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Twitter Networks during the Global COVID-19 Pandemic: Online Networking at the Time of Physical "Social Distancing"

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This longitudinal study examined Twitter networks during the global COVID-19 pandemic in 2020 and 2021. Networks and content from of 87,793 users, 109,204 connections, and 1,655 unique tweets were explored in a multimethod approach of social network analysis and content analysis. The findings show that Twitter users focused on medical issues, politics, and blaming during the COVID-19 pandemic more than other topics and relied more on news and self-information than official sources.

Keywords: COVID-19, coronavirus, Twitter, social networks, global health communication

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Coronavirus and COVID-19 have become global household names in the last three years. People in all corners of the planet have experienced the issues related to the COVID-19 pandemic and hear about it from the news, social media, schools, churches, mosques, offices, grocery stores, and neighbors with millions of people in lockdown or quarantine around the world (Diseko, 2020). The COVID-19 pandemic is an infectious disease caused by the outbreak of novel coronavirus which began in Wuhan, China, in December 2019 (Q & A on Coronavirus, 2020). The most common symptoms of COVID-19 are fever, tiredness, and dry cough. Although around 80% of the people who are infected with the disease recover without needing special treatment, around 1 out of every 6 people who get infected become seriously ill and have difficulty breathing (Q & A on Coronavirus, 2020). As of January 2022, the number of confirmed cases around the world has reached more than 377 million with about 5.6 million deaths (Coronavirus Map: Tracking the Global Outbreak, 2022). The United States has the highest number of confirmed cases (more than 76 million) followed by India (more than 41 million), and Brazil (more than 25 million) (Coronavirus Map: Tracking the Global Outbreak, 2021). In different parts of the world, at certain points, hospitals have been running out of space and supplies and begging for help for more ventilators and masks (Ducharme, 2020).

Social media have become one of the main bridges between people during this period of physical/social distancing. With the free time and lack of outdoor activities, millions of people have turned to social media such as Facebook, Twitter, YouTube, Instagram, Snapchat, Reddit, and TikTok to connect with others, share information, or entertainment. For instance, some people started making DIY videos of how to make hand sanitizer, facemasks, and food (#COVID19: Social media both a blessing and a curse during coronavirus pandemic, 2020). Others have turned to spreading conspiracy theories about the coronavirus and blaming and shaming certain countries and individuals.

This study seeks to examine social media networking and exchange of information among people during coronavirus pandemic in the world. Using social networks and selective exposure theory, the purpose of this study is to explore how people are interacting, sharing information, and supporting each other virtually during the time of physical social distancing. This longitudinal multimethod study is a combination of social network analysis (SNA) and content analysis of Twitter networks during on the COVID-19 pandemic in the world in 2020 and 2021. Twitter is one of the top social media platforms used by people of different ages and backgrounds that does not need very high-speed internet –it is easier for people with low-speed internet to use Twitter as opposed to YouTube and TikTok.

LITERATURE REVIEW

Social Media Use during Health Crisis

Social media are used for different purposes such as social interaction, content production, and sharing information from other sources in addition to social and political gatherings on pages and events (Ankerson, 2015; Himelboim et al., 2013). Online social network structures take shape when people get connected either via direct friendships and following or via content sharing, tagging, and replying to certain topics and issues (Himelboim et al., 2013; Lieberman, 2014; Himelboim et al., 2017). Social media create the environment for free expression and exchange of ideas and information in the forms of creating, sharing, spreading, and reflecting about any topics and problems in their lives (Arceneaux & Johnson, 2013; Barnidge, 2018; Castells, 2015). Twitter has become a virtual hub for political discourse, where people from all walks of life discuss their thoughts and opinions and take part in discussions they are interested (Himelboim et al., 2013). Twitter users have both the in-degree (being followed, being tweeted, being retweeted, being tagged, or being replied to) and out-degree (following, tagging, sharing, and replying to others) ties (Lieberman, 2014). These in-degree and out-degree ties shape the network structure and shows how dense or fragmented a network is.

Studies have shown that for some people, social media have become the main source of information during crisis situations (Jang & Baek, 2019; Ratzan & Moritsugu, 2014). Not only have social media played an important role in spreading awareness about socio-political crisis and natural disasters (Castells, 2015), but also during health crisis such as pandemics (Bulunmaz, 2019). Social media use can be effective for health communication because the interaction process is easier, cheaper, and faster (Bulunmaz, 2019). For instance, social media played an important role in spreading information about the Swine Flu pandemic of 2009 (Szomszor, Kostkova, & Louis, 2011) and the Ebola epidemic in 2014 (Allgaier & Svalastog, 2015; Fung, Fu, Chan, Chan, Cheung, Abraham, & Tse, 2016).

Existing research show that people use a variety of information sources to communicate with each other during health pandemics (Allgaier & Svalastog, 2015; Fung et a., 2016), which are briefly discussed in the following section.

News media. Research has found that during health crisis, people often use social media to spread factual information, mainly from mainstream media. Fung el al. (2016), examined the social media use for the information and misinformation on Ebola after a major Ebola outbreak in 2014. They analyzed data from Twitter and Sina Weibo, the leading Chinese microblog platform from August 8-9 and again seven days after from August 15-16. Their findings showed that most of the information on social media came from the mainstream news media that referred to the information from health organizations.

Official sources. Government officials and Public Health Organizations (PHOs) have been among the key sources of information in social media discussions during health crisis. Studies have found that during health crisis, people actively search for information from official sources on social media (Strekalova, 2016; Szomszor, Kostkova, & Louis, 2011). Strekalova (2016) found that during the Ebola pandemic, Facebook posts about Ebola received more comments and attention than other posts and that users were actively searching for previously published Ebola posts while engaging with the immediate health promotion posts. Similarly, during Swine Flu pandemic of 2009, Twitter users mostly promoted articles on Swine Flu from official media organizations such as WHO and CDC (Szomszor et al., 2011).

In the context of the United States of America during the past health crisis, people were less likely to seek health information from the CDC website, and instead, they searched for other sources such as social media (Ratzan & Moritsugu, 2014). Thus, CDC has started reaching out to people via an official Twitter account to initiate conversation with the public through live chat (Crook, Glowacki, Suran, Harris, & Bernhardt, 2016). A content analysis of the tweets during a live chat hosted by CDC found that public wanted to get information about individual behavior, the environment, policy, etiology, and the spread of the Ebola virus (Crook et al., 2016). This can be seen as an example that the public want to get verified information from a trusted source when they want to understand and tackle a health issue. Therefore, health organizations such as CDC and WHO, used social media platforms such as Twitter and Facebook to share relevant updates with people during the H1N1 flu pandemic (Biswas, 2013).

Word of mouth. Although, the public mostly rely on official information sources during a health crisis, there have been instances when people had to turn to word-of-mouth and social media for information during a health crisis (Jang & Baek, 2019). This was the case of 2015 MERS outbreak in South Korea. After the PHOs withheld important information on the disease outbreak in the country, the public sought information from alternative channels such as online media (Jang & Baek, 2019).

Social media influencers. The term "viral" is popular in social media where messages are transmitted from an individual to another through a chain process like transmission of an infectious disease (Liang et al., 2019). Messages on social media are often spread through broadcast model where many individuals get the information from the same source, for example, a tweet is retweeted many times from the original source (Liang et al., 2019). A social network analysis on Twitter during Ebola outbreak found that broadcast model was dominant in Ebola-related Twitter communication (Liang et al., 2019). The results further found that influential users (such as celebrities) and hidden influential users triggered more retweets than disseminators and common users. Influential users are the users with more followers than followees and get retweeted more by their followers than retweeting their followees (Liang et al., 2019). Hidden influencers are the users who have more followees than the followers and are retweeted more by their followers than retweet their followees (Ligan et al., 2019).

Misinformation. The nature of social media makes it easy for the incorrect and misleading information to spread from one individual to another in a short time. While the Ebola virus disease (EVD) was spreading in West Africa, misinformation and rumors were spreading in Iowa, USA. The rumor stated that the virus has spread among the citizens in Iowa and compelled the Department of Public Health to issue a statement dismissing the rumor (Allgaier & Savalastog, 2015). Similarly, Biswas (2013) found that some users participated in dissemination of rumors about the H1N1 flu on Facebook and Twitter (Allgaier & Savalastog, 2015; Smallman, 2018). During the Swine Flu pandemic of 2009, Twitter users promoted blog posts that were not scientific (Szomszor et al., 2011). Funng et al. (2016) found that misinformation on Ebola was distributed at a very low level globally (Fung et al., 2016).

The spread of misinformation can also increase mistrust among affected people during a pandemic (Algaier & Savalastog, 2015). According to a recent survey by Pew Research Center, Americans who most commonly use social media for political and election news are less likely than others to follow the news coverage of the COVID-19 outbreak. And 57% of those who rely mostly on social media for political and election news said that some or a lot of news and information about the outbreak seemed to be completely made up (Jurkowitz & Mitchell, 2020). Hence, from a selective exposure theory perspective, choosing social media as the only source of information can lead to exposure to misinformation during health crisis.

Blaming Others on Social Media. Social media are not only used for information during a health epidemic or pandemic but are also the platforms where the public try to make sense of a health crisis through discussions with each other and blaming (Roy et al., 2019). During health crisis, blaming is “a specific part in the process of sense-making of the outbreak” (p. 58). Roy and colleagues’ study on Twitter and Facebook content found that blames circulating on these social media targeted national governments more than global figures such as global elites, global health authorities and others. Based on this study, conspiracy theories were not at the center of discussion on social media about the Ebola epidemic. The instance of blame was also found during the 2003 Severed Acute Respiratory Syndrome (SARS) epidemic. The rumor that a local restaurant owner had died of SARS was circulating via emails warning residents to avoid the Chinatown restaurants (Eichelberger, 2007). Chinese system (Chinese societal-government forces) and its “culture” of eating meat and being “inferior” to American culture were blamed for the SARS epidemic (Buus & Olson, 2006; Eichelberger, 2007). During the 2009 H1N1 flu pandemic, the pharmaceutical companies and media were framed as villains and media was blamed for exaggeration and fear mongering by laypersons in Switzerland (Mayor et al., 2012). With the COVID-19 pandemic, the online scapegoating, blaming, and heroization have started circulating on social media (Atlani-Duault, Ward, Roy, Morin, & Wilson, 2020). People who tend to enact selective exposure to health message are at risk of spreading the virus. Tracking these messages of hate, blame and heroism in real time can be beneficial for health authorities to comprehend public attitudes about the disease and discourage the online scapegoating and blaming (Atlani-Duault et al., 2020).

Selective Exposure in Social Media Networks

Selective exposure theory suggests that people often rely on or pay attention to news and information that supports their existing attitudes and viewpoints (Iyengar & Hahn, 2009; Knobloch-Westerwick, 2014; Knobloch-Westerwick & Meng, 2009; Sweeney & Gruber, 1984). Such preferences of information sources can limit the users' understanding of the world and viewpoints to those sources (Metzger, Harsell, & Flanagin, 2020). Online media have deepened the information gap between people with the rise of niche media sources and users' control over information choices (Metzger et al., 2020). Exposure to information in line with users' existing thoughts and opinions can increase the chance of biased information sharing from the users in the online world (Iyengar & Hahn, 2009; Knobloch-Westerwick, 2014; Metzger et al., 2020). Existing literature has also explored people's selective exposure in relation to cognitive dissonance theory (Metzger et al., 2020; Zillmann, 2000). Cognitive dissonance theory suggests that people feel mental discomfort when they are aware of inconsistencies between their own attitudes and behaviors or between their multiple attitudes (Festinger, 1957). According to this theory, people avoid or are motivated to reduce dissonance as a result of which they rationalize their existing attitudes and behaviors, diminish the importance of others' views that are in conflict with their own, and selectively seek information that confirms their existing attitudes and behaviors (Festinger, 1957). Dissonance on sources of information can occur due to conflict in ideology, lack of confidence in accuracy of the information based on one's own beliefs, or fear that one's own opinion will come under question (Metzger et al., 2020). Meanwhile, selective exposure to information consistent with one's own thoughts and behaviors can reduce dissonance and further reaffirm them (Taber & Lodge, 2006). Metzger et al. (2020) examined differences in people's experiences of cognitive dissonance when exposed to attitude-challenging, attitude-consistent, and ideologically balanced information. Their findings showed that participants reported higher levels of cognitive dissonance when exposed to attitude challenging news source than exposer to attitude consistent news sources. Selective exposure is not inherently dangerous to people, but when individual, family, and community health require people to be safe, selective exposure puts more than the individual at risk.

Research Questions and Hypotheses

Selective exposure in a community health crisis like COVID-19 needs to be studied. Overall, literature on social media networks show that people are fragmented into cliques and clusters of people around certain topics and issues (Himelboim et al., 2013; Lieberman, 2014; Ankerson, 2015; Himelboim et al., 2017). Studies have found similar patterns in social media networks during health crisis (Liang et al., 2019). Thus, the following research question was asked.

RQ1: How were the Twitter networks structured during the COVID-19 global pandemic?

Based on selective exposure theory, people are more likely to talk about topics that are related to their own problems and ideas rather than issues and topics that are not relevant to them (Iyengar & Hahn, 2009; Knobloch-Westerwick, 2014; Metzger et al., 2020). Existing literature shows that during health crisis, people tend to talk about a series of topics including the number of cases, affected areas, how to prevent the spread of the disease, conspiracy theories, and blaming (Allgaier & Savalastog, 2015; Crook et al., 2016; Liang et al., 2019; Roy et al., 2019). Thus, the following research question was asked.

RQ2: What were the topics of discussions on Twitter during the COVID-19 global pandemic?

According to selective exposure theory, people tend use sources that are in line with their own viewpoints in their conversations with others and that social media have given more power and control to users to do so (Allgaier & Svalastog, 2015; Fung et al., 2016; Metzger et al., 2020; Taber & Lodge, 2006). Studies have found that during health crisis, social media users rely more on credible sources of information such as news media and government and health officials (Fung et al., 2016; Strekalova, 2016; Szomszor et al., 2011). Hence, the next research questions focused on sources of information on Twitter during the COVID-19 global pandemic.

RQ3: What were the sources of information on Twitter during the COVID-19 global pandemic?

RQ 4: How were the sources of information used by users on Twitter associated with their topics of discussion during the COVID-19 global Pandemic?

METHODS

The population of this study included all the English tweets related to coronavirus in the world. The current software programs are not able to draw a random sample from the millions of online tweets. They can only collect a snapshot of the most recent posts or tweets at a specific point of time (Himelboim et al., 2017). The data was collected from Twitter through NodeXL Pro, a software program designed as a template in Microsoft Excel that not only retrieves network data from social media into an excel sheet, but also analyzes the network structures and visualizes them in graphs (Himelboim at al., 2017). The term "coronavirus" was chosen because it is broad enough to be included in almost every tweet about the COVID-19 pandemic. Coronavirus is a general term that most people have been using (regardless of their language, geography, and education level) since the emergence of the first cases in China. The data included tweets, mentions, and replies.

To make sure the sample is representative of diverse geographies, four Twitter networks were retrieved on March 25, 2020, and one on March 25, 2021, one in the morning (8:00a.m. central time) and one in the evening (9:00p.m. central time) in America.

A general graph metrics of data and of the clusters were calculated on NodeXL and then the clusters or groups were ordered in descending order based on the number of Twitter users in each one of them (Hansen et al., 2010; Himelboim at al., 2013). A sample of the 10 largest groups from each of the two networks was chosen for analysis. These 10 groups represented the largest and most active groups in the network which means they were most representative of the primary Twitter discourse for the networks sampled (Himelboim et al., 2013). The 40 groups contained 1,655 tweets, replies, and unique retweets (one retweet each). For March 2020 sample, there were 1091 unique tweets in the ten largest groups in the morning (521) and the evening (570) networks. For March 2021 sample, there were 563 unique tweets, from which 377 were from the morning and 187 from the evening sample. All tweets and retweets in other languages were also excluded from the sample.

There were two levels of analysis in this study. First, the network structures were analyzed for both morning and evening networks. The measures included were density, modularity, reciprocity, and geodesic distance. Network density deals with interconnectivity among individuals in a network (Himelboim et al., 2017). It is "a function of pairwise ties between actors or between events," which is at the heart of a community, social support, and high visibility (Wasserman & Faust, 1994, pp. 29-31). Dense communities are cohesive, good sources of social support, and effective transmitters, which helps with the transmission of information, ideas, rumors, and diseases (Kadushin, 2012). A low-density score means loosely connected nodes, and high-density score means highly interlinked nodes either as a result of “sparse but connected set of users or a network of isolated with a few clustered subgroups of users” (Himelboim et al., 2017, p. 6). Network modularity is a measure of quality of clustering that measures the extent to which nodes within clusters are interconnected with themselves, but the clusters are disconnected from other clusters in the network. Modularity measure ranges from 0 to 1. A 0 modularity means the nodes are very divided within their clusters and 1 means the node are very unified. Together network density and modularity explain how divided or unified a network is. A network with a high-density score and low modularity is a single dense group or a unified community. Conversely, a network with low density and high modularity has “a few highly intraconnected clusters that are loosely interconnected” (Himelboim et al., 2017, p. 4). Reciprocity is about whether the relationship between actors is two-way (Lieberman, 2014). It is the ratio of the number of pairs with reciprocal ties with the number of pairs with any ties –meaning person A may have a relationship with person B, but person B may not have the same relationship with A (Hanneman & Riddle, 2005). Twitter ties are directional where a tie is reciprocal when two users follow each other, which will enable both sides to have each other’s tweets on their Twitter pages (Lieberman, 2014). Geodesic distance refers to the short paths among the nodes in a network shows how close the nodes are to each other (Choi, Thomee, Friedland, Cao, Ni, Borth, & Poland, 2014; Ghosh & Lerman, 2010; Kadushin, 2012; Wasserman & Faust, 2009). Different paths give different interpretations about information flow in a network. Thus, “it is important to be on many efficient paths in networks that reach out to various parts of the extended network” (Krebs, 2016, para. 9).

The second level of analysis examined the tweets from the top 10 largest groups of each network. The measure included country, topic, and source of information. Country was coded based on the information retrieved from the Twitter networks via NodeXL. The Countries of the users that didn’t mention their country or geographical location in their Twitter account, were coded N/A (not available). Topic was coded as blame, celebrity, crime, economy, medical, politics, quarantine, religion, statistics, and other (Heldman et al., 2013; Arceneaux & Weiss, 2010; Allgaier & Svalastog, 2015; Liang et al., 2019; Fung et al., 2016; Roy et al. 2019). Source of information was coded as news, official, self, social media, data website, and other (Fung el al.2016; Strekalova, 2016; Liang et al., 2019; Szomszor et al., 2011).

Inter-Coder Reliability

All tweet (N = 1,655) were coded by one of the researchers. To ensure a level of consistency in coding, the other researcher coded slightly over 10% of the sample (n =166) of the tweets. According to Wimmer and Dominick (2011), using 10% of the sample can establish inter-coder reliability. Cohen’s kappa was calculated to measure the inter-coder reliability, or the level of agreement between the coders on each variable (Riffe, Lacy, Fico, & Watson, 2019). The kappa coefficients were .891 for topic and .959 for sources of information, which showed high levels of reliably between the coders (Fleiss, Levin, & Paik, 2013).

RESULTS

This study was a combination of social network analysis and content analysis of public discourse on Twitter during the COVID-19 pandemic. In order to explore the social network of people from different parts of the world with time differences, the study included four Twitter networks from morning and evening of March 25, 2020, and March 25, 2021, with 81,793 nodes and 109,204 edges.

Research question 1 asked about the Twitter network structures during the global COVID-19 pandemic. As the Table 1 shows, the 2020 samples had higher number of nodes/user (24,044 and 22,171) and edges (28,472 and 27,813) than the 2021 samples 18,626 and 16,952 nodes, and 27,650 and 25,269 edges. This means that the 2020 networks (Figures 1 and 2) were larger than the 2021 networks (Figures 3 and 4) because of having more users and ties.

Table 1
Twitter Networks During COVID-19 Pandemic

Networks	Nodes	Total Edges	Graph Density	Modularity	Reciprocity	Geodesic Distance
March 2020 Morning	24044	28472	0.000003	0.796	0.001	10.5
March 2020 Evening	22171	27813	0.000004	0.792	0.001	8.7
March 2021 Morning	18626	27650	0.000005	0.779	0.010	9.6
March 2021 Evening	16952	25269	0.000006	0.745	0.007	9.4

Figure 1. March 2020 Morning Network

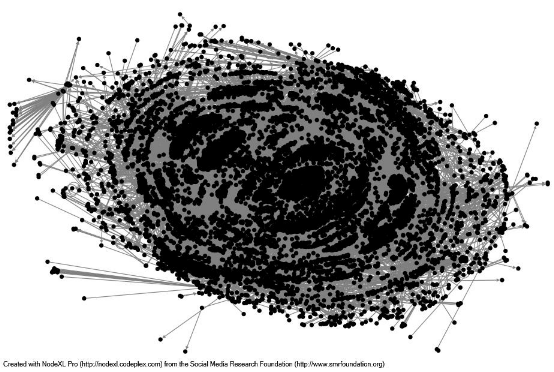


Figure 2. March 2020 Evening Network

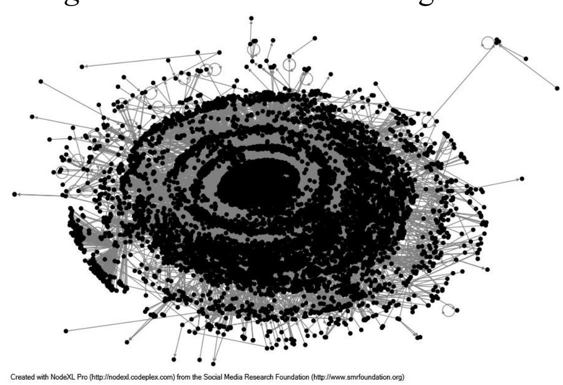
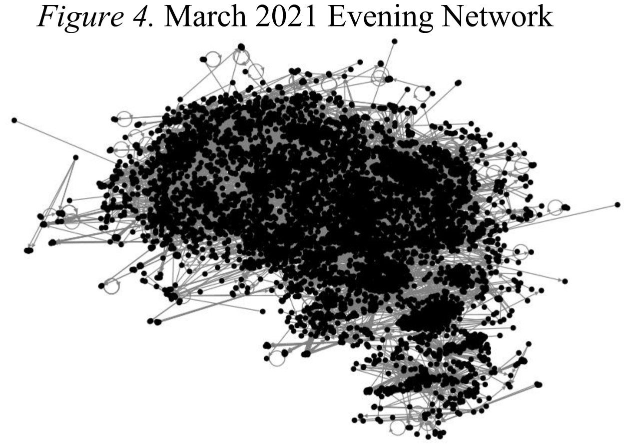


Figure 3. March 2021 Morning Network

Figure 4. March 2021 Evening Network



The graph density scores were very low for all four networks, which showed a low level of interconnectivity among nodes across the entire network. Considering that network density ranges from 0 to 1 (Hanneman & Riddle, 2005; Wasserman & Faust, 2009), the density scores of 0.000003 and 0.000004 mean that there were 0.0003% and 0.0004% general interconnections among the users in the morning and evening network. In contrast, the modularity scores in all networks were higher than 0.7, which suggest high levels of interconnectivity among nodes within clusters groups (Himelboim at al., 2017). In other words, more than 70% of the users were connected to people within their own clusters, not with nodes from other clusters in the network. The reciprocity scores in all networks were the same (0.001), which indicate that Twitter users responded to only 0.1% of the total number of tweets in each network. In other words, one out of 1,000 tweets drew a response, or interaction. The average geodesic distance (e.g., diameter) score was similar across the four networks ranging from 8.7 t0 20.5, which means on average, the shortest distance between two nodes ranged from 8 to 10 paths in the networks.

The next research questions are discussed based on the data from the top 10 largest groups from each of the four networks, a total of 40 groups (N = 1,655) unique tweets and retweets).

Research question 2 asked about topics of discussion on Twitter during the COVID-19 pandemic. As Table 2 shows, about one-third of the discussions were on medical issues (29.4%), followed by politics (22.5%), blame and statistics (10.9%), economy (10.8%), quarantine (5.4%), celebrity (2.6%), crime (1.9%), and religion (0.7%), which means that together, users focused more on medical issues, politics, and blaming related to the COVID-19 pandemic. A chi-square test was conducted to find whether there were significant differences in topics of discussion between the 2020 and 2021 networks and found significant differences ($\chi 2 = 216.233$; df = 9; $p < .000$).

Table 2

Topic of Discussion on Twitter during the COVID-19

Topics	Network		Total
	March 2020	March 2021	
Medical	266 (24.4%)	220 (39.0%)	486 (29.4%)
Quarantine	68 (6.2%)	22 (3.9%)	90 (5.4%)
Blame	150 (13.7%)	31 (5.5%)	181 (10.9%)
Politics	301 (27.6%)	72 (12.8%)	373 (22.5%)
Statistics	96 (8.8%)	84 (14.9%)	180 (10.9%)
Economy	125 (11.5%)	53 (9.4%)	178 (10.8%)
Celebrity	38 (3.5%)	5 (0.9%)	43 (2.6%)
Crime	27 (2.5%)	5 (0.9%)	32 (1.9%)
Religion	9 (0.8%)	3 (0.5%)	12 (0.7%)
Other	11 (1.0%)	69 (12.2%)	80 (4.8%)
Total	1091	564	1655

$\chi^2 = 216.233$; $df = 9$; $p < .000$

As Table 2 shows, users in 2021 networks significantly talked more about medical issues (39.0%) than users in 2020 networks (24.4%). Political discussions were significantly higher in 2020 networks (27.6%) than 2021 networks (12.8%). Users in 2021 networks talked about statistics in relation to Covid-19 (14.9%) significantly more than users in 2020 (8.8%).

The 2020 networks had significantly more blaming (13.7%) than the 2021 networks (5.5%). Also, users in 2020 networks talked about quarantine (6.2%) than users in 2021 networks (3.9%).

Research question 3 about the asked information sources in Twitter networks during the global COVID-19 pandemic. Overall, more than 60% of the information sources were from the news, more than 26% from self, and about 6% from official sources. There were significant differences in the use of sources among the users in the 2020 and 2021 networks ($\chi2 = 99.727$; $df = 5$; $p < .000$). Users in 2020 networks significantly relied more on self (29.1%) than users in 2021 networks (14.2%). The 2021 networks significantly relied more on official sources (8.0%), and social media (6.4%) than the 2020 networks (4.8%, and 1.8%).

Table 3

Sources of information on Twitter during the COVID-19

Source	Network		Total
	March 2020	March 2021	
News	666 (61.0%)	350 (62.1%)	1016 (61.4%)
Officials	52 (4.8%)	45 (8.0%)	97 (5.9%)
Self	318 (29.1%)	80 (14.2%)	398 (24.0%)
Social Media	20 (1.8%)	36 (6.4%)	56 (3.4%)
Data Websites	15 (1.4%)	8 (1.4%)	23 (1.4%)
Other	20 (1.8%)	45 (8.0%)	65 (3.9%)
Total	1091	564	1655

Research Question 4 asked about the association between topics of discussion and source of information among Twitter users during the COVID-19 pandemic. There were significant differences between the use of information sources and topics of discussion among Twitter users ($\chi2 = 169.751$; $df = 45$; $p <.000$). As Table 4 shows, users significantly relied on news sources for discussing crime (81.3%) more than statistics (47.5%), religion (58.3%), blame (59.1%), politics (63.5%), medical issues (63.6%), economy (65.2%), and quarantine (66.6.7%), celebrity (65.1%), and religion (65.9%). The discussions on statistics (35.6%), politics (31.6%) and blames (31.5%) significantly relied more self-sourcing than crime (12.5%), quarantine (13.3%), and medical issues (15.4%). This means that people gave numbers and percentages about new cases, deaths, recoveries, political and economic issues without mentioning any sources. Medical issues (11.5) and quarantine (5.6%) were significantly discussed based on official sources than religion (0.0%), blame (0.6%), politics (1.3%), statistics (1.3%), celebrity (2.3%), and economy (3.9%). Discussing blaming (7.8%), quarantine (7.8%) and celebrity

(7.0%) users significantly relied on social media as a source of information compared to crime (0.0%), politics (2.4%), economy (2.8%), statistics (2.8%), and medical issues (2.8%).

Table 4

Information sources for Discussions on Twitter during the COVID-19 Pandemic

Sources	Topics										Total
	Medical	Quarantine	Blame	Politics	Statistics	Economy	Celebrity	Crime	Religion	Other	
News	309 (63.6 %)	60 (66.7%)	107 (59.1%)	237 (63.5 %)	85 (47.5%)	116 (65.2%)	28 (65.1%)	26 (81.3%)	7 (58.3%)	41 (51.2%)	1016 (61.4 %)
Officials	56 (11.5%)	5 (5.6%)	1 (0.6%)	5 (1.3%)	17 (1.3%)	7 (3.9%)	1 (2.3%)	1 (3.1 %)	0 (0.0%)	4 (5.0%)	97 (5.9%)
Self	75 (15.4%)	12 (13.3%)	57 (31.5%)	114 (30.6%)	64 (35.6%)	38 (21.3%)	10 (23.3%)	4 (12.5%)	3 (25.0%)	21 (26.3%)	398 (24.0%)
Social Media	14 (2.9%)	7 (7.8%)	7 (7.8%)	9 (2.4%)	5 (2.8%)	5 (2.8%)	3 (7.0%)	0 (0.0%)	2 (16.7%)	4 (5.0%)	56 (3.4%)
Data Websites	7 (1.4%)	2 (2.2%)	2 (2.2%)	2 (0.5%)	7 (3.9%)	1 (0.6%)	0 (0.0%)	1 (3.1%)	0 (0.0%)	0 (0.0%)	23 (1.4%)
Other	25 (5.1%)	4 (4.4%)	4 (4.4%)	6 (1.6%)	2 (1.1%)	11 (6.2%)	1 (2.3%)	0 (0.0%)	0 (0.0%)	10 (12.5%)	65 (3.9%)
Total	486	90	181	373	180	178	43	32	12	80	1655

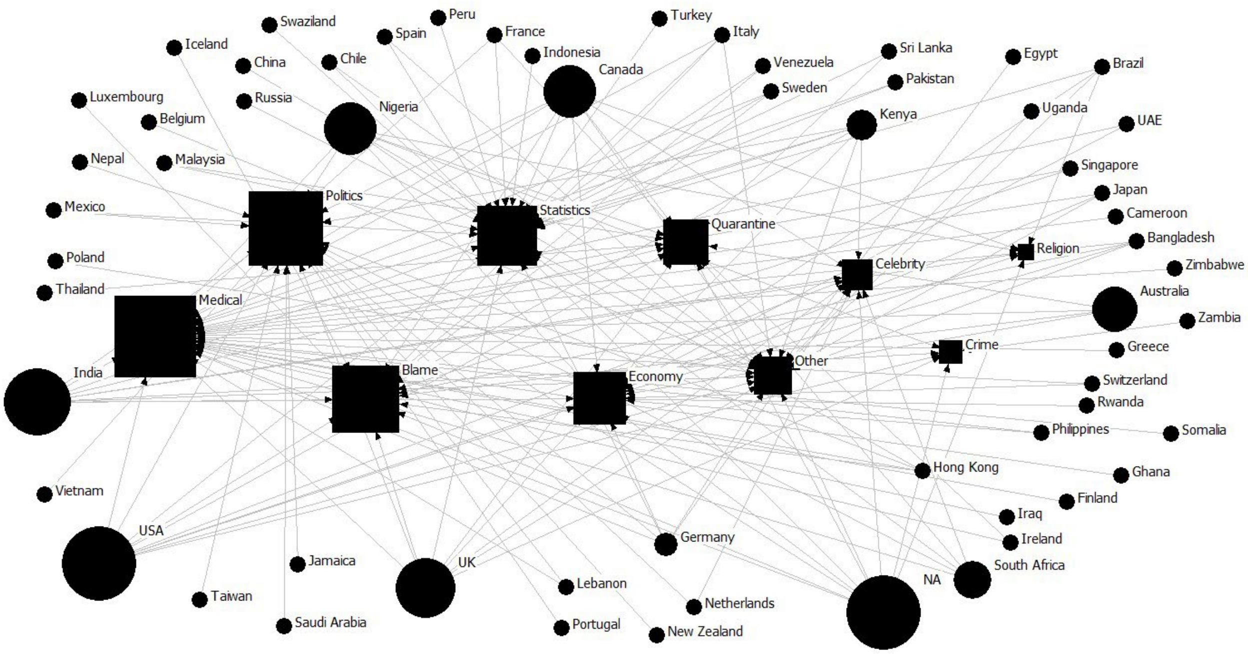
$\chi^2 = 169.751$; $df = 45$; $p <.000$

DISCUSSION

This study analyzed Twitter networks during the COVID-19 pandemic. Twitter has been one of the dominant social media in recent years that has played an important role in health communication among people during health crisis. Users of Twitter and other social media have the access and control over a variety of information sources they can select from regardless of physical and geographic boundaries. Yet, as selective exposure theory suggests, not only do these users rely on information sources that confirm their existing thoughts and opinions, but also share such information with their social media friends and followers (Iyengar & Hahn, 2009; Knobloch-Westerwick, 2014; Metzger et al., 2020). Therefore, social media networks are structured with clusters of like-minded people who rely on similar sources of information who talk about shared ideas and problems (Himelboim et al., 2013; Lieberman, 2014; Himelboim et al., 2017). The findings of this study generally illustrate the selective choices of topics and sources that people make during health crises in social media networks (Metzger et al., 2020). This study raises some interesting points in relation to the selective exposure theory and social media networks during global health crisis.

First, this study found that politics is one the most discussed topics among social media users, which suggests that from every five tweets about the pandemic, one of them discussed politics –meaning the pandemic was politicized. Studies on previous pandemic crisis such as Ebola (Crook et al., 2016; Fung et al., 2016; Strekalova, 2016), the Swine Flu (Szomszor et al., 2011), the H1N1 flu pandemic (Biswas, 2013), and MERS (Jang & Baek, 2019) have shown that people relied more on social media to inform themselves and others about the latest updates on the pandemics in addition to share misinformation and blaming others (Allgaier & Savalastog, 2015; Jang & Baek, 2019; Jurkowitz & Mitchell, 2020; Smallman, 2018). Figure 5 shows the network of 60 countries (shown in circled shapes) and their topics of discussion (shown in squared shapes) during the COVID-19 pandemic. The largest group of users in the Twitter network (39.8%) did not have their countries' information on their Twitter accounts.

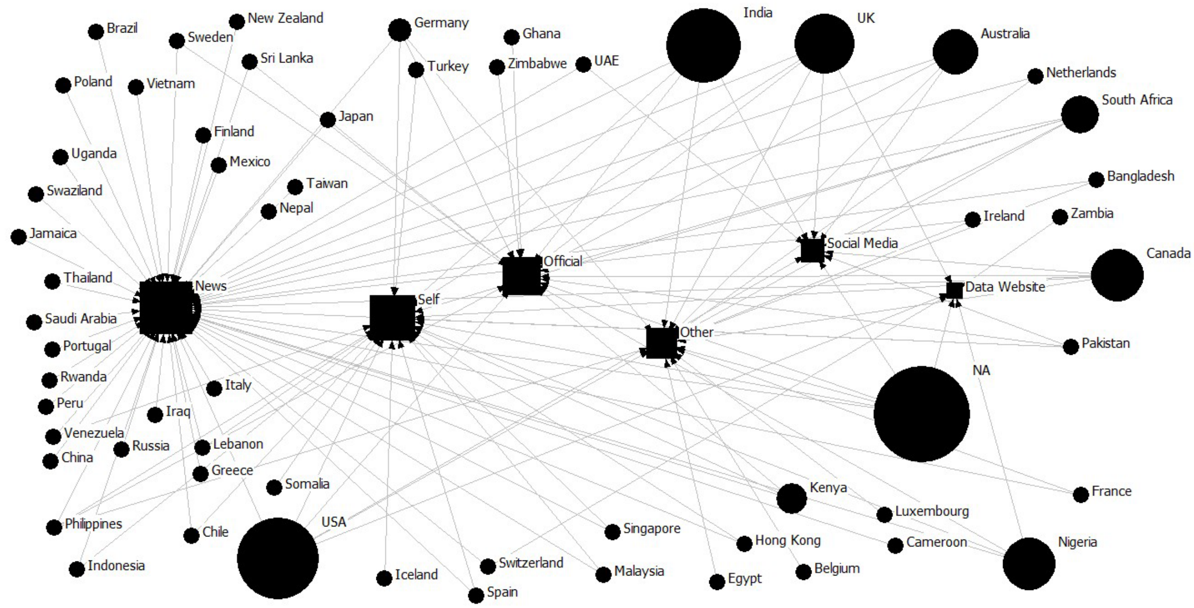
Figure 5. Topics of Discussion among Countries on Twitter during COVID-19 Pandemic



The second largest group consisted of people from the USA (34.9%), followed by India (6.2%), the UK (5.8%), Nigeria (1.8%), and Canada (1.8%), and the rest of the countries made 9.7% of the users in the networks. People from different countries talked about the issues that were more relevant and important to them. For example, users from the top five groups engaged in discussions about a variety of topics while people from the remaining countries focused on specific topics. The dominance of English-speaking countries in these networks might be because exclusion of non-English Tweets from the data. Also, the U.S., India, and Brazil have reported the highest number of confirmed COVID-19 cases and deaths in the world (Coronavirus Map: Tracking the Global Outbreak, 2022).

Second, the study found that news media were the most dominant source of information among Twitter users during the COVID-19 pandemic. The finding supports Fung et al. (2016) that social media users tend to rely more on news sources in their discussions during health crisis and pandemics. Figure 6. illustrates the network of 60 countries and their sources of information during the COVID-19 pandemic. The second largest source of information among Twitter users was self or personal thoughts and views with no reference to any sources. Research shows that spread of false information, word-of-mouth, and rumors are also common phenomena on social media during health pandemics (Allgaier & Savalastog, 2015; Biswas, 2013; Jang & Baek, 2019; Szomszor et al., 2011). Based on selective exposure theory, people tend to reinforce their existing world views and thoughts to avoid dissonance (Iyengar & Hahn, 2009; Metzger et al., 2020).

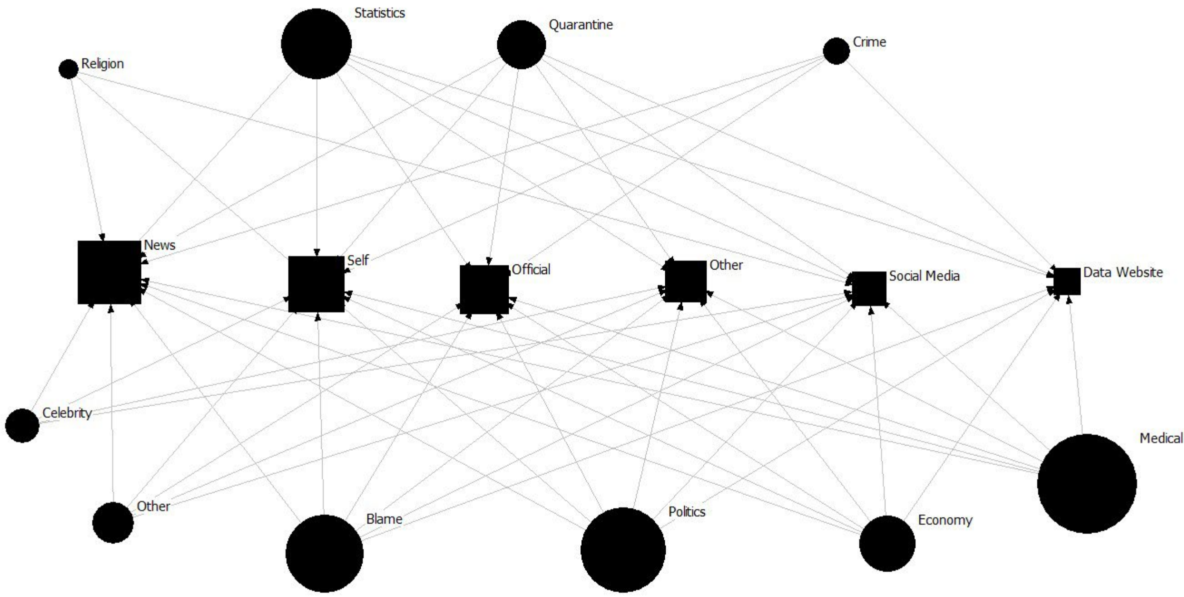
Figure 6. Sources of Information among Countries on Twitter during COVID-19 Pandemic



The third source of information among users was government and non-government officials. This indicates that although official sources are still valuable for social media users during health crisis, they tend to pay little attention to it (5.9%) compared to news media (62.1%) and their self-thoughts and opinions (24.0%). This finding supports the existing research that people seek information from government and health officials during health crisis (Strekalova, 2016; Szomszor et., 2011). Furthermore, users blamed countries, organizations, politicians, and individuals for the COVID-19 pandemic in 10.9% of the discussions on Twitter. This finding supports the findings of previous studies that showed social media users' blaming and circulating conspiracy theories against global figures, health authorities, the media, and other entities and individuals (Atlani-Duault et al., 2020; Buus & Olson, 2006; Eichelberger, 2007; Mayor et al., 2012; Roy et al., 2019). With the findings about the connection between coronavirus and bats and pangolins in Wuhan, China, both news media, social media, and some politicians have been blaming China for the Covid-19 global pandemic (Goodwin, 2020). Former President Donald Trump even called it the "Chinese Virus" (Trump defends calling coronavirus the 'Chinese virus', 2020).

Finally, this study found significant differences in how users use different sources of information for different topics of discussion. In other words, those who were using news media, tended to spread awareness about crimes during COVID-19 pandemic (81.3%), quarantine (66.7%), and economy (65.2%) more than other topics. Self-sourced tweets discussed COVID-19 statistics (35.6%), politics (30.6%), and blames (30.5% more than other topics (See Figure 7). Those who relied on self-sourcing, shared random statistics about positive cases, number of deaths, and recoveries, which supports previous findings that users share rumors and nonscientific information on social media during health pandemics (Allgaier & Savalastog, 2015; Biswas, 2013; Szomszor et al., 2011). Due to the increase in the misinformation about coronavirus disease, WHO has dedicated a page for myth busters on its website (Coronavirus disease (COVID-19 advice), 2020).

Figure 7. Topics of Discussion and Use of Sources in the Twitter Networks on COVID-19



Conclusion

Twitter has become one the most popular sources of information and networking platforms in the world where people share the information, ideas, and opinions about any topics and problems (Himelboim et al., 2013; Himelboim et al., 2017). The COVID-19 pandemic has become one the most dominant topics of discussion on Twitter and people discussing a variety of information and ideas about this health crisis. This study contributes to the existing literature about selective exposure theory, health communication, and social media networks during health crisis. The findings show that Twitter users tend to focus on medical issues, politics, and blaming related to COVID-19 pandemic more than any other topics. Also, users relied more on news and self-information during the COVID-19 pandemic rather than officials.

Despite the significant contributions to research on selective exposure theory, health communication research, and social media networks, this study has two main limitations. First, this study only analyzed Twitter networks and English language content during the COVID-19 pandemic in 2020 and 2021. Future research can further explore other social media networks with content in other languages such as Spanish, French, Arabic to name a few. Second, this study examined Twitter social networks from two days (over two months) during the COVID-19 pandemic in 2020 and 2021. Future research can go beyond this time frame to further analyze the social media networks on this pandemic. This would potentially deepen the understanding of users' emphasis on topics, sources, as well as their virtual interactions over a longer period during the COVID-19 pandemic.

REFERENCES

#COVID19: Social media both a blessing and a curse during coronavirus pandemic (2020). Retrieved from https://theconversation.com/covid19-social-media-both-a-blessing-and-a-curse-during-coronavirus-pandemic-133596

Adamic, L. A., & Glance, N. (2005). The political blogosphere and the 2004 US election: divided they blog. In *Proceedings of the 3rd international workshop on Link discovery* (pp. 36-43). ACM.

Aiello, L. M., Barrat, A., Schifanella, R., Cattuto, C., Markines, B., & Menczer, F. (2012). Friendship prediction and homophily in social media. *ACM Transactions on the Web (TWEB)*, *6*(2), 9. doi: 2180861.2180866

Algaier, J., & Svalastog, A. L. (2015). The communication aspects of the Ebola virus disease outbreak in Western Africa–do we need to counter one, two, or many epidemics?. *Croatian Medical Journal*, *56*(5), 496. doi: 10.3325/cmj.2015.56.496

Ankerson, M. S. (2015). Social media and the "Read-Only" web: reconfiguring social logics and historical boundaries. *Social Media+ Society*,*1*(2). doi: 2056305115621935.

Arceneaux, K., & Johnson, M. (2013). *Changing minds or changing channels?: Partisan news in an age of choice.* Chicago: The University of Chicago Press.

Atlani-Duault, L., Ward, J. K., Roy, M., Morin, C., & Wilson, A. (2020). Tracking online heroisation and blame in epidemics. *The Lancet Public Health*, *5*(3), e137-e138. doi: 10.1016/S2468-2667(20)30033-5

Bakshy, E., Messing, S., & Adamic, L. (2015). Exposure to ideologically diverse news and opinion on Facebook. Science, 348, 1130–1132. doi:10.1126/science.aaa1160.

Barnidge, M. (2018). Social affect and political disagreement on social media. *Social Media+ Society*, *4*(3). doi: 2056305118797721.

Biswas, M. (2013). Health organizations' use of social media tools during a pandemic situation: An H1N1 flu context. *Journal of New Communications Research*, *5*(1), 46-81. doi: 10.1016/j.ajic.2018.02.010

Bulunmaz, B. (2019). A Research on Using Social Media in Health Communication Practices in the United States: Twitter, Health Institutions and Interaction1. *Global Media Journal: Turkish Edition*, *10*(19). Retrieved from https://globalmediajournaltr.yeditepe.edu.tr/sites/default/files/11_baris_bulunmaz.pdf

Buus, S., & Olsson, E. K. (2006). The SARS crisis: Was anybody responsible? *Journal of Contingencies and Crisis Management*, *14*(2), 71-81. doi: https://doi.org/10.1111/j.1468-5973.2006.00483

Castells, M. (2015). *Networks of outrage and hope: Social movements in the Internet age.* Malden, MA: John Wiley & Sons.

Choi, J., Thomee, B., Friedland, G., Cao, L., Ni, K., Borth, D., ... & Poland, D. (2014, November). The placing task: A large-scale geo-estimation challenge for social-media videos and images. In *Proceedings of the 3rd ACM Multimedia Workshop on Geotagging and Its Applications in Multimedia* (pp. 27-31). New York: Association for Computing Machinery

Coronavirus (COVID-19) death rate in countries with confirmed deaths and over 1,000 reported cases as of April 3, 2020, by country (2020, April 3). Statista. Retrieved April 3, 2020 from https://www.statista.com/statistics/1105914/coronavirus-death-rates-worldwide/

Coronavirus disease (COVID-19) advice for the public: Myth busters (2020). World Health Organization. Retrieved April 3, 2020 from https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters

Coronavirus Map: Tracking the Global Outbreak (2020). Retrieved from https://www.nytimes.com/interactive/2020/world/coronavirus-maps.html

Crook, B., Glowacki, E. M., Suran, M., K. Harris, J., & Bernhardt, J. M. (2016). Content analysis of a live CDC Twitter chat during the 2014 Ebola outbreak. *Communication Research Reports*, *33*(4), 349-355. doi: https://doi.org/10.1080/08824096.2016.1224171

Diseko, L. (2020). Coronavirus: How do you celebrate a religious festival while social distancing? Retrieved from https://www.bbc.com/news/world-52198508

Ducharme, J. (2020). Inventors Are Whipping Up Homemade Ventilators to Fend Off a Shortage. Some Doctors Are Wary. Retrieved from https://time.com/5812678/ventilator-innovations-covid-19/

Eichelberger, L. (2007). SARS and New York's Chinatown: the politics of risk and blame during an epidemic of fear. *Social Science & Medicine*, *65*(6), 1284-1295. doi: https://doi.org/10.1016/j.socscimed.2007.04.022

Fleiss, J. L., Levin, B., & Paik, M. C. (2013). *Statistical Methods for Rates and Proportions*. Hoboken: John Wiley & Sons.

Fox, S., & Jones, S. (2009). *The social life of health information: Americans' pursuit of health takes place within a widening network of both online and offline sources*. Pew Internet & American Life Project. Retrieved from https://www.pewresearch.org/internet/2009/06/11/the-social-life-of-health-information/

Fung, I. C. H., Fu, K. W., Chan, C. H., Chan, B. S. B., Cheung, C. N., Abraham, T., & Tse, Z. T. H. (2016). Social media's initial reaction to information and misinformation on Ebola, August 2014: facts and rumors. *Public Health Reports*, *131*(3), 461-473. doi: 10.1177/003335491613100312

Goodwin, M. (2020). Blaming China for coronavirus is reasonable – not racist: Goodwin. Retrieved from https://nypost.com/2020/04/07/blaming-china-is-reasonable-not-racist-goodwin/

Hansen, D., Shneiderman, B., & Smith, M. A. (2010). *Analyzing social media networks with NodeXL: Insights from a connected world*. MA: Morgan Kaufmann.

Hanson, C., West, J., Neiger, B., Thackeray, R., Barnes, M., & McIntyre, E. (2011). Use and acceptance of social media among health educators. *American Journal of Health Education*, *42*(4), 197-204. Retrieved from: https://files.eric.ed.gov/fulltext/EJ936502.pdf

Heldman, A. B., Schindelar, J., & Weaver, J. B. (2013). Social media engagement and public health communication: implications for public health organizations being truly “social”. *Public health reviews*, *35*(1), 13. doi: https://doi.org/10.1007/BF03391698

Himelboim, I., McCreery, S., & Smith, M. (2013). Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of Computer-Mediated Communication*, *18*(2), 40-60. doi: https://doi.org/10.1111/jcc4.12001

Himelboim, I., Smith, M. A., Rainie, L., Shneiderman, B., & Espina, C. (2017). Classifying Twitter Topic-Networks Using Social Network Analysis. *Social Media+ Society*, *3*(1). doi: 2056305117691545.

Jang, K., & Baek, Y. M. (2019). When information from public health officials is untrustworthy: The use of online news, interpersonal networks, and social media during the MERS outbreak in South Korea. *Health communication*, *34*(9), 991-998. doi: 10.1080/10410236.2018.1449552

Jurkowitz, M. & Mitchell, A. (2020, March 25). *Americans who primarily get news through social media are least likely to follow COVID-19 coverage, most likely to report seeing made-up news.* Pew Research Center. Retrieved from https://www.journalism.org/2020/03/25/americans-who-primarily-get-news-through-social-media-are-least-likely-to-follow-covid-19-coverage-most-likely-to-report-seeing-made-up-news/

Kaplan, Frias, & McFall-Johnsen (2020, April 9). *A third of the global population is on coronavirus lockdown-here’s our constantly updated list of countries and restrictions.* Business Insider. https://www.businessinsider.com/countries-on-lockdown-coronavirus-italy-2020-3.

Kadushin, C. (2012). *Understanding social networks: Theories, concepts, and findings*. OUP USA.

Krebs (2016). “Social Network Analysis: An Introduction.” Retrieved from http://www.orgnet.com/sna.html.

Liang, H., Fung, I. C. H., Tse, Z. T. H., Yin, J., Chan, C. H., Pechta, L. E., ... & Fu, K. W. (2019). How did Ebola information spread on twitter: broadcasting or viral spreading?. *BMC public health*, *19*(1), 438. doi: https://doi.org/10.1186/s12889-019-6747-8

Lieberman, M. (2014, March). Visualizing big data: Social network analysis. In *Digital research conference*.

Mayor, E., Eicher, V., Bangerter, A., Gilles, I., Clémence, A., & Green, E. G. (2013). Dynamic social representations of the 2009 H1N1 pandemic: Shifting patterns of sense-making and blame. *Public Understanding of Science*, *22*(8), 1011-1024. Doi: https://doi.org/10.1177/0963662512443326

Plummer (2020). Coronavirus: Six industries crying out for help. Retrieved from https://www.bbc.com/news/business-52200386

Q&A on coronaviruses (2020, March 9). World Health Organization. Retrieved April 3, 2020 from https://www.who.int/news-room/q-a-detail/q-a-coronaviruses

Ratzan, S. C., & Moritsugu, K. P. (2014). Ebola crisis--communication chaos we can avoid. *Journal of health communication*, *19*(11), 1213. Doi: 10.1080/10810730.2014.97768

Riffe, D., Lacy, S., Fico, F., & Watson, B. (2019). *Analyzing media messages: Using quantitative content analysis in research*. Routledge.

Roy, M., Moreau, N., Rousseau, C., Mercier, A., Wilson, A., & Atlani-Duault, L. (2020). Ebola and localized blame on social media: analysis of Twitter and Facebook conversations during the 2014–2015 Ebola epidemic. *Culture, Medicine, and Psychiatry*, *44*(1), 56-79. doi: https://doi.org/10.1007/s11013-019-09635-8

Singer, J. B (2011). Journalism and digital technologies. In W. Lowery & P. J. Gade, *Changing the news: Forces shaping journalism in uncertain times* (pp. 213-229). New York: Routledge.

Smallman, S. (2018). Conspiracy Theories and the Zika Epidemic. *Journal of International & Global Studies*, *9*(2). doi: https://doi.org/10.1057/s41599-019-0243-8

Strekalova, Y. A. (2017). Health risk information engagement and amplification on social media: News about an emerging pandemic on Facebook. *Health Education & Behavior*, *44*(2), 332-339. doi: https://doi.org/10.1177/1090198116660310

Suhay, E., Bello-Pardo, E., & Maurer, B. (2018). The polarizing effects of online partisan criticism: Evidence from two experiments. *The International Journal of Press/Politics*, *23*(1), 95-115. Doi: https://doi.org/10.1177/1940161217740697

Szomszor, M., Kostkova, P., & St Louis, C. (2011). Twitter informatics: tracking and understanding public reaction during the 2009 swine flu pandemic. In *2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology* (Vol. 1, pp. 320-323). IEEE.

Trump defends calling coronavirus the 'Chinese virus.' (2020). Retrieved from https://www.aljazeera.com/programmes/newsfeed/2020/03/trump-defends-calling-coronavirus-chinese-virus-200323102618665.html

Tsatsou, P., & Zhao, Y. (2016). A "two-level social capital analysis" of the role of online communication in civic activism: Lessons from the role of Facebook in the sunflower movement. *Social Media+ Society*, *2*(4). doi: 2056305116671967.

US stock rally fizzles, (2020). Retrieved from https://www.cnn.com/business/live-news/dow-stock-market-today-040720/index.html

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge: Cambridge university press.

Wimmer, R., & Dominick, J. (2011). Mass media research: An introduction. Boston: Wadsworth.

World Health Organization (2000). *WHO report on global surveillance of epidemic-prone infectious diseases* (No. WHO/CDS/CSR/ISR/2000.1). World Health Organization. Retrieved from https://apps.who.int/iris/bitstream/handle/10665/66485/WHO_CDS_CSR_ISR_2000.1.pdf?sequence=1&isAllowed=y

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