Factors Affecting Public's Engagement with Tweets by Authoritative Sources During Crisis

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ABSTRACT

People increasingly use social media at the time of crisis, which produces a social media data deluge, where the public may find it difficult to locate trustworthy and credible information. Therefore, they often turn to authoritative sources: official individuals and organizations who are trusted to provide reliable information. It is then imperative that their credible messages reach and engage the widest possible audience, especially among those affected. In this study, we explore the role of metadata and linguistic factors in facilitating three types of engagement — retweets, replies, and favorites— with posts by authoritative sources. We find that many factors are similarly important across models (popularity, sociability, activity). However, some features are salient for only a specific type of engagement. We conclude by providing guidance to authoritative sources on how they may optimize specific types of engagement: retweets for information propagation, replies for in-depth sense-making, and favorites for cross-purpose visibility.

Keywords

Crisis informatics, social media, public engagement, authoritative sources, topic modeling

Over the past two decades, crisis preparedness, response, and recovery have increasingly relied on Information and Communication Technologies (ICT) (Soden and Palen 2018). Crisis informatics (Hagar and Haythornthwaite 2005; Palen and Anderson 2016) has emerged at the intersection of Human-Centered Computing and crisis-related domains, focusing on how people use ICTs—including social media (Soden and Palen 2018)—in creative ways to navigate and manage complexity and uncertainty of crisis situations. Social media platforms are playing an increasingly important role in disseminating crisis-related information, including safety-critical messages aiding in situational awareness (MacKay et al. 2022; Vieweg et al. 2010). The affected populations use social media to communicate with each other, share their emotions and experiences (Smith 2010; Soden and Palen 2018; Sutton et al. 2008), grapple with and make sense of information (Kogan and Palen 2018; Li et al. 2021), and self-organize to accomplish specific tasks they deem important, such as forming search and rescue teams and managing volunteers (Reuter et al. 2012; Starbird and Palen 2011), event reporting (B. C. Keegan 2012; B. Keegan et al. 2012; Perng et al. 2013) and other community needs (White et al. 2014). They also actively seek out timely safety-critical information and propagate useful and relevant reports (MacKay et al. 2022; Qu et al. 2011; Starbird and Palen 2010).

However, with the extensive use of social media in crisis, it becomes difficult for the public to distinguish between credible information, and rumors and misinformation. Therefore, many users rely on authoritative sources (Tapia et al. 2011; Kogan and Palen 2018) who provide trustworthy and actionable crisis-related information based on their official status or government role (Cangialosi et al. 2018) (see section 3.1). Authoritative sources can also slow down the flow and prevent the spread of misinformation by actively participating in discussions, correcting rumors, and posting denials (Andrews et al. 2016). Thus, authoritative sources are ideal vehicles for disseminating important crisis-related information to the affected population. Yet, while authoritative accounts often have large audiences (Castillo 2016), the reach of their messages and the engagement they generate among the public varies dramatically based on a variety of factors. Research found that some influential factors include author's popularity, presence of visual information, and likely message tone (Glunt and Kogan 2019). However, this preliminary work has focused on posts' metadata and did not explore linguistic features. Furthermore, it focused only on the number of retweets and replies as the indicators of messages' engagement.

Here, we consider the number of retweets, replies, and favorites garnered by a tweet as indicators of its engagement. Moreover, we explore a variety of factors—including linguistic features: topics, and sentiments—that can facilitate broader public engagement with messages by authoritative sources. By elucidating these factors and determining their relative importance, we aim to enable authoritative accounts to formulate their crisis-relevant tweets in a way that would increase their chances of reaching and engaging a wider audience. Moreover, we highlight and contrast specific factors that are most effective in facilitating each type of engagement, enabling authoritative sources to maximize the kinds of engagement most salient for their crisis communication.

In sum, we answer the following research questions:

1. What linguistic and metadata features facilitate engagement with posts by authoritative users?
2. What is the relative importance of these features in facilitating public engagement?
3. What factors are most salient for facilitating each type of engagement?

BACKGROUND

Affected Population Often Turn to Authoritative Sources for Actionable-Credible Information

In crisis situations, affected people often use social media to propagate locally-actionable information that tends to support situational awareness, including updates about damaged areas, infected populations, power outages, and road closures (Castillo 2016; Gurman and Ellenberger 2015; Starbird and Palen 2010; Vieweg et al. 2010). They also use social media to communicate with each other, inquire about friends and family (Austin et al. 2012; Palen 2008; Velev and Zlateva 2012), and meet emotional needs and support others (Kaur and Kumar 2015; Qu et al. 2011). Microblogging platforms like Twitter have been especially effective at facilitating communication in crisis as they provide accessible platforms where short messages can be swiftly composed and shared among people (Brynielsson et al. 2013; Qu et al. 2011). The volume of the microblogging content is amplified by the well-studied process of convergence, where people, resources, and information coalesce around the disaster-affected area and the online discussions about it (Fritz and Mathewson 1957; Huang and Xiao 2015). This produces a social media data deluge, in which the affected users often find it difficult to locate useful and credible information. Further, the spread of inaccurate information, may even increase the risk to public safety. Therefore, affected populations often turn to authoritative sources for authentic crisis-related information (Peters et al. 1997) and expect authorities to exercise leadership, especially when perceived threats are severe (Hwang and Cameron 2008).

Some studies have suggested that certain content features can further increase the trustworthiness of microblogging content. For example, Castillo and colleagues found that trustworthy tweets often include URLs (Castillo et al. 2011). This is consistent with an earlier finding that disaster-related tweets more frequently contain URLs and are retweets from media and government sources, spreading information from confirmed credible sources and echoing the government's guidelines (Hughes and Palen 2009).

Public Engages with Crisis Communication at Various Scales and for Different Purposes

The information posted by authoritative sources tends to garner broader engagement in crisis, especially with respect to retweets. Veiweg and colleagues showed that the most retweeted sources were almost always from mainstream media, service organizations, or authoritative accounts whose main purpose was to cover the emergency event (Vieweg et al. 2010).

Retweets Are Recommendation and Information Diffusion Systems

Among various types of engagement offered on social media, retweets are most well-studied, likely due to their dual purpose: informal recommendation system (for either the content or its author) (Starbird and Palen 2010; Starbird, Muzny, et al. 2012) and information diffusion facilitator which is a result of a collective effort of users exposing a post to new audiences (Taxidou and Fischer 2014). Information diffusion across various platforms has been widely investigated (Alrajebah 2015; Lerman and Ghosh 2010; Taxidou and Fischer 2014), with special attention paid to modeling how content spreads through the network (Luo et al. 2013; Taxidou and Fischer 2014), exploring factors facilitating the dissemination of information (MacKay et al. 2022; Kwak et al. 2010; Petrovic et al. 2011), and predicting which content is likely to be propagated and how far it will reach (Kwak et al. 2010; Luo et al. 2013; Petrovic et al. 2011).

Less attention has been paid to retweets as an informal recommendation system (Starbird and Palen 2010; Starbird, Muzny, et al. 2012), though the two roles are difficult to disentangle. Kwak and colleagues studied the topological characteristics of Twitter for information sharing (Kwak et al. 2010). They found that any retweeted tweet will reach an average of 1000 users, regardless of Twitterer's number of followers. Rueter et al. studied 2011 USA Tornados and found that people coalesced into informal organizations, in which they played different roles, including retweeters; helpers, who were participating in search and rescue groups and managing volunteers and aid; and reporters, who shared their experiences and information about the affected area (Reuter et al. 2012).

Different Engagement Types Play Different Roles in Crisis Communication

Various types of engagement on Twitter can be conceptualized as representing different scales. For instance, retweets can be seen as macro-scale engagements, because of their contribution to the collective process of information dissemination — "macro-level flow of messages across longer-term follower/followee networks" — (Bruns and Burgess 2015). On the other hand, the "micro-scale communicative exchanges" (Bruns and Burgess 2015) of replies are by definition interpersonal, geared towards a dialog or a small group discussion (Kogan and Palen 2018).Favorites are the least understood form of engagement, as people use them in variety of ways (Gorrell and Bontcheva 2016). They can be used as likes — recommendations to the followers without propagation (meso to micro level), as bookmarks for retaining content (individual/micro level), as tokens of appreciation (interpersonal/ micro level), and other haphazard uses (Gorrell and Bontcheva 2016). This mix of use makes favorites difficult to place, though aggregating across uses, we may position favorites as a meso-micro level engagement.

This difference in scales suggests that the three modes of engagement would provide different benefits for the authoritative sources responsible for crisis communication. Retweets ensure a broad (global) reach (breadth diffusion) for crisis communication (Bica, Demuth, et al. 2019). Replies indicate that the public is actively engaging, grappling, and following up with questions (Li et al. 2021), contextualizing to their own situation (depth diffusion) (Bica, Demuth, et al. 2019). In addition, replies also provide localized factual information to the authoritative sources, signaling the situation and the needs of the affected public. Finally, favorites signal general recommendations and promote cross-purpose visibility. Thus, here we examine the most impactful factors for each of these engagement types and thus contribute to fulfilling different needs of authoritative sources in crisis communication.

Factors that May Facilitate Engagement

For engagement types other than retweets, the effect of specific factors has been rarely examined. In one study, Glunt & Kogan found that politicians garnered the most replies (and retweets), among official authoritative sources. While they identified some metadata that correlated with politicians' higher number of replies (and retweets), they did not examine the relative effects of these factors nor account for linguistic features in tweets' engagement. Thus, here we fill these gaps.

A small but growing area of crisis informatics has been focusing on the role of images in the sensemaking activities in crisis (Bica, Palen, et al. 2017; Bica, Demuth, et al. 2019; Rogers 2014). Such research shows that images receive more engagement on social media than text-only contents (Rogers 2014). Thus, we include visual features such as containing photos and videos and expect them to increase engagement. Hashtags position a tweet within a conversation or an ad hoc public (Bruns and Burgess 2015), making a tweet more visible and findable. URLs have been shown to increase the perceived credibility of a tweet, especially in crisis (Castillo et al. 2011; Hughes and Palen 2009; Morris et al. 2012); thus, URLs are likely to be an important factor in engagement.

While these metadata features have been highlighted in the literature as important for engagement, to the best of our knowledge no work has elucidated whether they are equally important for different types of engagement. In this study, we disentangle the relative importance of these features, and linguistic features like topics and sentiment, to a tweet garnering different types of engagement.

2017 Atlantic Hurricane Season — One of the Most Damaging Hurricanes on Record

Among natural disasters that threaten the United States, hurricanes are one of the most frequent and damaging. Large shares of the U.S. population live in coastal areas, prone to hurricanes.

Here, we focus on the 2017 Atlantic hurricane season, which was one of the costliest seasons on record, with a total damage cost of at least $295 billion. Further, at least 3,364 deaths were recorded as a result of the ten hurricanes that formed, six of which were Category 3 or stronger with winds greater than 110 mph. Most of the season's damage was due to hurricanes Harvey, Irma, and Maria, which are this study's main interests(Blake and Zelinsky 2018).

METHODS

Data Collection

The GNIP PowerTrack API was used to collect authoritative sources' tweets relating to the most active period of the 2017 hurricane season: Aug. 17 to Sep. 25, 2017, starting with Harvey first forming, and ending with the dissipation of Maria. We identified authoritative sources using two methods. First, we collaborated with the National Center for Atmospheric Research (NCAR) to select meteorological, humanitarian, government and news-related Twitter accounts local to the affected areas. Next, we collected other accounts by identifying user-created lists compiling official information. 724 authoritative sources were identified in total, 693 of which were then classified into one of five categories: Politicians — governors and congressional representatives for the affected states; Government Agencies — city, county, and state governments, federal emergency-response agencies (FEMA); Media — local through international news and media agencies, reporters; Weather experts; and Humanitarian Organizations — non-governmental organizations that are a part of disaster response. All tweets by these 724 sources and all the interactions (replies, retweets, quoted tweets, and mentions) of other users with each source were collected.

Three media accounts (@cnn, @telemondo, and @nasa) were excluded because of their extremely broad coverage that brought a significant amount of non-crisis-related noise. Biterm topic modeling (BTM) (Yan et al. 2013) was further used to categorize and filter out noisy tweets. After clustering all tweets into 20 topics (see section 3.2.1), each topic was manually labeled. For BTM topics that did not appear to be crisis-related, a set of hurricane-related keywords like hurricane, shelter, warning, evacuation, etc., was used to retain tweets that were likely to be related to Harvey, Irma, and Maria. Tweets that were likely to be spam were also removed; specifically, duplicate posts (including the same user mention aimed at popular national sources) were often advertisements of commercial products or services. The number of users and tweets in the final dataset is shown in Table 1 for each authoritative account type.

Authoritative Account Type	Number of Accounts	Number of Tweets
Politicians	22 (3.2%)	3,308 (2%)
Government	200 (30%)	30,319(20%)
Media	290 (42%)	68,004(44%)
Meteorologists	174 (25%)	51,698(33%)
Humanitarians	4 (1%)	578 (1%)
Total	690	153,906

Table 1. Authoritative Account Types

Data Analysis

When acquiring Twitter data from most APIs, the counts for retweets and favorites are set to zero, as the tweets have not yet acquired any engagements. Instead, we need to rely on the later copies of the tweet — its retweets — to know how many times the original tweet was propagated or favorited within the particular study time period. For the retweet count, we reconstructed how many times each tweet has been retweeted based on its later copies in the data set. For the number of favorites, we followed a similar process of retaining the number of favorites received by the last-updated retweet of an original tweet. The number of replies was calculated by adding up all the replies that reference the same original tweet. Next, we discuss all the factors we examined for each type of engagement (See Table 2 for an overview of the factors examined.

Classifying Data into Crisis-Related Topics Using BTM

Topic modeling of disaster-related social media content allows researchers to glean useful information from large text corpora (McCreadie et al. 2019; Zade et al. 2018) and to analyze the perspectives of the users who create the content (Pereira-Sanchez et al. 2022; Kaschesky et al. 2011; Stieglitz et al. 2017). We used topic modeling to explore the role of the topics covered in authoritative tweets in garnering engagement (Tang et al. 2021; Lee and Yu 2020; Liu et al. 2020; Yan et al. 2013). Although previous work has mainly used LDA (Latent Dirichlet Allocation), it is not well-suited for platforms like Twitter, as it suffers from a sparsity of word co-occurrence patterns in short text (Yan et al. 2013). Therefore, here, we use BTM (Yan et al. 2013), which has been developed specifically for short text topic modeling (Hong et al. 2018).

We first stemmed the words by reducing them to their roots, then we removed stop words and other high-frequency words (e.g., see, while, this, that) which are not helpful for topic recognition. We further removed tweets with less than three tokens remaining after pre-processing, as they suffer from severe data sparsity. URLs, hashtags, and user mentions were also removed from the text body. The resulting dataset consisted of 153,907 pre-processed tweets, on which we ran a BTM with 300 iterations. To find an optimal number of topics, we used three coherence metrics of C_v, $C_u ci$, and $C_n\ pmi$. For all, the highest coherence occurred at the number of topics k=20, which we selected for our model. For interpretability, we manually labeled each resulting topic based on the top 20 most probable words and a random ample of tweets (5% of tweets in each topic). For Topic16, which contains Spanish tweets, a native Spanish speaker assisted with the labeling. Table 3 shows the human-labeled topics.

Using VADER and LiWC to Explore Tweets' Polarity and Sentiment

VADER was developed specifically for social media and uses a sentiment lexicon (including emojis) to assigns a polarity score to the text based on their frequency (Hutto and Gilbert 2014). We also used LiWC 2015 to explore the effect of emotional and psychological aspects of tweets' language on tweets' engagement. LiWC computes the frequency of specific pre-defined lexicon-based word categories in the text. We specifically focused on affective, cognitive, and social processes which have been frequently used to study the emotional and psychological aspects of language people use in crisis (Hong et al. 2018).

Various Authoritative Account Types Can Garner Different Levels of Engagement

Previous studies showed that tweets from different types of authoritative sources might receive a different level of engagement (Tang et al. 2021; Glunt and Kogan 2019; Neppalli et al. 2016; Starbird and Palen 2010). Thus, we explore how the five categories of the authorittaive sources — Politicians, Government, Media, Weather experts, and Humanitarian Organizations — affect tweets' engagement.

Metadata Features

User popularity and activity level often play a primary role in engagement garnered by tweets, especially for retweets (Glunt and Kogan 2019; Gurman and Ellenberger 2015; Neppalli et al. 2016). To explore the effect of twitterer's popularity, sociability, and activeness on their tweets' engagement, we used their number of followers (as with a higher number of followers, tweets will be exposed to a larger audience); the number of friends (as it indicates how socially active they are); status count — the number of tweets ever posted by a user; and the number of users mentioned in their tweets (as it again relates to sociality and activity). Since all the popularity and activity-related features are long-tailed, as is common in the real-world complex networks (Clauset et al. 2009; Lerman and Ghosh 2010), for the regressions analysis we log-transformed these features to better fit the assumptions of linear regression. To examine the effect of visual features, we defined two binary variables: containing video and containing photo. Whether a tweet contains hashtag(s) and URLs are other binary features that we inspect.

Events

Although our data mostly includes tweets related to Harvey, Irma, and Maria, we also have some tweets not specifically related to any of these three hurricanes including safety tips and information general to hurricane situations. As the three hurricanes have been covered rather unevenly by the media, we also examined whether posting about different hurricanes could affect tweets' engagement.

Regression Models

To investigate to what degree each factor influences the three types of engagement, we construct three separate linear regression models: for the number of retweets, number of replies, and number of favorites garnered by authoritative sources' tweets. Prior to model construction, we examined the correlation between each engagement type and the factor described above and included only factors with significant correlation in the corresponding regression model. Then we examined the relative influence based on regression coefficients. All continuous variables were log-transformed for the regression models. This includes the dependent variables—number of retweets, number of replies, and number of favorites — and continuous predictor variables: number of followers, number of friends, status count, and number of users mentioned in tweet.

Linguistic features	Topic Variables	Topics 1-20
	Sentiment variables (LiWC categories)	Standard linguistic dimensions
		Psychological processes
		Personal concerns
		Spoken categories
	Authoritative account types	Politicians
		Government
		Meteorologists
		Media
		Humanitarian
	Events	Harvey
		Irma
		Maria
		General
Content variables	Continuous metadata features	Number of retweets
		Number of favorites
		Number of replies
		Number of followers
		Number of friends
		StatusCount
		Number of mentioned users
	Binary metadata features	containsPhoto
		containsVideo
		containsURLs
		containsHashtags

Table 2. Predictor Variables

FINDINGS

Table 3 displays human-annotated labels for the topics produced by the BTM. We include them among other linguistic features in the linear regression models for each type of engagement.

Table 4 presents the results of the three regression models. It excludes the sentiment variables, which, while sometimes statistically significant, had very low regression coefficients, indicating no practical effect. All the presented coefficients have been exponentiated for interoperability since the dependent variables were log-transformed. Additionally, coefficients for the log-transformed independent variables were exponentiated again. For all the categorical variables, we chose the lowest coefficient category as the reference. This produces positive coefficients for all the other categories, allowing us to identify the factors that *increase* engagement more easily and intuitively. All our models achieved moderate to strong fit, with R^2=0.837 for the retweet model, R^2=0.561 for the reply model, and R^2=0.773 for the favorites model.

Tweets with Actionable Info More Widely Shared, Tweets Facilitating Sensemaking Garner More Replies

For all three models, most Topic categories are statistically significant. Exceptions for the retweet model are: Topic2 (Hurricane live coverage), and Topic3 (Power outage and restoration). Compared to other topics, these topics rarely include actionable information that may aid in situational awareness. This finding suggests that less actionable topics may be deemed less important for propagation by the public. In contrast, Topics11 and 13, respectively, include safety-critical flooding and hurricane-related information and are some of the most influential topics in the retweet model.

The following tweet examples are from Topic11 and 13 with 11,893 and 18,783 retweets, respectively:

(Topic11) 2017-09-10 16:40:16 BrianEntin:
Water still rising in downtown Miami along Brickell Avenue. Storm surge is intense. Neck deep in areas. @wsvn... https://t.co/EpaQFpmvA1
(Topic13) 2017-08-30 11:43:12 JimCantore:
Catastrophic Rainfall outside Houston: vidor: 52.37"

Topics	Labels	Explanations
1	Hurricane forecast	Hurricane model forecast and track
2	Hurricane live coverage	Live coverage from hurricanes - prayers for affected people
3	Power outage and restoration news	Asking the public to report their address if they experience power outage
4	Concerns for Caribbean islands	Concern for Puerto Rico, Caribbean - hurricane damage reports
5	Weather forecast	Weather forecasts, probability of shower and storm prediction
6	Evacuation and shelter announcements	Evacuation zone announcements, shelters information
7	Road closure	Traffic and road closure information
8	Free supplies and shelter	Free supplies open shelters, Hurricane Irma preparation tips
9	Hurricane crime news	Hurricane crime news, Missing people
10	Florida Keys damage	Florida Keys hurricane damage
11	Flooding announcements and tips	Flooding and heavy rain announcements and tips
12	Hurricane, wind speed updates	Hurricane tracking, wind speed updates
13	Texas flood warning and tips	Safety tips and evacuation compliance, tornado, and flood warning for Texas
14	Tornado and flood warning	Tornado and flood warning
15	Asking for volunteers' help	Volunteer and donation requests, appreciating volunteers for help, shelter information
16	Hurricane Maria in Puerto Rico	Hurricane Maria in Puerto Rico (Spanish)
17	Football cancellation	Football reschedule/ cancellation due to hurricane
18	Politics around hurricane	Political news around the hurricanes
19	Solar eclipse	Solar eclipse and hurricane Maria
20	Tornado warnings	Tornado warnings

Table 3. Human-Annotated labels for Topics and Explanations

bridge city: 51.17" orange: 43.82" port neches: 45.74" nederland 45.33" beaumont 45.35"

Topic16 also has a high effect on retweets. It includes Spanish-language tweets about hurricane Maria in Puerto Rico. Poor coverage of hurricane Maria by the mainstream media is well-documented. Thus, users likely used social media to propagate information about their condition.

For the reply model, Topic9 (Hurricane crime news), Topic13 (Texas flood warnings and tips), and Topic16 (Hurricane Maria in Puerto Rico) are not significant. Qualitatively analyzing samples of tweets, we find that tweets in these topics tend to be rather news-like, broadcasting in their style, which does not necessarily promote responding. Instead, topics with the most impact either include controversial content as Topic18 (Politics around hurricane) or facilitate a dialog about the situation as Topic3 (Power outage and restoration), where the public was responding with specific grievances, updates, and requesting updates on the power outage situation. The following examples show some of the most replied tweets in Topic18 and 3, respectively, with one of their replies.

Variables	Retweet Model Coefficients (R2=0.837)	Reply Model Coefficients (R2=0.561)	Favorites Model Coefficients (R2=0.773)
Topic1 (Hurricane forecast)	Ref	2.59	2.98
Topic2 (Hurricane live coverage)	not sig	2.28	3.83
Topic3 (Power outage and restoration)	not sig	2.69	1.94
Topic4 (Concerns for Caribbean islands)	1.72	1.79	2.02
Topic5 (Weather forecast)	1.09	2.09	1.95
Topic6 (Evacuation and shelter announcements)	1.81	1.57	1.51
Topic7 (Road closure)	1.40	1.85	1.82
Topic8 (Free supplies and shelter)	1.06	2.36	3.23
Topic9 (Hurricane crime news)	1.43	not sig	2.25
Topic10 (Florida Keys damage)	1.58	1.88	1.8
Topic11 (Flooding announcements and tips)	2.04	1.42	1.47
Topic12 (Hurricane, wind speed updates)	1.95	1.47	1.59
Topic13 (Texas flood warning and tips)	2.36	not sig	0.64
Topic14 (Tornado and flood warning)	1.84	Ref	Ref
Topic15 (Asking for volunteers' help)	1.28	1.71	2.73
Topic16 (Hurricane Maria in Puerto Rico)	2.09	not sig	1.67
Topic17 (Football cancellation)	not sig	not sig	4.52
Topic18 (Politics around hurricane)	not sig	4.99	2.24
Topic19 (Solar eclipse)	not sig	not sig	2.11
Topic20 (Tornado warnings)	1.48	2.32	2.04
Subgroup=Politicians	Ref	3.50	3.45
Subgroup=Government	1.30	Ref	1.60
Subgroup=Media	1.10	1.46	1.49
Subgroup=Meteorologists	not sig	1.64	1.89
Subgroup=Humanitarians	2.50	not sig	Ref
ContainsVideo	1.20	not sig	1.78
ContainsPhoto	1.30	not sig	1.13
ContainsHashtags	1.30	0.98	0.95
ContainsURLs	0.90	0.77	0.80
Event=Harvey	18.69	not sig	not sig
Event=Irma	17.88	not sig	not sig
Event=Maria	7.65	not sig	not sig
Event= general	18.16	0.83	not sig
Number of Followers	13.68	12.02	14.11
Number of Friends	8.67	34.72	11.19
StatusCount	7.73	7.43	8.56
Number of Mentioned users	7.12	13.99	10.66
Number of Retweets	N/A	95.57	44024.08
Number of Replies	20.00	N/A	129.24
Number of favorites	7126738	11.21	N/A

Table 4. First column indicates the predictor variables. The second, third, and last columns respectively correspond to the coefficients and fits of the retweet, reply, and favorite models.
"not sig" means not statistically significant. "Ref" signifies the reference variable.

(Topic18) 2017-08-26 00:25:24 jacobsoboroff:
Unreal. As nation focuses on massive Texas Cat-4 hurricane, Trump pardons Joe Arpaio, convicted of criminal contempt for RACIAL PROFILING. https://t.co/xh5sdlHl3d
Reply: 2017-08-26 00:25:24 user1
@jacobsoboroff What's wrong with that? He basically said he was going to do it. Arpaio is a patriot

(Topic3) 2017-09-12 18:37:58 GeorgiaPower:
2:30 PM HurricaneIrma Update - We have restored power to approximately 270,000 customers across the state. https://t.co/I4TmyS4Rzj
Reply: 2017-09-12 20:31:04 user2
@GeorgiaPower How bout 14 days no power, normal in Louisiana. This is a cake walk!

Three other highly impactful topics in the reply model offer information that may aid in situational awareness and facilitate active sensemaking by the public: Topic1 (Hurricane model forecast), Topic2 (Hurricane live coverage), and Topic8 (Free supplies and shelter). Users actively grappled with the information, contextualizing it for their own situation, and asking follow-up questions:

(Topic1) 2017-08-27 15:44:09 NWS:
This event is unprecedented all impacts are unknown beyond anything experienced. Follow orders from officials to ensure safety. Harvey https://t.co/IjpWLey1h8
Reply: 2017-08-28 12:55:40 user3
@NWS @crampell Houston is 600 square miles of flat land 80 feet above sea level. Dallas gets major floods and is 400 feet above sea level.

(Topic8) 2017-09-09 20:42:19 PascoSheriff:
Please share NO ONE is being turned away at ANY shelters. This includes pets without papers/tags or people without ID. Seek shelter!
Reply: 2017-09-10 16:22:08 user4
@ PascoSheriff What about threats to run warrant checks at shelters? Have you evacuated jails? Are they locked... https://t.co/BRoVD4oAUQ

Finally, Topic17 (Football cancellation) and Topic19 (Solar eclipse) are not significant for either retweet or reply models. Topics17 and majority of tweets in Topic19 are only tangentially related to the hurricane hazard. Some of the tweets in Topic19 are related to hurricane Maria, which unfortunately has not been covered effectively. Thus, these two topics did not garner much of either kind of engagement.

All topics are statistically significant in the favorite model. Here, the most influential topics are Topic17 (Football cancellation), Topic2 (Hurricane live coverage), Topic8 (Free supplies and shelter), Topic1 (Hurricane forecast), and Topic15 (Asking for volunteers' help). With the exception of 17, all influential topics relate to information about preparation, current events surrounding the hurricane and shelter, and donation information. This combination of safety-critical, actionable content and emotionally-laden, community-oriented calls to help are useful and evocative in different ways. Even football-related tweets often have humanitarian overtones. Here are examples of highly favorited tweets in Topic8 and Topic17:

(Topic8) 2017-09-13 14:40:58 PascoSheriff:
Volunteers putting together bags of food to hand out to residents without power in Lacoochee. Deputies on hand to assist and help out!

(Topic17) 2017-09-14 13:04:24 UFPublicSafety:
hurricane relief efforts at their upcoming games the decal that the football team will wear on their helmets.

Many more sentiment LiWC features are significant for the retweet model than for replies, with favorites somewhat in between, potentially suggesting that emotions may play a different role across engagements. However, no sentiment features had a practical effect (neither LiWC nor VADER). This may be due to the limitations of lexicon-based sentiment tools when applied to sparse text like social media posts.

Metadata Features Related to Tweets' Popularity Are Highly Predictive in All Three Models

The continuous metadata variables in our models either relate to author popularity (number of followers), sociability (friends count, number of mentions), or level of activity (status count). All of these are statistically significant and highly predictive in all three models. The overall visibility of the author makes their tweets more visible and possibly more credible, increasing chances of engagement. The number of users mentioned in the tweet and the number of followers are among the most impactful features, which is consistent with prior findings (Comarela et al. 2012) even when the model includes other significant predictors. Interestingly, among popularity and sociability variables, the number of friends is the most predictive of number of replies, suggesting that sociability in curating one's social network potentially translates into the sociability of reply conversations. The number of user mentions also has a strong effect on replies, likely making the tweets more approachable and inviting.

Notably, each type of engagement is highly predictive of two others. Number of retweets is strongly predictive of number of replies and dramatically predictive of number of favorites: Tweets that have a high retweet count get propagated across new audiences, which in turn leads to higher favorite and reply counts. Similarly, favorites have a strong effect on replies and extreme effect on retweets. Finally, replies have a strong impact on retweet counts and even more so on favorite counts. These results suggest that retweets and favorites are somewhat related types of engagement — strongly fueled by visibility and popularity — as they are highly predictive of each other. While the number of replies garnered is certainly affected by the other two, the coefficients suggest a milder relationship, likely less predicated on sheer popularity.

All binary metadata variables (containsVideo, containsPhoto, containsURLs, and containsHashtags) are significant for retweet and favorites models. This is intuitive, as these features have been shown to make tweets more findable, perceived as more credible, and visually engaging. However, all of these features have low practical effects for all the models. Moreover, only containsHashtags and containsUrls are significant for the reply model, suggesting that visual engagement is not as important for the deep sensemaking that is often represented by replies. Instead, features like hyperlinks may spur more in-depth engagement, like in the following tweet. The URL here points to the NOAA site providing hurricane forecasts, with users responding by discussing the potential impact of the hurricane on various locations, based on the forecasts.

2017-09-06 1:06:29 NWS:
The next complete Irma advisory will be issued at 11*pm* EDT/11pm AST. Follow @NHC Atlantic or visit http://nhc.noaa.gov for the latest.

Tweets by Humanitarian Organizations Widely Retweeted, but not Replied or Favorited

Most types of authoritative accounts are significant for all the models. For the retweet model, subgroup=Meteorologists is the only exception. This suggests that Meteorologists, on average, produce content less suitable for information propagation compared to other authorities (and similar to the reference group subgroup=Politicians). Although this may seem contradictory to our findings with the topics, where severe whether announcements and flood warnings were prominent, this information is usually communicated by the government officials (who do show significant impact on retweets), not meteorologists. Conversely, subgroup=Humanitarians has the highest effect on retweets, suggesting that the content authored by humanitarian organizations is more persuasive for diffusion. The effect is likely due to higher visibility and public trust towards them, as the effect remains strong after accounting for all the metadata and linguistic variables. Most Humanitarians' tweets include information about shelters, supplies, organizing volunteer groups for rescue, safety tips, and other information relevant to a broad population in affected areas. The following tweet examples received 546 and 350 retweets, respectively:

2017-09-09 18:46:47 RedCrossHouston:
Irma expected to strengthen as it moves north towards Florida by @NWS https://t.co/u22bT6NOwH', If have to leave your home due to flooding need a safe place to stay, visit https://t.co/plngykFgQN for a list of shelters in your area.

2017-09-05 23:12:30 SCEMD:
We recommend 2 gallons of water per person per day for at least 3 days. One gallon for drinking, one gallon for sanitary needs. Irma https://t.co/kDPXBqybWP

For the reply model, subgroup=Humanitarians is not significant, suggesting that their content solicited less sensemaking and follow-up questions (similarly to the reference subgroup=Government). Here, subgroup=Politicians has the most impact. Examining tweets qualitatively suggests that politicians' use of controversial language, may garner a higher number of replies compared to other authorities.

For the favorites model, all of the subgroups are statistically significant. Subgroup=Politicians is the most impactful category, similar to the reply model. The next most impactful subgroup for both models is Subgroup=Meteorologists. Looking at a sample of replies suggests that users try to make sense of situation by asking meteorologists hurricane-related questions, expressing their fear, sympathy, and sharing their knowledge about the hurricanes. This suggests that weather updates and new hurricane information tend to elicit active sensemaking (replies) and get marked for cross-purpose visibility (favorites), if not propagated as much through the network:

2017-08-26 00:49:45 Jeff_Piotrowski:
Live Hurricane Harvey damaging winds gusting -110 MPh.
Reply: 2017-08-26 19:23:00 user5Watching @Jeff Piotrowski periscope from Rockport may be the most intense storm coverage I have ever seen. Insane.

Specific Hurricanes Differentially Retweeted, but not Replied or Favorited

For the retweet model, all events are significant and have a strong effect. For the reply model, none of the events are significant, except for Event=general, which has a very weak practical effect. Similarly, none of the events in the favorites model are statistically significant. Thus, what specific hurricane a tweet is about has a strong impact on how much it was retweeted, but essentially no effect on how much it was replied to or favorited. Specifically event=Harvey is most predictive of more retweets and event=Maria is the least. This coincides with the differential media coverage of the hurricanes, suggesting that retweets' strong connection to popularity and global visibility would likely bias it towards events already well covered by the traditional media and away from under-served populations. Interestingly, more micro-scale engagements of replies and favorites seem to be immune from this bias, as each community makes sense of, contextualizes, asks follow-up questions, and marks for visibility content that relates to their own situation, collectively producing no difference between events in terms of these two engagements.

Table 5 summarizes the main findings by arranging the most impactful variables of each model in the order of their relative importance.

Retweet Model	Reply Model	Favorite Model
Favorite Count	Retweet Count	Retweet Count
Event=Harvey	Friends Count	Reply Count
Reply Count	User Mentions Count	Followers Count
Event=General	Followers Count	Friends Count
Event=Irma	Favorites Count	User Mentions Count
Followers Count	Status Count	Status Count
Friends Count	Topic18 (Politics around hurricane)	Topic17 (Football cancellation)
Event=Maria	Subgroup=Politicians	Subgroup=Politicians
Status Count	Topic3 (Power outage and restoration)	Topic2 (Hurricane live coverage)
User Mentions Count	Topic8 (Free supplies and shelter)	Topic8 (Free supplies and shelter)
Subgroup=Humanitarian	Topic1 (Hurricane forecast)	Topic1 (Hurricane forecast)
Topic13 (Texas flood warning and tips)	Topic20 (Tornado warnings)	Topic15 (Asking for volunteers help)
Topic11 (Flooding announcements and tips)	Topic2 (Hurricane live coverage)	Topic5 (Weather forecast)
Topic16 (Hurricane Maria in Puerto Rico)	Topic5 (Weather forecast)	Topic9 (Hurricane crime news)

Table 5. Comparison of important features across all models

DISCUSSION

In the context of uncertainty in crisis, authoritative sources generally strive to disseminate credible information to a wider audience in the affected communities, collect information from affected areas for effective help and rescue, and overall provide impactful crisis communication. Through disentangling the factors that facilitate three kinds of engagement with their tweets — retweets, replies, and favorites — this study's findings may help them get closer to these goals.

We found that these types of engagement play different roles in crisis communication, and yet the most impactful factors in predicting them are surprisingly consistent. Popularity-, sociability-, and activity-based metrics — such as follower count, friends count, number of mentioned users, and status count — are highly predictive for all three types of engagement. Therefore, these salient mechanisms of visibility (Blackwell et al. 2015) are important for garnering the public's attention across the board, especially in the attention economy (Ciampaglia et al. 2015) competitiveness of which is amplified by disaster. Authoritative sources who hope to expand the reach of their crisis communication through *any* kind of engagement should first focus on the overall visibility of their content/account. As some of these mechanisms take time to improve (increasing follower or status count), alternatively, communicating the safety-critical information that is vital to people's well-being could be relegated to the most visible, well-established, and active accounts.

Interestingly, the role of sociability and social capital seems to be vastly amplified in the reply engagement, with the friends count being its second strongest predictor. Thus, the sociability of being well-embedded in an online social network may translate into conversational sociality through replies. Further, the number of users mentioned is another strong predictor for replies. Mentioning users imparts a more conversational and inviting tone, and the mode of addressing a conversation partner significantly affects the likelihood of response and the tone of the resulting conversation (Sacks et al. 1978; Schegloff 1972). Additionally, mentioning others is an effective way to increase the tweet's chance of reaching a larger audience.

The three engagement types are also strongly dependent on each other. Yet, this reinforcing relationship is dramatically stronger between retweets and favorites, with replies being comparatively less impactful and impacted. As the former two engagements are driven by similar mechanisms relating to visibility and popularity, the rich get richer (Rigney 2010) and engagement begets more engagement (Perc 2014). Replies seem to be a somewhat different mode of engagement, less predicated on the global dynamics of popularity.

Aiming for retweets and favorites, authoritative sources should optimize "macro" features of their accounts, relating to global network structure and volume (follower counts, status counts). This is consistent with findings from an earlier hurricane event that the most retweeted content was not locally-actionable information, but instead, the abstract overview of the event suited for global consumption (Kogan, Palen, and Anderson 2015). Optimizing for retweets, and possibly favorites, would mean optimizing for the "macro" of the network and for the global audience. However, such information may not be as useful for the affected population. Alternatively, authoritative accounts may choose to design their messages in a manner potentially appealing to both the local population and global audiences. Additionally, social media platforms may choose to amplify or directly recommend to the affected populations locally-actionable information, which otherwise gets out-competed by the global take on crisis events.

A similar dilemma surfaces with increasing the number of replies and favorites based on the authoritative account type. Here, politicians are more impactful than any other types of accounts. Yet, this impact largely comes from their controversial and often insensitive statements. However, controversy is probably not the best way of increasing engagement authoritative sources are seeking in crisis communication. Meteorologists are the next most impactful type of accounts, though with considerably less effect. Their engagement is not driven by controversy, but rather by deep sensemaking the public engages in when trying to localize and otherwise contextualize the information to their specific situation (Bica, Demuth, et al. 2019). To take advantage of both pathways to engagement, meteorologists could periodically inject a bit of humor into their messages (and some successfully do). While not the same as controversy, we predict humor might have similar engaging properties, without loss of credibility. We did not specifically measure humor in this analysis and plan to test this hypothesis in future work.

Finally, posts received a disparate number of retweets based on the hurricane they discussed, with Harvey being the most conducive to propagation and Maria — the least. Yet, the events were essentially not predictive for replies and favorites. As retweets are closely intertwined with visibility and popularity, they are likely affected by the media coverage of these events, generating a bias towards mainland US events and under-covering Puerto Rico. Another possible explanation of the difference in retweets is hurricanes' chronological order, with Harvey being the earliest and Maria last. It is possible that global retweet audience grew weary of sharing information about the hurricanes coming one after another. This makes the lack of effect for replies and favorites even more impressive: even after two major hurricanes, these two engagements did not diminish by hurricane Maria. This may suggest a more localized, community-based engagement, where affected populations actively grapple with locally-relevant information. If authoritative accounts aim to cultivate this type of in-depth local engagement, in addition to more global, macro-scale engagement of retweets, we hope our findings guide them toward producing crisis communication designed specifically for those purposes.

CONCLUSION AND FUTURE WORK

In this study, we disentangled the relative effects of metadata and linguistic factors on three types of public engagement with authoritative sources' tweets in times of crisis: retweets, replies, and favorites. We found that some factors related to user popularity and activity play an important role across all three models, while others are more specific to a particular model. This distinction may help authoritative sources seeking a particular type of public engagement. In the future work, we plan to include interaction terms in the regression models, excluded here for interpretability. Additionally, we plan to utilize more advanced and robust techniques for sentiment analysis, as well as more sophisticated topic modeling tools, such as BERTopic.

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