


# The Sentiments of Indonesian Urban Citizens Regarding the Lockdown-Like Policy During the COVID-19 Pandemic: A Path Towards an Urban E-Planning Process in a Pandemic Situation

## INTRODUCTION

Zulfikar Dinar Wahidayat Putra, Gadjah Mada University, Indonesia\*

 <https://orcid.org/0000-0001-9280-4425>

### ABSTRACT

Indonesia implemented large scale social restrictions (LSSR) to cope with COVID-19. This policy generated various opinions between people that demonstrated their sentiments in daily life and social media. This study aims to analyse the sentiments of Indonesian urban citizens with respect to the policy. Using Drone Emprit Academic, a data mining tool that retrieved data from Twitter, this study examined tweets that mentioned “Pembatasan Sosial Berskala Besar” or “PSBB” from March 2nd, 2020 to January 11th, 2021. It reveals that significant events in the real world influence the sentiments pattern and classification during that particular period. The spatial distribution of the tweets reveals that the conversation is concentrated in cities throughout Java. Twitter-based sentiment analysis can be an alternative method for the government to monitor and evaluate its policies in the future, specifically in a pandemic situation.

### KEYWORDS

Digital Planning, E-Planning, Grassroots Planning, Large-Scale Social Restrictions, Machine Learning, Planning Process, Sentiment Analysis, Smart Cities, Social Media, Twitter, Urban Planning

The world is currently fighting the Novel Coronavirus Disease 2019 (COVID-19), which was initially reported by the World Health Organisation (WHO) China Country Office after it detected an unknown pneumonia virus in Wuhan City, Hubei Province, China, on December 31<sup>st</sup>, 2019 (WHO, 2020a). The disease became an outbreak when on January 13<sup>th</sup> – 20<sup>th</sup>, 2020, Thailand, Japan and the Republic of South Korea confirmed similar cases (WHO, 2020a). Since then, most countries have confirmed cases of the virus. As of January 2021, virtually every country was exposed to this pandemic, with more than 80 million confirmed cases and approximately 2 million confirmed deaths (WHO, 2021a). In March 2020, the WHO announced that COVID-19 was a global pandemic. Subsequently, most countries implemented various policies to combat the spread of this virulent disease.

With regard to Indonesia, the first case was reported on March 2<sup>nd</sup>, 2020, in Depok City. Since then, confirmed cases increased, as of January 2021, more than 900,000 cases were confirmed and more than 25,000 deaths confirmed (WHO, 2021b). On March 31<sup>st</sup>, 2020, the President issued a “lockdown-like”

DOI: 10.4018/IJEPR.297515

\*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

policy by means of Government decree number 21/2020 on the implementation of “Large Scale Social Restrictions” (LSSR) to manage the COVID-19 pandemic. The policy has become a guideline for government officials across Indonesia to reduce the spread of the virus domestically on a large scale. However, the policy does not imply a lockdown because it only limits the mobility and activities of people within a city. The policy stated that the minimum restrictions for limiting the spread of COVID-19 is the closure of schools and offices (working/studying from home), limiting religious activities, along with restricting activities in public places. The decree does not mention the minimum number of COVID-19 cases within a city to implement the LSSR. It can be enforced by the Governors and the Regents/Mayors by assessing the situation in their area of authority. On account of this procedure, several issues emerge, such as the fragmented policies pertaining to the implementation of the LSSR throughout provinces and cities in Indonesia and the challenges related to restricting office-related activities (i.e., services-based offices), besides those performed in public places (i.e., traditional markets).

The policy generated discussion between people, with people revealing their sentiments on social media and in daily life. According to data provided by Wearesocial & Hootsuite (2021), 57% of people live in urban areas and 345.3 million people use mobile connections (125.6% of the total population), comprising 202.6 million internet users (73.7% of the total population), whereas 170 million people are active social media users. Twitter is a social media commonly used by most Indonesians, with more than 60% of Indonesians being active social media users (Wearesocial & Hootsuite, 2021). Demographically, people aged 18-34 dominate the use of social media (more than 50% of total users), with male users dominating (Wearesocial & Hootsuite, 2021). Furthermore, Indonesian users typically use Twitter to conduct conversations on prominent actual events on a text-based post, making it much more straightforward to track sentiments that emerge from each tweet. However, there is a dearth of studies concerning Indonesian urban citizens’ sentiments towards the LSSR policy and how this could affect urban management decision-making during COVID-19. From the perspective of urban planning, these sentiments could provide a more profound sense of how urban citizens react to a situation, which overlaps with aspects within the urban area, such as economy, social, activity and mobility. This study aims to analyse the sentiments of Indonesian urban citizens on the subject of the lockdown-like policy throughout Indonesian cities. Two research questions were raised to achieve the objective: (1) What is the pattern of Indonesian urban citizens’ sentiments regarding the lockdown-like policy? (2) What is the spatial distribution of the sentiments? It should be mentioned that the data and analysis on the sentiments and its spatial distribution primarily employed the Drone Emprit Academic (DEA) tool, which will be explained in section 3.

## **THEORY**

### **Sentiment Analysis**

An urban area is a field of social practice where people interact and share their views towards current things occurring in a city. They need to communicate to make the interaction happen. A type of communication is an opinion that becomes a form in relation to revealing their views towards a city. It can include an opinion on the quality of city services, current and future urban policies, besides urban issues (Ciuccarelli et al., 2014). In this digital era, opinion can be stated via social media. An opinion that is expressed by way of social media is commonly recognised as sentiment that can be further analysed (Pozzi et al., 2017). According to Liu (2012), sentiment analysis focuses on mining and investigating people’s opinions regarding certain objects, such as products, organisations, issues and trends. The term sentiment refers to a person’s positive, negative or neutral feelings that appear as a result of their opinion (Liu 2017). Liu (2015), explained that a neutral feeling can be assumed as a “no opinion.” In the context of urban planning and management, this sentiment can be a valuable material used to make a shrewd planning decision (Thakuriah et al., 2017; Liu, 2015).

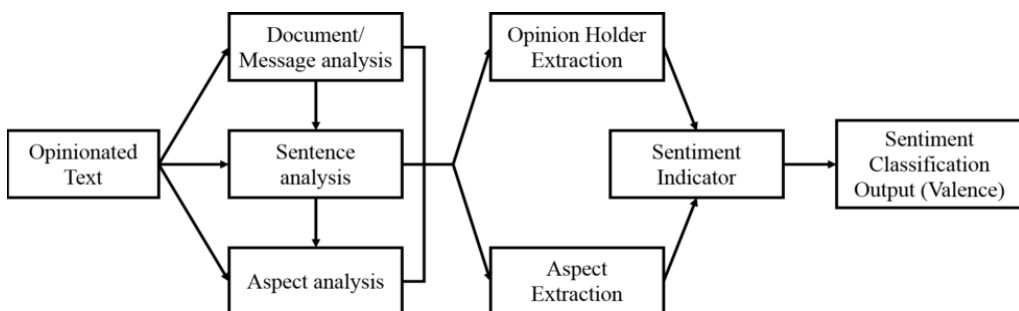
Sentiment analysis is a natural language problem (see Liu, 2012) and is commonly analysed using lexicon-based or machine learning approaches. The lexicon-based approach focuses on the collection of the

opinion's words to be compared with the synonyms and antonyms of a word within dictionaries (dictionary-based) or labelled by using semantics analysis (corpus-based) (Prakash & Aloysius, 2019; Liu, 2015). The Machine Learning approach focuses on the classification of opinion's words by comparing them with trained and tested datasets that either use predefined categories (supervised learning) or without predefined categories (unsupervised learning) (Verma & Thakur, 2018; Liu, 2015). Most scholars ascertained that the result of the machine learning approach is more accurate than the lexicon-based method (Verma & Thakur, 2018; Kharde & Sonawane, 2016; Liu, 2015). This is because the machine can dynamically decide on opinion's words without depending on the lexicon words database. The machine continuously learns words that are fed into it and increases its accuracy gradually. Additionally, continuous learning will deliver more reliable results when supervised (validating samples of the results over time) (Yadav et al., 2021).

Through both approaches, sentiment analysis is predominantly investigated in three different task levels, from higher to smaller levels, namely document/message level, sentence level and aspect level (Pozzi et al., 2017; Liu, 2012). At the document/message level, the machine will be given a task to classify all of the feelings found within the document/message. This is based on the assumption that a document/message contains a single entity that is too bias to be taken for a conclusion (Liu et al., 2015). Hence, a more detailed task is performed at the sentence level in which the machine will identify sentences within the document/message and determine the sentiment. It is assumed that a sentence contains a single feeling intended for an entity (Pozzi et al., 2017), and the machine will only focus on the subjective opinion, which is not always true (Kharde & Sonawane 2016; Liu et al., 2015). However, occasionally a sentence still comprises more than one expression, either a positive or negative feeling. Therefore, tasks at the aspect level have to be conducted to correctly classify the sentiment (Liu, 2015). At this level, the machine will identify each word in the sentence, correlate it and assess the target's sentiment (see Pozzi et al., 2017). Thus, each entity's sentiment within the sentence will be valued differently, hence giving a fine-grain result. Currently, most sentiment analysis tools execute tasks at the aspect level.

The machine will be given a task to consider four elements within the text in a computational approach, specifically opinion holder, aspect, sentiment indicator and valence (Li & Hovy, 2017). The opinion holder is the user (individual or non-individual) who delivers and has the opinion, aspect refers to topics presented in the opinion, sentiment indicator denotes the polarity of the text within the given opinion, whereas valence means the output of feelings identified from the sentiment indicator (positive, negative or neutral). The elements work in a sequential step and level of analysis to extract the real feelings (see Figure 1).

Figure 1. Steps in the Sentiment Extraction



Source: Modified from Kharde and Sonawane (2016)

In urban planning and COVID-19, similar Twitter sentiment analysis work has been completed using machine learning approaches. It includes identification of public sentiments as regards urban green spaces by using either supervised or semi-supervised learning techniques (Plunz et al., 2019; Roberts et al., 2018)

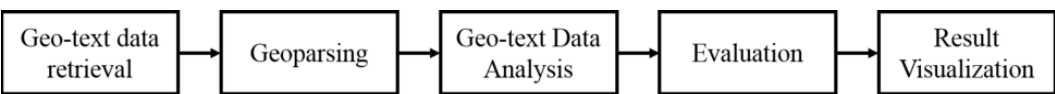
and public sentiments concerning related changes during the COVID-19 pandemic by using supervised learning techniques (Li et al., 2020; Xue et al., 2020). All works suggested that the machine learning approach is suitable for classifying a large-real-time Twitter dataset. Nonetheless, the training datasets must be manually labelled first. Moreover, the number of trained datasets will influence the accuracy of the sentiment classification result.

Furthermore, Giachanou & Crestani (2016), explained five main challenges in relation to Twitter sentiment analysis and ways to overcome it: (1) Text length. A tweet is allowed a maximum of 280 characters, which means it can be difficult to identify its context. This can be addressed by using a Support Vector Machine, a supervised learning technique, to identify the context of a tweet within short sentences; (2) Topic relevance. Sentiment classification cannot consider the significance of a tweet towards a particular topic. This can be addressed by using a word and hashtag to determine the topic; (3) Data sparsity. This includes multilingual language, misspelled words and slang or uncommon local terms. Scholars are still exploring in order to solve this challenge accurately; (4) Negation. Several people use positive words to show negative meaning to offend or complain about something (sarcasm/satire). This is addressed by training the data to any common terms that commonly emerge in negation tweets even though it does not guarantee the accuracy improvement; (5) Stop words. This refers to conjunction and subordinating conjunction words (i.e., the, which, like). A word such as “like” can be classified as positive, whereas it is only a conjunction. It is addressed by removing such words in a tweet to deliver greater accuracy. Pozzi et al. (2017), added that supervised learning is facing a challenge to classify implicit opinions.

### Spatialised Sentiment

Text with geolocation, which is typically termed geo-text, can be spatialised in a map to reveal the source location’s distribution. Hu (2018) formulated a framework to process geo-text data, which consists of five workflows (see Figure 2) (for further explanation, see Hu (2018)). First, the geo-text data is retrieved by using one of these approaches, namely geo-based data retrieval, text-based data retrieval and hybrid approach (retrieve both geo-based and text-based data). Second, the geo-text is then parsed by its location name. The exact location name can be directly taken for analysis. However, an implicit location name has to be resolved to reduce the location ambiguity (for instance, a location stated using an informal or “slang” term). Third, the parsed data is then analysed using spatial analysis, temporal analysis, natural language processing or sentiment analysis. Fourth, the analysed data is then evaluated by using a qualitative and quantitative approach. Hu (2018), suggested that both procedures should be completed to obtain an intuitive and robust evaluation. Finally, the data is visualised in various ways; a map is one of the popular ways to visualize the geo-text data. In this study, geo-text data will be analysed using a hybrid approach, evaluated using qualitative and quantitative approaches and visualised using a map.

Figure 2. Steps in the Spatialised Sentiment Extraction



Source: Hu (2018)

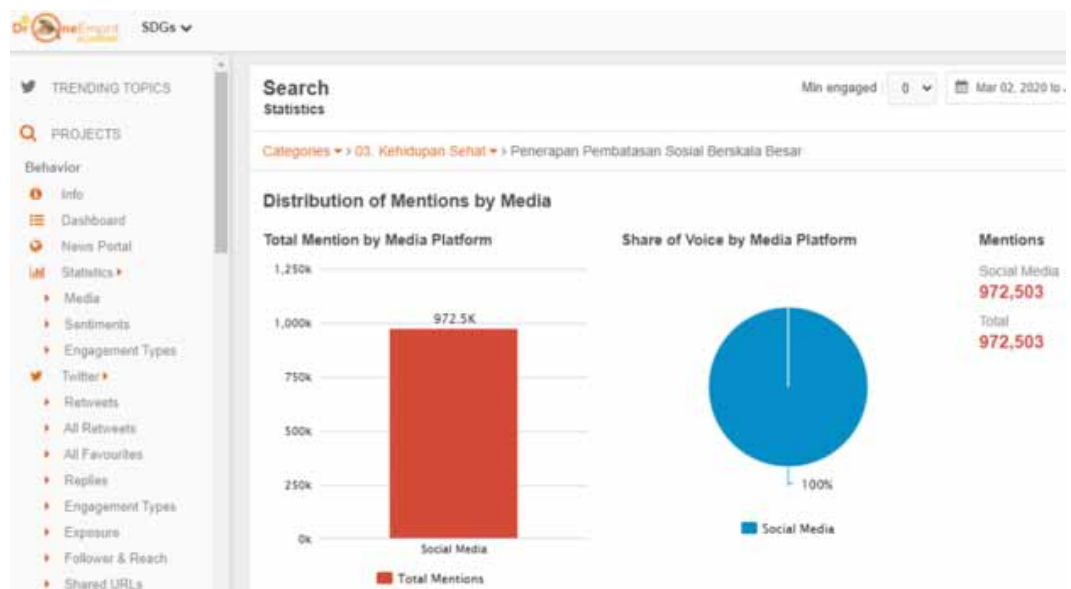
### METHODS

This study focuses on geo-text data from Twitter as 60% of 160 million Indonesian social media users use Twitter to interact with each other (Wearesocial & Hootsuite, 2021). It gives a sense of the

richness of geo-text data produced within social media. Additionally, compared with other highly active social media users, for instance Instagram and Facebook, Twitter has a free and open API (Application Program Interface). People can access any geo-texts data conveniently, although there are certain limitations on the number of tweets that can be accessed at a particular time based on the API resources (Napitupulu et al., 2020; Russell & Klassen, 2019). This richness of geo-text data with easy-to-access API means that Twitter is extensively used as a data source for studying current events from the perspectives of social media users (Grandjean, 2016).

To make the geo-text data analysis more holistic, this study uses Drone Emprit Academic (DEA) as a web-based tool to retrieve, monitor and analyse text-based and geo-based data from Twitter's API. Media Kernels Netherlands B.V. developed the tool under Ismail Fahmi's guidance (see Fahmi 2017). It can be accessed at <https://dea.uui.ac.id/> and academics have free access to this tool (see Figure 3). It retrieves, parses, analyses and evaluates social media texts in real-time by using machine learning and natural language processing approaches and adopting significant data architecture. The data is retrieved using a private crawler developed using Perl programming language supported by Apache Solr. The gathered data is processed within the Apache Solr and submitted to a database using MySQL. Apache Solr analysis includes segmentation, sentiment analysis, opinion analysis, term extraction, quote extraction and named entity recognition (Fahmi, 2017). Finally, data gathered from Apache Solr and saved in MySQL are streamed in real-time to a visualised dashboard using the ZEND Framework. This study only used the sentiment analysis and geolocation of tweets generated by the tool.

Figure 3. The Dashboard Interface of Drone Emprit Academic



Regarding the sentiment analysis, the tool uses the Supervised Learning approach, namely Naive Bayes and Maximum Entropy, which is characterised as Probabilistic Classifiers (for further explanation on this approach see Medhat et al., 2014). Compared to others, these approaches are adopted because it will only generate minor errors in predicting the geo-text data (Prusa et al., 2015). The data training is performed using a minimum of 81,000 datasets (tweets) size to acquire an accurate sentiment (Fahmi, 2017; Prusa et al., 2015). Apart from the method, in this study, the result of the

sentiment analysis is also evaluated qualitatively by sampling the population of gathered tweets in each type of sentiment (positive, negative and neutral). Based on Kim et al. (2018) and Morstatter et al. (2013), simple random sampling is sufficient to obtain a representative Twitter data sample. Additionally, the sampling bias for Twitter data is limited, meaning that data bias in simple random sampling is minimal for Twitter data (Priedhorsky et al., 2014). Therefore, Slovin's formula was used to identify the sample size followed by a random sequence of tweets retrieved from Drone Emprit Academic, expressed by the equation

$$n = \frac{N}{1 + Ne^2}$$

Where  $n$  is the sample size,  $N$  is the population size, 1 is a constant value and  $e$  is the preferred margin of error. The data sample from machine learning can be tested qualitatively and then calculated to show whether it has a high or low variation. The low variation of the data sample indicates the lower bias and higher accuracy of the sentiment classification result from DEA (this procedure follows explanations in Kim et al. (2018) and Bryman (2012)). The calculation result for this procedure will be shown in the next paragraph.

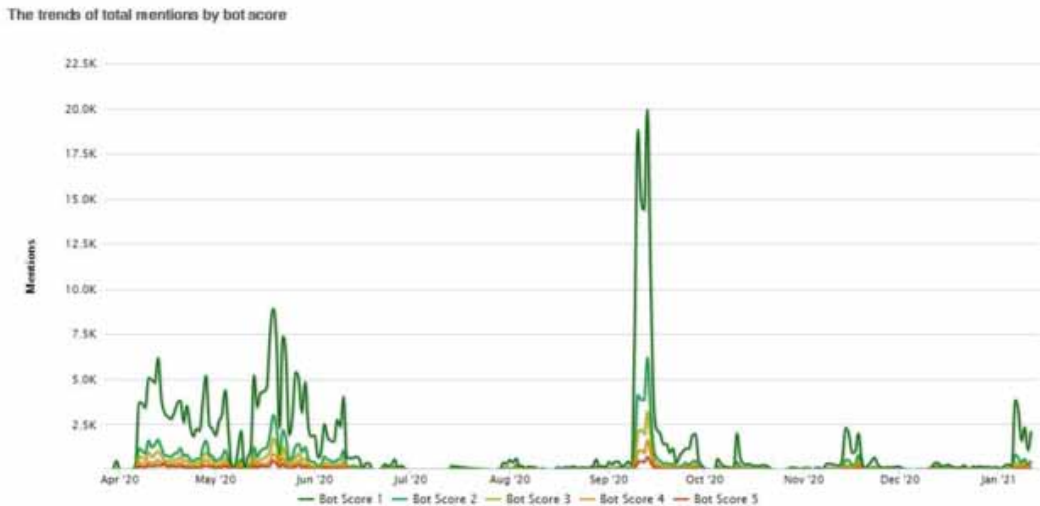
Regarding the data collection, this study uses DEA's Twitter geo-text from March, 2<sup>nd</sup> 2020 to January, 11<sup>th</sup> 2021 (10 months) to better observe Indonesian Twitter users' dynamics in responding to the Indonesian Government's lockdown-like policy (the Large Scale Social Restrictions). The input keywords for the DEA analysis are "*Pembatasan Sosial Berskala Besar*" and "*PSBB*." The tool analysed all texts containing these keywords in all tweets during the period. This primary data is subsequently compared with secondary data: literature, official reports and media news to deliver a valid conclusion. This study assumes that most Twitter users live in urban areas, hence, it is representing the sentiments of urban citizens. During the data collection, 970,394 tweets were gathered consisting of 522,215 positive sentiments, 404,871 negative sentiments and 43,308 neutral sentiments. Based on these populations, using Slovin's formula, the sample size is, sequentially, 400, 400 and 396 tweets, with a 95% level of confidence.

The qualitative evaluation is validated by calculating its coefficient of variation (CV), which is concluded by assessing the CV result. The value of the  $CV \geq 1$  indicates a relatively high variation. In contrast, a  $CV < 1$  demonstrates a relatively low variation (for further explanation, see Marek, 2013). For this study, the CV has to have a value of  $< 1$  to attain an accurate result. It is identified by verifying each sample tweet's sentiment status, calculating the sum of the different sentiment results between the qualitative and quantitative evaluation, calculating its mean, standard deviation and finally, the coefficient of variation. The CV in each sentiment is 0.66 for positive, 0.61 for negative and 0.23 for neutral sentiments. Therefore, the generated sentiments are accurate enough to be used for this study.

Additionally, in using Twitter data, a study has to take into account "malicious" accounts (i.e., fake accounts and internet robots (BOTs)) within the tweets data even though not all of them are malicious (Salvatore et al., 2020). These accounts can influence the entire topic's sentiments within Twitter conversations, hence biasing the sentiment data classifications. This study identified the tweets data that are generated by BOTs by relying on the analysis of DEA. It analyses the BOTs by sampling the tweets that appeared each day and resulted in five different score categories to classify whether or not BOTs might generate a tweet. The interpretation is that the higher the score category, the greater the possibility that BOTs generated the tweet. It is also illustrated in colour as follows: score category 1 and 2 are displayed in green (lower number of BOTs); score category 3 and 4 are presented in orange (medium number of BOTs); score category 5 is indicated in red (high number of BOTs). Based on the result of the DEA analysis, the overall BOTs score for tweets used by this study is 1.61 (score category 1), with only around 2.35% of tweets indicated by BOTs. Additionally,

in a data series format, from March, 2<sup>nd</sup> 2020, to January, 11<sup>th</sup> 2021, the number of BOTs within the score category 5 is considered low (see Figure 4).

Figure 4. The Trends of Samples of Tweets by BOTs Score



Source: Drone Emprit Academic (2021)

Regarding the geolocation analysis, the tool gathers tweets containing coordinate information from the time it is tweeted. It should be noted that not all tweets have geolocation information, therefore, the distribution of tweets will be limited. This is because not all tweets contain a geolocation attribute (represented by the longitude and latitude of the user's location), because not all Twitter users either activate the GPS location on their smartphone or activate their geolocation profile within their account (Ciuccarelli et al., 2014). In regard to Twitter, the geolocation profile of each user is set to off by default. DEA gathered the tweets' geolocation and categorised them by administrative characteristics, namely country, province and city. Each of the administrative boundaries contains data pertaining to tweets that is quantified to reveal its total tweets. Likewise, the sentiment analysis result is revealed in each administrative boundary, which can display the distribution of sentiments spatially. This study used the smallest boundary unit visualised within the tool, "city," to understand urban citizens' sentiments clearly. As this study only needs to identify the spatial distribution at the city level, DEA data are adequate. The geolocation precision rate can be disregarded because this study does not require a specific location for the tweets (i.e., the tweet's location in a particular area of the city). Regarding the geo-text data visualisation, this study adopted the sentiment extraction framework developed by Hu (2018) by using several tools, specifically DEA (text and geo-text data mining), Microsoft Excel (data cleaning and evaluation) and Tableau (data analysis and visualisation).

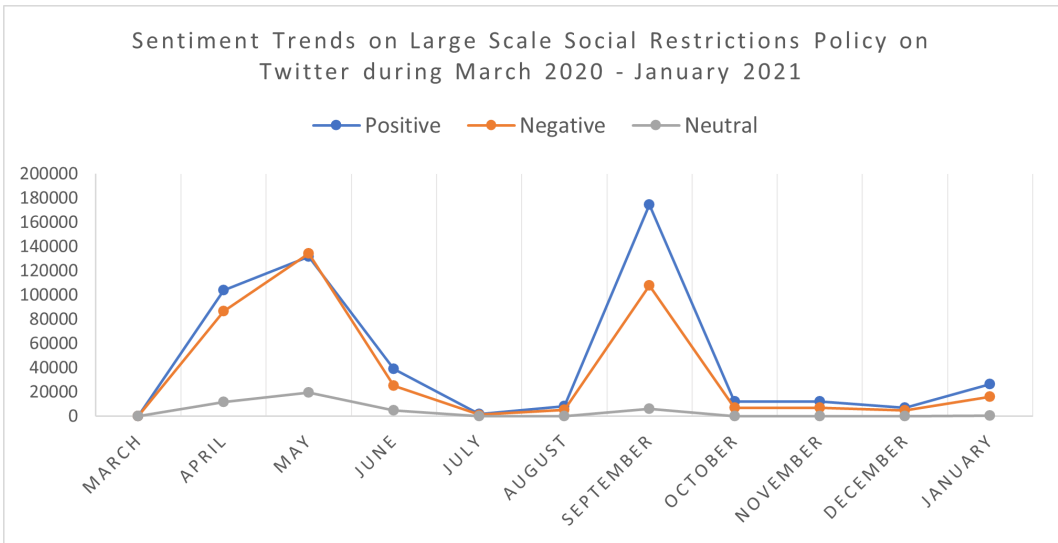
## RESULT AND DISCUSSION

### The Pattern of Indonesian Urban Citizens' Sentiments Regarding the Lockdown Policy

The result of the sentiment analysis concerning the LSSR policy from the DEA is identified by way of a comparative assessment between the sentiment trends and significant events in the real world

taking place at that time. It is recapped based on each month's sentiment trends, from March 2020 to January 2021 (see Figure 5). Overall, the graph fluctuates over time. From March to May 2020, tweets mentioned “*Pembatasan Sosial Berskala Besar*” and “*PSBB*” increased to roughly 140,000 tweets in May. The negative sentiment was slightly higher than the positive sentiment. It then decreased from May to August yet increased again from August to September to approximately 180,000 tweets in September, in which positive sentiment was significantly higher than negative sentiment. It then reduced considerably from September to December and appeared to increase again in January 2021. Hence, this study focuses on significant events that increased the number of tweets, from March to May 2020, August to September 2020 and December 2020 to January 2021.

Figure 5. Sentiment Trends on LSSR Policy



Source: Data retrieved from Drone Emprit Academic (2021)

Four significant events influenced the increasing number of tweets, namely opinions on the lockdown, the Government's Decree on the LSSR, the second full LSSR implementation in Jakarta, along with the introduction of a new lockdown-like policy. First, related to opinions on the lockdown, people started to tweet as regards ideas about the lockdown from March 10<sup>th</sup>, 2020, owing to the announcement of the first Covid-19 confirmed death in Surakarta City.

Although only a small number of tweets mentioned “lockdown” gathered by DEA, from March 10<sup>th</sup> to March 30<sup>th</sup>, 2020, people started to implement an “independent lockdown”. Local inhabitants closed their the main streets in their neighbourhoods with any materials and messages to limit the number of outsiders entering their neighbourhood (see Figure 6). Their actions rapidly spread to other neighbourhoods, primarily via Twitter. During that particular period, the Government did not announce any decisions regarding the independent lockdown acts that were occurring in society.



Figure 6. Screenshots of Several Photos related to the “Independent Lockdown” Acts (in the Indonesian language)

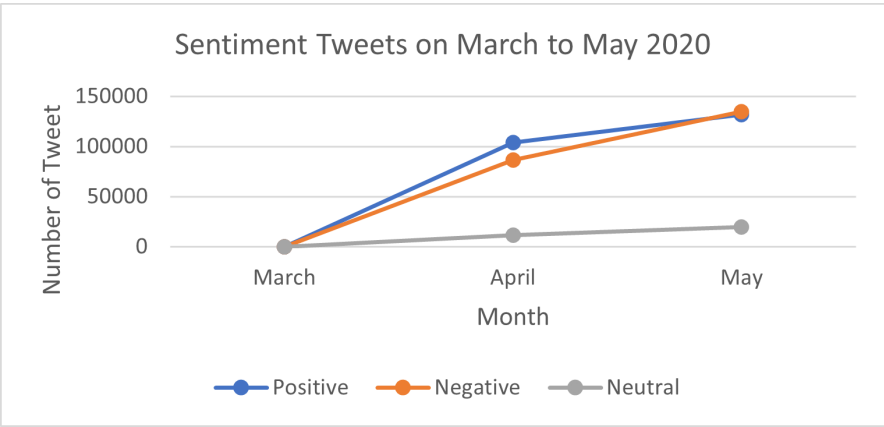


Source: Merapi News (2020)

Second, on March 31<sup>st</sup>, 2020, the President issued Government Decree No: 21/2020 on implementing LSSR to handle the COVID-19 pandemic. Since then, the number of tweets discussing the policy rose significantly (see Figure 7). From March to April, overall sentiment with respect to the policy was positive because it was in line with the people's desire for the Government to restrict any activities that might cause the pandemic to spread. However, in May, most tweets indicate a negative sentiment because on May 4<sup>th</sup>, 2020, the President announced an evaluation of the LSSR policy across the most significantly impacted districts and provinces (WHO, 2020b). It resulted in a decision taken on May 16<sup>th</sup>, 2020 which stated that the Government would gradually allow certain businesses and offices to open and ease their operational time (WHO, 2020c). This was the first time the Government introduced the so-called “New Normal” approach, meaning that people could conduct their activities. Simultaneously, they still had to implement the health protocol (wear a mask, wash hands and apply 1-metre physical distancing). Consequently, more people disagreed with the decision because, at that time, Muslims who were fasting in *Ramadhan* were instructed not to return to their hometowns for Eid. At the same time, the Government intended to relax the LSSR policy by introducing the “New Normal” approach.

At the end of May, several ministries issued protocols regarding the “New Normal” approach, such as public transport protocols and private vehicles as well as protocols pertaining to public facilities. In June, most Provincial and District governments applied the “New Normal” approach within their authority area, such as Jakarta (WHO, 2020d). From this month onwards, the number of tweets decreased as the Government issued no prominent policy related to the LSSR. From June to July, conversations on Twitter focused on the LSSR transition in Jakarta and the “New Normal” approach, which the WHO identified as a relaxation of the LSSR (WHO, 2020e).

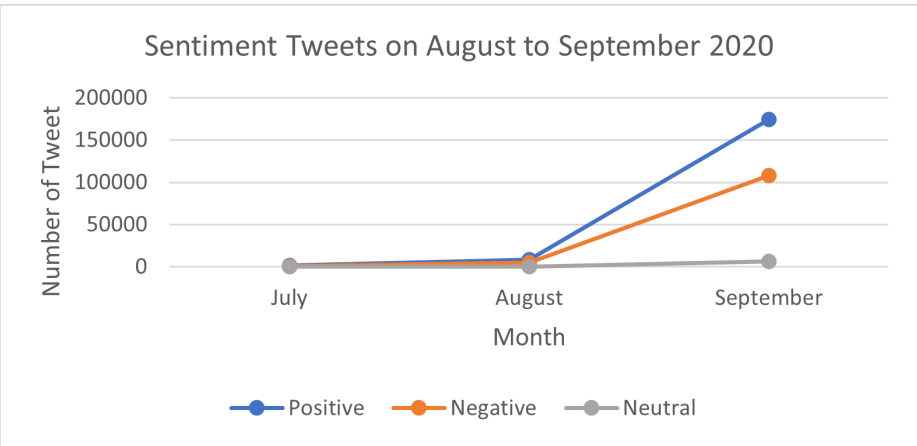
Figure 7. Sentiment Tweets related to the LSSR period from March-May 2020.



Source: Data retrieved from Drone Emprit Academic (2021)

Third, at the end of July, the Ministry of Education and Culture announced the opportunity to reopen schools within the “yellow” zones (an area which has 1-10 confirmed COVID-19 cases), a decision that was taken on August 7<sup>th</sup>, 2020 by a Joint Ministerial Decree (WHO, 2020f). This decision increased the tweets related to the LSSR policy again and there were debates within Twitter regarding the decision, although only a small number of tweets. The prominent topic that increased tweets concerning the LSSR policy was the second full LSSR implementation in Jakarta, which started at the beginning of September (see Figure 8) (for further elaboration on this second implementation of the LSSR, see WHO, 2020g). This policy received more positive than negative sentiments from Twitter users. It appears that the conversations related to the LSSR policy were centralised to Jakarta ignoring situations in other cities. From this month onwards, the number of tweets reduced to less than 20,000 tweets.

Figure 8. Sentiment Tweets related to the LSSR Policy for the period July-September 2020

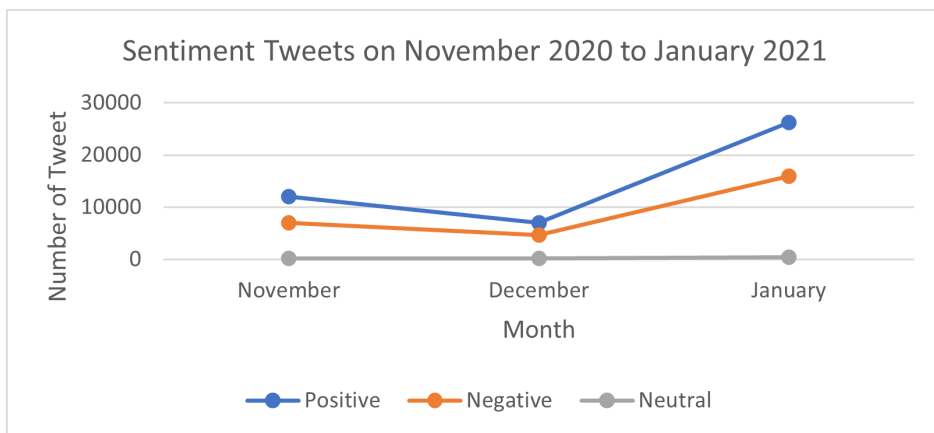


Source: Data retrieved from Drone Emprit Academic (2021)

From October to November, the tweets related to the LSSR were stable at roughly 19,000 tweets comprising more positive than negative sentiments. At that time, conversations on Twitter were more focused on the second LSSR transition in Jakarta (WHO, 2020h) and several debates on policy injustice related to the LSSR. For instance, people in most cities were still forced to follow the LSSR policy by staying, working, praying and studying at home, as well as limiting their business and office hours, while several religious groups held a large scale events. Moreover, the election of the Governor and Regent/Mayor was still implemented at the beginning of December. At this point, most sentiments were still positive. Nonetheless, looking in more detail, most tweets employed satire and metaphorical words to criticise the Government, which in turn, the machine translated into positive sentiment. Therefore, there might be a false positive in the sentiment result leading to a miscalculation (in line with Giachanou & Crestani, 2016). This might be applied to all sentiment data in which the machine cannot delve deeper to identify various satire and metaphoric words.

Finally, in December, most conversations related to the LSSR policy focused on sanctioning the LSSR policy offender. This was a follow-up debate on the events in November and the beginning of December stated in the previous paragraph. Other conversations focused on the continuation of the LSSR transition policy in Jakarta (EKONID, 2021), reducing holiday times and restricting the Christmas and New Year vacation. Subsequently, on January 6<sup>th</sup>, 2021, the Government, through the Ministry of Home Affairs, issued Instruction No. 1/2021 on the implementation of restrictions to control people's activities and reducing the spread of COVID-19. This instruction marked a new policy related to the lockdown-like policy in Indonesia. From this point onwards, the LSSR policy was not used anymore. It was then replaced by the “PPKM” (Micro-Scale Activity Restriction – MSAR), which tends to focus more on limiting the amount of time people have to undertake activities by regulating the amount of Work from Home and limiting the operating hours of public institutions. This instruction was introduced on January 11<sup>th</sup>, 2021. Hence, tweets on the LSSR policy slightly increased at the beginning of January. At that time, people still discussed the lockdown-like policy in relation to the LSSR policy (see Figure 9). However, since January 2021 after the Government introduced a new lockdown-like policy known as MSAR, which replaced the LSSR policy, people refer to the lockdown-like policy as MSAR. Most tweets comprise more positive than negative sentiments regarding the new policy. After the new policy was introduced, conversations among Twitter users focused more on comparing the LSSR and MSAR policy in which the MSAR replaced tweets concerning the LSSR.

Figure 9. Tweet Sentiments related to the LSSR Policy for the period November 2020 January 2021



Source: Data retrieved from Drone Emprit Academic (2021)

Based on the explanation, it can be concluded that the pattern of sentiments with respect to the lockdown-like policy (both the LSSR and MSAR policies) was primarily positive over time, except in May, where negative sentiments were slightly higher than the positive sentiments. Several actual events related to the LSSR policy caused the increase in tweets to happen. It reveals that the pattern of sentiments positively correlated with the prominent events taking place in the real world. Therefore, the Government needs to understand the pattern of people's sentiments from their tweets in developing and evaluating their lockdown-related policy in handling COVID-19 in Indonesia. However, it is essential to note that the Government should filter the tweets from bots or buzzers first before they use them as material for policy evaluation. With this finding, the sentiment analysis using social media data can open a pathway in relation to the urban e-planning process, particularly during the pandemic and in rapidly changing circumstances.

The finding confirms other studies revealing that government policy on prominent occasions triggers the polarity of the sentiment. The correlation can support policy-makers (Tsai & Wang, 2021). Challenges on analysing Twitter sentiments as mentioned by Giachanou & Crestani (2016) and Pozzi et al. (2017), can be anticipated by taking a sample of sentiment classification results and undertaking a manual evaluation on each classification (positive, negative and neutral) to establish its variance. Most related studies did not mention the BOTs accounts that might bias the result of the sentiment. This study conducted the sentiment analysis by considering the BOTs analysis. Hence, the accuracy of the result improved.

### **Spatial Distribution of the Sentiments as Regards Lockdown Policy**

The spatial distribution of the sentiments is analysed by identifying the tweets' geolocation at a city level. These tweets are the same as tweets employed to identify the sentiments pattern in section 4.1, while the geolocation was retrieved from Drone Emprit Academic (at the city level). However, as explained in section 3, not all tweets contain geolocation attributes. Hence, this section's spatial distribution analysis only focuses on tweets with the geolocation attribute. This indicates that the number of tweets that are analysed in the spatial distribution section is lower than in the previous section. Of the 970,394 gathered tweets (23.31% of total tweets), 226,216 tweets have geolocation attributes. Reflecting on the number of geolocated tweets, it is important to state that there might be differences in the result of the spatial distribution analysis as the total tweets count of each city might be slightly different than shown in this analysis. Additionally, other cities might appear if there are more geolocated tweets during the period.

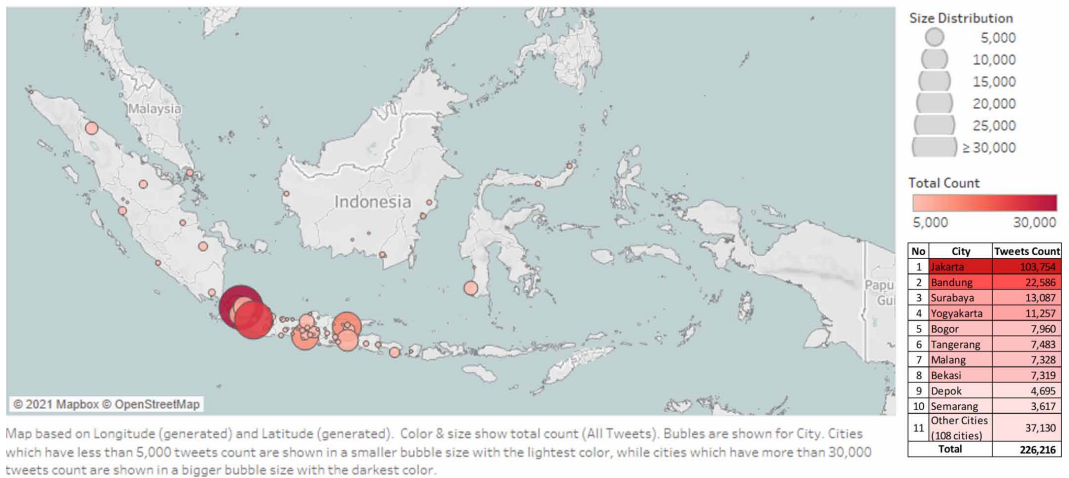
The spatial distribution is represented by city level, which is displayed in a coloured bubble. Its size represents the number of tweets count, meaning the higher the total tweets count, the bigger the bubble, together with the darkest bubble colour. Concerning all the gathered geolocated tweets, 118 Indonesian cities have been identified. This paper will only show the top ten cities with the highest tweet counts. Meanwhile, the remainder of the cities in which the number of tweets from these cities is summed, will be grouped and named "other cities". Nevertheless, it should be noted that the number of tweets counts for each city within the "other cities" group is less than the top ten cities. Therefore, the summed tweets count in the "other cities" group cannot be compared with the tweet counts belonging to the top ten cities. Furthermore, the 10 cities that have the highest tweets are visualised in the spatial distribution map.

First, the spatial distribution of all the geolocated tweets' shows that tweets related to lockdown-like policy are concentrated in Java island, the most developed island in Indonesia (see Figure 10). The top ten cities are large and medium cities within Java, with Jakarta (represented by the dark red bubble) comprising the highest number of tweets (45.87% of all tweets). Bandung followed with 22,586 tweets (9.98%), showing a considerable gap at around 80,000 tweets (78%) compared to Jakarta. Surabaya and Yogyakarta amount to roughly 5% of the total tweets count; Bogor, Tangerang, Malang and Bekasi approximately 3% of the total tweets count, while Depok and Semarang are equivalent to 2% of the total tweets count. The "other cities" group has less than 1% of the total tweets.

It reveals that Jakarta has the most active Twitter users who mentioned the lockdown-like policies. It is in line with the pattern of prominent events identified in section 4.1. Most tweets appear to focus on the LSSR policy employed in Jakarta and several significant events during the pandemic in Jakarta, such as sanctions for critics of the LSSR policy and large-scale activities held by a religious group. From this point of view, most Twitter conversations regarding the lockdown-like policy concentrate on users in Jakarta. They primarily focus on the COVID-19 situation and the implementation of the LSSR policy in Jakarta only.

**Figure 10. Spatial Distribution of All Tweets**

Spatial Distribution on All Tweets

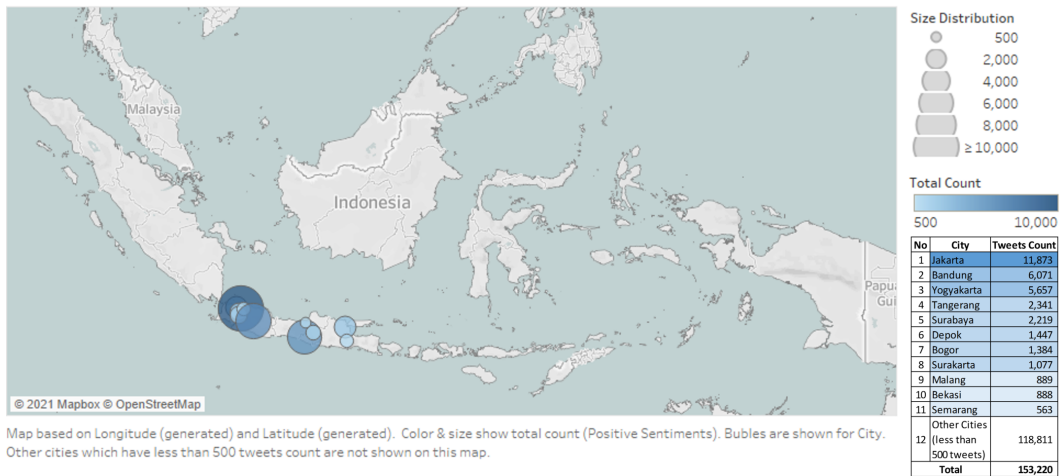


Source: Data retrieved from Drone Emprit Academic (2021)

Second, in the positive sentiments, it shows that Jakarta (represented by the dark blue bubble) has the highest positive sentiments (7.75% of all positive tweet sentiments) (see Figure 11). It is followed by Bandung and Yogyakarta that have around 3.5% of the total positive sentiments. Tangerang and Surabaya comprise roughly 1.5% of the positive sentiments, while Depok, Bogor, Surakarta, Malang, Bekasi and Semarang have less than 1% of the total positive sentiments. The “other cities” group has less than 0.5% of the total positive sentiments.

Figure 11. Spatial Distribution of Positive Sentiments

Spatial Distribution of Positive Sentiments

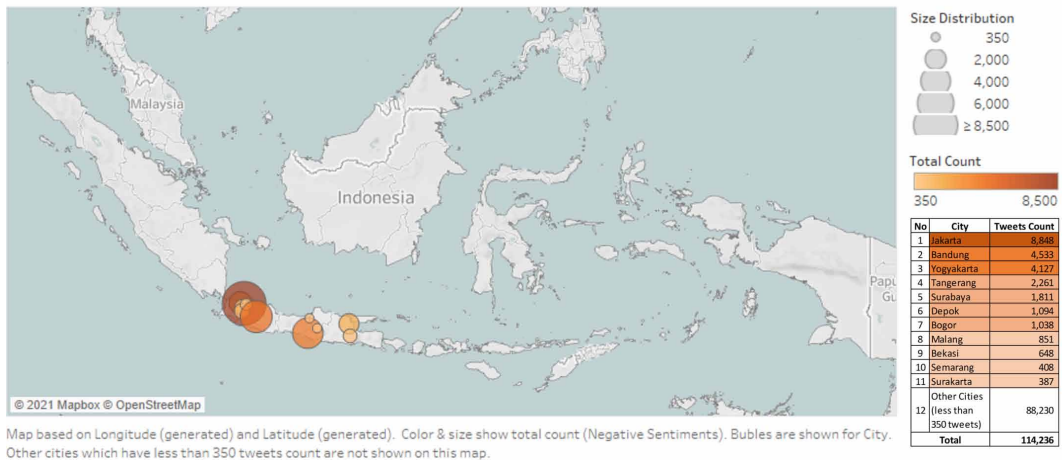


Source: Data retrieved from Drone Emprit Academic (2021)

Third, the negative sentiments illustrate that Jakarta (represented by the dark orange bubble) has the highest number of negative sentiments (7.75% of all negative tweet sentiments) (see Figure 12). It is followed by Bandung and Yogyakarta that have in the region of 3.5% of the total negative sentiments. Tangerang and Surabaya consist of approximately 1.5% of the total negative sentiments, while Depok, Bogor, Malang, Bekasi, Semarang and Surakarta have less than 1% of the negative sentiments. The “other cities” group has less than 0.4% of the total negative sentiments.

Figure 12. Spatial Distribution of Negative Sentiments

Spatial Distribution of Negative Sentiments



Source: Data retrieved from Drone Emprit Academic (2021)



Finally, the neutral sentiments shows that Jakarta (represented by the dark grey bubble) has the highest percentage of neutral sentiments (3.70% of all neutral sentiment tweets) (see Figure 13). It is followed by Yogyakarta that has around 2% of the total neutral sentiments. Tangerang and Bandung comprise around 1% of the neutral sentiments, while Surabaya, Depok, Malang, Bogor, Bekasi, Surakarta and Semarang have less than 1% of the total neutral sentiments. The “other cities” group has less than 0.4% of the neutral sentiments total.

**Figure 13. Spatial Distribution of Neutral Sentiments**

Spatial Distribution of Neutral Sentiments



Source: Data retrieved from Drone Emprit Academic (2021)

The results illustrate that large and medium-size cities in Java dominate the entire tweets and the spatial distribution. It possibly represents the most and less active regions and cities in Indonesia. It might be caused by the media coverage of the LSSR policies that are more frequently reported in cities within Java. Hence, people tend to focus more on the cities, specifically Jakarta, which attracts more interest because of its role as the capital city. The results confirm that most active Twitter users are from urban areas represented by cities that dominate the spatial distribution.

This result may well contribute to the adoption of social media-based geo-text analysis in relation to urban planning and management. Planners can develop and subsequently evaluate their plans by identifying the distribution of local inhabitant’s sentiments concerning the plans. Then they could either revise, alter, adapt or negotiate their plans based on the sentiments. A literature review conducted by Lin & Geertman (2019), reveals that Twitter and other social media data have been frequently used to analyse and model people’s activity patterns, land use, mobility patterns, besides the quality of the landscape. It has become the new platform for citizen participation, collaboration and self-organisation for collective urban planning actions. Specifically, Kovács-Győri et al. (2018), assert that Twitter geo-text-based sentiment analysis can enhance urban planning and management outcomes for large temporal events by enabling the Government to track the mobility, sentiment and opinions of residents and visitors on Twitter during an event. Owing to this, urban planners and managers can manage urban transportation during an event in real-time practically based on the actual conditions occurring in the field.

Therefore, the Government or any other stakeholder can implement their decision without confrontations and local inhabitants can (directly or indirectly) voice their opinions and concerns within conventional participatory meetings and social media. Consequently, the urban government can develop better policies pertaining to managing related issues.

However, in Indonesia, the Government (at national, provincial and municipal levels) only uses social media to disseminate governmental-related information and urban plans that result in limited mutual interactions with the people (Idris, 2018). In fact, these various levels of government do not make use of sentiment analysis as regards specific issues. Additionally, Twitter is typically employed to organise social movements to protest against particular government policies, which are often neglected by the policy-makers (Sutan et al., 2021). Hence, Twitter sentiment analysis does not yet influence the policy-making or policy-evaluation process in Indonesia. This also occurs in India, where people's sentiments on Twitter do not influence policy improvement (Rathore et al., 2021).

## CONCLUSION

This study aimed to analyse the sentiments of Indonesian urban citizens regarding the lockdown-like policy across Indonesian cities. In achieving this objective, this study analysed the pattern of sentiments of Indonesian urban citizens with respect to the lockdown-like policy and its spatial distribution using Twitter's geo-text data from March 2<sup>nd</sup>, 2020 to January 11<sup>th</sup>, 2021. From the analysis, two main results were identified. First, during that particular period tweet patterns were observed to have been influenced by four significant events: opinions on the lockdown, the implementation of the National Government's Decree on the LSSR, the second full implementation of the LSSR in Jakarta, besides the introduction of the new lockdown-like policy at the national level. The sentiments pattern as regards the lockdown-like policy were primarily positive over time, except in May 2020. It confirms that the pattern of sentiments related to the LSSR policy positively correlated with prominent events in the real world. Thus, it is relevant to consider people's sentiments presented on social media when considering the implementation of a policy or when a policy has been implemented. More specifically, the Government can utilise these sentiments over time as an evaluation material in regard to their policy-making process.

Second, the spatial distribution of all geolocated tweets reveals that tweets related to lockdown-like policy are concentrated on Java. Most tweets appear to focus on prominent events that took place in Jakarta during the pandemic by employing positive sentiments primarily. The result of the spatial distribution is most likely to represent the most active and less active regions and cities in Indonesia that use Twitter to deliver their opinions as regards lockdown-like policy in Indonesia. It confirms that live tracking on sentiment classification spatially can enhance urban planning and management by providing context and situation-based policy for each city, rather than a general policy without considering the uniqueness of people's opinions. It is worth noting that there is a drawback concerning this result because not all gathered tweets have the geolocation attribute, which might suggest the volume and spatial distribution of tweets in each city. Additionally, further questions can be raised: (1) How might the city government deal with Twitter sentiment analysis in the urban policy-making process? (2) How does the current spatial planning approach adopt social media-related methods to enrich its analysis?

Benefitting from the use of Twitter data, it is essential for the Government to understand the pattern of people's sentiments from their tweets and utilise the knowledge to develop and evaluate their lockdown-related policies. Sentiment analysis using social media data can open a pathway with respect to the urban e-planning process, especially in times of pandemic and rapidly-changing situations. Likewise, the spatial distribution of the sentiments can guide the Government and planners to prepare, implement and evaluate their plan in a particular urban area. This can be an alternative method for the Government to monitor and assess their policies in the future.



## **FUNDING INFORMATION**

This work was supported by the Department of Architecture and Planning, Faculty of Engineering, Gadjah Mada University [grant number 417/UN1.FTK/SK/HK/2020] and was presented in the 5th International Conference 'Urban e-Planning'. The author would like to acknowledge the conference panel discussants and three anonymous reviewers who gave constructive feedback for this article.

## **ACKNOWLEDGMENT**

The publisher has waived the Open Access Processing fee for this article.

## REFERENCES

- Bryman, A. (2012). *Social Research Methods* (4th ed.). Oxford University Press.
- Ciuccarelli, P., Lupi, G., & Simeone, L. (2014). *Visualising the Data City: Social Media as a Source of Knowledge for Urban Planning and Management*. Springer. doi:10.1007/978-3-319-02195-9
- Drone Empirt Academic. (2021, January 10). *The Trends of Total Mentions by BOTs Score*. <https://dea.uui.ac.id/>
- EKONID. (2021). *COVID-19 Developments in Indonesia*. Available at: <https://indonesien.ahk.de/en/infocenter/news/news-details/covid-19-developments-in-indonesia>
- Fahmi, I. (2017). *Drone Emprit: Konsep dan Teknologi*. Media Kernels Indonesia.
- Giachanou, A., & Crestani, F. (2016). Like It or Not: A Survey of Twitter Sentiment Analysis Methods. *ACM Computing Surveys*, 49(2), 28:1–28:40. 10.1145/2938640
- Grandjean, M. (2016) A social network analysis of Twitter: Mapping the digital humanities community. *Cogent Arts and Humanities*, 3(1), 1–14. 10.1080/23311983.2016.1171458
- Hu, Y. (2018). Geo-Text Data and Data-Driven Geospatial Semantics. *Geography Compass*, 12(11), 1–19. doi:10.1111/gec3.12404
- Idris, I. K. (2018). Government Social Media in Indonesia: Just Another Information Dissemination Tool Article. *Jurnal Komunikasi: Malaysian Journal of Communication*, 34(4), 337–356. doi:10.17576/JKMJC-2018-3404-20
- Kharde, V. A., & Sonawane, S. S. (2016). Sentiment Analysis of Twitter Data: A Survey of Techniques. *International Journal of Computers and Applications*, 139(11), 5–15. doi:10.5120/ijca2016908625
- Kim, H., Jang, S. M., Kim, S. H., & Wan, A. (2018). Evaluating Sampling Methods for Content Analysis of Twitter Data. *Social Media + Society*, 4(2), 1–10. doi:10.1177/2056305118772836
- Kovács-Györi, A., Ristea, A., Havas, C., Resch, B., & Cabrera-Barona, P. (2018). #London2012: Towards Citizen-Contributed Urban Planning Through Sentiment Analysis of Twitter Data. *Urban Planning*, 3(1), 75–99. doi:10.17645/up.v3i1.1287
- Li, J., & Hovy, E. (2017). Reflections on Sentiment/Opinion Analysis. In E. Cambria, D. Das, S. Bandyopadhyay, & A. Feraco (Eds.), *A Practical Guide to Sentiment Analysis* (pp. 41–59). Springer International Publishing AG. doi:10.1007/978-3-319-55394-8\_3
- Li, L., Zhang, Q., Wang, X., Zhang, J., Wang, T., Gao, T. L., Duan, W., Tsoi, K. K. F., & Wang, F. Y. (2020). Characterizing the Propagation of Situational Information in Social Media during COVID-19 Epidemic: A Case Study on Weibo. *IEEE Transactions on Computational Social Systems*, 7(2), 556–562. doi:10.1109/TCSS.2020.2980007
- Lin, Y., & Geertman, S. (2019). Can Social Media Play a Role in Urban Planning? A Literature Review. In S. Geertman, Q. Zhan, A. Allan, & C. Pettit (Eds.), *Computational Urban Planning and Management for Smart Cities* (1st ed., pp. 69–84). Springer Nature Switzerland AG. doi:10.1007/978-3-030-19424-6\_5
- Liu, B. (2012). *Sentiment Analysis and Opinion Mining: Synthesis Lectures on Human Language Technologies*. Morgan & Claypool Publishers. doi:10.2200/S00416ED1V01Y201204HLT016
- Liu, B. (2015). *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions Sentiment*. Cambridge University Press. doi:10.1017/CBO9781139084789
- Liu, B. (2017). Many Facets of Sentiment Analysis. In E. Cambria, D. Das, S. Bandyopadhyay, & A. Feraco (Eds.), *A Practical Guide to Sentiment Analysis* (1st ed., pp. 11–39). Springer International Publishing. doi:10.1007/978-3-319-55394-8\_2
- Marek, M. (2013). *Practical Application of Coefficient of Variation*. Academic Press.
- Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment Analysis Algorithms and Applications: A Survey. *Ain Shams Engineering Journal*, 5(4), 1093–1113. doi:10.1016/j.asej.2014.04.011

- Merapi News [@merapi\_news]. (2020, May 26). *Panjang Umur Warga Berdaya* [Tweet]. Twitter. [https://www.twitter.com/merapi\\_news](https://www.twitter.com/merapi_news)
- Morstatter, F., Pfeffer, J., Liu, H., & Karley, K. M. (2013). Is the Sample Good Enough? Comparing Data from Twitter's Streaming API with Twitter's Firehose Fred. In *Proceedings of the 7th International Conference on Weblogs and Social Media, ICWSM 2013*. AAAI Press.
- Napitupulu, A., Embi, M. A., & Briando, B. (2020). Public Sentiment Analysis on the Existence of Foreign Worker during the COVID 19 Pandemic. In *International Conference on Law and Human Rights*. Ministry of Law and Human Rights.
- Plunz, R. A., Zhou, Y., Carrasco Vintimilla, M. I., Mckeown, K., Yu, T., Uguccioni, L., & Sutto, M. P. (2019). Twitter Sentiment in New York City Parks as Measure of Well-being. *Landscape and Urban Planning*, 189, 235–246. doi:10.1016/j.landurbplan.2019.04.024
- Pozzi, F. A., Fersini, E., Messina, E., & Liu, B. (2017). Challenges of Sentiment Analysis in Social Networks: An Overview. In F. A. Pozzi, E. Fersini, E. Messina, & B. Liu (Eds.), *Sentiment Analysis in Social Networks* (1st ed., pp. 1–11). Elsevier. doi:10.1016/B978-0-12-804412-4.00001-2
- Prakash, T. N., & Aloysius, A. (2019). A Comparative study of Lexicon based and Machine learning based classifications in Sentiment analysis. *International Journal of Data Mining Techniques and Applications*, 8(1), 43–47. doi:10.20894/IJDMTA.102.008.001.005
- Priedhorsky, R., Culotta, A., & Del Valle, S. Y. (2014). Inferring the Origin Locations of Tweets with Quantitative Confidence. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. Association for Computing Machinery. doi:10.1145/2531602.2531607
- Prusa, J., Khoshgoftaar, T. M., & Seliya, N. (2015). The Effect of Dataset Size on Training Tweet Sentiment Classifiers Joseph. In *Proceedings - 2015 IEEE 14th International Conference on Machine Learning and Applications*. IEEE. doi:10.1109/ICMLA.2015.22
- Rathore, A. K., Maurya, D., & Srivastava, A. K. (2021). Do Policy-makers Use Social Media for Policy Design? A Twitter Analytics Approach. *AJIS. Australasian Journal of Information Systems*, 25, 1–31. doi:10.3127/ajis.v25i0.2965
- Roberts, H., Resch, B., Sadler, J., Chapman, L., Petutschnig, A., & Zimmer, S. (2018). Investigating the Emotional Responses of Individuals to Urban Green Space Using Twitter Data: A Critical Comparison of Three Different Methods of Sentiment Analysis. *Urban Planning*, 3(1), 21–33. doi:10.17645/up.v3i1.1231
- Russell, M., & Klassen, M. (2019). *Mining the Social Web: Data Mining Facebook, Twitter, LinkedIn, Instagram, GitHub, and More* (3rd ed.). O'Reilly Media, Inc.
- Salvatore, C., Biffignandi, S., & Bianchi, A. (2020). Social Media and Twitter Data Quality for New Social Indicators. *Social Indicators Research*, 148(1), 601–630. 10.1007/s11205-020-02296-w
- Sutan, A. J., Nurmandi, A., Mutiarin, D., & Salahudin, S. (2021). Using Social Media as Tools of Social Movement and Social Protest in Omnibus Law of Job Creation Bill Policy-Making Process in Indonesia. In T. Antipova (Ed.), *Advances in Digital Science: ICADS 2021* (1st ed., pp. 261–274). Springer. doi:10.1007/978-3-030-71782-7\_24
- Thakuriah, P., Tilahun, N. Y., & Zellner, M. (2017). Big Data and Urban Informatics: Innovations and Challenges to Urban Planning and Knowledge Discovery. In P. Thakuriah, N. Y. Tilahun, & M. Zellner (Eds.), *Seeing Cities Through Big Data: Research, Methods and Applications in Urban Informatics* (pp. 11–45). Springer International Publishing. doi:10.1007/978-3-319-40902-3\_2
- Tsai, M. H., & Wang, Y. (2021). Analysing Twitter Data to Evaluate People's Attitudes towards Public Health Policies and Events in the Era of COVID-19. *International Journal of Environmental Research and Public Health*, 18(6272), 1–14. doi:10.3390/ijerph18126272 PMID:34200576
- Verma, B., & Thakur, R. S. (2018). Sentiment Analysis Using Lexicon and Machine Learning-Based Approaches: A Survey. In B. Tiwari, V. Tiwari, K. C. Das, D. K. Mishra, & J. C. Bansal (Eds.), *Proceedings of International Conference on Recent Advancement on Computer and Communication, Lecture Notes in Networks and Systems* (Vol. 34, pp. 441–447). Springer Nature Singapore. doi:10.1007/978-981-10-8198-9\_46
- Wearesocial & HootSuite. (2021). *Digital 2021: Indonesia*. Author.

World Health Organisation. (2020a). *Novel Coronavirus (2019-nCoV) Situation Report-1*. World Health Organisation. WHO.

World Health Organisation. (2020b). *Coronavirus Disease 2019 Situation Report-7*. World Health Organisation. WHO.

World Health Organisation. (2020c). *Coronavirus Disease 2019 Situation Report-9*. World Health Organisation. WHO.

World Health Organisation. (2020d). *Coronavirus Disease 2019 Situation Report-11*. World Health Organisation. WHO.

World Health Organisation. (2020e). *Coronavirus Disease 2019 Situation Report-14*. World Health Organisation. WHO.

World Health Organisation. (2020f). *Coronavirus Disease 2019 Situation Report-20*. World Health Organisation. WHO.

World Health Organisation. (2020h). *Coronavirus Disease 2019 Situation Report-29*. World Health Organisation. WHO.

World Health Organisation. (2021a). *Weekly Operational Update on COVID-19*. World Health Organisation. WHO.

World Health Organisation. (2021b). *Coronavirus Disease 2019 Situation Report-39*. World Health Organisation. WHO.

World Health Organisation Indonesia. (2020g). *Coronavirus Disease 2019 Situation Report-25*. World Health Organisation. WHO.

Xue, J., Chen, J., Hu, R., Chen, C., Zheng, C., Su, Y., & Zhu, T. (2020). Twitter discussions and emotions about the COVID-19 pandemic: Machine learning approach. *Journal of Medical Internet Research*, 22(11), 1–14. doi:10.2196/20550 PMID:33119535

Yadav, N., Kudale, O., Rao, A., Gupta, S., & Shitole, A. (2021). Twitter Sentiment Analysis Using Supervised Machine Learning. In *Intelligent Data Communication Technologies and Internet of Things* (pp. 631–642). Springer. doi:10.1007/978-981-15-9509-7\_51