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# Mapping User Dissatisfaction in Mobile Banking Applications Using Ensemble Clustering LDA and LSA

Kartikadyota Kusumaningtyas[1], Alfirna Rizqi Lahitani[2], Irmma Dwijayanti[3], Muhammad Habibi[4]
[1,4]Informatics, Universitas Jenderal Achmad Yani Yogyakarta, Yogyakarta, Indonesia
[2] Information Technology, Universitas Jenderal Achmad Yani Yogyakarta, Yogyakarta, Indonesia
[3] Information System, Universitas Jenderal Achmad Yani Yogyakarta, Yogyakarta, Indonesia
[1]kartikadyota@gmail.com, [2]alfirnarizqi@gmail.com, [3]irmmadwijayanti@gmail.com,
[4]muhammadhabibi17@gmail.com

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***Abstract*— The large number of user complaints about mobile banking applications in Indonesia is a significant concern, considering the role of these applications in supporting people's financial activities. Negative reviews across the Google Play Store reflect user dissatisfaction with the application's features, performance, or services. This background encourages research to analyze negative user reviews in depth to identify the main topics of dissatisfaction. This study aims to map the topics contained in negative reviews using an ensemble clustering approach that combines the Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA) methods. The research stages are divided into three main stages: Data Collection, Sentiment Analysis, and Topic Modeling. The built SVM model obtained evaluation results of 90% accuracy, 92% precision, 95% recall, and 94% F1-score. Based on the analysis of user review topics for mobile banking applications using the ensemble clustering LDA and LSA methods, it was found that each application has a different topic focus. The BCA mobile application is more associated with user interaction, ease of login process, features, and ease of use. Then BRImo complained about application service fees and speed, transaction security, transaction convenience, transaction balance, customer features, BRImo login, and BRImo application menu improvements.**

***Index Terms*— Topic Modeling; LDA; LSA; SVM; Ensemble Clustering.**

## I. INTRODUCTION

The digital era has significantly changed various aspects of life, including financial services. Now, many banks provide online services to make transactions easier for their customers. Online banking services in Indonesia have experienced rapid growth in recent years. Based on data from Bank Indonesia, the value of digital banking transactions in August 2023 reached IDR 5.1 trillion or increased by 11.9% compared to 2022 [1]. This growth was driven by several factors, such as increasing internet penetration in Indonesia[2], government policies through the Gerakan Nasional Non-Tunai (GNTT) [3], and innovation from banks [4], [5]. Among the online services available, mobile banking is one of the most popular services because of the benefits felt by customers, such as ease of access, flexibility, and the ability to carry out various types of transactions, such as fund transfers, bill payments, and real-time balance monitoring [6], [7]. Amid the various conveniences and benefits offered, users of mobile banking applications also have an essential role in building a better online banking service ecosystem. One way is to share experiences in using mobile banking applications. The Google Play Store is an Android application store platform that allows users to provide ratings and comments on their experiences using the application. Positive reviews usually contain good experiences that indicate user satisfaction, while negative reviews usually contain bad experiences that indicate user complaints and dissatisfaction.

Currently, Google Play Store can automatically group user reviews into positive and negative. However, Google Play Store does not yet have a feature to map the main topics in positive and negative reviews automatically. This problem can make it difficult for service providers to understand the root of the problem and take appropriate corrective steps, especially for negative reviews. Negative reviews need to be handled more quickly. Slow handling of negative reviews can reduce customer reputation and loyalty [8].

This study aims to identify topics of user dissatisfaction based on negative reviews of popular mobile banking applications in Indonesia using ensemble clustering LDA and LSA. According to a survey conducted by Top Brand Award, two popular mobile banking applications in Indonesia are BCA Mobile and BRImo [9]. The application of the LDA method in this study was used to find the topics underlying the reviews, while the LSA method was used to reduce dimensions and extract semantic patterns from the review text. Previous research in digital banking has focused on understanding service quality and its impact on customer satisfaction and loyalty. Commonly used methods include multiple regression, Kendall-Tau correlation analysis, and SEM, which evaluate variables of responsiveness, device compatibility, ease of use, risk, and service features that affect user satisfaction. Meanwhile, user satisfaction affects customer loyalty [10], [11], [12].

Furthermore, sentiment analysis on application reviews has become popular to measure user perception. This analysis utilizes machine learning techniques such as Support Vector Machine and Naive Bayes to analyze positive and negative sentiments contained in user reviews, providing an overview of factors that affect user experience [13], [14].

The main topics in mobile banking user review data were identified using the LDA method [15]. The data used were overall user reviews on the BNI, BCA, and BRI applications. Based on the data analysis, differences and similarities in service quality between the three applications were seen. These findings provide important insights into user preferences and experiences in using mobile banking applications. Given that complaint handling affects customer loyalty, mapping topics to user dissatisfaction is essential to encourage improvements in mobile banking services. This study introduces an ensemble approach that combines LDA and LSA to identify and analyze key topics that cause dissatisfaction in mobile banking user reviews [15], [16].

## II. Method

This study consists of three main stages: data collection, sentiment analysis, and topic modeling (as shown in Fig. 1). It utilizes user reviews from the Google Play Store as the primary data source.

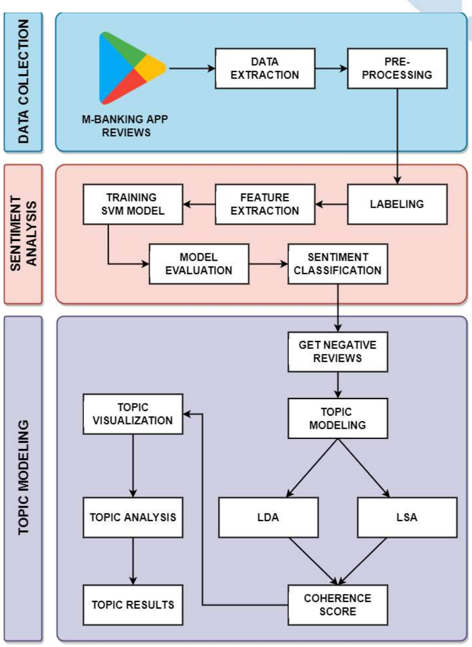


Fig. 1. Research phase

### A. Data Collection

Data collection is the process of collecting mobile banking app review data. The input includes user reviews, ratings, and other Google Play Store platform metadata. At the same time, the output is a raw dataset in a structured format that is ready for further analysis.

The first step is to collect review data from mobile banking applications. This extraction data stage focuses on four mobile applications: BCA Mobile and BRImo. This study used a scraper to gather the data.

The next step is to clean the raw data through the preprocessing stages:

- Tokenization: The process of splitting sentences into tokens.
- Stopword removal: Removing common words that do not contribute significantly to the sentence's meaning, such as "and," "the," or "or."
- Stemming: Converting words to their base form.

### B. Sentiment Analysis

The sentiment analysis process starts with the crucial labeling step, which involves categorizing text data based on sentiment to distinguish between positive and negative reviews. This labeling is essential for providing the SVM model with the necessary data to learn and make predictions.

Following labeling, the next step is feature extraction using the Term Frequency-Inverse Document Frequency (TF-IDF) method. TF-IDF is a method for assessing the importance of a word in a document relative to a set of documents. This process will change each word as a token that has gone through a preprocessing stage into a vector representing the existing word. Term Frequency (TF) measures how often a word appears in a document. Inverse Document Frequency (IDF) measures how unique or rare the word appears across all documents in the corpus. The equation for calculating TF-IDF is shown in (1).

$$TF - IDF = f_{t,d} \; x \; log\left(\frac{N}{n_t}\right) \quad (1)$$

Where:
ft,d= number of occurrences of word t in document d
N = total number of documents in the corpus
nt = number of documents containing word t

Support Vector Machine (SVM) is a supervised machine learning algorithm based on vectors [17]. SVM works by finding the best hyperplane (line or dividing plane) that separates data into two categories in the feature space [18]. The hyperplane is between two classes with a distance d at the closest point of each class. This distance *d* is called the margin and the points on this margin are called support vectors.

Once the feature extraction is complete, the SVM model is trained using data from the BCA Mobile application. The data is split into 70% for training and 30% for testing, ensuring that the model learns from most of the data while its performance is evaluated on the test data. The training process helps the model understand the patterns in the data that correlate with positive or negative sentiment.

After training, the model's performance is assessed using a confusion matrix. A confusion matrix is a table used to evaluate the performance of a classification algorithm by comparing the actual labels with the predicted ones (as shown in Fig. 2). It summarizes the results into four categories: True Positives (correctly predicted positives), True Negatives (correctly predicted negatives), False Positives (incorrectly predicted positives), and False Negatives (incorrectly predicted negatives) [20].

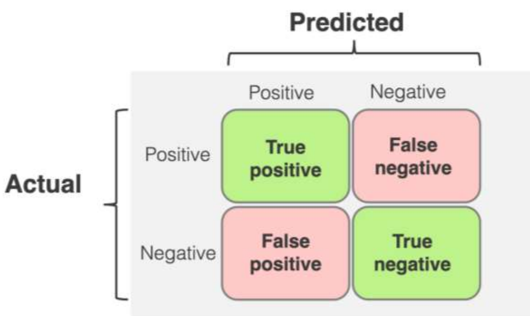


Fig. 2. Confusion matrix (Source: [21])

The confusion matrix provides the foundation for calculating key evaluation metrics in classification tasks. Accuracy measures the proportion of correct predictions (2), while precision evaluates the correctness of optimistic predictions by comparing true positives to all predicted positives (3). Recall (or sensitivity) measures the model's ability to correctly identify actual positive cases (4). The F1-score is the harmonic mean of precision and recall, offering a balanced metric when the class distribution is uneven (5).

$$Accuracy = \frac{TP}{TP+FP} \; x \; 100\% \tag{2}$$

$$Precision = \frac{TP+TN}{TP+TN+FP+FN} \; x \; 100\% \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \; x \; 100\% \tag{4}$$

$$F1 - score = 2 \; x \; \frac{Precision \; x \; Recall}{Precision+Recall} \; x \; 100\% \tag{5}$$

In the final step, sentiment classification is conducted using the trained SVM model, which classifies the reviews from four mobile banking applications into positive and negative categories.

### C. *Topic Modeling*

Ensemble clustering is a approach to solve this problem. It combines two topic modeling methods to group data based on identified topics.

Latent Dirichlet Allocation (LDA) is an algorithm that distributes the words in the comments into several topics, where one comment can have one or more topics [22]. Latent Semantic Analysis (LSA) algorithm uses matrix decomposition to identify hidden relationships between words and documents, providing an overview of recurring topics in the comments [23].

Choosing the correct number of topics is a crucial step in topic modeling. A commonly used metric for this purpose is the coherence score, which evaluates how semantically consistent or interpretable a set of top words in a topic is. A higher coherence score suggests that the topic contains words that frequently appear together in the corpus and are more likely to be interpreted as a meaningful theme. In practice, multiple models with different topic numbers ($k$) are trained, and the model with the highest coherence score is selected as optimal.

Once the LDA or LSA model is trained, topic visualization becomes important to help users interpret and explore the results. Visualization tools are commonly used to display the inter-topic distance map and the relevance of terms to each topic. The visual interface allows users to explore how distinct or overlapping topics are and which words are most representative of each topic.

In topic analysis, the top keywords from each topic and their associated documents are reviewed to assign descriptive labels to the topics. This involves human judgment and is crucial for deriving actionable insights from the model output.

Each method (LDA and LSA) assigns a topic label to each comment. In the next stage, the results of LDA and LSA will be combined using the voting method. The voting method selects the most frequently occurring label as the final label (majority voting) [24].

## III. RESULT AND DISCUSSION

### A. *Data Collection*

The data collection phase is a critical process of gathering data from various sources. This study uses user reviews from BCA Mobile and BRImo mobile banking applications .

1. First, data is extracted from the Google Play Store site to get the raw user review comments. The result from this stage is text data.
   *"Aplikasinya sangat membantu, transfer cepat dan mudah* digunakan*!" (BCA)*
2. Preprocessing stage in this study involves tokenization, stopword removal and stemming. Result from this stage is clean data.
   *"Aplikasi, sangat, bantu, transfer, cepat, mudah, guna"*
3. Next, feature extraction using TF-IDF produce the weighted terms.

### B. *Sentiment Analysis*

The BCA mobile application review dataset consisting of 1990 reviews was divided into 70% (1393 reviews) for training and 30% (597 reviews) for testing. The evaluation results of the SVM model are shown in Fig. 3.

```
Accuracy of the SVM model: 0.90
Precision: 0.92
Recall: 0.95
F1-Score: 0.94

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.79      0.82        81
           1       0.92      0.95      0.94       213

    accuracy                           0.90       294
   macro avg       0.89      0.87      0.88       294
weighted avg       0.90      0.90      0.90       294
```

Fig. 3. Evaluation results

Based on the evaluation results shown in Figure 3, the SVM model performs well, with an accuracy of 95%, precision of 92%, recall of 95%, and F1-score of 94%. Furthermore, the model is used to classify all review data on each m-banking application. The distribution of negative and positive reviews on each m-banking application is shown in Fig. 4 and Fig. 5.

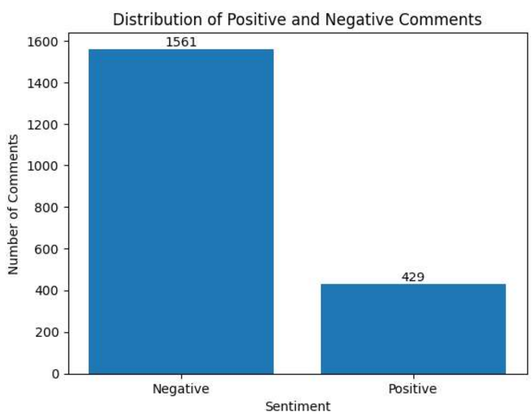


Fig. 4. Sentiment analysis of BCA Mobile reviews

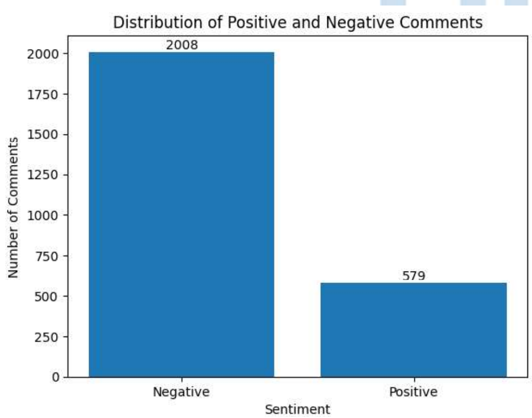


Fig. 5. Sentiment analysis of BRImo reviews

Based on the distribution of sentiment analysis from Fig. 4 and Fig. 5, the results show that negative sentiment data has a larger proportion than positive sentiment data.

## C. Topic Modeling

In this experiment, we tried to generate 1 to 15 *k*-topics. Fig. 6 and Fig. 7 show the coherence score graphs of LDA and LSA on the BCA mobile and BRImo.

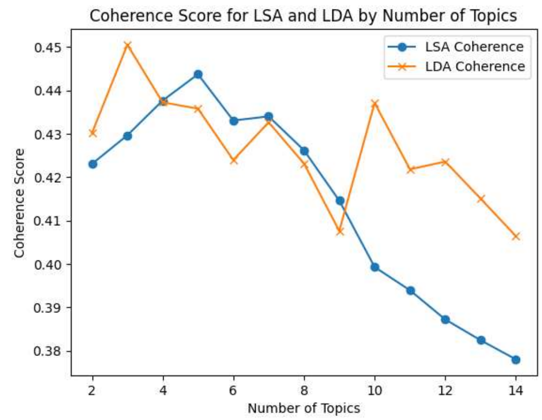


Fig. 6. Coherence score for LDA and LSA of BCA Mobile

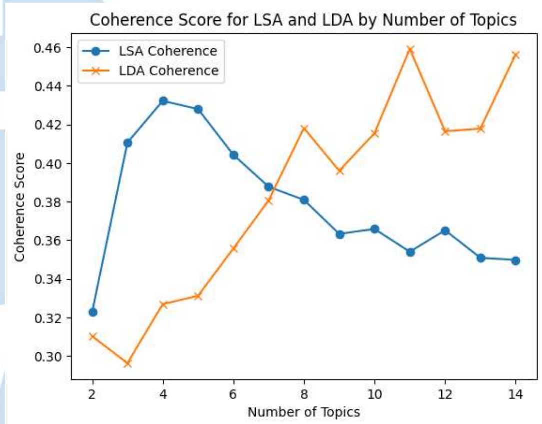


Fig. 7. Coherence score for LDA and LSA of BRImo

The higher the coherence score, the better the quality of the topic. Table 1 summarizes the highest coherence score and the number of topics for each m-banking application.

TABLE I. NUMBER K-TOPICS FOR LDA AND LSA

| App | LDA | | LSA | |
|---|---|---|---|---|
| | Coherence Score | Number of *k*-topics | Coherence Score | Number of *k*-topics |
| BCA mobile | 0.450540 | 3 | 0.443739 | 5 |
| BRImo | 0.459125 | 11 | 0.432213 | 4 |

Fig. 8 and Fig. 9 show the results of the distance map between topics generated by the LDA method.

Meanwhile Fig. 10 and Fig. 11 show the results of t-SNE generated by the LSA method.

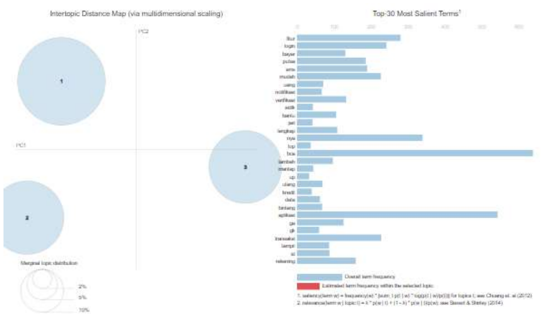

Fig. 8. Distance map generated by the LDA for BCA Mobile

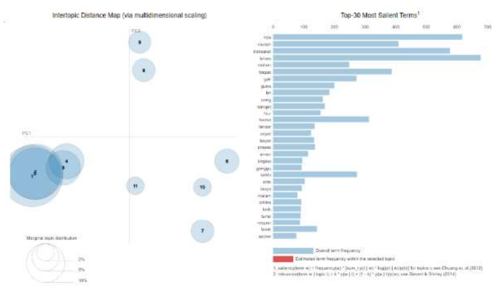

Fig. 9. Distance map generated by the LDA for BRImo

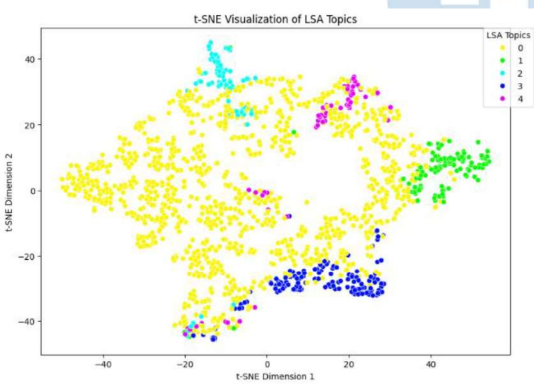


Fig. 10. t-SNE generated by the LSA for BCA Mobile

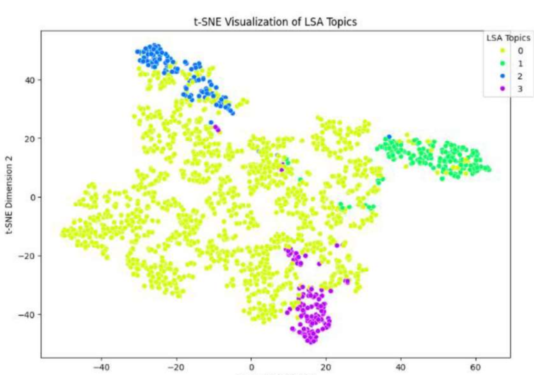


Fig. 11. t-SNE generated by the LSA for BRImo

In Fig. 8, there is no overlapping LDA topic, while in Fig. 9, there are several overlapping LDA topics. The overlapping topics indicate that similar words build different topics. Based on the LDA visualization, the relationship between topics can be identified by grouping overlapping topics. Tables 2 and 3 display the topic analysis of LDA for BCA Mobile and BRImo.

TABLE II. TOPIC ANALYSIS OF LDA FOR BCA MOBILE

| Topic Category | Related Topics | Description | Number of reviews |
|---|---|---|---|
| A-1 | - | User interaction | 568 |
| A-2 | - | Ease of login process | 405 |
| A-3 | - | Features and ease of use of the application | 582 |

TABLE III. TOPIC ANALYSIS OF LDA FOR BRIMO

| Topic Category | Related Topics | Description | Number of reviews |
|---|---|---|---|
| B-1 | 1, 2, 3, 4, 5 | Application service fees and speed | 827 |
| B-2 | 6 | Transaction security | 35 |
| B-3 | 7 | Transaction convenience | 66 |
| B-4 | 8 | Transaction balance | 157 |
| B-5 | 9 | Customer features | 12 |
| B-6 | 10 | BRImo login | 400 |
| B-7 | 11 | BRImo application menu improvements | 511 |

Meanwhile, the LSA visualization in Fig. 10 and Fig. 11 show that 5 LSA topics were formed on the BCA mobile application and 4 LSA topics were formed on the BRImo application. Topic 0 on BCA Mobile and BRImo dominates and is widespread, indicating that this topic has a more general scope. While the other topics on BCA Mobile and BRImo are grouped more specifically in certain areas, indicating that this topic is homogeneous. Table 4 and Table 5 show the analysis results for each LSA topic of the BRImo application.

TABLE IV. TOPIC ANALYSIS LSA FOR BCA MOBILE

| Topic Category | Description | Number of reviews |
|---|---|---|
| C-1 | Application usage | 1164 |
| C-2 | Convenience, speed, and efficiency | 116 |
| C-3 | Technical constraints | 81 |
| C-4 | Payment features, notifications, and financial transactions | 133 |
| C-5 | BCA services | 61 |

TABLE V. TOPIC ANALYSIS LSA FOR BRIMO

| Topic Category | Description | Number of reviews |
|---|---|---|
| D-1 | Use of the BRImo application | 1576 |
| D-2 | Ease of transactions | 181 |
| D-3 | Authentication, login, password, and account creation | 118 |
| D-4 | Management of balances, notifications, fees, and transfers | 133 |

### *D. Ensemble Clustering: Voting Method*

A voting-based ensemble clustering begins by collecting the topic or cluster labels assigned to each document by LDA and LSA models. For each document, the system gathers the labels produced by these models and counts how often each label appears. The label with the highest frequency, or the majority vote, is then chosen as the final ensemble label for that document. This method helps to stabilize clustering outcomes by combining the perspectives of different models. However, if a tie occurs—meaning two or more labels appear with the same frequency—, the system must apply a tie-breaking strategy. Common approaches include selecting the label from the model with the higher coherence score, which indicates better topic quality. Table 6 shows an example of the implementation of the voting method.

TABLE VI. EXAMPLE OF VOTING METHOD OF BCA MOBILE

| Reviews | LDA Topic | LSA Topic | Voting Result |
|---|---|---|---|
| koneksi internet stabil bisa muter loading doang … | 2 | 0 | 2 (Tie) |
| servernya berat intip saldo buka tampil rekening ... | 0 | 0 | 0 |
| moga tambah fitur bca mobile bayar via qris topup flazz | 1 | 3 | 1 (Tie) |
| bagus keluh adain via chat gak musti telpon hallo bca | 2 | 2 | 2 |

As we know, Table 1 shows that the LDA topic coherence score is higher than the LSA coherence score on BCA Mobile. Therefore, if a tie occurs, the LDA topic is chosen.

After conducting the voting method, the final label is obtained for each document. Table 7 shows the topics on the BCA Mobile and BRImo applications after conducting the voting method on the results of the LDA topic and the LSA topic.

TABLE VII. FINAL TOPIC FOR BCA MOBILE AND BRIMO

| Application | Topic | Description |
|---|---|---|
| BCA Mobile | A-1 | User interaction |
| | A-2 | Ease of login process |
| | A-3 | Features and ease of use of the application |
| BRImo | B-1 | Application service fees and speed |
| | B-2 | Transaction security |
| | B-3 | Transaction convenience |
| | B-4 | Transaction balance |
| | B-5 | Customer features |
| | B-6 | BRImo login |
| | B-7 | BRImo application menu improvements |

## IV. CONCLUSION

This process provides a clear overview of the negative issues frequently complained about by users of mobile banking applications, as well as the appreciated features. The following topics were successfully identified based on ensemble clustering using LDA and LSA for BCA Mobile: user interaction, ease of login process, and the applications' features and ease of use. Then, for BRImo there are: application service fees and speed, transaction security, transaction convenience, transaction balance, customer features, BRImo login, and BRImo application menu improvements. This study allows application developers to take more appropriate actions to improve the application.


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## REFERENCES


[1] A. Ahdiat, "Transaksi Digital Banking di Indonesia Tumbuh 158% dalam 5 Tahun Terakhir," Katadata Media Network, 2023. Available: https://databoks.katadata.co.id/datapublish/2023/07/05/transaksi-digital-banking-di-indonesia-tumbuh-158-dalam-5-tahun-terakhir. [Accessed: Mar. 15, 2024]

[2] A. Ahdiat, "Penetrasi Internet Indonesia Capai 78% pada 2023, Rekor Tertinggi Baru," 2024. Available: https://databoks.katadata.co.id/datapublish/2024/01/30/penetrasi-internet-indonesia-capai-78-pada-2023-rekor-tertinggi-baru. [Accessed: Mar. 21, 2024]

[3] I. Ulfi, "Tantangan dan Peluang Kebijakan Non-Tunai: Sebuah Studi Literatur," Jurnal Ilmiah Ekonomi Bisnis, vol. 25, no. 1, pp. 55–65, 2020, doi: 10.35760/eb.2020.v25i1.2379

[4] Y. B. Adji, W. A. Muhammad, A. N. L. Akrabi, and N. Noerlina, "Perkembangan Inovasi Fintech di Indonesia," Business Economic, Communication, and Social Sciences Journal (BECOSS), vol. 5, no. 1, pp. 47–58, Jan. 2023, doi: 10.21512/becossjournal.v5i1.8675

[5] E. B. Yusuf, M. I. Fasa, and Suharto, "Inovasi Layanan Perbankan Syariah Berbasis Teknologi sebagai Wujud Penerapan Green Banking," Istithmar : Jurnal Studi Ekonomi Syariah, vol. 7, no. 1, pp. 34–41, Jun. 2022, doi: 10.30762/istithmar.v6i1.33

[6] Dirwan, "Keputusan Nasabah Menggunakan Mobile Banking dari Sisi Kemudahan, Manfaat dan Kenyamanan," SEIKO: Jurnal of Management and Business, vol. 5, no. 1, pp. 323–332, 2022.

[7] A. F. Iriani, "Minat Nasabah dalam Penggunaan Mobile Banking pada Nasabah Bank Syariah Mandiri Kota Palopo," DINAMIS-Journal of Islamic Management and Bussines, vol. 2, no. 2, pp. 99–111, 2019.

[8] M. Ade Kurnia Harahap, Normansyah, S. Nurhayati, I. M. Nawangwulan, and S. P. Anantadjaya, "Pengaruh Penanganan Keluhan Dan Komunikasi Pemasaran Terhadap Loyalitas," COSTING: Journal of Economics, Business and Accounting, vol. 7, no. 2, 2024.

[9] Mutia Annur C. Katadata Media Network. 2022 [cited 2024 Mar 15]. Aplikasi Mobile Banking Terpopuler di Indonesia, Siapa Juaranya? Available from: https://databoks.katadata.co.id/datapublish/2022/06/22/aplikasi-mobile-banking-terpopuler-di-indonesia-siapa-juaranya

[10] Hariansyah FA, Wardani NH, Herlambang AD. Analisis Pengaruh Kualitas Layanan Mobile Banking terhadap Kepuasan dan Loyalitas Nasabah pada Pengguna Layanan BRI Mobile Bank Rakyat Indonesia di Kantor Cabang Cirebon. Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer [Internet]. 2019 Apr;3(5):4267–75. Available

from: https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/5177

[11] Makmuriyah AN, Vanni KM. Analisis Faktor-faktor yang Mempengaruhi Kepuasan Nasabah dalam Menggunakan Layanan Mobile Banking (Studi Kasus Pada Nasabah Bank Syariah Mandiri di Kota Semarang). Eduka: Jurnal Pendidikan, Hukum, dan Bisnis . 2020;5(1):37–44.

[12] Parera NO, Susanti E. Loyalitas Nasabah dari Kemudahan Penggunaan Mobile Banking. International Journal of Digital Entrepreneurship and Business. 2021;2(1):39–48.

[13] Ivana Ruslim K, Pandu Adikara P, Indriati. Analisis Sentimen Pada Ulasan Aplikasi Mobile Banking Menggunakan Metode Support Vector Machine dan Lexicon Based Features. 2019 [cited 2024 Mar 15];3(7):6694–702. Available from: https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/5792/2748

[14] Nadira A, Yudi Setiawan N, Purnomo W. Analisis Sentimen Pada Ulasan Aplikasi Mobile Banking Menggunakan Metode Naive Bayes dengan Kamus InSet. INDEXIA : Informatic and Computational Intelligent Journal [Internet]. 2023 [cited 2024 Mar 15];5(1):35–47. Available from: https://journal.umg.ac.id/index.php/indexia/article/view/5138/3113

[15] Tondang BA, Muhammad Rizqan Fadhil, Muhammad Nugraha Perdana, Akhmad Fauzi, Ugra Syahda Janitra. Analisis pemodelan topik ulasan aplikasi BNI, BCA, dan BRI menggunakan latent dirichlet allocation. INFOTECH : Jurnal Informatika & Teknologi. 2023 Jun 17;4(1):114–27.

[16] Fiqri M, Setya Perdana R. Klasifikasi Data Twitter pada Masa Transisi Pandemi menuju Endemi menggunakan Latent Semantic Analysis (LSA) [Internet]. Vol. 7. 2023. Available from: http://j-ptiik.ub.ac.id

[17] Malihatin S U, Findawati Y, Indahyanti U. TOPIC MODELING IN COVID-19 VACCINATION REFUSAL CASES USING LATENT DIRICHLET ALLOCATION AND LATENT SEMANTIC ANALYSIS. Jurnal Teknik Informatika (Jutif). 2023 Oct 3;4(5):1063–74.

[18] J. Ipmawati, S. Saifulloh, and K. Kusnawi, "Analisis Sentimen Tempat Wisata Berdasarkan Ulasan pada Google Maps Menggunakan Algoritma Support Vector Machine," MALCOM: Indonesian Journal of Machine Learning and Computer Science, vol. 4, no. 1, pp. 247–256, Jan. 2024, doi: 10.57152/malcom.v4i1.1066.

[19] J. A. Costales, E. M. Lorico, and C. M. de Los Santos, "A Comparative Sentiment Analysis about HIV and AIDS on Twitter Tweets Using Supervised Machine Learning Approach," in 2023 5th International Conference on Computer Communication and the Internet (ICCCI), 2023, pp. 27–32. doi: 10.1109/ICCCI59363.2023.10210162.

[20] scikit learn developer, "Confusion Matrix." Accessed: Mar. 29, 2025. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html

[21] Evidently AI, "How to interpret a confusion matrix for a machine learning model." Accessed: Mar. 29, 2025. [Online]. Available: https://www.evidentlyai.com/classification-metrics/confusion-matrix

[22] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet Allocation," *Journal of Machine Learning Research*, vol. 3, pp. 993–1022, 2003.

[23] T. Hofmann, H. Schütze, and CD. Manning, *Introduction to Information Retrieval (Updated Edition)*. Cambridge University Press, 2019. Accessed: Mar. 29, 2025. [Online]. Available: https://nlp.stanford.edu/IR-book/

[24] A. Göker and G. Demir, "Topic Ensemble: Combining Topic Models Using Clustering Ensembles," *Inf Process Manag*, vol. 58, no. 6, 2021.