COVID-19 Vaccine Hesitancy on Social Media: Building a Public Twitter Data Set of Antivaccine Content, Vaccine Misinformation, and Conspiracies

Goran Muric1*, PhD; Yusong Wu1*, BA; Emilio Ferrara1,2,3, PhD

1Information Sciences Institute, University of Southern California, Marina del Rey, CA, United States
2Department of Computer Science, University of Southern California, Los Angeles, CA, United States
3Annenberg School for Communication and Journalism, University of Southern California, Los Angeles, CA, United States

*these authors contributed equally

Corresponding Author:
Goran Muric, PhD
Information Sciences Institute
University of Southern California
4676 Admiralty Way
Suite 1001
Marina del Rey, CA, 90292
United States
Phone: 1 213 740 2467
Email: gmuric@isi.edu

Abstract

Background: False claims about COVID-19 vaccines can undermine public trust in ongoing vaccination campaigns, posing a threat to global public health. Misinformation originating from various sources has been spreading on the web since the beginning of the COVID-19 pandemic. Antivaccine activists have also begun to use platforms such as Twitter to promote their views. To properly understand the phenomenon of vaccine hesitancy through the lens of social media, it is of great importance to gather the relevant data.

Objective: In this paper, we describe a data set of Twitter posts and Twitter accounts that publicly exhibit a strong antivaccine stance. The data set is made available to the research community via our AvaxTweets data set GitHub repository. We characterize the collected accounts in terms of prominent hashtags, shared news sources, and most likely political leaning.

Methods: We started the ongoing data collection on October 18, 2020, leveraging the Twitter streaming application programming interface (API) to follow a set of specific antivaccine-related keywords. Then, we collected the historical tweets of the set of accounts that engaged in spreading antivaccination narratives between October 2020 and December 2020, leveraging the Academic Track Twitter API. The political leaning of the accounts was estimated by measuring the political bias of the media outlets they shared.

Results: We gathered two curated Twitter data collections and made them publicly available: (1) a streaming keyword–centered data collection with more than 1.8 million tweets, and (2) a historical account–level data collection with more than 135 million tweets. The accounts engaged in the antivaccination narratives lean to the right (conservative) direction of the political spectrum. The vaccine hesitancy is fueled by misinformation originating from websites with already questionable credibility.

Conclusions: The vaccine-related misinformation on social media may exacerbate the levels of vaccine hesitancy, hampering progress toward vaccine-induced herd immunity, and could potentially increase the number of infections related to new COVID-19 variants. For these reasons, understanding vaccine hesitancy through the lens of social media is of paramount importance. Because data access is the first obstacle to attain this goal, we published a data set that can be used in studying antivaccine misinformation on social media and enable a better understanding of vaccine hesitancy.

(JMIR Public Health Surveill 2021;7(11):e30642) doi: 10.2196/30642
**KEYWORDS**

vaccine hesitancy; COVID-19 vaccines; dataset; COVID-19; SARS-CoV-2; social media; network analysis; hesitancy; vaccine; Twitter; misinformation; conspiracy; trust; public health; utilization

**Introduction**

The opposition to vaccination dates back to the 1800s, immediately after the English physician Edward Jenner created the first vaccine in human history. The opponents to the vaccine were vocal and could be found in all segments of society: religious communities protested the unnaturalness of using animal infection in humans, parents were concerned about the invasiveness of the procedure, and vaccinated people were often illustrated with a cow’s head growing from their neck [1]. Although vaccination is an effective way to prevent diseases such as diphtheria, tetanus, pertussis, influenza, and measles, almost 1 in 5 children still do not receive routine lifesaving immunizations, and an estimated 1.5 million children still die each year of diseases that could be prevented by vaccines that already exist [2]. These fatalities are not only caused by objective reasons, such as lack of access to vaccines due to poverty, but also by the unwillingness and fear regarding vaccines from the parents of these children. The term “vaccine hesitancy” refers to delay in acceptance or refusal of vaccines despite availability of vaccine services [3]. Vaccine hesitancy has emerged as a factor in vaccine delay and refusal for adults. A common example is the annual seasonal influenza vaccine. It has been observed that greater hesitancy, both general and specific to the influenza vaccine, is associated with lower vaccine uptake [4,5]. A variety of factors contribute to vaccine hesitancy, including safety concerns, religious reasons, personal beliefs, philosophical reasons, and desire for additional education [6]. During the COVID-19 pandemic, although the inoculation of large populations is increasingly important, antivaccine narratives are spreading rapidly, endangering public health, human lives, and the social order.

With the rise of social media, the dissemination of information (and hence, potentially, misinformation) has become easier than ever before. Unsurprisingly, antivaccine activists have also begun to use platforms such as Twitter to share their views. As a result, their activism has expanded its jurisdictions to include web-based propaganda. Compared with traditional communication channels, social media offers an unprecedented opportunity to spread antivaccination messages and allow communities to form around antivaccine sentiment [7]. Social media can amplify the effects of antivaccination misinformation; multiple studies have shown links between susceptibility to misinformation and both vaccine hesitancy and a reduced likelihood to comply with health guidance measures [7-10]. Based on these findings, vaccine-related misinformation on social media may exacerbate the levels of vaccine hesitancy, creating pockets with low vaccination rates in the United States and globally; this can hamper progress toward vaccine-induced herd immunity and can potentially increase the number of infections related to new COVID-19 variants, possibly leading to vaccine-resistant mutations. For these reasons, understanding vaccine hesitancy through the lens of social media is of paramount importance. Because data access is the first obstacle to attain this goal, to enable the research community, we built and made public a social media data set of antivaccine content, vaccine misinformation, and related conspiracies. Although researchers have been collecting data related to COVID-19 vaccines [11], per our knowledge, there are no public data sets focused specifically on the historical activities of antivaccination accounts on Twitter.

Here, we present a data set that focuses on antivaccine narratives on Twitter. The data set consists of two complementary collections: (1) the streaming collection contains tweets collected using the Twitter Streaming application programming interface (API) from a set of antivaccine keywords, and (2) the account collection contains historical tweets from approximately 70,000 accounts that engaged in spreading antivaccination narratives. Additionally, we present initial statistical analyses of the data, including the frequencies of hashtags, analysis of the news sources, the most likely political leaning of the accounts, and geographic distribution.

The published data set includes tweet IDs of publicly available posts, in compliance with the Twitter Terms of Service [12]. This collection builds on the previously published data sets by DeVerna et al [11], which is focused on general vaccine narratives, and it complements the previous work by Chen et al [13] and Lamsal [14], who published some of the largest Twitter data sets related to COVID-19 discourse to date. The complete data set in the form of a list of tweet IDs is openly available on GitHub [15].

**Methods**

**Tracked Keywords for the Streaming Collection**

To create a set of keywords that indicate opposition to vaccines, we used a snowballing sampling technique similar to that of DeVerna et al [11]. We started from a small set of manually curated keywords used exclusively in the context of strong vaccine hesitancy that appear on Twitter, such as #vaccineskill or #vaccinedamage. Using the Twitter Streaming API and the set of seed keywords, we collected the data for one day (October 18, 2020), after which we extracted other keywords that co-occurred with the seed keywords. We added the newly collected keywords to the list of seed keywords, checking them manually for relevance. We then repeated this step several times until we exhausted all the significant co-occurrences and narrowed our selection to approximately 60 keywords. The Twitter API can be queried with a substring of a longer keyword, and it will return the tweets that contain the substring. For example, the keyword novaccine will return the tweets that contain novaccineforme. We attempted to retain only the most informative and relevant stem words to capture most vaccine-related tweets and to avoid collecting less relevant tweets. The list of all keywords used to collect the streaming collection is listed in Table 1.

---

https://publichealth.jmir.org/2021/11/e30642
## Table 1. Set of keywords used to collect the tweets in the streaming collection.

| Keyword                        | Date on which tracking began |
|--------------------------------|------------------------------|
| abolishbigpharma               | 12/30/2020                   |
| antivaccine                    | 12/30/2020                   |
| ArrestBillGates                | 10/19/2020                   |
| betweenmeandmydoctor           | 12/30/2020                   |
| bigpharmafia                   | 10/19/2020                   |
| bigpharmakills                 | 12/30/2020                   |
| BillGatesBioTerrorist          | 10/19/2020                   |
| billgatesevil                  | 12/30/2020                   |
| BillGatesIsEvil                | 10/19/2020                   |
| billgatesisnotadoctor          | 12/23/2020                   |
| billgatesvaccine               | 12/14/2020                   |
| cdcfraud                       | 10/19/2020                   |
| cdctruth                       | 10/19/2020                   |
| cdcwhistleblower               | 10/19/2020                   |
| covidvaccinesispoison          | 12/23/2020                   |
| depopulation                   | 10/19/2020                   |
| DoctorsSpeakUp                 | 10/19/2020                   |
| educateb4uvax                  | 10/19/2020                   |
| exposebillgates                | 12/30/2020                   |
| forcedvaccines                 | 12/30/2020                   |
| Fuckvaccines                   | 10/19/2020                   |
| idonotconsent                  | 12/30/2020                   |
| informedconsent               | 12/14/2020                   |
| learntherisk                   | 10/19/2020                   |
| medicalfreedom                 | 12/30/2020                   |
| medicalfreedomofchoice         | 12/30/2020                   |
| momssofuvaccinatedchildren    | 12/30/2020                   |
| mybodymychoice                 | 12/30/2020                   |
| noforcedflashes                | 12/30/2020                   |
| NoForcedVaccines               | 10/19/2020                   |
| notomandatoryvaccines          | 12/30/2020                   |
| NoVaccine                      | 10/19/2020                   |
| NoVaccineForMe                 | 10/19/2020                   |
| novaccinemandates              | 12/30/2020                   |
| parentalrights                | 12/30/2020                   |
| parentsoverpharma              | 12/30/2020                   |
| saynotovaccines                | 12/30/2020                   |
| stopmandatoryvaccination       | 10/19/2020                   |
| syringeslaughter               | 12/30/2020                   |
| unvaccinated                   | 12/30/2020                   |
| v4vglobaldemo                  | 12/30/2020                   |
| vaccinationchoice              | 12/30/2020                   |
Collecting Tweets for Account Collection

First, we identified a randomly sampled set of approximately 70,000 accounts that appeared in the streaming collection and that engaged in antivaccine rhetoric between October and December 2020, either by tweeting some of the tracked keywords or by retweeting tweets that contained some of the tracked keywords. Then, for those accounts, we collected their historical tweets using the Twitter API. By leveraging Twitter’s Academic Research product track, we were able to access the full archival search and overcome the limit of 3200 historical tweets of the standard API. In this way, we collected almost all the historical tweets of the most queried accounts.

Our collection relies upon publicly available data in accordance with the Content Redistribution clause under Twitter’s Developer Agreement and Policy [12]. We released the data set with the stipulation that those who use it must comply with Twitter’s Terms and Conditions. The complete data set is publicly available on a GitHub repository and is accessible on the web [15].

Calculating the Political Leanings of the Accounts

We calculate the political leaning of each account by measuring the political bias of the media outlets it shared. We use a methodology proposed in prior work [16-18], and we identified a set of 90 prominent media outlets and accounts that appeared on Twitter. Each of these outlets and their associated Twitter accounts were placed on a political spectrum (left, lean left, center, lean right, right) per ratings provided by the nonpartisan service AllSides [19]. For each account in the data set, we maintained a record of all retweets and the original tweets that contained a domain name affiliated with the selected media outlets. The political bias of each account was calculated as the average political bias of all media outlets it shared content from.

Identifying Low- and High-Credibility Media Sources

We leveraged urllib, the Python URL handling module, to parse the URLs found in the data set. Each URL was broken into several components, including the addressing scheme, network location, and path. A third-party data set that contains the domains associated with websites that share misinformation was used as a ground truth to tag the domain names [20]. For URLs that were not in the data set, we queried the Media Bias/Fact Check website [21] for further identification. Because URL shortening services such as Bitly [22] are widely used on Twitter, shortened URLs appeared frequently. We used urlExpander [23] to expand the shortened URLs and retrieve the full URLs where possible. Domain names of popular news aggregators and social networks such as Twitter, Facebook, Instagram, Periscope, and YouTube were ignored in the analysis.

Generating Geolocation Distribution Maps

To infer a tweet’s geolocation, we used the information of the self-reported location of the account and matched it to a corresponding state in the United States. To calculate the average activity level per population, the absolute number of Tweets was normalized by the 2010 Census-reported population of that state as follows: \[ I = \frac{N}{P_i} \times 1,000,000 \], where \( N \) is the number of tweets originating in state \( i \) and \( P_i \) is that state’s population in 2010. This normalization provided information on the average number of collected tweets per million inhabitants. Note that we did not generate the geolocation map for the account collection, as it contains a relatively small number of accounts with self-reported locations.

Topic Network Analysis

A topic network was constructed to analyze the co-occurrence of hashtags in the streaming data set. Each node in the graph represented a hashtag, and an edge was added if two hashtags occurred in the same tweet. The node size was proportional to its degree of centrality, and the edge weight was the number of times two hashtags appeared together. For better visualization, nodes with fewer than 25 neighbors were ignored. To investigate the community structure of the network, we used the Louvain algorithm [24] on the topic network, which provided further insights about the links between antivaccine topics.
Results

The primary contribution of this study is the data set that we made publicly available. As of this writing (May 2021), we had collected over 137 million tweets organized in two collections. The streaming collection was gathered using the set of antivaccine keywords in Table 1. The account collection, on the other hand, contains the historical activities of accounts prone to spreading antivaccination narratives; thus, it is a significantly larger data set compared to the streaming collection. The basic statistics on the two data sets are shown in Table 2. The data set is available on GitHub [15] and was released in compliance with the Twitter Terms and Conditions. We are unable to provide the full text of the tweets; therefore, we are releasing the Tweet IDs, which are unique identifiers tied to specific tweets. Researchers can retrieve the full text and the related metadata by querying the Twitter API. Because the streaming data collection is still ongoing, the statistics shown below can vary in future versions of the data set. In the following sections, we will describe the streaming collection and account collection separately.

Table 2. Basic statistics on tweets collected in the streaming collection and account collection.

|                      | Streaming collection | Account collection |
|----------------------|----------------------|--------------------|
| Tweets, n            | 1,832,333            | 135,949,773        |
| Accounts, n          | 719,652              | 78,954             |
| Average number of tweets per account | 2.5                 | 1721.8             |
| Verified accounts, n | 9032                 | 239                |
| Accounts with location, n | 5661               | 363                |
| Date of oldest tweet | 10/19/2020           | 3/6/2007           |
| Date of most recent tweet | 4/21/2021          | 2/2/2021           |

Streaming Collection

The streaming collection consists of 1.8 million tweets created by 719,000 unique accounts between October 18, 2020, and April 21, 2021. As shown in Figure 1, the number of relevant tweets in the streaming collection gradually increases from the start date. The chatter is relatively stable, with small spikes that do not often correspond to major announcements regarding vaccine research or vaccine authorization. We find this surprising, as the news usually drives the discussion on Twitter. Additionally, we observed a large spike in activity near the end of November 2020 that was not caused by any single event but rather by the increased activity of a small number of accounts.

Figure 1. Number of tweets over time in the streaming collection. The times of adverse events related to vaccines are marked by dashed vertical lines. Further descriptions of the news items are provided in the legend below the chart. CDC: US Centers for Disease Control and Prevention; FDA: US Food and Drug Administration.
The overwhelming majority of tweets originated from countries with predominantly English-speaking populations. Out of 1,832,333 tweets in the streaming collection, 1,245,986 (68%) originated in the United States, 229,041 (12.5%) in Great Britain, 100,778 (5.5%) in Canada, 21,987 (1.2%) in Ireland, and 20,155 (1.1%) in Australia; the rest of the tweets originated from other countries. In Figure 2, we show the geographical distribution of tweets in the United States. As expected, states with a large population, such as California, Texas, Florida, and New York, have more tweets in absolute terms (Figure 2, top). The number of tweets normalized by state population is depicted in Figure 2 (bottom), with the most tweets per capita originating from Hawaii, Alaska, and Maine, respectively.

Figure 2. Geographical distribution of the tweets from the streaming collection originating in the United States. The location of the tweets was inferred from the self-reported location of the account. Top: absolute number of tweets in each state; bottom: number of tweets normalized by the state population.

Table 3 lists the top 15 most tweeted hashtags in the streaming collection. The count column represents the total number of times a hashtag appears, and the proportion column quantifies the proportion of tweets that contain a specific hashtag out of all tweets with any hashtag. Note that many tweets contain no hashtags, and many tweets with a hashtag contain more than one hashtag. In addition to the most common general hashtags that we expected to find, such as #vaccine and #covid19, we observed a high proportion of hashtags that carry strong antivaccine sentiment, such as #novaccineforme, #vaxxed and #vaccineinjury. For example, #novaccineforme can be found in more than 25,000 tweets, accounting for 6.6% of all tweets in the streaming collection that contain any hashtags. A large set of common hashtags is related to some debunked conspiracy theories that claim there is a global plot by rich individuals to reduce the world population, often expressed through hashtags such as #depopulation, #billgatesbioterrorist and #arrestbillgates. Another set of very frequent hashtags appears benign on the surface. Hashtags such as #learntherisk and #informedconsent appear to communicate genuine concerns about the safety of the vaccines; however, those hashtags are usually decoys and are very often used by the same accounts that strongly oppose vaccination and that otherwise often use more explicit antivaccine hashtags.
Table 3. Top 15 hashtags in the streaming data set. The count is the total number of times a hashtag appears, and the proportion quantifies the proportion of tweets that contain a specific hashtag out of all tweets with a hashtag.

| Hashtag            | Count, n | Proportion (%) |
|--------------------|----------|----------------|
| vaccine            | 41,069   | 10.66          |
| vaccines           | 33,050   | 8.58           |
| covid19            | 26,616   | 6.91           |
| novaccineforme     | 25,642   | 6.66           |
| learntherisk       | 23,340   | 6.06           |
| billgatesbioterror| 20,197   | 5.24           |
| study              | 20,166   | 5.23           |
| novaccine          | 19,410   | 5.04           |
| mybodymychoice     | 19,166   | 4.97           |
| informedconsent    | 16,578   | 4.30           |
| depopulation       | 15,021   | 3.90           |
| vaxxed             | 12,691   | 3.29           |
| vaccineinjury      | 12,640   | 3.28           |
| vaccination        | 10,873   | 2.82           |
| arrestbillgates    | 9991     | 2.59           |

Account Collection

The account collection differs from the streaming collection, as it is focused on historical tweets from a set of accounts. The process of collecting the historical tweets is explained more in detail in the Methods section. The current account collection consists of more than 135 million tweets published by over 78,000 unique accounts, and it spans the period from March 3, 2007, to February 8, 2021. In Figure 3, we illustrate some of the most important statistics from this data collection. The left panel in Figure 3 shows the distribution of the number of tweets per account. Out of 78,954 accounts, 39,350 (49.8%) published fewer than 1500 tweets, 31,581 (40%) have more than 2000 tweets, and 1184 (1.5%) have more than 5000 tweets. The right panel in Figure 3 shows the number of tweets over time. Most of the tweets originate in the year 2020, with the oldest tweet dating back to 2007. For 55,267 (70%) of the 78,954 accounts, the oldest collected tweet dates from 2020. There is a significant portion of accounts whose historical tweets date much earlier; for 14,211 (18%) of the 78,954 accounts, the earliest tweet was dated before 2018, and for 5368 (6.8%) of the accounts, the earliest tweet was dated before 2014. This relatively long-spanning collection of historical tweets at the account level may allow for a comprehensive temporal analysis of vaccine hesitancy development on Twitter over several years.

Figure 3. Tweets in the account collection. Left: distribution of tweets per account; right: distribution of tweets over time.

The 15 most common hashtags appearing in the account collection are displayed in Table 4. In addition to the common COVID-19–related hashtags, we observe many hashtags referring to US politics. During the period of the US 2020 presidential election and the political campaign, the accounts that appear in our collection were particularly active. Hence, we can see that many politically motivated narratives in the data originated during that period.
Table 4. Top 15 hashtags in the account collection. The count is the total number of times a hashtag appears, and the proportion quantifies the proportion of tweets that contain a specific hashtag out of all tweets with a hashtag.

| Hashtag    | Count  | Proportion (%) |
|------------|--------|----------------|
| covid19    | 474,481| 2.55           |
| endsars    | 203,297| 1.09           |
| maga       | 164,332| 0.88           |
| coronavirus| 158,574| 0.85           |
| trump      | 156,262| 0.84           |
| stopthesteal| 121,069| 0.65           |
| trump2020  | 115,002| 0.62           |
| breaking   | 111,274| 0.60           |
| obamagate  | 110,046| 0.59           |
| covid      | 106,095| 0.57           |
| china      | 98,026 | 0.53           |
| oann       | 96,943 | 0.52           |
| antifa     | 79,157 | 0.43           |
| biden      | 77,728 | 0.42           |
| fakenews   | 66,599 | 0.36           |

News Sources in the Streaming Collection

Vaccine hesitancy is usually fueled by misinformation originating from websites with questionable credibility. In Figure 4, we list the top 10 URLs that can be found in the streaming collection, and we illustrate the number of times each appears. The vast majority of those websites can be found in the Iffy+ database of low credibility sites [20]. One of the most commonly shared sources is the website of an American antivaccine group called Learn The Risk; it is known for its campaigns against vaccination, which assert that vaccines are responsible for a large number of deaths of young children. It is followed by Vaccine Impact, a well-known news and information website that promotes pseudoscience; this website often shares antivaccination propaganda and promotes alternative medicine, holism, and alternative nutrition. The only website on the list with high credibility is the website of the National Center for Biotechnology Information (NCBI), a PubMed parent company.

Figure 4. Top 10 news sources in the streaming collection. The URLs of the news aggregators and the large social platforms were omitted.

News Sources in the Account Collection

In Figure 5, we list the top 10 URLs that can be found in the account collection, and we illustrate the number of times each appears. Figure 5 shows that many far-right news media sites appear frequently in the account collection. The Gateway Pundit [25], which is known for publishing falsehoods, hoaxes, and conspiracy theories, occurs more than 400,000 times. Other far-right media outlets, such as Breitbart News [26] and the Epoch Times [27], also appear very often. Considering the sources that usually fall in the group of mainstream news media sites, such as Fox News [28] and the New York Post [29], conspiracy spreaders selectively quote reports from these sources to increase the credibility of often false claims.
Political Leanings of the Antivaccination Accounts

In Figure 6, we show the distribution of political leanings of the accounts. The political leaning of an account was estimated based on its media diet (see the Methods section). The x-axis represents the account’s political leaning and can take any value between “far left” and “far right.” The y-axis is the normalized number of accounts with a corresponding political leaning. The political leaning of the accounts engaged in the antivaccination narratives is shown in orange. We observed a bimodal distribution with a significantly higher right peak. The blue bars illustrate the distribution of the political leanings for random Twitter accounts. The random Twitter accounts are a random sample of approximately 6000 accounts from the previously published Twitter data set related to the US 2020 Presidential election by Chen et al [30]. It has been previously shown that the Twitter users are younger on average and more likely to vote Democrat than the general public [31,32]. These results are not surprising, as they align with earlier studies showing that political orientation is a strong predictor of vaccine hesitancy in the United States [33,34].

Clusters of Antivaccine Narratives in the Streaming Collection

To obtain further insights into the provided data set, we explored the clusters of antivaccine narratives by identifying the antivaccine topics that usually co-occurred. We ran the Louvain community detection algorithm on the topic co-occurrence network, as described in the Methods section. The topic network is illustrated in Figure 7. We identified 3 distinct communities: all of them contained antivaccine keywords, but with different
focuses on topics. The largest topic community, colored purple, focuses on debunked claims around the conspiracy narrative that the vaccine is a plot by rich people to reduce the world population. The second topic community, colored orange, mostly focuses on vaccine safety, as hashtags such as #doctorsspeakup, #vaccinesafety, and #vaccineinjury appear often. The smallest topic community, in green, contains a mixture of various hashtags that range from strongly antivaccine, such as #informedconsent, #learntherisk, and #vaxxed, to some neutral hashtags, such as #vaccine, to some provaccine hashtags, such as #vaccineswork.

**Figure 7.** An overview of the prominent hashtags in the data set, clustered into 3 communities. The nodes are the hashtags, and the links are drawn between two hashtags that appear together in the same tweet. Clustering was performed using the Louvain algorithm. For readability, we do not show all the node labels.

**Discussion**

**Principal Findings**

In this paper, we present a comprehensive data set consisting of tweets related to antivaccination narratives, organized in streaming and account collections. We characterized the data in several ways, including frequencies of prominent keywords, news sources, geographical location of the accounts, and political leaning of the accounts. The streaming collection consists of a random sample of tweets that contain any of the specific keywords promoting strong antivaccination sentiments. This is a common method used to collect Twitter data on vaccination hesitancy and other similar topics [35-42]. It is well understood by academics and is often used to provide useful insights about the chatter on the web about a particular topic in a specific period. The account collection was gathered using a relatively new method of collecting Twitter data by querying the historical activities from a set of tracked accounts. This collection was made possible after Twitter introduced the Academic Research product track API. In this way, by gathering massive amounts of historical tweets, researchers can characterize individual accounts rather than populations on average. This data set will be useful for scientists interested in the demographic and psychographic characteristics of Twitter users who are prone to spreading antivaccination narratives.

The news sources shared by the users in the streaming collection are predominantly websites with low credibility. However, the most shared URL is the website of the NCBI [25], which is part of the United States National Library of Medicine, a branch of the National Institutes of Health. NCBI houses PubMed, the largest bibliographic database for biomedical literature. This finding can create a false impression that the tweets from the streaming collection contain information from legitimate scientific sources. When we examined the context in which those papers were shared, we discovered that most of the papers from PubMed were cited with false and misleading conclusions. Sometimes, antivaccine advocates would share legitimate scientific papers documenting rare side effects of the vaccines, while overemphasizing the observed adverse effects and calling for vaccine boycotts. Sharing a scientific study in a tweet provides an illusion of credibility. Cherry-picking desirable sentences and relying on the fact that most of the audience will not make an effort to read a scientific paper in detail is a very effective strategy for manipulation.

It is often valuable to know the political affiliation of users who share antivaccine narratives. Knowing users’ position on a political spectrum can be useful in identifying their most likely moral values and possible stances toward specific societal issues. This knowledge can be used to design appropriate future messaging and campaigns. We were able to identify the political
Affiliation for the accounts collection, as we had enough tweets for each account. Accounts that share common misinformation related to vaccines often share other conspiracy narratives, usually politically charged ones. The population susceptible to such narratives strongly skews conservative [18]; therefore, we expected that a large number of accounts in the account collection would be right leaning.

Limitations
Although the data sets give an overview of vaccine hesitancy on Twitter, potential limitations warrant some considerations. First, our streaming collection relies on a defined set of keywords. The antivaccine lingo is constantly evolving as the COVID-19 pandemic unfolds. Although we have made our best efforts to find the most representative keywords, they may not fully cover all antivaccine topics. The set of keywords we used was designed to capture the strongest antivaccine sentiments and may have missed various nuances in the multifaceted nature of vaccine hesitancy. Second, this data set should not be used to draw conclusions for the general population, as the Twitter user population is younger and more politically engaged than the general public [31]; this means that our data may be biased in various ways. Additionally, the keywords used for the collection were derived from the English vocabulary, highly biasing the geographical distribution of the tweets toward the English-speaking regions of the world. Finally, to prevent the spread of misleading COVID-19 information, Twitter has enacted specific rules and policies. The accounts violating these rules and policies may be banned by Twitter, making their tweets unreachable. At the time of writing, our estimate is that more than 40% of the accounts in the streaming collection and 30% of accounts in the accounts collection had been either banned or deleted. With each update of the streaming data set, we expect this proportion to change.

Conclusion
In addition to the streaming collection, which tracks tweets as they appear in real time, perhaps the most important contribution of this study is the account collection, a data set consisting of almost all historical tweets for a sample of users who were actively sharing antivaccination narratives. This data set can be used to provide further insights into the accounts that engage in antivaccine propaganda. Our intention in publishing this paper and data sets is to provide researchers with assets to enable further exploration of issues revolving around vaccine hesitancy and to study them through the lens of social media. The data sets collected and provided here could be useful for researchers interested in tracking the longitudinal characteristics of accounts engaging with antivaccine narratives. It can help provide better insights into the socioeconomic, political, and cultural determinants of vaccine hesitancy.

Use Notes
The data set is released in compliance with the Twitter Terms and Conditions and the Developer’s Agreement and Policies [12]. Researchers who wish to use this data set must agree to abide by the stipulations stated in the associated license and conform to Twitter’s policies and regulations.

Data Availability
The data are available at GitHub [15].

Acknowledgments
The authors are grateful to the Defense Advanced Research Projects Agency (DARPA), contract W911NF-17-C-0094, for their support. The authors appreciate the support of the Annenberg Foundation.

Authors’ Contributions
All authors conceived and designed the study. GM and YW collected and analyzed the data. All authors wrote and revised the manuscript.

Conflicts of Interest
None declared.

References
1. Jacobson RM, St Sauver JL, Finney Rutten LJ. Vaccine hesitancy. Mayo Clin Proc 2015 Nov;90(11):1562-1568. [doi: 10.1016/j.mayocp.2015.09.006] [Medline: 26541249]
2. Vaccine hesitancy: a growing challenge for immunization programmes. World Health Organization. 2015. URL: https://www.who.int/news/item/18-08-2015-vaccine-hesitancy-a-growing-challenge-for-immunization-programmes [accessed 2021-11-02]
3. Butler R, MacDonald NE, SAGE Working Group on Vaccine Hesitancy. Diagnosing the determinants of vaccine hesitancy in specific subgroups: The Guide to Tailoring Immunization Programmes (TIP). Vaccine 2015 Aug 14;33(34):4176-4179 [FREE Full text] [doi: 10.1016/j.vaccine.2015.04.038] [Medline: 25896376]
4. Quinn S, Jamison A, Freimuth V, An J, Hancock G, Musa D. Exploring racial influences on flu vaccine attitudes and behavior: results of a national survey of White and African American adults. Vaccine 2017 Feb 22;35(8):1167-1174 [FREE Full text] [doi: 10.1016/j.vaccine.2016.12.046] [Medline: 28126202]
5. Quinn S, Jamison A, An J, Hancock G, Freimuth V. Measuring vaccine hesitancy, confidence, trust and flu vaccine uptake: results of a national survey of White and African American adults. Vaccine 2019 Feb 21;37(9):1168-1173 [FREE Full text] [doi: 10.1016/j.vaccine.2019.01.033] [Medline: 30709722]
6. McKee C, Bohannon K. Exploring the reasons behind parental refusal of vaccines. J Pediatr Pharmacol Ther 2016;21(2):104-109 [FREE Full text] [doi: 10.5863/1551-6776-21.2.104] [Medline: 27199617]

7. Burki T. Vaccine misinformation and social media. Lancet Digit Health 2019 Oct;1(6):e258-e259 [FREE Full text] [doi: 10.1016/s2589-7500(19)30136-0]

8. Broniatowski D, Jamison A, Qi S, AlKulaib L, Chen T, Benton A, et al. Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. Am J Public Health 2018 Oct;108(10):1378-1384 [FREE Full text] [doi: 10.2105/AJPH.2018.304567]

9. Roozenbeek J, Schneider C, Dryhurst S, Kerr J, Freeman A, Recchia G, et al. Susceptibility to misinformation about COVID-19 around the world. R Soc Open Sci 2020 Oct;7(10):201199 [FREE Full text] [doi: 10.1098/rsos.201199] [Medline: 33204475]

10. Johnson N, Velásquez N, Restrepo N, Leahy R, Gabriel N, El Oud S, et al. The online competition between pro- and anti-vaccination views. Nature 2020 Jun;582(7811):230-233 [FREE Full text] [doi: 10.1038/s41586-020-2281-1] [Medline: 32496650]

11. DeVerna M, Pierri F, Truong B, Bollenbacher J, Axelrod D, Loynes N, et al. CoVaxxy: a global collection of English-language Twitter posts about COVID-19 vaccines. ArXiv.

12. Developer agreement and policy 2021. Twitter Developer Platform. Preprint posted online on January 19, 2021. URL: https://developer.twitter.com/en/docs/twitter-api/agreement-and-policy [accessed 2021-09-01]

13. Chen E, Lerman K, Ferrara E. Tracking social media discourse about the COVID-19 pandemic: development of a public coronavirus Twitter data set. JMIR Public Health Surveill 2020 May 29;6(2):e19273 [FREE Full text] [doi: 10.2196/19273] [Medline: 32427106]

14. Lamsal R. Coronavirus (COVID-19) tweets dataset. IEEE Data Port. 2020. URL: https://doi.org/10.21227/781w-ef42 [accessed 2021-11-02]

15. Muric G, Wu Y, Ferrara E. AvaxTweets dataset. GitHub. URL: https://github.com/gmuric/avax-tweets-dataset [accessed 2021-05-17]

16. Bovet A, Makse H. Influence of fake news in Twitter during the 2016 US presidential election. Nat Commun 2019 Jan 02;10(1):7 [FREE Full text] [doi: 10.1038/s41467-018-07761-2] [Medline: 30602729]

17. Badawy A, Lerman K, Ferrara E. Who falls for online political manipulation? In: Companion Proceedings of The 2019 World Wide Web Conference. 2019 May Presented at: WWW '19: The Web Conference; May 13-17, 2019; San Francisco, CA p. 162-168. [doi: 10.1145/3308560.3316494]

18. Ferrara E, Chang H, Chen E, Muric G, Patel J. Characterizing social media manipulation in the 2020 US presidential election. First Monday 2020 Oct 19 [FREE Full text] [doi: 10.5210/fm.v25i11.11431]

19. AllSides. URL: https://www.allsides.com/unbiased-balanced-news [accessed 2021-05-17]

20. Iffy+ mis/disinfo sites. Iffy. URL: https://iffy.com/ [accessed 2021-05-17]

21. URL shortener. Bitly. URL: https://bitly.com/ [accessed 2021-05-17]

22. BreitNews Network. URL: https://www.breitbart.com/ [accessed 2021-05-23]

23. The Epoch Times. URL: https://www.theepochtimes.com/ [accessed 2021-05-23]

24. Fox News. URL: https://www.foxnews.com/ [accessed 2021-05-23]

25. The Gateway Pundit. URL: https://www.thegatewaypundit.com/ [accessed 2021-05-23]

26. BreitNews Network. URL: https://www.breitbart.com/ [accessed 2021-05-23]

27. The Epoch Times. URL: https://www.theepochtimes.com/ [accessed 2021-05-23]

28. New York Post. URL: https://nypost.com/ [accessed 2021-05-23]

29. The Gateway Pundit. URL: https://www.thegatewaypundit.com/ [accessed 2021-05-23]

30. Fox News. URL: https://www.foxnews.com/ [accessed 2021-05-23]

31. Chen E, Deb A, Ferrara E. #Election2020: the first public Twitter dataset on the 2020 US Presidential election. J Comput Soc Sci 2021 Apr 02:1-18 [FREE Full text] [doi: 10.1007/s42001-021-00117-9] [Medline: 33824934]

32. Wojcik S, Hughes A. Sizing Up Twitter Users. Pew Research Center. 2019 Apr 24. URL: https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/ [accessed 2021-05-22]

33. Eady N, Nagler J, Guess A, Zilinsky J, Tucker J. How many people live in political bubbles on social media? Evidence from linked survey and Twitter data. SAGE Open 2019 Feb 28;9(1):215824401983270 [FREE Full text] [doi: 10.1177/2158244019832705]

34. Fridman A, Gershon R, Gneeezy A. COVID-19 and vaccine hesitancy: a longitudinal study. PLoS One 2021;16(4):e0250123 [FREE Full text] [doi: 10.1371/journal.pone.0250123] [Medline: 33861765]

35. Ruiz J, Bell R. Predictors of intention to vaccinate against COVID-19: results of a nationwide survey. Vaccine 2021 Feb 12;39(7):1080-1086 [FREE Full text] [doi: 10.1016/j.vaccine.2021.01.010] [Medline: 33461833]

36. Guntuku S, Sherman G, Stokes D, Agarwal A, Seltzer E, Merchant R. Tracking mental health and symptom mentions on Twitter during COVID-19. J Gen Intern Med 2020;35:2798-2800 [FREE Full text] [doi: 10.1007/s11606-020-05988-8]

37. Elhadad M, Li K, Gehali F. COVID-19-FAKES: a Twitter (Arabic/English) dataset for detecting misleading information on COVID-19. In: INCoS 2020. Advances in Intelligent Systems and Computing, vol 1263. 2021 Presented at: The 12th
International Conference on Intelligent Networking and Collaborative Systems (INCoS-2020); August 31-September 2, 2020; Victoria, BC. [doi: 10.1007/978-3-030-57796-4_25]

37. Gargiulo F, Cafiero F, Guille-Escuret P, Seror V, Ward J. Asymmetric participation of defenders and critics of vaccines to debates on French-speaking Twitter. Sci Rep 2020 Apr 20;10(1):6599 [FREE Full text] [doi: 10.1038/s41598-020-62880-5] [Medline: 32313016]

38. Shapiro G, Surian D, Dunn A, Perry R, Kelaher M. Comparing human papillomavirus vaccine concerns on Twitter: a cross-sectional study of users in Australia, Canada and the UK. BMJ Open 2017 Oct 05;7(10):e016869 [FREE Full text] [doi: 10.1136/bmjopen-2017-016869] [Medline: 28982821]

39. Surian D, Nguyen D, Kennedy G, Johnson M, Coiera E, Dunn A. Characterizing Twitter discussions about HPV vaccines using topic modeling and community detection. J Med Internet Res 2016 Aug 29;18(8):e232 [FREE Full text] [doi: 10.2196/jmir.6045] [Medline: 27573910]

40. Featherstone J, Barnett G, Ruiz J, Zhuang Y, Millam B. Exploring childhood anti-vaccine and pro-vaccine communities on twitter – a perspective from influential users. Online Soc Netw Media 2020 Nov;20:100105 [FREE Full text] [doi: 10.1016/j.osnem.2020.100105]

41. Gunaratne K, Coomes E, Haghbayan H. Temporal trends in anti-vaccine discourse on Twitter. Vaccine 2019 Aug 14:37(35):4867-4871 [FREE Full text] [doi: 10.1016/j.vaccine.2019.06.086] [Medline: 31300292]

42. Tomeny T, Vargo C, El-Toukhy S. Geographic and demographic correlates of autism-related anti-vaccine beliefs on Twitter, 2009-15. Soc Sci Med 2017 Oct;191:168-175 [FREE Full text] [doi: 10.1016/j.socscimed.2017.08.041] [Medline: 28926775]

Abbreviations

API: application programming interface
DARPA: Defense Advanced Research Projects Agency
NCBI: National Center for Biotechnology Information

©Goran Muric, Yusong Wu, Emilio Ferrara. Originally published in JMIR Public Health and Surveillance (https://publichealth.jmir.org), 17.11.2021. This is an open-access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in JMIR Public Health and Surveillance, is properly cited. The complete bibliographic information, a link to the original publication on https://publichealth.jmir.org, as well as this copyright and license information must be included.