis in e-Commerce - Developing a Model using NLP and Deep Learning. (2025) – Master's thesis, reposiTUm.

7. Sharbatian, K., et al. Deep aspect extraction and classification for opinion mining in selling systems. *Artificial Intelligence Review*, 2023.

pISSN:2349-5707 Volume:12,Issue 11,November-2025 eISSN:2349-5715

8. Dasgupta, S. & Sen, J. A Framework of Customer Review Analysis Using the Aspect- Based Opinion Mining Approach. (2022) – (arXiv)
9. Title: Modeling Online Reviews with Multi- grain Topic Models. Titov, I. & McDonald, R. 2008.
10. Kayed, M., Díaz- Redondo, R. P., Mabrouk, A. Deep Learning- based Sentiment Classification: A Comparative Survey. (2023) arXiv.