


Identifying public concerns and reactions during the COVID-19 pandemic on Twitter: A text-mining analysis

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Abstract

Efforts to control the current coronavirus disease 2019 (COVID-19) pandemic have led to national lockdowns around the world. Reactions to the rapidly evolving outbreak were shared on social media platforms. We conducted a mixed-methods analysis of tweets collected from May 10 to May 24, 2020, using MAXQDA software in conjunction with Twitters search API using the keywords: "COVID-19," "coronavirus pandemic," "Covid19," "face masks," and included terms such as "Queens," "Bronx," "New York." A total of 7, 301 COVID-19-related tweets across the globe were analyzed. We used SAS Text Miner V.15.1 for descriptive text mining to uncover the primary topics in unstructured textual data. Content analysis of tweets revealed six themes: surveillance, prevention, treatments, testing and cure, symptoms and transmission, fear, and financial loss. Our study also demonstrates the feasibility of using Twitter to capture real-time data to assess the public's concerns and public health needs during the COVID-19 pandemic.

KEYWORDS

coronavirus, COVID-19, pandemic, social media, Twitter

1 | INTRODUCTION

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) emerged from Wuhan, China, in December 2019 (Huang et al., 2020). By June 17th, 2020, over 8.2 million people worldwide had been confirmed positive and 445,012 had died from coronavirus disease 2019 (COVID-19), the disease caused by SARS-CoV-2 (Dong, Du & Gardner, 2020). Since the first outbreak, COVID-19 has become a worldwide pandemic (World Health Organization, 2020) and has now spread to over 100 countries with substantial occurrence in the United States (2,143,193 cases), Brazil (923,189 cases), and India (354,065 cases) (Dong, Du & Gardner, 2020). Public health infection control strategies rely heavily on early detection of disease and strict social containment measures to contain spread. However, ongoing disease containment and surveillance has proven to be a challenge

even in developed countries like the United States. Furthermore, barriers to optimal public health outbreak surveillance exist in resource-limited settings. Creating and communicating health information that is essential in outbreak surveillance efforts.

The COVID-19 pandemic demands attention to the rapidly changing messages about public health to enable individuals to take actions to minimize their risk for infection and spread of the virus (Malecki et al., 2020). Social media outlets such as Twitter enable people to share their knowledge, opinions, and concerns, creating a rich array of user-generated content (Atefeh & Khreich, 2015). The analysis of Twitter data allows for an assessment of the public's knowledge, personal experiences, and concerns during rapidly evolving outbreaks such as COVID-19 (Signorini et al., 2011; Sullivan et al., 2012). Twitter data are increasingly used by researchers to evaluate the public reaction to outbreaks (Ahmed, Bath, Sbaffi &

Demartini, 2019; Glowacki et al., 2016; Glowacki, Glowacki, Chung & Wilcox, 2019)

As the COVID-19 pandemic evolves and social media are inundated with information about the virus (Rosenberg et al., 2020), public health practitioners need to understand public opinion and reactions to the COVID-19 pandemic as a step towards identifying health information needs. Accordingly, the purpose of our study was to examine the public's concerns and reactions during the COVID-19 pandemic.

2 | METHODS

2.1 | Data acquisition

We used text-mining approach to analyze key patterns and extract meaningful associations and patterns in unstructured text data. Tweets and retweets were collected using MAXQDA 2020 (VERBI Software, 2019) in conjunction with Twitters search API application program interface. We used the following search terms to capture relevant Twitter messages: "COVID-19," "coronavirus pandemic," "Covid19," "face masks", and included terms such as "queens," "bronx," "new york." We focused our search on the intersection of COVID-19 and New York because our search was conducted during the early phases of relaxed lockdown mandates in New York and New York City had emerged as a hotspot in the global COVID-19 pandemic (McKinley, 2020). Given that a phased reopening of the economy in New York started on May 16, 2020, we selected May 10, 2020, as our start date to ensure that we captured a wider breadth of potential topics. Twitter messages were captured for 2 weeks from May 10th to May 24th. This time period covered a week before and after reopening. The study analysis period was divided over two distinct, one-week periods to allow for comparison over time: May 10, 2020 to May 17, 2020 ($n = 4,441$ tweets) and May 18, 2020 to May 24, 2020 ($n = 2,860$ tweets). This resulted in a total number of 7,301 tweets. The use of publicly available data in this study did not require Institutional Review Board approval.

2.2 | Text mining

The tweets were analyzed using SAS Text Miner Version 15.1 (SAS) and SAS version 9.4 (SAS Institute, Inc). Using SAS Text Miner, the tweets were analyzed for frequency of posts, key terms, and words. SAS Text Miner provides the ability to extract information from text, and assemble tweets into related topics to gain insight into the content of the tweets from the unstructured data (Chakraborty et al., 2014). First, using the text parsing function, each tweet was divided into individual words listed in a frequency matrix. We then reviewed and excluded words which contributed little to the topic such as auxiliary words or conjunctions. Second, a text filter was activated to exclude words that appeared in fewer than four messages. We created synonym list of COVID-19 to capture and relabel

all occurrence of varied definitions of COVID-19. Third, a text topic node was used to combine terms into 10–12 mutually exclusive Text Topic groups. After both topic groups were visually assessed, a 10 Text Topic group was selected which best captured the main themes. Two co-authors inspected the individual tweets of the 10 final Text Topic groups to analyze the themes. The same process was used to analyze tweets for both time periods. We used base SAS version 9.4 for descriptive analysis of the unique users and location of the unique users.

2.3 | Qualitative analysis

The Text Topics were imported into Excel (Microsoft) for qualitative thematic analysis. First, content analysis focused on detection of each Text Topic's theme to characterize the online discussions. Next, one co-author (B.A) reviewed 50% of the entire tweets. Finally, both co-authors (Z.O and B.A) compared their individual assessments and discussed the emergent themes.

3 | RESULTS

During the first week of analysis (May 10, 2020 to May 17, 2020), 1,974 unique users generating 4,441 tweets. During the second time period (May 18, 2020 to May 24, 2020), 1,506 unique users were observed, generating 2,860 tweets. The 10 mutually exclusive Text Topics generated from each time period are presented in Tables 1 and 2, respectively. During the first week of analysis, the greatest concerns revealed by the number of tweets: were about the rapid increase in the number of COVID-19 cases globally, alarming death rates, and mental health burden of the lockdown (Table 1). Reactions from the second week more focused on the economy, mental health, risk of premature re-opening, questions about re-infection after treatment for COVID-19, and treatment/cure (use of disinfectants to prevent reinfection, effectiveness of hydrochloroquine, and demands for a vaccine or a cure; Table 2). The 10 Text Topics generated in each time period were further categorized into six main themes. The six main themes include: (a) Surveillance—number of deaths, number of cases, and affected locations; (b) Prevention – social distancing, use of face mask and contact tracing; (c) Treatments, Testing, and Cure—vaccine, disinfectants, research, and medications; (d) symptoms and transmission; (e) fear—impact of lockdown on mental health, fear of reopening, emotional distress about lifestyle change, and susceptibility to infection; and (f) financial loss—the economy, unemployment, furloughs, and impact of lockdown on small businesses.

A major theme identified in both time periods (May 10, 2020 to May 17, 2020 and May 18, 2020 to May 24, 2020) was surveillance, illustrated by updates on the number of deaths, number cases, and affected locations in the United States and worldwide. A total of Text Topics ($n = 940$) included status updates by users about rising COVID-19 cases and deaths, with frequent reference

TABLE 1 COVID-19 tweets by topic 5/10 to 5/17

	Topic	n	Description
1	+COVID 19, coronavirus pandemic, health, +help	694	Tweets highlights mental health impact of lockdown, need for mental health help in COVID-19 relief, and mental health of Nurses working during Pandemic. Theme highlights need to use Face mask and salute to healthcare workers
2	News, global, test,+COVID 19	539	Tweets focus on stimulus bill in the United States, adherence to lockdown. Rise in global number of COVID-19 cases, refer positively on need to use face mask. Restaurants testing what a sage dine in experience would be during the pandemic
3	covid, lockdown, India, delhi, Mumbai	357	Tweets mentions high-risk groups of dying from COVID-19. India's coronavirus contact tracing app and Enforcement of Lockdown in Mumbai, India, and rise in cases in Delhi. Handwashing India and UV sanitation. College classes in the fall go online
4	+case, +death, coronavirus update, infectious disease, +total	351	Tweet are about new cases, rise in total number of COVID-19 cases in Oman, India, Singapore, Arizona, California, Michigan, and Illinois. Reference to Arizona Stay at Home order ending and newdeath rates in India and Oman
5	Batflu, Wuhan, +quarantine, corona, social distancing	173	Tweets focus on Wuhan's plan to test entire population and COVID-19 return to countries that eased lockdown restrictions. Reference to social distancing and wearing mask
6	+disease, +kid, kawaski disease, +child Europe	158	Tweets focus and children, impact of COVID-19 on children's normal play and COVID-19 in children. Tweets link Kawasaki to COVID-19
7	Israel, Italy, +vaccine, +cure, +calm	111	Tweets echo a demand for a cure for COVID-19. Urgent need for a vaccine to cure coronavirus and development of vaccines in Italy and Israel. Tweets also mention number of deaths in COVID-19 U.S
8	Brazil, +president, bolsonaro, jairbolsoaro, jair	81	Tweets focus on rising number of COVID-19 deaths in Brazil. Tweets criticizing the Brazilian president's approach to managing the pandemic
9	+work, unemployment rate, +foreigner, unemployment rate, h1b	81	Tweets are messages to temporarily banning work visas in the United States and unemployment rate in the United States
10	gujarat, ahmedabad, +high-risk potential coronavirus super-spreader, +super -spreader, high-risk	52	Tweets are about high-risk individuals spreading COVID-19 in Ahmadabad city, Number of new cases (Indian cities: Delhi and Chennai)

to emerging COVID-19 hotspot locations such as India, Brazil, California, Michigan, and New York. In the second week, discussions about COVID-19 cases included several tweets related to concerns about increased cases and death rates in countries that reopened their economies prematurely.

The second theme was prevention (social distancing, facemasks, and contact tracing), reflected in four Text Topics and 834 tweets. Within this category, in week 1 and week 2, several tweets called out a need to stay home, wear a mask, and enforce social distancing in efforts to prevent transmission of the virus. In one Text Topic, users

TABLE 2 COVID-19 tweets by topic 5/18 to 5/24

	Topic	n	Description
11	+COVID19, coronavirus pandemic, +business, +help, health	420	Tweets refer to furloughs, job loss, and unemployment. Social distancing worsening mental health during pandemic. Call for help in expanding access to mental health services. Comments on how the pandemic has disrupted businesses
22	+case, +death, +report, coronavirusupdate, total	303	Rising death rates and new cases of COVID-19 in India, Kuwait, Oman, Ontario, Greece, and Saudi Arabia and the United States
33	india, lockdown, covid, +man, +swim	199	Enforcement of lockdown in India. PPE shortage in India. Man swims to escape lockdown in India/
44	brazil, covid, +people, +drug, +president	166	Tweets about how Brazil's president bets on hydrochloroquine to save the country from Coronavirus. Latin America overtakes United States and Europe in new cases 3 days in a row
45	news, information, newsalert, coronavirusdisease2019, newsupdate	106	Tweets focus on news about New York's deadliest ZIP codes, alarming death rates in NY. Rising cases in India and the News alerts on positive cases and death rates in United States. Calls to increase use of face mask and social distancing
66	batflu, wuhan, news_pandemic, pandemictech, socialdistancing	105	Tweets focused on increasing use of digital technology to control spread. Utility of contact tracing apps. Calls to adhere to social distancing
77	+disinfectant, +spray, tokyo, covid, delhi	82	Tokyo Pub installs disinfectant tunnel to spray customers on entry. WHO warning that spraying disinfectants on streets doesn't eliminate COVID-19. Migrants in India have been most affected by the pandemic
88	+mink, dutch, netherlands, +infect, +human	56	Tweets about fighting COVID-19 with disinfectants and use of pandemic Robot to disinfect the streets. Netherlands installs plastic shields around student's desk to maintain social distancing
99	+work, unemployment rate, +foreigner, unemploymentrate, h1b	56	Tweets refer to U.S. plan to temporarily ban work visas issued to non-U.S. citizens, and the worsening unemployment rate
110	bihar, pillion, haryana, riding, +cycle	47	So many people are turning to cycling during the coronavirus pandemic. Bihar has reported 1,423 confirmed COVID 19 cases, and most are migrant laborers

also expressed concerns about strategies businesses could use to enforce the use of facemasks.

The third theme was focused on treatment, testing, and demand for a cure or vaccine. This theme was observed in several tweets ($n = 415$) with users reporting: (a) studies about clinical trials for vaccines; (b) misinformation about hydrochloroquine, disinfectants, or suspicions that a cure exist; and (c) an increase in the number of positive tests. During the week of May 10 to May 17, one Text Topic captured discussions that mentioned an urgent need for a vaccine and a cure. By May 18 to 24, tweets focused on the need to increase the use of disinfectants to treat COVID-19 and criticism against the use of hydrochloroquine to treat COVID-19. Several tweets mentioned the use of pandemic robots to disinfect the streets during the second week. Tweets also circulated with reference to a World Health Organization (WHO) report, which specified that spraying disinfectants on the streets does not eliminate COVID-19. One Text Topic included alarms about the Brazilian government's effort to support hydrochloroquine to treat COVID-19.

The fourth theme identified was symptoms and transmission. From May 10 to 17, 2020. One Text Topic ($n = 158$ tweets) focused

on symptoms of COVID-19 in children, with emphasis on symptoms of Kawasaki disease as an indicator of COVID-19 in children. Tweets called out a need for parents to monitor symptoms of Kawasaki disease in children. Several tweets also described specific symptoms of Kawasaki disease that parents and caregiver should monitor.

Fear was clearly a dominant theme in both periods. This category included tweets related to the increasing number of confirmed cases and deaths, coupled with uncertainty about if the pandemic will ever end. Some tweets referred to COVID-19 as the "U.S. death toll." The theme of fear was also evident in one Text Topics during the first week and three Text Topics during the second week. By the second week, one topic included tweets with calls for help related to the mental health crises during the lockdown.

Finally, financial loss was a common theme across both time periods. Two Text Topics in each time period detailed concerns and suffering related to unemployment, job loss, and furloughs during the pandemic. These stories included a temporary ban on work visas (H1B) for non-U.S. citizens who currently reside in the United States and financial losses incurred by small business that had to shut down during the lockdown.

4 | DISCUSSION

Our text-mining analysis generated 10 Text Topics in each time period (time period 1: May 10, 2020 to May 17, 2020 and time period 2: May 18, 2020 to May 24, 2020). The Text Topics in both time periods yielded six themes related to COVID-19. The themes included surveillance, prevention, symptoms, treatment, fear, and financial loss. The themes we identified provide a snapshot of the public's concerns during the pandemic, particularly during the early phase of reduced lockdown restrictions in the United States and many other countries in the world (Lopez & Rodo, 2020). This is important given that even while U.S. states and countries lifted lockdown restrictions, public health messaging including the use of face mask and testing remained critical topics, themes echoed in the present study (Omer et al., 2020). We found notable differences in the nature of the content posted during the two time periods – tweets from the second time period were more focused on treatment and demands for a vaccine or cure.

Prior work using Twitter data has identified themes similar to ours that echo the public's concerns during outbreaks. Following the Ebola virus outbreak in 2014, Twitter content analysis showed that twitter users sought and disseminated information regarding disease trends, transmission, infection, and prevention (Odlum & Yoon, 2018). During the Zika virus epidemic, computational content analysis of Zika-related Twitter content identified mounting public concerns that included societal impact of the outbreak, negative health consequences related to pregnant women and babies, and transmission routes (Fu et al., 2016). Amidst the current pandemic, a study by Odlum and colleagues highlighted the promise of using Twitter for assessing online conversations about the COVID-19 pandemic. Comparing COVID-19 knowledge by misinformation source, they identified four themes in 1,763 publicly available COVID-19-related tweets specific to the African American Twitter community (Odlum et al., 2020). Similar to our present study, themes identified by Odlum and colleagues included symptom and transmission patterns, treatment, and fear. They also identified online discussions related to COVID-19 prevention behaviors (e.g., use of masks and social distancing).

In the week of May 10 to 17, 2020, mental health impact of the lockdown and the use of face mask was the first major Text Topic tweeted. This topic consisted of a demand for mental health support during the pandemic and a call to expand access to mental health services, including for Nurses working during the pandemic. These findings provide insight into the potential impact of the rapidly spreading COVID-19 outbreak and lockdown on mental health concerns (Galea et al., 2020). Indeed, the pandemic has created fear and anxiety in the general public that warrants greater attention to mental health needs in our communities. The vulnerability of the public to mental health issues during a pandemic can arise from various factors. For example, we identified one Text Topic related to the anxiety and emotional distress children struggled with during the lockdown and lack of adequate relief to meet these challenging needs. Some tweets clearly expressed fear of increased community transmission

of the virus if the economy reopened. Indeed, The Pew Research Center recently reported that about half of the U.S. public voiced that COVID-19 pandemic is a major threat to the health of the U.S. population (Krogstad et al., 2020).

The week of May 18, 2020 to May 24, 2020 reflects the early stage of reopening after lockdown in the United States. Similar to the U.S., countries in Europe, such as Italy, most businesses reopened by May 18, 2020 (BBC, 2020). During this time period, twitter users disseminated COVID-19 information regarding concerns related to re-infection, prevention, treatment (e.g., hydrochloroquine/hydroxychloroquine, pandemic robots for disinfecting the streets, and spraying customers with disinfectants), mental health, and economic instability. By May 16, 2020, the WHO provided guidance to dispel the rumour that spraying disinfectants is effective to prevent or treat COVID-19 (World Health Organization, 2020). This message was evident in twitter conversations about disinfectants from May 18 to 24, 2020. In a demand for treatment, some of the tweets we captured raised questions about use of hydrochloroquine/ hydroxychloroquine as a potential treatment for COVID-19. In the United States, hydroxychloroquine gained most media attention related to its effectiveness as a form of treatment during our study period (Geleris et al., 2020).

Tweet content is not only a rapid and inexpensive way to preview public opinion in general (Glowacki et al., 2016; Sinnenberg et al., 2017) but also for purposes such as assessing public health information needs (Odlum & Yoon, 2018) and developing tailored interventions (Yoon et al., 2020). Using SAS Text Miner, the methods of Text Topic detection may help public health nurses utilize the identified topics for effective public health messages that enhance dissemination of accurate information and alleviate fear and anxiety during the pandemic. Text Topic modeling may also suggest potential areas for targeted intervention strategies. For example, in our analysis two Text Topics representing 1,114 tweets were related to mental health issues facing the general public. In recognition of these concerns and challenges that have confronted the public during the COVID-19 pandemic, public health nurses have an important role to play in using platforms such as Twitter for assessing health information needs and as a platform for dissemination of public health information.

Public health nurses have been at the forefront of the COVID-19 pandemic in a myriad of roles, from public health providers in the community, researchers to policy development (Edmonds et al., 2020). Findings from this study support the need for public health nurses to integrate social media surveillance as an essential tool to identify the pressing concerns during the COVID-19 pandemic and expand public health nursing recovery efforts (Jakeway et al., 2008). Understanding how Twitter data can be harnessed to gather information about the impact of the pandemic, and disseminate target information to meet the public's information needs remains critical to engaging communities with timely and appropriate public health messages during the COVID-19 Pandemic.

A strength of this study is that we captured tweets during the first week of reduced lockdown restrictions in New York and in

many other countries in the world. Our findings thus reflect the public's reactions to key concerns related to COVID-19 restriction. Nevertheless, there are limitations that should be considered. While this analyses captured a wide breadth of tweets amid a critical period during the pandemic, tweeter users are unique and not representative of the general population. The generalizability of this study is also limited because we utilized a single language. Additionally, using our search strategy we attempted to capture COVID-19-related tweets focused on New York city, the tweets we captured included COVID-19-related information from countries around the world during the pandemic. However, this strengthened our study, given the global restrictions imposed during the pandemic. Furthermore, our search strategy employed possible variations with hastags in an attempt to capture the maximum number of relevant tweets. Future studies should examine additional languages.

5 | CONCLUSION

Findings from this study contribute to better understanding the use of Text mining of Twitter data in assessing the public's reaction during the COVID-19 pandemic. Public health organizations need to engage more in monitoring and evaluating information, questions, and trends within the public's tweets, as these have crucial implications for public health interventions. Being abreast with real-time conversations on Twitter allows for the identification of emerging public concerns and provides an opportunity for prevention and mitigation of the spread of misinformation and fear.

DISCLOSURES

The authors have no disclosures.

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How to cite this article: Osakwe ZT, Ikhapoh I, Arora BK, Bubu OM. Identifying public concerns and reactions during the COVID-19 pandemic on Twitter: A text-mining analysis. *Public Health Nurs.* 2021;38:145–151. <https://doi.org/10.1111/phn.12843>