

Analysis of Banking Application Reviews Using a Topic-based Sentiment Analysis Approach with Rule-based Lexicon and LDA

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ABSTRACT

This study analyzed banking user reviews using the Livin' by Mandiri app as a case study to understand user perceptions of digital banking services. A topic-based sentiment analysis approach was implemented by integrating a rule-based lexicon method and Latent Dirichlet Allocation (LDA). Text preparation steps such as cleaning, tokenization, stopword removal, and stemming were applied to 13,539 Google Play Store reviews that were gathered between January and June 2025. Sentiment labeling using the INSET lexicon indicated that 58.7% of reviews were negative, while 41.3% were positive. Topic modeling identified five main themes representing key service aspects, with authentication issues, such as login and facial verification failures, emerging as the dominant topic in negative reviews and achieving the highest coherence score of 0.486909. Model evaluation was conducted using coherence measurement and manual validation to ensure interpretative consistency. The findings indicated that authentication system stability significantly influenced negative user perceptions, whereas transaction efficiency and ease of use contributed to positive evaluations. This approach provided interpretable insights to support data-driven service improvement in digital banking applications.

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1. INTRODUCTION

The rapid growth of digital banking services has significantly changed the way customers interact with financial institutions, particularly through mobile and web-based applications. According to a Statista report, the number of digital banking users in Indonesia reached 2.29 billion in recent years and continues to grow steadily, reflecting a significant shift towards mobile-first financial services. In Indonesia, data from the Financial Services Authority (OJK) shows that digital banking transactions are increasing by more than 30% annually, highlighting the growing reliance on banking applications. This surge is accompanied by a growing volume of user-generated reviews on platforms like the Google Play Store and Apple App Store, where users express satisfaction, complaints, and suggestions [1]. In addition to this expansion, user ratings on websites like the Google Play Store are crucial in determining how the general public views the caliber of digital banking applications [2]. The large number of unstructured reviews makes it difficult for the development team to understand the aspects and issues that are most frequently complained about or appreciated by users. Related studies using text mining and sentiment analysis on banking application reviews have examined which service attributes most strongly determine

customer satisfaction with mobile banking apps [3], [4] as well as the classification of customer feedback toward mobile banking applications on the Google Play Store [5].

Sentiment analysis has become one of the most widely used approaches for mapping user perceptions of digital applications. The lexicon rule-based method is relevant in modern research because of its ability to automatically label emotional polarity based on a dictionary [6], [7]. However, conventional sentiment analysis has not been able to identify the context or specific aspects that users are concerned about. As a result, a method is needed that not only categorizes feelings but is also capable of extracting the main topics or themes from reviews. This study's sentiment analysis methodology uses Latent Dirichlet Allocation (LDA) and lexical rule-based techniques in a topic-based manner. The LDA method's ability to precisely extract topics from big data sets is one of its advantages [8].

LDA topic modeling has proven effective in identifying hidden themes in large text data sets. Studies such as [9], [10], show that LDA produces high topic coherence in application reviews and multi-aspect domains, putting it among the most popular structured approaches for subject modeling. Similar LDA-based sentiment and topic modeling approaches have also been applied to other mobile application domains, including banking app reviews [11], and travel booking app reviews [12], both of which confirm that combining sentiment labeling with topic modeling yields more interpretable insights than sentiment classification alone. In recent years, sentiment analysis and *topic modeling* research have undergone significant developments. Transformer-based models like BERTopic, IndoBERT, and Contextualized Topic Modeling (CTM) have emerged in recent years. Recent studies utilize the IndoBERT method to understand the nuances of the Indonesian language with 51% accuracy and an F1-Score of 31% [13], while modern topic modeling techniques such as BERTopic excel as tools for exploring themes that can be matched with sentiment analysis for operational insights (e.g., feature improvements) [14]. Meanwhile, CTM combines the depth of BERT embedding and the advantages of neural topic models to overcome the limitations of LDA in capturing semantic context, and has been proven to provide higher topic coherence [15]. However, the adoption of these models in the context of Indonesian digital banking applications is still limited, mainly due to high computational requirements, the lack of large-scale datasets, and the absence of comprehensive studies that integrate sentiment and topic analysis simultaneously for a specific application.

Empirically, there has been no research combining lexicon rule-based and LDA to produce topic-based sentiment analysis on Livin' by Mandiri user reviews. Using the same item, [16] earlier study employed the Support Vector Machine (SVM) approach with TF-IDF and Word2Vec feature extraction to examine user satisfaction with the Livin by Mandiri application. Unlike previous studies that focused on improving sentiment classification accuracy using supervised methods such as SVM, the approach in this study not only classifies sentiment polarity but also associates each sentiment with a probabilistically identified latent topic structure.

This study contributes methodologically by proposing an interpretable topic-based sentiment analysis framework that integrates rule-based sentiment assessment-based sentiment assessment with LDA-based topic modeling to simultaneously identify sentiment polarity and latent service aspects in Indonesian digital banking reviews without relying on large annotated datasets as supervised or Transformer-based models do, making it more adaptive to the Indonesian language context with limited computational resources and datasets. It is anticipated that the research's conclusions will give Mandiri Bank useful operational insights to enhance application performance, respond to user complaints in a more targeted manner, and design data-driven feature development priorities.

2. RESEARCH METHOD

The workflow technique for sentiment analysis research utilizing lexicon tagging and LDA on reviews of the Livin by Mandiri application from January to June 2025 is shown in Figure 1. Python programming and web scraping were used in this study to acquire data. The precise aim for scraping was reviewing data pertaining to the Livin by Mandiri app that was accessible on the Google Play Store. Using the random stratified sampling technique, 13,539 review data points will be obtained from a population of 14,193 (January–June 2025) [17]. The reduction in the amount of

data is not a subjective selection process, but rather the result of data quality filtering. However, this study has several potential biases. First, there is self-selection bias because only users who voluntarily provide reviews are included in the dataset. Next, there is platform bias because the data only comes from Android users through the Google Play Store and does not include iOS users. Then there is language bias, as reviews written in informal Indonesian or mixed language expressions can affect the accuracy of lexicon-based sentiment detection.

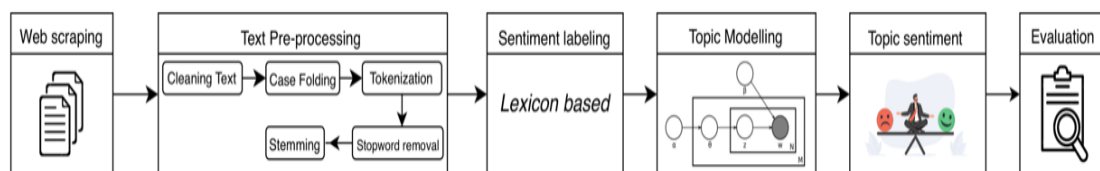


Figure 1. Methodological process for Topic-Based Sentiment analysis approach

2.1. Pre-Processing Text

The preprocessing process converts unstructured data into usable data [18]. User reviews are generally unstructured textual data that frequently contains noise, including symbols and misspellings. To make the dataset easier to process in the following step, the preprocessing stage seeks to eliminate superfluous words and lower the dataset's dimensionality [19].

Text cleaning, case folding, tokenization, stopwords removal, and stemming are just a few of the preprocessing methods used in this work. By fixing contractions, eliminating word repeats, and eliminating superfluous punctuation, one can purge text of extraneous letters and symbols. In order to maintain uniformity among all of the text's words, case folding is in charge of changing all of the text to lowercase. Tokenization separates sentences or text into its constituent words. Removing stopwords, or fewer significant words, lowers the dataset's dimensionality. Words in the text are reduced to their most basic form through stemming. The results of the data before and after preprocessing are presented in Table 1.

Tabel 1. Preprocessing result sampler

Before Preprocessing	After Preprocessing
rusak kah?? setelah unistall jadi ga bisa login	['rusak', 'uninstall', 'login']
dari bank BRI transfer ke mandiri dan transfer dari saldo Lazada ke bank mandiri sampai sekarang belum ada yg masuk, bagaimana ini admin, biasanya lancar, sekarang mengecewakan, apa kejadian ini hanya terjadi sama saya aja 🙄?...	['bank', 'bri', 'transfer', 'mandiri', 'transfer', 'saldo', 'lazada', 'bank', 'mandiri', 'masuk', 'admin', 'lancar', 'kecewa', 'jadi']

2.2. Lexicon rule-based

This study uses a lexicon rule-based approach to determine polarity, namely by comparing the scores of positive and negative words based on the Indonesian sentiment dictionary. Each word in the review is matched with the INSET sentiment dictionary, where if the score is > 0 , it is positive, and if it has a score < 0 , it is considered negative. Sentiment polarity quantifies a sentence's subjectivity and objectivity [20].

The data annotation results show that out of a total of 12,539 reviews, 5,591 reviews were classified as positive sentiment and 7,348 reviews as negative. This rule-based approach was chosen because it is consistent, transparent, and suitable for Indonesian-language review datasets, which have a wide variety of contexts and sentence structures [21]. Figure 2 shows that positive reviews account for 41.4% of the total reviews, while negative reviews account for 58.8%.

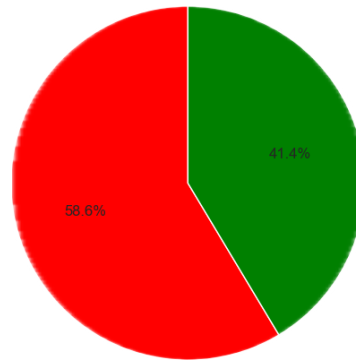


Figure 2. Sentiment Proportion

3. RESULTS AND DISCUSSION

3.1. Topic modelling using Latent Dirichlet Allocation

Textual data is analyzed using the LDA approach, which encodes documents as word frequency vectors. Using a probabilistic model, this approach can also pinpoint the themes or subjects that underlie a group of documents [22]. Therefore, a critical step calculating coherence scores is needed to ascertain the ideal number of subjects.

Emotion preprocessing and labeling, subject modeling with institutional genism were performed on the corpus data. Mathematically, coherence was calculated as the average association score of word pairs in a topic. The optimal number of topics is determined by maximizing the coherence value. The model with the highest coherence of 0.4657 is selected because it shows better semantic consistency and higher interpretability. The coherence of each topic can be seen in Table 2 and the visualization results in Figure 4.

Tabel 2. Coherence Value Results for Each Topic

Topik	Coherence Value
Topic 1	0.3241
Topic 2	0.4256
Topic 3	0.4657
Topic 4	0.4448
Topic 5	0.4540

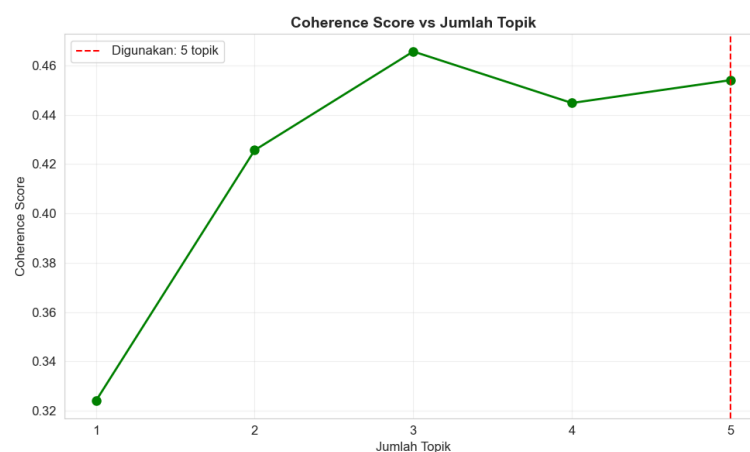


Figure 4. Visualization of Coherence Values

According to Table 2's coherence value computation findings, it was found that topic 3 had the highest coherence value, namely 0.4657. This value indicates that the two topics have comparable semantic strength and are relatively easy to interpret. In the context of LDA, a high coherence value indicates that the words in the topic often appear together in documents and form a strong thematic unity. Topic 3, which has the highest coherence, is dominated by words such as login, verification, failure, and face, which represent issues of authentication and transaction stability. The high coherence indicates that this issue appears consistently and repeatedly in user reviews, so it

can be identified as a major source of dissatisfaction. Topic 2 focuses on transaction activities such as transfers, balances, and payments, which reflect the core functions of banking applications. The appearance of words with a negative connotation in this topic indicates that the stability of the transaction system also affects user perception. Meanwhile, Topic 4 represents positive perceptions regarding the ease and speed of service, with dominant words such as easy, fast, and good. This shows that when the system is running optimally, users give positive evaluations of the app's efficiency and convenience. Other topics relate to card services and app system updates, reflecting the dynamics between feature requirements and technical stability.

Overall, the LDA results show that authentication and transaction stability issues are dominant themes in user reviews. The dominance of the authentication topic also shows that users are more sensitive to access barriers than to feature innovations. This finding implies that in digital financial services, system stability and ease of access have a higher perceived weight than the addition of new features. In other words, reliability plays a major role in determining satisfaction, while feature expansion plays a secondary role. The following are the groups of words per topic in Table 3.

Tabel 3. Collection of Topics

<u>Topic 1</u>	bantu, kartu, mantap, atm, mandiri, rekening, nomor, kirim, debit, blokir, pinjam, moga, online, fitur, hilang
<u>Topic 2</u>	mandiri, bank, transaksi, jam, saldo, transfer, layan, uang, bayar, ganggu, potong, top, atur, otomatis, tanggal
<u>Topic 3</u>	login, masuk, susah, gagal, verifikasi, suruh, wajah, daftar, enggak, ulang, ribet, bikin, akun, cabang, bisa
<u>Topic 4</u>	bagus, mudah, transaksi, cepat, bintang, ribu, loading, oke, pulsa, tarik, gampang, dikit, tunai, lengkap, apa
<u>Topic 5</u>	aplikasi, buka, baik, update, sistem, error, error, muncul, aman, dukung, lot, guna, lancar, operasi, suka

Topic modeling was also conducted for positive and negative classes. In this study, topic modeling was used to gather information from evaluations of the Livin by Mandiri app. This data will be interpreted using the collection of primary subjects in the positive and negative groups. The coherence value computation results for items in the positive and negative classes are displayed in Table 4.

Tabel 4. Topic Coherence Value

Topik	Coherence	
	Score Positif	Score Negatif
<u>0</u>	0.404969	0.293090
<u>1</u>	0.404098	0.391936
<u>2</u>	0.393463	0.425311
<u>3</u>	0.399247	0.486909
<u>4</u>	0.406269	0.457506

The results of Table 4 show that topic 4 has the best coherence value for the positive class with a value of 0.406269, while topic 3 has the best coherence value for the negative class with a value of 0.486909. Tables 5 and 6 show the groups of words that make up the positive and negative topics, where the coherence value indicates that the topic is easier to interpret based on the set of words that make it up. The more frequently the words in the topic occur together, in other words. The more coherent the topic is written.

Tabel 5. Collection of Topics for Positive Classes

<u>Topic 1</u>	buka, baik, dukung, aman, kecewa
<u>Topic 2</u>	jam, login, transaksi, baik, otomatis
<u>Topic 3</u>	mudah, transaksi, bantu, mandiri, baik
<u>Topic 4</u>	update, kartu, kirim, login, atm
<u>Topic 5</u>	mantap, saldo, top, layan, dana

Tabel 6. Collection of Topics for Negative Classes

<u>Topic 1</u>	bagus, verifikasi, gagal, wajah, ribet
<u>Topic 2</u>	jam, transfer, saldo, bank, mandiri
<u>Topic 3</u>	mandiri, bantu, bank, layan, buruk
<u>Topic 4</u>	kartu, daftar, enggak, login, suruh
<u>Topic 5</u>	aplikasi, buka, masuk, login, susah

The subject modeling visualizations were created using pyLDAvis, as shown in Figures 5 and 6, to facilitate interpretation of the topic modeling results from the LDA method. In this visualization, each topic is represented as a circle, the size of which indicates the proportion of occurrences of the topic in the data, while the distance between the circles illustrates the degree of difference between topics. Furthermore, the most relevant keywords for each topic are displayed, thus helping to understand the context of the discussion, both positive and negative sentiments, in a more intuitive and structured manner.

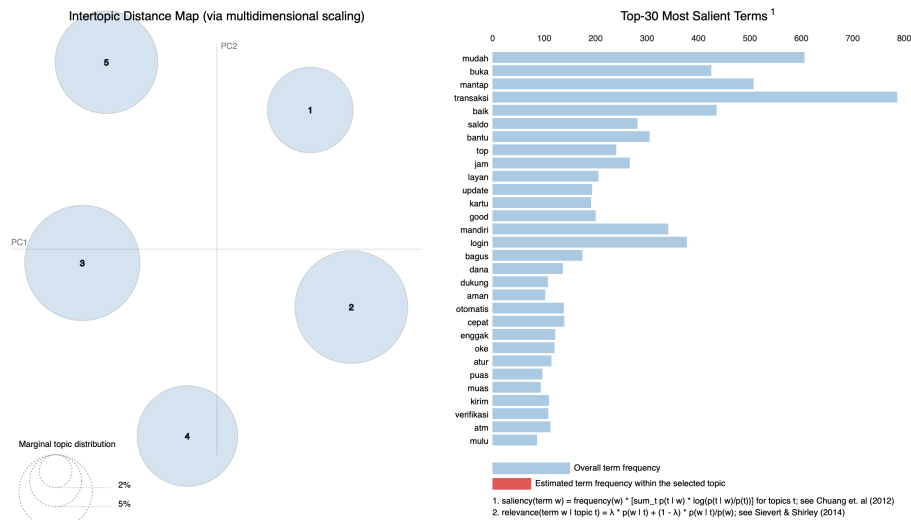


Figure 5. Visualization of Positive Class Topics

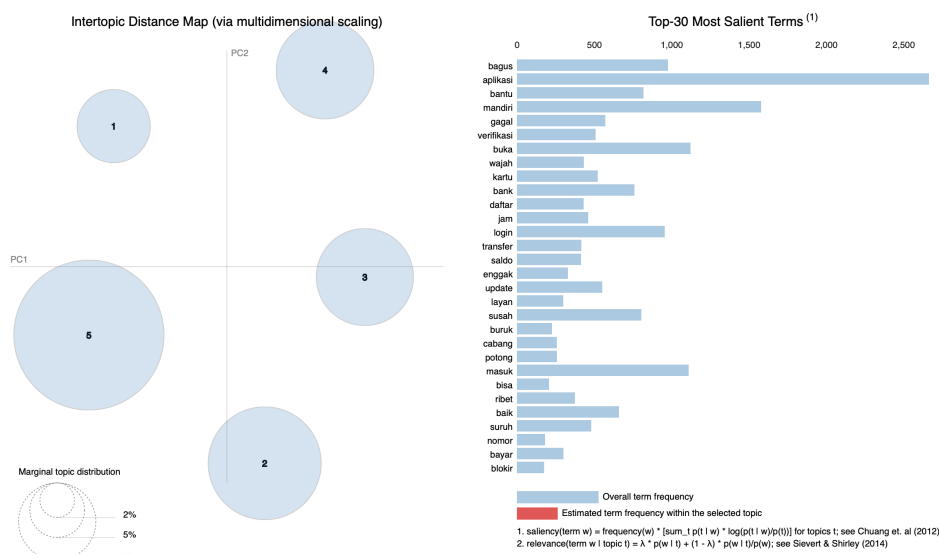


Figure 6. Visualization of Negative Class Topics

Viewing Wordcloud is considered quite representative for displaying topic modeling results because it can identify terms that frequently appear based on the modeled topic [23]. Figure 7 presents a wordcloud visualization that represents the main terms in each topic resulting from LDA modeling. Each word cloud displays the most frequently mentioned words for each topic, and the font size indicates how many times the word appears in the data set.



Figure 7. Representation of the underlying terms of each topic

From this visualization, it can be seen that words such as "login," "mandiri," "transaksi," and "saldo" appear prominently in several topics, reflecting that access to applications and transaction services are the two issues most frequently discussed by users. In several other topics, words such as "mudah," "mantap," and "cepat" indicate positive perceptions regarding the ease of use and efficiency of the application's features.

Conversely, the presence of words such as "gagal," "verifikasi," "masalah," "susah," and "tidak masuk" indicates technical complaints related to authentication and transaction issues. Thus, the word cloud not only provides a quick overview of the dominant words, but also reinforces the previous finding that technical issues are the main source of negative reviews.

This visualization clarifies the relationship between word frequency and sentiment polarity, and shows how the LDA model successfully separates topics based on the focus of user discussions. These results also confirm that the topics seen in user reviews reflect the operational reality of the Livin' by Mandiri app, and can therefore be used as a basis for more targeted service improvements

3.2. Topic-Based Sentiment Analysis

Sentiment analysis is conducted with the aim of discovering opinions, emotions, and evaluations expressed in natural language [24]. This approach combines lexicon-based sentiment labeling results with LDA topic modeling, providing a better understanding of what users talk about most often and how they view certain features or services.

After the labeling process produces positive and negative reviews, each class is analyzed using LDA. Figure 8 shows the top 20 words in the positive class, confirming that the Livin' by Mandiri app offers a fast, stable, and easy user experience.

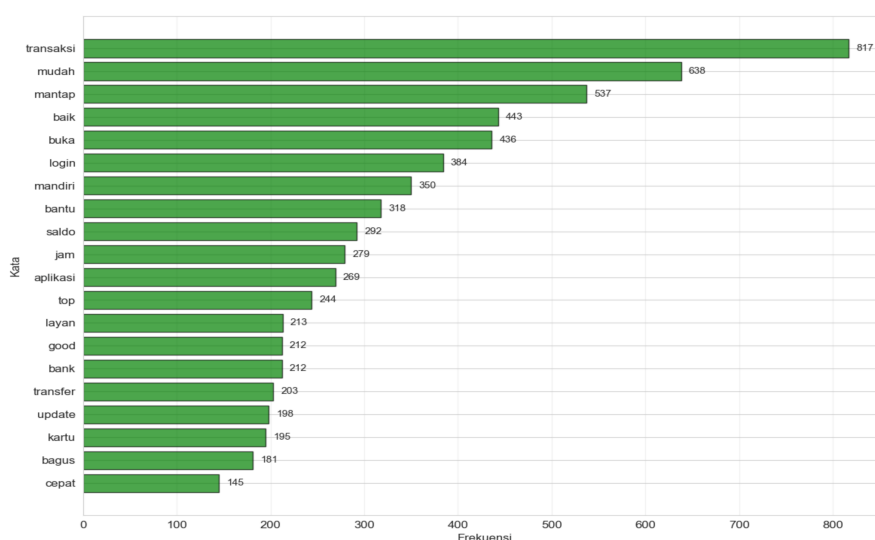


Figure 8. Representation of Top 20 Positive Words

Unlike the positive class, topics in the negative class are mostly dominated by technical issues, such as failed face verification, login difficulties, missing balances or transfers, and system disruptions. Although negative reviews are considered more critical in influencing app usage, the following image shows the top 20 words in negative topics.

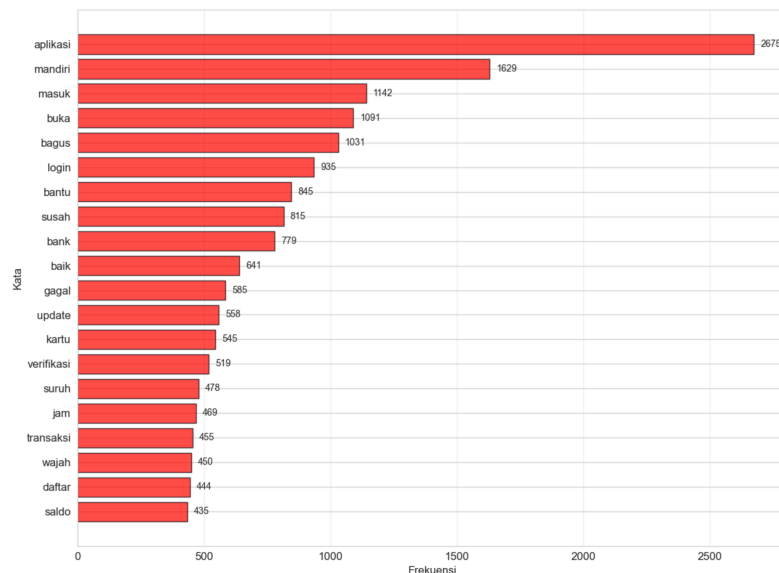


Figure 9. Representation of Top 20 Negative Words

3. 3 Evaluation

The quality of the LDA model was evaluated at an early stage using the coherence score as an intrinsic metric to measure the semantic cohesion between words in each topic. This metric assesses the extent to which words in a topic tend to appear together in the corpus and form statistically meaningful themes. Based on the test results, the highest coherence value was obtained in topic 3, at 0.4657. This value indicates that these topics have relatively better semantic consistency than other topics. Because the words that make up a topic have strong contextual relevance, the higher the coherence score, the more likely it is that the topic will be easily grasped conceptually. In this study, the topics with the highest values were dominated by words such as login, verification, failure, and face, which consistently represent user authentication issues.

However, the coherence score is an intrinsic metric that only evaluates the statistical relationship between words and does not fully guarantee contextual relevance to the substantive content of the document. Therefore, to improve the validity of the results, interpretive validation was carried out through manual examination of a random sample of approximately 10% of the documents from each dominant topic. This validation aims to assess the suitability between the words that make up the topic, the probability distribution of topics in the document, and the actual content of user reviews. Documents with the highest topic probability are analyzed directly to ensure that their content truly reflects the theme generated by the model. The results of the examination show that most documents on the topic of authentication consistently discuss login issues, facial verification, and application access failures. Similarly, the topic of transactions contextually represents issues of fund transfers, balances, and payments. These findings indicate that the LDA model not only forms statistically coherent word clusters, but is also capable of capturing real phenomena in the user experience. Thus, the combination of intrinsic evaluation and interpretive validation provides a stronger basis for ensuring the credibility and substantive validity of topic modeling results.

In a previous study conducted by [16], using the Support Vector Machine (SVM) approach with TF-IDF and Word2Vec feature extraction, sentiment analysis of Livin by Mandiri app evaluations yielded an accuracy of 87%, a precision of 90% for positive sentiment, and a recall of 82%. On the other hand, the Word2Vec method demonstrated an 83% accuracy rate, a 92% positive precision rate, and a 71% recall rate. There are fundamental differences in terms of both

the methodological approach and the type of analysis output. However, the main focus of the study was limited to evaluating sentiment classification performance, without providing an explanation of the specific topics or aspects behind positive and negative sentiments. This is consistent with a more recent study on mobile banking applications in Southeast Europe, which used BERT-based sentiment analysis and BERTopic modeling to derive experience dimensions from user reviews and found that authentication- and reliability-related themes were similarly influential in shaping user satisfaction [25].

Based on the introduction, through the examination of unstructured text evaluations on the Google Play Store, this study emphasizes how crucial it is to comprehend how users evaluate the Livin' by Mandiri app. By comparing sentiment labeling using the InSet lexicon with the sentiment derived from ratings, sentiment analysis was used to examine these disparities. From January to June 2025, 14,193 user reviews of the Livin' by Mandiri app were gathered for this study, of which 13,539 were examined. To verify the quality of the text data prior to sentiment labeling using the InSet lexicon, data pre-processing techniques included text cleaning, case folding, tokenization, stopword removal, and stemming. The sentiment labeling results showed that 41.3% of reviews were positive (5,591 reviews), while the other 58.7% were negative (7,348 reviews).

4. CONCLUSION

This study successfully implemented a topic-based sentiment analysis approach by integrating lexicon rule-based and Latent Dirichlet Allocation (LDA) methods to analyze 13,539 user reviews of the Livin' by Mandiri application for the period January–June 2025. The analysis results show that 58.7% of reviews had negative polarity and 41.3% had positive polarity, indicating the dominance of user complaints about the application's performance during the observation period. Topic modeling using LDA identified five main themes representing aspects of digital banking services, with authentication issues (login and facial verification) emerging as the most dominant topic in the negative sentiment class. This topic also had the highest coherence value in the negative class (0.486909), indicating strong semantic consistency and repeated frequency of occurrence in the review corpus.

The model was evaluated using coherence score measurements as an intrinsic evaluation, and manual validation of document samples to ensure that the interpretation of topics was consistent with the actual content of the reviews. This approach ensures that the model is not only statistically optimal, but also substantively valid and operationally relevant. In practical terms, the findings show that the stability of the authentication system is a major determinant of negative user perceptions, so that improvements to the login and verification mechanisms have the potential to significantly reduce negative reviews, while the aspects of fast and easy transactions need to be maintained as factors that shape positive perceptions.

However, this study has limitations in its use of lexicon and LDA approaches, which are not yet fully capable of capturing complex semantic contexts, irony, or mixed informal language. Further research is recommended to compare with Transformer-based models such as BERTopic or IndoBERT, as well as to consider fake review detection and cross-platform analysis to improve the validity and generalization of the findings.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the research, authorship, and/or publication of this article. This study was conducted purely for academic purposes as part of the student's final thesis project.

DATA AVAILABILITY

<https://bit.ly/DataAvailability-LDA>

AUTHOR CONTRIBUTIONS

Zahratussyafitri: conceived the study, conducted the data collection, performed the pre-processing and topic modeling analysis, and wrote the original draft of the manuscript. **Kristoko**

Dwi Hartomo: supervised the research project, validated the methodology, and contributed to the interpretation of the results. **Yessica Nataliani:** Writing-Review & Editing, provided critical feedback on the discussion section.

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