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

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

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Annotation: In the environment of modern e-commerce, the ability to aggregate, interpret and act upon consumer opinions represents a strategic differentiator. This article explores models for identifying consumer opinions using digital technologies in e-commerce activities. Drawing on recent literature, it outlines key modeling approaches—ranging from rule-based sentiment lexicons to advanced deep neural networks—explores their methodological foundations, presents core results from empirical studies, and discusses implications for practice and future research. The findings suggest that integrated architectures combining natural-language processing (NLP), machine-learning classification, and digital trace analytics offer the strongest potential to convert raw consumer feedback into actionable insight.

Keywords: consumer opinion; e-commerce; digital technologies; sentiment analysis; opinion-mining; machine learning; deep learning; topic modelling; user-generated reviews

Introduction

E-commerce has transformed the retail landscape by enabling direct online interactions between consumers and vendors. As consumers increasingly leave reviews, ratings, comments and other digital traces on e-commerce platforms, the challenge for businesses becomes how to draw meaningful insight from this mass of unstructured data. Identifying consumer opinions efficiently—not merely quantitative ratings, but the qualitative nuances of sentiment, evaluation and feedback—is critical for product improvement, customer service, marketing strategies and competitive differentiation.

Digital technologies—ranging from algorithms for natural language processing (NLP), machine learning classifiers, topic modelling, network analytics and big-data pipelines—have enabled organisations to move beyond manually reading reviews to automated, scalable models that classify, aggregate and interpret consumer sentiment. In this context, the core research question addressed in this article is: **Which modelling approaches are being used to identify consumer opinions in e-commerce, how effective are they, and what methodological and practical issues remain?**

To address this, the article proceeds as follows. The next section describes the methodology of the article: literature review strategy, model classification, and criteria for comparison. The subsequent section summarises major results from recent empirical and modelling studies. Then the article examines those results through analysis and discussion of strengths, weaknesses, and gaps. Finally, it draws conclusions and outlines implications for both academics and practitioners.

Methodology

This article adopts a structured literature-review approach combined with conceptual synthesis of modelling frameworks. The review begins by identifying peer-reviewed papers published in the last roughly five years, focused on e-commerce consumer opinion or review-mining. As part of the selection criteria, studies needed to: (a) employ digital technologies (e.g., NLP, machine learning, deep learning, topic modelling) to extract or classify consumer opinions; (b) focus on e-commerce or online retail contexts; (c) provide empirical performance metrics or methodological insights.

Selected papers were then categorised by modelling type: (1) lexicon- or rule-based sentiment models; (2) classical machine learning classifiers (e.g., Naïve Bayes, SVM); (3) deep-learning and transformer-based models; (4) hybrid or aspect-based sentiment models incorporating

feature extraction or topic modelling. For each category the article summarises methodological characteristics (data sources, preprocessing, feature engineering, classifiers, evaluation metrics) and key findings (accuracy, precision, recall, applicability).
To highlight practical relevance, we also draw attention to studies that link model outputs to business insights in e-commerce (e.g., identifying pain-points, topic clusters, component-level sentiment). Finally, the review outlines limitations and future directions: for example, issues of multilingual data, domain shift, explainability, real-time processing, and integration with e-commerce decision systems.
Results
Modelling approaches and findings
1. **Lexicon- and rule-based sentiment models**
Early work in opinion mining relied on sentiment lexicons (lists of positive/negative words) and simple rules (negation handling, intensifiers). While they have low resource requirements, they tend to struggle with domain-specific language, sarcasm, and context. For example, general surveys of opinion-mining highlight that lexicon-based approaches often serve as baseline models but are less accurate than learning-based methods.
2. **Classical machine learning classifiers**
Several empirical studies apply algorithms such as Naïve Bayes, Logistic Regression, Support Vector Machine (SVM) to classify review polarity (positive/negative/neutral). For example, one study comparing logistic regression, naïve Bayes, neural networks and SVM for e-commerce product-reviews found the Naïve Bayes model reached ~94% accuracy, logistic regression and neural networks ~93%, and SVM ~92%. Advantages of these models include interpretability, relatively modest computational cost, and solid performance with well-engineered features (e.g., TF-IDF, n-grams). However, they require careful feature-engineering and may plateau in performance with complex text.
3. **Deep-learning and transformer-based models**
More recent studies apply deep neural networks, recurrent architectures (LSTM, BiGRU), and transformer models (BERT, RoBERTa). For example, one study proposed a BERT-BiGRU-Softmax model for e-commerce review sentiment, achieving ~95.5% accuracy on a dataset of over 500 000 reviews. Another study of aspect-based sentiment classification on e-commerce platform reviews used RoBERTa and manually annotated 3000 + reviews across 14 aspects, achieving >90% accuracy. These models demonstrate strong performance in capturing semantic nuances and context, but come with greater computational cost, need for large annotated datasets, and less interpretability.
4. **Aspect-based sentiment and hybrid modelling**
Given the limitations of global polarity classification, more recent research focuses on aspect-based sentiment analysis (ABSA)—identifying not only the overall sentiment but sentiment towards specific aspects (e.g., delivery, price, product quality, website usability) of the purchase process. For example, Davoodi, Mezei & Heikkilä (2025) identified fourteen aspects via manual annotation of ~3 500 reviews and applied machine-learning models to classify each aspect's sentiment. Other frameworks propose unsupervised extraction of "pain-points" from review text (e.g., Painsight) using pre-trained language models and topic modelling/attribution scoring. Hybrid models are promising because they yield more actionable insights for businesses: e.g., "customers complain about return-policy speed" rather than "negative review".
Empirical findings relevant to e-commerce
- Studies show that consumer opinion extracted via digital-technology-enabled models can correlate strongly with purchase intention, satisfaction and repurchase behaviour. Meta-analytical work indicates that online review sentiment, volume and recency are significant predictors of consumer decisions.
- The use of digital technologies (social media, live streaming, AI/AR/VR) in e-commerce is rapidly expanding, affecting consumer engagement and enabling richer opinion generation. A

systematic review found increasing studies post-2017, though systematic integration remains limited.

- From a marketing perspective, digital marketing factors (trust, perceived ease of use, perceived usefulness, compatibility) have significant influence on shaping consumer behaviour. One study with 285 respondents found significant positive relationships between those factors and consumer behaviour in e-commerce.

Analysis and Discussion

The systematic examination of modelling approaches for identifying consumer opinions using digital technologies in e-commerce highlights several key themes, strengths, limitations, and future directions. The growing body of research indicates that businesses increasingly rely on digital tools to extract sentiment, preferences, and feedback from user-generated content, but the complexity of these methods and the diversity of consumer data present both opportunities and challenges. This section provides a comprehensive analysis of the state of the art, evaluates methodological and practical considerations, and reflects on the implications for both e-commerce research and managerial practice.

One of the most significant developments in the field is the evolution from simple rule-based or lexicon-based methods to sophisticated machine learning and deep learning models. Early sentiment analysis relied on precompiled dictionaries of positive and negative words and simple rules to handle negation or intensification. These methods were computationally inexpensive and easy to implement, but they often failed to capture nuanced or context-specific expressions common in online reviews. For example, sarcasm, idiomatic expressions, and mixed sentiments within a single review posed substantial challenges for lexicon-based models. Despite their limitations, these approaches provided a foundational understanding and established a baseline for comparison with subsequent methods. They were particularly useful in environments where data were limited or annotated datasets were unavailable, offering a first approximation of consumer sentiment patterns. However, as consumer communication became increasingly complex, with longer, multi-faceted reviews and cross-platform discussions, the inadequacy of lexicon-based methods became evident.

The transition to classical machine learning algorithms, such as Support Vector Machines (SVM), Naïve Bayes classifiers, and logistic regression models, represented a significant improvement in sentiment detection accuracy. These models rely on numerical representations of text, such as TF-IDF (Term Frequency–Inverse Document Frequency) or n-grams, to capture the frequency and co-occurrence of terms. When trained on labeled datasets, these models can learn patterns that distinguish positive, negative, and neutral sentiment. Empirical studies have demonstrated that classical machine learning models achieve higher accuracy than lexicon-based approaches while retaining interpretability and relatively low computational costs. For example, SVM models trained on e-commerce product reviews often achieve accuracy rates above 90%, while logistic regression and Naïve Bayes classifiers provide comparable performance with the added advantage of model transparency. Moreover, feature engineering plays a critical role in maximizing the performance of these algorithms. Careful selection of features, including linguistic markers, part-of-speech tags, and domain-specific vocabulary, significantly enhances sentiment classification.

The rise of deep learning has revolutionized sentiment analysis in e-commerce contexts. Recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, Bidirectional LSTMs (BiLSTMs), and, more recently, transformer-based models such as BERT, RoBERTa, and GPT-style architectures have shown remarkable ability to capture contextual nuances and long-range dependencies in text. Unlike traditional models, these architectures can understand not only individual words but also the relationships between them across entire sentences or documents. Deep learning models can handle complex expressions of sentiment, including mixed or subtle emotional tones, and can be fine-tuned for specific domains or product categories. For instance, transformer-based models applied to thousands of e-commerce product

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

reviews have achieved accuracies exceeding 95%, surpassing classical models by several percentage points. Additionally, these models are highly adaptable to multilingual datasets and can process large volumes of data, making them ideal for global e-commerce platforms that must analyze consumer feedback in multiple languages and regions.

Another important advancement is the development of aspect-based sentiment analysis (ABSA). While global polarity classification (positive, negative, neutral) provides a useful overview of consumer opinion, it fails to identify sentiment related to specific product or service features. ABSA addresses this gap by identifying and evaluating sentiment towards particular aspects, such as product quality, price, delivery service, website usability, or customer support. This approach yields actionable insights for businesses. For example, a company might learn that overall satisfaction with a product is high, but complaints consistently arise regarding shipping times. By isolating sentiment at the aspect level, businesses can prioritize interventions where they are most needed. Hybrid models that combine ABSA with deep learning and topic modeling further enhance the extraction of meaningful insights from unstructured review data, enabling the identification of emerging issues and latent consumer concerns.

Despite these advancements, several methodological challenges remain. First, deep learning models require large labeled datasets for training, which may not be readily available for all product categories, languages, or niche markets. Transfer learning and pre-trained language models mitigate some of these limitations, but domain adaptation remains a significant challenge. For example, a model trained on electronics reviews may not generalize well to fashion or food products due to differences in terminology, sentiment expression, and review structure. Second, interpretability is an ongoing concern. Transformer-based models, while highly accurate, often operate as "black boxes," providing predictions without transparent reasoning. This lack of explainability can hinder managerial decision-making, as business leaders may require not just the sentiment classification but also the rationale behind it to develop effective interventions. The need for explainable AI (XAI) frameworks in e-commerce sentiment analysis is therefore pressing, particularly when decisions based on model outputs impact customer satisfaction, marketing strategies, or product development.

Another limitation involves the scope of available data. Much of the existing literature focuses on English-language reviews from major platforms such as Amazon, eBay, or Alibaba. However, e-commerce is a global phenomenon, and sentiment analysis models must accommodate multilingual, multicultural, and regionally specific expressions of opinion. Low-resource languages, niche markets, and non-standardized review formats pose significant challenges for model development and evaluation. Expanding research into these contexts is essential to ensure the applicability of sentiment analysis methods beyond dominant market platforms.

Real-time opinion mining is another area requiring further exploration. Many models operate on static batches of reviews, processed periodically. However, consumer opinions evolve continuously, influenced by new product releases, promotional campaigns, service failures, or social media trends. Real-time sentiment analysis can provide e-commerce businesses with immediate feedback, enabling rapid response to emerging issues and more agile marketing strategies. Implementing real-time systems necessitates consideration of streaming data architectures, incremental learning methods, and computational efficiency to ensure timely and accurate sentiment evaluation.

Integration of sentiment analysis with broader business decision systems remains limited. Academic studies frequently focus on extracting sentiment metrics without demonstrating how these insights translate into concrete operational actions, such as inventory management, customer support prioritization, or marketing campaign adjustments. Bridging this gap requires the development of end-to-end frameworks that link opinion-mining outputs to business KPIs, enabling organizations to quantify the impact of sentiment on revenue, customer retention, and brand loyalty. This integration is particularly critical for aspect-based sentiment models, as they provide nuanced information that can inform targeted interventions and resource allocation.

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

Ethical, privacy, and bias considerations are increasingly salient in the deployment of opinion-mining models. Algorithms may inadvertently reinforce biases present in training data, privileging certain consumer demographics while marginalizing others. Additionally, extracting sentiment from reviews raises concerns about user privacy, data protection, and compliance with regulations such as GDPR. Businesses must implement governance frameworks to mitigate bias, ensure transparency, and uphold consumer trust while leveraging opinion-mining technologies. Emerging research in ethical AI, fairness, and privacy-preserving machine learning offers valuable guidance for addressing these challenges.

From a managerial perspective, several practical implications emerge. Investment in robust digital infrastructure, including NLP pipelines, sentiment classification models, and visualization dashboards, can provide strategic advantages by enabling businesses to monitor consumer sentiment in near real-time. Aspect-based analysis, in particular, allows organizations to prioritize interventions in areas that directly impact customer satisfaction, such as delivery efficiency, product quality, or website functionality. Smaller firms or those operating in resource-constrained environments may initially adopt classical machine learning models to achieve cost-effective sentiment detection before scaling to deep learning solutions as data availability and computational resources increase.

Attention to multimodal data is also crucial. Textual reviews are just one component of consumer feedback; images, video reviews, live chat transcripts, and social media interactions provide additional layers of opinion that may reveal insights not captured in written text. Incorporating multimodal analysis enhances the richness of sentiment evaluation and allows businesses to capture a more holistic view of consumer experience. For example, analyzing video reviews in conjunction with textual reviews may reveal inconsistencies or amplify key sentiments, providing deeper understanding of consumer perceptions.

Future research should address several critical gaps. Multilingual and multicultural sentiment analysis remains underdeveloped, particularly for low-resource languages and regional e-commerce platforms. Real-time, streaming analysis methods that can adapt to evolving consumer opinions are needed to maintain the relevance and timeliness of insights. Emphasis on explainable AI will facilitate business adoption by providing interpretable outputs that can directly inform decision-making. Integration of multimodal data sources—text, audio, video, and images—represents a promising frontier for future study. Moreover, longitudinal research linking sentiment outputs to tangible business outcomes, such as conversion rates, repeat purchases, or churn, will strengthen the empirical basis for adopting these models. Ethical considerations, including fairness, privacy, and bias mitigation, must be central to both research and practice, ensuring that opinion-mining technologies are deployed responsibly and equitably.

Finally, the dynamic nature of e-commerce platforms underscores the importance of adaptive, flexible models. Consumer behavior is influenced by rapid technological, social, and market changes, and sentiment analysis models must evolve accordingly. Incorporating mechanisms for continuous learning, model updating, and monitoring of concept drift can enhance model performance and maintain alignment with consumer expectations. Additionally, collaboration between data scientists, domain experts, and business managers is critical to ensure that sentiment models not only provide technical accuracy but also yield actionable, business-relevant insights.

Conclusion

In sum, models for identifying consumer opinions using digital technologies have matured significantly, moving from lexicon-based rule systems to sophisticated deep-learning architectures and aspect-based analytics. In the context of e-commerce, these models enable firms to tap into rich streams of user-generated content, extract sentiment and aspect-level insights, and thereby respond more effectively to consumer needs. The empirical evidence suggests strong predictive power of opinion-mining for consumer satisfaction, purchase intention and behavioural outcomes. However, challenges remain—data availability, domain

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

adaptation, interpretability, ethical governance and integration with business systems. For practitioners, adopting a tiered approach (starting with simpler models, progressing to deep models as data scales) combined with aspect-based dashboards offers a pragmatic path forward. Scholars should continue exploring multilingual settings, multimodal data, real-time ingestion, longitudinal linkage to business KPIs and ethical frameworks. Ultimately, the strategic adoption of opinion-mining models in e-commerce can enhance organisational responsiveness, customer experience and competitive position.

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