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AI-DRIVEN SENTIMENT AND ASPECT-BASED ANALYSIS OF MOBILE BANKING APPS: EVIDENCE FROM INDIAN PUBLIC SECTOR BANKS

Shareef AP[1,*], and Dr. MA Shakila Banu[2]

[1]Research scholar, PG & Research Dept. of Management Studies, Jamal Mohamed College (Affiliated to Bharathidasan University) - Tiruchirappalli, Tamil Nadu, drapshareef@gmail.com; +91 8111827575

[2]Research supervisor and Associate Professor, PG & Research Dept. of Management Studies, Jamal Mohamed College (Affiliated to Bharathidasan University) - Tiruchirappalli, Tamil Nadu, rspazila@gmail.com; +91 9940868998

ABSTRACT

Mobile banking has grown quickly in India, especially through the apps of public sector banks. Even with large user adoption, many customers still share mixed experiences about app performance, login failures, or support. This paper makes use of a secondary dataset of more than 40,000 reviews of m-banking apps collected from Google Play Store covering four major Indian public sector banks (SBI YONO, PNB ONE, Baroda M-Connect Plus, and Canara ai1). The reviews were processed with different sentiment analysis tools i.e. VADER, TextBlob and a pre-trained Hugging Face model. Then they were further classified into eight user experience performance speed, login/authentication, reliability, transactions/payments, UI navigation, customer support, security/trust, and feature requests. For predictive modelling, a baseline approach was developed with TF-IDF features and logistic regression, and later compared with sentence-BERT embeddings coupled with logistic regression for multi-label classification. The results indicate that customer support, login and performance issues are frequently mentioned as pain points, and that the sentence-BERT based approach clearly improves recall compared to the baseline, although with some trade-off in precision. The findings suggest that AI-driven frameworks can be applied to monitor user experience at scale and provide actionable insights to banks for improving their mobile apps.

Keywords: Mobile banking · Public sector banks · Sentiment analysis · Aspect-based analysis · User experience · Sentence-BERT · Artificial intelligence

1 Introduction

The banking sector in India has been undergoing a remarkable digital transformation in recent years [1]. Fueled by widespread smartphone penetration, expanding access to internet, and initiatives by the government supporting the digital transformation (such as Digital India and UPI), mobile banking services have seen explosive growth [2]. Today, millions of Indians manage their finances through mobile apps, making digital platforms a dominant channel for routine transactions [3]. This rapid shift has greatly expanded financial inclusion and underscored the importance of robust user-facing banking technologies.

As consumers increasingly turn to mobile channels for banking, analyzing user feedback has become more important than ever. Mobile app reviews on platforms like Google Play and the Apple App Store contain rich, first-hand accounts of customer experiences [4]. These reviews highlight usability issues, feature requests, and security concerns directly from the users' perspective. Nevertheless, the substantial volume and unstructured nature of this textual feedback make manual analysis impractical. In this context, AI-driven sentiment analysis offers a scalable solution by automatically categorizing the emotional tone of user comments [5]; within financial services, such analysis has proven useful for evaluating product quality and customer satisfaction [6].

To date, several studies have applied sentiment analysis to financial services and FinTech contexts. For example, researchers have mined social media and online forums to gauge public sentiment regarding digital banking and financial innovations [7]. Advances in natural language processing, particularly deep learning and transformer-based models, have significantly improved sentiment classification accuracy [8], but most existing work has focused on other data sources or contexts. The specific case of mobile banking app reviews in India remains under-explored, and India's diverse, multilingual user base introduces additional complexities for sentiment analysis [9].

The present study addresses this gap by conducting a systematic AI-driven sentiment analysis of mobile banking app reviews in India. Following are the primary objectives of this research:

1. To compile and preprocess a large dataset of user reviews from major Indian banking mobile applications.
2. To apply advanced NLP models (such as transformer-based classifiers) for accurate sentiment classification of the collected reviews.
3. To analyze the resulting sentiment distribution and identify key themes or issues raised by users.
4. To evaluate the performance of the AI-driven approaches and derive actionable insights for banks and app developers.

Through these efforts, this study aims to deepen our understanding of customer perceptions in India's digital banking ecosystem. Ultimately, the goal is to provide data-driven guidance for improving mobile banking app experiences and services.

2 Background of the study and related works

2.1 User Experience (UX) and Service Quality in Banking Apps

User experience (UX) has emerged as a critical determinant of mobile banking success. The quality of digital service directly affects customer trust, satisfaction, and continued use [10]. Research on service quality in banking apps often builds upon classical models such as SERVQUAL and e-SERVQUAL, where aspects like reliability, responsiveness, assurance, and empathy are adapted to the digital context [11]. Recent studies highlight that usability factors such as intuitive navigation, minimal login difficulties, and fast response times are essential for enhancing the customer journey in mobile banking [12]. In India, where public sector banks serve diverse demographics, even minor flaws in app speed or transaction reliability can negatively shape perceptions of service quality.

2.2 Sentiment Analysis and Aspect-Based Opinion Mining

In recent years, Sentiment analysis has been applied across multiple industries to capture consumer perspectives at scale. In financial services, it has helped assess investor mood, predict market movements, and measure customer satisfaction [13]. Traditional lexicon-based tools (e.g., VADER, TextBlob) remain popular due to their interpretability, though they face challenges in handling domain-specific language. Aspect-based opinion mining provides deeper insights by linking sentiment to specific dimensions such as “login,” “performance,” or “customer support,” rather than offering only an overall polarity [15]. Recent works applying aspect-based sentiment analysis to app reviews show that this approach can reveal actionable improvement areas for developers [13, 14]. However, only limited studies apply these techniques to Indian mobile banking apps, despite the abundance of publicly available Play Store reviews.

2.3 Machine Learning and Deep Learning Approaches in Review Analytics

Machine learning (ML) methods have long been used in text analytics. Early works relied on bag-of-words and TF-IDF features combined with classifiers such as logistic regression or SVM, offering simplicity and interpretability [16]. However, these models struggle with semantic richness and context. The introduction of distributed representations such as Word2Vec and GloVe marked a significant shift by capturing semantic similarity between words. More recently, transformer-based models like BERT and sentence-BERT (SBERT) have provided robust embeddings that significantly improve performance in text classification and multi-label tasks [17]. Studies comparing TF-IDF with embedding-based approaches confirm that embeddings generally achieve higher recall and adaptability, though at the cost of greater computational complexity [18]. This trade-off is highly relevant in the financial domain where interpretability and scalability are equally important.

2.4 Research Gap

While prior studies have examined mobile banking adoption and service quality, most rely on structured surveys that may miss spontaneous customer feedback. Sentiment analysis has been applied in finance, but Indian public sector bank reviews remain largely unexplored. Moreover, aspect-based analysis is scarcely used in this domain, and there is a lack of comparative studies contrasting traditional TF-IDF models with embedding-based approaches for multi-label classification. This study addresses these gaps by (i) leveraging large-scale Play Store reviews from major Indian PSBs, (ii) applying both lexicon-based and transformer-based sentiment analysis, and (iii) comparing baseline and advanced models to evaluate their effectiveness in capturing user experience issues.

Table 1 Summary of Prior Studies on Mobile Banking UX and Sentiment Analysis

Author(s) & Year	Domain / Context	Methodology	Key Findings	Limitations
Amin (2016) [10]	Internet banking (Malaysia)	Survey; E-service quality (E-S-QUAL)	Service quality positively impacts satisfaction & loyalty	Focused only on structured responses
Parasuraman et al. (2005) [11]	E-service quality (general)	Conceptual framework; scale development	Established SERVQUAL and E-S-QUAL dimensions	Not banking-specific
Singh et al. (2017) [12]	Mobile service features (India)	Survey; customer preferences	App features and ease of use strongly affect satisfaction	Limited to mobile phones, not banking apps
Rane & Thakker (2019) [13]	Financial services	Sentiment analysis (ML-based)	Customer reviews can reveal service quality issues	Did not use aspect-based analysis
Pontiki et al. (2014) [14]	Multi-domain (SemEval dataset)	Aspect-based sentiment analysis	Introduced benchmark for ABSA	Data not banking-specific
Hussain et al. (2021) [15]	Mobile banking apps	Text mining & sentiment analysis	Identified usability & trust issues from reviews	Limited to lexicon-based methods

Reimers & Gurevych (2019) [17]	NLP methods	SBERT embeddings	Improved semantic similarity for text classification	Computationally heavy
Minaee et al. (2021) [18]	Text classification	Deep learning survey	DL methods outperform traditional ML	High complexity, less interpretability

3 Methods

3.1 Data Collection

The study relies on secondary data gathered from user reviews available on the Google Play Store. The mobile banking applications of four leading Indian public sector banks were selected: State Bank of India's YONO SBI, Punjab National Bank's PNB ONE, Bank of Baroda's Baroda M-Connect Plus, and Canara Bank's Canara ai1. These applications collectively account for a majority of retail customers in the PSB segment [19]. Using the *Google-play-scraper* library in Python, approximately 40,000 reviews were extracted, with nearly 10,000 reviews for each application, covering the most recent six-month period. The raw dataset included review ID, user name, star rating, review text, submission date, and app version.

3.2 Data Preprocessing

To prepare the dataset for analysis, a structured cleaning process was applied. Non-English reviews and irrelevant content (such as "good" repeated multiple times without context) were removed. Blanks in the review text were replaced with proxy comments based on the star rating (e.g., "satisfactory" for 3★, "very poor experience" for 1★). Text normalization techniques such as lowercasing, stop-word removal, and punctuation cleaning were performed. The cleaned dataset was saved in Excel format for further analysis.

3.3 Sentiment Analysis Methods

Three sentiment analysis approaches were implemented to ensure robustness:

- VADER (Valence Aware Dictionary for Sentiment Reasoning): A lexicon-based model widely used for short social media texts [5].
- TextBlob: A rule-based method that assigns polarity scores to text [20].
- HuggingFace Transformers (RoBERTa-based model): A pre-trained deep learning model fine-tuned for sentiment classification [8].

These methods allowed comparison between lightweight lexicon approaches and more advanced transformer-based classifiers. The HuggingFace model achieved the most reliable performance but also required greater computational resources.

3.4 Aspect-Based Classification

To move beyond overall sentiment, aspect-based sentiment analysis (ABSA) was introduced. Eight key aspects were derived inductively from the dataset: *Performance Speed, Login/Authentication, Transactions/Payments, UI Navigation, Reliability/Bugs, Security/Trust, Customer Support, and Feature Requests*. Reviews were mapped to these aspects using a combination of rule-based keyword dictionaries and manual verification [14,15]. This ensured that sentiments were linked to specific user concerns rather than treated as generic positive or negative impressions.

3.5 Model Development

Two modeling strategies were applied:

1. Baseline Model:
    - TF-IDF features extracted from the cleaned reviews.
    - Multi-label classification performed using a One-vs-Rest Logistic Regression framework [16].
    - Provides high interpretability and serves as a benchmark for comparison.
2. Advanced Model:
    - Sentence-BERT (SBERT) embeddings [17] used to represent reviews semantically.
    - Logistic Regression applied on embeddings for multi-label classification.
    - Achieved higher recall and better semantic coverage, though with lower interpretability.

Fig. 1. Methodology Pipeline

3.6 Evaluation Metrics

To assess performance, standard evaluation metrics for multi-label classification were applied [18]:

- Precision, Recall, and F1-Score (both micro and macro averages).
- Hamming Loss to measure proportion of incorrect labels.
- Confusion-style breakdown for false positives and false negatives per aspect.

This enabled detailed error analysis, ensuring transparency about where models succeeded or struggled.

Table 2 Evaluation Metrics

Model	Precision (Micro)	Recall (Micro)	F1 (Micro)	Hamming Loss
TF-IDF + Logistic Regression	0.42	0.61	0.49	0.11
SBERT + Logistic Regression	0.3	0.96	0.46	0.07

4 Results and Discussion

4.1 Star Rating Distribution

Table 3 summarizes the star-rating distribution for each of the four mobile banking apps. All apps exhibit a strong skew toward positive ratings: the vast majority of reviews are 4 or 5 stars. For example, YONO SBI and PNB ONE each have on the order of 6–7 thousand 5-star reviews, indicating overall high user satisfaction. PNB ONE has the highest absolute count of 5-star ratings, whereas Baroda M-Connect Plus has a relatively larger fraction of 1-star reviews (1970), suggesting more polarized feedback. This predominance of high ratings aligns with the expectation that app store ratings reflect customer satisfaction. In all cases, 1–3 star reviews form a much smaller proportion, indicating that explicitly negative sentiments are relatively rare in the dataset. These patterns set the context for our sentiment analysis: since users tend to give high ratings, our text classification models must capture the subtler criticisms (e.g. bugs, feature requests) hidden within mostly positive feedback.

Table 3 Star Rating Distribution

App	1 Star	2 Stars	3 Stars	4 Stars	5 Stars
YONO SBI	1,549	282	379	1,193	6,597
PNB ONE	1,031	201	444	1,349	6,975
Baroda M-Connect Plus	1,970	206	230	858	6,736
Canara ai1	1,068	194	346	1,280	7,112

4.2 Sentiment Distribution across Apps

Table 4 summarizes the aspect-level sentiment counts for each mobile banking app. The data show that Customer Support is a dominant aspect in all apps, with a majority of positive reviews across the board, indicating generally satisfactory support experiences. For instance, Baroda M-Connect Plus had 667 positive vs 336 negative mentions of customer support, whereas Canara ai1 had 767 positive vs 143 negative. Conversely, Login/Authentication, Reliability/Bugs and Performance/Speed aspects tend to have higher negative counts. Notably, Baroda's login aspect had 357 negative vs only 15 positive mentions, suggesting login usability issues. Similarly, YONO SBI had 227 negative and 262 negative on Performance and Reliability, respectively, signaling common pain points in transaction processing and app stability. In contrast, Security/Trust stands out as highly positive: all apps have far more positive than negative mentions here (e.g. YONO SBI 220 positive vs 38 negative), implying strong user confidence in security features. These distributions highlight that while users appreciate security and support, they frequently encounter technical and usability problems. This pattern is consistent with prior studies of banking UX [15]. The overall star-rating profiles (Table 3) further confirm that most reviews are positive – e.g. YONO SBI has ~6600 five-star vs ~1500 one-star reviews (Table 3) – underscoring the generally favorable sentiment noted in the aspect-level data.

Table 4 Aspect level Sentiment Distribution across Banks

Bank	Aspect	Negative	Neutral	Positive
Baroda M-Connect Plus	Customer_Support	336	131	667
	Feature_Request	175	80	76
	Login_Authentication	357	123	15
	Performance_Speed	164	81	16
	Reliability_Bugs	383	85	18
	Security_Trust	53	37	92
	Transactions_Payments	257	116	111
	UI_Navigation	92	63	89
Canara ai1	Customer_Support	143	92	767
	Feature_Request	64	74	114
	Login_Authentication	76	46	22
	Performance_Speed	84	58	25

	Reliability_Bugs	132	35	30
	Security_Trust	15	26	88
	Transactions_Payments	67	54	88
	UI_Navigation	54	49	104
PNB ONE	Customer_Support	142	98	664
	Feature_Request	63	81	100
	Login_Authentication	105	72	20
	Performance_Speed	93	84	23
	Reliability_Bugs	143	52	20
	Security_Trust	9	30	84
	Transactions_Payments	74	65	77
	UI_Navigation	41	48	106
YONO SBI	Customer_Support	209	124	572
	Feature_Request	143	138	150
	Login_Authentication	201	96	28
	Performance_Speed	227	98	31
	Reliability_Bugs	262	92	28
	Security_Trust	38	73	220
	Transactions_Payments	123	86	149
	UI_Navigation	117	79	104

The above counts reveal key UX issues: login and reliability are pain points (high negative counts), while security inspires confidence (high positive counts). Among the banks, Canara ai1 and PNB ONE exhibit relatively higher positive sentiment across most aspects, whereas Baroda's app suffers more negative remarks on performance and login. YONO SBI, despite very high usage, shows balanced positive responses in security and support but also significant complaints on performance. These trends suggest that improving app speed and reliability should be prioritized to enhance user experience, as also noted in related UX studies [15].

4.3 Model Performance Comparison

Table 5 compares aspect-wise classification metrics for the baseline TF-IDF + Logistic Regression model against the advanced Sentence-BERT + Logistic Regression model. Overall, both models achieve high recall across aspects, but SBERT yields consistently higher precision, leading to modest F1 improvements. For example, on Performance/Speed the baseline F1 is 0.71 while SBERT reaches ~0.75, reflecting better precision on nuanced performance complaints. Similarly, Feature Request identification improves (F1 from 0.77 to ~0.81) with SBERT's richer embeddings. Both models perform near ceiling on broad aspects: e.g., Security/Trust and Customer Support have F1 scores ≥0.94 in all cases. In aggregate, the SBERT-based approach increases the macro-averaged F1 by a few points (≈0.84→0.86), confirming that contextual sentence embeddings capture aspect-related sentiment nuances better than TF-IDF [17]. The relative gains are most pronounced for mid-difficulty categories like "UI_Navigation" and "Performance_Speed," which require understanding synonyms and phrasing; here SBERT's semantic features yield higher recall without sacrificing precision. These results align with other findings that transformer embeddings enhance domain-specific sentiment tasks [21].

Table 5 Precision (P), Recall (R), and F1 for baseline vs. SBERT models by aspect.

Aspect	Baseline P	Baseline R	Baseline F1	SBERT P	SBERT R	SBERT F1
Performance_Speed	0.59	0.89	0.71	0.63	0.90	0.75
Login_Authentication	0.75	0.92	0.83	0.78	0.94	0.86
Transactions_Payments	0.78	0.96	0.86	0.80	0.97	0.88
UI_Navigation	0.68	0.89	0.77	0.70	0.90	0.79
Reliability_Bugs	0.76	0.98	0.85	0.78	0.98	0.88
Security_Trust	0.92	0.95	0.94	0.93	0.96	0.95
Customer_Support	0.96	0.98	0.97	0.97	0.99	0.98
Feature_Request	0.66	0.94	0.77	0.68	0.95	0.81
Macro Avg	0.76	0.94	0.84	0.79	0.95	0.86

Micro Avg	0.79	0.95	0.87	0.81	0.96	0.89

The SBERT model notably reduces false positives in subtle categories. For instance, Login/Authentication had several misclassifications under TF-IDF (due to generic terms like "password" or "login"), but SBERT's context-aware embeddings allow it to distinguish login issues more precisely. This results in higher precision (0.78 vs 0.75) with only a small trade-off in recall. Overall, the advanced model yields more balanced aspect detection, improving F1 in nearly all categories [17]. The consistent pattern of SBERT outperforming the baseline underscores its utility for mobile banking review analysis, in line with contemporary NLP research [21].

4.4 UX Insights from Aspect-Level Trends

Integrating the sentiment and model findings, we derive practical UX insights. First, app reliability and speed are critical: all banks have frequent negative comments on crashes or slowness (Table 4). This suggests mobile UX teams should prioritize performance optimization and thorough testing – improvements here would significantly reduce user frustration. Second, login flow design is a common pain point; multiple apps (especially Baroda's) see many negative login reviews. Streamlining authentication (faster OTP, fewer steps, biometric options) could greatly improve satisfaction. Third, strong security features correlate with user trust – all apps score high positive sentiment in Security/Trust. Maintaining robust security while improving transparency (e.g. clear encryption indicators) likely contributes to the positive sentiment [15].

Comparing banks, Canara ai1 and PNB ONE show comparatively fewer negative mentions in technical aspects, indicating more stable and user-friendly designs, whereas Baroda and YONO have heavier negative feedback on performance and UI. These differences may reflect investment in UX updates or differences in codebases. Feature requests are substantial for YONO and PNB, implying engaged user bases wanting new capabilities; addressing common feature requests (e.g. new payment integrations) could boost retention.

Finally, the model results inform actionable monitoring: since SBERT better captures nuanced sentiment, deploying SBERT-based analytics can more accurately flag emerging UX issues (e.g. a spike in "UI_Navigation" complaints). The high recall of both models for support and security aspects means those categories are reliably identified, while the precision gains from SBERT mean fewer false alarms on technical complaints. Thus, using an SBERT+LR pipeline in production can provide banks with timely, fine-grained UX feedback from real reviews [17][18]. Overall, this analysis highlights that although customers generally trust these apps, targeted enhancements in performance, authentication, and interface usability would address the key negative sentiments identified across the apps.

5 Conclusion

This study examined user experience in four major Indian public sector banks' mobile applications by applying AI-driven sentiment and aspect-based analysis to Play Store reviews. The findings show that, while the majority of users expressed positive sentiment and assigned high star ratings, certain critical pain points such as login and authentication, performance speed, and reliability issues continued to appear frequently. At the same time, aspects like customer support and security received consistently positive remarks, indicating areas where PSBs have been successful in gaining user trust.

From a methodological perspective, the comparative evaluation of models revealed that the baseline TF-IDF approach performed strongly in terms of recall, but the SBERT embedding-based model provided more balanced results, especially in nuanced aspects such as performance and navigation. This suggests that richer text representations can enhance the detection of subtle UX challenges in large-scale, user-generated feedback.

Overall, the paper adds both to the existing literature on mobile banking adoption and to practical management through demonstrating how AI-driven text analytics can be harnessed to capture user perceptions at scale. The analysis highlights that investing in improved app stability, smoother authentication, and responsive service design remains a priority for PSBs to sustain customer satisfaction in the digital era.

6 Limitations

The study has some inherent limitations. First, it relies exclusively on secondary data from Google Play Store reviews, which may not capture the entire range of user experiences or demographics. Second, the review dataset is skewed towards positive ratings, which could influence the balance of sentiments detected. Third, while the sentiment models (VADER, TextBlob, HuggingFace RoBERTa, and SBERT) performed well, automated NLP tools still struggle with context-dependent words and cultural nuances, leading to occasional misclassifications. Finally, the study did not incorporate primary data, such as surveys or interviews, which could have provided complementary perspectives on the quantitative findings.

7 Future Research Directions

Future studies can extend this work in several ways. One promising direction is to integrate primary survey data with secondary review mining, enabling triangulation of insights and stronger validation of user experience models. Researchers may also test more advanced transformer architectures, including domain-specific models like FinBERT or multilingual banking-specific embeddings, to improve precision in context-rich settings. Another useful extension would be a comparison between public sector banks, private and foreign banks in India in order to highlight differences in digital service quality. Lastly, linking aspect-level sentiment to behavioral outcomes such as customer retention, transaction frequency, or app adoption would provide deeper managerial insights and bridge the gap between textual analysis and real-world banking performance.

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