Logistics and Domestic Delivery Services Performance in Covid-19 Era: a Sentiment Analysis Approach

Yusak Sutikno and Zulkarnain Zulkarnain

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Yusak Sutikno

Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia, Kampus UI Depok 16424, Indonesia, yusak.sutikno@ui.ac.id

Zulkarnain

Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia, Kampus UI Depok 16424, Indonesia, zulkarnain@ie.ui.ac.id

ABSTRACT

The Covid-19 pandemic has hurt the business sector as badly as the health sector, including the logistics sector and delivery services. This sector is entering a period of uncertainty both in terms of government policies and demand which can affect the performance of the services provided. Evaluation needs to be done to see whether the logistics and shipping services sector, especially in Indonesia, is ready to face a pandemic. The availability of official service accounts of each service provider on Twitter social media as a forum for complaints and public aspirations can be used to evaluate service performance by measuring customer satisfaction levels through sentiment analysis before and during the pandemic. Various kinds of research on sentiment analysis have been carried out, but the time window sentiment analysis especially Time-Window Lexicon TF-IDF SVM integrating model approach has not been widely used. The data were obtained by scrapping the entire data for October 2019 until September 2020. ± 10.000 random stratified training samples data per month per service provider were taken and labeled using lexical approach for classification model creation The classification model was done with 89,01% accuracy, which is then deployed to predict the sentiment label of the whole data. This study provides the results that: (1) the Covid-19 pandemic significantly increase the number of tweet that indicate more people use the service, (2) the Covid-19 pandemic have decreased the performance of logistics and delivery services especially at the first three months of the pandemic period, and (3) the most frequent negative opinion that significantly affects service performance is late in delivery.

CCS CONCEPTS • Information systems---Information retrieval---Retrieval tasks and goals---Sentiment analysis

Additional Keywords and Phrases: Logistic sentiment analysis, Time window sentiment analysis, Indonesia sentiment analysis, logistic in pandemic

ACM Reference Format:

1 INTRODUCTION

Logistic and delivery service are the ones of the important sector that its performance affected to the economic growth. The logistic performance data index released by World Bank showed that the logistic and delivery service performance index has a positive correlation with the GDP [1]. The service performance index is rated on how efficiently the service was provided, which is currently Indonesia at 46th position that is worse than Thailand, India, Malaysia, or even Vietnam.

Since appear in early 2020, the Covid-19 pandemic harmed the business sector is as bad as the health sector, including the logistics and delivery services sector, in many countries. This sector is entering a period of uncertainty both in terms of government policy and demand that may affect the performance of the services provided. In Indonesia, the logistic and domestic delivery service became fundamental needs that its service performance may affect to overall society daily live [6]. To ensure that people's needs are not disturbed, the government has been issued a policy that the logistics and delivery services sector is included as one of the business sectors that can operate normally during a pandemic soon after the psbb policy is enforced.

Twitter is one of the largest microblogging social media used by 166 million Indonesians [2]. This user's majority are consumers, namely users who do not have a blog or content creator but frequently update their status. This large number of Twitter users can be a potential source of data insights for business research and development purposes. In addition, the availability of official service accounts of each service provider on Twitter social media as a forum for complaints and public aspirations is very suitable for service performance evaluation by measuring the level of customer satisfaction through sentiment analysis. Sentiment analysis, also called opinion mining, is a branch of text classification that has the aim of classifying text/documents containing opinions, sentiments, appraisals, attitudes, and emotions [9].

Opinions are very important for businesses and organizations because they always want to find consumers or public opinion about their products and services, especially the negative opinion because negative opinion or negative word-of-mouth (NWOM) is consumer response to dissatisfaction [16]. The majority of this Twitter's opinions themselves are negative opinions that it is expressing dissatisfaction about the service performance and many non-negative opinions that have very wide conversation topic that does not correlate with its service. Thus, this study only focuses on negative opinions as a basic analysis.

The main purpose of this study is to determine the correlation of the Covid-19 pandemic on the logistics and domestic delivery service sector by comparing service performance indicated by negative tweets before and during the pandemic using a time window sentiment analysis. In addition, text summarization is used to find out the most common topics that significantly affect service performance which can be used as an improvement input for the interested parties.

In the following sections, we present some of the sentiment analysis works that we use to define our approach to determining, comparing, and finally summarizing the logistics and domestic delivery service performance before and during the pandemic.

2 RELATED WORKS

Many studies related to sentiment analysis have been carried out using both lexicon and statistical approaches. In general, the lexicon approach utilizes lexical sources in the feature extraction process, while the statistical approach uses statistical calculations. The lexical approach is relatively new when compared to the statistical approach and theoretically has better accuracy and can avoid the possibility of reverse sentiment [4]. However, in practice, the lexicon approach requires a larger computational resource than the statistical method.

Several researchers have conducted studies for the lexicon sentiment analysis approach to microblogging in Indonesian. In lexicon sentiment analysis, lexical sources are a fundamental component of sentence weighting and labeling. The more complete the lexical source used, the more precise the results will be. Vania, Ibrahim and Adriani [12] also Koto and Rahmaningtyas [8] proposed a variant of the Indonesian sentiment lexicon to identify written opinions that can be used to analyze public sentiment on certain topics, events, or products/service reviews.

The statistical sentiment analysis approach is widely used and more computationally efficient but requires training data sets from labeled historical data to train classification models that we can build manually or adopt existing lexical sources to label training data [9]. Many researchers compared several classification methods to get better performance and accuracy for this sentiment analysis approach, and the majority of their studies gave the result that the Term Frequency – Invers Document Frequency (TF-IDF) feature extraction and Support Vector Machine (SVM) is one of the best classification methods especially for sentiment analysis task [7,10,11]. SVM is a mature classification method that can handle large data and appropriate for both linear and nonlinear regression [15].

To determine the effect of events on certain entities or to analyze trends through sentiment analysis, researchers use a time window approach to detect social media user responses to an event. Time window sentiment analysis uses the unit of time as the basis for sampling/scraping text and analyzes it based on the predetermined time. The time window sentiment analysis can identify the critical time or event effectively [13]. Time window sentiment analysis not only effective to identify the critical time or event, but also can be used for predicting or forecasting tasks such as a stock price prediction by correlating it with the trend of sentiment in the Twitter discussion [17]. Time window sentiment analysis can also be used to analyze and predict specific user sentimental paths based on historical data and can be applied in real-time conditions [18].

Text summarization is needed in sentiment analysis to find out important topics of sentiment. Text summarization is similar to sentiment analysis in terms of techniques and methods so that it is possible to be integrated [3]. Summary text with extractive method is suitable for products/services because this method is more accurate and displays the summary text as the original [5]. Textrank, a kind of document and topic-word topic distribution method, is one of the most widely used extractive text summaries and fast algorithms in which the method is carried out by assessing the sentence score based on the similarity of words among all documents and the top-ranking sentence is selected as representative of the whole document topics [14].

This study aims to determine whether the Covid-19 pandemic and related policies in its handling have a significant correlation with the customer sentiment on logistic and domestic delivery service. This study proposes the time window sentiment analysis by adopting lexical resources to create a labeled training dataset to classification whole data through statistical-based TF-IDF SVM sentiment analysis. Various kinds of research on sentiment analysis may have been carried out but the time window sentiment analysis especially the Time-Window Lexicon TF-IDF SVM integrating model approach has not been widely used. Finally, the textrank text summarization will provide a text summary about the most common topic of this sentiment.

3 METHODS

This study mainly determines and compares logistic and domestic delivery service performance before and during the pandemic as an effect of the Covid-19 pandemic. In this study, we are focused on negative opinion as a basic performance comparison since negative opinion or negative word-of-mouth is a customer response to dissatisfaction, which is the lower number of negative opinions it's mean higher service performance, and vice versa. Figure 1 shows the schematic diagram of the method proposed in this paper.

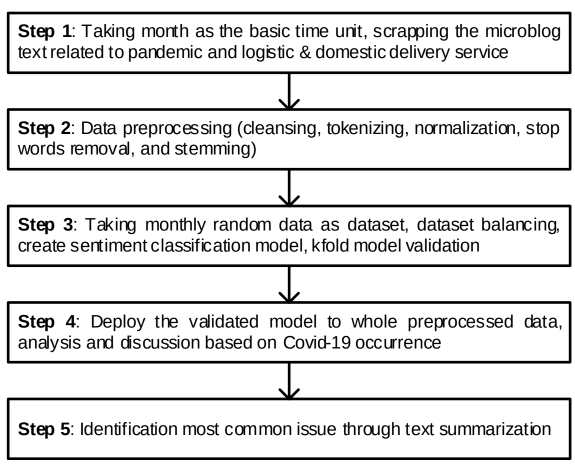

Figure 1: Schematic diagram of the time window sentiment analysis

The first step of the analysis begins by determining the analysis time span, namely October 2019 to September 2020 as the base time unit. The tweet data is taken from the top 5 representing logistic and domestic delivery service providers in Indonesia. Data collection was carried out by taking tweet data from Twitter which mentioned the official accounts of each service provider and the hashtag '#covid' & '#psbb' for tweet data about Covid-19 pandemic occurrence.

The next step is data preprocessing which consists of several processes, namely:

- Cleansing & Case folding. Cleaning is the process of removing non-alphabetical characters to reduce noise. The characters removed are punctuation marks, symbols such as the '@' sign for usernames, hashtags (#), emoticons, and URLs from websites. Case folding is done to convert all previously cleaned alphabet characters to lowercase.
- Tokenizing. This is a process of separating words from their constituent sentences which are necessary for further processing.
- Normalization. This stage is carried out to normalize shortened words, slang words, and misspelled words into Indonesian standard words.
- Stop word removal. This stage is done to eliminate words that are meaningless and have no effect on the sentiment analysis.
- Stemming. This process is done to change words that have affixes into words in their basic form. This process is only needed for the sentiment labeling process for the sample data. The Sastrawi python library is used at this stage.

Lexicon-based sentiment modeling begins by taking part of the preprocessed data by stratified random sampling method with service provider and month as the base of data elements. We adopt the lexicon source proposed by Koto and Rahmaningtyas [8] as the sentiment baseline with some adjustments to obtain a context-appropriate classification. After all the sample data have received their respective sentiment labels, then they are used as a training dataset for the TF-IDF SVM model classification train. The 10-fold cross-validation is used as the final stage of modeling to evaluate and test model performance. The model that has been created and validated is then deployed to classify the sentiments of all preprocessed data. The sentiment classification task has been completed, the analysis continues with the interpretation of insight data by correlating it to the psbb/covid-19 policy.

The extractive textrank text summarization method will be used to extract the most common issues/topics. This method is done by counting the most frequently used words or word similarity which are then used to rate the sentences containing those words. The sentence that has the highest score is a sentence that can be considered to represent the entire text document.

4 RESULT AND DISCUSSIONS

In this study, we use Python 3.8 software with related libraries and google collaboration notebook as the main analysis tool. The data was collected by scraping method using the Twitter Intelligence Tool (Twint) python library, month by month starting from October 2019 until September 2020 for each service provider, then combine it all at the end of the scrapping process. We use keyword respected to each service provider's Twitter official account to detect all tweets that mention their account. These keywords are '@JNE' and '@JNE_ID' for scraping data related to JNE service provider, '@jntexpressid' for JNT, '@PosIndonesia' for Pos Indonesia, '@sicepat_ekspres' for SiCepat, and '@IdTiki' for Tiki. We also use keywords 'covid' and 'psbb' to detect tweets about covid and psbb that indicate the pandemic occurred and psbb policy was enforced. The data collection phase was done in December 2020.

Total 354,999 data were collected with this method. This raw data contains at least 35 parameters, so we are only using the parameters required for the analysis. These parameters include:

- id – the unique code of each tweet
- date – date the tweet was posted
- origin – an additional parameter for service provider identity
- username – account information for the user who posted the tweet
- language – Twitter language settings used by the user
- tweet – text content posted by users

The next step is to carry out the pre-processing stage of this data. The preprocessing process consists of cleansing data, word case folding and tokenizing, word normalization, stopword removal, and stemming. From the preprocessing stage, we obtained 200,957 data which can then be used in the analysis. Most of the deleted data were tweets from the official account of the service provider itself, duplications of post retweets, and tweets from the account suspected as a dummy account. Table 1 shown the example data before and after preprocessing phase.

Table 1: Example data before and after preprocessing

Before preprocessing	After preprocessing (clean_tweet)
@PosIndonesia cek dm ya. Makasih	periksa dm terima kasih
@PosIndonesia mohon dm direspon	mohon dm respons
@PosIndonesia Min paketanku ko lama ya? https://t.co/xqwgkdoraE	paket kok lama
@sicepat_ekspres Resi No 000178369880 kenapa selalu statusnya unpick? status pengiriman "Paket gagal diambil sigesit Akmaludin Azam?	kenapa status unpick status kirim paket gaga, ambil akmaludin azam
@sicepat_ekspres min kalau criss cross itu knp ya :(paketku ga sampe2	criss cross kenapa paket tidak sampai

4.1 Covid-19 pandemic effect to tweet activity

The psbb policy came into effect in Indonesia, especially Jakarta, in early April 2020, based on PP 21 2020 about social distancing and restriction due to accelerating the corona-virus disease 2019 (Covid-19) handling. This is in accordance with tweet data about covid and psbb which were first tracked at the very late of March 2020 or the beginning of April 2020. Thus, based on this data, the calculation of this pandemic period starts in April 2020. Figure 2 shows the amount of tweet activity data before and during the pandemic that mentioning service providers account graphically.

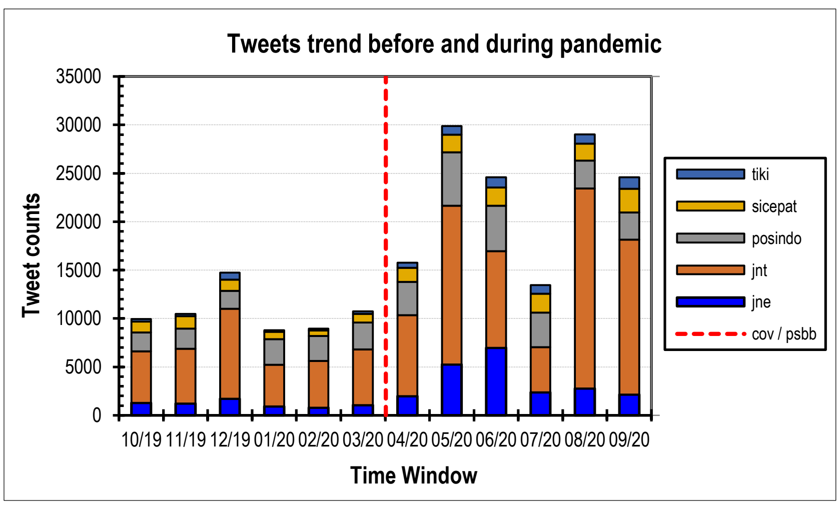

Figure 2: Tweet activity counts before and during pandemic

Figure 2 implicitly shows changes in the amount of data before and during a pandemic, where there is an increase in tweet activity during the pandemic period except in July 2020. However, statistical evidence is needed to prove whether there is a correlation between a pandemic and the increasing number of this tweet activity data.

Table 2: Spearman correlation and p-value test for tweet activity

provider	cov/psbb	jne	jnt	posindo	sicepat	tiki
cov/psbb		0.0002*	0.0484*	0.0002*	0.0002*	0.0011*
jne	0.8690		0.0114*	0.0058*	0.0003*	0.0001*
jnt	0.5794	0.6993		0.1993*	0.0666*	0.0092*
posindo	0.8690	0.7413	0.3986		0.0185*	0.0548*
sicepat	0.8690	0.8671	0.5455	0.6643		0.0001*
tiki	0.8208	0.8881	0.7133	0.5664	0.9021	

* p-value test

Statistical evidence to determine the relationship between the pandemic and this tweet activity data can be done by calculating the Spearman correlation and the p-value test between them as provides in Table 2. From this table, it can be concluded that the Covid-19 pandemic has a significant effect on the changes in tweet activity for all logistics and delivery service providers (p-value <0.05 in correlation with covid/psbb). This table also provides evidence that the Covid-19 pandemic has an impact on increasing the number of tweet activity for each provider, which is indicated by a positive correlation. From these facts, we can assume that there has indeed been a significant increase in the number of people use the service which has occurred to all providers.

4.2 Covid-19 Pandemic effect to service performance

A total of ±10,000 of preprocessed data were selected by stratified random sampling, then sentiment labeling was carried out using the Lexicon method. We use Koto's lexicon source as a basis for sentiment labeling. Koto's lexicon source is general nature, so we just took the words as needed, make some modifications and adjustments to fit them with the research context. The sentiment labeling process in this sample data resulted in 7,287 (72.84%) classified negative and 2.717 (27.16%) classified as non-negative then used it as a training dataset in the TF-IDF SVM classification model. This dataset has unbalanced polarity since the negative polarity is three times greater than the non-negative polarity which can cause overfitting/underfitting problems in the model learning process and need to be balanced. The balancing methods that commonly used is the over-sampling and down-sampling methods. In this study, the synthetic minority over-sampling technique (SMOTE) was used to balancing the data.

Table 3: Classification performance report

	Precision	Recall	F1-score	Support
Negative	0.9415	0.9053	0.9231	1458
Non-Negative	0.7696	0.8490	0.8074	543
Accuracy	0.8901	0.8901	0.8901	2001
Macro average	0.8556	0.8772	0.8652	2001
Weighted Average	0.8949	0.8901	0.8917	2001

By using the 80-20 train-test configuration on a balanced dataset, the trained classification model gave us relatively high performance in the test and validation stages. This classification model has an accuracy of 89.01%, an average precision of 85.59% (correct prediction), an average recall of 87.72% (the ratio of true negative or true non-negative), and 86.52 f1-score average (precision and recall weighted harmonic mean) with 2,001 of testing support data as shown in Table 3. The 10-fold cross-validation test for this trained model giving a score between 84.10-93.80% accuracy and 89.21% on average. Details of the validation results can be seen in the Figure 3.

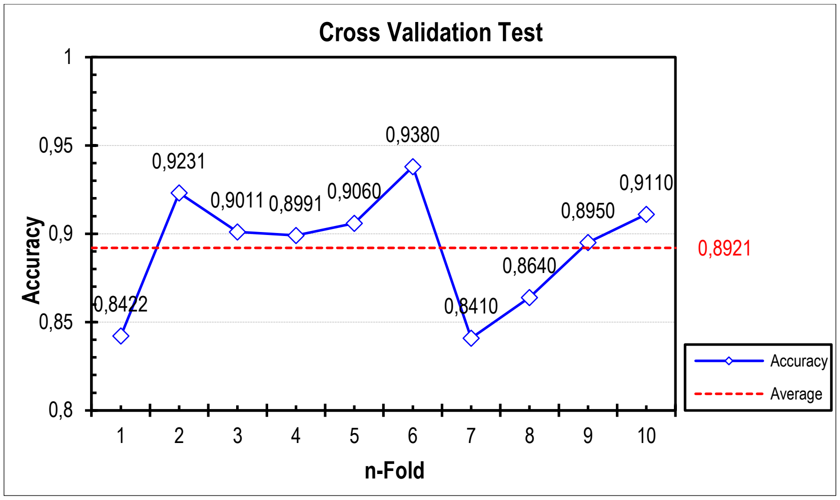

Figure 3: 10-fold cross validation test of TF-IDF SVM trained model

The deployment model across the data gives a sentiment polarity result similar to that of the sample. Where negative polarity dominates the sentiment classification, but slightly different in the proportion, namely 128,215 (63.80%) classified as negative polarity and 72,742 (36.20%) classified as non-negative polarity. The polarity comparison between them can be seen in the Figure 4.

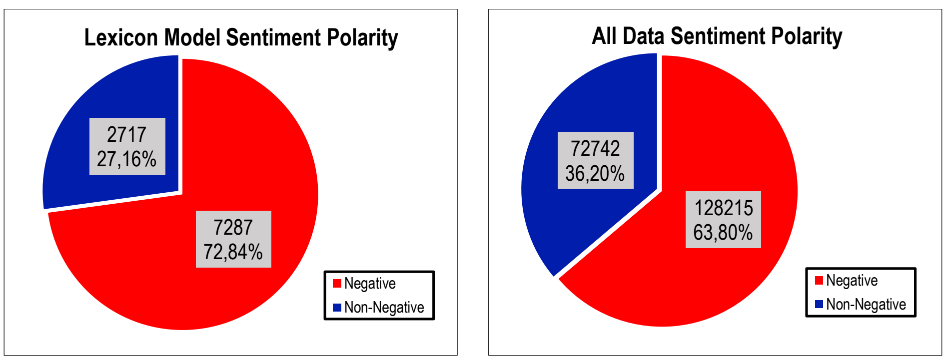

Figure 4: Polarity proportion between model and the whole data

Since we only use negative polarity as the basis for measuring service performance where the smaller the better, Figure 5 provides the negative polarity tweet for each provider service performance before and during the period of pandemic graphically. Figure 5 shows that there was a change in the amount of negative tweet data before and during the pandemic, where there was an increase in negative tweet activity during the pandemic period, especially in the first 3 months and . For this reason, we analyze the effects of a pandemic over a period of three months, namely the first three-months and the second three-months after covid/psbb enforced. Statistical testing for each analyzed time span after covid/psbb can be seen in Table 4 for the first three-months and Table 5 for the second three-months.

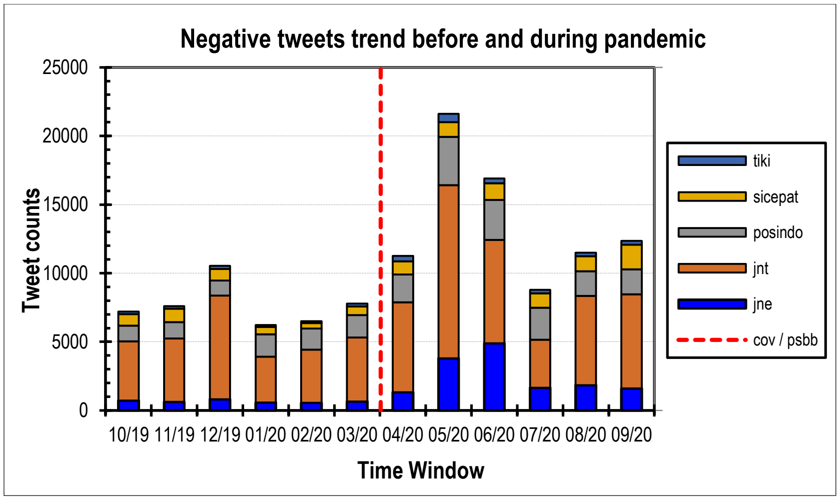

Figure 5: Negative polarity tweet before and during pandemic

The Spearman correlation and p-value statistic testing for the first three months of the pandemic, as shown in Table 4, gave the evidence that covid-19 pandemic decreases the logistic and delivery service performance significantly for all service providers indicate by positive correlation and p-value <0.05 in correlation with covid/psbb. This positive correlation means more negative tweets about the services or there has been a decline in the performance of the service.

By comparing the increasing number of tweets and the trend of negative polarity before and during the pandemic, it is shown that the increasing number of tweets leads to the increasing number of negative polarity also. With this fact, we can assume that more service was provided there are more customer dissatisfaction occur. It indicates that in general, our delivery system is not robust or they are not ready yet to deal with the demand fluctuation.

Table 4: Spearman correlation and p-value test for negative tweet for 1st three month of pandemic

provider	cov/psbb	jne	jnt	posindo	sicepat	tiki
cov/psbb		0.0066*	0.0255*	0.0066*	0.0255*	0.0066*
jne	0.8216		0.0002*	0.1875*	0.0001*	0.0005*
jnt	0.7303	0.9333		0.2242*	0.0016*	0.0009*
posindo	0.8216	0.4833	0.4500		0.2242*	0.2242*
sicepat	0.7303	0.9500	0.8833	0.4500		0.0072*
tiki	0.8216	0.9167	0.9000	0.4500	0.8167	

*p-value test

In the second three months of the pandemic, as shown in Table 5, the correlation between pandemics and negative polarity tweets provides slightly different statistical tests result. Spearman's correlation still has a positive value for all providers but the p-value is no longer significant as in the first. In this period, the significant correlation occurs only on JNE, Pos Indonesia, and SiCepat (p-value <0.05), while JNT and Tiki have no significant correlation (p-value >0.05).

This suggests that service providers have varying resilience and adaptability in response to this increasing demand. During this period, JNT and Tiki had better recovery and adaptation capabilities compared to JNE, Pos Indonesia, or SiCepat. The positive correlation between covid / psbb and negative sentiment but insignificant means that service performance is slowly returning to its pre-pandemic condition.

Table 5: Spearman correlation and p-value test for negative tweet for 2nd three month of pandemic

provider	cov_occur	jne	jnt	posindo	sicepat	tiki
cov/psbb		0.0066*	0.6382*	0.0066*	0.0062*	0.0639*
jne	0.8216		0.2054*	0.1544*	0.0041*	0.0037*
jnt	0.1826	0.4667		0.6682*	0.1942*	0.0159*
posindo	0.8216	0.5167	-0.1667		0.1942*	0.6059*
sicepat	0.8250	0.8452	0.4777	0.4770		0.0135*
tiki	0.6390	0.8500	0.7667	0.2000	0.7782	

*p-value test

4.3 Most common topic affecting the service performance

The main purpose of this text summarization is to find out what topics most common occur in negative tweets that affect service performance. This text summarization is done using the textrank method approach. This the most common tweet that affects logistic and domestic delivery service performance are:

- 'paket kok tidak sampai sampai'
- 'halo paket sudah sampai mana'
- 'paket sudah berhari hari belum sampai'
- 'paket kok tidak sampai'
- 'paket kok belum sampai'

This most common tweet basically has the same topic, which is late delivery. The problem of late delivery affects service performance during a pandemic, but it is not a problem that only occurs during a pandemic but is a classic problem that has not been resolved until now. It should be noted that this is the most common problem and occurs most often.

5 CONCLUSIONS AND FUTURE RESEARCH

5.1 Conclusions

This study provides the results that: (1) The Covid-19 pandemic had a significant impact on the increasing number of tweet activity indicate by its positive correlation. Thus, it can be concluded that there is an increase in the number of people who use the service during the pandemic means an increasing amount of delivery service demand which has occurred to all providers. (2) The Covid-19 pandemic significantly decreases logistics and delivery service performance for all service providers, especially in the first three months, indicated by increasing the number of negative tweets means increasing the number of dissatisfaction about the service. Increasing the number of services provided, but also increasing dissatisfaction against it means that the delivery system is not robust or the service provider capability is not ready yet to deal with fluctuations in demand, in our case is increasing delivery demand. The second three-month period shows the contrast of the recovery capability and adaptation between service providers. In this period, JNT and Tiki a better recovery capability and adaptation comparing to JNE, Pos Indonesia, or SiCepat. Although it still has a positive correlation between covid/psbb and negative sentiment, this value is no longer significant. This means that service performance is slowly returning to its pre-pandemic condition. Thus, we can conclude that the pandemic has decreased the overall delivery service performance, but the recovery capability and adaptation to normal conditions depend on each provider itself. (3) The text summary related to the most frequent complaint/aspiration that significantly affects service performance is talking about late delivery. May this need more attention about this problem because this is a classic problem that occurs most often.

5.2 Future Research

In this study, the performance measure relies on negative tweets in bulk, for further research we propose to use the service quality dimension (reliability, responsiveness, assurance, empathy, and tangibles) with sentiment analysis to get a better and specific evaluation. Theoretically, it can be done by sorting the terms/sentences according to each dimension of service quality in logistics and delivery services context.

In further research, it can be considered the use of the Latent Dirichlet Allocation (LDA) method as a text summary algorithm to get a better generalization of the topic, considering that the document-topic and topic-word distribution methods such as the text-rank approach currently used still have some shortcomings in terms of topic interpretation of the summarized text.

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