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Aspect-Based Sentiment Analysis of BRImo and Livin' by Mandiri Reviews

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Abstract

Transformasi layanan perbankan digital menghasilkan volume ulasan pengguna yang besar dan tidak terstruktur, sehingga analisis sentimen tingkat dokumen belum cukup untuk menunjukkan sumber kepuasan atau ketidakpuasan pada fitur tertentu. Penelitian ini menerapkan Aspect-Based Sentiment Analysis (ABSA) pada ulasan aplikasi BRImo dan Livin' by Mandiri dengan membandingkan representasi TF-IDF dan Word2Vec yang diklasifikasikan menggunakan Support Vector Machine (SVM). Data dikumpulkan dari Google Play Store menggunakan google-play-scraper dengan urutan ulasan terbaru dan target hingga 30.000 ulasan per aplikasi. Setelah pembersihan dan seleksi, terdapat 41.461 ulasan bersih; distribusi sentimen diseimbangkan menjadi 8.943 data untuk pemodelan. Ekstraksi aspek dilakukan secara dictionary-based, sedangkan sentimen tiga kelas ditetapkan dari rating bintang. TF-IDF menggunakan n-gram (1,2) dengan maksimum 5.000 fitur, sedangkan Word2Vec menggunakan Skip-gram berdimensi 100 dan average pooling. SVM dioptimasi dengan Grid Search dan 5-Fold Cross-Validation. Kedua skema menghasilkan akurasi 64,6%, presisi makro 66,7%, recall makro 64,6%, dan F1-score makro 65,3%. BRImo didominasi sentimen positif 64,1%, sedangkan Livin' by Mandiri didominasi sentimen negatif 49,2%; aspek Login menjadi sorotan utama pada Livin'. Hasil menunjukkan bahwa pada dataset ini TF-IDF dan Word2Vec memberikan kinerja praktis yang setara, sementara ABSA memberikan informasi yang lebih actionable untuk menentukan prioritas perbaikan layanan.
Keywords—Aspect-Based Sentiment Analysis, BRImo, Livin' by Mandiri, TF-IDF, Word2Vec, Support Vector Machine

Abstract

The rapid adoption of digital banking generates a large volume of unstructured user reviews, making document-level sentiment analysis insufficient to identify the specific sources of satisfaction and dissatisfaction. This study applies Aspect-Based Sentiment Analysis (ABSA) to user reviews of BRImo and Livin' by Mandiri by comparing TF-IDF and Word2Vec representations using Support Vector Machine (SVM). Reviews were collected from Google Play Store with google-play-scraper using newest-first ordering and a target of up to 30,000 reviews per application. After cleaning and selection, 41,461 clean reviews remained, and sentiment classes were balanced to 8,943 records for modeling. Aspect extraction used a dictionary-based approach, while three sentiment classes were assigned from star ratings. TF-IDF used 1–2 grams with a maximum of 5,000 features, whereas Word2Vec used a 100-dimensional Skip-gram model with average pooling. SVM hyperparameters were optimized using Grid Search and 5-Fold Cross-Validation. Both feature schemes achieved 64.6% accuracy, 66.7% macro precision, 64.6% macro recall, and 65.3% macro F1-score. BRImo was dominated by positive sentiment (64.1%), whereas Livin' by Mandiri was dominated by negative sentiment (49.2%), with Login as the most prominent issue. The findings indicate that TF-IDF and Word2Vec were practically equivalent on this dataset, while ABSA provides actionable evidence for prioritizing digital banking service improvements.
Keywords—Aspect-Based Sentiment Analysis, BRImo, Livin' by Mandiri, TF-IDF, Word2Vec, Support Vector Machine

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1. INTRODUCTION

Digital transformation in Indonesia's financial sector has shifted customer interaction from branch-based services toward mobile banking channels that provide fast and self-service access. Increasing internet penetration and smartphone adoption have reinforced this transition. Data reported in the source article indicate that Indonesia's internet penetration reached 80.66% in 2025, representing approximately 229 million users [1]. In this context, BRImo and Livin' by Mandiri are two relevant state-owned-bank mobile banking applications because they support large-scale daily financial transactions [2].

Increasing adoption does not automatically guarantee a high-quality user experience. Google Play Store reviews contain complaints related to login, verification, transactions, balances, bugs, connectivity, and interface changes [3], [4]. These reviews provide a rich source of user experience information, but they are written in free-form text containing abbreviations, spelling errors, slang, mixed languages, and opinions about multiple features in a single review. Such characteristics make manual analysis difficult to perform consistently and efficiently.

The methodological problem becomes more apparent when a single review contains different polarities for different aspects. A user may state that transactions are fast while simultaneously complaining about login or verification. Document-level sentiment classification would force the entire review into one label and therefore lose information needed to determine improvement priorities. Aspect-Based Sentiment Analysis (ABSA) addresses this problem by mapping opinions to aspect-polarity pairs, producing more granular analytical outputs [20].

Feature representation also influences classification quality. TF-IDF is effective at identifying discriminative words or phrases, but it produces sparse vectors and does not explicitly model semantic similarity. Word2Vec produces dense representations that can capture semantic relationships between words [26]. SVM is selected because it is suitable for high-dimensional feature spaces and has been widely used in text classification tasks [23].

Previous studies have reported inconsistent results. Suharman and Sulaeman compared TF-IDF and Word2Vec for Livin' by Mandiri and reported an advantage for TF-IDF in their experimental setting [5]. Hardiartama et al. demonstrated that ABSA on Wondr by BNI can provide more detailed service-level insights [6], while Alviyanti et al. examined the influence of feature extraction on multi-aspect Livin' classification [7]. Devi et al. applied Word2Vec and SVM to Access by KAI [8], while Supian et al. used a similar combination for DANA [9]. ABSA studies involving BRImo and other digital banks also emphasize the importance of aspect-level granularity [10], [11].

The research gap is the absence of a uniform comparative evaluation of TF-IDF and Word2Vec with SVM within an ABSA framework applied simultaneously to two state-owned-bank mobile applications. This study retains recent user reviews and maps service aspects using a dictionary-based approach. Its contributions are a controlled comparison of two feature representations for three-class sentiment classification, aspect-level sentiment mapping for both applications, and interpretation of the results for service improvement priorities.

Based on this gap, the study addresses three questions: how does SVM perform with TF-IDF compared with Word2Vec; how do preprocessing and class balancing affect data readiness; and which service aspects most frequently become sources of complaints in each application? The ultimate objective is not merely to obtain classification accuracy, but to produce an aspect-level opinion map that can support digital service improvement.

2. METHODS

This research adopts a quantitative experimental approach based on text mining and machine learning. The research workflow consists of problem identification, data collection, aspect and sentiment labeling, preprocessing, class balancing, feature extraction, SVM modeling, evaluation, and interpretation.



Figure 1 Research workflow of the proposed ABSA experiment.

2.1 Data Collection

The research objects are user reviews of the BRImo and Livin' by Mandiri applications on Google Play Store. Data were collected using the google-play-scraper library with newest-first ordering and a target of up to 30,000 reviews per application. This approach was intended to represent relatively recent user perceptions. In addition to review text, star ratings were used as the basis for sentiment labeling [5], [10]. After quality checking and data selection, 41,461 clean reviews remained.

2.2 Aspect and Sentiment Labeling

Aspect extraction uses a dictionary-based approach. Each review is matched against keywords representing service categories. A review may receive more than one aspect because ABSA is inherently multi-aspect. This approach is transparent and easy to audit, but its quality depends on the completeness of the aspect dictionary.

Table 1 Service-aspect dictionary used for ABSA mapping

No.	Category	Keyword examples
1	Login & Akun	login, logout, akun, password, PIN
2	Registrasi & Verifikasi	registrasi, pendaftaran, aktivasi, verifikasi
3	OTP	OTP, kode, SMS, token
4	Transaksi	transaksi, bayar, beli, tarik, setor
5	Transfer	transfer, kirim, rekening
6	QRIS	QRIS, QR, scan, barcode
7	Top-Up & Saldo	top-up, isi pulsa, saldo, e-wallet
8	Pembayaran	pembayaran, tagihan, PLN, BPJS
9	Performa & Kecepatan	lambat, lemot, cepat, loading, hang, crash
10	Bug & Error	bug, error, gagal, rusak, kendala
11	Update	update, pembaruan, versi, upgrade
12	Keamanan	aman, keamanan, fraud, penipuan, data
13	Antarmuka (UI)	tampilan, desain, menu, tombol, layout
14	Pengalaman Pengguna (UX)	mudah, sulit, ribet, nyaman, praktis
15	Notifikasi	notifikasi, pemberitahuan, pesan
16	Layanan Pelanggan	CS, customer service, bantuan, call center, admin
17	Koneksi	koneksi, jaringan, server, internet, maintenance
18	Fitur	fitur, fasilitas
19	Lainnya	tidak memuat kata kunci aspek spesifik

Three sentiment classes were assigned based on star ratings: 4–5 stars as Positive, 3 stars as Neutral, and 1–2 stars as Negative. This scheme is consistent and reproducible, although it is not identical to semantic sentiment annotation because star ratings do not always perfectly reflect the content of the review text.

2.3 Text Preprocessing

Preprocessing consisted of cleaning, case folding, tokenization, normalization of non-standard words, stopword removal, and stemming using Sastrawi [19], [24]. After preprocessing, the sentiment distribution was Positive 21,647 (52.21%), Negative 16,833 (40.60%), and Neutral 2,981 (7.19%) out of 41,461 clean reviews. Because Neutral was the minority class, balancing was performed by reducing each class to 2,981 records, resulting in 8,943 records. The data were then divided using a stratified 80:20 split into 7,154 training and 1,789 testing records.

2.4 Feature Extraction

TF-IDF was used as a frequency-based representation with 1–2 grams and a maximum of 5,000 features. The term weight was calculated using Equation (1).

$$W(t,d) = TF(t,d) \times IDF(t), \quad IDF(t) = \log(N / DF(t)) \quad (1)$$

Word2Vec used the Skip-gram architecture with 100 dimensions, a window size of 5, and minimum count of 2. Because Word2Vec produces word-level vectors, review-level representations were obtained using average pooling. This configuration follows the source article and enables a consistent comparison with TF-IDF.

2.5 Support Vector Machine and Hyperparameter Tuning

SVM was used as the classifier. The linear decision function can be expressed as $f(x) = w \cdot x + b = 0$. For three classes, a one-versus-one strategy was used. Grid Search with 5-Fold Cross-Validation used macro F1 as the selection criterion, with $C \in \{0.1, 1, 10\}$, linear/RBF/polynomial kernels, and gamma=scale.

Table 2 Experimental configuration.

Component	Configuration
TF-IDF	n-gram (1,2); maksimum 5.000 fitur
Word2Vec	Skip-gram; 100 dimensi; window 5; min_count 2; average pooling
SVM	One-vs-one; linear/RBF/polynomial
Grid Search	C = 0,1; 1; 10; gamma = scale
Validasi	5-Fold Cross-Validation; macro F1
Split	80% training; 20% testing; stratified

2.6 Evaluation

Performance was evaluated using accuracy, precision, recall, macro F1-score, and a confusion matrix. Macro F1 was used so that all three classes received equal evaluation weight, while the confusion matrix was used to analyze inter-class error patterns.

3. RESULTS AND DISCUSSION

3.1 Dataset Characteristics

The pre-balancing distribution shows a dominance of Positive and Negative reviews, while Neutral accounts for only 7.19%. This condition can bias a classifier toward the majority classes. Balancing is therefore important because the study focuses on three-class classification and a fair comparison of feature representations.

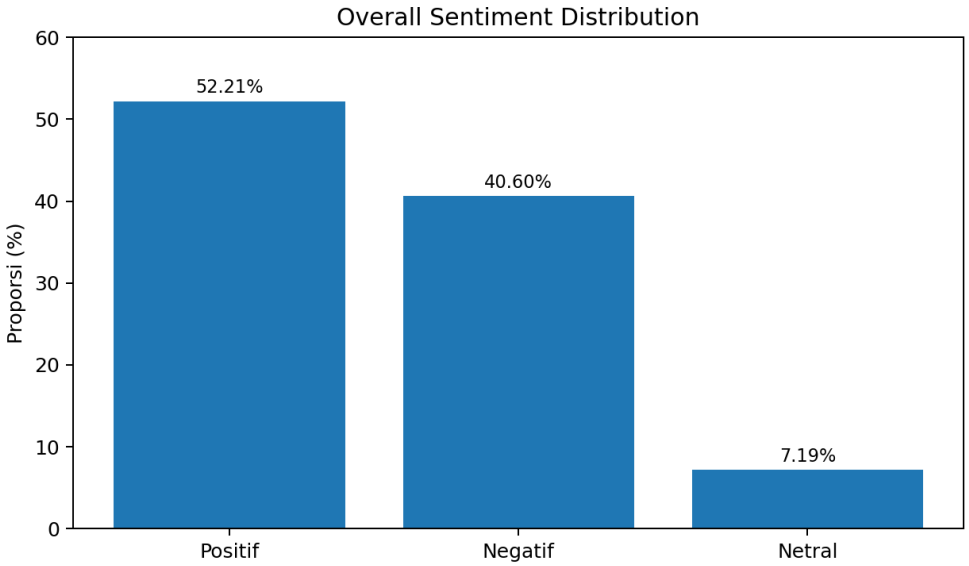


Figure 2 Overall sentiment distribution before class balancing.

3.2 Aspect Distribution

Category Lainnya memiliki sekitar 12.100 kemunculan. Di luar kategori tersebut, User Experience (~9.700), Login (~7.500), Transaksi (~6.300), Bug (~4.900), dan Kecepatan (~4.800) merupakan aspek yang paling sering dibicarakan. Pola ini menunjukkan bahwa pengguna terutama menilai kemudahan penggunaan, akses masuk, kelancaran transaksi, stabilitas, dan kecepatan.

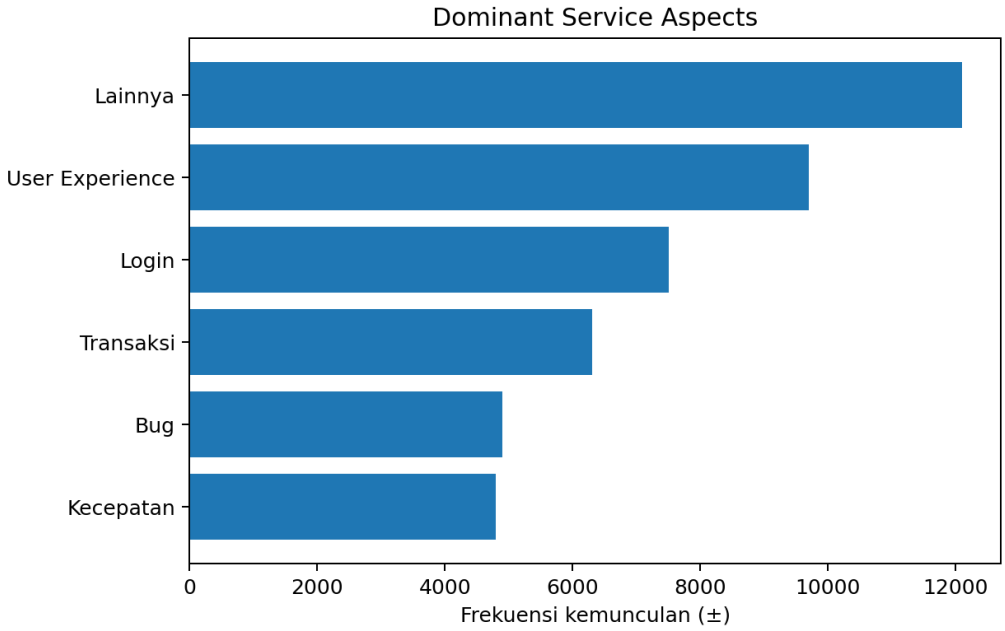


Figure 3 Dominant service aspects in the combined corpus.

For BRImo, the six leading aspect proportions are Other 27.7%, User Experience 23.8%, Transaction 14.5%, Bug 12.0%, Login 11.9%, and Speed 10.1%. For Livin' by Mandiri, Login reaches 20.7%, followed by User Experience 19.5%, Transaction 13.3%, Speed 10.9%, and Bug 9.7%. This difference indicates that improvement priorities should not be treated as identical across applications.

Table 3 Leading service aspects by application.

Application	Main aspect	Proportion

BRImo	User Experience	23,8%
BRImo	Transaksi	14,5%
BRImo	Bug	12,0%
BRImo	Login	11,9%
Livin' by Mandiri	Login	20,7%
Livin' by Mandiri	User Experience	19,5%
Livin' by Mandiri	Transaksi	13,3%
Livin' by Mandiri	Kecepatan	10,9%
Livin' by Mandiri	Bug	9,7%

3.3 Sentiment Comparison

BRImo has 64.1% positive, 30.5% negative, and 5.4% neutral sentiment. Livin' by Mandiri has 42.1% positive, 49.2% negative, and 8.7% neutral sentiment. The difference indicates that user perceptions of the two applications are not homogeneous.

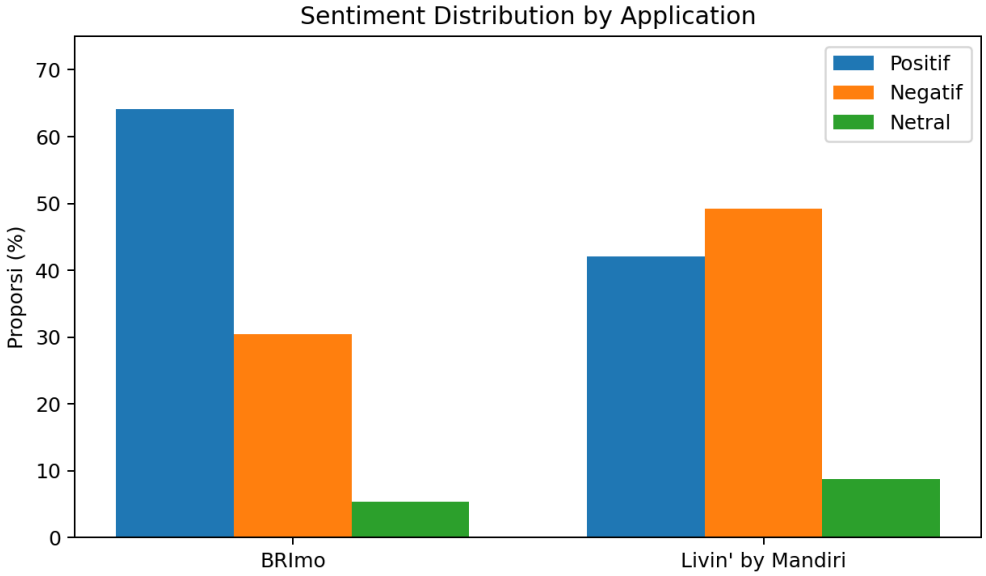


Figure 4 Sentiment distribution by application.

Table 4 Sentiment distribution.

Application	Positive	Negative	Neutral
BRImo	64,1%	30,5%	5,4%
Livin' by Mandiri	42,1%	49,2%	8,7%
Combined	52,21%	40,60%	7,19%

3.4 Model Performance

On the 1,789 test records, both SVM + TF-IDF and SVM + Word2Vec achieved 64.6% accuracy, 66.7% macro precision, 64.6% macro recall, and 65.3% macro F1-score. A difference below 0.1% indicates that the two representations provide practically equivalent performance on this corpus and experimental configuration.

Table 5 Comparison of SVM performance

Feature scheme	Accuracy	Precision (macro)	Recall (macro)	F1-score (macro)
SVM + TF-IDF	64,6%	66,7%	64,6%	65,3%
SVM + Word2Vec	64,6%	66,7%	64,6%	65,3%

.

This result differs from Suharman and Sulaeman [5], who reported that TF-IDF outperformed Word2Vec for Livin' by Mandiri. The difference may result from non-identical experimental designs, particularly the number of classes, balancing strategy, ABSA approach, and the simultaneous use of two applications. Therefore, the present study does not claim that Word2Vec is always equivalent to TF-IDF; rather, its advantage was not observed in the dataset used here.

3.5 Confusion Matrix and Error Analysis

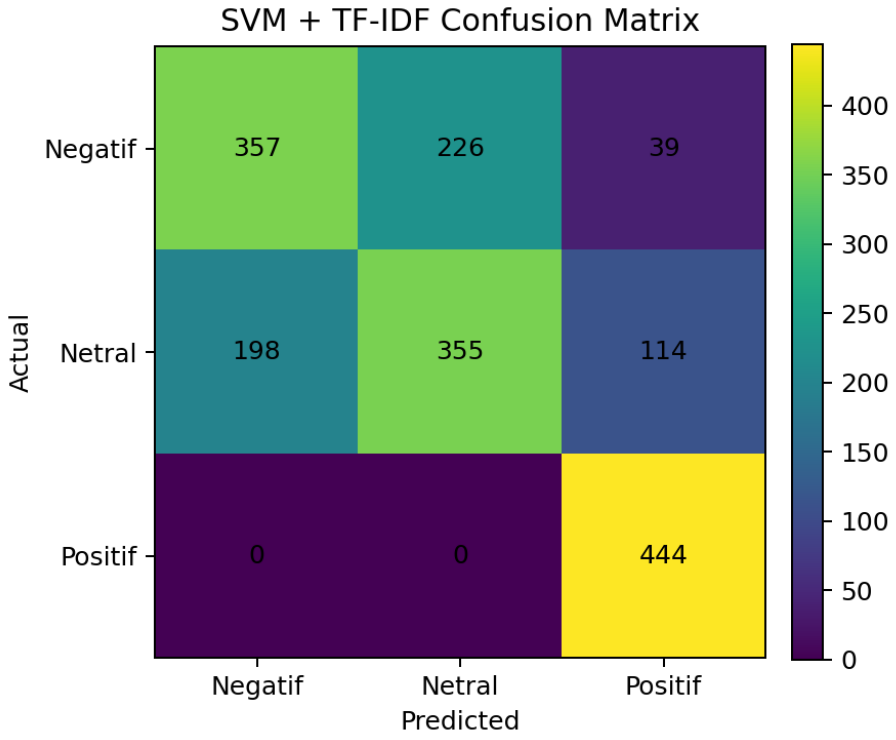


Figure 5 Confusion matrix of SVM + TF-IDF based on the reported test results.

Of the 1,789 test records, the TF-IDF model correctly classified 357 Negative, 355 Neutral, and 444 Positive records. The largest errors occurred between Negative and Neutral: 226 Negative records were predicted as Neutral and 198 Neutral records were predicted as Negative. This pattern indicates substantial overlap between the two classes, particularly because the Neutral label was derived from three-star ratings.

This finding helps explain why the semantic representation of Word2Vec did not automatically improve performance. Average pooling compresses the contextual information of an entire review into a single vector, while application reviews are often short. At the same time, label noise introduced by using star ratings as a sentiment proxy affects both models.

3.6 Discussion and Reviewer-Oriented Interpretation

From a practical perspective, ABSA indicates that service improvements should be prioritized by aspect rather than by overall sentiment alone. For BRImo, User Experience and Transaction are major concerns, followed by Bug and Login. For Livin' by Mandiri, Login has a substantially higher proportion and should therefore be treated as a priority for improving access reliability. Bug, Speed, and User Experience should also be monitored.

From a methodological perspective, the 64.6% performance should be interpreted proportionally. The model is not sufficiently strong to serve as the sole basis for automated decisions. Its outputs should be combined with manual validation and operational indicators such as error logs, latency, and transaction success rates. This interpretation avoids overclaiming the model's capabilities.

The main limitations include dictionary-based aspect extraction, rating-based sentiment labels, majority-class reduction during balancing, and evaluation focused on a single classifier family. Future research should use validated manual annotations, enrich the aspect dictionary, conduct repeated cross-validation or statistical significance testing, and compare transformer-based models such as IndoBERT for end-to-end ABSA.

3.7 Comparison with Previous Studies

The comparative results should be interpreted against the methodological differences reported in previous studies. Suharman and Sulaeman [5] studied Livin' by Mandiri using SVM with TF-IDF and Word2Vec and reported higher accuracy than the present experiment. Their result is not directly contradictory because the present study uses three sentiment classes, balances the dataset to the minority class, and integrates aspect extraction across BRImo and Livin' by Mandiri. These differences change both the difficulty of the classification task and the error profile.

Studies using ABSA also support the value of aspect-level interpretation. Hardiartama et al. [6] demonstrated the usefulness of ensemble learning for Wondr by BNI, while Azarya and Budi [10] analyzed BRImo using aspect categories. Irianandra et al. [11] extended ABSA to several Indonesian digital banking applications. Compared with those works, the present study emphasizes a controlled feature comparison under the same SVM classifier, allowing the effect of TF-IDF versus Word2Vec to be isolated more clearly.

The practical implication is that model selection should not be based on feature representation alone. When the dominant errors arise from label ambiguity and short-text context, replacing a sparse representation with an embedding may not yield a measurable gain. The current findings therefore suggest that future improvements should address data quality and contextual modeling before increasing model complexity.

For reproducibility, the study reports the corpus size after cleaning, balancing strategy, train-test ratio, feature parameters, SVM search space, and evaluation metrics. This information enables future researchers to reconstruct the experimental protocol and test whether a newer model genuinely improves performance under comparable conditions. A subsequent study should additionally report random seeds, exact scraping date, deduplication rules, annotation agreement, and repeated cross-validation results.

3.8 Operational Implications for Service Monitoring

The aspect distribution can be translated into a practical monitoring priority. The first layer is access reliability because Login appears prominently in both applications and becomes particularly dominant for Livin' by Mandiri. Monitoring should include failed login attempts, authentication latency, OTP delivery, biometric verification failures, and the frequency of repeated access complaints. These operational indicators can be compared with the sentiment trend so that an increase in negative Login reviews can be investigated against actual system events.

The second layer is transaction and user experience. For BRImo, User Experience and Transaksi represent the most prominent specific aspects. A monitoring dashboard can therefore combine sentiment counts with transaction success rate, average response time, and complaint categories. The purpose is not to replace operational telemetry with sentiment analysis, but to use public reviews as an additional signal that helps identify issues that may not be visible from technical logs alone.

The third layer is prioritization. A high-frequency aspect is not automatically the most critical aspect; therefore, frequency should be combined with negative proportion and business impact. A simple prioritization score can be defined as the product of aspect frequency, negative sentiment ratio, and an operational impact weight. Although the present study does not calculate this composite score, the ABSA outputs provide the variables needed to construct it in future work. This distinction prevents management from focusing only on the most frequently mentioned feature while ignoring less frequent but high-impact failures.

From a governance perspective, the analysis should be implemented as a human-in-the-loop process. Automated classification can screen thousands of reviews, while domain analysts validate emerging clusters and investigate the associated service metrics. This is especially important because the current model achieves moderate performance and the largest errors occur between Negative and Neutral. Such a workflow reduces the risk that a noisy automated label is interpreted as a definitive customer complaint.

Finally, the proposed monitoring approach is portable to other Indonesian banking applications. The aspect dictionary can be extended with domain-specific vocabulary, while the same experimental protocol can be used to benchmark alternative classifiers. Future studies can compare classical models with IndoBERT or other transformer architectures and evaluate not only aggregate accuracy but also per-aspect F1-score, calibration, annotation agreement, temporal stability, and robustness to slang and spelling variation. These extensions would strengthen the scientific and practical value of the research.

4. CONCLUSIONS

This study applied three-class ABSA to BRImo and Livin' by Mandiri reviews by comparing TF-IDF and Word2Vec as feature representations for SVM. From 41,461 clean reviews, balancing produced 8,943 modeling records followed by an 80:20 stratified split. Both schemes achieved 64.6% accuracy, 66.7% macro precision, 64.6% macro recall, and 65.3% macro F1-score, indicating no meaningful practical advantage between the two representations under the experimental configuration.

ABSA provides more specific findings: BRImo has a dominant positive sentiment of 64.1%, whereas Livin' by Mandiri has a dominant negative sentiment of 49.2%. Login is the most prominent aspect for Livin', while User Experience and Transaction are important aspects for BRImo. The main classification errors occur between Negative and Neutral.

The results can support aspect-based monitoring of digital service quality, but they should not be used as an automated decision system without additional validation. Future research should use validated annotations, an expanded aspect dictionary, transformer-based models, and stability testing to provide stronger evidence of performance improvements.

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