Social Media During the COVID-19 Pandemic: A Public Health Crisis or a Political Battle?

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Abstract. Since the start of coronavirus disease 2019 (COVID-19) pandemic, social media platforms have been filled with discussions about the global health crisis. Meanwhile, the World Health Organization (WHO) has highlighted the importance of seeking credible sources of information on social media regarding COVID-19. In this study, we conducted an in-depth analysis of Twitter posts about COVID-19 during the early days of the COVID-19 pandemic to identify influential sources of COVID-19 information and understand the characteristics of these sources. We identified influential accounts based on an information diffusion network representing the interactions of Twitter users who discussed COVID-19 in the United States over a 24-hour period. The network analysis revealed 11 influential accounts that we categorized as: 1) political authorities (elected government officials), 2) news organizations, and 3) personal accounts. Our findings showed that while verified accounts with a large following tended to be the most influential users, smaller personal accounts also emerged as influencers. Our analysis revealed that other users often interacted with influential accounts in response to news about COVID-19 cases and strongly contested political arguments received the most interactions overall. These findings suggest that political polarization was a major factor in COVID-19 information diffusion. We discussed the implications of political polarization on social media for COVID-19 communication.

Keywords: COVID-19, Twitter, social media influencers, and information dissemination.

1 Introduction

Beginning in late 2019, coronavirus disease 2019 (COVID-19) emerged and spread around the world at an alarming rate, creating a large-scale public health emergency (World Health Organization, 2020). It is crucial that public health agencies deliver information to the public in a timely manner during the health crisis. As a result, people turned to social media for news and discussion about this global health crisis. Social media has been widely used to gather and share information following disaster events (Starbird & Palen, 2012; Zade et al., 2018). For instance, a report from Hether et al. (2014) suggests that 60% of adult Americans (80% of internet users) use online media as their main source of health information. However, uncertainty and conflicting information have created obstacles for public health communication and posed dangerous consequences to people's lives (Spencer, 2020; Zarocostas, 2020). Therefore, health authorities have highlighted the importance of seeking credible sources of information related to COVID-19 (Zarocostas, 2020). Given the importance of social media during health crises, 'social media influencers' have been considered 'critical actors' during the pandemic, since these influencers deliver timely information about COVID-19 to people who use social media platforms (Abidin et. al, 2020). We analyzed influential sources of information on Twitter that people engaged with to understand how the dissemination of information during COVID-19 reflects governments' and public health agencies' efforts to promote credible sources on social media.

In this study, we identified Twitter influencers in the United States by scraping 13,492 Tweets from a 24-hour period between June 16, 2020 and June 17, 2020. In the U.S. at this time, reported COVID-19 cases had decreased relative to the preceding spike in March and April[1]. However, during this week, the U.S. Centers for Disease Control and Prevention (CDC, 2020) reported that while the number of cases of COVID-19-like illnesses was lower at the national level, cases were increasing in certain regions. Tension between economic and public health concerns led to disputes between health experts and politicians over appropriate government responses to COVID-19, with public health officials warning that reopening the economy could result in a surge in cases (Cher, 2020). During this time, U.S. President Donald Trump clashed with health officials, prioritizing reopening and downplaying the risk of increased COVID-19 spread (Forgey, 2020). Additionally, Trump received significant attention and criticism for moving forward with a planned campaign rally in Oklahoma, despite a major increase in COVID-19 cases in the state (Shumaker & Schwartz, 2020). Meanwhile, reflecting both the uneven impact of COVID-19 across U.S. states, as well as partisan division across the nation, local and state governments took divergent paths when it came to reopening the economy or extending stay-at-home orders and business closures, leading to confusion and uncertainty (Gross, 2020; Karimi et al., 2020; Olson, 2020). Ultimately, these events culminated in a significant surge in COVID-19 cases nationwide in the weeks and months to follow [1].

A clear identification of the main influential sources of information about COVID-19 on social media can provide insights into the types of engagement and information that people sought for COVID-19 updates and news during the early days of the pandemic. There is a need for research to provide an identification of U.S. sources of information from online digital trace data to better understand this phenomenon. Thus, we pose the following research questions:

- **RQ1:** *Who were the most influential sources (based on interactions) of COVID-19 information on Twitter during the early stages of the pandemic?*
- **RQ2:** *What are the characteristics of these accounts/users and the information they shared?*
- **RQ3:** *How did users interact with these influential accounts and the COVID-19 information they share?*

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[1] https://covid.cdc.gov/covid-data-tracker

To answer RQ1, we first created an interactions network demonstrating information diffusion of the collected data to identify which users are the most influential information sources. To address RQ2, we then conducted qualitative and quantitative analyses of the identified influential accounts. For RQ3, we examined the types of interactions received by the influential accounts. Based on our network analysis, we identified 11 influential accounts. The influential accounts included public figures, such as elected government officials and news organizations, along with personal accounts. While the majority of influential accounts were verified with a large following, the influencers also included non-verified accounts with fewer followers. We found the influential accounts varied in the types of interactions they received. Additionally, we found the content receiving the most interactions from these users included news and updates about COVID-19 cases, as well as personal commentary. However, politically charged arguments received the most interactions overall.

By identifying the influential sources of COVID-19 information, we make the following unique research contributions: 1) We highlight the differences in users' interactions with different types of influential sources of information, and 2) We identify the influence capacity of influencers based on the received interactions using the visualized network. At the end, we discuss the implications of our findings for understanding polarization in health communication and provide recommendations for future research on the role of influencers in COVID-19 information diffusion.

2 Related Work

In this section, we explore relevant studies that discussed information diffusion and COVID-19 news diffusion on social media.

2.1 Information Diffusion on Social Media

Information diffusion happens when a piece of knowledge spreads from a source to a recipient(s) or audience through interactions. Zafarani et al. (2014) described the diffusion process with three main components: a sender of the information, a receiver, and a medium. Katz and Lazarsfeld (1955) pointed out that information can go viral through a person-to-person diffusion process. Large-scale of information distribution relies on social media networks. One study showed that people tended to imitate majority behavior in the diffusion process because they believed that the wisdom of the group could help them make the right decision (Levitan & Verhulst, 2016). It is important to address how the bigger groups, or hubs, on social media can affect diffusion speed. This is introduced in the Barabási and Albert (1999) preferential attachment model. The preferential attachment model is based on the concept of "rich get richer" where a network is constructed randomly at the beginning. Then, a new node or individual connects randomly to an existing node with a preference to attach to the popular nodes or users. According to Freberg et al. (2011), these popular users emerge on social media platforms as third-party endorsers, or 'influencers.'

Influencers have a significant impact on people's attitudes, behavior, and decisions (Casaló et al., 2018). Influencers' abilities to gain trust and influence other users has become an advantage for them in reaching target users in an effective way (Pestek et al., 2017). Chae (2018) defined influencers as micro-celebrities, since they gained popularity over time using social media. Influencers on social media varied from "unknown actresses and models, fitness trainers and musicians to wealthy people" (Chae, 2018). Examining the influencers' following network was one of the ways to identify influencers using social network analysis (Stieglitz et al., 2018). The capacity of influence of these influencers is usually linked with following size (Okuah et al., 2019). However, following size is not the only indication for quantifying influence; valuable interactions can also be considered another successful influence metric (Gräve & Greff, 2018). Studies have shown that influencers with a "mid number of followers" can hold more engagement and trust than some influencers with a large number of followers (Pestek et al., 2017). In marketing, for example, the impact of influencers can be quantified by a two-way conversation on a product via social media (Booth & Matic, 2011). Level of engagement can be defined by the interactivity of a piece of content shared on social media. Therefore, the influence indication used in this study to identify influencers of COVID-19 discussions was the number of engagements received.

2.2 COVID-19 Information Diffusion via Social Media

Since the beginning of the COVID-19 pandemic, many efforts have arisen to explore the reflection of this major health event in different social media platforms. Researchers have begun to investigate the sources of information related to the pandemic on social media, such as Ko et al. (2020), who were able to identify the sources of information on Twitter based in Taiwan using an online survey. Budhwani and Sun (2020) found that, there was a significant increase in using hashtags related to COVID-19 on Twitter. This resulted in the production of a large scale of data that can help researchers understand public perceptions about COVID-19. Some early research efforts focused on publishing datasets about COVID-19 discussions on social media to the public for analysis. Dimitrov et al. (2020) emphasized the role of Twitter as a tool for the research community to study online conversation dynamics, including information dissemination. The researchers published a publicly available dataset that has potential for analyzing COVID-19-related tweets. One of the major findings from the initial analysis of the published dataset was that it verified that "Twitter discourse statistics reflect major events." It was also observed that verified accounts "are the most active when major events occur."

Studies that involve the creation and/or analysis of datasets of online public postings to identify the influential sources of information are particularly useful in guiding the actions and policies of public agencies. For example, Rufai and Bunce (2020) stated that government leaders and public agencies can leverage pandemic-related studies of online discourse and information diffusion to evaluate the effectiveness of implemented policies and to inform future policy decisions. There was a noticeable trend of conducting sentiment analysis, a methodology that utilizes Natural Language Processing (NLP) to assess the connotation of a given text, on public discussions about COVID-19 on social media. Lwin et al. (2020) explored the sentiments from COVID-19 related discussions focusing on four emotions: fear, anger, sadness, and joy. The researchers found that during the pandemic, there was a significant shift in the public emotions from fear to anger "while sadness and joy also surfaced." Most fear emotions appeared around shortages of COVID-19 tests and medical supplies while the anger was shown in the tweets related to the stay-at-home notices. Sad emotions were shown clearly on topics related to losing friends and family members while tweets including words of gratitude and good health highlighted the joyful emotions. Another sentiment analysis based on positive and negative sentiments was done by Dimotrov et al. (2020) toward four prespecified prominent sources of pandemic-related information: Donald Trump, The World Health Organization, Breitbart, and CNN. Tracking the positive and negative sentiments of the tweets sent to the predefined sources revealed a possible controversy by synchronous increase in positive and negative sentiments in the week of Trump's State of the Union address.

Analyzing major sources of information was also an interest of Rufai and Bunce (2020) who conducted a content analysis on the COVID-19 responses from eight of the Group of Seven (G7) world leaders on Twitter. The analysis yielded 203 viral tweets: 166 (82.8%) were categorized as 'Informative,' 48 (28.6%) had weblinks to government-based sources, 19 (9.4%) were 'Morale-boosting,' and 14 (6.9%) were 'Political.' These studies used predefined lists of sources for analysis, while in this study, we obtained data using a scraper that collects data from Twitter users in the United States and then created a visualized network that illustrates the interactions between users who discussed COVID-19 related topics to identify the sources based on the accounts that received the highest number of interactions.

3 Methods

3.1 Study Overview

We performed an analysis of the interactions between Twitter users who posted tweets related to COVID-19 in order to identify and investigate the main sources of information that people engaged with during the early stages of the global pandemic. This analysis was done based on a visualized network constructed using the collected data (the interactions) and in-depth analysis on the identified sources. Further analysis was performed on the main identified sources of information in order to understand the shared characteristics of these users and extract the different types of accounts. In order to achieve this understanding, we performed a manual analysis on information related to the identified influencers' activity on Twitter based on number of followers, date of account creation, profile description, and whether the account was verified. The visualized network, along with the deep analysis of the identified accounts, allowed us to frame a comprehensive understanding of Twitter sources of COVID-19 information.

3.2 Data Collection

We selected Twitter as the data source for this study because it is a powerful tool for analyzing COVID-19 discussions (Dimitrov et al., 2020). We used the TwitterStreamingImporter on Gephi (Levallois and Totet, 2020) to collect COVID-19 related tweets along with the interactions that were recorded for these tweets including mentions, retweets, and quote tweets between the users. Trending hashtags about COVID-19 were used to filter tweets. The terms used for filtering were: "COVID-19," "Coronavirus," "COVID Pandemic," "Covid-19 vaccine," "corona cure," and "corona vaccination." Based on these search terms, we collected 13,492 Twitter user interactions over a 24-hour period from June 16, 2020, to June 17, 2020. This allowed us to conduct a detailed mixed method (quantitative and qualitative) analysis of influence within a short period of time. The scraper collected English-language tweets from Twitter users who were in the United States.

Using the same Twitter scraper software, further meta data were extracted for each user for in-depth analysis of the identified sources. This further investigation helped explore more information about the different types of accounts that dominate Twitter during the global pandemic. The meta data that were collected for the sources' analysis are described in the following subsections.

Number of followers. The number of followers is defined as the number of Twitter users who follow a given user. The number of followers is considered as an influence indicator because the more followers a user has, the faster information can be spread. Therefore, we expected that most of the identified influential sources would be users with a high number of followers.

Profile creation date. The creation date of a Twitter profile indicates the date the user created their Twitter account. Based on early Twitter reports, there was approximately a 6% increase of new users accounts on Twitter who engaged in discussions about COVID-19 between November 2019 and March 2020 (Sharma et al., 2020). In this study, we investigated the creation date of influential accounts in order to check whether newer accounts dominate Twitter discussion during the pandemic.

Profile description. Profile description refers to a short autobiography written by Twitter users to introduce themselves. Using profile descriptions helped us understand the identities behind accounts whose COVID-19 tweets receive the most interactions.

Verified accounts. Verified accounts are Twitter accounts that have been authenticated by the platform. In this study, we collected a Boolean variable that indicated whether a given user was verified. Verification status may enhance the account's credibility, since González-Bailón and Domenico (2020) confirmed that verified accounts were significantly more visible to other Twitter accounts during events. Usually, these verified accounts were celebrities or public figures (Twitter, 2013). This motivated us in this study to explore whether the main sources of COVID-19 news were verified accounts and to compare that with the number of followers to check which factor had more influence on reaching a wider audience. This provided a clear understanding about what types of accounts people would seek and trust for news and updates about COVID-19. Next, we describe the data analysis methods used in this study.

3.3 Data Analysis Approach

We performed network analysis by creating a directed network using Gephi, an open-source network visualization software (Bastian et al., 2009), to better understand the information flows between Twitter users who discussed COVID-19 during the data collection time period (Borgatti et al., 2009). For the visualized network, our aim was to visually identify the Twitter user accounts that were influential sources of COVID-19 information. Two indications used for identifying these sources were node size and edge direction. Twitter users were represented in the network graph as nodes, where node size was an indication of the number of interactions a node (user) had received. Bigger nodes showed a high number of interactions sent to the user and vice versa. The interactions (mentions, retweets, and quote tweets) between the users were represented by the edges' direction. After identifying the main sources of information in the network, we filtered the data in order to explore and deeply analyze these accounts.

In this analysis, interactions received by these accounts along with the previously defined variables (number of followers, profile creation date, profile description, verified account) about users were used in order to explore the different types of users that the public Twitter audience would seek for information about COVID-19. We followed a qualitative thematic approach (Braun & Clarke, 2006) to find themes across tweets and extract patterns between the accounts based on the collected features. We analyzed the tweets of the influential sources that were collected during the collection time and received the highest number of interactions. This process started by reading the tweets and discussing what these posts were, how the content could impact the number of interactions received, and what were the topics of these tweets. In the next section, we present our results regarding the network interactions and influential users.

4 Results

In this section, we identify the influential sources of information on Twitter (RQ1), along with their characteristics, including account types, profile creation date, number of followers, and verification (RQ2). We also describe characteristics of the interactions received by the identified influential accounts (RQ3).

4.1 Influential Sources of Information from Engagement Network

Figure 1 illustrates the engagement network that was created based on the collected sample of data from Twitter, where 6707 Twitter accounts were the nodes in the graph and 13,492 interactions (mention, retweet, and quote tweet) between these accounts were the directed edges that connected two nodes (users). The network graph clearly showed dense interactions between users, which took place mostly on the network center. The nodes, or users, who were placed in the outer area showed lighter interactions observed by one interaction between only two nodes. In this study, we focused on the dense interactions between users because analyzing this type of interactions helped us identify Twitter accounts that people interacted with heavily regarding their COVID-19 tweets.

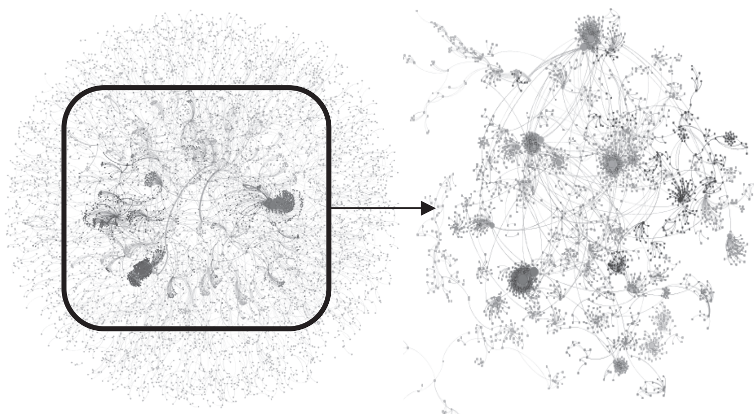

Fig. 1. Twitter users' interactions network where nodes represented users and edges represented the form of interaction between these users.

Node size was proportional to the number of interactions a given node received. After filtering the network to focus only on the dense interactions area, the major visualized finding was that most users were found to be small nodes, which indicated that these users interacted with other users, rather than receiving interactions themselves. Another major visualized finding was that we found a small number of large size nodes, denoting that people heavily interacted with these accounts' tweets. To identify influential sources of information in the interaction network (see Figure 1), we filtered the large size nodes (sources) along with the other users' that connected to it that are shown in Figure 1 on the right. Based on the collected sample, the average number of interactions was 70.51. This number was used as a threshold to identify the influencers on the created network. We included usernames for verified accounts, which were all associated with public figures or news agencies. However, we anonymized the identity of the non-verified accounts to respect their privacy. As a result, we found 11 users who received more than 70 interactions (listed in Table 1). We consider these identified as influential, since people not only passively read their tweets, but were also motivated to actively interact with the tweets.

Having a small minority of users as influential sources of information out of the 6707 total users was a notable pattern of information diffusion. Typically, there is a high number of users who provide content to social media, but what we found was the opposite: people tend to be more interactive by responding to tweets posted by a few accounts. Therefore, it is worth navigating through these accounts to understand who these users are and why they received disproportionately greater attention than other users based on the collected sample. By applying the manual iterative approach to qualitatively analyze the top 11 influential accounts, the identified sources were categorized into three main account types: personal accounts (6), news agencies (3), and political authorities (2).

Table 1. Twitter influential sources of COVID-19 information, based on the collected sample of users who received interactions above the mean.

Twitter username	Account type	Number of interactions	Followers count	Verified	Created date
@realDonaldTrump	political authority	210	**82193259**	TRUE	2009
@thehill	news	182	3817296	TRUE	2007
@anonymized_a	personal	135	61380	FALSE	2008
@Newsweek	news	110	3448350	TRUE	2007
@anonymized_b	personal	109	**660**	FALSE	2010
@funder	personal	88	701056	TRUE	2008
@perlmutations	personal	86	987380	TRUE	2012
@AP	news	85	14286804	TRUE	2009
@anonymized_c	personal	82	2444	FALSE	2009
@anonymized_d	personal	75	4281	FALSE	2011
@SenSanders	political authority	71	9946708	TRUE	2010

Political and Personal Accounts were the Dominant Influencers. The two political authority accounts were @realDonaldTrump, U.S. President Donald Trump, which was found to be the dominant influencer in discussions about COVID-19, and @SenSanders, who is Bernie Sanders, U.S. Senator of Vermont. Trump and his administration were under pressure to provide a precise plan and clear instructions to inform people about the pandemic in a timely manner (Rufai & Bunce, 2020). Trump used his Twitter account to disseminate information about the pandemic by posting tweets and videos daily, which received the most attention from people inside the US. Receiving such a high number of interactions to COVID-19 related tweets demonstrated the importance of the existence of active government accounts on Twitter during times of crisis. Whether people agreed with Trump's actions or plans, nobody can deny that the usage of Twitter as a medium to provide fast-paced pandemic updates was an advantage. Another government official among the list of influencers was Senator Bernie Sanders (@SenSanders). Sanders received attention from people during data collection based on a posted tweet about COVID-19:

@SenSanders: "I'll be damned if when a COVID-19 vaccine is developed, more people die because they can't afford to purchase it. Any life-saving vaccine must be free."

This tweet triggered users' emotions by mentioning that people may die because they cannot afford the COVID-19 vaccine even before the vaccine was developed during a health and economic crisis, which resulted in a high number of retweets as a sign of agreeing with the Senator's demand. The usage of emotional language has shown to be effective in manipulating people, which mostly resulted in a high number of retweets (Stieglitz & Dang-Xuan, 2013). Based on Rufai and Bunce (2020), Trump used Twitter as an informative platform to post updates about COVID-19. In our data, Sanders used Twitter to express opinions that generally seemed to be against Trump's actions.

A surprising result was that we found (54.54%) six personal accounts among the influencers who received a high number of interactions for COVID-19 tweets. These accounts varied from private individuals to public figures, such as @funder and @perlmutations. @funder is the account of Scott Dworkin, a political commentator and founder of a super PAC (Political Action Committee). Dworkin is the executive director of the Democratic Coalition, which was founded with the express purpose of opposing Trump's presidency[2]. Reflecting his partisan preference, Dworkin's tweets about COVID-19 focused on criticizing Trump's decisions and actions during the pandemic. For example, one of Dworkin's most retweeted tweets in our dataset was:

@funder: "BREAKING: Trump's going to Dallas today to do a photo op, go to a fundraiser, then to his NJ golf resort. We're at the height of a <u>pandemic</u> where over 115,000 Americans have died with over 2 million infected. And he's on vacation. Trump's the laziest, most pathetic failure ever."

Although Dworkin's Twitter account is an active and popular account that mostly publishes political tweets, not all of Dworkin's tweets received as many interactions as the previously quoted example; the reason for this might be the tweet's content, which included the number of infected people and harsh criticism of Trump for being on a vacation during the pandemic. This triggered fear over the increasing number of infected people and anger towards Trump which was reflected by interactions with this tweet. Another public figure in the personal accounts list was @perlmutations, the celebrity actor Ron Perlman. Perlman also used similarly emotional language to express anger against Trump's actions in the following tweet:

@perlmutations: "Over 118,000 American souls have been lost to the <u>coronavirus</u> and that number is not slowing down. Instead of formulating an actual plan to save lives, the president is tweeting in all caps about the stock market. There's only so much tequila I can drink so please VOTE."

Perlman shared his frustration regarding how the pandemic had negatively impacted the lives of people in the United States while the president was paying attention to other topics and encouraged people to vote in the upcoming presidential election.

Dworkin and Perlman's tweets might have received a high number of interactions because their tweets criticized Trump and prompted anger and fear by juxtaposing the

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[2] https://www.democraticcoalition.org/about.html

number of COVID-19 cases with examples of Trump’s alleged failure to respond appropriately in favor of self-serving interests and actions. This implied that people were not only interacting with Trump’s own account, but also with other accounts criticizing Trump during the pandemic. This left us questioning whether the influencers, along with the users interacting with them, were against the Trump administration in general or how Trump responded to the COVID-19 crisis. Since these accounts had a political interest, our results imply that people who were against Trump framed discussions of the pandemic to emphasize Trump’s poor management of COVID-19 in the U.S., using the same medium Trump used for posting updates about it. This political debate has concerning implications for health communication, especially during the pandemic.

Next, we looked into the remaining personal accounts that were not public figures (@anonymized_a, @anonymized_b, @anonymized_c, and @anonymized_d) and found that the emerging theme from these users' tweets is that these accounts were also critical of the U.S. government’s pandemic response. Most of these personal accounts also amplified news sources in addition to providing their personal views about how the government was handling the pandemic. For instance, @anonymized_a shared political news content from other sources, such as Fox News and MSNBC. One of the users (@anonymized_b) used humor in the form of memes to criticize government responses to the pandemic. Another user, @anonymized_d, shared a persuasive argument on how it is important to stay safe, along with personal commentary criticizing the poor performance of the government to the detriment of public safety. A tweet from @anonymized_d stated the current number of COVID-19 cases in the U.S., then argued that this meant that efforts to reopen only considered economic consequences rather than safety. The user concluded the tweet by claiming those in charge of reopening the economy did not care about people’s lives.

Finally, the identified influential accounts only included three official news agencies. Although @AP (Associated Press) has the highest number of followers, it received the lowest number of interactions compared with the other news accounts. @thehill (The Hill), which is a political news account, received the highest number of interactions of the three news accounts, while @Newsweek (Newsweek) had the lowest number of followers out of the three news accounts and had the second highest number of interactions out of the news accounts (with a ranking of 4 out of 11 overall). The news accounts posted informative updates on COVID-19 cases. During the data collection time, news accounts gained interactions on tweets that were mostly about the number of infected people with COVID-19 or Trump’s decisions. Below, we present descriptive characteristics, themes, and patterns identified based on our in-depth analysis of the tweets.

Most of the Identified Influencers were Popular Accounts. Based on Table 1, all influencers, regardless of other account characteristics, had accounts that were created over seven years prior to the COVID-19 pandemic. This was the only shared characteristic between all the identified influencers. The number of followers for each identified source were reported during the data collection time. From Table 1 we can summarize that the identified sources had an average of 10,495,420 followers (median = 987,380). This could suggest that all the identified influencers were popular accounts on Twitter;

however, Figure 2 illustrates heavy skewness in the follower counts which affected the mean significantly. We found that @anonymized_b, @anonymized_c, and @anonymized_d, accounts with fewer than 5000 followers, received high attention from users that contributed to the high interaction counts. For example, @anonymized_b, a personal non-verified account with the lowest number of followers (660) out of all the influencers, posted two tweets during the data collection period that went viral and received over 8000 retweets. The tweets included the same cartoon meme image with different captions on the tweets criticizing one state's response to COVID-19. The text accompanying the image mocked a governor for reopening the state while encouraging close contact without masks, only to act surprised when COVID-19 cases increased.

The two meme tweets received much more engagement than the user's other tweets during the same time period that were not about COVID-19 but focused on other social and political issues.

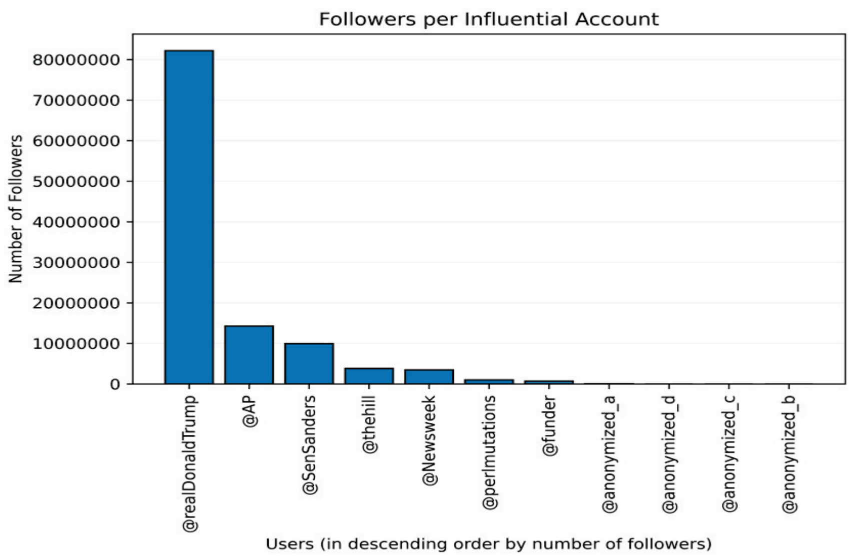

Fig. 2. Follower counts of the identified influencers.

Seven Out of the Eleven Influential Sources were Verified Accounts. Verified accounts constituted the majority of influential accounts in our sample and included elected government officials, news organizations, and other public figures in entertainment and politics. The four accounts that were not verified appeared to be personal accounts run by individuals who are not acting in any official capacity. Table 1 shows that 7 out of 11 information sources were verified accounts. This aligned with our expectations, since most of the listed accounts were either public figures, such as @realDonaldTrump, @funder, @perlmutations, and @SenSanders, or accounts for major news agencies such as @thehill, @Newsweek, and @AP. On the other hand, we found personal accounts for private individuals, such as @anonymized_a, @anonymized_b,

@anonymized_c, and @anonymized_d, were not verified, but people interacted heavily with their COVID-19 tweets. While we might expect that verified accounts with the most followers might also receive the most interactions, this was not always the case. Although the accounts that received the most interactions were verified, there were also verified accounts that received relatively fewer interactions. For example, @AP and @SenSanders were both in the bottom half of interactions received, with @AP ranking 8 out of 11 and @SenSanders receiving the lowest number of interactions of all 11 influencers.

Finally, when examining profile descriptions, the verified influential accounts tended to list their official job positions and affiliations. On the other hand, while two of the non-verified influential accounts also included professional information, only one included specific information about professional affiliation, while the other alluded to be a healthcare worker without adding any personally identifiable information. The other two non-verified accounts had the shortest profile descriptions of all of the influencers and also contained the least personal information about the users.

4.2 Interactions Received by Influencers Varied Based on Account Type

We found that among the three forms of interactions (mentions, retweets, quote tweets), there was a tendency to use mentions rather than using other forms of interactions with an average of 46.36 for mentions, 28.78 for retweets, and 37 for quote tweets. Mentions can include direct replies to one's own tweet, indirect replies (which notify a user of a reply to a different user's tweet), and any other mentions in the tweet (e.g., including a user's @ username in the body of a tweet to draw their attention to it). Retweets share another user's tweet to one's own profile, while quote tweets allow users to retweet other content while adding their own commentary to it. Different forms of interactions were found to vary based on the account type.

Another pattern that can be seen in Figure 3 was that @thehill, @Newsweek, and @anonymized_a have many more quote tweets than retweets or mentions, but for the other accounts (except @realDonaldTrump), they show the reverse pattern, with relatively more mentions and retweets compared to quote tweets. It was expected to find more retweets than quote tweets since retweeting takes less effort than quote tweeting. For the three accounts that received the most quote tweets, this could suggest more people were not only sharing their content, but also adding their own commentary (whether agreeing or disagreeing, such as in the case of a controversial tweet that is shared for the purpose of either supporting or opposing it).

Another major finding was that although the two political authority accounts (Trump and Sanders) were verified and popular accounts with a high number of followers (82,193,259 and 9,946,708, respectively), the types of interactions they received were entirely different. Figure 3 illustrates the number of interactions for each identified influencer per interaction type. One interesting pattern that Trump's account received the highest number of mentions among all accounts. Twitter users sought Trump's account for updates and news about the coronavirus; however, these users tended to mention Trump (by mentioning his username in a tweet or replying to his tweets) rather than using other forms of engagement. On the other hand, Twitter users used a relatively equal number of retweets and mentions to engage with @SenSanders on tweets about COVID-19.

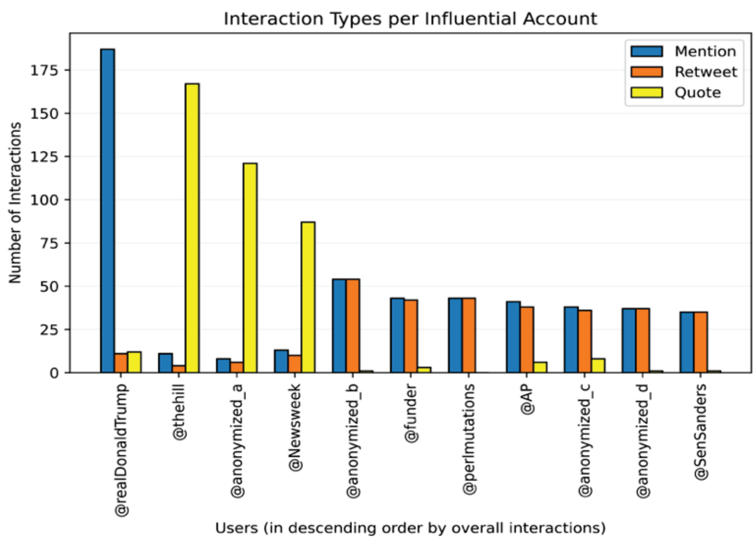

Fig. 3. Interactions rates sent to the influential sources of information on Twitter.

Overall, the major interaction patterns can be summarized in three points. First news-focused accounts (official organization accounts and @anonymized_a, which is a personal account that frequently shares news content) have the highest proportion of quote tweets compared to other interactions (with the exception of @AP). Second, unlike the other influential accounts, @realDonaldTrump received many more mentions compared to the number of retweets and quote tweets received. Third, all other accounts received about equal numbers of retweets and mentions, which made up the majority of their interactions, and very few quote tweets.

In sum, we discussed in this section that mentions were the most common type of interaction among users overall, yet the relative proportion of mentions to other interactions varied across influencers. We also found that some non-verified users with a smaller number of followers gained visibility through the content they shared, but verified accounts were more common for our identified influencers. In the following section, we discuss broader implications of our study.

5 Discussion

5.1 Social Media as a Source of Information during COVID-19

The COVID-19 pandemic demonstrates the evolving role of social media in public health communication. The most influential sources of information in the dataset included political authorities, news organizations, public figures, and personal accounts. By network analysis we found that most users interacted with other users rather than receiving interactions. This pattern of engagement was expected because people experienced a significant level of uncertainty and anxiety during the outbreak (Steinert et al., 2020). This uncertainty has persisted over time, unlike previous crises where uncertainty is mostly resolved within a few days. In addition, with COVID-19, the situation was ambiguous at all levels from public health authorities to the general public. This high degree of uncertainty can motivate people to speculate, which can affect people's ability to judge the veracity of news (Karduni et al., 2018). Above this uncertainty, certain nonpharmaceutical interventions, such as stay-at-home orders and physical distancing policies, have made the use of social media more crucial than before to connect with others in addition to staying informed about COVID-19 updates. This study showed a relatively high number of mentions, which suggests that people may have been seeking to resolve their uncertainty by replying to the influencers' tweets, as well as connecting with other users to share information with them. The dense network engagement denoted that people absorbed information and decided to diffuse the shared tweets about the coronavirus which had two sides. The positive impact of people's engagement in social networks can be seen in campaigns to help provide awareness, food, and masks for people (Al-Dmour et al., 2020). On the other hand, there was a negative impact of people's dense engagement which made them vulnerable to misinformation, political polarization, and strategic manipulation (Mian et al., 2020). Therefore, it was important to identify who the Twitter accounts people interacted with the most and discuss these interactions with more scrutiny.

5.2 COVID-19 and Political Polarization on Social Media

When examining influential sources of information about COVID-19 on Twitter, we found that users were drawn to controversial politically oriented content, demonstrating the polarization of COVID-19 communication. In fact, our results showed that during the time period we examined, U.S. President Donald Trump's Twitter account was the most influential source of information in our dataset. Additionally, our analyses revealed the overwhelmingly political nature of COVID-19 discussions on Twitter. Because several of the influential users we identified were either political authorities or otherwise engaged in political activity and commentary, especially in a partisan manner, our results may raise concerns about the impact of political ideology on the type of information that is shared about COVID-19. For instance, one of the influential users in our dataset, @funder (Scott Dworkin), received significant interactions in response to tweets harshly criticizing another influential user in our dataset, @realDonaldTrump (Donald Trump). Emerging research has found political ideology predicted perceptions of COVID-19 and belief in COVID-19 misinformation (Calvillo et al., 2020). Future research should continue to investigate the effects of political ideology on the types of information shared during the pandemic, along with polarization of users who engage with this information.

Additionally, the impact of politicized health communication on both social media behavior and public health outcomes needs to be examined further. For example, a recent study by Yaqub (2020) on tweets by Donald Trump over a 159-day period from January 24 to June 30, 2020 found a correlation between the sentiment of Donald Trump's tweets and the number of COVID-19 cases in the United States. They ascertained that the positive tone of President Trump's tweets decreased as the number of COVID-19 cases increased. An area of research that merits further exploration, and to which similar methodologies may be applied (sentiment analysis, statistical methods), is the investigation of the relationships between the sentiment of prominent sources of information regarding certain COVID-19 mitigation measures and public sentiment about those measures. A specific timeframe, source, and social media platform may be selected for study.

Finally, on January 8, 2021, Twitter announced the permanent suspension of @realDonaldTrump due to "risk of further incitement of violence" following the storming of the U.S. Capitol on January 6, 2021[3]. Future work should investigate how the suspension of Trump's account and the transition to the newly elected President Biden affect COVID-19 information influencers.

5.3 Heterogeneity of Influencers and Implications for Mechanisms of Influence

One noteworthy finding was that consistent with prior findings (e.g., Gräve & Greff, 2018), the high number of interactions received by the influencers in our study cannot be attributed to follower counts alone. This sheds light on the importance of differentiating between the impact of the number of followers and other factors involved in influence. Overall, we observed that during the time period of data collection, the most influential users discussing COVID-19 comprised both verified public figures with a large following, as well as smaller personal accounts. In the latter case, it is possible that the interactions received by these personal accounts were anomalous compared to their typical engagement (e.g., due to receiving a burst of interactions in response to a viral tweet), whereas we would expect to observe the verified influencers receive a relatively high number of interactions in general. This suggests there may be different mechanisms of gaining influence for these different account types. Because we examined interactions within a 24-hour time period, we were able to detect different types of influential users in our dataset.

5.4 Limitations and Future Work

Our analyses focused on influential sources of information during a short period of time, so we analyzed Twitter user interactions over a duration of 24 hours. This means that the results are not reflective of larger periods of time for user interactions and may not generalize to other social media platforms. For future work, researchers can investigate influencers across larger periods of time and across other social media platforms to have a more comprehensive view of influential sources of information during the pandemic. Our analyses also focused on English-language tweets based in the U.S.

[3] https://blog.twitter.com/en_us/topics/company/2020/suspension.html

Therefore, the interactions and political polarization we observed are only applicable to users in the U.S. Future work can seek to identify the degree to which political polarization related to COVID-19 is occurring in other geographic regions.

6 Conclusion

In this study, we identified influential sources of information during a one-day period of COVID-19 discourse on Twitter. From this, we examined account features to characterize these influential users. During this investigation, we discovered the content of information being shared during this time focused heavily on politically charged discussions. Our findings illustrate the ongoing need to understand the impact of social media interactions and political polarization on public health outcomes.

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