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Crisis Communications in the Age of Social Media: A Network Analysis of Zika-Related Tweets

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Abstract

While emerging technologies such as social media have demonstrated value for crisis communications, significant question remains regarding how these tools can be most effectively leveraged to facilitate the flow of valid information under crisis conditions. In an effort to address these issues, this article examines the use of Twitter during the 2015–2016 Zika virus outbreak in the United States. Particular attention is paid to network structures within the Zika conversation and how different actors and communities contribute to the flow of information throughout the broader Twitter community. Public-facing organizations can benefit from a deeper understanding of the nature and structure of spontaneously occurring communities on social media as well as the types of content that they create and circulate. As such, these findings have significant implications for the development of effective social media strategies during natural disasters and public health emergencies. In particular, this analysis identifies several predominant themes communicated through Zika-related tweets as well as a number of distinct communities and influential actors. The findings suggest that respected political actors, public institutions, as well as those with valid scientific credentials can help to facilitate the flow of accurate and vital information across disparate communities.

Keywords

Zika, health emergency management, social network analysis, Twitter, crisis informatics

Public emergencies place unique strains on information networks, and as such, effective crisis communications are essential to successful emergency management (Houston et al., 2014; Pechta, Brandenburg, & Seeger, 2010; Steelman, Nowell, Bayoumi, & McCaffrey, 2014). Crisis communications are typically defined by high levels of ambiguity, fluid conditions, and a diversity of informational needs (Kapucu, Arslan, & Demiroz, 2010; Pechta et al., 2010; Steelman et al., 2014). During these incidents, public information seeking increases (i.e., Nelson, Spence,

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& Lachlan, 2009; Spence & Lachlan, 2005; Stewart & Wilson, 2016), as a greater number of individuals and organizations search out critical information, further taxing communication networks when they are most vulnerable (Simon, Goldberg, & Adini, 2015). Public emergencies therefore pose formidable challenges, both for official actors (i.e., agencies and organizations tasked with informing the public) and for individual citizens (i.e., those seeking reliable, accurate, and up-to-date information). Given these challenges, a considerable body of literature has focused on how best to facilitate the flow of reliable information under crisis conditions (i.e., Houston et al., 2014; Pechta et al., 2010; Steelman et al., 2014).

Historically, mass media have played a principal role in this process (Pechta et al., 2010), serving as a conduit for the flow of information from official actors to the general public. However, over recent years social media has become increasingly prominent in crisis communications (Bernier, 2013; Merchant, Elmer, & Lurie, 2011; Mergel, 2012). As social media usage expands, citizens frequently turn to these platforms for public health updates and emergency information (American Red Cross, 2012; Jin, Liu, & Austin, 2014; Lachlan, Spence, Lin, Najarian, & Greco, 2016; René, 2016). Consequently, many public-facing organizations are now using social media to distribute critical preparedness, mitigation, response, and recovery information to citizens across a wide spectrum of emergency scenarios, including public health scares, natural disasters, and even terrorist attacks (i.e., Bernier, 2013; Merchant et al., 2011; Simon, Goldberg, Aharonson-Daniel, Leykin, & Adini, 2014).

A nascent body of literature suggests that these technologies may augment the efficient, effective, and targeted flow of information during public emergencies, due in large part to their widespread accessibility and the collaborative nature of social networking sites (i.e., Graham, Avery, & Park, 2015; Hughes & Palen, 2009, 2012). However, despite these claims, research on the use of social media in emergency scenarios is still embryonic (Graham et al., 2015), and significant questions remain regarding the efficacy and reliability of these technologies, as well as how best to deploy them in a manner consistent with the unique challenges of crisis communications. This study builds on previous research in the fields of public health and emergency management in an attempt to address these key issues and contribute to the knowledge base in this area. In order to do so, we look specifically at the use of Twitter during the 2015–2016 Zika virus outbreak in the United States.

Focusing on the flow of information surrounding the U.S. Zika outbreak, we present findings from both content and network analyses conducted on a sample of Zika-related tweets. In particular, we focus on the structure of communication networks, the content of Zika-related tweets, and the identification of influential actors. Through content analyses, we identify six predominant themes communicated in Zika-related tweets: (1) the spread of Zika, (2) criticism of government responses, (3) symptoms of Zika, (4) scientific news about Zika, (5) reports about bee killing incidents in South Carolina, and (6) government outreach efforts. We also identify three primary groups within the Zika conversation: (1) the Senator Rubio community, (2) authoritative institutions, and (3) boundary spanners. We believe that these findings can help to improve the practice of crisis communications by allowing researchers as well as public agencies to better understand the structure of communication networks that emerge via social media and to develop communicative strategies aimed at identifying and partnering with those social media actors who are best positioned to distribute valid and reliable information to the public.

Literature Review

Social Media and Public Information Seeking

The past decade has seen an exponential rise in the adoption of social media technologies. A recent study by the Pew Research Center reported that 72% of American adults now use at least one social networking site (Perrin, 2015). This marks a sharp increase over the past 10 years, up from only 8% in 2005. While younger, more educated Americans continue to use social media at higher rates, many of the recent gains have occurred among nontraditional users such as senior citizens, ethnic minorities, rural residents, and individuals from low-income households (Madden & Zickuhr, 2011; Perrin, 2015). Collectively, these numbers demonstrate that social media applications, once considered a novel form of personal networking, have become an established means of communication in American society.

As these emerging technologies have become more ubiquitous, they have also become more amenable to the distribution of media content and substantive information. The ability of social media platforms to rapidly transmit information, including embedded links, news content, and videos, has produced fundamental shifts in both patterns of usage and the content of social media communications. As a result, Americans increasingly engage in active information seeking via social media (Gottfried & Shearer, 2016; Kim, Sin, & Tsai, 2014)—alongside the passive information seeking and learning that inevitably occurs in networked social environments. For example, Gottfried and Shearer (2016) recently noted that 62% of American adults seek out news content and public information through their social media accounts. Along with these shifts in online behavior have come heightened expectations regarding the adoption and usage of social media on the part of official actors, such as political officeholders, public agencies, and nonprofit service providers. As users become more adept at communicating via social media, they expect these actors to communicate with them through similar means (American Red Cross, 2012; Mergel, 2012).

These trends have been particularly acute in the fields of public health and emergency management, which are traditionally marked by high levels of information seeking. Evidence shows that many Americans now turn to social media during times of crisis when seeking information such as safety instructions and news updates, as well as weather, traffic, and damage reports (American Red Cross, 2012; Jin et al., 2014; Lachlan et al., 2016; René, 2016). Furthermore, the public increasingly expects official actors to respond to public requests through social media. A recent study conducted by the American Red Cross (2012) found that 70% of Americans believe emergency responders should actively engage the public during crises via social media, while 68% expect timely responses when placing requests for assistance on social media.

Social Media in Public Health and Emergency Scenarios

These heightened expectations are due in large part to the perceived benefits of social media for crisis communications. It is believed that social media can hasten the dissemination of information in times of crisis by linking end users directly to critical information sources in real-time (i.e., Graham et al., 2015; Hughes & Palen, 2012). Research appears to support these claims. A number of studies now show that social media allows emergency responders, public health officials, and even media outlets to communicate directly with the public, eliminating the time it takes for emergency information to flow through traditional communication channels (i.e., Hughes & Palen, 2012; Palen & Liu, 2007).

This functionality was prominently displayed during Hurricane Sandy in 2012. While the storm knocked out power and disrupted cellular service throughout much of the Northeast, many citizens still had access to social media outlets. This allowed official actors (such as the Governors of New York and New Jersey as well as Con Edison and local emergency response agencies) to continue transmitting critical updates even after citizens had been cut off from many traditional information sources. These actors used social media sites such as Twitter to directly distribute storm-related information to the public, including power outage updates, evacuation plans, and notices about clean drinking water (Stewart & Wilson, 2016). In total, more than 20 million hurricane-related tweets were sent in the days immediately surrounding the storm—more than half of them included news, information updates, and storm-related videos (Guskin & Hitlin, 2012).

Targeted social media campaigns have also become commonplace among public health organizations such as the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO; Yun et al., 2016). In similar fashion, local health departments and hospitals/emergency rooms (ERs) have also begun providing up-to-date information via social media, including ER wait times and instructions for disease prevention (Merchant et al., 2011; Thackeray, Neiger, Smith, & Van Wagenen, 2012). In the case of acute public health emergencies, social media can be deployed quickly to disseminate critical information to the public. For example, in 2009, the Alexandria Virginia Health Department effectively used Twitter to direct citizens to vaccination sites during the H1N1 influenza outbreak (Merchant et al., 2011), and extensive research has been conducted regarding the use of social media as a source of public information during the Ebola outbreak in West Africa (Fung, Tse, Cheung, Miu, & Fu, 2014).

On top of allowing direct access to end users, social media may help to curtail the workload for emergency response organizations. Prior studies have supported this contention, suggesting that the proactive dissemination of information through online mediums reduces the number of information requests received from the public (Hughes & Palen, 2012; Latonero & Shklovski, 2011). Furthermore, the collaborative nature of social media facilitates a multidirectional flow of information, allowing citizens to become engaged in the emergency response process by redistributing information, posting incident updates, making requests for information or assistance, and even creating news content (Hughes & Palen, 2009; Hughes, Palen, Sutton, Liu, & Vieweg, 2008; Hughes & Tapia, 2015; Palen & Liu, 2007; Yoo, Rand, Eftekhar, & Rabinovich, 2016). During Hurricane Sandy, private citizens utilized social media extensively to redistribute emergency updates, connect with loved ones, and provide eyewitness accounts in the form of microblogs and videos, many of which were subsequently used by traditional media outlets reporting on the storm (Stewart & Wilson, 2016). Similarly, during the 2013 Boston Marathon Bombing, social media users actively redistributed official information via Twitter regarding the Federal Bureau of Investigation's ongoing manhunt, facilitating public engagement and vigilance, which ultimately assisted in the capture of the bombing suspects (*CBS News*, 2013).

Over recent years, an expanding body of research has demonstrated the breadth of social media's application in both natural and man-made disasters. These analyses have often focused on event-specific case studies—attempting to explicate specific uses as well as the pros and cons of social media usage during disaster scenarios such as widespread flooding (Bird, Ling, & Haynes, 2012), typhoons and tsunamis (Acar & Muraki, 2011; Cool et al., 2015), earthquakes (Yates & Paquette, 2011), oil spills (Starbird et al., 2015), and even terrorist attacks (Simon et al., 2014).

While the existing literature has tended to identify social media as a positive tool in crisis communications, significant concerns have been raised over the potential for negative externalities and misuse (both by official and anonymous actors). Both researchers and practitioners have cautioned against social media's propensity to proliferate inaccurate data, unverified rumors, and even malicious misinformation (Conrado, Neville, Woodworth, & O'Riordan, 2016; Hughes & Palen, 2012; Webb et al., 2016). Because information disseminated through social media is often unverified, identifying accurate data and valid sources can be challenging. This concern is exacerbated by both the fluid pace of crisis communications and the potential for information overload in open-access media platforms. For example, in the wake of Japan's Tohoku Earthquake (2011), emergency responders received a high volume of requests for assistance via Twitter. In many cases, these requests were retweeted by other users even after the victims had been rescued, making it difficult for first responders to distinguish between current and outdated information (Acar & Muraki, 2011). Similarly, after the Boston Marathon bombing in 2013, initial social media posts misidentified the appropriate suspects, leading to both wrongful accusations and a misallocation of critical resources

(Henn, 2013). These negative externalities underscore some of the unique challenges of crisis communications and how they can be amplified by unregulated social networks. Thus, a critical challenge facing emergency managers is how to proactively develop online communication strategies that emphasize and facilitate the spread of accurate and reliable information via social media.

Research Questions

One way to optimize the strategic value of social media for crisis communications is to better understand the nature of emergency content communicated via platforms such as Twitter as well as the structure of naturally forming communities within a social network. When analyzing the content of social media communications, we should bear in mind that users are social learners who tend to be influenced by information received from others in their social network (Burke, Marlow, & Lento, 2009). Some social media users set professional and political agendas, while far more users redistribute this information to others (Smith, Rainie, Shneiderman, & Himelboim, 2014). This means that network structures may have a significant influence over the topics communicated via social media. Computational efforts to detect and characterize naturally occurring communities in complex networks are called *community detection* (Newman, 2006).

Communities within a social network can be anything from issue-oriented communities in health-related conversations (Xu, Chiu, Chen, & Mukherjee, 2015) to polarized political retweet networks (Conover, Goncalves, Ratkiewicz, Flammini, & Menczer, 2011). These communities can be identified because people are more inclined to communicate with others who hold similar interests (Barberá, 2015; Xu et al., 2015). In addition, people form communities through the process of interaction. According to Choi and Park (2013), retweeting appears to help form collective identity through affirmative validation and quick responsiveness to participants with similar interests (Choi & Park, 2013). Detecting communities in social networks is important because it shows how people are interconnected when engaging in conversations. With the explosion of big data availability in addition to advancements in computational technologies, scholars, especially mathematical scientists, have developed community detection techniques such as modularity to efficiently detect densely connected groups of actors compared to "sparser connections between groups" (Newman, 2006, p. 8577). In order to optimize emergency communication efforts, we need to consider the structure of communities as well as the content of emergency communications. Hence, the following research questions are posed:

Research Question 1: What distinctive communities naturally emerged within the Zika conversation on Twitter?
Research Question 2: What are the primary topics discussed within these communities?

In order to optimize the strategic value of social media for crisis communications, it is also important to understand which types of actors are most influential in terms of communicating emergency information to the public. Doing so will allow public agencies and official actors to proactively develop effective information networks to meet the challenges of emergency communications. Understanding power dynamics and detecting influential actors is important because these actors can influence others' attitudes and behaviors as well as ensure the flow of accurate and reliable information (Rogers, 1995). Traditionally, scholars have detected influential actors in social networks based on three attributes: popularity, authority, and connectivity. First, an actor can be influential if he or she is connected to important actors (Bonacich, 2007; Borgatti & Halgin, 2011). For example, an actor with five famous friends is considered more influential when compared to an actor with five unpopular friends. Second, as an extension of the previous idea, one can be an influential actor if he or she is considered to be an authoritative source of information among people who are also popular (Giménez-Garcıa, Thakkar, & Zimmermann, 2016). For example, when an authoritative actor creates online information, their content will be more highly read and circulated if they have an established reputation for creating/distributing high-quality, reliable information (Franceschet, 2011). Third, an actor can be influential if he or she connects two or more otherwise disconnected communities (Lusseau & Newman, 2004). These influential actors are generally located on the boundary between communities and thus are called boundary spanners or bridges. Given the perceived importance of influential actors in emergency communication networks, we posed the following research questions:

Research Question 3: Who are the most popular actors within the Zika conversation?
Research Question 4: Who are considered the most authoritative actors within the Zika conversation?
Research Question 5: Which actors are most effective at connecting disparate communities within the Zika conversation?

Method

Data

Using the Twitter stream application programming interface with "Zika" as the query, we collected Twitter data from August 25 to September 5, 2016, during which reported cases of Zika increased dramatically, particularly in the Miami, Florida, area (Dapena & Alcantara, 2017).

Following standards set by Barberá, Jost, Nagler, Tucker, and Bonneau (2015), we limited our analysis to Twitter accounts with less than 25 followers and following less than 100 accounts (Barberá et al., 2015). We also excluded Spanish language Tweets from our analysis. As a result, a total of 359,043 tweets were used for analysis. In order to conduct social network analysis, we created edge lists by using retweet relations. An edge means a connection between two nodes. In our study, an edge is a retweet. For example, we created an edge when a tweet from Account A is retweeted by Account B. Each node in the network is an account that retweeted at least one tweet about Zika during the survey window. From these nodes and edge lists, we created a directed graph of the network. As a result, a total of 112,165 nodes and 150,324 edges were generated. The data cleaning, as well as the initial creation of nodes and edges, was conducted using the R programming language (R Core Team, 2015). The R scripts used to parse the Twitter stream JavaScript Object Notation files and construct the retweet network are available at http://information-analytics.cas.usf.edu/zikastudy/contents.html

Filtering for Meaningful Community Detection in Gephi

We used Gephi Version 0.9.1, an open-source software package (Bastian, Heymann, & Jacomy, 2009), for data analysis and network visualization. We chose to use the graph layout ForceAtlas2 (Jacomy, Venturini, Heymann, & Bastian, 2014), which efficiently displays the strategic importance of actors. We have filtered in the giant component—a functionality embedded in Gephi for filtering—and nodes with more than 30 degrees. Filtering was necessary for two reasons: First, large complete networks are too complex to meaningfully visualize the detected patterns. Second and more importantly, large samples of nodes (such as over 100,000) create too many communities (over 5,000 communities are detected), which inhibits interpretation of the characteristics of each community. As a result of the filtering, a total of 593 nodes and 2,536 edges were used for the retweet analysis.

Community Detection and Content Analysis

Community detection has been formulized as an optimization task in which "one searches for the maximal value of the quantity known as modularity over possible divisions of a network" (Newman, 2006, p. 8582). Modularity captures the strength of density in the graph and divides a network into modules. Density is calculated by dividing the number of edges by the number of possible edges and is used to separate a network into subgroups in which nodes are connected closely to each other, but loosely connected to nodes outside of their group (McSweeney, 2009). Therefore, information can diffuse rapidly inside the high-density group, but it may not spread as quickly (if at all) outside of the group. In contrast, low-density networks are advantageous for fast diffusion of information throughout the entire network. Using Blondel's algorithm as the modularity function (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008), we created 10 communities as a result of implementing the default setting of Gephi (resolution = 1.0, randomize, use weights) for the modularity algorithm.

Using the major communities detected, we conducted manual content analysis in order to understand the topics of tweets that were highly retweeted. Traditional content analysis depends on manual reading of text data in order to understand particular phenomena (Krippendorff, 2012). A manual content analysis includes two major tasks: category development and coding. A category scheme can be developed based on previous research (deductively) or using the grounded theory approach (inductively)—a new category is created until no new categories emerge. Once a category scheme is developed, annotators code documents using the category scheme.

Network Analysis for Finding Influential Twitterers

As stated above in the Literature Review, we consider three types of influential Twitterers in this study based on connectivity, popularity, and authority. First, we use *betweenness centrality* to measure the level of importance and influence of a node in controlling the flow of information (Brandes, 2001; Easley & Keinberg, 2010; Freeman, 1978; Golbeck, 2013). The betweeness of a node *n*, for example, can be calculated by summing up the fractions of all of the shortest paths between two nodes that go through the node *n* in a network (Golbeck, 2013, p. 30). Nodes (actors) with high betweenness centrality are important because they are considered to have "early access to information that originates in multiple, noninteracting parts of the network" (Easley & Keinberg, 2010, pp. 60–62). Betweenness centrality has been frequently used to identify individuals with high brokerage potential. Actors with high betweenness centrality are sometimes called boundary spanners. These actors are important since they connect groups that otherwise would not have been connected to each other. Studies show that betweenness centrality follows a power law distribution, thus a small number of key individuals control the flow of information (Lusseau & Newman, 2004). Second, *eigenvector centrality* acknowledges that some nodes are more influential because they are connected to important actors. Eigenvector centrality is considered to be a good measure for the power of individual nodes to spread information across a network. Therefore, an actor with high eigenvector centrality is considered to have a high information spreading power (Canright & Engø-Monsen, 2006). Third, *PageRank* is a variant of eigenvector centrality that finds the nodes highly endorsed by surrounding actors (Brin & Page, 1998). Previous studies show that PageRank accurately indicates reliability and trust of a node (actor; Caverlee, Liu, & Webb, 2008; Giménez-Garcıa et al., 2016). For calculating betweeness centrality and eigenvector centrality, we implemented the Brandes (2001) algorithm (Brandes, 2001), the output of which was normalized. To calculate PageRank, we implemented Brin and Page's (1998) PageRank algorithm, which we used with the default parameter settings (Brin & Page, 1998).

Findings

Communities in the Zika Retweet Network and Contents Communicated

We calculated modularity to automatically detect communities within the Zika retweet network based on the observed retweet relations between Twitterers. Using the Blondel's modularity

Table 1. Content Analysis of Zika Retweet.

Category	Example Tweet	Number of Assigned Tweets (Percentage)
Spread of Zika	Singapore confirms 26 more cases of locally transmitted Zika virus infection. Zika explained: https://t.co/DS0KFaWogD	71 (36)
Congress	Every day the Republican Party stalls funding #Zika response, more people get sick. More babies risk being born with heartbreaking head deformities	49 (25)
News about Zika	.@ziyatong Symptoms of #Zika are milder and more infrequent than Chikungunya and Dengue. @EverydayHealth #atozika https://t.co/v7nPwlOXg0,	38 (19)
Scientific news about Zika	Spread of Zika virus pushes testing labs to expand capacity https://t.co/IM3IMiBle6	25 (13)
Bee killing	"Stop. This is crazy . . . We can't live without these honeybees": Zika spraying kills millions of honeybees https://t.co/VHfMe2kffo	8 (4)
Government outreach	Now's your chance to ask your #Zika questions; hear from top US health experts. Tweet your questions with #AtoZika. https://t.co/DCLEhy64EW	6 (3)
Others	I'll try to tweet a few things during the mosquito/arbovirus meeting so keep an eye on #MCAA2016! #zika #dengue https://t.co/N3UjPyceet	3 (2)
Total		200 (100)

algorithm embedded in Gephi, we produced ten communities, each of which has an identification number between 0 and 9—we call these "Modularity Class IDs" below. Each modularity class indicates that there are more frequent retweets inside that unique cluster when compared to the connections of that community with the rest of the social network (Fortunato, 2010). In general, a modularity class can be interpreted as representing a unique community. Of the ten communities identified in our analysis, over 83% of tweets belong to the top 4 communities (Modularity Class IDs #3, #4, #6, and #7 in Online Supplementary Figure 1).

To understand the content of retweets more fully, we randomly sampled 200 tweets of the tweets from the four largest modularity classes. Then we coded these tweets using the seven mutually exclusive and exhaustive categories appearing in Table 1. The seven categories were developed using a grounded theory approach (Corbin & Strauss, 1990).

The content analysis shows that 36% of tweets express concerns regarding the spread of Zika in the United States as well as in East Asian countries and Africa. Twenty-five percent of tweets express frustration with the U.S. Congress for its slow legislative response to the outbreak. Nineteen percent of retweets discuss the health impact of Zika as well as education and prevention measures. Thirteen percent of tweets include scientific news about Zika, such as research findings about possible treatments and vaccine development. Four percent of tweets discuss the millions of bees killed in South Carolina during spraying to combat Zika. Although not highly retweeted, government efforts to encourage citizen participation in the Zika conversation represented 3% of the sampled tweets.

We then combined these coded tweets with the modularity class results and depicted the number of tweets categorized in each of the seven content categories. Although Modularity Classes #4 and #5 include over 50% of Twitterers, the majority of retweets sampled for the content analysis are created by Twitterers clustered in Modularity Class #7. This means that tweets created by entities in Modularity Class #7 are disproportionally retweeted.

Among the topics discussed by Twitterers in each of the four modularity classes, concerns about spreading Zika in diverse geographic areas are a common concern shared by all groups. In addition,

Table 2. The Top ten Entities With High Eigenvector Centrality.

Twitter Account	Eigenvector Centrality	Description of the Account
Toddkron	1.00	Digital Marketing Manager at XOOM Energy. Sen Marco Rubio supporter
jennanjack	0.96	Joined March 2009, has 7,233 followers, she is a republican and Marco Rubio supporter
SenRubioPress	0.91	Official account of U.S. Senator Marco Rubio's Press Shop
msksweetness	0.74	Joined October 2010, has 1,238 followers, she is a Marco Rubio supporter for Senate
Zika_News	0.74	Bots that detect and share news circulating in the Twitter community on Zika virus
lisetteh0325	0.65	Joined June 2012, has 710 followers, she is a Marco Rubio supporter and critic of Hillary Clinton
AlexConant	0.62	Partner at Firehouse Strategies. Former Communications Director for Marco Rubio
pessell_anna	0.62	Joined March 2016 has 4,665 followers, a teacher, Marco Rubio supporter
rose10052	0.59	Joined November 2015, has 3,873 followers, she is a Marco Rubio supporter who criticizes Hillary Clinton
stevenacurtis	0.57	Conservative Christian, Marco Rubio supporter. Joined February 2009, has 2,008 followers

Note. The account description is the summary of each account based on the account holder's description.

Twitterers in Modularity Class #3 are disproportionally interested in discussing Congress's lack of action against the spread of Zika. It is worthwhile to note that the vast majority of discussions about scientific news occur in Modularity Class #7. Although the size of Modularity Class #7 is relatively small (17% of Twitterers, see Online Supplementary Figure 1), it has the highest number of retweets among the four sampled modularity classes. We will discuss this in the following subsection on betweenness centrality and the discussion section.

Influential Twitterers

Identifying influential Twitterers in the Zika network is important because the speed and scope of information diffusion depends on the level of influence an actor has in the social network (Yoo et al., 2016). We identify three types of influential Twitterers based on their connectivity, popularity, and authority by acquiring their betweenness centrality, eigenvector centrality, and PageRank measures, respectively.

Eigenvector centrality indicates an actor's power to spread information considering both the number of contacts of an entity and the connections of these contacts. Of the top ten Twitter accounts with the highest eigenvector centralities, nine Twitter accounts belong to Modularity Class #8, which clusters around Senator Marco Rubio's (Florida) supporters (see Online Supplementary Figure 1 for network topology and see Table 2 and 5). *Zika_News* (an automatic information aggregator) is the only one that is not a part of the Marco Rubio cluster. It seems that the Marco Rubio cluster is a manifestation of the Republican Senate primary that took place on August 30, 2016. The first 6 days of data collection overlap with local politics in Florida since the Zika outbreak was one of the top social and political issues in Florida. The fact that most of the entities in the Marco Rubio cluster have high eigenvector centrality suggests that they are savvy political activists, who are connected with popular Twitter users and actively have engaged with the conversation on Zika. The topology in Table 5 shows that the Senator Rubio cluster (Modularity Class #8) has the greatest distance from Modularity Class #3, which includes many tweets that are highly critical of the

Table 3. Top ten Entities With High PageRank Value.

Twitter Account	PageRank	Description of the Account
TheDailyEdge	.05	Entertainment and gossip, political news, commentary, and liberal humor
NYTHealth	.02	Health news from the science desk of *The New York Times*
NYTScience	.02	Science, environment, space, and cosmos news from the science desk of *The New York Times*
WHO	.02	World Health Organization, the United Nations' health agency
vj44	.01	Senior Advisor to President Barack Obama. Chair of the White House Council on Women and Girls
WHOSEARO	.01	Official Twitter account for the World Health Organization Regional Office for South-East Asia (SEARO)
DrFriedenCDC	.01	Centers for Disease Control and Prevention (CDC) Director, MD, and Acting Administrator of the Agency for Toxic Substances and Disease Registry
WhiteHouse	.01	Tweets from POTUS and their administration
gov	.01	Updates from the @Twitter Government and Elections team
HHSGov	.01	News and info from U.S. Dept. of Health and Human Services

government's response. Perhaps Modularity Class #3 may include more actors who are ideologically opposed to the Marco Rubio cluster (we revisit this issue later). The topology and the actors with high eigenvector centralities highlight the complex context wherein the Zika conversation takes place. In this case, it was the Republican Senate Primary. In addition, they underscore the fact that political communities may be highly influential in framing public emergency conversations on Twitter (Groshek & Al-Rawi, 2013).

PageRank values indicate the level of authority and trust given to Twitterers by other Twitterers (Caverlee et al., 2008; Giménez-Garcıa et al., 2016). The Daily Edge, an Internet news publication for entertainment and gossip, has the highest demonstrated authority vis-à-vis Zika retweets. The other two of the top three PageRank Twitter accounts are news media outlets specializing in health and science (*NYTHealth* and *NYTScience* in Table 3). Most of the top ten accounts with high PageRank are related to actors with specialties in health and science policies: three of them are media outlets and the rest of them are either public institutions or individuals associated with public institutions. It is noticeable that public and government agencies appear to be highly authoritative. For example, *WHO*, *WHOSEARO*, *WhiteHouse*, and *HHSGov* all have high PageRank values, meaning they are regarded as highly authoritative information sources.

Actors with high betweenness centrality are considered to have "substantial influence" and are often referred to as boundary spanners (Newman, 2008). Boundary spanners are considered to be influential because they can amplify social dialog by widely redistributing information from diverse communities. Thus, they function as liaisons between communities, regulate access to information sources, and control the ways in which information passes between disparate groups. Since actors with high betweenness centrality get information from diverse sources, the information they acquire and redistribute is expected to be balanced, rather than one-sided.

We found that entities with the highest betweenness centrality are mostly experts in infectious disease. For example, *MackayIM* is a PhD who works at the Australian Infectious Diseases Research Center with a focus on infection. In addition, *neil_bodie* is the CEO of a company developing disruptive technology for infectious agents. Similarly, *greg_folkers* works at the National Institute of Allergy and Infectious Diseases. These individuals have credentials and respect in a specialized area (in this case, infectious disease).

We also found several actors involved in politics, such as *Ssimms777*, *courtchauncey*, *margo94*, *RealMuckmaker*, *LeChatNoire4*, and *annie5133*, to have high betweenness centrality (see Table 4).

Table 4. The Top ten Entities With High Betweenness Centrality.

Account Name	Betweenness Centrality	Description of the Account
MackayIM	.053	Joined April 2013, 8,258 followers, PhD, and adjunct associate professor at the Australian Infectious Diseases Research Centre (AID) with a focus on infectious diseases
neil_bodie	.040	CEO, developing disruptive technology for infectious agents/Zika and autoimmune diseases
Ssimms777	.032	Democrat, a Hilary Clinton supporter, believes in prochoice, proequal pay, and civil rights for all
greg_folkers	.030	Joined May 2009, 2,239 followers, he works at the National Institute of Allergy and Infectious Diseases (NIAID) and direct the NIAID Immediate Office of the Director and a core staff of senior-level staff members with NIAID-wide program coordination and operations responsibilities
maiamajumder	.026	PhD candidate at Massachusetts Institute of Technology (MIT). Research fellow at healthmap. Tufts University alum
courtchauncey	.019	A supporter of Marco Rubio for FLSenator. Joined January 2012 has 2,254 followers
margo94	.015	Manufacturer and formulator luxury natural grooming products for family, a Hillary Clinton supporter whose tweets criticize Donald Trump
RealMuckmaker	.015	A Hillary Clinton supporter who started the twitter account May 2016, and 7,914 people are following him. He writes tweets supporting Hillary Clinton and criticizing Donald Trump
LeChatNoire4	.015	A Hillary Clinton supporter, who joined twitter March 2014, and has 7,011 followers. Tweets are supporting Hillary Clinton and criticizing Donald Trump
annie5133	.014	Retired, supporting progun safety laws, a Hillary Clinton supporter

Note. The gray background indicates political entities according to account holders' description.

Other than *courtchancey*, who is a Marco Rubio supporter, most of these political actors are noted Hillary Clinton supporters. As found above, most of the Marco Rubio supporters have high eigenvector centrality, which means having the ability to spread information, whereas Hillary Clinton supporters function more as bridges that connect otherwise segregated groups. Political actors seem to be highly influential in Zika communications on Twitter since the Zika outbreak was an important political and policy issue at the time.

Discussion and Conclusions

In this article, we conducted content and network analyses to better understand influential topics and actors in the social media dialog surrounding the 2015–2016 Zika outbreak in the United States. We have synthesized these findings in Table 5.

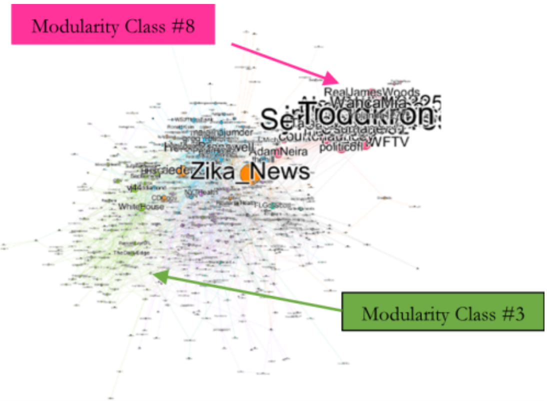
Content of Tweets During the Spread of Zika in the United States

In a previous study, Fu et al. (2016) extracted the major topics expressed on Twitter regarding the Zika outbreak using tweets collected between May 1, 2015, and April 2, 2016, while Zika was still a relatively unknown phenomenon. According to their findings, the primary topics discussed on Twitter included Zika's impact (39.5%), reactions to Zika (23.7%), pregnancy and microcephaly (18.1%), transmission routes such as sex or mosquitoes (10.7%), and case reports (8.1%).

Our data set includes a much shorter time span (12 days). However, our study captures tweets during the summer of 2016 when Zika was spreading extremely fast in United States and other

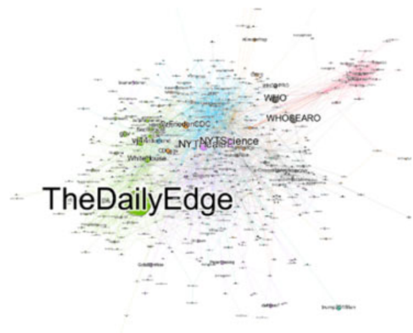
Table 5. Synthesizing the Influential Actors With Network Structure.

Senator Rubio supporters: Actors with high eigenvector centrality (well connected to popular actors) are mostly strong supporters of Florida Senator Rubio's primary campaign (Modularity Class #8). Since the data collection took place during the Republican primary, and since there was heightened concern about Zika in Florida, Senator Rubio supporters were actively engaged with the Zika conversation



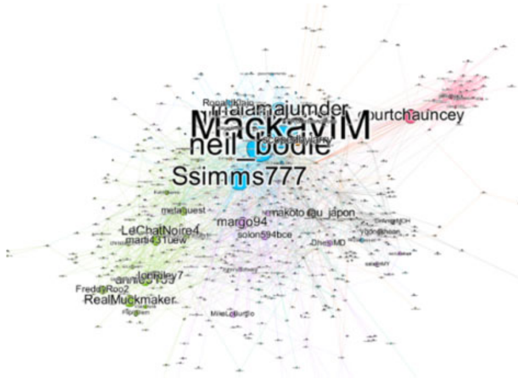
Visualization of the Eigenvector centrality
Note. Larger font size means higher eigenvector centrality.

Authoritative Public Institutions: Twitterers with high PageRank (highly endorsed by popular Twitterers) are dispersed around the network. Topologically, these actors are positioned in between communities rather than in the middle of one community. Also, these authoritative actors are predominantly public institutions such as *WHO*, *WHOSEARO*, *White House*, and *HHS* or news agencies such as *TheDailyEdge*, *NYTHealth,* and *NYTScience*.



Visualization of the PageRank
Note. Larger font size means higher PageRank values.

Boundary spanners: Most of the top Twitterers with high betweenness centrality are in the Modularity Class #7, which is located in the middle of the network. Tweets created by these entities are highly retweeted: 47% of retweets in our sample belong to the Modularity Class #7. Distinctively, many tweets circulated in Modularity Class #7 are about scientific news. In fact, several top actors with high betweenness centrality are experts in infectious diseases research



Visualization of the betweenness centrality
Note: Larger font size means higher betweenness centrality.

countries. The findings of our study differ from Fu et al. (2016), as the major topics include the spread of Zika (36%), criticism of Congress (25%), news about Zika (19%), scientific information about Zika (13%), bee killing (4%), and government outreach (3%). These differences may be attributed to the timing of our data collection efforts. While Fu et al.'s (2016) study reflects Twitterers' initial effort to understand the new disease, the topics in our data set reflect concerns about the spread of the Zika virus as well as prevention measures and expressed frustration with the slow Congressional response. At the same time, similar to Fu et al. (2016), the Twitterers are interested in sharing news about the Zika virus, such as symptoms, worries of parents-to-be, and stories about pregnant women who are infected with Zika.

Sharing Scientific Information on Twitter

Twitter is known as a popular platform that circulates scientific information more than other online platforms. For instance, Twitter mentioned scientific studies about 4 times more frequently than online news media and 21 times more than public Facebook pages (Hitlin, 2016). Our study also supports this by demonstrating a high volume of discussions related to scientific inquiries, such as vaccine development and the effects of the Zika virus. In fact, a Pew study by Hitlin (2016) found that the sixth most highly circulated scientific article on Twitter in 2016 was "Zika Virus and Birth Defects—Reviewing the Evidence for Causality," published in the *New England Journal of Medicine* (Rasmussen, Jamieson, Honein, & Petersen, 2016).

Most of the tweets about scientific news were initiated by Twitterers in Modularity Class #7. We also found that experts affiliated with reputable institutions who held scientific credentials were likely to function as boundary spanners, demonstrating the ability to spread information quickly throughout the Twitter network. Experts on infectious disease such as *MackayIM*, who works at Australian Infectious Diseases Research Center, and *greg_folkers*, who works at the National Institute of Allergy and Infectious Diseases, are good examples. Engaging with potential boundary spanners to distribute scientific information could be an impactful approach to communicating with the public during emergencies since they play key roles in acquiring, translating, and disseminating information throughout their own social networks (Whelan, Golden, & Donnellan, 2011).

Practical Implications

These findings are important for the development of communication strategies during public health emergencies, where the rapid dissemination of reliable information can be crucial. The diffusion of false information has been one of the major concerns in adopting Twitter for emergency communications. Our findings show some evidence of Twitterers' efforts to ensure the spread of trustworthy, scientific information during public emergencies. Similarly, Mendoza, Poblete, and Castillo (2010) showed that Twitterers more often raise questions on false rumors compared to confirmed truths in comparison to other social media platform users (Mendoza, Poblete, & Castillo, 2010). In our case, Twitterers seemed to have exerted some efforts to diffuse reliable information by retweeting scientific content distributed by reputable experts on infectious disease, rather than distributing second-hand and unverifiable information. Further, government institutions such as the *White House*, *CDC*, and *HHSGov* were found to be highly authoritative and trustworthy sources. For practitioners, connecting these authoritative information sources with boundary spanners may ensure that the public receives trustworthy, scientific information quickly. Our findings provide a snapshot of a particular case, which can help in the development of strategies for responding to future public health emergencies. For example, public-facing organizations can benefit by understanding the kinds of content that is transmitted through specific social media platforms and by identifying key participants who are authoritative, popular, and connected to disparate communities in order to efficiently communicate with the public.

The influence of political actors in the Twitter network highlights an apparent reality that health communication is inherently political. Our findings support the claim that official actors and public-facing organizations are increasingly utilizing social media as a means of managing acute public health emergencies and crisis scenarios. As public consumption of traditional media declines, these findings seem to indicate that emerging technologies such as social media are filling the communication void, particularly in emergency scenarios.

While our study focuses exclusively on the Zika virus outbreak, we expect that the communication pattern observed in this case may share similarities with other emergency scenarios, such as public health scares and natural disasters. As noted earlier, crisis communication on social media can have dangerous consequences—such as the misidentification of suspects in a killing, as was the case during the Boston Marathon bombings. Our study highlights a way to identify highly trusted actors within a network, so that public-facing organizations can depend on them for communicating with the public during emergencies.

Limitations and Future Research

Of course, there are a number of limitations to this study and many unanswered questions remain about crisis communications on Twitter and throughout social media more broadly. Twitter users are not representative of the entire population, and this study does not suggest that patterns found here would prevail if the entire population was examined (Gottfried & Shearer, 2016; Mitchell & Guskin, 2013). Therefore, the choice of topics discussed on Twitter may be influenced by certain professional and political dynamics (Smith et al., 2014). However, we believe our study does accurately reflect the communication pattern of Twitter and has the potential to be useful for crisis communications during public health emergencies. Moreover, the particular influential Twitterers observed in the network structure of this study are specific to the Twitter platform. Future studies may include other social media platforms such as Facebook, whose popularity is known to be higher than that of Twitter.

Methodologically, the initial filtering of nodes to reduce dimensions can raise a question as to whether this filtering process will result in bias. Our validation experiments show that the filtering does not seem to cause notable bias. We have identified and compared the top ten Twitterers with high PageRank using the original 112,165 nodes and the filtered 593 nodes. Of the top ten Twitterers, seven of them were identical, which indicates that filtering from 112,165 to 593 nodes did not dramatically impact the outcomes, and it was necessary in order to achieve the goal of reducing data dimensionality to enable the analysis. Although it was not our main focus of this study, the issue of filtering and the use of thresholds to reduce data dimensionality are important issues in big data analysis that require further attention in future studies.

While focusing on specific research questions in this analysis, we have chosen to defer other important inquires for future studies. In particular, we plan to investigate the impact of multimedia-use and content on retweetability. This future study will look at the extent to which embedded media content is circulated throughout social networks and how it passes among members of disparate communities. We also plan to pursue a more extensive qualitative analysis of Zika-related tweets, focusing specifically on how messaging differs across unique communities.

Despite these limitations, our study detected naturally occurring communities in the Zika retweet network and six predominant themes emerged within these tweets. In an effort to identify influential actors within the social network, we focused on the criteria of popularity, authority, and connectivity. The most popular actors included many of Senator Rubio's supporters. The most authoritative actors included primarily public institutions, individuals associated with public institutions, as well as news media outlets that specialize in health and science. The primary boundary spanners (i.e., those who connect diverse communities that would not otherwise be connected) were typically political activists and those with professional/subject matter expertise in infectious diseases. We also noted efforts by influential Twitterers to redistribute reliable and trustworthy information. We hope that researchers and practitioners will be able to utilize the network analysis we have carried out to aid in communication efforts during future public emergencies.

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Supplemental Material

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