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Dissatisfaction of a Mobile-Based Application from Different Platforms using Naïve Bayes for Sentiment Analysis and LDA for Topic Modelling

Anastasya Ohoilulin*, Dedi I Inan, Ratna Juita, Marlinda Sanglise

Faculty of Engineering, Informatics Engineering Study Program, Papua University, Manokwari,West Papua, Indonesia
Email: tasyaohoilulin04@gmail.com, d.inan@unipa.ac.id, ratnajuitaa@gmail.com, m.sanglise@unipa.ac.id
Correspondence Author Email: tasyaohoilulin04@gmail.com
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Abstract−A mobile application that is built and runs on different platforms, such as iOS (Apple App Store) and Android (Google Play Store), may not necessarily have the same user satisfaction (dissatisfaction) reviews understood by both user segments. This is due to, for example, the differences in the technology used, which ultimately result in different user behaviors. This can be observed from the average ratings on each platform, even though it is the same application. Therefore, this research aims to provide a foundation for the assumptions made. The case study used is the Satu Sehat mobile application, a widely utilized health service application. Text mining methods: sentiment analysis using Naive Bayes and topic modeling using Latent Dirichlet Allocation (LDA) were chosen due to their relevance to the research objectives. A total of 21,750 reviews from the Google Play Store and 7,350 reviews from the Apple App Store were collected using scraping techniques. The results showed that sentiment analysis model on negative sentiment in the Apple App Store excelled with a precision of 93%, recall of 93%, and F1-score of 95%, while in the Google Play Store it had a precision of 82%, recall of 87%, and F1-score of 85%. However, the performance of the positive sentiment model in the Apple App Store was very low, with a precision of 63%, recall of 33%, and F1-score of 43%, compared to the Google Play Store which had a precision of 78%, recall of 71%, and F1-score of 74%. This indicates that a higher level of dissatisfaction is observed in the Apple App Store compared to Android. These results are consistent with the average ratings of the application on both platforms. Topic modeling results, which presented 15 topics from each platform, showed similar common issues such as login, OTP verification, and data input errors on both platforms. However, reviews of the Satu Sehat running on the Apple tend to be more negative compared to the one of Android. Therefore, improving the application quality of the Apple platform is more expected to meet user expectations and enhancing the overall rating as in the Andrond one.

Keywords: LDA; Naive Bayes; Satu Sehat Mobile on Different Platforms; Sentiment Analysis; Topic Modelling

1. INTRODUCTION

In this fast-paced digital era, mobile health applications like Satu Sehat play a crucial role in providing easily accessible healthcare services to the public [1]. The Satu Sehat mobile application is designed to support the health of the Indonesian population by providing medical information, health tips, and other features [2]. This application is an enhancement of Peduli Lindungi, developed by the Indonesian Ministry of Health. In Indonesia, telecommunications networks, particularly mobile technology, are rapidly advancing [3]. With the increasing use of smartphones, this application not only offers ease in accessing medical information but also allows users to monitor their health in real-time. Through the application, the government and the public can communicate with each other [4]. Therefore, research on understanding and experiencing users from various platforms becomes highly relevant.

The Satu Sehat mobile application has a rating of 3.5 on the Google Play Store and 2.6 on the Apple App Store. The lower rating on the Apple App Store indicates higher dissatisfaction among iOS users compared to Android users. This research aims to understand user satisfaction levels from both platforms by comparing reviews of the Satu Sehat Mobile application obtained from the Google Play Store and Apple App Store using sentiment analysis and topic modeling. Sentiment analysis is the process of extracting, identifying, and understanding sentiments or opinions contained in text [5]. It allows us to understand users' attitudes, opinions, or emotions towards a topic. These factors can be positive or negative, stemming from both internal and external sources [6]. In this study, sentiment analysis employs the Naive Bayes model, a popular and widely used machine learning algorithm useful for classification tasks. Topic modeling, as stated by Sagvekar & Sharma, 2021, is used to uncover hidden structures in large document sets, which in this context are user reviews of the application [7]. One of the methods in topic modeling is Latent Dirichlet Allocation (LDA). LDA is a topic modeling method used to identify patterns in a document that can generate topics [8]. This method analyzes the relationships between words in the text to group frequently co-occurring words, thereby generating main topics that provide an overview of the document's content.

Conducting sentiment analysis and topic modeling is important because it provides deep and objective insights into how user reviews from two different platforms, Android and iOS, evaluate the same application. Differences between the two platforms can significantly affect user experiences, such as differences in user interfaces and application performance, leading to varied perceptions of the same application [9]. By analyzing reviews from both platforms, significant differences in satisfaction levels, complaints, and user expectations can be identified. Using sentiment analysis and topic modeling in this study can elucidate patterns and main topics emerging from user reviews [10]. The results of this research can benefit the developers of the Satu Sehat Mobile application by providing necessary improvements, both technically and in services, to enhance user experience and satisfaction. Additionally,

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this research can serve as a reference for other health application developers to understand changes and needs of users from various platforms, allowing them to design more responsive applications that meet user expectations.

Several similar studies have been conducted using Twitter data to analyze topics frequently discussed by the public regarding flood disasters in Jakarta. Choirul Rahmadan, 2020 found that the majority of public opinions showed 79% negative sentiment[11]. Through topic modeling using Latent Dirichlet Allocation (LDA), topics such as hopes for flood receding, affected areas, feedback to the government on flood management, and general disaster conditions were identified. Another study by Mujahid (2021) also utilized Twitter data containing 17,155 tweets about e-learning, applying sentiment analysis with classifiers Random Forest and Support Vector Machine [12]. The results indicated that the classifier achieved the highest accuracy of 0.95 when used with BoW features. Additionally, Topic Modelling was employed to identify issues related to e-learning, revealing uncertainties regarding campus reopening dates, difficulties for children in understanding online education, and delays in efficient network connectivity for online education.

A study by Ashari in 2023 used sentiment analysis on the Google Translate application in the Google Play Store using the Support Vector Machine (SVM) method [13]. The analysis results showed a 95% accuracy, with "no" being the most frequent positive and negative review from 1580 reviews. Patmawati & Yusuf (2021) used Latent Dirichlet Allocation (LDA) for topic analysis on tweets shared by state officials [14]. Model evaluation results produced a perplexity value of -8.069 and a coherence score of 0.375 for seven topics. Another study by Nurlayli & Nasichuddin (2019) used topic modeling on publication titles of lecturers from the Department of Electronic and Informatics Engineering Education (JPTEI UNY) [15]. The results showed that JPTEI UNY lecturers tended to have research titles on vocational education, system development, learning media, and learning systems in vocational schools. The difference between this study and previous studies lies in its focus on using a single application, the Satu Sehat Mobile application, but from two different platforms, Google Play Store and Apple App Store, using topic modeling with the Latent Dirichlet Allocation (LDA) method to understand user satisfaction levels from both platforms. Additionally, sentiment analysis with the Naive Bayes model was conducted to identify user sentiments on the Google Play Store and Apple App Store towards the Satu Sehat Mobile application.

2. RESEARCH METHODOLOGY

There are several stages in this research, namely Data Scraping, Research Model Design, Sentiment Data Labeling, Preprocessing Stage, Sentiment Analysis, Topic Modeling, and Visualization. The steps can be seen in Figure 1.

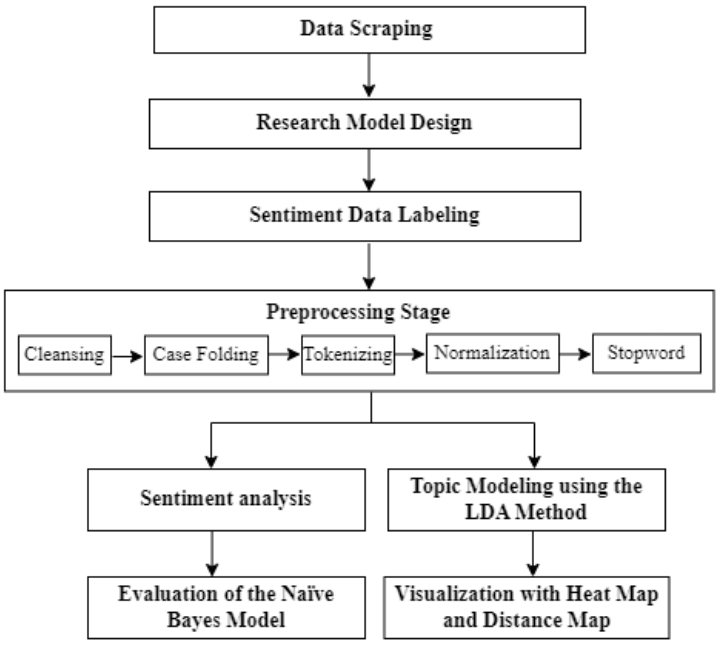

Figure 1. Research Workflow

2.1 Data Scraping

The data used in this research was collected using scraping techniques. Scraping is a method for automatically obtaining information from applications without manual copying [16]. By utilizing Python libraries such as pandas, datetime, and json, and using the google-play-scraper and app-store-scraper libraries to fetch data from the Google Play Store and Apple App Store platforms, the data was then cleaned, processed into a structured format, and saved as an xlsx file for preprocessing.

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2.2 Research Model Design

Orange Data Mining software is designed with three main components: widgets, workflows, and data. Widgets are the core components of Orange software. They are the primary elements used for data processing, analysis, visualization, and user interaction [17]The widgets in Orange software have a user-friendly interface, allowing users to operate them effectively and efficiently. The design of the Orange widgets used in this research is shown in Figure 2.

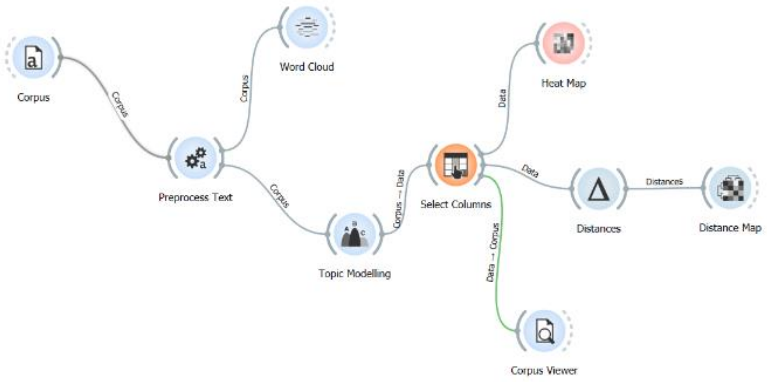

Figure 2. Research Model Design in Orange Software

In this study, the widgets used in the Orange software are as follows:
a. Corpus is a collection of texts or writings used for analysis.
b. Preprocess Text is used to clean and prepare the text before analysis.
c. Word Cloud is an image that displays words from the analyzed text.
d. Topic Modelling (LDA) is a technique used to identify the main topics or themes within a collection of texts.
e. Select Column is a tool for choosing specific data columns that you want to analyze.
f. Heat Map is a colored image that represents data, where darker or lighter colors indicate higher or lower values.
g. Distances is a measure of how similar or different two data points are.
h. Distance Map is a map that shows how close or far apart data points are from each other based on "distances."
i. Corpus Viewer is a tool for viewing and reading texts within the corpus (collection of texts).

2.3 Sentiment Data Labeling

The review data from the Google Play Store and Apple App Store used in the study were labeled and classified based on positive, neutral, and negative sentiments. Classification based on ratings and sentiment grouping was done manually.

2.4 Preprocessing Stage

In the field of Text Mining, preprocessing is a stage used to extract valuable and significant knowledge from unstructured text data [18]. This stage is conducted to clean and transform raw data, making it easier for subsequent stages. The following are several preprocessing steps used in this study:
a. Cleansing involves removing elements unrelated to the data, such as URLs, hashtags (#), converting new lines to spaces, emoticons (: @ , : *, : D), deleting single characters, punctuation marks like commas (,), periods (.), and other punctuation.
b. Case Folding converts all characters in the text to lowercase.
c. Tokenization is the process of breaking text into sequential tokens. The primitive tokenization process typically splits text based on whitespace as delimiters and converts them to lowercase for uniformity.
d. Normalization adjusts non-standard or non-conforming words to adhere to the Indonesian Dictionary (KBBI). This step involves using a file downloaded via the browser, supplemented by manually adding words based on the data used.
e. Stopwords removal follows normalization. This step eliminates a number of connector word classes or frequently occurring words that do not significantly affect the overall content of the document. Stopwords utilize the NLTK library and employ an external stopwords file in .txt format. Additionally, it leverages the text preprocessing process available in the Orange software.

2.5 Sentiment Analysis

Sentiment analysis is the process of using algorithms and computational techniques to identify, understand, and interpret the sentiments contained in text or comment data [19]. The sentiment analysis method is used to determine whether the sentiment of a text or comment is positive, negative, or neutral [20]. The results of sentiment analysis can be classified to predict the polarity of user sentiments. Sentiment analysis has been applied in various fields, such as

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health, politics, and economics, and has proven useful in supporting decision-making. In this study, the Naive Bayes model is used to perform sentiment analysis on user reviews of the Satu Sehat Mobile application on the Google Play Store and Apple App Store. This classification involves several key stages, including dataset splitting, data transformation, model training, and model performance evaluation using the Python programming language executed through Jupyter Notebook.

2.6 Naïve Bayes

Naive Bayes (NB) is a classification method that can predict the probability of a class in making decisions based on training data [21]. Naive Bayes assumes that the features in a dataset are independent of each other, which simplifies calculations and makes this algorithm efficient and easy to implement [22]. The general formula for Naive Bayes is as follows:

$$P(A/B) = \frac{P(B|A).P(A)}{P(B)} \quad (1)$$

P(B|A) is the probability of the prior label, P(B) is the prior probability of the occurrence, and P(A) is the prior probability that has been classified as the label [23].

2.7 Topic Modelling

Topic modeling is a technique used to automatically organize, understand, search, and summarize large document archives [24]. This technique analyzes the relationships between words in text to identify and group frequently co-occurring words, thereby generating main topics that aid in understanding the overall content of documents. It facilitates information retrieval and simplifies complex and voluminous text. The basic idea of topic modeling is to form topics consisting of specific words that can summarize the essence of the data used. In this study, topic modeling is employed to discover topics from user reviews of the Satu Sehat Mobile application running on two different platforms, Android and iOS, to determine whether users of these platforms discuss similar or different topics.

2.8 Latent Dirichlet Allocation (LDA)

LDA is the most popular topic modeling method introduced by Blei, Ng, and Jordan in 2003. This method transforms a collection of texts into a series of coherent topics within a large text corpus [25]. By understanding the patterns of word occurrences and relationships between topics, LDA provides a robust method for organizing, understanding, and summarizing information from large texts. The underlying idea of LDA is to depict documents as random mixtures of hidden topics, and each topic is characterized as a distribution over a set of specific words, as illustrated in Figure 3.

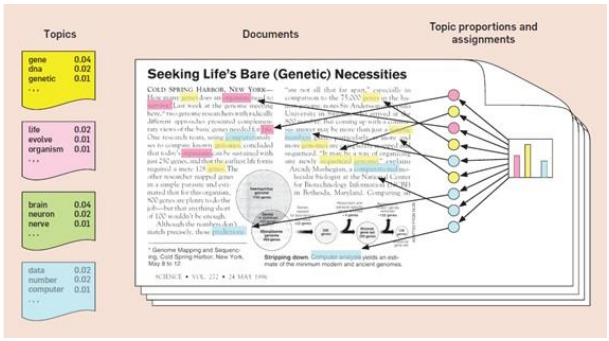

Figure 3. General Process of LDA

According to Blei, LDA assumes the following generative process, which is the mathematical formula for each document www in a corpus DDD as follows:

a. Choose $N \sim$ Poisson(ξ).
b. Choose $\theta \sim$ Dir (α).
c. For each of the N words w_n:
   1. Choose topic $z_n \sim$ Multinomial(θ).
   2. Choose a word w_n from $p(w_n|z_n,\beta)$, a multinomial probability conditioned on the topic z_n.

3. RESULT AND DISCUSSION

3.1 The Results of Data Scraping

In this study, data were collected using a staged scraping technique utilizing Python libraries executed on the Google Colab platform. The process involved identifying the 'com.telkom.tracencare' token to extract data from the Google Play Store and using IDs to extract data from the Satu Sehat mobile application on the Apple App Store. The

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researchers gathered 21,750 data points from the Google Play Store and 7,350 from the Apple App Store. The interface of the Satu Sehat Mobile application on both platforms can be seen in Figure 4.

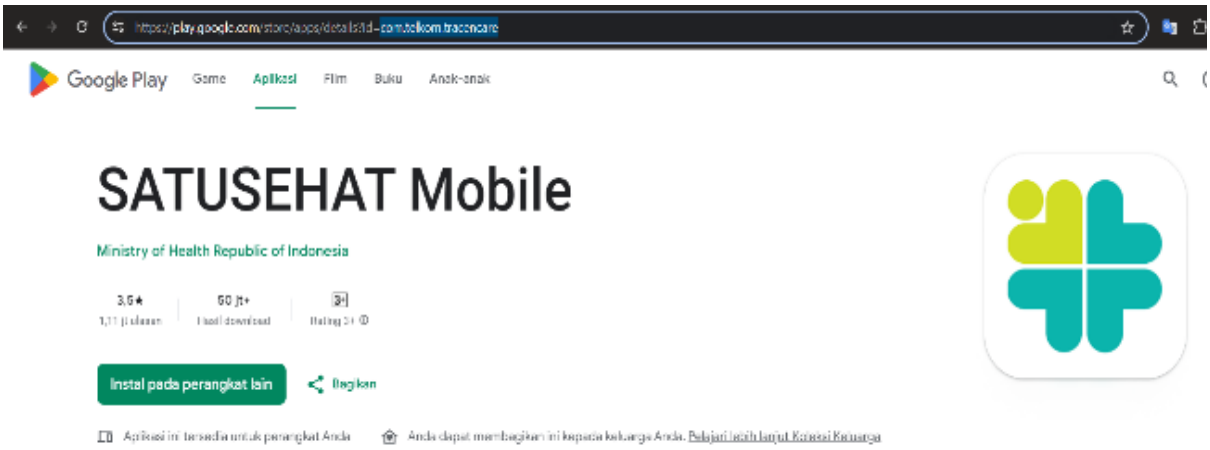

Figure 4. The Satu Sehat Mobile Application on Play Store and App Store

The data collected from scraping includes usernames, scores, access dates, and comments (content) provided by users regarding their usage of the Satu Sehat mobile application on two platforms: Android and iOS. Examples of the scraped data from Play Store and App Store can be seen in Table 1.

Table 1. Example Data Result from Scraping Play Store and App Store for the Satu Sehat Application

Username	Score	At	Content
Prasetyo Aji	1	2023-03-01	Unable to log in
Reza Nur Hidayat	1	2023-03-01	Can’t login at all
Faisal Amri	5	2023-03-01	Okay
yuline kartika sari	1	2023-03-01	Can't access the application
deny123456789937	1	2021-08-20	Unable to click "Agree" on the policy and privacy
Player Biasa	1	2023-10-26	How do I access the vaccine certificate?
Yanunyilunyil	1	2023-03-4	Forced to update, but now can't log in
Jirjis75	1	2022-02-25	Very slow update of swab test results
uvus etrucn	4	2021-12-2	If possible, please improve the version
hayiakhmad	2	2021-11-14	The app closes itself when clicked
Instagramusers	1	2021-11-7	The app immediately exits upon opening
lalaqwr	3	2021-08-31	"Agree" button does not appear

The following is an explanation related to the figure above:
a. The first column contains the name of the reviewer.
b. The second column contains the rating given, ranging from the lowest of 1 star to the highest of 5 stars.
c. The third column contains the date the review was given.
d. The fourth column contains the explanation from the user who provided the review of the Satu Sehat application.

As an example, reviewer Reza Nur Hidayat gave a score of 1 out of 5 stars on March 1st, 2023 with the explanation "Can’t login at all".

3.2 Data Preprocessing

The primary goal of preprocessing is to enhance data quality and make it suitable for analysis. This involves removing irrelevant or problematic data, handling missing values, addressing outliers, standardizing or normalizing data to a consistent scale, and reformatting data into a standard structure. These preprocessing steps are crucial as they can significantly impact the success and accuracy of data analysis and machine learning models built using this data. In this study, data preprocessing was performed using Python programming language executed through Jupyter Notebook, followed by the use of Orange Data Mining software. The process involved five stages: cleansing, case folding, tokenizing, and normalization. The preprocessed data is then presented as separate texts displayed through a word cloud, as shown in Figure 5. The word cloud widget feature displays the frequency of word occurrences [26]. The more frequently a word appears, the larger it is displayed in the word cloud.

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Playstore **Appstore**

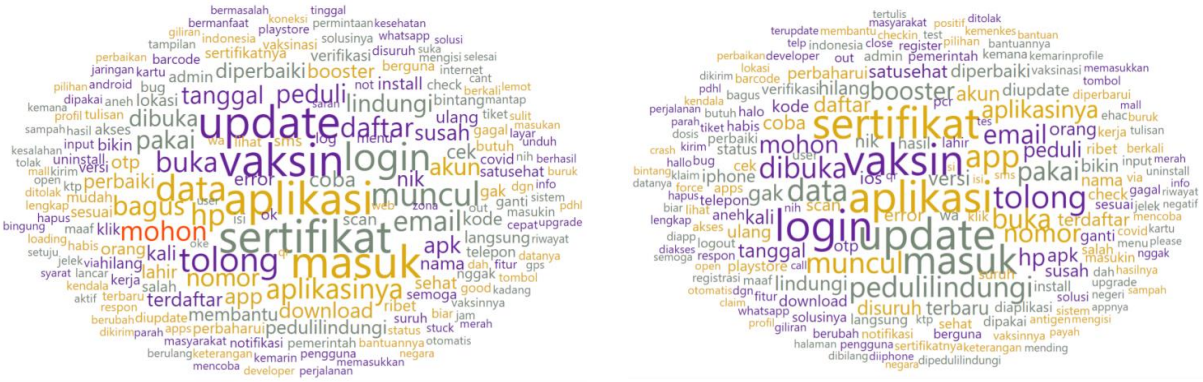

Figure 5. Word Cloud Display on Play Store and App Store

3.3 Sentiment Analysis

The data collected from the Google Play Store and Apple App Store have been classified based on ratings and grouped by negative, neutral, and positive sentiments, as shown in Table 2.

Table 2. Number of Reviews by Rating and Sentiment

Rating	Number of Reviews	Sentiment	Rating	Number of Reviews	Sentiment
★	6481	positive	★	4740	positive
★★	4072	positive	★★	1167	positive
★★★	4322	neutral	★★★	770	neutral
★★★★	3268	negative	★★★★	281	negative
★★★★★	3607	negative	★★★★★	392	negative
Total	**21750**		**Total**	**7350**	

Based on the table above, the data shows that user ratings for the Satu Sehat mobile application running on Android and iOS platforms are largely concentrated in ratings 1 and 2, which indicate negative sentiments, followed by rating 3, indicating neutral sentiment. From the data used in this study, ratings 4 and 5 are significantly different from the previous ratings, as users of the Satu Sehat mobile application on both Play Store and App Store are very few in giving ratings 4 and 5, which represent positive sentiments.

3.4 Evaluation of the Naïve Bayes Model

In this stage, an evaluation of the Naïve Bayes model is conducted between the Google Play Store and Apple App Store. The evaluation metrics of accuracy, precision, recall, and F1-score on both platforms can be seen in Table 3.

Table 3. Evaluation Matrix of Both Platforms

Playstore	Precision	Recall	F1-Score	**Appstore**	Precision	Recall	F1-Score
Negatif	0.82	0.87	0.85	Negatif	0.93	0.93	0.95
Postitif	0.78	0.71	0.74	Postitif	0.63	0.33	0.43
Accuracy			0.81	Accuracy			0.92

Based on the sentiment analysis results using the Naive Bayes method for the Satu Sehat Mobile application on Google Play Store and Apple App Store, several significant differences in model performance were found between the two platforms. The model on the Apple App Store showed higher accuracy at 92% compared to Google Play Store, which achieved only 81%. For negative sentiment, the model on the Apple App Store excelled with precision of 93%, recall of 93%, and F1-score of 95%, while on Google Play Store it had precision of 82%, recall of 87%, and F1-score of 85%. However, the model's performance on positive sentiment on the Apple App Store was notably low, with precision of 63%, recall of 33%, and F1-score of 43%, compared to Google Play Store which had precision of 78%, recall of 71%, and F1-score of 74%. Therefore, although the model on the Apple App Store showed higher overall accuracy, its performance in detecting positive reviews was significantly lower compared to Google Play Store. Consequently, it can be concluded that negative sentiment towards the Satu Sehat Mobile application is lower on the Apple App Store compared to Google Play Store, indicating that users on the Apple App Store tend to give less positive reviews. This is followed by rating 3, which is also frequently given by users. However, it is unclear whether

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rating 3, which represents neutral sentiment, tends towards negative or positive sentiment. Hence, there is a need to determine how neutral sentiment leans towards either positive or negative sentiment.

3.5 Topic Modeling Using the LDA Method

In addition to sentiment analysis, this study also conducts analysis using topic modeling. This section presents a comparison of reviews for the Satu Sehat mobile application between the Google Play Store and the Apple App Store using the Latent Dirichlet Allocation (LDA) method. LDA is used to discover hidden themes or topics within text collections in the Orange Data Mining software, displaying the top 15 topics generated from both platforms. The results of the topic modeling using the LDA method from both platforms and the interpretation of comments can be seen in Table 4.

Table 4. Results of Topic Modeling with LDA from Play Store and App Store

Topic	Topic Keywords	Interpretation of the comments	Topic	Topic Keywords	Interpretation of the comments
1	great, solid, claims, travel, Indonesia, health, please, safe, country, application	Users provide positive reviews, particularly concerning health claims, safety, and travel in Indonesia.	1	great, solid, claims, travel, Indonesia, health, please, safe, country, application	Explaining user experiences related to vaccine cards, application loading issues, and the need for complete data and internet connectivity to access the application.
2	otp, code, verification, log in, not, email, sms, login, send, via	Focuses on issues related to OTP codes and verification processes often involving email and SMS.	2	otp, code, verification, log in, not, email, sms, login, send, via	Discussing issues related to vaccine data, date of birth, user data input errors concerning Care Protect.
3	login, register, number, account, email, log in, registered, application, use, phone	Describes the process of user account login and registration, and issues with phone numbers and email addresses.	3	login, register, number, account, email, log in, registered, application, use, phone	Covering user complaints related to antigen tests, login processes, issues with EHAC (Electronic Health Alert Card), and difficulties in registration concerning the Care Protect application.
4	name, data, person, history, application, care protect, web, result, ID number, vaccination	Discusses issues related to users' personal data, such as names, ID numbers (NIK), and vaccination histories accessed through the application.	4	name, data, person, history, application, care protect, web, result, ID number, vaccination	Addressing issues related to vaccine certificates not appearing, the need to scan QR codes, and claims related to travel.
5	apps, application, open, app, can't, useful, government, log, trash, migration	General perspectives on the application, including issues with app opening and comments on usability, as well as strong criticisms of the application.	5	apps, application, open, app, can't, useful, government, log, trash, migration	Focusing on technical issues such as applications force closing, uninstallation, login problems, and account profile management.
6	vaccine, certificate, appear, booster, application, check, disappear, data, please, update	Addresses issues with vaccine certificates not appearing or disappearing, and requests for updating information.	6	vaccine, certificate, appear, booster, application, check, disappear, data, please, update	This topic includes complaints about the application being considered complicated and troublesome, as well as disruptive error issues affecting users' work.
7	helpful, good, hopefully, beneficial, button,	Discusses positive reviews regarding the application's benefits, hopes for continued	7	helpful, good, hopefully, beneficial, button,	Issues related to the need for application updates, problems opening the application, and requests

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	birth, app, agree, size, click	usefulness, and minor technical issues like button size.		birth, app, agree, size, click	to update applications running on the Play Store.
8	open, download, application, try, certificate, app, fail, update, care protect, download	Focuses on technical issues in opening and downloading the application, and failures in certificate updates.	8	open, download, application, try, certificate, app, fail, update, care protect, download	This topic contains mixed reviews, with some finding the application useful while others criticize it as trash and poor.
9	app, zone, update, okay, covid, register, red, can, can't, use	Addresses issues with application updates and features related to Covid-19 zones, as well as registration and usage issues.	9	app, zone, update, okay, covid, register, red, can, can't, use	Similar to Topic 4, addressing issues of vaccine certificate not appearing or disappearing and requests for application updates.
10	update, application, open, install, log in, application's, error, open, restart, please	Discusses technical issues with application updates, errors when opening, and requests for application improvements.	10	update, application, open, install, log in, application's, error, open, restart, please	Focusing on barcode scan features, profile data entry, and negative reviews about the application.
11	okay, check, scan, out, qr, code, feature, mall, application, barcode	Focuses on the use of QR code and barcode features in the application, particularly related to checks in malls and public places.	11	okay, check, scan, out, qr, code, feature, mall, application, barcode	Pertaining to PCR test result status, Covid vaccination, and requests for assistance regarding negative or positive test results.
12	Care, protect, application, open, health, update, satu sehat, stuck, log in, application's	Covers specific issues related to the Peduli Lindungi and SatuSehat applications, including frequent crashes or inability to open.	12	care, protect, application, open, health, update, satu sehat, stuck, log in, application's	Specific issues with iPhone devices, including application updates and opening problems on iOS.
13	date, data, birth, application, ID number, fill, accordance, input, name, please	This topic relates to inputting personal data such as date of birth and ID numbers (NIK), and issues with data accuracy.	13	date, data, birth, application, ID number, fill, accordance, input, name, please	Discussing login issues, phone numbers, OTP verification, and account registration processes.
14	application, update, please, fix, easy, create, society, care protect, complicated, star	Discusses requests for application improvements for easier use, as well as criticisms regarding usability difficulties.	14	application, update, please, fix, easy, create, society, care protect, complicated, star	This topic relates to registration processes, issues with emails, ID numbers (NIK), and account registration in the application.
15	version, phone, application, android, latest, page, update, screen, close, register	Technical issues related to the application version on Android, updates, and registration.	15	version, phone, application, android, latest, page, update, screen, close, register	This topic focuses on data consistency with ID numbers (NIK) and ID cards, as well as check-in and check-out features in the application.

From the comparative analysis of topic modeling on both platforms based on the table above, the results indicate that the majority of discussed topics between Google Play Store and Apple App Store exhibit similarities. Main topics such as login issues, application updates, account registration, OTP verification, vaccine certificates, data input errors, and technical complaints frequently appear on both platforms. Despite the similarity in topics discussed on both platforms, reviews on the Apple App Store tend to be more negative, reflected in its lower rating of 2.6 with more complaints. Issues such as ineffective updates and difficulties in entering personal data are more commonly mentioned by iOS users. This suggests that while both platforms address similar issues, users on the Apple App Store face more challenges or have higher unmet expectations, resulting in lower ratings for the Satu Sehat mobile application. However, both platforms equally show demands for application improvements and updates in features.

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Following this, a Heat Map was visualized to identify correlations among frequently co-occurring topics and their relationships. With 15 topics generated from the LDA method on the x and y axes representing different topics, the color scale indicates the strength of relationships among topics. Subsequently, a dendrogram illustrates the grouping of similar topics based on similarities, where closer proximity in the dendrogram indicates greater similarity [27]. Heat map visualizations for Google Play Store and Apple App Store can be seen in Figure 6.

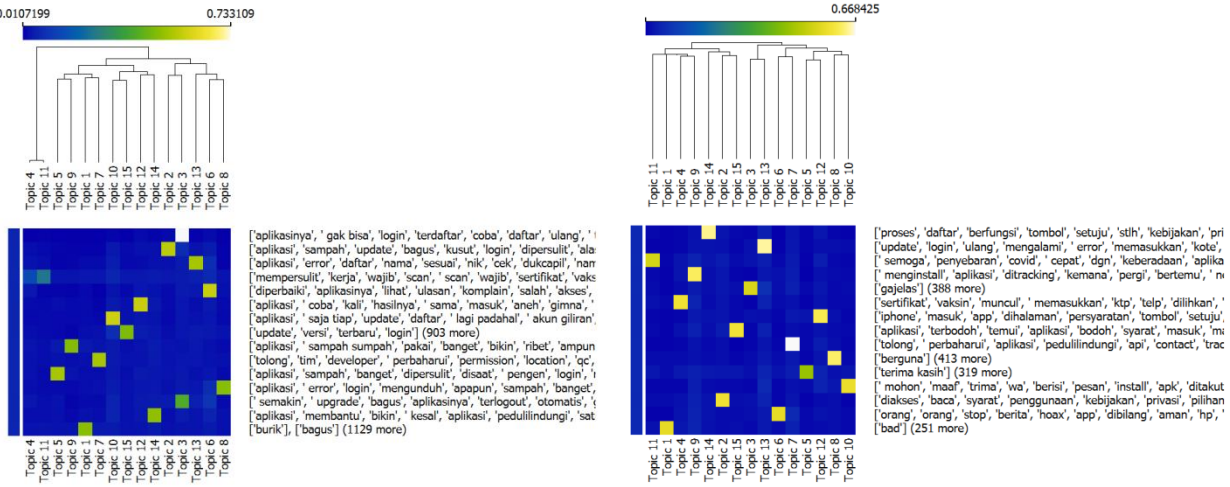

Figure 6. Visualization of Heat Map on Play Store and App Store

The heatmap visualization of user reviews for the Satu Sehat application on Google Play Store and Apple App Store reveals several similarities in topic correlations. On the Google Play Store heatmap, topics such as Topic 12 and Topic 14 exhibit a high correlation indicated by the yellow color scale, while moderate correlations, such as between Topic 10 and Topic 15, suggest that Google Play Store users frequently discuss technical issues related to updates and user experience improvements. Similarly, the heatmap from the Apple App Store shows a high correlation between Topic 5 and Topic 7 in yellow, and a moderate correlation between Topic 2 and Topic 15, indicating that Apple App Store users often discuss technical issues such as login problems, app force closures, input errors, and the need for application updates. However, overall, topic correlations in the Apple App Store tend to be more dispersed compared to those in Google Play Store. This reflects a broader focus or more diverse issues faced by iOS users compared to Android users, such as frequent complaints about specific technical details like login issues, errors in data input such as birth dates, and the accuracy of NIK and ID card data. Thus, from the displayed topic correlations in the heatmap, it is possible to identify the main issues experienced by Satu Sehat application users on Google Play Store and Apple App Store. Strong correlations between specific topics indicate that these issues often co-occur, providing valuable insights for application developers to focus on improvements in these areas. Subsequently, a Distance Map was generated to confirm the distances between topics and aid in understanding how topics in reviews relate to each other compared to the previous heatmap [28]. The Distance Map uses cosine metric to measure the distance between topics. Dark blue indicates low cosine values, implying high cosine similarity, while yellow or white indicates high cosine values, suggesting low cosine similarity, meaning differences. Distance visualization for Google Play Store and Apple App Store can be seen in Figure 7.

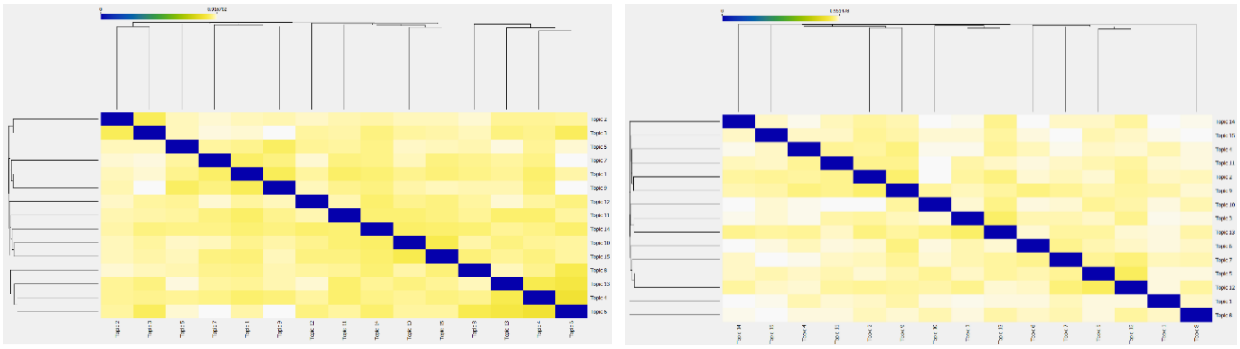

Figure 7. Distance Map Visualization on Play Store and App Store

Comparison between the distance map of Google Play Store and Apple App Store shows that while both platforms have diverse review topics, there are differences in the similarity of these topics. In Google Play Store, highly similar topics (small cosine distance) include pairs such as Topic 1 and Topic 7, and Topic 4 and Topic 6. Meanwhile, in

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Apple App Store, highly similar topics include pairs such as Topic 1 and Topic 12, and Topic 6 and Topic 8. For moderately similar topics (medium cosine distance), Google Play Store displays pairs like Topic 3 and Topic 12, whereas Apple App Store shows pairs like Topic 2 and Topic 11. Low similarity (large cosine distance) in Google Play Store includes pairs like Topic 2 and Topic 4, while in Apple App Store it includes pairs like Topic 2 and Topic 14. These differences in similarity patterns reflect variations in the reviews present on both platforms.

Comparing the results of reviews for the Satu Sehat mobile application from Google Play Store and Apple App Store can provide valuable insights for application developers. Differences and similarities in user perceptions on both platforms can be identified, allowing developers to understand user experiences on Android and iOS. Furthermore, this research helps identify specific issues that may only occur on one platform, enabling more targeted improvements. Topic analysis discussed in the reviews also assists developers in developing more relevant features that meet user needs. Thus, overall application quality improvement can be achieved by responding to user feedback quickly and effectively, thereby enhancing user satisfaction and commitment.

4. CONCLUSION

From the results of this study, it can be concluded that the Satu Sehat mobile application faces similar challenges on both the Google Play Store and Apple App Store, albeit with differing levels of dissatisfaction. Sentiment analysis indicates that the model performance and user perceptions on the Apple App Store are more accurate (92%) compared to the Google Play Store (81%). Negative sentiments detected on the Apple App Store show precision, recall, and F1-score of 93%, 93%, and 95%, respectively, while the Google Play Store has values of 82%, 87%, and 85% for each metric. However, the detection of positive sentiment on the Apple App Store is lower with precision of 63%, recall of 33%, and F1-score of 43%, compared to the Google Play Store which has precision of 78%, recall of 71%, and F1-score of 74%. This indicates that negative sentiments towards the Satu Sehat Mobile application on the Apple App Store are more dominant than on the Google Play Store, suggesting that users on the Apple App Store tend to give less positive reviews, although it cannot be definitively determined whether neutral sentiments lean towards negative or positive. The majority of negative reviews highlight an urgent need for improvements in the application, particularly regarding technical issues and ineffective updates. Furthermore, the results of topic modeling using Latent Dirichlet Allocation (LDA) demonstrate similarities in the topics discussed by users on both platforms, such as login issues, OTP verification, and data input errors. However, reviews on the Apple App Store tend to be more negative compared to the Google Play Store, as evidenced by the lower average rating on the Apple App Store (2.6) compared to the Google Play Store. Visualization of the heatmap and distance map shows that while there are some similarities in correlation and topic similarity, reviews on the Apple App Store are more scattered and cover a wider range of detailed technical issues. iOS users appear to encounter more problems or have higher unmet expectations compared to Android users. Therefore, although the issues faced by users on both platforms are similar, indicating that the issues lie within the application itself, Apple App Store users exhibit greater dissatisfaction. This suggests that application developers need to focus on more specific and comprehensive improvements to enhance user experience and improve application ratings on both platforms. The data and time constraints for this study were limited because the research was conducted as part of a thesis replacement through publication. Additionally, the sentiment data used for neutral sentiments cannot definitively determine whether they tend towards negative or positive sentiments. Therefore, the researcher suggests for future research to explore methods to determine whether neutral sentiments lean towards positive or negative directions. Furthermore, comparisons with various algorithms could be conducted to obtain results that are easier to interpret.

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