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Analysis of Google Play Store Reviews Using Natural Language Processing (NLP) and Importance Performance Analysis (IPA) for the Development of Mobile Banking Application Businesses Wondr BNI

Ade Naufal Febrianto, Siska Noviaristanti
Universitas Telkom Bandung, Indonesia
Email: naufaladee@student.telkomuniversity.ac.id , siskamarhen@telkomuniversity.ac.id

ABSTRACT

In the digital era, mobile banking applications have become essential services for modern society. The study aims to identify user sentiment toward the Wondr BNI application using Natural Language Processing (NLP) methods and analyze the application's performance through Importance Performance Analysis (IPA). This study employs a mixed-method approach, utilizing qualitative data from Google Play Store reviews and quantitative data from questionnaire results. Review data were collected through web scraping and analyzed using NLP based on a Support Vector Machine (SVM) algorithm. Quantitative data from the questionnaire were evaluated to map the key elements that need improvement in the application. The research findings indicate that 50.5% of user sentiments were positive, while 49.95% were negative, with application instability, access and login difficulties, and transaction performance emerging as the main issues based on sentiment analysis of 18,820 user reviews. Through the Importance Performance Analysis (IPA) method applied to 422 respondents, service attributes were mapped into four quadrants. Although no attributes were positioned in Quadrant I (Top priority), several issues identified in the qualitative findings should remain a focal point for developers' evaluation. Attributes located in Quadrant II, such as security and transaction performance, are recommended to be maintained. Based on the integration of findings and the SERVQUAL theoretical framework, application development strategies should be directed toward enhancing technical reliability and service responsiveness, with a particular emphasis on improving application stability, ease of access, and continuous evaluation of features that align with user needs.

Keywords: Sentiment Analysis; Importance Performance; Mobile Banking; Support Vector Machine.

INTRODUCTION

Digital transformation in the era of industry 4.0 has resulted in changes in business models and formed new ecosystems that are more innovative, complex, and dynamic in various sectors (Winasis & Riyanto, 2020). Technological developments in this digital era have had a significant impact on how people interact and transact in various sectors, one of which is the banking industry (Septiani & Isabela, 2022; Siyamto, 2017; Suarna & Prihartono, 2024). With technological advances and the ease of internet access, the banking industry has provided financial technology that people can use to conduct economic activities easily and practically (Tobing & Febriandirza, 2024; Widodo et al., 2023; Wulandari & Sunardi, 2024).

One of the technologies utilized by the public to facilitate economic activities and which is universally available in the banking industry is Digital Banking Service technology. This service allows bank customers to obtain information, communicate, and conduct banking transactions through electronic media (Sveningsson et al., 2019; Syah, Hakim, & Tahir, 2021; Syahidah Mujahidah & Rusydiana, 2022). With this service, the public's flexibility in conducting economic activities will be easier with the help of the internet and smartphones, which are already widely used by many people (Medhat, Hassan, & Korashy, 2014; Muktafin, Kusrini, & Luthfi, 2020; Novendra et al., 2022).

The development of the banking industry has clearly had an impact on national economic growth. This is because banks play an important role in the economy by operating payment systems, which are the main source of credit for most economies (Omarini, 2017). However, on the other hand, this phenomenon will also have an impact on competition between banks, both conventional and digital banks (Gurcan, Ozyurt, & Cagiltay, 2021; Kurniawan & Febrianti, 2022). In today's digital era, conventional banks are not outcompeted by digital banks that do not have physical offices and only operate online. Banks have created many technological innovations in an effort to support the convenience of the community in economic activities and to increase competitiveness among other banks, one of which is Mobile Banking technology (Septiani & Isabela, 2022; Siyamto, 2017; Suarna & Prihartono, 2024).

Mobile banking is a service designed to facilitate online transactions for customers. Almost all banks in Indonesia offer mobile banking services, intensifying competition among banks, one of which is BNI (Bank Negara Indonesia).

Factors that can influence users and their continued use of mobile banking are assessed based on satisfaction levels, service quality, and user expectations (Baabdullah et al., 2019). Therefore, it is important for all banks to pay attention to the satisfaction and feedback provided by mobile banking users in order to improve service quality, particularly Bank BNI, which has a lower percentage than BCA, BRI, and Mandiri, and is the subject of this study.

In July 2024, Bank BNI launched its latest mobile banking application named Wondr by BNI. Roykee Tumilaar, President Director of Bank BNI, stated that the launch of the Wondr by BNI application is the realization of BNI's transformation in delivering innovative banking applications to simplify transactions and optimize future planning for the public (Tirto.id, 2024). According to Putrama Wahju Setyawan, Deputy President Director of Bank BNI, the launch of Wondr by BNI aims to provide a one-stop solution (from Cash Management services to Host-to-Host services) and the best transaction experience for customers, as well as ensuring transaction convenience and fostering customer engagement. Therefore, fast, accurate, and stable digital services are BNI's target in delivering the best performance quality for customers. Updating online banking services for both retail and corporate segments is crucial for BNI to increase its market share and compete in the era of globalization (PT Bank Negara Indonesia, 2024). Additionally, Wondr by BNI is expected to better meet customer needs compared to previous app services, as this app will replace BNI Mobile Banking during a 6-month or 12-month transition period (Kompas.com, 2024).

The Wondr mobile banking app provides features for financial management, including fund transactions, bill payments, investments, and savings (BNI, 2024). The distribution of the Wondr app is conducted through the Google Play Store, one of the two largest platforms in the world for downloading apps on smartphones. Based on data collected in November 2024, the Wondr app has been downloaded and used over 1 million times, with a rating of 2.4 on the Google Play Store (Google Play Store, 2024).

Previous research by Soliha et al. (2023) applied the Naïve Bayes Classifier to conduct sentiment analysis on Google Play Store reviews of digital banking applications such as Allo Bank and Line Bank, achieving a classification accuracy of 78–81%. However, the study only focused on simple classification without integrating performance evaluation or prioritization of service improvements, which limited its ability to provide strategic recommendations for app developers. Similarly, Amirkhalili and Wong (2025) analyzed mobile banking app reviews in Canada using sentiment analysis and topic modeling with LSTM and Naïve Bayes, reaching an accuracy of 82% and identifying usability, system performance, and updates as major drivers of user satisfaction or dissatisfaction. Yet, their approach did not incorporate the Importance-Performance Analysis (IPA) framework to determine which aspects should be prioritized for improvement (PT Bank Negara Indonesia, 2018).

The study aims to identify user sentiment toward the Wondr BNI application using Natural Language Processing (NLP) methods and analyze the application's performance through Importance Performance Analysis (IPA). This research contributes to the academic literature on sentiment analysis in digital banking while providing practical tools for developers and BNI to enhance user experience, strengthen competitiveness, and accelerate digital transformation in the banking sector.

METHOD

The research used mixed methods, combining quantitative and qualitative research. The types or designs of mixed methods include Convergent Design, Explanatory Sequential, and Exploratory Sequential:

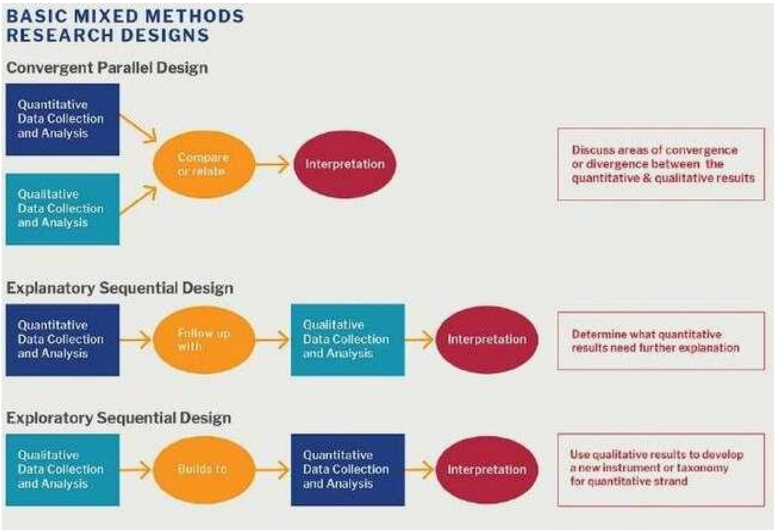

Figure 1 Types of Mixed Method Designs
Source: (Harvard Catalyst, 2024)

This research was conducted in two stages or phases, namely the exploratory (qualitative) stage with the aim of understanding users' perceptions of the Wondr by BNI application through sentiment analysis. In this phase, qualitative findings are needed to gain a deep understanding of the issues and obtain an overview of user sentiment. These findings and overview include specific aspects of the Wondr by BNI mobile banking application, such as security, transaction speed, and ease of use, as well as identifying which features most frequently receive positive or negative reviews. The next stage is the instrument development stage using a questionnaire (quantitative) after obtaining an overview of user sentiment. This stage aims to collect quantitative data based on findings from the exploratory phase. The final stage is the Verification Stage (Quantitative) through IPA (Importance Performance Analysis). The purpose of this stage is to test hypotheses or theories generated based on findings from the previous phase. Based on the stages and types of mixed method designs described above, the research design used is Exploratory Sequential Design (Three-Phase Design).

In this study, statistical data processing of data obtained using questionnaires is an aspect of quantitative research that is applied. Meanwhile, the qualitative aspect of this study is the analysis of data in the form of text reviews obtained from scraping on the Google Play Store. The next stage is data reduction with the aim of simplifying, transforming, and organizing text data that is important for the study. (Nur Hikmatul Auliya et al., 2020)

The approach used in this study is a descriptive approach. By using the survey method, researchers can obtain the data needed to answer the research questions that have been set. (Nur Hikmatul Auliya et al., 2020).

The operationalized qualitative variable here is E-Service Quality, which refers to the quality of digital services perceived by customers when using the application. The measurement focus is directed at how customers evaluate their experience in using the application, as reflected in various indicators such as efficiency, ease of access, and navigation convenience.

Comments or responses from application users on platforms such as Google Play Store are the main sources of qualitative data. These responses are then categorized based on an ordinal scale to enable more systematic analysis and interpretation.

The following will explain the stages of qualitative research. There are several stages that need to be carried out, starting with data collection using scraping techniques, followed by data pre-processing, which includes several stages within it, the labeling process, data classification using the Support Vector Machine algorithm model, and then the processed data is visualized and analyzed. The design or stages of qualitative research are shown in the following figure:

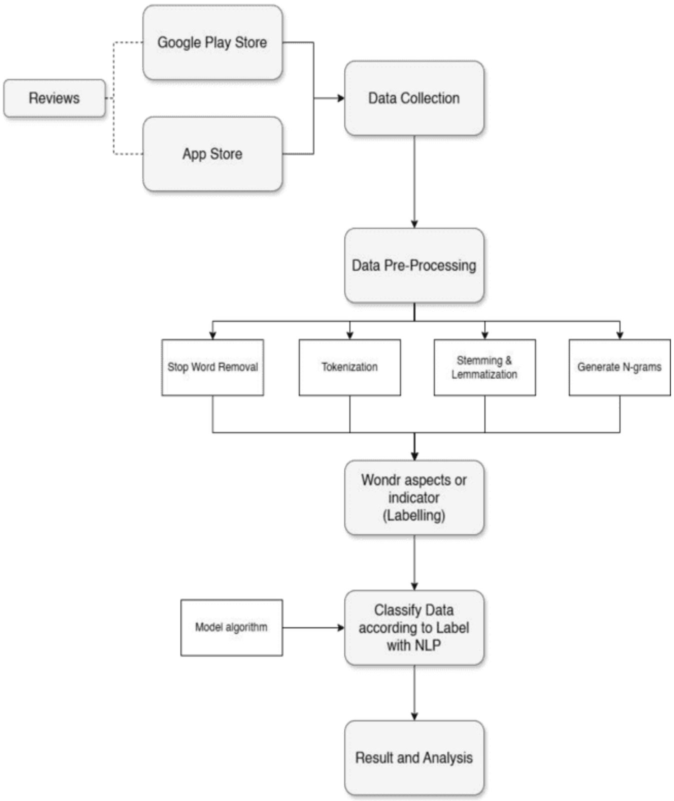

Figure 2 Qualitative Research Stages

This research stage began with the collection of data in the form of reviews on the Google Play Store platform. Review data was taken from the Wondr by BNI mobile banking application with the google-play-scrapper library using the Python programming language. Review data was collected on (date) with a total of (number of reviews) review data. After the data has been successfully obtained, the next stage is data pre-processing. Next, the classification process using the Support Vector Machine algorithm is performed on the research data. The Support Vector Machine algorithm model is capable of predicting classes based on patterns derived from machine learning-based supervised learning. In simple terms, the concept of support vector machine can be explained as an effort to find the optimal hyperplane that can separate two classes in the input space.

By calculating the margin value and finding its maximum point, the optimal hyperplane can be obtained. The SVM algorithm has a kernel function, one of which is the linear kernel, which will be used in this research, and each kernel has its own parameter values. In the kernel function, there are parameters that determine the distance between points in the input space. By calculating the margin value and finding its maximum point, the optimal hyperplane is obtained. The SVM algorithm has a kernel function, one of which is the linear kernel, which will be used in this study, and each kernel has its own parameter values. In the linear kernel function, the parameter C is used. This parameter C serves to control the trade-off between margin and classification error (Styawati et al., 2021).

The classified and processed data is then displayed or visualized in the form of graphs such as Stacked Column Charts and clustered column charts, along with descriptive explanations of the analysis conducted. Presenting data in the form of graphs or tables can help application developers manage information quickly and efficiently, thereby making the decision-making process more effective and easier.

The population consists of all user reviews of the Wondr by BNI app on the Google Play Store. The sample size is the number of samples to be taken from a population. In this study, all reviews on Wondr by BNI on Google Play Store will be taken and used as samples.

The secondary data consists of reviews obtained from the Google Play Store. This data was obtained through a scraping process using the Python programming language. The data collection process in qualitative research involves data collection through text scraping. The following is an explanation of each process in qualitative data collection:

The data collection methods used by the researcher consist of three stages: literature review, data scraping, and questionnaires.

a. Literature Review

The research began with a literature review, which involved collecting theories from journals, books, the internet, and previous studies related to sentiment analysis, data mining, the use of the Support Vector Machine algorithm model, and importance-performance analysis.

b. Data Scraping

Data scraping is the process of collecting data from various sources, such as websites or databases. In this study, text mining was performed using the Jupyter application with the Python programming language on reviews of the Wondr by BNI application on the Google Play Store to obtain secondary research data.

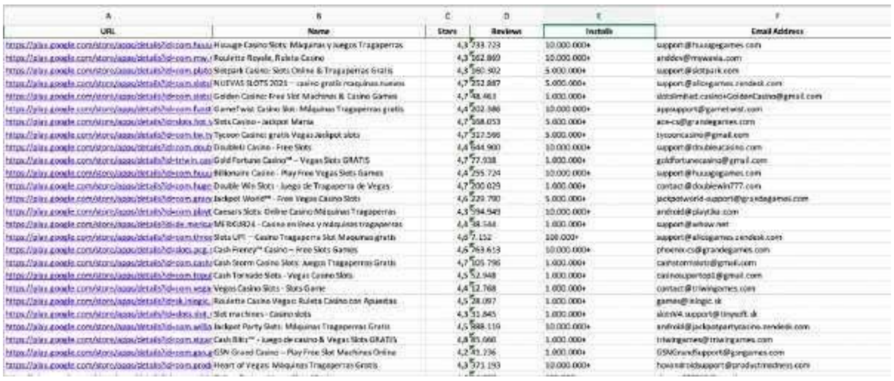

Figure 3 Example of Data Scraping Results on Google Play Store

Source: (Heredia, 2024)

Data pre-processing involves four stages, namely:

a. Tokenizing

Sentences in reviews will be broken down into individual words from long sentences. The purpose of tokenizing is to make it easier to assign weights to each word.

b. Stop Word Removal

This method is used to remove unrelated words, words that have no meaning such as conjunctions/connectors "to," "so that," or "that," and words that are not related to adjectives.

c. Stemming & Lemmatization

This process involves changing a word to its root form by removing all affixes consisting of prefixes and suffixes, thereby reducing the length of the string.

d. Generate N-grams

This method is used to predict the next words in a text. N-Grams refer to sequences of n words that appear consecutively in a text. These N-Grams are divided into 3 types:

1) Unigram: “I”, ‘like’, “appearance”
2) Bigram: “I like,” “like appearance”
3) Trigram: “I like appearance” “like application appearance”

After the data has undergone the data pre-processing stage, the next process is word weighting using the Term Frequency-Inverse Document Frequency (TF-IDF) method. This method assigns different scores or weights to each word in the document. The meaning in this method is based on the fact that the more a word appears, the more common it is, and the more documents contain a term, the higher the weight value will be.

Multi-class Support Vector Machine

Multiclass Support Vector Machine is used to classify each data point into different classes, where there are more than two classes. The idea behind this method is to map data points to a dimensional space to obtain a linear separation between each pair of classes. There are two approaches in the Multi-class Support Vector Machine method for classifying multiclass data: the One-to-one Approach and the One-to-rest Approach.

The One-to-All Approach addresses the problem of multiclass classification by treating it as N independent binary classifiers. When performing binary classification for a data class, the data reviews tested in that class are considered positive examples, and the remaining reviews are considered negative examples. Each classifier calculates a score indicating the degree of relevance (margin) between related class reviews to classify new reviews. After that, the class with the highest score is assigned to the review. Single Machine Multiclass SVM uses a single machine approach to build a classification function by considering N classes simultaneously.

The following multiclass classification Support Vector Machine is illustrated in the image below:

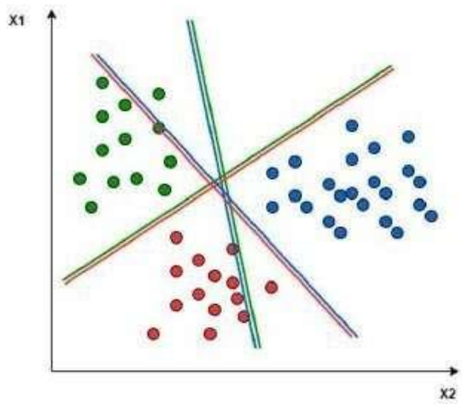

Figure 4 One-to-One Approach

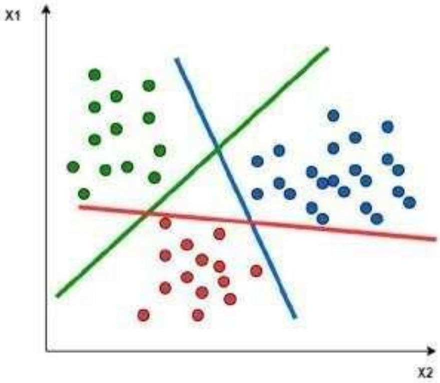

Figure 5 One-to-Rest Approach
Source: (Martin, 2024)

In the One-to-One approach, a hyperplane is required to separate each pair of classes and ignore points from the third class. This implies that the separation only considers points from the two classes in the separation. In the illustration of Figure 3.2, the red-blue line attempts to maximize the separation of data only between blue and red points. The line has no connection to the green points. In the One-to-Rest approach, a hyperplane is needed to separate one class from all other classes simultaneously. This means that the separation considers all points, dividing them into two groups: one group for the class points and one group for all other points. In the illustration of Figure 3.3, the green line attempts to maximize the separation between the green points and all other points simultaneously.

In this study, the model implementation method to be used is One-to-Rest based on the number of classes required in the study and the computational efficiency of data processing. One-vs-Rest only requires one binary classification model for each class, while One-vs-One requires a combination of every class pair. The use of the One-vs-Rest model requires shorter training time compared to One-vs-One, especially for moderately large datasets, and it is easier to implement.

Qualitative Data Analysis Techniques

The analysis technique used is sentiment analysis. Sentiment analysis is conducted to classify reviews in order to understand users' perceptions of the mobile banking application through their reviews. These reviews or perceptions can be positive or negative based on the user experience in using the application. The decision-making process in sentiment analysis is that if the perceptions identified from the reviews are positive, it can be stated that the application users are satisfied. Conversely, if the perceptions identified from the reviews are negative, it can be stated that the application users are dissatisfied. The Google Play Store rating system is based on a rating scale of 1–5, indicated by star symbols. Ratings of 1 and 2 can be classified as negative ratings, while ratings of 4 and 5 can be classified as positive ratings.

In order to classify user perceptions, weighting is first performed using the TF-IDF method. The results of the weighting are then classified using the multiclass Support Vector Machine method. The purpose of classification using this method is to identify the topics or subjects discussed in the reviews based on these variables.

Miles and Huberman in Sugiyono (2021) state that activities in qualitative data analysis are carried out interactively and continuously until completion, so that the data is saturated. The following figure illustrates several stages modeled in the qualitative analysis process:

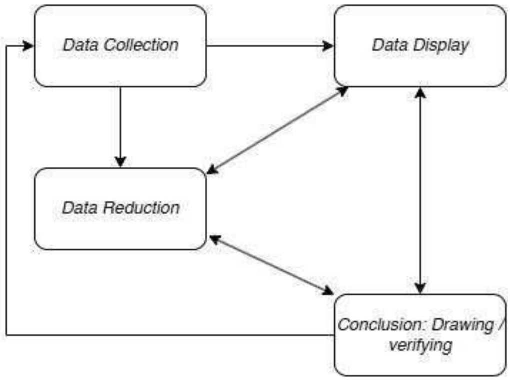

Figure 6 Qualitative Data Analysis Model
Source: (Sugiyono, 2021)

Based on the figure above, the qualitative analysis consists of several stages. First, the researcher conducts initial exploration by comprehensively collecting data through participatory observation, documenting all data in the form of words, actions, or documents (Sugiyono, 2021). Next, data reduction simplifies large and complex data by summarizing and selecting key points to provide a clearer picture, facilitating further data collection (Sugiyono, 2021). Then, the reduced data is presented in an organized and structured manner through descriptions, charts, or flowcharts to enhance understanding (Sugiyono, 2021). Finally, preliminary conclusions are re-evaluated based on the collected data, and verified conclusions supported by consistent data are considered reliable (Sugiyono, 2021).

The quantitative phase begins with defining respondent characteristics, followed by data collection using a questionnaire developed based on insights from the qualitative stage. Data is processed using SPSS for validity and reliability tests to ensure measurement accuracy. After processing, the data is visualized and interpreted to support the research analysis (Kavabilla, Widiharih, & Warsito, 2023; Khusnul et al., 2024).

Quantitative variables are operationalized by determining appropriate indicators to measure customer satisfaction related to the Wondr by BNI mobile banking application. These indicators include expectation fulfillment, willingness to revisit, and willingness to recommend (Indrasari in Masili et al., 2022). Each indicator is measured using a Likert scale to capture customer perceptions effectively.

The study population consists of approximately 5 million mobile banking app users in Indonesia as of January 2025 (Google Play Store). The sample includes about 400 users of the Wondr by BNI mobile banking app, selected through purposive sampling, which targets participants relevant to the research objectives (Sinaga, 2021).

Primary data were collected using an online questionnaire distributed through the web or Google Forms. This questionnaire measured the importance and performance of various aspects of Wondr by BNI mobile banking services to provide data crucial for the study.

Quantitative data analysis involved descriptive statistics to summarize data variations by calculating mean, median, mode, and standard deviation. Importance Performance Analysis

(IPA) was then used to map attribute distributions in a Cartesian diagram, helping to prioritize areas for improvement based on the Importance Performance Matrix. In this Exploratory Sequential Mixed Method Design, qualitative data informed the quantitative design and data collection; analyses of both data types were conducted separately and integrated during result interpretation (Creswell, 2020).

The IPA method evaluates user perceptions of the Wondr by BNI services to guide application developers on how to optimize or maintain service quality. It prioritizes issues identified from sentiment analysis by measuring the relationship between users' perceptions and improvement priorities based on performance suitability.

RESULTS AND DISCUSSION

Overview of Qualitative Findings

This study uses an exploratory sequential mixed method approach, where the qualitative stage is conducted first through sentiment analysis of user reviews of the Wondr By BNI application. A total of 21,269 reviews were obtained from the Google Play Store platform on February 12, 2025. The review data was obtained through a web scraping process using the Python programming language. The raw data collected consisted of free text from the comment (review) column written by app users. In the initial stage, the system successfully scraped 21,269 review data, but after the pre-processing stage, the sample review data consisted of 18,820 reviews.

The data pre-processing process was carried out using several stages of text analysis based on Natural Language Processing (NLP), namely Cleaning, Case Folding, Normalization, Tokenizing, Stopword Removal, and Stemming.

1. Pre-Processing Cleaning Results

   The first stage in the pre-processing process begins with cleaning, which involves removing irrelevant characters or characters that interfere with analysis, such as numbers, symbols, punctuation marks, emoticons, hyperlinks, or special characters. In addition, foreign words that are irrelevant to the context are also filtered out (Saefullah, 2023; Rizky Pratama, Ramadhan, & Komara, 2023; Romadoni, Umaidah, & Sari, 2020).
2. Pre-Processing Case Folding Results

   The next stage after the data has been cleaned is case folding. This stage aims to standardize letters to lowercase. This is important to avoid differences in word identification due to the use of uppercase and lowercase letters.
3. Pre-Processing Results: Tokenizing

   Tokenizing is the process of breaking sentences or text into smaller parts called tokens, usually in the form of individual words. Tokenizing is an NLP model for analyzing data at a granular level, i.e., based on word units. At this stage, each previously complete sentence is broken down into a series of separate words that can later be counted for frequency or analyzed for context. This process forms the foundation for subsequent statistical stages such as term frequency (TF) and TF-IDF.
4. Pre-Processing Results Stopword Removal

   In the topword removal stage, common words that have no significant meaning in the context of sentiment analysis will be removed. Stopwords usually include conjunctions such as “and,” “which,” “in,” “to,” “with,” and the like. Removal of important words that contribute to meaning and sentiment. The stopword list is generally taken from NLP libraries and adapted to the research context.

5. Pre-Processing Results: Stemming

   The final stage of the pre-processing process is stemming, which involves converting words to their root form (root word).

Quantitative Findings

In the quantitative phase, primary data were collected from 422 respondents through a questionnaire distributed via Google Forms in May 2025. Prior to the analysis, validity and reliability tests were conducted to ensure data quality, followed by an analysis of respondent characteristics to confirm accuracy. Each attribute in the questionnaire was coded as Performance (X) and Importance (Y). The mean values (Xi and Yi) were calculated from all respondents and then plotted on a Cartesian diagram using SPSS to determine the position of each attribute within the IPA quadrants (Cvelbar & Dwyer, 2013; Nurmakhlufi, Arsyad, & Mulyani, 2024).

Importance–Performance Analysis (IPA) is an effective method to prioritize improvement areas based on user perceptions by mapping attributes into four quadrants: "Concentrate Here," "Keep Up the Good Work," "Low Priority," and "Possible Overkill" (Wong, 2011). For instance, applications of IPA in e-government services have demonstrated its usefulness in understanding user needs and satisfaction levels from the demand-side perspective. Similarly, a study on e-service quality in sustainable banking in Indonesia utilized IPA to evaluate 16 service quality dimensions, highlighting aspects such as communication, security, speed, feature variety, and staff competence as key areas requiring improvement (Cintyawati et al., 2022).

In addition, research on the GoPay e-wallet application combined the Technology Acceptance Model (TAM) with IPA to conduct a gap analysis, showing how IPA effectively identifies which features should be improved immediately (Quadrant I) and which features already meet user needs and must be maintained (Quadrant II) (Saputra & Gürbüz, 2021). Following these examples, this study applies the same IPA framework to the Wondr by BNI application in order to identify priority improvement areas based on average Performance (X) and Importance (Y) values, mapping attributes into IPA quadrants to determine precise strategies for feature development and service quality enhancement (Prabaningtyas, Surjandari, & Laoh, 2019; Prajwal & Sangeetha, 2020).

Results of Importance Performance Analysis (IPA)

The Importance Performance Analysis (IPA) method was used to assess the extent to which the quality of the Wondr by BNI application was able to meet consumer expectations in order to achieve their satisfaction. This process was carried out through a series of processes, such as analyzing user opinions and expectations, as well as evaluating its implementation. The total score for each attribute is collected from each respondent. The assessment of the performance or satisfaction level (Xi) and the expectation level (Yi) is calculated based on the average of 422 respondents or participants in this study. Thus, the average perception of the fulfillment of expectations for each attribute is obtained. The average performance value (X) is used to determine the position of the attribute on the horizontal axis, while the average expectation value (Y) indicates the position on the vertical axis. All values are then mapped in a Cartesian diagram using SPSS software to determine the location of each attribute in a specific quadrant.

CONCLUSION

The analysis of 18,820 reviews revealed a nearly even split between positive (50.5%) and negative (49.95%) sentiments, with negative feedback primarily focusing on application instability, access and login difficulties, and transaction performance issues. Importance Performance Analysis (IPA) with 422 respondents showed no attributes in the highest priority quadrant, yet the critical problems identified qualitatively—instability, login, and transaction challenges—require attention from developers. Attributes related to security, technical performance, service, and safety should be maintained. Combining these insights with the SERVQUAL framework suggests that future application development should prioritize improving technical reliability and responsiveness to ensure a seamless user experience, alongside enhancing customer service accessibility and aligning feature development with user needs. Future research could explore user behavior over time to assess the impact of implemented improvements and investigate additional factors influencing user satisfaction and retention.

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