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Sentiment Analysis of Tweets on Coronavirus Disease 2019 (COVID-19) Pandemic from Metro Manila, Philippines

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Abstract: *From the outbreak of a novel COronaVIrus Disease* (*COVID-19*) *in Wuhan to the first COVID-19 case in the Philippines, Filipinos have been enthusiastically engaging on Twitter to convey their sentiments. As such, this paper aims to identify the public opinion of Filipino twitter users concerning COVID-19 in three different timelines. Toward this goal, a total of 65,396 tweets related to COVID-19 were sent to data analysis using R Statistical Software. Results show that "mask", "health", "lockdown", "outbreak", "test", "kit", "university", "alcohol", and "suspension" were some of the most frequently occurring words in the tweets. The study further investigates Filipinos' emotions regarding COVID-19 by calculating text polarity of the dataset. To date, this is the first paper to perform sentiment analysis on tweets pertaining to COVID-19 not only in the Filipino context but worldwide as well.*

Keywords: *Sentiment analysis, coronavirus disease, Philippines, Twitter, opinion mining, COVID-19, NCOV, virus, tweets, Data Mining.*

1. Introduction

The World Health Organization (WHO) recently characterized COronaVIrus Disease 2019 (COVID-19) a pandemic, or a global spread of a new disease, demonstrating the severity and alarming levels of the COVID-19 spread. First appeared in Wuhan in the Hubei Province of China last 2019 [1], it is now reported that there are more than 118,000 cases in 114 countries as of early March 2020. According to records, COVID-19 is the third severe epidemic caused by coronaviruses in the past 20 years [2] but it cannot still be detected by commercially available multiplex NAAT tests [3]. As of writing, there are 54 confirmed cases and five deaths recorded due to the coronavirus pandemic in the Philippines. Consequently, countries around the world have issued travel restrictions [4] and imposed extreme quarantine measures [2] not only to safeguard both healthy and sick citizens but also to "buy time" for science to catch up [1]. In general, community anxiety is expected from a mass quarantine [5]. However, numerous studies revealed a deeper issue in terms of the psychological impact of quarantine as it is linked with anger, confusion, and post-traumatic stress symptoms due to stressors such as boredom, fears, and frustration when examined in a personal level [6]. In addition to self-quarantine recommendations, a new safety measure known as social distancing is being imposed [7]. With more time available, people find themselves spending more of it in social media to find the latest health information [8] and share their sentiments about the novel coronavirus outbreak as a way of connecting to other people [9] who are likely quarantined as well at home. It has become a standard activity for people to post various types of information (e.g., situational information), opinions (e.g., on the response speed of relief operations), and sentiments (e.g., sympathy for those affected) in vast volume and at a rapid rate on social media. This information, in return, provide an assistance to the concerned authority in terms of gaining a high-level understanding of the actual situation.

Because opinions and its interconnected concepts such as sentiments, attitudes, and emotions are central to human activities [10], the opinionated postings in social media opened a door for researchers to gauge the emotional tone behind the data. In the case of Twitter, the process of analysing people's opinions towards entities (also known as sentiment analysis) is not as novel as the coronavirus disease. For years, sentiment analysis has been performed on Twitter data for different purposes from simply exploring crowd sentiments [11] to a more advanced data analysis like stock price forecasting [12]. In fact, recent studies have successfully exploited emotions from tweets [13] and used it for different applications and usages such as predicting movie awards [14], presidential election [15], and during emergency situations [16]. Subsequently, the contribution of this paper lies on the sentiment analysis of Twitter feeds during a pandemic known as COVID-19 through the analysis of textual-only tweets assembled from three different timelines, and tweeted from National Capital Region (Metro Manila) of the Philippines. Specifically, the study intends to disclose the polarity present in these tweets, and identify the most frequently used keywords for both English and *Taglish* languages. To date, this study is the first to cover the sentiment analysis on tweets related to COVID-19 not only in the Filipino context but worldwide as well. Section 2 describes the importance of microblogging sites as an alternative information channel for boosting situational awareness as well as how sentiment analysis techniques are used on disaster-related tweets. The collection of data and how important phases of sentiment analysis were performed is discussed in Section 3. Then, Section 4 presents the results and summarizes the findings of the study. Finally, the conclusion and future direction of the research is discussed in Section 5. Implications and limitations are also discussed in this section.

2. Related work

2.1. The use of microblogging platform during disaster events

Microblogging platforms have prevalently played an increasing role as an important alternative information conduit for disseminating and extracting essential situational data during emergency situations like disaster events and natural calamities [17-19]. Such data that are rich with personal experiences, sentiments, and feelings enhance time-critical situational awareness necessary for discovering important insights into the event as the situation unfolds [20]. Consequently, prompt situational awareness accelerates disaster response through a fast generation of actionable data and at the same time minimizes both infrastructure damage and human loss. Truthfully, recent studies have exhibited that the use of Twitter during disaster significantly improves situational awareness [16] and execution of disaster response [21] through constant tweets of the affected population from requesting food and medicine to reporting missing people and infrastructure damage. Consequently, concerned authorities and first responders have been using Twitter for disaster relief, crisis management, and providing real-time situation updates [22-24]. Due to the strong contribution of such tweets, different methods are now being utilized to exploit more, hidden data from these short messages from automatic disaster-related information extraction [19, 25, 26] to the development of applications and analysis tools [27-31].

Fig. 1. Example of disaster-related tweet

2.2. Sentiment analysis of disaster-related tweets

Various studies have performed sentiment analysis on disaster-related tweets. In the Philippines, one study explored the nature of citizen engagement in Twitter during the events of typhoon Yolanda [32]. By using topic modelling and content analysis, Twitter was pronounced as a tool for igniting acts of citizenship (e.g., expression of solidarity and will for volunteer work) during calamities. In addition, sentiments of Twitter users were also studied during the events of Hurricane Sandy – the deadliest and strongest hurricane in the United States of America at that time. This study [33] provided an online visualization of users’ sentiments on a geographical map and the divergence of tweets according to both location and distance from the disaster area. Just like any other sentiment analysis experimentations, disaster-related tweets also used sentiment words that express positive or negative sentiments (e.g., good, nice, and amazing are positive words while bad, terrible, and poor are negative words). In addition, tweets related to disaster events are written in a more formal and objective linguistic style [34] and do not usually involve euphemisms and sarcasms [35]. The length of tweets is also advantageous as the positive and negative sentiment scores are not subjected to zero average which then produces good results [35].

2.3. Sentiment analysis applications for disaster management

The explosive growth of microblogging and social media networks in the previous decades has attracted researchers to devise applications that track, extract, analyse, and monitor disaster-related posts that can help people, humanitarian organizations, and the government. The datasets that are commonly used for evaluations are social media posts related to events such as Typhoon Yolanda, Hurricane Sandy, Sichuan Earthquake, and Red River Flood, to name a few. Modern applications of sentiment analysis used visual analytics to provide an intuitive way of understanding a large amount of tweets for geographical and exploratory data analysis. For example, there exist some Websites with online visualization tool for tweets (Fig. 2) including *Twitalyzer*, *TrendsMap*, *#onemilliontweetmap*, and *Geotwitterous*. Similarly, these sentiment analysis tools are characteristically categorized either for the purpose of situational awareness or information sharing. Nonetheless, these tools are useful for understanding dynamics of one's feelings, panics, and concerns by determining the polarity of sentiments expressed in the platform during disaster-related situations. In terms of the designs and algorithms used in such applications, both rule-based and machine learning approaches are common for sentiment analysis [36]. Nonetheless, a study [37] revealed that matching-based approach produced higher quality results than learning-based in disaster-related tweets. For machine learning algorithm used in sentiment analysis of tweets, Naïve Bayes classifier is more accurate than Support Vector Machine (SVM) and Random Forest [38]. Other studies [39, 40] have similar findings, however, SVM outperforms Naïve Bayes when feature space is increased. For features, the used of bag-of-words, sentiment-based words, and emoticons from the AFINN word list [41] and SentiWordNet [42] are commonly employed. Finally, the sentiment analysis of microblogs is tested by separating subjective and objective documents and then tagging filtered documents as either positive or negative [43].

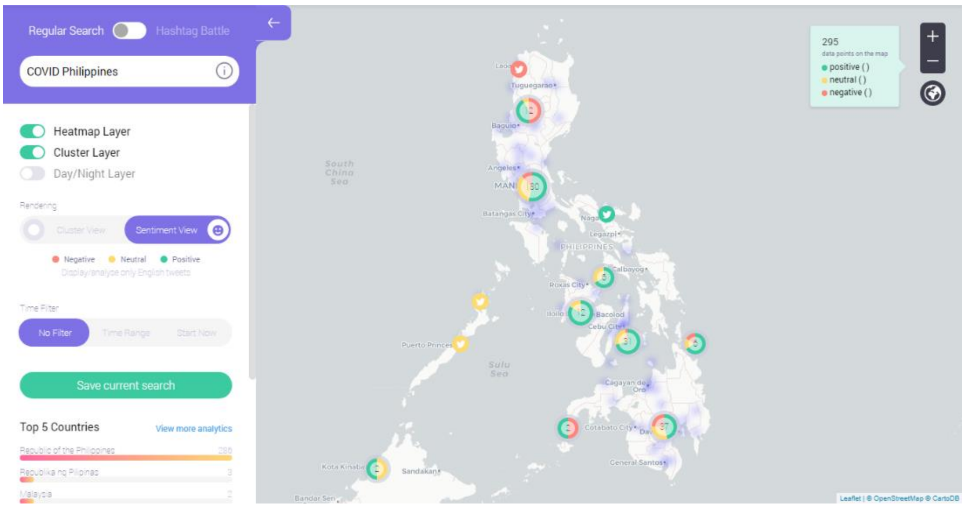

Fig. 2. Real-time heat map of COVID-related tweets in the Philippines

3. Methodology

3.1. Data collection

Twitter data, particularly tweets (a slang term referring to a message posted on the social network), related to COVID-19 tweeted from the National Capital Region (NCR) of the Philippines was collected, processed, and analyzed using R Statistical Software and its packages such as *sentimentr* (for calculating text polarity), *rtweet* (for accessing Twitter’s APIs) and *tidytext* (for text mining). Both *Taglish* and English tweets were collected although separated for analysis. To extract related tweets, keywords such as “#coronavirus”, “Coronavirus”, “COVID”, “COVID-19”, “#COVID19”, “#COVID19PH”, and “NCOV” were used. Retweets were excluded on the search results. Since the majority of COVID-19 cases are from the NCR, tweets were filtered using the geocode of Metro Manila (Latitude: 14.599512, Longitude: 120.984222) with a 10-mile radius. The dataset was then divided into three timelines: before COVID (November 2019 to 29 January 2020), during COVID (31 January to 11 March 2020), and after President Duterte’s Address to the Nation (12 March to 16 March 2020). The R Software returned 41,213 and 24,183 tweets for English and *Taglish*, respectively, together with other Twitter data such as tweet timestamp, author profile information, etc. It is important to note that the dataset was not expectedly large enough due to the combined search keywords that limits the tweet results (e.g., omitting coronavirus-related tweets that did not mention Philippines although the tweets have the geocode of Metro Manila) and the absence or lack of precise geospatial metadata. *Taglish* tweets were taken into account not only because of the study context but also the fact that *Taglish*, or mixed Tagalog and English, is a common code-switching system in the country.

Fig. 3. Frequent words in COVID-19 tweets in three different timelines

3.2. Data pre-processing

For each coronavirus-related tweet entry in the dataset, a series of standard text pre-processing operations were executed before applying a sentiment analysis approach. For the sake of dimensionality reduction and to remove noisy and inconsistent data, the following text pre-processing steps were performed on the dataset:

- **Elimination of special characters.** The removal of special characters such as “ ’ ? ; : # $ % & ( ) * + − / < > = [ ] \ ˆ _ | ~ aims to avoid unwanted concatenations that render the words unavailable to a dictionary and resolve unwarranted discrepancies during polarity assignment phase.
- **Elimination question and stop words.** Both question (e.g., “which”, “why”, “what”, “how”, “ano”, “bakit”, etc.) and stop (e.g., “the”, “a”, “an”, “ang”, “ito”,

“mga”, etc.) words available in English and Filipino do not contribute to polarity. These words were removed to ensure complexity reduction.

- **Elimination of keywords.** Without removing keywords used for the dataset collection, the report for most frequently used words will be biased as these keywords will surely top the list. Hence, keyword terms (e.g., “virus”, “coronavirus”, “COVID-19”, “NCOV”, “Philippines”) were removed.
- **Elimination of URLs.** Domain address could affect sentence polarity as it is composed of real words. For instance, a tweet of “visit www.bonus.com if you hate that you cannot work because of coronavirus” may denote positive sentiment because of the word “*bonus*” although the sentiment is negative.
- **Elimination of noise letters and words.** Whitespace and other unnecessary letters (e.g., coooool instead of cool) are eliminated either completely or by part. For words with repeated letters of more than three times, extra letters are automatically removed (e.g., viruuusssss to be converted into virus).

After dataset cleaning, the sentences were converted into words. Moreover, all uppercase letters were then converted into lowercase, and all Filipino words were translated into English using a Translator API. Similar method was used in a recent twitter sentiment analysis study where Urdu was translated into English first before performing any analysis [38]. Such technique avoids doing separate sets of analysis that is performed in some study with multilingual dataset. These were performed in R Statistical Software together with the conversion of dataframe into a plain corpus, and finally outputted as a CSV file to allow importation to other tools.

- **Example of tweet before cleaning.** “Wash your hands regularly with soap and water rather than buying and using alcohol. Mas super effective daw po kung magwash ng hands at least 20 seconds. gargle! #COVID19PH”.
- **Example of tweet after cleaning.** “wash your hands regularly with soap and water rather than buying and using alcohol mas super effective daw po kung magwash ng hands at least 20 seconds gargle covid19ph”.
- **Example of tweet before translation.** “Dapat may temporary ban sa mga dayuhan lalo na yung possible carrier ng virus e.”
- **Example of tweet after translation.** “There should be a temporary ban on foreigners especially the possible carriers of the virus.”

3.3. Data analysis

The sentiment analysis approach used for this study is the application of lexicons to classify tweets in terms of polarity and emotion. A lexicon-based approach involves a sentiment calculation on the semantic orientation of words present on the dataset [44]. A study [37] broadcasted that such matching-based approach produced higher quality results than learning-based in disaster-related tweets. Furthermore, it avoids the requirement to generate a labelled training data which the lack thereof can lead to a reduced classification performance [45, 46]. However, short social texts such as Twitter tweets produced limited number of features [45]. Fortunately, recent studies [45-48] have proposed numerous methods on how to extend and improve lexicon-based sentiment analysis. This includes the following techniques:

- **Emoticons.** Twitter is rich with emoticon-bearing tweets – the simplest way for people to show their emotions in a given limited number of characters. For instance, an emoticon of ":)" denotes happiness and positive polarity.
- **Degree modifiers.** Words such as "extremely", "very", and "most" conveys more intensity compared to the lack thereof. For instance, "Coronavirus is very scary" denotes more negative sentiment that "Coronavirus is scary".
- **Negation.** Terms such as "never" and "not" influence the overall polarity of the dataset. A common technique is by reversing the polarity of the affected words (e.g., "not good" conveys negative sentiment although the keyword "good" normally denotes a positive sentiment from a person).
- **Abbreviations.** Slangs such as LOL (Laugh Out Loud), FTW (For the Win), and FOMO (Fear of Missing Out) are commonly used on Twitter as well. It is a lexicon expansion needed for a more accurate sentiment classification.

The expansion of lexicon-based approach though the aforesaid techniques lead to a more accurate classification of tweets [45-48]. These serve as sentiment-based features together with polarity cues (e.g., positive words, negative words, and the number of positive per negative words), and combined with unigrams (frequency of words). Tweets were then scored and classified by polarity (i.e., positive, negative), and emotions (i.e., joy, sadness, fear, anticipation anger, trust surprise, disgust) for supplemental analysis. The R package "sentiment" was used to achieve a sentence-level sentiment analysis, which adopts a dictionary lookup approach. This package was recommended by a study that reviewed common R packages used for sentiment computations as compared to *syuzhet*, *SentimentAnalysis* and *RSentiment* [49].

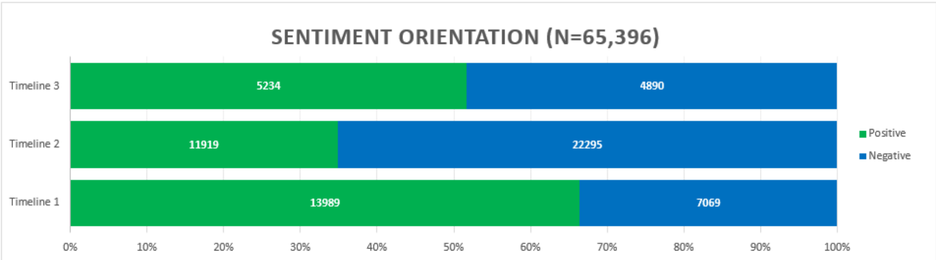

Fig. 4. Sentiment orientation of tweets related to COVID-19

4. Results and discussion

This study analysed the tweets coming from Metro Manila with regards to COVID-19 pandemic. It intends to understand the sentiments of Filipino from Metro Manila in three time frames: before COVID-19 (Timeline 1), during COVID-19 (Timeline 2) and after President Duterte's Address to the Nation (Timeline 3). The results of this sentiment analysis may serve as a basis for the concerned authorities on how to handle such pandemic. Fig. 5 shows the sentiment orientation of pandemic tweets and One-way χ^2 test revealed that there is an equal number of positive and negative sentiments in each timeline ($t_1(2)$, χ^2 = 75.64; $t_2(2)$, χ^2 = 102.19; $t_3(2)$, χ^2 = 34.24; p < 0.05). In general, more negative sentiments (n=34,254) were expressed compared to positive sentiments (n=31,142). Because pandemics like COVID-19 yield negative consequences (social, economic, and political) [50], it is expected that people react negatively (e.g., "corona virus is going to kill us all…" @nielsypol, "we are more afraid to lose our job more than the virus…" @SiMarcoJoseAko). Nevertheless, there are still positive sentiments being posted by Filipinos (e.g., "Lord God, save us and your world from this virus. We glorify and praise you." @PauloCrzLugue).

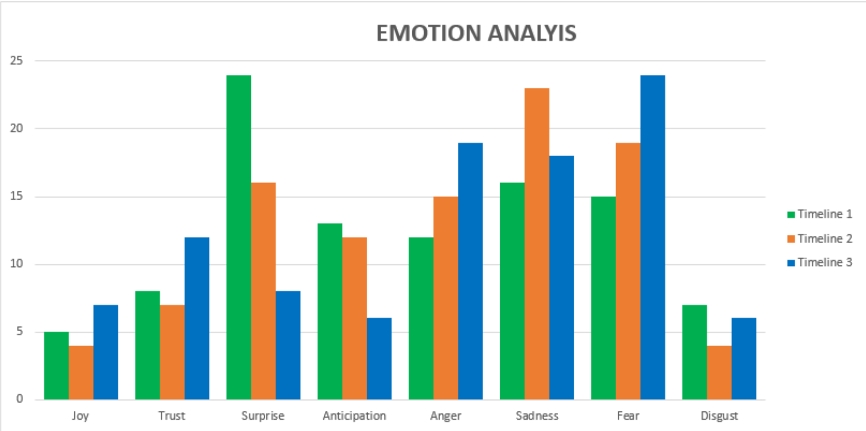

Fig. 5. Emotion analysis of tweets related to COVID-19

In the first timeline, only the word "Kobe" has an indirect connection to the thread of COVID-19 tweets. Filipino twitter users made a connection between the death of the *Black Mamba* and other disastrous events happening worldwide – signifying the bad start of the year 2020. The rest of the keywords on Table 1 is interrelated with one another. For instance, "travel" and "flight" denote disappointment of not being able to travel anymore because of cancelled flights. On the other hand, "travel" and "ban" signify the request of citizens to temporarily prohibit "*chinese*" from entering the country in order to prevent the virus "outbreak" from spreading as people were starting to get scared (e.g, "sobrang nakakatakot") and paranoid (e.g., "so much people coughing loudly, I wanted to run"). Nevertheless, sympathetic tweets were still expressed towards "china" saying "not all Chinese have the virus" and that "We can't blame China and Chinese as whole. We need to stop being Racist". Either way, evidence suggests that social tension and discrimination is heightened during pandemics [51]. At this point in time, people were afraid (e.g., "My worst fear, the virus reaching metro manila" @jecorius)" that the virus will spread on the country.

During Timeline 2, the first and succeeding confirmed cases of and deaths due to the coronavirus in the Philippines was announced. Fear of the diseases led people to do "hoarding" (e.g., "What's happening with the world???? People are hoarding…" @Halililuz) of "alcohol", "mask", and "tissue", to name a few. Appeal for stopping the panic buying was expressed (e.g., "Please stop hoarding and panic buying" @savingandi, "please stop hoarding the supplies" @danacrzz). As concluded from previous epidemics with potential of high morbidity, "suspension" of classes is one of the negative social impacts [52]. School institutions were forced to conduct their classes online. Although online learning is widely adopted in the Philippines [53], negative sentiments were still expressed due to several limitations (e.g., “Not all students can afford to buy a computer or laptop” @amsvillena, “I need fast internet to communicate with my students for online classes” @RoxHoey). In addition to the negative sentiments related to the “suspension”, workers showed disappointment by claiming “suspension of work must at least be considered”. In general, Timeline 2 generated the most negative sentiments. Aside from confirmed cases and death toll, another possible explanation is the wide implementation of social distancing which has been long observed during epidemics [54, 55]. According to several studies [56, 57], social distancing is associated with higher anxiety. Panic buying that enhances food shortages is another population behaviour that the government should monitor [58] as it increases more fear and helplessness of the poor. Based from the emotion analysis, fear significantly changed from Timeline 1 to Timeline 2 together with surprise and sadness ($p<0.05$), which agree on the timeline’s number of negative sentiments.

Table 1. Tweets from Timeline 1 related to COVID-19 pandemic

Keyword	Sample tweet (username)	Date posted
Outbreak	Odk. What is the meaning of this Asia on alert over mysterious virus **outbreak** in China (@Verg_innomore)	4 January 2020
Flight	Sana mag cancel ng **flight** si cebpac kung sakali malala na yung virus (@lorena_camille)	6 January 2020
Ban	Dapat may temporary **ban** sa mga dayuhan lalo na yung possible carrier ng virus e. (@PauIwa)	22 January 2020
Chinese	This is stupid but can we ban **chinese** from entering the PH for a while until they resolved the deadly virus issue?? (@PauIwa)	22 January 2020
Travel	As much as I want to be inclusive and welcoming to other nationalities, I believe it is a vital time to impose **travel** ban for now. It’s just simply for the better. This will also lessen the risks of the virus for our countrymen. (@jmppangilinan)	23 January 2020
China	I pray for **China**. Not only for the virus that spreading, but their government and whatever non-humanitarian things they’ve been doing. They are humans to, they are victims of their own Authorities. We can’t blame china and chinese as whole. We need to stop being Racist. (@kurtca9)	25 January 2020
Symptoms	Hi. There are rumors, text msgs, and posts from social media that say about CONFIRMED cases of Corona Virus in Makati Med. FYI, we screen and triage patients coming from Wuhan, China in Emergency Department & those with **symptoms** & recent travel within 12-14days. (amagnezing)	26 January 2020
Kobe	Taal volcano eruption, Corona virus, the death of the legend **Kobe** Bryant and her daughter. And it’s still January 2020. Take it easy, 2020. (@KentLimpot)	27 January 2020
Epidemic	Huhu kinda scared of going to hospitals. There were so much people coughing loudly, I wanted to run huhu. This shitty virus **epidemic** is getting into my head. (@kimalexisgarcia)	28 January 2020
Safety	Guys please observe proper hygiene and **safety** precautions to combat ourselves against the nCov. The virus is spreading sporadically. It is just right for us to stay responsible and always on the look out as it appears to be pandemic (@gentlerob)	28 January 2020

Table 2. Tweets from Timeline 2 related to COVID-19 pandemic

Keyword	Sample tweet (username)	Date posted
Mask	si mama nalaman lang na may patient ng corona virus sa bgc, binili nako ng sandamakmak na **mask** hshshshs labyu ma!! (@theycallmeJeee)	8 March 2020
Suspension	I hope the government should consider the **suspension** of work in public and private offices or encourage employees to work from home for the meantime to assure safety from the virus. (@johnatlastumlos)	9 March 2020
University	With billions spent on UP as a research **university**, I think this is good news that the university has come up with a useful product. We can even export this kit if it is of international standard. (@marletbadeo)	10 March 2020
Hoarding	why are people **hoarding** rubbing alcohol???? was at the grocery earlier and there's literally someone in line with a whole ass cart and basket of rubbing alcohol. imagine how many people are doing this remember other people need to protect themselves too (@mikaelriveraa)	10 March 2020
Hygiene	Stay safe everybody! Wag kalimutan magtakip ng bibig pag nabahing or naubo. Please practice proper hand **hygiene**. God bless! (@jaiyieee)	10 March 2020
Tissue	**Tissue** or napkins muna para iwas sa paggamit ng basahan or hand towels na pwede bahayan ng germs or virus. (@TitaFangirl)	10 March 2020
FDA	Test kit na dinivelop ng Pinoy scientists mula sa University of the Phils., aprub na ng **FDA**. #ACSBalita #DZRHat80 (@dzrhnews)	11 March 2020
Panic	I don't get why people do **panic** buying when they can just always to be updated in right information and following guidelines. + Hand soap > alcohol because the virus has mostly fatty membrane (@ImnidaOne)	11 March 2020
Positive	Lord, pls heal those people who are virus **positive**, protect our country and the whole world. I trust you, we trust you. AMEN. (@dizon_emyrie)	11 March 2020
Alcohol	To those people buying a lot of sanitizers, **alcohol** or any disinfectants and hoarding them, you are not thinking rationally coz your actions have a negative domino effect by spreading the virus fast coz others can't protect themselves! #NoToPanicBuying (@kintrue)	12 March 2020

Although COVID-19 pandemic is still active during Timeline 3, it was intentionally separated from Timeline 2 to identify whether the government and its policies affect the sentiments of people. The 1918 pandemic (H1N1) taught a lesson that political leaders must be truthful to its citizen rather than minimizing what is happening [59] as the lack of transparency may overwhelm the needed solidarity of the nation. The announcement of WHO categorizing COVID-19 as pandemic and the president's address to the nation led to more security measures being imposed (e.g., community *quarantine* and enhanced community *quarantine*). Based from the emotion analysis, anger, surprise, sadness, and fear significantly changed in Timeline 3 (p<0.05). One possible explanation is the negative psychological impact of quarantine [6] leading to anger, low mood, irritability, emotional disturbance, and even depression [60-62] as learned from papers reviewing the SARS outbreak. Boredom and isolation cause distress and it is of utmost important that people should be provided with practical advice on stress management techniques [6]. Further, a clear line of communication must be provided by public health officials to consistently establish reassurance that could subsequently decrease feelings such as fear, worry, and anger [6].

Table 3. Tweets from Timeline 3 related to COVID-19 pandemic

Keyword	Sample tweet (username)	Date posted
Quarantine	During a **quarantine**, shouldn't it be the private sector that slows down, while government remains at full operation? How will they contain the virus with skeletal government forces, while people in "manufacturing, retail, and services" are encouraged to go to work? (@PepeDiokno)	12 March 2020
Lockdown	We need more details and guidelines about this "community quarantine" a.k.a "**lockdown**". While waiting for it, let's do our part in preventing the spread of the virus. Stay safe! (@yanidedios)	12 March 2020
Duterte	Government specially Pres. **Duterte** giving their best to save our country. It's not them who spreading the virus, it's the people that lacks discipline and cooperation. (@abbymhariee)	13 March 2020
Italy	In the Philippines, poeple are complaining saying community quarantine is a martial law. Meanwhile, in **Italy** people are all cooperative and singing in their balconies. #OnlyInThePhilippines (@melitonbolitojr)	14 March 2020
Pandemic	Huge respect to the doctors, health workers, and all the frontliners who are taking risks to save lives during the coronavirus **pandemic**. And to those people who discredit their effort because "it's their job / they get paid to do so" — shame on you (@benedict_cua)	14 March 2020
Militar	Unpopular opinion: the narrative of "solusyong medikal, hindi **militar**" is not realistic with our limited numbers of medical workers. Even Italy and South Korea used their military in their checkpoints (@jcmlambino12)	14 March 2020
Curfew	Dear Makatizens, we are implementing a **curfew** from 8pm to 5am starting 16 March 2020 with exceptions. (@Mayora_Abby)	15 March 2020
Home	Ang taas ng fatality rate ng COVID19 dito sa Pilipinas. Shows the weakness of our healthcare system. Prevention is better than cure folks. Stay at **home**! Ung mga gen z's/millenials na laging nasa twitter FORCE your families to stay **home**! (@BipolarDK)	15 March 2020
Infect	What scares me the most is the fact that, just like Sen. Zubiri, I may do my usual routine, socially distance myself from everyone not knowing I'm already positive but asymptomatic. What's worse is that I may **infect** my family with it. Imagine this reality. #COVID19PH (@maleedus)	16 March 2020
Travel	How do health workers and hospital staff get to work if you suspend transportation? How about patients who need to travel for dialysis/radiotherapy/chemotherapy? Do you have provisions for this? Ang sakit sa ulo, pero mas masakit sa puso. #COVID19PH (@ronibats)	16 March 2020

In this study, the sentiments of tweets concerning the COVID-19 pandemic were analysed. The results suggest that Twitter users from NCR expressed more negative sentiments, and significant emotions such as anger, fear, sadness, and surprise. This may serve as eye-opening lessons and a vital basis for concerned authorities on how to handle and prepare for similar events in the future. One implication that may be considered from this work is the role of authorities in lessening the considerable and disastrous negative impacts of a pandemic to people by controlling what they could. As an example, community quarantine is associated with various negative emotions such as distress, fear, boredom, worry, and anger, and psychological impact such as irritability, emotional disturbance, and depression. The SARS outbreak provided the necessary lessons for mitigating such consequences. For instance, enough supplies of basic needs for quarantined households must be rapidly provided. In the City of Manila, the local government was quick enough to act to set aside a P227.5-million budget to feed about 350,000 families [63] for three days. Unfortunately, this is not the same in other cities (e.g., "Quarantine, work from home, getting worried about food supply" @alexzablan) and requests for food supplies were tweeted (e.g., "Sana they give at least weekly na food supply, alcohol, and face masks" @dyjoice). In addition, a clear line of communication must be provided by public health officials to establish reassurance that could decrease feelings such as fear, worry, and anger.

5. Conclusion

Through sentiment analysis, negative sentiments and emotions such as anger, fear, sadness, and surprise expressed by tweeter users from NCR concerning COVID-19 were determined. This study contributes to the thread of knowledge on social media mining by constructing the first sentiment analysis towards COVID-19, and what people expressed during this pandemic that may help in preparing an action plan for future pandemic and similar events. As part of the quarantine zone and the seat of the government, Twitter messages of people from NCR provide rich situational data and information updates necessary for discovering important insights into the event as the situation unfolds. Just like other disaster events and natural calamities, twitter feeds may be used by concerned authorities and first responders during pandemics not only as a source of personal experiences, sentiments, and feelings of citizens but also as a line of communication for providing real-time situation updates.

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