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Assessment of mobile payment service based on user review in Indonesia

Intan Novita Dewi[a,*], Rahmat Nurcahyo[b], Farizal[b]

[a]*Department of Industrial Engineering, Faculty of Engineering, Universitas Pembangunan Nasional Veteran Jakarta, Jakarta 12450, Indonesia*
[b]*Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia, Depok 16424, Indonesia*

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Abstract

This study evaluates user satisfaction with mobile payment services with a focus on the sentiment of user reviews from Twitter. Four key dimensions—reliability, economic benefits, assurance, and responsiveness—were analyzed for two applications. This study used Support Vector Machine algorithm with an accuracy measurement via the Confusion Matrix reaching 82,58% - 83.83%. The ROC curve showed the best AUC result of 0.900 - 0.909 (Excellent Classification). Meanwhile, sentiment analysis revealed that both applications faced predominantly negative sentiment, except for the economic benefit dimension. Major issues identified included slow problem resolution, unresponsive customer service, and occasional application errors. These challenges highlight user dissatisfaction and the need for the improvement of customer service and system reliability. The findings underscore the importance of addressing user complaints promptly to enhance satisfaction and foster loyalty.

Keywords: Mobile payment; sentiment analysis; support vector machine

1. Introduction

Global non-cash transaction is rapidly growing around the world. In 2016, 8,6% of global non-cash transaction was done through mobile payment, approximately 41,8 billion transactions (Bose & Mellado, 2018). Mobile payment refers to all forms of payment carried out via smartphone devices (Singh et al., 2020). In Indonesia, its applications have several service features offered to users, including food ordering, public transportation payments, cinema ticket purchases, e-commerce payments, logistics service payments, P2P (peer to peer), mobile prepaid top up, monthly bill payment and cash withdrawals (Devita, 2019).

In 2018, mobile payment in Indonesia grew rapidly in which the transaction value increased by 380% from 2017, approximately at 47,2 trillion Rupiah. The total value predicted in 2020 was more than $15 billion (Timones, 2019). Mobile payment market in Indonesia was expected to grow more in 2020, leading to an inevitable competition between mobile payment applications. A survey conducted by JAKPAT (JAKPAT, 2020) revealed that users tend to use more than one mobile payment.

Customer satisfaction is an important factor that can motivate users to be loyal in using mobile payment applications (Amoroso & Ackaradejruangsri, 2018). User satisfaction also positively influences users to recommend mobile payment apps to others (Singh et al., 2020). In the service sector, customer satisfaction is directly dependent on service quality and is based on a subjective comparison between customer expectations, their experience with the service, service outcomes, regular service delivery and effective problem handling (Juneja et al., 2011).

Meanwhile, dissatisfaction refers to a factor for users to switch to other products (Wang et al., 2019). Users who are dissatisfied will tell their complaints to others; therefore, it is important for companies to quickly identify problems with their services through user reviews (Zuo et al., 2019). User reviews and complaints can be used to identify problems encountered by users. User reviews shared via the internet are called as electronic words-of-mouth (e-WOM) (Ismagilova et al., 2017) and many users post a review through their social media. A user review may contain information about the user's experience with the app and opinions on it, feature requests, and bug reports (Genc-Nayebi & Abran, 2017). Such user reviews can help new users to determine whether they should use the app (Rodrigues et al., 2017).

A number of studies have discussed the sentiment analysis of mobile payment user reviews in Indonesia. Mobile payment app discussed, for instance, include GoPay (Prabaningtyas et al., 2019; Septiani, 2022; Ningri et al., 2023), OVO (Prabaningtyas et al., 2019; Saputra et al., 2019; Kristiyanti et al., 2020; Putri et al., 2020; Septiani, 2022; Ningri et al., 2023), DANA (Kristiyanti et al., 2020; Zahra & Alamsyah, 2022; Ningri et al., 2023), ShopeePay (Ningri et al., 2023), and LinkAja (Sianipar & Devega, 2024). Meanwhile, algorithms used for classification in sentiment analysis study include Naive Bayes (Saputra et al., 2019; Kristiyanti et al., 2020; Putri et al., 2020; Zahra & Alamsyah, 2022; Septiani, 2022; Ningri et al., 2023), K-Nearest Neighbor (Mustaqim et al., 2024), and

* Corresponding author.
Email: intan.dewi@upnvj.ac.id
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Support Vector Machine (Prabaningtyas et al., 2019; Kristiyanti et al., 2020; Putri et al., 2020).

Based on the studies mentioned above, there is still a gap in study on mobile payment sentiment review using Indonesian language from Twitter, which also uses the Support Vector Machine algorithm. This study compared the sentiment user review of a mobile payment owned by private parties (Idris, 2024) and a mobile payment affiliated with the government (Wijayanti, 2022). Therefore, the two mobile payments can be compared whether there is a difference in the service quality provided based on user reviews on Twitter.

2. Methodology

2.1 Previous research

Several previous studies discussed the sentiment of mobile payment user review in Indonesia. Septiani (2022) compared sentiment analysis between two mobile payments, GoPay and OVO using Naive Bayes algorithm. The data used in the study were user opinions obtained from user tweets with the keywords @gopay and @ovo. In line with Septiani (2022) study, Ningri et al. (2023) compared the sentiment analysis of several mobile payment user tweets, and used Naive Bayes algorithm as the classification method. Saputra et al. (2019) also used Naive Bayes algorithm to classify the sentiment of OVO mobile payment review; however the reviews used were different that is from user reviews on Google Play. The study of Zahra & Alamsyah (2022) also used Google Play review and Naive Bayes algorithm to find out user sentiment towards the mobile payment. Zahra & Alamsyah (2022) conducted a multiclass classification to categorize reviews into seven dimensions of electronic service quality: efficiency, responsiveness, fulfillment, system availability, contact, privacy, and compensation. They found that the top problem with the mobile payment is related to the issue of customer compensation.

There are other algorithms besides Naive Bayes that can be used for sentiment classification, such as the K-Nearest Neighbor and Support Vector Machine algorithm. Mustaqim et al. (2024) studied K-Nearest Neighbor algorithm to classify the sentiment of PosPay user review in Google Play. PosPay is a mobile payment application owned by a state-owned company, PT Pos Indonesia. Unlike other mobile payments, to use PosPay, users must open a Giropos account (Mustaqim et al., 2024). Kristiyanti et al. (2020) compared Naive Bayes and Support Vector Machine algorithms on user sentiment of two mobile payments. The reviews used were in English and were obtained from Google Play. Putri et al. (2020) study also compared PSO based Naive Bayes and PSO based Support Vector Machine algorithms on the user sentiment of OVO via Google Play. Putri et al. (2020) found that Support Vector Machine algorithm was better than Naïve Bayes algorithm in classifying text.

This study also labeled user reviews into several dimensions to identify which dimensions need to be improved. Based on user complaints on mediakonsumen.com page, problems experienced by users can be grouped into four dimensions adopted from (Parasuraman et al., 1988, 2005; Zeithaml, 2000) study such as reliability, assurance and responsiveness and economic benefit from J. Park et al. (2019) study.

Reliability is an ability to perform the technical functioning of the service accurately (Parasuraman et al., 2005). It is important for services to be accepted by users based upon standards. Unreliable applications cause transaction errors and make users dissatisfied (Safi'I et al., 2019).

Study conducted by J. Park et al. (2019) revealed that economic benefits had a positive impact on user attitudes towards mobile payment application services. Users seek benefits in return for something it provides, for example, a reward (J. Park et al., 2019). As such, this value drives motivation. Mobile payment companies often give benefits to users in the form of cashback, discounts and vouchers (Indrawati & Putri, 2018). This then leads to price saving orientation defined as the benefits of price reduction when using mobile payments (Indrawati & Putri, 2018). Price saving orientation variable is highly significant as one of the factors determining users to continue using mobile payment applications (Indrawati & Putri, 2018). Rewards are one of the factors attracting users to switch to other mobile payment applications (Wang et al., 2019).

Assurance is the trust a consumer has for the application because of its reputation and the quality of its goods and services (Parasuraman et al., 2005). It also refers to the perceptions about the efficacy of the institutional environment legal provisions for ensuring a secure mobile transaction environment (Chandra et al., 2010). Chandra et al. (2010) found that assurance is strongly correlated to trust in mobile payment systems. In the realm of mobile payments, characterized by transactions between unfamiliar parties and many uncertainties and risks, consumer trust stands out as the paramount predictor of adoption (Chandra et al., 2010). Assurance also has a negative relationship with risk, and one way to reduce perceived risk in mobile payment systems is to develop adequate assurance (Chandra et al., 2010).

Furthermore, responsiveness is defined as the quick response and ability of the service provider in addressing any issues or questions raised by users (Parasuraman et al., 2005; Lin, 2013). It is also crucial when automated transactions deviate from expectations and warrant human interaction due to technical or procedural complications. Faster human intervention in such matters is thought to have a positive impact on usage satisfaction (Kar, 2021). Customer service representatives are often the main reflection of the company's image and become an important player in recovery from problems experienced by users (Maxham & Netemeyer, 2003).

The assessment of mobile payment services from these four dimensions includes several significant variables in previous studies such as transfer and payment (Bagla & Sancheti, 2018) in reliability dimension, cashback; rewards; price saving orientation (Bagla & Sancheti, 2018; Indrawati & Putri, 2018; J. K. Park et al., 2019; Wang et al., 2019) in economic benefit dimension, security (Bagla & Sancheti, 2018; Chawla & Joshi, 2019; Hyun Soon et al., 2019; Wang et al., 2019); (Azizah et al., 2018; Chawla & Joshi, 2019; Indrawati & Putri, 2018) and trust (Azizah et al., 2018; Chawla & Joshi, 2019; Indrawati & Putri, 2018) in assurance dimension and customer service (Maxham & Netemeyer, 2003; Salim et al., 2018) in responsiveness dimension.

2.2 Methods

The method applied in this study was divided into three steps data collection, data preparation and assessment of service providers.

2.2.1 Data collection

Indonesia is a country with the fifth largest Twitter user in the world with a total of 4.1 billion tweets in 2016 (Herman & Mononimbar, 2017). Twitter can be used to share reviews and information among the users. User review or electronic word-of-mouth (e-WOM) constitutes a dynamic and continuous information exchange among prospective, current, or past consumers regarding a product, service, brand, or company, accessible to numerous individuals and organizations through the internet (Ismagilova et al., 2017). This study used the data referring to e-WOM from Twitter about the mobile payment owned by private parties and the mobile payment affiliated with the government. To retrieve the tweets, the Spyder application (Python 3.7) and the Twitter scrapper module were applied. This study analyzed tweets taken from September to November 2019. Only tweets in Bahasa Indonesia were used in this study.

2.2.2 Data preparation

Data preparation began by sorting the tweets, only keeping the ones from customers and selecting the ones matching with the predetermined dimensions. In this case, the tweets from the company's account were deleted from the data set. It was continued by pre-processing the data to convert any unstructured and semi-structured text into an understandable format. Pre-processing is one of the key features of many text mining algorithms (Allahyari et al., 2017). This must be done prior to do any advanced analytics. The pre-processing steps can be summarized as follows (Miner et al., 2012; Prabaningtyas et al., 2019).

- Text standardization
  Standardization is critical considering that data from Twitter typically contains numerous non-standard terminology. It is important to adapt these words to their normal form. This method also explains incorrect writing or typos.
- Lower case and cleansing
  Replacing all letters to lowercase aims to ensure consistency. It is continued by removing any extraneous terms like username, hashtag, e-mail, and punctuation.
- Filtering
  It refers to the process of deleting any unimportant words from a token. Stop words are popular words that have no meaning, such as "who", "and", "in", or "from".
- Tokenizing
  It is the process of breaking up a flow of text into words or other meaningful pieces.
- Stemming
  It is a process for converting a token into its core word.

An application was used to pre-process data in Bahasa Indonesia. After pre-processing the text, the tokens must be converted into a vector that is suitable for input to text mining algorithms. Vector generation requires weighting, the most widely used approach being Term Frequency-Inverse Document Frequency (TF-IDF). Frequency is the number of times the word appears in the document. Unless they also exist in other documents, words that appear often will be given more weight (Miner et al., 2012).

2.2.3 Sentiment analysis

The goal of sentiment analysis is to determine people's opinions, general sentiments, and emotive conditions as expressed in a collection of text. This sentiment represents their emotional response to each other's products, and it is integrally related to the success or failure of a company. Classification is done to assign data into a class collection that has been determined (Miner et al., 2012). There are various classification algorithms, and Support Vector Machine (SVM) algorithm used in this study to classify the data with the help of RapidMiner software version 9.6.0.

SVM has three types of kernel functions that can be used, including sigmoid, polynomial, and radial basis function (RBF) (Wu, 2009). We used radial basis function (RBF) in this study. In the RBF kernel type, there are two parameters that must be determined, namely the C and gamma parameters. Then, all interval points (C, gamma) are tried to find the combination that gives the highest cross validation (CV) accuracy. The user then uses the best parameters to train the entire training set and generate the final model (Chang & Lin, 2011).

Gamma values are determined at the intervals of 0,1 to 0,5 with an increase of 0,1 and the C value is determined at intervals of 1 to 100. Then, all interval points (C, gamma) are tried to find combinations that provide the highest cross validation accuracy.

2.2.4 Model Classification Evaluation

The most obvious criterion to use for estimating classifier performance is prediction accuracy. There are several steps that can be taken to evaluate classification models. First, it is by using k-fold cross validation. If the dataset consists of N data, divided into k equal parts, k usually consists of a small number such as 5 or 10. Each of the k parts will in turn be used as test data and other k-1 parts are used as training data (Bramer, 2007). In this study, the k used was 10.

The second step to evaluate the model is the confusion matrix that shows how often data of a class is correctly classified as that class or misclassified as another class. In the confusion matrix, there are accuracy, precision, recall, and F1 values. The higher the accuracy, the more the data classified correctly. This study divided sentiment into positive and negative sentiment.

Receiver Operating Characteristic (ROC) curves refer to a technique that can be used to visualize, organize and select classification models based on their performance. The area under the ROC curve or AUC is used to see which is the better classifier. A guide to classify the accuracy of diagnostic tests using AUC is the traditional system as presented below (Gorunescu, 2011):

- 0,90 - 1,00: Excellent classification
- 0.80 - 0.90: Good classification
- 0.70 - 0.80: Fair classification
- 0.60 - 0.70: Poor classification
- 0.50 - 0.60: Failure classification

3 Results and Discussion

3.1 Result

The sentiment classification model for the mobile payment owned by private parties achieved an accuracy of 83.83% and an average F1-score of 80.09%, using a gamma value of 0.1 and a C value of 3. Based on the Receiver Operating Characteristic (ROC) curve, the Area Under the Curve (AUC) for the a mobile payment owned by private parties model was 0.909, placing it in the excellent classification category.

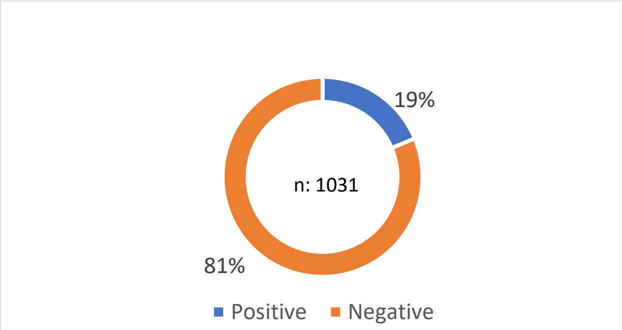

Fig. 1. The mobile payment owned by private parties sentiment proportion

Fig. 1 illustrates the sentiment distribution for the mobile payment owned by private parties dataset where negative sentiment dominated at 81%, compared to only 19% positive sentiment. Of the dimensions analyzed, responsiveness had the highest number of tweets (431), followed by economic benefits (289), reliability (168), and assurance (143).

Similarly, sentiment analysis for the mobile payment affiliated with the government reviews achieved an accuracy of 83.32% and an average F1-score of 82.58% with a gamma value of 0.5 and a C value of 3. The AUC for the mobile payment affiliated with the government model was 0.900, also placing it in the excellent classification category.

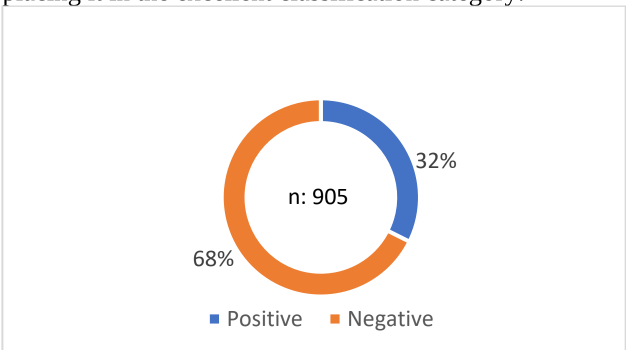

Fig. 2. The mobile payment affiliated with the government sentiment proportion

Fig. 2 depicts the sentiment distribution for the the mobile payment affiliated with the government dataset where negative sentiment constituted 68% (612 tweets), while positive sentiment accounted for 32% (293 tweets). The reliability dimension dominated with total tweets of 432, followed by responsiveness of 180 tweets, assurance of 179 tweets, and economic benefits, which had the fewest mentions of 114 tweets.

3.2 Discussion

Both mobile payment applications exhibited a significant disparity between negative and positive sentiments. Fig. 3 illustrates the sentiment distribution for each user review dimension, revealing that all dimensions had more negative than positive sentiment. The responsiveness dimension showed the highest negative sentiment, focusing on how customer service representatives (CS) handle user complaints. Most tweets in this category expressed dissatisfaction, highlighting issues such as unanswered complaints, delays in problem resolution exceeding three business days, and the reliance on generic response templates. This finding contrasts with Zahra & Alamsyah (2022) where the responsiveness dimension had a positive sentiment of up to 70%. These results suggest that the company should investigate these responsiveness issues and prioritize improvements to enhance the user experience.

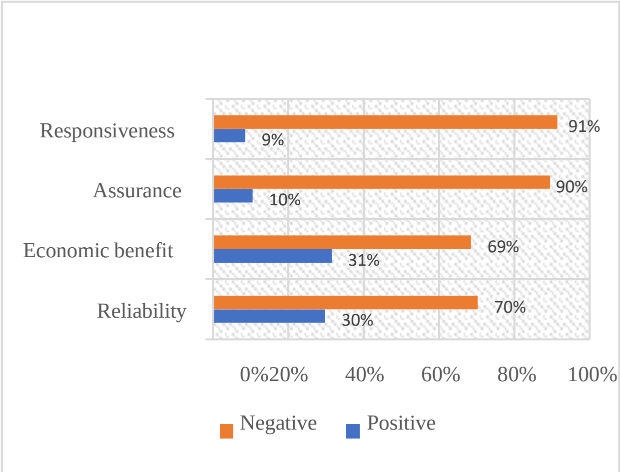

Fig. 3. Sentiment graph of a mobile payment owned by private parties

The assurance dimension also had a high sentiment gap at 80%. The dimension itself focused on the application security and reliability. Some users complained that an application error caused them unable to log into their accounts so they could not make transactions. This issue should be a priority for the company, particularly for the developers responsible for enhancing system reliability.

On a more positive note, the economic benefit dimension recorded the highest number of positive tweets compared to other dimensions. Many users praised the mobile payment owned by private parties for its cashback offers and promotional deals, noting how these benefits made their transactions more cost-effective, such as bill payments, credit purchases, and merchant cashback incentives. This aligns with the findings of J. Park et al. (2019) showing that economic benefits positively influenced user attitudes toward mobile payments. However, the negative sentiment in this dimension remained considerable, echoing the results of Zahra & Alamsyah (2022) where the compensation dimension similarly faced substantial negative sentiment.

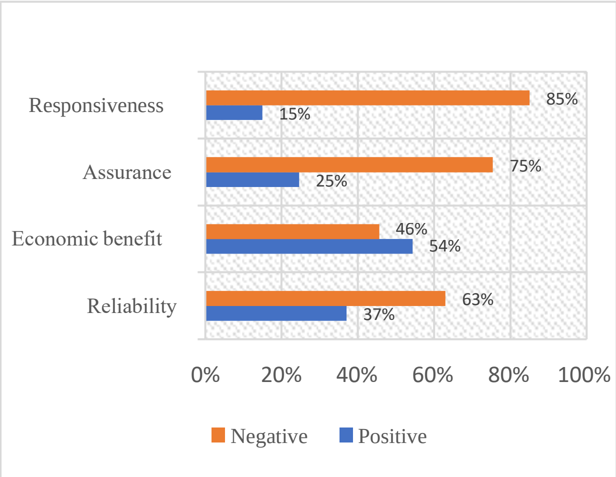

Fig. 4. Sentiment graph of the mobile payment affiliated with the government

Fig. 4 highlights the sentiment distribution across various dimensions of user reviews. All dimensions showed more negative sentiments than positive, except for the economic benefit dimension, standing out with a higher proportion of positive sentiment. Users appreciate the cashback received from transactions such as bill payments, prepaid mobile payments, and gas purchases. However, some users express disappointment over not receiving the promised cashback for their transactions.

The responsiveness dimension exhibited the largest sentiment gap. Similar to the mobile payment owned by private parties, A mobile payment affiliated with the government was found to face significant issues in responsiveness. Many users reported that their direct messages (DMs) went unanswered by A mobile payment affiliated with the government 's customer service (CS). Additionally, problem resolution times were excessively long, often exceeding three days. In some cases, users reported unresolved issues even after two weeks, making them frustrated due to the slow response.

To address these issues, improving customer service operations is deemed essential. Strategies include increasing the number of customer service staff and conducting regular monthly performance evaluations to ensure quality and efficiency. Effectively resolving user issues and providing satisfactory solutions can significantly enhance user loyalty, increasing it by up to 30% compared to users who have not encountered complaints (Goodman, 2019).

4 Conclusion

This study aims to evaluate user sentiment with mobile payment services based on user reviews on Twitter. Four key dimensions influenced the evaluation of mobile payment service providers: reliability, economic benefits, assurance, and responsiveness. For the mobile payment owned by private parties, sentiment analysis based on the number of tweets for each dimension revealed a higher proportion of negative sentiment compared to positive one. In contrast, the mobile payment affiliated with the government demonstrated a greater positive sentiment in the economic benefit dimension, while other dimensions showed more negative than positive sentiments. Overall, both mobile payment applications had a predominance of negative sentiment, indicating the dissatisfaction of most users with the services provided. Addressing user complaints effectively is expected to enhance satisfaction and foster greater user loyalty.

This study possesses some limitations. First, this study relied solely on Twitter data, which may not fully represent the opinions of all users of the mobile payment applications. Many users may prefer other platforms to express their feedback. Second, the data analyzed was time-bound and may not account for changes in user sentiment due to updates in the applications or external factors like market trends. For future research we suggest to expand the data collection to include reviews from other media platforms such as Instagram, Google Play and App Store to capture a more diverse set of user opinions.

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