

## Characterization of Anonymous Physician Perspectives on COVID-19 Using Social Media Data

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Physicians' beliefs and attitudes about COVID-19 are important to ascertain because of their central role in providing care to patients during the pandemic. Identifying topics and sentiments discussed by physicians and other healthcare workers can lead to identification of gaps relating to the COVID-19 pandemic response within the healthcare system. To better understand physicians' perspectives on the COVID-19 response, we extracted Twitter data from a specific user group that allows physicians to stay anonymous while expressing their perspectives about the COVID-19 pandemic. All tweets were in English. We measured most frequent bigrams and trigrams, compared sentiment analysis methods, and compared our findings to a larger Twitter dataset containing general COVID-19 related discourse. We found significant differences between the two datasets for specific topical phrases. No statistically significant difference was found in sentiments between the two datasets, and both trended slightly more positive than negative. Upon comparison to manual sentiment analysis, it was determined that these sentiment analysis methods should be improved to accurately capture sentiments of anonymous physician data. Anonymous physician social media data is a unique source of information that provides important insights into COVID-19 perspectives.

*Keywords: Social media, Covid-19, Physicians*

## 1. Introduction

Physicians treating COVID-19 patients have unique insights into the current pandemic response, some of which may identify opportunities for immediate improvements as well as improved responses to possible future pandemics. Their insights and perspectives during this difficult time are unique in understanding the impact that COVID-19 has had on frontline healthcare workers, patients, and perhaps even the public as a whole.<sup>1</sup> Understanding these physicians' attitudes and beliefs can improve health outcomes and drive successful health policies, particularly as patient safety and organizations' safety culture have been shown to be deeply affected by healthcare worker beliefs.<sup>2-4</sup>

Social media platforms, such as Twitter, are rich resources for opinionated data with respect to a myriad of topics, and can lead to a deeper understanding of ideas, opinions, and perspectives about a specific topic of interest, including COVID-19, and do so in real-time.<sup>5</sup> Twitter data is publicly available and relatively accessible for download; it is an exceptional resource for evaluating public discourse and sentiments given that it is the third most popular social media platform with approximately 330 million active users per month.<sup>6</sup> Unfortunately, in the midst of the COVID-19 pandemic, many physicians are hesitant to publicly discuss topics such as lack of sufficient personal protective equipment, testing equipment, and other issues they are facing in their workplace for fear of being reprimanded or even fired from their jobs.<sup>7</sup> For this reason, social media data posted specifically by physicians about COVID-19 is less likely to be an honest representation of their beliefs and attitudes regarding the pandemic response.<sup>8</sup>

In light of these concerns, a user handle on Twitter was set up where administrators collected direct messages (DMs) from physicians in the United States, and posted them anonymously under that handle, giving physicians some anonymity and a platform to express their perspective as it relates to the pandemic. In this study, we analyze the topics and sentiments of anonymous COVID-19 physician tweets and compare them to a broad baseline of public comments about the disease.

## 2. Methods

### 2.1. Data Collection

We extracted all tweets from the specific Twitter user account, @Covid19Docs, wherein the administrators collected direct messages (DMs) from physicians, and posted them to the page on behalf of those physicians, giving them some anonymity and a platform to express their perspective as it relates to the COVID-19 pandemic. Our extracted anonymous physician COVID-19 tweets are in English and span from March 16-July 17, 2020, with 875 total tweets. To prepare the tweets for analysis, punctuation, special characters, URLs, and stop words were removed from tweets, and words lemmatized. A dataset containing the tweet identifiers and other relevant datasets have been deposited at <http://doi.org/10.5281/zenodo.4060340>.

In order to put the specific Twitter account dataset within a larger scope of Twitter COVID-19 discourse, we compared our findings against a dataset of 513 million tweets gathered from the public Twitter streaming API<sup>9</sup>, which contains a sampled set of 1 percent of all Tweets generated in real time. The dataset which is publicly available, is the result of an international collaboration and is maintained by researchers at Georgia State University.<sup>9</sup> It contains the top 1000 bigrams and

trigrams we used for direct comparison of frequency in our smaller dataset. Note that to extract the mentions of our terms of interest, we removed all retweets, all tweets not in the English language, and tweets from accounts that are determined to be bots. Bot accounts are identified as accounts that are very recently created, and tweet more than 1000 times per day or are described on the account as a bot.

## 2.2. *N-gram Frequency Measures*

In order to understand the subject matter of the tweets, we counted frequencies of the most common lemmatized bigrams and trigrams in the anonymous physician tweets, and compared those to the more general COVID-19 dataset. This allowed us to qualitatively assess the topics discussed among physicians versus the general public with regard to COVID-19.

In addition, an experienced hospitalist physician helped us to identify four specific topics to assess within the anonymous physician data and the general COVID-19 data. These specific topics were identified because they were recognized to be of importance within the public discourse, and particularly within the physician discourse, during the COVID-19 pandemic. These topics were personal protective equipment (PPE), unemployment, telemedicine, and racial injustice. We measured the frequency of the topics and sentiments of tweets about these topics.

## 2.3. *Sentiment Analysis*

Sentiment analysis is a tool used to analyze and understand the opinions, emotions, and sentiments of language.<sup>8</sup> It is often used in marketing to understand opinions of certain brands, for prediction of political candidates' likelihood to win an election, and crowd opinions about events or policies.<sup>10</sup> The advent of social media has created a rich data source filled with sentiments and opinions about a myriad of topics, and is increasingly being used in the healthcare arena.<sup>11</sup> There are different sentiment analysis approaches, which all have their own strengths and weaknesses.

We wished to evaluate the sentiments of the anonymous physician data, and garner insight about whether these approaches accurately assess the sentiments of anonymous physician tweets. To do this, we began by conducting two popular sentiment analysis methods on the anonymous physician data. The first was the National Research Council (NRC) Word-Emotion Association Lexicon, which contains 10,170 English words and their associations with eight emotions (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) and two sentiments (negative and positive), making this a lexicon-based sentiment analysis.<sup>12</sup> The NRC method is unique in that it measures eight emotions, taken from the psychologist, Robert Plutchik's theory that people have eight basic emotions.<sup>13</sup> We used the Natural Language Toolkit (NLTK) in Python 3 and the NRC-Sentiment-Emotion-Lexicons to conduct this NRC sentiment analysis.<sup>12,14</sup>

We then used the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis approach, which is specifically designed for analyzing social media data using a lexicon and rule-based approach to assess sentiments (negative, neutral, and positive).<sup>15</sup> VADER has the benefit of providing a normalized, weighted composite score of each tweet by summing valence scores of each word in its lexicon, adjusting them according to grammatical and syntactical rules, and then normalizing them to give a compound score between -1 and +1.<sup>16</sup> We used the Natural Language Toolkit (NLTK) for VADER (nltk.sentiment.vader) in Python 3 to carry out this

analysis.<sup>17</sup> We then compared the sentiments from the VADER sentiment analysis approach, which is thought to be more accurate for capturing sentiments of social media data, to the general COVID-19 dataset.<sup>15</sup>

Manual classification of all 875 tweets in the anonymous physician tweets was done by one of the authors. Tweets for which the sentiment was unclear in the first round of annotations were then annotated by two co-authors to determine the sentiment for those tweets. Each tweet was given an overall ranking of -1 (negative), 0 (neutral), or +1 (positive). To determine whether VADER accurately captured the sentiments of these tweets compared to the manual classification of tweets, precision, recall, and F1 scores were calculated. Data collection and analyses for this project were done using Python (3.7.0), R (3.6.0), SAS (9.4), and Microsoft Excel (2016).

### 3. Results

#### 3.1. *Frequency of terms and n-grams*

We measured the most frequent bigrams and trigrams that occurred in the anonymous physician tweets and compared them to the general COVID-19 tweets (Figure 1). The top two phrases in the anonymous physician tweets might be expected, “health care” and “covid patients;” others point to concerns that might be more specific to physicians and other frontline healthcare workers, such as “need ppe,” “elective cases,” and “surgical masks.”

Top phrases in the more general COVID-19 dataset look a bit different. The top two phrases are perhaps obvious, “covid 19” and “coronavirus cases,” with frequency of “covid 19” far exceeding the other phrases. This general Twitter dataset captures public COVID-19 chatter specifically, so the very high frequency of the phrase “covid 19” is reasonable. The more general COVID-19 tweets also have a number of phrases associated with the political sphere of COVID-19 that the physician tweets do not have, such as, “white house,” “trump administration,” and “dr fauci.” These phrases give a qualitative understanding of what physicians are talking about compared to the general public with regard to the COVID-19 pandemic.

Taking a step further, we identified specific topics of interest that are of importance within public discourse, and particularly within the physician discourse, given the emergence of the COVID-19 pandemic (Table 1). By doing this, we can further our understanding of physicians’ perspectives regarding these topics. We measured and compared the frequency of tweets containing the specific topical phrases in the anonymous physician tweets and the general COVID-19 tweets. Using a chi-square test, we found significant differences between proportions of tweets containing all of the four phrases of interest, with a larger proportion of topics discussed among the anonymous physician tweets, except for phrases surrounding “racial injustice,” which had a slightly higher proportion in the general COVID-19 tweets.

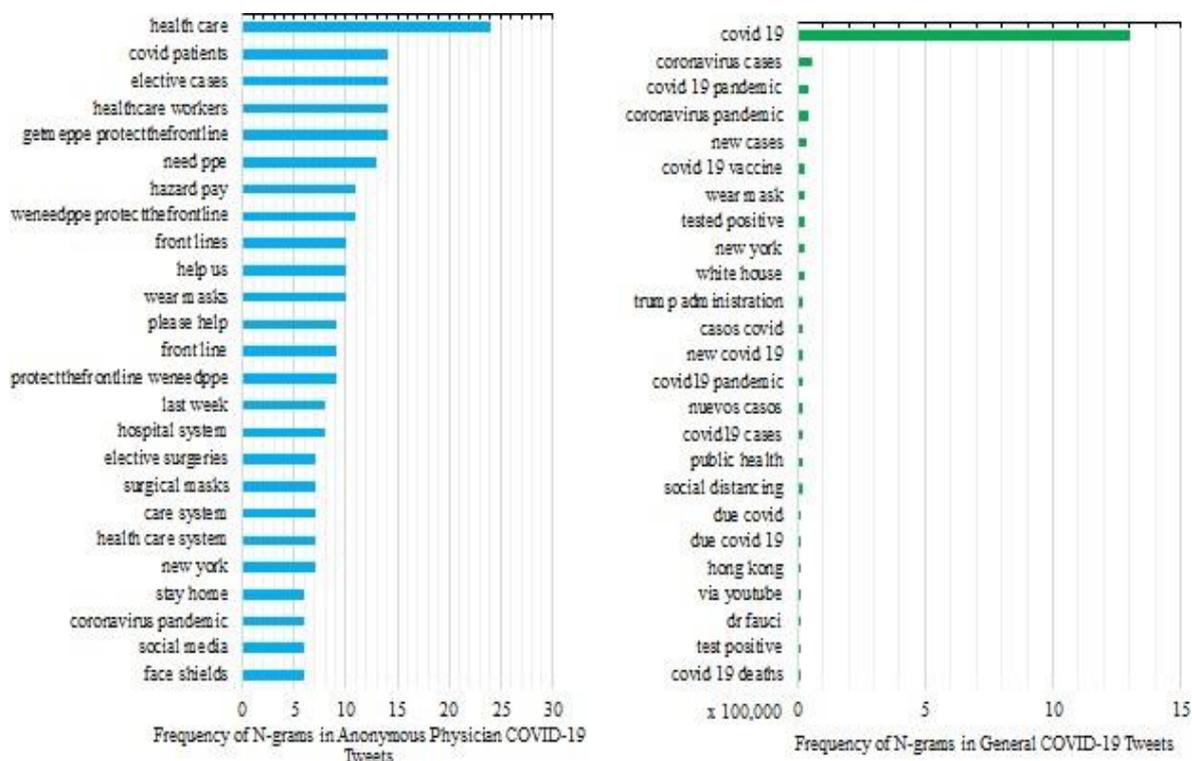


Fig. 1. Top 25 Most Frequent Bigrams and Trigrams in Anonymous Physician COVID-19 Tweets and in General COVID-19 Tweets

Table 1. Frequency of Topics in Anonymous Physician Tweets and General COVID Tweets

	Anonymous physician COVID-19 Tweets		General COVID-19 Tweets		
	Frequency (n <sub>total</sub> =875)	Percent of Total Tweets	Frequency (n <sub>total</sub> =73,377,056)	Percent of Total Tweets	p-value
Personal Protective Equipment	118	13.49%	22,155	0.03%	< .00001
Unemployment	15	1.60%	138,965	0.19%	< .00001
Telemedicine	12	1.37%	50,308	0.07%	< .00001
Racial Injustice	2	0.23%	198,906	0.27%	0.01

Specific terms used to capture phrases: “PPE,” “personal protective equipment,” “N95,” “face shield”; “telemedicine,” “telehealth”; “furlough,” “unemployed,” “pay cut”; “racial injustice,” “racial discrimination,” “racism,” “racial inequality”

### 3.2. Sentiment analysis

We did two sentiment analyses in order to learn which sentiments these methods associated with the anonymous physician tweets, and also to determine if sentiment analysis could accurately capture sentiments of anonymous physician tweets compared to a manual assessment. We also did a sentiment analysis on the general COVID-19 Twitter data for comparison.

Figure 2 shows the number of tweets that contain each sentiment-emotion pair. Assessment of emotions is unique to the NRC method; most other methods only capture negative and positive

sentiments. The most frequent emotion identified by NRC was “trust” in the anonymous physician tweets, and there were more positive words among the tweets than negative.

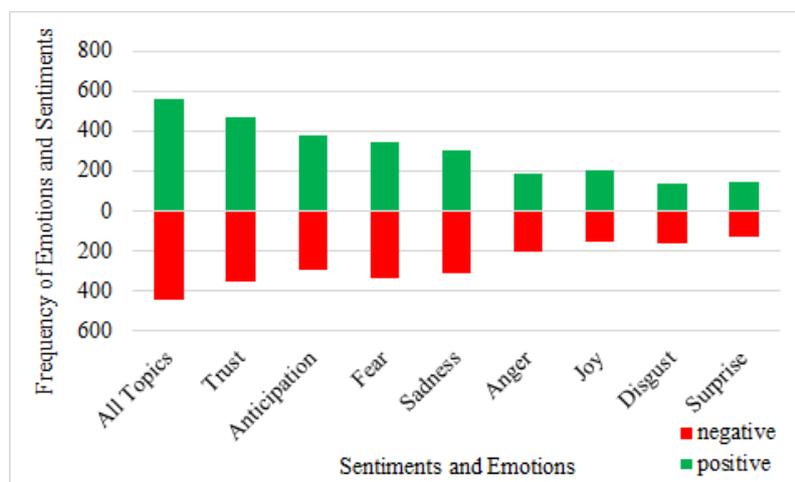


Fig. 2. NRC Word-Emotion Association Lexicon Sentiment Analysis of Anonymous Physician COVID-19 Tweets

Figure 3 shows negative, positive, and neutral sentiments over time for the anonymous physician data and general COVID-19 data using the VADER sentiment analysis method. We compared the VADER sentiments of the anonymous physician data to that of the general COVID-19 tweets to discern if sentiments differed between the two datasets. We used VADER for this comparison because it is tailored toward sentiment analysis of social media data.

Over time, there was usually a slightly higher proportion of positive tweets compared to negative tweets in the general COVID-19 tweets. The anonymous physician tweet sentiments show less of a distinction among the sentiments compared to the general COVID-19 assessment.

During the week of June 1, 2020, there was a spike in positive tweets in the anonymous physician data (Figure 3). During this particular week many physicians describe the work they are doing for patients during the COVID-19 pandemic, which might explain the positive spike. Tweets from this week contain the following words and phrases: “take care of,” “boost,” “help save our community,” “promise to do better,” “beautiful children,” “stand tall,” “best medical care possible,” “hold the hands,” “equanimity and grace,” “cheerfully,” and “with a smile.”

It is possible that with more tweets and over a longer period of time, the sentiments of the anonymous physician tweets would result in a comparable pattern over time to that of the general COVID-19 tweets. It is also possible that VADER sentiment analysis has trouble discerning sentiments from the anonymous physician tweets compared to the more general COVID-19 tweets, perhaps due to its more specialized clinical vocabulary. While this method is considered suitable for social media data, this may not be true for anonymous physician social media data specifically; we further elaborate on this point in the discussion section by comparing these results to a manual review of the tweets.

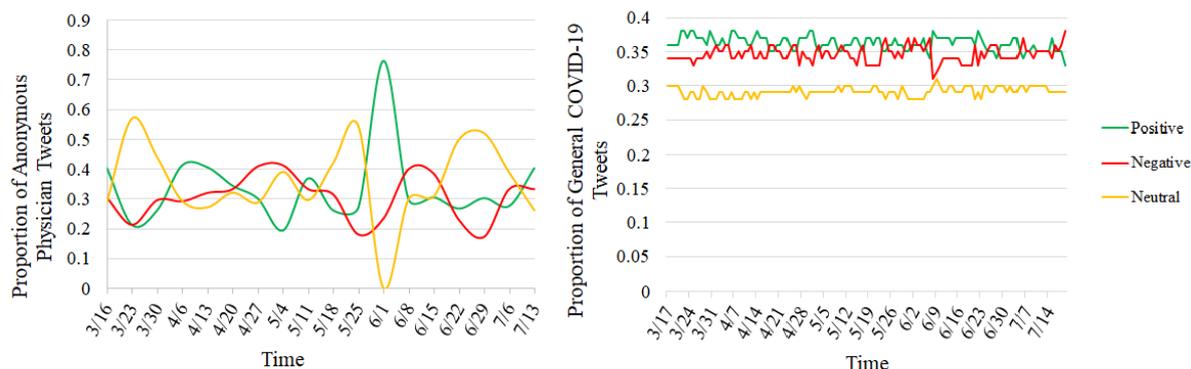


Fig. 3. Proportion of Positive, Negative, and Neutral Tweets Over Time for Anonymous Physician COVID-19 Tweets (left) and General Covid-19 Tweets (right) using VADER Sentiment Analysis

There was not a statistically significant difference in the average overall sentiments between the anonymous physician and general COVID-19 tweets, according to VADER sentiment analysis ( $p$ -value= 0.76). A majority of tweets were assessed as being positive for both datasets (Positive Anonymous Physician = 34.4 percent; Positive General COVID-19 = 36.25 percent). There were 31.7 percent and 34.6 percent of tweets that were negative for the anonymous physician data and general COVID-19 data, respectively.

### 3.3. Sentiments of tweets containing specific terms

We also assessed the sentiments associated with tweets that contained specific topical phrases, which were captured using the same terms described in Table 1. The small size of the anonymous physician dataset prevented us from assessing topic-specific sentiments over time, so we measured frequencies and proportions instead (Table 2). The sentiments over time for tweets containing these phrases in the general COVID-19 tweet dataset can be seen in Figure 4.

Table 2. Frequency of Sentiments for Tweets Containing Specific Topics in Anonymous Physician Tweets According to VADER Sentiment Analysis

Topic	Positive		Negative		Neutral	
	Frequency (n)	Percent (%)	Frequency (n)	Percent (%)	Frequency (n)	Percent (%)
Personal Protective Equipment (n=118)	45	38.14%	42	35.59%	3	26.27%
Unemployment (n=14)	4	28.57%	9	64.29%	1	7.14%
Telemedicine (n=12)	5	41.67%	3	25.00%	4	33.33%
Racial Injustice(n=2)	0	0.00%	2	100.00%	0	0.00%

Percent calculated from tweets containing the specific topic of interest as denominator

There were more positive than negative tweets about telemedicine in the anonymous physician data. The general COVID-19 dataset presented a larger proportion of tweets that trended positive with regard to telemedicine too. In both datasets, the proportion of tweets about personal protective equipment were more positive, while the proportion of tweets about unemployment were more

negative. There were few tweets about racial injustice captured in the anonymous physician data, but both presented as having negative sentiments. The larger COVID-19 dataset showed a much larger proportion of negative sentiments than positive sentiments over time with respect to social injustice phrases.

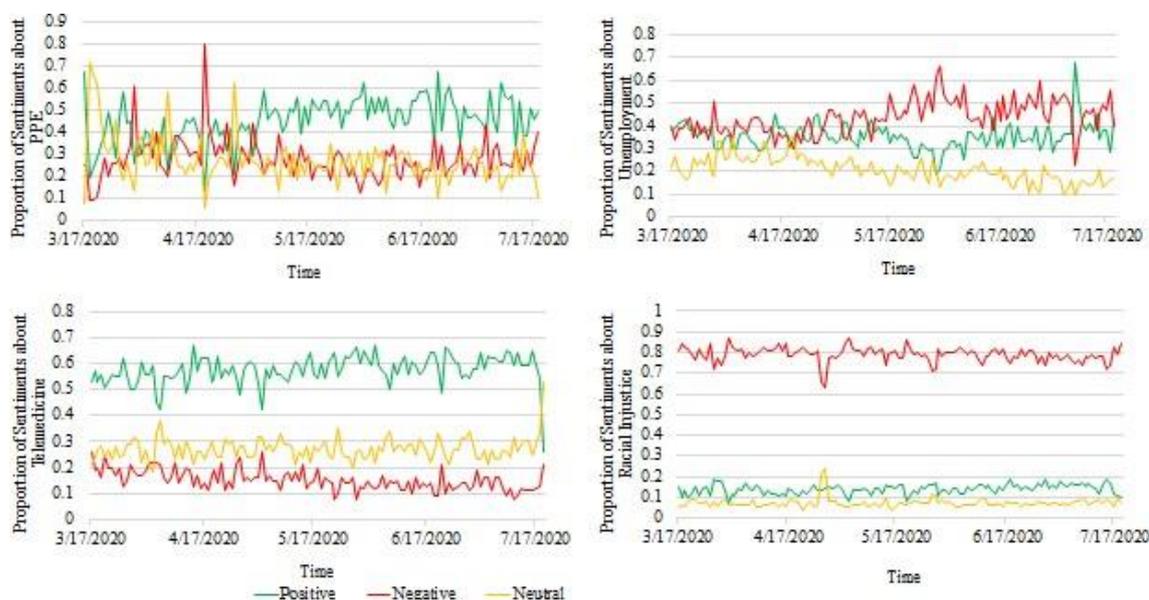


Fig. 4 Proportion of Sentiments for Tweets Containing Phrases about PPE, Unemployment, Telemedicine, and Racial Injustice for General COVID-19 Tweets

#### 4. Discussion and Conclusion

Top phrases in the anonymous physician data, such as “help us,” and “need ppe,” paint a poignant picture of physician perspectives during COVID-19. This research shows how Twitter data can be used to qualitatively assess physician attitudes, beliefs, and perspectives as they relate to the COVID-19 pandemic. We showed that the discourse of anonymous physician tweets is different from the discourse of more general tweets with regard to COVID-19. The anonymous physician tweets are more clinically oriented with phrases such as “health care”, “elective cases”, and “covid patients.”

Our analysis also showed that current lexicon and rule-based sentiment analysis methods should be improved in the future to be specifically targeted for clinically oriented social media data. As social media data is being used more often in the health arena, and healthcare professionals face stricter regulations from employers with regard to posting on social media, it would be of interest to create sentiment analysis methods that more aptly capture this specific type of data.

The uniqueness of anonymity of the physician tweets is important. Koohikamali and Gerhart (2018) found that anonymous social media data is in fact different from more general discourse of social media data, particularly during a social crisis.<sup>8</sup> They report that because anonymity lowers inhibitions, it often results in posting more honest opinions due to less risk of repercussion, such as job loss or unpaid suspension, which some frontline healthcare workers are currently facing.<sup>8</sup> This

can lead to valuable insights that would otherwise not be captured in more public discourse, and paints a truer picture necessary for implementing more impactful change during the COVID- 19 pandemic, and in the future. For this reason, it will be beneficial in future work to improve sentiment analysis tools so they are capable of assessing anonymous physician social media data.

That being said, sentiment analysis is difficult because human language is complex; this is particularly apparent for social media data, where contextual understanding of the language is very meaningful to the overall sentiments.<sup>18</sup> For example, while VADER is tailored toward social media data, a manual assessment of the anonymous physician tweets found far more negative tweets than positive. Upon manual analysis of the anonymous physician tweets, the F1 score was 0.52 (precision = 0.63, recall = 0.56), indicating that sentiment analysis using this method might need to be improved in order to more accurately capture sentiments of anonymous physician tweets. Manual assessment of these tweets resulted in 67 percent of tweets having a negative sentiment (22 percent neutral and eleven percent positive), while VADER resulted in only 32 percent of tweets having a negative sentiment (Table 2).

The NRC method captured more positive than negative words among the tweets, but after manual review, the overall sentiments of the tweets leaned far more negatively. Additionally, the most frequent emotion NRC identified among the tweets was “trust.” Upon reading the tweets, “trust” did not fit the overall emotional sentiment of these tweets. For example, “trust” was the most frequent emotion identified in the following, and “positive” was the resulting sentiment: “Top academic institution cut MD Salaries; includes frontline hospitalists and intensive care no offer of hazard pay, pay for extra shifts, and no promise of back pay.” It is possible that this lexicon-based method does not capture the negations within the text. Table 4 shows some examples of how the lexicon and rule-based methods failed to capture the overall sentiment of the anonymous physician tweets compared to the manual analysis.

Table 4. Examples of Misinterpreted Paraphrased Tweets by Sentiment Analysis Compared to Manual Assessment of Tweets

Tweet	Sentiment Analysis	Manual Assessment
How is it fair for admin to silence doctors asking for help?	Positive	Negative
Physicians are afraid of losing jobs.	Positive	Negative
When faced with PPE shortages, the program director sourced 3D printers to make face shields!	Negative	Positive
Please help! No PPE!! Please help!	Positive	Negative
We are doctors and have NO PPE. Please donate if able-stop hoarding please! We need it to care for patients.	Positive	Negative

While we found some interesting and important results, there were some limitations in our study we wish to address. The first is that the tweets from the anonymous physician data were likely just a small sample of tweets representing this type of data. Anonymous physician social media data is unique, and as frontline healthcare workers in the U.S. face pressures from their administration to stay off of social media platforms, pages that allow them to share their thoughts with a more anonymous approach are an important, perhaps overlooked source of information to better understand healthcare workers' perspectives. It is certainly possible that our small sample did not represent this type of data in full; further evaluation of how well our sample represents this population is warranted.

Also, while there was some amount of anonymity to the physician tweets, administrators of the user page likely knew the user name of the physicians through the DMs. This means the tweets were unknown to only those who were not administrators of the page. Still, understanding that their name would not be attached to the posted tweet provided some amount of anonymity to the physicians. Having a sense of anonymity may also encourage physicians to post tweets that lean more negatively in sentiment, but further assessment should be done to understand if anonymity leads to a negative bias.

Another limitation is with regard to selection of the four specific topical phrases that we chose to explore. We used a small number of exact terms to capture these phrases, and they could probably be expanded to capture tweets about each of these phrases. For example, we captured very few anonymous physician tweets about the topic, "racial injustice," and it is possible that expanding the list of exact phrases would improve detection of this topic and others. There are also, of course, other topical phrases that might be of interest to assess that we did not assess in our analysis. Future studies should widen the scope of topical phrases of interest.

A final limitation is simply that social media data can be difficult to work with in many ways. It contains many informal, idiomatic phrases, special characters, emoticons, grammatical mistakes, misspellings, and abbreviations that make it challenging for text analysis methods.<sup>18</sup> Despite this, valuable insights and perspectives can be obtained through this rich source of data, particularly sentiments and opinions that might have impactful meaning for healthcare workers, patients, and the general public health. There are many future avenues that this body of work might take. The development of a lexicon for sentiment analysis that is specific to anonymous social media data, physician or other healthcare professional social media data, or even more specifically, anonymous physician social media data might be very useful for future sentiment analysis studies of this type of data. It would also be of interest to mine the public discourse for more general healthcare professional social media data for comparison to anonymous data, as there might be large differences in topics and sentiments discussed.

This study has identified interesting underlying topics and sentiments from anonymous physician data with regard to the COVID-19 pandemic. We found these topics and sentiments are usually different from the overall COVID-19 discourse on Twitter. It is likely that anonymous social media data from physicians and other frontline healthcare workers will become more popular as they continue to experience the effects of the COVID-19 pandemic. This is especially true as they are hesitant to post publicly their perspectives on social media about the current state of affairs in their working environment for fear of being reprimanded or fired.<sup>7</sup> Frontline healthcare workers have

an important impact on patients' lives, and this is especially true during times of exceptional difficulty or social crisis, both of which are relevant to today's current atmosphere. Understanding frontline healthcare workers' perspectives, needs, and opinions may help improve patients' experience and health outcomes, and perhaps even guide improvements to public health strategies in the future.

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## References

1. Wu JT, McCormick JB. Why Health Professionals Should Speak Out Against False Beliefs on the Internet. *AMA Journal of Ethics*. 2018; 20 (11): E1052-E1058.
2. Wakefield JG, McLaws M-L, Whitby M, Patton L. Patient safety culture: factors that influence clinician involvement in patient safety behaviours. *Qual Saf Health Care*. 2010; 19 (6): 585-591.
3. Kirk S, Parker D, Claridge T, Esmail A, Marshall M. Patient safety culture in primary care: developing a theoretical framework for practical use. *Qual Saf Health Care*. 2007; 16 (4): 313-320.
4. Tavares APM, Moura ECC, Avelino FVSD, Lopes VCA, Nogueira LT. Patient safety culture from the perspective of the nursing team. *Rev Rene*. Published online January 15, 2018.
5. Ledford H. Computing humanity. *Nature*. 2020; 582 (June 18): 328-330.
6. Kellogg K. The 7 Biggest Social Media Sites in 2020. Published online 2020.
7. Carville BO, Larson E. Doctors and Nurses Beware: Hospitals Are Watching Your Facebook. *Bloomberg Law*. 2020: 1-6.
8. Koohikamali M, Gerhart N. Yaks versus Tweets: Sentiment Discrepancy During a Social Crisis. *Proceedings of the 51st Hawaii International Conference on System Sciences*. 2018; (March).
9. Banda JM, Tekumalla R, Wang G, et al. A large-scale COVID-19 Twitter chatter dataset for open scientific research -- an international collaboration. *ArXiv*. Published online April 7, 2020.
10. Liu B. *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers; 2012.
11. Garcia-Rudolph A, Laxe S, Saurí J, Guitart MB. Stroke survivors on Twitter: Sentiment and topic analysis from a gender perspective. *J Med Internet Res*. 2019; 21 (8).
12. Mohammad S, Turney P. Emotions Evoked by Common Words and Phrases: Using Mechanical Turk to Create an Emotion Lexicon. *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*. 2010; (California, US): 26-34.
13. Plutchik R. The nature of emotions. *Am Sci*. 2001; 89 (4): 344-350.
14. Natural Language Toolkit — NLTK 3.5 documentation.

15. Hutto CJ, Gilbert EE. VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. Eighth International Conference on Weblogs and Social Media (ICWSM-14).” *Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014*. Published online 2014.
16. Hutto CJ. vaderSentiment. Published online 2020.
17. Hutto CJ, Klein E, Pantone P, Berry G, Malavika S. Source Code for nltk.sentiment.vader. Published online 2020.
18. Burkhardt S, Siekiera J, Glodde J, Andrade-Navarro MA, Kramer S. Towards identifying drug side effects from social media using active learning and crowd sourcing. *Pac Symp Biocomput.* 2020; 25 (2020): 319-330.