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Review

Social media for intelligent public information and warning in disasters: An interdisciplinary review

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ABSTRACT

Social media offers participatory and collaborative structure and collective knowledge building capacity to the public information and warning approaches. Therefore, the author envisions the intelligent public information and warning in disaster based on social media, which has three functions: (1) efficiently and effectively acquiring disaster situational awareness information, (2) supporting self-organized peer-to-peer help activities, and (3) enabling the disaster management agencies to hear from the public. To achieve this vision, authors of this study examined 304 studies conducted 2008 through 2018 to systemically evaluate the current literature in understanding the phenomena of communication on social media and the state-of-the-art studies on social media informatics in disasters. This review then identified the challenges of existing studies and proposed a research roadmap to address the challenges of achieving the vision. This review could serve as a bridge for researchers working on social media in disasters to understand the state-of-the-art of this problem in other related domains. The findings of this review highlight the value of certain research areas, e.g., (1) a fine-grained disaster social media ontology with semantic interoperability, (2) network pattern of trending information and emerging influential users, (3) fine-grained assessment of societal impacts due to infrastructure disruptions, and (4) best practices for social media usage during disasters.

1. Intelligent public information and warning using social media: vision and review motivation

Communication of timely and reliable information, such as situational awareness and protective and preventative measures, in the face of devastating natural disasters, can mean the difference between life or death of disaster victims (Shklovski, Burke, Kiesler, & Kraut, 2010). Public information and warning is the delivery of “coordinated, prompt, reliable, and actionable information to the whole community through the use of clear, consistent, accessible, and culturally and linguistically appropriate methods to effectively relay information regarding any threat or hazard, as well as the actions being taken and the assistance being made available, as appropriate (U.S. Department of Homeland Security, 2008).” In recent years, social media has established itself as a new channel of public information and warning in disasters besides mass media (e.g., radio, television, and newspapers) or by word-of-mouth communication between family members and friends (Al-Saggaf & Simmons, 2015; Bunce, Partridge, & Davis, 2012; Dabner, 2012; Houston et al., 2014; Jung & Moro, 2014; Kaufhold & Reuter, 2016; Qu, Huang, Zhang, & Zhang, 2011; Silver & Matthews, 2017; Tim, Pan, Ractham, & Kaewkitipong, 2017; Yates & Paquette, 2011). Compared with traditional communication channels, social media offers participatory and collaborative structure and collective knowledge building capacity to the public information and warning approaches (Dabner, 2012; Kamboj, Sarmah, Gupta, & Dwivedi, 2018; Tagliacozzo & Magni, 2018; Vieweg, 2012). Based on existing studies, the authors identified three functions of public information and warning to which social media can contribute (Fig. 1):

Function 1 is efficiently and effectively acquiring disaster situational awareness information. The information on social media is updated in a highly timely manner (Al-Saggaf & Simmons, 2015; Bunce et al., 2012; Jung & Moro, 2014; Murphy, 2013), and the networked communication structure of social media platforms can quickly convey disaster situational information to a large audience (Dabner, 2012; Tagliacozzo & Magni, 2018). Using social media, disaster management agencies and professionals provides the disaster victims the searchable and trackable information and notifications (Brengarth & Mujkic, 2016; Kaigo, 2012; Valenzuela, Puente, & Flores, 2017). In addition, social media enhances communication and connection of local communities (e.g., family, friends, and neighbors), and people impacted by disasters will have better access to localized and personalized disaster situational information from the social media users in the same community (Bunce

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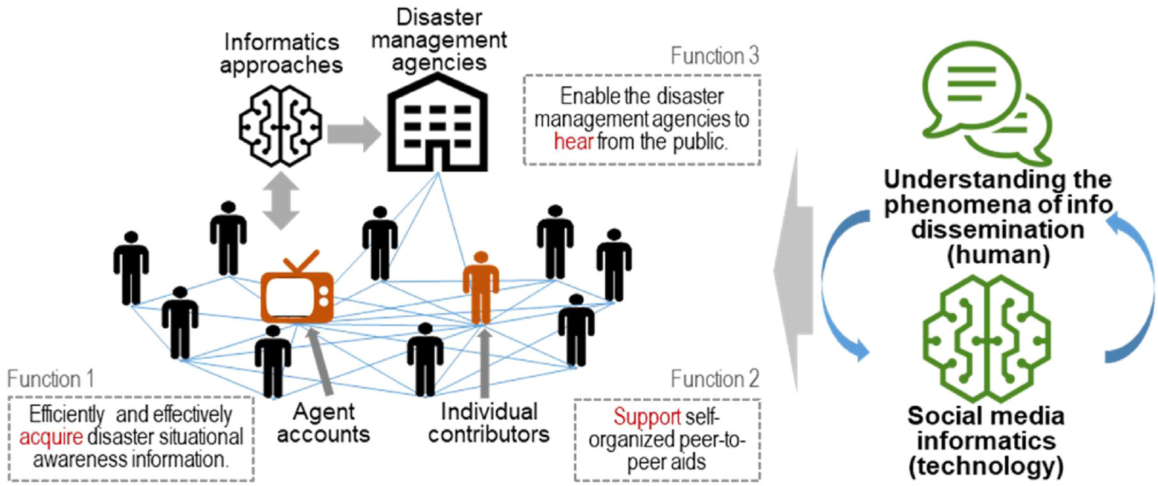

Fig. 1. The vision of intelligent public information and warning in disasters.

et al., 2012; Dabner, 2012; Resnyansky, 2014).

Function 2 is supporting self-organized peer-to-peer aids. Social media platforms allow people to increase the exposure of information (e.g., retweeting) or users (e.g., following). Such self-organized and decentralized information dissemination leads to trending information and evolving information hubs in disasters (Aladwani & Dwivedi, 2018). In this case, sources which contribute cogent disaster management and response may become popular and more available to disaster-impacted people by the action of promotion on social media. Aid seekers (e.g., people who need rescue) and providers (e.g., rescue providers, disaster response professionals, and donation organizers) can gain attention through social media during disasters (Purohit et al., 2014; Singh, Dwivedi, Rana, Kumar, & Kapoor, 2017; Varga et al., 2013).

Function 3 is enabling disaster management agencies to hear from the public. Social media informatics (also termed as social sensing (Arthur, Boulton, Shotton, & Williams, 2018)), could complement traditional surveying techniques, such as direct observations and interviews, and could mitigate the need for significant resources for data collection (Avvenuti, Bellomo, Cresci, Polla, & Tesconi, 2017; Huang & Xiao, 2015). First, social media platforms enable direct communication and interactions between the agencies and the public with different forms (e.g., following, mentioning, commenting, and replying) (Kim, Bae, & Hastak, 2018). Second, social media content generated by the public captures the actual human behaviors in response to disaster events (Shiau, Dwivedi, & Lai, 2018), which enables the agencies to hear the societal considerations of the public indirectly. Social media informatics techniques can acquire, interpret, and map social media content to support (1) the detection or prediction of critical events and (2) the identification of underlying patterns of social media users for better information dissemination in disasters (Reuter & Kaufhold, 2018), which help the agencies assess the damage and impact on the public.

Based on the three functions, the authors thus envision the "intelligent public information and warning" system in disasters supported by social media to improve information flow and self-organization among populations affected by disasters. The core of the envisioned system is the coordination and integration between the public, disaster management agencies, social media platforms, and informatics approaches. Ideally, this system enables people in impacted areas to receive and share situational information in a networked and decentralized manner effectively and on a timely basis. The authors illustrate the vision of intelligent public information and warning system (hereafter referred to as "Vision") with the following imaginary scenario:

"Waking up in the morning, Sarah received multiple pushes from social media platforms from disaster management agencies about an upcoming hurricane in her city. She instantly informed her neighbor, a granny who lived alone, and found that the granny is already well-prepared because she also learned everything about the hurricane through the easy-access version of social media platforms. During the hurricane, Sarah searches on the social media platforms 'where can I buy food,' and the platform automatically returned all the open grocery stores and supermarket and the available food in each store based on people's posts. Sarah is always available to the latest information about the hurricane because the social media platform can aggregate and visualize the disaster situational information posted by the users. She also followed the professionals and local help providers who quickly gained influence in this hurricane event and are recommended by the platform. In the local social media community, Sarah also worked as a volunteer to verify the information about seeking and providing help so that the intelligent system can automatically match them together. Finally, people feel that the disaster management agencies are making decisions effectively and efficiently with the help of the aggregated social media posts and posts from verified sources about the disaster situation."

This vision shows us that, achieving reliable and efficient public information and warning process requires (1) new technologies that align with human behavior, and (2) guided/trained human behavior during disaster that maximize the effectiveness of technologies (Imran, Castillo, Diaz, & Vieweg, 2015; Kapoor et al., 2018; Reuter & Kaufhold, 2018). To understand where we are and how far we are from this promising vision, the authors argue that the academic need to explore two mutually interacted domains: disaster information dissemination phenomena and social media data analytics techniques. Hence, the objective of this paper is to review this fast-developing research domain related to social media in disasters and to answer the following research questions (RQs) (Fig. 2):

- Q1: What do we know about the communication phenomena on social media in disasters?
- Q2: What has been done on developing data analytics techniques for retrieving and sharing critical information on social media in disasters?
- Q3: What are the knowledge gaps in the achievement of timely, self-organized, and networked information flow?
- Q4: What is the research roadmap for achieving intelligent public information and warning in disasters?

Compared to existing literature review studies on social media in disasters, this paper proposes three unique contributions to the body of knowledge: (1) a clear vision for future public information and warning approaches; (2) the research roadmap to realize the Vision, and (3) a

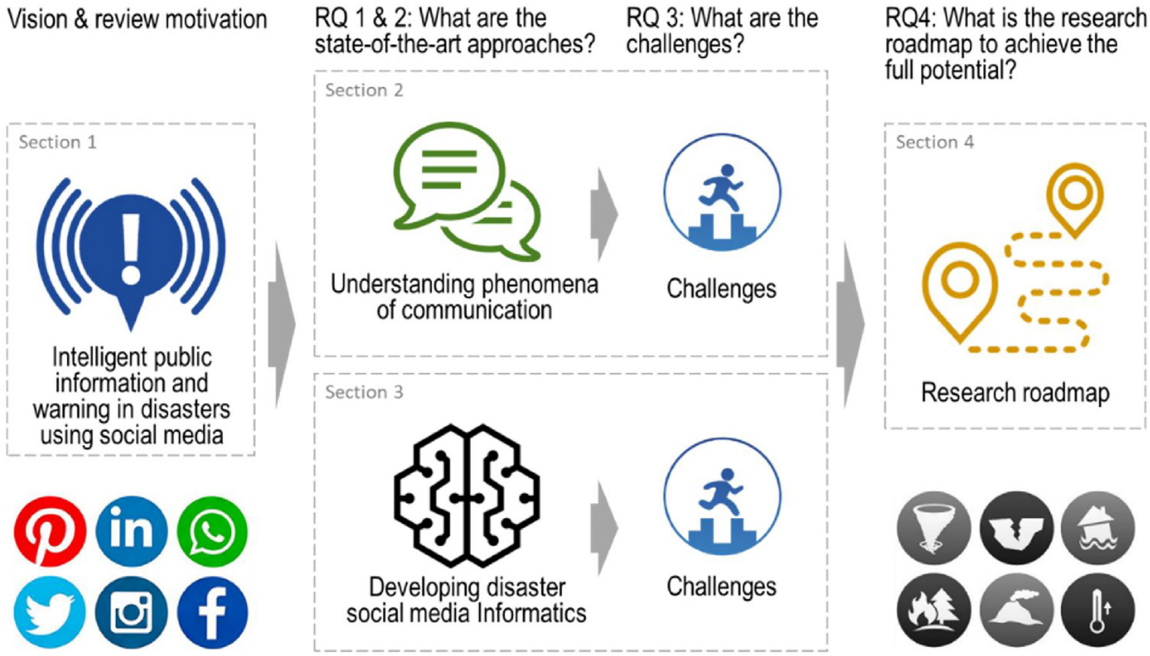

Fig. 2. The framework of the literature review.

bridge for researchers working on social media in disasters to understand the state-of-the-art of this problem in other related domains (Shiau, Dwivedi, & Yang, 2017) (Alalwan, Rana, Dwivedi, & Algharabat, 2017; Dwivedi, Kapoor, & Chen, 2015).

1.1. Literature search and selection criteria

To create a comprehensive repository of relevant literature, the authors applied a two-step search to create a repository of relevant literature. The date range of the search and selection criteria was 2008 through 2018 because the major disaster that involved social media activities (e.g., China 2008 earthquake, Haiti Earthquake, Hurricane Sandy, etc.) happened after 2008 and the number of related literature increased dramatically since 2008. The first step is a title-based search to the Web of Science database. The titles of the selected papers should contain at least one keyword from both categories: (1) disaster-related: disaster(s), emergency (emergencies), crisis (crises), hazard(s) resilience, flood(s), hurricane(s), earthquake(s), fire(s); and (2) social media-related: social media, social sensing, social network, Twitter, Facebook, tweet(s). 504 studies were found in the database. In the second step, to include important studies that are not included in the Web of Science database, the authors processed a title-based search to Google Scholar using the same criteria and reviewed the top 10% papers sorted by relevance (Google Scholar's relevance ranking considers the number of citations of each paper with a very high weight (Martin-Martin, Orduna-Malea, Harzing, & López-Cózar, 2017)) in each year. 371 studies were included. The authors then reviewed titles and the abstracts of the selected literature and removed irrelevant ones (e.g., social network or resilience studies that are not about online social media platforms, studies about the social behavior of “fire” flies, or studies about the use of social media platforms but not relevant to public information and warning). The final number of selected literature was 304 papers. The authors then categorized the reviewed studies according to two topics: (1) understanding the phenomena of communication, which focused on exploring how people use social media as a communication tool in disasters; and (2) developing social media informatics techniques, which analyze social media data to retrieve more disaster situational awareness information.

Fig. 3A depicts the increasing trend in the number of studies focused on the topic of social media analytics in disaster and urban resilience domains, which shows that Social media informatics studies are gaining attention quickly since 2016. Fig. 3B shows the distribution of the departments of the authors. Computer science, geography/civil/environmental engineering, and social science are the three major departments that produce related studies. Also, the large proportion of studies done via collaborations of multiple departments shows the interdisciplinary nature of this domain. Fig. 3C–E also show the distribution of the reviewed studies regarding social media platforms, disaster type, and location of disasters. Twitter is the most widely-studied social media platform. Studies focusing on earthquakes, hurricanes, typhoons, and floods are most prevalent due to the frequency of these disasters and their impacts upon affected areas, duration of impact, damage to property, and loss of life. Regarding geographic areas, social media analytics studies in disasters occurring in North America, Asia, and Europe are the most relevant in the existing literature.

2. Understanding the phenomena of communication through social media in disasters

This section examines the phenomena of communication through social media in disasters from five aspects (Fig. 4): (1) the content of social media, (2) spatiotemporal patterns of social media usage distribution, (3) information dissemination patterns, (4) rumor and trust issues, and (5) public's experience of social media use.

2.1. The content of social media posts in disasters

Exploring the content (Section 2.1) and spatiotemporal patterns (Section 2.2) of social media posts can help understand the current effective and ineffective communication activities in disasters. Such an understanding will guide the design of social media tools that help the public acquire situational information. Also, the social media content and identified spatiotemporal patterns also reflect the impact of the public, which supports social sensing for disaster damage assessment. Therefore, studies on social media content and spatial–temporal pattern of social media posts will jointly contribute to Function 1 and 3 of the Vision.

Many studies focused on the content analysis of social media posts

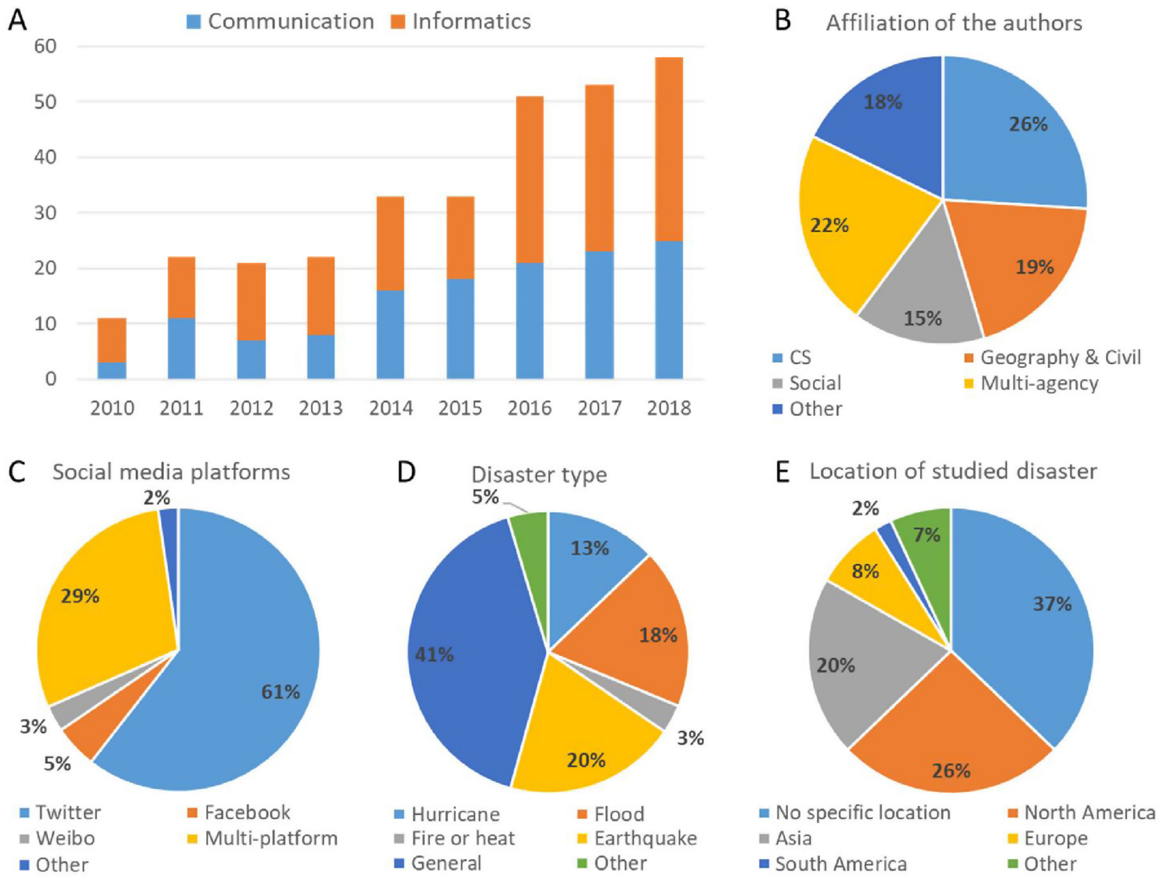

Fig. 3. Statics of reviewed literature. A: number of studies annually on understanding the phenomena of information dissemination and developing informatics techniques in disasters. B–E: the affiliation of the authors, social media platforms, disaster type, and location of disasters involved in the reviewed studies.

Fig. 4. Five dimensions of understanding the phenomena of information dissemination.

(Mahdiloo et al., 2014). Most reviewed studies on social media content analysis collected data using a keyword or account search, with only a few studies used geographic search. In other words, current social media content analysis is primarily based on filtering social media posts using a disaster name. Table 1 summarizes the social media content analysis results related to three major disasters: Hurricane Sandy (Spence, Lachlan, Lin, & Greco, 2015), Typhoon Haiyan (Takahashi, Tandoc, & Carmichael, 2015), and Japan's 2011 Earthquake (Cho, Jung, & Park, 2013). In general, the analysis results show that disaster situational information (posted by officials or regular users) accounts for about 40% of all social media posts that include keywords, such as disaster name, related to disasters. Another major category of social media content is related to expressing emotions (e.g., memorializing, anger, humor), which occupies about 20% to30% of all posts. Comparing the content analysis of different studies across different disasters shows an inconsistency in the classification of disaster-related contents.

In addition to the coarse-grained categorization of disaster-related social media content (Takahashi et al., 2015; Cho et al., 2013; Spence et al., 2015), fine-grained categorization can contribute to the investigation of events and facts related to human, natural environment, and the built environment vis-a-vis the preparedness, response, and recovery phases of disasters. In an effort toward standardizing the classification of social media content in disasters, a study related to Hurricane Sandy (Huang & Xiao, 2015) collected, coded, and analyzed more than 10,000 disaster-related tweets with geolocation information and classified them into detailed categories during different disaster phases and mapped them over space and time. The categorization framework in the study contained four major categories: preparedness, response, impact, recovery. The study then defined sub-categories for each major category respectively and identified the frequently-used keywords of the tweets in each sub-category. This categorization framework and keywords provided a comprehensive ontology for understanding hurricane-related tweet contents. The proposed ontology, however, has not been widely adopted and tested by other studies and in different disasters to refine the classification structure toward a standard framework social media content analysis in disasters.

Another phenomenon related the social media content is the

Table 1
Major types of social media content in different disasters.

Hurricane Sandy (Spence et al., 2015)		Japan's 2011 Earthquake (Cho et al., 2013)		Japan's 2011 Earthquake (Cho et al., 2013)	
Content	%	Content	%	Content	%
Information	34.6	Reporting	48.3	Information-related	12.9–18.1
Affect display	43.0	Memorializing	32.3	Personal experiences	25.3–34.7
Humor	16.4	Coordinating relief	14.6	Opinion-related	19.8–26.0
Insult	3.6	Discussing causes	1.5	Technology/media-related	5.0–10.3
Spam	2.4	Reconnecting	1.2	Emotion-related	5.3–23.8
		Criticizing government	1.2	Action-related	4.0–13.8

variation among the content posted by the general public compared to that posted by organization users. The general public posts the majority of the original posts related to disasters, and they mainly use social media to express emotion and share personal information during disasters (David, Corpus Ong, & Legara, 2016). On the other hand, organization users, including government organizations (GOs), non-government organizations (NGOs), and newsagents, post content related to official disaster information, such as evacuation orders and relief coordination (Kim & Hastak, 2018; Kim et al., 2018). For example, in the Typhoon Haiyan case study (Takahashi et al., 2015), most tweets posted by traditional mass media (about 85%) and government organizations (52.9%) were official disaster information updates. NGOs posted mainly information for coordinating disaster-relief activities (52.8%). The Hurricane Sandy case study (Wang & Zhuang, 2017) identified a similar pattern for the tweet content of GOs, NGOs, and traditional mass media. Of tweets from GO users, 58% of tweets were about disaster preparedness and response measures. Information updates were about 21% for all GO-posted tweets. Mass media, whose major function is distributing information, tweeted two major types of content: disaster situational information updates (this study used the term of information updates) (38%) and suggestions about protective and preventative measures (this study used the term information tips) (23%). The differences between the content of posts shared by ordinary users versus organization users affect the diffusion of situational information in social media during disasters. The current literature, however, lacks studies to examine the diffusion patterns of content posted by a different type of users.

2.1.1. Challenges

One obvious phenomenon about the existing studies on social media content in disasters is the difference in classifying content among the studies. These studies agree that social media content in disasters contains situational information, emotional expression, and other societal considerations, such as complaining or criticizing. One challenge emerging from existing studies relates to the semantic interoperability of the ontologies categorizing social media posts. In the absence of well-accepted, interoperable ontologies supporting classification and evaluation of social media content during different disasters, a cross-comparison among the results from different studies is nearly impossible. Such absence prevents unveiling of common patterns about social media usage in different disasters and different types of disasters. The authors do not suggest using a uniform ontology to describe all the disasters considering the highly dynamic and unpredictable nature of disasters. Rather, the authors propose the integration of existing disaster ontologies into an interoperable "meta-ontology" that supports the cross-event analysis of existing disasters, enables exchanging information from different research domain or disaster management agencies, and can be easily adapted to future disasters (Zdravkovic, Noran, Panetto, & Trajanovic, 2015). Studies on disaster ontology with semantic interoperability exists and can be potentially adapted to social media domain (Panetto et al., 2016; Roman, Sukhobok, Nikolov, Elvesæter, & Pultier, 2017; Zdravkovic et al., 2015).

2.2. Spatial–temporal patterns of social media posts

As mentioned in Section 2.1, studies on the spatial–temporal pattern of social media posts together with that on social media content will contribute to Function 1 and 3 of the Vision.

One significant spatial pattern of social media usage during disasters is that users in affected areas tend to post more information on social media compared with unaffected users (Crooks, Croitoru, Stefanidis, & Radzikowski, 2013; Kent & Capello, 2013; Kropivnitskaya, Tiampo, Qin, & Bauer, 2017a; Kropivnitskaya, Tiampo, Qin, & Bauer, 2017b; Wang, Wang, Ye, Zhu, & Lee, 2015). A case study related to the Horsethief Canyon Fire of 2012 confirmed that distance from a certain location to the fire had the most significant negative correlation with the frequency of fire-related tweets posted at that location compared with other demographic indicators, such as user age and population density (Kent & Capello, 2013). A study related to Hurricane Sandy also confirmed the correlation between some tweets and the size of the affected population. The study also showed that demographic indicators (e.g., age, sex, and literacy) had a stronger influence on the number of disaster-related tweets posted than population size (Xiao, Huang, & Wu, 2015). Also, contents generated by users affected by disasters is different from the content produced outside the affected areas (Takahashi et al., 2015). A study on Typhoon Haiyan showed that users residing in the Philippines, the country most affected by the disaster, posted more tweets about coordinating relief, while users outside the Philippines posted more information about memorializing (Takahashi et al., 2015). A study on River Elbe Flood of June 2013 (Albuquerque, Herfort, Brenning, & Zipf, 2015) confirmed that geo-coded tweets posted close (up to 10 km) to severely flooded regions have a high likelihood of being related to floods.

Different types of disasters have different temporal patterns related to the evolution of social media content and number of posts. In other words, the geographic context and disaster type affect the temporal patterns of social media content and number of posts. For example, earthquakes often cause sharp spikes on the number of related social media posts (number of posts reaches the local maximum within an hour) (Cresci, Avvenuti, La Polla, Meletti, & Tesconi, 2018), which is consistent with previous studies on phone call activities during earthquakes (Bagrow, Wang, & Barabási, 2011; Gao et al., 2015). On the other hand, such a pattern does not exist for floods and hurricanes. Another example would be, one significant pattern observed in a case study on Japan's 2011 earthquake is that the percentage of emotion-related tweets decreased from 23.8% between 1 and 10 h to 5.3% between 31 and 40 hours after the earthquake (Cho et al., 2013). This pattern, however, was different for studies related to hurricanes and typhoons. In the Hurricane Sandy study (Spence et al., 2015), from October 27th to 30th, 2012, the percentage of affect-display tweets that expressed worry or fear about the impact of Hurricane Sandy occupied the most significant portion (35–49%) of all hurricane-related tweets, and the percentage of affect-display tweets increased consistently from October 27th to 29th (Spence et al., 2015). Due to the increasing proportion of affect-display tweets and other types of emotional tweets, information for disaster response recommendations became challenging to locate as the damage of the hurricane became more widespread and devastating during the hurricane (Spence et al., 2015). Another case study on to Typhoon Haiyan shows that the percentage of informational tweets about the damage of the disaster decreased significantly and tweets about disaster relief increased sharply while the rate of emotional tweets remained constant from November 7th to 13th, 2013 (David et al., 2016). The dynamic and uncertain nature of disasters could be the explanation of such diverse patterns of the evolution of social media content.

2.2.1. Challenges

The reviewed studies show the need for more studies to compare the temporal patterns of content across different disasters to characterize the temporal evolution of content. According to this literature review, many previous studies have analyzed the spatial–temporal, content, and usage patterns of social media posting and transferring. Thus far, the patterns of information generation and dissemination that are confirmed by more than one study are: (1) people who are closer to the location of the disaster or impacted more severely tend to post more social media information; (2) information posted by users with more followers are more likely to be forwarded; (3) ordinary citizens, instead of organizational agents or news outlets, post most of the information on social media platforms; and (4) earthquakes causes sharp spikes on the number of related social media posts. Those findings align with common knowledge, and some of them are currently the base of social sensing for disaster damage assessment (will be introduced in detail in Section 3.3). However, these identified patterns usually lack considering the factor of the demographical attributes of people. Especially, vulnerable communities (e.g., members of racial/ethnic minorities, the elderly, poor and persons living with disabilities) experience more severe impacts during disasters due to their greater social and physical vulnerabilities and inadequate knowledge and adaptive capacity. General spatiotemporal patterns may not correctly reflect the hardship experienced by vulnerable people. Further studies need to focus on more spatiotemporal patterns that provide more insights on the effectiveness and efficiency of information acquisition or the experienced impact of different communities. Understanding their communication patterns and difficulties during disasters is an essential part of achieving overall urban resilience.

2.3. Dissemination patterns of social media posts

The information dissemination patterns indicate the information that people need or favor, which supports accelerating the spread of critical situational information (Function 1 of the Vision). Furthermore, information dissemination patterns also guide the behavior of aid-seekers or providers to increase their influence on social media, which accelerates realizing Function 2 of the Vision.

2.3.1. Information reposting analysis

Reposting other users' message (e.g., retweeting) is a phenomenon characterizing information dissemination between different users. Generally, tweets by users with more followers realize higher exposure to tweets and thus more retweets. News sources, media celebrities, and organizations involved in disaster relief and response often achieve the most retweets (David et al., 2016; Dong, Li, Zhang, & Cai, 2018). A case study on Sina Weibo, the largest microblogging platform in China), after China-Yiliang earthquake (2012) and before Yaan earthquake (2013) showed that the number of reposts of a user is positively correlated with the user's number of followers (Dong et al., 2018). These findings jointly show that verified users (including both verified individuals and organizations) who have a large number of followers during disasters make a significant contribution to information dissemination. Also, reposts from strangers (i.e., the user who posts the original content and the user who reposts the content do not have a follower-followee relationship) contribute to 37–52% of all retweets, indicating that the diffusion of disaster-related information expands beyond the follower-followed relationship.

Tweet content and style (e.g., containing webpage links/images or not, using all capital letters, etc.) also influence the retweet rate. A study related to tweets from official government accounts during Waldo Canyon Fire explored the influence of message content, style, and public attention to tweets on the reposting activity (i.e., retweeting) in disasters (Sutton et al., 2014). The results showed that disaster-related topics (especially protective action guidance, hazard impact, and hazard location), the use of an imperative sentence (i.e., commanding or requesting), and accounts with a large number of followers are positively correlated with retweets during the disaster (Gurman & Ellenberger, 2015; Sutton et al., 2014).

2.3.2. Network-based analysis

Another way to understand the phenomena related to information diffusion is through network-based analysis. Social network analysis uses graph theory and network modeling techniques to investigate the dynamics of social networks, the formation, and evolution of communities, as well as information diffusion in response to disasters. Currently, the social network analysis for understanding community behavior in disasters is still in its early stages. The findings from the existing literature, however, have started to cast light on some characteristics of online social networks in disasters. For example, as a universal phenomenon in social networks, the distribution of the count variables (e.g., follower counts and retweet counts) follows the "power law" (Arenas, Danon, Díaz-Guilera, Gleiser, & Guimerá, 2004; Dong et al., 2018; Qu et al., 2011; Wang & Zhuang, 2017). In other words, online social networks in disasters show a similar characteristic of scale-free networks. This "power law" pattern implies that the hub users (i.e., users with a large number of followers) and critical posts (i.e., posts that get reposted several times and become trendy) dominate the information diffusion processes in online social networks.

Another stream of research has examined the structural properties of online social networks for community detection in disasters. (Lu & Brelsford, 2014) developed a systematic community detection framework for Twitter in disaster response. This framework first generates the Twitter social network model by using nodes to represent users and links from user A to B to represent A retweeting or mentioning B. The link weight is the number of times A mentions B or retweets B's tweets. The framework utilizes the Infomap method (Rosvall & Bergstrom, 2008) to detect communities in the Twitter user network. Another study examined the case study on the 2016 Louisiana flood (Kim & Hastak, 2018) and generated the social network model based on users' interaction on Facebook. This study examined the out-degree, in-degree, eigenvector, and "betweenness" centrality in the network and found that the individuals and organizations have different roles in disaster social network. The findings of the study showed that Individuals with a greater degree and centrality (more connections) tend to play a more critical role in distributing emergency information. On the other hand, organizations are pivotal in connecting different communities of individuals.

2.3.3. Challenges

For the studies about understanding information reposting patterns, the findings from these studies explain the characteristics of social media posts that influence the extent of reposting. However, the current literature lacks studies that consider the influence of reposting by different users (e.g., individual users versus organization users) on the diffusion of information. Another missing piece is the speed of reposting information and to what extent the attributes of the posts (tweets) influence the speed of reposting.

For networked-based analysis, as mentioned earlier, the number of studies examining the information diffusion on online social networks in a disaster scenario is rather limited. This limitation is mainly due to the challenges in mapping social network communications to model social network structures. Twitter studies cannot obtain follower and following relationship among the users before, during and after the disasters. Hence, the limited number of available studies investigating social networks are based on the retweeting of posts among the users. For Facebook, if the communication instances are not private, the social network structures can be modeled based on mapping communications among users. The ability to map the networks, however, would be limited to specific communities for which Facebook communication instances are public. Regarding network diffusion phenomena, the current literature focused primarily on structural properties (Ma & Yates, 2017) as well as network communities in online social networks in disasters. If the challenges related to mapping and modeling online social networks is resolved, understanding the dynamics of networks would enable a better understanding of the temporal properties and evolution of network structures throughout a disaster.

The understanding of information reposting behaviors and network dynamics may hold the key to improving information diffusion in communities in disasters through social media. One promising research direction is the identification and characterization of influential users or trending contributing to situational awareness (Kumar, Morstatter, Zafarani, & Liu, 2013; Lee, Ybañez, De Leon, & Estuar, 2018). This knowledge will accelerate the design of tools to guide and accelerate the self-organized information dissemination during disasters.

2.4. Rumors and the trust issue of social media content

One of the major limitations of social media compared with traditional mass media is that it allows the spreading of rumors, which could cause huge life and property loss during disasters (Alexander, 2014; Takayasu et al., 2015). Understanding the spreading of rumor and how to improve trust between social media users can improve the quality of information acquisition, which directly contributes to Function 1 of the Vision.

According to existing studies, rumors are easily spread yet often questioned. (Wang & Zhuang, 2018) found that a misinformed Twitter user has a high probability of spreading rumors (85.86–91.40%) without seeking confirmation (5.39–9.37%) or doubting the rumor (0.71–8.75%). After the Twitter users were debunked, however, users tended to take no action to control the rumor spreading, such as deleting rumor tweet(s) (2.94–10.00%) or clarifying rumor information with a new tweet (0–19.75%). Another study on faking images during Sandy found that 0.3% of all users involved in spreading fake images resulted in 90%of the retweets of fake images (Gupta, Lamba, Kumaraguru, & Joshi, 2013). On the other hand, rumors are questioned much more compared to confirmed news (Mendoza, Poblete, & Castillo, 2010). (Takayasu et al., 2015) studied the rumor spreading pattern during the 3.11 earthquake, which found that official announcement can significantly reduce the spread of rumors.

Due to the possible dissemination of fake information, disaster management agencies find limited usefulness in the information acquired from the public through social media due to lack of trust (Mehta, Bruns, & Newton, 2017; Tapia & Moore, 2014). Tapia and Moore conducted 21 in-depth qualitative interviews with the members of 12 disaster management organizations about the complex nature of information gathering about the Haiti earthquake from social media (Tapia & Moore, 2014). This study shows that the dynamic and urgent nature of disasters always forces disaster management organizations to make decisions based on insufficient, unreliable data from different sources (e.g., volunteers, other disaster management teams, etc.). The interviewees also point out that currently disaster responders will use social media to acquire information only from trusted sources, including known people, communities, or organizations. Mehta et al. (2017) highlighted the value of verifying processes as a foundation for building interpersonal trust and acquiring reliable information from social media in disasters. Based on a multi-year project, this study proposed three models to verify the information on social media: (1) intelligence gathering, which means identifying unusual patterns in social media activities rather than individual posts; (2) quasi-journalistic verification, which means confirming any unit of information through at least two independent sources; (3) crowdsourcing, which means recruiting and training volunteers to proactively verify information on social media. Overall, these studies highlighted the needs for an online, reliable, and shared a network of the disaster information source.

2.4.1. Challenges

The reviewed literature shows that rumors spread easily during disaster events and are difficult to control. Disaster management agencies tend to lack trust in social media content posted by random users. Existing studies on rumor spreading tent to focus on analyzing identified rumors, which means rumor detection is a nascent technology (Truelove, Vasardani, & Winter, 2015). Future work should focus on answering the following research questions: (1) for self-organized rumor control, how to motivate social media user to clarify spreading rumors; (2) what is the earliest possible time and what features should we use to identify a spreading rumor; and (3) what is the best practice to integrate crowdsourced clarification and official announcements for debunking rumors? In addition to fake information and the spreading of rumors, other types of deception (e.g., spambots and fake followers) in social media also compromise the effectiveness and efficiency of information dissemination and acquisition. Cresci (2018) presented a series of studies on accurate and efficient detection malicious accounts and future work may explore this application in a disaster scenario.

2.5. The public's experience of social media use in disasters

This section reviews the studies on the public's experience of social media use in disasters, which include whether people are willing to use social media and their difficulties of using social media during disasters. These studies can directly help identify the challenges of acquiring disaster situational information (Function 1).

According to existing survey-based studies, the public does not consider social media as the main source of information compared to traditional media, even for disaster management agency accounts. Williams et al. showed that among the respondents who use social media, only 29.3% have experience using social media in a disaster (Williams, Valero, & Kim, 2018). Furthermore, the respondents trust friends, family, and news media more than local disaster management agencies and federal agencies on social media. Similarly, conducted two studies using simulation experiments to explore how information source and forms influence citizen's information seeking behavior during disasters (Liu, Fraustino, & Jin, 2015; Liu, Fraustino, & Jin, 2016). These studies jointly show that the public trust more on local federal agencies websites than through twitter and Facebook pages. Another negative aspect of the public's experience of using social media in disasters are that the elderly and disabled people have experienced more difficulties on using social media technologies (Feldman et al., 2016; Kent & Ellis, 2015).

2.5.1. Challenges

The review in this section shows that there is still a long way to make social media more user-friendly and reliable until social media plays a major role in public information and warning in disasters. Much needs to be done before people get used to and trust social media in disasters so that the three functions of social media can benefit the public. Other sections of this review paper also highlight the aspects that can be improved (e.g., rumor control, automation in information acquisition). One important task is to develop social media tools that are friendly to the elderly and disabled people to improve their coverage of important disaster information and notices.

Table 2 summaries the significant studies of understanding the

Table 2
Summary of communication phenomena using social media in disasters.

Aspects	Major findings of social media usage patterns in disasters	Challenges
Content	• Disaster situational information and expressing emotions are major types of social media contents about the disasters (Takahashi et al., 2015; Cho et al., 2013; Spence et al., 2015). • Fine-grained social media content categorization framework provided a comprehensive disaster ontology (Huang & Xiao, 2015). • The public posted the majority of the original posts (David et al., 2016). • Contents from different users (GOs, NGOs, newsagents and the public) have unique patterns (Mortensen, Hull, & Boling, 2017; Takahashi et al., 2015).	A cross-comparison among the results from different studies requires well-accepted, interoperable ontologies supporting classification and evaluation of social media content during different disasters
Spatial–temporal patterns	• Users in the affected area tend to post more about the disaster on social media (Kent & Capello, 2013; Kropivnitskaya et al., 2017a, 2017b; Crooks et al., 2013). • Universal temporal patterns of the evolving of social media content do not exist for different types of disasters (Cho et al., 2013; David et al., 2016; Spence et al., 2015).	More studies to compare the temporal patterns of content across different disasters is in need. Understanding the communication strategy and difficulties of the vulnerable population is an essential part of achieving overall urban resilience.
Dissemination patterns	Information reposting patterns: • More followers lead to more retweets (David et al., 2016; Dong et al., 2018) • Tweet content and style will also influence the retweet rate (Gurman & Ellenberger, 2015; Sutton et al., 2014) Network-based analysis • Count variables in social network analysis follow “power law” (Arenas et al., 2004; Dong et al., 2018; Qu et al., 2011; Wang & Zhuang, 2017). • Graph theory and network modeling techniques help investigate the formation and evolution of communities in response to disasters (Kim & Hastak, 2018; Kryvasheyeu & Chen, 2014; Lu & Brelsford, 2014; Rosvall & Bergstrom, 2008; Yeo, Knox, & Jung, 2018).	Lacks studies that consider the influence of reposting by different users. Difficulties exist in obtaining the actual follower and following relationship among the users before, during and after the disasters.
Rumors and the trust issue	• People preferred not to take action to control the rumor spreading (Wang & Zhuang, 2018) • The official *announcement* can significantly reduce the spread of rumors (Takayasu et al., 2015) • Disaster management agencies lack the trust of social media content (Mehta et al., 2017; Tapia & Moore, 2014).	Existing approaches can only analyze identified rumors but cannot detect and control spreading rumors.
Public's experience	• The public do not consider social media as the main source of information compared to traditional media, even for disaster management agency accounts (Williams et al., 2018) (Liu et al., 2015; Liu et al., 2016). • Existing social media platforms may not be user-friendly for elderly and disabled populations in disasters (Feldman et al., 2016; Kent & Ellis, 2015).	There is still a long way to make social media more user-friendly and reliable until social media plays a major role in public information and warning in disasters.

phenomena of information dissemination on social media in disasters discussed in Section 2.

3. Informatics techniques for analyzing social media data in disasters

This section presents the state-of-the-art techniques for retrieving and analyzing information content of social media posts for evaluating communities' information sharing in disasters (Castillo, 2016) (Adam, Shafiq, & Staffin, 2012). This section will review the techniques used for social media informatics in three categories (Fig. 5): (1) information retrieval, (2) information integration, (3) information interpretation. These widely-used informatics techniques collectively support all three functions of the Vision.

3.1. Information retrieval

This section reviews the approaches that retrieve disaster-related information from social media posts, which is the basis of other information integration and interpretation approaches.

3.1.1. Labeling disaster-related social media posts

The techniques that distinguish posts related to disasters from irrelevant posts is the first step for retrieving timely and trustworthy situational information from social media data (Pohl, Bouchachia, & Hellwagner, 2018; Laylavi, Rajabifard, & Kalantari, 2017). Many approaches focus on identify whether each social media post is (1) related to the disaster and (2) informative or not by using a set of lexical and grammatical linguistic features, e.g., *n*-gram, part-of-speech tags, hashtags, emoticons, URLs, etc. (Cresci, Tesconi, Cimino, & Dell’Orletta, 2015; Win & Aung, 2017). Imran, Elbassuoni, Castillo, Diaz, and Meier (2013b) trained a conditional random fields (CRF) model to classify tweets into personal (if a message only conveys information to its author) or informative (if the message is informative (useful to other people beyond the author). Hashtags—words or short phrases preceded by the hash sign (#) to indicate topics of social media posts—are commonly used. Some studies identified disaster-related hashtags to filter related posts (Murzintcev & Cheng, 2017; Shen, Murzintcev, Song, & Cheng, 2017). Identified hashtags can support disaster situational awareness extraction from multiple social media platforms, such as Twitter, Facebook, and Instagram.

Automatic labeling approaches according to the fine-grained disaster social media taxonomy will potentially be beneficial to many aspects in disaster studies (Ghosh, Srijith, & Desarkar, 2017; Hofmann, Betke, & Sackmann, 2015). By collecting data from three hurricanes (Nguyen, Yang, Li, Cao, & Jin, 2018) presented a sequence to sequence approach for predicting people's needs during disasters using weather data and social media data. Burel, Saif, and Alani (2017) developed a wide and deep CNN for classifying tweets into the fine-grained information-category label (e.g., affected individuals, infrastructures, etc.). Burel and Alani (2018) introduced an open-source web API that provides annotations for crisis-related documents (i.e., related vs unrelated), event types (e.g., hurricane, floods, etc.) and information categories (e.g., reports on affected individuals, donations and volunteers,

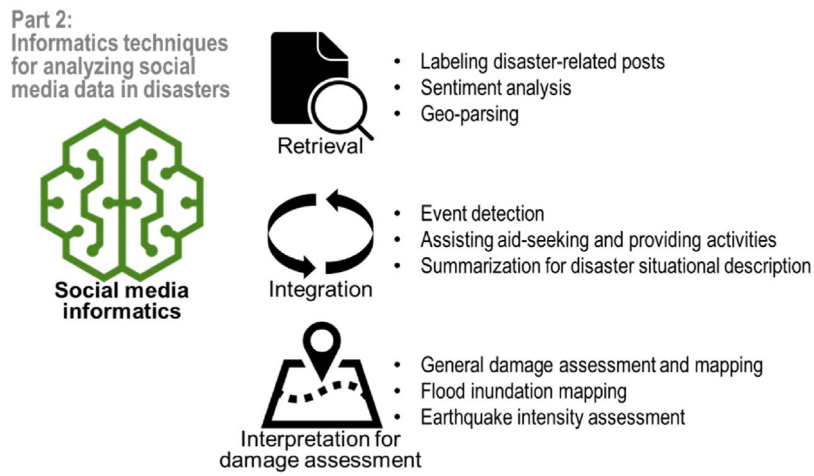

Fig. 5. The organization of reviewing social media informatics.

etc.) and trained Convolutional Neural Network (CNN) models to classify crisis situations.

Identifying disaster-related images within social media posts is also an important branch of existing social sensing approaches. At MediaEval 2017 workshop, the Multimedia Satellite task focused on integrating social media data and satellite imagery for emergency response for flooding events, one subtask of which is retrieving disaster images from social media (Bischke et al., 2017). Researchers presented many effective systems to address this task (Ahmad, Konstantin, Riegler, Conci, & Holversen, 2017; Avgerinakis et al., 2017). Concerning image-based disaster awareness on social media platforms (Nguyen, Ofli, Imran, & Mitra, 2018) fine-tuned a deep Convolutional Neural Networks (CNN) for determining the level of damage caused by the disasters. (Alam, Imran, & Ofli, 2017) designed a system that can collect, denoise, and classifying image content into damage images, injured people and rescue efforts for gaining situational awareness. By applying recent object detection and image classification techniques from computer vision, (Daly & Thom, 2016) presented a model to detect whether a fire event occurred at a particular time and place using geotagged photos.

3.1.2. Sentiment analysis of social media posts

Sentiment analysis studies focus on analyzing people's sentiments, attitudes, emotions and opinions about events and facts (Beigi, Hu, Maciejewski, & Liu, 2016). For disaster relief, social media sentiment analysis identifies the polarity of sentiments using quantitative evidence about public users' feelings, concerns, and panic (Brynielsson et al., 2018; Woo, Cho, Shim, Lee, & Song, 2015). Detected sentiment trends on social media platforms help the decision makers to identify the most affected areas and people's needs without the need for additional efforts for information gathering. One major category of sentiment analysis studies is labeling the posts with positive, neutral, or sentiments (Beigi et al., 2016). Studies in this category often use supervised machine-learning approaches, including bag-of-words, part-of-speech tagging, *n*-grams, emoticons, and keywords representing different sentiments. Meanwhile, visual analytics (e.g., word clouds, spatial maps dynamics, and online activity graphs) facilitates pattern discovery in the disaster relief domain. Through a comprehensive literature review and an interview with officials from emergency response agencies, Brynielsson et al. (Brynielsson et al., 2018) identified the need for a timely assessment of the public's sentiment in disaster management. This system labels the sentiment of social media posts from Twitter and Flickr as positive, fear, anger, and others; however, this work did not validate sentiment-labeling performance.

Researchers also used the social media platform as a surveying platform for understanding sentiment. Ben-Ezra et al. compared the results of Facebook and face-to-face interviews on physical or psychological functioning after the 2011 Japan earthquake (Ben-Ezra et al., 2013). The result suggested that the Facebook-based surveys tended to underrate the impact of large-scale disasters in contrast with the face-to-face interview group, which showed a significantly higher level of negative sentiment (e.g., post-traumatic stress disorder) than the Facebook group.

3.1.3. Geo-parsing

Most disaster information mapping approaches rely heavily on social media posts with geo-location information (Pond, 2016), which accounts for only about 1% of all disaster-related posts (Granell & Ostermann, 2016). To mitigate this drawback, existing studies focus on geoparsing (or geo-tagging) that predicts the locations of social media posts or the users based on the content of the posts and the users' social network information (Avvenuti, Cresci, Nizzoli, & Tesconi, 2018). A geoparsing approach usually identifies the name entities in social media posts, and then matches them with external databases of geographical entities (termed as "gazetteers") (Ghahremanlou, Sherchan, & Thom, 2014). Middleton et al. proposed a real-time disaster mapping system with a geoparsing system that retrieves street-level name entities from texts (Middleton, Middleton, & Modafferi, 2014). The multi-lingual geoparsing approach developed in this study first tokenizes the text *n*-grams (n = 2–5) using sequential combinations of one-gram tokens. The location-matching algorithm will then match the tokens with known place names, street names, and region names. Heuristic rules (Ghahremanlou et al., 2014) and behavioral patterns (Kumar, Hu, & Liu, 2014; Morstatter, Lubold, Pon-Barry, Pfeffer, & Liu, 2014) are commonly used in geoparsing approaches to disambiguate the results. Semantic annotation that can also help the geoparsing process. Cresci, Cimino, Dell'Orletta, and Tesconi (2015) utilize existing semantic annotation tools to link tweets to Wikipedia/DBpedia pages and then check matched places or locations.

3.1.4. Challenges

Overall, supervised learning approaches are the mainstream for information retrieval from social media contents. The major challenges of supervised learning are related to the difficulty of obtaining sufficient manually-annotated posts for training classifiers.

The first challenge is that a high inter-annotator agreement for each category during the annotation process is hard to achieve (Stowe et al., 2018). The high inter-annotator agreement means that the social media contents in different categories are linguistically distinguishable, which is important for developing machine learning classifiers. (Stowe et al., 2018) listed interdependent factors that may cause disagreements between annotators: individual social media post contains insufficient context for clear categorization and different annotators have a different level of inference. Future studies may focus on developing disaster ontologies that support linguistically distinguishable categorization and designing annotation guideline that constrains the level of inference of the annotators.

Another challenge is the huge time and labor cost of acquiring annotated data, which prevents the real-time labeling approach during disasters. Existing studies focus on reducing the amount of needed annotated data. Li, Caragea, Caragea, and Herndon (2018) proposed a domain adaptation method that iteratively updates the training dataset of the Naïve Bayes classifier using automatically labeled tweets with the highest confidence. Based on the hypothesis that historical microblogs could provide useful information of tweets classification during disasters, (Zhang & Vucetic, 2016) cluster unlabeled microblogs words into several clusters and use the word clusters as features for classifying tweets as related or unrelated to disasters. Also, unsupervised and weakly supervised approaches are also promising while rarely seen. Further studies on these directions are needed to address this challenge better.

Besides the general challenge for information retrieval, specific challenges exist for sentiment analysis. The first challenge is the resolution of vagueness in social media texts. For example, people often use irony and sarcasm when complaining, which may disguise sentiment (Ravi & Ravi, 2015). Another important but challenging area is fine-grained sentiment labeling, which will further distinguish different negative sentiment such as anger, fear, disgust, sadness, surprise, and worry. Some studies in NLP domain have made significant progress in this problem (Poria, Cambria, Howard, Huang, & Hussain, 2016; Yu & Wang, 2015), but more work is expected within the disaster context. Such fine-grained sentiment labeling will provide disaster management personnel more context for understanding people's need and the impact of disasters.

3.2. Information integration

This section reviews the approaches that identify the spatial, temporal, and logical relationships between different social media posts to mine additional information beyond the content of each posts.

3.2.1. Event detection

The first branch of event detection is detecting the occurrence of disasters. Identifying burst topics is widely used in detecting earthquakes (Avvenuti, Cresci, Marchetti, Meletti, & Tesconi, 2014; Sakaki, Okazaki, & Matsuo, 2013). Poblete, Guzman, Maldonado, and Tobar (2018) shows massive Twitter messages can be used to detect unusual bursts which can detect earthquake worldwide. Their approach is based on a log-normal distribution the data frequency and burstiness can be detected via Z-score of the relative arrival rate. Earle et al. (2010) and Earle, Bowden, and Guy (2011) identified the possibility of detecting an earthquake in less than a minute by counting the frequency of geocoded tweets containing the keywords "earthquake." These studies also suggested that the content of earthquake-related geocoded tweets could potentially help generate the earthquake intensity map. Another commonly used approach is using statistic classifiers to identify the appearance of social media posts that indicating the occurrence of disasters. (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013a) trained naïve Bayesian classifiers with, some symbolic (e.g., hashtag, mention), scalar (e.g., tweet length), and text features (e.g., Part-Of-Speech tags) together with other ontology knowledge (e.g., WordNet). (Power, Robinson, & Ratcliffe, 2013) trained a Transductive SVM (TSVM) with a small number of labeled positive/negative tweets together and an extensive set of unlabeled Tweets to boost final classification performance.

The second branch of event detection approaches is sub-event detection, which focuses on understanding the details about the damage and impact of disasters. A sub-event is "a specific incident that originates in the context of a disaster (Pohl, Bouchachia, & Hellwagner, 2016)," which is much more challenging to be detected than the occurrence of a disaster (Wu, Ma, & Liu, 2016). The general workflow of sub-event detection consists of three major modules: detecting burst topic, clustering similar social media posts, and geo-mapping (Pohl, Bouchachia, & Hellwagner, 2015; Pohl et al., 2016; Yin, Lampert, Cameron, Robinson, & Power, 2012) (Abhik & Toshniwal, 2013). The burst detection module usually monitors the social media posts containing certain disaster-related keywords and alarms when the frequency of the keyword is above a threshold. The keywords could be related to major disaster events (e.g., earthquake) or sub-events (e.g., airports, evacuation, flooding). The clustering module identifies subevents by grouping major clusters in disaster-related posts by content similarity. (Yin et al., 2012) also used a supervised learning approach to filter infrastructure-related tweets (e.g., railways, hospitals, airports) to assess the impacts and disruptions of the disaster. The geo-mapping module then identifies the most probable location of each cluster of social media posts and plots their topics on a map to provide situational awareness information for disaster management personnel. The topic of each sub-event (i.e., cluster) is often represented using keywords (Pohl et al., 2016) of key tweets (Yin et al., 2012). In (Pohl et al., 2016), the authors investigated the problem of sub-events identification in realtime social media data during emergencies. They proposed a framework using both online indexing and online clustering for tracking the evolution of sub-events vocabulary over time.

3.2.2. Assisting aid-seeking and aid-providing activities

Seeking and providing aid between people is an important feature of achieving self-organization in disaster management (Purohit, Castillo, Diaz, Sheth, & Meier, 2013). Approaches exist in supporting the automation in identifying and matching help-seeking and providing tweets. Singh et al. (2017) proposed an algorithm to identify victims are asking for help in flood-related disasters. Their system takes tweets as inputs and classifies them into high or low priority. For high priority users, they built a Markov chain to predict current location using historical geo-location of a specific user. Purohit et al. proposed an annotation model that labels tweets as help-supplying and help-seeking based on linguistic heuristic rules (Purohit et al., 2014). The output of the proposed system is a query-able repository of annotated tweets with the resource-need type, behavior (seeker or supplier) and spatiotemporal metadata. Focusing on a similar research question, Varga et al. proposed a method that can match aid-seeking and aid-providing messages (Varga et al., 2013). This method first to recognize tweets that report problems or provide aids, and then match problem-aid tweet pairs using a supervised SVM.

3.2.3. Summarization of social media posts for disaster situational description

Summarization of social media posts can reduce the time and effort of people understanding disaster situations. Chen, Elmes, Ye, and Chang (2016) proposed a social media-based disaster GIS system with twitter collection and storage components. Xu et al. (2016, 2017) developed an emergency event storytelling method that mines and integrates semantic, spatiotemporal, and image information from Weibo posts. Rudra et al. (2016) proposed a summarization framework which first retrieves a group of important tweets using an Integer-linear programming (ILP) approach. Then they apply content word based abstractive summarization technique on producing the final summary. Rogstadius et al. (2013) proposed a crowdsourced social media curation approach, CrisisTracker, to detect and map clusters of tweets with lexical similarity. After streaming tweets based on the filter of keywords and geographic bounding box, CrisisTracker vectorizes the collected tweets using the bag-of-words approach and clusters similar tweets based on the angle between the vectors of tweets. The CrisisTracker then supports crowdsourced human intervention to combine duplicated stories, annotate the location and category of the stories, and remove stories irrelevant to disasters. Finally, the disaster responders can filter the disaster-related stories based on their time, location, category, and name entities.

3.2.4. Challenges

One major challenge of existing information integration approaches is including the context of each social media post. Most research studies reviewed (including studies reviewed in other sections) focuses on the analysis of individual piece of social media post but tend to ignore the context of these posts (Purohit et al., 2014 is a good example of utilizing conversational context). Two types of context can enrich the information in single social media posts (Palen and Anderson, 2016): monologic context (related information posted by one user) and conversational context (information posted by multiple users during a conversation or discussion). The causal relationship, together with spatial or temporal proximity, of social media posts is a critical clue for retrieving context. Specifically, based on the strength (i.e., entail or affect) and the direction (i.e., contribute or hamper), causal relations can be categorized into five types: causing, being pre-condition, preventing, positively affecting, and negatively affecting (Do, Chan, & Roth, 2011; Radinsky, Davidovich, & Markovitch, 2012; Zhao et al., 2017). However, prior work on event/information causality extraction is sparse. Tracking how events are evolving and interacting with each other through social media is challenging, which requires further study in the future.

3.3. Information interpretation for disaster impact assessment

This section reviews the approaches that assess the damage caused by disasters, which is critical for providing understandable actionable information to the public and disaster management personnel (Cresci, 2018). Therefore, approaches reviewed in this subsection unveils the societal considerations and social impacts of disaster victims, which can help achieve Function 3 of the Vision.

3.3.1. General damage assessment and mapping

This subsection reviews the damage assessment techniques that are not designed for a specifical type of disaster. Cresci et al. proposed a supervised classifier based on SVM that can label tweets as “not relevant,” “no damage,” and “damage” based on whether a tweet is related to the disaster and carries infrastructure damage information (Cresci, Cimino, et al., 2015). Cervone et al. (Cervone et al., 2016; Cervone, Schnebele, Waters, Moccaldi, & Sicignano, 2017) used flood-related tweets to assess the damage of transportation infrastructures in flooded areas. In addition, social media posts with images and geolocation information are very helpful in identifying the damages caused by floods (Dashti et al., 2014). Some studies (Guan & Chen, 2014; Kryvasheyeu et al., 2016) developed approaches to unfold the correlation between tweet content and built environment damage. (Guan & Chen, 2014) found that the percentage of disaster-related tweets in all tweets termed disaster-related ratio correlated with hurricane impacts (measured by dollars). Similarly, (Kryvasheyeu et al., 2016) shows that the per-capita number of disaster-related tweets corresponds with per-capita property loss and such correspondence is stronger for small-scale (low-cost) disasters (e.g., tornados compared to hurricanes).

3.3.2. Flood inundation mapping

Timely inundation mapping, which includes identifying the flood areas and depth of the floodwaters, is pivotal in flood response and management (Cervone et al., 2017) (Rosser, Leibovici, & Jackson, 2017; Jongman, Wagemaker, Romero, & de Perez, 2015). Existing studies focused on utilizing social media data to identify the inundation depth of different locations. For example, Fohringer, Dransch, Kreibich, and Schröter (2015) proposed a computational tool, PostDistiller, to map the geo-coded tweets containing flood-related keywords to a GIS system (Arthur et al., 2018). By reading texts and images on the tweet map, users can identify flooding details, including flooded areas, dike breaches, and inundation depth at certain locations. Brouwer et al. (2017) developed a probabilistic approach to transform social media information into rainfall values and water depth for inundation mapping. The study calculated water levels relative to the nearest drainage channel using an elevation model to identify the height of certain locations above nearest drainage and employed an interpolation to determine the flood extent of certain locations. The findings indicated that the uncertainty near the inner-city is limited, while the uncertainty outside the city is considerable due to the low density of observations (Restrepo-Estrada et al., 2018).

Researchers often integrate social media posts and hydraulic modeling techniques in flood modeling. Geotagged tweets and the hydraulic and terrain information can support estimate the flooding probability of a certain location using the technique proposed by Wang et al. (Li, Wang, Emrich, & Guo, 2018). This approach identifies flooding areas using geotagged flood-related tweets. Second, this method derives the flood probability index from the distance and elevation difference between a known flooded location and a targeted location. In a recent study on flood simulation (Smith, Liang, James, & Lin, 2017), the real-time high-resolution hydrodynamic modeling use social media posts containing flooding and geolocation information (e.g., water is knee deep) as references to guide the parameter modification so that the hydrodynamic model is realistic.

3.3.3. Earthquakes intensity assessment

Estimating the intensity and affected area of earthquakes is pivotal to earthquake management and response (Avvenuti et al., 2014) (Avvenuti, Cresci, Del Vigna, Fagni, & Tesconi, 2018). For estimating the intensity of the earthquake, Kropivnitskaya et al. explored the relationship between earthquake intensity and tweet rate (Kropivnitskaya et al., 2017a, 2017b). These two studies focused on the quantitative relationship between the intensity of an earthquake and the number of tweets containing the keyword “earthquake” posted within the 10-min window after the earthquake. The authors identified that the logarithm of the number of tweets posted per minute at a certain location is proportional to the earthquake's modified Mercalli intensity at the location. The authors validated this finding using the tweets posted after eight earthquakes in Japan, Chile, and California. These studies argue that the quantitative relationship between social media posts and earthquake intensity can be a supplementary data source to the networks of seismic stations for earthquake intensity estimation.

The geo-coded Twitter posts with the keyword “earthquake” can also work as a sensor system for detecting the impacted area of earthquakes. Crooks et al. conducted a study on the Mineral, Virginia, earthquake and found that as the distance between the epicenter and the geo-location of the tweet with the keyword earthquake increased, the number of earthquake-related tweets decreased and the average time interval between the earthquake and the tweet post increased (Crooks et al., 2013). The authors further argued that related tweets posted within 5–10 min after the earthquake were caused mainly by physical perception about the earthquake per se instead of a discussion about the earthquake on social media platforms, which can be a proper indicator of the impact of the earthquake. This result is consistent with the record of the official crowdsourced system for earthquakes Did You Feel It (DYFI)? of the United States Geological Survey (United States Geological Survey, n.d.).

3.3.4. Challenges

Existing studies show that much has been achieved on using social media for disaster damage assessment. In general, the amount of social media activities (e.g., the number of disaster-related tweets) is correlated with the damage (e.g., property loss) caused by the disaster at the city level. In addition, specific damage assessment techniques focus on specific disasters (i.e., floods and earthquakes) also present their value. On top of existing studies, an important challenge is assessing people's experienced hardship due to the different types of lifeline infrastructure

Table 3
Summary of social media informatics studies in disasters.

Aspects	Major findings and important works	Challenges
Information retrieval	Labeling disaster-related posts: • Studies focus on labeling posts as related to disaster and informative or not (Cresci, Tesconi, et al., 2015; Imran et al., 2013b). An important branch is identifying disaster-related hashtags (Murzintcev & Cheng, 2017; Shen et al., 2017). • Fine-grained social media labeling approaches are more informative. Existing works use various labeling taxonomies, most of which are based on supervised learning (Burel & Alani, 2018; Burel et al., 2017; Nguyen et al., 2018b). • Identifying disaster-related images within social media posts is also an important branch (Alam et al., 2017; Nguyen et al., 2018). Sentiment analysis • Sentiment analysis techniques can label posts with positive, neutral, or negative sentiments (Beigi et al., 2016) • The sentiment of social media posts indicates human mobility during disasters (Wang & Taylor, 2018). Geo-parsing • A geoparsing approach usually identifies the name entities in social media posts, and then matches them with external databases of geographical entities (termed as "gazetteers") (Ghahremanlou et al., 2014) (Middleton et al., 2014).	The major challenges of supervised learning, which is the mainstream of information retrieval, are related to the difficulty of obtaining sufficient manually-annotated posts for training classifiers: • high inter-annotator agreement for each category during the annotation process is hard to achieve • the huge time and labor cost of acquiring annotated data
Information integration	Event detection • Two approaches of detecting the occurrence of disasters: (1) Burst detection of keywords or topics (Sakaki et al., 2013; Poblete et al., 2018; Earle et al., 2011), (2) statistic classifiers to identify the appearance of social media posts indicating the occurrence of disasters (Imran et al., 2013a; Power et al., 2013) • Three major modules of the general workflow of sub-event detection: detecting burst topic, clustering similar social media posts, and geo-mapping (Pohl et al., 2016; Pohl et al., 2015; Yin et al., 2012). The topic of each sub-event (i.e., cluster) is often represented using keywords (Pohl et al., 2016) of key tweets (Yin et al., 2012). Assisting aid-providing and seeking activities • Approaches exist in supporting the automation in identifying and matching help-seeking and providing tweets (Singh et al., 2017; Purohit et al., 2014; Varga et al., 2013) Summarization of social media posts for disaster situational description • Summarization of social media posts can reduce the time and effort of people understanding disaster situations (Chen et al., 2016; Rudra et al., 2016; Rogstadius et al., 2013).	Including the context of each social media post, including monologic context and conversational context, is important yet challenging. The spatial, temporal, and causal relationship between social media posts is important relationships to identify contexts. More work is expected in identifying the causal relationship between social media posts or events.
Information interpretation for disaster impact assessment	General damage assessment approaches • The correlation between the number of disaster-related social media posts and the damage caused by the disasters is commonly-used in social sensing for disaster damage assessment (Cervone et al., 2016; Cervone et al., 2017; Guan & Chen, 2014; Kryvasheyeu et al., 2016). Flood inundation mapping • Flood mapping tools can enable mapping geocoded tweets to GIS systems and also estimate rainfall values in a certain location (Fohringer et al., 2015; Brouwer et al., 2017; Li et al., 2018b). • Geolocations of flood-related tweets can prioritize the collection of remote-sensing high-resolution images for assessing the impact on the built environment (Guan & Chen, 2014; Kryvasheyeu et al., 2016; Cervone et al., 2016). Earthquake intensity mapping • The number and the geospatial distribution of earthquake-related social media posts can indicate the intensity and affected area of earthquakes (Crooks et al., 2013; Kropivnitskaya et al., 2017a, 2017b)	A challenge is assessing people's experienced hardship due to the different types of lifeline infrastructure disruptions, especially for vulnerable populations. If the voice of vulnerable communities is low on social media platforms, disaster management plans and activities that use social media as a reference may exaggerate the imbalance between the majority of the urban population and the vulnerable communities.

disruptions, especially for vulnerable populations. It is possible that the correlations between social media activities and disaster damage cannot reflect the experienced hardship of the vulnerable population properly because of their potentially less availability to new communication technologies supporting social media usage. If the voice of vulnerable communities is low on social media platforms, disaster management plans and activities that use social media as a reference may exaggerate the imbalance between the majority of the urban population and the vulnerable communities. Therefore, examine the effectiveness of social sensing for specifying risk disparities and well-being among vulnerable populations due to infrastructure disruptions and identifying the solutions to level the potential imbalance can enable disaster management agencies to hear the voice of the public better.

Table 3 summaries the reviewed social media informatics studies discussed in Section 3. In addition, existing studies summarizes the state-of-the-art datasets (Alam, Ofli, & Imran, 2018; Imran, Mitra, & Castillo, 2016), analysis tools (Anson, Watson, Wadhwa, & Karin, 2017), practical systems (Poblet, García-Cuesta, & Casanovas, 2018), and important periodicals and conferences (Martínez-Rojas, Pardo-Ferreira, & Rubio-Romero, 2018), which are helpful resources for researchers working in this area.

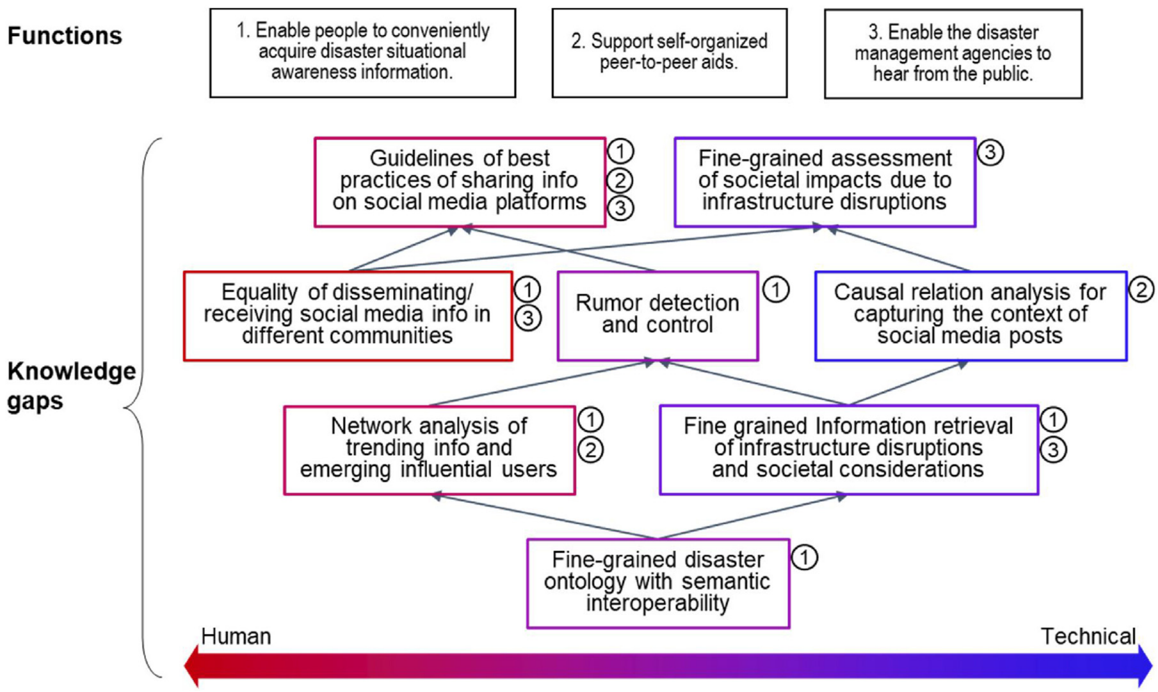

Fig. 6. Research roadmap for achieving intelligent public information and warning in disasters. The color of the boundary of each research task shows its level of integration between human study and technical study. The circled numbers indicate the correspondence between the proposed approaches and the functions of intelligent public information and warning.

4. Research roadmap for achieving the vision of intelligent public information and warning in disasters using social media

At the beginning of this review, the authors defined the Vision as a means to improve information flow and self-organization by the timely and effective exchange of situational information in a networked and decentralized manner among a population affected by a disaster. Studies of information dissemination and social media informatics techniques will support the three functions of the Vision, which are (1) enabling people to conveniently acquire disaster situational awareness information, (2) supporting self-organized peer-to-peer help activities; and (3) enabling the disaster management agencies to hear from the public. Incorporating these three functions to achieve the goal of intelligent public information and warning, the authors propose the following research roadmap (shown in Fig. 6) according to the identified challenges of existing studies about social media in disasters:

(1) *Fine-grained disaster ontology with semantic interoperability.* Sections 2.1 and 3.1 highlight the need for a semantically interoperable, fine-grained disaster social media ontology. The ontology with interoperability can not only boost the research progress about social media content analysis (Function 1 of the Vision) but also the foundation of social sensing approaches that retrieve actionable information from social media posts (Ghosh et al., 2017). The proposed disaster ontology should include the concepts about the disaster situation, the experience of affected people, and the disaster management and response procedures. Also, interoperable disaster ontology should support learning-based (bottom-up) identification of new concepts or patterns from data of future disasters (Moreira, Pires, van Sinderen, & Costa, 2015). However, the unified interoperability theory and methodological base for ontology engineering are still in need (Panetto et al., 2016). Future studies may focus on the following research directions: optimizing the ontology structure to formalize the concepts (and their relations) describing the disaster/people/tasks, selecting the appropriate modeling languages and technologies for implementation, exploring the linguistical or visual features to identify posts related to different concepts, etc.

(2) *Fine-grained information retrieval from social media posts*. Section 3.1 highlight the need of general, fine-grained information retrieval approaches, which can automatically acquire disaster-related information such as different infrastructure disruptions, social dimensions, geo-location information, and sentiments (e.g., sad, angry, surprised, happy). Therefore, developing the fine-grained information retrieval can directly accelerate the process of achieving Function 1 and 3 of the Vision. This technical approach is also the foundation of more advanced data integration and interpretation approaches (e.g., infrastructure disruption event detection). Specific research direction to achieve the objective is 1) approaches to reduce the needed annotated data for supervised learning; 2) best practice to develop annotation guideline to reduce the difference in the level of inference of the annotators to improve the annotation quality; 3) unsupervised or weakly supervised machine learning approaches.

(3) *Social network analysis for understanding the trending information and emerging influential users*. Section 2.3 highlighted the importance of understanding the trending information and emerging influencers on social media platforms. This approach can potentially reduce social disparity, amplify the voice of aid seekers and providers, which would direct help achieving Function 1 and 2 of the Vision. The core research questions that should be answered by this approach are: (1) why this information is trending, and (2) why this user is gaining influence during a disaster? The answers to these questions can provide practical suggestions about boosting the influence of people that need attention during disasters. Understanding the dynamics of networks using social network structure data before and after a disaster is promising in answering these research questions. Based on the social media content and posting behavior patterns, the researchers can apply network percolation theory (Dorogovtsev, Goltsev, & Mendes, 2008; Morone & Makse, 2015) and community detection and analysis (Fortunato, 2010) to answer these research questions.

(4) *Equality of disseminating/receiving social media info in different communities*. Sections 2.2 and 2.5 highlighted the importance of understanding how the vulnerability communities in underserved neighborhoods receive information from and disseminate information on social media platforms. Studies in this direction will help level the potential imbalance in social sensing for specifying risk disparities and well-being among vulnerable populations in disasters, which is critical to achieving the Function 1 and 4 of the Vision.
(5) *Causal relation analysis for capturing the context of social media posts*. Section 3.2 highlights the importance of using the spatial, temporal and causal relationship between social media posts to include context in social sensing. Context analysis will enrich the retrieved information from social media posts and help identify the links between different event social media posts, which supports matching aid seeking and providing information. Therefore, causal relation analysis can directly accelerate the process of achieving Function 2 of the Vision. Furthermore, upper-level information integration and interpretation approaches (e.g., sub-event detection and disaster damage analysis) will also benefit from causal relation and context analysis. Future study may focus on understanding 1) identify different types of causal relationship from noisy social media data; 2) monologic and conversational context retrieval and analysis considering the spatial, temporal, and causal relationship between social media posts; 3) tracking how events are evolving and interacting with each other through social media.
(6) *Rumor detection*. Rumor detection studies can effectively improve the accuracy of information retrieval from social media posts by identifying and discarding fake or suspect information, which helps achieve Function 1 of the Vision. Existing studies about rumors in disasters focus on analyzing the spreading and dispelling of known rumors after the disaster but have not achieved the timely detection of rumors. Future studies could focus on early detection of rumors and inaccurate information through event detection and causal analysis.
(7) *Fine-grained assessment of societal impacts due to infrastructure disruptions*. According to Section 3.3, using social sensing to assess the disruption of lifeline infrastructures and experienced hardship pivotal and not yet achieved. Therefore, future studies should focus on generating the model describing the relationship between social media activities, infrastructure disruptions, and experienced hardship for people, especially for vulnerable communities. Addressing the knowledge gap will help to achieve Function 3 of the Vision. Besides collecting social media data, capturing the ground truth of the vulnerable communities' experienced hardship is the key to address this research task. The outcome of addressing this knowledge gap is two-fold: modified social sensing techniques that adequately reflect the experienced hardship of the vulnerable communities and suggestions to general social media users for amplifying the attention received by the vulnerable people. Different types of infrastructure disruptions, and different community, especially vulnerable communities.
(8) *Best practices for social media usage during disasters.* Finally, based on the understanding of communication through social media and the developed social sensing approaches, the public needs the guidelines and procedures describing the best practices of posting social media information during disasters. Achieving this approach will accelerate the process of achieving all three functions of the Vision. People should learn to work with state-of-the-art social sensing approaches to improve the efficiency of communication while providing high-quality content for social sensing (e.g., provide accuracy geo-location information in the posts). The proposed best practices should include the following aspects: (1) how to search for situational awareness information; (2) what information to provide when seeking help; (3) how to post help-providing information to maximizing the influence; (4) how to recognize and control the spreading of rumors; (5) how to help a vulnerable population to access social media information.

Finally, the authors would argue that academia alone cannot realize this research roadmap and achieve this promising Vision. Rather, achieving the Vision needs the close coordination between the public, the disaster management agencies, the social media developers, and the academia to achieve the fast iteration of learning and practicing in disasters (Avvenuti, Cresci, Vigna, & Tesconi, 2018). Specifically, existing study highlights the importance of practicing: 'what is necessary is to have sufficient permission by emergency management to support solutions as they emerge from grassroots operations and then to foster those ideas deliberately in subsequent events (Palen and Anderson, 2016).' Only by practicing can we gain the data and experience to identify the flaws in existing approaches and achieving better ones (Avvenuti, Cimino, Cresci, Marchetti, & Tesconi, 2016).

5. Concluding remarks

Studies of social media and disasters have burgeoned in the last decade, and the review of existing studies can better guide researchers and planning entities to achieve better disaster management and response. This paper defines the vision of intelligent public information and warning in disasters then identifies three functions of this vision. To achieve these functions, the authors reviewed studies and identified challenges in understanding the phenomena of communication using social media and social media informatics in disasters. This paper finally proposes a research roadmap to address these challenges in the research. Overall, the vision and future research areas proposed in this paper may shed lights on achieving a more disaster-resilient society using social media.

Statement of competing interests

The authors have no competing interests to declare.

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