

Meta-Analysis of Sentiment Analysis on E-Commerce Platforms for Mobile Phones

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Abstract

This meta-analysis synthesizes findings from 30 studies examining sentiment analysis techniques applied to mobile phone reviews on e-commerce platforms. The analysis reveals that Amazon is the predominant data source, with datasets ranging from 158 to 400,000 reviews. Machine learning approaches span classical algorithms (Random Forest, SVM, Naive Bayes) to deep learning models (LSTM, CNN) and transformer-based architectures (BERT, RoBERTa). Performance metrics vary widely, with reported accuracies ranging from 51.33% to 97.48%. Common preprocessing techniques include tokenization, stopword removal, and POS tagging, while feature extraction methods encompass Bag-of-Words, TF-IDF, Word2Vec, and contextual embeddings. Consumer sentiment analysis consistently identifies key themes including battery life, camera quality, display performance, user interface, and device performance issues. Random Forest and BERT-based models emerge as top performers; though comprehensive comparative evaluation remains limited across the literature.

JEL Classification: C88, D83, L86

(C88 – Methodology of data collection and data estimation; D83 – Search; Learning; Information and Knowledge; Communication; L86 – Information and Internet services; Computer software)

Keywords: *Artificial Intelligence, BERT, RAG, Language Models.*

1. INTRODUCTION

Sentiment analysis of mobile phone reviews on e-commerce platforms has become increasingly important for understanding consumer preferences, improving product design, and informing purchasing decisions. As mobile phones represent one of the most reviewed product categories online, they provide rich datasets for developing and evaluating sentiment analysis techniques.

This meta-analysis examines 30 studies published between 2017 and 2025 to synthesize current knowledge on datasets, algorithms, performance metrics, and consumer sentiment patterns in this domain. The primary objectives of this meta-analysis are to:

- 1) Identify and compare datasets used across studies
- 2) Evaluate the performance of different sentiment analysis algorithms
- 3) Document common preprocessing and feature extraction techniques
- 4) Identify best-performing models, and synthesize common consumer sentiment themes related to mobile phone features.

2. DATA SOURCES AND DATASETS

2.1 Primary Data Sources

Amazon emerges as the dominant e-commerce platform for sentiment analysis research on mobile phones, appearing in the majority of reviewed studies [2], [3], [5], [7], [12], [19], [26], [29]. Other platforms include Flipkart, Shopee, and various regional e-commerce websites [26], [1]. The prevalence of Amazon data reflects both its market dominance and the accessibility of its review corpus for research purposes.

2.2 Dataset Characteristics

Dataset sizes vary substantially across studies, reflecting different research objectives and computational constraints. Table 1 summarizes the dataset characteristics reported in the reviewed literature.

Table 1: Dataset Characteristics Across Studies

Study	Platform	Dataset Size
Unlocking Customer Sentiments [2]	Amazon	400,000 reviews
Sentiment Analysis on Amazon Reviews [5]	Amazon	Not specified
Comparison of Sentiment Analysis Methods [19]	Amazon	Not specified
SVM-Based Sentiment Analysis [26]	Shopee	Not specified
Analisa Sentimen Review [29]	Amazon	Not specified
Emotion Recognition-oriented Analysis [30]	Online shopping	500 reviews (158 analyzed)
Statistical and Sentiment Analysis [7]	E-commerce	Not specified
Sentiment Analysis Using XGBoost [12]	Not specified	Not specified

The largest reported dataset contains 400,000 Amazon reviews of unlocked mobile phones, demonstrating the scale at which modern sentiment analysis can operate [2], [3]. Smaller datasets, such as the 158 Xiaomi reviews analyzed for emotion recognition, enable more detailed qualitative analysis [30]. Multi-platform approaches combining Kaggle and Amazon datasets are also employed to increase diversity and generalizability [6].

2.3 Dataset Quality and Preprocessing Challenges

Several studies note challenges with dataset quality, including mismatches between numerical ratings and textual sentiment [2], [3]. Approximately 30% of reviews in one large-scale study showed discrepancies between star ratings and the sentiment expressed in review text, highlighting the importance of text-based sentiment analysis over simple rating aggregation [2].

3. METHODOLOGICAL APPROACHES

3.1 Classical Machine Learning Approaches

Classical supervised learning algorithms remain widely used for sentiment classification. Support Vector Machines (SVM) appear frequently in comparative studies, often using LinearSVC implementations for computational efficiency [2], [3], [5], [19]. Naive Bayes classifiers are employed as baseline models due to their simplicity and interpretability [5], [10], [19]. Decision Tree algorithms, including ensemble variants, are evaluated across multiple studies [5], [10].

3.2 Ensemble Methods

Random Forest consistently demonstrates strong performance across studies, with one investigation reporting 97.48% accuracy on Amazon mobile phone reviews [5]. The algorithm's ability to handle high-dimensional feature spaces and reduce overfitting makes it particularly suitable for sentiment analysis tasks with diverse vocabulary [5], [7].

XGBoost, another gradient boosting ensemble method, is specifically applied to mobile phone review sentiment analysis with reported success [12].

3.3 Deep Learning Approaches

Deep learning architectures have gained prominence in recent sentiment analysis research. Long Short-Term Memory (LSTM) networks are employed to capture sequential dependencies in review text [2], [3], [7].

Convolutional Neural Networks (CNN) are applied to extract local features from text representations [22], [28]. Comparative studies suggest that deep learning models can outperform classical approaches, particularly on large datasets with complex sentiment patterns [7].

3.4 Transformer-Based Models

State-of-the-art transformer architectures represent the current frontier in sentiment analysis. BERT (Bidirectional Encoder Representations from Transformers) and its variants are increasingly adopted for contextual understanding of review text [6].

RoBERTa-driven embeddings are specifically applied to aspect-oriented review mining for mobile phones, enabling fine-grained sentiment analysis at the feature level [13]. Sentence transformers facilitate topic clustering and sentiment classification with improved semantic understanding [6].

3.5 Lexicon-Based Approaches

Lexicon-based methods using sentiment dictionaries such as SentiWordNet provide an alternative to supervised learning [29]. One study implementing a lexicon-based approach with SentiWordNet achieved 51.33% accuracy, suggesting that purely lexicon-based methods may be less effective than machine learning approaches for this domain [29]. However, hybrid approaches combining lexicon features with machine learning classifiers may offer benefits [30].

3.6 Aspect-Based Sentiment Analysis

Several studies move beyond document-level sentiment to analyze sentiment toward specific product aspects. Latent Dirichlet Allocation (LDA) is used to identify aspects in mobile phone reviews before applying sentiment classification [15].

Aspect-oriented approaches using RoBERTa embeddings enable recommendation systems that consider sentiment toward individual features such as camera, battery, and display [13].

4. PREPROCESSING AND FEATURE EXTRACTION TECHNIQUES

4.1 Text Preprocessing Pipeline

Text preprocessing is consistently applied across studies, though specific steps vary.

Common preprocessing operations include:

- URL and HTML Removal: Cleaning review text of web links and markup [29].
- Punctuation Removal: Eliminating punctuation marks that do not contribute to sentiment [29].
- Case Normalization (Casefolding): Converting all text to lowercase to reduce vocabulary size [29].
- Stopword Removal: Filtering common words that carry minimal sentiment information [29].
- Tokenization: Segmenting text into words or sentences for further processing [29].
- Part-of-Speech (POS) Tagging: Identifying grammatical categories to support feature extraction and lexicon matching [29].

One comprehensive preprocessing pipeline includes URL deletion, punctuation removal, casefolding, stopword deletion, POS tagging, sentence tokenization, and word tokenization, applied sequentially to structure review data [29].

4.2 Feature Extraction Methods

Bag-of-Words (BoW): The BoW model represents text as unordered collections of words, widely used with classical machine learning algorithms [2], [3]. Despite its simplicity, BoW provides competitive performance when combined with appropriate classifiers.

TF-IDF (Term Frequency-Inverse Document Frequency): While not explicitly detailed in all abstracts, TF-IDF weighting is a standard technique for emphasizing discriminative terms in sentiment classification [7].

N-grams: Bigrams and trigrams capture local word sequences that convey sentiment more effectively than individual words [2], [3].

Word Embeddings: Word2Vec models learn dense vector representations that capture semantic relationships between words [2], [3]. These embeddings serve as input to neural network classifiers, enabling better generalization than sparse BoW representations.

Contextual Embeddings: Transformer-based models generate context-dependent embeddings where word representations vary based on surrounding text [6], [13]. BERT and RoBERTa embeddings capture nuanced semantic and sentiment information that static embeddings cannot represent.

Sentence Transformers: These models encode entire sentences or reviews into fixed-length vectors suitable for similarity comparison and clustering [6].

4.3 Feature Engineering for Aspect-Based Analysis

Aspect-based sentiment analysis requires identifying product features mentioned in reviews. LDA topic modeling extracts latent aspects from review corpora, enabling aspect-specific sentiment classification [15].

POS tagging helps identify aspect terms (typically nouns) and opinion words (typically adjectives) for aspect-opinion pair extraction [14], [15].

5. ALGORITHM PERFORMANCE COMPARISON

5.1 Reported Performance Metrics

Performance evaluation across studies is hampered by inconsistent reporting of metrics. Table 2 summarizes the quantitative performance metrics explicitly reported in the reviewed literature.

Table 2: Algorithm Performance Metrics

Study	Algorithm	Accuracy	F1-Score	Dataset
Sentiment Analysis on Amazon Reviews [5]	Random Forest	97.48%	Not reported	Amazon mobile reviews
Sentiment Analysis on Amazon Reviews [5]	SVM	Not reported	Not reported	Amazon mobile reviews
Sentiment Analysis on Amazon Reviews [5]	Decision Tree	Not reported	Not reported	Amazon mobile reviews
Analisa Sentimen Review [29]	Lexicon (SentiWordNet)	51.33%	0.26	Amazon mobile reviews
Sentiment Analysis Using Supervised Learning [10]	Not specified	88%	Not reported	Mobile phone reviews
Unlocking Customer Sentiments [2]	LSTM	Not reported	Not reported	Amazon (400k reviews)

The limited availability of comprehensive performance metrics across studies prevents rigorous quantitative meta-analysis. However, the available evidence suggests several trends.

5.2 Best-Performing Models

Random Forest: Achieves the highest reported accuracy (97.48%) among classical machine learning algorithms on Amazon mobile phone reviews [5]. Multiple studies identify Random Forest as a top performer in comparative evaluations [5], [7]. **Deep Learning Models:** LSTM and CNN architectures demonstrate competitive performance, with some studies reporting these models as best performers, though specific metrics are often not provided in abstracts [7], [22], [28]. **BERT and Transformer Models:** Qualitative assessments indicate improved accuracy with BERT-based approaches compared to classical methods, though quantitative comparisons are limited in the reviewed abstracts [6], [13]. **Ensemble Methods:** XGBoost shows promise for mobile phone sentiment analysis, leveraging gradient boosting to achieve strong performance [12].

5.3 Performance by Task Type

Document-level sentiment classification (positive/negative/neutral) generally achieves higher accuracy than aspect-based sentiment analysis, which requires identifying both aspects and their associated sentiments [15]. The lexicon-based approach achieving only 51.33% accuracy suggests that supervised learning methods substantially outperform unsupervised lexicon matching for this domain [29].

5.4 Limitations in Performance Reporting

The majority of reviewed studies do not report F1-scores, precision, or recall in their abstracts, limiting the ability to assess performance on imbalanced datasets [2], [3], [5], [6], [7], [10], [12], [13], [19], [22], [26], [28], [30]. This represents a significant gap in the literature, as accuracy alone can be misleading when positive and negative reviews are not equally represented.

6. CONSUMER SENTIMENT THEMES AND INSIGHTS

6.1 Positive Sentiment Themes

Analysis of review content across studies reveals consistent themes in positive consumer sentiment toward mobile phones.

Camera Quality: Camera performance is frequently mentioned as a positive feature in mobile phone reviews [2], [3], [30]. Consumers express satisfaction with image quality, low-light performance, and camera features.

Battery Life: Battery performance emerges as a critical positive factor, with consumers praising long battery life and efficient power management [2], [3], [30].

Display Quality: Screen quality, including resolution, brightness, and color accuracy, receives positive mentions in consumer reviews [2], [3].

User Interface: Intuitive and responsive user interfaces contribute to positive sentiment, with consumers valuing ease of use and smooth navigation [2], [3].

Device Fluency: Overall system performance and responsiveness (device fluency) are positively evaluated when phones operate smoothly without lag [30].

Value for Money: Consumers express positive sentiment when perceived value matches or exceeds price expectations, particularly for mid-range devices.

6.2 Negative Sentiment Themes

Negative reviews consistently focus on specific problem areas.

Software Issues: Software-related problems, including slow performance, freezing, and crashes, are primary sources of negative sentiment [2], [3].

Hardware Malfunctions: Device malfunctioning, hardware defects, and build quality issues generate negative reviews [2], [3].

Network Compatibility: Network connectivity problems and compatibility issues with carriers contribute to negative sentiment, particularly for international or unlocked phones [30].

Overall Performance: General performance issues, including slow processing and multitasking problems, are frequently cited in negative reviews [30].

Heating Issues: Device overheating during use or charging is mentioned as a negative factor in consumer reviews.

6.3 Sentiment Distribution

One large-scale study of 400,000 Amazon reviews found approximately 70% positive sentiment, 30% negative or neutral sentiment [2], [3]. This distribution suggests generally favorable consumer perception of mobile phones on e-commerce platforms, though the substantial minority of negative reviews highlights ongoing quality and performance concerns.

6.4 Rating-Sentiment Discrepancies

An important finding is the mismatch between numerical star ratings and textual sentiment in a significant portion of reviews [2], [3]. Some users assign high ratings despite expressing negative sentiment in text, or vice versa. This discrepancy underscores the value of

text-based sentiment analysis over simple rating aggregation for understanding true consumer sentiment.

6.5 Brand-Specific Insights

Analysis of Xiaomi mobile phone reviews reveals positive attitudes toward battery performance, device fluency, and camera, but negative tendencies toward network compatibility and overall performance [30]. This brand-specific pattern illustrates how sentiment analysis can identify targeted improvement areas for manufacturers.

7. DISCUSSION

7.1 Methodological Evolution

The literature demonstrates clear evolution from classical machine learning to deep learning and transformer-based approaches. Early studies relied on SVM, Naive Bayes, and Decision Trees with BoW or TF-IDF features [7], [10], [19]. Recent work increasingly adopts LSTM, CNN, and BERT architectures with learned embeddings [2], [6], [13], [22]. This progression reflects broader trends in natural language processing and the availability of larger datasets and computational resources.

7.2 Dataset Dominance and Limitations

Amazon's dominance as a data source raises questions about generalizability. Platform-specific factors—review solicitation practices, user demographics, product selection—may influence sentiment patterns. The limited representation of other e-commerce platforms (Flipkart, Shopee, regional platforms) in the literature suggests a need for more diverse dataset collection [26]. Additionally, most studies focus on English-language reviews, with only a few examining Chinese or Indonesian reviews [12], [26], [29], [30].

7.3 Performance Metric Reporting Gap

The inconsistent and incomplete reporting of performance metrics represents a critical limitation in the current literature. While Random Forest's 97.48% accuracy is impressive, the absence of precision, recall, and F1-scores prevents assessment of performance on minority classes [5]. Future studies should adopt standardized reporting practices, including confusion matrices and class-specific metrics, to enable meaningful cross-study comparisons.

7.4 Aspect-Based Analysis as Future Direction

The shift toward aspect-based sentiment analysis reflects growing recognition that document-level sentiment is insufficient for actionable insights [13], [15]. Manufacturers and retailers benefit more from knowing that consumers are dissatisfied with battery life specifically than from knowing overall sentiment is negative. However, aspect-based approaches introduce additional complexity in aspect extraction and aspect-sentiment pairing, potentially reducing accuracy compared to document-level classification.

7.5 Practical Applications

The reviewed studies demonstrate multiple practical applications of sentiment analysis for mobile phones:

Product Improvement: Identifying specific features (battery, camera, performance) that drive positive or negative sentiment enables targeted product development [2], [3], [30].

Quality Control: Detecting patterns of hardware or software issues in reviews can trigger quality investigations [2], [3].

Recommendation Systems: Aspect-based sentiment analysis supports personalized recommendations based on feature preferences [13].

Competitive Intelligence: Comparing sentiment across brands reveals competitive strengths and weaknesses [30].

Marketing Insights: Understanding which features consumers value most informs marketing messaging and positioning.

7.6 Challenges and Limitations

Several challenges persist in mobile phone sentiment analysis:

Sarcasm and Irony: Detecting sarcastic reviews remains difficult for most algorithms, potentially misclassifying negative sentiment as positive.

Multilingual Reviews: E-commerce platforms increasingly feature reviews in multiple languages, requiring multilingual models or translation pipelines.

Evolving Vocabulary: New product features and technical terms continuously emerge, requiring model retraining or adaptation.

Context Dependence: Sentiment toward a feature may depend on price point, brand expectations, or comparison with alternatives.

Spam and Fake Reviews: Distinguishing genuine consumer sentiment from manipulated reviews is an ongoing challenge not addressed in most reviewed studies.

8. FUTURE DIRECTIONS AND RECOMMENDATIONS

8.1 Standardized Benchmarks

The field would benefit from standardized benchmark datasets with consistent train/test splits and evaluation protocols. Such benchmarks would enable rigorous comparison of algorithms and facilitate reproducible research. The community should establish shared datasets covering multiple e-commerce platforms, languages, and time periods.

8.2 Comprehensive Performance Reporting

Future studies should report complete performance metrics including accuracy, precision, recall, F1-score, and confusion matrices for all classes. Class-specific metrics are particularly important given potential imbalance between positive and negative reviews. Statistical significance testing and confidence intervals should accompany performance claims.

8.3 Cross-Platform and Multilingual Studies

Research should expand beyond Amazon to include diverse e-commerce platforms and languages. Cross-platform studies can reveal how platform characteristics influence sentiment expression and analysis performance. Multilingual models and cross-lingual transfer learning approaches deserve greater attention.

8.4 Temporal Dynamics

Consumer sentiment toward mobile phone features evolves as technology advances and expectations change. Longitudinal studies tracking sentiment over time can reveal emerging trends and shifting priorities. Models should be evaluated for temporal robustness and adaptation capabilities.

8.5 Explainable AI for Sentiment Analysis

As models become more complex, interpretability becomes crucial for practical deployment. Explainable AI techniques that highlight which words or phrases drive sentiment predictions can increase trust and enable error analysis. Attention mechanisms in transformer models offer one avenue for interpretability.

8.6 Integration with Structured Data

Combining review text with structured product specifications, pricing data, and sales figures could yield richer insights. Multi-modal approaches integrating text, images (from reviews), and metadata may improve sentiment analysis and recommendation systems.

8.7 Real-Time Sentiment Monitoring

Developing systems for real-time sentiment monitoring as reviews are posted can enable rapid response to emerging issues. Stream processing architectures and online learning algorithms are needed to support such applications.

8.8 Addressing Fake Reviews

Future research should incorporate fake review detection as a preprocessing step. Sentiment analysis of manipulated reviews can mislead manufacturers and consumers. Combining sentiment analysis with authenticity assessment would improve reliability.

9. CONCLUSION

This meta-analysis of 30 studies on sentiment analysis for mobile phone reviews on e-commerce platforms reveals a maturing field with diverse methodological approaches and practical applications. Amazon dominates as a data source, with datasets ranging from hundreds to hundreds of thousands of reviews. Algorithmic approaches span classical machine learning (SVM, Naive Bayes, Decision Trees), ensemble methods (Random Forest, XGBoost), deep learning (LSTM, CNN), and transformer architectures (BERT, RoBERTa). Random Forest achieves the highest reported accuracy (97.48%), while transformer-based models show qualitative promise. Common preprocessing techniques include tokenization, stopword removal, and POS tagging, with feature extraction methods ranging from Bag-of-Words and TF-IDF to Word2Vec and contextual embeddings. Consumer sentiment analysis consistently identifies camera quality, battery life, display, and user interface as positive themes, while software issues, hardware malfunctions, and performance problems drive negative sentiment. Approximately 70% of reviews express positive sentiment, though rating-sentiment discrepancies complicate interpretation. The field faces challenges including inconsistent performance reporting, limited dataset diversity, and the complexity of aspect-based analysis. Future research should establish standardized benchmarks, expand to multiple platforms and languages, adopt comprehensive performance metrics, and explore explainable AI approaches. As sentiment analysis techniques continue to advance, they offer increasingly valuable insights for manufacturers, retailers, and consumers in the mobile phone market.

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