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Review Article

A Review of Natural Disaster Management Trends in Social Media from 2009 to 2018

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Abstract

Natural disaster management in social media is becoming an important research subject in disciplines such as public administration and emergency response. In this study, an integrated bibliometric framework of qualitative and quantitative analyses was created to determine the research objectives, characteristics, and development trends of natural disaster management in social media. By using bibliometric analytical software tools, a co-keyword matrix was built to conduct spatiotemporal and clustering analyses of a bibliometric dataset on natural disaster management in social media research articles obtained from the Web of Science. Then, several major themes were summarised from the perspectives of emergency management and information dissemination. Based on the results of the spatiotemporal and qualitative analyses, the main themes and future trends of natural disaster management in social media research are identified. The findings of this study show that increasing attention is focused on the social media aspect of disaster management. Although the stability of research hotspots in social media used during times of disaster is changing, the research methods are becoming highly diverse. This study helps to map the present and future conditions of social media use in disaster management.

Keywords: Disaster management, Social media, Spatiotemporal analysis, Cluster analysis, Social network analysis

1. Introduction

Disaster emergency decision-making requires strong support from a fast-responding emergency information system. Efficient information communication is a key part of disaster management and can reduce the casualties and losses resulting from disasters [1]. With the rapid development of social networking services (SNS), the role of Internet technology in disaster management has become increasingly significant. Social media has become an influential Internet communication technology that contributes toward improving disaster communication processes in terms of information capacity, dependability, and interactivity [2]. Advanced big data tools, such as Hadoop, enable a large amount of social media information to be collected, stored, and processed easily [3, 4]. A case study of Hurricane Katrina revealed that social media are more important sources of information during disaster events than any conventional form of media [5]. In a social survey of adults in the United States, majority of the respondents perceived the usefulness of social media when informing their relatives and friends about what is going on during emergencies (American Red Cross 2012). Social media have also changed the entire process of communicating disaster information to society [6]. According to Bruns et al. [7], 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 issues such as the role of social media in disaster events and how the process of communicating disaster information can 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.

To address this research gap, the present study analyses articles on this topic from the Web of Science (WOS) database, explore the latest international research subjects and examines the key research topics in various areas to forecast the direction of research in this field. Usually, the analysis of a significant amount of scientific literature in a research field is followed by bibliometrics, which provides a systematic analysis of the research system across periods and places [8, 9]. The bibliometric analysis uses data on authors, articles, and citations to measure the influence of researchers, identify research networks, and map the development of new fields of scientific study [10]. Various mathematical and statistical methods are frequently used in quantitative bibliometric research to reveal hidden internal relations in the literature. This study conducts spatiotemporal analysis, cluster analysis, and social network analysis (SNA) to explore and trace the development of networks of natural disaster management in social media research. In bibliometrics, spatiotemporal analysis collects data from scientific articles and publications classified based on their authors and/or institutions, scientific field, and country to construct simple "temporal productivity" and "spatial productivity" indicators for academic research.

2. Methodology

Cluster analysis is commonly applied in statistical data analysis and fields such as machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics. In bibliometrics, cluster analysis of group articles is based on keywords and their relationships. The main idea behind cluster analysis is that papers that need to be clustered into a group must be similar to other papers in the same group and different from those in other groups.

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This study focuses on the semantic co-occurrence of keywords.

Co-word analysis uses the co-occurrence patterns of keyword pairs in a corpus of papers to discover relationships among the ideas presented in these papers. Previous studies have identified co-word analysis as a powerful tool for identifying focused themes on a specified subject and determining their relationships, which are key to the development of an entire research field. This study employs hierarchical cluster analysis to extract such themes. A co-word matrix of high-frequency keywords can be created by processing the samples from the WOS database (see section 3 for details). Each value in this co-word matrix represents the co-occurrence frequency of its row-keyword and col-keyword. However, due to the large difference in the frequency of the co-word matrix, converting the co-word matrix into a dissimilar matrix before clustering is necessary. A few methods are available for pre-processing differences in frequencies of the keywords in a co-occurrence matrix. Following Zhou and Leydesdorff [11], this study normalizes this matrix by using Ochiai coefficient, which measures the similarity between two datasets. This coefficient is also known in biology as Ochiai–Barkman or Otsuka–Ochiai coefficient, which is defined as the quotient of the intersection and the average size of two sets.

Thereafter, this study constructs 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. Then, this study transforms this matrix into a dissimilarity matrix to eliminate the effect of the differences in frequencies between co-words. The values in this matrix are computed by adding -1 to the values in the correlation matrix. The matrix processing flow is shown in Fig. 1.

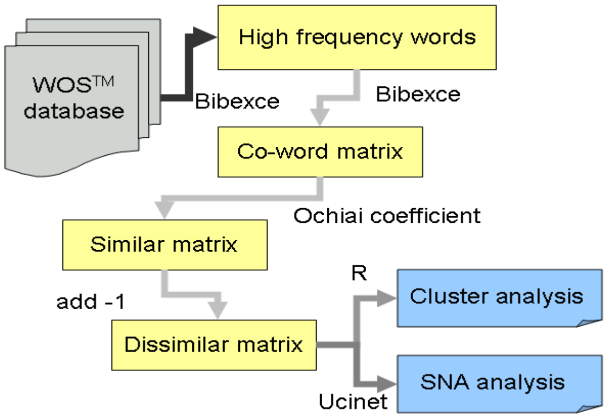

Fig. 1. Co-word matrix processing steps

3. Results Analysis

The sample dataset used in this study was obtained from the WOSTM database on December 31, 2018. To retrieve the maximum number of samples, the study adopted the search strategies TS = (“calamity *OR “disaster*” OR “catastrophe*” OR “hazard*”) and TS = (“social media” OR “twitter* OR “micro-blog” OR “microblogging*” OR “micro-blog” OR “microblog” OR “Weibo OR “Tweet*”). Eventually, a sample dataset of 539 articles was obtained. To refine the sample data, this study manually judges whether “disaster” and “social media” are the main research objects of these studies by checking their titles, abstracts, and keywords. Thereafter, 451 of the 539 documents have been stored. Then, we perform several pre-processing steps, that is, the HistCite online analysis tool was used for the spatiotemporal analysis. HistCite can perform bibliometric process on the literature data downloaded from the WOS database and produce a TXT list of articles, authors, and journals for spatiotemporal analysis. By uploading the dataset into HistCite, the statistics of publication date and author’s country were directly obtained, as shown in Fig. 2.

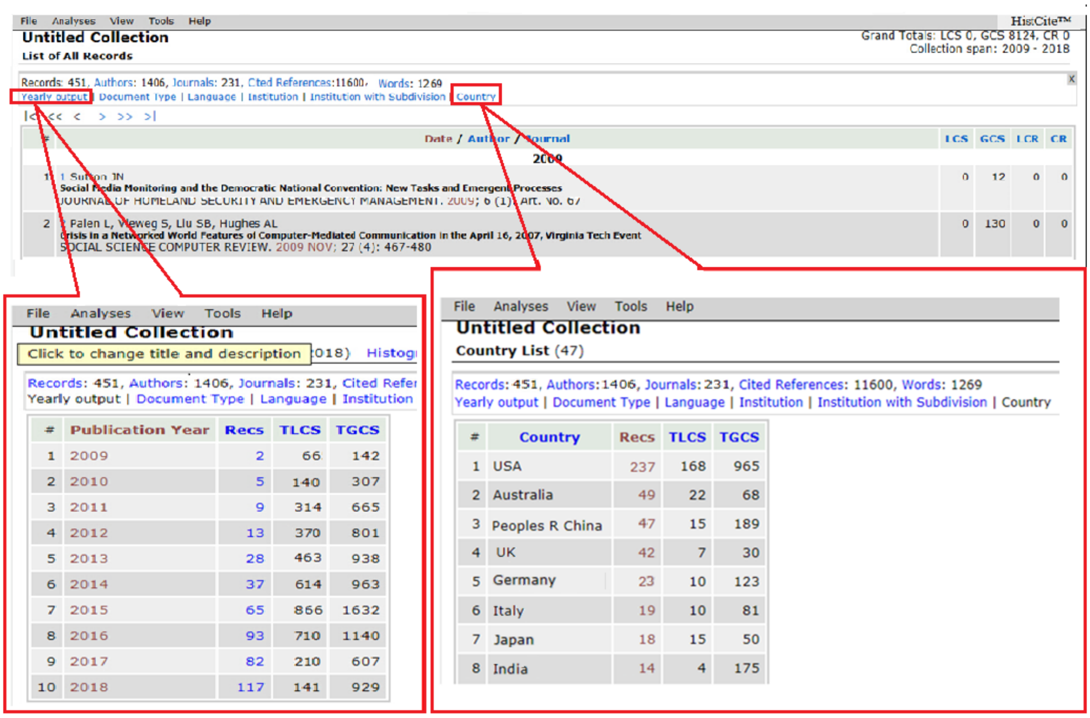

Fig. 2. Screenshots of HistCite online analysis tool

Then, the keyword co-occurrence matrices were built based on the sample dataset by using BibExcel, a bibliometric software developed, which can produce net files for co-keywords, co-citations, and other data. Thereafter, this study converts these files to conduct further analysis and visualisation with Ucinet. The detailed steps are shown in Fig. 3.

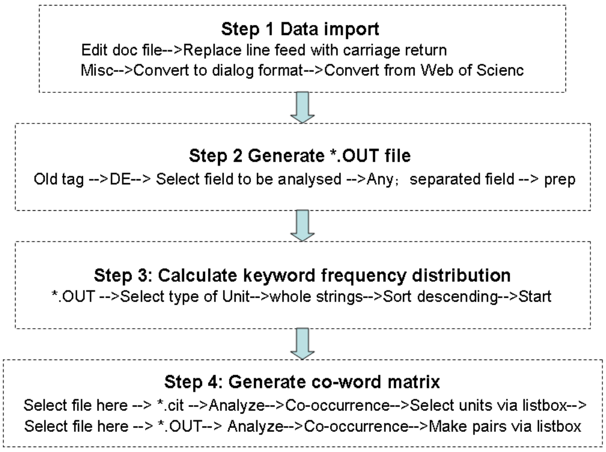

Fig. 3. Steps in co-word matrix generation by BibExcel software

Several steps are followed to obtain the sample dataset in a format applicable to BibExcel. As shown in Fig. 3, to import and convert the files, this study performs the commands “Edit doc file/Replace line feed with carriage return” and “Misc/Convert to dialog format/convert from Web of Science” from the menu as the first step in using BibExcel. Then, step 2 (Fig. 3) helps us obtain .a file for further analysis. Frequencies of the keywords in the output file are generated by selecting and sorting the information to obtain a .cit format file (see step 3 in Fig. 3). From the .cit file, the most popular keywords in the source papers can be viewed. Finally, a co-word matrix was generated from the .cit format file by conducting step 4, as shown in Fig. 3.

3.1 Spatiotemporal Analysis

Distribution of the article publication time effectively reflects the theoretical level and development pace of academic research in this area. As shown in Fig. 4, the Recs bar indicates the number of published papers in the WOS database. In recent years, social media has played an important role in disaster management. Although early social media tools, such as blogs and Facebook, can also disseminate disaster information, the technology that promotes research in this area is Twitter, where every Tweet has a 140-word limit. This platform reflects the perfect combination of instant messaging and social media.

As shown in Fig. 4, due to delays in publishing, the first journal paper in our database was published in 2009. Then, a growing number of researchers started focusing on the role of social media in disaster management. From 2009 to 2018, the number of studies (illustrated by the value of each bar) gradually increased, which means that the use of social media during disaster events is transforming from a new frontier into a major issue.

In the following sections, data from the countries of authors are analyzed statistically. This task is also done on HistCite. As shown in Fig. 3, the country shortcut helps to obtain statistics on the authors’ country items. The results show that 1,406 authors are actively publishing articles in this field. By exploring the nationality of these authors, we screen out the affiliations of the first 93 authors and set a threshold of two publication records. This study finds that the most productive authors are from top universities, research institutions, and international organizations. As shown in Fig. 5, the universities and research institutions from the US and Europe have published the largest number of papers on social media usage in times of disaster. Asian (e.g., Japan and China) and South Pacific (e.g., Australia) countries have published several articles, while Russia and other countries from Africa and South America have published only a few articles in this area. Although this phenomenon is influenced by both English language proficiency on the WOS database and the poor research foundation of some developing countries, this statistic also objectively reflects the basic regional situation of natural disaster management in social media research.

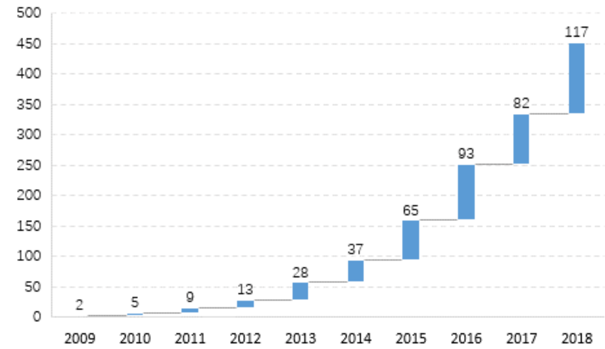

Fig. 4. Publication years of sample papers

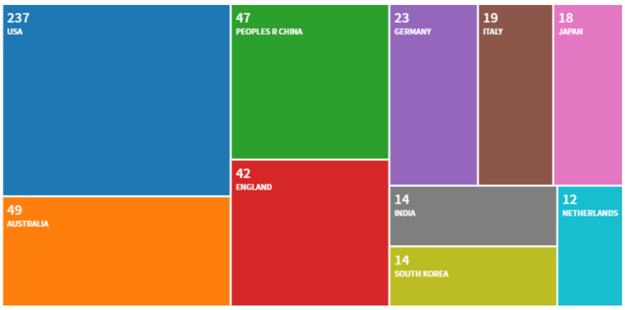

Fig. 5. Global distribution of related papers based on nationality of their first authors

The spatiotemporal analysis of the sample data shows that the important role of social media in disaster management has been widely recognized and valued worldwide. Due to the popularity of the technologies, many early studies are from developed countries and a core research group from the US, Europe, Australia, and Japan has been formed. At the same time, relevant research in developing countries is rapidly unfolding and deepening. The number of papers in this field coming from developing countries is expected to increase in the future.

3.2 Cluster Analysis

As illustrated in Section 2, co-word analysis is the basis of cluster analysis, which can be statistical metadata in the knowledge discovery process. Co-word analysis uses co-occurrence patterns of word pairs in a document dataset to identify the relationships between content presented in the documents. The objective of the co-word analysis is to establish a co-word matrix. BibExcel software is used in this study to analyze sample datasets, identify keywords and their co-occurrence patterns, and build co-word matrices. By importing a sample dataset with 451 extracted papers into BibExcel (see Fig. 2 for detailed steps), 1,269 keywords provided by the authors were identified and examined.

Then, according to the third step presented in Fig. 3, the frequencies of all the keywords were calculated. In general, only high-frequency keywords were selected to construct a co-word matrix and low-frequency keywords were disregarded due to insufficient representation. Thus, 100 keywords with the highest frequencies were selected for the next quantitative analysis.

Table 1 shows the top 30 keywords highlighting significant differences in their occurrences. Several other high-frequency keywords, such as “social media” and “Twitter,” were not deemed meaningful for the subsequent analysis, so these keywords were removed and their synonyms manually were merged. Thereafter, 89 keywords in the sample were retained to use in constructing an 89*89 co-occurrence matrix.

Table 1. Top 30 keywords with the highest frequencies

Frequency	Keywords	Frequency	Keywords	Frequency	Keywords
25	Crowdsourcing	9	Data mining	6	Hurricane Sandy
22	Emergency management	8	Sentiment analysis	6	Earthquakes
18	Risk communication	7	Event detection	6	Disaster communication
18	Disaster response	7	Crisis management	5	Content analysis
17	Communication	6	Risk perception	5	Earthquake
16	Crisis communication	6	Text mining	5	Crisis informatics
14	Social network analysis	6	Flood	5	Crisis mapping
10	Volunteered geographic information	6	Information retrieval	5	Natural language processing
10	Big data	6	Machine learning	4	Situational awareness
10	Emergency response	6	Mass media	5	Evacuation

As mentioned, the distance between the keywords is calculated by hierarchical clustering on co-word matrices, and then the keywords with more co-occurrences are gathered into the same group. The research content of natural disaster management in social media can be divided into two large groups, and each can continue to be divided further into several smaller groups. This clustering algorithm uses mathematical statistics to conduct bibliometric analysis, which is fast, accurate, and objective. Additionally, the algorithm overcomes the subjective disadvantage of expert manual classification. However, hierarchical clustering cannot identify important representative keywords. Analysis of each group of keywords is needed to infer the characteristics of various groups after the hierarchical clustering. In addition, one keyword can be placed into a class through hierarchical clustering, causing some relationships between the groups to be neglected. In fact, different groups often interact with one another and share keywords. Due to the deficiencies in hierarchical clustering, SNA was introduced to explore the internal characteristics of the group in depth and analyze the relationships between the groups carefully.

In summary, after the manual investigation of 100 high-frequency keywords selected through BibExcel software, an 89*89 high-frequency keyword co-occurrence matrix is determined. From hierarchical clustering analysis of this co-word matrix, all the ideas within the subject areas presented in these sample papers are grouped into “emergency management” and “crisis information dissemination” core direction and several sub-issues embodied by them.

3.3 SNS

By using UCINET software, an SNS knowledge graph (as shown in Fig. 6) is mapped according to the co-word matrix. Social network centrality analysis is an important part of SNS analysis to explore the status of each node. In general, degree centrality is widely used in SNS analysis to identify the important nodes in a social network map. In this study, each node acts for a keyword in the aforementioned co-word matrix. A link between two nodes (keywords) means that the keywords have a co-occurrence relationship in the sample dataset. Specifically, the degree centrality of a node (keyword) is the number of its links with the other nodes (keywords). Thus, the degree centrality of one node can reflect its connection (co-occurrence) to the other nodes (keywords). A node, which is a keyword with a higher degree centrality, has a better chance of being in a hot research issue.

As shown in Fig. 6, the size of the keyword node is proportional to its degree centrality (links/frequency of occurrence in the co-word network), that is, the larger the node is, the greater is its influence in the network. According to the degree centrality calculation results and the node sizes shown in Fig. 6, the following 10 keywords are ranked the highest: “response,” “communication,” “disaster management,” “crowdsourcing,” “information management,” “mapping,” “situation awareness,” “sentiment analysis,” “crisis informatics,” and “event detection”. These keywords occupy the centre “status” in the co-word network, which means that they are more important than the other words. Many papers use these terms as keywords, and they are closely related to other important keywords. For example, the keywords “communication” and “disaster management” occupy the central position with many connected keywords that echo the clustering results. Then, we look back at the public time of these important keywords and find that some emerging keywords such as “mapping” and “sentiment analysis” appear relatively late, but their degree centralities are very high. This result indicates that the research directions they represent are emerging hot issues. Besides, density reflects the closeness of node members in social networks. A greater density indicates a closer relationship among members.

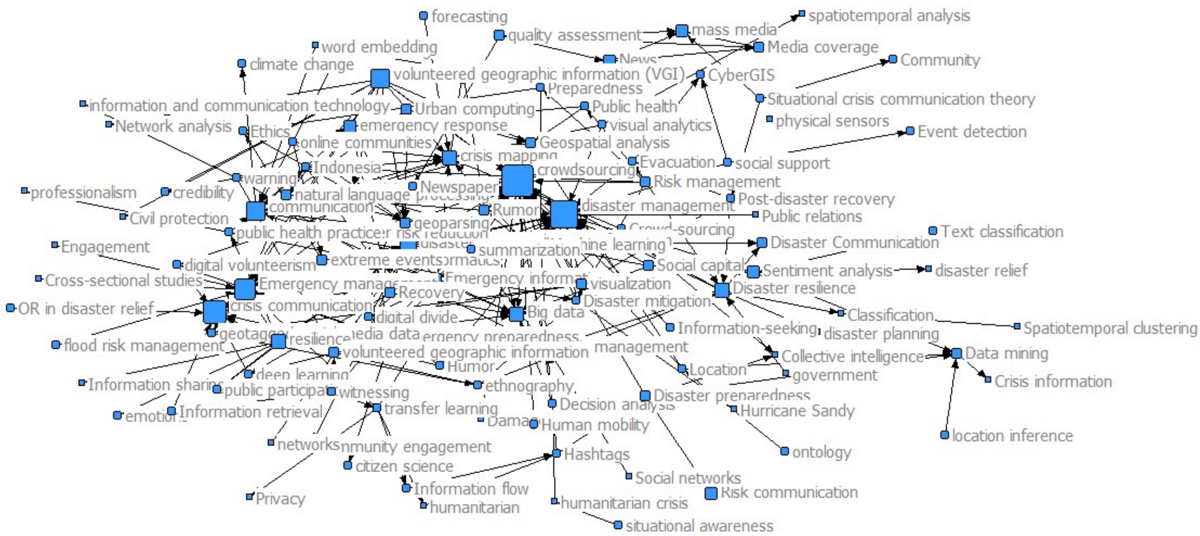

Fig. 6. SNS knowledge map

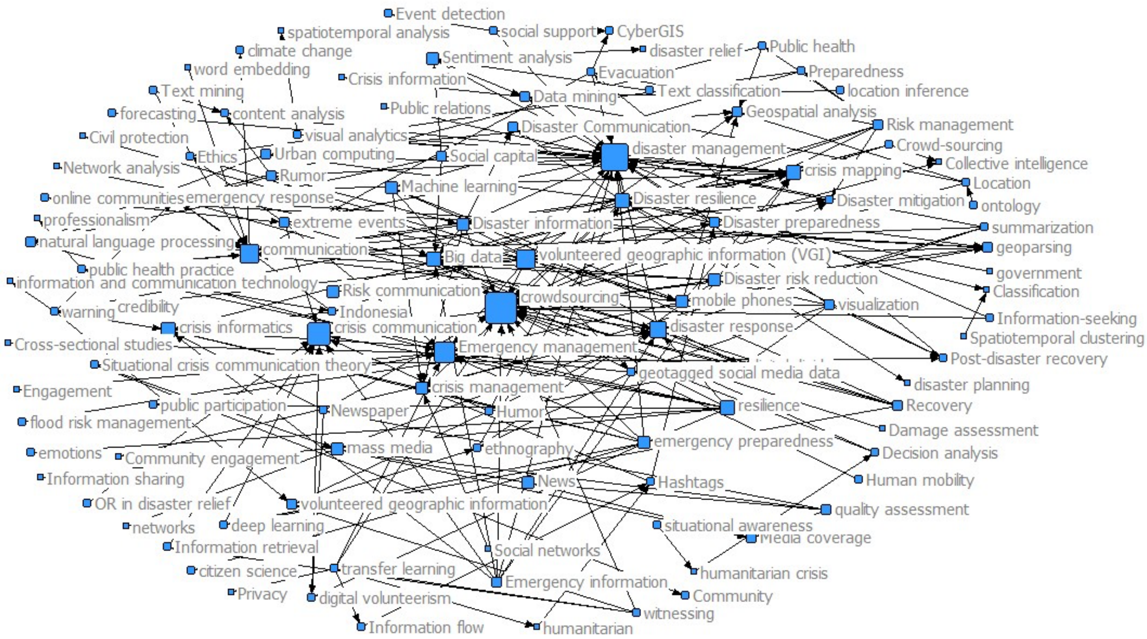

Fig. 7. Comprehensive knowledge map

Thus, considering the results of the analyses, the articles were examined that contain high-frequency keywords to determine the content behind these keywords. Eventually, we group the research topics into two research areas focusing 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 centre and eventually form a comprehensive knowledge map as shown in Fig. 7. The two aforementioned research areas represent two internally clustered keyword groups, with each group containing representative keywords that reflect the core content.

Fig. 7 shows the complex connections among the keywords used in social media research about natural disaster management. To a certain extent, these connections reflect the knowledge fusion and multidimensional characteristics of international social science research on the usage of social media in disaster situations from the perspective of emergency management and information dissemination. The following sections further analyze and discuss the relevant research topics from these two perspectives.

The WOS dataset was used to conduct spatiotemporal analysis of a randomly selected published year and author's countries. The result indicates that a growing number of researchers pay attention to disaster management in social media. Recently, most of the papers have come from developed countries such as the US, Australia, and others. This phenomenon may be related to the widespread use of social media tools in these countries. Then, on the basis of the co-keyword matrix, hierarchical clustering is conducted to classify high-frequency keywords into different groups. The preceding results indicate that all the papers are focused on two processes: emergency management and crisis information dissemination. Then, SNS is performed to explore the importance and interaction with keywords, which concludes that the overall structure of disaster management in social media research is characterized by partial concentration. Some hot keywords are closely related to the central node (communication and disaster management), constituting the main structure of the SNS map. Hierarchical clustering helps us know the details of all keyword classes but does not analyze the importance of keywords and the interaction between different classes. SNA can explore the keyword connections and their strength, but cannot reflect a clear class of the keywords. Thus, according to the results of hierarchical clustering and SNS, a comprehensive knowledge map is created manually. On this map, each keyword is around the central node in its group, which is useful and intuitive for the following qualitative discussion.

4. Key Research Topics

By using the bibliometric tools to draw the knowledge maps, the structural research relationship of disaster management in social media can be determined. However, this study needs a deeper understanding of the research status and development based on the knowledge map. According to the results of the preceding quantitative analysis, this section combines the meanings of keywords and related highly cited papers to explore the main viewpoints, research paradigms, internal connections, and structures of the international academic community on disaster management in social media.

4.1 Emergency management

Previous case studies on disasters, such as the Asian tsunami and Queensland flooding, reveal that social media provide a large amount of first-hand information for disaster relief and mitigation processes [12]. As effective platforms for exchanging messages, social media platforms play an important role in disaster management and can significantly improve disaster emergency management processes [13].

4.1.1 Disaster event detection and early warning

Lasswell cited three functions of communication in his work “Communication Process and Its Function in Society”. The first of these functions is environmental monitoring, which focuses on the most important function of mass communication. The mass media constantly provides 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 the US Geological Survey (USGS) [14].

Twitter is another social media platform with plenty of information related to natural disasters, such as the earthquakes in Wenchuan (China, 2008), Los Angeles (US, 2009), and Morgan Hill (US, 2009). Earle et al. [15] proved that social media can detect disaster information much quicker than traditional media can. 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 prepare for evacuation before disaster happens [16]. Crooks et al. [17] also considered social media superior to the “Did You Feel It?” program of the USGS in terms of speed and capacity of information dissemination.

Social media has also been widely used in detecting other disasters. The number of studies on using social media during emergencies, such as wildfires [18], flu outbreaks [19], and storms [20], has recently increased. Chew and Eysenbach [19] found that during the 2009 H1N1 outbreak, people used Twitter to share information from credible sources, their personal experiences, and their opinions. Musaev et al. [21] 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 timely tracking and reporting of earthquake information, Sakaki et al. [22] designed a real-time earthquake detection system based on Twitter data and then improved this system to achieve a 96% detection rate. After launching “Did You Feel It?,” the USGS developed a Twitter earthquake detector that operates over a filtered Tweet stream and even outperforms the USGS program [15]. CSIRO developed an emergency awareness platform in 2009 that analyses Twitter messages posted during disasters and crises. This platform uses natural language processing (NLP) and data mining techniques to achieve early detection of events and extract crowd-sourced relevant information about a disaster [23]. Other systems that monitor disaster information in real-time by using social media are CrisisTracker [24], Twitter earthquake detector [15], Emergency Situation Awareness, and EARS.

Several types of disasters may be difficult to detect by using social media platforms. These disasters include (1) those occurring in less populated areas, (2) those that cannot be easily felt (e.g., earthquakes with magnitudes of less than 3), and (3) those 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.

4.1.2 Rescue function

Social media are timely and interactive; these are typical features of user-generated content. Therefore, social media platforms allow users to utilise their collective wisdom effectively and may provide disaster emergency responders with useful information that can help them in their work [25]. Natural disasters often cause serious damage to humans and their homeland and may even result in homelessness and a large number of casualties. Providing timely and reliable information on emergency services [26] and an accessible shelter [27] is very important during the onslaught of disasters. People can also use social media to learn about health problems brought by these disasters [28], find missing persons and disaster-struck areas [29], and obtain the latest information about disasters [30].

The timely provision of emergency supplies can effectively reduce the number of casualties and losses resulting from disasters. Apart from information dissemination, social media also play an important role in facilitating rescue processes and identifying the demands of victims [31]. The American Red Cross developed an application that detects tweets for help and plans the allocation of emergency supplies. By using NLP technology on social media data, some researchers such as Deng et al. [32] and Wang et al. [33] have examined the disaster crowdsourcing process, which has introduced a new hotspot and 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. [34] separately applied the named entity recognition method developed by Stanford University and the manual method to extract detailed location information from the collected tweets. The researchers also highlighted the importance of the place name dictionary and the NLP method in automatically identifying the location information of tweets.

Simulation technologies are useful in emergency management [35]. 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 provides rescuers with detailed information on disaster-struck areas so that they can assess service risks and the extent of damage [36].

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 encourage donations and participation in volunteer activities. After a disaster, the public is naturally concerned about what has happened in disaster-struck areas and how they can help victims. People use social media to obtain the current information on rescue efforts and 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 [37]. Seo et al. [38] examined the social media posts published around the time of the Wenchuan earthquake and confirmed that publishing more disaster-related information motivated 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 number of donations to support the victims [39, 40]. In general, public participation in emergency management often leads to chaos, but Sutton et al. [41] 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 prevent confusion and facilitate mutual coordination among volunteers.

Another important function of social media during disasters is providing psychological, emotional, and social support to the victims and their relatives and friends [42, 43]. The public can express their concerns about the disaster and mourn the deaths of victims through social media [44]. As a user-based platform, social media can provide potential psychological and emotional support for individuals who have experienced a disaster [45]. Lev-On [46] showed that people who have experienced disasters turn to social media for emotional support. Survivors of disasters can also contact their relatives and friends through social media, which can help in their rapid recovery [47]. Ben-Ezra et al. [48] and Miura et al. [49] examined the March 2011 earthquake in Japan and found that Facebook effectively provided emotional support to the victims of the disaster. Similarly, Cao et al. [50] 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 residents, but social media can provide people with tools to repair or improve their social connections [51]. This finding has been confirmed by a related study on the L'Aquila earthquake in Italy [52]. After a disaster, people often explore ways to prepare for a disaster and prevent another one. Therefore, social media serves as a platform where people can discuss their experiences and the implications of disasters. This platform can also help rescue agencies communicate with the victims of disasters [53]. In addition, as Gandomi et al. [54] pointed out, the key feature of social media is big data. To use social media data reasonably and efficiently, scholars have employed various content-based and structure-based analytic techniques to extract information from the noisy big data stream. Notably, topic discovery and event detection algorithms are expected to solve a large volume of problems involving social media data [2].

The application of social media tools, such as Twitter in disaster management, has become more extensive and deep. In 2008, after the Wenchuan earthquake in China), situation awareness tweets appeared immediately, followed by updates after the first post. This phenomenon has attracted the attention of many researchers in this area. After the Japan earthquake in 2011, a large amount of first-hand information was published on Twitter, which was the fastest source of information after the event. When Hurricane Sandy hit the United States in 2012, social media was already an indispensable part of disaster response, filling the gap in traditional telecommunication services. Millions of American citizens used Twitter to find friends and relatives after the disaster, as well as to inform organizations and express their support for the victims. During the 2013 flood in Yuyao, China, many people who were trapped in their homes shared their situation information through Weibo (a Chinese platform similar to Twitter), and organizations scanned their posts to find victims and deliver supplies as soon as possible. Facebook also provided a person-tracing service during the Nepal earthquake in 2016. Recently, with the further integration of GIS and NLP technology, social media has gradually penetrated disaster relief operations. The Mexico earthquake in 2017 was another good example of the widespread use of social media to organize civic volunteers to save lives. The victims used social media to ask for food, clothing, and medical assistance. Volunteers then coordinated with others to deliver the necessary supplies.

From the perspective of social media users, this study divides all the users in disaster communication into two types: individuals and organizations. Individuals refer to persons who use social media, while organizations are official and unofficial rescue agencies (including news organizations). Fig. 8 shows the ideas presented in the sample papers and briefly lists the important role of social media in different stages of disaster emergency management from the perspectives of individuals (lower part) and organizations (upper part). In other words, as an important mode of interaction and source of first-hand disaster information, social media has become an inevitable part of disaster management.

4.2 Crisis information dissemination

Previous studies show that Internet users mainly use ICT tools to seek information and reduce the uncertainty they perceive [55]. However, during 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 [56]. Moreover, using social media is an effective way to generate, share, and disseminate disaster-related information [7]. From the perspective of information dissemination, studies on the use of social media in times of disaster have mainly focused on several aspects, which are discussed in the following sections.

4.2.1 User behaviour characteristics

Social media has changed the traditional way of communicating disaster-related information [57]. In general, shortly after the occurrence of a disaster, people use mobile terminals to create disaster-related information [22] and publish such information in large amounts [58]. People also use the “reply” and “comment” functions of these terminals to promote information exchange [59]. People who are in the areas that are not damaged heavily usually let their relatives and friends know about their situation through social media and are willing to repost tweets related to the disaster.

Sakaki et al. [22] found that in times of disaster, social media users share some similar characteristics. For instance, their information dissemination activities increase their demand for additional information and stimulate their communication behaviour. The information published by official sources tends to have a higher number of reposts and comments compared with those shared by unofficial sources [60]. Meanwhile, gossip and rumours are often shared by anonymous users [61].

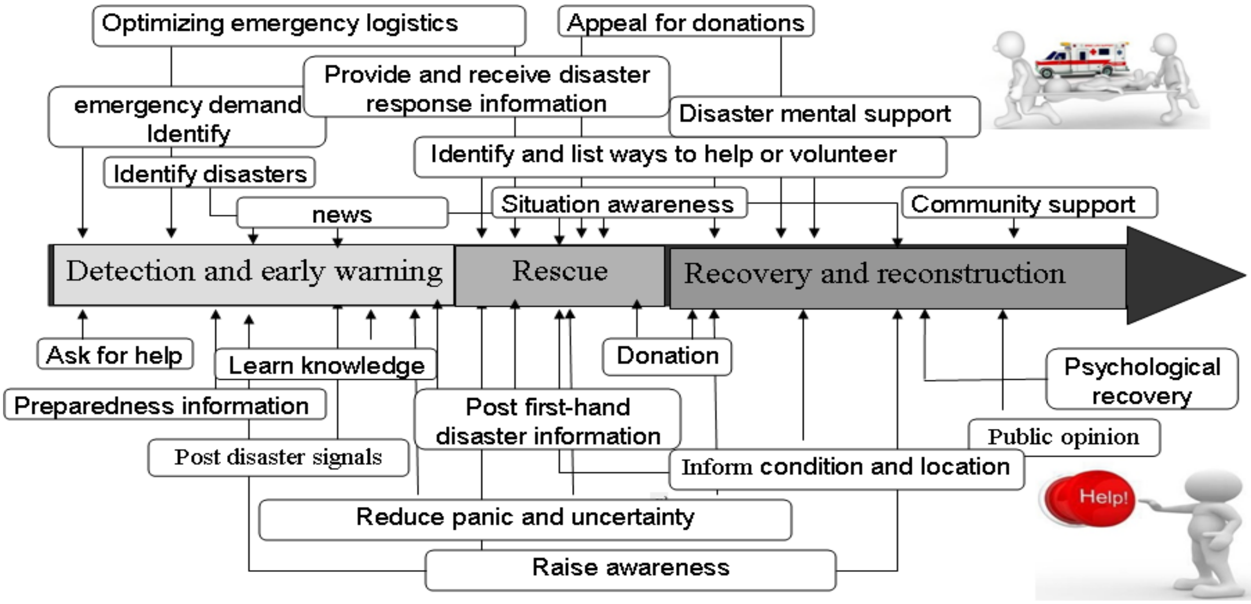

Fig. 8. Actions of social media in disaster management process

4.2.2 Spread of public opinion

Given the interactive diversification and rapid dissemination of information in 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 [62]. After the occurrence of a disaster, users often publish their opinions through their social media accounts, thereby contributing to a large volume of opinions that are updated in real-time. Tracking this type of information can help other users assess 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, influencing public perception, and protecting one’s reputation [56]. These crisis communication activities only represent a one-way use of social media in disaster situations, but they can be used in two-way communication. Users can also investigate public opinion trends through social media [63]. When disasters greatly affect the daily lives of social media users, many people post negative information about these events on their social media platforms [64]. The emotional and direct tone of some posts increases 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 [65].

5. Conclusion

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 disaster-related information from social media, this study constructed a comprehensive knowledge network by performing cluster and social network analyses on a dataset taken from the WOS database. The high-frequency keywords were mapped to the differences in the publication times of highly cited articles. The relevant studies on each topic were summarised and analyzed, and the findings revealed the following:

(1) The importance of social media in 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 increased over the years, showing that the use of social media during disaster periods has become an important research area.

(2) The stability of research hotspots in social media use in times of disaster continues to change. The subjects represented by the identified keywords with the highest frequency keywords are believed to be hotspots of natural disaster management in social media. As the level of research in this area continues to grow deeper, related studies adopt new techniques, such as time-series, voluntary geographic information, sentiment, and space-time analyses.

(3) The available research methods are becoming highly diverse. Early works on the use of social media in 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 behavioural patterns and information dissemination characteristics of social media users during such times. Most of these studies have also adopted statistical analysis methods, such as descriptive statistical analysis and logistic regression. With the continuous improvement of NLP technologies and data mining methods, as well as the flow of noisy disaster information on social

media platforms, some scholars have begun to introduce improved automatic data mining technologies to analyze location information, URLs, text, and diffusion networks from social media. The applicability and generalisability of their findings are also gradually improving.

A closer look at the literature, however, reveals gaps and limitations. First, each type of disaster event, such as earthquakes, heavy rains, and wildfires, is characterized by different content and induces various interaction characteristics on social media platforms. However, previous studies have mostly focused on a single type of disaster and neglected its differences from other types. Second, most studies in this field have relied on statistical analysis of historical data without considering temporal changes. In fact, disaster events and rescue processes are constantly evolving. Therefore, the content and dynamic interaction characteristics of social media users must be considered. Third, many scholars have relied on a content-based qualitative analysis of social media posts that are published in times of disaster yet failed to conduct 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, few studies have analyzed the emotions of disaster victims. Most studies have also failed to link the group emotions of these victims to the cluster behaviour of people living in disaster-struck areas. Social media are powerful tools that enable people to learn about the emotions and central issues 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, dynamic analysis, quantitative mining, and emotional calculations may become a trend in natural disaster management in social media.

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References

1. Houston, J. B., Hawthorne, J., Perreault, M. F., Park, E. H., Goldstein Hode, M., Halliwell, M. R., Turner McGowen, S. E., Davis, R., Vaid, S., McElderry, J. A. & Griffith, S. A. "Social media and disasters: a functional framework for social media use in disaster planning, response, and research", *Disasters*, 39(1), 2015, pp. 1-22.
2. Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. "Social media analytics–challenges in topic discovery, data collection, and data preparation," *International Journal of Information Management*, 39, 2018, pp. 156-168.
3. Venganzones-Bodon, M. "Machine learning challenges in big data era", *DYNA*, 94(5), 2019, pp. 478-479.
4. Picon Ruiz, A. R. T. Z. A. I., Alvarez Gila, A. I. T. O. R., Irusta, U., & Echazarra Huguet, J. O. N. E. "Why deep learning performs better than classical machine learning?," *DYNA* ,95(2), 2020, pp. 119-122
5. Macias, W., Hilyard, K., & Freimuth, V. "Blog functions as risk and crisis communication during Hurricane Katrina," *Journal of Computer-Mediated Communication*, 15(1), 2009, pp. 1-31.
6. Jung, J. Y., & Moro, M. "Multi-level functionality of social media in the aftermath of the Great East Japan Earthquake," *Disasters*, 38(s2), 2014, pp. 123-143.
7. Bruns, A., & Hanusch, F. "Conflict imagery in a connective environment: audiovisual content on Twitter following the 2015/2016 terror attacks in Paris and Brussels. *Media Culture & Society*, 39(8), 2017, pp. 016344371772557.
8. Ospina-Mateus, H., Quintana Jiménez, L. A., Lopez-Valdes, F. J., & Salas-Navarro, K. "Bibliometric analysis in motorcycle accident research: a global overview," *Scientometrics*, 121, 2019, pp.793-815.
9. Bambo, T. L., & Pouris, A. "Bibliometric analysis of bioeconomy research in South Africa", *Scientometrics*, 125, 2020, pp. 29-51.
10. Latapi Agudelo, M. A., Johannsdottir, L. & Davidsdottir, B. A. "Literature review of the history and evolution of corporate social responsibility," *International Journal of Corporate Social Responsibility*, 4, 2019, pp. 1.
11. Zhou, Q., & Leydesdorff, L. "The normalization of occurrence and Co-occurrence matrices in bibliometrics using Cosine similarities and Ochiai coefficients," *Journal of the Association for Information Science and Technology*, 67(11), 2016, pp.2805-2814.
12. Thelwall, M., & Stuart, D. "RUOK? Blogging communication technologies during crises," *Journal of Computer-Mediated Communication*, 12(2), 2007, pp.523-548.
13. Murphy, R. R. "Emergency informatics: using computing to improve disaster management," *Computer*, 5, 2016, pp.19-27.
14. Kropivnitskaya, Y., Tiampo, K. F., Qin, J., & Bauer, M. A. "Real-time earthquake intensity estimation using streaming data analysis of social and physical sensors," *Pure and Applied Geophysic*s, 174(6), 2016, pp.1-19.
15. Earle, P., Guy, M., Buckmaster, R., Ostrum, C., Horvath, S., & Vaughan, A. "OMG earthquake! Can Twitter improve earthquake response?", *Seismological Research Letters*, 81(2), 2010, pp. 246-251.
16. Allen, R. M. "Transforming earthquake detection?", *Science*, 335(6066), 2012, pp. 297-298.
17. Crooks, A., Croitoru, A., Stefanidis, A., & Radzikowski, J. "# Earthquake: Twitter as a distributed sensor system", *Transactions in GIS*, 17(1), 2013, pp. 124-147.
18. Sachdeva, S., Mccaffrey, S., & Locke, D. "Social media approaches to modeling wildfire smoke dispersion: spatiotemporal and social scientific investigations," *Information Communication & Society*, 20(7-8), 2016, pp. 1146-1161.
19. Chew, C., & Eysenbach, G. "Pandemics in the age of Twitter: content analysis of Tweets during the 2009 H1N1 outbreak", *PloS One*, 5(11), 2010, pp. 1-10.
20. Robert, G., Rice, & Patric R. S. "Thor visits lexington: Exploration of the knowledge-sharing gap and risk management learning in social media during multiple winter storms," *Computers in Human Behavior*, 65, 2016, pp. 612-618.
21. Musaev, A., Wang, D., & Pu, C. "LITMUS: a multi-service composition system for landslide detection," *IEEE Transactions on Services Computing*, 8(5), 2014, pp. 715-726.
22. Sakaki, T., Okazaki, M., & Matsuo, Y. "Tweet analysis for real-time event detection and earthquake reporting system development," *IEEE Transactions on Knowledge and Data Engineering*, 25(4), 2012, pp.919-931.
23. Kaya Keleş, M. "An overview: the impact of data mining applications on various sectors," *Tehnicki Glasnik*, 11(3), 2017, pp. 128-132.
24. Rogstadius, J., Vukovic, M., Teixeira, C. A., Kostakos, V., Karapanos, E., & Laredo, J. A. "CrisisTracker: Crowdsourced social media curation for disaster awareness," *IBM Journal of Research and Development*, 57(5), 2013, pp.4.
25. Yates, D., & Paquette, S. "Emergency knowledge management and social media technologies: A case study of the 2010 Haitian earthquake," *International Journal of Information Management*, 31(1), 2011, pp.6-13.
26. Bird, D., Ling, M., & Haynes, K. "Flooding Facebook-the use of social media during the Queensland and Victorian floods", *Australian Journal of Emergency Management*, 27(1), 2012, pp. 27-33.

27. Kim, J., Hastak, M. "Social network analysis: Characteristics of online social networks after a disaster," *International Journal of Information Management*, 38(1), 2018, pp.86-96.
28. Kamel Boulos, M. N., Resch, B., Crowley, D. N., Breslin, J. G., Sohn, G., Burtner, R., Pike, W. A., Jezierski, E., & Chuang, K. Y. S. "Crowdsourcing, citizen sensing and sensor web technologies for public and environmental health surveillance and crisis management: trends, OGC standards and application examples", *International Journal of Health Geographics*, 10(1), 2011, pp. 67.
29. Hjorth, L., & Kim, K. H. Y. "The mourning after: A case study of social media in the 3.11 earthquake disaster in Japan", *Television & New Media*, 12(6), 2011, pp. 552-559.
30. Feldman, D., Contreras, S., Karlin, B., Basolo, V., Matthew, R., Sanders, B., Houston, D., Cheung, W., Goodrich, K., Reyes, A., Serrano, K., Schubert, J., & Luke, A. "Communicating flood risk: Looking back and forward at traditional and social media outlets. *International Journal of Disaster Risk Reduction*, 15, 2016, pp. 43-51.
31. Gao, H., Barbier, G., & Goolsby, R. "Harnessing the crowdsourcing power of social media for disaster relief", *IEEE Intelligent Systems*, 26(3), 2011, pp. 10-14.
32. Deng, Q., Liu, Y., Zhang, H., Deng, X., & Ma, Y. "A new crowdsourcing model to assess disaster using microblog data in typhoon Haiyan", *Natural Hazards*, 84(2), 2016, pp. 1241-1256.
33. Wang, R. Q., Mao, H., Wang, Y., Rae, C., & Shaw, W. "Hyper-resolution monitoring of urban flooding with social media and crowdsourcing data," *Computers & Geosciences*, 111, 2018, pp.139-147.
34. Gelernter, J., & Mushegian, N. "Geo-parsing messages from microtext", *Transactions in GIS*, 15(6), 2011, pp.753-773.
35. Liu, S. S., Liu, J. & Wei, W. "Simulation of crowd evacuation behaviour in outdoor public places-a model based on shanghai stampede," *International Journal of Simulation Modelling*, 18(1), 2019, pp. 86-99.
36. Shklovski, I., Burke, M., Kiesler, S., & Kraut, R. "Technology adoption and use in the aftermath of Hurricane Katrina in New Orleans," *American Behavioral Scientist*, 53(8), 2010, pp. 1228-1246.
37. Zook, M., Graham, M., Shelton, T., & Gorman, S. "Volunteered geographic information and crowdsourcing disaster relief: a case study of the Haitian earthquake," *World Medical & Health Policy*, 2(2), 2010, pp. 7-33.
38. Seo, M., Sun, S., Merolla, A. J., & Zhang, S. "Willingness to help following the Sichuan Earthquake: Modeling the effects of media involvement, stress, trust, and relational resources," *Communication Research*, 39(1), 2012, pp.3-25.
39. Lobb, A., Mock, N., & Hutchinson, P. L. "Traditional and social media coverage and charitable giving following the 2010 earthquake in Haiti," *Prehospital and Disaster Medicine*, 27(4), 2012, pp. 319-324.
40. Martin, J. A. "Closing gaps in international knowledge and participation: News attention, online expression, and the 2010 Haiti earthquake," *Mass Communication and Society*, 16(3), 2013, pp.417-440.
41. Sutton, J., Gibson, C. B., Phillips, N. E., Spiro, E. S., League, C., Johnson, B., Fitzhugh, S. M., & Butts, C. T. "A cross-hazard analysis of terse message retransmission on Twitter," *Proceedings of the National Academy of Sciences*, 112(48), 2015, pp.14793-14798.
42. Neubaum, G., Rösner, L., Rosenthal-von der Pütten, A. M., & Krämer, N. C. "Psychosocial functions of social media usage in a disaster situation: A multi-methodological approach," *Computers in Human Behavior*, 34, 2014, pp. 28-38.
43. Bai, H., & Yu, G. "A Weibo-based approach to disaster informatics: incidents monitor in post-disaster situation via Weibo text negative sentiment analysis", *Natural Hazards*, 83(2), 2016, pp. 1177-1196.
44. Taylor, M., Wells, G., Howell, G., & Raphael, B. "The role of social media as psychological first aid as a support to community resilience building," *Australian Journal of Emergency Management*, 27(1), 2012, pp. 20-26.
45. Keim, M. E., & Noji, E. "Emergent use of social media: a new age of opportunity for disaster resilience," *American Journal of Disaster Medicine*, 6(1), 2011, pp. 47-54.
46. Lev-On, A. "Communication, community, crisis: Mapping uses and gratifications in the contemporary media environment," *New Media & Society*, 14(1), 2012, pp.98-116.
47. Vicary, A. M., & Fraley, R. C. "Student reactions to the shootings at Virginia Tech and Northern Illinois University: Does sharing grief and support over the Internet affect recovery?," *Personality and Social Psychology Bulletin*, 36(11), 2010, pp. 1555-1563.
48. Ben-Ezra, M., Palgi, Y., Aviel, O., Dubiner, Y., Baruch, E., Soffer, Y., & Shrira, A. "Face it: collecting mental health and disaster related data using Facebook vs. personal interview: the case of the 2011 Fukushima nuclear disaster", *Psychiatry Research*, 208(1), 2013, pp.91-93.
49. Miura, A., Toriumi, F., Komori, M., Matsumura, N., & Hiraishi, K. "Relationship between emotion and diffusion of disaster information on social media: Case study on 2011 Tohoku earthquake," *Transactions of the Japanese Society for Artificial Intelligence*, 31(1), 2016, pp.1-9.
50. Cao, Q., Lu, Y., Dong, D., Tang, Z., & Li, Y. "The roles of bridging and bonding in social media communities", *Journal of the American Society for Information Science and Technology*, 64(8), 2013, pp. 1671-1681.
51. Smith, B. G. "Socially distributing public relations: Twitter, Haiti, and interactivity in social media," *Public Relations Review*, 36(4), 2010, pp. 329-335.
52. Casacchia, M., Pollice, R., & Roncone, R. "The narrative epidemiology of L'Aquila 2009 earthquake", *Epidemiology and Psychiatric Sciences*, 21(1), 2012, pp. 13-21.
53. Muralidharan, S., Dillistone, K., & Shin, J. H. "The gulf coast oil spill: extending the theory of image restoration discourse to the realm of social media and beyond petroleum," *Public Relations Review*, 37(3), 2011, pp. 226-232.
54. Gandomi, A., & Haider, M. "Beyond the hype: Big data concepts, methods, and analytics", *International Journal of Information Management*, 35(2), 2015, pp.137-144.
55. Boyle, M. P., Schmierbach, M., Armstrong, C. L., McLeod, D. M., Shah, D. V., & Pan, Z. "Information seeking and emotional reactions to the September 11 terrorist attacks", *Journalism & Mass Communication Quarterly*, 81(1), 2004, pp. 155-167.
56. Utz, S., Schultz, F., & Glocka, S. "Crisis communication online: How medium, crisis type and emotions affected public reactions in the Fukushima Daiichi nuclear disaster," *Public Relations Review*, 39(1), 2013, pp.40-46.
57. Brengarth, L. B., & Mujkic, E. "WEB 2.0: How social media applications leverage nonprofit responses during a wildfire crisis", *Computers in Human Behavior*, 54, 2016, pp. 589-596.
58. Acar, A., & Muraki, Y. "Twitter for crisis communication: lessons learned from Japan's tsunami disaster", *International Journal of Web Based Communities*, 7(3), 2011, pp. 392-402.
59. Tsubokura, M., Onoue, Y., Torii, H. A., Suda, S., Mori, K., Nishikawa, Y., Ozaki, A. & Uno, K. "Twitter use in scientific communication revealed by visualization of information spreading by influencers within half a year after the Fukushima Daiichi nuclear power plant accident," *Plos One*, 13(9), 2018, pp.e0203594.
60. Steinberg, A., Wukich, C., & Wu, H. C. "Central social media actors in disaster information networks," *International Journal of Mass Emergencies & Disasters*, 34(1), 2016, pp.47-74.
61. Mondal, T., Pramanik, P., Bhattacharya, I., Boral, N., & Ghosh, S. "Analysis and early detection of rumors in a post disaster scenario," *Information Systems Frontiers*, 20(5), 2018, pp.961-979.
62. Cheng, J., Sun, A. R., Hu, D., & Zeng, D. D. "An information diffusion based recommendation framework for micro-blogging", *Journal of the Association for Information Systems*, 12(7), 2010, pp. 45-73.
63. Heath, R. L., Palenchar, M. J., & O'Hair, H. D. "Community building through risk communication infrastructures", In *Handbook of Risk and Crisis Communication*, Routledge, 2011, pp. 471-487.
64. Chen, J., Chen, H., Wu, Z., Hu, D., & Pan, J. Z. "Forecasting smog-related health hazard based on social media and physical sensor", *Information Systems*, 64, 2017, pp. 281-291.
65. Austin, L., Fisher Liu, B., & Jin, Y. "How audiences seek out crisis information: Exploring the social-mediated crisis communication model", *Journal of Applied Communication Research*, 40(2), 2012, pp. 188-207.