Present and Future Status of Disaster Social Media

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ABSTRACT: Purpose: *Disaster social media has become an important research topic in many disciplines, such as public management and emergency response. To understand the present and future status of disaster social media, the purpose of this paper is to systematically summarize the topic distribution, characteristics, and development trends of disaster social media research.*

Design/Methodology/Approach: *By using Bibexcel, R and Ucinet, temporal-spatial analysis, clustering analysis, and social network analysis are performed on a bibliometric dataset of disaster social media articles obtained from the Web of Science database. And then, based on the results of the clustering and social network analyses, several major topics under the perspectives of emergency management and information dissemination were qualitative summarized in detail. Based on the results of the temporal-spatial analysis and qualitative analysis, the hot topics and future trends in disaster social media research are identified.*

Findings: *The results indicate that the available research hot topics and methods are becoming highly diverse, and dynamics analysis, quantitative mining, and emotional calculations may become a future trend in social media research.*

Research limitations/Implications: *This proposed research is designed for the English articles and Web of Science database.*

Originality/Value: *An integrated Bibliometric framework of integrating qualitative and quantitative are performed in this work to mining the present and future status of social media research in disaster situation. The findings provide important theoretical and technical references for disaster information management practice and research.*

Subject Categories and Descriptors: K.4.2 [Social Issues]; H.3.4 Systems and Software**: [*Information networks*];** H.2.8 Database Applications: [*Spatial databases*]

General Terms: Social Networks, Social Media, Bibliometrics, Information Services, Databases, Bibliometric Packages

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1. Introduction

Information communication is a key part of disaster management, specifically in reducing the number of casualties and losses resulting from disasters (Houston *et al*., 2015). With the rapid development of social networking services, the role of Internet technology in disaster management has become increasingly significant. Social media are emerging Internet communication technologies which information capacity, dependability, and interactivity significantly contribute to improving disaster communication processes. A case study of Hurricane Katrina revealed that social media are more dependable sources of information during disaster events compared with traditional forms of media (Macias *et al*., 2009). In a social survey of US adults, the majority of the respondents perceived the usefulness of social media when informing their relatives and friends about their situations during emergency situations (American Red Cross, 2012). Social media have also changed the entire process of communicating disaster information (Jung and Moro, 2014). According to Bruns *et al*. (2012) using social media during a disaster "is still emerging and evolving." Mining disaster information from social media has also attracted the attention of many researchers, whose works have focused on several questions, such as what is the role of social media in disaster events and how can the process of communicating disaster information be changed and reshaped. However, a systematic summary and analysis of the methods and theories for mining disaster information from social media are still lacking. Therefore, the study analyzes articles on this topic from the Web of Science (WOS) database, explores the latest international research subjects, and focuses on the hot research topics in different areas to forecast the direction of future research in this field.

The rest of this study is organized as follows. Section 2 explains the research methods employed in this study. Section 3 analyzes the experimental results, including those of the temporal-spatial analysis (Section 3.1), cluster analysis (Section 3.2), and social network analysis (Section 3.3). Section 4 discusses the key findings of the above analyses in detail. Section 5 concludes the paper and presents directions for future work.

2. Methodology

Bibliometric analysis uses data on authors, articles, and the citations therein to measure the influence of researchers, to identify research networks, and map the development of new fields of scientific study. Various mathematical and statistical methods are frequently used in quantitative bibliometric research to reveal hidden internal relations in the literature. This study conducts temporal-spatial analysis, cluster analysis, and social network analysis (SNA) to explore and trace the development and networks of disaster social media research.

In bibliometrics, temporal-spatial analysis collects data from scientific articles and publications classified based on their authors and/or institutions, fields of science, and country to construct simple "temporal-productivity" and "spatial-productivity" indicators for academic research.

Cluster analysis is commonly applied in statistical data analysis and in many fields, including machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics. In bibliometrics, this technique groups' documents are based on the information they contain about certain objects and their relationships. The main idea of this technique is that those documents that need to be clustered into a group must be similar with the other documents in the same group and different from those in other groups. This study focuses on the semantic co-occurrence of keywords. The co-word analysis uses the co-occurrence patterns of keyword pairs in a corpus of documents to discover the relationships among the ideas presented in these documents. Previous studies have identified co-word analysis as a powerful tool for identifying topics on a specified subject and determining their relationships, which are core to the development of an entire research field. We employ hierarchical cluster analysis in this paper to extract such topics. To date, only a few methods are available for pre-processing the differences in the frequencies of keywords in a co-occurrence matrix. Following Zhou and Leydesdorff, we normalize this matrix by using the Ochiai coefficient, which we calculate as

$$K_{ab} = \frac{n(a \cap b)}{\sqrt{n(a) \times n(b)}} \tag{1}$$

Where $n(a \cap b)$ denotes the co-occurrence frequency of keywords a and b, $n(a)$ denotes the occurrence frequency of keyword a, and $n(b)$ denotes the occurrence frequency of keyword b.

Afterward, we construct a correlation matrix of the *Ochiai* coefficients obtained from this equation. The numbers on the diagonal of this matrix, which represent the relationship between a word and itself, are all equal to 1. We then transform this matrix into a dissimilarity matrix to eliminate the impact of the differences in the frequencies between co-words. The values in this matrix are computed by adding -1 to the values in the correlation matrix.

SNA examines various social structures by using networks and graph theory. This method characterizes networked structures in terms of nodes (i.e., individual actors, people, or things within the network) and the ties, edges, or links (i.e., relationships or interactions) that connect them. Social media networks are often visualized through sociograms, in which nodes are represented as points and ties are represented as lines. SNA also analyzes the structure and attributes of social relationships among different social units by focusing on a series of connections between nodes. This method has also been widely used in bibliometric research to explore the important hidden relationships among citations, subject words, and authors, among others. SNA can also effectively avoid the defects of cluster analysis by converting the co-word matrix format. Therefore, after the cluster analysis, we apply SNA to analyze the high-frequency word co-occurrence network, where the keywords are represented as nodes and the co-occurrence relationships are represented as the undirected edges between the nodes.

3. Result Analysis

The sample dataset used in this study is obtained from the WOSTM database on May 31, 2016. To obtain the maximum number of samples, we adopt the search strategies "TS = ("calamity *"OR"disaster*"OR" catastrophe *"OR"hazard*") and "TS = ("social media"OR" twitter*"OR"micro blog"OR"microblogging*"). We eventually obtain a sample dataset of 387 articles. To refine the sample data, we manually judge whether "disaster" and "social media" are the main research objects of these studies by checking their titles, abstracts, and keywords. After this process, 324 of the 387 documents have been retained, including 185 articles, 5 reviews, 1 book review, 7 editorial materials, and 126 articles. We conduct several preprocessing steps after building the sample dataset. First, we use the *Histcite* online analysis tool for the econometric analysis, which results (e.g., publishing time, keywords, and citation frequency) are saved in TXT format. Second, we build the keyword co-occurrence and reference co-occurrence matrices based on the sample dataset by using the *Bibexcel* software.

3.1. Temporal-spatial Analysis

The distribution of the publication time of articles in the specific area can effectively reflect the theoretical level and the development pace of academic research in this area. As shown in Figure 1, Recs indicates the number of published papers, TLCS indicates the number of times a paper is cited in the sample, and TGCS indicates the number of times a paper is cited in the WOS database. The first research on using social media at times of disaster was published in 2009 when the reliance of people on such technologies has become evident. The number of studies in this field has gradually increased over the subsequent years according to the Recs curve.

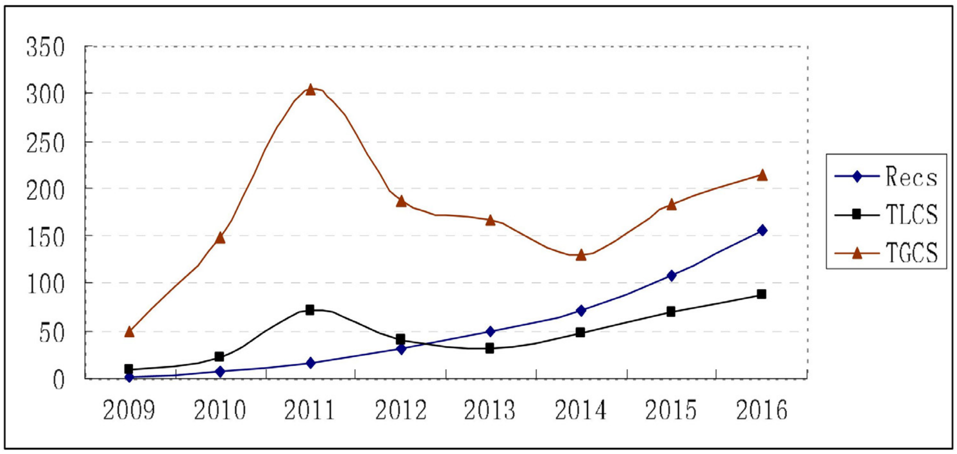

Figure 1. Article publication time curve

Next, we statistically analyzed the author's data. The results show that 1575 authors are actively publishing articles in this field. Among them, Vieweg *et al*. from the University of Colorado is the most prolific author (indexed six papers). Based on the nationality of these authors, we screen out the affiliations of the first 93 authors based on a threshold of two publication records. We find that most high-yield authors are from well-known universities, research institutions, and international organizations, such as the University of Colorado, CSIRO, and USGS. By using the Bibexcel software and GIS geocoding technology, we scale these results into a global map as shown in Fig. 2. The scaling results show that universities and research institutions from the US and Europe have the most number of papers on social media usage at times of disaster, Asian (e.g., Japan and China) and South Pacific countries (e.g., Australia and New Zealand) have published several articles, while Russia and other countries from Africa and South America have published very few articles in this area. Although this phenomenon is influenced by both the English language limitation of the WOS database and the poor research foundation of some developing countries (Dabija, 2017), this statistic also objectively reflects the basic regional situation of disaster social media research.

3.2. Cluster Analysis

As illustrated in section 2, co-word analysis is the basis and premise of cluster analysis, which could be statistical metadata in knowledge discovery process. We use the Bibexcel software to analyze the sample dataset. The 324 extracted documents contain 1652 keywords. Based on their definitions and number, we select the 100 keywords with the highest frequencies for the next quantitative analysis.

Table 1 shows the top 20 keywords and highlights a significant difference in their frequencies. Several other high-frequency keywords, such as "social media," are deemed not meaningful for the subsequent analysis. Therefore, we have deleted these keywords, and then merged their synonyms artificially. After this process, we retain 89 keywords in the sample and use them to construct an 89*89 co-occurrence matrix.

Figure 2. Global distribution of related articles based on the nationality of their first authors

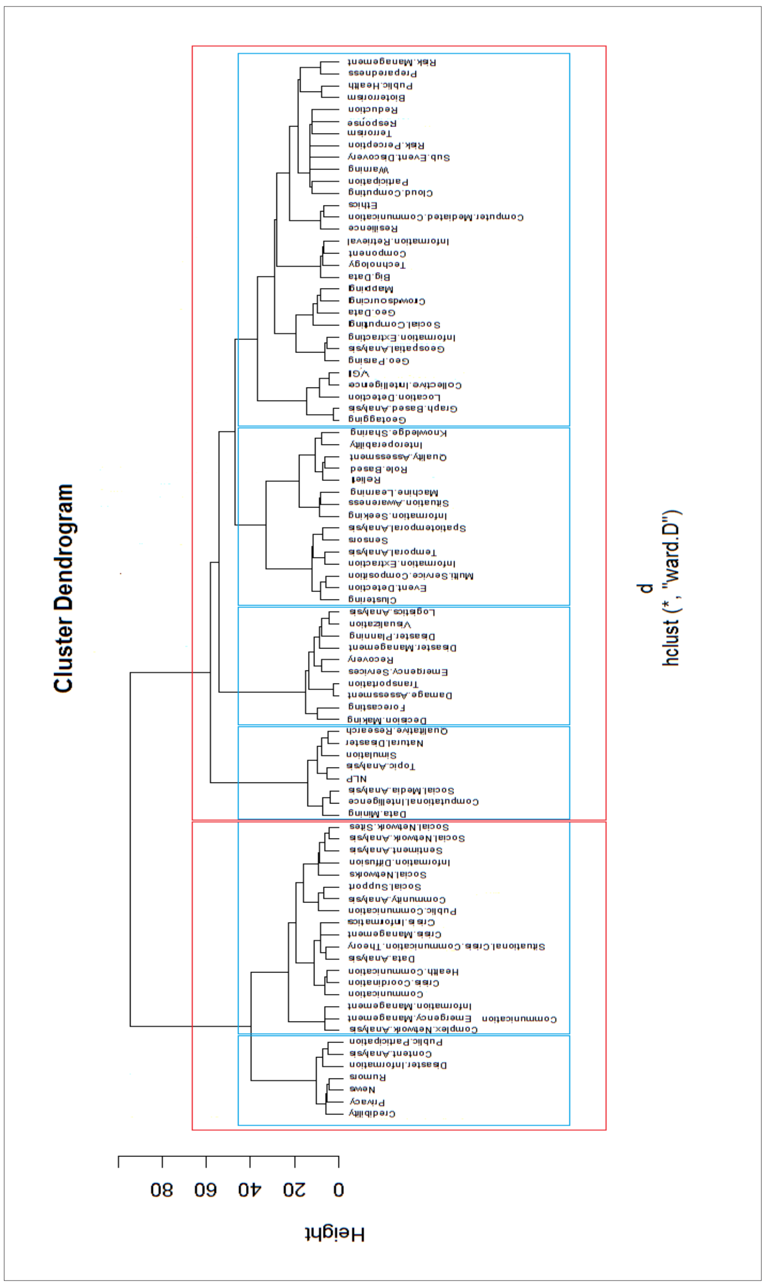

Figure 3. Clustering analysis results

Frequency	Keywords	Frequency	Keywords	Frequency	Keywords
147	Social Media	20	Emergency Management	12	VGI
58	Communication	19	Sentiment Analysis	12	Crisis Informatics
52	Twitter	19	Situation Awareness	12	Community Analysis
31	Disaster	17	Information Diffusion	11	Sensors
30	Disaster Management	17	Social Networks	11	Crisis
27	Response	16	Mapping	11	Visualization
25	Crowdsourcing	15	Credibility	10	Information Extraction
24	Data Mining	13	Content Analysis	9	Natural Disasters
20	Information Management	12	Crisis Management	9	Decision Making
20	Event Detection	12	Spatiotemporal Analysis	9	Relief

Table 1. Top 30 keywords with the highest frequencies

We perform a hierarchical clustering analysis on the above dissimilarity matrix by using the *R* software. Figure 3 presents the treemap produced by this software. Figure 3 shows that all keywords are distributed in two main boughs and several small twigs. After analyzing the graphic features and comparing the keywords in different branches, we divide them into two groups based on two key research directions, namely, (1) to improve the emergency management process (i.e., what is the role of social media in disaster precaution, response, handling, and recovery?) and (2) to change the information dissemination process (i.e., how does social media change the processes of disaster information diffusion and user interaction?).

3.3. SNS

By using the SNA tool Ucinet, we map a high-frequency keyword co-occurrence network as shown in Figure 4.

As can be seen in Figure 4, the size of the keyword node is proportional to its frequency of occurrence in the co-word network, that is, the larger the node, the higher the frequency of co-occurrence and the greater its influence in the network. The point degree of one node can reflect its connection to other nodes. A node with a higher point degree has a higher chance to be a hot research topic. As can be seen in the calculation results, the following 10 keywords are ranked the highest: “Response,” “Communication,”“Disaster Management,” Crowd sourcing,” “Information Management,” “Mapping,” “Situation Awareness,” “Sentiment Analysis,” “Crisis Informatics,” and “Event Detection.” These keywords occupy the center “status” in the co-word network. Density reflects the closeness of node members in social networks. A greater density indicates a closer relationship among members.

Figure 4 also shows that the keyword network in the middle of the map is relatively dense and that the links among the edge keywords are relatively scattered. In addition to the density indicator, the central potential measures the overall aggregation degree of social networks. The calculation results reveal the concentration trend of the

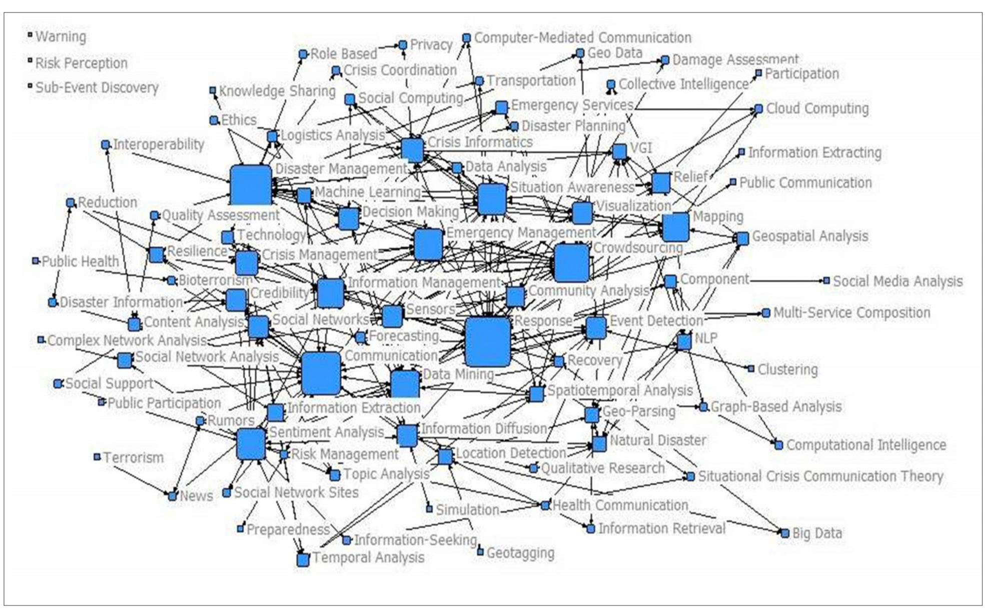

Figure 4. SNS map

network, with the keywords "Communication" and "Disaster Management" occupying the central position with many connected keywords.

In sum, research on the use of social media at times of disaster shows a concentration trend as reflected in the high frequency of keywords in the sampled articles. This trend reflects the key aspects of the research area and identifies several hot topics (e.g., event detection, voluntary geographic information, and public opinion management) and key vocabulary (e.g., disaster management and information communication). The above analysis also presents a good overview of this research topic.

Cluster analysis aims to generate clustering results from different non-overlapping keywords yet tends to ignore the diffusion relationship among different classes. The results of this analysis also cannot reflect the strength of the connection between the keywords. Although SNA can reflect the connection and connection strength among members, the classification results are generally unclear.

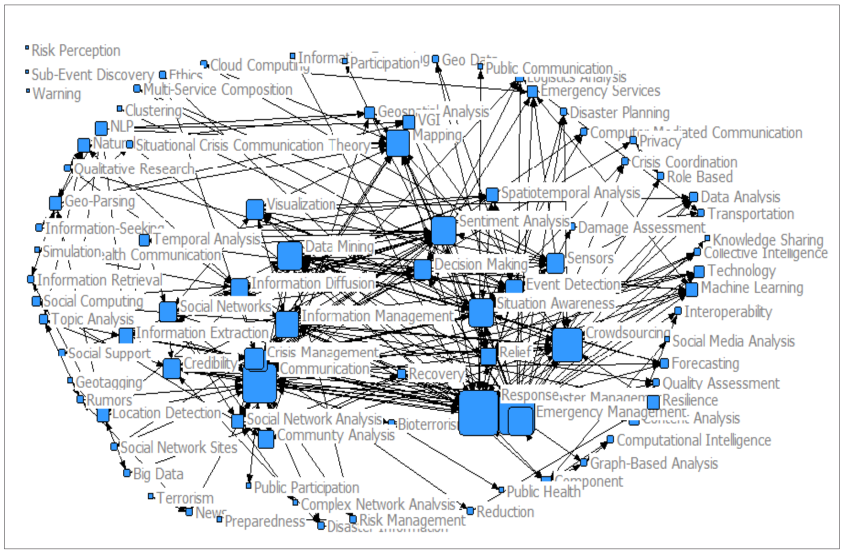

Figure 5. Comprehensive knowledge map

Based on the results of the above analyses, we examine those articles containing high-frequency keywords to determine the content behind these keywords. We eventually group the research topics into two research areas centering on "emergency management" and "information communication." By using the above co-word network and based on the SNA and clustering results, we manually drag the keywords to condense them in the network center and eventually form a comprehensive knowledge map as shown in the figure below. The two aforementioned research areas comprise two internally clustered keyword groups, with each group containing representative keywords that reflect its core content.

Figure 5 shows the complex connections among the keywords used in disaster social media research. To some extent, these connections reflect the fusion of knowledge and the multidimensional characteristics of international social science research on the usage of social media in disaster situation from the perspective of emergency management and information dissemination. The following sections further analyze and discuss the relevant key research topics from these two perspectives.

4. Discussion of Key Research Topics

4.1. Emergency Management

Previous case studies on disasters, such as the Asian tsunami and the Queensland flooding, reveal that social media provide a large amount of first-hand information for disaster relief and mitigation processes (Thelwall and Stuart, 2007). As effective platforms for exchanging messages, social media play an important role in disaster management and can significantly improve disaster emergency management processes (Gimenez-Duque *et al.*, 2016; Murphy, 2016).

4.1.1. Disaster Event Detection and Early Warning

Lasswell (1948) cited three functions of communication in his work, "Communication Process and Its Function in Society." The first of these functions is environmental monitoring, which is considered the most important function of mass communication. The mass media constantly provide information to the public about different incidents, including upcoming and ongoing disaster events. The spread of low-cost Internet access has prompted many countries to develop Web-based disaster incident monitoring systems, such as the "Did You Feel It?" program of USGS (Atkinson and Wald, 2007).

Twitter is another social media platform with plenty of information related to natural disasters, such as the Wenchuan earthquake (China, 2008-04-29), the Los Angeles earthquake (USA, 2009-01-24), and the Morgan Hill earthquake (California, USA, 2009-03-30). Ian O'Neill and Michal explored the possibility of monitoring earthquakes by using Twitter. Earle (2010) also proved that social media can detect disasters much quicker compared with traditional methods. In the case of earthquakes, the transmission rate of messages on Twitter is significantly faster than that of seismic waves, thereby allowing potential victims to escape before the onset of the disaster (Allen, 2012). Crooks (2013) also considered social media superior to the “Do You Feel It?” program of USGS in terms of its speed and capacity of information dissemination.

Social media has also been commonly used for detecting other disasters. The number of studies on using social media during emergency situations, such as wildfires (De Longueville, 2009), flu outbreaks (Chew, 2010), storms (Neubauer *et al*., 2014), has recently increased. Chew (2010) found that during the 2009 H1N1 outbreak, people used Twitter to share information from credible sources, their personal experiences, and their opinions. De Longueville (2009) analyzed the temporal, spatial, and social dynamics of Twitter activity during a major forest fire event in Southern France in July 2009 and found that Twitter can act as a wildfire sensor that receives rich, free signals from the public. Tsuchida *et al*. (2012) constructed a neural network learning model that detects meteorological disasters by using social media data. Neubauer (2014) studied the trend of the social media data flow from 2013 to 2014 and successfully detected the outbreak of the Egyptian storm events. Musaev (2014) found that using social media data was more effective than using satellite remote data in monitoring dammed lakes.

Many researchers have also produced excellent outputs in this research area. To achieve a time tracking and reporting of earthquake information, Sakaki *et al*. (2010, 2013) designed a real-time earthquake detecting system based on Twitter data and then improved this system to achieve a 96% detection rate. After launching “Did You Feel It?,” USGS developed a Twitter Earthquake Detector, an earthquake detection system that operates over a filtered Tweet stream and even outperforms the “Did You Feel It?” program (Earle *et al*., 2012). CSIRO (Yin *et al*., 2012) developed an Emergency Situation Awareness platform in 2009 that analyses Twitter messages that are posted during disasters and crises. This platform uses natural language processing and data mining techniques to achieve an early detection of events and to extract crowdsource relevant information about a disaster.

Several other systems that monitor disaster information in a real-time by using social media include Twicident (Abel *et al*., 2012), Tweet4act (Chowdhury *et al*., 2013), CrisisTracker (Rogstadius *et al*., 2013), Ushahidi (http://www.ushahidi.com/), Twitter Earthquake Detector (Earle *et al*., 2012), Emergency Situation Awareness (Power, 2014), and EARS (Avvenuti *et al*., 2014).

Several types of disasters that may be difficult to detect cannot be easily felt (e.g., earthquakes with magnitudes of less than 3), and (3) occurring in less developed areas where most of the population do not use social media. The first two types of disasters often bring minimal damage, while the detection of the third type of disaster can be improved through the continuous development of ICT.

4.2.2. Rescue Function

Social media have the advantages of timeliness and interactivity, which are typical features of user-generated content. Therefore, social media platforms allow users to utilize their collective wisdom effectively and may provide disaster emergency responders with useful information that can help them in their work (Yates and Paquette, 2011). Natural disasters often cause serious damage to humans and their homeland and may even result in a large number of casualties and homelessness. Therefore, providing timely and reliable information about emergency services (Bird, 2012) and available shelter (Iwanaga, 2011) through social media is very important during the onslaught of disasters. People can also use social media to learn about health problems brought by these disasters (Boulos, 2011), to find missing persons and disaster-struck areas (Hjorth, 2011), and to obtain the latest information about disasters (Feldman, 2016).

The timely provision of emergency supplies can effectively reduce the number of casualties and losses resulting from disasters. Murakami *et al*. (2012) collected tweets published around the 2011 Japan earthquake and found dynamic changes in the demands of the earthquake victims. Specifically, the demands of these victims differed across each stage of the disaster response process. Therefore, apart from information dissemination, social media also plays an important role in facilitating rescue processes and identifying the demands of victims (Gao, 2011). The American Red Cross developed an application that detects tweets for help and plans the allocation of emergency supplies (Warner, 2010). By using social media data, Wang (2014) examined the disaster crowdsourcing medical rescue process, which has introduced a new hotspot in both research and practice and has inevitably attracted the attention of many researchers.

The location information available in social media also plays a key role in disaster relief processes. By using tweets published in Christchurch, New Zealand, Gelernter *et al*. (2011) separately applied the named entity recognition method (developed by Stanford University) and the manual method to extract detailed location information from the collected tweets. They also highlighted the importance of the place name dictionary and the natural language processing method in automatically identify the location information of tweets. Li (2012) built a buffer zone in the disaster impact area based on a set of collected tweets that can be used in disaster simulation research. Social media relies on three types of data, namely, registration data, automatic GPS recognition data, and local text information, to extract geographic information. The geographic information carried by disaster-related tweets provide rescuers with detailed information on the situation of disaster-struck areas (Vieweg *et al*., 2010) that can help them assess service risks and damages (Shklovski *et al*., 2010; Chun *et al*., 2012).

4.1.3. Recovery and Reconstruction Functions

Social media serve two important functions during the onset of disasters, namely, to meet the information needs of the public and to encourage their donations and participation in volunteer activities. After the occurrence of a disaster, the public is naturally concerned about what has happened in the disaster-struck areas and how they can help the victims. They can use social media to obtain the latest information about rescue efforts and to know about the state of the victims, thereby meeting their information demands and developing their awareness of the situation. Social media can also significantly broaden the channels for donations and volunteer recruitment (Zook *et al*., 2010). Seo *et al*. (2012) examined the social media posts published around the time of the Wenchuan earthquake and confirmed that publishing more disaster-related information will motivate the public to help the victims. Some studies have also shown that the number of social media posts during disasters is significantly and positively correlated with the amount of disaster donations (Lobb and Hutchinson, 2012; Martin, 2013). In general, public participation in emergency management often leads to chaos, but Sutton *et al*. (2008) showed that exchanging information over the Internet is more important than participating in emergency management efforts given that the effective communication of useful data over the Internet, including social media, can facilitate mutual coordination among volunteers and avoid confusion.

Another important function of social media during disasters is to provide psychological, emotional, and social support to the victims and their friends, families, or relatives(Neubaum *et al*., 2014, Bai and Yu, 2016).The public can also express their concerns about the disaster event and mourn the deaths of victims through social media (Taylor *et al*., 2012). As a user-based media platform, social media can also provide potential psychological and emotional support for those users who have suffered from a disaster (Keim, 2010). Lev-On (2012) showed that those people who have experienced disasters turn to social media to meet their emotional needs. Survivors of disasters can also contact their relatives and friends through social media to gain their social support, which is important in their rapid recovery (Vicary and Fraley, 2010). Ben-Ezra *et al*. (2013) examined the March 2011 earthquake in Japan and found that Facebook effectively provided emotional support to the victims of this disaster event (Karna *et al*., 2017). Similarly, Cao *et al*. (2013) examined the Wenchuan earthquake and found that social media can affect the personal and collective well-being of people living in disaster-struck areas. Disasters often destroy the social ties among local residents. However, social media provide these people with tools to repair or improve their social connections (Smith, 2010). This finding has been confirmed by related research on the L'Aquila earthquake in Italy (Casacchia *et al*., 2012).

After a disaster, people often explore ways to prevent and prepare themselves for the onslaught of disasters (Norris *et al*., 2008).Therefore, social media also provide people with a platform where they can discuss their experiences and the implications of disasters; this platform can also help rescue agencies communicate with the victims of disasters(Muralidharan *et al*.,2011).

4.2 Crisis Information Dissemination

Previous studies show that Internet users mainly use ICT tools to seek information and to reduce their uncertainty (Boyle, 2004). However, during the time of disasters, social media users not only receive but also create information. Therefore, social media are more effective than other tools in disseminating disaster-related information (Utz *et al*., 2013). Moreover, using social media is an effective way for generating, sharing, and disseminating disaster-related information (Bruns and Burgess, 2012; Hancer, 2017).

From the perspective of information dissemination, studies on the use of social media at times of disaster have mainly focused on several aspects will be discussed in the following sections.

4.2.1. User Behavior Characteristics

Social media has changed the traditional way of communicating disaster-related information (Brengarth and Mujkic, 2016). Generally, shortly after the occurrence of a disaster, people use mobile terminals to create disaster-related information (Sakaki *et al*., 2011) and publish such information in large amounts (Acar and Muraki, 2011). These people also use the reply and comment functions of these terminals to promote information exchange (Miyabe *et al*., 2012). Those people who are located in areas that are not heavily hit by the disaster usually let their relatives and friends know about their situation through social media and are willing to repost tweets related to the disaster (Thomson *et al*., 2012).

Sakaki *et al*. (2013) found that users of social media at times of disaster share some similar characteristics. For instance, their information dissemination activities increase their demand for additional information and stimulate their communication behavior (Sakaki *et al*., 2013). The information published by official sources tends to have a higher number of reposts and comments compared with those shared by unofficial sources (Toriumi *et al*., 2013; Steinberg *et al*., 2016). Meanwhile, gossip and rumors are often shared by anonymous users (Takahashi and Igata, 2012).

4.2.2. Spread of Public Opinion

Given the interactive diversification and rapid dissemination of information on social media, the impact of these technologies on public opinion continues to increase. Social media have gradually evolved from messaging technologies to important platforms where individuals and organizations seek and share real-time information (Cheng *et al*., 2011). After the occurrence of a disaster, users often publish their opinions about the disaster event through their social media accounts, thereby contributing to the publication of a large number of public opinions that are updated in real time. Tracking this type of information can also help other users assess the public opinion about disaster events. Social media can also be used to perform traditional crisis communication activities, such as restoring the normal state of an organization, affecting the perceptions of the public, and protecting one's reputation (Muralidharan *et al*., 2011; Utz *et al*., 2013). These crisis communication activities only represent a one-way use of social media in disaster situations. However, in fact, these tools must be used in two-way communication. Users can also investigate public opinion trends through social media (Heath *et al*., 2009). When disasters greatly affect the daily lives of social media users, a large number of these people post negative information about these events in their social media platforms (Chen *et al*., 2017). Their posts also sound emotional and direct, thereby increasing their diffusion rate. Unfortunately, studies in this field have largely focused on crisis communication and have completely ignored the importance of promoting public awareness about disasters through social media (Austin, 2012).

4.2.3. Authenticity and Security

Sakaki (2010) defined Twitter users as social sensors and their tweets as sensor signals that can be used to construct a large sensor network. He added that the path of the forwarding network of information related to earthquakes, typhoons, and other emergencies is very short and not as dense as the forwarding network of information related to other topics. Therefore, distinguishing rumors from accurate information in social media by using special features, such as burst points and forwarding rates are highly feasible. Previous studies have not only proposed effective methods for predicting the authenticity of disaster-related information posted on social media (Castillo *et al*., 2013) but also confirmed that social media have a self-cleaning function, that is, the false information is more likely to be questioned by social media users compared with real news. In his case study of the Haiti earthquake, Oh *et al*. (2010) found that reliable information can effectively relieve the panic and anxiety of social media users, thereby controlling the generation and spread of rumors.

5. Conclusions and Future Research

Social media are typical user-generated content platforms that use collective intelligence to support emergency response processes.

To provide a general overview of the research on mining disaster-related information from social media, this study constructs a comprehensive knowledge network. by performing a cluster analysis and social network analysis on a dataset taken from the WOS database. The high-frequency keywords are also mapped to the differences in the publication times of highly cited articles. The relevant studies on each topic have been analyzed and summarized in depth. The findings reveal the following characteristics of current research on this topic:

1. The importance of social media at times of disaster has been highlighted in many disaster emergency management practices and has attracted the attention of governments and research institutions. The statistical analysis of the sample dataset shows that the number of published documents and citations has obviously increased over the years, thereby indicating that using social media at times of disaster has become an important research area.

2. The stability of research hotspots in social media uses at times of disaster continues to change. The statistical analysis of the high-frequency keywords extracted from the sampled articles identifies the top 20 keywords with the highest frequency, including "crisis management," "crowdsourcing," "social networks," "emergency management," "information diffusion," "emergencies," "decision support," and "visualization." The subjects represented by these keywords are believed to be hotspots of disaster social media research. As the level of research in this area continues to grow deeper, related studies adopt new techniques, such as time series analysis, voluntary geographic information analysis, sentiment analysis, and space-time analysis.

3. The available research methods are becoming highly diverse. The early works on the use of social media at times of disaster have mostly relied on case studies, while many scholars take the Haiti earthquake, Japan earthquake, Hurricane Katrina, Queensland flooding, and other disaster events to study the behavioral patterns and information dissemination characteristics of social media users at times of disaster. Most of these studies have also adopted statistical analysis methods, such as descriptive statistical analysis and logistic regression. With the continuous improvement of natural language processing technologies and data mining methods as well as the flow of noisy disaster information in social media platforms, some scholars have begun to introduce improved automatic data mining technologies to analyze location information, URLs, texts, and diffusion networks from social media. The applicability and generalizability of their findings are also gradually improving.

A closer look at the literature, however, reveals a number of gaps and shortcomings. First, each type of disaster event, including earthquakes, heavy rains, and wildfires, has different contents and induces different interaction characteristics in social media platforms. Howaction characteristics in social media platforms. However, previous studies have mostly focused on a single type of disaster and have neglected its differences from the other types of disasters. Second, most studies in this field have relied on a statistical analysis of historical data without considering the temporal changes. In fact, disaster events and rescue processes are constantly evolving. Therefore, the content and dynamic interaction characteristics of users in social media must be considered. Third, many scholars have relied on a content-based qualitative analysis of social media posts that are published at times of disaster yet failed to conduct an in-depth quantitative mining of the emergency response functions of social media. Fourth, although many researchers are concerned about the spread of disaster-related public opinion on social media, only few studies have analyzed the emotions of disaster victims. Most studies have also failed to link the group emotions of these victims with the cluster behavior of people living in the disaster-struck areas. Social media are powerful tools that allow people to learn about the emotions and central issues being faced by disaster victims in real-time. Therefore, post-disaster crisis opinion must be analyzed and predicted by conducting a social media study. In sum, dynamics analysis, quantitative mining, and emotional calculations may become a future trend in disaster social media research.

6. Acknowledgement

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