Machine learning on Big Data from Twitter to understand public reactions to COVID-19

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Abstract

The study aims to understand Twitter users’ discussions and reactions about the COVID-19. We use machine learning techniques to analyze about 1.8 million Tweets messages related to coronavirus collected from January 20\textsuperscript{th} to March 7\textsuperscript{th}, 2020. A total of salient 11 topics are identified and then categorized into 10 themes, such as “updates about confirmed cases,” “COVID-19 related death,” “cases outside China (worldwide),” “COVID-19 outbreak in South Korea,” “early signs of the outbreak in New York,” “Diamond Princess cruise,” “economic impact,” “Preventive/Protective measures,” “authorities,” and “supply chain”. Results do not reveal treatment and/or symptoms related messages as a prevalent topic on Twitter. We also run sentiment analysis and the results show that trust for the authorities remained a prevalent emotion, but mixed feelings of trust for authorities, fear for the outbreak, and anticipation for the potential preventive measures will be taken are identified. Implications and limitations of the study are also discussed.
Introduction

COVID-19 is affecting 2,134,465 people in more than 110 countries (Center for systems science and engineering, 2020) and declared by WHO as a global health pandemic. Social media has played a key role before the virus outbreak and continues to do so as it spreads globally. After China took strict quarantine measures as an intervention (e.g., cities on locked down, school closure, and employed self-isolation), Chinese social media platforms (e.g., Weibo, Wechat, Toutiao) become the lifeline for almost all isolated people who have been housebound for 30+ days, relying on these channels to obtain information, exchange opinions, socialize, and order food (Wu, 2020). Existing studies (Chew & Eysenbach, 2010; Jones & Salathe, 2009; Kim & Kim, 2020; Signorini, Polgreen & Segre, 2010) show that Twitter data can provide useful information for epidemic disease (e.g., H1N1, Ebola), including tracking rapidly evolving public sentiments, measuring public interests and concerns, estimating real-time disease activity and trends, and tracking reported disease levels. However, these studies have limitations with only qualitatively manual coding a very small number of Tweets and require more advanced techniques to improve accuracy and precision. In addition, it remains unknown about public reactions to the COVID online. The vast majority of searched articles about COVID-19 and 2019-nCoV focus on epidemic control, such as the transmissibility of the virus (Chen, 2020), clinical characteristics of the infected cases (Chen et al., 2020), and patient screening (Quilty, Clifford, Cmmid nCov, Flasche & Eggo, 2020). The present study employs our developed Artificial intelligence-based Response and Surveillance System (AIRSS) using tremendous amounts of collected Big Social Media Data to respond and add knowledge to our understandings for the pandemic. AIRSS refers to automatically and continuously collecting and analyzing large-scale (e.g., billions+) digital textual
data in real-time. Responding to the COVID-19, AIRSS is a unique approach that supports immediate machine learning of millions of collected textual data from millions of Twitter users and identifying changes in public responses on the platform. In this study, we use machine learning approach to explore these information and communication patterns and further examine (1) What latent topics related to COVID-19 can we identify from these Tweets? (2) What are the themes of these identified topics? (3) How Twitter users react to the COVID-19 pandemic? And (4) How do these sentiments change over time?

**Methods**

**Research design**

We used purposive sampling approach to select all the tweets contained defined hashtags (e.g., #2019nCoV) related to COVID-19 on Twitter. We use natural language processing method to find salient topics and terms related to COVID-19. Our Twitter data mining approach included data preparation and data analysis. Data preparation includes three steps: (1) sampling; (2) data collection; and (3) pre-processing the raw data. After pre-processing the raw dataset, we proceed to the data analysis stage, including (1) unsupervised machine learning; (2) qualitative method; and (3) sentiment analysis. The unit of analyses is each message-level Tweets posted on Twitter.

**Sampling and Data collection**

We purposely select a list of 19 trending hashtags related to COVID-19 as key search terms to collect Tweets on Twitter, including #CoronaOutbreak, #coronaviruschina, #Wuhan, #coronavirus, #ChinaCOronavirus, #Wuhan #WuhanCoronavirus, #Wuhanoutbreak, #ChinaVirus, #2019nCoV, #ChineseDon'tComeToJapan, #NoSoyUnVirus, #IamNotVirus, #JeNeSuisPasUnVirus, #Xenophobia, #PrayForChina, #DrLiWenLiang, #ItWillGetBetter, #BeStrongChina. We use
Twitter’s open application programming interface (API) to collect Tweets published between Jan. 1\textsuperscript{st} 2020 and Mar. 7\textsuperscript{th}, 2020. A total of 1.8 million Tweets have been downloaded and is our dataset for this study. We used the Python code provided by Twitter Developer (Get Tweet timelines, 2020) to access the Twitter API. The following features are collected for each single Tweet message (1) each message-level tweets (full text); (2) function features of (a) hashtags; (b) number of favourites; (c) number of followers; (d) number of friends; (e) number of retweets; (f) user location; and (g) user description.

**Pre-processing the raw dataset**

We pre-process the raw data to ensure quality. We use Python, a programming language to conduct data analysis (https://www.python.org/). The pre-processing plan is as follows:

1. We remove the hashtag symbol and its content (e.g., #COVID19), @users, and URLs from the messages because the hashtag symbols or the URLs do not contribute to the message analysis.
2. We remove all non-English characters (non-ASCII characters) because the study focuses on the analysis of messages in English.
3. We remove repeated words. For example, sooooo terrified is converted to so terrified.
4. We remove special characters, punctuations, and numbers from the dataset as they do not help with detecting the profanity comments.

**Data analysis**

*Unsupervised machine learning:* we use unsupervised machine learning to examine data for patterns because it is commonly used when existing studies have little observations or insights of
the unstructured text data. Since a qualitative approach has challenges analyzing large scale of Twitter data, unsupervised learning derives a probabilistic clustering based on the data itself, allowing us to conduct exploratory analyses of large text data in social science research. We configured topic modelling, an unsupervised machine learning method to generate top latent topic distributions. Latent Dirichlet allocation (LDA, Blei et al., 2003) is a probabilistic model of word counts that analyzes a set of documents. We use LDA to identify patterns, themes and structures of the Tweets texts and examine how these themes are connected to each other. It enables us to efficiently categorize the large bodies of data based on patterns and features. LDA has been used to do sentiment analysis of Tweets related to health (Paul & Dredze, 2014). Topic modelling has been widely used to gain a descriptive understating of unstructured Twitter big data in social science research (Schwartz et al., 2013).

**Qualitative analysis:** We triangulated and contextualized findings from unsupervised learning in the study. We employ the qualitative approach to support deeper qualitative dives into the dataset, such as labeling popular words and Tweet topics, assigning meanings and themes to the topics, interpreting the themes and patterns identified from the Tweets (Braun & Clarke, 2006), and inductively developing themes for the latent topics generated by machine algorithms. Qualitative approach relies on the diverse in-depth interpretations from human, which allows for inductive exploratory analysis and the application of theoretical approaches (Murthy, 2017).

**Sentiment analysis:** Sentiment analysis is a computational and natural language processing-based method that analyzes the people’s sentiment, emotions and attitudes in given texts (Beigi, Hu, Maciejewski & Liu, 2016), and an essential method in social media research. The emotion
sentiment analytics in the present study is based on the NRC Emotion Lexicon. The NRC Emotion Lexicon refers to the two sentiments (negative and positive) and eight basic emotions (anger, anticipation, fear, surprise, sadness, joy, disgust and trust) that are associated with English words and languages (Mohammad & Turney, 2013). The annotations were manually done by crowdsourcing. In NRC Emotion Lexicon one word could refer to multiple emotions, for example, the word “abandoned” could be negative, anger, fear and sadness. Based on the NRC Lexicon, we take four steps to calculate the emotion index for each twitter message:

(1) We remove the words that may cause noises, including removing common language articles, pronouns and prepositions such as “and”, “the” or “to” in English. In this streamlined process, a list of common words that appear to provide little or no contribution to our NLP objectives are filtered and excluded from further processing.

(2) We stem from the text by using a snowball stemmer. We apply a stemmer before calculating the emotion scores. Stemmers remove the predefined list of prefixes and suffixes if they are found at the beginning or the end of a word. For example, the word “running” after stemming become “run”. The goal of this step is to reduce inflectional forms and derivationally related forms of the words to a more commonly based form (Manning, Raghavan, & Schütze, 2008), and thus generate more solid results with the stemmed text.

(3) We calculate the emotion index. Given Twitter sentences and associated emotion lexicon, we compute the emotion index (EMI) as follows. We match all the words in processed Tweets corpus with the NRC Lexicon and count the matchings with the corresponding emotion type. For each tweet, we only keep one emotion with the maximum matching
counts as the final emotion. Although, NRC Lexicon allows one sentence to have multiple emotions, we only keep the dominant one for the analytics for a more significant result.

(4) We map EMI to the themes. For each theme generated by LDA aforementioned, we calculated the scores for each eight-emotion type. The scores are calculated by adding up the EMI from all tweets under the same emotion type.

Results

Descriptive results

After pre-processing the collected tweets, our final dataset consisted of 1,739,553 Tweets after removing the duplicates mentioning at least one of the nineteen hashtags from January 22nd to March 7th, 2020. Figure 1 present the number of Tweets under the top 9 hashtag by dates (“#coronavirus”, n = 1,405,254, “#wuhan”, n = 144,240, “#wuhancoronavirus”, n = 73,393, “#coronaoutbreak”, n = 73,147, “#2019ncov”, n = 60,278, “#Chinacoronavirus”, n = 19,188, “#Chinavirus”, n = 17,865, “#coronaviruschina”, n = 16,371, “#wuhanoutbreak”, n = 10,548). The number of Tweets using hashtag #coronavirus gradually increased since Feb 14th and dropped on March 1st when the hashtag #wuhanoutbreak suddenly increased for 4 days.
COVID-19 related topics

The automated machine learning LDA approach generated frequently co-occurring words and organized them into different topics. We calculated the most appropriate number of topics based on coherence model – gensim (Roder, Both & Hinneburg, 2015). We choose the number of topics to be 11 returned by LDA for this dataset because it has the highest coherence score. Figure 2 shows the number of topics for the LDA model.
We analyze the document-term matrix with the chosen 11 topics and obtained the distributions of 11 topics. Table 1 presents the results of identified 11 salient topics and most popular pairs of words within each topic.

| Topic | Bigrams within topics                                                                                                                                                                                                 | Numbers of Tweets |
|-------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------|
| 1     | toilet paper, wecosearch, ecosearch news, news web, health emergency, corona virus, fake news, xi jinping, dont want, self isolate, want know, covid 19, number people, breaking news, read here, good idea, health officials, spanish flu, new York | 334,193           |
| 2     | diamond princess, disease control, donald trump, li wenliang, covid 19, tests positive, dr li, corona virus, common cold, shaking hands, south korea, details gt, hong kong, supply chains, tested positive, centers disease, control prevention, president trump, supply chain | 158,704           |
| 3     | face masks, social media, people die, new York, panic buying, corona virus, 1 1, loved ones, coronavirus outbreak, case confirmed, watch video, u s, tested positive, million people, medical staff, like this, shake hands, high school, coronavirus update | 161,361           |
| 4     | u s, death rate, mortality rate, mike pence, 3 4, coronavirus death, toll rises, fatality rate, white house, dont know, confirms case, south korea,                                                                                                                                 | 160,237           |
|Page| Text| Preprint Line Count|
|---|---|---|
|3| rate 3, chief medical, coronavirus spread, public health, medical officer, china coronavirus, climate change| 9|
|5| tested positive, outside china, total cases, sars cov, cov 2, cases confirmed, year old, date total, coronavirus case, north korea, deaths date, confirmed worldwide, covid 19, infectious disease, new case, positive case, communist party, confirmed cases| 145,781|
|6| coronavirus outbreak, year old, gt gt, covid 19, thank you, amid coronavirus, confirmed case, wall street, economic impact, united states, travel ban, good news, stock market, amp a, press conference, q amp, whats happening, corona virus, years old| 152,724|
|7| washing hands, south korea, prevent spread, 2019 ncov, test kits, covid 19, novel coronavirus, 20 seconds, need know, stock market, soap water, happy birthday, 2019 novel, 1 000, coronavirus outbreak, coronavirus cases, help prevent, hands soap, reported today| 151,935|
|8| diamond princess, stay home, 14 days, work home, princess cruise, tested positive, looks like, face mask, test positive, task force, supply chain, san Francisco, wearing masks, corona virus, coronavirus fears, hong kong, ship japan, dont forget, 14 day| 165,730|
|9| world health, health minister, health organization, press conference, washington state, coronavirus covid, live updates, tested positive, number cases, state emergency, 19 cases, new York, 19 outbreak, bbc news, health ministry, people died, right now, coronavirus disease, novel coronavirus| 162,623|
|10| stay safe, corona virus, stop spread, chinese people, corona beer, infectious diseases, s amp, ive seen, dont know, health minister, health crisis, worst case, good thing, god bless, amp p, case scenario, pence charge, help stop, im worried| 157,064|
|11| confirmed cases, south korea, bringing total, cases confirmed, total confirmed, cases reported, total number, new deaths, total deaths, wash hands, coronavirus cases, number confirmed, touch face, cases coronavirus, hubei province, number cases, 2 new, cases bringing, new confirmed| 170,834|
COVID-19 related themes

In addition, we also randomly generate some Tweets samples in each topic to explain the themes of these topics. Two research assistants discussed about these terms and sample Tweets in 11 topics and categorized them into common themes (Table 2). Topic 1 present the identified topics and themes, and each row of bi grams represents one topic under the theme. We identify 10 themes such as the “updates about number of COVID-19 cases (confirmed cases, total confirmed, cases reported),” “COVID-19 related death [(new deaths, total deaths) and (people die, loved ones)],” and “preventive/protective measures [(toilet paper, self-isolate), (face masks, panic buying), travel bans, and (washing hands, test kits, 20 seconds, soap water, hands soap)].”

| Theme | Bigrams within topics |
|-------|-----------------------|
| Updates about number of COVID-19 cases | • confirmed cases, bringing total, cases confirmed, total confirmed, cases reported, total number, coronavirus cases, number confirmed, cases coronavirus, number cases, 2 new cases bringing, new confirmed  
• tested positive, total cases, cases confirmed, date total, coronavirus case, new case, positive case, confirmed cases |
| COVID-19 related death | • new deaths, total deaths  
• death rate, mortality rate, fatality rate, coronavirus spread  
• people die, loved ones |
| Cases outside China (worldwide) | • tested positive, outside china, confirmed worldwide, covid 19, infectious disease, new case, positive case  
• South Korea, Hong Kong  
• ship Japan |
| Outbreak in South Korea | • south Korea, 2019 ncov, covid19, novel coronavirus  
• washing hands, prevent spread |
| Early signs of the outbreak in New York city | • health emergency, corona virus, fake news, want know, covid 19, New York  
• people die, New York, panic buying, corona virus, case confirmed, tested positive, high school |
| Diamond princess cruise | • diamond princess, disease control, tests positive  
| | • diamond princess, princess cruise, tested positive, ship japan |
| Economic impact | • wall street, economic impact, united states, stock market |
| Preventive/protective measures | • toilet paper, self-isolate  
| | • shaking hands, control prevention  
| | • face masks, panic buying  
| | • travel ban  
| | • washing hands, test kits, 20 seconds, soap water, hands soap  
| | • stay home, 14 days, work home, supply chain, wearing masks |
| Authorities | • Xi jinping, health officials  
| | • disease control, donald trump, president trump  
| | • Li wenliang, dr li  
| | • medical staff  
| | • white house, chief medical, public health, medical officer  
| | • North Korea, communist party  
| | • health minister, health organization, Washington state, health ministry  
| | • Mike pence |
| Supply chain | • supply chains |

Table 3 highlight two or three representative Tweets within each topic. To protect the privacy and anonymity of the Twitter users of these sample Tweets, we use either excerpts of Tweets or paraphrase several terms in the message.

**Table 3. Sample Tweets within themes**

| Theme | Excerpts of Tweets samples |
|-------|----------------------------|
| Updates about number of COVID-19 cases | • “…over 5,000 cases of confirmed #COVID19 …”  
| | • “…there are 101,765 confirmed cases of the coronavirus …”  
| | • “…47,885 recovered (+2,270)…” |
| COVID-19 related death | • “@healthdirectAU: there are currently 33 confirmed cases of coronavirus in Australia…”  
| | • “…coronavirus… and 3,461 deaths globally…”  
| | • “…US has near 10% death rate from #coronavirus…” |
| Cases outside China (worldwide) | • “…beyond China, total confirmed cases reach 4,154 as of Feb.27th …”  
| | • “…#covid19 is now in 50 countries/regions… several countries declared their confirmed cases of covid…” |
| **Outbreak in South Korea** | “…excluding #China: 10,283 confirmed, 792 recovered, 173 deaths…” |
|----------------------------|-------------------------------------------------------------------|
|                            | “…a vast majority of coronavirus patients in Korea are linked to the Shincheonji church…” |
|                            | “…South Korean city face shortage of hospital bed as #outbreak expands…” |
|                            | “#southkorea declares ‘war’ on #coronavirus …” |
| **Early signs of the outbreak in New York city** | “…in the news, NYC orders mandatory coronavirus testing for public workers …” |
|                            | “@homedepot,@lowes, and any respectable hardware store from the bottom of NYC all the way upstate to Rochester is completely sold out of all respiratory masks…” |
| **Diamond princess cruise** | “…approx..100 more people on Princess Diamond showed symptoms like a fever, and will be tested soon…” |
|                            | “…passenger of Diamond Princess ship tested positive for the virus #2019nCoV…” |
|                            | “…61 people now infected on #DiamondPrincess cruise ship off japan #coronavirus…” |
| **Economic impact**        | “…IMF chief says the outbreak could derail global economic growth…” |
|                            | “… https://t.co/OtsbHOZBTW #economicoutlook #markets #globaleconomy #Coronavirus likely to impact…” |
|                            | “…airline stocks crash, face turbulence amid coronavirus…airline stocks fell significantly on Thursday …” |
|                            | “…a crappy coronavirus shortage toilet paper …” |
|                            | “…my understanding is that the best way to stop the spread of #covid19 is to use hand sanitizer and not touch my face…” |
|                            | “…stay safe wearing masks, avoid outside plans, stay at home as much as you can #coronavirusoutbreak…” |
|                            | “…we’ve had travel bans for over 4 weeks…” |
| **Preventive/protective measures** | “… Trump lied about #coronavirus, vote him out #voteblue #JoeBiden2020…” |
|                            | “coronavirus ‘likely’ to hit UK – professors say public health officials must do more #coronavirus…” |
|                            | “Mike pence will stop #coronavirus with gender segregated workplaces and don’t tell him otherwise…” |
|                            | “…Chinese doctor #LiWenLiang, one of the eight HERO whistleblowers who tried to warn other …” |
|                            | “…is the the figure #WHO told us the coronavirus is under control? Let there be no panic…” |
“…the PRESIDENT OF THE UNITED STATES said the coronavirus was not a concern anymore #CDC…”

“with #wuhancoronavirus, the supply chain in China will soon collapse, better prepare for the global shortage of supply of everything…?

“…@Catalysis3D can help with low cost and fast additive manufactured bridge tooling and part…#supplychain…”

“…companies re-evaluating supply chains due to #coronavirus… let’s revisit how #PLM can help…”

### Sentiment analysis:

Tweets contain information about people’s thoughts and emotions (Griffis et al., 2020). Using NRC Emotion Lexicon that includes 8 emotions of trust, anticipation, joy, surprise, anger, fear, disgust, and sadness as a measure, we present individuals’ emotion reactions to COVID-19 pandemic in Figure 3. Trust (brown line), Anticipation (orange line) and fear (yellow line) have been growing and decreasing at similar rates, and dominate all 8 types of emotions over time, followed by sadness (green line), and anger (light blue line). However, all eight types of emotions gradually increased overtime, and suddenly dropped on March 1st. The drop-down rate was consistent with the decrease of number of Tweets collected on March 1st in our dataset.
Figure 3. Emotions change by date

Sentiments within 11 topics

Table 4 shows the percentage of each emotion within each of the 11 topics. Across all topics, we observe that feeling of *anticipation* has consistently dominated all emotions. For example, about 24.35% of the emotions within Tweets in Topic 8 express the feeling of *anticipation* that “necessary steps and precautions will be taken” (Kaila & Prasad, 2020, p. 131). Approximately 19% of the emotions within Tweets under Topic 11 relate to feelings about public’s *Trust* for the health authorities. People’s feeling of *fear* and *anger* for the impact of COVID-19 (e.g., social distancing, shortage of supply) are also prevalent in most topics.

### Table 4. Percentage of each emotion within 11 topics

|            | Anger | Anticipation | Disgust | Fear   | Joy   | Sadness | Surprise | Trust |
|------------|-------|--------------|---------|--------|-------|---------|---------|-------|
| Topic 1    | 9.57% | 14.92%       | 3.02%   | 9.37%  | 2.58% | 2.33%   | 1.76%   | 8.46% |
| Topic 2    | 12.87%| 19.41%       | 2.67%   | 14.68% | 2.82% | 3.40%   | 2.77%   | 13.37%|
| Topic 3    | 11.81%| 19.80%       | 3.52%   | 16.99% | 2.61% | 3.19%   | 2.15%   | 11.43%|
Since the feeling of *anticipation* dominates all eleven topics, we further ran one-tailed z test and assess if each of the eight emotions is statistically significant different across topics. We use $p$ value smaller than .01 as a threshold and presents the results in Table 5. *Anger* for the impact of COVID-19, is found to have a higher probability to be prevalent in Topic 2 and/or Topic 4. *Anticipation* for the measures is statistically significant salient in Topics 3, 4, 6, 7, 8 and 10. *Fear* for the pandemic is statistically significant prevalent in Topics 3, 4, 5, 6, 7, 9 and 10. *Sadness* feeling for the COVID-19 outbreak is statistically significant prevalent in Topics of 2, 3, 5, 6, 8 and 10. *Trust* for the authorities is statistically significant dominant in Topics, 2, 5, 9 and 11.

**Table 5. $p$ value from Z-test**

|        | anger | anticipation | disgust | Fear  | joy   | sadness | surprise | trust |
|--------|-------|---------------|---------|-------|-------|---------|----------|-------|
| Topic1 | 1     | 1             | 0       | 1     | 0     | 1       | 1        | 1     |
| Topic2 | 0     | 0.02652       | 1       | 0.09156 | 5.44E-15 | 0       | 0        |
We run sentiment analysis for each of the 11 identified topics to track the changes of each of the emotions over time. Figure 4 presents results of sentiment changes over time in Topics 11. Topic 11 specifically refers to the updates about number of COVID-19 cases (total number, confirmed cases, total confirmed cases reported, new confirmed). Trust for the authorities dominates all 8 types of sentiments over time, and in particular it become more prevalence after March 1st.

Figure 4. Sentiment changes over time in Topic 11
Topic 4 relates to COVID-19 (*death rate, mortality rate, coronavirus death, fatality rate*), and we find out that *fear* is consistently most prevalent within Topic 4. Surprisingly, *anticipation* for potential measures is still prevalent within this topic.

**Figure 5. Sentiment changes over time in Topic 4**

Discussion and Conclusion

Our findings facilitate an understanding of public discussions and sentiments to the outbreak of COVID-19 in a rapid and real-time way, contributing to the surveillance system for an understanding of the evolving situation. The study overcomes the limitations of traditional social science approach which relies on time consuming, retrospective, time-lagged, small-scale surveys and interviews. Our findings demonstrate Twitter users’ discussion and reactions related to COVID-19 from January 20\(^{th}\) to March. 7\(^{th}\), 2020. The study identifies several interesting results.

First, the number of Tweet messages gradually increase over time suggesting public has been given more attention to the issue. A small peak is identified in terms of the Tweets volume between Feb
10\textsuperscript{th} and 14\textsuperscript{th}, and then gradually increase again after Feb.14\textsuperscript{th}. The result is found to be timed with very first CDC’s suggestions on its Twitter on Feb 10\textsuperscript{th}. CDC posted its warning on its Twitter indicating “If you’ve recently from China, know the symptoms of #2019nCoV. These include mild to severe respiratory illness with fever, cough, shortness of breath. See bit.ly/38znYo.” It was the time when CDC posted that “few cases have been found in the U.S.” Since Feb. 10\textsuperscript{th}, CDC has been posting at one COVID-19 related Tweets on its account daily.

Second, LDA analysis generates several prevalently discussed topics on Twitter, suggesting the public and health officials’ attention have been given to updates about the confirmed cases (e.g., number of confirmed cases), death related to COVID-19 (e.g., mortality rates), preventive measures (e.g., washing hands, soap, face mask), and government and/or health authorities (e.g., Dr. Li, Trump, Xi Jinping). These categorized themes reveal that public discussions focus on statistics related to COVID-19 and negative consequences. Discussions around symptoms related contents (e.g., cough, fever, difficulty breathing) or treatment related contents (e.g., vaccine, rest and sleep, drink liquids, WHO, 2020) are not prevalent. It is possible that the public are not using Twitter as a platform for posting symptoms or seeking medical help. Results inform health authorities or public health communities that more treatment related messages can be posted as an education tool for the public on social media.

Third, our findings suggest that public discussions and attention focus on the COVID-19 in China, South Korea, Diamond Princess, Japan and the United States prior to March 7\textsuperscript{th}. In particular, the study shows that early signs in the case of outbreak in New York city are revealed in Twitter messages. Public discussions about the COVID-19 outbreak in Europe regions are not prevalently discussed on Twitter. For example, two visitors from Wuhan of China were known as first cases
in Italy on January 29th, and all flights to and from China were blocked declared by Italy Prime Minister Giuseppe Conte on January 30th (Besser, 2020). Even though Italy was the first European state to take actions as early as end of January, it hasn’t attracted much attention from the public to discuss the risk on Twitter.

Fourth, sentiment analysis of the COVID-19 pandemic related contents contribute to our understanding of the dynamics of online users’ concerns and feelings during the pandemic, which inform public health and policy makers’ decision making. Overall, trust for the authorities is prevalent, and in particular it dominates public’s reactions in the face of updated confirmed numbers of COVID-19. Findings inform health authorities that open information about the increasing numbers are not leading to great panic among the public, instead, people are holding trust for the authorities and anticipation for potential solutions. We also find that fear is significantly prevalent in all topics. The results are consistent with another study (Kaila & Prasad, 2020) which find that negative sentiments dominated the Tweets. Our results also suggest that mixed feeling indicated in massive Tweet messages exist, including trust for authorities, anticipation for potential measures and treatments, and feeling of fear. Our result is consistent with the sentiment analysis in a Chinese study (Li, Wang, Xue, Zhao and Zhu) which shows that individuals’ psychological conditions are significantly impacted by COVID-19. Our results have implications for health authorities that mental health and psychosocial well-being support is needed during this time (WHO, 2020).

There are several limitations in the study. First, we only sample a trending of 19 hashtags as search terms to collect Twitter data. Some new hashtags have become new trending terms for Twitter
users to group topics over time. For example, #COVID19 has been widely used after it become
the official name for the virus. Second, Twitter users are not representative to the whole population,
and only indicate online users’ opinions and reactions about COVID-19. Even though, Twitter
dataset is a value source for us to understanding the real-time Twitter user-generate contents related
to COVID-19 disease activities. Third, non-English Tweets are removed from analysis and results
are limited to a particular population. Future studies are recommended to include Italian, Germany
and Spanish languages for COVID-19 analysis.
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