Evaluating city-scale urban mobility restriction in Jakarta due to the COVID-19 pandemic: the impact on subjective wellbeing

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ABSTRACT
The COVID-19 pandemic has forced cities worldwide to implement social distancing on a large scale and even lockdowns. City lockdowns are considered a public health policy to reduce virus spread and at the same time to protect vulnerable groups of the population. However, studying the implications of city lockdowns on urban populations’ mental and emotional wellbeing has been widely neglected. Using a case study of Indonesia’s capital and the largest metropolitan area of Jakarta, this study investigates the temporal dynamics of emotions experienced by the citizen during two months of city-scale lockdown. This paper uses Twitter text data as the source for emotional analysis with almost 9000 tweets. The study suggests that positive emotions were more common than negative texts across all periods under study, with lockdown acting as momentum for enhancing family gatherings and serving as a reminder of the importance of health, as the common positive emotions identified. The study provides evidence on the possibility of crowdsourcing data such as Twitter as an alternative source of data for urban analytics that allows researchers to understand the effect of activities and events in a certain location on its citizens.

I. Introduction
The coronavirus (COVID-19) pandemic has forced governments worldwide to implement local and national lockdowns to limit the spread of the virus. Lockdowns have inevitably resulted in the limited movement and mobility of people in cities. Present studies highlight the impact of COVID-19 urban restrictions on health issues and wellbeing in various countries (Brooks et al., 2020; González-Sanguino et al., 2020; Wang et al., 2020).

However, there is a lack of studies examining these health and wellbeing issues utilising social media data. Furthermore, as these studies investigate at one point in time, they lack specific analysis on how different periods impact wellbeing differently. As such, contemporary studies have neglected the potential of social media as a source of information to investigate the impact of urban restrictions and how this changes...
over time. This is particularly appropriate in Indonesia, where in 2019, the Twitter social networking site had 22.8 million active users. Overall, in the country, more than 77% of social media (including Twitter and Facebook) users are younger than 34 years old.

The rise of social media coupled with location sharing services has made it possible to capture users’ perceptions and preferences over certain issues such as sentiment over parks (Plunz et al., 2019) and disaster response (Kusumo et al., 2017; Carley et al., 2016). These studies showed that social media analysis is not limited to examining sentiments per se but also categorises users based on characteristics and is location-based, which may influence their preferences.

This paper examines the urban population’s experience of city lockdown in Jakarta through their tweets by looking at three time periods. The region chosen was Jakarta, as it is the capital city and the largest metropolitan area in Indonesia, with a combined population of approximately 11 million people. Furthermore, Jakarta has more than 16 million Facebook accounts in 2018 and was then named as the capital of Twitter Nation, with more than 15 tweets per second in 2012.

The research questions proposed in this study are to what extent is the impact of urban mobility restriction on people’s movement and wellbeing, and how does this change after more than two months of implementation. The paper hypothesizes that, as tweet users are dominated by the young and urban citizens, we would observe the impact of wellbeing on this particular population. The impact of urban restriction policies is examined through urban population movement dynamic analysis using urban mobility data and wellbeing analysis using the natural language processing (NLP) techniques on Twitter data.

The paper is structured as follows; section two explores lockdown and subjective wellbeing. In section three, we elaborate on research data and methodology, and in section four, we examine the impact of urban restriction policies and how they have impacted the wellbeing of people. In section five, we conclude the paper’s findings and contributions.

II. Approaches to investigate the relationship between lockdown and wellbeing

Urban lockdown leads to a large number of populations being quarantined. Here, ‘Quarantine’ refers to the separation and restriction of people’s movement that has been potentially exposed to a contagious disease to reduce the risk of them infecting others (Cetron et al., 2004). Recently, following the COVID-19 outbreak, quarantine has been applied globally at the city, region, and country scale.

Studies show that quarantine is an unpleasant experience. The combination of the separation from loved ones, the loss of freedom, uncertainty over disease status, and boredom can, on occasion, create dramatic effects (Brooks et al., 2020). Furthermore, people in quarantine report a high prevalence of psychological distress and disorder such as general psychological symptoms, emotional disturbance, depression, stress, low mood, irritability, insomnia, post-traumatic stress symptoms, anger, and emotional exhaustion.

Recent studies on people that were quarantined in China (Wang et al., 2020) and Spain (González-Sanguino et al., 2020) during the initial phase of the COVID-19 outbreak reveal the psychological impact of stress, anxiety, and depression have a clear relationship
with loneliness. Furthermore, studies show that longer durations of quarantine, more than ten days, would amplify the negative effects above. Quarantine also increased people’s worries as they had fears over the health of themselves and their family members. In addition, restrictions on mobility also lead to significant socioeconomic distress that causes symptoms of psychological disorders. This may become more pronounced for workers in specific industries due to disruption of social networks and loss of leisure activities (Brooks et al., 2020).

**Urban social restriction and wellbeing**

To examine the impact of urban restrictions on citizen’s psychological state, we borrow the notion of ‘subjective wellbeing’ from health and psychology disciplines, referring to people’s assessment of their own life that includes both general and specific satisfaction (Diener, 1984), and also likely affects the function of social systems (Fahmi & Sari, 2020). In this sense, the subjective wellbeing of individuals shows important information on the perceived quality of life in neighbourhoods, cities, and between population subgroups (Helliwell & Barrington-Leigh, 2010).

Policymakers and researchers could benefit by observing wellbeing at the individual as well as at the society level. Recent studies referred to subjective wellbeing in a large spectrum that consists of cognitive elements, such as satisfaction with life as a whole or in specific domains, and affective elements, such as positive affect (e.g. excitement, affection pleasant) and negative affect (e.g. sad, worried, depressed) (Diener & Ryan, 2009; Fahmi & Sari, 2020). As such, these elements are relevant with the growing interest and debate in the semantic and language studies that try to understand these elements through people’s sentiments from their speech.

Using social media analysis, we could obtain these sentiments through mobility and text studies. As tweets also embedded location data, we could define wellbeing’s impact on a particular location or city. In addition, the platform provides real-time information that can be studied for various socioeconomic, political, and cultural issues (Plunz et al., 2019; Shirky, 2011). The two leading social media sources for study are Facebook and Twitter. They have been deployed as sources for social media studies to examine present society. Thus, Twitter data potentially offers researchers large and real-time data for temporal, semantic, and social content, a ‘richly contextual’ data source for various research fields (Malik et al., 2021).

The above discussion provides several benefits of using social media for urban analysis; first, social media allows current, real-time, and abundant data on people’s physical and digital activities in any particular city or area. Second, variations of analytical methods make it possible to analyse specific topics such as mobility, sentiment, and political views. Third, consequently, urban researchers should carefully determine the required data, period of analysis and should have a contextual understanding of the topics and cities that are used as case studies.

In this paper, we examined wellbeing in three main dimensions; health, relationship, and finance, as commonly described in wellbeing literature elsewhere (Diener & Lucas, 2000; Fahmi & Sari, 2020; Nussbaum & Sen, 1993). The disruptions to any combination of these dimensions lead to the interference of the subjective feeling of wellbeing. The health dimension is linked to both physical and mental health issues. For instance, the
paper by González-Sanguino et al. (2020) approximates this dimension with psychological impacts such as possible symptomatology, Generalised Anxiety Disorder Scale-2, and Post-Traumatic Stress Disorder and spiritual wellbeing.

Our present study builds on previous similar studies that attempt to understand how Twitter data capture impacts on wellbeing and daily activities. Despite not discussing the pandemic directly, the paper by Plunz et al. (2019) and Carley et al. (2016) suggest the importance of location proximity of tweets with the event of the topic discussed, such as parks or disaster occurrence. Several data collection strategies are required, such as the collection of geo-spatial information, sufficient spatial coverage, assessing the spatio-temporal patterns, and identification of opinion leaders. The study by Xue et al. (2020) shows that Twitter analytics allow understanding health-concern topics such as ‘confirmed cases and death rates’, ‘preventive measures’, and ‘health authorities and government policies’. The paper also highlights how topics change as the situation rapidly evolves, providing a sense of real-time monitoring of the public’s health concerns and their response. Another study by Lu et al. (2020) suggests a longer period analysis of tweets could identify changing patterns of mental status where anxious depression levels heighten in the early days of quarantine but gradually diminish, reaching their lowest point after two weeks. Similarly, with daily activities analysis over a certain period, Abd-Alrazaq et al. (2020) found that topics of economic loss and increased racism were found the most during the pandemic.

On the other hand, this study attempts to widen the literature by specifically identifying the social media users’ dominant specific age group and urban context. Urban restriction policies may significantly cause social mobility decline and psychological concerns among this particular age group. The study also highlights the impact on wellbeing changes over time by analysing more than two months of urban restriction implementation, capturing people’s shift of concern about their jobs and health. In this sense, urban restrictions impact on wellbeing is seen a series of periods and variations of activities and concern topics. Furthermore, this study also extends the study by Aritenang et al. (2021) by deploying statistical test, the Friedman tests, on Twitter sentiment data to determine the significance of Large-Scale Social Restrictions (Pembatasan Sosial Berskala Besar/PSBB) impact on subjective wellbeing in the capital and largest city in Indonesia, Jakarta.

The Indonesian government did not implement a city lockdown policy as found in Europe, rather it utilised PSBB to contain the spread of COVID-19. The PSBB refers to a partial lockdown where offices and factories remain open, in contrast with total lockdowns that were preferred by other countries. Before the implementation of PSBB, in the early phase of the outbreak, the study by Riyanti Djalante et al. (2020) reveals the government’s scepticism, hesitance, and denial of the potential pandemic occurrence in the country. It was not until late March that the government reluctantly implemented nationwide PSBB with contemporary terminologies slowly entering the public acceptance to self-isolation or stay at home advice (Riyanti Djalante et al., 2020). These local terms included introductions to the risk, such as ‘social distancing’ and stay at home (di rumah saja), including songs to encourage people to stay home. However, as PSBB was implemented and schools were closed, the news reported mass family holidays.
The impact of urban lockdown may be different across generations as online meetings is the new form of communication to collaborate ideas, meetings, and webinars. However, this may be a new form of meeting only for older adults, whereas the younger generations are already using these mediums to communicate such as vlogging (videoblogging), content writing, copywriting, and programming (Wibowo, 2020). Urban lockdown meant less health care. This was confirmed by Zachary et al. (2020), who showed that during the lockdown, roughly 22% of the sample reported gaining weight during self-quarantine. The predictors include getting adequate sleep, not snacking after dinner, practising dietary restraint, altering stress coping mechanisms, and maintaining an exercise regimen.

III. Data and Methodology

The Jakarta metropolitan, as a case study, was strictly under PSBB for more than two months from mid-March to mid-May 2020. The PSBB significantly shifted the population’s living and mobility behaviour. The period of analysis included two days with one weekday and one day over the weekend, within the weeks of mid-March, mid-April, and mid-May. The period of analysis was chosen to reflect the diversity of tightness of policy in PSBB implementation. The mobility data collected from Facebook and text data from Twitter are considered to represent the school and working population group aged between 13 to 44 years that made up 89% of active users in the country.³

The filter included location, proximity area, and tweets related to the keywords. First, the geolocated tweets were calculated 50 km within the National Monument (Monumen Nasional/Monas), with geocode −6.175036,106.827192, considered as the centre of Jakarta. The 50 km distance used corresponds to the commuting distance of the Jakarta Metropolitan Area (JMA). Second, the number of tweets were limited to keywords ‘PSBB’, ‘dirumahaja’, and ‘dirumahsaja’ which were the most common words and hashtags used during March-May 2020.⁴ During the peak of the early period of the pandemic, these keywords were the most common as it represents the situation at that time; ‘PSBB’ highlights the urban-level social restrictions and ‘dirumahsaja’ or “dirumahaja” represent government advice to stay at home.⁵ The tweets data included text and metadata, such as timestamp, user profile description, source, and volunteered geolocations.

To examine the dynamics of the topic of wellbeing, this study analysed three periods of PSBB as a study sample; the early phase from March 21st to 25th, the peak phase from April 19th-23rd, and then towards the transition phase from May 17th – 22nd. The data collection returned 3900 tweets, 2900 tweets, and 1900 tweets for each phase, respectively. As the study is interested in examining the wellbeing of people in the PSBB period, the selected dates are Monday-Wednesday to represent the weekdays where people go to work and school.

Data categorization

Tweet texts are subsequently cleaned to remove URLs, extra spacing, and hyperlinks. Afterwards, the stemming⁶ process is conducted by referring to the bag of words from the Sastrawi⁷ package, a python library specially developed for stemming in the Indonesian
language. The result is used to analyse tweet sentiments and compare throughout the period. The sentiment analysis refers to analysing the sentiment of a given text, in this case, the tweets, and categorising them into specific categories (positive, neutral, and negative). As we analysed the Indonesian language that has limited resources for sentiment analysis, we use the Twitter labelled dataset published by Ferdiana et al. (2019) as a training data set to label our tweet texts.

Second, the model tokenises each sentence up to length 2, referring to a pair of words that occur consecutively in a text (e.g. ‘Jakarta City’ is an ngram of length 2). For each ngram, the model counts the number of times that the ngrams appear that will be used in the model for the machine to learn. In the next step, we introduce stopwords to train the model to recognise commonly used words (such as ‘the’, ‘a’, ‘an’ in English or ‘kenapa’, ‘lagi’, ‘apa’ in Indonesian) and ignore these words to reduce search query or processing time. The selected words are then processed through stemming analysis that allows the words in the text to be transformed into their basic form, for instance, ‘buying’ to ‘buy’ (‘membeli’ to ‘beli’). Fortunately, the Sastrawi package allows conducting text stemming in the Indonesian language.

The transformed words are analysed to; (i) topic model to classify text into a particular topic using the algorithm that automatically calculates the word frequencies of tweets to identify words and phrases relevant to the topic. These keywords are then assigned to the corresponding domain dictionary with several topics automatically. We analyse these keywords and correspond them to the subjective wellbeing for three domains; health, relationship, and finance. (ii) we assess tweet sentiment, looking at frequencies of positive, negative, and neutral tweets.

**Research methodology**

The urban mobility restriction is performed using visualisation of the Facebook Movement Range Maps that provides daily data on people mobility at the city level. From the data, we present two types of people mobility, which are daily movement changes and the stay-put metric data (showing the population fraction staying within a small area surrounding the residences).

To examine subjective wellbeing, we conducted two NLP techniques; topic modelling and sentiment analysis. Topic modelling was conducted by grouping the cleaned texts into several topics using the Latent Dirichlet Allocation (LDA) that has been widely used to achieve adequate classification in text mining analysis (Zhou et al., 2020). In this analysis, the researcher’s knowledge and understanding of a particular city’s culture are critical to capture main topics or discussions that occur in the specific city.

Sentiment analysis is a process of labelling cleaned tweet texts into three categories – i.e. negative, positive, and neutral – to capture a tweet’s tone. Positive (or negative) sentiment refers to the positive (or negative) expressions identified in the tweet text, such as happiness, joy, sadness, and health concerns. Whilst neutral sentiment refers to texts without any positive or negative expression, for instance, information provision and fact sharing. This labelling process uses the machine learning method, where the algorithm learns from and subsequently classifies texts from the training dataset using the labelled tweets published by Ferdiana et al. (2019). As commonly found in studies with machine
learning, we split the dataset into 70% as training data and 30% data as test data. To examine the robustness of classified text, we conducted temporal analysis using the Friedman tests to identify the differences between the periods.

Despite it being considered as a promising emerging method, there are concerns over the use of machine learning for sentiment classification (Puschmann & Powell, 2018). First, sentiment analysis requires context understanding. Thus training datasets should be the same or similar to the data being analysed to suggest accurate labelling. Second, researchers need to identify opinion or promotion spam that may influence the labelling process. As such, it is common that researchers may have to manually check and label the tweet once machine learning labelling is completed.

Last, to examine the significance of PSBB tweets on subjective wellbeing on a different period, the difference in tweet numbers between the periods is analysed using Friedman tests following H. Roberts et al. (2019).

IV. Results and discussions

In this section, we examine the effect of urban restriction on mobility and subjective wellbeing.

Mobility analysis

In the early phase, the Jakarta provincial government only recommended work from home activities during the third week of March 2020. However, considering the increasing COVID-19 new cases, the government issued the first PSBB that formally began on 10 April 2020, for two weeks until 23 April 2020. The PSBB was extended for 28 days before it was extended for 14 days until 4 June 2020, as the 3rd PSBB. In early June, the government further extended the 4th PSBB to the end of June 2020.

During the 3rd PSBB there were issues and notions of Jakarta citizens urges to return to the village for the Eid al-Fitr holy day. To address the return to the villages wave and afterwards, the government issued the entrance-exit permit for travelling to Jakarta. There are two types of permit; the regular travelling permit and the once travelling permit. However, this permit is not required for commuters that live in the neighbouring cities such as Bogor, Depok, Tangerang, and Bekasi.

During the PSBB, the government has been very concerned with people’s wellbeing as, while health was the reason for the PSBB in the first place, mobility restriction would affect their income. As these are more pronounced by the local government, there are cases where it seems they are more responsive and take more initiative compared to the central government. This was found in various cities in the country, where local leaderships showed various forms of ‘lockdowns’ that proved effective for local infection control and management responses (Lane, 2020).

In JMA, with more than 16 million Facebook accounts and 15 tweets per second, many active users of social media platforms may provide an interesting population to study for wellbeing. The graphs below depict the changes in the Jakarta population’s activities in retail and recreation locations and staying in their houses as a percentage compared to January-February 2020 (Figures 1 and 2).8 First, the figures reveal the
significant shift of activities in both locations with a sharp decline (about 45–70%) for people visiting retail and recreation visits, whilst a steep increase (about 15–25%) in staying in the residents.

**Subjective wellbeing analysis**

First, we analyse the topic modelling to examine topics that are most presently related to the PSBB. After pre-processing, the process continues with a separate Term-Document Matrix (TDM) for each text using TF-IDF (term frequency-inverse document frequency) to normalise term frequency data by summing the term appearances in the various documents. This process allows the weighting scheme used in text mining to reduce
irrelevant terms as found in previous research (Hananto, 2015). The result is the Latent Dirichlet location (LDA) model that presents topic models that could be identified with our study (Figure 3).

The LDA analysis figure suggests the topic modelling of most relevant terms for the two month period with terms such as stay at home (dirumahaja), friendship (sahabat), covid, health (sehat), and psbb in Jakarta. The highest trending topic is the #dirumahaja, noting the hashtag and reminder for people to stay at home. The next highest topic is relationships that are represented with a high number of friendships (sahabat), followed by health with topics on COVID-19 and health. Only a small number of tweets are related to finance, such as linkaja (a fintech company) and saldo (bank balance).

Second, sentiment analysis is assigned to almost 9000 tweets, with only about 7000 tweets that could be assigned to positive or negative sentiment analysis. The remaining tweets are assigned to a neutral sentiment that consisted of news reports, advertising events and other individual statuses that could not be identified in terms of emotions. As such, numerous downloaded tweets that are assigned to neutral are also found in previous studies (K Roberts et al., 2012; H. Roberts et al., 2019). Thus, we could collect emotional information through Twitter data to monitor and evaluate interventions and

![Top-30 Most Relevant Terms for Topic 1 (33.5% of tokens)](image-url)
community restrictions during the pandemic. The implication of PSBB by the government and subsequent activity restrictions by the police could be used as an evaluation to establish how the community responded.

In the first period (March 21st to 25th, 2020), we analyse 500 tweets with a result of sentiments of 43 negative, 420 neutral, and 37 positive). The example is presented in the following table (Table 1).

Using the NLP technique, tweet texts that could be assigned as having positive signs are much fewer compared to negative ones, suggesting that more people are tweeting about the negative aspects of PSBB. These findings confirm our hypothesis and previous studies that PSBB would result in negative emotions following mental hardship, such as health concerns, loneliness, and financial problems.

A smaller number of tweets do spread positive emotions such as encouragement and support during the pandemic PSBB. The positive sentiment tweets include keywords such as stay at home, help, online, home, health, keep the spirit, hope. Furthermore, a smaller number of positive keywords are friends, medic, workout, drama, Korea, and protection. The positive responses could be used to justify that the community and citizens understand the importance of the above policies. The ‘help’ notion was present in association with notions of feeling together during the pandemic. This is reflective of the fact that people are social human beings and that relationships can boost spirits during the PSBB (Alakeson & Brett, 2020).

On the other hand, negative tweets included keywords such as work, home, us, sick, and corona. While a smaller number of categories are learning/school, PSBB, assignment, and individual concerns. Furthermore, boredom by staying at home was the

| No | Category | Example                                                                 |
|----|----------|-------------------------------------------------------------------------|
| 1  | Positive | ‘bareng2 kita lawan #Covid19 dengan #SocialDistancing #RengganganSosial #DirumahAja’ (‘together we fight #Covid19 with #SocialDistancing #RengganganSosial #DirumahAja’)  
‘Isi waktu anak-anak selama #stayathome dengan yang bermanfaat. Salah satunya ada waktu luang untuk menghafal Al-Qur’an. #ayomengaji #generasialquran #Dirumahaja #homeschooling’ (‘During #stayathome kids should do useful activities, such as reading the holy Al-Qur’an. #ayomengaji #generasialquran #Dirumahaja #homeschooling’) |
| 2  | Neutal   | ‘Lockdown sudah saatnya, gue udah liat sendiri kondisi salah satu mall gede di jakarta kembali. Sepiii, artinya dari masyarakat sendiri sudah mulai sadar akan kampanye #dirumahaja. Ayok pak presiden’ (Its time for lockdown, yesterday I saw that one of the main shopping centre in Jakarta (has closed). The city is empty, this shows that people has realized the campaign on #dirumahaja. come on Mr. president)  
‘Hai, selamat sore. gw hari ini WFH meliburkan diri sndr. but so much work to do juga dr pagi depan laptop. kw jenuh, workout. lanjut lagi kerja. tidur. nonton, kerja lagi. How about yours?’ (‘Hai,good afternoon.today I will be working from home (WFH), taking a day off, but so much to do working in the front of the laptop since morning if I get bored, I will do workout, then work again. sleep.watch (television/movie),work again … how about yours?) |
| 3  | Negative | ‘Sebagai anak rambut yg tak punya kendaraan pribadi selain motor, aku sangatlah galau. Pengen nurut #dirumahaja diem di kosan tp resah. Pengen pulang kampung tp takut bawa virus. Ate tes kok larang dn mari tes numpak e kendaraan umum. Galau melebihli tema sahur tiap ramadan’ (‘As a person who comes from another city who only have a motocycle, I am very confused. I would like to follow the #dirumahaja campaign and stay at the boarding house but I am confused. I want to go home but concerned to became a virus carrier.the confusion is just like Suhoor/Pre-dawn Meal during Ramadhan’)  
‘Ini sebenarnya belajar online apa nugas online sih, dirumahkan bukannya belajar online malah yg dikasih TUGASS MULU TUGASS MULUUUU … #dirumahaja’ (‘is it online learning or online task, there is not so much learning yet so many class tasks … #dirumahaja’) |
main issue, as represented by corona, online learning, and illness. Interestingly, keywords analysis included the notion of work, suggesting that still working during the pandemic raises negative emotions such as financial and health concerns, as we expected earlier. The analysis did not find specific keywords related to financial problems due to the PSBB. However, in March, there were concerns over jobs survival. Furthermore, we may explain the lack of financial issues being a result of Twitter users being predominantly young people and students who may still be financially supported by their parents. The negatively annotated tweets were largely associated with activities rather than the PSBB and mobility restrictions themselves. For example, the sadness peak observed could be attributed to working during the pandemic, stay at home that hinders meetings with friends, online learning, or a lack of communication.

This study identified several senses of togetherness tweets in response to the PSBB, which is in contrast to several previous studies that suggested lockdown leads to stressful and depressing situations (Brooks et al., 2020; Wang et al., 2020). The occurrences display a sense of community response to keeping a positive spirit or helping each other with behaviours such as food and money donations, community work, and raising funding for the marginalised. The high level of sense of community responses was more pronounced in the second month or during the peak of the PSBB and attributed to the declining number of economic activities and in the city. The rise of concern to keep spirits high and help each other was sustained across the periods as a response to the economic and social PSBB.

The positive sentiments that were found suggested the presence of positive responses despite the hard times due to lockdown with citizens as social human beings intuitively supporting each other during all periods of PSBB. The findings in this article highlight that emotions by individuals are crucially important to understand experiences by citizens during a lockdown and how it impacts their wellbeing. The analysis reveals several recurring themes that may represent emotional expression in their tweets. For instance, positive tweets may include reminders to stay healthy, do sports, and stay at home (Table 1). While negative emotions were often sarcastic, require reading the whole sentence, or require specific keywords for the machine to identify.

The above analysis provides evidence that researchers could gather and understand citizens’ experiences to address public health problems and provide consultations required by the government.

Identifying activities that may bring happiness and joy encouragement may help the government design appropriate policies. As such, H. Roberts et al. (2019) argue that Twitter text analysis allows researchers to identify the causes of emotional responses that would be valuable input for appropriate policy-making.

The temporal analysis over the two months in this study also suggests a temporal variation of responses in each period. Using the Friedman tests provide evidence of significant differences in the total number in each period ($\chi^2 (2) = 0.0222, p = 0.8816$) and the total number of negative tweets, although this relationship was less strong ($\chi^2 (2) = 1.0254, p = 0.3112$). As our finding is less significant, a longer period and larger area of analysis may be required to examine PSBB’s impact on subjective wellbeing.
V. Discussion and conclusion

The above discussion and findings have demonstrated the impact of urban mobility restriction on subjective wellbeing using citizen tweets. The analysis shows a significant decline and changes in mobility behaviour. The crowdsourced data from Facebook users capture the significant drop of Jakarta citizens’ mobility during the pandemic compared to the pre-pandemic period. Whilst the emotions and perspectives of people during the pandemic lockdown were captured using tweet data analysis, movement and Twitter data provide new insights to investigate urban activities and events through the perspective of its citizen as the data are freely available via the API for a certain period, including geocode and date details, and it is updated daily. Our sentiment analysis identifies emotional concerns such as boredom and financial issues, although there are also positive sentiment tweets related to urban restrictions and lockdowns, such as reminders on the importance of family affection and health in the pandemic.

However, it should be underlined that these analyses represent the dominant proportion of social media users, people aged 13–44 years old, that represent the school and working-age group that are most affected in terms of mobility and wellbeing. Nevertheless, the above findings confirm previous research on individuals’ common negative emotional responses to city lockdown. Nevertheless, the study also suggests a positive response from the city lockdown, such as how citizens attempt to make the most of the situation and to stand together through difficult times. The findings explored how Twitter texts are used for sentiment analysis and subsequent corpus analysis to examine their experience to city lockdown, as well as specific themes associated with citizens’ emotions. Two important advancements in social media analysis allow a wide opportunity to expand urban studies, especially research related to citizen perception and emotions. First, the availability of crowdsourced generated data such as Facebook and tweet data, and second, the NLP technique analysis allows capturing the emotional experiences of urban citizens during the city lockdown from the above social media data.

This finding highlights the potential use of social media to investigate citizen’s perspectives on social and physical distancing that hinders conventional face-to-face meetings. This information is valuable for the government and policymakers to understand citizens’ perspectives and emotions in various urban issues. However, we also acknowledge several shortcomings from social media analysis to capture citizen well-being. Previous studies have acknowledged some limitations of tweet texts as a source for studies involving emotional response to space, such as the limited characters cannot represent highly complex emotions and subjective experiences. Another issue that has to be considered is the potential of data manipulation due to Twitter’s data being publicly accessible and being an unmonitored platform (H. Roberts et al., 2019). As this study is not related to politics or other high-interest issues that may use spam tweets and fake accounts to bring certain opinions, we can safely argue that our study could address spam.

Additionally, literature also points to possible issues as users may not represent emotions and perspectives of the whole population for the study, rather only specific age groups, socioeconomic statuses, or ethnicities. Thus, there is the possibility of bias from social media data (Hannay & Baatard, 2011). However, we have highlighted at the beginning of the paper that, as social media users are dominated by school and working-
age population groups between 13 to 44 years, we could investigate the impact of urban restrictions on their mobility and wellbeing. Hence, the above limitation and concerns over research validity could be addressed.

The paper contributes to the literature in two ways; first, governments and researchers could study the impact of urban mobility restriction policies on subjective wellbeing through social media texts such as Facebook Mobility and Twitter data. By addressing limitations of social media data, such as identifying the users’ dominant specific age group and understanding the urban context where the data are analysed, the paper shows that urban restrictions significantly cause a decline of social movement, leading to psychological concerns and wellbeing issues.

Furthermore, our study highlights that this impact on wellbeing changes over time. The study captures that people are concerned with their jobs and efforts to stay healthy in the early days of urban restriction. However, after two months of urban restriction, people have accepted the new normal, and daily activities have risen again with a consistent reminder on health protocols by the government. Thus, we argue that urban restrictions impact on wellbeing should not be seen as a one-point study; rather, it should be seen through a series of studies that allow policymakers and urban managers to design appropriate policies to address the dynamics of wellbeing issues.

Notes

1. https://www.thejakartapost.com/life/2018/03/04/indonesia-fourth-highest-number-of-facebook-users-in-the-world.html
2. https://www.ipra.org/news/title/indonesia-falls-for-social-media-is-jakarta-the-worlds-number-one-twitter-city/
3. https://www.statista.com/statistics/997297/indonesia-breakdown-social-media-users-age-gender/
4. https://getdaytrends.com/indonesia/jakarta/trend/%23dirumahaja/
5. ‘dirumahaja’ or ‘dirumahsaja’ has the same meaning which is stay at home. The informal language and daily conversation used in the social media is seen with the omitted ‘s’ in the latter.
6. process of reducing a word to its word stem that affixes to suffixes and prefixes or to the roots of words.
7. See https://pypi.org/project/Sastrawi/
8. The data is analysed from the Google community mobility report (for more detail information see https://www.google.com/covid19/mobility/)

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Disclosure statement

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References

Abd-Alrazaq, A., Alhuwail, D., Househ, M., Hamdi, M., & Shah, Z. (2020). Top concerns of tweeters during the COVID-19 pandemic: infoveillance study. *Journal of Medical Internet Research, 22*(4), e19016. https://doi.org/10.2196/19016

Alakeson, V., & Brett, W. (2020). Local Heroes How to sustain community spirit beyond COVID-19. Power to Change Report.

Aritenang, A., Drianda, R. P., & Zohra, L. (2021). *Analysing the Correlations between Restricted Mobilities and Subjective Wellbeing through Social Media during the COVID-19 Pandemic: The Cases of Bandung and Surakarta Cities.* Indonesia Regional Science Association (IRSA) Serial Books.

Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., & Rubin, G. J. (2020). The psychological impact of quarantine and how to reduce it: Rapid review of the evidence. *Lancet (London, England), 395*(10227), 912–920. https://doi.org/10.1016/S0140-6736(20)30460-8

Carley, K. M., Malik, M., Landwehr, P. M., Pfeffer, J., & Kowalchuck, M. (2016). Crowd sourcing disaster management: the complex nature of twitter usage in Padang Indonesia. *Safety Science, 90*, 48–61. https://doi.org/10.1016/j.ssci.2016.04.002

Cetron M, Maloney S, Koppaka R, and Simone, P. 2004. Isolation and Quarantine: Containment Strategies for Sars 2004. In: Institute of Medicine (US) Forum on Microbial Threats; Knoobler S, Mahmoud A, Lemon S, et al., editors. Learning from SARS: Preparing for the Next Disease Outbreak: Workshop Summary. Washington (DC): National Academies Press (US). Available from: https://www.ncbi.nlm.nih.gov/books/NBK92450/

Diener, E. (1984). Subjective wellbeing. *Psychological Bulletin, 95*, 542–575. https://doi.org/10.1037/0033-2909.95.3.542

Diener, E., & Lucas, E. R. (2000). Explaining differences in societal levels of happiness: relative standards, need fulfillment, culture, and evaluation theory. *I.https://doi.org/10.1023/A:1010076127199*

Diener, E., & Ryan, K. (2009). Subjective wellbeing: A general overview. *South African Journal of Psychology, 39*(4), 391–406. https://doi.org/10.1177/008124630903900402

Fahmi, F. Z., & Sari, I. D. (2020). *Rural transformation, digitalisation and subjective wellbeing: A case study from Indonesia.* Habitat International.

Ferdiana, R., Jatmiko, F., Purwanti, D. D., Ayu, A. S. T., & Dicka, W. F. (2019). Dataset Indonesia untuk analisis sentimen. *Jurnal Nasional Teknik Elektro Dan Teknologi Informasi (JNTETI), 8*(4), 334–339. https://doi.org/10.22146/jnteti.v8i4.533

González-Sanguino, C., Ausín, B., Castellanos, M. Á., Saiz, J., López-Gómez, A., Ugidos, C., & Muñoz, M. (2020). Mental health consequences during the initial stage of the 2020 coronavirus pandemic (COVID-19) in Spain. *Brain, Behavior, and Immunity, 87*, 172–176. https://doi.org/10.1016/j.bbi.2020.05.040

Hananto, A. (2015). Application of text mining to extract hotel attributes and construct perceptual map of five star hotels from online review: study of Jakarta and Singapore five-star hotels. *Asean Marketing Journal, VII*(2), 58–80. https://doi.org/10.21002/amj.v7i2.5262

Hannay, P., & Baatard, G. (2011). GeoIntelligence: data mining locational social media content for profiling and information gathering. In *Proceedings of the 2nd international cyber resilience conference*, 1–2 August 2011, Perth, Australia: Edith Cowan University.

Helliwell, J., & Barrington-Leigh, C. (2010). Measuring and understanding subjective wellbeing. *NBER Working Paper No. 15887.* NBER Working Paper.

Kusumo, A. N. L., Reckien, D., & Verplanke, J. (2017). Utilising volunteered geographic information to assess resident’s flood evacuation shelters. Case study: Jakarta. *Applied Geography, 88*, 174–185. https://doi.org/10.1016/j.apgeog.2017.07.002

Lane, M. (2020). The Politics of National and Local Responses to the COVID-19 Pandemic in Indonesia. In *ISEAS Perspective.* ISEAS–Yusof Ishak Institute.
Lu, W., Yuan, L., Xu, J., Xue, F., Zhao, B., & Webster, C. (2020). The psychological effects of quarantine during COVID-19 outbreak: sentiment analysis of social media data. medRxiv. https://doi.org/10.1101/2020.06.25.20140426

Malik, M., Lamba, H., Nakos, C., & Pfeffer, J. (2021). Population Bias in Geotagged Tweets. Proceedings of the International AAAI Conference on Web and Social Media, 9(4), 18–27. Retrieved from https://ojs.aaai.org/index.php/ICWSM/article/view/14688

Nussbaum, M., & Sen, A. (1993). The quality of life. Oxford University Press.

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 wellbeing. Landscape and Urban Planning, 189, 235–246. https://doi.org/10.1016/j.landurbplan.2019.04.024

Puschmann, C., & Powell, A. (2018). Turning Words Into Consumer Preferences: How Sentiment Analysis Is Framed in Research and the News Media. Social Media + Society.

Riyanti Djalante, R., Lassa, J., Setiamarga, D., Sudjatma, A., Indrawan, M., Haryanto, B., Mahfud, C., Sinapoy, M. S., Djalante, S., Rafliana, I., Gunawan, L. A., Surtiari, G. A. K., & Warsilah, H. (2020). Review and analysis of current responses to COVID-19 in Indonesia: period of January to March 2020. Progress in Disaster Science, 6:100091. http://dx.doi.org/10.1016/j.pdisas.2020.100091

Roberts, H., Sadler, J., & Chapman, L. (2019). The value of twitter data for determining the emotional responses of people to urban green spaces: A case study and critical evaluation. Urban Studies, 56(4), 818–835. https://doi.org/10.1177/0042098017748544

Roberts, K., Roach, M., & Johnson, J. (2012). EmpaTweet: annotating and detecting emotions on twitter. In: Proceedings of the eight international conference on language resources and evaluation (LREC’12), 23–25th May 2012, Istanbul, Turkey.

Shirky, C. (2011). The political power of social media: technology, the public sphere, and political change. Foreign Affairs, 28–41. https://www.foreignaffairs.com/articles/2010-12-20/political-power-social-media

Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C. S., & Ho, R. C. (2020). Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. Int. J. Environ. Res. Public Health, 17(5), 1729. https://doi.org/10.3390/ijerph17051729

Wibowo, J. M. (2020). Lockdown Generation: Pengangguran di Masa COVID-19. Lembaga Ilmu Pengetahuan Indonesia. https://kependudukan.brin.go.id/mencatatcovid19/lockdown-generation-pengangguran-di-masa-covid-19/

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), e20550. https://doi.org/10.2196/20550

Zachary, C., Forbes, B., Lopez, B., Pedersen, G., Welty, J., Deyo, A., & Kerekes, M. (2020). Self-quarantine and weight gain related risk factors during the COVID-19 pandemic. Journal of Obesity Research and Clinical Practice, 14(3), 210–216. https://doi.org/10.1016/j.jorcp.2020.05.004

Zhou, Z., Qin, J., Xiang, X., Tan, Y., Liu, Q., & Xiong, N. N. (2020). News text topic clustering optimised method based on tf-idf algorithm on spark. Computers, Materials & Continua, 62(1), 217–231. https://doi.org/10.32604/cmc.2020.06431