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Analyzing public perception toward COVID-19 vaccines in Indonesia

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ABSTRACT

The research is prompted by the dearth of studies addressing public perceptions of various COVID-19 vaccines in Indonesia using extensive datasets spanning and a wide timeframe. This study examined public perception toward COVID-19 vaccines in Indonesia using a dataset of tweets. We further detect whether there are any changes in sentiment toward each type of vaccine. The five most commonly used vaccines in Indonesia (AstraZeneca, Moderna, Pfizer, Sinopharm, and Sinovac) were analyzed for sentiment using a lexicon-based method: Valence Aware Dictionary and Sentiment Reasoner (VADER), with changes in sentiment detected using Pruned Exact Linear Time (PELT). The 280,826 tweets collected between 2021 and 2022, 39% were positive, 18% were negative, and 43% were neutral. While Indonesian citizens generally responded positively and neutrally to each vaccine, with Sinopharm and Pfizer receiving the highest sentiment scores and AstraZeneca receiving the lowest, some change points in sentiment were associated with real-world events. Jakarta had the highest number of tweets (22%), while Maluku had the highest sentiment score (0.498). A significant positive correlation was also found between the total number of tweets and two variables: new cases of COVID-19 (r=0.9, p=0.001) and total new deaths caused by COVID-19 (r=0.8, p=0.008). Overall, the discussion of COVID-19 vaccines is still ongoing, and Indonesian citizens tend to respond neutrally and positively regardless of location or time.

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1. INTRODUCTION

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is the virus that caused the Corona Virus Disease 2019 (COVID-19) illness. According to WHO, the symptoms for COVID-19 are varied, ranging from mild (such as fever, cough, loss of taste or smell) to serious (such as difficulty breathing, loss of speech, and chest pain) [1]. The first case of COVID-19 was confirmed in Wuhan, China in November 2019, and started to spread outside China in January 2020 [2]. Since then, the virus has spread rapidly throughout the world. On June 7th, 2022, there was a total of 536,021,397 confirmed cases and 6,321,719 deaths in the world as a result of COVID-19 [3].

Indonesia was ranked 19th in the world for the highest number of confirmed COVID-19 cases [3], and 6th in Asia. On December 12th, 2022, the number of infections had reached 6,704,268 cases, with a total of 160,311 deaths [4]. The first case of COVID-19 in Indonesia was confirmed on March 2, 2020 [5]. In response, the government tried to prevent the spread of the virus by implementing various levels of lockdown policies [6] and mandating vaccination. It is critical to prevent the spread of COVID-19. For this purpose, scientists began developing COVID-19 vaccines [7], which are now used in many countries around world. President Joko Widodo was the first to receive COVID-19 vaccination in Indonesia on January 13, 2021 [8]. To promote vaccination coverage, the Indonesian Ministry of Health lists thirteen different types of legal vaccines [9], while the five most commonly used vaccines in Indonesia are: Sinovac, AstraZeneca, Moderna, Sinopharm, and Pfizer. Today, Indonesia's COVID-19 vaccine coverage has reached 401,308,016 doses [10].

Twitter is one of the most popular social media platforms in Indonesia. Indonesia is ranked fifth in the world in terms of Twitter users (18,45 million) [11]. This massive amount of tweet data can be used to extract useful information, such as the public sentiment in Indonesia toward COVID-19 vaccines. We contend that this information is beneficial for the Indonesian government in making sound decisions. For example, because the Indonesian government is currently encouraging the public to get "booster vaccines," the findings of this study may be useful for health policymakers in determining which vaccines are appropriate for use.In this study, we conduct sentiment analysis on public perception toward the five most commonly used COVID-19 vaccines in Indonesia, i.e., Sinovac, AstraZeneca, Moderna, Sinopharm, and Pfizer. The results of the sentiment scores are then used for temporal, geographical, and correlation analysis. Temporal and geographical analyses are performed to identify the variation in sentiment for each type of vaccine across time and geography, respectively. Then, correlation analysis was conducted to identify the relationship between some potentially related variables.

This study was aimed to analyze the public sentiment toward COVID-19 vaccination especially on five types popular vaccine types in Indonesia. We raise four research questions in this study: i) How does public perception toward five types of vaccines in Indonesia?; ii) Does public sentiment of each vaccine Indonesia changes across time?; iii) Does public sentiment in Indonesia differ based on geographic location in Indonesia?; and iv) Is there any significant correlation between related variables (total tweet, sentiment score, new case, new death)?. To answer these research questions, we collected the twitter dataset from January 2020 to December 2021 with total 280,826 datasets categorized based on vaccine type.

2. RELATED WORKS

A lot of previous studies on sentiment analysis towards COVID-19 focuses on improving the accuracy of sentiment classification model [12]–[15]. In contrast to them, this study did not develop a classification model, but we analyze the public sentiments on five types of COVID-19 vaccines using an available sentiment analysis tool and look deeper into temporal and geographical perspectives.

Analyzing public sentiments using existing sentiment analysis tools or lexicons have also been explored in previous work. Yousef *et al*. [16] examined the effect of public health campaigns and COVID-19 related events on sentiment and vaccine uptake, while the sentiment was identified using AI-based tool, BytesView. Shim *et al*. [17] analyzed changes in public perception of COVID-19 vaccines in Korea using Korean sentiment lexicon. Wang *et al*. [18] and Melton *et al*. [19] examined examined public sentiments and opinions regarding the COVID-19 vaccine using TextBlob. In our study, Valence Aware Dictionary and Sentiment Reasoner (VADER), is used to analyze Indonesian public sentiments towards COVID-19 vaccines.

A previous study that is mostly related to our study is that of Liu *et al*. [20] analyzed public attitudes toward COVID-19 vaccines over a three-month period using English-language tweets and the sentiment analysis tool VADER [21]. Their analyses focused on the COVID-19 vaccine in general and did not examine changes in sentiment toward specific types of vaccines. Our study differs from them in that we analyze public perception on specific types of COVID-19 vaccines, rather than COVID-19 vaccines in general. Furthermore, while Liu *et al*. analyzed the sentiments in English-speaking countries using English-language tweets over a three-month period, we analyzed sentiments in Indonesia using tweets written in Bahasa Indonesia over a two-year period. Their geographical analysis research was conducted at the country level, whereas our research was conducted at the province level when analyzing the variation in sentiment.

Sentiment analysis of COVID-19 vaccines has received a lot of attention in Indonesia [22]–[32] All the analyses, however, are focused on the development of more accurate classification models using machine learning and deep learning models. A few previous studies have been conducted on Indonesian attitudes toward specific types of vaccines [23], [25], [26]. However, these studies only used a few types of vaccines and a short-time interval, and did not analyze temporal, geographical, or correlational data. In this study, we use a broad range of vaccines and long-time interval data. While Saadah *et al*. [24] who worked on classifying the sentiment for Indonesia vaccine tweets actually conducted the geographic analysis based on province in Indonesia, however, they focused on observing the opinion polarity for free and paid vaccination program. But our focus in this work is to analyze public sentiments towards COVID-19 vaccines in general.

3. RESEARCH METHOD
3.1. Data collection
We used Twitter API for Academic Research and the Python library Tweepy to collect Indonesian-language tweets about COVID-19 vaccines from January 1, 2020 to December 31, 2021. We only retrieved non-retweeted tweets and tweets with the language code "in" which means that their text was identified as Bahasa Indonesia by Twitter. To crawl tweets about Sinovac, Moderna, Sinopharm, and Pfizer, we used the corresponding queries: "vaksin sinovac", "vaksin moderna", "vaksin sinopharm", and "vaksin pfizer", respectively. Because AstraZeneca is frequently spelled as AstraZeneca, Astra Zeneca, or AZ, our query to collect tweets about this vaccine is ((vaksin astrazeneca) OR (vaksin astra zeneca) OR (vaksin az)). Note that "vaksin" is the Indonesian word for vaccine, and we included that term at the beginning of our queries to filter out tweets that are possibly not belong to Bahasa Indonesia or are not related to the vaccine. In total, there were 378,697 tweets retrieved by our queries. We filter out tweets that discuss more than one type of vaccine. This process resulted in a total of 280,826 tweets.

3.2. Sentiment analysis
A sentiment analysis tool VADER is used to assign a sentiment score for each tweet [21]. VADER is chosen because it has been demonstrated to perform well for sentiment analysis on social media datasets such as Twitter [20]. In previous studies, VADER was shown to outperform human annotators in predicting the sentiments of tweets [21]. In general, VADER generates a sentiment score (compound score) for a given text that is further used to classify the tweet as positive (compound score >=0.05), negative (compound score <=0.05), or neutral (compound score -0.05 <compound <0.05). In order to use VADER, the tweets in our dataset were first translated into English using the Python library googletrans, which uses the Google translate API to perform translation.

3.3. Temporal analysis
Temporal analysis is performed using Pruned Exact Linear Time (PELT) [33] algorithm to determine the trend of sentiment scores. Here, PELT is applied to detect change points in the sentiments scores across times. PELT applied the procedure that minimized the cost function to find change points. PELT also could detect more change points compared to other change points method [33]. It has been demonstrated that PELT is a precise research method with a high sensitivity to detect change points [34] and it is efficient and more accurate [33]. Before PELT is applied, following Liu *et al*. [20], 14-day moving average is applied to smooth out the sentiment scores fluctuations and obtain the trends of these scores.

3.4. Geographical analysis
In order to examine the variation in sentiment across Indonesian geography, we identify tweets that contain user's province information using a simple lookup against the list of Indonesian provinces and cities that we built. The resulting tweets are then grouped according to their province. Since in 2021, Indonesia still has 34 provinces, then there are 34 province categories. The sentiment scores of tweets in each province were calculated. Furthermore, we also applied One-Way ANOVA using the SPSS tool to examine if vaccine type had a significant effect on sentiment scores.

3.5. Correlation analysis
Pearson Correlation is used to analyze the correlation between some potentially related variables, such as number of confirmed cases, number of deaths, number of tweets, and sentiment scores. These variables were calculated for each month, and then the correlation was calculated based on these values. The information about the number of new cases of COVID-19 as well as new deaths because of COVID-19 in Indonesia within 2020-2021 were obtained from the official WHO dashboard for COVID-19.

4. RESULT
4.1. Total tweets for each vaccine type
A total of 280,826 tweets were collected containing five different types of vaccines that were posted between January 1, 2020 and December 31, 2021. Table 1 summarizes the total tweets for each vaccine. In general, the number of tweets discussing about COVID-19 vaccines in 2021 is higher than that in 2020 because the vaccination rollout in Indonesia starts in January 2021. The type of vaccine that is mostly discussed by Indonesian public is found to be Sinovac, then is followed by AstraZeneca. These two vaccines are in fact the earliest vaccines used in Indonesia. Sinovac was started to use in Indonesia on January 13, 2021 [10] and AstraZeneca was around March-April 2021.

Table 1. Statistics of total tweet for each vaccine

No	Vaccine type	Total tweets 2020	2021	Overall
1	AstraZeneca	2,485	71,924	74,409
2	Moderna	1,863	24,493	26,356
3	Pfizer	6,407	33,672	40,079
4	Sinopharm	599	7,484	8,083
5	Sinovac	16,667	115,232	131,899
	Total	28,021	252,805	280,826

In addition, among 5 types of COVID-19 vaccines studied in this work, Indonesia receives the highest doses for these two vaccines. Sinopharm has the lowest number of tweet because among 5 vaccines, it is the least used vaccine in Indonesia.

4.2. The results of sentiment analysis

Table 2 shows the average sentiment score for each type of vaccine. We found out that there are 39% positive tweets (108.817 tweets), 18% negative tweets (51.384 tweets), and 43% neutral tweets (120.613 tweets). We found out that the average sentiment score calculated by VADER for all vaccine types is >0.05, indicating that the sentiments for all vaccines are positive. Sinopharm and Pfizer had the highest average sentiment scores, while AstraZeneca had the lowest. This indicates that Sinopharm and Pfizer were the two most preferred vaccines in Indonesia, while AstraZeneca was the least.

Table 2. Average sentiment score for each vaccine type

Vaccine type	Average sentiment score 2020	2021	Overall
AstraZeneca	0.200	0.151	0.152
Moderna	0.407	0.204	0.220
Pfizer	0.313	0.216	0.233
Sinopharm	0.348	0.251	0.258
Sinovac	0.224	0.204	0.207
Overall Average	0.298	0.205	0.214

The total tweets for each sentiment category for each vaccine is presented in Figure 1. We can see that in general, for each vaccine, the number of neutral tweets is the highest, followed by the number of positive tweets, then the negative tweets. It indicates that all COVID-19 vaccines receive mostly neutral and positive sentiments from Indonesian public.

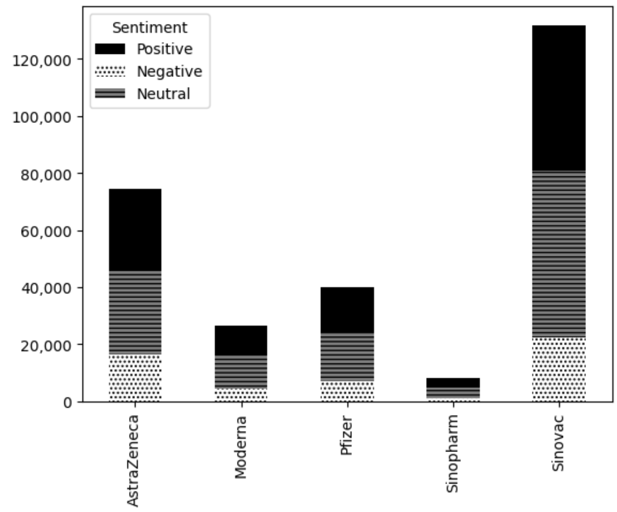

Figure 1. Total tweets by sentiment classification

We calculated a One-Way ANOVA on sentiment scores across all vaccine types to examine the statistically significant differences of sentiment scores between vaccine types. The results show that the type of vaccine had a significant effect on sentiment scores ($F(4,280826)=91.690$, $p<0.001$). A Tukey post-hoc test was then performed to determine which pairs of vaccine types had significantly different sentiment scores. The result shows that all vaccine types appear to have significant differences in sentiment scores toward AstraZeneca, which indicates that Sinopharm, Pfizer, Sinovac, and Moderna are significantly more preferred than AstraZeneca. Then, Sinopharm is also shown to have significant differences in sentiment scores with all other vaccines, indicating it is valued/perceived more positive than all other vaccines by Indonesian public.

4.3. The results of temporal analysis

In this section, we will explain change points for each type of vaccine and explain the reasons behind it. The change points can be seen in Figure 2 (see the red lines). The blue lines illustrates the 14-day moving average of sentiments scores for each vaccine, while the vertical red lines illustrate the change points detected. The change points indicated that some sentiment scores were significantly increasing or decreasing.

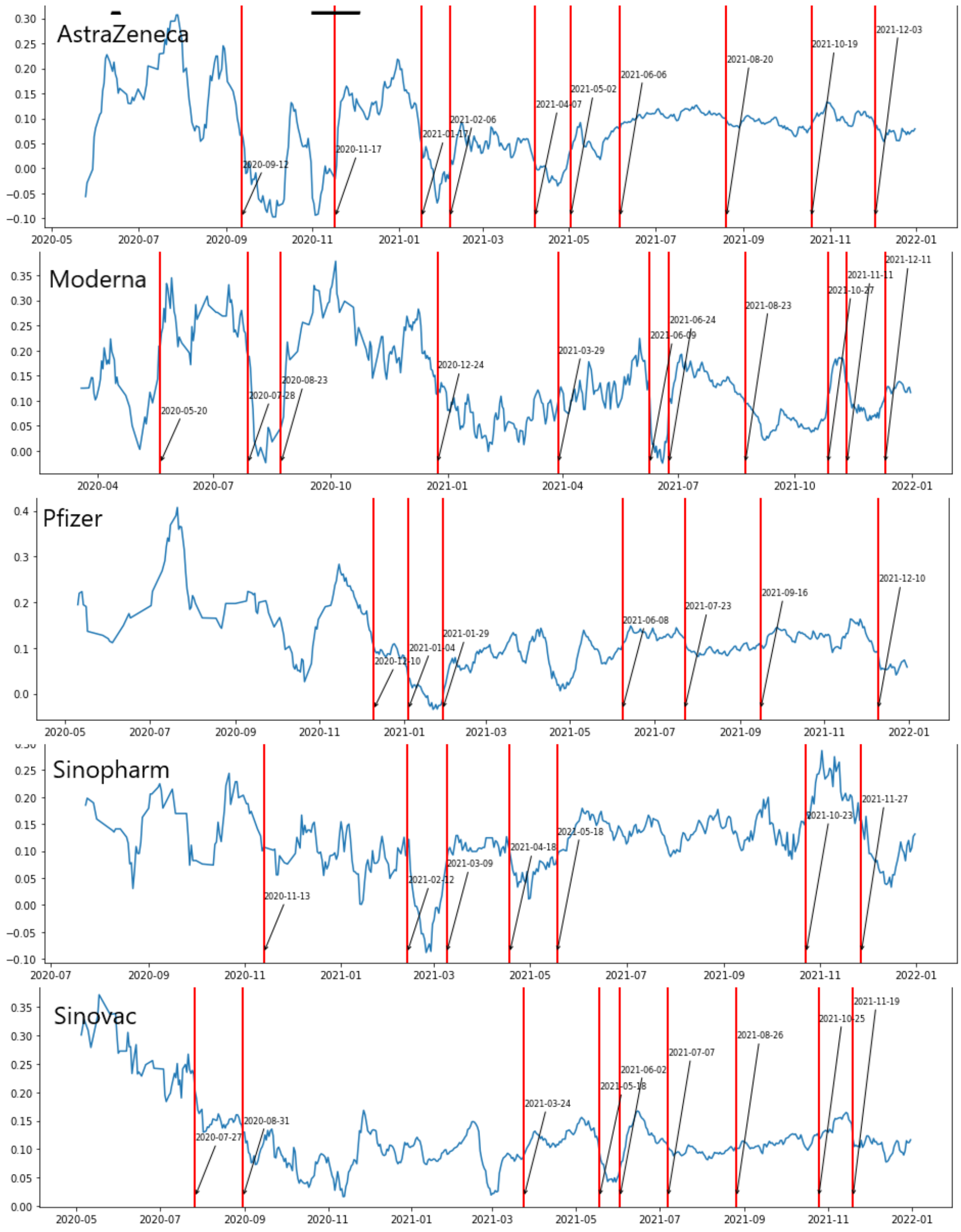

Figure 2. Change points of sentiment scores across time

For the Sinovac vaccine, the first change point occurred on July 27, 2020, when we identified an increase in sentiment score. This shift occurred as a result of tweets claiming that Sinovac had no serious side effects and was proven to be safe. The next change point occurred on August 31, 2020, indicating a decrease in sentiment score, with most of the discussion centered on out of stock Sinovac.

For AstraZeneca, the first change point was observed on September 12,2020, when the sentiment score decreased drastically. This was due to the issues around AstraZeneca vaccination such as side effect of AstraZeneca, disbelief to AstraZeneca efficacy and the misleading information that AstraZeneca caused the blind. These factors collectively led to a sharp decline in public trust and confidence in the AstraZeneca vaccine, triggering a notable shift in public sentiment towards the vaccine.

For the Pfizer vaccine, the first change point was observed on December 10, 2020. There were several tweets about the Pfizer vaccine only providing an average amount of antibodies, implying that some Pfizer vaccine recipients have lower antibody levels and less protection. This discussion caused the sentiment score to fall. The sentiment score stay in negative till the beginning of 2021 since there were many issues about serious side effects of the Pfizer vaccine, ranging from allergic reactions to death. The first change point for Moderna occurred on May 20, 2020, when we observed that the sentiment score was gradually increasing. The majority of the tweets discussed the third phase of the Moderna clinical test [35] and Moderna was shown to produce antibodies. However, on 2021 several change points shown to be decreasing because Moderna was targeted to the health workers and was inaccessible for public that caused public angers. For Sinopharm, the first change point occurred on November 13, 2020 when we noticed a decreased in its sentiment score, with most of the discussion centered on collaboration Indonesia and Republic Of China on vaccine production, where some people had the negative thoughts of China. The sentiment score increased as a result of these positive tweets. The score rose in on November 27, 2021 in response to tweets claiming that Sinopharm had obtained an emergency use permit for 2021 [36].

4.4. The results of geographical analysis

Figure 3 depicts the distribution of Overall, there are 91,379 tweets with province location information out of a total of 280,814 tweets. To obtain the tweets that contained province location, first we identify tweet that contained terms of cities or provinces in Indonesia. We mapped city level to province level. We mapped the location tags to 34 provinces in Indonesia. Finally, we obtained 34 tweet groups according to the province. Jakarta has the highest number of tweets, followed by West Java, East Java, Central Java, and Yogyakarta. While the lowest number of tweets gained by West Papua province.

Sentiment scores across all provinces in Indonesia. The stronger the color indicates the higher the sentiment scores. It implies that the more positive the attitudes of public towards COVID-19. The sentiments in all provinces (except West Papua) are classified as positive, as they are larger than 0.05. This indicates that Indonesian public in any provinces tend to react positively to the COVID-19 vaccines. The sentiment scores of West Papua may be inaccurate since this province only has 6 tweets.

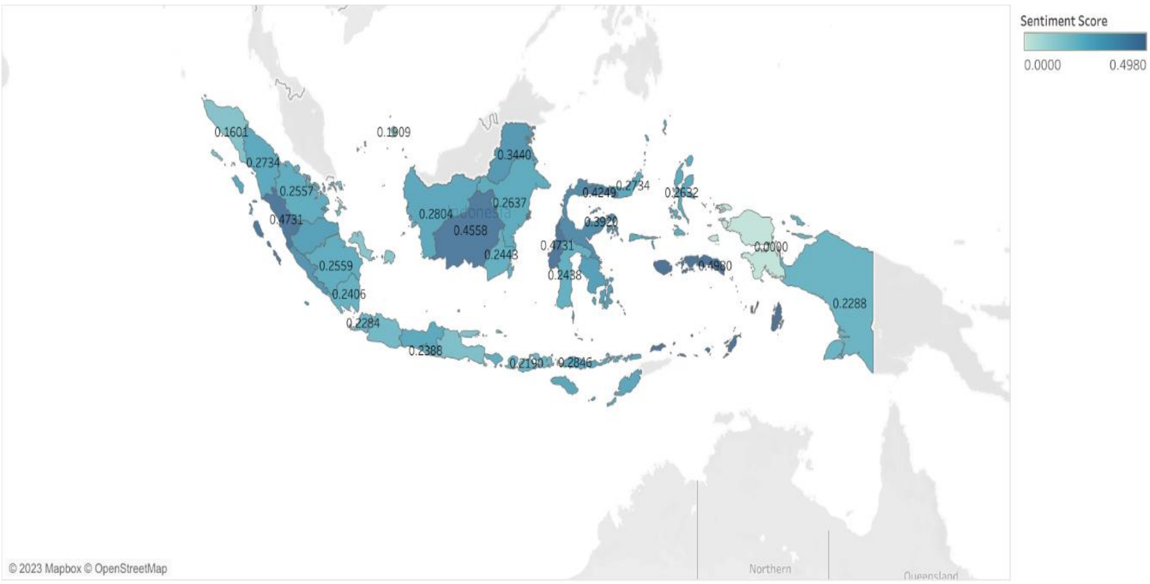

Figure 3. Sentiment score distribution in every province

It appears from the figure that the province with the strongest blue color is Maluku with the sentiment score of 0.498. It is followed by West Sumatera (*Sumatera Barat*), West Sulawesi (*Sulawesi Barat*), and Middle Kalimantan (*Kalimantan Tengah*), and Gorontalo provinces, with the sentiment scores of 0.4731, 0.4731, and 0.4558, 0.4249, respectively. The result of one-way ANOVA test shows that there is significant differences of sentiment scores between provinces ($F(33, 91379)=91.690$, $p<0.001$). It indicates that there is significant effect of province on the sentiment scores.

4.5. The results of correlation analysis

The correlation analysis examines the correlation between the total number of tweets, the total number of positive, negative, neutral tweets, new deaths, and new cases, followed by the relationship between sentiment score, new deaths, and new cases. We discovered a strong positive correlation between i) total tweets and new cases; ii) total tweets and new deaths; iii) total positive tweets and new cases; iv) total positive tweets and new deaths; v) total negative tweets and new cases; vi) total negative tweets and new deaths; vii) total neutral tweets and new cases; viii) total neutral tweets and new deaths. This demonstrates that the increase in total tweets was linearly proportional to the increase in new confirmed cases and confirmed deaths. Significant correlation between sentiment scores and new deaths as well as new cases, however, were not found since the p-value is greater than 0.05.

5. DISCUSSION

This work used twitter data to observe about people's opinion and sentiment regarding COVID-19 vaccine in Indonesia. By applying sentiment analysis tools; VADER, to classify the tweets into three classes, positive, negative and neutral. The result we obtained showed that our dataset dominated by neutral tweets by 43% (120,613 tweets) following by positive tweets 39% (108,817 tweets) and negative tweets 18% (51,384 tweets) and the amount of tweet started to increase drastically at 2021 where the people discussed about the vaccination more than the previous year. This is reasonable because the vaccination rollout in Indonesia starts in January 2021 [8].

Our results showed that the majority of Indonesian tend to react neutrally upon a vaccine policy even though the vaccination program surrounded by the misleading information [37]. Furthermore, the vaccination coverage in Indonesia reach to 60% from the total population [4]. Our result is different from Wang *et al*. [18] and Melton *et al*. [19] who reported that in general, public in United States of America tend to react positively toward COVID-19 vaccine and the positive sentiment increased as more people got vaccinated. Our results are also different from Yousef *et al*. [16] who demonstrated that negative sentiment was dominated in their dataset on Australia vaccination program on Twitter. Nevertheless, our result was similar with Choi *et al*. [38] who demonstrated that public sentiments towards COVID-19 vaccines in South Korea were dominated by neutral sentiment.

We applied PELT, to observe the change points of sentiments within 2020-2021. Our findings identified 10 change points in average for each type of vaccine. This is almost similar with the finding of Liu *et al*. [20] who also applied PELT in their study and identified 8 change points. Although Liu *et al*. [20] dataset was ranged in four months (November 2020–February 2021) while our dataset ranged for 24 months (January 2020–December 2021), but we found comparably similar number of change points. In our research, several change points indicated the vaccine efficacy that results in the extremely increasing sentiment score. Our result similar with Liu *et al*. [20] who detected a change point when Pfizer was announced to achieve 90% effective rate.

Furthermore, we conducted geographic analysis to get the sentiment polarity based on provinces in Indonesia. Overall, we mapped our dataset to 34 provinces in Indonesia. We found out that Jakarta placed the top as the highest province in total tweet, as the capital city of Indonesia, Jakarta was being the central of information where the twitter user is actively discussed about the latest vaccination information, the sentiment also dominated by positive sentiment. In this case, our result similar with Liu *et al*. [20] where they stated that Washington DC as the capital city of the United States dominated by positive sentiment. This shows that both capital city in the United States and Indonesia obtained the positive sentiment score as the majority.

Finally, we applied Pearson correlation analysis to conduct the correlation between seven variables: total tweet, total positive tweets, total negative tweets, total neutral tweets, sentiment score, new case, and new deaths. A study conducted by Shim *et al*. [17], had similar variables to conduct correlation analysis using social media data in Korea, but our result differed from them. We discovered a strong correlation between total tweets and new cases ($r=0.9$, $p=0.001$), and total tweets and new deaths ($r=0.8$, $p=0.008$), but did not find significant correlation between sentiment scores and new cases or new deaths. However, the findings differed from those of Shim *et al*. [17], who found some correlation between sentiment score and newly confirmed cases, but no significant correlation between the number of tweets and the number of confirmed COVID-19 cases. Then, we also discovered the strong correlataion between total positive, negative, neutral tweets to new case and new deaths. Which show that for every increasing of total positive, negative, and neutral tweet grow linearly with the daily total confirmed cases and new deaths.

The study faced some notable constraints, including the fact that the majority of tweets in the dataset were written in slang language, which is a non-standard language that is commonly used in informal communication. This presented a significant challenge to the study, as slang words can be highly contextual and difficult to interpret, even for native speakers. Additionally, the dataset also included tweets written in Malaysian language, which is similar to Indonesian but has some notable differences. This made it more challenging to accurately classify the sentiment of these tweets. Despite these constraints, the study was able to provide valuable insights into the sentiment of the Indonesian public towards COVID-19 vaccine, which can be useful for policymakers and public health officials in their efforts to encourage vaccine uptake.

6. CONCLUSION

In this study, we analyzed public sentiment toward COVID-19 vaccinesin Indonesia. The analysis unveiled a diverse spectrum of sentiments within the tweets. A substantial portion reflected positivity, while another segment conveyed negativity, and a significant proportion maintained a neutral standpoint. The sentiment scores varied between different vaccines, with Sinopharm being the most preferred and AstraZeneca being the least preferred. The sentiment toward each vaccine also changed over time, with various topics influencing the sentiment scores. Additionally, we conducted a geographical analysis and discovered that public sentiment differed between provinces. The top-three provinces producing the most tweets are Jakarta, West Java, and East Java. Three provinces with the highest sentiment scores are Maluku, West Sumatera, and West Sulawesi. Finally, the correlation analysis revealed significant positive correlations between various pairs of variables, but no significant correlation was found between sentiment scores and new cases or deaths.

Our findings answer all four research questions. The results suggest that public sentiment toward COVID-19 vaccines in Indonesia tends to be neutral or positive, but varies between vaccines and provinces. The study highlights the importance of monitoring public sentiment and identifying the factors that influence it, as this information can inform vaccine distribution and communication strategies. Future research will involve applying a pre-trained language model to the dataset, aiming to enhance performance rather than relying on lexicon-based methods.

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