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Conversing or Diffusing Information? An Examination of Public Health Twitter Chats

Lauren C. Bayliss, Yuner Zhu, King-Wa Fu, Lindsay A. Mullican, Ferdous Ahmed, Hai Liang, Zion Tsz Ho Tse, Nitin Saroha, Jingjing Yin, Isaac Chun-Hai Fung

Georgia Southern University, City University of Hong Kong, University of Hong Kong, Georgia Southern University, Georgia Southern University, Chinese University of Hong Kong, University of York, University of Georgia, Georgia Southern University, Georgia Southern University

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Abstract

This study examines the one-way information diffusion and two-way dialogic engagement present in public health Twitter chats. Network analysis assessed whether Twitter chats adhere to one of the key principles for online dialogic communication, the dialogic loop (Kent & Taylor, 1998) for four public health-related chats hosted by CDC Twitter accounts. The features of the most retweeted accounts and the most retweeted tweets also were examined. The results indicate that very little dialogic engagement took place. Moreover, the chats seemed to function as pseudoevents primarily used by organizations as opportunities for creating content. However, events such as #PublicHealthChat may serve as important opportunities for gaining attention for issues on social media. Implications for using social media in public interest communications are discussed.

Introduction

Using communication to build relationships can be an important step in bringing about social change, and such dialogue can lay an important foundation for public interest communicators' work (Brunner, 2017). Twitter "chats," as the term would suggest, may be useful tools for facilitating dialogue as part of such strategic communication efforts. Research on dialogic communication in social media can either address a relational orientation between organizations and their publics or principles for communication practice (Zhou & Xu, 2020). This paper

**Please send correspondence about this article to Lauren Bayliss, Department of Communication Arts, Georgia Southern University. E-mail: lbayliss@georgiasouthern.edu.*

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addresses the latter; rather than focusing on the quality of the relationships between publics and organizations as exemplified through chat, we will address whether Twitter chats seem to follow dialogic principles for promoting engagement.

Past research has indicated that science communication, (e.g., Lee & Van Dyke, 2015), health communication (e.g., Park et al., 2016), and nonprofit communication (e.g., Lovejoy et al., 2012) that take place on Twitter outside of chats do not engage outsider users in conversation-like communication. If Twitter chats resemble these more general tweets, then many Twitter chats likely follow one-way patterns of diffusion instead of the "two-way, relational, give-and-take between organizations and stakeholders" characteristic of dialogic engagement (Taylor & Kent, 2014, p. 391). In the case that organizations do use Twitter chats for broadcasting information rather than conversing, further analysis can be used to determine what can make organizations more successful in broadcasting to audiences through retweets, increasing the opportunities for reaching new audiences about topics that benefit public health and the social good.

To explore whether Twitter can be used effectively for dialogic engagement in the public interest, this paper examines the Centers for Disease Control and Prevention's (CDC) use of Twitter chats. The CDC was chosen as the subject of this research so that multiple chats could be compared from the same organization. The CDC occasionally initiates Twitter chats using one of its 69 Twitter profiles (CDC, 2012). For crisis communication, the CDC's chats have lacked dialogue (Dalrymple et al., 2016), so only public interest topics not linked to a crisis were examined. Of particular interest are the features of chats and Twitter users that promote dialogue and the spread of information regarding the designated chat topics. By examining chat and user features, we hope to determine how public interest practitioners can improve their own efforts to use Twitter chats and similar social media platforms for public interest communications.

Literature review

Dialogic principles and Twitter

Twitter chats are designed to create synchronous conversations on Twitter. These conversations are marked by a chat sponsor-designated hashtag and moderated by a host (Cooper, 2013). The term "chat" implies that a genuine, two-way conversation takes place. A broad view of two-way communication appears in the theoretical framework of the symmetrical model of communication, which includes a variety of public relations activities ranging from listening to research on the target publics (J. E. Grunig, 2001, 2009; J. E. Grunig & Kim, 2021). Dialogic theory, on the other hand, has a narrower focus on two-way communication, though it has some of the same goals, including "the building of relationships" (J. E. Grunig & Kim, 2021, p. 306). Dialogic theory has strong philosophical underpinnings that accept that "the outcome [of dialogue] is not always predictable and that the precise outcome cannot always be achieved"

(Theunissen & Noordin, 2012, p. 7). Dialogic theory has also been applied specifically to understand the nature of organizations' online communication efforts (Kent & Taylor, 1998, 2014). Therefore, this paper will take a dialogic approach to exploring the use of Twitter chats for public interest communications.

Although internet-based communication channels were once heralded as an opportunity for dialogic communication (Kent & Taylor, 1998), social media have not been found to be particularly dialogic or conducive to two-way, relationship-building communication in practice (Kent & Li, 2020; Lovejoy et al., 2012; Taylor & Kent, 2014). This study addresses whether Twitter chats adhere to the dialogic loop, one of the key principles for online dialogic communication (Kent & Taylor, 1998). A dialogic loop exists if the infrastructure exists for individuals and organizations to respond to one another. Twitter has the technical features required for a dialogic loop (Watkins, 2017), and past research indicates that Twitter can sometimes serve as a better dialogic loop than company websites (Rybalko & Seltzer, 2010). In addition to the presence of technical features allowing organizations and publics to interact, accounts would need to actively communicate with publics during a chat for a functioning dialogic loop to exist. Therefore, this paper examines whether the CDC is using the platform features that allow for the dialogic loop to visibly occur during Twitter chats.

Retweets should be considered a key component of the dialogic loop. Both replies and retweets may be considered types of conversation-oriented, rather than broadcasting, tweets (Grant et al., 2010). A major difference between retweets and replies lies in who is likely to see the conversation. Replies are likely to be viewed by followers only under certain circumstances, such as when audience members follow both accounts or when Twitter predicts that the audience would enjoy the conversation; otherwise, audiences must seek out the information in replies (Twitter, 2020). In contrast, retweets share information with all followers. Retweets bring the rest of the audience into the context of the original comment and extend the public conversation between different participating accounts (Boyd et al., 2010).

To study the flow of information and the dialogic nature of Twitter chats, network centralization can be examined. When peers share information with one another instead of relying on opinion leaders, the network will be noncentralized (Bastos et al., 2018). In other words, when many accounts—rather than a select few—are retweeted, the network will be noncentralized. Therefore, the first way to examine if CDC-sponsored Twitter chats promote a dialogic form of communication is to determine if networks are noncentralized. Past research indicates that Twitter-based discussions tend to be less centralized and more characteristic of two-way conversations when broad topics are discussed (Bastos et al., 2018). Therefore, a Twitter chat with a broad focus will be examined in this study and will be compared with chats with narrower focuses; this type of approach ensures that the study's assessment of the one-way or two-way nature of communication is not unduly influenced by the topic of the chat.

RQ1a: Are retweet networks centralized, indicating that one-way interactions of diffusion or limited two-way communication is taking place, or decentralized, indicating that dialogic communication may be taking place as account users share information with one another?

In the case that chat retweet networks are centralized around a few accounts, further examination of the opinion leader accounts will be necessary to determine if the one-way nature of the conversation is truly being driven by the lack of a dialogic loop. If the dialogic principles are in place for the Twitter chats, any opinion leaders that do appear should not primarily be from organizations with close ties to the host. For example, when a CDC account hosts a chat, the primary opinion leaders in dialogic communication would not be drawn primarily from the other 68 CDC Twitter accounts. Instead, individuals not associated with the organization should appear among the opinion leaders. If the opinion leaders are primarily from the CDC's own accounts, then any dialogue in the chats would appear to be fully orchestrated, and the chats may simply serve as an excuse to generate and distribute content. Such orchestrated social media chats would serve the role of a virtual pseudoevent, or event planned for the purpose of gaining media coverage; in such cases the meaning of the event is ambiguous and the meaning the organizers give the event is a sort of "self-fulling prophecy" (Boorstin, 1992, p. 12). However, in an age of social media, coverage by the press may not be required, and the virtual pseudoevent may simply give the organization justification to distribute a high volume of content all at once on social media.

RQ1b: If networks are centralized, which types of accounts serve as opinion leaders (e.g., organizations or individuals), and do the types of opinion indicate that dialogic principles may be in place for Twitter chats (anyone can become an opinion leader) or the chat operates only as a one-way channel of diffusion?

Opinion leadership and retweet prediction

If health and science communicators promoting ideas in Twitter chats do persist in using one-way communication as indicated by organization-dominated centralized networks, further analysis of the chat networks also may indicate how opinion leader accounts, and particularly any organization's accounts supporting the chat, can strategically improve the rate of diffusion.

Opinion leaders' influence has previously been operationalized as "the frequency of one's remarks being passed along by others" and, in the case of Twitter, the frequency of retweets (Choi, 2014, p. 217). Therefore, this study will seek to predict how likely an individual account is to be retweeted. Potential predictors of whether a tweet will be retweeted can be categorized into two types, including social features and tweet features (Petrovic et al., 2011). Social features (user's attributes) are about user's background information while tweet features (tweet's attributes) are only about the tweet itself. A better understanding of how user attributes and tweet attributes contribute to opinion leadership in the context of a Twitter chat could be useful for both communication practitioners and participants who wish to reach a broad audience during chats.

On Twitter, followers are the accounts that subscribe to tweets from a given Twitter account; in contrast, followees are accounts to which users are subscribed. Both Adnan et al. (2018) and Petrovic et al. (2011) found that the account features of follower and followee numbers predict retweets; however, relatively little consensus exists about which tweet features best predict retweets. Using a dataset of 21 million tweets, Petrovic et al. (2011) found that social features, such as follower and followee numbers, predicted retweets better than features of the tweets themselves. Suh et al. (2010) found that both social features (the age of account, the number of followers, and the number of followees) and tweet features (hashtags and URLs) predicted retweets; however, Suh et al. (2010) also found that the number of past tweets (a social feature) did not have a significant effect on retweets. Therefore, social features such as follower and followee numbers appear to be important predictors of retweets, but other social features and account features merit further study.

Of the limited number of studies that focus on retweets, few focus on the domain of public health (e.g., Petrovic et al., 2011; Suh et al., 2010), and many use only descriptive statistics without showing associations and predictive relationships (e.g., Weitzel et al., 2011). Blankenship et al.'s (2018) study of a sample of tweets with the hashtag #vaccine serves as one of the few studies that focus on predictive relationships between retweets and public health topics. Their results indicated that users with a high follower count (at or above the geometric mean in the sample) are retweeted nearly four times as often as users with a low follower count (below the geometric mean in the sample) after controlling for vaccine sentiment and other user characteristics. In another study of a sample of tweets with the hashtag #pneumonia around World Pneumonia Day in 2011 to 2016, Adnan et al. (2018) found that, after controlling for other factors, a 10-fold increase in follower count will increase the odds of a user's tweet being retweeted by nearly fourfold and, if retweeted, increase the retweet frequency by nearly fivefold.

Communicators in public health could benefit from research regarding the account and tweet features that predict retweets. In trying to improve the diffusion of information over Twitter, the information in this study will help strategic communicators determine whether to prioritize strategies such as increasing the number of account followers, following more accounts, using a more well-established account, or communicating via trusted channels. This study will test various predictors of retweets in the previously described Twitter chats, including both account features (e.g., $\log_{10}$ of follower count, $\log_{10}$ of followee count, $\log_{10}$ of account age in days, and user type), and tweet features (e.g., count of relevant tweets and retweets issued). Results may also inform strategies for how often communicators should tweet and/or retweet during a Twitter chat.

RQ2a: Which social (user account) features predict retweets during Twitter chats?

RQ2b: Which tweet features predicted retweets during Twitter chats?

Method

To study these patterns, this research focuses on #PublicHealthChat, a chat organized in September 2016 and hosted by the National Center for Emerging and Zoonotic Infectious Diseases (NCEZID) at the CDC. The event was used to promote official policies and to increase public awareness of public health work. Therefore, #PublicHealthChat serves as an example of how the CDC communicates about public health in a nonemergency situation when no specific health issue is being addressed.

To address *RQ2*, only #PublicHealthChat will be used to examine the effects of tweet and account features. However, to contextualize the level of centralization present in #PublicHealthChat when addressing *RQ1*, three additional chats also organized by CDC Twitter accounts during this same month also were examined as a point of comparison for #PublicHealthChat's level of centralization and opinion leader characteristics: #AMRChallenge, #HIVAgingChat, and #CDCPrep2016 (see Table 1). In contrast to #PublicHealthChat, the other three Twitter chats focused on specific issues, such as HIV (#HIVAgingChat), antimicrobial resistance (#AMRChallenge), and emergency preparedness (#CDCPrep2016). Because all four events occurred in the same month, the comparison controls for possible changes in the external environment, such as secular change in the number of Twitter users. Therefore, these three case-focused Twitter chats will be used to compare the spread of information for specific public health topics with the spread of information for a broad, topic-nonspecific campaign, #PublicHealthChat.

Table 1

Participant Demographics

Hashtag	Event	Date and time*	Event hosts
#PublicHealthChat	Future of Public Health Twitter Chat	Sep 22, 2016 1pm-2pm	NCEZID** (@CDC_NCEZID) American Public Health Association (@GetReady)
#AMRChallenge	Antimicrobial Resistance Diagnostic Challenge Twitter Chat	Sep 15, 2016 2pm-3pm	CDC (@CDCgov) NIH Director (@NIHDirector)
#HIVAgingChat	HIV Aging Chat, part of the event of "National HIV/AIDS and Aging Awareness Day"	Sep 16, 2016 3pm-4pm	Randomized Trial to Prevent Vascular Events in HIV (@reprievetrial) National Library of Medicine (@NLM_HIVplus50) AIDS Clinical Trials Group (@ACTGNetwork)
#CDCPrep2016	National Preparedness Month Twitter Chat	Sep 27, 2016 1pm-2pm	CDC Emergency (@CDCEmergency)

*All times in Eastern Daylight Saving Time (USA), 4 hours behind Universal Coordinated Time (UTC-4).
**NCEZID: National Center for Emerging and Zoonotic Infectious Disease

Data collection

Tweets containing #PublicHealthChat, #AMRChallenge, #HIVAgingChat, and #CDCPrep2016, were obtained through a combination of Twitter Search Application Programming Interface (API) and web scraping techniques. Because developers can only retrieve tweets via the Twitter Search API published in the past 7 days with a frequency of less than 180 requests per 15 minutes, the process is somewhat limited; to address this problem, collection was supplemented with a web scraping technique, namely TwitterScraper (https://github.com/taspinar/TwitterScraper), which was developed based on Twitter's website search to automatically retrieve tweets' IDs. This inventory of IDs is more complete than API data. To collect data consistently for all four chats, only tweets from 5 hours before each Twitter chat started to 1 hour after the event ended were retained for analysis. In total, 5,169 tweets were eventually retained and analyzed from the four Twitter chats, 1,074 of which were from #PublicHealthChat.

Measures

For the included tweets, several variables were measured, including retweets received, follower count, followee count, account age, original tweets, and user type. Retweets issued were measured to answer both research questions. Retweets received, follower count, and user account creation dates were obtained directly as part of the API calls. Account age then was calculated as the number of days between the date on which the account was created and the date on which the Twitter chat occurred.

Retweets issued refers to the number of posts that a given user retweets from others pertaining to a specific hashtag. As defined by Suh et al. (2010), there are two ways to identify retweets: regular expression method and feature retweet method. The feature retweet method identifies retweets by checking the column of retweeted_status through API calls; however, this method excludes retweets created using the copy and paste method and RT @ to designate tweets as retweets. In contrast, the regular expression method identifies retweets by scanning for retweet text markers, namely RT @ syntax; therefore, the regular expression method was used to identify retweets in this study. A related variable, original tweets count, refers to the number of tweets a user has created originally and excludes all retweets. Tweets that were not found to be retweets using the regular expression method were sorted by user ID and the number of original tweets each user has posted was counted.

Finally, account user types were identified using content analysis. Three coders were trained to classify all users who had participated in at least one of four hashtag events into four mutually exclusive categories of identities: government agencies and non-governmental organizations (NGOs); media organizations; individual health-related professionals; and miscellaneous accounts. To establish inter-coder reliability, a random subset of 150 users was obtained. Two coders independently looked through these listed users' Twitter profiles and annotated their categories according to the definitions. After that, Cohen's Kappas (1960) were calculated to measure the interrater reliability. The initial reliability scores were lower than 0.70. Therefore, the two coders discussed the disparities one by one until consensus was reached. Then the codebook was extended to include clarifications over those disparities. Two coders continued to code another 103 users separately and calculated a second run of interrater reliabilities. Ultimately, the reliabilities of four categories were 0.92 (Government agencies and NGOs), 0.85 (Media organizations), 0.89 (Individual health-related professionals), and 0.86 (Miscellaneous) respectively. The average Kappa was 0.88, indicating a high level of interrater reliability.

One coder then coded the remaining users. In our analysis, we operationalize opinion leaders as the top 10% of users who tweeted most (both original tweets and retweets) in the sample. In the generalized linear regression model, user type was dichotomized into three dummy variables—i.e. Health-related Organizations or Not, Media or Not, and Professionals or Not. However, because too few users qualified as media organizations, they were excluded from the regression analysis.

Analysis

Health chat networks

Social network analysis was used to determine whether information shared during the chats more closely resembled broadcasting or dialogic communication (*RQ1*). Four retweeting networks were constructed from four datasets respectively—#PublicHealthChat, #AMRChallenge, #HIVAgingChat, and #CDCPrep2016. Nodes can represent everything from individuals to countries, and networks represent any ties between these nodes (Opsahl et al., 2010). For this study, nodes denoted the Twitter users who mentioned the hashtag, while edges denoted retweeting relations. For example, when user A retweeted a post from user B, an edge, starting from node B and targeting at node A, was constructed to illustrate this retweeting relationship.

Furthermore, several critical network attributes such as network density, node centrality, and network centralization were calculated and compared. Density in social network analysis is the ratio of potential connections that has turned into actual edges. Higher density means the network's nodes are more closely related.

Node centrality is a series of measurements used to define how important a node is for the whole network structure. The most widely used measurement is called degree centrality, which is the number of other nodes to which a given node is adjacent. In social network analysis, degree is equivalent to the number of edges. In our study, the retweet network is a directed graph, as the retweeting relation (edge) is asymmetric; user A could retweet B's post without the need to ask B for permission, and B may not reciprocate by retweeting user A. Therefore, directionality of edges does and can be divided into two sub-categories: in-degree and out-degree. In-degree centrality is the number of other users from whom a given user has retweeted, while out-degree centrality is the number of other users who have retweeted posts from a given user.

Based on node centrality, Freeman (1979) developed a measurement of network centralization, which is the sum of difference of node centrality divided by its maximum in a graph with the same size. Using numeric expression, network centralization = $100^* \Sigma(C^*-C_i) / \text{Max } \Sigma(C^*-C_i)$, where C^* is the maximum centrality and C_i refers to centrality of *i*th node. This value unveils how the most central node exceeds others' centrality. The most centralized network is the star network, where nodes are all related to the star (in the center of the network) but not to each other. In this network, the star dominates the whole message's transmission activity, and its centralization value equals to 1. It will decrease to 0 only when the network is completely inter-connected.

Retweet prediction

Regression analysis was performed to examine which tweet and user features predicted retweets (*RQ2a* and *RQ2b*). R package pscl (version 3.1.3) in R 3.1.2 was used. For tweet features, we examined the number of relevant original tweets posted (in the limited time range) and the number of relevant tweets retweeted from others. The following account features were also examined: the logarithm (base 10) of one's number of followers, the logarithm (base 10) of one's followee count, the logarithm (base 10) of the age of one's Twitter account (in day), whether the Twitter user was an organization or not, and whether the Twitter user was a professional or not.

Given that retweet data is usually over-dispersed count data with excessive zero values, the best fit model would be a hurdle count model (Fu & Chau, 2013; Mullahy, 1986) with one truncated model for positive counts and one hurdle model for zero counts. Specifically, for zero vs non-zero values, binomial distribution with logit link function was fitted (logistic hurdle model). For positive count values, negative binomial distribution with log link was fitted. Since retweet frequency is count data and is often skewed with long tail, negative binomial distribution is more appropriate than other discrete distribution such as Poisson, which assumes the mean value to be equal to the variance. The analysis revealed a dispersion parameter (theta) of 3.72, indicating an overdispersion of the distribution of retweet count, justifying this decision.

Results

In our sample, the CDC-initiated Twitter chat #PublicHealthChat generated 1,074 tweets and involved up to 348 unique users (see Table 2). For all unique users, although the average number of total tweets per unique user (including retweets) was 3.09, the average number of original tweets per user was 1.14. Furthermore, the 398 original tweets (37.1% of the sample) were originally written by only 74 unique users. This low number of original tweets explains why the median of original tweet per user in the sample was 0.

Table 2

Descriptive Statistics for the Twitter Events

Account and tweet features	#PublicHealthChat	#AMRChallenge	#HIVAgingChat	#CDCPrep2016
Number of tweets	1,074	1,440	887	1,768
Original tweets	398 (37.1%)	361 (25.1%)	238 (26.8%)	601 (34.0%)
Total unique users	348	444	99	548
Unique users with original tweets	74 (21.3%)	43 (9.7%)	46 (46.5%)	65 (11.9%)
Mean tweets per unique user (SD)	3.09 (6.19)	3.24 (9.21)	8.96 (20.64)	3.23 (9.26)
Median tweets per unique user (Q1, Q3)	1 (1, 2)	1 (1, 2)	2 (1, 8.5)	1 (1, 2)
Mean original tweets per unique user* (SD)	1.14 (4.52)	0.81 (4.64)	2.40 (3.53)	1.10 (6.46)
Median Original tweets per unique user* (Q1, Q3)	0 (0,0)	0 (0,0)	0 (0,4)	0 (0,0)

Q1: first quartile; Q3: third quartile; SD: standard deviation.

*The denominator is the total number of unique user and not the number of unique users who posted original posts.

#PublicHealthChat, #AMRChallenge, and #CDCPrep2016 had similarly high levels of unique users and relatively high levels of nonoriginal, retweeted content compared to #CDCPrep2016 (see Table 2). Although #HIVAgingChat generated the highest average number of posts per unique user (8.96, including both original and retweets) and the highest percentage of unique users who tweeted original tweets (46.5%), it had the fewest participants (*N* = 99). #CDCPrep2016 involved the most unique users (*N* = 548) and elicited the greatest number of tweets (*N* = 1,768). #AMRChallenge had the lowest percentage of users who drafted their own posts (9.7%), indicating that most users simply retweeted rather than posted their own tweets during the #AMRChallenge event.

Table 3

Statistics of Retweet Networks

Hashtag	Nodes*	Edges	Density	Centralization	Highest out-degree centrality**
#PublicHealthChat	328	507	0.004	0.26	@CDCgov (92)
#AMRChallenge	438	563	0.003	0.65	@CDCgov (284)
#HIVAgingChat	97	319	0.003	0.21	@NIAIDNews (23)
#CDCPrep2016	534	836	0.003	0.60	@CDCemergency (321)

*These retweet networks do not include those solitary users who have never retweeted others nor have been retweeted by others. Therefore, the numbers of nodes in these network might be inconsistent with unique users reported in Table 1.

**Out-degree centrality denotes the number of other users who have retweeted posts from given users. It is different from the count of retweets received as some other users might retweet more than one time from the given user.

RQ1: Twitter chat networks

Centralization

All four chat's network analysis revealed that, comparatively speaking, the retweet network of #PublicHealthChat is moderately centralized, less centralized than #AMRChallenge or #CDCPrep2016 but more centralized than #HIVAgingChat (see Table 3). However, the distribution of out-degrees of #PublicHealthChat was skewed with a long tail, clustering around 0.

Opinion leaders

Opinion leaders, as represented by the top 10% users (n = 32) of #PublicHealthChat, dominated the retweet network, as they were responsible for over 97% of the total number of retweets (outdegrees). Similarly, the top 10% of users for #AMRChallenge and #CDCPrep2016 were responsible for 100% of the retweets for each of those chats. In contrast, less than half of the retweets for #HIVAgingChat (48%) were generated by the top 10% of users.

Table 4

Makeup of Top 10% of Users

Hashtag	Count	Share of out-degree*	Organization	Professional	Media	Others
#PublicHealthChat	32	97.0%	26 (81.2%)	4 (12.5%)	0 (0.0%)	2 (6.3%)
#AMRChallenge	46	100.0%	16 (36.4%)	18 (40.9%)	1 (2.3%)	9 (20.5%)
#HIVAgingChat	10	48.0%	7 (70%)	1 (10.0%)	0 (0.0%)	2 (20.0%)
#CDCPrep2016	53	100.0%	15 (28.3%)	11 (20.8%)	2 (3.8%)	25 (47.2%)

*The "share of out-degree" refers to the percentages of edges in the retweet network that were originated from the top 10% users.

When compared with the other three Twitter chats, #PublicHealthChat was found to have the largest portion of organization profiles (81.2%, *n* = 26) for its 32 opinion leaders (top 10% of users), although all four chats' opinion leaders were dominated by organization profiles (see Table 4). The most retweeted account for #PublicHealthChat was @CDCgov, even though it was not the host of this event (the hosts were @GetReady and @CDC_NCEZID). The accounts @CDC_NCEZID, @DrFriedenCDC, @CDCGlobal, and @PublicHealth were also among the top five retweeted users, all of which were held by health-related organizations. For the other three Twitter chats examined, the top users were similarly all government agency accounts (see Table 3 for the accounts with the highest out-degree centrality).

#PublicHealthChat as well as #HIVAgingChat had no media accounts among their top 10% of users. In contrast, of the 53 top users for #CDCPrep2016, two (3.8%) were media accounts and only 15 (28.3%) were organization profiles. #PublicHealthChat also had a low proportion of professional accounts involved as opinion leaders (4/32, 12.5%) similar to #HIVAgingChat (1/10, 10.0%) and #CDCPrep2016 (11/53, 20.8%). #AMRChallenge had the highest percentage of professionals (18/46, 40.9%) involved as top users. In short, although #CDCPrep2016 and #AMRChallenge showed some variation in the types of opinion leaders involved, opinion leaders for all the chats tended to be organizations.

Table 5

Factors Associated with the Number of Retweets Received Using a Hurdle Model

Hurdle model (logistic)	Odds ratio	95% CI	P
Log10(followers)	2.2563	0.8611, 5.9117	0.0978
Log10(followees)	1.2652	0.2208, 7.2511	0.7917
Retweets issued	0.9353	0.7785, 1.1237	0.4749
Original tweets	4.8496	2.5403, 9.2583	<0.0001
Organization	4.3759	0.7144, 24.8214	0.0955
Professional	0.0179	0.0003, 1.2706	0.0643
Log10(account age)	4.3849	0.0883, 217.6836	0.4581
Count model (neg. binomial)	Relative risk	95% CI	P
Log10(followers)	2.1513	1.6234, 2.8508	<0.0001
Log10(followees)	0.8003	0.4470, 1.4329	0.4535
Retweets issued	1.0047	0.9551, 1.0569	0.8560
Original tweets	1.0635	1.0372, 1.0904	<0.0001
Organization	1.7763	0.6688, 4.7178	0.2490
Professional	1.9318	0.6391, 5.8392	0.2433
Log10(account age)	0.6729	0.2208, 2.0506	0.4859

Dispersion parameters (theta) = 3.7781. Log-likelihood = -145.9 (degree of freedom = 17)

RQ2: Retweet prediction for #PublicHealthChat

For #PublicHealthChat, both account features (*RQ2a*) and tweet features (*RQ2b*) were examined using a two-component hurdle model over the retweet frequencies. The original tweets issued (tweet feature) were found to significantly predict retweets (see Table 5). If users posted one more original tweet, the odds of their #PublicHealthChat tweet being retweeted (the possibility of being retweeted divided by the possibility of not being retweeted) would increase by 4.85 times (95% CI, 2.54, 9.26; $p < 0.001$); if retweeted (tweet feature), there would be a 6% increase in its retweet count (adjusted prevalence ratio = 1.06, 95% CI, 1.03, 1.09, $p < 0.001$). If a tweet is retweeted, a tenfold increase in the number of followers (account feature) increases the count of retweets by 2.15 times (95% CI, 1.62, 2.85, $p < 0.001$). However, the two-fold increase in the odds of being retweeted in the first place by a ten-fold increase in follower count was not statistically significant (adjusted odds ratio = 2.2563, 95% CI, 0.8611, 5.9117, *p* = 0.0978). Therefore, users who generated a higher number of original tweets (tweet feature) as part of #PublicHealthChat were more likely to be retweeted by others, and the number of followers they had (account feature) did not necessarily increase the number of retweets.

Discussion

This study has compared four Twitter chats hosted by the CDC to identify communication patterns relevant to public interest communicators and constitutes one of the first studies that compare multiple Twitter chats pertinent to public health communication. As discussed in the results related to *RQ2*, the findings have practical implications for those wishing to become influential opinion leaders in Twitter chats, in that certain factors like original tweets lead to more retweets. Moreover, the nature of the network of tweets addressed in answer to *RQ1* has important implications for interpreting Twitter chats in terms of the dialogic loop. The lack of structure allowing for dialogue in these chats should be further explored, as well as the features of the chats that public interest organizations could improve in practice.

Twitter chat outcomes: Diffusion rather than dialogue

The relatively low number of users generating original tweets for all four chats, including #PublicHealthChat, indicates that Twitter chats often may lead to one-way interactions of diffusion, rather than dialogic engagement, despite the use of the term 'chat.' In particular, #PublicHealthChat reflected the power-law phenomenon, indicating that the retweet network is centralized around health-related organizations. Although past research has indicated that tweets regarding less specialized information tend to have less centralized networks (Bastos et al., 2018), in this case the broad topic of discussion seems to have been mainly an opportunity for various organization-sponsored accounts to diffuse their ideas.

The strong role of organization-run accounts as opinion leaders for #PublicHealthChat is consistent with past findings of how science organizations approach communication on social media (e.g., Lee & Van Dyke, 2015; Su et al., 2017). Given that many of the opinion leaders at the center of the centralized network were health organization accounts related to (or under the umbrella of) the CDC, the chat appears largely to have been orchestrated. In other words, accounts related to the CDC tweeted content and then retweeted one another as part of this chat. Public interest communicators in other organizations may similarly recruit sister and partner organizations to further diffuse information as part of Twitter chats. However, such strategies cannot improve the functional structure of the dialogic loop (Kent & Taylor, 1998), and, more importantly, such a strategic, instrumentalist approach to Twitter chats makes the chats inherently not dialogic (Kent & Lane, 2021).

Twitter chats as pseudoevents

Given that these chats appear to have been orchestrated, the chats seem to function as a sort of social media pseudoevent. Public interest communications develop through trigger events (Fessmann, 2017), and organizations may be using such pseudoevents to draw attention to issues when no trigger events occur naturally. Two potential strategies can be derived from this observation: organizations can use timeliness to make the events more authentic, or they can lean into pseudoevents as a strategy for marshalling resources for promoting dialogic engagement.

To make Twitter chats more authentic as events, timeliness may be a key strategy. The only chat that appeared less like a pseudoevent was #CDCPrep2016. This chat involved a more diverse array of opinion leaders than #PublicHealthChat (see Table 4) even though it had a similar network shape in terms of density and centralization. This finding may explain, in part, #CDCPrep2016's relatively higher number of total tweets and number of unique users compared to #PublicHealthChat. The very specific and relatable subject matter, compared to that of #PublicHealthChat, may have made opinion leader diversity possible, as the chat centered on National Preparedness Month during September, when hurricanes are common. The timeliness of the #CDCPrep2016 topic may have lent authenticity lacking in the other chats, making it less like a pseudoevent. However, the highly centralized network and low rate of original tweets of #CDCPrep2016 still means that the chat was primarily characterized by interactions of diffusion rather than interactions of conversation. As such, although the chat avoided the inauthenticity of pseudoevents, it did not engage audiences in dialogue.

The tweets regarding emergency preparedness during a time when emergencies are likely to occur may have made the #CDCPrep2016 chat more useful, leading to more involvement from a diverse array of users. While studying the dialogic nature of Twitter, Watkins (2017) found that the usefulness of the information, one of the five principles of dialogic communication, can change the dialogic quality of tweets and improve target publics' reactions to tweets. To set the grounds for interactions of conversation for a science-focused Twitter chat, therefore, strategic communicators should ensure that chat topics are timely and provide information that the public can use. An emphasis on timely Twitter chats gives more authentic news value to the chat and avoids the potential inauthenticity of a virtual pseudoevent.

Redeeming the pseudoevent: An opportunity for improving the dialogic loop?

However, an alternative to making the chats timely is to begin to take advantage of the time flexibility of a pseudoevent. Although the technical features are present in Twitter for the dialogic loop to exist, the CDC's procedures during a chat do not appear to allow for a dialogic loop. These procedures, wherein individual accounts are not engaged, may be due to a lack of available personnel within the host organization. Particularly in science and health communications, knowledgeable employees would need to be available to support direct engagement and, hopefully, dialogue with social media accounts during chats. Although organizational resources may limit the number of qualified individuals available to assist in dialogic communication, organizations should consider dedicating employees to the task of supporting engagement during dedicated chats because Twitter chats offer an opportunity for authentic dialogic engagement for a short burst. Organizations such as the CDC may see dedicating employees to engaging with the public as a strain on resources; however, from another perspective, dialoging on social media would ideally take place all the time, and Twitter chats serve as a compromise, making dialogic public interest communications available for a manageable, limited amount of time.

Public interest communicators may therefore use Twitter chat pseudoevents to promote communication during times when the greatest number of personnel are available to help assist in engaging with participants. More personnel may allow the structure of a dialogic loop to exist and improve the opportunity for truly dialogic communication, which requires that dialogue allow for information based on personal experience instead of only scientific information (Kent & Lane, 2021). A true exchange of ideas could be used to reduce any perceived power differentials, build mutual understanding between organizations and their publics, and establish greater trust. Dialogic communication on social media is difficult and may be even more so with a large governmental organization, but Twitter chats' structure could be redesigned to make dialogue at least possible.

Characteristics that predict retweets

Despite the merits of dialogic communication, the focus of Twitter chats currently seems to be on information diffusion. Organizations hoping to become opinion leaders should take note that, in our study, only users who tweeted original material rather than retweets were likely to then be retweeted. To attract more retweets, more relevant tweets will further improve accounts' influence in this retweet-able group, leading to more retweets. This finding may be encouraging for organizations that are late to joining conversations on Twitter and wish to use such chats primarily for diffusion. Despite having shorter account ages and fewer followers, these organizations may still be able to reach a large audience if they compose original tweets during Twitter chats. However, this finding also could have important implications for encouraging organizations to take part in a more dialogic approach to communication (Kent & Lane, 2021). Original tweets, rather than merely sharing what others have stated, offer opportunity for a dynamic response to the Twitter conversation even as they provide opportunity for more attention.

Limitations

Through a comparative study design, our study reveals the nature of public health Twitter chats in terms of dialogue and opinion leadership. However, the method does have limitations. First, our analysis was limited to Twitter data, as we have no knowledge regarding the intent of the

Twitter chat hosts; therefore, although we assume that elements of the chats are orchestrated by multiple CDC accounts, we have no proof. Second, in the analysis of retweets we took three predictors into account but may have omitted other, unknown confounding variables. Finally, Twitter does not show a complete retweeting route to its audience (Liang et al., 2019; Meng et al., 2018). It only displays the starting and ending node, thus skipping all intermediaries. User A could read a post, originally written by user B, from user C's page and retweet it afterwards. Literally speaking, the message flowed from B to C to A. In practice, however, we can only recognize retweeting relation between A and B, leaving out C's role as an intermediary. Thus, the retweeting networks we tested below may miss some details which might lead to an overestimation of the social impact of the source, whose voice may not reach out that broadly without those intermediaries.

Conclusion

Current use of Twitter chats indicates that organizations communicating information relevant to the public good do not support the dialogic loop during these so-called chats. To improve the dialogic potential for chats, strategic communicators would need to spend more time reading and responding to other users' tweets. The centralized nature of the retweet network indicates that chats currently serve, perhaps intentionally, as organization-dominated platforms for information diffusion rather than conversation. The fact that dialogic potential, much less actual dialogue, is so obviously lacking in these chats may increase the perception of power differentials between public interest organizations like the CDC and its publics, and such perceived distance could in turn undermine Twitter users' trust in those organizations.

Given the limited time and resources of the people running organization accounts, strategic communicators may need more resources to improve the dialogic potential of the chats by assembling groups of individuals to read and respond to nonorganization Twitter users. Considering the communication and trust problems that can occur during public health emergencies, health organizations should develop opportunities to improve public trust through dialogic communication during nonemergency situations as well.

In conclusion, this paper describes how Twitter users may broaden their reach in the context of Twitter chats and provides the encouraging finding that those who post original content can dramatically increase their ability to become opinion leaders. This paper also suggests that such chats have potential for bringing attention to issues lacking naturally occurring trigger events, and we submit that creating such opportunities may allow for the marshalling of resources to improve the structure of the dialogic loop. Because such trigger events are important for the development of public interest communications (Fessmann, 2017), public interest communicators may choose to use Twitter chats as a tool when key issues are receiving little attention. However, overall, Twitter chats currently do not appear to be implemented in a way that encourages dialogic engagement or the building of trust.

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