Charting the Information and Misinformation Landscape to Characterize Misinfodemics on Social Media: COVID-19 Infodemiology Study at a Planetary Scale

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Abstract

Background: The novel coronavirus, also known as SARS-CoV-2, has come to define much of our lives since the beginning of 2020. During this time, countries around the world imposed lockdowns and social distancing measures. The physical movements of people ground to a halt, while their online interactions increased as they turned to engaging with each other virtually. As the means of communication shifted online, information consumption also shifted online. Governing authorities and health agencies have intentionally shifted their focus to use social media and online platforms to spread factual and timely information. However, this has also opened the gate for misinformation, contributing to and accelerating the phenomenon of misinfodemics.

Objective: We carried out an analysis of Twitter discourse on over 1 billion tweets related to COVID-19 over a year to identify and investigate prevalent misinformation narratives and trends. We also aimed to describe the Twitter audience that is more susceptible to health-related misinformation and the network mechanisms driving misinfodemics.

Methods: We leveraged a data set that we collected and made public, which contained over 1 billion tweets related to COVID-19 between January 2020 and April 2021. We created a subset of this larger data set by isolating tweets that included URLs with domains that had been identified by Media Bias/Fact Check as being prone to questionable and misinformation content. By leveraging clustering and topic modeling techniques, we identified major narratives, including health misinformation and conspiracies, which we present within this subset of tweets.

Results: Our focus was on a subset of 12,689,165 tweets that we determined were representative of COVID-19 misinformation narratives in our full data set. When analyzing tweets that shared content from domains known to be questionable or that promoted misinformation, we found that a few key misinformation narratives emerged about hydroxychloroquine and alternative medicines, US officials and governing agencies, and COVID-19 prevention measures. We further analyzed the misinformation retweet network and found that users who shared both questionable and conspiracy-related content were clustered more closely in the network than others, supporting the hypothesis that echo chambers can contribute to the spread of health misinfodemics.

Conclusions: We presented a summary and analysis of the major misinformation discourse surrounding COVID-19 and those who promoted and engaged with it. While misinformation is not limited to social media platforms, we hope that our insights, particularly pertaining to health-related emergencies, will help pave the way for computational infodemiology to inform health surveillance and interventions.
KEYWORDS
social media; social networks; Twitter; COVID-19; infodemics; misinfodemics; infodemiology; misinformation

Introduction
As COVID-19 forced more of the world to undergo lockdowns and to adopt physical distancing, the public sought refuge and community support online to replace the interactions that were no longer possible in person. Social media platforms soon became a means for messaging involving the COVID-19 pandemic, with policy makers and medical experts taking to social media to reach the public, and the public using these platforms as forums for debate and information exchange.

Twitter remains one of the main platforms used as a vehicle for communication in the COVID-19 era. This and other similar platforms, however, enabled false or misleading information with the potential to cause harm to public health to take root. The increasing reliance on platforms as a means for communication during COVID-19 underscored the importance of infodemiology, which is the study of the spread of “health information and misinformation” on online platforms [1,2], and brought the concept of infodemics, defined as the epidemic-like spread of information, to the public eye [3]. While the intensity of its effects varies based on country and culture, infodemics was and continues to be a salient issue in COVID-19 discourse [4,5]. Misinformation, particularly during a pandemic, can dissuade some individuals from readily adopting health practices that would contribute to curbing the spread of the disease [6].

Efforts are being made to combat misinformation, including identifying intervention points in social networks to mitigate misinformation [7], teaching the community how to identify misinformation [6], rating source reliability [8], and using both crowdsourced and official fact checkers to identify misinformation [9,10]. Social media platforms have also begun adding notifications to remind users to be cautious when reading certain information [11].

In this paper, we take a deeper look into both the general COVID-19 conversation and the misinformation narratives on Twitter between January 2020 and April 2021 (Figure 1). The contributions we make in this paper are as follows: (1) We identified 11 major topics of general discussion present throughout our overarching data set, which are temporally in line with the progression of current events; (2) We detected 3 prominent misinformation narratives (namely, hydroxychloroquine and alternative medicines, US officials and governing agencies, and COVID-19 prevention efforts); (3) We found that there are distinct political echo chambers and that a user’s political alignment is linked to the misinformation narratives the user engages with; and (4) We took a closer look at the types of misinformation domains that are shared and found that the consumption of conspiratorial and questionable content is on the rise. Users who share unreliable health-related content also tend to be in more tightly connected communities compared with the average Twitter user.

Methods
Data
We began collecting and curating a COVID-19 Twitter data set right at the beginning of the pandemic, in January 2020, to continuously track, in real time, public discourse about the coronavirus pandemic. We have made the data set publicly accessible to the wider research community [12]. This study uses publicly available data, and the data collection and analysis are approved by the University of Southern California Institutional Review Board (protocols UP-17-00610 and UP-21-00005).

Our complete data set, as of this writing (mid-July 2021), contains 1,497,893,426 tweets from January 21, 2020, through July 9, 2021 (release v2.55). While we provide a brief overview of our data set here, a full description of our data set can be found elsewhere [12]. We leveraged release v2.45 for this paper, which contains 1,443,871,621 tweets from January 21, 2020, through April 30, 2021. All our tweets were collected in real time using Twitter’s streaming application programming interface (API), which gave us access to a 1% stream of tweets [13]. We leveraged a manually curated list of keywords to filter for tweets that contained content related to the COVID-19 pandemic and surrounding issues. We list a sample of the keywords we tracked in Table 1. The full list of up-to-date
keywords can be found in our GitHub repository [14]. While we did our best to capture as much discourse as we could in our collection, a limitation of our data set is that our keywords were all in English and were manually selected for tracking. This may have influenced the collected tweets and our subsequent observations. A language breakdown for the tweets found in release v2.45 can be found in Table 2.

Table 1. A sample of keywords that were tracked during this release (v2.45; May 3, 2021).

| Keyword      | Tracked since   |
|--------------|-----------------|
| Coronavirus  | January 28, 2020|
| CDC          | January 28, 2020|
| Wuhanlockdown| January 28, 2020|
| Kungflu      | January 28, 2020|
| corona virus | March 2, 2020   |
| covid        | March 6, 2020   |
| covid19      | March 6, 2020   |
| sars-cov-2   | March 6, 2020   |
| COVID–19     | March 8, 2020   |
| coronapocalypse | March 13, 2020 |
| SocialDistancing | March 13, 2020 |
| shelteringinplace | March 18, 2020 |
| flatten the curve | March 18, 2020 |

We do not need to track every permutation of a keyword. As of this writing, Twitter returns all tweets that contain the keyword as a substring, and it is case insensitive.

Table 2. The top 10 languages and their prevalence in all tweets collected in this release (v2.45; May 3, 2021).

| Language | ISO | Tweets (N=1,443,871,621), n (%) |
|----------|-----|---------------------------------|
| English  | en  | 928,225,493 (64.29)              |
| Spanish  | es  | 186,880,167 (12.94)              |
| Portuguese| pt  | 62,398,113 (4.32)                |
| French   | fr  | 44,097,563 (3.05)                |
| Undefined| und | 41,140,188 (2.85)                |
| Indonesian| in  | 35,683,876 (2.47)                |
| German   | de  | 25,970,256 (1.80)                |
| Japanese | ja  | 16,865,989 (1.17)                |
| Italian  | it  | 15,697,293 (1.09)                |
| Turkish  | tr  | 14,931,506 (1.03)                |

The language tags are automatically detected by Twitter and returned in the tweet metadata.
ISO: International Organization for Standardization.

Identifying Discussion Topics

To understand the general COVID-19–related topics that were discussed on Twitter, we identified the bigrams (ie, consecutive word pairs) used in our data set and clustered bigrams that share similar temporal usage characteristics.

Bigrams

To retrieve bigrams, we first tokenized the tweets, lowercased all tokens, and removed stop words and select punctuations (including hash signs used for hashtags in Twitter). For example, the (fictitious) tweet “Thousands of new #covid cases reported in Los Angeles County!” reduces to the sequence of tokens “thousands new covid cases reported los angeles county;” all bigrams would be extracted, such as “thousands new,” “new covid,” “covid cases,” “cases reported;” etc. To avoid sparsity of data and to reduce computational costs, we focused on only the 50,000 most frequent bigrams that appeared in this data set. We replicated this step with 10,000 and 100,000 bigrams and found the results to be consistent. We built a time-series vector for each bigram to characterize its popularity over time. This
time series was built by counting the number of times each selected bigram was used on a weekly basis and normalizing that count by the total number of bigrams used that week.

**Temporal Clustering**

With the normalized bigram usage counts, we used dipm-SC [15], a shape-based time-series clustering algorithm that we designed specifically for social media data. The algorithm finds $K$ clusters of bigrams that exhibit similar temporal behaviors, within a certain prespecified time window $W$. We set the window to $W=21$ days to detect topics that had been trending for at the most 3 weeks, automatically filtering out general trending topics that had a tendency to continuously dominate the discussion over time (eg, bigrams like “covid 19” or “corona virus”). The results were consistent with similar assignments of $W$. We also explored various settings of $K$, the number of clusters, ranging from 5 to 15. While results were robust with similar assignments of $K$, we found that $K=11$ produced the optimal number of clusters in terms of the coherency of extracted topics and the amount of temporal overlap observed in the detected temporal shapes (eg, Figure 2A) via manual inspection.

**Figure 2.** (A) Detected shapes of identified clusters, ordered by when each cluster peaked in popularity. Each line indicates the respective cluster’s popularity over time. (B) The top 10 most used bigrams associated with each cluster and bar chart showing their total usage in terms of raw volume of tweets. The 11 clusters were (1) general coronavirus concerns, (2) public health measures, (3) Black Lives Matter, (4) Trump rallies, (5) 6 months after the first COVID-19 case, (6) Indian national exams, (7) the second COVID-19 wave, (8) Trump tests positive, (9) vaccine development, (10) vaccine rollout, and (11) COVID relief bill.

**Topic Clustering**

Latent Dirichlet allocation (LDA) [16] is a popular topic modeling approach, which finds $N$ latent topics in a group of documents (in our case tweets). The number of clusters (or topics) that yields the largest coherence value is determined to be the optimal $N$ value [16]. We again tokenized, lowercased, and removed all stop words and select punctuations from the tweets, and used LDA to cluster tweets by general topic. We found that $N=4$ yielded the largest coherence value.
Misinformation Subset

From our broader COVID-19 data set, we wanted to understand the kinds of narratives and discourse that promoted questionable content and misinformation. We created a subset of our data set for published tweets that contain a URL belonging to a domain that has been determined to be prone to publish questionable or conspiracy-pseudoscience–related content according to the third-party service Media Bias/Fact Check (MBFC) [17]. We used this as a proxy to identify users who have engaged with misinformation. This resulted in a COVID-19 misinformation data set totaling 12,689,165 tweets.

Identifying Conspiratorial, Questionable, and Random Sources

To identify conspiratorial and questionable tweets, we used the following 2 lists compiled by MBFC: conspiracy-pseudoscience sources and questionable sources. MBFC is “an independent website that rates the bias, factual accuracy, and credibility of media sources” [17]. MBFC classifies domains as conspiracy-pseudoscience if the domain “may publish unverifiable information that is not always supported by evidence. These sources may be untrustworthy for credible or verifiable information” [17]. For the sake of brevity, we also refer to these conspiracy-pseudoscience domains as simply conspiracy or conspiratorial domains. MBFC states that questionable sources are domains that “exhibit one or more of the following: extreme bias, consistent promotion of propaganda/conspiracies, poor or no sourcing to credible information, a complete lack of transparency and/or is fake news. Fake news is the deliberate attempt to publish hoaxes and/or misinformation for the purpose of profit or influence” [17].

We also obtained a set of randomly selected sources by taking a random sample from the set of media sources that appeared in the full data set. We called this set of sources “random sources.” The set of random sources has the same number of elements (URLs) as conspiratorial and questionable sources. The random sources served as a baseline for comparison with conspiratorial and questionable sources.

Identifying a Source’s Political Bias

MBFC also classifies media domains by their political affiliations, with the following 5 political affiliation categories: left bias, left-center bias, least biased, right-center bias, and right bias. We used their lists of domains to identify tweets with a particular political affiliation. Left and right bias sources are “moderately to strongly biased,” may be untrustworthy, and can “publish misleading reports and omit reporting of information that may damage [their] cause” [17]. Left-center and right-center bias sources have “slight to moderate” bias and are “generally trustworthy for information but may require further investigation” [17]. MBFC goes on to describe sources tagged as least biased as sources with “minimal bias,” “factual and usually sourced,” and “the most credible media sources” [17].

Classifying a User’s Misinformation and Political Engagement

For every user in our misinformation subset, we tabulated the number of times they shared domains and identified the political bias of these domains. This gave us a proxy of each user’s political lean. The political lean was determined by the political lean of the majority of a user’s shared domains. In the case of a tie between 2 political biases, we randomly assigned the user a political bias. Any user who shared one or more questionable or conspiracy-pseudoscience domains (as identified by MBFC) within our data set was considered to have engaged with misinformation. This does not mean that a user in our misinformation subset exclusively or mostly shared misinformation content. We restricted our analysis to only users who had shared more than five URLs.

User Retweet Network Misinformation Analysis

Taking advantage of the retweeting dynamics of Twitter, we constructed a network to conduct social network analysis on the users in our misinformation subset. Nodes represent users and links (or ties) represent retweets between users. If user A (retweeting) retweets user B (retweeted), then the strength of their tie increases with the frequency of retweets. To visualize this network, we adopted a force-based algorithm, Force Atlas [18], which plots nodes that share strong links close together. For the sake of clarity, the ties are not explicitly shown. There were a total of 4,164,572 users and 22,894,165 unique ties between users in our misinformation subset. We labeled the most prominent users, sorted by their highest out-degree.

This retweet network is constructed from the tweets of users who had retweeted at least one tweet that contained a domain that MBFC had classified as a questionable or conspiracy-pseudoscience domain. This means that each link between a retweeted and retweeting user does not necessarily mean that the retweet contained a misinformation domain or that the retweeted user engaged with a misinformation domain. Thus, the entire retweet network (contained within our dataset) included users who had interacted with a misinformation domain at least once.

Linear Regression Model Over Time

We analyzed the content coming from the following 3 groups of sources, each containing 250 URL domains: conspiracy sources, questionable sources, and random sources. Conspiracy and questionable sources were domains classified as such by MBFC, whereas random sources were chosen from a set of URLs selected at random to serve as a baseline for comparison.

To calculate the temporal trends in the amount of news coming from unreliable sources, we performed 2 multiple linear regression analyses using standard ordinary least-squares models. The first model estimated the association between the number of conspiratorial URLs and time, adjusting for an average number of URLs observed on a platform. The model can be represented as follows: $V_C = \beta_1 + V_R \beta_2$, where $V_C$ is the number of conspiratorial URLs shared, $t$ is time measured in days, and $V_R$ is the number of random URLs shared on Twitter. The second model estimated the association between the number of questionable URLs and time, adjusting for an
average number of URLs on a platform. Similarly, it can be represented as follows: \( V_0 = t \beta_1 + V_R \beta_2 \), where \( V_0 \) is the number of questionable URLs shared.

**Domain Sharing Network Analysis**

To better understand the relative impact of unreliable sources, we looked at their respective audiences and the communities that formed around sharing these unreliable sources. It is important to quantify the community structure and relationships between the consumers of certain kinds of information, as the strength of these communities can be indicative of the potential of an idea within the community to grow and become dominant over time. According to organizational theory, interpersonal networks that exhibit densely configured ties have a greater likelihood of attaining their goals and retaining the network structure (committed to staying together). Networks of strong ties are also significantly more robust with respect to the connectivity and small world property of social networks [19,20].

To quantify the relative strength of a connection between information sources that spread unreliable information about COVID-19, we constructed 3 networks of the following group of domains as defined earlier: conspiracy, questionable, and random sources. The nodes in the network represent the domains, and a link was drawn between 2 domains if a user shared content from both domains. The weight of a link was set to the number of users who shared both domains. To quantify the density of connections in these networks, we calculated the average clustering coefficient [21] and the average link weight for each respective audience network.

**Results**

**Clusters of Major Discussion Topics About COVID-19 on Twitter**

We used a clustering strategy based on dipm-SC [15], described in the Methods section, to identify topics that exhibit similar temporal behaviors and group them into distinct clusters. The detected clusters are visualized in Figure 2. We found that all clusters exhibited distinct peaks, suggesting minimal overlap between distinct clusters and hence robust and reliable clustering results. We now briefly describe the key topics that were detected in the 11 clusters we identified.

**General Coronavirus Concerns**

This concerns general coronavirus-related tweets, including reminders to “wash hands,” which was the first and most repeated advice to safeguard against the virus. It peaked in popularity early in the outbreak, in January and February 2020. It gradually declined in popularity until June 2020, from which point on it sustained its popularity consistently by accounting for around 10% of all tweets. This topic’s popularity trajectory tracks well with the initial phase of the COVID-19 outbreak unfolding worldwide.

**Public Health Measures**

Messages promoting public health measures, such as “social distancing” and to “stay home,” have been popular during COVID-19. This kind of messaging peaked in popularity during March and April 2020, after the lockdowns were imposed, and commanded attention throughout the rest of the study period. While this cluster had the shortest peak in terms of temporal shapes, we noticed that it was overwhelmingly the single most popular topic of all time points (Figure 2B). This contrast is due to the fact that this trending topic is relatively steady overtime rather than bursty during a short timeframe, like the other clusters. The high level of total activity indicates the high level of attention that the Twitter audience paid to public safety measures.

**Black Lives Matter**

The killings of George Floyd, Breonna Taylor, and others sparked national outrage [22]. This topic was brought up along with COVID-19 in late May through early June due to concerns that public protests would increase case counts. The protests were later found to have had no significant impact on the number of COVID-19 cases [23].

**Trump Rallies**

In June, former President Trump resumed his in-person rallies for his 2020 presidential re-election campaign. Rallies had been halted due to widespread coronavirus concerns over in-person gatherings [24].

**Six Months After the First COVID-19 Case**

Six months after the first COVID-19 case was reported, people were still battling the pandemic and isolating at home, unable to resume normal activities. The topic also includes the Trump administration’s use of the anti-Asian term “China virus.”

**Indian National Exams**

This temporal cluster of bigrams is primarily concerned with India’s NEET and JEE national exams, which had been postponed twice due to COVID-19. This became controversial when the exams were scheduled for September 2020 during a time when cases in India were steadily rising [25]. This topic anticipates, by several months, the outbreaks associated with the Delta variant in India that began in December 2020 [26].

**The Second COVID-19 Wave**

The United States braced itself for another wave of COVID-19 cases in September 2020 [27], with major concerns for the younger population.

**Trump Tests Positive**

On October 2, 2020, the White House announced that former President Trump tested positive for the coronavirus; soon after, Trump was transported to Walter Reed Medical Center [28].

**Vaccine Development**

By November 2020, both Pfizer and Moderna published promising results regarding their vaccines [29]. Shortly thereafter, both vaccines were approved for emergency use by the United States Food and Drug Administration (FDA) [30].

**Vaccine Rollout**

In the final weeks of 2020, vaccine administration began rolling out in the United States and in many other parts of the world [29,30].
**COVID Relief Bill**

After more than a year since the first case of COVID-19 was reported, many parts of the world continued to operate under mask and social distancing mandates. The vaccine rollout promised to facilitate a long-anticipated return to normalcy. The 2021 COVID-19 stimulus package, or American Rescue Plan Act, was eventually passed and was signed into law in March, which amounts to US $1.9 trillion [31].

**COVID-19 Misinformation Narratives**

We then turned to investigating misinformation and questionable narratives that spread in the context of COVID-19. We used our misinformation data subset, which contains tweets with URLs whose domains were deemed to be from a conspiracy-pseudoscience or questionable source according to MBFC, and leveraged both dipm-SC [15] and LDA [16] to cluster tweets by general topic. From the topics found in both clustering methods, we identified the following 3 major misinformation narratives that encapsulate the tweets that spread questionable media content on Twitter: (1) hydroxychloroquine and alternative medicines, (2) US officials and governing agencies, and (3) COVID-19 prevention interventions.

For each narrative of interest, we filtered our misinformation data set based on several defining keywords (Table 3). We identified the keywords in Table 3 by first isolating the most used keywords and bigrams in each narrative’s cluster, and then manually selecting neutral keywords most reflective of the 3 narratives. This enabled us to isolate subsets of tweets that specifically mentioned keywords related to each misinformation narrative. We then plotted the volume of tweets from each narrative over time (Figure 3) to understand temporal trends in each narrative. We found that a constant flow of misinformation exists, despite Twitter’s efforts to mitigate its spread. However, when we isolated tweets by narratives, we saw that each narrative experiences differing levels of engagement over time. Most of these spikes are driven by active retweeting of viral posts and/or articles that are sometimes related to real-time events. For each narrative, we also found the top hashtags that were used and grouped them into their relevant categories. We did a manual inspection of the tweets during these peaks and describe a few of the prominent topics that drove the volume surges in each narrative as seen in Figure 3.

| Topic                        | Keywords                      | Total number of tweets |
|------------------------------|-------------------------------|------------------------|
| Hydroxychloroquine and alternative medicines | hq, hydroxychloroquine | 368,883 |
| US officials and governing agencies | fauci, brix, cdc | 1,205,824 |
| COVID-19 prevention            | mask, vaccine, social distance*, test | 2,804,985 |

Note that a tweet can fall under multiple topics and count toward the narrative’s total number of tweets.

**Figure 3.** Visualization of the 7-day moving average of the volume of tweets that have tweeted a URL from a domain that has been identified as having spread conspiracy-pseudoscience or questionable content according to Media Bias/Fact Check. We identify 3 major narratives and plot the volume of tweets over time that mention keywords related to each of the narratives (hydroxychloroquine [HCQ], US officials and governing agencies, and COVID-19 prevention) in the bottom figure. The top figure plots the same narratives but also includes the total volume of tweets that shared a conspiracy-pseudoscience or questionable domain (which we generalize as misinformation).
Hydroxychloroquine

Hydroxychloroquine was, at the beginning of the pandemic, considered to be a potential treatment for COVID-19. However, while the US FDA had issued an emergency use authorization for the drug and the World Health Organization (WHO) had considered hydroxychloroquine in clinical trials, the drug had not been proven to be effective against the novel coronavirus [32,33]. As it became clear that hydroxychloroquine was not an effective treatment, the US FDA withdrew the emergency use authorization in June 2020 [32,33] and the WHO removed it from its trials in July 2020 [34]. Despite the evidence of ineffectiveness brought by clinical testing, hydroxychloroquine remained a fixture to many as an alleged cure for the coronavirus, and henceforth, it is considered medical misinformation. The top hashtags used in this narrative can be found in Textbox 1.

Textbox 1. The top 20 hashtags from the misinformation data set related to hydroxychloroquine and alternative medicines (classified into 5 general topics).

| Hydroxychloroquine-related | General coronavirus | Fauci | Politics | Misinformation |
|----------------------------|---------------------|-------|----------|---------------|
| hydroxychloroquine, hcq, hcqworks, hydroxychloroquineworks, and earlytreatmentworks | covid19, coronavirus, and covid | arrestfauci, fauci, firefauci, politicalcoup, and liberalfascism | kag, tds, twgrp, and fauci fraud | ccpvirus, chinavirus, and scamdemic |

Period From July 30, 2020, to August 14, 2020

Upon a manual inspection of the most prevalent content, we found that many users on Twitter were still circulating early and preliminary studies that suggested that hydroxychloroquine might be a candidate for treating COVID-19. Many of these users also blamed Dr Anthony Fauci and other medical authorities for ignoring the alleged “evidence” that hydroxychloroquine was effective. These users also cited the Ohio Department of Health’s prohibition on the use of hydroxychloroquine that was announced but rescinded before its July 30, 2021, effective date [35,36]. Finally, Twitter and other social media platforms began removing viral videos that featured Dr Stella Immanuel promoting unproven and unsubstantiated claims that hydroxychloroquine was an effective treatment for COVID-19 [37]. This resulted in users who engaged in hydroxychloroquine misinformation during this time claiming that Twitter was attempting to violate their freedom of speech.

US Officials and Governing Agencies

Perhaps unsurprisingly, US officials and governing authorities were also a target for misinformation on online platforms such as Twitter. Given that our data set was curated with English keywords, there was a higher concentration of discourse surrounding events occurring in primarily English-speaking countries. In our prior work, we also found that a large percentage of Twitter users were located in the United States [38]. Thus, the major misinformation narratives surrounding authorities centered around US officials and authority figures. The top hashtags used in this narrative can be found in Textbox 2.

Textbox 2. The top 20 hashtags from the misinformation data set related to US officials and governing agencies (classified into 4 general topics).

| General coronavirus | Fauci | Misinformation | Miscellaneous |
|---------------------|-------|---------------|---------------|
| coronavirus, covid19, cdc, covid, vaccine, and vaccines | fauci, firefauci, fauci thefraud, arrestfauci, and anthonyfauci | qanon2018, qanon2020, thedefender, ccpvirus, and chinese coronavirus | trump, china, un, and who |

Period From July 4, 2020, to July 8, 2020

Users cited a report that the Centers for Disease Control and Prevention (CDC) was overcounting COVID-19 cases and used this to claim that the CDC was purposefully trying to force Americans to remain under lockdowns throughout the summer [39,40].
**Period From August 4, 2020, to August 10, 2020**

Reports from the far-right news outlet The Gateway Pundit surfaced claims from Robert F Kennedy Jr, an antivaxxer who was banned from Instagram in February 2021 for spreading misinformation [41]. He claimed that Dr Anthony Fauci would be heavily profiting off the success of vaccines, falsely stating that Fauci was a partial owner of a COVID-19 vaccine patent [42]. There was also another report from The Gateway Pundit that disparaged US government medical authorities for downplaying the benefits of hydroxychloroquine and ignoring lower mortality rates in countries that used hydroxychloroquine as a treatment [43].

**Period From August 30, 2020, to September 4, 2020**

The Gateway Pundit published a report claiming that only 9,210 Americans had died specifically from COVID-19, while all other deaths were related to other illnesses [44]. They then used this as grounds to push the narrative that the CDC was overreacting to and exaggerating the effects and impact of COVID-19.

**Period From September 15, 2020, to September 19, 2020**

Former President Donald Trump issued an order for agencies to stop racial sensitivity training [45]. The Gateway Pundit published an article claiming that the CDC was disregarding Trump’s orders [46].

**General coronavirus**

- covid19, covid, cdc, coronavirus, covid—19, covid 19, and fda

**Prevention mechanisms**

- pfizer, moderna, vaccine, vaccines, masks, lockdown, and covidvaccine

**Misinformation**

- ccpvirus, billgates, and thedefender

**Miscellaneous**

- unmaskamerica, hankaaron, and science

**Period From August 2, 2020, to August 9, 2020**

The Gateway Pundit interviewed Robert F Kennedy Jr, who claimed that Dr Fauci would “make millions” from vaccine developments. This is the same story that drove a peak of activity surrounding US officials and authorities (see the time frame August 4, 2020, to August 10, 2020, in the US Officials and Governing Agencies section). During this time, Ohio governor Michael DeWine tested positive with an antigen test (also referred to as a rapid test) when being screened for a White House event with former President Trump. DeWine later tested negative after taking the more accurate polymerase chain reaction test [52,53]. This discrepancy in test results, despite the known difference in accuracy, caused users on Twitter to question the necessity and effectiveness of testing.

**Period From September 4, 2020, to September 13, 2020**

The Bill and Melinda Gates Foundation has invested heavily into developing vaccines for diseases such as Polio [54]. Zerohedge, a far-right news blog, published a post about the United Nations reporting a new vaccine-related polio outbreak in areas of Africa, specifically identifying the vaccine as a “Gates-Funded” vaccine [55,56]. This caused conspiracy theorists who were circulating this misinformation to blame Bill Gates for supposedly “funding” polio and for benefiting from it [57,58]. The same Zerohedge article then used this as evidence to try to bring the efficacy and safety of COVID-19 vaccines into doubt [55].

**Period From September 26, 2020, to October 2, 2020**

The CDC posted and then retracted a post on the airborne transmission of COVID-19 [47,48]. In reaction to the retraction, users accused the CDC of lying and intentionally misleading the public.

**Period From October 13, 2020, to October 19, 2020**

The CDC released a report that surveyed a small group of individuals who had contracted COVID-19. One of the questions posed to the participants was regarding their mask usage, and over 70% of the COVID-19 patients reported using a mask [49]. Users on Twitter used this information to bolster their belief that masks are not effective. This claim has been fact checked and debunked, showing that these users disregarded the context and other findings that these numbers were presented with [50,51].

**COVID-19 Prevention**

The last major narrative we identified in our misinformation data set focuses on COVID-19 prevention mechanisms. This includes testing, vaccines, masking, and social distancing. Many of the suggested and proven COVID-19 prevention strategies have been and continue to be at the center of much controversy, and as a result, are subject to much misinformation. The top hashtags used in this narrative can be found in Textbox 3.
then-scarce personal protective equipment for hospital workers and those on the front line [61].

**Period From November 13, 2020, to November 29, 2020**
A post by a former Pfizer employee, Michael Yeadon, claimed that the pandemic was over in the United Kingdom and that a vaccine was not needed for COVID-19 to be overcome [62]. While this claim was debunked and marked false by news and social media platforms [63], users online capitalized on Yeadon’s past association with Pfizer, one of the producers of the COVID-19 vaccine. They cited this as validation of their belief that the pandemic was a “scam” and that vaccines are not necessary. During this time, it was also revealed that Maryland governor Larry Hogan had spent over US $9 million on COVID-19 tests that were discovered to be flawed. This caused Hogan to purchase replacements for US $2.5 million using state funds, while not disclosing these flaws [64]. **Breitbart**, a far-right news platform, criticized Hogan on this, labeling Hogan as a Republican “anti-Trump hero” for the purchase of these tests [65], which had drawn former President Trump’s ire [66].

**Period From December 8, 2020, to December 17, 2020**
Sources, such as **NationalFile** and **DailyMail**, both of which MBFC has rated as having low credibility, claimed that the Chinese Communist Party had “infiltrated” both Pfizer and AstraZeneca and that these pharmaceutical companies had provided employment to these individuals [67]. This information was then used to discredit and cast doubt upon the vaccines that both companies were producing. A claim also stated that the pharmaceutical company GlaxoSmithKline owned both the Wuhan Institute of Virology and pharmaceutical company Pfizer. These debunked claims [68,69] were an attempt to tie the Pfizer COVID-19 vaccine development to Wuhan, where the first cases of COVID-19 were reported. Finally, there was a false claim that 87,000 nurses from the Netherlands declined the COVID-19 vaccines [70,71]. This alleged “refusal” was used to promote the narrative that many medical professionals were against vaccination and as a reason for the public to also follow suit.

**Characterizing Misinformation Adoption**
After identifying and describing the misinformation narratives permeating online discourse, we looked to understand the audience that is more susceptible to misinformation and the trends within the kind of misinformation that is being consumed. In the following text, we used network science as a lens to understand the structure and characteristics of misinformation echo chambers on Twitter, and suggest this as a possible mechanism to explain the spread of misinformation in specific communities.

**Existence of Political Echo Chambers**
**Figure 4** shows the retweet social network structure of Twitter users who engaged with at least one post containing a misinformation domain, as classified by MBFC, over the course of more than a year, which has been laid out using Force Atlas [18]. Some users, such as former President Donald Trump (realDonaldTrump) and President Joe Biden (JoeBiden), have rings of users around them, and these rings contain users that retweet almost exclusively from these prominent accounts. As a feature of the visualization, prominent users are also accompanied with “negative space” around them, which is a direct result of using the Force Atlas layout, where prominent users attract many small accounts who also repel each other.

**Figure 4.** (A) The political leanings of the users within our misinformation subset. Political leanings are determined by the political affiliation (as determined by Media Bias/Fact Check) of the domains a user tweets the most. (B) The 100-core decomposition of the graph into the top 1403 accounts.
addition to certain journalists and physicians. Interestingly, international media outlets, such as BNO news, SkyNews, and Spectator Index, attracted a mix of both left- and right-leaning users, suggesting that they are more impartial than US-based media outlets. Figure 4B further breaks down the visualization through a 100-core decomposition. Here, we additionally pruned out bots by removing those who tweet frequently but are never retweeted. This showed a similar partition of the network into communities, with left-leaning users on the left and right-leaning users on the right. Among elite users, as generated by the K-core decomposition, we can see how many more left-leaning users are engaging with COVID-19 messaging.

What is more interesting is how these topics map on the Twitter social network, as illustrated in Figure 5B. We observed COVID-19 prevention discourse throughout the graph. However, within the left-leaning cluster from Figure 4, we observed an absence of discourse about US officials and hydroxychloroquine. Users near the conservative core in Figure 4 are active in nature, and their position in the network is indicative of their higher retweeting frequency. Two types of users emerged from the right-leaning cluster. One type included users who discuss both prevention and US officials (Figure 5, red portion). They appeared concentrated around specific prominent users, such as Donald Trump and Dr Samadi (these users are labeled in Figure 4). The other type included users who engaged in discourse about all 3 narratives (Figure 5, orange portion) in tandem. These users tended to retweet a diverse number of prominent users. This not only indicates that hydroxychloroquine-related discourse is largely concentrated around right-leaning users and absent among left-leaning users, but also suggests that there exists a fracture within the right-leaning base, with some users following political content exclusively and others engaging more generally with COVID-19 discourse. Additionally, we can conclude that hydroxychloroquine is contingent on the presence of 1 of the 2 other topics (US officials and COVID-19 prevention).

Discussions of the Misinformation Narratives are Politically Fractured

Given the political orientation of users and the central users for which they coalesce around, we considered how the 3 narratives from Table 3 emerge. Figure 5A shows the overlap of these topics, aggregated over all users. We observed that users engaged primarily with COVID-19 prevention discourse, followed by discussion of US officials and governing authorities, and then hydroxychloroquine and alternative medicines. Additionally, 97,033 users discussed all 3 (Figure 5A), making up 13% of the 737,722 users tagged for engaging in these 3 topics.

Social Media Consumption of Unreliable Sources

The Rise of COVID-19 Information Coming From Unreliable Sources

The prevalence of information shared from unreliable sources is known to be high on Twitter and can reach up to 40% depending on the classification criteria [72]. In our analysis, we did not focus solely on quantifying the amount of obviously false claims, but rather focused on the prevalence of information coming from domains known to share news with questionable factualness. To obtain a more complete picture of the spread of unreliable information related to COVID-19, we performed a longitudinal analysis by quantifying the temporal trends in the volume of content shared from conspiracy, questionable, and random sources (see the Methods section). Figure 6 illustrates the volume of content shared from conspiracy, questionable, and random sources over time, plotted using a 7-week moving average. By observing the absolute trends, we can conclude that the volume of content coming from unreliable sources is growing faster than the random baseline. We modeled the change in the amount of content over time and observed a
statistically significant increase in the volume of content from both groups of tracked sources, with $\beta_C=4.4740$ and $\beta_Q=5.6964$ representing the linear coefficients for conspiracy and questionable sources, respectively, and with $P<.001$ for both categories of sources.

**Figure 6.** Volume of unreliable information on Twitter over time. Total number of times the news from various groups of sources were shared. The points represent the values aggregated weekly, plotted as a 7-week moving average. The lines reflect the linear trends, and the shaded areas are the 95% CIs.

We observed a large and significant increase in the amount of content from conspiracy and questionable sources. Every day, on average, we observed an increase in the amount of conspiratorial URLs of 4.47 and questionable URLs of 5.69, when corrected for the average increase of random content on the platform. This trend should not be overlooked, as it shows that unreliable information is on the rise despite the known efforts by Twitter to curb the spread of misinformation.

**Audiences and Communities Sharing Unreliable Information**

We considered the audiences and communities formed by users sharing from unreliable resources. We used the 3 domain sharing networks constructed for each group of domains: conspiracy, questionable, and random domain sources. The link between 2 domains was equal to the number of users who shared content from both domains. Each network comprised 250 nodes (domains). In Figure 7, only a sample of each network with 30 nodes is illustrated. From visual inspection, the networks of unreliable URLs clearly appeared to be more densely connected, suggesting greater levels of information sharing between the users and a tighter community structure.

The average clustering coefficients [21] of the questionable sources network and conspiracy sources network were 66.2 times and 27.4 times higher, respectively, than the average clustering coefficient of the random sources network (see Table 4 for network density measures). This is a strong indication that the connections between the URLs belonging to both groups of unreliable sources are more tightly grouped than the average set of URLs. Similarly, the average link weights of both unreliable sources’ networks are orders of magnitude higher than the average link weight of the random source’s network. The average link weights, which quantify the average number of users sharing the information from the same pair of domains, indicate that the audience sharing content from unreliable sources clusters more tightly together than the audience sharing random sources on Twitter.
Figure 7. The network of audiences sharing information from various types of sources: (A) conspiracy sources, red; (B) questionable sources, green; and (C) random sources, blue. The nodes are domains that serve as the source of information. A link is drawn between the nodes if the corresponding domains have been shared by the same account. The weight of the link quantifies the number of users sharing the information from 2 domains. Each network consists of 30 nodes, randomly selected from the corresponding group of sources.

Table 4. Some measures quantifying the connectivity of the URL networks.

| Variable                                | Questionable sources | Conspiracy sources | Random sources |
|-----------------------------------------|----------------------|--------------------|----------------|
| Average clustering coefficient          | 0.0004               | 0.00016            | 0.000006       |
| Relativea average clustering coefficient| 66.21                | 27.43              | 1              |
| Average link weight                     | 4.69                 | 1.36               | 0.01           |
| Relativea average link weight           | 346.69               | 103.15             | 1              |

aRelative to the network of random sources.

Discussion

Understanding COVID-19 Narratives on Twitter

In this paper, we provide a comprehensive overview of public COVID-19 discourse on Twitter by analyzing 1.4 billion COVID-19–related tweets that spanned the course of over a year. We make several important contributions in this work.

First, using temporal clustering of bigrams, we report 11 major topics of discussion. Aside from 1 topic with general COVID-related phrases that had sustained interest throughout our study period, the rest of the 10 topics were bursty and closely aligned with the progression of current events. We observed 2 types of topics. The first type included political topics that arise due to congregation, such as the protests that occurred in the wake of George Floyd’s death, Trump’s rallies, and India’s national exams. The second type encompassed news events that generated significant online traction, such as Trump testing positive, vaccine updates, and the relief bill.

This demonstrates that observing Twitter usage is a valid way to monitor public sentiment and important events as they unfold in the real world.

We then identified misinformation narratives by analyzing latent topics detected from tweets that shared domains that have been identified as unreliable media sources. We found that the following 3 prominent misinformation narratives emerged: hydroxychloroquine and alternative medicines, US officials and governing agencies, and COVID-19 prevention practices. Each of these narratives experienced surges in mentions and engagement, the majority of which occurred in tandem with and in response to real-world events occurring at the same time.

We also characterized misinformation adoption by analyzing the retweet social network structures of users who had retweeted at least one tweet that contained a domain classified as unreliable by MBFC. We found that there exists an alignment between the misinformation topic a user tends to engage in and that user’s political party. A large portion of the left-leaning userbase engaged specifically in COVID-19 prevention misinformation. The right-leaning userbase discussed COVID-19 prevention in the context of alternative medicines (such as hydroxychloroquine), and US officials and governing authorities. Interestingly, we observed a fracture in the right-leaning user base. Some users primarily discussed only 2 of the identified narratives (COVID-19 prevention and US officials), while others engaged with tweets surrounding all 3 narratives.

Lastly, and of great concern, we found that engagement with unreliable sources is increasing at a faster rate compared to engagement with our baseline of random sources. Our results show that, in the space of public health messaging on social media platforms, there is still significant work that needs to be done in order to combat misinformation. Although social media platforms are making efforts to stem the flow of misinformation and raise awareness of its presence, the dangers of misinformation, particularly regarding public health, are increasingly apparent. In our network, there are dense and highly connected communities that form around unreliable sources (so-called misinformation bubbles [73]), which can serve to further promulgate health misinformation online.
Implications

Our study highlights how social media platforms can help us to shed light on the issue and consequences of misinfodemics, particularly during an unforeseen global health crisis. Social media platforms, such as Twitter, currently employ various tactics to counter misinformation, including the use of automated misinformation tags to raise awareness and partnerships with third-party fact checkers. Our research suggests that, while efforts are being made to mitigate misinformation, misinformation continues to be a mainstay on Twitter and is still growing in prevalence in the narratives we detected on online social platforms. We can also continue to understand the kinds of communities that form around sharing unreliable sources. In particular, we found that misinformation echo chambers exist within the COVID-19 misinfodemic landscape, and that the major echo chambers align with users’ political affiliations (as determined by the political lean of the sources they engage with). This has significant implications for how we can use unreliable domain usage to not only identify more communities that are susceptible to misinformation, but also funnel resources and develop strategies to combat misinformation flow in these communities.

Limitations

While our study leverages a large tweet data set, there are still several limitations that need to be considered when interpreting the results of our study. First, when collecting data through Twitter’s free API, we were only able to collect 1% of all tweets in real time. Even with this limitation, we were able to collect several million tweets each day. We also only conducted our study on Twitter, which has been found to be used in the United States by a more liberal and left-leaning audience [74].

Due to the ever-evolving nature of misinformation, it is difficult to accurately judge and tag individual stories on Twitter as being misinformation or not. Thus, we used MBFC’s list of unreliable domains and the domains a user decides to share as a proxy for misinformation and engagement with a known unreliable source. This, however, does not necessarily mean that every URL shared from these domains has misinformation.

We did not focus on delineating social bots from human users in our analysis [75]. The term social bot generally refers to an account that is automated through software, and detecting and characterizing bot behavior is an active research area on its own [76]. Bots are incredibly salient to the misinfodemics conversation and have been found playing roles in the perpetuation of misinformation on social networks [75,77-79]. However, this study focused on the content and veracity of narratives shared on Twitter, and we hope to explore automated manipulation in the context of infodemics in future expansions of this work.

Conclusion

In this paper, we analyzed over 1 billion tweets posted during the COVID-19 pandemic and about the pandemic, spanning the course of over a year. We described the major topics of discussion that occurred over the broader COVID-19 Twitter discourse and identified the primary misinformation narratives that permeated the Twittersphere. We demonstrated that there are distinct misinformation echo chambers that form around specific topics and narratives, and that these echo chambers are also political echo chambers. This suggests that these echo chambers are driven by not only misinformation narratives, but also political alignment. Finally, we brought awareness to the increasing presence and consumption of unreliable content on Twitter, despite the current efforts being made to mitigate misinformation spread.

The COVID-19 pandemic and subsequent lockdowns around the world forced much of our forms of communication online, creating an environment where misinformation could more easily target a wider audience. We hope that our work will provide valuable insights into which communities are more susceptible to misinformation and contribute to laying the groundwork for other researchers in the field of misinfodemics.

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Conflicts of Interest

None declared.

References

1. Eysenbach G. Infodemiology: the epidemiology of (mis)information. The American Journal of Medicine 2002 Dec;113(9):763-765. [doi: 10.1016/S0002-9343(02)01473-0]
2. Eysenbach G. Infodemiology and infoveillance: framework for an emerging set of public health informatics methods to analyze search, communication and publication behavior on the Internet. J Med Internet Res 2009 Mar 27;11(1):e11 [FREE Full text] [doi: 10.2196/jmir.1157] [Medline: 19329408]
3. Rothkopf D. When the Buzz Bites Back. The Washington Post. 2003. URL: https://www.washingtonpost.com/archive/opinions/2003/05/11/when-the-buzz-bites-back/bc8ed84f-cab6-4648-bf58-0277261af6cd/ [accessed 2022-01-21]
4. Gallotti R, Valle F, Castaldo N, Sacco P, De Domenico M. Assessing the risks of ‘infodemics’ in response to COVID-19 epidemics. Nat Hum Behav 2020 Dec 29;4(12):1285-1293. [doi: 10.1038/s41562-020-09994-6] [Medline: 33122812]
5. Cinelli M, Quattrociocchi W, Galeazzi A, Valensise CM, Brugnoli E, Schmidt AL, et al. The COVID-19 social media infodemic. Sci Rep 2020 Oct 6;10(1):16598 [FREE Full text] [doi: 10.1038/s41598-020-73510-5] [Medline: 33024152]
6. van der Linden S, Roozenbeek J, Compton J. Inoculating Against Fake News About COVID-19. Front Psychol 2020 Oct 23;11:566790 [FREE Full text] [doi: 10.3389/fpsyg.2020.566790] [Medline: 33192844]

7. Young LE, Sidnam-Mauch E, Tywman M, Wang L, Xu JJ, Sargent M, et al. Disrupting the COVID-19 Misinfodemic With Network Interventions: Network Solutions for Network Problems. Am J Public Health 2021 Mar;111(3):514-519. [doi: 10.2105/ajph.2020.306063]

8. Kim A, Moravec PL, Dennis AR. Combating Fake News on Social Media with Source Ratings: The Effects of User and Expert Reputation Ratings. Journal of Management Information Systems 2019 Aug 04;36(3):931-968. [doi: 10.1080/07421222.2019.1628921]

9. Pennycook G, Rand DG. Fighting misinformation on social media using crowdsourced judgments of news source quality. Proc Natl Acad Sci U S A 2019 Feb 12;116(7):2521-2526 [FREE Full text] [doi: 10.1073/pnas.1806781116] [Medline: 30692252]

10. Kim J, Tabibian B, Oh A, Schölkopf B, Gomez-Rodriguez M. Leveraging the crowd to detect and reduce the spread of fake news and misinformation. In: WSDM '18: Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining. 2018 Presented at: Eleventh ACM International Conference on Web Search and Data Mining; February 5-9, 2018; Marina Del Rey, CA, USA p. 324-332. [doi: 10.1145/3159652.3159734]

11. Updates to our work on COVID-19 vaccine misinformation. Twitter. URL: https://blog.twitter.com/en_us/topics/company/2021/updatesto-our-work-on-covid-19-vaccine-misinformation [accessed 2022-01-21]

12. 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]

13. Consuming streaming data. Twitter Developer Platform. URL: https://developer.twitter.com/en/docs/tutorials/consuming-streaming-data [accessed 2022-01-23]

14. COVID-19-TweetIDs. GitHub. URL: https://github.com/echen102/COVID-19-TweetIDs [accessed 2022-01-23]

15. Ozer M, Sapienza A, Abeliuk A, Muric G, Ferrara E. Discovering patterns of online popularity from time series. Expert Systems with Applications 2020 Aug;151:113337. [doi: 10.1016/j.eswa.2020.113337]

16. Blei D, Ng A, Jordan M. Latent Dirichlet Allocation. The Journal of Machine Learning Research 2003;3:993-1022. [doi: 10.5555/944919.944937]

17. Search and learn the bias of news media. Media Bias / Fact Check. URL: https://mediabiasfactcheck.com/ [accessed 2022-01-21]

18. Jacomy M, Venturini T, Heymann S, Bastian M. ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. PLoS One 2014 Jun;9(6):e98679 [FREE Full text] [doi: 10.1371/journal.pone.0098679] [Medline: 24914678]

19. Balkundi P, Harrison DA. Ties, Leaders, And Time In Teams: Strong Inference About Network Structure's Effects On Team Viability And Performance. AMJ 2006 Feb;49(1):49-68. [doi: 10.5465/amj.2006.20785500]

20. Shi X, Adamic LA, Strauss MJ. Networks of strong ties. Physica A: Statistical Mechanics and its Applications 2007 May;378(1):33-47. [doi: 10.1016/j.physa.2006.11.072]

21. Saramäki J, Kivelä M, Onnela J, Kaski K, Kertész J. Generalizations of the clustering coefficient to weighted complex networks. Phys. Rev. E 2007 Feb 23;75(2):027105. [doi: 10.1103/physreve.75.027105]

22. Altman A. Why The Killing of George Floyd Sparked an American Uprising. Time. 2020. URL: https://time.com/5847967/george-floyd-protests-trump/ [accessed 2022-01-21]

23. Neyman G, Dalsey W. Black Lives Matter protests and COVID-19 cases: relationship in two databases. J Public Health (Oxf) 2021 Jun 07;43(2):225-227 [FREE Full text] [doi: 10.1093/pubmed/fdaa212] [Medline: 33215199]

24. Cohen M. Trump to resume campaign rallies with June 19 event in Tulsa. Politico. 2020. URL: https://www.politico.com/news/2020/06/10/trump-campaign-rally-tulsa-311516 [accessed 2022-01-21]

25. India NEET, JEE exams: 'Conducting these exams will be a giant mistake'. BBC. 2020. URL: https://www.bbc.com/news/world-asia-india-53887701 [accessed 2022-01-21]

26. Bever L, Achenbach J, Bellware K, Beachum L. What you need to know about the highly contagious delta variant. The Washington Post. 2021. URL: https://www.washingtonpost.com/health/2021/07/07/delta-variant-covid/ [accessed 2022-01-21]

27. Oehsená A. As Americans brace for 2nd wave of COVID-19, here’s why experts predict more infections but lower death rate. ABC News. 2020. URL: https://abcnews.go.com/Health/americans-brace-2nd-wave-covid-19-experts-predict/story?id=72817318 [accessed 2022-01-21]

28. Schwartz M. Live Updates: Trump Tests Positive for Coronavirus. NPR. 2020. URL: https://www.npr.org/sections/latest-updates-trump-covid-19-results [accessed 2022-01-21]

29. Zimmer C, Corum J, Wee S. Coronavirus Vaccine Tracker. The New York Times. 2021. URL: https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html [accessed 2022-01-21]

30. Wilson C. The U.S. COVID-19 Vaccine Rollout Is Getting Faster. But Is It Enough? Time. 2021. URL: https://time.com/5938128/covid-19-vaccine-rollout-biden/ [accessed 2022-01-21]

31. Segers G. Biden signs $1.9 trillion American Rescue Plan into law. CBS News. 2021. URL: https://www.cbsnews.com/news/biden-signs-covid-relief-bill-american-rescue-plan-into-law/ [accessed 2022-01-21]
32. Bull-Otterlson L, Gray EB, Budnitz DS, Strosnider HM, Schieber LZ, Courtney J, et al. Hydroxychloroquine and Chloroquine Prescribing Patterns by Provider Specialty Following Initial Reports of Potential Benefit for COVID-19 Treatment - United States, January-June 2020. MMWR Morb Mortal Wkly Rep 2020 Sep 04;69(35):1210-1215 [FREE Full text] [doi: 10.15585/mmwr.mm6935a4] [Medline: 32818455]

33. Edwards E. World Health Organization halts hydroxychloroquine study. NBC News. 2020. URL: https://www.nbcnews.com/health/health-news/world-health-organization-halts-hydroxychloroquine-study-n1231348 [accessed 2022-01-21]

34. WHO discontinues hydroxychloroquine and lopinavir/ritonavir treatment arms for COVID-19. World Health Organization. 2020. URL: https://www.who.int/news/item/04-07-2020-who-discontinues-hydroxychloroquine-and-lopinavir-ritonavir-treatment-arms-for-covid-19 [accessed 2022-01-21]

35. Requirements for Dispensing or Selling Chloroquine and Hydroxychloroquine in Ohio. State of Ohio Board of Pharmacy. 2020. URL: https://www.pharmacy.ohio.gov/Documents/Pubs/Special/COVID19Resources/Requirements%20for%20Dispensing%20or%20Selling%20Chloroquine%20and%20Hydroxychloroquine%20in%20Ohio.pdf [accessed 2022-01-21]

36. Filby M. Ohio pharmacy board reverses ban on hydroxychloroquine after GOP Gov. DeWine’s request. USA Today. 2020. URL: https://www.usatoday.com/story/news/health/2020/07/30/ohio-pharmacy-board-reverses-hydroxychloroquine-ban-mike-dewine-request/5547751002/ [accessed 2022-01-21]

37. Olewe D. Stella Immanuel - the doctor behind unproven coronavirus cure claim. BBC News. 2020. URL: https://www.bbc.com/news/world/africa-53579773 [accessed 2022-01-21]

38. Jiang J, Chen E, Lerman K, Ferrara E. Political Polarization Drives Online Conversations About COVID-19 in the United States. Hum Behav Emerg Technol 2020 Jun 18;2(3):200-211 [FREE Full text] [doi: 10.1002/hbe2.202] [Medline: 32838229]

39. Hoft J. Huge: Massive CDC Fraud Uncovered – CDC Grossly Overcounting Active China Coronavirus Cases Causing States to Keep Their Economies Closed Indefinitely. The Gateway Pundit. 2020. URL: https://tiniurl.com/2p86p2ww [accessed 2022-01-21]

40. Blair E. CDC Latest Update On Antibody Testing Results. The Gateway Pundit. 2020. URL: https://www.thegatewaypundit.com/2020/07/how-even-common-cold-counted-positive-covid-19-result-cdc-says/ [accessed 2022-01-21]

41. Chappell B. Instagram Bars Robert F. Kennedy Jr. For Spreading Vaccine Misinformation. NPR. 2021. URL: https://www.npr.org/sections/coronavirus-live-updates/2021/02/11/966902737/instagram-bars-robert-f-kennedy-jr-for-spreading-vaccine-misinformation [accessed 2022-01-21]

42. Hoft J. UNBELIEVABLE: In New Interview Bobby Kennedy Jr. Claims Dr. Fauci will Make Millions on Coronavirus Vaccine and Owns Half the Patent. The Gateway Pundit. 2020. URL: https://www.thegatewaypundit.com/2020/08/unbelievable-new-interview-bobby-kennedy-jr-claims-dr-fauci-will-make-millions-coronavirus-vaccine-owns-half-patent/ [accessed 2022-01-21]

43. Hoft J. KILLER FAUCI: Even Developing Nations Algeria, India, Indonesia, Cuba That Used HCQ Fared Better than US in Treating Coronavirus — By an Average of 79% Better!. The Gateway Pundit. 2020. URL: https://www.thegatewaypundit.com/2020/08/killer-fauci-even-developing-nations-algeria-india-indonesia-cuba-used-hcq-fared-better-us-treating-coronavirus-average-79-better/ [accessed 2022-01-21]

44. Hoft J. SHOCK REPORT: This Week CDC Quietly Updated COVID-19 Numbers – Only 9,210 Americans Died From COVID-19 Alone – Rest Had Different Other Serious Illnesses. The Gateway Pundit. 2020. URL: https://www.thegatewaypundit.com/2020/08/shock-report-week-cdc-quietly-updated-covid-19-numbers-9210-americans-died-covid-19-alone-rest-serious-illnesses/ [accessed 2022-01-21]

45. Schwartz M. Trump Tells Agencies To End Trainings On ‘White Privilege’ And ‘Critical Race Theory’. NPR. 2020. URL: https://www.npr.org/2020/09/05/910053496/trump-tells-agencies-to-end-trainings-on-white-privilege-and-critical-race-theor [accessed 2022-01-21]

46. Hoft J. CDC Ignores Presidential Order and Moves Forward with Critical Race Theory Program — Pushing Marxist Garbage that Accuses Police of Racism. The Gateway Pundit. 2020. URL: https://www.thegatewaypundit.com/2020/09/cdc-ignores-presidential-order-moves-forward-critical-race-theory-program-pushing-marxist-garbage-accuses-police-racism/ [accessed 2022-01-21]

47. Gumbrecht J, Christensen J, Cohen E, Thomas N. CDC abruptly removes guidance about airborne coronavirus transmission, says update ‘was posted in error’. CNN. 2020. URL: https://edition.cnn.com/2020/09/21/health/cdc-reverts-airborne-transmission-guidance/index.html [accessed 2022-01-21]

48. What we know about the airborne spread of the coronavirus. PolitiFact. 2020. URL: https://www.politifact.com/article/2020/sep/23/what-we-know-about-airborne-spread-coronavirus/ [accessed 2022-01-21]

49. Fisher KA, Tenforde MW, Feldstein LR, Lindsell CJ, Shapiro NI, Files DC, CDC COVID-19 Response Team. Community and Close Contact Exposures Associated with COVID-19 Among Symptomatic Adults ≥18 Years in 11 Outpatient Health Care Facilities - United States, July 2020. MMWR Morb Mortal Wkly Rep 2020 Sep 11;69(36):1258-1264 [FREE Full text] [doi: 10.15585/mmwr.mm6936a5] [Medline: 32915165]
50. Dapcevich M. Did CDC Report ‘Majority’ of People Who Contracted COVID-19 Wore Masks? Snopes. 2020. URL: [https://www.snopes.com/fact-check/cdc-report-majority-wore-masks/][accessed 2022-01-21]
51. Dupuy B. Posts misrepresent CDC study examining mask use. AP News. 2020. URL: [https://apnews.com/article/fact-checking-af-s-content:9573390682][accessed 2022-01-21]
52. Mervosh S. Gov. Mike DeWine of Ohio Tests Positive, Then Negative, for Coronavirus. The New York Times. 2020. URL: [https://www.nytimes.com/2020/08/06/us/mike-dewine-coronavirus.html][accessed 2022-01-21]
53. Wise A, Treisman R. Ohio Gov. Mike DeWine Tests Positive, Then Negative For COVID-19. NPR. 2020. URL: [https://www.npr.org/sections/coronavirus-live-updates/2020/08/06/899798411/ohio-gov-mike-dewine-tests-positive-for-the-coronavirus][accessed 2022-01-21]
54. Polio. Bill & Melinda Gates Foundation. URL: [https://www.gatesfoundation.org/our-work/programs/global-development/polio][accessed 2022-01-21]
55. Durden T. UN Forced to Admit Gates-Funded Vaccine Is Causing Polio Outbreak In Africa. ZeroHedge. 2020. URL: [https://www.zerohedge.com/markets/un-forced-admit-gates-funded-vaccine-causing-polio-outbreak-africa][accessed 2022-01-21]
56. Cheng M. UN says new polio outbreak in Sudan caused by oral vaccine. AP News. 2020. URL: [https://apnews.com/article/virus-outbreak-health-middle-east-africa-united-nations-619efb65b9e69c56501f1b960a152e9][accessed 2022-01-21]
57. Ngo Mayag M, Valmary S. Polio vaccine in the crossfire of misinformation. Yahoo! News. 2020. URL: [https://news.yahoo.com/polio-vaccine-crossfire-misinformation-013221439.html][accessed 2022-01-21]
58. Fact Check-List of claims about Bill Gates includes falsities. Reuters. 2021. URL: [https://www.reuters.com/article/us-nepra-polio-vaccine-crossfire-misinformation-013221439][accessed 2022-01-21]
59. Fact Check-List of claims about Bill Gates includes falsities. Reuters. 2021. URL: [https://www.reuters.com/article/us-nepra-polio-vaccine-crossfire-misinformation-013221439][accessed 2022-01-21]
60. A timeline of Trump’s battle with Covid-19. CNN. 2020. URL: [https://edition.cnn.com/interactive/2020/10/politics/trump-covid-battle/][accessed 2022-01-21]
61. Hoft J. CDC First Said Not to Wear Masks, Then to Wear Masks, Then Masks Were Better than Vaccines – Now New Evidence Shows Masks Are Ineffective. The Gateway Pundit. 2020. URL: [https://www.thegatewaypundit.com/2020/10/cdc-first-said-not-wear-masks-wear-masks-masks-better-vaccines-now-new-evidence-shows-masks-dont-work/][accessed 2022-01-21]
62. Molteni M, Rogers A. How Masks Went From Don’t-Wear to Must-Have. Wired. 2020. URL: [https://www.wired.com/story/how-masks-went-from-dont-wear-to-must-have/][accessed 2022-01-21]
63. Yeaden M. What SAGE Has Got Wrong. Covid19 Assembly. 2020. URL: [https://www.covid19assembly.org/2021/03/what-sage-has-got-wrong/][accessed 2022-01-21]
64. McCarthy B. Former Pfizer employee wrong that coronavirus pandemic is ‘effectively over’ in UK. PolitiFact. 2020. URL: [https://www.politifact.com/factchecks/2020/dec/02/blog-posting/former-pfizer-employee-wrong-coronavirus-pandemic/][accessed 2022-01-21]
65. Thompson S. Hogan’s first batch of coronavirus tests from South Korea were flawed, never used. The Washington Post. 2020. URL: [https://www.washingtonpost.com/local/md-politics/hogan-korea-coronavirus-tests/2020/11/20/f0486c1c8-251b-11eb-a688-5298ad5d580a_story.html][accessed 2022-01-21]
66. Pollak J. Report: Maryland Gov Larry Hogan, Anti-Trump Hero, Paid for Flawed Coronavirus Tests From South Korea. Breitbart. 2020. URL: [https://www.breitbart.com/health/2020/11/22/report-anti-trump-maryland-governor-larry-hogan-paid-for-flawed-coronavirus-tests-from-south-korea/][accessed 2022-01-21]
67. Booker B. Maryland Buys 500,000 Test Kits From South Korea, Drawing Criticism From Trump. NPR. 2020. URL: [https://www.npr.org/sections/coronavirus-live-updates/2020/04/21/839919655/maryland-gets-500-000-test-kits-from-south-korea-drawing-criticism-from-trump][accessed 2022-01-21]
68. Pappert T. Chinese Virus, Chinese Vaccine?: CCP Leak Confirms Pfizer, AstraZeneca Employed 123 Communist Party Members. National File. 2020. URL: [https://www.nationalfile.com/chinese-virus-chinese-vaccine-ccp-leak-confirms-pfizer-astrazeneca-employed-123-communist-party-members][accessed 2022-01-21]
69. Lee E. Fact check: False connections drawn between Wuhan lab, vaccine research affiliates. USA Today. 2021. URL: [https://www.usatoday.com/story/news/factcheck/2020/12/30/fact-check-wuhan-lab-vaccine-research-affiliates-not-linked/4086363001][accessed 2022-01-21]
70. Fact check: The Wuhan Institute of Virology is not owned by GlaxoSmithKline. Reuters. 2020. URL: [https://www.reuters.com/article/us-fcn-facts-wuhan-institute-investigation-false-virus-research-propagation-idUSKBN28R2UK][accessed 2022-01-21]
71. FALSE: 87,000 Dutch nurses refused to be vaccinated against COVID-19. Poynter. 2020. URL: [https://www.poynter.org/?fnc_misinformation=87000-dutch-nurses-refused-to-be-vaccinated-against-covid-19][accessed 2022-01-21]
72. FALSE: 87,000 Dutch nurses refused to be vaccinated against COVID-19. VoxUkraine. 2020. URL: [https://voxukraine.org/nepravda-87-000-niderlandskhi-medsester-vidmovilisya-vaktsinuvatysya-vid-covid-19/][accessed 2022-01-21]
73. Bozarth L, Saraf A, Budak C. Higher Ground? How Groundtruth Labeling Impacts Our Understanding of Fake News About the 2016 U.S. Presidential Nominees. SSRN Journal 2019:1-12. [doi: 10.2139/ssrn.3340173]
74. Wojcik S, Hughes A. Sizing Up Twitter Users. Pew Research Center. 2019. URL: https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/ [accessed 2022-01-21]

75. Ferrara E, Varol O, Davis C, Menczer F, Flammini A. The rise of social bots. Commun. ACM 2016 Jun;24(7):96-104. [doi: 10.1145/2818717]

76. Yang K, Varol O, Hui P, Menczer F. Scalable and Generalizable Social Bot Detection through Data Selection. In: Proceedings of the AAAI Conference on Artificial Intelligence. 2020 Presented at: AAAI Conference on Artificial Intelligence; February 7–12, 2020; New York, NY, USA p. 1096-1103. [doi: 10.1609/aaai.v34i01.5460]

77. Ferrara E, Chang H, Chen E, Muric G, Patel J. Characterizing social media manipulation in the 2020 U.S. presidential election. First Monday 2020 Oct 19;25(11):11431. [doi: 10.5210/fm.v25i11.11431]

78. Bessi A, Ferrara E. Social bots distort the 2016 U.S. Presidential election online discussion. First Monday 2016 Nov 03;21(11):7090. [doi: 10.5210/fm.v21i11.7090]

79. Shao C, Ciampaglia GL, Varol O, Yang K, Flammini A, Menczer F. The spread of low-credibility content by social bots. Nat Commun 2018 Nov 20;9(1):4787 [FREE Full text] [doi: 10.1038/s41467-018-06930-7] [Medline: 30459415]

Abbreviations

- API: application programming interface
- CDC: Centers for Disease Control and Prevention
- FDA: Food and Drug Administration
- LDA: latent Dirichlet allocation
- MBFC: Media Bias/Fact Check
- WHO: World Health Organization

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