Social media and COVID-19: Characterizing anti-quarantine comments on Twitter

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Abstract
Social media has become a mainstream channel of communication during the COVID-19 pandemic. While some studies have been developed on investigating public opinion on social media data regarding COVID-19 pandemic, there is no study analyzing anti-quarantine comments on social media. This study has collected and analyzed near 80,000 tweets to understand anti-quarantine social comments. Using text mining, we found 11 topics representing different issues such as comparing COVID-19 and flu and health side effects of quarantine. We believe that this study shines a light on public opinion of people who are against quarantine.

KEYWORDS
COVID-19, quarantine, social media, twitter, text mining

1 | INTRODUCTION
As of June 4, 2020, the number of positive cases was more than 6.6 million globally, with over 390,000 deaths.1 The outbreak has posed significant threats to international health and the economy. In the absence of treatment for this virus, US states imposed a quarantine period. In addition, the COVID-19 pandemic caused the largest global recession in history,2 and the US unemployment rate reached 14.7% in April 2020.3

Social media has become a mainstream channel of communication (Turner-McGrievy, et al., 2020). For example, 72% of U.S. adults use at least one social media site in 2019.4 In the last decade, social media platforms such as Twitter have grown in popularity. Social media has received a great deal of academic interest to investigate public opinion on different issues such as politics and health (Karami, Lundy, et al., 2020). Some studies, such as (Abd-Alrazaq et al., 2020), have been developed on analyzing public opinion on social media data during the COVID-19 pandemic. While these studies have provided valuable insights, they did not consider anti-quarantine comments on social media. This study characterizes tweets containing anti-quarantine hashtags with text mining to present a new perspective on public opinion during the COVID-19 pandemic.

2 | METHODOLOGY
2.1 | Data collection and preprocessing
We explored Twitter search to identify hashtags representing anti-quarantine semantic. We found six hashtags including #AntiLockdown, #AntiQuarantine, #ReOpenAmerica, #EndtheLockdown, #EndtheLockdown, and #ReOpenAmericaNow. Then, we utilized a data provider service (Brandwatch) to collect tweets containing at least one of the six hashtags. Next, we removed URLs, hashtags, username, duplicate tweets and tweets with less than five words. This process has provided 79,738 tweets.
In order to disclose hidden semantic layer in our data, we utilized topic modeling. This technique assigns words semantically related to each other into a cluster, called topic. Different topic models have been developed using Latent Dirichlet Allocation model (LDA) (Blei et al., 2003). LDA is an efficient and effective topic model that has been applied on different social media applications such as analyzing exercise patterns (Karami and Shaw, 2019) and mobile work (Hemsley et al., 2020) on Twitter. The outputs of LDA for \( n \) documents (tweets), \( m \) words, and \( t \) topics, are two matrices (Karami, Ghasemi, et al., 2019). The first one is the probability of each word in each topic or \( P(W_i|T_k) \), and the second one is the probability of each topic in each document or \( P(T_k|D_j) \) (Figure 1).

The \( P(W_i|T_k) \) matrix output represents the probability of each word belonging to a specific topic, whereas the \( P(T_k|D_j) \) matrix represents the probability of each topic belonging to a specific document (Karami, White, et al., 2020). The top words in each topic based on the descending order \( P(W_i|T_k) \) represent a topic. For example, the top words in topic 4 in Table 1 are people, home, stay, sick, masks, live, care, risk, wear, and safe, representing a theme related to wearing masks. We used a pre-processing step to find the optimal number of topics based on the level of consistency and coherence with the associated topic using the C_V method developed in the gensim Python package. The estimation process offered the number of topics at 11. Next, we applied Mallet, a Java implementation of LDA, at 11 topics and 4,000 interactions on our corpus.

#### 3 | TOPIC ANALYSIS

We then moved to a qualitative coding process to inductively interpret topics. Our coding was based on reviewing the top related words within each topic using \( P(W|T) \) and the top related tweets within each topic using \( P(T|D) \) (Karami, Swan, et al., 2019).

#### 4 | RESULTS

We found anti-quarantine tweets discussed in 11 topics, as seen in Table 1. The first topic showed discussions on the order of governors to close businesses and impose self-quarantine. These tweets argued that the order was unconstitutional because it was against people’s liberty and freedom. The second topic represented arguments around the physical and mental health issues due to quarantine. The third topic focused on this question: “Why were big businesses (e.g., Walmart) open while small businesses were closed?”

The fourth topic was about the uselessness of wearing a mask for safety. The fifth topics considered blocking a republican bill that added small business loans by senate democrats. The sixth and seventh topics showed requests for open businesses and the Opening Up America, respectively. The next topic illustrated debates on fake news and wrong models on predicting
TABLE 2  

| Topic               | Tweet example                                                      | Topic          | Tweet example                                                                 |
|---------------------|--------------------------------------------------------------------|----------------|-----------------------------------------------------------------------------|
| Unconstitutional   | Please support Elon Musk @elonmusk as he battles against Leviathan (the government) for our rights and liberty as individuals and private businesses. A true revolutionary is one who defies the State at his potential peril. #business #tesla #covid #california #ReopenAmericaNow | Open businesses | America MUST get back to work. Click here to sign the petition to save jobs, small business, and America as we know it! #reopenamerica #reopenamericanbusiness |
| order               |                                                                     |                |                                                                             |
| Health issues       | Absolutely & we MUST also remember those that have lost their lives during this dangerous lockdown due to addiction, suicide & other reasons, all due to the extended unnecessary lockdown. The lockdown has caused immense harm to MANY! #ReopenAmericaNow | Opening plan   | President Trump unveiled ‘Opening Up America’ plan, aims for May 1. The guidelines were developed by #coronavirus task force members, Drs. Birx & Fauci in coordination with CDC & Prevention chief Robert Redfield. #ReopenAmerica |
| Small Business      | Ian Smith, owner of Atilis Gym, is right “enough is enough”. Small business are just as “essential” as big box stores like Wal-Mart. If big box stores servicing over a 100 customers can take the necessary precautions to remain open so can small businesses. #ReopenAmericaNow | Wrong models and fake news | An analysis from Bot Sentinel, a bot tracking platform, found that bots and trolls have been stoking sentiments online that have fueled the protests, using hashtags like #ReopenAmericaNow and #StopTheMadness. |
| Masks               | Absolutely & we MUST also remember those that have lost their lives during this dangerous lockdown due to addiction, suicide & other reasons, all due to the extended unnecessary lockdown. The lockdown has caused immense harm to MANY! #ReopenAmericaNow | Protests       | There are protests planned in California, Oregon, Washington, Arizona, New Mexico, Colorado, Kansas, Minnesota, Iowa, Missouri, Illinois, Wisconsin, Indiana, Michigan, Kentucky, Tennessee, Ohio, Pennsylvania, N. Carolina, Delaware and Maine. #ReopenAmerica |
| Blocking small      | You’re not making lists of US taxpayers. #ReopenAmericaNow! Democrats withheld critical funding for the people who pay their salaries; who are struggling to feed their families, pay their bills, save their businesses. You did it for political gain, without missing a paycheck. | Political consequences | Trump now losing ground in a key swing state. Remember, even Winston Churchill got crushed right after he won World War Two! Want to reelect Trump? #ReopenAmerica |
| business support    |                                                                     |                |                                                                             |
| Flu vs COVID-19     | @realDonaldTrump TESTS are not even required to confirm deaths as Coronavirus. Total deaths for each week in March as compared to FOUR prior years are DOWN. Many flu & pneumonia deaths are coded falsely as coronavirus. That is the only logical conclusion. #ReopenAmericanow |                |                                                                             |

COVID-19 related issues. The ninth topic was about protests against quarantine in different US states such as California and Michigan. The next topic was discussion on political consequences of the COVID-19 quarantine in elections. The last topic compared flu and COVID-19 based on different statistics such as the number of deaths. Table 2 also provides an example tweet for each of topics.
5 | DISCUSSION AND CONCLUSION

This study investigated anti-quarantine tweets to understand hidden topics Twitter with a cost and time effective approach. Our findings show the anti-quarantine tweets were about different issues related to the COVID-19 quarantine. Our research shines a light on US public opinion regarding anti-quarantine efforts.

While this study provided a new perspective in public opinion mining, we did not study non-English tweets and this paper was limited to six hashtags. Future work could investigate non-English tweets and consider more hashtags.

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ENDNOTES

1 https://www.worldometers.info/coronavirus/
2 https://www.businessinsider.com/countries-on-lockdown-coronavirus-italy-2020-3
3 https://data.bls.gov/timeseries/LNS14000000
4 https://www.pewresearch.org/internet/fact-sheet/social-media/
5 https://radimrehurek.com/gensim/models/coherencemodel.html

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