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Social Media Analysis for Investigating Consumer Sentiment on Mobile Banking

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ABSTRACT

This paper is aimed to give more insight for Indonesian banks to understand consumers' sentiment in social media towards their mobile banking service, determining area(s) that requires improvement, and giving recommendation where refinement is due. Nine highly mentioned mobile banking features in Indonesian language are determined through manual observation on Twitter, translated as: payment, block, open new bank account, login, transaction report, bank balance, top-up, transaction, and transfer. Twitter entries from January 1st, 2019 to December 31st, 2020 which include the words 'mobile banking', 'm-banking', or '*mbanking*' plus one of the nine features are collected and classified according to their sentiment. In total, 5014 tweet data are collected. Negative tweets have the biggest proportion at 49.8%, followed by neutral tweets with 44.5% and positive tweets with 5.7% only. Proportion of negative tweets are way higher than the positive tweets for all nine features. From highly mentioned words and representative example tweets, some preferred features can be derived, including no extra fee to access any mobile banking feature, providing record that can be recalled after important transactions, keeping mobile banking app updated to customer needs while also maintaining steadiness, speed, and ease-of-use, along with better synchronization with third party entities.

Keywords: Mobile Banking, Sentiment Analysis, Social Media Analysis, Text Classification, Text Mining

JEL Classification: G20, M15, O30, Y10

INTRODUCTION

Today's life is closely related to the existence of the internet. The internet originally started to build networked computer systems, but now it is seamlessly accessible from handheld devices. A variety of methods of cashless payments using financial technology are also becoming very popular on the internet. Financial technology, or commonly referred as fintech for short, is a universal term for computer-based, mobile-based, and even hardware technology software, algorithms, and applications that extend, streamline, digitize, or disrupt traditional financial services (Walden, 2020). Various FinTech of many brands generally offer services that help users make transactions without having to carry cash or even a card. All of these can be accessed from smartphone. Not only are they faster and easier, they are also safer and reduce the risk of money clutter and crime of theft by carrying cash (Thakor, 2019).

Especially in Indonesia, financial technology for payments is usually released by private companies under licenses from Otoritas Jasa Keuangan (OJK) and / or Bank Indonesia (BI). Commercial banks also have their own version of financial technology integrated into their smartphones. This is called mobile banking, or mbanking for short. These applications are launched by their respective banks, each with its own unique user interface and ease of use.

Especially in Indonesia, commercial banks have their own version of financial technology integrated into their smartphones. This is called mobile banking, or m-banking for short. These applications are launched by each bank with its own user interface and ease of use. Some of the most common features are money transfers and balance checks. Some savings account programs, typically aimed at young, low-income consumers, are moving to abolish bank books as they can replace their functionality with mobile apps.

In the second quarter of 2019, major Indonesian banks reported an increase in online transaction traffic of 50-150%, which varies from bank to bank. This increase was consistent with a steady decline in physical transactions, either directly at banks or through ATMs. (Kontan.co.id, 2019). In addition to the general increase in mobile banking use, there is a silver lining within the COVID 19 pandemic. Representatives of various Indonesian banks said that in addition to changing consumer behavior according to health guidance to reduce physical contact as much as possible, this also includes payments and banking transactions (Kee, et. al., 2021). Not only bank visits, but also traffic through ATMs is declining (Rizal, 2020). On the other hand, online traffic is increasing. In May 2020, according to an official statement of Bank Indonesia, e-commerce transactions increased significantly by 17.31% year-on-year and digital banking transactions increased by 30.33% (Pink, 2020), despite the 2% economic slowdown in Indonesia according to IMF data (Handayati, et al., 2021).

Current trends in everything online require banks to keep up with mobile banking quality in order to keep their customers happy and competitive in the market. Failure to meet consumer needs can damage a bank's reputation and lead to gradual loss of customers. However, developing and maintaining mobile applications is certainly an expensive investment. Not to mention the rapid pace of smartphone evolution, it increases the planning and development cycle of outdated and irrelevant apps (Flora et al., 2014). Banks need to know exactly what their customers really want. Banks also need to have up-to-date information so that the improvements made can be accurately tailored to the needs of the consumer.

One way to recognize the needs of customers who meet current fast-paced standards is to use social media. Social media acts as a platform for directly exchanging and obtaining ideas with like-minded people. Social media also influences people's values, attitudes, intentions, and behaviors. Especially for businesses, all this information and opinions shared by users on social media is like a gold mine to learn consumer sentiment towards products, services, and brands (Hangya & Farkas, 2017). In addition to sharing with friends, most organizations and brands have built their reputation online through social media. Many companies, large and small, used social media to communicate with their users in order to achieve the following business values: driving customer traffic, increasing sales and revenue, retain customer loyalty, establish brand awareness, and many more (He, et al., 2013).

With about 150 million internet users in Indonesia, the average daily connection time is 8 hours and 36 minutes, which is higher than the world average of 6 hours and 42 minutes. Of the more than eight hours, 3 hours and 26 minutes are spent on social media platforms, making Indonesia the fourth largest in the world (Wong, 2019). You can take advantage of this large data source using social media analytics. Social media analytics are widely used for a variety of research and business purposes in each discipline. One method is sentiment analysis. It categorizes people's thoughts and attitudes into textual data commonly used to collect business intelligence from social media (Kim et al., 2016).

This paper is intended to provide banks with insights to understand consumer sentiment towards services that can be used as the next step in improving mobile banking performance and quality, especially in mobile banking.

LITERATURE REVIEW

Social Media Analysis

Social media analysis is a way to collect data from all types of social media and analyze that data for insights. The most common format is text-based data. This data contains hidden knowledge that can be useful in a variety of areas, including business analytics. In business, social media is typically used to understand brand popularity and performance details compared to competing brands, understand customer behavior, and understand competitor readiness and shift in trends (Dey, et al., 2011).

Sentiment Analysis

Sentiment analysis, also known as opinion mining, is defined as the task of determining the author's opinion on a particular topic. Due to the recent surge in social media use, it is possible to collect data from social media such as Facebook, Twitter, blogs and other user forums and use the collected data as a source for performing sentiment analysis (Feldman, 2013). On the other hand, some researchers believe that sentiment analysis and opinion mining are slightly different. Opinion mining extracts and analyzes people's opinions on a broader scale, while sentiment analysis focuses only on the polarity of emotions expressed in the text (Medhat et al., 2014).

Mobile Banking

Today's mobile banking is an application on your smartphone that is connected to the internet and registered by phone number. It is equipped with several security procedures released by each bank and you can perform banking functions anytime, anywhere. However, its origins have rooted back to branchless banking. Before everything fits on your smartphone, banks have a variety of options to give a wider range of users access to banking services (Sastiono & Nuryakin, 2019).

Seamless 24/7 service not only simplifies day-to-day banking operations, but also improves life quality. The presence of mobile banking exposes countries with limited infrastructure and education to banking services such as loans, installments, and investments, ultimately improving the country's economy (Gupta, 2013). While mobile banking apps offer different features for each bank, there are some standard features that are always available in modern mobile banking apps, such as checking account balances and sending money. However, different app from different banks also has different features and details. These differences are often advertised as their strength by banks in the hope of attracting new customers, especially young consumers who are generally tech-savvy. It also aligns with the biggest demography of mobile banking user being consumers aged 26-35 years old as opposed to people above 46 years old are the least to adopt mobile banking technology (Chawla & Joshi, 2021). Having other daily activities that are inseparable from the internet technology, such as online shopping, also boost the high usage of mobile banking among millennials (Astuti, et al., 2019).

Data Mining

The definition of data mining is the process of discovering compelling, unexpected, or valuable information from large datasets. Initially, data mining is more commonly performed as a secondary analysis of previously collected data for other purposes. Modern data mining uses tools and methods in the field of computer science, machine learning, and classical statistics that apply to much larger datasets (Hand, 2007).

Data mining typically follows some standard procedure and repeats as needed. First, collaborative actions are performed in the data analysis. Collect and understand data, know relevant prior knowledge, and define research goals. The collected data is preprocessed and cleaned up, including processing of missing data and removal of irrelevant variables. Too many variables make it difficult to rationalize the results. When clean data is ready, the appropriate data mining algorithms are applied. Examples of algorithms include neural networks, decision trees, and fuzzy logic. This part performs the actual data mining operation. If analysts consider the results to be possible (the results are physically possible), consistent (the results are consistent with each other), and plausible (the associations found are reliable), then the results are studied. It can be interpreted to achieve the purpose. The results will be reported. If the results of the data mining process are inadequate, you can rerun the case with modified or improved queries and conditions (Chung & Gray, 1999).

Text Mining

Text mining can be defined as the discovery of previously unknown new information by automatically extracting information from a variety of written resources through a computer. In contrast to searching for existing information on the Web, the purpose of text mining is to reveal unknown information that no one has ever written down and therefore cannot be found on the web. Text mining is one of data mining variations, the difference being in the shape of the data. Data mining uses a structured database designed to be read programmatically, while the text mining process uses natural language text data that is human-readable and understandable (Hearst, 2003).

Text Classification

Text classification is part of a text mining technique that aims to classify text documents into one or more predefined categories. Text classification uses machine learning techniques to automatically classify text into classes or categories (HaCohenKerner, et al., 2020). There are several methods for text classification modeling, including neural networks, Bayesian, and support vector machines (Patra & Singh, 2013). Some of the textual data for training data is first subjected to a feature extraction process and converted to computer-readable numbers. Then, in the second phase, the machine learning model created during the training phase is used to predict new unlabeled data for class labels (Rasool, et al., 2019). This study uses text classification to determine sentiment classes: negative, neutral, and positive.

RESEARCH METHOD

Research Methodology

This research is meant to extract information from a big number of data, and therefore is quantitative research (Williams, 2007). Since data collected and analyzed are originated from data shared freely on the internet, this research also classifies as netnography (Kozinets, 2015). Through manual observation on Twitter, found 9 most talked features about mobile banking; '*bayar*' (payment), '*blokir*' (block), '*buka rekening*' (open new account), 'login', '*mutasi*' (transaction report), '*saldo*' (bank balance), 'top-up', '*transaksi*' (transaction), and 'transfer'.

Data Collection

Data analysis begins with data collection. Tweets containing the word 'mobile banking' and its variations, plus one of the nine features listed before are collected. To keep data relevant with the current situation, only tweets from January 1st, 2019 until December 31st, 2020 were collected. From 90 attributes, only 4 are used in the research; namely 'created_at' (date and time of posting), 'screen_name' (username of tweet author), 'Text' (text content of the tweet), and 'lang' (language of the posted tweet).

Data Pre-processing

Data mining is intended to collect a big amount of data via computer. It results in a lot of data, some of them irrelevant and in forms that are unusable. Data pre-processing is a process of cleaning and converting data so that it they are readable and can be used to build a model (Pahwa, et al., 2018). Filter is intended to eliminate data that does not suit the condition of research, while selection is intended to only include relevant data attributes. In this research, Twitter posts from banks themselves are filtered out and only 4 data attributes are selected out of 90 attributes.

Due to the large amount of data, sentiment classification can be automated using machine learning process. In this study, 30% of each dataset is manually scored and used as training data. This step only requires the 'Text' attribute of the data. The results of this step will be used as a benchmark for the machine learning process to determine the output.

Tweets are categorized into negative, neutral, or positive sentiment. For example, a tweet by user @dreamjournalfst:

"mbanking bni kenapa harus error gabisa topup shopeepay di saat 12.12 astagaa"

contains disappointment showed by the words 'error', '*gabisa*' (unable), '*astagaa*' (geez!) and therefore classified as negative sentiment.

Another example from a tweet by user @mayafw:

"#CeritaBarengBCA ku itu banyak banget. Salah satunya aku terbantu banget punya mobile banking @BankBCA, karena aku punya jualan online, bikin jadi gampang banget setiap kali transaksi."

shows customer satisfaction with positive sentiment from words "terbantu (helped)" and "gampang (easy)".

An example of tweet with neutral sentiment is posted by user @G87Marif, saying:

"@TelkomCare bagaimana cara bayar tagihan bulanan via mobile banking?"

does not contain any word that express either satisfaction or dissatisfaction. "Bagaimana (how)" is a question word and in this context fits neither negative nor positive sentiment class.

The last stage of pre-processing is text cleaning. Texts are transformed, where all capital letters are changed into lower case and punctuation are removed. The next one is tokenization and normalization, where words' format are digitally broken down so that computer can read them as single words instead of sentences. Words with no polarity traits which gives no impact for sentiment classification (commonly referred as stop words) are also removed in a step called stop word removal. Indonesian stop word list from research by F. Z. Tala titled" A Study of Stemming Effects on Information Retrieval in Bahasa Indonesia" is used (Tala, 2003).

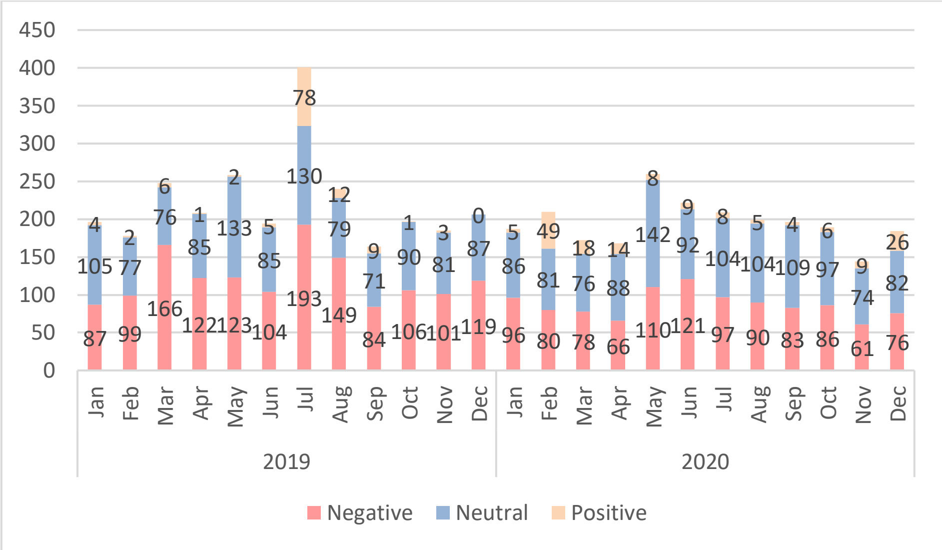
Model Building and Evaluation

Two prediction models are built using the 30% of data previously labeled to be applied to the rest of full data. The first model is built using neural network method and the second model is built using naïve bayes method. Neural network model reached classification accuracy of 79.8% and F1-score of 79.6%, while naïve bayes only reached classification accuracy of 57.5% and F1-score of 59.3%. With better scores, neural network model is to be used in classifying tweets' sentiment.

RESULTS

Sentiment analysis is performed on mobile-banking-related Twitter entries from January 1st, 2019, until December 31st, 2020. Over the course of 24 months, tweets about mobile banking are varying in amount, although with gap that are not too drastic. In total, there are 5014 Twitter entries that suits the criteria of research. July 2019 scored the highest total number of tweets, more so in positive sentiment class, caused by "Kuis Twitter: Mobile Banking Muamalat Bikin Simpel" event held by Bank Muamalat in collaboration with ATM Bersama. The event encourages users to tweet what they like about Bank Muamalat's mobile banking app for a chance to win a certain amount of digital payment balance, hence the surge in positive tweets. In February 2020, positive tweets also recorded a higher number than usual, in celebration of Bank BCA's 63rd anniversary with #CeritaBarengBCA campaign. Other fluctuations present in the data were not caused by any noticeable special event. Illustration of tweet amounts in each sentiment class for each month is presented in Figure 1.

Figure 1. Tweet Amounts in Each Month from January 2019 to December 2020



With the assumption that the COVID-19 pandemic in Indonesia started in March 2020, there seems to be no significant change in user tweets before and after the pandemic. Between January 2019 and February 2020, a total of 3,072 tweets were sent, with an average of 219 tweets sent each month. After the pandemic that lasted from March 2020 to December 2020, there were 1942 tweets, with an average of 194 tweets per month. The data for May 2020 is higher than the previous month, but the number will soon settle in the next month. Compared to 2019 data, the number of tweets in May was always higher than in most other months.

In number, there indeed a decrease of tweets about mobile banking before and after COVID-19 outbreak. However, number alone is unable to tell the shift in consumer sentiment. Total number of tweets also include outlier data caused by special events, as stated previously. To get a more representative result, outlier is removed from the data. Table 1 compares the proportion of average tweets in each sentiment classes before and after COVID-19 outbreak, which shows decrease in negative tweets, and increase in neutral and positive tweets.

Table 1. Proportion of Average Tweet(s) in a Month of Each Sentiment Class Before and After COVID-19 Outbreak

	Negative (%)	Neutral (%)	Positive (%)
Before COVID-19	56.28	41.6	2.12
After COVID-19	46.27	48.93	4.8

Table 2 presents the result of sentiment text classification in each mobile banking feature. Number shown is the number of tweets in each category. The total will be higher than 5014 tweets, as some tweets mentions two or more features and therefore will be included in more than one category.

Table 2. Sentiment Text Classification in Each Mobile Banking Feature

	Negative	Neutral	Positive
Payment	347	438	38
Block	62	125	2
Open new account	51	95	10

Login	83	32	0
Transaction report	118	67	6
Bank balance	804	397	17
Top-up	468	261	9
Transaction	758	653	201
Transfer	506	534	51

To make a binary classification, neutral sentiment is removed in the following parts of research.

Based on the number of tweets, the bank balance function has the most negative sentiment in 804 tweets, and the transaction function has the most positive sentiment in 201 tweets. However, in relation to negative sentiment, the percentage of top-up and login is higher, compared to "only" 97.93% for bank balance, the former at 98.11% and the latter at 100%. For a positive sentiment, a large number of tweets also represents a 20.96% share of the transaction category. The complete comparison can be seen in Table 3.

Table 3. Proportion between Negative and Positive Tweet(s) on Each Category

	Proportion of Negative Tweet(s) (%)	Proportion of Positive Tweet(s) (%)
Payment	90.13	9.87
Block	96.875	3.125
Open new account	83.61	16.39
Login	100	0
Transaction report	95.16	4.84
Bank balance	97.93	2.07
Top-up	98.11	1.89
Transaction	79.04	20.96
Transfer	90.84	9.16

Figure 2 shows the frequent words that are highly used when expressing their opinion on mobile banking. The left diagram shows words from the negative sentiment while the right diagram shows words from the positive sentiment. Negative sentiment contains complaints including ‘failure’, ‘error’, ‘disturbance’, and more. Positive sentiment contains praise expression including ‘easy’ and ‘simple’. A series of example negative and positive tweets are provided in the appendix to give more in depth and detailed understanding of users’ desire.

Figure 2. Frequent Words in Negative Tweets (left) and Positive Tweets (right)

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DISCUSSION

All categories received negative sentiment rather than positive sentiment. Based on numbers, mobile banking services, regardless of functionality, are unsatisfactory and at best mediocre. Customers were not content with any of the services offered by mobile banking.

The first goal of finding customer sentiment about mobile banking expressed on social media before and after COVID 19 is solved by classifying tweets from each sentiment class by year and month of publication. Negative tweets indicate customer dissatisfaction, and positive tweets indicate customer satisfaction. Based on the results of the analysis, the average number of tweets per month regarding mobile banking decreased, in contrast to the claim that the use of mobile banking increased after the Indonesian government declared a pandemic state. Still, it seems that negative emotions are diminishing, with the growth of neutral and positive emotions.

Nonetheless, 2015 research by Střítezký and Stránská found that people perceived damage to the brand's image by creating negative experiences on social media and are taking advantage of them (Střítezký & Stránská, 2015). This means that social media posts that mention brand often tend to feel more negative. Therefore, as the number of complaints (negative tweets) decreases, so does the average number of tweets per month. If so, it could be an indicator that mobile banking performance has successfully improved their services comparing before and after the outbreak of COVID-19.

In all nine categories rated, the percentage of tweets with negative sentiment is more dominant than the positive ones. A common transaction feature can be completed as the most popular mobile banking feature, with the highest percentage of positive tweets. This is followed by "Open New Account", "Payment", "Transfer", "Transaction Report", "Block", "Bank Balance", and "Top up". The login feature is the least desirable as it is the only category with no positive emotional tweets. We can conclude that neither feature is yet satisfactory. Given this fact, all nine features evaluated in this study need to be improved to address business issues that require rapid and accurate innovation of technology services to keep up with customer demand and competition.

By learning from common words and example tweets in each category, banks can suggest some areas to improve to improve their mobile banking services. In general, customers want access to all features at no additional charge. This usually happens with mobile banking systems that are based on SMS systems. Eliminating additional costs increases user enjoyment and reduces resistance of using mobile banking for activities. Another improvement is providing records for users to keep track of their important actions when using mobile banking.

One of the main advantages when using mobile banking is that you don't have to go to the bank all the time, so it's very important that the app has enough features to handle all issues remotely. One area that needs improvement in this issue is the block feature. Users with locked accounts, locked phone numbers, or other locked issues often cannot resolve the issue online through the app, which is considered annoying.

Although various feature is highly commended, it also functions as a double-edged sword. Without a stable, fast, and easy-to-use user interface, not all improvements can serve their intended purpose. Indonesia is a country with different economic classes and regions. This is especially relevant on user's smartphone power and internet speed. Users with low economic status and in remote locations are less likely to use more advanced technology (Oke et al., 2014). "Heavy" applications will not work on devices with limited capacity or weak internet connectivity. There have been many complaints about video call issues, app crash reports, or registration processes that don't progress with video call, especially when it comes to opening a new bank account feature. This is an important step in the identity verification process. To address this issue, further investigation is needed to determine if it is due to heavy apps, poor internet connectivity, or other reasons.

Finally, there are issues related to bank balances, top-up, and transfer. Funds are being withdrawn from the bank's balance even if the transfer is deemed unsuccessful. Alternatively, the charge or transfer is considered successful, but the bank balance has not been added correctly. The cause of this error cannot be determined by this study only, as mobile banking users do not know the cause and cannot explain it in a tweet. Banks and developers of their mobile banking apps need to dig deeper to find the cause of the problem and fix it accordingly. Since charging and forwarding are two features that are closely related to third parties (other banks & digital wallets), development may need to include simultaneous synchronization with these other parties as well.

CONCLUSION

To conclude the research, we go back again to the problem happening now, when life is inseparable from the presence of internet, seamless accessible through a handheld device. One thing that has also become very popular through the presence of internet is various methods of cashless payment through financial technology. The growth of fintech adoption is constantly increasing every year, including Indonesia. Commercial banks usually have their own version of fintech called mobile banking. Due to COVID-19 pandemic and people's fear of making physical contact, mobile banking usage grows even more. Seeing the current trend of everything online, banks need to keep up with their mobile banking service to satisfy their customer and stay competitive in the market. However, failure to understand customers will result in costly, ineffective development.

Nine mobile banking features are assessed, determined through manual observation on Twitter, namely: payment, block, open new bank account, login, transaction report, bank balance, top-up, transaction, and transfer. Twitter entries from January 1st, 2019 to December 31st, 2020 which include the words 'mobile banking' and its variations plus one of the nine features are collected through a text mining process. January 2019 until February 2020 is considered a condition before COVID-19 pandemic and March 2020 until December is considered a condition after COVID-19. For the whole data, negative tweets have the biggest proportion at 49.8%, then followed by neutral tweets with 44.5% and positive tweets with 5.7% only.

It is found that average number of total tweets per month decreases from before to after COVID-19 breakout, negative tweets per month decreases, while neutral and positive tweets increase. Another finding is that the proportion of negative tweets are way higher than the positive tweets for all categories, with transaction feature receiving the least negative tweets at 79.04% and login feature receiving the most negative tweets at 100%.

In conclusion, although average total tweets before and after COVID-19 is decreasing, the average for positive tweets shows growth. This indicates growing user satisfaction overtime. Based on the proportion of negative and positive tweets, most to least favored features in mobile banking are transaction, open new account, payment, transaction report, block, bank balance, top up, and finally log in. Since all features garnered more negative sentiment compared to the positive ones, it can be concluded that all nine assessed features require refinement. Based on highly mentioned words alongside some example tweets, points of improvements and complaints from customer can be derived. Some recommendations that can be given to banks to improve their mobile banking service performance are no extra fee policy to access any feature, providing follow up or record that can be recalled after every important action or transaction, making sure that the mobile banking app stays updated to customer needs while also keeping it steady, fast, and easy-to use, and better synchronization especially in transactions with third party entities such as other banks as well as e-money and digital wallet service provider.

LIMITATION

The social media data forms available for standard social media analysis are limited to text-based ones. The data is collected from Twitter and downloaded into a CSV file format. Social media has a lot of raw data requires a data cleansing and pre-processing process. Because these steps are a combination of manual and computerized steps, it is important for researchers to understand the language and context described in the tweet. Researchers also need to be familiar with mobile banking brands and features. As a result, only available tweets are written in Indonesian. The time frame of the collected data is from January 1, 2019 to December 31, 2020. January 2019 to February 2020 as "occurrence before COVID 19", from March 2020 to December 2020 as "occurrence after COVID 19".

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DECLARATION OF CONFLICTING INTERESTS

The author declares that there is no conflict of interest by any form.

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Appendix: Example Representative Tweets about Mobile Banking

Tweet Text	Interpretation	Sentiment
"Saya mau bayar Kartu kredit pakai mobile banking @BNI ga bisa udah 3 hari ini...gimana solusinya?"	Failure in credit card bill payment through mobile banking	Negative
"@kykuu @BNICall Udah bisa lewat App Mobile Banking BNI lhoo untuk blokir kartu debit"	Satisfaction over easy process in debit card blocking via mobile banking	Positive
"@HaloBCA buka rekening via mobile banking, video call nya kok ga nyambung terus ya? Sudah 3x hapus dan install ulang aplikasi"	Failure to commence video call for registration process	Negative
"@mandiricare min tolong dibntu, isi emoney dr mobile banking. Mutasi kepotong tp saldo tidak masuk. Telp ke 14000 tidak bisa terhubung"	Mismatch between transaction report and bank balance	Negative
"@askmenfess Sy top up pakak mobile banking mandiri/bca gratis kok"	Satisfaction over free-of-charge top-up process via mobile banking	Positive
"@kontakBRI mobile banking saya tidak bisa digunakan. Isi ulang, cek saldo, cek mutasi, semua tidak bisa padahal pulsa mencukupi. Kalau error tolong segera diperbaiki."	Failure in several mobile banking functions	Negative
"@HaloBCA Halo min , saya sehabis buka rekening di mobile banking bca ngga dapet informasi mengenai rekening saya ya , bisa dibantu ? Terimakasih"	Confusion for not receiving follow up after an attempt of opening new bank account via mobile banking	Negative