



Examining risk and crisis communications of government agencies and stakeholders during early-stages of COVID-19 on Twitter

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ABSTRACT

During COVID-19, social media has played an important role for public health agencies and government stakeholders (i.e. actors) to disseminate information regarding situations, risks, and personal protective action inhibiting disease spread. However, there have been notable insufficient, incongruent, and inconsistent communications regarding the pandemic and its risks, which was especially salient at the early stages of the outbreak. Sufficiency, congruence and consistency in health risk communication have important implications for effective health safety instruction as well as critical content interpretability and recall. It also impacts individual and community-level responses to information. This research employs text mining techniques and dynamic network analysis to investigate the actors' risk and crisis communication on Twitter regarding message types, communication sufficiency, timeliness, congruence, consistency and coordination. We studied 13,598 pandemic-relevant tweets posted over January to April from 67 federal and state-level agencies and stakeholders in the U.S. The study annotates 16 categories of message types, analyzes their appearances and evolutions. The research then identifies inconsistencies and incongruencies on four critical topics and examines spatial disparities, timeliness, and sufficiency across actors and message types in communicating COVID-19. The network analysis also reveals increased communication coordination over time. The findings provide unprecedented insight of Twitter COVID-19 information dissemination which may help to inform public health agencies and governmental stakeholders future risk and crisis communication strategies related to global hazards in digital environments.

1. Introduction

The outbreak of the 2019 novel coronavirus disease (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in the U.S. in January 2020, has resulted in explosive and escalating communication across online environments related to the disease, outbreak trajectory, impact on human mortality, and global and local implications faced by government and health system agencies. The quick and exponential spreading of SARS-CoV-2 has ignited social media with a diversity of information. The increasing rate of detected incidents of COVID-19 along with massive amounts of related posts has triggered divergent reactions (Shimizu, 2020) and interactions across government agencies and stakeholders at various levels.

Among all media sources, Twitter, the largest microblogging

platform nationally and globally, has played a particularly important role in communicating SARS-CoV-2 and COVID-19 information. This is especially apparent in information dissemination on personal protective action inhibiting disease spread (e.g. wearing masks, reducing travel, social distancing, and teleworking). The World Health Organization (WHO) and the U.S. federal and state health agencies (*agencies* hereafter) and other federal agency stakeholders (*stakeholders* hereafter) whose operations are related to stemming the COVID-19 outbreak have consecutively published virus and disease-related content through their Twitter accounts. These actors' crisis and risk communication can provide credible sources of information during the unfolding of a crisis (Lin et al., 2016). The predominated information from trusted sources can also suppress the propagation of rumors (Aguirre & Tierney, 2001). Previous studies have identified several other key factors for the best

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practices of risk and crisis communication, such as the message update speed (Lin et al., 2016), and cooperation with the similar organization (Seegar, 2006).

There have been noted insufficient communications, inconsistent and incongruent messages regarding SARS-CoV-2 and COVID-19 and risks from different agencies and stakeholders. This phenomenon was especially salient at the early stage of the outbreak. Twitter users have difficulties in assimilating and making meaningful interpretations of disparate information from multiple sources (Ippolito et al., 2020). Both consistency and congruence are the key factors to effective communication about SARS-CoV-2 transmission and COVID-19 (Seeger, 2020) as individuals' sense of the perceived threat rests largely on the information that they have received from agencies and stakeholders. Consistency refers to "similarity between the tone of the message and the information contained therein" (Glik, 2007, p. 38). We use this metric to stress the reinforcement of similar messages and attitudes over time. Congruence implies communication agencies and stakeholders have settled on a single, unifying interpretation of the risk and crisis (Sellnow et al., 2008). We use congruence to differentiate with consistency by addressing the message uniformity across communication actors during a similar timeframe. Additionally, sufficient communications can lead to higher perceived risk and increased appropriate response while general and vague messages may cause people not to act (Glik, 2007).

Research in communication related to health warnings suggests that message congruence may evoke semantic priming effects that increase processing fluency of message recipients and improve attention-recall of relevant information (Lochbuehler et al., 2018). Timely and transparent dissemination of accurate, science-based information about the virus and pandemic and the progress of the response can build public trust and confidence (Reynolds, Galdo, & Sokler, 2002). Barriers to effectively communicating the situation, risk and controlling actions can also cause confusion. This phenomenon can lead to inappropriate behavioral contagion that can span a continuum of ignoring recommendations for physical distancing and self-quarantine on one end of the spectrum to panic buying, aggression, and unnecessary visits to health-care facilities on the other. All of which can have devastating consequences—burdening the medical system and causing unnecessary anxiety or deaths (Kalaichandran, 2009). Communication that elicits a specific behavioral response from intended message recipients emphasizes a need for understanding the context of persuasion, relevance of content, and strategy for action (Oinas-Kukkonen and Harjumaa, 2008).

Existing studies on risk communication mainly focus on disaster and emergency management during natural or man-made hazards (e.g. hurricanes and earthquakes). The ability to investigate risk communication in terms of information consistency and congruence during a relatively long-term pandemic (e.g. COVID-19) in online environments is a novel and historically unparalleled opportunity. Valid research communities provide useful insights and methods for tackling the challenges in communicating information about SARS-CoV-2 and COVID-19. However, the unprecedented global emergency requires timelier, domain- and context-specific research in understanding the communication dynamics on social media. Therefore, our overarching research goal is to examine the risk and crisis communication of SARS-CoV-2 and COVID-19 among agencies and stakeholders in terms of communication sufficiency, timeliness, congruence, consistency and coordination on Twitter, over the early stages of the outbreak in the U.S. The content of SARS-CoV-2 information refers to the *situation, risks and controlling actions*. Specifically, this manuscript intends to answer the following research questions (RQ):

RQ1: How do agencies and stakeholders communicate information about SARS-CoV-2 transmission and COVID-19 incidence on Twitter in terms of timeliness and sufficiency (i.e. frequencies) across types of messages? How do agencies and stakeholders' messages evolve with the infectious disease outbreak progression?

RQ2: How were critical messages relevant to preventative behaviors (e.g. strategies, guidance and order) communicated?

RQ3: Did different agencies and stakeholders communicate risk and crisis messages congruently and sufficiently?

RQ4: Did it appear that the agencies and stakeholders coordinated their risk and crisis communications over time?

The proposed research will focus on Twitter data posted by federal and state-level public health agencies and stakeholders. We collected the actors' tweets posted from January 1, 2020, to April 27, 2020, through a Twitter Search API. We filtered 13,598 messages (i.e. Tweets) relevant to COVID-19 and manually categorized all relevant tweets into 16 message types including strategies and guidance, orders, situational information, closures, openings, rumor management, and education. We analyzed the risk and crisis communication in terms of tweeting frequencies and timing of message types across actors. We also studied the evolution of different message types and identified incongruities and inconsistencies in several risk communication messages. Lastly, we employed text mining and network analyses to retrieve the communication networks among actors and identify the influential actors in communicating the risk of SARS-CoV-2 transmission and the health crisis of what would become the COVID-19 pandemic. A set of network metrics were adopted to evaluate communication coordination within and across agencies and stakeholders. The findings advance the existing knowledge body of risk and crisis communication during extreme events by studying an unprecedented pandemic with exploding online information using longitudinal social media data. The outcomes regarding communication sufficiency, consistency, congruency and coordination also inform public health agencies and government stakeholders of effective risk communication of virus transmission and prevention in fragmented online communication environments.

2. Related work

Understanding the risk and crisis communication behaviors of agencies and stakeholders during the early stage of COVID-19 on social media requires convergent knowledge that was dispersedly studied in public health, disaster and emergency management, and information science. Existing studies on crisis and risk communication on social media focused on the design of messages or aggregated social responses. Few have comprehensively investigated the message types, timing, sufficiency, congruency of information dissemination and coordination among actors over time. We used the following categories to cover the most relevant work.

2.1. Risk and crisis communication and social media

Concepts of risk communication and crisis communication have both been used in the research of disaster and emergency communication. The two concepts share concerns but also have distinguished features, so they have been used together to supplement each other or separately to address the specific research context. Based on the descriptions in the current literature body, research on crisis communication focuses on concerns about public relations and communication management under different discrete disasters (business/corporate, organizational hazards, food safety, organizations, community, social amplification, government). Risk communication research studies communication from a "risk management" aspect and the goal of communication is to control or moderate risks. This approach has been more frequently used in public health events such as disease outbreak, because of the necessity for integration of proactive and adaptive strategy to stem the further adverse impact of crisis (Linkov et al., 2010). It is used in more diverse disciplinary contexts (e.g. disaster, environmental hazards, climate change, infectious disease, food, psychology, and ecology) with long-term effects and impacts than crisis communication which deals with short term events. Seegar (2003) has summarized the main features of both concepts to differentiate their usages. Specifically, risk communication focuses on the projection of some harm that may happen in the future (i.e. risk centered) while crisis communication is event

centered. Thus, their message contents (probabilities of negative consequences vs. current state and conditions), communication bases (known vs. unknown), and actors may also be different. The agencies and stakeholders' communications of SARS-CoV-2 and COVID-19 address the current situations as well as the risks, so we use "risk and crisis communication" in this research to cover various aspects of the communication.

In the public health domain, many risk and crisis communication guidelines and policies published in the past decade have incorporated a general introduction of the importance of social media in such communication. For example, a WHO (2017) guideline for emergency risk communication policy and practice highlighted social media's role in "engaging the public, facilitate peer-to-peer communication, create situational awareness, monitor and respond to rumors, public reactions and concerns during an emergency, and to facilitate local-level responses". The U.S. Center for Disease Control and Prevention (CDC) (2014)'s crisis and emergency risk communication manual also identified social media's important role in information gathering and dissemination and its advantages in fast communication (dispelling rumors and providing accurate information).

Due to the increasing attention on the usage of social networking platforms in extreme events (e.g., Wang, et al., 2017; Wang & Taylor, 2018a, 2018b, 2020; Yao & Wang, 2020; Hao & Wang, 2020), more case studies on social media risk communication emerge across hazard types, such as hurricane, earthquake, infectious diseases, and environmental events. These studies can be categorized to; i) content-focused studies such as examining the message elements and formats (Wang et al., 2020) and risk narratives; ii) effective communication strategies and best practices before, during and after an event, such as the importance of providing honest, timely, accurate and reliable information (Steelman & McCaffrey, 2013); iii) the impact of risk communication such as modeling the impact of risk communication on evacuation decision making, especially hurricane warnings (Watts et al., 2019), and iv) perceptions of social media risk or crisis communications (Wirz et al., 2018). However, none of the existing studies have investigated the social media risk and crisis communications across agencies and stakeholders with their longitudinal social media messages nor focus on communication sufficiency, timeliness, congruence, consistency and coordination.

2.2. Coordinating risk and crisis communication on social media

Coordinating risk communication during crises and emergencies among agencies and stakeholders is critical because an individual actor simply does not have all the necessary resources needed to address unanticipated problems for all (Reynolds & Seeger, 2020). One major concern in response coordination during the disease outbreak is ensuring timely and consistent information sharing as the uncertainty of an emergency increases the need for information by the public (Hughes & Tapia, 2015) because appropriate information could make substantial improvements in the response process (Glik, 2007). Existing studies that have examined the organizational emergency and crisis response on social media have to date mainly concerning disasters. These studies that consider governmental agencies can be categorized into; (a) coordination within agencies, such as online cross-sector communication behaviors for emergencies on social media (Wukich et al., 2019); (b) coordination between agencies and the public, e.g. challenges in coordination between professional emergency responders and digital volunteers (Hughes & Tapia, 2015); and (c) coordination within and across groups, e.g. four-channel communication model (Pechta et al., 2010). However, among prior work, not many studies specifically focus on social media or comprehensively examine the influences and reactions between agencies, stakeholders, and the general public through the lens of social media risk communication. Few have evaluated the risk communication coordination in terms of information consistency and congruency among agencies on social media during a pandemic

outbreak.

2.3. Infectious disease outbreak and social media analysis

In the research field of public health, social media has been studied for early detection of epidemic outbreaks as part of the web surveillance system and to predict infectious disease outbreaks (Velasco et al., 2014; Yousefinaghani et al., 2019). Most of these studies emerged when an infectious disease occurred in the past decades, such as Ebola, H1N1, SARS COV, and MERS. Social media has also been widely studied as it diffuses health information, particularly misinformation (Mian & Khan, 2020; Leung & Leung, 2020), which is regarded as a global public-health threat as false information and affects people's preventive behaviors and increases the epidemic and pandemic risk (Larson, 2018). Thus, much research on the Internet-based social response intended to understand social media's effects on preventive behaviors and most of the efforts have devoted to vaccination hesitancy (Vinck et al., 2019; Oh et al., 2020; Arif & Ghezzi, 2018). Relevant domains that study different categories of information include natural disasters, political or social events, and environmental crises (Rajdev & Lee, 2015; Starbird et al., 2014; Getchell & Sellnow, 2016). However, few studies have had the chance to fully examine the digitally enabled social response considering the dissemination of time-inferred communication messages across agencies and stakeholders at both federal and state levels and well as their interactions to such a pandemic (COVID-19) with unprecedented speed and scale over time.

3. Data and methods

3.1. Data collection and case description

We focused on Twitter, from which 22% of people living in the U.S. retrieve news (Hughes & Wojcik, 2019). We used the Twitter User Timeline API (Twitter, 2020) to query Tweets posted by the official accounts of the WHO, 12 federal agencies, six governmental stakeholders, and 50 state-level public health agencies (i.e. Department of Health or DOH). Two agencies, the Wyoming DOH and the Department of Homeland Security (DHS), were found to post no tweet during the study period and were hence excluded from the analyses. Table 1 listed our studied communication actors and their Twitter user names.

The parameters of our study period are from January 1, 2020, the day after the WHO officially announced the presence of the novel virus, to April 27, 2020 (117 days in total) when the virus resulted in nearly one million confirmed cases and claimed about 56,000 lives in the U.S. (Johns Hopkins University, 2020). We chose this timeframe for the study period due to the amount of observed conflicting information, misinformation, and other risk communication incongruencies across agencies and stakeholders. These early months are also critical for crisis responders to impact the general public's preventative behaviors (CDC, 2020b).

3.2. Data preprocessing and social media messages classification

First, we filtered tweets using COVID19-relevant keywords including "coronavirus," "corona," "sars-cov-2," "ncov," and "covid," and identified 13,598 relevant tweets, which roughly equals one-third of the total tweets' volume posted by the agencies and stakeholders in our study period. Tweets posted over the study period not adhering to the basis of study context that was omitted from the analysis address other diseases such as seasonal flu, HIV, smoking, heart attack, and other health-related events and activities.

Then we manually annotated the 13,598 relevant messages with 16 categories by reading each message and assigning the category. One tweet can be maximally assigned to two message types based on the conveyed major information. The 16 categories and descriptions are listed in Table 2. The 16 categories were generated based on a study of

Table 1
The studied communication actors and their Twitter accounts.

	Full Name of Agencies	Abbreviated Names	Twitter Usernames
Global (1)	World Health Organization	WHO	WHO
Federal Health Agencies (12)	Centers for Disease Control and Prevention	CDC	CDCgov
	U.S. Food and Drug Administration	US_FDA	US_FDA
	U.S. Department of Health & Human Services	US_HHS	HHSgov
	Centers for Medicare & Medicaid Services	CMS	CMSGov
	Agency for Healthcare Research and Quality	AHRQ	AHRQNews
	Weekly Report	MMWR	CDCMMWR
	National Institute of Health	NIH	NIH
	Center for Health Care Strategies, Inc.	CHCS	CHCSHealth
	Infectious Disease Society of America	IDSA	IDSAInfo
	National Institute of Mental Health	NIMH	NIMHgov
	Society of Healthcare Epidemiology	SHEA	SHEA_Epi
	National Institute of Allergy and Infectious Disease	NIAID	NIAIDNews
Government Stakeholders (6)	Federal Emergency Management Agency	FEMA	fema
	United States Department of Transportation	USDOT	USDOT
	Federal Transit Administration	FTA	FTA_DOT
	Federal Aviation Administration	FAA	FAANews
	Department of Homeland Security	DHS	HLSNUSA
	The United States Environmental Protection Agency	US_EPA	EPA
State DOH (50)	An example of the 50 state-level DOHs:		
	Florida Department of Health	FDOH	HealthyFla

Wukin (2016) which proposed 22 types of social media messages for emergency management. We refined the list based on our collected data and produced new descriptions for each message type in COVID-19.

3.3. Dynamic network analysis of communication coordination

We conducted dynamic network analysis to examine the communication coordination among different actors. Dynamic network analysis has demonstrated its effectiveness in investigating cross-actor risk and crisis communications during events e.g. West Virginia water crisis (Getchell & Sellnow 2016). We extracted the communication networks among the agencies of focus by analyzing the retweeting (RT) and mentioning (@) relationships using Gephi (Bastian et al., 2009). We used a directed network to represent the information flows. Specifically, If Agency A retweets (RT) a post of Agency B, the information flows from B to A; if Agency A mentions (@) Agency B in a tweet, the information flows from A to B. Then we examined the dynamic relations and influences between federal agencies, stakeholders, and the state health agencies in communicating SARS-CoV-2 and COVID-19. We divided the communication actors into groups, i.e. federal public health and disease prevention agencies (Group 1), state-level public health agencies (Group 2), the other government stakeholders (Group 3), and the international health agency (i.e., the WHO) (Group 4). We evaluated in-group and

Table 2
Tweet topics and definitions.

# Type	Definitions
1	Strategies and guidance. The tweets describing strategies or guidance recommended by health agencies to individuals, households, and other stakeholders to minimize the risk of infection or contain the spreading. Example strategies can be "wash hands", "wear masks", and "disinfect the house".
2	Order The executive orders, policies, announcements that are issued by governmental agencies in the context of pandemics. For example, many states have issued "social distancing" and "stay at home" order. The federal government also issued orders to restrict national and international traveling.
3	Situational information The message describing the influence or associated risks of the pandemic, which supports situational awareness of the general public. Examples can be the number of infection cases or deaths or the assessed risks by authoritative agencies.
4	Closures The message about the closure of critical facilities, businesses, services, etc., for example, the closure of non-essential businesses.
5	Openings The message about the openings of critical facilities, businesses, services, etc., for example, the openings of testing sites, temporary hospitals, call centers.
6	Operations. The operations that the agency implemented or planned or the change of policies that the agency will follow. For example, some agencies automatically extended expired driver licenses. FEMA constructed new hospitals.
7	Resource provision The message providing information about resources (e.g., research funding, hospital capacities, medical supplies, relief funding and benefits, childcare services for front-line workers) that are available for relieving the pandemic impacts.
8	Clarification The clarification or explanation on the issued orders or policies or the correctness of before statements made by authoritative agencies. For example, some states specifically mentioned that people won't break the law if they do not observe the stay at home order.
9	Rumor/scam management Tweets that are posted to correct the rumor, false news, and warn scams and frauds. For example, some states warned the public to be aware of fake medical supplies/suppliers.
10	Volunteer/donation Tweets calling for volunteers and donations.
11	Employment Tweets advocating job positions or administrative roles. For example, many state agencies have posted tweets to recruit healthcare workers and professionals.
12	Opinion and commentary Tweets that express opinions (e.g. sadness, gratefulness), ideas, or comments toward situations caused by the pandemic, news, policies, events, and so on.
13	External resources/knowledge. Tweets that provide links to external information resources (e.g. websites, hotlines, videos, newsletters, presses, briefings, interviews, articles, fact sheets, science reports, online portals, apps, etc.) or advocate general knowledge or scientific findings related to the pandemic.
14	Guidance on other diseases or events. Tweets that provide information sharing and extra guidance on individuals managing other diseases or health conditions such as asthma, heart attack, mental stress, or other impacted events (e.g. voting, census) during the pandemic.
15	Event schedules and agendas. Tweets providing information on planned events such as media briefing, interview, meeting, conference, etc. For example, many state governors provide routine briefing during the pandemic and the state agencies held meetings to interview experts to talk about the COVID-19.
16	Intelligence gathering Tweets that collect answers, ideas, and solutions from the public. For example, some states encourage recovered patients to share their experiences and coping strategies.

cross-group communication networks and their information congruency, based on the time-inferred contents from their disseminated information and communication networks.

We constructed weekly communication networks and computed their metrics (i.e. network density, average weighted degree, average path length, network diameter, and modularity). In this study, the average weighted degree and density represent the general frequencies of retweeting and mentioning among studied actors. Higher degree or density refers to more coordination between agencies, which suggests more congruent information to the public. The average path length is the mean of links between all actor pairs, and diameter is the maximum number of links that connect two agencies. Shorter path length or diameters suggests a more connected communication network (Tabassum et al., 2018). We also used the modularity optimization to divide the network into communities, which is determined by comparing the number of edges within communities and expected numbers when the edges are randomly distributed (Blondel et al., 2008).

4. Results and discussions

4.1. Timeliness and frequencies of overall COVID-19 risk and crisis communication across message types

Different communicating actors started to communicate pandemic-related information at different time points. We regarded the time of their first COVID-19 message (either original tweets or retweet) as the initial dates of their communication. The IDSA was the first to communicate COVID-19 on January 9 among the investigated agencies and stakeholders. We calculated frequencies of COVID-19 messages for each actor per day from January 9 to April 26 (Fig. 1). The overall communication frequencies of the 67 actors are presented with the blue points and line (see the right y-axis). The numbers of agencies communicating risks at distinct daily frequencies are shown with grey circles (see the left y-axis). The values of the left y-axis is the number of tweets posted per actor and the size of the circles represents the number of actors who posted that number of tweets. In the first one and a half months of the disease outbreak in the U.S., the actors' communication frequently was very low. Over the beginning two weeks, less than ten messages were posted for the public each day. The communication frequencies increased significantly over late February to middle March when the actors averagely posted four to five tweets on weekdays and two to three tweets on weekends to communicate COVID-19.

We then analyzed the communication frequencies and percentages of the 16 message types over time (Fig. 2a and b). Message types, e.g. *situational information*, which introduces the present pandemic situations, and *external resources/knowledge* which directs users to other

media, dominate the messages posted by the health agencies and stakeholders. *Strategies and guidelines*, *order*, and *opinion and commentary* are the second major messages. Although communication frequencies of almost all types of messages increased over time, crisis risk communication on *strategies, guidelines and order* that encourage the public's preventative behaviors could be considered insufficient for the beginning month. This circumstance may have contributed to a lack of situational awareness of the general public on safe health practices which is a condition can contribute to poor public health outcomes (Hernandez & Blazer, 2006). The CDC confirmed the first infection case on January 20 (Holshue et al., 2020) and tweeted it on January 21. A local increment of tweeting frequencies is observed in the week of January 20. In the week of January 27, the CDC found a handful of more infection cases. The U.S. Department of State and CDC issued the Level 3 Health Alert (Avoid Nonessential Travel) to China on January 28 (CDC, 2020a). Many agencies reported the situation and policy order on Twitter and started to introduce the novel virus to the public. Therefore, message types of *situational information* and *external resources/knowledge* experienced their communication frequencies' peaks with around 100 messages posted in this week. This suggests the beginning time when most agencies started to pay attention or noticed the importance of communicating the COVID-19 situation and the risk to the public. The tweeting frequencies of *situational information*, *external resources/knowledge*, and *strategies and guidelines* increase significantly over mid-February to mid-March and then became stable. This period also saw more versatile message types. The stacked frequency (Fig. 2b) shows that the health agencies started to promote *volunteer recruitment* and *donations* (e.g. food, blood, shelters, and medical supply) at the beginning of March. The *guidance on other diseases and events* does not raise agencies' awareness at the beginning but has attracted more attention while the situation continually worsens. Similarly, the increased event schedules and agendas suggest the increased level of communication among governmental officers, experts, professionals, and the general public. The weekly frequency of posts related to the *resource provision* also saw steady increments from five in the week of February 17 to 67 one month later (March 16–23), possibly due to the increased impacts of the pandemic on citizens and economics. After mid-March, the tweeting frequencies of many message types fluctuated around a steady level. The *rumor management* and *order* peaked in the week of March 23–30 and then decreased. Many agencies started to officially issue the stay at home and social distancing orders in this week. The communications of *strategies and guidelines* such as sanitizing hands, disinfecting houses, and wearing masks also decrease a bit after mid-March.

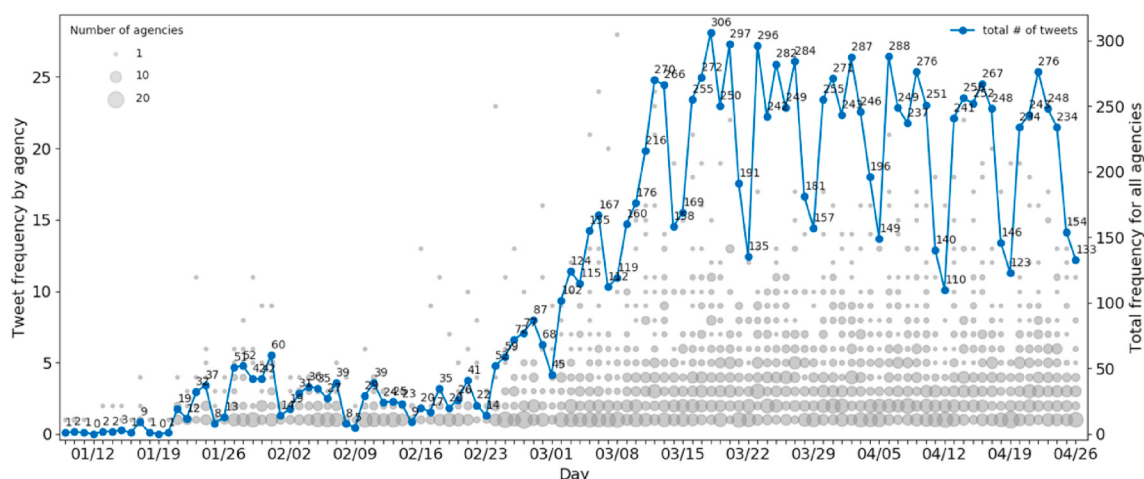


Fig. 1. The distribution of tweeting frequencies for different agencies across time.

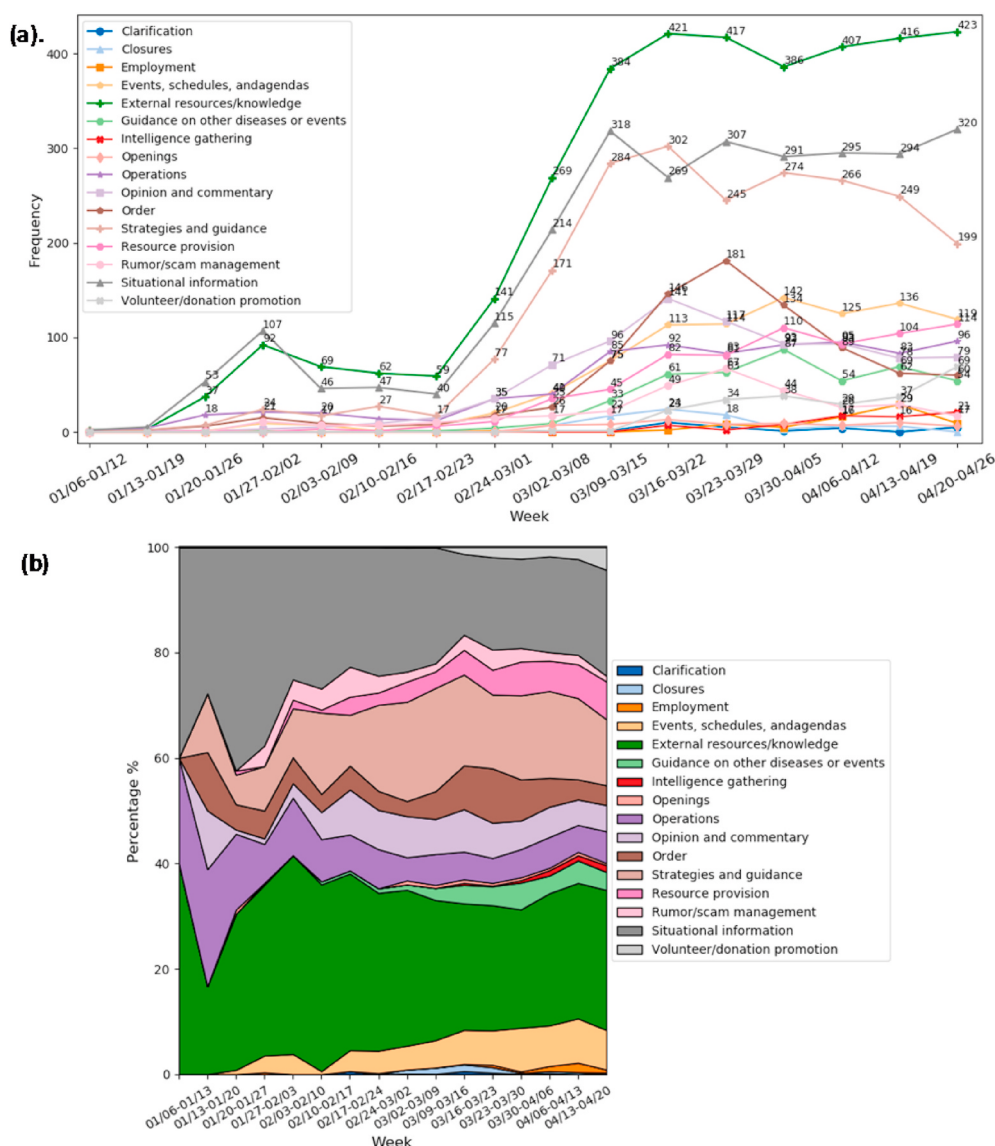


Fig. 2. Changing data volumes (a) and percentages (b) of different message types over weeks.

4.2. Identified inconsistency, incongruency, and insufficiency in critical preventative messages

We have identified four critical topics (wearing masks, assessment of risks, stay at home order, and disinfectant and sanitizer) that significantly impact individuals' preventative behavior under distinct message types that worth more detailed examination in terms of communication congruence, consistency and sufficiency during our investigated time window. These messages are listed in the Supplementary Tables.

4.2.1. Strategies and guidance messages: inconsistent attitudes toward wearing masks

Preventative strategies e.g. wash hands and disinfect surfaces have been congruently communicated across actors, but guidance on whether the general public should wear masks and what type of masks they wear presents an idea that has evolved over time (see [Supplementary Table 1](#)). In the beginning, the CDC specifically advocated that people with good health should not wear face masks. Until April 3, the CDC started to recommend the cloth face coverings for the U.S. citizens, however, clarifying that the surgical masks and N-95 respirators should be reserved to medical personnel. The state DOHs have been following the attitude of the CDC on wearing masks. Many have retweeted the CDC's

messages. Similarly, in the beginning, wearing masks is only recommended to people who are sick, wait in medical rooms for doctors, have symptoms like coughing or sneezing, and take care of a person with suspected infection. After the CDC posted content to advocate wearing face coverings, the state agencies put this strategy into routinely recommended actions. People donning face masks reliable for containing the spread of oral fluid in public settings is considered a valid safety behavior that helps to limit the transfer of the virus amongst humans when other social distancing measures are difficult to maintain. Anecdotal, the early debate in the U.S. on the idea of public adoption of wearing face masks in public spanned the continuum of no demonstrable efficacy to mask adoption causing negative impacts to the hospital Personal Protective Equipment supply chain. The WHO advice on the use of masks in the context of COVID-19 has also evolved over the early stages, from "no evidence that wearing masks would limit the virus spread" in April to "simulations indicate that universal masking that includes non-symptomatic health persons may reduce potential exposure risk from SARS COV-2" in June ([WHO, 2020](#)). These changing attitudes across agencies toward wearing masks can incur inconsistent behavior of the public. This is despite the fact that wearing masks can lower the transmission of oral fluid, aid in the reduction of SARS COV-2 virus transmission ([Stadnytskyi et al., 2020](#)), and synergizes with other

non-pharmaceutical measures to contain the virus spreading (Greenhalgh et al., 2020; Cowling et al., 2020). Early adoption of masks demonstrated a reduction in 17–45% deaths in New York and 24–65% deaths in Washington (Eikenberry et al., 2020). Simulation models of universal masking (80% population adoption rate) have suggested a reduction in COVID-19 spread if adopted sufficiently early even if the masks are nonmedical (Kai et al., 2020).

4.2.2. Situational information messages: the incongruent assessment of the coronavirus risk

During the pandemic, agencies have assessed the overall risk of the coronavirus several times (see Supplementary Table 2). In the beginning, agencies reported low-risk levels of coronavirus to U.S. citizens. For example, the CDC and WA both posted contents mentioning the low-risk situation of the U.S. after the confirmation of the first infection case. Some agencies showed more concern for the seasonal flu than SARS-COV-2. In late February, it was still believed that the risk of coronavirus to people in the U.S. was low, but the rapidly evolving global situation has arisen many agencies' awareness. The initial relevant messages highlighted that older people and those with underlying health conditions are at higher risk. Guidelines and strategies for health protection are especially recommended to this population. This statement changed as more cases were reported for young adults. ME DOH and SD DOH reminded the public that young people were not immune to coronavirus by sharing the hospitalization data. Another concern about the virus is the presence of community spreading. In the early stage, there was little evidence of community spreading in the U.S. CDC reported this on February 25 in two tweets based on available data during that moment. The two tweets have been retweeted more than 14,000 times. The CDC reported the community spread cases in California, Oregon, and Washington on February 29, but still hold optimistic attitudes on the situation. The prevalence of optimistic bias has precedence in recent pandemics including H1N1 and the first SARS outbreaks (Taylor, 2019, pp. 1071–1091). The psychological construct of optimistic bias refers to beliefs individual and collectively held beliefs that negative events are more likely to happen to others than to oneself (Kim & Niederdeppe, 2013). Given that two recent coronavirus epidemics (e.g. SARS COV-1 and MERS) did not have a widespread impact on U.S. health and mortality this construct may help to explain this in the early beliefs about COVID-19 disease risk and associated response of U.S. health agencies. Effective and congruent public health messaging that accurately qualifies disease threat level has been suggested as an effective moderator for this type of optimistic bias (Mongiello et al., 2016).

4.2.3. Order messages: incongruent stay-at-home order

Stay-at-home orders were given at different levels not synchronously among states (see Supplementary Table 3 for examples). In the beginning, stay-at-home order is only recommended for all sick people. In early March, ND DOH and the CDC recommended people who returned from infectious countries and were possibly exposed to COVID-19 to stay home for 14 days. Later in mid-March, people in good health, especially the non-essential workers, children, and older adults, are also recommended to stay at home to limit their contact with sick people. States started to issue executive orders and make the stay at home a mandated strategy in late March but differed in the starting time. NJ, ID, and OH were among the first to issue the order on March 21 and 22. Some states closed some counties or regions at the beginning but turned to state-wide order later. Accompanied by the stay-at-home order are the closure or reduced services of nonessential businesses, schools, and long-term care facilities, and nursing homes. Some states initially scheduled the order for a while around three weeks but later extended it for a longer time. Agencies also posted external resources to explain and clarify the stay-at-home order to relieve the public's panic.

4.2.4. Strategies and guidance messages: insufficient communications on the use of disinfectant and sanitizer

Many agencies advocated cleaning and disinfecting often-touched surfaces, sanitizing hands as effective countermeasures to slow down the virus spreading (Supplementary Table 4). However, the communications appear to be insufficient in volume in January and February (see Figs. 2 and 4). Some states forwarded videos on house-made sanitizers in March when experiencing the shortage of disinfectant products. The advocating of sanitizers and disinfectants, unfortunately, increased the exposure of the public to poisonous substances and vapors as well as improper use cases. For instance, the FDA reported increased cases of ingestion of hand sanitizers on March 28 and April 15 respectively. ID and NM posted tweets to avoid ingesting disinfectant as a treatment for the novel coronavirus on April 24 following a comment made by the president during a televised press briefing related to COVID-19 status in the U.S. This resulted from several states reporting that their Poison Control Centers had received calls about individuals ingesting household disinfectant as a way to combat COVID-19 after the April 2020 White House briefing. A subsequent survey conducted by the CDC on the appropriate use of household disinfectants also indicated that 39% of respondents had misused cleaning agents in some manner that resulted in adverse health effects (Gharpure et al., 2019).

4.3. Sufficiency and congruence of COVID-19 risk and crisis communication across agencies and stakeholders

To identify the spatial disparities in communication frequency and timeliness on Twitter, we mapped frequencies of relevant messages over 50 states in the U.S. (See Fig. 3). In general, states in the Northeastern area of the U.S. have posted more tweets than other states. The Massachusetts DOH tweeted the most while the Wyoming DOH did not post any Twitter messages during the study period. We have also summarized the first dates of the actors communicating the pandemic on Twitter in Fig. 4. Each colored grid represents the first date (x-axis) when the actor (y-axis) started to post the type of message (legend) on Twitter. We found that most state agencies started to post COVID-related tweets during the week of January 20 to 26 while several federal health agencies (i.e., CDC, IDSA, NIAID, and HHS) started the discussion before January 20. Two federal stakeholders, FEMA and FAA joined the dissemination on Twitter in late January while stakeholders including FTA, DOT, and EPA did not start until March. *Situational information*, *external knowledge*, and *operations* are the message types that agencies conveyed the most at the beginning stage. When looking into the tweet contents over the weeks, these agencies mainly retweeted the CDC's tweets to report confirmed cases in the U.S. The state agencies estimated the overall risk of the novel virus to be low for U.S. citizens. Some also pointed out the flu as a more serious public health issue at that time. For operations, agencies mentioned that they would continue monitoring

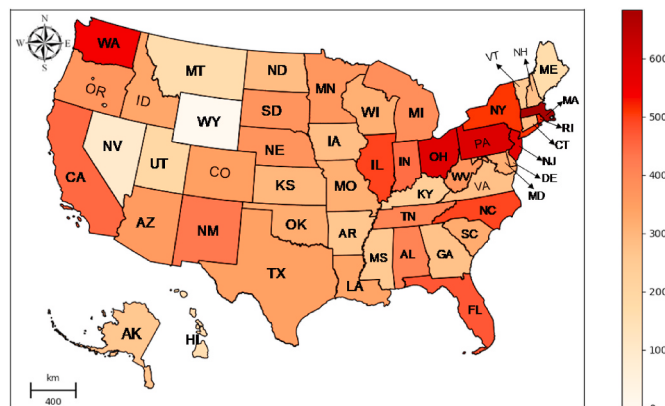


Fig. 3. Tweeting frequencies across states.

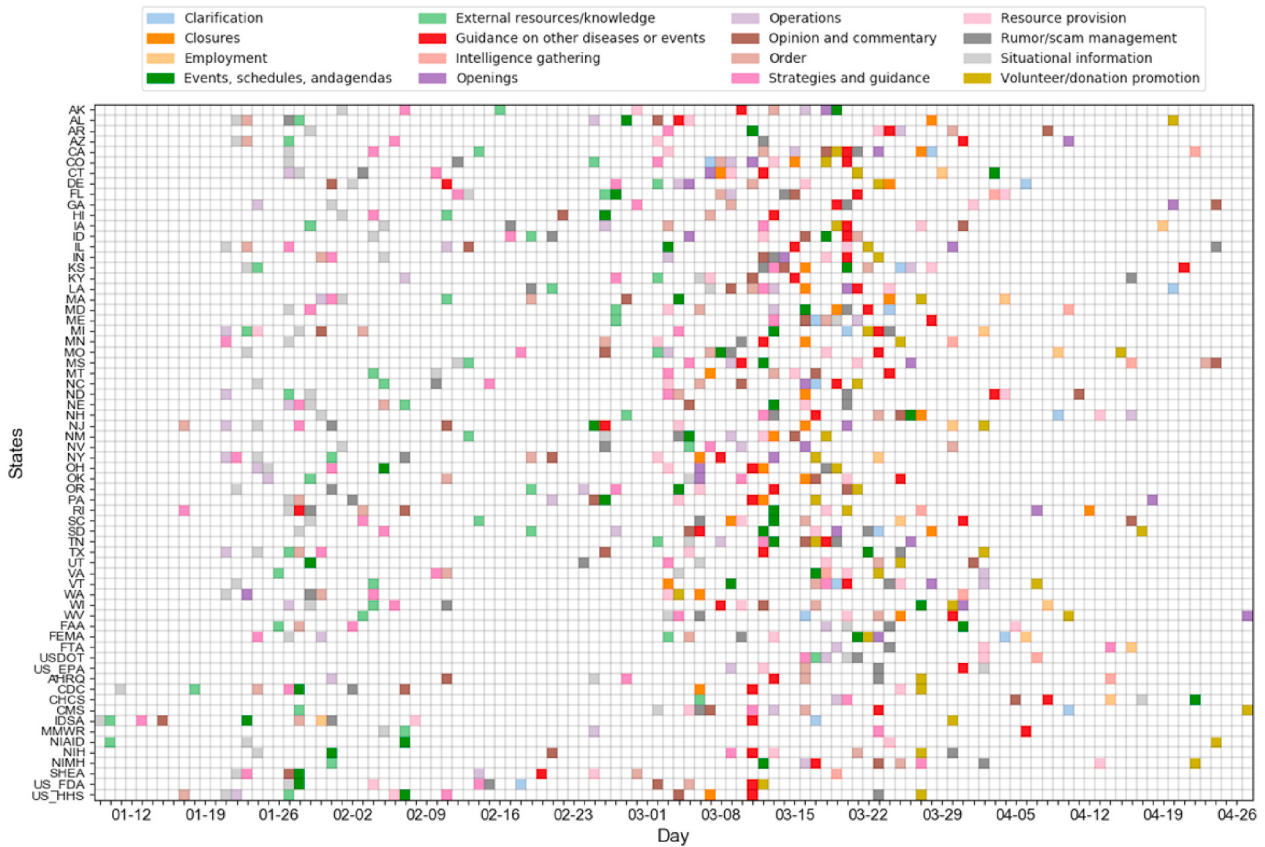


Fig. 4. Starting date of communicating different message types across agencies and stakeholders.

the situation and coordinating responses. Agencies generally started to promote external resources/knowledge before March.

The starting time of different actors communicating a specific message type varies much, indicating incongruent crisis risk communication across states. In general, federal health agencies started communicating many message types, e.g., external resources/knowledge, operations,

opinion, and commentary, and resources provision first, followed by state health agencies and then federal stakeholders. For example, on average, federal health agencies started disseminating messages on resources/knowledge since late January, while early February for state health agencies and mid-March for federal stakeholders. State health agencies also contributed more discussions to situational awareness,

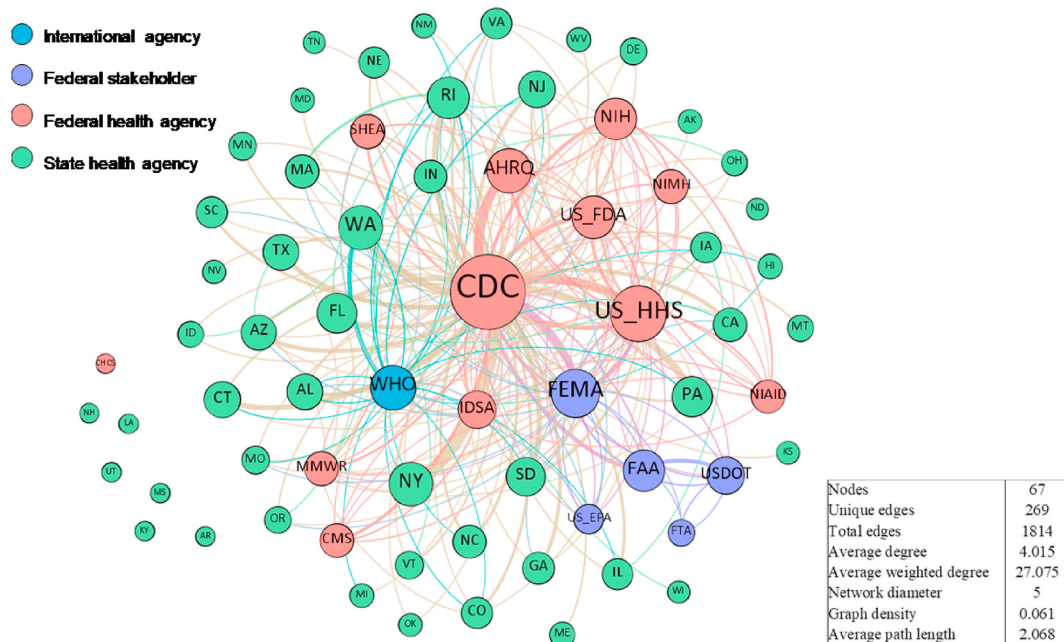


Fig. 5. The aggregated communication network across studied actors.

strategies and guidance, and rumor/scam management in the early stage compared to other actors. Message types such as openings and closures are mostly sent by state health agencies.

4.4. Disentangling dynamic interactions among actors in communicating SARS-COV-2

We employed dynamic network analysis to investigate how information flows among the investigated agencies and stakeholders over time. In total, we have 67 nodes representing the 67 investigated agencies including federal stakeholders, health departments, state health departments, and the WHO.

4.4.1. Aggregated communication networks among actors

We constructed the aggregated communication network over our study period (Fig. 5). Different colors represent distinct groups of communication actors. The size of nodes is determined by the *degree* of each node (i.e. the level of the agency connects with other agencies). A clockwise curve linking Agency A and B represent the information flows from A to B and vice versa. The average and the average weighted degree of the aggregated network is 4 and 27, respectively, suggesting an overall connected communication network among actors in terms of mentioning and retweeting. The network diameter (5) demonstrates the

shortest distance between the most distant nodes in the network. On average, a communication actor's message needs to travel two links to reach another actor. The CDC's Twitter account has the highest degree, followed by the HHS, FEMA, and WHO. For state agencies, the WA DOH and NY DOH have higher degrees than others. Seven agencies do not connect in the network as they did not retweet nor mention messages from the other studied actors, including the Center for Health Care Strategies (CHCS), NH DOH, LA DOH, UT DOH, MS DOH, KY DOH, and AR DOH. These agencies mainly connected with state governors, and health professionals that are not discussed in this paper.

We further partitioned the networks into communities that are densely connected internally. We identified four closely connected communities in the aggregated network (Fig. 6). Specifically, Community 1 includes 42 agencies with the CDC as the central node. Community 2 has four nodes, three of which are federal health departments that concern research and laboratory tests of the novel coronavirus (i.e. NIH, NIMH and NIAID). Community 3 is centered with the WHO, and Washington is the state who retweets the WHO's messages most frequently and Community 4 includes four state agencies (MA, RI, VT, and WI) that retweet or mention each other. Among them, RI retweeted much information from MA. This may be explained by RI residents' commuting patterns being higher to MA than many surrounding states (RI Department of Labor and Training, 2019).

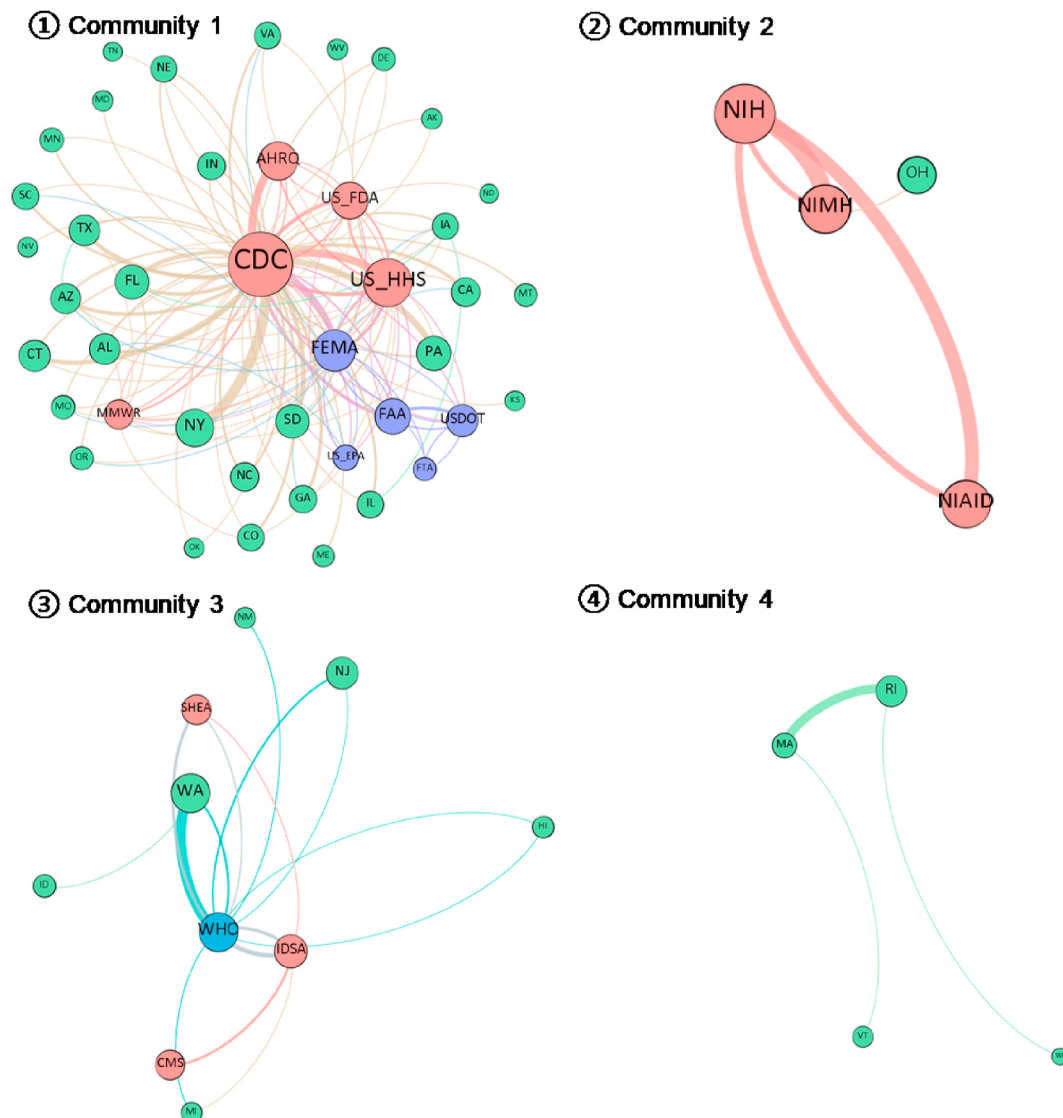


Fig. 6. Network communities in agencies' communication.

4.4.2. Dynamic communication networks

We further examined the dynamics of the weekly communication networks among actors over the 16 consecutive weeks (Figs. 7 and 8). The network is very sparse in the first three weeks (Fig. 8). In Week 1, only two U.S. agencies, IDSA (posted the first COVID-19 related tweet on January 9) and CDC, started to post the COVID-19 information. In Week 2, additional two federal health departments (NIAID and HHS) and two state DOHs (RI DOH and NJ DOH retweeted the WHO and CDC's posts) started to communicate the situation. Federal stakeholders including FEMA and FAA began to communicate the crisis and risk in Week 3. Other stakeholders (e.g. DOT, FAA and FTA) did not disseminate the crisis/risk of the pandemic using their social media accounts until Week 9. We also noticed that federal stakeholders retweeted information from the CDC and HHS. Some transportation-related stakeholders, i.e., DOT, FAA, and FTA more frequently communicate with each other. The network connectivity reaches the first small peak in Week 4 (see network density and average weighted degree in Fig. 7). In that week, the CDC tweeted an order that advised the public to cancel nonessential traveling to China. The network connectivity then decreases over the following three weeks (January 27 - February 17), though more agencies started to post relevant messages independently (evident in the increased network diameter and average path length). The COVID-19 pandemic has been collectively considered as a pandemic since Week 4 due to increasing reported cases across countries. The connectivity in

agencies and stakeholders' communication network also kept growing since late February to early April as more suspected or confirmed cases were reported.

5. Conclusion

Large-scale infectious disease outbreaks are a devastating public health "disaster" around the world. The epidemiology of viruses such as SARS CoV-1, MERS, and SARS-CoV-2 has been varied making the virulence trajectories of emergent coronaviruses difficult to predict. More uncertainties of the disease will be revealed, and more response actions will be implemented. It is urgent and time-critical that we track and understand the dynamics and influences of risk communications of agencies and stakeholders on social media. This study analyzed the risk and crisis communication in terms of sufficiency, timeliness, congruence, consistency, and coordination among public health agencies and federal stakeholders at the early stage of an infectious disease outbreak. The analysis results reveal that agencies and stakeholders, though underestimating the pandemic risk at the beginning, have paid increasing attention to the crisis over the study period. Substantial efforts on the part of US health agencies are being made to convey situational awareness and to educate the public on preventative strategies. The analysis of agencies and stakeholders' tweets identifies insufficiency, incongruency and inconsistency across critical message types.

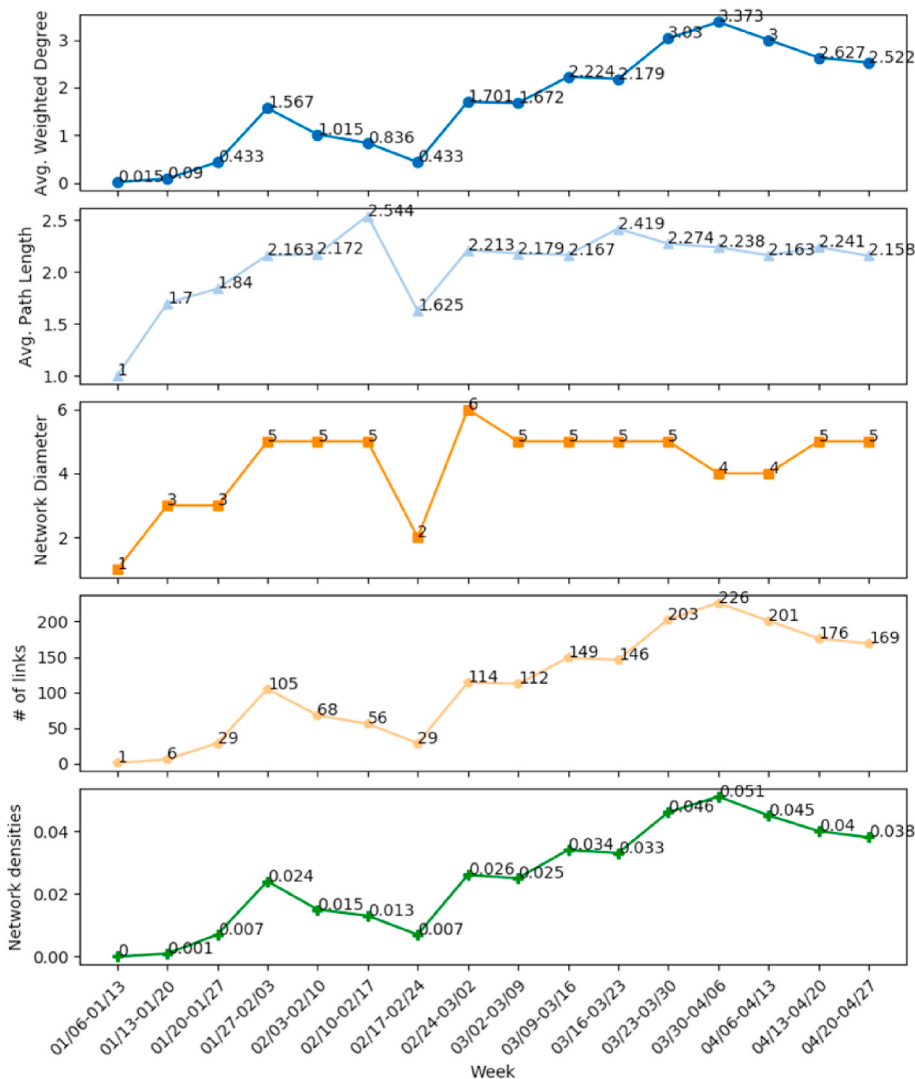


Fig. 7. Weekly changes in communication network metrics.

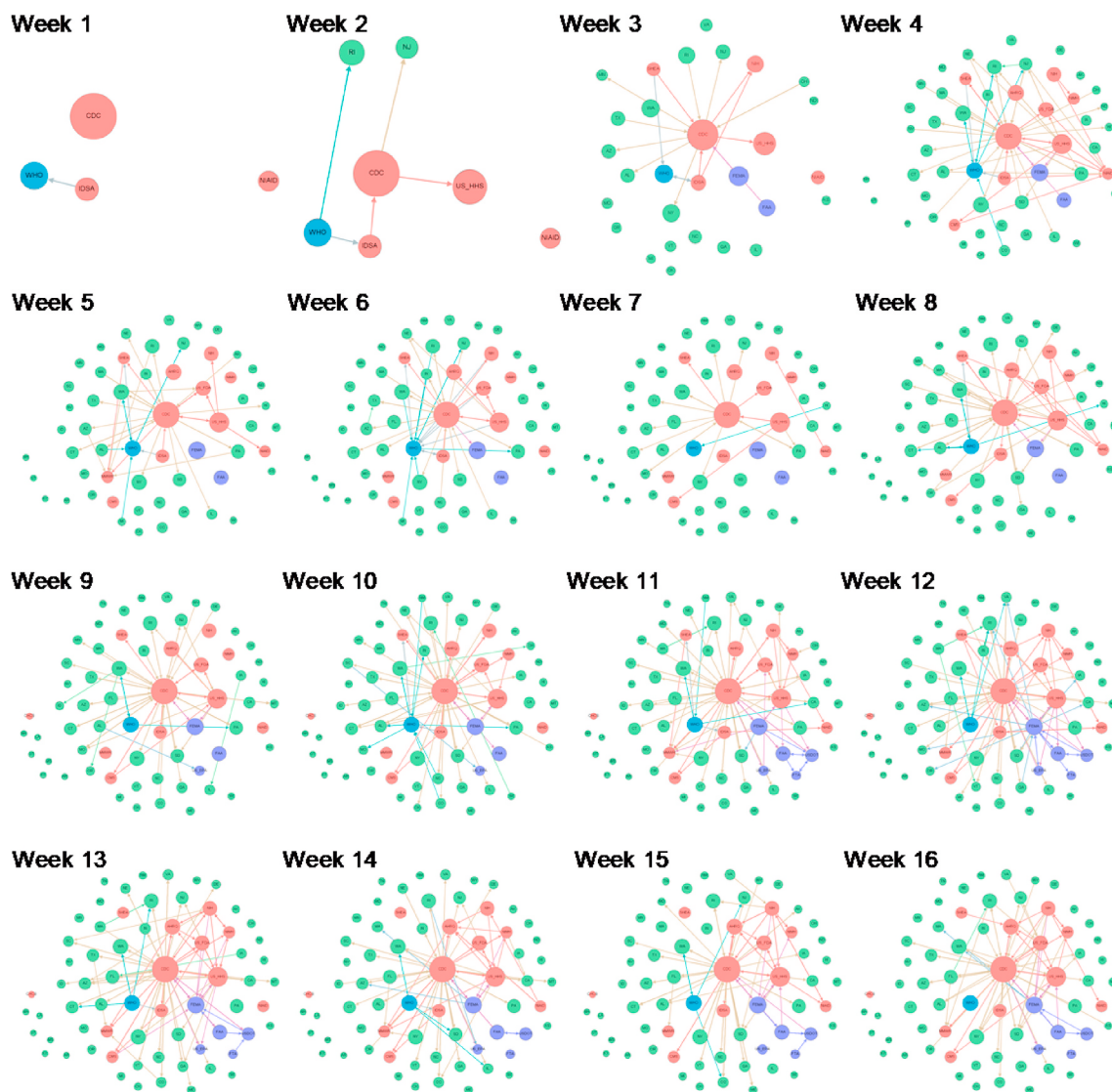


Fig. 8. Network dynamic change over the weeks from January 6 to April 26.

The dynamic network analysis showed a changing communication pattern among agencies and stakeholders with an increased level of connectivity and coordination during the study period (early-stage response). Disentangling the interactive influences of risk communication actors is instrumental in furthering information and education about the communication science of virus transmission and prevention on social media. The study also has a few limitations that will be addressed in future research. First, this research focuses on risk and crisis communication of agencies and stakeholders, so we only studied tweets posted by their official accounts. Future empirical studies can also investigate public behavioral impacts responding to insufficient, inconsistent and incongruent risk communication over the full cycle of the pandemic. Because this research is an observational study of Twitter-based communication related to COVID-19, it is not appropriate to draw inferences about behavioral impacts related to platform or message type dissemination of specific social media (e.g. Twitter) users. Second, the research conducts an analysis for COVID-19. Future research can be extended to different types of infectious disease outbreaks to identify general strategies for sufficient, congruent, and effective risk communication. Third, we used data collected from Twitter only as Twitter is one of the largest short blogging platforms in the U.S. and it provides open APIs. In the future, a cross-platform investigation may generate more comprehensive findings once data from other social media become

available. Lastly, future work can also compare findings of communication congruency from public health crises and natural hazards disasters to compare the commonalities and differences in persuasive communication strategies.

The ultimate success of a public health campaign in the wake of a pandemic such as COVID-19 is dependent on effective population interaction with health agency communication and uptake of ideas. Considering that both individual and community responses to health communication are emergent in nature it can be difficult to ascertain the effectiveness of such a health crisis campaign with the immediacy needed to ensure alignment of health information provision and consequent human reaction. Using Twitter message dissemination analysis provides an important basis for the understanding of health crises and risk communication of official agencies and stakeholders. This would offer potential for insight generalizability on information dissemination attributes (e.g. frequency, timing, message types and coordination) helpful in guiding future global emergent health crisis communication strategies. Furthermore, this study of social media-based crisis risk communication related to a global health event such as COVID-19 provides an opportunity for these findings to be parsed and evaluated further and more extensively within the public response. This would be valuable in interpreting to what extent sufficient, congruent, consistent, or coordinated risk and crisis communication can generate

meaningful and effective reaction from messaging targets. The research findings lead to fundamental knowledge of social media risk and crisis communication in large-scale hazards (e.g. pandemic and disasters) by bridging public health and disaster and emergency management. The research also provides public health agencies, first responders and other government stakeholders with an updated understanding of their role in disseminating crisis and risk information on social media. The outcomes will have the potential to understand how to better reduce the risk of inappropriate behaviors and preventable deaths caused by insufficient risk communication, incongruent and inconsistent information harmful to human health and wellbeing as well as how to improve existing crisis risk communication plans, critical health information dissemination efficacy and coordination during unprecedented health crises in the fragmented communication world.

CRediT authorship contribution statement

Yan Wang: Conceptualization, Methodology, Validation, Writing - original draft, Supervision, Project administration, Funding acquisition. **Haiyan Hao:** Data curation, Formal analysis, Writing - original draft, Visualization. **Lisa Sundahl Platt:** Conceptualization, Validation, Writing - review & editing, Funding acquisition.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chb.2020.106568>.

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