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@Houstonpolice: an exploratory case of Twitter during Hurricane Harvey

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@Houstonpolice: an exploratory case of Twitter during Hurricane Harvey

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Abstract

Purpose – The purpose of this paper is to examine the Houston Police Department (HPD)'s public engagement efforts using Twitter during Hurricane Harvey, which was a large-scale urban crisis event.
Design/methodology/approach – This study harvested a corpus of over 13,000 tweets using Twitter's streaming API, across three phases of the Hurricane Harvey event: preparedness, response and recovery. Both text and social network analysis (SNA) techniques were employed including word clouds, *n*-gram analysis and eigenvector centrality to analyze data.
Findings – Findings indicate that departmental tweets coalesced around topics of protocol, reassurance and community resilience. Twitter accounts of governmental agencies, such as regional police departments, local fire departments, municipal offices, and the personal accounts of city's police and fire chiefs were the most influential actors during the period under review, and Twitter was leveraged as *de facto* a 9-1-1 dispatch.
Practical implications – Emergency management agencies should consider adopting a three-phase strategy to improve communication and narrowcast specific types of information corresponding to relevant periods of a crisis episode.
Originality/value – Previous studies on police agencies and social media have largely overlooked discrete periods, or phases, in crisis events. To address this gap, the current study leveraged text and SNA to investigate Twitter communications between HPD and the public. This analysis advances understanding of information flows on law enforcement social media networks during crisis and emergency events.

Keywords Social network analysis, Crisis information, Twitter, Policing, Text analysis, Citizen interaction
Paper type Research paper

Introduction

On Saturday, August 26, 2017, Hurricane Harvey descended upon Houston, Texas, the fourth largest city in the USA. Days of record setting rain resulted in over 50 deaths in the metropolitan area, thousands were stranded with one third of the city underwater and billions of dollars in damage. While local officials reported that over 56,000 cases of 9-1-1 calls were made, citizens also turned to social media for asking rescues and help (Rhodan, 2017). While steadily growing, not enough work has focused on how police departments (PD) leverage social media to communicate with the public during times of crisis in emergency or mass convergence events. We seek to expand this burgeoning area of research adopting a framework of crisis informatics to situate our analysis. Crisis informatics is simultaneously an interdisciplinary field of study, and a framework for

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viewing contemporary crisis and mass emergency events. Hagar (2006) broadly defined crisis informatics as a field that examines "the interconnectedness of people, organizations, information, and technology during crises" (p. 10). Crisis informatics also considers a full life cycle of disaster events including the preparedness, response and recovery phases, which influenced data collection and analysis in this study. We leverage crisis informatics as lens to critically examine: how information production and dissemination evolves during the phases of a crisis event, and an information environment when traditional "technology infrastructure breaks down" (Hagar, 2006).

In this paper, we investigate the Houston Police Department (HPD)'s public engagement on Twitter during Hurricane Harvey by applying the framework of crisis informatics. We address four fundamental questions:

RQ1. What types of informational content was shared between HPD and the public?

RQ2. What social network patterns evolved within @Houstonpolice network?

RQ3. Was the formation of clusters in the @Houstonpolice network observed? If so, what were the main topical interests in those clusters?

RQ4. Did @Houstonpolice serve as an alternative 9-1-1 emergency dispatch?

The HPD is one of the largest police agencies in the USA, with over 5,000 sworn officers, and patrols a jurisdiction of over 2m citizens and an area of 601.7 square miles (1,560 km^2). The department launched its Twitter account in 2010, and maintains an active social media presence via a blog, YouTube channel, Facebook and Instagram accounts. We present the literature review in the next section, followed by our methodologies for collecting and analyzing data in the third section. The results of our analysis are described in the fourth section. We further discuss results and summarize our study in the fifth section.

Related studies

Policing and social media

The relationship between PD and media entities is nothing new. Law enforcement agencies have long interacted with local and national media, particularly news outlets, to inform the citizenry on a myriad of issues. Since 2009, this relationship has broadened to include social media platforms, whose design has distinctive affordances such as the ability to share "information in the form of visual, audio, and text, […] on demand […] by most anyone, anywhere" (Schneider, 2016, p. 17). The integration of social media into contemporary policing is in part related to a global open government movement in the West (Bertot *et al.*, 2012; Dadashzadeh, 2010; Ubaldi, 2013). Snead (2013) posits that the eGovernment movement in the USA increased momentum in 2009 when the Obama administration's Open Government Initiative required federal agencies to distribute more information on the Web and increase public participation in governance. Popular social media platforms such as Facebook, YouTube and Twitter were adopted as a strategy to connect digital denizens with an emerging eGovernment. While several researchers have posited that information communication technologies (ICTs) are an effective means for governmental agencies to increase public trust by fostering a culture of "transparency" and "anti-corruption," there is still not enough of attention on how law enforcement agencies leverage ICTs, and their resulting impact on local communities (Bertot *et al.*, 2012, p. 265).

Most of the published research on policing and ICTs emanates from the disciplines of public administration, political science and police science (Schneider, 2016). As such, we have noticed that this burgeoning area of academic inquiry receives relatively little attention in the information science discipline. Heverin and Zach (2010) examined the Twitter accounts of 30 PD in the USA. Using an open coding methodology, they developed ten content categories collecting 300 of the most recent tweets from each agency. PD in their analysis used Twitter to principally broadcast content on criminal activities and to promote community events. Information around safety campaigns and traffic incidents comprised the most frequent content categories. Dai *et al.* (2017) adopted a similar but regional approach examining 7 PD in and around Norfolk, Virginia. Using both content analysis and text mining approaches, data were collected over six months from each department. They found that local PD demonstrated two tweet content patterns: law enforcement oriented or community oriented. This grouping of PD not only tweeted irregularly, but also curiously rarely "interact[ed…] with citizens" using the microblogging service (p. 792).

Meijer and Thaens (2013) position governmental agencies' social media activity as an instance of a broader offline communication framework, rather than a random assemblage of social media production. Their qualitative study on three large PD in North America, identified push (Boston PD), push/pull (Washington DC) and networking (Toronto) as prevalent social media strategies in police organizations. The Boston PD ostensively used Twitter as a venue for organizational branding, increasing effectiveness was the Washington DC Metropolitan Police's objective, and humanizing the department was the impetus for the Toronto PD's Twitter deployment. Meijer and Thanes did not find much evidence for the "transformational potential of social media," as posited by some researchers, noting "governmental organizations do not develop radically different relations with citizens through social media (p. 329). Meijer found similar results in a later analysis on Dutch police social media usage (Meijer and Torenvlied, 2016).

Police agencies and social media use during crisis

There exist multiple studies of social media use in the context of natural disasters (Bruns and Liang, 2012; Scifleet *et al.*, 2013; Shklovski *et al.*, 2010; Olteanu *et al.*, 2015), and the trend is that an increasing number of government agencies are expanding their use of social media. Denef *et al.* (2013) observed bifurcated communication styles their analysis of British police agencies" use of Twitter during a mass convergent event, during summer protests in 2011. London Metropolitan police used Twitter as a means to maintain social order and as a public relations tool for "seeking or providing information or demonstrating police performance" (p. 3479). Similar to the Toronto, Manchester police adopted a more personable approach using the microblogging service as a way to "reassure the public" and maintain calm in the city (p. 3474). Sutton*et al.* (2014) studied serial transmission of Twitter messages that were disseminated by official Twitter government accounts during two days of the Waldo Canyon wildfire. The focus of their study was on the content and style of Twitter messages, and how public attention influences retweets. However, the findings showed that thematic content or styles of the messages were not significant factors in affecting the retweet behavior. Rather, the increase of followers had a direct connection to the predicted retweet rates, and thus suggests that building a larger network would increase the diffusion of messages beyond first-order friends.

Bruns *et al.* (2012) examined the utility of social media platforms such as Twitter during the Queensland floods looking into the use of Twitter by everyday citizens and the Queensland PD. They found that a specific hashtag, #qldfloods, quickly became the "central coordinating mechanism for flood-related user activity" (p. 13). That hashtag stayed on topic for sharing relevant situational information based on retweets and embedded links to the expanded information on the Web. Emergency services and media organizations were among the most frequent entities participating in that hashtag. The researchers also found that there were dedicated Twitter users who were retweeting the #qldfloods messages, acting as "amplifiers of emergency information" in the Twitter network (p. 7).

The previous studies have done much to advance our understanding of police information dissemination using ICTs, particularly Twitter, and also highlight a distinctive area of everyday information interactions of local citizens during both peacetime and periods of crisis using the features of social media (Hughes St *et al.*, 2014).

Our investigation is an effort to further expand the dearth of current literature in information science, by examining a major North American police agency during an emergency event, within a framework of crisis informatics, an interdisciplinary lens that examines the "interconnectedness of people, organizations, information and technology during crises/disasters" (Hagar, 2010). Additionally, our analysis leverages social network analysis (SNA) and text mining techniques of the content as well.

Methods

Hurricane Harvey served as the backdrop to the current study. We selected Houston because it was the largest city impacted by Harvey, and the city's PD maintained an active Twitter profile. We harvested tweets containing "@houstonpolice" using Twitter's Streaming API by following Suh *et al.*'s (2010) model of data extraction. This strategy allowed us to harvest bidirectional tweets emanating from HPD, as well as tweets directed toward the HPD Twitter account. Data were collected from August 18, through September 10, 2017. We collected tweet data over a period of three phases:

- Phase 1 (August 18–25, 2017) spans eight days, beginning when Houston was under the influence of Harvey but was not yet flooded.
- Phase 2 (August 26–September 2, 2017) includes eight days in which HPD was actively responding after Houston was flooded due to the heavy rainfall of 14–16 inches.
- Phase 3 (September 3–10, 2017) follows the response period and Harvey began dissipating in the beginning of this phase. In this eight-day period, HPD and emergency agencies began long-term recovery efforts.

Text analysis for tweets

In order to examine the overall volume of our tweet data, we computed and plotted the frequency distribution of tweets over the three phases of the study. As a preprocessing procedure, we cleaned the collected data set by removing noise that is typical in tweet datasets. Considering that the analyses for the tweet sentiments and the embedded URLs were not a focus of this study, we removed the symbol characters (which are used as a feature in sentiment analysis) and the URLs in tweets as well. We accomplished the preprocessing in three steps:

- Step 1: removing stop words (e.g. a, the, this, Monday, he, is, would, etc.);
- Step 2: removing symbol characters (e.g. &, #, @, !, etc.); and
- Step 3: removing (shortened) URLs.

For each phase, we collected a mixture of tweets originating from HPD and posted by the public tweeted to HPD. Using the textual content of this bi-directional mixture of tweets, we developed word clouds as a visual summary representation of communications between HPD and the public. Word clouds aid quick identification of frequent words within a body of text (McNaught and Lam, 2010; Kuo *et al.*, 2007; Viégas and Wattenberg, 2008; Collins *et al.*, 2009).

For more detailed text analysis, we separated the tweets in each phase into two groups: posted by HPD and posted by the public. We then applied an *n*-gram (a set of co-occurring words) analysis to each of the two groups. Examining frequent n-grams provides richer information about the text, which might be lost in a simple word cloud analysis due to the tokenization of words in the process. For this reason, *n*-gram analysis has been used extensively for text mining and natural language processing tasks (Suen, 1979; Ghiassi, *et al.*, 2013). In this study, unigrams (single word), bigrams (two-word pair), trigrams (three-word groups) and their normalized frequencies were computed using the *n*-grams package in Python programming language, and then the ten most frequent *n*-grams were selected. Finally, we adopt the coding scheme developed by Hughes *et al.* (2014) to classify tweet categories. Comprised of 19 categories, the schema was developed in the study of fire and PD's online communication during Hurricane Sandy.

Social network analysis

The SNA has its origin in the Gestalt theory and graph theory in the early 1900s, further developed with the addition of sociograms (Moreno and Jennings, 1938) and blockmodeling (positional analysis and the matrix rearrangement approaches) (White *et al.*, 1976), and then finally forged in 1960s and 1970s (Scott, 1988; Freeman, 2004). With the advancement of computing devices and algorithms, SNA allows analysis of massive social network data – usually generated from large-scale social media platforms – for investigating the diffusion of information, identifying important actors and communities, uncovering communication patterns, or modeling the spread of diseases and misinformation in various contexts.

We applied SNA in this study by first constructing at-mention (e.g. attaching "@houstonpolice" in a tweet text to direct messages to HPD) networks to assemble and analyze the HPD tweets during the period of examination. Specifically, we were interested in discerning who the most influential actors or influencers in the HPD Twitter networks are. For this, we used the eigenvector centrality measure, which is known to perform well in capturing the most central actors by considering a node's global, as well as local distances to the other nodes (Bonacich, 2007; Hanneman and Riddle, 2005; Ruhnau, 2000).

Additionally, we identified communities, whose members have dense connections within each community, for the social network in each phase by using the network modularity (Newman, 2006; Wakita and Tsurumi, 2007). Considering that modularity has a limitation in detecting smaller communities, we color coded only the top eight biggest communities. We used Gephi visualization software (Bastian *et al.*, 2009) to create social network visualizations, and to compute both the eigenvector centrality scores of actors and network modularity.

Results

In this section, we examine the dynamic volume of our data set in Phases 1–3. We then present results for addressing *RQ1*, *RQ2* and *RQ3* by examining the shared content and social network patterns between HPD and the public. For *RQ4*, we analyze Twitter messages which contain at least one of three keywords, namely, "rescue," "need" and "help," in order to understand how Twitter may act as a *de facto* 9-1-1 dispatch in emergency situations when landlines and mobile phones may not be available due to a bottleneck or destroyed infrastructure (Acar and Muraki, 2011; Peary *et al.*, 2012; Jung and Moro, 2014).

Data set

The size of the collected tweet data in each phase is as follows:

- Phase 1: 591 tweets;
- Phase 2: 11,629 tweets; and
- Phase 3: 1,157 tweets.

The resultant corpus contains a total of 13,377 tweets. Our data set is a mixture of tweets posted by HPD, as well as those posted by the public tweeted to HPD. In order to look at the volume of tweets generated by HPD and the public individually, we divided our data set into two groups: HPD tweets and public tweets. Figure 1(a) and (b) illustrate the volumes of daily tweets for HPD and public tweets, respectively. Note that the scales for the y-axis are different in these figures; the y-axis in Figure 1(a) ranges from 0 to 100 and the y-axis in Figure 1(b) spans from 0 to 4,000 (400 times larger than that of Figure 1(a)). In Figure 1(a), we see the volume of the HPD tweets peak (approx. 26 tweets/day) in the early stage of the response phase (August 27–29). This was the period when Houston began to flood and when HPD were actively engaged in response activities. The number of tweets from HPD began decreasing on August 30, and this trend continued throughout the recovery phase. For public tweets, represented in Figure 1(b), the volume also peaked around August 27–29, reaching a maximum number of 3,522 tweets on August 29. This phenomenon was partially due to many prayer-related tweets for fallen police officer, Sergeant Steve Perez. The tweet volume then decreased gradually over the remainder of the response and recovery phases.

Shared content in Twitter communications (RQ1)

To examine the textual content of Twitter communications between HPD and the public, we applied two text-mining approaches: word clouds (McNaught and Lam, 2010; Heimerl *et al.*, 2014) and n-gram analysis (Suen, 1979; Ghiassi, *et al.*, 2013). Figure 2 presents the three-word clouds, which represent the shared content in Phases 1–3. As a quick overview of the content posted by HPD and the public as a whole, we created the word clouds after combining the Twitter data from HPD and the public for each phase.

In Phase 1, a keyword, such as "Harvey," is present below the word "Thank" (a) as a medium-size font among other words representing a moderate level of interest in Harvey.

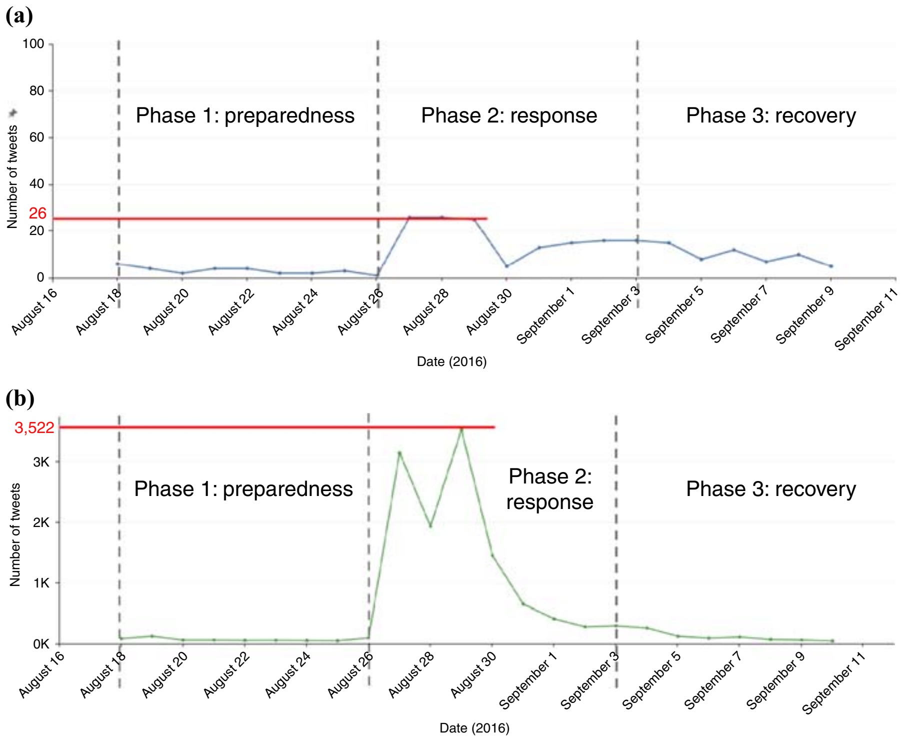


Figure 1. Daily tweets posted by (a) HPD and (b) the public to HPD

However, there are more prominent words in larger fonts such as "HPD," "Thank," "@ArtAcevedo" (HPD chief), "@HCSOT," "safe," "Texas," etc., which may not have strong semantic connections to the impending hurricane disaster. From this, we may postulate that Harvey-related information is being communicated between HPD and public to some extent, but that may not be the primary theme of communications in Phase 1-preparedness.

In Phase 2, in the word cloud in Figure 2(b), "help" is the most frequent keyword, followed by "family," "Perez," "Retweeted," and "Thank." During this response phase, which started immediately after the heavy rainfall in Houston began, many residents requested help for themselves, family and friends, and expressed sympathy for the family of the deceased police officer, Sergeant Perez. In relation to "help," keywords such as "need" and "rescue" also illustrate that the many affected people asked for rescue actions. The keyword "Retweeted" in the bottom left of Figure 2(b) may indicate that the many users were actively forwarding information. The public also expressed appreciation for HPD ("Thank" in the middle right of Figure 2(b)). We elaborate on the use of keywords "rescue," "need" and "help" as a *de facto* 9-1-1, in our discussion of *RQ4*. The word cloud for Phase 3 in Figure 2(c) depicts Houston one week after Hurricane Harvey made landfall and marks the beginning of long-term recovery activities in the region. Once again, we observed many "thank you" tweets directed toward the HPD and Chief Art Acevedo, as well as individuals who had come to Houston from other cities (e.g. Arlington, TX) to volunteer.

After examining the word clouds for Phases 1–3, we computed *n*-grams and their normalized frequency scores in each phase for assessing a deeper analysis of tweet messages. We divided our tweet data into HPD tweets and Public tweets. Thus, showing two *n*-gram tables for each phase to compare the shared content from these two groups.

Phase 1 (preparedness) n-gram analysis. Phase 1: HPD tweets. Table I presents the ten most frequent unigrams, bigrams and trigrams identified from HPD tweets in Phase 1. These *n*-grams show that HPD was on TV (i.e. Fox News) and performing regular police tasks related to patrolling, chasing wanted fugitives and investigating sex trafficking issues. Hurricane Harvey-related content was not shared frequently in their Twitter messages.

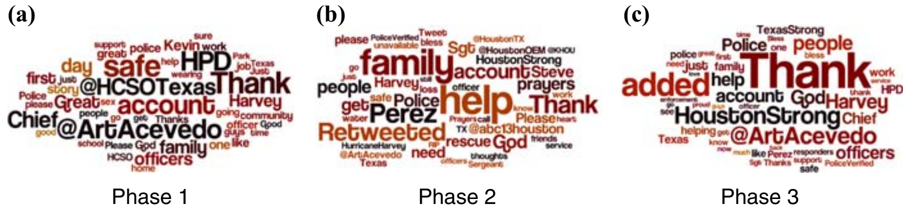


Figure 2.
Word clouds of tweets (HPD + public) for Phases 1–3

Table I.
Top 10 most frequent unigrams, bigrams and trigrams in HPD tweets for Phase 1

Unigram	Score	Bigram	Score	Trigram	Score
hpdintheair	0.26	hpd fox	0.22	hpd fox air	0.15
fox	0.26	cc4 hpdintheair	0.19	cc4 hpdintheair hpd	0.11
media	0.22	fox air	0.19	fox air patrolling	0.11
air	0.19	briefs media	0.15	fugitive 8600 gulf	0.07
cc4	0.19	air patrolling	0.11	assisting patrol units	0.07
chief	0.19	patrol units	0.11	patrolling hpdintheair cc8	0.07
sex	0.19	gulf freeway	0.11	8600 gulf freeway	0.07
block	0.15	hpdintheair hpd	0.11	wanted fugitive 8600	0.07
briefs	0.15	freeway cc4	0.07	media downtown assembly	0.07
assembly	0.15	larry satterwhite	0.07	sex traffickers hcsotexas	0.07

Phase 1: public tweets. From the *n*-grams identified in public tweets directed toward HPD (Table II), Harvey-related *n*-grams were not found. Instead, only tweets concerning routine police activities were communicated.

Phase 2 analysis (response). Phase 2: HPD tweets. Phase 2 was the response phase, in which HPD was actively engaged with emergency response activities, as evidenced by *n*-grams in Table III. For example, unigrams such as "support," "community," "help," and bigrams such as "high water," "volunteer help," and "emergencies 311" are all related to emergency response activities and are not present in the Phase 1 *n*-grams. HPD also disseminated multiple phone numbers during this phase for residents seeking help. Another frequently communicated theme in this phase was about a fallen officer, Sergeant Steve Perez, who drowned on August 29, 2016, while reporting to duty.

Phase 2: public tweets. Sergeant Perez's death dominated tweets posted by the public, who shared news and offered prayers (Table IV). Examples include "prayers," "god," "sgt perez," "heavy heart," "tragic duty death" and "sgt perez family." Additionally, many people tweeted asking for personal rescue or for the rescue of family and friends. They also asked for food, water and shelter in their Twitter posts. However, these communications were not captured well enough – except for unigrams "harvey" and "rescue" – by our *n*-gram analysis considering that the number of tweets about the fallen police officer, Sergeant Perez, was relatively dominant compared to those tweets used as *de facto* 9-1-1. We will detail this use of Twitter as a *de facto* 9-1-1 when discussing *RQ4*.

Phase 3 analysis (recovery). Phase 3: HPD and public tweets. In Phase 3 recovery, the *n*-grams in HPD tweets (Table V) show a clear distinction from those in Phase 2. Here we see a transition from rescue-related content to themes concerning local travel, including traffic conditions and road closures. This content reveals the HPD's efforts to restore vital transportation infrastructure and help local residents navigate the city's new landscape.

Unigram	Score	Bigram	Score	Trigram	Score
safe	0.07	god bless	0.02	son fallen officer	0.01
great	0.07	stay safe	0.02	sam houston park	0.01
artacevedo	0.05	harris county	0.01	250 sex buyers	0.01
chief	0.05	chief artacevedo	0.01	fallen officer kindergarten	0.01
hcsotexas	0.05	police officers	0.01	sex buyers pimps	0.01
officers	0.04	son fallen	0.01	buyers pimps jail	0.01
family	0.04	chief art	0.01	idiots don kill	0.01
don	0.04	law enforcement	0.01	police officers escort	0.01
harvey	0.04	great job	0.01	kevin firstdayofschool kevin	0.01
good	0.04	translate Spanish	0.01	hey idiots don	0.01

Table II.
Top 10 most frequent unigrams, bigrams and trigrams in public tweets for Phase 1

Unigram	Score	Bigram	Score	Trigram	Score
houstonstrong	0.32	dispatch dispatch	0.06	911 life threatening	0.04
officers	0.20	life threatening	0.04	life threatening emergencies	0.04
hurricaneharvey	0.16	911 life	0.04	dispatch dispatch dispatch	0.03
patrol	0.13	threatening emergencies	0.04	call 713 881	0.02
dispatch	0.13	patrol officers	0.03	hpd emergency number	0.02
support	0.09	forward dispatch	0.02	help call 713	0.02
community	0.09	emergencies 311	0.02	number 713 884	0.02
help	0.09	volunteer help	0.02	881 3100 hurricaneharvey	0.02
call	0.08	high water	0.02	heart tragic duty	0.02
number	0.06	dispatch call	0.02	death sergeant steve	0.02

Table III.
Top 10 most frequent unigrams, bigrams and trigrams in HPD tweets for Phase 2

The public tweets also contain themes related to recovery efforts and the city's devastated infrastructure (Table VI). As previously mentioned, we observed continued expressions of gratitude for the city's first responders.

Social network patterns (RQ2)

To capture and analyze HPD's dynamically changing patterns of communication throughout its Twitter space, we constructed three @mention (at-mention) networks based on our Twitter data set for Phases 1–3 (Figures 3–5) (Cha *et al.*, 2010; Yu *et al.*, 2011). In the network graphs, node (i.e. circles) labels are Twitter user IDs. Node colors have the following specific meanings. Purple nodes are the source of information and they only send out information to their neighboring nodes. Orange nodes are the target and only receive information. Finally, the

Table IV.
Top 10 most frequent unigrams, bigrams and trigrams in public tweets for Phase 2

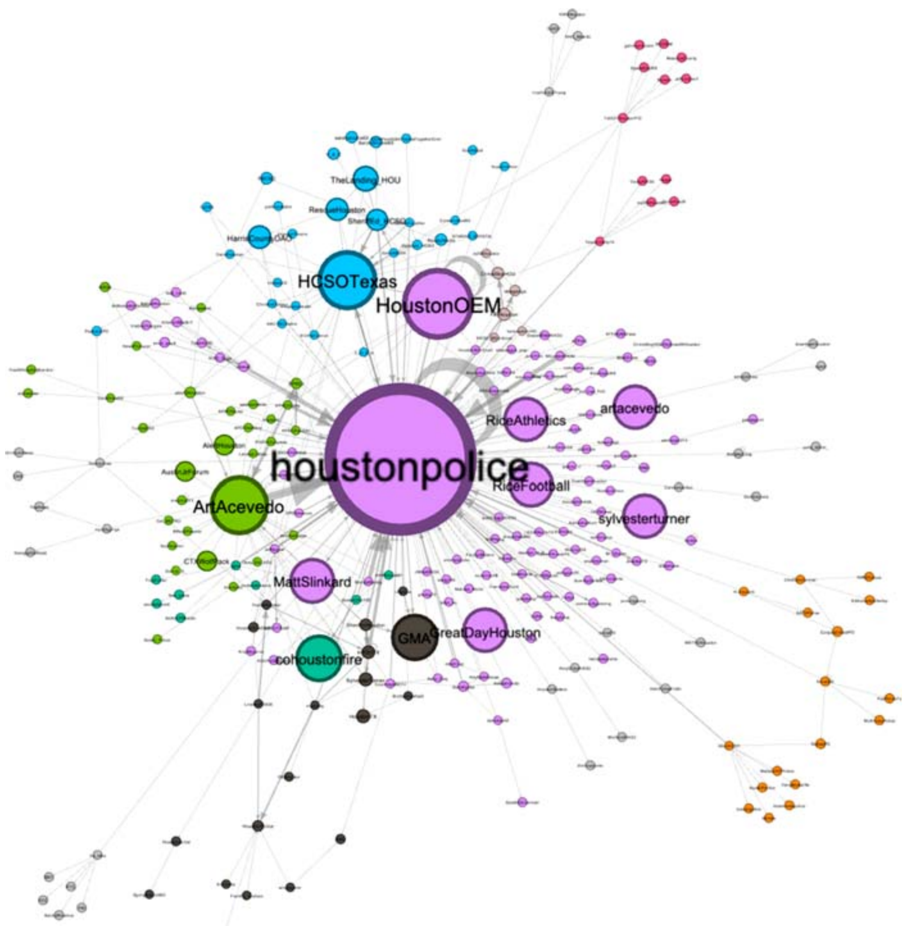
Unigram	Score	Bigram	Score	Trigram	Score
help	0.16	steve perez	0.05	sgt steve perez	0.02
family	0.13	god bless	0.05	sergeant steve perez	0.02
perez	0.10	sgt perez	0.03	heavy heart tragic	0.01
prayers	0.08	thoughts prayers	0.03	tragic duty death	0.01
retweeted	0.08	sgt steve	0.02	death sergeant steve	0.01
god	0.07	family friends	0.02	duty death sergeant	0.01
twitter	0.06	prayers family	0.02	heart tragic duty	0.01
harvey	0.06	sergeant steve	0.02	account heavy heart	0.01
rescue	0.06	perez family	0.02	houston police officer	0.01
sgt	0.06	heavy heart	0.01	sgt perez family	0.01

Table V.
Top 10 most frequent unigrams, bigrams and trigrams in HPD tweets for Phase 3

Unigram	Score	Bigram	Score	Trigram	Score
houstonstrong	0.29	houtraffic cc3	0.12	expect delays houtraffic	0.10
cc3	0.18	hpd fox	0.10	hpd fox air	0.10
houtraffic	0.15	expect delays	0.10	blocked expect delays	0.08
patrol	0.14	delays houtraffic	0.10	delays houtraffic cc3	0.08
accident	0.12	fox air	0.10	fox air patrolling	0.08
texasstrong	0.12	blocked expect	0.08	air patrolling hpdintheair	0.08
expect	0.11	air patrolling	0.08	lane blocked expect	0.04
blocked	0.11	patrolling hpdintheair	0.08	patrolling hpdintheair cc3	0.04
air	0.11	lanes blocked	0.07	accident lanes blocked	0.04
patrolling	0.11	accident lanes	0.05	houston police chief	0.04

Table VI.
Top 10 most frequent unigrams, bigrams, and trigrams in public tweets for Phase 3

Unigram	Score	Bigram	Score	Trigram	Score
artacevedo	0.07	god bless	0.05	false federal resources	0.01
help	0.07	chief artacevedo	0.02	spreading false federal	0.01
harvey	0.07	law enforcement	0.01	investigate houston spca	0.01
houstonstrong	0.07	hurricane harvey	0.01	patti mercer investigate	0.01
officers	0.06	houston spca	0.01	account drove memorial	0.01
god	0.06	sgt perez	0.01	traffic plz patient	0.01
chief	0.06	chief art	0.01	chief artacevedo directing	0.01
bless	0.05	omnihotels jillrenick	0.01	mercer investigate houston	0.01
family	0.04	fake news	0.01	patient houstontx lights	0.01
officer	0.04	directing traffic	0.01	houstontx lights working	0.01

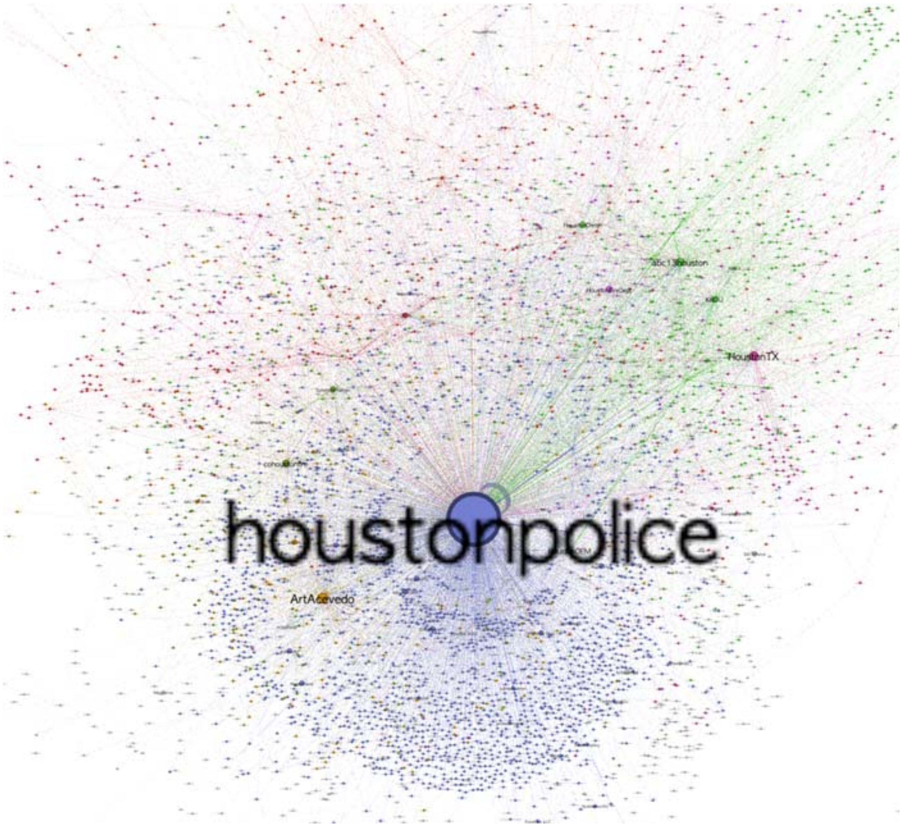


Note: The color coding was used to represent the top 8 biggest communities, and the size of the node shows the node's significance in the network computed by the eigenvector centrality

Figure 3.
Social network graph for Phase 1 using the Force Atlas Layout with repulsion strength 1,000 in Gephi software

green nodes are source-targets and they send out and receive information. In addition, nodes with a bigger circle have a larger eigenvector centrality score, and are considered to be more significant nodes compared to other smaller nodes in the network. We suggest that Phase 1 (Figure 3) represents the typical HPD network during periods of non-crisis, mass emergency episodes, and it is presented here for comparative purposes only.

Social network in Phase 2. The @mention network in this response phase shows that there were very active communications between HPD and the public, as well as amongst the members of the community themselves (Figure 4). The number of nodes is 5,072, and the number of edges is 8,798. This is approximately a 20-times increase in both nodes and edges compared to those in Phase 1 (preparedness). The portion of posting information (i.e. sources) increased to 59.82 percent in this response phase, compared to 45.6 percent in Phase 1, which may indicate that a higher percentage of users were information producers. In contrast, the percentage of users who only received information (i.e. targets) was reduced to 33.62 percent, compared to 42.3 percent in Phase 1. The percentage of the source-target



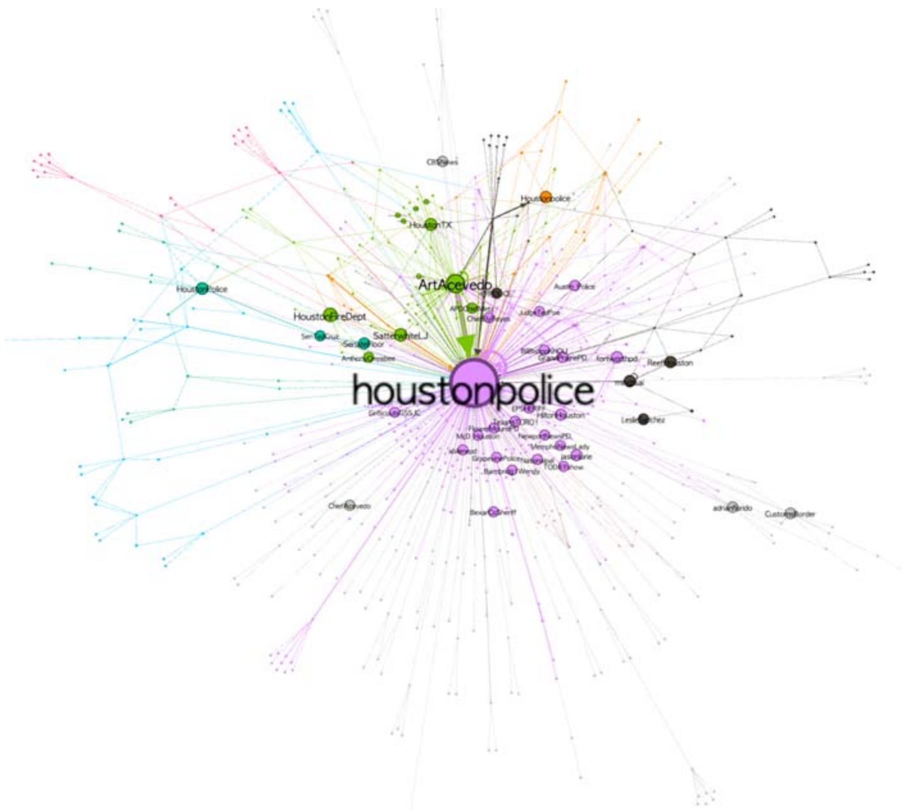
Note: The color coding was used to represent the top 8 biggest communities, and the size of the node shows the node's significance in the network computed by the eigenvector centrality

Figure 4.
Social network graph for Phase 2 using the Force Atlas Layout with repulsion strength 1,000 in Gephi software

nodes (i.e. source-targets) was also reduced to 6.57 percent compared to 12.1 percent in Phase 1. Based on these proportions, we can postulate that a larger percentage of the public were actively disseminating information.

The two nodes with the highest eigenvector centrality score are Houstonpolice and ArtAcevedo, which are also identified in Phase 1's network as well. This was followed by two local news outlets, KHOU and abc13houston. Various news media were involved in sharing and communicating the news regarding the hurricane. The fifth-most significant node was HoustonTX, which is an official city of Houston Twitter account. All of these significant nodes were source-target nodes and were acting as information hubs for the public's communications.

Social network in Phase 3. Phase 3 (recovery phase) began eight days after Harvey made landfall in Houston. During this period, rescue missions were ongoing, but their frequency had decreased. Instead, various recovery efforts started to appear, including those providing food, shelter and long-term financial aid. These efforts were led by various emergency and humanitarian agencies. As shown in Figure 5, the overall size of the communication network in Phase 3 is smaller than that of Phase 2 (response), and larger than that of Phase 1 (preparedness). In total, 625 nodes were observed with 865 edges. These numbers are



Note: The color coding was used to represent the top 8 biggest communities, and the size of the node shows the node's significance in the network computed by the eigenvector centrality

Figure 5. Social network graph for Phase 3 using the Force Atlas Layout with a repulsion strength 1,500 and an attraction strength 5.0 in Gephi software

one-ninth and one-tenth of those in Phase 2, respectively. The percentage of source nodes was reduced to 50.24 percent, compared to that of 59.82 percent in Phase 2. The percentage of users who only received information (targets) increased to 42.4 percent, compared to 33.63 percent in Phase 2, which was almost identical to the 42.3 percent target nodes in Phase 1. The percentage of source-target nodes (green) was increased to 7.36 percent, compared to 6.57 percent in Phase 2. From this, we identify that the communication patterns between HPD, the public and other significant nodes in the network reverted back to their original (pre-disaster period) statuses, similar to Phase 1.

Cluster formation (RQ3)

To examine the potential evolution for clusters of Twitter users around different topics during Hurricane Harvey, we applied network layouts such as OpenOrd and Force Atlas 2 provided by the Gephi visualization software to our network data. However, the formation of clusters was not observed. Instead, the public was actively communicating directly with HPD. This is likely because the public was more eager to send out emergency messages and receive the up-to-date information from more authoritative entities such as HPD or FEMA.

Twitter as an alternative 9-1-1 (RQ4)

In addition to the 9-1-1 emergency calls, social media (e.g. Twitter) and crowdsourcing-based websites (e.g. Ushahidi) are often used during disasters by the public to facilitate reporting of their emergency situations, their locations, and requesting rescue and help (Gao *et al.*, 2011; Yates and Paquette, 2011; Fraustino *et al.*, 2012; MacMillan, 2017). Figure 6 shows frequency graphs of such tweets over Phases 1–3. During the preparedness phase (August 18–25), all three graphs showed almost negligible tweet volumes. This fact dramatically changed in the beginning of Phase 2 (August 26–September 2), which is in response phase to Houston flooding. The volume graph of tweets for each of "rescue," "need" and "help" peaked on the first two days. For example, the number of "rescue" tweets is approximately 1,500, followed by 1,050, the count of "need" tweets and 680, the number of "help" tweets. The graphs then show a fairly steep decrease in the next five days – about 100 tweets for "rescue" and less than 100 tweets for both "need" and "help" tweets in August 31. A strong correlation is also observed from these three graphs.

To further examine the role of Twitter as an alternative 9-1-1 emergency dispatch, we sampled 100 tweets from each keyword set, namely, "rescue," "need" and "help," and subsequently developed categories for each grouping to compare categorical differences. These three groups had multiple common categories, such as "requesting rescues," "help for families," "praise for HPD," "animal rescue and shelters" and "social commentaries."

Discussion

Previous studies on police agencies and social media have largely overlooked discrete periods, or phases, in crisis events. To address this gap, the current study leveraged text and SNA to investigate Twitter use by the HPD across three phases of the disaster caused by Hurricane Harvey: preparedness, response and recovery. Specifically, we explored information sharing, network patterns, cluster formation, and Twitter as an alternative 9-1-1 dispatch. Therefore, this study presents a more nuanced understanding of how police agencies and the public use Twitter during mass convergent episodes.

Shared information

We observed a rapid evolution of communication strategies throughout the August–September 2018 event. Tweets during Phase 1 (preparedness) reveal little content related to hurricane

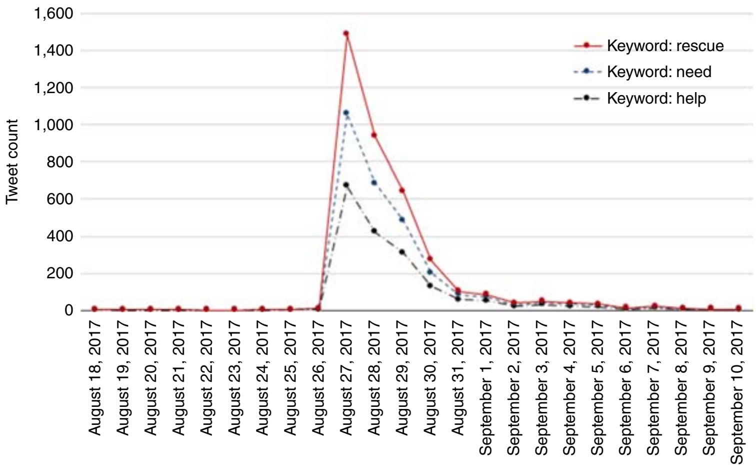


Figure 6.
Frequency of tweets with keywords: rescue, need and help

preparation or readiness and where overwhelmingly characterized by one-way interaction with followers. It reflects a general trend among police agencies in both the USA and Europe police agencies' that overwhelmingly push information content but rarely respond to citizens via social media (Dai *et al.*, 2017; Su *et al.*, 2013; Reuter *et al.*, 2016). After observing a massive increase of communication between HPD and the public in Phase 2 (response), we saw the emergence of rumors or at best misinformation in Phase 3 (recovery). This was in contrast to Kurian and John's (2017) findings that did not identify misinformation, although their study did not appear to occur during a crisis event. Other studies however suggest that the presence of misinformation/disinformation is expected in information flows during crisis events (Hughes and colleagues, 2014) and some police agencies actively monitor the spread of rumors to suppress misinformation. During the Queensland flooding event, for example, local police leveraged Facebook and Twitter to "mythbust' rumors," which were disseminated by the public (Bird *et al.*, 2012). However, we did not observe much communication that pushed back against erroneous information in the present study. This is likely related to the high labor allocations required to monitor social media in this way (Wukich and Mergel, 2015). One solution that may ease the labor issues in rumor control management is to develop a social media team, comprised of individuals from both local police and fire departments tasked with this objective, or utilize algorithms that are capable of detecting fake and false information spreading online.

Network patterns

Metrics used in this study indicate that governmental agencies, such as local police and fire departments and regional police agencies, such as Fort Worth and Arlington, Texas PD and the city of Houston, were the most influential nodes or accounts, and they communicated with each other in the Twitter network of @Houstonpolice. This finding is important because these accounts, which also have significant followers, were able to generate a much wider impact on information dissemination, spreading content well beyond their immediate follower constituency. Additionally, the personal Twitter accounts of Houston Police Chief, Art Acevedo, and Houston Fire Chief, Samuel Peña, were also very influential during Phases 2 and 3 of this crisis event. It is likely that the professional Twitter accounts of local Chiefs provided a different but more interpersonal relationship to the public to receive information, which was simultaneously reverberated into the @Houstonpolice network. This finding suggests that ancillary Twitter accounts maintained by police and emergency management agency leaderships are integral to information sharing and are viewed as sources of information for the public. Additionally, professional accounts offer another venue to cultivate trust and build relationships with local communities, as well as share information around preparedness during crisis episodes.

Twitter as an alternative 9-1-1

In the case of Hurricane Harvey, Twitter served as an alternative emergency dispatch resource. This activity was not only observed in the public's tweets seeking assistance (see Figure 6), but also in our *n*-gram analysis of the HPD's tweets during Phase 2 (see Table III). In this instance, the HPD attempted to calm and reassure the public, addressed bottlenecked phone lines by urging citizens to call 9-1-1 only in extreme emergencies, and provided several alternative phone numbers for those seeking help. In this aspect of our analysis, we were able to see how quickly the public's information needs evolve during crisis events, and also how information production and coordination drastically intensifies. This finding was particularly noteworthy because, to the best of our knowledge, other studies have not examined Twitter during a crisis event in this manner.

Limitations

There are limitations in this study that may be addressed in future work. Our study only pulled data from the microblogging service Twitter. This only provides a snapshot of the crisis event as other communications with the PD may have occurred in other social media outlets (e.g. Facebook or Instagram). Additionally, Twitter streaming API data provides only a small portion of the actual tweets posted. Therefore, our Twitter data are opportune samples and may represent only a fraction of actual communication networks within the Twitter universe during the Hurricane Harvey event. Lastly, the demographics of Twitter users skew toward a rather young and technologically savvy user base and may therefore not represent the general public.

Implications

Results of our analysis have practical implications for both PD as well as other governmental agencies' information dissemination activity via social media during crisis events. First, emergency management agencies should consider adopting a three-phase strategy to not only improve communication, but also narrowcast specific types of information corresponding to relevant periods of a crisis episode. In Phase 1, information dissemination might focus on citizen preparation and readiness activities as well as care of pets. Also, Phase 1 may be viewed as an ongoing baseline status where citizens are remained of hurricane or winter preparation activities at the start of each season. Furthermore, our results revealed that disinformation was particularity active during Phase 3 recovery; it would be helpful if citizens were warned to be alert of erroneous information. Consequently, agencies could also disseminate official information channels that citizens may turn to for updates throughout the crisis episode. During the recovery period, information dissemination may coalesce around resilience: connecting citizens with shelters, volunteer organizations and appropriate status updates pertaining to local infrastructure. Our study also has research implications for other topical areas. For example, our social network and text analysis methods can be applied to investigate civil problems such as opioid epidemic, gang-networks, misinformation detection and prevention, and other crimes and man-made disaster events.

Conclusion and future directions

Our study investigated the HPD's public engagement activity using the microblogging service Twitter during Hurricane Harvey. This analysis is one of the first to consider discrete periods during the Hurricane Harvey crisis event comprising: preparedness, response and recovery. The study reveals that departmental tweets coalesced around topics of protocol, reassurance and community resilience. The most influential actors during the Harvey crisis event were the Twitter accounts of governmental agencies, such as regional PD, local fire departments and municipal offices. Unexpectedly, the personal accounts of both the Houston Fire and Police Chiefs were also prominent in network activity during the period. Lastly, we found evidence that some members of the public leveraged Twitter as an alternative 9-1-1 dispatch service. We suggest that researchers examine crisis and mass convergent events as multiple phases, rather than as a single corpus, in order to obtain a more nuanced understanding of the ebb and flow of crisis episodes. Additionally, we observed significant awareness of volunteer groups such as the "Cajun Navy" and "Habitat for Humanity" in our network analysis. Therefore, the online presence of citizen rescue and volunteer organizations may be a fruitful population to study during crisis events. Future studies may also investigate the HPD's other social media platforms, including Facebook and Instagram, to compare how these forms of social media were leveraged during Hurricane Harvey. Other governmental agencies in Houston may also be considered, such as the local fire and sheriff departments and city government social media accounts. Future studies may also examine community tweet patterns in disasters across age, gender, and racial/ethnic background and may so include non-English tweets as well (e.g. Spanish).

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