International Journal of Business Accounting Management Social Science
Volume 2, Number 1, 2026
E-ISSN: 3109-2284
Home Page : https://manajemenmultitalenta.com/IJBAMS

Identifying Customer Satisfaction through Negative Sentiment Analysis using Support Vector Machine in the JIWA+ App

Muhammad Faqih Maulana[1]
Rizki Yudhi Dewantara[2]

[1] Faculty of Administrative Sciences, Universitas Brawijaya, Malang, 65145, Indonesia

[2] Faculty of Administrative Sciences, Universitas Brawijaya, Malang, 65145, Indonesia

*Corresponding Author
E- mail: riskyudhi@ub.ac.id

ABSTRACT
The rapid growth of mobile commerce has positioned mobile applications as critical touchpoints influencing customer satisfaction and business performance. This study aims to identify customer satisfaction patterns by analyzing negative user reviews of the JIWA+ mobile application using the Support Vector Machine (SVM) algorithm. A total of 1,025 reviews collected from the Google Play Store during the period 2022–2025 were processed through text preprocessing, TF-IDF feature extraction, and sentiment classification into positive, neutral, and negative categories. The SVM model achieved an overall accuracy of 0.746, demonstrating reliable capability in classifying sentiment polarity, particularly in detecting negative reviews. The findings indicate that 35.7% of reviews reflect negative sentiment, highlighting significant dissatisfaction among users. The dominant complaint themes include transaction failures ("pesan"), feature usability issues ("pakai"), and discrepancies between digital information and outlet conditions ("gerai"). These issues primarily relate to system reliability, payment functionality, and digital–offline integration. From a business management perspective, this study positions sentiment analysis as a strategic analytical tool that transforms unstructured customer feedback into actionable managerial insights. The results contribute to the literature on mobile applications, sentiment analysis, and customer satisfaction by demonstrating how machine learning–based approaches can support data-driven decision-making in enhancing digital service performance and sustaining competitive advantage.

Keywords: Sentiment Analysis, Mobile Applications JIWA+, Support Vector Machine, Customer Satisfaction

| Received March 2026 | Accepted April 2026 | Available online April 2026|
| DOI: https://doi.org/10.64530/ijbams.v2i1.47

1. INTRODUCTION

The development of digital platforms has reshaped how customers interact with firms in the food and beverage (F&B) industry. The increasing adoption of mobile applications has influenced purchasing behavior, service processes, and customer engagement in mobile commerce environments (Cheung & To, 2017, as cited in Tang, 2019). In this context, mobile applications function as key service interfaces that directly affect customer experience and satisfaction. Within digital service environments, customer satisfaction remains a crucial determinant of competitiveness and long-term performance (Oliver, 2014, as cited in Mittal et al., 2023).

JIWA+ is a mobile application developed by Jiwa Group, an Indonesian F&B company operating brands such as Kopi Janji Jiwa and Jiwa Toast. The application was launched on September 16, 2020, to facilitate digital transactions and strengthen customer loyalty (Group, 2021). Although Jiwa Group consistently ranks among the top three coffee shop brands in Indonesia based on the Top Brand Index from 2023 to 2025, the performance of its mobile application appears less aligned with its market position. As of 2025, JIWA+ holds a rating of 3.6 out of 5 on the Google Play Store with more than 500,000 downloads (Group, 2025).

This situation contrasts with the company's strong offline performance, supported by more than 1,100 active outlets and sales reaching US$71.3 million in 2022 (Muhamad, 2023). The divergence between established brand strength and moderate digital ratings suggests the presence of expectation–performance gaps. Such inconsistencies may occur when differences arise between the operational execution of digital platforms and the actual service delivery in physical outlets. According to the disconfirmation framework, dissatisfaction arises when perceived performance does not meet prior expectations (Oliver, 2014, as cited in Mittal et al., 2023). In digital contexts, such dissatisfaction is commonly expressed through online reviews.

Customer dissatisfaction in digital environments is often expressed through online reviews. User reviews represent actual experiences related to application performance, functionality, and service quality. Previous studies show that user reviews provide valuable insights for evaluating application quality and identifying areas that require improvement (Aldabbas et al., 2020; Fahim et al., 2024). Repeated negative reviews may signal critical service issues and reduce customer trust if not addressed systematically (Li et al., 2020; Sällberg et al., 2023).

Given the large volume of textual feedback, manual monitoring becomes inefficient and potentially biased. Sentiment analysis provides a structured method for extracting emotional meaning from textual data (Karne, 2022; Samanmali & Rupasingha, 2024). In business contexts, sentiment analysis enables companies to assess public perception and align strategic decisions with customer expectations (Akhouri et al., 2023; Montaser et al., 2025).

To implement automated sentiment classification, machine learning algorithms are required. Support Vector Machine (SVM) is widely recognized for its capability to handle high-dimensional textual data efficiently (Cervantes et al., 2020). Empirical studies demonstrate that SVM achieves high classification accuracy in digital application sentiment analysis (Imanuddin & Gernowo, 2023; Madyatmadja et al., 2025; Putra et al., 2024). Furthermore, SVM-based sentiment analysis can support managerial interpretation of customer feedback and generate strategic insights for service improvement (Karne, 2022; Siroot et al., 2024).

Despite its strong performance, prior research generally focuses on overall sentiment classification accuracy rather than conducting in-depth analysis of negative sentiment to uncover dissatisfaction drivers. In addition, sentiment analysis specifically targeting the JIWA+ application based on Google Play Store reviews has not been conducted. Previous research has examined brand perception on social media platforms rather than application-level performance (Pamungkas et al., 2025).

Therefore, this study aims to analyze user reviews of the JIWA+ mobile application by applying the Support Vector Machine (SVM) algorithm for sentiment classification. The research first classifies user reviews into positive, neutral, and negative sentiment categories in order to identify the overall distribution of sentiment within the dataset. Particular attention is then given to negative reviews to examine the dominant complaint themes that reflect sources of customer dissatisfaction. By combining machine learning based sentiment classification with thematic interpretation, this study positions sentiment analysis not only as a technical text-mining procedure but also as an analytical approach that can generate managerial insights for improving digital service performance.

2. LITERATURE REVIEW

Sentiment Analysis

Sentiment analysis is defined as the field that examines opinions, attitudes, and emotions expressed in textual data to determine sentiment polarity, whether positive, negative, or neutral (Liu, 2012). The rapid development of this field since the early 2000s has been driven by the increasing volume of digital opinion data derived from social media, online reviews, and discussion forums (Liu, 2012). In business contexts, sentiment analysis has been widely utilized to understand user perceptions, measure satisfaction levels, and identify service weaknesses.

In practical implementation, textual data must undergo preprocessing to be recognized by computational systems (Sharda et al., 2020). This stage includes cleaning irrelevant elements, normalizing words, tokenizing text, and reducing words to their root forms (stemming). These processes are essential because user-generated reviews are typically unstructured and linguistically varied. Proper preprocessing ensures data consistency and improves classification performance.

Mobile Applications

Mobile applications are defined as software specifically developed for use on small wireless computing devices such as smartphones and tablets rather than desktop computers (Weichbroth, 2020). With the advancement of smart device technology, mobile applications operate within intelligent operating systems and provide advanced computing capabilities through various functional features (Logan, 2016, as cited in Tang, 2019). These applications are generally designed to perform diverse functions, including calendar management, email access, social networking, web browsing, digital entertainment, and online service access (Hsiao & Chen, 2016, as cited in Tang, 2019).

Within business and mobile commerce (m-commerce) literature, mobile applications have become an integral component of consumer–organization interaction. Tang (2019) explains that mobile applications support technology adoption and influence consumer motivation, attitudes, and behavioral responses in digital service environments. Furthermore, mobile applications enable consumers to obtain information, share opinions, and make purchasing decisions, while simultaneously encouraging transformations in marketing strategy and customer relationship management (Cheung & To, 2017, as cited in Tang, 2019). The widespread adoption of mobile applications across productivity, lifestyle, entertainment, and business services further expands interaction between users and service providers (Chang, 2015; Hsu & Lin, 2015, as cited in Tang, 2019).

Based on these perspectives, mobile applications can be understood as digital service interfaces that facilitate user interaction with technology-based business systems. In service industries, their performance directly shapes how customers perceive digital service quality and operational effectiveness.

Support Vendor Machine

After preprocessing, textual data must be transformed into numerical representations to enable machine learning analysis. In this study, Term Frequency–Inverse Document Frequency (TF-IDF) is applied to assign weights to words based on their frequency within individual documents and their rarity across the entire dataset (Luo & Lu, 2024). This approach minimizes the influence of common, non-informative words while preserving contextually significant terms. The resulting numerical vectors serve as input for classification algorithms such as Support Vector Machine (SVM).

SVM was selected in this study due to its effectiveness in handling high-dimensional and sparse textual data, which are common characteristics of online review datasets. The algorithm constructs an optimal hyperplane that separates data into distinct sentiment categories, enabling reliable classification even when the feature space is large. Previous studies have demonstrated the strong performance of SVM in sentiment analysis of mobile application reviews, achieving high classification accuracy across various service platforms (Imanuddin & Gernowo, 2023; Madyatmadja et al., 2025; Putra et al., 2024).

From a business analytics perspective, sentiment analysis using SVM allows organizations to monitor customer perceptions at scale, prioritize service improvements based on empirical evidence, and strengthen data-driven decision-making processes.

Customer Satisfaction

Customer satisfaction is positioned as an evaluative outcome formed after service consumption. Oliver (2014, as cited in Mittal et al., 2023) defines customer satisfaction as an assessment of whether a service provides fulfilling and pleasurable experiences relative to expectations. Similarly, Solomon (1996, as cited in Zouari & Abdelhedi, 2021) explains that satisfaction emerges after customers compare their experiences with prior expectations. Service quality plays a critical role in shaping satisfaction levels, as it influences users' evaluations of service performance (Dabholkar, Thorpe, & Rentz, 1996, as cited in (Zouari & Abdelhedi, 2021).

The formation of satisfaction can be explained through the disconfirmation mechanism. Churchill and Surprenant (1982, as cited in Dwivedi et al., 2012) describe satisfaction as resulting from the comparison between perceived performance and expectations. This mechanism is influenced by prior expectations, which shape how users interpret service performance (Niedrich et al., 2005, as cited in Dwivedi et al., 2012).

Customer satisfaction is considered a critical construct because it influences post-consumption behavior. Oliver (1999, as cited in Dwivedi et al., 2012) emphasizes that satisfaction determines subsequent user behavior after service usage. Johnson (2001) further explains that satisfaction serves as an evaluative measure of service experience, providing insights into how users perceive system performance.

In digital service environments, dissatisfaction expressed through online reviews reflects performance gaps between expectations and perceived service outcomes. Therefore, analyzing negative feedback becomes essential for identifying areas of improvement and strengthening digital service quality.

3. METHODOLOGY

This study adopts a qualitative descriptive approach supported by machine learning techniques to analyze negative customer sentiment toward the JIWA+ mobile application. Although sentiment classification is performed computationally, the primary objective is interpretative, namely to understand patterns of dissatisfaction and their implications for service quality improvement. The methodological framework consists of data collection, preprocessing, feature extraction, classification using Support Vector Machine (SVM), and model evaluation.

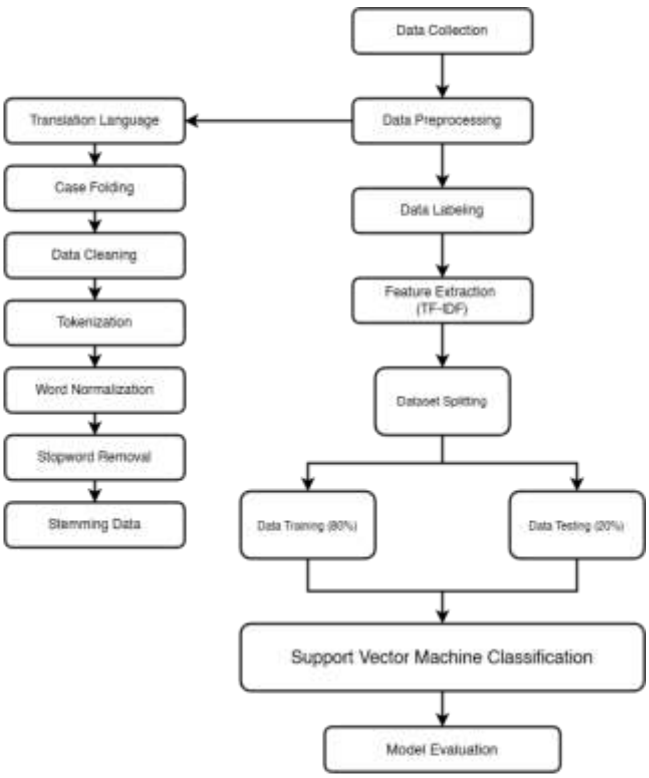

Figure 1. Research Framework

Data Collection

This study utilized secondary data obtained from user reviews of the JIWA+ mobile application available on Google Play Store. Data were collected using a web scraping technique, capturing review text, star ratings, and timestamps within the period 2022–2025. Google Play Store was selected as the data source due to its authenticity and its role as a direct digital feedback platform where users voluntarily express their experiences and evaluations.

Data Preprocessing

Given that online reviews are unstructured textual data, several preprocessing steps were conducted to improve data quality and analytical readiness. These steps included language translation, case folding, data cleaning, tokenization, word normalization, stopword removal, and stemming. The purpose of this stage was to reduce noise, standardize textual format, and enhance the effectiveness of subsequent feature extraction and classification processes.

Data Labeling

The dataset was classified into three sentiment categories (positive, neutral, and negative). The labeling process was conducted using a lexicon-based sentiment approach by identifying sentiment-bearing words within each review. Reviews expressing satisfaction, appreciation, or positive experiences were categorized as positive. Reviews indicating complaints, dissatisfaction, or negative experiences were labeled as negative. Meanwhile, reviews that did not show a clear positive or negative tendency were classified as neutral.

This categorization produced structured sentiment classes that were subsequently used for the sentiment classification model. The distribution of sentiment categories is presented in Table 1.

Table 1. Sentiment Summary

Sentiment	Frequency
Positive	402
Neutral	379
Negative	244

Source: Processed by the researcher (2025)

Feature Extraction

To transform textual data into numerical representation, the Term Frequency–Inverse Document Frequency (TF-IDF) method was employed. TF-IDF assigns weight to each word based on its importance within a document relative to the entire corpus, thereby improving the discriminative power of the classification model.

Dataset Splitting

The dataset consisting of 1,025 labeled reviews was divided into training and testing sets using an 80:20 ratio. A total of 820 reviews were allocated to the training set, while the remaining 205 reviews were used as the testing set.

The training dataset was utilized to build and train the classification model, enabling the algorithm to learn patterns from the labeled data. Meanwhile, the testing dataset was employed to evaluate the model's predictive performance and measure its generalization ability on unseen data.

Support Vector Machine Classification

The sentiment classification process was conducted using the Support Vector Machine (SVM) algorithm. SVM was selected due to its strong performance in analyzing high-dimensional textual data and its ability to generate reliable classification results. In the context of digital customer feedback, SVM enables structured identification of positive, neutral, and negative sentiments derived from user reviews. By transforming unstructured textual opinions into categorized information, the model supports systematic evaluation of customer perceptions toward the mobile application.

From a business perspective, the application of SVM contributes to data-driven customer satisfaction analysis. Accurate sentiment classification allows companies to detect dissatisfaction patterns, identify recurring service issues, and monitor digital service performance more effectively. In competitive mobile-based markets, such analytical capability supports managerial decision-making by providing measurable insights into customer experience and areas requiring service improvement.

Model Evaluation

Model evaluation was performed to measure the effectiveness of the Support Vector Machine (SVM) in classifying sentiment categories within user reviews. This stage was conducted to ensure that the classification results provide a dependable basis for interpreting customer satisfaction patterns derived from the JIWA+ application reviews. Rather than focusing solely on algorithmic performance, the evaluation emphasizes the model's reliability in capturing customer sentiment as a representation of user experience.

In this study, performance was assessed using accuracy, precision, recall, and F1-score. These metrics were selected to evaluate not only overall predictive correctness but also the model's consistency in identifying each sentiment class. As presented in Table 2, the model achieved an overall accuracy of 0.746. The positive sentiment class demonstrated the strongest performance, while the negative class also showed relatively high recall, indicating the model's effectiveness in detecting dissatisfied users. These results suggest that the SVM model provides sufficiently robust performance to support subsequent managerial interpretation of customer sentiment trends.

Table 2. Evaluation Summary

Sentiment	Precision	Recall	F1-Score	Accuracy
Positive	0,805	0,825	0,815	0,746
Neutral	0,647	0,458	0,537	
Negative	0,730	0,844	0,783	

Source: Processed by the researcher (2025)

4. RESULTS

This section presents the findings of the sentiment classification and the identification of dominant dissatisfaction themes derived from user reviews of the JIWA+ mobile application.

Sentiment Classification Results

The sentiment classification process produced three categories: positive, neutral, and negative. Based on the labeling results, positive reviews accounted for 402 entries, neutral reviews totaled 379, and negative reviews amounted to 244. These findings indicate that while positive sentiment dominates overall user feedback, a substantial portion of reviews reflects dissatisfaction and service-related concerns.

The classification model achieved an overall accuracy of 0.746, demonstrating adequate predictive capability in identifying sentiment polarity within user-generated content. The positive class showed strong performance across precision (0.805), recall (0.825), and F1-score (0.815), indicating consistent identification of favorable user experiences. Meanwhile, the negative class demonstrated high recall (0.844), suggesting that the model effectively captured expressions of dissatisfaction. From a business standpoint, this capability is particularly important, as negative sentiment detection provides critical insight into service weaknesses and potential risk areas affecting customer satisfaction. Overall, the results confirm that the Support Vector Machine (SVM) model provides a sufficiently reliable analytical foundation for interpreting customer perceptions and evaluating digital service performance.

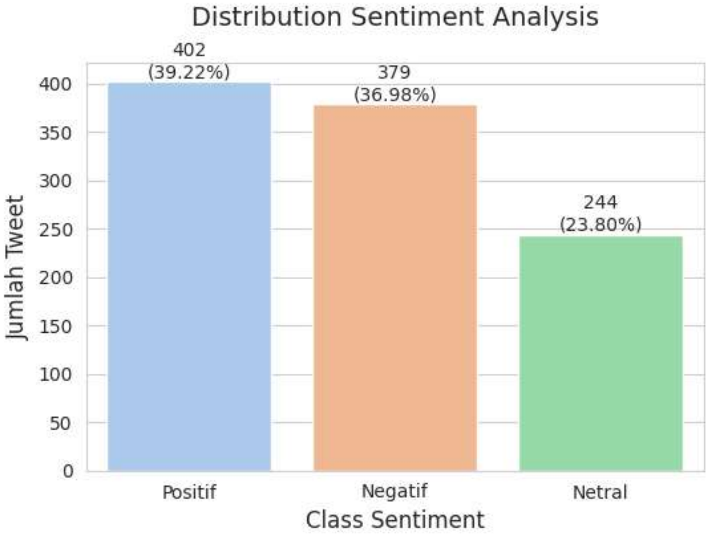

Figure 2. Sentiment Classification

Identification of Negative Sentiment Themes

Beyond sentiment polarity classification, the analysis further explored the textual content of negative reviews to identify recurring dissatisfaction patterns. This stage aims to uncover specific operational and service-related issues reflected in user feedback. The results indicate three dominant complaint themes frequently expressed by users: "pesan" (order), "gerai" (outlet), and "pakai" (use). These themes represent critical touchpoints in the customer journey within the JIWA+ mobile application.

The theme "pesan" is primarily associated with transaction failures, automatically canceled orders, and unsynchronized payment confirmations between the application and outlet systems. The theme "gerai" reflects discrepancies between information displayed in the application and actual conditions in physical outlets, such as inaccurate store availability or operational status. Meanwhile, "pakai" refers to user difficulties in utilizing application features, including vouchers, promotional offers, and digital payment methods. Collectively, these findings indicate that dissatisfaction is largely driven by operational reliability, digital system integration, and usability challenges rather than product-related concerns.

To provide an initial descriptive overview of dissatisfaction patterns, a word cloud visualization was generated from the negative review corpus. This visualization highlights frequently occurring terms and offers an exploratory perspective on dominant complaint drivers within the dataset. As illustrated in Figure 2, terms such as "pesan," "batal," "gerai," "error," and "pakai" appear prominently, reinforcing the presence of transaction-related and system-related issues. From a managerial standpoint, this visualization serves as an early diagnostic tool for identifying high-frequency service concerns in digital platforms.

Figure 2. Wordcloud Negative Sentiment

To strengthen the analysis, a frequency-based quantitative examination was conducted to identify the top 15 most frequently occurring words in negative reviews. This approach provides measurable evidence of recurring dissatisfaction themes and supports prioritization of service improvement initiatives.

Figure 3 illustrates the most frequently occurring words extracted from user reviews that were classified as negative by the sentiment analysis model. The distribution shows that transaction-related and outlet-related terms dominate the dataset, indicating that operational synchronization and service execution are central sources of user dissatisfaction. The frequency distribution helps highlight recurring issues reported by users and allows managers to prioritize improvements based on empirical evidence rather than anecdotal interpretation.

It should be noted that the presence of certain words that appear semantically positive, such as “baik,” does not indicate positive sentiment. Sentiment classification in this study is determined based on the overall context of each review rather than individual word polarity. Therefore, words such as “baik” may appear in the visualization because they occur within negative expressions (e.g., “tidak baik” or similar contextual usage) in reviews that were classified as negative. The word distribution in Figure 3 thus represents the most common terms appearing within negative reviews rather than words that independently convey negative meaning.

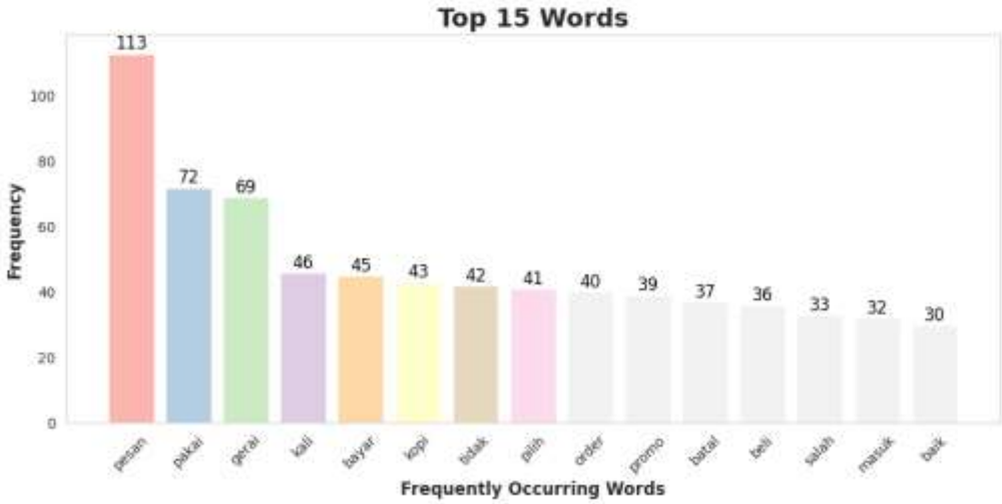

Figure 3. Top 15 Words Distribution

For deeper managerial focus, the three most dominant words were isolated and analyzed in greater detail. These top three terms represent the primary dissatisfaction drivers within the dataset and provide clearer direction for strategic intervention.

As shown in Figure 4, "pesan," "gerai," and "pakai" emerge as the most frequently mentioned issues in negative reviews. The dominant theme, "pesan," relates to failed orders, automatic cancellations, and unsynchronized payment confirmations despite successful deductions. Several users reported that payments were successfully processed but orders did not appear at the cashier, indicating instability in transaction processing and system synchronization. From a business perspective, these failures reflect weaknesses in system reliability and directly undermine user trust in the application's transactional integrity.

The theme "pakai" refers to difficulties in using application features, particularly vouchers, promotional codes, and digital payment methods. Users frequently experienced payment errors, unresponsive interfaces, or promotional codes that could not be applied during transactions. Meanwhile, the theme "gerai" highlights discrepancies between information displayed in the application and actual outlet conditions, including inaccurate store status and inconsistencies in menu or promotional details. These recurring complaints indicate challenges in the operational integration between the digital platform and physical outlets.

It should be noted that the words presented in the negative sentiment visualization represent terms appearing within reviews that were classified as negative at the review level. Therefore, some words that may appear neutral or context-dependent, such as "pakai," are included because they occur within negative user experiences rather than representing sentiment polarity on their own.

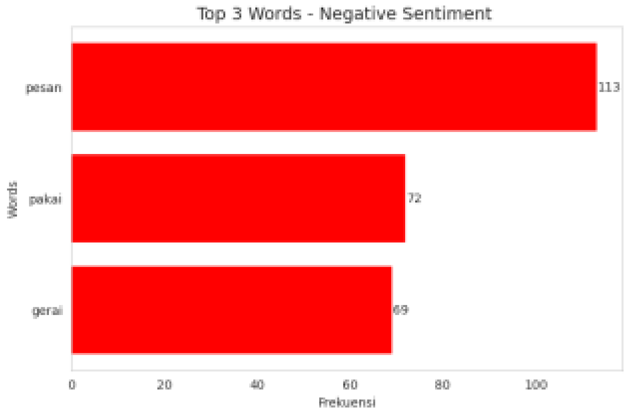

Figure 4. Top 3 Words Distribution

Overall, approximately 35.7% of total reviews were categorized as negative, indicating that a considerable proportion of users encountered service-related obstacles. Collectively, these findings demonstrate that customer dissatisfaction within the JIWA+ application is primarily driven by system reliability, transaction functionality, and digital–offline integration issues. From a managerial standpoint, structured sentiment analysis provides actionable business intelligence by identifying operational vulnerabilities that require strategic improvement to enhance customer satisfaction and service performance.

5. DISCUSSION

This study aims to provide a comprehensive understanding of user perceptions toward the JIWA+ mobile application by analyzing sentiment patterns derived from Google Play Store reviews using the Support Vector Machine (SVM) algorithm. The discussion interprets the empirical findings by linking the distribution of negative sentiment and the identified dominant complaint themes to the theoretical perspectives of mobile applications, sentiment analysis, and customer satisfaction. Rather than focusing solely on sentiment polarity classification, this study explains how recurring transaction failures, usability barriers, and information inconsistencies reflect performance gaps in digital service delivery.

Mobile Application Performance and Service Reliability

The findings indicate that dissatisfaction in the JIWA+ application is primarily associated with transaction failures, usability barriers, and inconsistencies in outlet information. From a theoretical perspective, mobile applications are designed as software systems that operate on smart devices to facilitate diverse functional activities and user interactions (Logan, 2016, as cited in Tang, 2019; Weichbroth, 2020) In business and m-commerce contexts, mobile applications function as digital service interfaces that shape consumer behavior and support service transactions (Tang, 2019). Therefore, when essential features such as order processing, payment confirmation, or real-time information display fail to operate reliably, the application does not perform its intended role as an effective digital service interface.

Furthermore, mobile applications are recognized as platforms that enable consumers to obtain information, share opinions, and make purchasing decisions, while influencing organizational marketing and customer relationship strategies (Cheung & To, 2017, as cited in Tang, 2019). The dominance of complaints related to ordering ("pesan"), usage ("pakai"), and outlet information ("gerai") suggests tshat instability in these core functions undermines the application's capacity to facilitate smooth digital interactions. From this perspective, operational instability reflects not only technical limitations but also challenges in maintaining digital service effectiveness within mobile-based business operations.

Sentiment Analysis as a Strategic Business Tool

By converting large volumes of unstructured reviews into categorized sentiment data, this approach enables the identification of recurring dissatisfaction patterns rather than isolated complaints. The prominence of specific negative themes reflects structural issues in transaction reliability and feature usability. Consistent with the business analytics perspective outlined in the literature review, sentiment analysis using SVM functions as a data-driven mechanism for monitoring customer perceptions and prioritizing service improvements based on empirical evidence rather than assumption.

The identification of dominant negative themes demonstrates the analytical value of sentiment analysis in capturing structured insights from user-generated content. Sentiment analysis examines opinions and emotional expressions in textual data to determine sentiment polarity (Liu, 2012). In business contexts, it has been widely applied to understand user perceptions, measure satisfaction levels, and identify weaknesses in service performance (Liu, 2012). In this study, textual reviews underwent preprocessing to ensure data consistency before being transformed into numerical representations using TF-IDF weighting (Luo & Lu, 2024; Sharda et al., 2020), allowing the SVM algorithm to classify sentiment systematically.

Customer Satisfaction and Expectation–Performance Alignment

The recurring negative themes identified in this study can be interpreted through customer satisfaction theory. Customer satisfaction is formed through evaluative judgments comparing perceived service performance with prior expectations (Oliver, 2014, as cited in Mittal et al., 2023; Solomon, 1996, as cited in Zouari & Abdelhedi, 2021). According to the disconfirmation mechanism, dissatisfaction arises when perceived performance falls below expectations (Churchill & Surprenant, 1982, as cited in Dwivedi et al., 2012).

The findings suggest that dissatisfaction in the JIWA+ application is largely driven by perceived performance gaps in digital service execution, particularly in transaction processing, payment functionality, and outlet information accuracy. When these aspects fail to operate as expected, users experience negative disconfirmation. Since service quality plays a critical role in shaping satisfaction evaluations (Dabholkar, Thorpe, & Rentz, 1996, as cited in Zouari & Abdelhedi, 2021), persistent system instability may negatively influence overall satisfaction and subsequent behavioral responses. As satisfaction is known to determine post-usage behavior and future user responses (Oliver, 1999, as cited in Dwivedi et al., 2012; Johnson, 2001), recurring dissatisfaction expressed through online reviews may signal potential risks to continued usage and long-term digital service acceptance.

From a managerial standpoint, these findings indicate that improving digital service reliability, ensuring accurate information delivery, and enhancing usability are essential to reduce negative disconfirmation and strengthen customer satisfaction in mobile-based service environments.

6. CONCLUSION

This study aimed to identify customer satisfaction patterns in the JIWA+ mobile application by analyzing negative user reviews using the Support Vector Machine (SVM) algorithm. The sentiment classification results indicate that although positive reviews dominate, 35.7% of total reviews reflect negative sentiment, signaling a substantial level of user dissatisfaction. The SVM model achieved an overall accuracy of 0.746, demonstrating reliable performance in detecting sentiment polarity, particularly in identifying negative reviews with high recall. This confirms that machine learning–based sentiment analysis can serve as a robust analytical foundation for examining digital customer perceptions in mobile commerce environments.

The thematic analysis of negative reviews reveals that dissatisfaction is primarily driven by three dominant issues: transaction failures “pesan”, feature usability constraints “pakai”, and inconsistencies between application information and physical outlets “gerai”. From a mobile application perspective, these findings highlight weaknesses in system reliability, real-time synchronization, and digital–offline service integration. In relation to customer satisfaction theory, dissatisfaction emerges from performance gaps between user expectations and actual service delivery. From a business and management standpoint, this study demonstrates that sentiment analysis should not be viewed merely as a technical classification tool, but as a strategic business intelligence mechanism. By systematically identifying dissatisfaction drivers, organizations can prioritize operational improvements, enhance digital service quality, strengthen customer trust, and ultimately improve competitive positioning in mobile-based service industries.

7. REFERENCES

Akhouri, S., Nigam, M. S., Shah, S., & Pandey, T. N. (2023). Automated Tweet Sentiment Analysis Using Machine Learning Models. 2023 International Conference In Advances In Power, Signal, And Information Technology (APSIT), 728–733. Https://Doi.Org/10.1109/APSIT58554.2023.10201677

Aldabbas, H., Bajahzar, A., Alruily, M., Qureshi, A., Latif, R. M. A., & Farhan, M. (2020). Google Play Content Scraping And Knowledge Engineering Using Natural Language Processing Techniques With The Analysis Of User Reviews. Journal Of Intelligent Systems, 30, 192–208. Https://Doi.Org/10.1515/Jisys-2019-0197

Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A Comprehensive Survey On Support Vector Machine Classification: Applications, Challenges And Trends. Neurocomputing, 408, 189–215. Https://Doi.Org/Https://Doi.Org/10.1016/J.Neucom.2019.10.118

Dwivedi, Y. K., Wade, M. R., & Schneberger, S. L. (2012). Information Systems Theory: Explaining And Predicting Our Digital Society, Vol. 1. Springer New York.

Https://Doi.Org/10.1007/978-1-4419-6108-2

Fahim, S. F., Sounok, S. A., Shaeed, N., Orpa, M. H., & Niloy, N. T. (2024). Analyzing User Sentiment In Google Play Store Reviews: A Natural Language Processing Approach. 2024 15th International Conference On Computing Communication And Networking Technologies (ICCCNT), 1–5. Https://Doi.Org/10.1109/ICCCNT61001.2024.10725684

Group, J. (2021). JIWA+. Jiwa Group. Https://Jiwagroup.Com/Id/Whaton/Detail/21/JIWA/

Group, J. (2025). JIWA+ By Kopi Kopi Janji Jiwa [Aplikasi Mobile]. Google Play Store. Https://Play.Google.Com/Store/Apps/Details?Id=Com.Jiwa.Jiwagroup

Imanuddin, S. H., & Gernowo, R. (2023). Sentiment Analysis On Satusehat Application Using Support Vector Machine Method . Journal Of Electronics, Electromedical Engineering, And Medical Informatics, 5(3 SE-Electronics). Https://Doi.Org/10.35882/Jeemi.V5i3.304

Johnson, M. D. (2001). Customer Satisfaction (N. J. Smelser & P. B. B. T.-I. E. Of The S. & B. S. Baltes (Eds.); Pp. 3198–3202). Pergamon. Https://Doi.Org/Https://Doi.Org/10.1016/B0-08-043076-7/04273-X

Karne, N. (2022). Harnessing Sentiment Analytics: Insights Into Customer Behavior And Decision-Making. International Journal Of Scientific Research In Computer Science, Engineering And Information Technology, 383–395. Https://Doi.Org/10.32628/CSEIT228462

Li, X., Zhang, B., Zhang, Z., & Stefanidis, K. (2020). A Sentiment-Statistical Approach For Identifying Problematic Mobile App Updates Based On User Reviews. In Information (Vol. 11, Issue 3). Https://Doi.Org/10.3390/Info11030152

Liu, B. (2012). Sentiment Analysis And Opinion Mining. Morgan & Claypool Publishers.

Luo, Y., & Lu, C. (2024). TF-IDF Combined Rank Factor Naive Bayesian Algorithm For Intelligent Language Classification Recommendation Systems. Systems And Soft Computing, 6, 200136. Https://Doi.Org/Https://Doi.Org/10.1016/J.Sasc.2024.200136

Madyatmadja, E. D., Harianto, V. E., Willson, A., Winsen, & Kent, R. (2025). Sentiment Analysis Of GOJEK User Reviews Using SVM, Naïve Bayes, And Random Forest Models. 2025 4th International Conference On Creative Communication And Innovative Technology (ICCIT), 1–7. Https://Doi.Org/10.1109/ICCIT65724.2025.11166956

Mittal, V., Han, K., Frennea, C., Blut, M., Shaik, M., Bosukonda, N., & Sridhar, S. (2023). Customer Satisfaction, Loyalty Behaviors, And Firm Financial Performance: What 40 Years Of Research Tells Us. Marketing Letters, 34(2), 171–187. Https://Doi.Org/10.1007/S11002-023-09671-W

Montaser, M. A. Al, Ghosh, B. P., Barua, A., Karim, F., Das, B. C., Shawon, R. E. R., & Chowdhury, M. S. R. (2025). Sentiment Analysis Of Social Media Data: Business Insights And Consumer Behavior Trends In The USA. Edelweiss Applied Science And Technology, 9(1 SE-Articles), 515–535. Https://Doi.Org/10.55214/25768484.V9i1.4164

Muhamad, N. (2023). 10 Restoran Dengan Jumlah Gerai Terbanyak Di Indonesia Pada 2022. In Databoks. Katadata. Https://Databoks.Katadata.Co.Id/Infografik/2023/10/16/10-Restoran-Dengan-Jumlah-Gerai-Terbanyak-Di-Indonesia-Pada-2022

Pamungkas, A. P., Mahendra, A., & Aziz, I. W. F. (2025). Comparison Of Machine Learning Models For Classifying Consumer Sentiment Of Coffee Shops On Social Media X. Jurnal Teknik Pertanian Lampung (Journal Of Agricultural Engineering), 14(5 SE-Articles), 1905–1912. Https://Doi.Org/10.23960/Jtepl.V14i5.1905-1912

Putra, R. A., Novita, R., Ahsyar, T. K., & Zarnelly. (2024). Implementation Of Classification Algorithm For Sentiment Analysis: Measuring App User Satisfaction. Teknika. Https://Doi.Org/10.34148/Teknika.V13i2.827

Sällberg, H., Wang, S., & Numminen, E. (2023). The Combinatory Role Of Online Ratings And Reviews In Mobile App Downloads: An Empirical Investigation Of Gaming And Productivity Apps From Their Initial App Store Launch. Journal Of Marketing Analytics, 11(3), 426–442. Https://Doi.Org/10.1057/S41270-022-00171-W

Samanmali, P., & Rupasingha, R. (2024). Sentiment Analysis On Google Play Store App Users' Reviews Based On Deep Learning Approach. Multimedia Tools And Applications, 83, 84425–84453. Https://Doi.Org/10.1007/S11042-024-19185-W

Sharda, R., Delen, D., & Turban, E. (2020). Analytics, Data Science, & Artificial Intelligence: Systems For Decision Support (11th (Ed.)). Pearson.

Siroot, H., Dwifebri Purbolaksono, M., & Dewi, U. (2024). Sentiment Analysis Of Raya Digital Bank Application Reviews Using The TF-IDF Method And Support Vector Machine. Https://Doi.Org/10.1109/ICICYTA64807.2024.10913051

Tang, A. K. Y. (2019). A Systematic Literature Review And Analysis On Mobile Apps In M-Commerce: Implications For Future Research. Electronic Commerce Research And Applications, 37, 100885. Https://Doi.Org/Https://Doi.Org/10.1016/J.Elerap.2019.100885

Weichbroth, P. (2020). Usability Of Mobile Applications : A Systematic Literature Study. IEEE Access, 8, 55563–55577. Https://Doi.Org/10.1109/ACCESS.2020.2981892

Zouari, G., & Abdelhedi, M. (2021). Customer Satisfaction In The Digital Era: Evidence From Islamic Banking. Journal Of Innovation And Entrepreneurship, 10(1), 9. Https://Doi.Org/10.1186/S13731-021-00151-X