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COVID-19 Twitter Communication of Major Societal Stakeholders: Health Institutions, the Government, and the News Media

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More than 200 million people worldwide have been afflicted with the coronavirus disease 2019 (COVID-19). To gain insights into COVID-19 communication on social media, we surveyed 354,200 tweets posted between January 1 and November 14, 2020, by some of the major societal stakeholders in the fight against COVID-19: government health agencies, hospitals, medical and scientific journals, and the news media. We uncover a sustained COVID-19 communication effort by government agencies, hospitals, and journals. By contrast, COVID-19 coverage by the news media on Twitter substantially declined after May 2020 and became increasingly more politicized. Using multivariate regression analysis, we identify medical, political, and socioeconomic elements of COVID-19 communication that predict user engagement on Twitter. A better understanding of the communication strategies that engage social media audiences may be vital to managing the current COVID-19 pandemic and saving human lives.

Keywords: COVID-19, coronavirus, health communication, communication, stakeholders, Twitter, social media

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The spread of the novel coronavirus SARS-CoV-2 and the ensuing coronavirus 2019 disease (COVID-19) pandemic have dramatically altered our society and our daily lives. As of September 1, 2021, more than 200 million people have been infected worldwide and more than 4.5 million have succumbed to COVID-19; in the United States, more than 38 million people have been infected, and over 600,000 people have died. The development of effective COVID-19 vaccines has dramatically reduced viral spread in many parts of the world, including the United States; however, the emergence of novel virus variants showing increased infectiousness represents a major challenge for public health. Besides potent vaccines and widespread vaccination, effective health communication—to inform the public about the risk of coronavirus infection, optimal personal hygiene practices, social behaviors, vaccination, and treatments—may be our most effective tool in curbing viral spread.

Health Communication in Times of Crisis

Viral outbreaks often pose a major or existential threat for humanity and a coordinated and sustained response must be implemented to eliminate deadly viruses. Lessons learned from the previous viral crises—the 2002–2004 severe acute respiratory syndrome (SARS) outbreak, the 2009 H1N1 pandemic, and the 2014 Ebola crisis—have lead to recent calls for the development of global health communication strategies to defeat the novel coronavirus (Ratzan, Sommariva, & Rauh, 2020). Among the proposed strategies are the establishment of effective communication strategies that (i) identify and engage diverse audiences via multiple communication channels; (ii) identify the sources of information and the best communicators, such as trusted government agencies, experts, and media entities, as well as ambassadors trusted by the public; (iii) engage these trusted ambassadors in coordinated actions; (iv) coordinate the dissemnation of messages; and (v) allow for information needs and effective strategies to change over the course of the outbreak (Ratzan et al., 2020).

Health experts and agencies are arguably the most trusted sources of medical information during a public health crisis. For example, in April 2020, over 90% of Americans said they trusted doctors as sources of information about COVID-19 (Earnshaw et al., 2020; Funk & Gramlich, 2020). We argue that these stakeholders, which are the first to gather and analyze medical and scientific data about COVID-19, represent the most effective and trusted sources of COVID-19 information. The information gathered by these stakeholders is then disseminated by the media, whose declared role is to ensure that the public is informed in a precise and timely manner.

The news media has emerged as a critical player in health communication and can significantly impact the public's understanding and reaction to a novel disease outbreak (Gislason, 2013; Mutua & Oloo Ong'ong'a, 2020). Evidence suggests that the framing of the coronavirus pandemic can directly change the societal perception of the public health crisis (Nwakpu, Ezema, & Ogbodo, 2020). It has thus been proposed that control of narratives about the biological and clinical aspects of COVID-19, as well as the pandemic containment and coordination efforts, may be necessary to maximize COVID-19 health communication (Garrett, 2020).

To understand the dynamics and the impact of large-scale COVID-19 communication efforts on social media, we analyzed the communication of several major societal stakeholders that play critical roles during the COVID-19 pandemic: health experts (hospitals, medical and scientifc journals, and government health agencies), who generate a large share of COVID-19 information; and the news media (print and broadcast), which disseminate COVID-19 information to large audiences. From a theoretical perspective, understanding how stakeholders shape health communication during health crises may lead to more accurate models of crisis management communication and risk communication, which can be incorporated into future communication strategies.

To characterize the *quantitative* aspects of COVID-19 communication by these stakeholders, we focused on their communication on social media. Social media has played a major role in disseminating information and has allowed stakeholders to influence public discourse and engage the public in mitigation efforts in various health crises, including viral epidemics (HIV, SARS, Ebola, and Zika; Amirkhanian et al., 2015; Moorhead et al., 2013; Schneider et al., 2013). We limited our analysis to COVID-19 communication on Twitter—the world's largest microblogging platform and a main source of health information. We thus asked the first research question (RQ):

RQ1: What is the volume and frequency of COVID-19 Twitter communication by the major societal stakeholders?

Shaping COVID-19 Perceptions During the Pandemic

Communicating diverse aspects of COVID-19, from medical, therapeutic, and management interventions to social, economic, and political aspects, can shape the public's understanding of COVID-19 and have far-reaching consequences for the overall viral containment efforts. For example, during the 2016 Zika viral epidemic, the coordinated news coverage at the national level, independently of the local risk of infection, has significantly increased the public's awareness across the country (Tizzoni, Panisson, Paolotti, & Cattuto, 2020).

We set out to characterize, *qualitatively*, the COVID-19 communication strategies of societal stakeholders during the coronavirus pandemic. We expected government health agencies, hospitals, and medical journals to engage in robust COVID-19 communication; however, we wanted to assess any differences in the topics of COVID-19 communication as well as their temporal profiles. We also expected news media to frame COVID-19 in both medical and nonmedical terms and wanted to identify these frames as well as their temporal evolution. Our second RQ is thus:

RQ2: What COVID-19 communication topics are covered by each stakeholder, and are there topic differences between stakeholders and differences in the temporal evolution of COVID-19 topics?

Engaging the Public During Health Crises

Theory-guided identification of health communication features that engage audiences can inform future health communication campaigns while promoting further theoretical developments in health communication and illness and health threat perception. Such advances could then be used to promote health management and psychosocial adjustment. It is thus paramount to identify those aspects of health communication that engage or deengage the public during health crises.

A widely used theoretical framework to understand how health information is perceived by individuals, leading to illness mental representation and adaptive behavior, is the common-sense model of illness self-regulation (CSM; Leventhal, Phillips, & Burns, 2016). The CSM integrates the processes by which individuals become aware of health threats, generate threat perceptions, create action plans, and integrate feedback to effectively address the threat. Five core components of illness representation have been identified: identity (representation of illness label and associated symptoms); cause (encoding the causes of illness); timeline (representation of the acute, cyclical, or chronic nature of illness); consequences (representation of potential health, social, and other outcomes); and control (treatment and management options and the ability to influence illness progression). The process of illness self-regulation also has a social component in which interpersonal communications shape perceptions, coping behaviors, and emotional well-being (Leventhal et al., 2016). As such, the CSM provides a theoretical framework for understanding individual and collective responses to health communication on social media. We used the CSM framework to identify elements of COVID-19 illness representation in Twitter posts. In addition, we also identified socioeconomic and political aspects of COVID-19 communication and set out to identify those elements of COVID-19 communication that are most engaging for Twitter audiences. Our third RQ is thus:

RQ3: What elements of COVID-19 communication predict user engagement on Twitter?

Methods

Tweet Retrieval

We used Twitter Application Programming Interface (API) access keys and Facepager (Jünger & Keyling, 2019) to scrape tweets. We identified the account handles and then translated them into Twitter IDs at gettwitterid.com. Data collected for each tweet included ID, post creation time, content, and the number of favorites and retweets. Because of software limitations, we couldn't retrieve the number of comments. Because of Twitter API restrictions, Facepager accessed only 3,200 tweets/account. To collect additional data, we used Brandwatch, a social media analytics service. In total, we collected 354,200 tweets posted between January 1 and November 14, 2020, on the 20 accounts surveyed. For Fox News, no tweets could be found between January 1 and March 18, 2020.

COVID-19 Filter

To automatically identify COVID-19–related tweets, we curated a list of COVID-19–related terms (*corona*, *covid*, *sars*, *pandemic*, *ncov*, *quarantine*, *lockdown*, *staysafe*, *socialdistancing*, *wearamask*). To test the efficacy of the automatic COVID-19 filter, we applied it to two datasets of 1,314 and 760 randomly selected, pooled tweets from medical journals and government health agencies accounts, respectively. The two datasets were also manually coded to identify all COVID-19 related tweets. The automatic filter identified 385/1,314 and 303/760 COVID-19 posts, and the manual method 393/1,314 and 313/760. The concordance of COVID-19 automatic and manual filtering is 96.8–97.9%, suggesting that the COVID-19 automatic filter is robust.

Structured Topic Modeling

Based on a latent Dirichlet Allocation algorithm, structured topic modeling (STM) is an unsupervised classification of a text document that recognizes, classifies, and extracts information by clustering words that frequently appear together across a collection of texts. STM generates a number of distinct and prevalent topics, a set of keywords that represent each topic, the expected prevalence of each topic, and the temporal evolution of topic prevalence, using time as a covariate. To determine the number of topics for each corpus, we computed the following metrics during simulations with increasing topic numbers: semantic coherence, held-out likelihood, residual, and lower bound. Semantic coherence measures the cooccurrence of words within a text to ensure that selected keywords are part of a single concept, thus enhancing the interpretability and topic quality. Held-out likelihood computes the probability of keywords appearing in documents to indicate the generalization capability of the topic model. We selected the number of topics that produced the most semantically coherent and distinct topics, while maintaining a low residual and lower bound (Roberts, Stewart, & Airoldi, 2016).

Coding

To identify aspects of COVID-19 illness representation, we were guided by the CSM. We coded the five key CSM components: identity, causal, timeline, consequence, and control information. In addition to illness representation, we also identified socioeconomic and political features of COVID-19 communication. Three authors reviewed over 1,500 tweets and compiled a list of COVID-19–related elements, related to public health, medical and scientific research, psychological health, social dynamics, the economy, and politics. Two independent coders were trained on an initial set (not included in the analysis) of 800 tweets. Each coder then independently coded the totality of COVID-19–related tweets in each of the six datasets. The coders also manually identified tweet features (presence of photos, videos, links, or infographics) by inspecting each tweet online. The inter-coder reliability for the individual datasets were $\kappa = 0.89$ for CDC, $\kappa = 0.81$ for Mayo, $\kappa = 0.79$ for NEJM, $\kappa = 0.84$ for NYT, $\kappa = 0.89$ for CNN and $\kappa = 0.86$ for the Fox News dataset. The inter-coder reliability for visual features was $\kappa = 0.96$. These coefficients suggest good agreement between coders. Disagreement was resolved by discussion between coders.

Multivariate Regression Analysis

To identify factors that predict user engagement, we modeled the responses to tweets using negative binomial regressions (for 22 of the 24 tweet datasets), or overdispersion Poisson regressions (for the CDC favorites and retweets datasets). Regression analyses were conducted separately for each of the two dependent measures (favorites, retweets) using selected binary (1-present, 0-absent) independent variables. Before regression analyses, we assessed the multicollinearity among the independent variables using the variance inflation factor (VIF). The variables included in the regression models had VIF values between 1 and 5 ($1 < VIF < 5$). Variables with a high degree of multicollinearity were excluded from the models. Regression analyses were performed using the SPSS software.

Supplementary Data

Fifteen supplementary figures (Figures S1 to S15) and one supplementary table (Table S1) can be downloaded online at https://twittercomm.github.io/twitter_communication_study/

Frequency and Temporal Dynamics of COVID-19 Communication

To gain insights into the COVID-19 communication on Twitter and the health messaging strategies of major societal stakeholders, we surveyed the COVID-19 Twitter communication of five major types of stakeholders between January 1 and November 14, 2020: (1) government health agencies; (2) top hospitals; (3) top medical and scientific journals; (4) top print news media; and (5) top broadcast news media networks (Table 1).

Table 1. Stakeholders Surveyed Between January and November 2020.

Twitter account	#Followers	#Tweets	#COVID tweets	COVID tweets (%)
@CDCgov	3.3M	2,934	1,472	50.2
@US_FDA	0.38M	1,937	797	41.1
@NIH	1.2M	1,488	557	37.4
Government (all)	4.88M	6,359	2,826	44.4
@ClevelandClinic	1.9M	5,531	714	12.9
@MayoClinic	2M	3,354	1,033	30.8
@HopkinsMedicine	0.6M	2,330	520	22.3
Hospitals (all)	4.5M	11,215	2,267	20.2
@NEJM	0.8M	2,735	976	35.7
@TheLancet	0.6M	2,193	911	41.5
@nature	2M	2,607	565	21.7
@ScienceMagazine	1.8M	3,153	698	22.1
Journals (all)	5.2M	10,688	3,150	29.5
@CNN	50.7M	44,064	13,527	30.7
@ABC	16.1M	41,879	10,430	24.9
@NBCNews	8M	39,880	11,178	28.0
@CBSNews	7.8M	34,888	8,434	24.2
@FoxNews	20M	2,996	145	4.8
Broadcast (all)	102.6M	163,707	43,714	26.7
@nytimes	47.9M	30,730	4,751	15.5
@washingtonpost	16.8M	31,831	7,104	22.3
@WSJ	18.2M	55,497	7,516	13.5
@politico	4.3M	21,676	5,314	24.5
@TIME	17.6M	22,710	5,694	25.1
Print (all)	104.8M	162,444	30,379	18.7

Collectively, the government health agencies we surveyed had 4.8 million followers; the top three hospitals had 4.5 million followers; and the scientific and medical journals had 5.2 million followers. The news media accounts have a far higher Twitter audience. Collectively, the top broadcast media networks have over 102.6 million followers, whereas the top print media have 104.8 million followers (Table 1).

To address RQ1 and gain insights into COVID-19 Twitter communication, we used a "COVID-19 filter" to automatically identify tweets containing COVID-19–related content (see Methods) in tweets posted between January 1 and November 14, 2020. We found that 44.4% of tweets by government agencies were about COVID-19. Moreover, 20.2% of hospital tweets and 29.4% of journal tweets featured COVID-19. On average, 18.7% and 26.7% of print and broadcast media tweets were COVID-19–related, respectively (Table 1). One notable outlier was Fox News, which covered COVID-19 in only 4.8% of its tweets, far fewer than the rest of broadcast media we surveyed (Table 1).

We then investigated the temporal dynamics of COVID-19 communication (Figure 1). COVID-19 communication increased after February 1 on all accounts. It then peaked around March–April on all accounts, and then only slightly decreased for government health agencies, while decreasing more significantly on news media accounts. A second, smaller peak of COVID-19 communication was seen around July, when COVID-19 mortality reversed its declining trend (compare Figure 1B with F, H, J, and L).

A comparison of the evolution of coronavirus cases or COVID-19–related deaths (Figure 1A, B) and the volume of COVID-19 communication suggested the following: (i) the increase in COVID-19 messaging was concomitant with the increase in infections in both early January and February for all surveyed accounts except Fox News; (ii) the decrease in COVID-19 communication closely parallels the decrease in COVID-19 deaths but not the evolution of COVID-19 new cases (Figure 1).

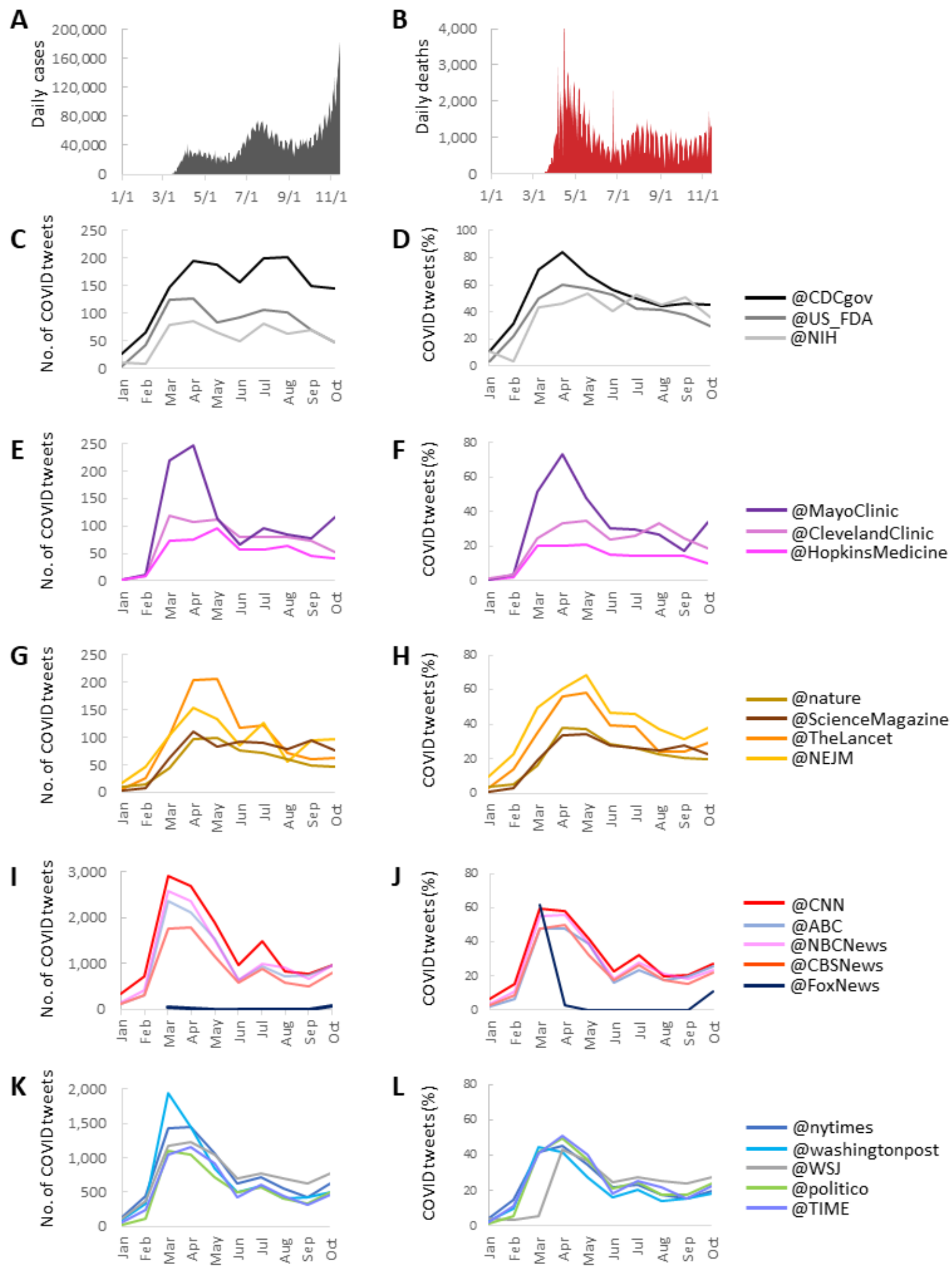

Figure 1. Coronavirus infections and COVID-19–related deaths (A, B) and COVID-19 communication between January and November 2020 (C–L).

To assess the degree of correlation between COVID-19 Twitter communication and coronavirus infections or COVID-19 deaths, we derived correlation coefficients between daily COVID-19–related tweets and daily coronavirus infections, or COVID-19–related deaths, between January 1 and November 14, 2020 (Table 2).

Table 2. Correlations Between Coronavirus Infections or COVID-19 Deaths and COVID-19 Communication.

Twitter account	Daily cases	Daily deaths
	r	r
@CDCgov	0.35^{d}	0.58^{d}
@US_FDA	0.17^{b}	0.38^{d}
@NIH	0.24^{c}	0.39^{d}
Government (all)	0.31^{d}	0.56^{d}
@ClevelandClinic	0.30^{d}	0.49^{d}
@MayoClinic	0.35^{d}	0.48^{d}
@HopkinsMedicine	0.22^{d}	0.46^{d}
Hospitals (all)	0.30^{d}	0.55^{d}
@NEJM	0.24^{c}	0.52^{d}
@TheLancet	0.19^{c}	0.42^{d}
@nature	0.25^{c}	0.57^{d}
@ScienceMagazine	0.47^{c}	0.63^{d}
Journals (all)	0.33^{d}	0.66^{d}
@CNN	0.05^{ns}	0.40^{d}
@ABC	0.18^{c}	0.50^{d}
@NBCNews	0.20^{c}	0.51^{d}
@CBSNews	0.19^{c}	0.47^{d}
@FoxNews	0.27^{c}	0.00^{ns}
Broadcast media (all)	0.16^{b}	0.49^{d}
@nytimes	0.06^{ns}	0.42^{d}
@washingtonpost	0.05^{ns}	0.40^{d}
@WSJ	0.20^{c}	0.52^{d}
@politico	0.18^{b}	0.51^{d}
@TIME	0.13^{a}	0.49^{d}
Print media (all)	0.12^{a}	0.50^{d}

Note. r-correlation coefficient, $^{a}p < 0.05$, $^{b}p < 0.01$, $^{c}p < 0.001$, $^{d}p < 10^{-7}$, ns-not significant.

Coronavirus case and mortality data was accessed at https://covid.cdc.gov/covid-data-tracker. We found a significant correlation between daily COVID-19–related tweets and daily COVID-19–related deaths, and a less-strong correlation with new cases; this was true for print media accounts as well as the broadcast accounts, with the notable exception of Fox News (Table 2). COVID-19 daily tweets by government agencies, hospitals, and journals also correlated more strongly with COVID-19 mortality than new infections (Table 2). Thus, COVID-19 coverage by most mainstream news media is highly correlated with COVID-19 mortality.

COVID-19 Communication Topics

To address RQ2 and gain a global view of Twitter COVID-19 communication by major stakeholders, we employed STM to model tweet datasets collected from each category of stakeholder, using the time of posting as a covariate.

We first modeled *all* communication between January 1 and November 14, 2020. Health agencies (Figure S1) focused heavily on COVID-19, with 11 of the 19 topics related to COVID-19, including new drugs (topic 10), spread and preventative measures (topic 18), deaths (topic 6), virus transmission (topic 8), antibody therapies (topic 7), vaccine trials (topic 14), and official press briefings (topic 12). The use of these topics remained relatively stable over time (Figure S2A–C). Hospitals (Figure S3) had four of 23 topics focused exclusively on COVID-19 topics: 10-clinical research and vaccines, 13-symptoms and protective measures, 3-caregivers, and 6-help and new information (Figure S4A–C). Medical and scientific journals (Figure S5) had four of 21 topics focused exclusively on COVID-19 topics: 13-testing and spread, 7-risks, 1-discussions and interviews, and 8-infection, antibodies, and vaccines; interestingly, topics 13, 7, and 1 were more prevalent in the early months of the pandemic (February–May) and less prevalent thereafter (Figure S6A–C).

Print media (Figure S7) covered medical and public health aspects of COVID-19 topics: 13-new cases, virus spread and economic crisis, 21-testing and vaccines; and 5-mask wearing and social distancing; interestingly, topic 13 peaked in April and declined thereafter (Figure S8A–C). Broadcast media (Figure S9) had only two of 22 topics directly related to COVID-19, and they together represented 20% of the corpus: 14-new cases, hospitalizations and deaths, and 10-mask wearing and work; both topics 14 and 10 peaked in April and declined thereafter (Figure S10A–C). Both print and broadcast media also covered the consequences of COVID-19 on remote work and homeschooling, the impact on work and unemployment, on cities and commnities, and on sports. Multiple topics in news media tweets were politicized and depicted President Trump, presidential elections, as well as street protests (Figures S8A and S10A).

To gain further insight into COVID-19 communication of major societal stakeholders, we next focused exclusively on tweets related to COVID-19 that were filtered automatically. COVID-19 communication between January 1 and November 14, 2020, was then modeled for the same five types of stakeholders.

Government agencies (Figure S11) communicated about COVID-19 preventive behaviors (topic 5); latest updates (topic 7); new treatments and vaccines, and discussions about causes and treatments (cluster of topics 10-12-8); risk factors, testing, and recommendations to reduce risk (cluster 3-4-9); as well as new cases and hospitalizations (topic cluster 2 and 6; Figure 2A, B). The prevalence of these topics increased in the early phases of the pandemic and remained stable thereafter (Figure 2C).

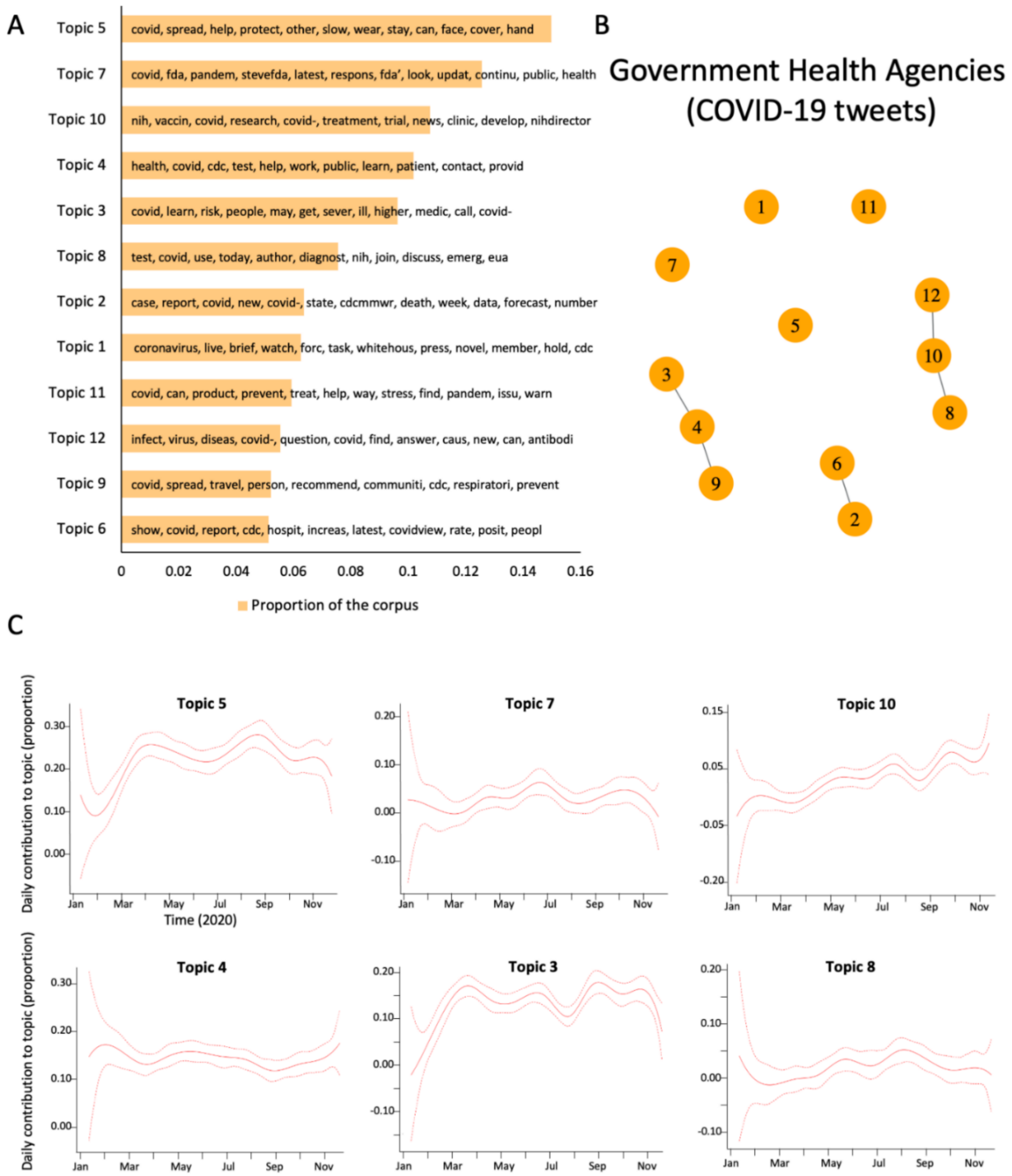

Figure 2. COVID-19 communication topics of government health agencies.

Hospitals (Figure S12) communicated about research and offered answers about COVID-19 risks, symptoms, and infections (cluster 1-10-9-2-11); patient care, caregivers, staff, and messages of appreciation (cluster 4-8-6-13); discussions and forums about viral spread, social distancing, mask wearing, and quarantine (cluster 7-15-16); as well as respiratory symptoms (topic 12) and latest news (topic 3) (Figure 3A, B). The prevalence of these topics increased early during the pandemic and remained stable thereafter (Figure 3C).

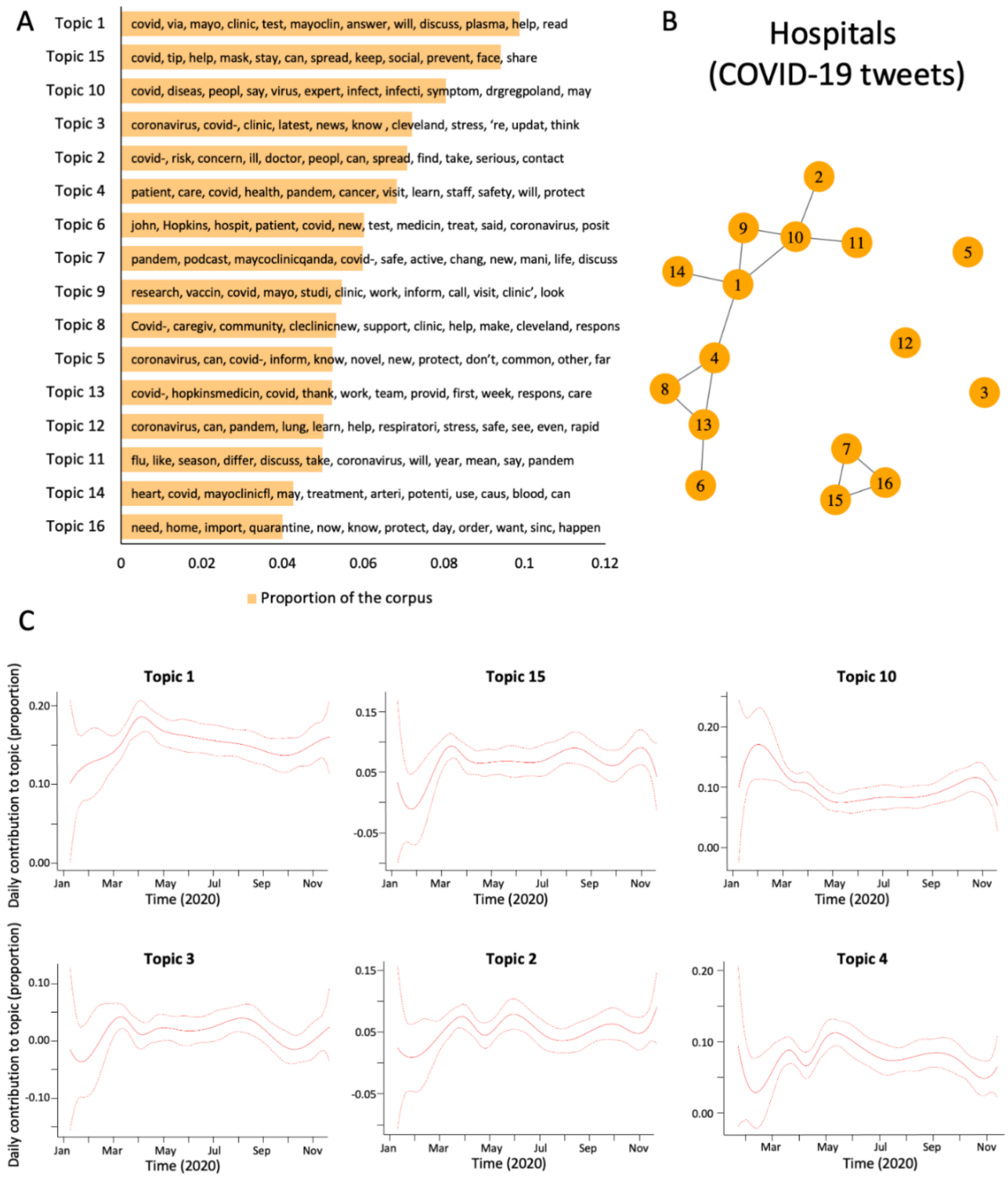

Figure 3. COVID-19 communication topics of top U.S. hospitals.

Medical and scientific journals (Figure S13) communicated about public and global COVID-19 health issues (topic 5); new vaccine trials (topic 1); research about the virus (topic 3); modeling of outbreaks (topic 4); new cases (topic 6); as well as COVID-19 patients (topic 2) (Figure 4A, B). The COVID-19 communication topics of journals showed only minor variations from April to November 2020 (Figure 4C).

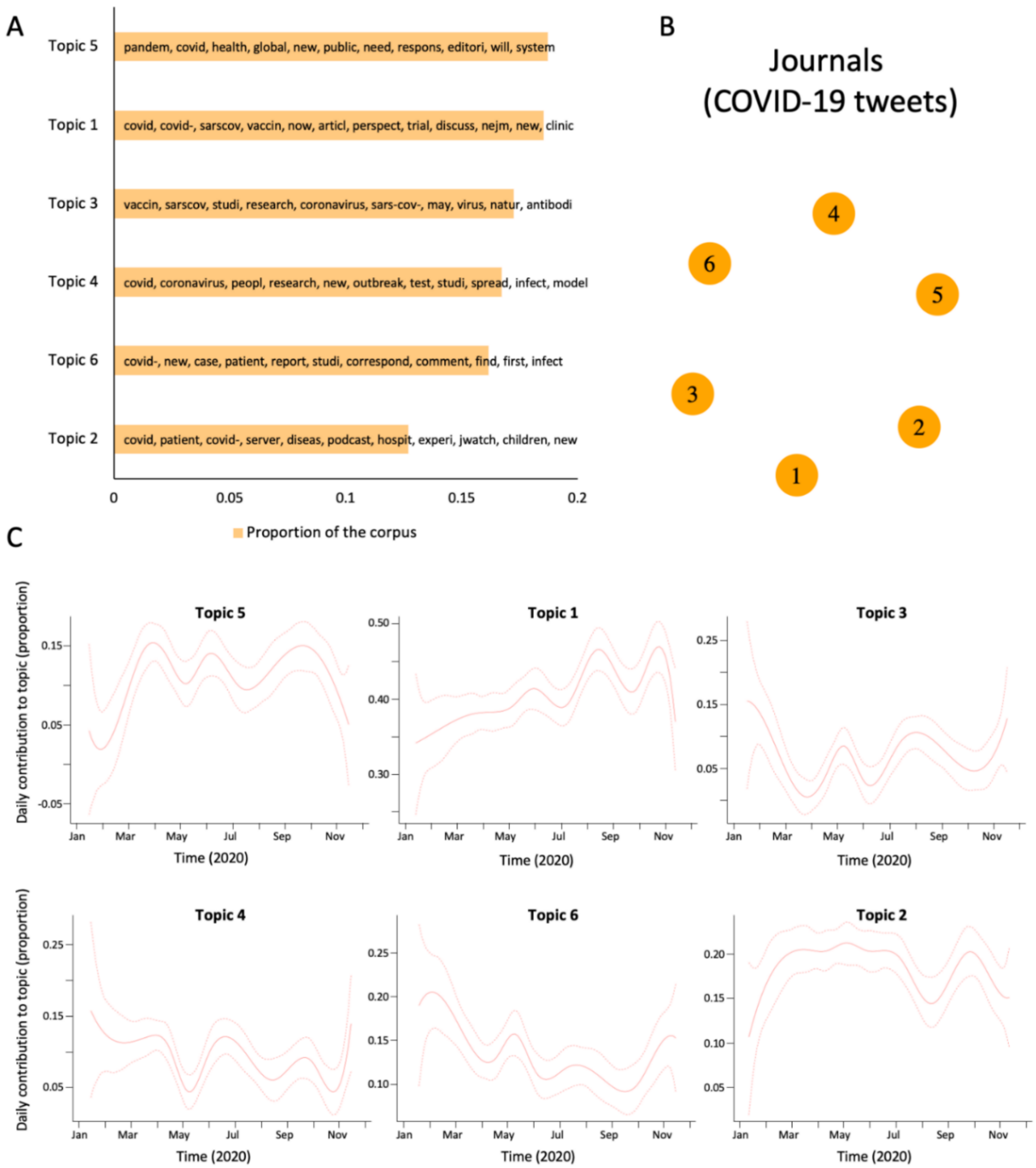

Figure 4. COVID-19 communication topics of top journals.

A large degree of COVID-19 communication by print media was about President Trump and political discourse (topics 15-10-1), as well as various aspects of the COVID-19 pandemic, such as economic impact (topics 5-9-14), remote work, quarantine, travel restrictions (cluster 8-20-2), effects on cities and communities (topics 6, 13), and international aspects (cluster 7-3-9) (Figure 5A, B). COVID-19 medical and public health topics were about testing and virus spread (topic 17), new cases (topic 11), COVID-19 vaccine research (topic 2), and protective measures (topic 22). Interestingly, topic 17, about the spread of infection, was very prevalent in early 2020 but rapidly declined thereafter—whereas topic 15, about President Trump, was more prevalent in September and October 2020 (after he tested positive for the novel coronavirus) and declined thereafter (Figure 5C).

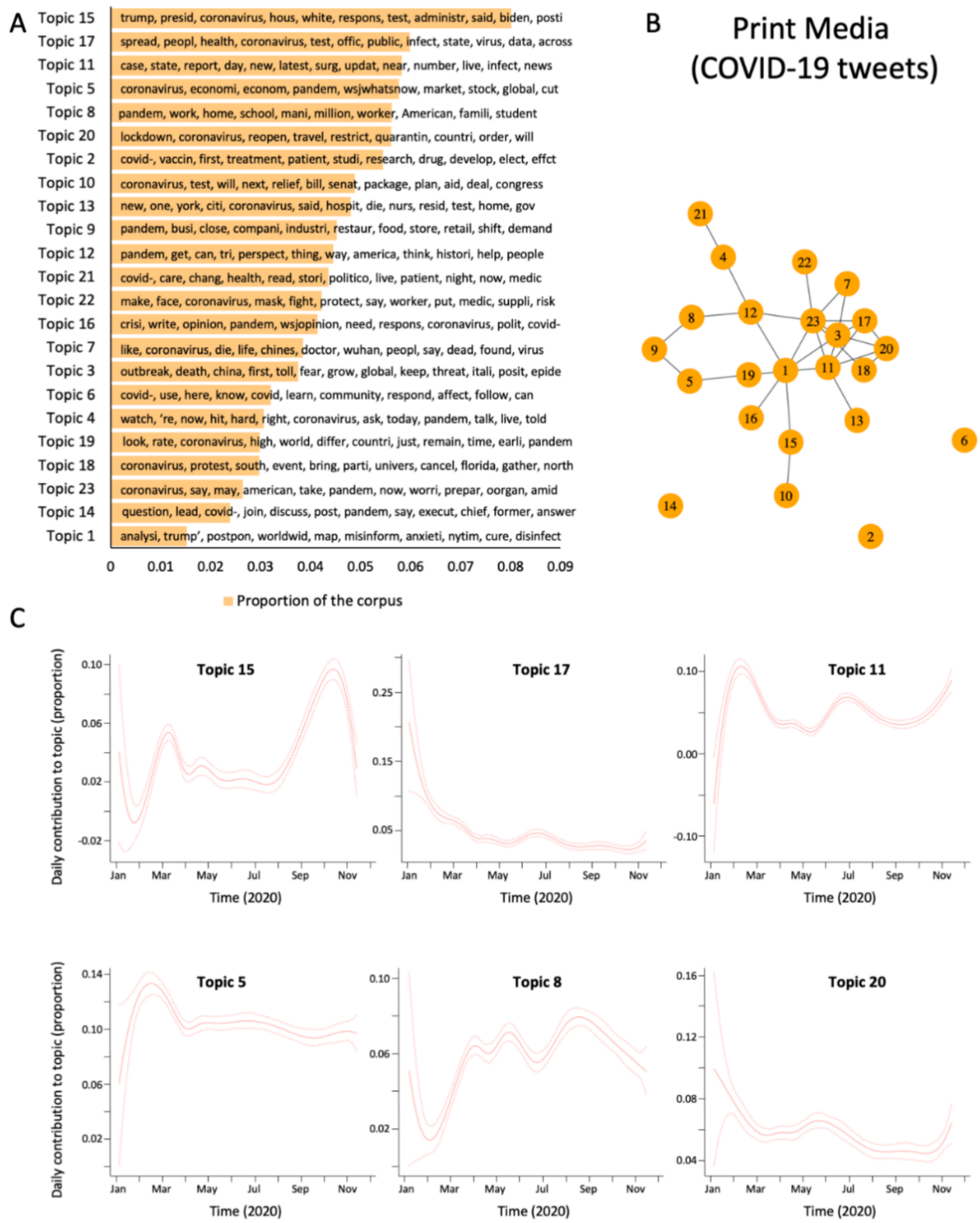

Figure 5. COVID-19 communication topics of print media.

Broadcast media (Figure S15) COVID-19 coverage included coverage of politicians, Congress, and elections (cluster 7-11-1); impact on the economy, economic relief measures (topics 4 and 5), and international and travel aspects related to the COVID-19 pandemic (topics 14); and stories of patients and the impact on nursing facilities (sub-cluster 9-15). COVID-19 medical and public health coverage included vaccine development (topic 6), information about symptoms (topics 3 and 10), and quarantine (topic 16), as well as the effects of the pandemic on cities (topic 13) and schools (topic 2) (Figure 6A, B). Interestingly, the coverage of new infections (topic 8) peaked in February and July, while coverage of COVID-19 linked to President Trump (topic 7) steadily increased between February and October 2020, and declined thereafter (Figure 6C).

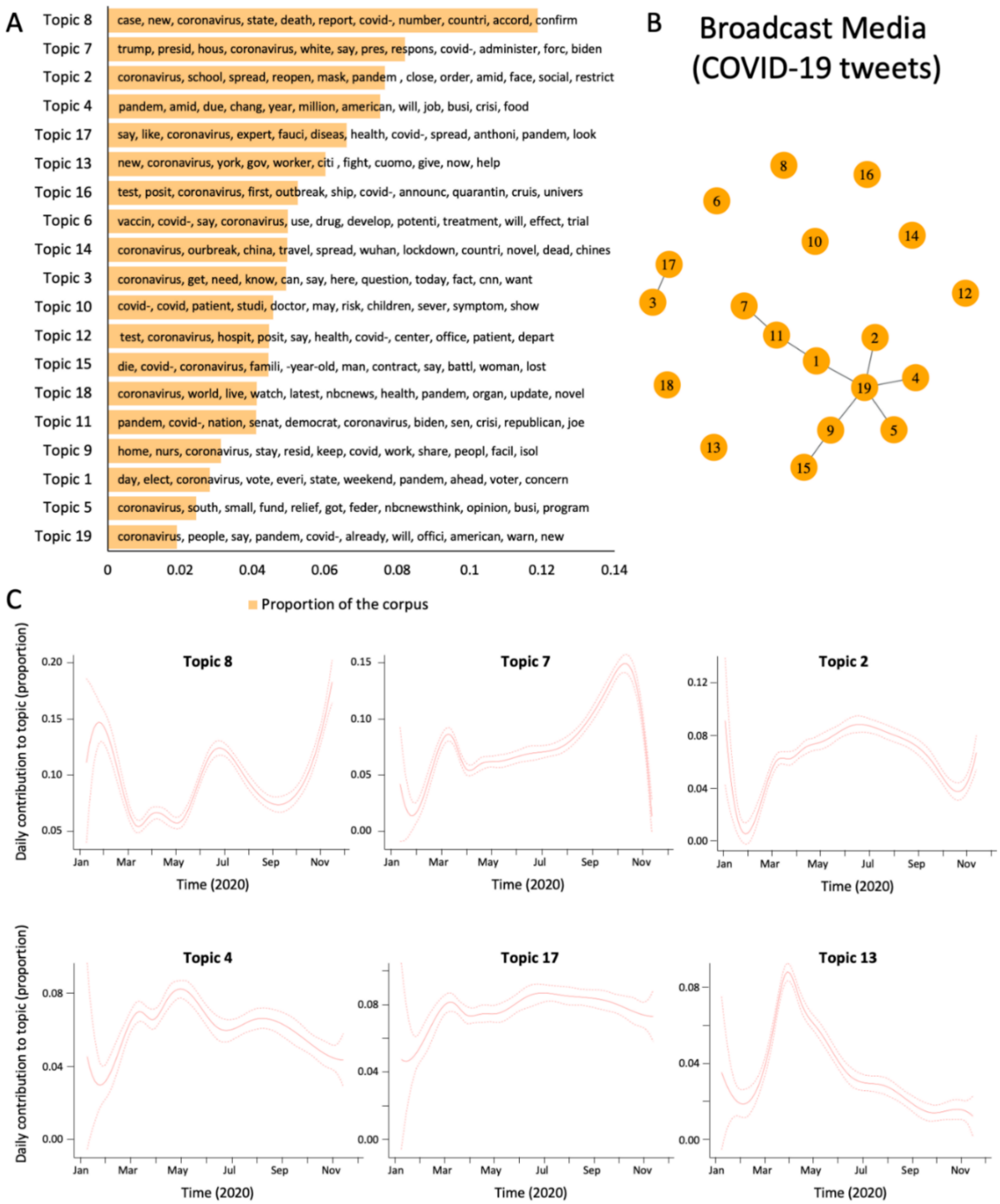

Figure 6. COVID-19 communication topics of broadcast media.

Taken together, these findings about COVID-19 communication topics (Figures 2–6), combined with information about the volume and temporal evolution of COVID-19 communication (Table 1 and Figure 1), suggest the following: (1) COVID-19 communication by government health agencies, hospitals and medical, and scientific journals was centered around medical and scientific issues as well as public health issues and the development of new therapies and COVID-19 vaccines. The volume of COVID-19 communication by these stakeholders was sustained during most of 2020; (2) news media entities framed COVID-19 in both medical, political, and socioeconomic, terms; (3) the volume of COVID-19 communication by the news media steadily declined after May 2020, and its content became more politicized. Thus, health, political, and socioeconomic dimensions underlie COVID-19 communication by the news media and may shape public perceptions and understanding of COVID-19.

Elements of COVID-19 Communication That Engage Twitter Audiences

To address RQ3 and identify the most-engaging elements of COVID-19 communication, we selected six Twitter accounts representative of the stakeholders we surveyed in this study: CDC, Mayo Clinic, NEJM, NYT, CNN, and Fox News. For broadcast media, we analyzed both CNN and Fox News, as Fox News was an outlier in terms of COVID-19 communication. We collected and analyzed individual tweets after they were seen by audiences for seven days—to ensure equal exposure—over a 38-day period, between September 21 and October 28, 2020. We then automatically filtered the tweets containing COVID-19 communication.

We first asked whether the presence of *any* COVID-19–related information in a tweet is associated with a higher (or lower) audience engagement. Favoriting or sharing a tweet (retweeting) can be seen as forms of user engagement online and may involve some of the same cognitive and emotional processes that underlie user engagement by other forms of media (Rus & Cameron, 2016). We found that the presence of COVID-19 information led to higher engagement of CDC, Mayo, and NEJM sudiences. There was a small positive correlation between the presence of COVID-19 communication and engagement on NYT and CNN accounts. By contrast, COVID-19 communication did not engage the Fox News audience on Twitter (Table 3). These observations uncover differential effects of COVID-19 communication on Twitter audiences.

Table 3. User Engagement by COVID-19 Communication on Twitter.

Account	Favorites	Retweets
	r	r
CDC	**0.33^{c}**	**0.20^{a}**
Mayo	**0.28^{c}**	**0.34^{c}**
NEJM	0.11^{ns}	**0.25^{b}**
NYT	**0.06^{b}**	**0.04^{a}**
CNN	-0.06^{ns}	**0.08^{d}**
Fox	-0.05^{ns}	-0.05^{ns}

Notes. r-correlation coefficient, $^{a}p < 0.01$, $^{b}p < 0.001$, $^{c}p < 10^{-6}$, ns-not significant. Statistically-significant coefficients are in bold.

We then asked which indvidual elements of COVID-19 communication are most (or least) engaging for Twitter audiences. To identify different aspects of COVID-19 communication on Twitter, we first manually coded tweets for categories related to COVID-19 illness representation, as well as public health, socioeconomic, and political aspects of the COVID-19 pandemic (Table 4).

Table 4. Elements of COVID-19 Communication, September 21–October 28, 2020.

	CDC	Mayo	NEJM	NYT	CNN	Fox
	n = 172	n = 125	n = 73	n = 712	n = 1,000	n = 77
COVID-19 Representation	57%	55.2%	6.8%	7.2%	6%	1.3%
Identity_information	0.6%	2.4%		0.8%	1.3%	
Causal_information	23.3%	12%	2.7%	2.2%	3.6%	1.3%
Timeline_information		5.6%		1.4%	0.3%	
Consequence_information		6.4%		1%	0.4%	
Control_information	35.5%	34.4%	4.1%	2.1%	0.4%	
Public Health	29.1%	8%	27.4%	11.1%	13.1%	10.4%
Official_guidelines	7.6%		1.4%	1.7%	1.6%	1.3%
Testing/tracing	3.5%	1.6%	2.7%	0.3%	0.7%	
Death_toll	1.7%		2.7%	1.1%	2.4%	2.6%
New_cases	10.5%	2.4%	1.4%	4.8%	6.6%	2.6%
General_health_tips	1.2%					
Prompt_officials_for_action	4.7%		9.6%	0.1%		
Non-COVID_health_tips	0.6%					
Lockdown_orders				0.1%	0.6%	1.3%
COVID-_government_funding				1.3%	1%	2.6%
Hospital performance		4.8%	5.5%	1.1%	0.8%	
Business_closing/reopening				0.8%		
Vaccines/drug_distribution				0.4%		
COVID_health_policy			4.1%			
Psychological Health	2.3%	1.6%	5.5%	1.4%	1.9%	1.3%
Mental_health_issues	1.2%		2.7%	0.6%	1.7%	
Mental_health_tips	0.6%					
Substance_abuse		1.6%	1.4%	0.3%	0.5%	1.3%
Domestic_abuse	0.6%			0.1%	0.1%	
Need_for_mental_healthcare			1.4%			
Loneliness				0.3%		
Anxiety			1.4%	0.1%		

Medical and scientific research	8.7%	74.4%	49.3%	9.4%	13.5%	5.2%
COVID_vaccine_research	5.2%	20%	26%	5.3%	3.8%	5.2%
Health_expert_quotes	1.2%	58.4%	1.4%	3.1%	6.9%	
Projections/modeling	2.9%			1.1%	1.9%	
Impact_on_clinical_research			1.4%			
Recruit_research_volunteers		1.6%				
Suggestions_for_professionals			9.6%			
Free_access_to_literature			11%			
COVID-flu_comparisons				0.1%		
Health_outcomes_in_general		1.6%	1.4%	0.1%		
Social Dynamics	8.7%	14.4%	11%	28.4%	18.5%	7.8%
Personal_stories		0.8%		3.5%	6.3%	3.9%
COVID_patient_stories					1.7%	1.3%
People_isolated/quarantine	0.6%			0.3%	0.2%	
COVID_death_stories				1%	2.3%	2.6%
Racial_disparities	2.9%	1.6%	5.5%	1%	2%	
Highlight_positive_actions	2.9%	4.8%		0.4%	1.2%	
Famous_people				2%	0.9%	
Impact_on_communities/cities				3.7%	1.5%	
Impact_on_education	2.3%			4.8%	1.4%	
Impact_on_sports		1.6%	1.4%	1.8%	1.9%	3.9%
Impact_on_travel		0.8%		1%	0.6%	
Immigration					0.5%	
People_ignoring_guidelines				0.7%	0.9%	
Food_insecurity	0.6%			0.4%	0.5%	
Social_disparities			5.5%	3.8%		
People_with_preexisting_conditions			1.4%			
COVID-related_xenophobia				0.1%		
Protesting_the_lockdown				0.3%		
Social_effects_of_lockdown		3.2%		1.5%		
Group_activities/gatherings				0.3%		
Work_from_home				0.4%		
Frontline_workers'_stories				0.6%		
Impact_on_prisons				0.3%		
Impact_on_daily_tasks				0.4%		
Beliefs_of_certain_groups				0.3%		
Holidays/celebrations		2.4%		0.1%		
Journalist_opinion				3.2%		

Economic Impact				10.7%	6.1%	15.6%
Impact_on_the_country				1.1%	1%	2.6%
Impact_on_stock_market/top_business				1.3%	1.1%	0%
Impact_on_business				1.8%	1.1%	2.6%
Impact_on_entertainment_industry				1.4%	1%	1.3%
Impact_on_small_business				0.3%	0.7%	
Impact_on_personal_finances				1.3%	0.7%	1.3%
Government_financial_relief_coverage					0.3%	7.8%
Impact_on_unemployment				1.8%		
Paying_for_hospitalization/treatment				0.6%		
Economic_impact_on_specific_groups				0.4%		
Economic_impact_on_communities/cities				0.7%		
Company_innovations				0.4%		
Politics	1.8%		12.3%	35.3%	36.7%	63.6%
Presidential_election	1.2%		2.7%	10.8%	9.6%	14.3%
Criticism_of_President_Trump			4.1%	3.7%	4.5%	1.3%
Trump_positive_for_coronavirus			4.1%	8.7%	5.7%	13%
All_other_Trump_coverage			1.4%	6%	7.5%	9.1%
COVID_cases_linked_to_Trump				4.2%	2.2%	3.9%
Trump_tweets_flagged/removed					0.6%	
Fact-checking				2.5%	1.5%	
Officials_(other_than_Trump)	0.6%			4.2%	6.1%	3.9%
Officials_test_negative				0.4%	1%	6.5%
Officials_test_positive				2.8%	3.2%	9.1%
Officials_isolate/quaratine				0.1%	0.4%	1.3%
Officials_ignoring_guidelines				0.6%	0.2%	1.3%
White_House_COVID_response					1.7%	2.6%
Congress_coverage			2.7%	1.7%	1.2%	7.8%
Coverage_of_other_countries	0.6%			15%	8.7%	3.9%
Environment/climate_change					1%	
Visual Link	4.7%	54.4%	82.2%	83.1%	80%	93.5%
Video	7%	6.4%	0%	2.0%	13.1%	0%
Photo	44.8%	32.8%	6.8%	6.3%	4.9%	1.3%
Infographic	35.5%	0%	9.6%	4.2%	0.4%	0%
Text Only	8.1%	5.6%	0%	3.4%	1.3%	3.9%

Note. β-correlation coefficient, SE-standard error; $^{a}p < 0.05$, $^{b}p < 0.01$, $^{c}p < 0.001$.

In agreement with the STM modeling of COVID-19 communication between January and November 2020 (Figures 2–6), the manual coding of COVID-19–related tweets posted between September 21 and October 28, 2020, found that a majority of COVID-19 communication by the CDC and Mayo Clinic was about COVID-19 illness representation. Moreover, we found that both Mayo and NEJM focused heavily on medical research. In contrast to government agencies, hospitals, and journals, the media accounts had decreased COVID-19 health and medical content (Table 4).

Remarkably, COVID-19 communication on NYT, CNN, and Fox News accounts was substantially more politicized, with 35.2%, 36.7% and 63.6% of all COVID-19–related tweets, respectively, containing political information. Economic content was also prominent, especially on the Fox News account. Together, political and economic content accounted for 45% of NYT, 42.8% of CNN, and 79% of Fox News COVID-19 communication. These findings uncover a marked politicization of COVID-19 coverage by the news media.

After having identified the content of COVID-19 communication in individual tweets, we asked which elements of COVID-19 communication are associated with significant increases or decreases in audience engagement. We first asked which *major* categories of COVID-19 communication are most engaging to audiences. We conducted multivariate regression analyses using the major categories of COVID-19 communication (Table 4) as well as the major tweet features (the presence of photos, videos, links, or infographics) as independent variables, and the measures of user engagement (number of favorites or retweets) as dependent variables.

We found that COVID-19 illness representation predicted more favoriting on CDC's account and more retweeting on CDC, Mayo, NYT, and CNN accounts. Posts containing COVID-19–related public health information were more likely to be favorited by CDC audiences and more likely to be retweeted by CDC and NYT audiences. Information about COVID-19 research predicted higher engagement of NEJM, NYT, and CNN audiences. COVID-19 political content predicted higher favoriting by NEJM, NYT, CNN, and Fox audiences, and higher retweeeting by NYT and CNN audiences. Interestingly, economic aspects linked to COVID-19 decreased engagement on CNN and NYT's accounts. Moreover, issues related to psychological health impacted by COVID-19 were less likely to be retweeted by CNN audiences (Table 5).

Table 5. Predicting User Engagement by COVID-19–Related Content.

	Favorites						Retweets					
Variables	CDC	NEJM	Mayo	NYT	CNN	Fox	CDC	NEJM	Mayo	NYT	CNN	Fox
	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE
(Intercept)	3.6±0.3	4±0.3	3±0.2	6.3±0.1	6.2±0.08	4.6±1	2.7±0.3	3.6±0.4	2.3±0.2	5.3±0.1	5.3±0.07	4.3±1
COVID_representation	**1±0.1**[c]	-0.6±0.4	0.4±0.2	0.05±0.1	0.2±0.1	-0.05±1	**1.1±0.1**[c]	5.7±11.8	**0.5±0.2**[a]	**0.4±0.1**[b]	**0.3±0.1**[a]	0.01±1.1
Public_health	**0.8±0.1**[c]	-0.2±0.4	-0.7±0.4	0.1±0.1	-0.04±0.1	-0.6±0.4	**0.7±0.1**[c]	1.2±0.8	-0.5±0.5	**0.4±0.1**[b]	0.09±0.1	-0.7±0.4
Psychological_health	-0.3±0.5	**1.3±0.5**[a]	-0.3±0.7	0.09±0.3	-0.1±0.2	0.5±1	-0.03±0.5	0.6±0.8	-0.4±0.7	-0.2±0.3	**-0.5±0.2**[a]	0.6±1
Biomedical_research	0.4±0.2	**1±0.3**[b]	0.1±0.2	**0.4±0.1**[b]	**0.5±0.1**[c]		0.5±0.3	**1.3±0.4**[b]	0.1±0.2	**0.5±0.1**[c]	**0.4±0.1**[c]	
Social_dynamics	-0.5±0.2	0.6±0.4	0.1±0.2	-0.05±0.1	**0.5±0.1**[c]	-0.4±0.5	-0.4±0.3	0.2±0.5	-0.4±0.2	0.05±0.1	**0.2±0.1**[b]	-0.5±0.5
Economic_impact				**-0.2±0.1**[a]	**-0.3±0.1**[a]	0.1±0.4				0.07±0.1	**-0.6±0.1**[c]	0.4±0.4
Politics	-0.2±0.5	**4.3±0.5**[c]		**0.9±0.1**[c]	**1.3±0.1**[c]	**1.2±0.3**[a]	-0.6±0.5	9.6±5		**0.9±0.1**[c]	**0.9±0.1**[c]	0.6±0.3
Omnibus_test_(df)	10	6	5	12	9	9	10	6	5	12	9	9
Likelihood_ratio_χ^2	**86.0**[c]	**173**[c]	7.2	**207**[c]	**362**[c]	**32.3**[c]	**100**[c]	**19.1**[b]	**16.9**[b]	**172**[c]	**196**[c]	14.0
Significance	*p* <0.001	*p* <0.001	*p* =0.208	*p* <0.001	*p* <0.001	*p* <0.001	*p* <0.001	*p* <0.01	*p* <0.01	*p* <0.001	*p* <0.001	*p* =0.124
Goodness_of_fit_(df)	161	66	119	699	990	67	161	66	119	699	990	67
Pearson_χ2	154	**186**[c]	68	**2851**[c]	**3016**[c]	**120**[c]	**200**[a]	77.9	68.3	**2557**[c]	**4649**[c]	69.2

Note. β-correlation coefficient, SE-standard error; [a]$p < 0.05$, [b]$p < 0.01$, [c]$p < 0.001$ Statistically-significant coefficients are in bold.

The analysis of the impact of post features on engagement showed that tweets containing only text were more likely to be favorited by NYT audiences, but less likely to be favorited and retweeted by CNN audiences (Table S1). These findings uncover a pattern of differential user engagement by COVID-19 communication that is dependent on the type of account, the type of COVID-19 information being communicated, and the presence or absence of visual features in a post.

To understand which granular aspects of COVID-19 communication are most (or least) engaging, we conducted regression analyses in which we included *all* subcategories of COVID-19 communication that were coded manually in seven-day-old posts. We found that COVID-19 illness representation information (identity, causal, and control) was engaging for CDC audiences, and COVID-19 control information predicted higher engagement of CNN audiences. Interestingly, COVID-19 causal information and consequence information was more shared, but not more favorited, by Mayo and CNN audiences (Table 6).

Table 6. User Engagement by COVID-19-Related Communication.

Variables	Favorites						Retweets					
	CDC	NEJM	Mayo	NYT	CNN	Fox	CDC	NEJM	Mayo	NYT	CNN	Fox
	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE	β±SE
(Intercept)	4.1±0.1	3.4±0.3	2.8±0.3	5.9±0.1	6.4±.09	5.9±0.3	3.8±0.1	3.2±0.2	2.0±0.3	5.3±0.1	5.3±.09	4.8±0.3
Identity_information	**1.7±0.6**[b]		0.2±0.6	-0.5±0.4	-0.04±0.2		**1.8±0.5**[b]		0.2±0.6	-0.2±0.4	0.3±0.2	
Causal_information	**0.4±0.1**[a]		0.4±0.3	0.05±0.2	0.2±0.1	-0.4±1	**0.3±0.1**[a]		**0.6±0.3**[a]	0.2±0.2	**0.4±0.1**[a]	-0.5±1
Timeline_information			0.2±0.4	0.1±0.3	-0.3±0.5				0.7±0.4	-0.01±0.3	-0.1±0.5	
Consequence_information			0.7±0.4	0±0.4	-0.4±0.5				**0.9±0.4**[a]	0.6±0.4	-0.1±0.5	
Control_information	**1.0±0.1**[c]	0.2±0.6	0.4±0.2	0.3±0.3	**1.4±0.5**[b]		**1.1±0.1**[c]	0.2±0.6	0.4±0.2	0.5±0.2	**1.1±0.5**[a]	
Official_guidelines	**1.3±0.1**[c]			0.2±0.3	**-0.7±0.2**[b]		**1.1±0.1**[c]			-0.06±0.3	**-0.6±0.2**[a]	
Testing/tracing	0.2±0.4	0.2±0.7	-0.5±0.8	-0.4±0.7	-0.6±0.3		0.07±0.5	0.1±0.7	-0.7±0.8	-1.0±0.7	-0.3±0.4	
Death_toll	**2.2±0.2**[c]	-1.1±0.8		0.6±0.3	0.4±0.3	-0.3±0.7	**2.4±0.2**[c]	-0.8±0.9		**0.8±0.3**[a]	**1±0.3**[b]	-0.3±0.7
New_cases	**0.8±0.2**[c]		-0.7±0.6	0.2±0.2	0.1±0.3	0.3±1.2	**0.7±0.2**[c]		-0.2±0.6	**0.5±0.2**[b]	0.09±0.3	0.5±1.2
General_health_tips	0.2±0.6						-0.2±0.7					
Prompt_officials_to_act	0.1±0.5	**2.5±0.4**[c]		0.6±1			-0.1±0.5	**2±0.5**[c]		0.8±1		
Lockdown_orders				1.4±1		-0.06±1				1.8±1		-0.6±1
COVID_gov't_funding				0.0±0.3	**-0.7±0.3**[a]	**-3.6±1**[b]				0.04±0.3	**-0.9±0.3**[b]	-0.4±0.8
Hospital performance		**1.9±0.6**[b]	0.4±0.4	-0.2±0.4	0.07±0.3			**1.2±0.6**[a]	-0.04±0.4	-0.5±0.4	0.4±0.3	
Businesses_closed/reopened				-0.2±0.4						**-0.9±0.4**[a]		
Vaccine/drug_distribution				0.09±0.6						-0.91±0.6		
COVID_health_policy		-0.01±1						-0.4±1				
Mental_health_issues	-0.6±0.8	-0.05±1		0.3±0.5	-0.1±0.3		0.03±0.5	-1.3±1.1		-0.1±0.5	-0.3±0.3	
Mental_health_tips	-0.9±1.3						-1.5±1.6					
Substance_abuse			-0.3±0.7	1±0.7	-0.3±0.5	0.7±1			-0.4±0.7	0.1±0.7	-0.3±0.5	0.8±1
Domestic_abuse	0.7±1			0.2±1			0.9±0.8			-0.2±1		
Mental_care_needs		-0.8±1.1						-1.0±1.1				

Loneliness				-0.9±0.7						**-1.6±0.7**[a]		
Anxiety				-0.3±1						-0.76±1		
COVID_vaccine_research	0.4±0.3	**1.9±0.3**[c]	0.2±0.3	-0.08±0.2	0.2±0.1	**-1.5±0.6**[a]	0.2±0.3	**1.4±0.3**[c]	0.2±0.3	0.2±0.2	0.1±0.1	-0.3±0.6
Health_expert_quotes	0.3±0.8	1.5±1.4	0.2±0.2	**0.5±0.2**[a]	**0.3±0.1**[a]		-0.03±0.9	1.7±1.4	0.2±0.2	0.4±0.2	**0.3±0.1**[a]	
Projections/modeling	**0.8±0.4**[a]			**2.1±0.4**[c]	-0.09±0.3		**1±0.4**[b]			**1.7±0.4**[c]	0.09±0.3	
Impact_on_clinical_research		0.5±1						0.07±1				
Recruit_research_volunteers			0.8±0.7						1.4±0.7			
Suggestions_for_professionals		-0.4±0.4						-0.8±0.4				
Free_access_to_literature		**1±0.4**[b]						0.4±0.4				
COVID-flu_comparisons				-0.1±1						-0.7±1		
Health_outcomes_in_general		0.3±1	0.2±0.7	-0.3±1	-0.4±0.4			-0.8±1	0.09±0.7	-1.3±1	-0.2±0.5	
Personal_stories			**2.1±1**[a]	0.1±0.2	0.3±0.2				0.4±1	**0.5±0.2**[a]	0.1±0.2	
COVID_patient_stories					-0.09±0.1						0.1±0.1	
People_isolated/quarantine				0.4±0.7	0.7±0.4					0.01±0.7	0.7±0.4	
COVID_death_stories				0.3±0.4	0.01±0.2	0.09±0.8				0.3±0.4	**0.5±0.2**[a]	0.2±0.7
Racial_disparities	-0.3±0.5	1±0.6	0.3±0.8	-0.09±0.4	-0.2±0.2		-0.2±0.5	0.8±0.7	0.1±0.8	-0.1±0.4	-0.2±0.2	
Highlight_positive_actions	-0.9±0.7		-0.4±0.5	**2.1±0.5**[c]	**1.3±0.3**[c]		-1.2±0.8		-0.3±0.5	**1.2±0.5**[a]	**0.6±0.3**[a]	
Famous_people				0.5±0.2	**1±0.3**[b]					0.3±0.3	0.6±0.3	
Impact_on_communities/cities				-0.2±0.2	-0.1±0.2					**-0.7±0.2**[a]	0.03±0.2	
Impact_on_education	0.1±0.5			-0.08±0.2	0.2±0.2		-0.04±0.6			-0.1±0.2	-0.1±0.2	
Impact_on_sports			-0.8±0.7	**-0.7±0.3**[a]	**-0.6±0.2**[b]	-1.3±1			-1.3±0.8	**-1.1±0.3**[c]	**-0.9±0.2**[c]	-1.8±1
Impact_on_travel			0.1±1	0.2±0.4	-0.5±0.4				-0.7±1.1	-0.1±0.4	-0.3±0.4	
People_ignoring_guidelines				0.5±0.4	-0.3±0.3					0.08±0.4	-0.5±0.3	
Food_insecurity				-0.4±0.5	-0.4±0.4					-0.6±0.5	-0.6±0.4	
Social_disparities		0.9±0.8		0.2±0.2				0.4±0.8		0.1±0.2		
People_w/_preexisting_conditions		-0.05±1						-0.4±1				
COVID-related_xenophobia				0.3±1						0.1±1		
Protesting_the_lockdown				0.4±0.7						0.3±0.7		

Social_effects_of_lockdown			0.1±0.5	-0.6±0.3					-0.03±0.6	**-1.3±0.3**[c]		
Group_activities/gatherings				0.06±0.7						-0.6±0.7		
Work_from_home				-0.4±0.6						-0.4±0.6		
Frontline_workers'_stories				-0.3±0.5						-0.9±0.5		
Impact_on_prisons				-0.8±0.7						-0.5±0.7		
Impact_on_daily_tasks				0.04±0.5						-1±0.6		
Beliefs_of_certain_groups				**1.7±0.7**[a]						**1.4±0.7**[a]		
Holidays/celebrations			-0.08±0.6	-2±1					-0.3±0.6	-2.7±1		
Journalist_opinion				-0.1±0.2						**-0.7±0.2**[b]		
Impact_on_the_country				0.2±0.3	-0.2±0.3	**2±0.8**[a]				0.6±0.4	-0.09±0.3	**2±0.7**[b]
Impact_on_stock_market				-0.4±0.3	-0.4±0.3					**-0.8±0.3**[a]	-0.4±0.3	
Impact_on_business				-0.4±0.3	-0.5±0.3					**-0.9±0.3**[a]	**-0.8±0.3**[a]	
Impact_on_entertainment				-0.2±0.3	0.07±0.3					**-0.7±0.3**[a]	-0.3±0.3	
Impact_on_small_business				-0.9±0.7	-0.5±0.4					-1.3±0.7	-0.6±0.4	
Impact_on_personal_finances				**-0.7±0.3**[a]	**-1±0.3**[b]					**-1±0.3**[b]	**-0.9±0.3**[a]	
Gov't_financial_relief_coverage						**-4.8±1**[c]						-0.4±0.5
Impact_on_unemployment				-0.06±0.3						-0.2±0.3		
Paying_for_hospitalization				**1.4±0.5**[a]						**2.2±0.5**[c]		
Economic_impact_on_groups				0.06±0.5						-0.08±0.5		
Economic_impact_communities				-0.6±0.4						**-1.2±0.4**[b]		
Company_innovations				0.9±0.6						0.2±0.6		
Presidential_elections	0.3±0.5	1.9±1.2		**0.5±0.1**[b]	**0.8±0.1**[c]	0.5±0.5	-0.02±0.6	1.6±1.2		-0.07±0.1	**0.2±0.1**[b]	0.2±0.4
Criticism_of_President_Trump		**6±0.6**[c]		**1.5±0.2**[c]	**1.4±0.1**[c]	0.06±1		**5.7±0.6**[c]		**1.3±0.2**[c]	**1.2±0.1**[c]	-0.2±1
Trump_positive_for_coronavirus		0.6±0.7		**0.9±0.1**[c]	**0.8±0.1**[c]	**1.5±0.4**[b]		0.2±0.7		**0.6±0.1**[c]	**0.6±0.1**[c]	0.8±0.4
All_other_Trump_coverage		0.4±1		**0.8±0.1**[c]	**0.3±0.1**[b]	**4.7±1**[c]		-0.04±1		**0.4±0.1**[a]	0.2±0.1	**1±0.4**[a]
COVID_cases_linked_to_Trump				**0.6±0.2**[b]	**1±0.2**[c]	-0.4±0.6				**0.6±0.2**[b]	**1.2±0.2**[c]	**-0.5±0.6**[a]
Trump_tweets_flagged/removed					**2.2±0.4**[c]						**1.6±0.4**[c]	
Fact-checking				**1.2±0.2**[c]	**1.2±0.2**[c]					**1.4±0.2**[c]	**1.3±0.2**[c]	

Officials_(other_than_Trump)				0.1±0.2	**0.5±0.1**[c]	**1.6±0.7**[a]				-0.1±0.2	**0.5±0.1**[b]	1.1±0.6
Officials_test_negative				0.5±0.6	0.5±0.3	**1.7±0.5**[b]				0.1±0.6	-0.2±0.3	1±0.5
Officials_test_positive				**1.2±0.2**[c]	**0.4±0.2**[a]	**1.7±0.5**[b]				**0.9±0.2**[c]	0.1±0.1	0.8±0.5
Officials_isolate/quaratine				1.2±1		-0.09±1				1.2±1		-0.5±1
Officials_ignoring_guidelines				**1.5±0.5**[b]		-0.2±1				**1.6±0.5**[b]		-0.1±1
White_House_COVID_response					-0.09±0.2	**1.9±0.7**[b]					0.09±0.2	1.1±0.7
Congress_coverage				**0.6±0.3**[a]	**0.7±0.3**[a]	0.4±0.5				0.1±0.3	**0.7±0.3**[a]	0.7±0.5
Coverage_of_other_countries		-0.7±1		**0.4±0.1**[b]	**-0.3±0.1**[a]	0.05±0.7		-0.03±1		-0.1±0.1	-0.03±0.1	0.02±0.6
Environment/climate_change					**0.95±0.3**[b]						**1.3±0.3**[c]	
Omnibus_test_(df)	19	22	20	73	50	24	19	22	20	73	50	24
Likelihood_ratio_χ2	**146**[c]	**248**[c]	20.4	**437**[c]	**473**[c]	**90.4**[c]	**156**[c]	**261**[c]	27.3	**447**[c]	**339**[c]	36.1
Goodness_of_fit_(df)	152	50	104	638	948	52	152	50	104	638	948	52
Pearson_χ2	**18475**[c]	**84.1**[b]	45.7	**2038**[c]	**1683**[c]	**84.6**[b]	**13652**[c]	55.9	59.2	**1716**[c]	**2230**[c]	31.6

Note. β-correlation coefficient, SE-standard error; [a]$p < 0.05$, [b]$p < 0.01$, [c]$p < 0.001$. Statistically-significant coefficients are in bold.

COVID-related research, projections, and tweets featuring doctors and scientists were more engaging for several audiences. Posts about the impact of COVID-19 on hospital performance strongly engaged the NEJM audience. Tweets that highlight COVID-19–related positive actions of individuals and entities were more engaging for NYT and CNN audiences. Interestingly, posts about the impact of COVID-19 effects on sports were less liked and retweeted by NYT and CNN audiences.

Remarkably, we further found that tweets with COVID-19–related political content strongly engaged audiences. Furthermore, fact-checking and tweets announcing the removal of tweets by President Trump that violated social media guidelines were extremely engaging for NYT and CNN—but not Fox News—audiences.

Government agencies, hospitals, and journals posted virtually no COVID-19 political information (see Table 4), so the reaction of their audiences to political content remains unknown. One exception is criticism of President Trump, which strongly engaged the NEJM audience.

We also found that posts about the economic impact of COVID-19 on communities or businesses were less retweeted (but not less liked) by CNN and NYT audiences, whereas posts about the impact on personal finances were both less favorited and less retweeted. Posts about the social effects of the lockdown were less likely to be retweeted by NYT audiences.

The behavior of the Fox News audience differed from that of NYT and CNN audiences. For example, the Fox audience favorited many COVID-19 political tweets, but did not retweet them. The Fox audience was also less likely to share posts about coronavirus infections linked to President Trump. In contrast to NYT and CNN audiences, the Fox audience was engaged by information about the COVID-19 impact on the country. Notably, the Fox audience was strongly deengaged by information about the COVID-19 relief package, COVID-19 research, and government funding for research (Table 6).

Because of (i) the few daily posts on Mayo, NEJM, and Fox News accounts, and (ii) the few audience reactions to these posts (especially on Mayo and NEJM accounts; see Table 1 and data not shown) the multivariate regression models and predictions for these three accounts are less robust compared with those obtained for CDC, NYT, and CNN accounts.

Importantly, many of the most engaging features of COVID-19 communication were shared among several audiences—in particular, NYT and CNN audiences (Tables 5 and 6)—increasing the confidence about the best predictors of engagement by COVID-19 communication on Twitter.

Taken together, our findings uncover a differential pattern of user engagement by COVID-19–related information, and identify aspects of COVID-19 communication that are very engaging, as well as deengaging, for Twitter audiences.

Discussion and Conclusions

As the COVID-19 pandemic has taken global proportions, an effective health communication emerges as one of the most powerful ways to combat the spread of the coronavirus. Social media has become a major source of health information and emerges as a central tool for health communication during the COVID-19 pandemic. At least one-third of the world population uses social media. More than 68% of American adults use social media to receive information, including health-related information (Hitlin & Olmstead, 2018; Matsa & Shearer, 2018).

Social media facilitates not only the spread of information, but also real-time conversations, which can facilitate the interactions between the public and health organizations (Moorhead et al., 2013). Perhaps the biggest advantage of Twitter—the world's largest microblogging platform—during the COVID-19 pandemic, is the ability to rapidly share information in real time, which can prove critical to informing the local residents about new outbreaks, informing the public about the latest risk factors, transmission patterns, and other clinical and therapeutic studies. Twitter also facilitates the sharing of information among medical entities. For example, communication networks on Twitter have been identified among hospitals, medical journals, and medical associations, in which new protocols and expert opinion have been shared (Rosenberg, Syed, & Rezaie, 2020). Twitter is also the preferred social media outlets for sharing health information by state public health departments; however, an unmet need is the ability to go beyond simply distributing health information and more fully engage audiences (Thackeray, Neiger, Smith, & Van Wagenen, 2012).

Engaging the Public to Fight the COVID-19 Pandemic

It has been proposed that to successfully fight a pandemic, health communication by societal stakeholders should exhibit both *consistency* and *congruence*—two key factors for an effective COVID-19 communication (Seeger, 2020). The tone of messages and the information they contain should be similar (consistency; Glik, 2007) and stakeholders should communicate a unifying interpretation of risk and crisis (congruence; Sellnow, Ulmer, Seeger, & Littlefield, 2008).

Our results identify a disconnect between COVID-19 communication by government health agencies, hospitals, medical and scientific journals (which exhibit a robust and sustained COVID-19 communication about infection risk, as well as disease preventative and mitigating, and public health measures), and the news media (which frame COVID-19 mainly in sociopolitical terms and have only a secondary focus on risk, preventative and mitigating strategies, and public health measures). Interestingly, we also observed a disconnect between the ability of COVID-19 information to engage audiences: COVID-19 illness representation information about infection risk, prevention, and disease management, was most engaging for CDC audiences but less engaging for news media audiences.

Among the different types of COVID-19 illness representation, identity information (about the nature of the illness) and control information (about preventative and disease management approaches) were the most engaging aspects of COVID-19 for CDC audiences, followed by causal information (about the risk factors for infection and neagtive outcomes). As very little information was shared by the stakeholders about two other aspects of COVID-19 representation (timeline and consequence information), their ability to engage audiences remains unknown.

In contrast to government health agencies, hospitals, and medical and scientific journals, COVID-19 communication by the news media was heterogenous in its content, characteristics, topics, and temporal profile

(Figures 1, 5–6, and Table 4). Remarkably, we found that the frequency of news media posting about COVID-19 was positively and strongly correlated with the daily COVID-19 death toll and less well correlated with newly diagnosed coronavirus infections (Table 2). This suggests that COVID-19 mortality is a potent driver of news media coverage of COVID-19. An analysis of newspaper coverage of infectious diseases in the early 20th century found that newspaper coverage was correlated with the number of deaths because of disease and was more responsive to increases, rather than decreases, in death rates (Costa & Kahn, 2017).

Our STM modeling revealed distinct COVID-19 communication topics and clusters. The prevalence of COVID-19–related topics remained relatively stable over time (from January to November) on government agencies, hospitals, and journals' Twitter accounts (Figures 2–4). By contrast, COVID-19 communication on news media accounts was heavily politicized and also covered many socioeconomic aspects of COVID-19. COVID-19 illness representation topics were more prevalent during the early stages of the pandemic on news media accounts, but declined thereafter, while political frames became more prevalent in later stages of the COVID-19 pandemic (Figures 5–6).

An interesting observation is that political content was highly engaging for Twitter audiences, while economic content was often deengaging (Table 6). The economic impact of the COVID-19 pandemic has been unprecedented for many individuals, families, and communities. We speculate that many negative economic news may have deengaged audiences. Additional investigations into the framing of economic aspects during the pandemic are warranted.

Our survey of three major government health agencies suggests that they exhibited a robust and consistent COVID-19 communication. However, a more comprehensive study found inconsistencies and incongruencies between risk and crisis communications of 67 federal and state-level health agencies and stakeholders (including multiple government agencies) as well as a global stakeholder (the World Health Organization) during the earliest stages of the COVID-19 pandemic (Wang, Hao, & Platt, 2021). Among the differences observed were different timelines and frequencies of COVID-19 risk and crisis communication; inconsistent messages about preventative measures; and incongruent assessments of the coronavirus risk and of preventative approaches and behaviors (Wang et al., 2021). This suggests that additional, concerted efforts are required to synchronize COVID-19 communication among societal, as well as global, stakeholders.

Our findings that (i) COVID-19 communication lacks a unifying paradigm among major societal stakeholders, combined with (ii) the differences in how COVID-19 is framed by the news media, and (iii) the inability of news media to engage Twitter audiences with COVID-19 risk, prevention, and disease management communication raise the possibility that inconsistent and incongruent COVID-19 communication by societal stakeholders can have negative public health consequences and impair the management of the COVID-19 pandemic.

Politicization of COVID-19 Communication

We uncover a progressive decrease of COVID-19 coverage by the news media, which is paralleled by an increased politicization of COVID-19 communication. A recent study also found that media coverage of

COVID-19 by leading U.S. newspapers and televised networks was significantly politicized, as well as polarized (Hart, Chinn, & Soroka, 2020).

What is the impact of the politicization of COVID-19 coverage by the news media? Politicized COVID-19 news content may affect people in different ways, partly depending on their own political beliefs. A recent study found that political ideology has a strong influence on the perception of the COVID-19 threat, with conservatives more likely to treat COVID-19 as less threatening than liberals (Calvillo, Ross, Garcia, Smelter, & Rutchick, 2020). Similarly, right-leaning media consumption is correlated with false beliefs about the coronavirus (Motta, Stecula, & Farhart, 2020). In agreement with this, 68% of democrats and only 21% of republicans were concerned about COVID-19 (Badger & Quealy, 2020). A recent study further found that political polarization is directly responsible for the lack of social distancing of people identifying as republicans in the United States (Allcott et al., 2020). Thus, a combination of politically polarized news media coverage and personal political ideology may synergize to lead to a polarization of COVID-19 threat perceptions.

Our study found striking differences between COVID-19 coverage by Fox News and the other broadcast media networks. Fox News had the lowest coverage of COVID-19 and was a notable outlier (Table 1 and Figure 1). To assess whether the differences in COVID-19 coverage between most media networks and Fox News are specific to Twitter, we examined the COVID-19 communication on Facebook by the same entities, between June 1 and October 31, 2020. Using the COVID-19 filter, we found that Fox News had the lowest number of total COVID-19–related Facebook posts (801) relative to the other news media accounts (CNN: 1,511; ABC News: 2,577; NBC News: 3,226; CBS News: 1,829), despite having the second-highest number of followers (22.2 million). Thus, Fox News's COVID-19 coverage on Twitter and Facebook lags behind the other news media networks.

Can the decreased COVID-19 coverage by Fox News contribute to the beliefs and behaviors of its audience? In March 2020, only 38% of Fox News viewers were concerned about the pandemic, while 72% of national newspaper readers and 71% of CNN viewers were worried about the virus (Motta et al., 2020). Moreover, the more news viewers received from CNN, the more severe they believed COVID-19 was. By contrast, the more news viewers received from Fox News, the less vulnerable they felt, and the more they believed that the pandemic is a result of a conspiracy (Calvillo et al., 2020). Thus, news media can shape the public's perception of COVID-19, and qualitative and quantitative differences in COVID-19 coverage by news media entities may have direct health consequences for their audiences.

To successfully fight and eradicate the novel coronavirus, we argue that societal stakeholders should continue to build and strengthen strategic partnerships and engage the totality of the public through effective, consistent and congruent COVID-19 communication strategies.

Limitations and Perspectives

Our analysis of COVID-19 communication was restricted to the first part of the COVID-19 pandemic, from January 1 to November 14, 2020; the engagement analysis was conducted over a period of 38 days in September and October 2020. As such, some of our findings on COVID-19 communication may not be translatable to later stages of the pandemic, when COVID-19 communication may focus on other aspects of the societal response, such as large-scale vaccination. Our study did not address the contribution of other major societal stakeholders to COVID-19 communication; world leaders (Rufai & Bunce, 2020) and key opinion leaders (Quinn, 2020) are often trusted ambassadors and may play key roles in COVID-19 communication. We also did not evaluate all aspects of news media framing of COVID-19. Frames such as conflict, morality and religion, ethnicisation, fear, or attribution of responsibility have been employed by global media in COVID-19 reporting (Ogbodo et al., 2020) and warrant further investigation. Despite this, our study provides new insights into COVID-19 communication strategies of major societal stakeholders and may contribute to a better understanding of health communication during times of crisis.

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