Understanding Eyewitness Reports on Twitter During Disasters

Kiran Zahra
University of Zurich
Switzerland
kiran.zahra@geo.uzh.ch

Muhammad Imran
Qatar Computing Research Institute (HBKU)
Doha, Qatar
mimran@hbku.edu.qa

Frank O. Ostermann
University of Twente
The Netherlands
f.o.ostermann@utwente.nl

ABSTRACT

Social media platforms such as Twitter provide convenient ways to share and consume important information during disasters and emergencies. Information from bystanders and eyewitnesses can be useful for law enforcement agencies and humanitarian organizations to get firsthand and credible information about an ongoing situation to gain situational awareness among other uses. However, identification of eyewitness reports on Twitter is challenging for many reasons. This work investigates the sources of tweets and classifies them into three types (i) direct eyewitnesses, (ii) indirect eyewitness, and (iii) vulnerable accounts. Moreover, we investigate various characteristics associated with each kind of eyewitness account. We observe that words related to perceptual senses (feeling, seeing, hearing) tend to be present in direct eyewitness messages, whereas emotions, thoughts, and prayers are more common in indirect witnesses. We believe these characteristics can help make more efficient computational methods and systems in the future for automatic identification of eyewitness accounts.

Keywords

social media, disaster response, eyewitness accounts

INTRODUCTION

At times of natural and anthropogenic disasters, people use social media platforms such as Twitter and Facebook to share information (Vieweg et al. 2010) that potentially can support the disaster response. This information includes reports of injured and dead people, urgent needs of affected people, reports of missing and found people, and reports of bank robberies, among others (Imran, Castillo, Diaz, et al. 2015). Social media not only contains useful information, it also breaks stories and events faster than many other traditional information or news sources such as TV. For instance, the first report of the Westgate Mall attack[1] in Nairobi, Kenya in 2013 was published on Twitter, almost 33 minutes before a local TV channel reported the event. Similarly, the news about the Boston bombing incident[2] appeared on Twitter before any other news channel reported the event. Likewise, in the case of the California earthquake[3] it was observed that the first half dozen tweets were recorded by Twitter about a minute earlier than the recorded time of the event according to the USGS.

At the onset of a disaster event, people share massive amounts of data, but much of that data has redundant information, sharing the same news article, or same video. For instance, millions of messages were posted on Twitter during Hurricane Harvey in 2017.[4] However, studies have revealed that sources of this online information include

[1] https://en.wikipedia.org/wiki/Westgate_shopping_mall_attack
[2] https://en.wikipedia.org/wiki/Boston_Marathon_bombing
[3] http://latimesblogs.latimes.com/technology/2008/07/twitter-earthqu.html
[4] https://crisiscomputing.qcri.org/2017/09/27/hurricane_harvey_and_the_role_ai/

many local citizens, bystanders, and eyewitnesses, i.e. people who directly observe the occurrence of an event (Diakopoulos et al. 2012). From the perspective of an information seeker (affected citizen or institutional response agency), information from eyewitness accounts is preferred over other types of information sources (e.g., people outside the disaster area). For instance, law enforcement agencies look for firsthand and credible information for decision-making. Humanitarian organizations look for timely and trustworthy information that is directly observed from the disaster-hit areas to better estimate the severity of a disaster event, the scale of damage done by the disaster, and the amount of aid required to help save lives and fulfill the urgent needs of affected people.

Gaining rapid access to the information shared by eyewitness accounts, especially during an ongoing disaster event, is useful but challenging for many reasons (Imran, Mitra, et al. 2016). One solution is to identify local residents in disaster-hit areas through Twitter provided geo-information along with tweets. However, given only 1% to 3% of Twitter messages are geotagged, and relying solely on geotagged tweets to identify local residents does not provide enough data. Moreover, not all the tweets from local people can be considered as posted by eyewitness accounts. The location mentioned in the user profile is another opportunity, but research has shown that it is very noisy and inaccurate, and it does not indicate location of the source at the time when a Tweet is made.

Given the above issues, it remains a challenge to process millions of tweets to filter out those belonging to people outside disaster-hit areas followed by the identification of eyewitness accounts from local residents. Doggett and Cantarero 2016 identified a set of eyewitness and non-eyewitness linguistic features to categorize eyewitness news-worthy events by conducting their research on human-induced disasters such as protests, shooting, and police activities. Likewise, Fang et al. 2016 highlighted another similar set of linguistic and meta-features to identify witness accounts on various natural and human-induced disasters. They also used the topic of tweets as a feature to automatically classify tweets as witness accounts. Tanev et al. 2017 also identified a set of eyewitness features from several dimensions and categorized stylistic, lexical Twitter metadata and semantic features. Truelove et al. 2014 developed a generalized conceptual model of different types of eyewitness accounts for several events such as concerts, shark sightings, cyclones, and protests. However, most of the works do not differentiate between different types of eyewitnesses particular to natural disasters, and do not identify different characteristics associated with those types.

This paper aims to address this research gap by categorizing eyewitness characteristics for different types of disasters, and prepare the ground for including geographic location when possible to determine whether a particular piece of information is from an eyewitness source, and whether that source is vulnerable and at risk. The paper presents analyses of Twitter data related to different natural disasters and makes the following contributions: We first manually analyze the collected data to identify which tweets are posted by eyewitnesses. Next, we identify different types of eyewitness accounts and defining characteristics associated with each kind of eyewitness account. Finally, we make the annotated dataset available on the CrisisNLP repository[5] for research communities to further explore this area and develop computational methods to automatically identify eyewitness accounts from Twitter using the identified characteristics.

LITERATURE REVIEW

Twitter is a well established source to harvest opportunistically information during crisis events. Kwak et al. 2010 argue that Twitter serves also as news source and not only as social media platform. Their research reveals that over 85% of trending topics are news headlines. People are motivated to search for breaking news and real-time contents on Twitter (Teevan et al. 2011) as in case of disasters (Kryvasheyeu et al. 2016) ; (Schnebele et al. 2013) ; (Allen 2014) ; (Amaratunga 2014) . Oh et al. 2013 explore the use of Twitter during social crisis situations.

Tweets are micro-blogs, i.e. small packets of information which can be used by humanitarian and disaster relief organizations by developing real-time tweet crawler applications such as TweetTracker (Kumar, Barbier, et al. 2011), Artificial Intelligence for Disaster Response (AIDR) (Imran, Castillo, Lucas, et al. 2014), Twitcident (Abel et al. 2012), ScatterBlogs for situational awareness (Thom et al. 2015), cross-language aspects on Twitter (Imran, Mitra, et al. 2016), or using Twitter during a particular disaster such as Typhoon Haiyan in the Philippines (Takahashi et al. 2015). For more than a decade, Twitter has been used by researchers to study different aspects of social media because of its near real-time and free of cost nature. Academic research into Twitter and disaster management has mainly focussed on user contributed data in disaster response (Haworth and Bruce 2015) and relief phase (Landwehr and Carley 2014) such as the Haiti earthquake in 2010 (Meier 2012) or during forest fires (Ostermann and Spinsanti 2012).

According to Twitter usage statistics [6] , around 500 million tweets are posted per day. Research universally agrees on the noisy nature of Twitter due to this massive volume and the unstructured nature of tweets. In the case of

[5] http://crisisnlp.qcri.org/
[6] http://www.internetlivestats.com/twitter-statistics/

emergency events, extraction of relevant information from this noise is critical. Crowdsourced social media data generated by often anonymous users suffers from an absence of quality assurance (Goodchild and Li 2012) on the truthfulness, objectivity, and credibility of the information. Disaster response organizations search for eyewitness accounts as those are considered more credible (Truelove et al. 2015). Researchers have studied possibilities to identify eyewitness accounts out of millions of tweets for journalism (Diakopoulos et al. 2012), criminal justice and natural disasters (Olteanu et al. 2015). Morstatter et al. 2014 relate identification of eyewitness tweets to the use of language and linguistic patterns within the region during different crisis events. They also identified a set of features to automatically classify eyewitness accounts. Kumar, Morstatter, et al. 2013 relate location information of the users to assess local users and remote users on crisis reports.

However, both research strands have worked mostly in isolation until now, with the potential of location information not fully exploited for establishing whether a source is an eyewitnesses, who might be vulnerable and at risk. This paper aims to develop a holistic categorization of characteristics of eyewitness reports for different types of disasters.

DATA COLLECTION AND MANUAL ANALYSIS

Data collection

We followed the same data collection process as described in Zahra et al. 2017 from the Twitter streaming API to collect data related to three types of natural disasters: earthquakes, floods, and hurricanes. We used disaster type-specific keywords to collect data from 01-August-2017 to 28-August-2017. In total, we collected 243,194 tweets related to earthquakes using *"earthquake, foreshock, aftershock"* keywords. For hurricanes-related data, we collected 36,815 tweets using *"hurricane, cloud-burst"* keywords. And, for floods, we collected 671,503 tweets using *"flood, inundation, extensive rain, heavy rain"* keywords. The collected dataset contains multiple incidents of different earthquakes, floods, and hurricanes occurred around the world during the data collection period.

Manual analysis

To investigate different types of eyewitness accounts and their posting characteristics, next we perform a manual analysis of the collected data. For this purpose, we sampled 2,000 tweets from each disaster type. The sampled data do not contain any re-tweets. Two authors developed and tested the following annotation guidelines before applying these to the sampled Tweets:

- **Tweet source:** This task aims to determine the source of a given tweet. We only consider two types of sources: eyewitness account and non-eyewitness account.
- **Eyewitness account type:** If a tweet is an eyewitness account (identified by the previous task), then this task aims to further determine the type of eyewitness. If the author of a tweet claim to have directly seen or observed the incident, then he/she is considered as direct eyewitness. However, if the author of a tweet sourced a piece of information from his/her family or friends circle and has implicitly or explicitly mentioned the original sources, then the tweet is considered coming from an indirect eyewitness account. A further category of tweeters identified as vulnerable direct eyewitness who were reporting about an anticipated disaster and were present in the region.
- **Eyewitness characteristics:** Given a direct, indirect, or vulnerable direct eyewitness account tweet, this task aims to identify various characteristics and clues that help understand the source of a tweet.

Two authors of this paper used the above guidelines to annotate the sampled data. Table 1 shows the details of our data collection and the results of the manual analysis where both annotators agreed. Findings and discussion about these results are described in the next section.

Table 1. Data collection and manual analysis results

Event type	Total tweets	Sampled tweets	Direct eyewitness	Indirect eyewitness	Vulnerable direct witness	Non eyewitness	Don't know
Floods	671,503	2,000	62	2	84	113	1,739
Earthquakes	243,194	2,000	354	13	-	321	1,312
Hurricanes	36,815	2,000	95	16	185	100	1,604

FINDINGS AND DISCUSSION

Types of eyewitness accounts

Direct eyewitness

Our manual analysis has revealed that there are different ways in which direct eyewitness accounts report on events. Table 2 shows some examples of direct eyewitness reports taken from manually analyzed data from all three types of disaster events.

Table 2. Direct eyewitness reports from manual analysis

No.	**Floods direct eyewitness reports**
(1)	*I almost died driving home from work because it started to downpour and flood on the freeway and lightning and its 99 f**king degrees out*
(2)	*No one even notified me that this flood in our area has reached almost 3 feet. but atleast i was able to reach home safely.*
(3)	*Stuck in New Brunswick. High flood waters near Rutgers. Rt 1 south #Avoid*
(4)	*I just experienced a flash flood. they're intense*
	Earthquakes direct witnesses reports
(1)	*Most intense earthquake i've experienced in japan so far...that is*
(2)	*Big midnight earthquake and aftershocks now*
(3)	*Just felt the house shaking in Tokyo. Been awhile since I felt an earthquake. I hope it wasn't a bad one anywhere on the island.*
	Hurricanes direct eyewitness reports
(1)	*Please pray for us right now, the winds and rain is heavy and the hurricane hasn't even hit us yet. #hurricaneharvey2017*
(2)	*This hurricane ain't no joke, the rain and winds are heavy right now. #hurricaneharvey2017*
(3)	*It's starting to flood in our area (hurricane Harvey) so if I don't respond back within a 7++ days expect for the worse hope we'll be safe*
(4)	*first time is street is starting to flood and the power went out , hurricane harvey finally hit us*

The first tweet in the floods section reports the personal experience of the author about a flood situation. The second tweet is even more interesting since the author not only reports the event, he/she also complains that there were no notifications or flood warnings in his area. Similarly, in the third tweet the author reports about high flood waters and that he/ she has got stuck due to it. The fourth tweet is also about a personal experience of a flash flood situation.

Direct witnesses of earthquakes also report the event in different ways. All the earthquake-related tweets in Table 2 express personal experiences of the authors about some earthquake events. We observe that in most of the earthquake cases, people express or relate their messages to the sense of feeling such as "just felt" or "feeling shaking".

Regarding hurricane-related tweets, the first and second example tweet report about winds and heavy rain, which are obvious signs of a direct personal experience. Both authors experienced the situation and reported it, while the author of the third tweet not only reported a flood situation but also gave an indication that the situation could get worse. The last tweet is again a personal experience of an event where the author is also reporting a power outage.

One clear observation from the analysis of direct eyewitness accounts is that eyewitnesses often mention the severity of situation they are in. Moreover, people associate their messages to different senses like "seeing", "feeling", "hearing" or "smelling". For example, in case of an earthquake they relate it to the sense of "feeling" such as, *Just felt an earthquake...* Likewise, in case of a storm or floods, tweets are related to the sense of seeing or hearing such as; *I've never seen or heard such a violent thunder/hail/rain storm as the one we've just experienced.*

Indirect eyewitness

During our manual analysis, we found tweets where the author was not present in the disaster hit region. Hence, they were sharing valuable information received from direct witnesses (friends, relatives and social circle). However, we found a very small number of tweets from this category in our dataset. Table 3 shows some examples of indirect eyewitness reports taken from manually analyzed data from all three types of disaster events.

There were only two tweets found in the flood dataset where tweeters were reporting about disasters by referring to their family members, while for earthquakes, a tweeter was reporting about an ongoing earthquake with emotions of worry for his/ her family who are the direct witnesses of this earthquake. The second example shows a unique case where tweeter is reporting about an earthquake he/ she was experiencing live but distantly during a video call with one of their family members. The last tweet in this section is reporting about the safety of direct witnesses from a relative.

Finally, indirect eyewitness reports on hurricanes were rather interesting. The first and second examples are about tweeter's hometown conditions mixed with emotions of worry. The third example shows concern of tweeter about their relatives property due to the prospective hazard. In the last example, tweeter is sharing the witness account of his friend.

Table 3. Indirect eyewitness reports from manual analysis

No.	**Floods indirect eyewitness reports**
(1)	*Some days in Thailand has been insane, there has been massive flood on the road to the city (only have image on my dad's phone)*
(2)	*the hsm school and my uncles house are right behind eachother and they were ruined in the flash flood)):*
	Earthquakes indirect witnesses reports
(1)	*F*cking hell...my wife and kids are in Tokyo and they're in the middle of an earthquake Jesus Murphy just how crap can one day get?*
(2)	*Was Facetiming my brother in Tokyo when an earthquake . It wasn't strong but took a long time. Glad that he's ok. #tokyo #earthquake*
(3)	*Finally able to hear from my uncle and know that he and his daughters are safe, the earthquake did not affect them to much #bless #mexico*
	Hurricanes indirect eyewitness reports
(1)	*Texas has me going for a spin....my hometown was evacuated for the hurricane then an earthquake in Dallas where my entire family is*
(2)	*my city is getting a rain storm from the hurricane and hella winds but that's nothing compared to what's going on god i'm so worried*
(3)	*So this hurricane is heading for my brother and sister-in-law's brand new winery. Hope it doesn't get flooded before https://t.co/VBfAchRplM*
(4)	*Heard from friends in Houston, Austin and San Antonio. High winds and heavy rain last night. Everyone is safe. #hurricaneharvey*

Vulnerable direct eyewitness

During our manual analysis of sampled tweets we noticed tweets where users were anticipating a disaster and were reporting warnings and alerts they received from local authorities on their cell phones. This bunch of tweets was only found in floods and hurricanes dataset due to their predictable nature. Table 4 shows some examples of vulnerable direct eyewitness reports taken from manually analyzed data from all three types of disaster events.

The first tweet in the floods section reports the personal experience of the author about a flood warning where he relates the alert with the current weather situation. The second and third tweets depict emotions of fear created because of a hazard warnings. On the other hand, in fourth example tweeter is angry because of so many flood warnings. On the same note, in hurricane section the first, second and third examples are showing mixed emotions of hope and fear while reporting about an approaching hurricane. While in last example tweeter is relating their vulnerability to the intensity of approaching hazard.

In this particular category of tweets, we also noticed a mix of different types of emotions written in words (not emojis) such as hate, disgust, fear, anger, and humor.

Non-eyewitness and Don't know cases

In our dataset, tweets which do not possess explicit eyewitness characteristics, but either were re-tweets or were possessing non eyewitness characteristics (Doggett and Cantarero 2016) and were reporting about disasters were categorized as non eyewitness accounts. These accounts were sharing disaster related information primarily from news media sources. There were a number of tweets where users used disaster related keywords as metaphors,

Table 4. Vulnerable direct eyewitness reports from manual analysis

No.	**Floods vulnerable direct eyewitness reports**
(1)	*Flash flood warning yet it's not even raining*
(2)	*Why am I always napping when a flash flood warning comes on to my phone? #scared*
(3)	*Those flash flood alerts will kill me one day, they scare the f**k out of me*
(4)	*Ima throw my phone if I get another flood warning*
	Hurricanes vulnerable direct eyewitness reports
(1)	*Hurricane Harvey is approaching..Dun dun dun.. first hurricane I will experience in Texas in my new home omg I hope my area doesn't flood*
(2)	*Staying home for the hurricane,hopefully it doesn't flood*
(3)	*I'm so scared I hope this hurricane don't flood my apartment or my car*
(4)	*big hurricane is supposed to hit the area tonight and i live in one of the flood zones...*

such as, *Troll army will then flood social media with press cuttings, naughty headlines, whatsapp distortions to offset growing positive opinion*. Such tweets were categorized as "don't know" cases along with tweets which have disaster related keywords in URL's instead of tweet text.

Characteristics of different types of eyewitness accounts

This section describes different characteristics we observed in each type of eyewitness messages during our manual analysis. Posting information on social media platforms requires the following platform-specific constraints. For instance, Twitter previously had a 140 character limit, which is now increased to 280 characters. Such constraints force social media users to try different ways to, for example, shorten their messages while conveying their actual intent. A consequence of this makes social media communications different to our usual daily life communications such as conversations, email, etc. We believe identification of characteristics associated with each type of eyewitness accounts will help (i) differentiate among different types and (ii) to build automatic computational methods and systems to automatically identify and categorize eyewitness accounts.

Table 5. Direct eyewitness characteristics. EQ (earthquake), FLD (flood), HUR (hurricane). X indicates the presence of a characteristic

No.	Characteristic	Examples	EQ	FLD	HUR
(1)	Reporting small details of vicinity	window shaking, water in basement	X	X	X
(2)	Words indicating perceptual senses	seeing, hearing, feeling	X	X	X
(3)	Reporting impact of disaster	raining, school canceled, flight delayed	X	X	X
(4)	Words indicating intensity of disaster	intense, strong, dangerous, big	X	X	X
(5)	First person pronouns and adjectives	I, we, me	X	X	X
(6)	Personalized location markers	my office, our area	X	X	X
(7)	Exclamation and question marks	! , ?	X	X	X
(8)	Special/swear words	wtf, omg, s**t	X	X	X
(9)	Mention of a routine activity	sleeping, watching a movie	X	X	-
(10)	Time indicating words	now, at the moment, just	X	-	-
(11)	Short tweet length	one or two words	X	-	-
(12)	Caution and advices for others	watch out, be careful	-	X	X
(13)	Mention of disaster locations	area and street name, directions	-	X	X

Direct witness characteristics

Table 5 lists all the characteristics we have observed in direct eyewitness messages along with examples. We indicate the presence of a characteristic in a disaster type (e.g., flood) using an 'X' mark. As social media communications are short and to the point, users usually skip writing first person pronouns and adjectives. However, if a tweet has first person pronouns and adjectives, we observe that it is a strong indication of direct eyewitness account (Fang et al. 2016). Moreover, we observed that words related to perceptual senses such as seeing, hearing, feeling are another strong indication that a tweet belongs to a direct eyewitness.

Words indicating the intensity of a disaster situation such as intense, heavy, strong are extensively found in eyewitness messages posted during all three types of disasters. We suggest that the presence of intensity words is also a strong signal that the message is from an eyewitness, as a person far from the disaster area cannot describe the intensity of the situation. Eyewitnesses tend to mention more about their personalized locations such as my office, our area than non-eyewitnesses. Among other characteristics that are shared across all disaster types include use of exclamation and question marks and special/swear words like "wtf", "omg", and "s**t".

As shown in table 5 a number of characteristics, specifically from 1 to 8, are common across the three types of disasters. However, in our dataset characteristic 9 was not found in the hurricane dataset. This may be due to the predictable nature of the disaster as well as biased sampling. Characteristics 10 and 11 were only found in earthquake dataset due to sudden and somewhat unpredictable nature of the disaster. Similarly, the last two characteristics were only found in flood and hurricane datasets due to their predictable nature.

Indirect witness characteristics

Table 6 shows characteristics learnt from indirect witness messages for all three disasters. We observed that indirect witness accounts either mention a person or a place tweeters already know. The social circle of a user tends to be credible and so the indirect witness is also considered credible. If an indirect witness account is about the hometown of a user, then it is assumed that they know the geography of disaster hit region very well and can provide useful information if required. It was also observed that indirect witness accounts were reporting either emotions of worry or sense of relief. Indirect witness accounts were also reporting about damage, safety or missing people/property.

Table 6. Indirect eyewitness characteristics. EQ (earthquake), FLD (flood), HUR (hurricane). X indicates the presence of a characteristic

No.	Characteristic	Examples	EQ	FLD	HUR
(1)	Mention of locations or people the author knows	mom, dad, hometown	X	X	X
(2)	First person adjective	my, our	X	X	X
(3)	Expressing emotions	thoughts, worry, relief	X	X	X
(4)	Reporting safety, damage, missing	missing, safe	X	X	X

Vulnerable direct witness characteristics

Table 7 shows distinct characteristics of vulnerable direct witness accounts. This category was only found in flood and hurricane dataset due to their predictable nature. A number of characteristics, i.e., 5 to 9, and characteristic 14 in table 5 were common in both categories. Users were mostly found reporting about hazard warnings and associating it with current weather situations. As hazard alerts were sudden in nature, they provoked different types of emotions due to sudden disruptions in user's routine activities.

Table 7. vulnerable direct eyewitness characteristics. EQ (earthquake), FLD (flood), HUR (hurricane). X indicates the presence of a characteristic

No.	Characteristic	Examples	EQ	FLD	HUR
(1)	Warnings and alerts about expected disasters	flash flood warnings	-	X	X
(2)	Associating warnings with current weather situation	flash flood alert with rain	-	X	X
(3)	Expressing emotions	hate, disgust, anger, scare	-	X	X

CONCLUSIONS AND FUTURE WORK

Finding firsthand and credible information during disasters and emergencies is an important task for relief organizations and law enforcement agencies. The extensive use of social media platforms during disasters provides numerous opportunities for humanitarian organizations to enhance their response. Among them, identification of bystanders and eyewitnesses can help to get important information. In this work, we presented an analysis of tweets collected during three types of disasters to understand different types of eyewitness accounts. Our results show that we can categorize eyewitness accounts into direct, indirect, and vulnerable direct witnesses. Moreover, an important contribution of this work is to determine various characteristics associated with each type of eyewitness account. We observed that direct eyewitnesses use words related to perceptual senses such as seeing, hearing, feeling. Whereas, indirect eyewitness mainly express emotions such as thoughts, prayers, worry. And, the vulnerable category mostly share warnings and alerts about an expected disaster situation.

Future work: We believe this work provides a conducive ground for future research work in the direction of automatic identification of eyewitnesses on social media, specifically on Twitter. The identified characteristics will help design more robust automatic computational methods using artificial intelligence and machine learning techniques for automatic identification of eyewitnesses during a disaster situation.

REFERENCES

Abel, F., Hauff, C., Houben, G.-J., Stronkman, R., and Tao, K. (2012). "Twitcident: fighting fire with information from social web streams". In: *Proceedings of the 21st International Conference on World Wide Web*. ACM, pp. 305–308.

Allen, C. (2014). "A resource for those preparing for and responding to natural disasters, humanitarian crises, and major healthcare emergencies". In: *Journal of evidence-based medicine* 7.4, pp. 234–237.

Amaratunga, C. (2014). "Building community disaster resilience through a virtual community of practice (VCOP)". In: *International Journal of Disaster Resilience in the Built Environment* 5.1, pp. 66–78.

Diakopoulos, N., De Choudhury, M., and Naaman, M. (2012). "Finding and assessing social media information sources in the context of journalism". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, pp. 2451–2460.

Doggett, E. V. and Cantarero, A. (2016). "Identifying Eyewitness News-Worthy Events on Twitter". In: *Conference on Empirical Methods in Natural Language Processing*, p. 7.

Fang, R., Nourbakhsh, A., Liu, X., Shah, S., and Li, Q. (2016). "Witness identification in twitter". In: *Procceedings of the Fourth International Workshop on Natural Language Processing for Social Media, Austin, TX, USA*, pp. 65–73.

Goodchild, M. F. and Li, L. (2012). "Assuring the quality of volunteered geographic information". In: *Spatial statistics* 1, pp. 110–120.

Haworth, B. and Bruce, E. (2015). "A review of volunteered geographic information for disaster management". In: *Geography Compass* 9.5, pp. 237–250.

Imran, M., Castillo, C., Diaz, F., and Vieweg, S. (2015). "Processing social media messages in mass emergency: A survey". In: *ACM Computing Surveys (CSUR)* 47.4, p. 67.

Imran, M., Castillo, C., Lucas, J., Meier, P., and Vieweg, S. (2014). "AIDR: Artificial intelligence for disaster response". In: *Proceedings of the 23rd International Conference on World Wide Web*. ACM, pp. 159–162.

Imran, M., Mitra, P., and Srivastava, J. (2016). "Cross-language domain adaptation for classifying crisis-related short messages". In: *Proceedings of the 13th International Conference on Information Systems for Crisis Response and Management (ISCRAM).*

Kryvasheyeu, Y., Chen, H., Obradovich, N., Moro, E., Van Hentenryck, P., Fowler, J., and Cebrian, M. (2016). "Rapid assessment of disaster damage using social media activity". In: *Science advances* 2.3, e1500779.

Kumar, S., Barbier, G., Abbasi, M. A., and Liu, H. (2011). "TweetTracker: An Analysis Tool for Humanitarian and Disaster Relief." In: *ICWSM*.

Kumar, S., Morstatter, F., Zafarani, R., and Liu, H. (2013). "Whom should i follow?: identifying relevant users during crises". In: *Proceedings of the 24th ACM conference on hypertext and social media*. ACM, pp. 139–147.

Kwak, H., Lee, C., Park, H., and Moon, S. (2010). "What is Twitter, a social network or a news media?" In: *Proceedings of the 19th international conference on World wide web*. ACM, pp. 591–600.

Landwehr, P. M. and Carley, K. M. (2014). "Social media in disaster relief". In: *Data mining and knowledge discovery for big data*. Springer, pp. 225–257.

Meier, P. (2012). "Crisis mapping in action: How open source software and global volunteer networks are changing the world, one map at a time". In: *Journal of Map & Geography Libraries* 8.2, pp. 89–100.

Morstatter, F., Lubold, N., Pon-Barry, H., Pfeffer, J., and Liu, H. (2014). "Finding eyewitness tweets during crises". In: *arXiv preprint arXiv:1403.1773*.

Oh, O., Agrawal, M., and Rao, H. R. (2013). "Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises." In: *Mis Quarterly* 37.2.

Olteanu, A., Vieweg, S., and Castillo, C. (2015). "What to expect when the unexpected happens: Social media communications across crises". In: *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*. ACM, pp. 994–1009.

Ostermann, F. and Spinsanti, L. (2012). "Context analysis of volunteered geographic information from social media networks to support disaster management: A case study on forest fires". In: *International Journal of Information Systems for Crisis Response and Management (IJISCRAM)* 4.4, pp. 16–37.

Schnebele, E. et al. (2013). "Improving remote sensing flood assessment using volunteered geographical data". In: *Natural Hazards and Earth System Sciences* 13.3, p. 669.

Takahashi, B., Tandoc, E. C., and Carmichael, C. (2015). "Communicating on Twitter during a disaster: An analysis of tweets during Typhoon Haiyan in the Philippines". In: *Computers in Human Behavior* 50, pp. 392–398.

Tanev, H., Zavarella, V., and Steinberger, J. (2017). "Monitoring disaster impact: detecting micro-events and eyewitness reports in mainstream and social media". In:

Teevan, J., Ramage, D., and Morris, M. R. (2011). "# TwitterSearch: a comparison of microblog search and web search". In: *Proceedings of the fourth ACM international conference on Web search and data mining*. ACM, pp. 35–44.

Thom, D., Krüger, R., Ertl, T., Bechstedt, U., Platz, A., Zisgen, J., and Volland, B. (2015). "Can twitter really save your life? A case study of visual social media analytics for situation awareness". In: *Visualization Symposium (PacificVis), 2015 IEEE Pacific*. IEEE, pp. 183–190.

Truelove, M., Vasardani, M., and Winter, S. (2014). "Testing a model of witness accounts in social media". In: *Proceedings of the 8th Workshop on Geographic Information Retrieval*. ACM, p. 10.

Truelove, M., Vasardani, M., and Winter, S. (2015). "Towards credibility of micro-blogs: characterising witness accounts". In: *GeoJournal* 80.3, pp. 339–359.

Vieweg, S., Hughes, A. L., Starbird, K., and Palen, L. (2010). "Microblogging during two natural hazards events: what twitter may contribute to situational awareness". In: *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM, pp. 1079–1088.

Zahra, K., Ostermann, F. O., and Purves, R. S. (2017). "Geographic variability of Twitter usage characteristics during disaster events". In: *Geo-spatial information science* 20.3, pp. 231–240.