Discussion, news information, and research sharing on social media at the onset of Covid-19

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Abstract

Social media platforms provide valuable insights into public conversations. They likewise aid in understanding current issues and events. *Twitter* has become an important virtual venue where global users hold conversations, share information, and exchange news and research. This study investigates social network structures among *Twitter* users with regard to the Covid-19 outbreak at its onset and its spread. The data were derived from two *Twitter* datasets by using a search query, "coronavirus," on February 28th, 2020, when the coronavirus outbreak was at a relatively early stage. The first dataset is a collection of tweets used in investigating social network structures and for visualization. The second dataset comprises tweets that have citations of scientific research publications regarding coronavirus. The collected data were analyzed to examine numerical indicators of the social network structures, subgroups, influencers, and features regarding research citations. This was also essential to measure the statistical relationships among social elements and research citations. The findings revealed that individuals tend to have conversations with specific people in clusters regarding daily issues on coronavirus without prominent or central voice tweeters. Tweets related to coronavirus were often associated with entertainment, politics, North Korea, and business. During their conversations, the users also responded to and mentioned the U.S. president, the *World Health Organization* (*WHO*), celebrities, and news channels. Meanwhile, people shared research articles about the outbreak, including its spread, symptoms related to the disease, and prevention strategies. These findings provide insight into the information sharing behaviors at the onset of the outbreak.

Keywords

Covid-19; Coronavirus; *Twitter*; *NodeXL*; Altmetrics; Social media; Social networks; Social network structure; News information; Research sharing.

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1. Introduction

The coronavirus disease (Covid-19) has rapidly spread around the world since it was first detected in December 2019. The number of positive cases and deaths from the disease has increased throughout 2020 and early 2021 (**Peng**; **Ho**; **Hota**, 2020; **Rasmussen** *et al.*, 2020; *World Health Organization*, 2020). According to *Johns Hopkins University*'s Covid-19 dashboard by the *Center for Systems Science and Engineering* (2021), the total confirmed cases as of April 29th are already over 430 million. Additionally, there are more than 3.15 million deaths around the world.

Social media platforms can offer insights into the spread of infectious diseases, its management, and surveillance (**Mandeville** *et al.*, 2014). In 2010, researchers recognized *Twitter* as an effective means to identify public perceptions in emergencies following the spread of the H1N1 pandemic (**Chew**; **Eysenbach**, 2010). In a review of literature on the "viral power" of *Twitter*, **Kullar** *et al.* (2020) concluded that:

> "Particularly in infectious diseases, where bacteria and viruses can enter and exit borders anytime anywhere, global real-time information about outbreaks and AMR for both clinicians and the public is critical. *Twitter* has no hierarchy or barriers, serves as a conduit for global collaboration, and is a way for both HCPs and the public to 'social'ize on healthcare topics, if used appropriately" (Conclusions).

Twitter has become the most popular form of social media for health care communication (**Pershad** *et al.*, 2018). In this study, the researchers explore information sharing behaviors by using social network analysis in tracking public cognition about Covid-19. They likewise analyze trends on disease outbreaks in their early stages, effective prevention strategies, and emergent information networks.

> This study explores information sharing behaviors by using social network analysis in tracking public cognition about Covid-19

1.1. Background and context

Information about the Covid-19 outbreak spread rapidly on social media (**Cohen**, 2020). Researchers found that social media served an important function in helping people learn about issues through information sharing and discussion despite concerns that this communication medium may trigger public fears and diffusion of misinformation (**Dwyer**, 2019; **Patel** *et al.*, 2020; **Pershad** *et al.*, 2018; **Vosoughi**; **Roy**; **Aral**, 2018). This feature of social media led to the emergence of issue-specific social networks that examine public opinions and interactions between people and groups (**Salathé**; **Khandelwal**, 2011). These social networks can become essential for researchers during a crisis because connections are modeled to understand and monitor public knowledge, outbreaks, and the severity of symptoms (**Park**; **Chung**, 2020; **Park**; **Park**; **Chong**, 2020; **Schmidt**, 2012).

Recently, **Patel** *et al.* (2020) performed a study mapping of *Twitter* activity against the number of deaths during the Covid-19/SARS-CoV-2 outbreak. They concluded that social media platforms

> "can be crucial to spread research with rapid scrutiny, which may also impede the degree of misinformation."

Similarly, **Moukarzel**, **Rehm**, & **Daly** (2020) followed up on their research into breastfeeding information on *Twitter*. They found that a vast majority of tweets about Covid-19 contained current scientific guidance, updates from researchers about relevant studies, and community advocacy and support. Only 6% of tweets contained misinformation or commercial redirections.

Twitter may be a valuable social network data source in tracking public cognition and conversations about infectious disease outbreaks and effective prevention strategies (**Aiello**; **Renson**; **Zivich**, 2020). *Twitter* is often used to exchange medical news during pandemics. This is true, especially when people observe social distancing in the real world (**Park** *et al.*, 2020). Individuals are informed of up-to-date medical information, and they generate sentimental dialogue on emergent social networks. Whenever accurate information is shared, network discourse also helps balance out the limitations of traditional medical data sources. This is crucial because these sources can underrate the actual representativeness of the outbreak information (**Aiello** *et al.*, 2020). According to **Pershad** *et al.* (2018), the intersection of healthcare and social media can include disseminating health updates, sharing information about diseases, or coordinating relief efforts. These shall help in improving the quality of care for patients. However, they noted that specific guidelines for the use of this information are necessary.

Researchers have questioned the use of *Twitter* data beyond simple counting measures to track ongoing events. **Haustein** *et al.* (2014) noted that it could be a promising source of information for the public because *Twitter* is widely used in science and academic discourse. Following prior research, **Bornmann**, **Haunschild**, and **Patel** (2020) demonstrated that *Twitter* has broader applications that influence public behavior and attitudes toward health policy. Specifically, they hypothesized that research is reaching the people if people in highly affected areas are tweeting about research publications. The results of their study, which layered particular (geographic) data with tweets, showed promising correlations with spaces where the diseases were prevalent. The implications of bringing correct information directly to users are potentially helpful for improving health care surveillance and speeding up response time. It may likewise help in achieving more accurately targeted vaccines. Similarly, big data analysis using social networks provides actionable information that can be useful in identifying needs, providing services, and predicting and preventing crises (**Pershad** *et al.*, 2018; **Raghupathi**; **Raghupathi**, 2014).

1.2. Problem and rationale

This study investigated social network structures among *Twitter* users concerning the Covid-19 outbreak and its spread. Investigating the structure of the public's conversation on *Twitter* during the pandemic helps researchers understand how people communicate with other people about public health. This can support the decision-making of medical experts (**Park** *et al.*, 2020; **Salathé**; **Khandelwal**, 2011) and provides insights regarding information sharing behaviors at the outbreak's onset.

1.3. Research questions

This research addressed two questions about *Twitter*-mediated information sharing behaviors concerning Covid-19.

The first question asked,

> "What are the main characteristics of social networks on *Twitter* about coronavirus? Moreover, what kind of news do *Twitter* users share?"

This question is related to socially disseminated *Twitter* conversations based on the most comprehensive term, coronavirus.

The second question asked,

> "Which research publication dealing with coronavirus receives the most attention from *Twitter* users? Furthermore, how are they related to *Twitter* users?"

In these questions, we identified the most frequently mentioned scientific articles among *Twitter* users and the relationships among these articles.

2. Materials

2.1. Data sources

This study was conducted using two *Twitter* datasets. Both datasets were collected on February 28th, 2020, during a relatively early stage of the coronavirus outbreak.

The first dataset is a collection of coronavirus-related tweets on *Twitter*. The data covered the tweets posted over the past one week before the retrieval date. *NodeXL* (**Smith**, 2015) was utilized for this process. *NodeXL* is software used to conduct social network analysis and visualization. *NodeXL Pro* (*Social Media Research Foundation*, 2021a) enables users to retrieve tweets (i.e., posts that tweeters post on *Twitter*) with a search query, related hashtags and words, and tweeters through the use of *Twitter* API. It visualizes graphs of the relationships among tweeters (nodes) in terms of social-relational information. These include replies-to (i.e., replying to another tweeter who receives a tweet), mentions (i.e., referring to a tweeter in a tweet), and self-loops (i.e., tweeting to oneself) (*Twitter, Inc.*, 2020. Also, see Figure 1 and Table 1 for more detailed definitions).

The search query for retrieving tweets was "coronavirus." While other interchangeable terms, such as "Covid-19" and "SARS-CoV-2," could also have been considered, we selected "coronavirus" since it was more commonly used in academic articles during the retrieval period. For instance, we searched for the frequency of the three terms in *Google Scholar* ranging until 2019 and obtained the following numbers:

- about 398,000 results included "coronavirus";
- about 275,000 results for "Covid-19"; and
- 14,900 results for "SARS-CoV-2".

Therefore, we chose "coronavirus" as a representative search query when we collected the data. As a result, the total nodes of the data were 20,061. The total edges (i.e., connections between nodes) were 24,876.

The second dataset contained tweets citing scientific research articles on the same search query, "coronavirus." The dataset was downloaded from *Altmetric.com* using a search engine interface for the search query (**Priem**, 2014), as we commissioned *Altmetric.com* to retrieve the needed data. Using altmetrics is a complementary approach in evaluating the impact of research articles on social media. The traditional research evaluation method considers the number of received citations in published journal articles' references within specific year periods. Conversely, altmetrics values social media as a channel to spread out the research articles among a wider range of users. It likewise includes the mentions of research articles as an indicator to evaluate the studies' impact (**Haustein** *et al.*, 2014; **Park**; **Youn**; **Park**, 2019; **Robinson-García** *et al.*, 2014). *Altmetric.com* provides altmetric data of research articles mentioned on diverse social media sources such as *Twitter*, *Facebook, Mendeley, YouTube, F1000* reviews, blogs, news, and other sources.

> While conversations involving celebrities and politicians appeared conspicuously, health and social discussions on coronavirus were more observed in G1

Twitter is one of the most commonly used sources. Altmetric.com collects real-time tweets that include mentions of research articles with a search query. It then calculates the altmetric attention score, which is

> "a weighted count of the amount of attention for a research output from a variety of sources" (**Elmore**, 2018, p. 252).

In the present study, the publications' identification information was tracked to collect the tweets that mentioned of the coronavirus-related research publications. These include the DOI, ISBN, National Clinical Trial ID, URI, PubMed ID, PubMedCentral ID, ADS Bibcode, arXiv ID, and SSRN (*Altmetric*, 2021; **Elmore**, 2018; **Robinson-García** *et al.*, 2014). As a result, we obtained 7,269 retrieved tweets (7,200 users).

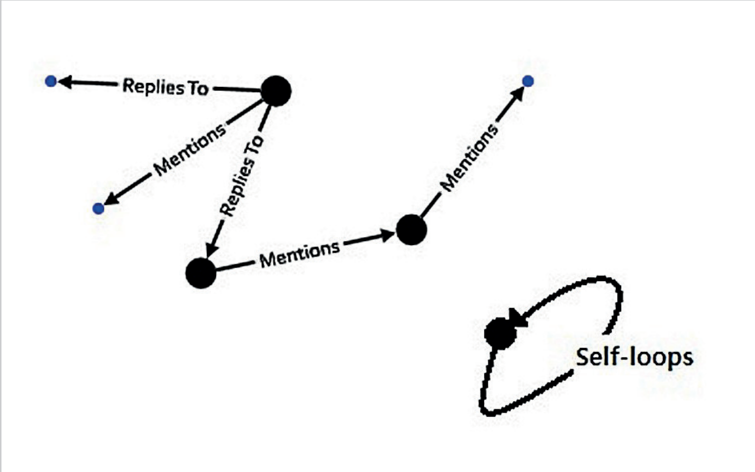

Figure 1. A mechanism of *Twitter* analytics about the relationships among tweeters (nodes) in terms of replies-to, mentions, and self-loops, obtained from *Social Media Research Foundation* (2021a). These were further modified.

2.2. Data analysis

The first dataset comprises a typical social network on *Twitter*. Individuals who post (i.e., tweeters) are considered nodes in the social network when it comes to social network analysis terminology. The cases are referred to as links or edges when the nodes are replied to or mentioned in tweets. A formal social network analysis was conducted using *NodeXL* to analyze this data. To identify tweeters who played as brokers to connect other tweeters in the network, betweenness centrality was computed and presented along with the results of replied-to and mentions for finding influential tweeters (**Borgatti**, 2005). Table 1 includes the indicators and explanations used in the analysis of this dataset.

The second dataset is similar to a 2-mode network matrix. The columns refer to the titles of the collective publications about the coronavirus. At the same time, the rows in the matrix represent information about publications (altmetric attention score). It likewise contains information on tweeters who shared the tweets citing the publications (i.e., the number of followers and the number of followings). This dataset shows a list of the coronavirus-related articles that tweeters cited, along with their information.

On a close examination of the 7,269 tweets conveying the citations of research publications in the second dataset, 2,601 tweets were identical as they were retweeted multiple times. There were no overlapped tweeters from the database of *NodeXL* and that of *Altmetric.com*. That is, the people who mentioned "coronavirus" in their tweets were different from those who shared research articles whose titles contained the term "coronavirus." These 7,269 tweets were compared with the first dataset and then converted into a separate excel file to list the articles mentioned in the 7,269 tweets according to social-relational information and altmetric attention score. Accordingly, the most cited articles were sorted. The further investigation explored the citer (i.e., tweeter who mentioned articles on *Twitter*) information of the articles, including tweeters (i.e., those who posted the tweets), their followings (i.e., those whom the tweeters follow), and their followers (i.e., those following the tweeters). Also, the altmetric attention score was measured, which is an indicator for tracking weighted attention to research items cited on social media channels (**Elmore**, 2018). *R version 3. 6. 1* (*R Core Team*, 2019) was used to test relationships between the variables of the datasets. A Spearman rank correlation was performed using the function cor.test( ) with the option method = "Spearman."

> Frequently mentioned news was related to political debates, tracking coronavirus cases, vaccine development, and businesses

3. Covid-19 discussion and news sharing

3.1. Numerical summary of the network

Table 1 displays a numerical results summary. It comes with indicators and explanations of the social network structures of the tweeters who discussed coronavirus. The numerical summary includes simple numbers of the indicators and ratios to compare the differences in results between indicators.

In the results, a total of 20,061 tweeters posted 5,901 tweets and 12,919 retweets. The ratio of retweets to tweets was 2.19:1. This means that a tweeter posted 2.19 times more retweets than tweets. The number of mentions was over two times that of replies-to. The ratio of replies-to to tweets was 0.17:1. On the contrary, the ratio of mentions to tweets was 0.35:1. This means that a tweeter replied to other tweeters 0.17 times per tweet and mentioned someone else 0.35 times per tweet. Meanwhile, the finding regarding self-loops showed that 5,957 tweets started and ended with the same tweeters. About 0.3 self-loops were generated per tweeter. This means that each tweeter posted a tweet to oneself 0.3 times on average. The number of total edges was 24,876, of which about 87 percent were unique edges, while only 13 percent were duplicate edges. This result indicates that a majority of the conversations occurred between respectively paired tweeters.

Individuals were more likely to talk about issues regarding Covid-19 in clusters without the influence of prominent or central voice tweeters

Looking into the social network structures in terms of grouping, the reciprocated vertex pair ratio of the total tweeters was 0.00067. Moreover, the reciprocated edges ratio of the total edges was 0.00134. The graph density value was not that high, being 4.45. However, the modularity of this network was relatively high, having a value of 0.77. This means tweeters belonging to the same subgroups had high internal fitness and were strongly connected. Furthermore, 4,372 connected components were found with 10,108 of maximum vertices (tweeters) value and 14,398 of maximum edges. On the one hand, 1,695 single-vertex connected components were discovered. The average geodesic distance value among tweeters was 9.05, and the maximum geodesic distance value was 36.

Table 1. Indicators, explanation, and summary of results of social network structures

Indicators	Descriptions	Results
Nodes (tweeters)	*Twitter* users, tweeters.	20,061 tweeters
Tweet	A posting that tweeters post on *Twitter*.	5,901 tweets
Retweet	Reposting a tweet. The result value includes the cases of retweets only, not tweets.	12,919 retweets
Replies to (ratio of replies-to to tweets)	Replying to another tweeter who receives a tweet. The result value indicates the number of cases of the "replies to" between tweeters.	999 (0.17:1)
Mentions (ratio of mentions to tweets)	Referring to another tweeter in a tweet. The result value indicates the number of cases of the "mentions" between tweeters.	2,081 (0.35:1)
Mentions in retweet	Referring to another tweeter in a retweet.	2,976
Total edges	Total edges mean the total number of connections, or conversations, where multiple conversations between the two tweeters are all counted. Total edges indicate either (a) the sum of tweet, retweet, mentions, replies to, and mentions in retweet or (b) the sum of unique edges and duplicate edges.	24,876
Unique edges (ratio of unique edges to total edges)	Unique edges are the number of conversations where multiple conversations between tweeter A and tweeter B are counted only once.	21,579 (0.87:1)
Duplicate edges (ratio of duplicate edges to total edges)	Duplicate edges count the total number of multiple conversations between two tweeters.	3,297 (0.13:1)
Self-loops (ratio of self-loops to tweeters)	Posting a tweet to oneself. Tweeters in self-loops are isolators in a network. The result value indicates the number of cases of the self-loops.	5,957 (0.30:1)
Reciprocated vertex pair ratio	Percentage of tweeters that build a reciprocal relationship as two tweeters are connected with each other.	0.067%
Reciprocated edge ratio	Percentage of conversations between two tweeters that have a reciprocal relationship with each other.	0.134%
Graph density	It measures the number of edges among a group of tweeters over the total possible number if everyone is connected to everyone. The higher the graph density value is, the more tweeters are connected.	4.45
Modularity	It measures the internal fitness of a set of tweeters who form a group created in a clustered network. The modularity value 1 indicates the most social relationships among the tweeters in a group, while 0 means the least social relationships.	0.77
Connected components	A component is composed of all interconnected tweeters. The connected components value is the number of the components in a network.	4,372
Single-vertex connected components	Tweeters that have no connections with other tweeters.	1,695
Maximum vertices in a connected component	The number of tweeters in the largest connected component.	10,108
Maximum edges in a connected component	The number of total edges in the largest connected component	14,398
Maximum geodesic distance (diameter)	The longest *shortest path* (a minimum number of connections that tweeter A needs to pass through other tweeters to reach tweeter B) of edges	36
Average geodesic distance	Average value of geodesic distance	9.05

Note. The indicators and descriptions in this table were obtained from the *Social Media Research Foundation* (2021b).

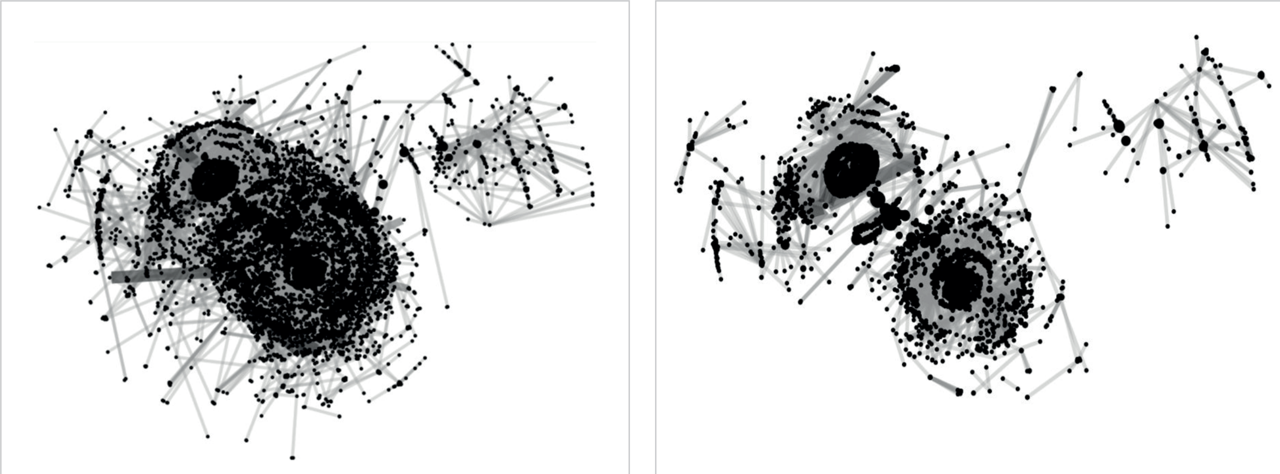

Figure 2. The social network structures of tweeters. The left graph is the network among 18,977 tweeters after excluding 5,901 tweets. The right graph is the network among 5,002 tweeters after filtering out 3,275 retweets with the mean value of the total retweets.

3.2. Visualized network of subgroups and top words

Social network structures of tweeters in the discourse about coronavirus were visualized utilizing *NodeXL*. First, Figure 2 shows the sub-structures of the entire social networks with a reduced number of tweeters to make the networks more visible. These graphs, which were visualized using the Harel-Koren Fast Multiscale layout algorithm (**Clauset**; **Newman**; **Moore**, 2004), show the entire pictures of the social network structures in two versions:

(1) The left graph is the network among 18,977 tweeters after excluding 5,901 tweets; and

(2) The right graph is the network among 5,002 tweeters after filtering out 3,275 retweets with the mean value of the total retweets.

The tweeters remained invisible when the number of times of being retweeted was less than the mean value of the total retweet counts. In doing so, we were able to uncover two sub-clusters within a tightly-knit core group.

Next, Figure 3 displays a zoomed-in visualized social network structure of all tweeters by groups, or clusters. The groups in the networks were generated through the Clauset-Newman-Moore cluster algorithm and visualized using the Harel-Koren Fast Multiscale layout algorithm (**Clauset** *et al.*, 2004). Nodes were depicted bigger in proportion to their betweenness centralities, and top words used in tweets in each subgroup were extracted by frequency.

The overall landscape of the network configuration revealed that people's initial response to coronavirus was similar to other issues that they encountered daily. We supposed that there would have been polarized clusters of people around organizations such as the *WHO* if the disease was recognized as a global pandemic. We would also have divided them

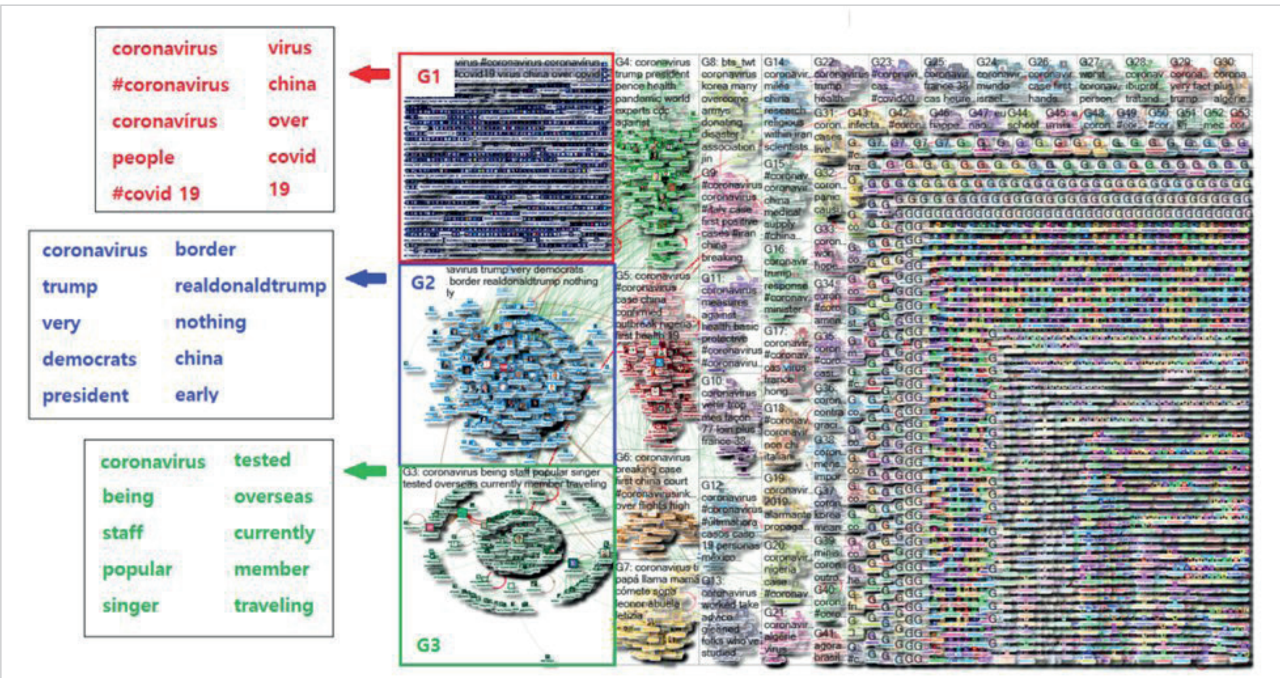

Figure 3. A visualized social network structure of tweeters in groups. Top words (sorted by frequency) used in the biggest groups, G1 (Group 1), G2, and G3, are highlighted.

into different opinions by forming polarized clusters. Our hypothesis was based on examples of this behavior presented in recent studies (**Moukarzel**; **Rehm**; **Daly**, 2020; **Patel** *et al.*, 2020). However, as shown in the left graph in Figure 2, only two small and medium-sized groups with few influential tweeters were evident. Thus, there were a few small groups in the center that were chatting. However, there were no central voices or influences.

> *Twitter* users mainly showed interest in discussing links between the pandemic and entertainment, politics, North Korea, and business

It is important to note that there is a qualitative, interpretive element to network analysis. As demonstrated by **Chung**, **Biddix**, and **Park** (2020), reviewing large-scale network data, including textual components, can be strengthened by creating researcher-informed interpretations of the data. This was likewise used in this study. For the present study, we randomly reviewed data to ensure the source text matched the network findings. This constructivist activity also aids in building "confirmability" by checking and verifying that data themes and clusters match the text. **Pershad** *et al.* (2018) advocated a similar approach in their study about social media use in medicine.

A closer look at the highlighted clusters reveals some interesting insights. A total of 2,749 groups were identified. The first group (Group 1, or G1) had the most tweeters (1,695 tweeters). On the contrary, the least number of tweeters (two tweeters) belonged to the groups between G1,050 and G2,749, respectively.

Table 2 shows a list of the ten largest groups. We looked into the first three largest groups in this section, as was likewise briefly seen in Figure 3. Specifically, while conversations involving celebrities and politicians appeared conspicuously, health and social discussions on coronavirus were more observed in G1. The primary feature of G1 was that it had a much denser form of mass interactions than other areas in the network. People were discussing the occurrence, spread, and coping mechanisms with respect to the coronavirus, while citing reliable resources such as bbc.co.uk, washingtonpost.com, and reuters.com. In G2, people were debating about the coronavirus by relating preparedness and readiness to deal with the pandemic. Within this, they talked about President Trump's speech and other U.S. political and economic issues. G3 showed a broadcasting station structure. This group centered on influential tweeters. Here, people focused on donations from Korean celebrities, such as *BTS*, and the cancellation of their events in Korea. Compared with G3, G2 had a much more inter-people dialogue about coronavirus. In other words, the concentration of a hub in G2 was relatively weak. Furthermore, one can see several small groups in the center of the network structure as satellite dialogue groups derived from G1, G2, and G3. To summarize, during the last week of February 2020, there was a perception among tweeters that coronavirus was a threat to human health. It was causing social fear at that time. However, the public's interest was much higher in entertainment, politics, North Korea, and business.

Table 2. The number of tweeters, total edges, and top words in subgroups

Subgroups	Tweeters	Total edges	Top words (frequency in parenthesis)
G1	1,695	1,864	coronavirus (1,238), #coronavirus (462), coronavírus (92), people (78), 19 (65), #covid19 (64), virus (62), china (58), over (56), covid (55)
G2	1,663	2,875	coronavirus (2,104), trump (1,161), very (621), democrats (535), president (499), border (455), realdonaldtrump (427), nothing (381), china (345), early (344)
G3	1,650	2,008	coronavirus (2,003), being (1,191), staff (1,125), popular (971), singer (971), tested (971), overseas (971), currently (914), member (894), traveling (894)
G4	711	971	coronavirus (816), trump (536), president (167), pence (161), health (154), pandemic (149), world (129), experts (128), cdc (125), against (113)
G5	603	947	coronavirus (493), #coronavirus (220), case (185), china (137), confirmed (110), outbreak (104), nigeria (97), first (89), health (85), 19 (82)
G6	367	480	coronavirus (409), breaking (166), case (154), first (133), china (116), court (101), #coronavirusinkenya (99), over (96), flights (94), high (77)
G7	351	388	coronavirus (398), ti (117), papa (111), llama (111), mama (111), cómete (111), sopa (111), leonor (111), abuela (111), letizia (111)
G8	267	308	bts_twt (256), coronavirus (248), korea (146), many (123), overcome (119), armys (95), donating (91), disaster (80), association (80), jin (79)
G9	252	442	#coronavirus (198), coronavirus (197), #italy (119), case (55), first (51), positive (43), cases (42), #iran (41), china (40), breaking (37)
G10	248	270	coronavirus (270), venir (72), trop (72), mes (70), façon (70), 77 (70), loin (70), plus (67), france (57), 38 (55)

3.3. Top news sources

Extended from the above results regarding the clusters and words, this section investigates the frequently shared new sources. This is essential to see what information people were more specifically interested in (see

> The more individual tweeters shared research publications, the more citations those publications received on *Twitter*

Table 3). Overall, the frequently mentioned news was related to political debates, tracking coronavirus cases, vaccine development, and businesses. For instance, the news reported the situations of coronavirus cases in North Korea (**Varghese**, 2020), travel restrictions (**Okuoro**, 2020), and the high expectation from the soon-to-developed vaccine (**Jaffe-Hoffman**, 2020). It likewise included tracking positive cases (*BNO News*, 2020) and political issues that involved budget cuts and censoring public health officials in the U. S. (**Benen**, 2020; **Halon**, 2020; **Pollak**, 2020). News about beer sales was also shared, which was written in Japanese and due to the similar name (*Gigazine*, 2020).

Table 3. The frequently shared news sources

News sources	Frequency
Varghese, J. (2020, March). "North Korea's first confirmed coronavirus Covid 19 patient shot dead: report". *International business times.* *https://www.ibtimes.sg/north-koreas-first-confirmed-coronavirus-covid-19-patient-shot-dead-report-40042*	53
Gigazine (2020, February). Corona beer sales company lost 31 billion yen. *https://gigazine.net/news/20200228-coronavirus-corona-beer-search*	44
Okuoro, S. (2020, February). "High court suspends flights from China over Coronavirus". *The Standard.* *https://www.standardmedia.co.ke/business/article/2001362250/court-suspends-flights-from-china-over-coronavirus*	34
Jaffe-Hoffman, M. (2020, February). "Israeli scientists: 'In a few weeks, we will have coronavirus vaccine.'" *The Jerusalem Post.* *https://www.jpost.com/HEALTH-SCIENCE/Israeli-scientists-In-three-weeks-we-will-have-coronavirus-vaccine-619101*	33
BNO News (2020, February). *Tracking coronavirus: Map, data and timeline.* *https://bnonews.com/index.php/2020/02/the-latest-coronavirus-cases*	26
Pollak, J. (2020, February). "AP confirms: Democrats are lying to the public about coronavirus readiness". *Breitbart.* *https://www.breitbart.com/health/2020/02/27/ap-confirms-democrats-are-lying-to-the-public-about-coronavirus*	25
Benen, S. (2020, February). "Is the White House starting to censor public-health officials?". *MSNBC.* *https://www.msnbc.com/rachel-maddow-show/white-house-starting-censor-public-health-officials-n1144411*	25
Sun, L.; **Abutaleb, Y.** (2020, February). "U.S. workers without protective gear assisted coronavirus evacuees, HHS whistleblower says". *The Washington Post.* *https://www.washingtonpost.com/health/2020/02/27/us-workers-without-protective-gear-assisted-coronavirus-evacuees-hhs-whistleblower-says*	25
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3.4. Top influencers

Table 4 shows the top influencers, obtained using *NodeXL*, in terms of betweenness centrality, replied-to (i.e., tweeters replied to by other tweeters in this section), and mentioned (i.e., tweeters mentioned by other tweeters) in the entire social network structure. Of the top influencers that week, @oh_****, an ordinary user who posted tweets about Korean celebrities, had the highest betweenness centrality. Next, @realdonaldtrump, the account of the U.S. president, ranked second. The account of the *WHO*, @WHO, ranked fifth. Such account was in the hub of the network of people concerned about the spread of coronavirus around the world. This indicates the importance of the *WHO* as an information source for people concerned with coronavirus. The account @bts_twt was ranked sixth. This is an account of a South Korean Pop boy band. This finding indicates that people were asking about celebrities in the coronavirus outbreak's early phase. Users posted tweets to ask about celebrities' performances and donations. The account of a news channel, @CNN, was ranked ninth.

In terms of replied-to, @realdonaldtrump was ranked 1st, followed by @who, news channels (@business, @skysportsnews), and public figures or politicians (@gabbardojoao, @jayinslee, @senwarren, @senrobportman, @sethabramson,

Table 4. Top influencers in terms of betweenness centrality, replied-to, and mentions

Betweenness centrality	Replied-to	Mentioned
@oh_**** (32946285.67)	@realdonaldtrump (113)	@realdonaldtrump (369)
@realdonaldtrump (29749982.92)	@who (25)	@bts_twt (266)
@alima**** (21134257.25)	@business (15)	@vp (248)
@kenwa******** (20040940.31)	@gabbardojoao (12)	@cnn (102)
@who (16435831.96)	@skysportsnews (10)	@rvsmtown (83)
@bts_twt (13383739.19)	@jayinslee (8)	@foxnews (80)
@fmohnigeria (12228889.09)	@senwarren (8)	@who (69)
@confl****** (12147845.99)	@senrobportman (7)	@speakerpelosi (69)
@cnn (10860938.75)	@sethabramson (7)	@layzhang (60)
@guyje*** (10450324)	@lhmandetta (6)	@trish_regan (60)

Note. Betweenness centrality value and frequency for replied-to and mentioned are indicated in parenthesis. The accounts of ordinary people are anonymized for ethical reasons.

@lhmandetta). Regarding the frequently mentioned accounts, @realdonaldtrump got the 1^{st} rank, and @bts_twt got the 2^{nd}. Similar to the lists of betweenness centrality and replied-to, the prominent accounts included @who, news channels (@cnn, @foxnews), and public figures or politicians (@vp, @speakerpelosi, @trish_regan) also including celebrities (@rvsmtown, @layzhang).

> An analysis of public conversations on social media is essential for identifying topics that the global public discusses and understanding how individuals broadcast specific issues

4. Covid-19 research sharing

The converged datasets of social information and altmetric attention score enabled to obtain the most tweeted or retweeted research publications (see Appendix I). The first publication shown on the list was "Update: Public health response to the coronavirus disease 2019 outbreak—United States, February 24, 2020" (**Jernigan**, 2020). Tweeters who cited this article had the highest number of followers and frequently followed other tweeters. This article described the coronavirus outbreak's situation and delivered the latest information on the symptoms. Moreover, it shared knowledge on how to prevent the virus. Other articles shared by the tweeters reported the coronavirus features and spread of the virus during the outbreak's early phase (e.g., **Guan** *et al.*, 2020; **Wu**; **McGoogan**, 2020). Such provided medical experts with information on the virus (**Peng** *et al.*, 2020; **Rasmussen** *et al.*, 2020), and it allowed for the discussion of a deep learning model in assisting medical experts (**Chen** *et al.*, 2020). A study by **Kampf** *et al.* (2020) gained the highest altmetric attention score from all the highly cited articles. This research reviewed studies to provide a direction for disinfecting the coronavirus from surfaces of inanimate objects (see Appendix I for more detailed articles on the list).

Statistical analysis was conducted to test the relationships between the numbers of tweeters, followers and followings of the tweeters, and altmetric attention scores of the 30 most highly cited research articles (Appendix I). Table 5 shows the means and standard deviations for each variable.

Table 5. Mean and standard deviation (SD) for tweeters, followers, followings, and altmetric attention score

	N	Minimum	Maximum	Mean	SD
Tweeters	30	21.00	780.00	119.43	159.38
Followers of the tweeters	30	38929.00	3223033.00	598779.33	799378.50
Followings of the tweeters	30	18624.00	2103643.00	222530.00	388639.88
Altmetric attention score	30	62.00	7477.00	1633.87	1968.09

The result of the Spearman rank correlation test (see Table 6) showed statistically positive associations between tweeters and altmetric attention scores ((28) = .377, $p < .05$) and between tweeters and their followers ((28) = .640, $p < .01$), respectively. This finding implies that research articles shared by more tweeters likely gain higher altmetric attention scores. Moreover, tweeters who shared the articles had more followers. However, no statistical association was found between altmetric attention scores and followers ((28) = .268, $p > .05$).

Table 6. A Spearman rank correlation

	Tweeters	Followers	Followings	Altmetric attention score
Tweeters	1	0.640**	0.805	0.377*
Followers of the tweeters		1	0.700	0.268
Followings of the tweeters			1	0.349
Altmetric attention score				1

*$p < .05$, **$p < .01$ (2-tailed)

5. Discussion and considerations

The present study investigated discussion, news information, and research sharing among *Twitter* users concerning the Covid-19 outbreak and its spread. The key findings from the social network analysis conducted at the end of February 2020 revealed that individuals were more likely to talk about issues regarding Covid-19 in clusters. Such is without the influence of prominent or central voice tweeters. *Twitter* users mainly showed interest in discussing links between the pandemic and entertainment, politics, North Korea, and business. During their conversations, they often responded to and mentioned the U.S. president, the *WHO*, entertainers, and news. Meanwhile, *Twitter* users still paid attention to medical information from research publications. They shared informational articles about the outbreak. Such information includes its spread, the symptoms that come with the disease, and some prevention strategies. Furthermore, the more individual tweeters shared research publications, the more citations those publications received on *Twitter*. However, the researchers did not see any direct association between citations and followers of the tweeters.

An analysis of public conversations on social media is essential for identifying topics that the global public discusses. It is furthermore important for understanding how individuals broadcast information about specific issues. *Twitter* is not a formal channel where experts typically publish authoritative information. However, social media is often used as a platform where the public rapidly shares expert-generated information and expresses reactions. Discourse can reveal how individuals process critical information within and beyond their personal networks. *Twitter* and other social media are widely used for "opinion mining." This is a way by which experts understand public discourse and behavior (**Babafemi**, 2019). This research is then used as decision support for businesses on product production, placement, and refinement.

In the context of a global pandemic, understanding individuals' sharing behaviors can provide medical experts and government officials with public perception and behavioral data for advanced decision-making (**Park** *et al.*, 2020; **Salathe**; **Khandelwal**, 2011). **Kuehn** (2015) noted that social media data concerning health care could provide early warnings about emergencies. However, such data should not be considered at its face value alone. This is where the value of social network metrics, such as centrality, thrive, as they can serve as evaluators of findings.

Concerning decision-making, related research provides some insight owing to the need for longitudinal or qualitative research to investigate the above question. This is true even though immediate links to Covid-19 are not yet evident. For example, **Mousavi** and **Gu** (2015) found that *Twitter* adoption influenced elected officials to vote more consistently with their constituents' interests. They found that U.S. Congressmen took more conservative or liberal voting stances on issues when *Twitter* conversations shifted. With regard to health and wellbeing research, **Graham**, **Cobb**, and **Cobb** (2016) found that despite the proliferation of available information, individuals still make decisions about health in the context of social relations. However, the research by **Moukarzel, Del-Fresno**, **Bode**, & **Daly** (2020) led them to the following finding:

> "Although we found more tweets about peer-reviewed research findings being sent compared with tweets about nonevidence-based lay recommendations, our data suggest that it is the lay public who 'carries the burden' of translating findings into practice and use and as such the translation activity is held in the hands of the informed public, not the research community" (Discussion).

> Social media is often used as a platform where the public rapidly shares expert-generated information and expresses reactions

Following the recent work which evaluated *Twitter* messages with influenza rates in the United States, Michael and Mark considered a wider range of public health applications for *Twitter*. They applied the recently presented Ailment Topic Aspect Model to more than 1.5 million wellbeing related tweets and found mentions of over twelve diseases, including hypersensitivities, weight and a sleeping disorder. They introduced expansions to incorporate earlier learning into this model and apply it to a few assignments: following diseases over time (syndromic observation), measuring behavioral danger components, limiting diseases by geographic district, and breaking down indications and medicine use. They demonstrate quantitative relationships with general wellbeing information and subjective assessments of model yield.

This research has some limitations. One limitation of the research approach concerns the cross-sectional characteristics of the data. When the outbreak was in its earliest stages in the beginning of 2020, both datasets were collected on the same day. This fact may be related to numerous *Twitter* users in the United States (*Statista*, 2021). Moreover, in the United States, the outbreak would not become evident increase for several more weeks. As such, future studies may compare these initial findings to a dataset that is collected a few months later. Additionally, the inclusion of selected text from *Twitter* posts would add voice to these findings. This may further help them be put in context. With a large scale of data, this can create a substantial amount of additional work. However, it may help in contextualizing the individual and collective perspectives on the spread of the virus. Also, the lack of specific spatial data analysis is another limitation of this study. As suggested in recent studies (e.g., **Patel** *et al.*, 2020), spatial data analysis may help interpret trends and differences by user location with regard to the networks' characteristics (research question 1) and research publications' circulation (research question 2). In addition, there were no overlapped tweeters from the database of *NodeXL* and that of Altmetric.com, which we indicated in the data analysis section. Current datasets may not be biggish enough to identify user groups in common. Thus, it must be careful to interpret present results in terms of scale-dependent datasets. However, the present paper is not to measure the magnitude of the errors but to examine the network structures of social and scientific discourse. In this regard, it may be suggested to adapt and apply the procedure of "big data analysis in qualitative style," or "big-qual data," proposed by **Davidson** *et al.* (2019), to the context of the corona epidemic.

Future studies using this method should examine additional discourses about the pandemic. For example, there was public disagreement in the United States on effective strategies to prevent the further spread of the virus (e.g., mask wearing) at the time data were collected for this study. There was also conflicting information about the development of a vaccine. Follow-up studies may investigate more recent discourses on social media regarding pandemic-related issues. Understanding social networks where information is shared through public discourse can help medical professionals, health officials, and researchers in determining the concerns and needs of communities at risk (**Salathé**; **Khandelwal**, 2011). Furthermore, it shall promote an understanding of how health-based information is received, processed, and acted on (**Aiello** *et al.*, 2020).

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7. Appendix

Highly cited (mentioned) research articles on *Twitter*, classified by the number of tweeters who tweeted or retweeted, with the numbers of followers, followings, and altmetric attention scores

Article	Journal	Tweeters	Followers	Followings	Altmetric attention score
"Update: Public health response to the coronavirus disease 2019 outbreak—United States, February 24, 2020"	*Morbidity and mortality weekly report*	780	3,223,033	2,103,643	2,752
"Characteristics of and Important Lessons From the Coronavirus Disease 2019 (Covid-19) Outbreak in China"	*JAMA: Journal of the American Medical Association*	389	1,281,324	493,232	5,425
"Clinical characteristics of coronavirus disease 2019 in China"	*The New England journal of medicine*	313	788,916	437,110	5,058
"Persistence of coronaviruses on inanimate surfaces and their inactivation with biocidal agents"	*Journal of hospital infection*	310	559,749	392,200	7,477
"Coronavirus disease 2019 and influenza"	*JAMA: Journal of the American Medical Association*	245	2,591,784	298,622	1,690
"Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: a prospective study"	*medRxiv*	169	1,023,006	496,353	649
"Estimating the asymptomatic proportion of 2019 novel coronavirus onboard the Princess cruises ship, 2020"	*Euro surveillance*	162	1,386,077	433,842	260
"Mystery deepens over animal source of coronavirus"	*Nature*	161	581,479	274,810	1,737
"Escaping pandora' box—another novel coronavirus"	*New England Journal of Medicine*	127	283,723	189,210	777
"Estimation of the reproductive number of novel coronavirus (Covid-19) and the probable outbreak size on the Diamond Princess cruise ship: A data-driven analysis"	*International journal of infectious diseases*	108	268,702	118,772	369
"Remdesivir and chloroquine effectively inhibit the recently emerged novel coronavirus (2019-nCoV) in vitro"	*Cell research*	96	87,698	89,167	2,856
"Scientists 'strongly condemn' rumors and conspiracy theories about origin of coronavirus outbreak"	*Science*	88	87,353	61,851	745
"Outbreak of a new coronavirus: what anaesthetists should know"	*BJA: The British journal of anaesthesia*	71	109,024	52,023	200
"Steps Nigeria is taking to prepare for cases of coronavirus"	*The conversation*	56	1,001,181	86,412	181
"Coronavirus is a breeding ground for conspiracy theories – here's why that's a serious problem"	The conversation	47	216,692	72,483	89
"Coronavirus infections keep mounting after cruise ship fiasco in Japan"	*Science (AAAS) news*	46	73,369	60,365	1,133
"Phylogenetic analyses of the severe acute respiratory syndrome coronavirus 2 reflected the several routes of introduction to Taiwan, the United States, and Japan"	*arXiv*	40	38,929	45,582	665
"Coronavirus latest: children are as susceptible as adults, study suggests"	*Nature*	36	2,073,618	68,035	4,695
"Network-based drug repurposing for human coronavirus"	*medRxiv*	36	44,365	49,863	62
"Progression, recherche sur les traitements, mortalité: le point sur l'épidémie de coronavirus"	*The conversation*	36	369,092	42,402	151

Article	Journal	Tweeters	Followers	Followings	Altmetric attention score
"The spike glycoprotein of the new coronavirus 2019-nCoV contains a furin-like cleavage site absent in CoV of the same clade"	*Antiviral research*	35	573,905	365,343	552
"Coronavirus infections: more than just the common cold"	*JAMA: Journal of the American Medical Association*	29	396,946	36,132	2,296
"It's now a matter of when, not if, for Australia. This is how we're preparing for a jump in coronavirus cases"	*The conversation*	29	107,010	90,253	241
"Is Covid-19 receiving ADE from other coronaviruses?"	*Microbes & infection*	27	116,756	93,007	291
"Coronavirus disease 2019 (Covid-19) and pregnancy: What obstetricians need to know"	*American journal of obstetrics & gynecology*	27	74,677	48,412	350
"Plans to fight coronavirus must pay attention to the environment"	*The conversation*	25	255,902	38,318	62
"A novel coronavirus from patients with pneumonia in China, 2019"	*New England journal of medicine*	25	59,357	18,624	3,953
"Coronavirus puts drug repurposing on the fast track"	*Nature biotechnology*	25	176,918	30,734	517
"A SARS-like cluster of circulating bat coronaviruses shows potential for human emergence"	*Nature medicine*	24	64,905	62,187	3,525
"Chest CT findings in coronavirus disease-19 (Covid-19): Relationship to duration of infection"	*Radiological Society of North America*	21	47,890	26,913	258

Note. The number of *followers* is the sum of those following the *tweeters* who posted the tweets. The number of *followings* is the sum of those whom the tweeters follow.