Understanding People's Sentiments of Government's Lockdown Policy Announcement: A Case of Indonesia

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Yulianti*
School of Business and Management, Institut Teknologi Bandung

Deddy Priatmodjo Koesrindartoto
School of Business and Management, Institut Teknologi Bandung

ABSTRACT

The Covid-19 pandemic not only has impacted health and the economy, but also has dramatically changed people's daily lives. The pandemic has become a trending issue on social media since 2020, and most people use social media to express feelings, gather, and share information about Covid-19. Concerning the issue, this paper discussed Indonesians' sentiments of lockdown policy, also known as *Pembatasan Sosial Berskala Besar* (PSBB). The data were collected from comments on Kaskus. The data were analyzed using Liu Hu's lexicon-based approach to investigate text mining. At the beginning of PSBB, people tended to express positive sentiments, but their sentiments have shifted into negative ones. An increasing negative sentiment shows people's tendency for the PSBB implementation. Overall, Indonesians show highly negative sentiments of PSBB. This research differed from previous studies because it had a longer timeframe and larger observations. This study suggests that the Government must ensure the people's basic need fulfillment and enforce PSBB regulations.

Keywords: COVID-19; Indonesia; lockdown; sentiments analysis.

1. INTRODUCTION

The Covid-19 outbreak firstly appeared in Wuhan in December 2019. The virus very rapidly spread to other countries by the end of January 2020 and was declared as a pandemic by the World Health Organization on 11 March 2020 (Ahmed, Rabin, & Chowdhury, 2020). Tens of millions of people worldwide suffered from Covid-19, and hundreds of thousands of people died. There were 32,730,945 confirmed positive cases and 991,224 deaths globally by the end of September 2020 (World Health Organization, 2020). Meanwhile, 24,891,149 people recovered (Worldometer, 2020).

The Covid-19 pandemic has occurred in Indonesia, and the first case was confirmed on 2 March 2020. Indonesia reported the highest number of new cases besides India, Bangladesh, and Myanmar by the end of September 2020 (World Health Organization, 2020). The case continuously grows. There were 287,008 positive cases, 10,740 deaths, and 214,947 recovered by the end of September 2020.

To stop the frightening spreading, World Health Organization has suggested social distancing (Le et al., n.d.). Social distancing will effectively limit the spread of a new virus or disease when a vaccine is unavailable or the vaccine efficacy is inadequate

(Choi & Shim, 2020). Therefore, some countries have implemented social distancing and self-quarantine. For example, Italy announced social distancing on 22 February 2020, Spain on 14 March 2020, the US on 16 March 2020, Germany in March (Thu et al., 2020). India also implemented lockdown on 24 March 2020 (Kaur & Ranjan, 2020) and Nigeria on 30 March 2020 (Ogbuju et al., 2020). Indonesia announced a lockdown policy, known as large-scale social restrictions or *Pembatasan Sosial Berskala Besar* (PSBB), on 10 April 2020. The policy was imposed after carrying out social distancing policies, dismissing schools, and closing entertainment venues on 14 March 2020. PSBB was regulated by the Government Act No 21/2020. PSBB restricted certain social activities in an area suspected of being infected by Covid-19 to prevent possible spreads of Covid-I9. The restrictions were applied to schools, offices, religious activities, public places or facilities, social and cultural activities, transportation modes, and other activities related to defense and security aspects (Peraturan Pemerintah RI No 21, 2020).

However, social distancing has several negative and positive effects. Thu et al. (2020) discover that implementing social distancing can stop the spread of the virus within 1-4 weeks. Moreover, it can decrease the daily confirmed cases and mortality rate. The level of social distancing and different spreads of Covid-19 will also affect social distancing effectiveness. The implementation of social distancing forces people to change their daily lives; they must follow the policies to protect their communities' safety. Unfortunately, long-time social activity restrictions during the pandemic period have brought several mental issues. The symptoms of these mental issues are worry, fear, frustration, depression, and anxiety (Yin, Yang, & Li, 2020). These issues will be worsened by infection fears, inadequate supplies, inadequate information, financial loss, and stigma (Brooks et al., 2020).

Emotions and sentiments encourage people to share their feelings, one of them through social media. Expressing their feelings can make them calmer and more comfortable during the lockdown and social distancing. We can discover people's insights, emotions, and sentiments by analyzing their posts. Besides, we can reveal what people's favorite, expectation, and primary concerns from the analysis (Ahmed, Rabin, & Chowdhury, 2020). Therefore, social media has become a primary communication mode in this century (Ainin et al., 2020).

One of the social media widely used is Twitter. Some studies have observed sentiments of Covid-19 and social distancing on Twitter. For example, Ahmed et al. (2020), Kayes et al. (2020), and Yin et al. (2020) have analyzed Covid-19 sentiments worldwide. Meanwhile, Dubey (2020) analyzes the sentiments in 12 specific countries. Therefore, investigating how people perceive social distancing and their sentiments of successful public policy during the pandemic is crucial (Kayes et al., 2020).

Regarding the complex conditions in Indonesia that require a comprehensive policy, this study aimed to observe Indonesians' sentiments when the PSBB policy was implemented. This study employed the text mining theory to analyze comments containing sentiments of PSBB on Kaskus. Kaskus is one of the biggest online group discussions in Indonesia. This research was different from previous studies because it had a longer timeframe and larger observations. Moreover, this study implemented a lexicon-based method to investigate Indonesian used in the comments. Few studies employing Indonesian to analyze sentiments because it has complex nature. Indonesian is a Malay language family and the most widely spoken language in Southeast Asia (Takari, 2017).

2. LITERATURE REVIEW

2.1. Sentiment Analysis

Sentiment analysis (SA), also called opinion mining, refers to a study analyzing people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions of entities, such as products, services, organizations, individuals, issues, events, topics, and attributes, usually from written language (Liu, 2012). SA lies at the intersection of information retrieval, natural language processing (NLP), and machine learning. Moreover, it includes sub-tasks, such as lexicon generation, subjectivity detection, and polarity detection (Mowlaei, Abadeh, & Keshavarz, 2020).

Medhat, Hassan, & Korashy (2014) divide SA into three major levels: document-level, sentence-level, and aspect-level SA. The document-level SA considers a whole document as an opinion expressing positive or negative sentiments. The sentence-level SA categorizes sentiments conveyed in each sentence. Moreover, this level is applied in a subjective sentence and will verify whether the sentence expresses a positive or negative opinion the aspect-level SA classifies sentiments associated with specific aspects of entities. Sentiment classification techniques are classified into a lexicon-based approach, a machine learning approach, and a hybrid approach. Recently, sentiment analysis measures texts and images.

SA has been used widely in every aspect to analyze online product reviews and political reviews. For example, (Chang & Wang, 2020) reveal that sentiment analysis in the sharing economy is applied to different contexts, but the focus has shifted from consumers to providers. Besides, SA is applicable to government policy, such as the credit card policy in Indonesia (Hasanah & Koesrindartoto, 2015), the electricity price policy in China (Sun et al., 2020), opinion on Brexit negotiations (Georgiadou, Angelopoulos, & Drake, 2020), tourism (Guerreiro & Rita, 2020), and halal tourism (Ainin et al., 2020).

2.2. Previous Studies on Sentiment Analysis of Covid-19

During the Covid-19 pandemic, many studies have proposed to use SA on social media to observe people's mental health. Most of the studies investigated tweets on Twitter as their sample. Some studies collect tweets globally (Dubey, 2020; Yin, Yang, & Li, 2020), and some collect the data in a specific region (Chehal, Gupta, & Gulati, 2020; Kaur & Ranjan, 2020; Ogbuju et al., 2020). They used specific keywords to gather the data, such as #covid19, #covid, #corona, #coronaviras, #corona-virus, #covid19-virus, and #sarscov2, #coronavirus, #2019nCoV, #COVID19, #coronaoutbreak, and #quarantine. This section reviewed the latest studies analyzing Covid-19 on social media.

In general, people's reactions to Covid-19 vary from day to day as seen from their posts on social media. The data portray how people, governmental organizations, and media agencies have broadcasted the situations (Manguri, Ramadhan, & Amin, 2020). Unfortunately, (Danowski, Yan, & Riopelle, 2020) find a negative bias in the news on broadcasting and non-broadcasting channels. Furthermore, the increase of sentiments is associated with an increasing volume of news stories and uncertain news coverage of Coronavirus over time. However, the sentiments can clarify the public's responses to Covid-19 and help officials handle the pandemic (Hung et al., 2020).

According to Thu et al., (2020) most countries announced lockdown in the second and third weeks of March. Many studies discover that most sentiments from the beginning to the end of March were positive; this situation means that Twitter users supported social distancing in the early stage of the lockdown (Saleh et al., 2020). (Kumar, Khan, & Kalra, 2020) exemplify tweets on 17-30 March 2020 demonstrated positive sentiments with a considerable trust tone. The most perceived negative sentiment was fear. The least perceived positive sentiments were joy and surprise, while the least perceived negative sentiments were disgust and anger.

Furthermore, (Yin, Yang, & Li, 2020) discovers that positive sentiment showed a higher ratio than negative sentiments in April. The study also finds that different aspects of Covid-19 have continuously been discussed and portrayed comparable sentiment polarities. Some topics like stay- safe-at-home are dominated by positive sentiments. Another topic, such as 'people die' consistently shows negative sentiments.

Investigations on a country's responses also indicate positive sentiments, though some others denoted negative sentiments. The countries showing dominantly positive sentiments are Australia (Kayes et al., 2020), India (Dubey, 2020; Kaur & Ranjan, 2020), and Belgia (Dubey, 2020). Meanwhile, Germany, France, Switzerland, and the US are the countries with nearly balanced sentiments (Dubey, 2020). Such situations point that social distancing to protect the community against Covid-19 has been well accepted, despite the resulting social isolation (Dubey, 2020; Kayes et al., 2020). On the contrary, Dubey (2020) discovers that 55% of people in China tweeted with negative sentiments. This different condition was probably caused by the fact that China was reportedly at the peak of the curve and is now following a downward trend while other countries are optimistically fighting to stop the corona spread.

Although most people took a positive and hopeful approach, fear, sadness, and disgust still exhibited worldwide. Most tweets about trust and surprise were found in Belgium, while tweets with the anticipation quotient were the most highly found in Germany. Many tweets with joyful emotions were attributed to various jokes and memes shared amid the lockdown. However, France, Switzerland, the Netherland, and the US have shown bigger distrust and anger than Australia, Spain, the UK, India, Italy, China, and Belgium (Dubey, 2020).

A study by (Hung et al., 2020) discovers that tweets were dominated by 48.1% of positive sentiments, 31.1% of negative sentiments, and 20.7% of neutral sentiments in the US in April 2020. Alaska, Wyoming, New Mexico, Pennsylvania, and Florida expressed the most negative sentiments, while Vermont, North Dakota, Utah, Colorado, Tennessee, and North Carolina expressed the most positive sentiments. Another study by (Xue et al., 2020) reveals that the American tweets were dominated by measurable anticipation, followed by a mixed feeling of trust, anger, and fear for different topics. Fear was dominant when people discussed Covid-19 new cases and deaths.

Pastor (2020) asserts that negative sentiment had been dominant although it was still the early stage of lockdown in the Philippines in April, and this sentiment kept increasing. Meanwhile, Kaur and Ranjan (2020) found that positive sentiments dominated the tweets at the beginning of the lockdown in India, except on 1, 9, and 14 April 2020. A study by (Chehal, Gupta, & Gulati, 2020) found that positive sentiments still dominated India's tweets during the second lockdown 2.0, and there were only a few instances of sadness and disgust. However, they discover that negative sentiments dominated tweets in the third lockdown 3.0 in India. Moreover, Ogbuju et al. (2020) report that Nigerians expressed positive sentiments of the lockdown, but only a few showed negative expressions from 30 March to 11 May 2020. Lastly, (Tuhuteru, 2020) informs that 28% of tweets in Indonesia, especially Ambon, showed positive sentiments, 27% of negative sentiment, and 45% of neutral sentiment from April to 12 June 2020.

3. RESEARCH METHODOLOGY

3.1.Dataset

The data of this study constituted comments gathered from Kaskus. The study employed PSBB as the keyword search collected 17,678 comments from Kaskus users (Kaskuser). These comments were related to 623 PSBB topics posted from 31 March to 31 July 2020. We choose 31 March 2020 as the starting point because it was the day when President Jokowi decided to implement PSBB. The collected data were manually scrapped using Parsehub software. The sample was taken by separating comments containing the word 'PSBB' from those not including the word. Moreover, the sample was taken from all comments discussing PSBB, such as the extension of PSBB in Jakarta. Apart from sentiments of the PSBB implementation, other sentiments, such as social assistance, online transportation, religious activities, and industrial closures, overlap with the topic of PSBB. To prevent a bias analysis, we removed these comments from the sample and comments in the forms of images and videos. Thus, this study analyzed 3,216 comments. To simplify the data collection, the observation was conducted in 18 weeks.

3.2.Data Preprocessing

Since the obtained data were unstructured, data that did not fit the research contexts were eliminated. Therefore, we applied the following preprocesses using a preprocessing text widget in Orange Data Mining from Biolab Systems. We transformed the input data by turning all texts to lowercases, removing all diacritics or accents into texts, parsing out texts, and removing the URLs from texts. The next step was tokenizing the input data into a small token (words). We also normalized the input data using WordNet Lemmatizer applying a network of cognitive synonyms to tokens based on the large lexical database for English. We removed some words and prepositions, such as and, or, in, and from, using the Stopword Removal. The Stopword list was taken from the GitHub repository. We also applied the lexical options that only kept the root words provided in the file.

3.3.Word Cloud

A word cloud refers to a weighted list to visualize language or text data. There are three primary word cloud maps applied in social networks distinguished by their algorithm instead of appearance (Jin, 2017). The first map is the frequency of type and the font size representing the number of keywords in the collection. The second is the categorization type and the font size indicating the number of collection subcategories. The third is the mixed type, frequency data, and categorization data, logically analyzing the detailed data before arranging the word cloud maps This study employed the frequency type. the data were analyzed using the word cloud widget in Orange Data Mining software from Biolab Systems.

3.4.Sentiment Analysis

We adopted the SA widget in Orange Data Mining software from Biolab System to find the sentiments from Kaskus users' comments. Moreover, we applied sentiment modules of Liu (2012) from the Natural Language Tool Kit. SA classified texts based on their contents and scored sentiments. A word's polarity can be identified by studying the word's occurrence frequency in a large annotated corpus of texts (Medhat et al., 2014). The lexicon-based approach analyzed texts and returned three polarity scores, as follows.

- The positive polarity had a positive score if the word occurred more frequently among positive texts. The maximal score was 100. Thus, a sentence with a score above 0 was categorized a positive sentiment.
- The negative polarity had a negative score if it occurred more frequently among negative texts. The minimal score was -100. Thus, a sentence with a score below 0 was categorized as a negative sentiment.
- A neutral score represented neutrality. If a word had equal frequencies with a score of 0, it was considered neutral. Words that did not appear in the lexicon were considered neutral (Georgiadou, Angelopoulos, & Drake, 2020).

Liu (2012) proposes two dictionary templates: English and Slovenian templates. This research employed the Slovenian template and replaced the Slovenian dictionary with Indonesian. We employed the lexicon dictionary from Liu (2012), Wahid and Azhari (2016), and GitHub Repository. Moreover, we changed the polarity of some dictionary words that had specific characteristics of Covid-19 spreads. For example, we put the words 'membatasi,' 'memutus,' 'memperlambat,' and 'hilang, which initially had negative polarity in the positive dictionary. Meanwhile, the word 'naik,' which initially had positive polarity was put in the negative dictionary. Furthermore, we categorized the phrases 'diam dirumah' or 'staying at home' as a positive sentiment. Table 1 presents the examples of positive and negative dictionaries and the stop words used in this research.

Table 1: Dictionary Examples

Positive Dictionary		**Negative Dictionary**		**Stop words**	
Membatasi	*Berhasil*	*Ampas*	*Basa-basi*	*Adalah*	*Seperti*
Memutus	*Sangat*	*Absurd*	*Berlarut-larut*	*Akan*	*Mending*
Memperlambat	*diperlukan*	*Bercanda*	*Bertele-tele*	*antara*	*Saya*
Hilang	*Setuju*	*Dagelan*	*Tidak efektif*	*apa*	*Kamu*
Segera	*Sehat*	*Dungu*	*Tidak*	*atau*	*Ente*
berakhir	*Menekan*	*Gagal*	*berpengaruh*	*bahkan*	*Tolong*
pakai masker	*Mantap*	*Hancur*	*Tambah*	*juga*	*Bagaimana*
jaga jarak	*Hilang*	*Kelaparan*	*banyak*	*kalau*	*Amat*
di rumah saja	*Membaik*	*Lawak*	*Kurang tegas*	*karena*	*Gitu*
yakin	*Patuh*	*Mati*	*Ga ngefek*	*maka*	*Begini*
efektif	*semoga*	*Melonjak*	*Herd*	*mungkin*	*sampai*
			Immunity		
			Seleksi alam		

Source: Primary Data

Table 2 denotes the samples of positive, negative, and neutral sentiments. We did not include personal sentiments in the analysis because it was not related to the implementation of the PSBB could create personal hatred.

Table 2: Types and Examples of Sentiment

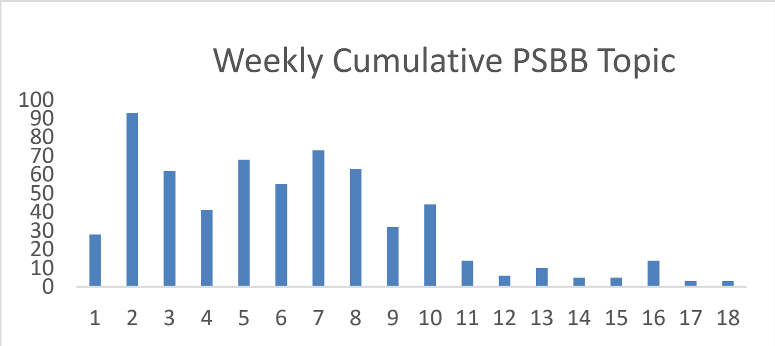
Types	**Comments**
Positive Sentiments	*"PSBB untuk kebaikan bersama"*; *"Doain aja mudah-mudahan efektif, dan bisa menekan penyebaran virus"*
Negative Sentiments	*"lockdown membunuhku"*, *"Gimana ya, orang-orang bandel begini yg bikin jakarta naik terus jumlah pasien positifnya"*
Neutral Sentiments	*"Sudah ada pedoman buat para pemimpin daerah soal PSBB"*
Personal Sentiments	*"Ni gaberner awal2 ngotot minta lockdown.. Skrg ada psbb,, minta kelonggaran.. Lockdown klo dituruti dr awal, bs jd rusuh tanpa persiapan.. Nah skrg dia mw ojol yang gaduh k pusat dia dpt nama.."*

Source: Primary Data

4. RESULTS AND DISCUSSION

This section provides the data analysis obtained during the study. Figure 1 shows several topics discussed on Kaskus during the research time.

Figure 1: Weekly Cumulative PSBB Topics (Source: Primary Data)



There were 623 discussion topics about PSBB in Kaskus during the study period. Figure 1 shows that the highest topic occurred on the second week (6-13 April 2020) or one week after President Jokowi had announced the implementation of PSBB. Some of the topics discussed were the Minister of Health's approval of the implementation of PSBB in Jakarta, the enactment of the PSBB in Jakarta and West Java, pros and cons of regulations of online transportation services, such as Gojek and Grab, in carrying passengers, and rules of the commuter line. PSBB was widely discussed for ten weeks (from 31 March to 6 June 2020). The number of PSBB discussion topics had decreased when PSBB in Jakarta ended and PSBB Transisi and Adaptasi Kebiasaan Baru in West Java were implemented.

The summary of the number of topic discussions on Kaskus is exhibited in Figure 2. The blue line shows each topic's total comments discussed with the PSBB keyword on Kaskus. Meanwhile, the orange line portrays the number of comments directly related to the PSBB implementation.

Figure 2: Weekly Cumulative Comments and Sentiments

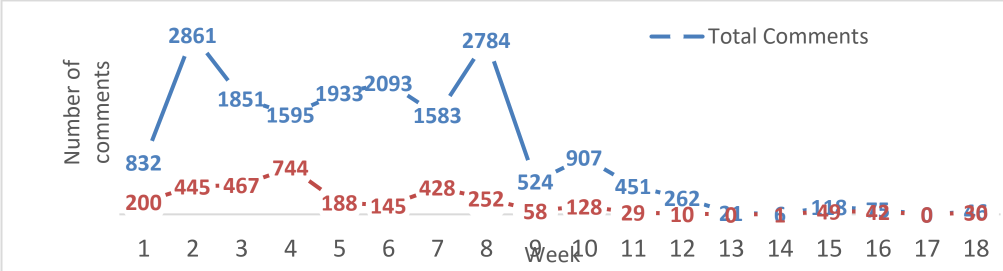
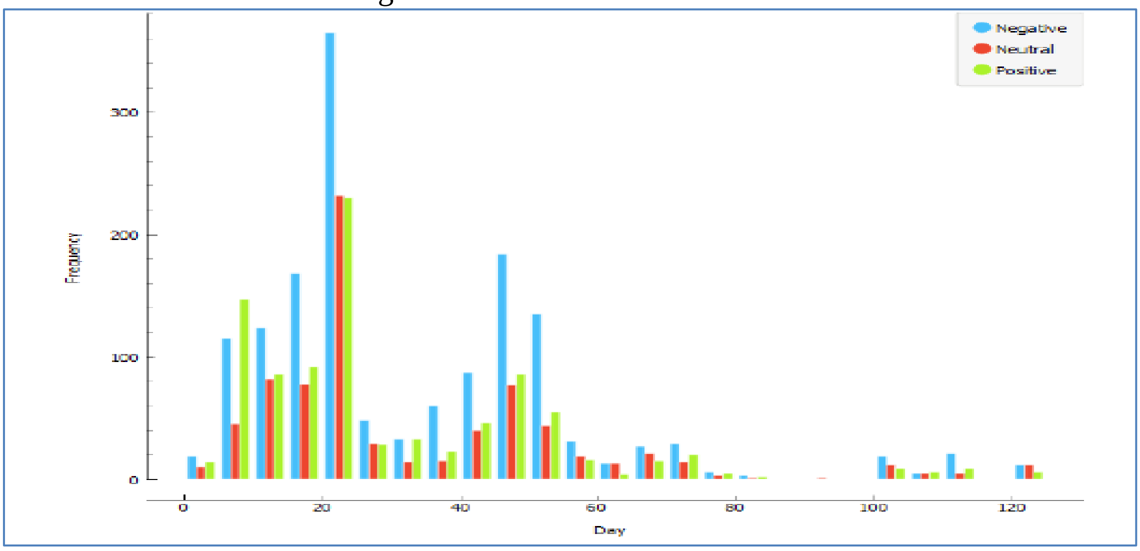


Figure 2 explains that the highest number of comments occurred on the second week. This result is consistent with that in Figure 1. Moreover, the highest number of comments occurred on the eighth week during the study time frame. Some discussion topics included the Minister of Health's approval of the PSBB implementation in Jakarta, the Governor of Jakarta's official announcement of the PSBB implementation in Jakarta, the PSBB information, and the initial evaluation of the PSBB implementation in Jakarta. Some topics with the most comments on the eighth week were PSBB violations in Surabaya by a religious leader, the end of PSBB in Tegal Central Java, a viral video of an invitation to stop the PSBB, and evaluation of foreign media about PSBB in Indonesia.

A different trend occurred in the sentiments directly related to the PSBB implementation. Figure 2 presents that even though week 2 had the highest number of PSBB topics and comments, 445 of 2,861 or 15.6% of the comments were directly about sentiments of PSBB. Sentiments of PSBB appeared mostly on week 4 for 744 of 1595 comments (46.6%). Topics with the highest sentiments were the Governor of Jakarta's official announcement of extending the PSBB and the crowded Cipulir market ahead of Idul Fitri. Figure 3 shows positive, negative, and neutral sentiments during the study period.

Figure 3: The Sentiment Distribution



Source: Primary Data

Figure 3 signifies that positive sentiments only dominated on the fifth to the ninth day of the study period. There were 307 sentiments with 147 positive sentiments (47.88%), 45 neutral sentiments (14.66%), and 115 negative sentiments (37.46%). The topics with the most sentiment in these weeks were rejection and acceptance of the

PSBB implementation in Jakarta by the Minister of Health and Kaskusers' assessments of the PSBB implementation. Meanwhile, the highest negative sentiment was recorded on the 20-24th day of the study period (19-23 April 2020). There were 827 sentiments of PSBB with 365 negative sentiments, 232 neutral sentiments, and 230 positive sentiments. Figure 3 signifies that the high sentiments in this period were the extension of PSBB in Jakarta, massive shopping at the Cipulir market before Eid, and ignorance of health protocols. Overall, there were 932 positive sentiments, 1509 negative sentiments, and 775 neutral sentiments during the observation.

To discover more sentiments, we conducted a word cloud analysis. Figure 4a describes the most appearing words in positive sentiments, Figure 4b shows the most appearing words in neutral sentiments, and Figure 4c shows the most appearing words in negative sentiments.

Figure 4: Word Clouds of Positive, Neutral, and Negative Sentiments

Positive (a)	Neutral (b)	Negative (c)
		

Source: Primary Data

Table 3 illustrates the list and number of words that appear the most in positive, neutral, and negative sentiments.

Table 3. N-Grams of Top 10 Positive, Neutral, and Negative Sentiments

Positive		**Neutral**		**Negative**	
1-gram	**Σ**	**1-gram**	**Σ**	**1-gram**	**Σ**
Efektif (effective)	120	Daerah (region)	67	Virus	124
Masyarakat (society)	107	Efektif (effective)	52	Daerah (region)	124
Daerah (region)	94	Masyarakat (society)	38	Rumah (home)	123
Kerja (work)	91	Jalan (street)	32	Masyarakat (society)	112
Makan (eat)	84	Rakyat (people)	31	Mati (death)	109
Normal	67	Makan (eat)	30	Ramai (crowded)	106
Rumah (home)	60	Rumah (home)	29	Karantina (quarantine)	103
Pusat (center)	56	Keluar (go out)	26	Keluar (go out)	102
Wilayah (territory)	49	Kerja (work)	25	Indonesia	102
virus	47	Buka (open)	25	Rakyat (people)	99

Source: Primary Data

Table 3 shows similarities between negative and positive sentiments in conveying emotions, but they differ in proportions. For example, the word 'effective' in the positive sentiments appeared the most frequently. It indicated that Kaskus users agreed with the PSBB as an effective way to encounter the Covid-19. The word 'society' was also widely used in the positive sentiments. Society is the main element in the PSBB implementation. The success of PSBB depends on their willingness and compliance with the regulation set by the central and regional governments.

The words virus, region, home, and society dominated the negative sentiments. Many Kaskusers expressed negative sentiments in the word 'ramai' referring to a busy traffic condition even though the PSBB was announced. The word also indicated that people still performed their daily activities leading to crowded streets and markets and violating the PSBB. Besides, the word 'death' was expressed in the negative sentiments because the death rate due to Covid-19 at the end of September 2020 was relatively high by 10,308 deaths; this number was the second-highest after India (WHO, 2020). Kaskuser mentioned that a long PSBB duration disabled people to work, created a fear of dying from hunger, and collapsed the economy.

Further analysis was conducted to explore sentiments of the prolonged PSBB in Jakarta. The data showed that this topic contained 108 negative sentiments, 69 neutral sentiments, and 71 positive sentiments supporting the policy. The most used words in this topic are summarized in Figure 5 and Table 4.

Figure 5: Word Cloud of Sentiments of the PSBB Extensions

Table 4: Top 10 PSBB Extensions N-gram

1-gram	Σ	**2-gram**	Σ
Efektif (effective)	15	Kerja makan (work and eat)	3
Daerah (region)	14	Pusat-daerah (central-regional)	3
Makan (eat)	14	Kantor buka (offices open)	3
Virus (virus)	13	Ramai efektif (crowded-effective)	2
Ramai (crowded)	13	Kerja rumah (work-from-home)	2
Rumah (home)	12	Cari duit (earning)	2
Pusat (central)	11	Bandel susah (very disobedient)	2
Duit (money)	11	Buka kantor (open offices)	2
Kerja (work)	10	Daerah duit (profitable area)	2
Rakyat (people)	10	Cari makan (find food)	2

Many previous studies report that social distancing is the most effective way to reduce the spread of infectious diseases when vaccines have not been discovered. Unfortunately, social distancing or PSBB requires many funds (Choi&Shim, 2020). For example, the government must fund the community's basic needs during the lockdown (PP No 21 Th 2020, 2020).

We found that people in Indonesia expressed positive sentiments at the beginning of the PSBB. This finding is consistent with a study by (Dubey 2020; Kumar et al., 2020; Ogbuju et al., 2020). Indonesian hoped that the implementation of PSBB could effectively flatten the curve, suppress the virus spread, and end the pandemic. In contrast, other studies deploy that this positive sentiment will not last long because they discover a different reality. Indonesia had conducted social distancing and closed schools and several public facilities in the mid of March before the PSBB was implemented in Jakarta on 10 April, then in several other areas. People assumed that PSBB would be ineffective as seen from their tense and negative responses at the beginning of PSBB implementation. Most people thought that social distancing and PSBB did not bring significant differences because some of them still worked, offices remained open, the traffic remained busy, many people gathered, and health protocols were ignored. Therefore, positive sentiment transformed into negative sentiments. The negative sentiments increased because there was no clear law enforcement against PSBB violations. Finally, Kaskus users considered that the PSBB was ineffective and failed, and thus, negative sentiments dominated the topic of the prolonged PSBB in Jakarta. The reason for rejecting the PSBB extension was shown by the word ‘food’. This reason agrees with a study investigating the Philippines (Pastor, 2020). Another sentiment was associated with ‘works’ implying that people could not eat if they did not work. They preferred ending the PSBB and returning to work while maintaining physical distancing and complying with health protocols. If the government decided to extend or reimplement the PSBB, the regulation must be enforced strictly and social assistance is delivered appropriately and adequately.

The open flow of information causes the rapid development of information, including information about Covid-19, social distancing, and lockdown policies. Nevertheless, lack of communication among government levels and public misinformation on social media frequently generate an ambiguous interpretation (Djalante et al., 2020). Understanding individuals’ and populations’ thoughts, beliefs, and attitudes can help public health organizations (e.g., the WHO) and government institutions identify public perceptions and gaps of communication and knowledge (Saleh et al., 2020). This research discovered that there were different daily sentiments during the observation. At the beginning of the observation, negative sentiments likely dominated because the people expected a tighter execution.

The positive emotions dominating at the beginning of PSBB were hopefulness and optimism about the government’s decision. This condition agrees with Yanti et al. (2020), who investigated 34 provinces from the beginning to the middle of March 2020. This study identified that 99% of respondents had adequate knowledge, 59% of positive attitudes, and 93% of good behavior towards social distancing. However, these sentiments changed because the people regarded that the PSBB implementation did not meet their expectations and not all people obeyed the PSBB rules. The negative sentiments continuously dominated as PSBB was prolonged. However, society regarded that this implementation was ineffective because the PSBB was not strictly complied with and did not have a sanction for violating it. People’s ignorance about the PSBB regulations was understandable because the poverty and unemployment rates in Indonesia escalated. Covid-19 has brought severe impacts that are different from any crisis caused by previous disruptions. The domestic and international economic activities substantially slowed down due to the Covid-19, particularly in the first half of 2020 (Abukhalifeh, Chandran, & Faller, 2020). The pandemic has brought immediate disruptions in economic activities across the region, including ASEAN (Indrastuti, 2021). Many economic sectors have been paralyzed and suffered losses (Rassanjani et al., 2021). Moreover, the pandemic has destroyed the global economy. The World Bank predicted that extreme global poverty rose in 2020 for the first time in over 20 years due to the Covid-19 pandemic, conflicts, and climate changes. Extreme poverty affected approximately 9.1% to 9.4% of the world population in 2020 (World Bank, 2020). Indonesia confronted a 4.99% of unemployment rate in February 2020 (Badan Pusat Statistik, 2020b), and it increased by 7.07% in August 2020 (Badan Pusat Statistik, 2020c). Meanwhile, compared to September 2019, the poverty increased by 1.63 million and became 26.42 million in March 2020 (Badan Pusat Statistik, 2020a). The increasing poverty was mostly found in Greater Jakarta, West Java, East Java, and Central Java because these provinces had a high number of Covid-19 cases and implemented the PSBB. Such conditions caused the emerging words to be mostly negative sentiments, such as 'eat' and 'work.' Moreover, people continuously left their homes to work and ignored the PSBB rules because the government did not fulfill their basic needs. Thus, the PSBB was considered ineffective. Reduced incomes, food insecurity, inadequate education, and increasing domestic violence worsen welfare and poverty conditions in developing countries (Wilkinson, 2020). The differences between the central and local governments in overcoming the pandemic has exacerbated the conditions in developing countries (Asmorowati, Schubert, & Ningrum, 2020)

5. CONCLUSION

Covid-19 has affects health, daily habits, and the economy. Governments of many countries have accomplished various actions and efforts, including social distancing, to prevent the virus spread and worsening conditions. However, social distancing does not only bring positive impacts, but also negative impacts. Social distancing has received various responses from society. This study revealed that Indonesians had positive sentiments at the beginning of the PSBB. However, the positive sentiments were only brief, while the negative sentiments kept increasing. Overall, people performed high negative sentiments of PSBB in Indonesia. This shift was triggered by various information that disagreed with the people's expectations. Moreover, the PSBB implementation did not match expectations. Inequal policies in various levels exacerbated the condition. This study suggests that if the Covid-19 conditions force the government to reintroduce PSBB, they must ensure that they can meet the citizens' basic needs and strictly enforce the PSBB rules.

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