

THE ROLE OF SOCIAL MEDIA FOR COLLECTIVE BEHAVIOUR DEVELOPMENT IN RESPONSE TO NATURAL DISASTERS

Research paper

Abstract

With the emergence of social media, user-generated content from people affected by disasters has gained significant importance. Thus far, research has focused on identifying categories and taxonomies of the types of information being shared among users during times of disasters. However, there is a lack of theorizing with the dynamics of and relationships between the identified concepts. In our current research, we applied probabilistic topic modelling approach to identify topics from Chennai disaster Twitter data. We manually interpreted and further clustered the topics into generic categories and themes, and traced their development over the days of the disaster. Finally, we build a process model to explore an emerging phenomenon on social media during a disaster. We argue that the conditions/activities such as collective awareness, collective concern, collective empathy and support are necessary conditions for people to feel, respond, and act as forms of collective behaviour.

Keywords: Social media, Topic modelling, Disasters, Collective behaviour

1 Introduction

In times of a crisis, fast and effective sharing of relevant information is of the utmost importance to rescue affected people. With the emergence of social media, disaster-related, user-generated content has gained significant importance, as it contains real-time information about the disaster situations (Palen et al. 2009; Qu et al. 2011; Sutton et al. 2008). Such real-time information is not only valuable for emergency management agencies to organize disaster response, but also helps directly affected people in self-organizing neighbourhood support (Kaufhold and Reuter 2016; Starbird and Palen 2011). Several research results have already elaborated on the merits of social media during disasters (Starbird et al. 2015; Stieglitz et al. 2017; Vieweg et al. 2010a; Vieweg et al. 2010b), which makes social media interesting for emergency management agencies as an additional channel to communicate disaster-related information (Bruns et al. 2012; Ehnis and Bunker 2012; Reeder et al. 2014). Furthermore, it is argued that social media also helps the inter-organizational collaboration efforts of emergency organizations (Simon et al. 2015a) to gain a better understanding of the on-going emergency situation during times of disaster (Carter et al. 2014). Thus, one can state that the information shared by affected people over social media not only helps to create broader awareness about the situation, but also provides the foundation for collectively responding and organizing relief activities (Eismann et al. 2016; Pandey 2015).

Although there are several social media platforms (such as, Flickr, Instagram, or Facebook) due to the swiftness of information exchange, Twitter has garnered the scholarly attention (Chatfield et al. 2014) as the most effective channel used during times of extreme events (Mirbabaie et al. 2014). In several research papers, disaster-related tweets have already been analysed, for example, around the Iquique earthquake in Chile (Ahmed and Sargent 2014), floods in Australia, Pakistan, India and the Philippines (Ehnis and Bunker 2012) (Lee et al. 2013; Mukkamala and Beck 2017; Murthy and Longwell 2013), hurricane Sandy in the US (Mukkamala and Beck 2016; Shelton et al. 2014), the Boston bombings in the US (Starbird et al. 2014), drug wars in Mexico (Monroy-Hernández et al. 2015), or terrorist attacks in Mumbai, India (Oh et al. 2011) or the more recent bombing attacks in Brussels (Mirbabaie and Zapatka 2017) and shootings in Munich (Bunker et al. 2017).

Disaster-related social media information typically not only comprises people's own observations and experiences, referred to as original sources, but also comprise re-tweets, URLs and @mentions from secondary sources (Starbird and Palen 2010). On Twitter, while communicating with others, users perceive the presence of others (Mukkamala and Beck 2017), play different roles (Lee et al. 2013; Reuter et al. 2013) while converging their behaviours to make sense of the situation at hand in order to cope with it (Bunker et al. 2017; Mirbabaie and Zapatka 2017; Stieglitz et al. 2017). Therefore, we argue that Twitter and its user-generated content plays an important role within the area affected by a catastrophe but that it is also useful for learning more about the discourse in the general public (Eismann et al. 2016; Takahashi et al. 2015).

In general, during disaster situations, despite the panic among the affected individuals, they still engage in pro-social behaviour. Individuals behave quite rational by evaluating the possible actions that they can undertake to face the crisis situation, for example resulting in ad hoc group initiatives to assist one another. Such informal, spontaneous group initiative around a specific purpose is termed collective behaviour (Quarantelli, E. L. 1986, Starbird, K., et al 2010). Existing research supports the claim that social media facilitates collective behaviour in disaster situations (Eismann, K.,2016), however, the underlying causal mechanisms need to be explored. Moreover, prior research has focused on identifying categories and taxonomies of the types of information being shared among users during times of disasters (Olteanu et al. 2015; Qu et al. 2011; Vieweg 2012). Yet, there is a lack of theorizing with regards to the dynamics of and relationships between the identified categories. Against this background, the main objective of our research is to identify the topics that are shared via social media during disasters to stimulate collective behaviour and to investigate how users' information sharing behaviour changes as the event unfolds. In other words, we aim at understanding the temporal and logical relationships between the topics that are shared on social media and corresponding activities during disasters. In this regard, we address the following research questions:

How does collective behaviour emerge on social media during a disaster and what are the causal mechanisms leading to the emergence of collective behaviour?

To identify how collective behaviour emerges, we have chosen an unsupervised method, topic modelling, where manual content analysis is not necessary to train the system, as it can be applied directly to extract the topics (DeBortoli et al. 2016). Topic modelling uses a pattern recognition approach to discover the hidden patterns in data, a process which requires that the results are further analysed and interpreted by the researchers. This is the reason why this research is also referred to as the computational grounded theory method, as interpretation and coding of the underlying data analytics is necessary (Berente and Seidel 2014; Yu et al. 2011). The fundamental aspect of grounded theory is its inductive nature where key issues emerge from the data rather than by analysing the data through preconceived categories. Analysing techniques known from grounded theory allow for identifying basic elements and relations in a data set. Grounded theory methods also help to conceptualize real life phenomena in a structured way to derive abstracted, theoretical insights (Strauss, A., & Corbin, J. 1994, Kathy Charmaz, 1996). In this research, we apply topic modelling as the computational grounded theory approach and analyse the topics that have been extracted from the data. Since the topics are data-driven, we manually interpreted and further clustered these topics into generic categories, and then further into themes, and traced their development over the period of the disaster. We focus on analysing the Twitter data of the Chennai flooding using topic modelling and subsequently code the results in order to conceptualise a collective behavioural process model.

The remainder of the paper is organised as follows. Section two provides the background of the literature review on Twitter during disasters. The main focus in section three is about methodology, which is twofold: first, we explain our data collection process and the topic modelling method we applied on the data. Second, we explain interpretation and coding of topics. In section four we explain about conceptualization of collective behaviour during disasters. Finally, in section five we discuss the results and the conclusions that can be drawn from them.

2 Literature Background

Because of its short message characteristics and low bandwidth requirements, Twitter is an efficient medium to share information during disasters in a timely manner (Chatfield et al. 2014; Java et al. 2007). Hence, its usage during disasters has increased as well as the nature of its use (Reuter and Spielhofer 2016). During disasters, social media platforms are enhancing the opportunities and back channel communication among community members (Shklovski et al. 2008; Sutton et al. 2008). Information produced and shared by the people from the affected areas during disasters not only contain original information, such as eyewitness reports or other personal observations, but also contains re-tweets or links (Fuchs et al. 2013; Simon et al. 2015b; Starbird and Palen 2010; Starbird et al. 2010). Users also change their communication mode on Twitter during disasters by sharing more factual information (Toriumi et al. 2013), while converging online (Bunker et al. 2017; Subba and Bui 2017) yet the problem remains as not all the messages shared are authentic. The credibility of messages is often drawn into question (Murakami and Nasukawa 2012; Starbird et al. 2014). However, it has been observed that users more often question rumors and try to verify the trustworthiness of information shared via Twitter than, more credible and traditional information sources (Mendoza et al. 2010).

Thus far, different methods have been applied to analyse disaster-related Twitter data. The widely used methods are qualitative content analysis techniques, quantitative computational methods and social network analysis to name a few (Landwehr and Carley 2014). Initially qualitative content analysis techniques are applied to examine the content of tweets. Through bottom-up approaches different categorization schemes and taxonomies were developed. For example, during the Yushu earthquake in China people shared different types of messages, which can be classified as information-, opinion-, emotion-, and action-related categories (Qu et al. 2011). Likewise, in the case of the Red River Floods and Oklahoma Grassfires in the US, most of the emergency-related messages are situation updates (Vieweg et al.

2010b). In particular, depending on the type of disaster, different types of situation updates were identified, to name a few, fire line information, hazard location, visibility, road conditions, or flood level and so on (Olteanu et al. 2015). Despite the fact that the amount and type of information shared on Twitter varies based on the disaster type, it is evident that there are certain commonalities (Olteanu et al. 2015). Moreover, it was also noticed that geo-location tags and other location references are of importance to extract the real-time information from the affected area (De Albuquerque et al. 2015; Graham et al. 2014; Mirbabaie et al. 2016; Mukkamala and Beck 2016). More recently, social network analyses (SNA) were also conducted to understand the information diffusion in the Twitter users' network, and also to understand influential actors and their different contributions in the form of information seeking, offering and sharing, which is also known as sense-making. Online users play different roles as information starters, amplifiers and transmitters in sense-making processes to face uncertain situations (Mirbabaie and Zapatka 2017).

Due to the volume of social media data generated during disasters, supervised (Imran et al. 2013; Mukkamala and Beck 2017; Sen et al. 2015; Verma et al. 2011) and unsupervised research methods (Imran and Castillo 2015; Kireyev et al. 2009; Lee et al. 2013) are applied to extract information and patterns. These methods are useful when one requires an analysis of the whole dataset instead of a sample data. To extract situation-awareness relevant tweets from disaster events in the US, supervised classifiers were trained to automatically categorize tweets into different situational-awareness classes and found that situational awareness information is often objective, impersonal, and formal (Verma et al. 2011). In order to automatically sort messages into different classes, such as, caution and advice, information source, donation, and causalities & damage, classifiers were trained to extract the intended information (Imran et al. 2013). To understand what makes people share information on Twitter and put in additional effort to help one another during disasters, tweets were analysed through social presence concepts and in addition, classifiers were built to extract the data (Mukkamala and Beck 2017).

More recently, topic modelling gained an increasing popularity in information systems research (Eickhoff, M. (2017)). In the area of disaster management and social media research, the use of topic modelling to derive insights is still in its infancy. For example, in a research on the 2012 Philippines flooding based on Twitter data, eight prevalent topics were extracted, such as, traffic updates, weather agency updates, suspension of classes, prayers & rescue, and relief goods & rescue, to understand information types shared by the people (Lee et al. 2013). Topic modelling has also been used to find latent categories in 26 different disaster related social media datasets in an attempt to improve and add more information types to already existing crowdsourcing-based or supervised learning-based systems (Imran, M., & Castillo, C. 2015, May). Moreover, topic modelling was used to understand emergency management organization's communication behaviour where it was found that organizations change their communication strategies with the public during disasters when compared to normal situations (Reeder, H. T. et al. 2014). Those studies also illustrated the potential of topic modelling to discover hidden patterns from the data. In other words, the method has proven to be successful in identifying new, previously unrecognized topics, which is perceived as a clear advantage over supervised machine learning approaches. In this paper, we applied topic modelling within a computational grounded theory approach to explore the causal mechanisms and to understand the emerging phenomena of collective behaviour.

3 Methodology

3.1 Data Collection

The Twitter dataset used for this research was collected using the social media monitoring tool Radian6. As a specific case, we used the Chennai flooding that took place between the last week of November and first week of December 2015. Soon after the disaster unfolded, one was able to not only notice that Twitter was used for sharing information but also for coordinating the disaster relief activities by the affected people themselves.

In general, the hashtags, indicated by the prefix “#” make it easier to extract tweets of a particular event and also increases the search ability of intended information. Most importantly, hashtags are established and recommended by the organizations that are affiliated to a particular event. For example, the American Red Cross encouraged individuals to use the #Haiti hashtag after the 2010 Haitian earthquake to ask questions and to share the information about their relief efforts (Lovejoy et al. 2012). Therefore, collecting Twitter data using hashtags especially during events like disasters will provide an opportunity to collect tweets related to the event. The hashtags we have used in our research to collect tweets are #TNflood, #chennaiRains, #chennafloods #chennaiRainsHelp, #IndiaWithChennai and #chennaiMicro. We collected Twitter data from November 30th to December 16th 2015, which covers the entire period of Chennai floods, resulting in an initial dataset consisting of 1.65 million tweets. However, the data collected using Radain 6 only provide a subset of all attributes of a tweet such as tweet Id, tweet text and so on. Therefore, in order to overcome this limitation, we have re-fetched the Twitter data using the Twitter search (Twitter 2016) by using the tweet Id from the data provided by Radain 6 to get complete data of a tweet provided by Twitter for the whole dataset of 1.65 M tweets.

After an exploratory data analysis, we noticed that around 74% of the total dataset are re-tweets. When it comes to the language of tweets, the majority of the tweets were written in the English language, while some of the tweets used the local Tamil language. Therefore, as part of data pre-processing, we have filtered out the tweets written in languages other than English and also filtered the retweets so as to not distort the analysis due to the duplication of some of the data caused by retweets. As our primary goal is to uncover the hidden information patterns or the topics that emerged during the disaster, considering only the original tweets for the analysis is fairly reasonable. After the pre-processing step, we ended up with 171,314 original tweet messages written only in English.

3.2 Topic Modelling

In contrast to supervised learning methods, techniques like topic modelling do not require pre-defined classes in order to cluster messages into groups with similar content but are able to detect categories through an indicative approach. Hence, these techniques can be compared to manual open coding approaches, in which codes and themes are suggested by the data, and not derived from literature and theory.

As mentioned before, our primary goal is to uncover the hidden topics that emerged during Chennai floods, therefore we have chosen unsupervised methods to perform text analysis on the tweets. Under text analytics, unsupervised methods can learn the underlying text features from a text corpus by using clustering methods without explicitly imposing the need for specifying the categories of interest before performing the textual analysis (Grimmer and Stewart 2013). Topic modelling is a popular unsupervised clustering method for text analysis that provides a quantitative technique for the analysis of qualitative data. Although the automated computational analysis of textual data is constrained by a computers’ limited ability to process the meaning of human language, it has shown to be a valid and reliable tool when fed with sufficiently large data sets (Halevy et al. 2009). Hence, statistical techniques like topic modelling are emerging as a novel and complimentary strategy of inquiry for researchers interested in analysing large collections of qualitative data in a scalable and reproducible manner.

Over the last couple of years, the Latent Dirichlet Allocation (LDA) has become a popular algorithm for unsupervised topic modelling in IS research (Debortoli et al. 2016). LDA is able to inductively identify topics running through a large collection of documents and to assign individual documents to these topics (Blei 2012; Blei et al. 2003). The idea behind LDA is rooted in the distributional hypothesis of linguistics (Firth 1957; Harris 1954), which posits that words that repeatedly co-occur in similar contexts (e.g., documents, paragraphs, sentences) tend to share meaning and, hence, can be used as proxies for describing the content of a text. For example, the co-occurrence of words like “temperature”, “wind”, “rain”, and “sunshine” in a set of tweets can be interpreted as a marker for a common topic of these tweets, namely “weather”. In contrast to hard classification or clustering methods, which assign each document to exactly one category, probabilistic topic modelling algorithms like LDA allow that docu-

ments belong to multiple categories (topics) with a varying degree of membership. Therefore, statistically speaking, LDA represents documents through a probability distribution over a fixed set of topics, and each topic, in turn, through a probability distribution over a fixed vocabulary of words. For example, a tweet may be 60% about the topic “weather”, which, in turn, is represented by words such as the ones mentioned above, and 40% about the topic “New York City”, which might contain words like “nyc”, “manhattan”, and “big apple”. Grouping and aggregating the topic distributions of a large number by metadata (e.g., author, time, geography) allows to quantitatively summarize their content, detect differences in content between subgroups of documents, or to track and trace the development of topics over time.

As described in the previous section, we applied the LDA topic-modelling algorithm¹ to the dataset of 171,314 tweets collected during the Chennai Floods in order to identify topics that were shared during the event via Twitter and to track and trace the development of these topics over the course of the disaster. As the LDA algorithm can be sensitive to variations in its input parameters and the input data, we performed the analysis in multiple iterative cycles. We followed the guidelines provided by (Debortoli et al. 2016), paid special attention to the pre-processing of the data (e.g., tokenization, stop-word removal, lemmatization) and to finding the appropriate number of topics to be extracted from the data. The number of topics one wants to extract is the most crucial LDA parameter (Blei et al. 2003; Boyd-Graber et al. 2014). If too many topics are chosen, the algorithm finds a multitude of only minimally distinct topics (e.g., topics differ in writing style but not in content), whereas choosing too few topics unnecessarily constrain the exploratory potential of the approach.

We analysed the data multiple times with different values for the number of topics, ranging from 10 topics to 100 topics using an increment of 10 topics in each successive trial. The resulting topics were analysed to see if the topics were either minimally distinct i.e. the topics differ only in the style, but not the content, or if the topics were too broad, a conglomeration of two or more topics. Based on the exploration, we found that 50 is suitable number, where the topics are neither too broad nor fine.

After automatically extracting the 50 topics from the dataset, we manually inspected, interpreted, labelled, and grouped them into overarching themes. For that, we not only tried to make sense of the word probabilities of each topic (Figure 1), but also inspected the 50 most strongly associated tweets for each topic. Finally, we grouped the tweets and their topic probability distributions by days (30th November 2015 and 7th December 2015) and calculated the mean prevalence of each topic at each day in order to trace the development of topics over time. The procedures and results for interpretation, labelling, and grouping of the topics will be discussed in more detail in the following sections.

3.3 Interpretation and coding of topics

During the process of interpreting and coding of the identified topics, two researchers independently inspected all 50 topics generated for each day along with the relevant tweet content and subsequently compared and synthesized their results in order to minimize errors due to subjective biases. For most of the topics (around 80%) the researchers generated very similar labels or, in some cases, even identical labels; the remaining disagreements in interpretation were discussed among the researchers until consensus was reached.

In order to illustrate the procedure and results of this step of the analysis, we have chosen Topic 5, which accounts for about 2.1% of all the words written in our dataset. The topic comprises highly likely words like “road” (10.64%), “route” (2.84%), “avoid” (1.68%), “safe” (2.34%), “travel” (2.25%), “clear” (2.04%), and “water” (1.9%) (Figure 1). Tweets associated with this topic contain phrases like “Shastry Ngr Road leading to Besant Ngr Bus Stop Besant Ngr beach Adyar Bridge are safe to travel. no water logging” or “Latest Traffic Update - Loyola bridge - fully drained”. By co-examining the word distribution and the tweets associated to this topic we decided to label this topic “updates on routes”. People shared information about road conditions to help and to create awareness regarding the routes that are

¹ We used cloud-based topic modelling tool www.MineMyText.com for pre-processing, analysing, and visualizing the dataset.

safe or passable, and the routes are flooded and thus blocked. Such cautionary information and situation updates are vital during heavy rainfall and has been shared predominantly by people who witnessed the road situation themselves (primary sources).

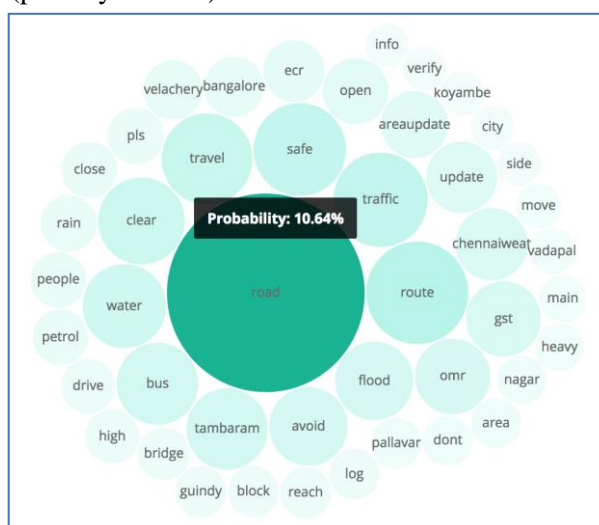


Figure 1 Bubble chart representing the most probable words for the topic labelled “Updates on routes” (volume and colour of bubbles represent the likelihood of words for this topic)

Table 1 provides some additional examples of topics, along with their most likely words, examples of associated tweets, and the researcher-generated labels. It can be seen that most of the topics are related to typical disaster situations, which reconfirms the findings reported in previous studies (Starbird and Palen 2010; Starbird et al. 2010; Vieweg et al. 2010a). Most of the topics represent vital concepts in situations of disaster, for example, “public places open for shelter”, “emergency numbers”, “sharing information of relief supplies”, “stay safe”, “request for help for/by stranded people”, “rescue boat service”, or “trying to reach friends and family”.

Topic Id	Most probable terms	Examples of strongly associated tweets	Topic label
12	Open, shelter, people, mall, cinema, door, mosque, hall, phoenix, food, accommodate, to-night, flood	"Sathyam Cinemas Royapettah AGS Cinemas Villivakkam Phoenix Mall Mayajaal OMR - open for people stuck in rain. #ChennaiRains"	Public places open for shelter
46	Update, friend, family, parent, reach, contact, pls, are, status, situation, unable	"People need urgent info of a friends Mom from #kotturpuram area. Stays in ground floor & no news since 24 hours #ChennaiRainsHelp"	Trying to reach friends and family
50	Helpline, number, emergency, army, navy, boat, rescue, contact, call	"#chennai rains Indian Navy positioned wit rescue personnel wit boats at Gandhi Nagar Adyar. This is officially verified. Contact 04425394240"	Emergency numbers

Table 1 Selected examples of identified topics and related tweets

We also found that certain topics were not directly related to the Chennai Floods (e.g., spam and advertising) or represented stylistic elements of tweets. For example, Topic 37 is almost exclusively made-up of purely hashtags, such as, #ChennaiFloods #ChennaiRescue #ChennaiVolunteer #ChennaiHelpRains #Helphennai #CuddaloreRains #CuddaloreRains. These topics do not provide any additional information as they contain only hashtags without any relevant content that is useful for the purpose of our study, therefore we excluded them in the subsequent analysis.

In order to identify how the information sharing behaviour on Twitter changes as the disaster situation unfolds, we plotted the mean prevalence of all topics over the days of the disaster, an example is shown in Figure 2.

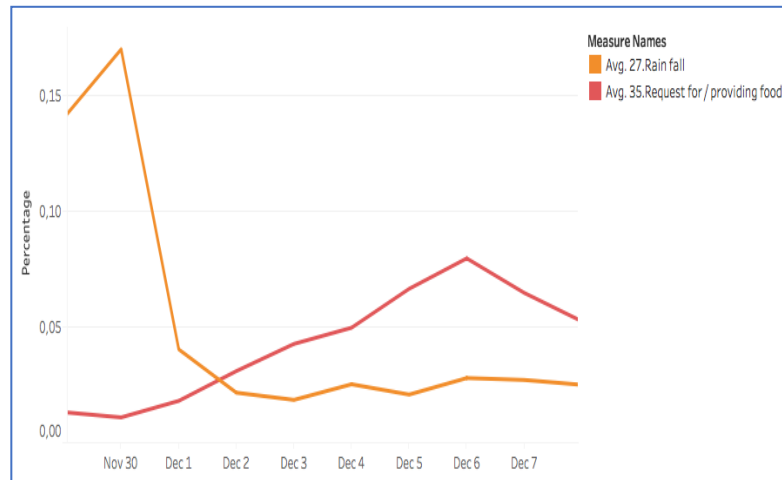


Figure 2 Mean prevalence of the example topics over the disaster period

In order to get a higher level of abstraction over the topics, we ordered all the 50 topics that were identified for a given day in the descending order of their probabilities of prevalence for that day. We then focused on the top ten most prevalent topics for each day and tried to manually cluster them into higher-order categories in order to get an overview of the most prevalent categories for each day. For example, we clustered Topic 5 (“updates on routes”), Topic 28 (“water level”), and Topic 42 (“public and private organizations opened / closed”) into the category ‘situation updates’, as all of these topics are related to the sharing of information about the disaster situation in real-time. Similarly, we followed the same procedure to cluster all the topics into different categories.

Categories	Topics	Date
Initial information about disaster	Sharing news headlines; past and future rain fall	30 th November
Situation updates	Updates on routes; updates about water levels; information of opened/closed public and private institutes	30 th November
Criticism about insufficient attention	Self-criticism and criticizing the politicians; criticizing the media channels	30 th November
Moral support	Praying; ask to stay safe	1 st December
Preparations	Community information for shelter & food; leveraging social media for relief activities; emergency numbers	1 st December
Criticism and control rumours	Criticising the media channels; trying to control rumours	1 st December
Help request	Request for help for/by stranded people; request for food	2 nd December
Offering help	Free mobile recharging; rescue boat service	2 nd December
Self-organising support	Sharing information of relief supplies; trying to reach friends/family	3 rd - 7 th December
Active volunteerism	Coming forward to volunteer, Collecting information of Volunteers, Volunteering	3 rd - 7 th December

Table 2 Clustering of the identified topics into sub-categories

Finally, we aggregated all the most prevalent topics into ten categories as shown in Table 2. In contrast to prior research using topic modelling (Kireyev et al. 2009), we clustered the topics day wise to see the temporal evolution of topics during the disaster and also grouped the topics into categories to identify

the emergence of the most prominent categories during the disaster timespan. Hence, for example, categories such as “criticism about insufficient attention” and “criticism and control rumours”, have been found to be prominent over two consecutive days.

4 Research results

We plotted topics along the timeline of the disaster and further clustered the topics into categories for two reasons: First, to recognize which categories emerge at which point in time, thereby signalling relevance while the disaster unfolds, as shown in Table 2; second, to develop a process model that explains collective engagement of social media users in times of disasters. After aligning the categories day-wise, on a more abstract level, we derived the themes and defined their names. For example, the categories (a) initial information about disaster, (b) situation updates, and (c) criticism about insufficient attention explicitly provide information on rain updates, road updates etc., but implicitly this information dissemination creates awareness among social media users. Hence, we grouped the three categories under the theme “collective awareness”. In the same manner, we created the rest of the themes, based on the prominent categories in each day. The main themes that emerged are: collective awareness, collective concern, collective empathy, and collective support. In the following sub-sections, we will describe them in more detail.

4.1 Collective awareness

Social media platforms allow for the creation of collective awareness among people. Especially information from the surrounding environment can lead to increased awareness among individuals and this awareness helps them to control their actions appropriately (Kellogg and Erickson 2002). Specifically, during disasters, online activity of social media users increases rapidly for information seeking and sharing. One of the uses of social media during a disaster is to “provide and receive disaster preparedness information” (Houston et al. 2015). On social media, people share news reports and various media sources to disseminate the information about anticipated events (Takahashi et al. 2015), and act as information brokers (Palen 2008) to create awareness. In the pre-event stage of a disaster people share secondary sources like media links or news reports to create awareness of the event (Starbird et al. 2010), because these are credible sources of information about anticipated events. Most importantly, people share the caution and advice (Vieweg 2012) type of information regarding road closures and rising water levels to create awareness of the disaster. Since social media is a many-to-many medium, the awareness of disaster is created collectively among users. Information about closure of public and private organizations is also important for the people to gain the understanding about the severity of the situation, as the following examples illustrate:

- *“Watch out. Heavy spell on the way. Intense storms near #chennai coast. #chennaiweather #chennairains <https://t.co/hgE3UskvNS>”*
- *“All trains from Chennai Central and Chennai Egmore stands cancelled till 05 December 2015-12 PM announces Southern Railway #ChennaiFloods”*

In addition to initial information and situational updates, criticism also creates awareness of responsibility for the event and of “socio-political causes and implications of events” (Qu et al. 2011; Takahashi et al. 2015). Despite the information not often being directly related to the events of the disaster, users’ opinion-related criticism nonetheless creates awareness. Moreover, frustration may arise among people because of a perceived lack of proper attention given to the disaster, either by media or by politicians:

- *“Its a shame that the so called national news channels arent even showing any news about #chennairains #shame @TimesNow @ndtv @abpnewstv”*

Collective awareness makes people more attentive towards the disaster. This attentiveness slowly leads to concern for people who are going to be affected by it. The concern may be shown in different ways on social media, which we will discuss in the following section.

4.2 Collective concern

Collective awareness of a disaster often leads to concern. During disasters, people start showing concern towards others, or among themselves, since everyone faces the same challenging conditions. The fears and concerns start when people notice worsening situations. On social media, the feeling of concern unfolds through expressing emotion-related (Qu et al. 2011) support for the community by showing moral support in the form of tweets (Takahashi et al. 2015). Being active online, people share up-to-date information, assist in preparation for the flood for those in need, share emergency contact details in advance and also share community information for shelter (Palen 2008). Examples of collective concern are:

- *"My prayers are with you Chennai. Be strong n tight until rains blows off. #chennairains ??"*
- *"Sathyam Cinemas Royapettah AGS Cinemas Villivakkam Phoenix Mall Mayajaal OMR - open for people stuck in rain. #ChennaiRains"*

Furthermore, concern motivates people to look for other means to support the community. Previous research shows that, when people lose trust in government agencies, different social media platforms emerge and people use them as a source and medium to share information (Takahashi et al. 2015). However, there is also the issue of false and misleading information that spreads very quickly on social media and can trigger anxiety among people. Yet, "rumor is a form of collective behaviour surrounding information and psychology" (Oh et al. 2010). Users question the unauthenticated information more often than they question credible sources (Mendoza et al. 2010) to stop spreading the rumours. The anxiety could be controlled by reliable information with credible sources (Oh et al. 2010). Importantly, in order to control the ensuing panic potentially caused by rumours, people try to control the flow of rumours and false information as conveyed by the tweet below:

- *"People forwarding pictures on Whatsapp of crocodiles in #ChennaiFloods please stop! Nothing of the sort has happened. Stop spreading panic."*

4.3 Collective empathy

Disasters disrupt normalcy and make societies vulnerable. The actual impact caused during and immediately after a disaster is observable online and in real-time through social media messages. The messages reflect the situations and in these situations, firstly, people request evacuation and then food, which evoke emotional responses among the online community. The potent source of emotional response displayed by many to help their fellow Samaritans is the empathy they feel towards others, even strangers (Muller et al. 2014). Social media users are bonded by common identity and purposes. People feel "what is important to me is also important to others" (Kaewkitipong et al. 2016). The help requests (the examples are presented below) create a perceived need, which is an antecedent to feeling empathy and increases helping behaviour (Batson et al. 2007). Furthermore, people take it upon themselves to ask for help on behalf of those in need. In addition, or alternatively, they actively provide help in completing requests made by those in need and start participating in relief activities such as evacuation. Along with perceived need, valuing others' welfare is also one of the antecedents of feeling empathy for people in need of help and increases the helping nature in individuals and produces their pro-social motivation (Batson et al. 2007).

- *"#ChennaiRainsHelp 5 families incl elderly kids stranded top floors no food water for 2 days. Urgent. 1/5 5th Cross st east CIT Nagar Ch35"*
- *"Need emergency boat cont number for Jafferkhanpet (Ashok Nagar). 6 month pregnant woman needs rescue #ChennaiRescue #ChennaiRainsHelp"*
- *"food packets needed: ashok nagar ALL HOMES raghavan colony 2nd cross st pls help #ashoknagar #ChennaiFloods #ChennaiRainsHelp"*

The motivation arising from empathy is taken to another level by actively participating in real-time relief coordinating activities, and are discussed in the following section.

4.4 Collective support

Positive cooperative social interactions on social media increase the real-time activities related to helping the affected individuals. The social practices, such as, gathering, reasoning, curating, stewarding and orchestrating, and acting are performed by different stakeholders during a disaster: the community as a whole, emergency responders, and affected people (Büscher et al. 2014). In order to support the victims, social structures emerge within online communities and people create their own ways to collaborate and cooperate using their own rules and resources (Kaewkitipong et al. 2016). Empathy and responsibility are the two main intrinsic motivators for volunteering (McDonald et al. 2015). During disasters, on social media a few active volunteers gather and collect the information of needs and urgencies pertaining to the affected individuals. Subsequently, they mobilize supplies and volunteers to complete the help requests of those in need. Volunteers self-organize themselves by sharing and categorizing the information regarding the location of the request and the collection and distribution of the necessities involved in completing the request. While coordinating the activities among themselves, volunteers take active, actionable, and real-time response and relief activities (Takahashi et al. 2015) (Takahashi et al. 2015), as illustrated by the following messages:

- "#VERIFIED truck full of essential Supplies reaching North Chennai. Pls CT Hijaz - +91 9995000009 for distribution and place. #ChennaiMicro"
- "Have 25 water bottles 25 biscuit packets. Can provide them to Ambattur Mogappair Anna Nagar. Ping ASAP. #ChennaiMicro #ChennaiRainsHelp"
- "10 people with car ready to transport food and supplies for the people in need Contact 9884400543 #ChennaiRainsHelp @ActorMadhavan"
- "Perambur food is ready for 500 ppl. Contact 9884386734 any volunteers available in north Madras plz help #ChennaiMicro @iamVikramPrabhu"

4.5 From collective awareness to collective support

So far, we have explained our method to extract topics, discussed how we grouped topics into categories, and explained the main themes subsuming these categories. In this section, we present a process model to explain how collective behaviour emerges through a sequence of activities. In general, a process model explains an emerging phenomenon and its outcomes with a set of sequential activities. Moreover, the observations enhance our understanding of the sequence of activities leading up to the outcomes (Crowston 2000). Although a process model typically describes necessary but not sufficient conditions, it still provides a form of explanation which combines and strings together conditions and activities (Markus and Robey 1988).

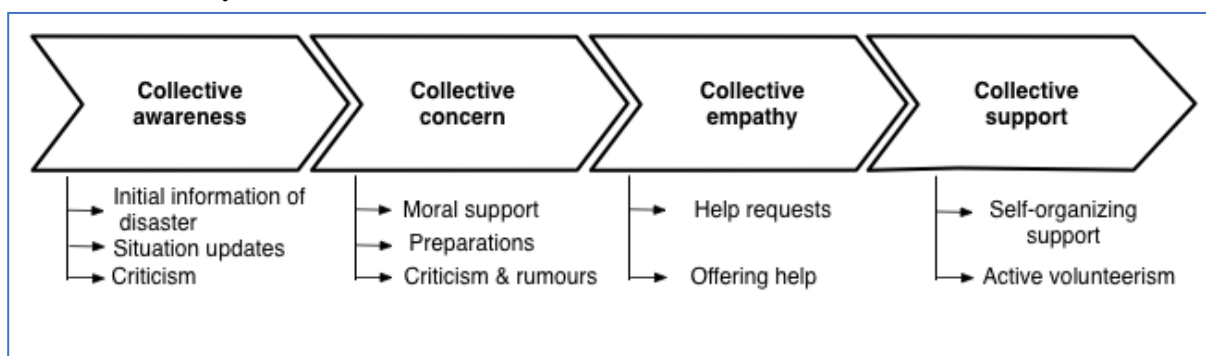


Figure 3 Change in collective behaviour during times of disaster

The process model depicted in Figure 3 illustrates the phases of collective behaviour as discovered in our research: 1) collective awareness, 2) collective concern, 3) collective empathy, and 4) collective support. The model illustrates how information sharing activities on social media turn into actions as the disaster unfolds. The overall emergent phenomenon of collective behavior is initiated by a trigger, such as a disaster commencing, that creates awareness among the social media users online. During the

initial phases of a disaster, online users begin to display concern for the affected individuals due to the awareness that was created by the trigger. The collective concern expressed by the social media users lead to a sense of empathy with the affected individuals and the vulnerable situation they find themselves in. The empathy leads to a mobilized effort of coordination and collaboration by the online users, to offer rescue and relief support to the affected individuals. This pro-social online collective behavior leads to both online and more importantly, offline rescue activities.

As mentioned above, we argue that the conditions/activities (collective awareness, collective concern, collective empathy and support) are necessary conditions for people to feel, respond, and act as forms of collective behaviour. The model provides an explanation for the people's actions and how their altruistic behaviour unfolds. Social media not only facilitates reaching and connecting with locally affected people, but also connects them with wider audiences who are not directly affected by the disaster ((Eismann et al. 2016; Takahashi et al. 2015). On social media, users' interactions, coordination, and coping mechanisms create dynamic and spontaneous social structures during disasters. Self-organized volunteer activities emerge because of a lack of top-down structures to guide them either in the information exchange process or in relief coordination activities. Hence, the by-product of social media's embedded features is bottom-up self-organized communities (Kaewkitipong et al. 2016).

5 Discussion

In recent years, a new form of digital volunteering emerged during disasters. Particularly, social media is facilitating the new forms of volunteerism during disasters (Starbird and Palen 2011) where groups of people come together to take active part in disaster response activities (Quarantelli and Dynes 1977). This collective behaviour of self-organized digital volunteerism during disasters (Kaufhold and Reuter 2016; Reuter et al. 2013; Starbird and Palen 2011) was explained through the theoretical lens of Krep's framework (Kreps 1984) by conducting a literature review (Eismann et al. 2016). However, the study did not explicitly focus on how collective behaviour on social media unfolds over time. We also noticed that the virtually formed groups not only take part on online response activities to coordinate but also actively take part to collaborate on the ground in relief activities. To answer our research questions our study aimed to identify the type of information that is shared via social media during disasters and also investigated how users' information sharing behaviour changes as the disaster event unfolds leads to collective behaviour. Based on the emerged topics, we build a process model to explore an emerging phenomenon on social media during a disaster, considering the flood in Chennai as a reference case. For this purpose, we applied topic modelling as a method to understand the emerging topics in a disaster. Later, we interpreted, coded, and finally grouped the topics into categories in a chronological order. Subsequently, we derived the four main themes from our analysis: collective awareness, collective concern, collective empathy and collective support, which are the forms of collective behaviour.

In our study, we have identified the sequence of activities in the process of unfolding collective behaviour. In contrast to previous research (Eismann et al. 2016), we applied the unsupervised machine learning approach to inductively extract the topics from disaster related social media data, to understand the evolving phenomena. The topics found in our research are similar to the topics identified in the recent research (Lee et al. 2013) that applied the topic modelling method on Twitter data of 2012 flooding in the Philippines. However, in contrast to their work, in our study, we analysed the topics that emerged over time, aligned and clustered them to understand the process with which collective behaviour unfolds. However, to the best of our knowledge, there is no research that explored the emergence of collective behaviour over the temporal dimension during a disaster.

The collective behaviour process has enhanced our understanding of the emerging phenomena on social media during a disaster situation. The process or sequence of categories explains firstly, the types of information people share on social media over the period of a disaster. Secondly, why and how peoples' information sharing behaviour changes and further leads to collaborative and cooperative activities as the event unfolds. In addition, the discovered process reveals situations and performed activities by affected as well as witnessing individuals. Moreover, there is a possibility to infer latent behavioural patterns through the activities performed or perceived by the individuals on social media during the

disaster. To some extent the exploration of themes through categories enhanced our understanding of those latent behavioural patterns, which is the sequence starting with collective awareness, concern, and empathy, finally leading to collective support. Social media is enhancing and influencing communities resilience in a positive manner (Kaufhold and Reuter 2016).

In our research, we shed light on the causal mechanisms through the process model we developed to show how collective behaviour progresses in virtual groups on social media (Reuter et al. 2013). The awareness about a disaster in an early phase makes social media users attentive in sharing and receiving information about an impending disaster. The collective awareness triggers or causes concern for “to be affected individuals”. Because of the concern, users start taking part in online preparation activities such as sharing emergency numbers in advance, list information of shelters and so on. This concern further leads to empathy towards the people who are in need of help. Feeling empathy motivates individuals to take active part in relief coordinating activities both on the online and offline platforms. We also noticed that as the disaster unfolds the needs of affected people change and so do the message types (information types) that are shared on social media.

It is evident from extant literature that during disasters groups of people come together to take active part in disaster response activities (Quarantelli and Dynes 1977) . We are able to show how collective behaviour progresses in virtual groups on social media in order to help the affected people during disasters and our results are also consistent with previous research as social media facilitates the synergies between virtual and emergent volunteer groups (Reuter et al. 2013) while self-organizing (Kaufhold and Reuter 2016) . However, we also argue that virtually formed groups not only take part on online response activities to coordinate but also actively take part in the ground relief activities.

6 Conclusion

Our contributions are twofold. Firstly, the contribution is to the theory of collective behaviour during disasters by explaining how it evolves through information sharing behaviour of users on social media. We especially noticed that from our case study, when people are challenged by the natural calamities, people come forward to self-organize themselves by sharing the disaster-related information such as collection and distribution of necessities and also to coordinate and volunteer themselves to take an active part in actionable, and real-time response relief activities. Secondly, our contribution is to the area of process theories, which basically explains the causal relationships and emerging phenomena. From our case study, we have illustrated that using unsupervised topic modelling approach on textual content, one could identify and uncover the prominent topics and categories that are hidden in the information to transform into a process that reveal behaviour patterns of the people involved in generating the textual content. Moreover, since the process visualizes a sequence of activities, the disaster management officials can make use of information that is relevant for their tactical decision making during disasters.

This study has a limitation as we developed a process model based exclusively on the data extracted from a flood situation. This affects the generalizability of the findings since different types of disasters (flooding, earthquake, hurricane) unfold in different ways and each of them has specific characteristics both in terms of magnitude of the damage they can cause to the people and also in terms of duration of disasters. In order to generalize the process model to other disasters, future research should analyse different disaster related datasets. Moreover, we only analysed tweets written in English, as they accounted for 95% of the total dataset. However, tweets in local languages (such as Tamil) have been not included in the analysis and thus we might have missed some information from these tweets. Future research should try incorporating more languages in such kind of research.

Moreover, we would also like to ask for research that is supplementing this kind of research with supervised machine-learning techniques on the textual content of Twitter data to do an in-depth analysis of the emerged collective behaviour. For example, we one can think of the development of domain specific models for text classification for each of the process steps: collective awareness, collective concern, collective empathy, collective support and use manual content analysis to code the tweets for these

models and apply supervised machine-learning algorithms to analyse the textual content for a more in-depth analysis.

References

- Ahmed, A., and J. Sargent. (2014). "Analysis of Post-Crisis Twitter Communication: A Study of the Iquique, Chile Earthquake," *In: Proceedings of the Australasian Conference on Information Systems ACIS*.
- Batson, C. D., J. H. Eklund, V. L. Chermok, J. L. Hoyt, and B. G. Ortiz. (2007). "An Additional Antecedent of Empathic Concern: Valuing the Welfare of the Person in Need," *Journal of personality and social psychology* (93:1), p. 65.
- Berente, N., and S. Seidel. (2014). "Big Data & Inductive Theory Development: Towards Computational Grounded Theory?,").
- Blei, D. M. (2012). "Probabilistic Topic Models," *Communications of the ACM* (55:4), pp. 77-84.
- Blei, D. M., A. Y. Ng, and M. I. Jordan. (2003). "Latent Dirichlet Allocation," *Journal of machine Learning research* (3:Jan), pp. 993-1022.
- Boyd-Graber, J., D. Mimno, and D. Newman. (2014). "Care and Feeding of Topic Models: Problems, Diagnostics, and Improvements," *Handbook of Mixed Membership Models and Their Applications*, pp. 3-34.
- Bruns, A., J. E. Burgess, K. Crawford, and F. Shaw. (2012). "# Qldfloods and@ Qpsmedia: Crisis Communication on Twitter in the 2011 South East Queensland Floods,").
- Bunker, D., M. Mirbabaie, and S. Stieglitz. (2017). "Convergence Behaviour of Bystanders: An Analysis of 2016 Munich Shooting Twitter Crisis Communication," in: *Australasian Conference on Information Systems*. Hobart, Australia.
- Büscher, M., M. Liegl, and V. Thomas. (2014). "Collective Intelligence in Crises," in *Social Collective Intelligence*. Springer, pp. 243-265.
- Carter, L., J. B. Thatcher, and R. Wright. (2014). "Social Media and Emergency Management: Exploring State and Local Tweets," *2014 47th Hawaii International Conference on System Sciences: IEEE*, pp. 1968-1977.
- Chatfield, A. T., H. J. Scholl, and U. Brajawidagda. (2014). "# Sandy Tweets: Citizens' Co-Production of Time-Critical Information During an Unfolding Catastrophe," *2014 47th Hawaii International Conference on System Sciences: IEEE*, pp. 1947-1957.
- Crowston, K. (2000). "Process as Theory in Information Systems Research," in *Organizational and Social Perspectives on Information Technology*. Springer, pp. 149-164.
- De Albuquerque, J. P., B. Herfort, A. Brenning, and A. Zipf. (2015). "A Geographic Approach for Combining Social Media and Authoritative Data Towards Identifying Useful Information for Disaster Management," *International Journal of Geographical Information Science* (29:4), pp. 667-689.
- Debortoli, S., O. Müller, I. Junglas, and J. vom Brocke. (2016). "Text Mining for Information Systems Researchers: An Annotated Topic Modeling Tutorial," *Communications of the Association for Information Systems (CAIS)*.

- Ehnis, C., and D. Bunker. (2012). "Social Media in Disaster Response: Queensland Police Service-Public Engagement During the 2011 Floods," *ACIS 2012: Location, location, location: Proceedings of the 23rd Australasian Conference on Information Systems 2012: ACIS*, pp. 1-10.
- Eismann, K., O. Posegga, and K. Fischbach. (2016). "Collective Behaviour, Social Media, and Disasters: A Systematic Literature Review," in: *European Conference on Information Systems*.
- Firth, J. R. (1957). "{a Synopsis of Linguistic Theory, 1930-1955},").
- Fuchs, G., N. Andrienko, G. Andrienko, S. Bothe, and H. Stange. (2013). "Tracing the German Centennial Flood in the Stream of Tweets: First Lessons Learned," *Proceedings of the second ACM SIGSPATIAL international workshop on crowdsourced and volunteered geographic information: ACM*, pp. 31-38.
- Graham, M., S. A. Hale, and D. Gaffney. (2014). "Where in the World Are You? Geolocation and Language Identification in Twitter," *The Professional Geographer* (66:4), pp. 568-578.
- Grimmer, J., and B. M. Stewart. (2013). "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts," *Political analysis* (21:3), pp. 267-297.
- Halevy, A., P. Norvig, and F. Pereira. (2009). "The Unreasonable Effectiveness of Data," *IEEE Intelligent Systems* (24:2), pp. 8-12.
- Harris, Z. S. (1954). "Distributional Structure," *Word* (10:2-3), pp. 146-162.
- Houston, J. B., J. Hawthorne, M. F. Perreault, E. H. Park, M. Goldstein Hode, M. R. Halliwell, S. E. Turner McGowen, R. Davis, S. Vaid, J. A. McElderry, and S. A. Griffith. (2015). "Social Media and Disasters: A Functional Framework for Social Media Use in Disaster Planning, Response, and Research," *Disasters* (39), pp. 1-22.
- Imran, M., and C. Castillo. (2015). "Towards a Data-Driven Approach to Identify Crisis-Related Topics in Social Media Streams," *Proceedings of the 24th International Conference on World Wide Web: ACM*, pp. 1205-1210.
- Imran, M., S. M. Elbassuoni, C. Castillo, F. Diaz, and P. Meier. (2013). "Extracting Information Nuggets from Disaster-Related Messages in Social Media," *Proc. of ISCRAM, Baden-Baden, Germany*.
- Java, A., X. Song, T. Finin, and B. Tseng. (2007). "Why We Twitter: Understanding Microblogging Usage and Communities," In: *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis: ACM*, pp. 56-65.
- Kaewkitipong, L., C. C. Chen, and P. Ractham. (2016). "A Community-Based Approach to Sharing Knowledge before, During, and after Crisis Events: A Case Study from Thailand," *Computers in Human Behavior* (54), pp. 653-666.
- Kaufhold, M.-A., and C. Reuter. (2016). "The Self-Organization of Digital Volunteers across Social Media: The Case of the 2013 European Floods in Germany," *Journal of Homeland Security and Emergency Management* (13:1), pp. 137-166.
- Kellogg, W., and T. Erickson. (2002). "Social Translucence, Collective Awareness, and the Emergence of Place," *Proc. of CSCW: Citeseer*.
- Kireyev, K., L. Palen, and K. Anderson. (2009). "Applications of Topics Models to Analysis of Disaster-Related Twitter Data," *NIPS Workshop on Applications for Topic Models: Text and Beyond: Canada: Whistler*.
- Kreps, G. A. (1984). "Sociological Inquiry and Disaster Research," *Annual review of sociology*), pp. 309-330.
- Landwehr, P. M., and K. M. Carley. (2014). "Social Media in Disaster Relief," in *Data Mining and Knowledge Discovery for Big Data*. Springer, pp. 225-257.

- Lee, J. B., M. Ybañez, M. M. De Leon, and M. R. E. Estuar. (2013). "Understanding the Behavior of Filipino Twitter Users During Disaster," *GSTF Journal on Computing (JoC)* (3:2), p. 37.
- Lovejoy, K., R. D. Waters, and G. D. Saxton. (2012). "Engaging Stakeholders through Twitter: How Nonprofit Organizations Are Getting More out of 140 Characters or Less," *Public Relations Review* (38:2), pp. 313-318.
- Markus, M. L., and D. Robey. (1988). "Information Technology and Organizational Change: Causal Structure in Theory and Research," *Management science* (34:5), pp. 583-598.
- McDonald, L. M., M. Creber, H. Sun, and L. Sonn. (2015). "Developing Public Disaster Communication for Volunteer Recruitment: Understanding Volunteer Motivations,").
- Mendoza, M., B. Poblete, and C. Castillo. (2010). "Twitter under Crisis: Can We Trust What We Rt?," *Proceedings of the first workshop on social media analytics: ACM*, pp. 71-79.
- Mirbabaie, M., C. Ehnis, S. Stieglitz, and D. Bunker. (2014). "Communication Roles in Public Events," *Working Conference on Information Systems and Organizations: Springer*, pp. 207-218.
- Mirbabaie, M., S. Stieglitz, and S. Volkeri. (2016). "Volunteered Geographic Information and Its Implications for Disaster Management," *System Sciences (HICSS), 2016 49th Hawaii International Conference on: IEEE*, pp. 207-216.
- Mirbabaie, M., and E. Zapatka. (2017). "Sensemaking in Social Media Crisis Communication—a Case Study on the Brussels Bombings in 2016,").
- Monroy-Hernández, A., E. Kiciman, D. Boyd, and S. Counts. (2015). "Narcotweets: Social Media in Wartime," *arXiv preprint arXiv:1507.01290*.
- Mukkamala, A., and R. Beck. (2016). "Enhancing Disaster Management through Social Media Analytics to Develop Situation Awareness What Can Be Learned from Twitter Messages About Hurricane Sandy?," in: *The Pacific Asia Conference on Information Systems (PACIS) AIS Electronic Library (AISeL)*, p. 165.
- Mukkamala, A., and R. Beck. (2017). "Presence of Social Presence During Disasters," *Pacific Asia Conference on Information Systems*.
- Muller, A. R., M. D. Pfarrer, and L. M. Little. (2014). "A Theory of Collective Empathy in Corporate Philanthropy Decisions," *Academy of Management Review* (39:1), pp. 1-21.
- Murakami, A., and T. Nasukawa. (2012). "Tweeting About the Tsunami?: Mining Twitter for Information on the Tohoku Earthquake and Tsunami," *In: Proceedings of the 21st international conference companion on World Wide Web: ACM*, pp. 709-710.
- Murthy, D., and S. A. Longwell. (2013). "Twitter and Disasters: The Uses of Twitter During the 2010 Pakistan Floods," *Information, Communication & Society* (16:6), pp. 837-855.
- Oh, O., M. Agrawal, and H. R. Rao. (2011). "Information Control and Terrorism: Tracking the Mumbai Terrorist Attack through Twitter," *Information Systems Frontiers* (13:1), pp. 33-43.
- Oh, O., K. H. Kwon, and H. R. Rao. (2010). "An Exploration of Social Media in Extreme Events: Rumor Theory and Twitter During the Haiti Earthquake 2010," *ICIS*, p. 231.
- Olteanu, A., S. Vieweg, and C. Castillo. (2015). "What to Expect When the Unexpected Happens: Social Media Communications across Crises," *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing: ACM*, pp. 994-1009.
- Palen, L. (2008). "Online Social Media in Crisis Events," *Educause Quarterly* (31:3), pp. 76-78.
- Palen, L., S. Vieweg, S. B. Liu, and A. L. Hughes. (2009). "Crisis in a Networked World: Features of Computer-Mediated Communication in the April 16, 2007, Virginia Tech Event," *Social Science Computer Review* (27), pp. 467-480.

- Pandey, V. (2015). "How Chennai Residents Are Helping Flood Affected Via Social Media." from <http://www.bbc.com/news/world-asia-india-34981360>
- Qu, Y., C. Huang, P. Zhang, and J. Zhang. (2011). "Microblogging after a Major Disaster in China: A Case Study of the 2010 Yushu Earthquake," *In: Proceedings of the ACM 2011 conference on Computer supported cooperative work*, pp. 25-34.
- Quarantelli, E. L., and R. R. Dynes. (1977). "Response to Social Crisis and Disaster," *Annual review of sociology*, pp. 23-49.
- Reeder, H. T., T. H. McCormick, and E. Spiro. (2014). "Online Information Behaviors During Disaster Events: Roles, Routines, and Reactions," *Center for Statistics and the Social Sciences, University of Washington, Working paper:144*.
- Reuter, C., O. Heger, and V. Pipek. (2013). "Combining Real and Virtual Volunteers through Social Media," *ISCRAM*.
- Reuter, C., and T. Spielhofer. (2016). "Towards Social Resilience: A Quantitative and Qualitative Survey on Citizens' Perception of Social Media in Emergencies in Europe," *Technological Forecasting and Social Change*.
- Sen, A., K. Rudra, and S. Ghosh. (2015). "Extracting Situational Awareness from Microblogs During Disaster Events," *2015 7th International Conference on Communication Systems and Networks (COMSNETS): IEEE*, pp. 1-6.
- Shelton, T., A. Poorthuis, M. Graham, and M. Zook. (2014). "Mapping the Data Shadows of Hurricane Sandy: Uncovering the Sociospatial Dimensions of 'Big Data'," *Geoforum* (52), pp. 167-179.
- Shklovski, I., L. Palen, and J. Sutton. (2008). "Finding Community through Information and Communication Technology During Disaster Events," *in: Proceedings of the 2008 ACM conference on Computer supported cooperative work*. ACM, pp. 1-10.
- Simon, T., L. Aharonson-Daniel, M. El-Hadid, and B. Adini. (2015a). "Cross-Border Emergency Coordination and Communications Using Social Media: Developing a Joint Israeli-Jordanian Standard Operating Procedure for Leveraging Social Media in Emergencies," *International Journal of Emergency Management* (11:2), pp. 169-190.
- Simon, T., A. Goldberg, and B. Adini. (2015b). "Socializing in Emergencies—a Review of the Use of Social Media in Emergency Situations," *International Journal of Information Management* (35:5), pp. 609-619.
- Starbird, K., D. Dailey, A. H. Walker, T. M. Leschine, R. Pavia, and A. Bostrom. (2015). "Social Media, Public Participation, and the 2010 Bp Deepwater Horizon Oil Spill," *Human and Ecological Risk Assessment: An International Journal* (21:3), pp. 605-630.
- Starbird, K., J. Maddock, M. Orand, P. Achterman, and R. M. Mason. (2014). "Rumors, False Flags, and Digital Vigilantes: Misinformation on Twitter after the 2013 Boston Marathon Bombing," *iConference 2014 Proceedings*.
- Starbird, K., and L. Palen. (2010). *Pass It On?: Retweeting in Mass Emergency*. International Community on Information Systems for Crisis Response and Management.
- Starbird, K., and L. Palen. (2011). "Voluntweeters: Self-Organizing by Digital Volunteers in Times of Crisis," *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems: ACM*, pp. 1071-1080.
- Starbird, K., L. Palen, A. L. Hughes, and S. Vieweg. (2010). "Chatter on the Red: What Hazards Threat Reveals About the Social Life of Microblogges Information," *In: Proceedings of the Conference on Computer Supported Cooperative Work (CSCW)*, pp. 241-250.

- Stieglitz, S., M. Mirbabaie, L. Schwenner, J. Marx, J. Lehr, and F. Brünker. (2017). "Sensemaking and Communication Roles in Social Media Crisis Communication,").
- Subba, R., and T. Bui. (2017). "Online Convergence Behavior, Social Media Communications and Crisis Response: An Empirical Study of the 2015 Nepal Earthquake Police Twitter Project," *Proceedings of the 50th Hawaii International Conference on System Sciences*.
- Sutton, J., L. Palen, and I. Shklovski. (2008). "Backchannels on the Front Lines: Emergent Uses of Social Media in the 2007 Southern California Wildfires," *In: Proceedings of the 5th International ISCRAM Conference: Washington, DC*, pp. 624-632.
- Takahashi, B., E. C. Tandoc, and C. Carmichael. (2015). "Communicating on Twitter During a Disaster: An Analysis of Tweets During Typhoon Haiyan in the Philippines," *Computers in Human Behavior* (50), pp. 392-398.
- Toriumi, F., T. Sakaki, K. Shinoda, K. Kazama, S. Kurihara, and I. Noda. (2013). "Information Sharing on Twitter During the 2011 Catastrophic Earthquake," *In: Proceedings of the 22nd international conference on World Wide Web companion*, pp. 1025-1028.
- Twitter. (2016). "Twitter Rest Apis." from <https://dev.twitter.com/rest/public>
- Verma, S., S. Vieweg, W. J. Corvey, L. Palen, J. H. Martin, M. Palmer, A. Schram, and K. M. Anderson. (2011). "Natural Language Processing to the Rescue? Extracting " Situational Awareness" Tweets During Mass Emergency," *ICWSM: Citeseer*.
- Vieweg, S., A. Hughes, K. Starbird, and L. Palen. (2010a). "Supporting Situational Awareness During Emergencies Using Microblogged Information," *SIGCHI 2010*).
- Vieweg, S., A. L. A. Hughes, K. Starbird, and L. Palen. (2010b). "Microblogging During Two Natural Hazards Events: What Twitter May Contribute to Situational Awareness," *In: Proceedings of the 28th international conference on Human factors in computing systems - CHI '10: ACM*, pp. 1079-1088.
- Vieweg, S. E. (2012). "Situational Awareness in Mass Emergency: A Behavioral and Linguistic Analysis of Microblogged Communications." University of Colorado at Boulder.
- Yu, C. H., A. Jannasch-Pennell, and S. DiGangi. (2011). "Compatibility between Text Mining and Qualitative Research in the Perspectives of Grounded Theory, Content Analysis, and Reliability," *The Qualitative Report* (16:3), p. 730.