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Big data and disaster management: a systematic review and agenda for future research

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Abstract The era of big data and analytics is opening up new possibilities for disaster management (DM). Due to its ability to visualize, analyze and predict disasters, big data is changing the humanitarian operations and crisis management dramatically. Yet, the relevant literature is diverse and fragmented, which calls for its review in order to ascertain its development. A number of publications have dealt with the subject of big data and its applications for minimizing disasters. Based on a systematic literature review, this study examines big data in DM to present main contributions, gaps, challenges and future research agenda. The study presents the findings in terms of yearly distribution, main journals, and most cited papers. The findings also show a classification of publications, an analysis of the trends and the impact of published research in the DM context. Overall the study contributes to a better understanding of the importance of big data in disaster management.

Keywords Big data analytics · Disaster management · Humanitarian services · Emergency services · Systematic literature review

1 Introduction

Numerous natural disasters strike across the globe every year, killing thousands, displacing many more, and destroying billion-dollars of property and infrastructure (Altay and Green 2006; Galindo and Batta 2013). For example, the economic impacts of the 2010 and 2011 Queensland floods were estimated to about A$ 6.8bn in direct losses (Menhart 2015), and the 2016 Japan's Kyushu Island earthquake economic losses were estimated to be between US $25 billion and US$ 30 billion. The overall global total economic losses from these disasters were estimated to about US$ 175 billion in 2016 (Swiss Re Institute Sigma 2017).

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The impacts of disaster events can disrupt the progress and developmental efforts of nations, often pushing them many years back (Smith and Matthews 2015; Huang and Cervone 2016). Moreover, McGuire (2012) noted that a major cause of these natural disasters is the changing climate, which affects human lives while exceeding the economic toll. As the number of disasters has increased over the years, a concern has grown worldwide about how to extend crtical knowledge and innovation to prevent, mitigate and manage disaster operations (Tin et al. 2013). In support of this argument, Zheng et al. (2013, p. 451) stated that “the techniques to efficiently discover, collect, organize, search, and disseminate real-time disaster information have become national priorities for efficient crisis management and disaster recovery tasks”. Although it may not be possible to entirely prevent all disasters, it is well acknowledged that an effective use of innovative technology can, to a great extent, reduce the magnitude of loss in life and property (Adriana et al. 2014; Starr and Wassenhove 2014). Indeed, emerging technological innovations including social media, location-based systems, radio frequency identification, and big data analytics (BDA) are considered as powerful tools that may help all stakeholders during the disaster management cycle.

BDA, defined a “holistic process to manage, process and analyze 5 Vs (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained competitive advantages” (Fosso Wamba et al. 2015), is now considered as a powerful tool that can transform all industries including manufacturing (Wilkins 2013), retailing (Marr 2015a), healthcare (Marr 2015b) and emergency services (Fosso Wamba et al. 2015). In this regard, Mehrotra et al. (2013) suggested that BDA can assist in creating the next generation of emergency response technologies as it has the potential to mitigate the effects of disasters by enabling access to critical real-time information. Combined with real-time analytics, such information can definitely help to prevent and face disasters. It can indeed prevent any damage to life and property by detecting various disasters, such as earthquakes, wild fires, cloudbursts, tornadoes and volcanic activities (Wang et al. 2016a, b, c).

The role of big data in disaster management (DM) has been evolving. Nowadays, scientists are facing one of the biggest challenges of managing large volumes of data generated at times of disasters. As a huge amount of disaster-related data is getting generated, traditional data storage and processing systems are facing challenges in fulfilling performance, scalability and availability needs of big data (Grolinger et al. 2016). Moreover, the current data storage systems are diverse and offer very limited scope for collaboration. Therefore, there is a need to develop techniques that can help efficiently in data integration, aggregation and visualization, while optimizing the decision-making process, since the quality of decisions taken by the DM officials depends on the quality of available information (Emmanouil and Nikolaos 2015). Mehrotra et al. (2013, p. 6) emphasized that “accurate and timely assessment of the situation can empower decision makers during a crisis to make more informed decisions, take appropriate actions, and better manage the response process and associated risks”. Thus, it is essential to reconsider how data on disasters should be properly and efficiently produced, organized, stored, and analyzed (Hazen et al. 2014).

Prior research activities have extensively discussed the use of timely, accurate and effective disaster information in disaster management and preparation scenarios (Hristidis et al. 2010; Zhang et al. 2012; Velev and Zlateva 2012). The most common data resources include news/articles/blogs from web, social networks platforms such as Twitter, Facebook, and Flickr, as well as multimedia data like images and videos (Tin et al. 2013). By utilizing BDA in the disaster context, Wang et al. (2016a, b, c) conducted a systematic study on emergency communication networks, drawing on the fact that BDA provides all possible solutions to understand any disaster-related issues while the results from analysis may assist in optimally deploying the limited resources. In addition, Hristidis et al. (2010) conducted a comprehensive survey of the efforts on utilizing and advancing the management and on data analysis to serve disaster management situations. The extant literature suggests the need to collect, manage, find, and present disaster information in the context of DM phases: preparation, response, recovery, and mitigation (Bish et al. 2014; Jahre et al. 2007; Pyakurel and Dhamala 2017; Wang et al. 2016a, b, c). Recently, Goswami et al. (2016) reviewed the application of data mining and analytical techniques for predicting, detecting, and developing appropriate DM strategy based on disaster-generated data.

Unlike other reviews on the subject, our review specifically aims to analyze and organize the recent DM literature in the broadest sense, without focusing on the evolution of DM from the beginning up to now, but rather on the latest developments in the DM field. In particular, we have chosen to concentrate on DM studies published in recent years, that is, from 2010 to January 2017; for the corresponding period, we have identified 76 DM-related papers. We have carefully selected our sources using a structured approach to identify the journals with higher value to the academic community as a whole. On the other hand, we have adopted a methodology that visibly differs from the one used in other reviews. The bibliometric and network analysis review methodology is recognized by various authors as an important methodology to be adopted when it comes to carrying out an in-depth analysis of the current state of a field and exploring the related future research directions (e.g., Bouchard et al. 2015; Fahimnia et al. 2015). We categorize the studies according to their status (in terms of publication distribution), research context, authors, and affiliations.

This paper is structured as follows: the next section describes the methodological approach used to conduct the review. This is followed by an analysis of the data collected, and then by a discussion of the results obtained and an outline of suggestions for future research on DM. The final section reports the conclusions.

2 Methodology

Application of Big data in DM is yet to fully mature into a specific area of academic research. Through the bibliometric and network analysis, this paper aims to ascertain the current development in the field and acknowledge that there is sufficient scope for a comprehensive study to explore new possibilities and directions for research in the future.

Gamal Aboelmaged (2010) pointed out that academicians and practitioners often make use of journals to obtain and publish the highest level of research outcomes. Therefore, following the systematic review guidelines of Altay and Green (2006), Galindo and Batta (2013) and Akter and Wamba (2016), we focused on studies published in journals with findings that add to the available theoretical body of knowledge and applications. Since we found very few articles published prior to 2010, we restricted ourselves to consider only relevant papers published between 2010 and January 2017. This resulted in a comprehensive set of articles on the chosen topic. However, it is very likely that we have missed a few papers unintentionally. For our literature review, we have used a four-stage protocol:

1. A search was conducted in the title and abstract field of the SCOPUS database with the following search terms and their variants: (“disaster management” OR “emergency service” OR OR “disaster relief operations” OR “disaster resilience” OR “emergency management”) AND “big data”. This resulted in a total of 382 relevant articles.
2. The shortlisted articles were then screened to include only the journal articles. This led to a reduced number of 123 articles.

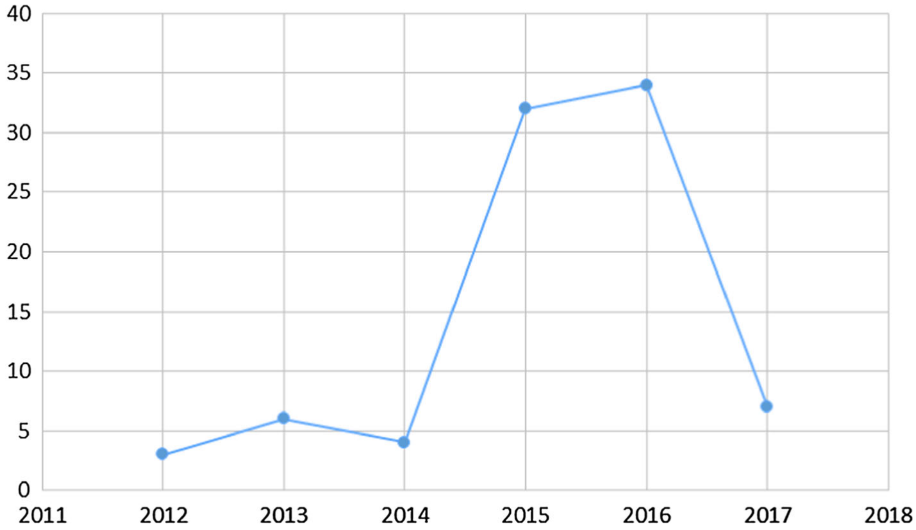

Fig. 1 Distribution of shortlisted articles by publication year

3. From among them, 94 articles were retained after removing the duplicate results using the Mendeley desktop software.
4. Full text articles were retrieved and reviewed individually by all the authors for additional screening. The remaining records were abstracted for analysis. This search brought the final total to 76 articles, spread across 66 journals.

Figure 1 shows the distribution of 76 shortlisted articles by publication year. Through our literature search, we found that there were no specific papers on the topic till 2012, but the growth has improved significantly since then. Interestingly, a dramatic rise in publications can be observed after 2014. This may be due to the fact that big data and its emerging technologies seem to have overtaken every segment of the market and society (Generro et al. 2016). The proven success of big data has motivated practitioners and academicians to identify its role in DM. Hence, researchers have tacitly accepted it as a powerful technique for dealing with disasters, and it is among the most promising research trends of the decade.

3 Review results and classifications

In this section, we employ different methods to classify the shortlisted articles based on authors, universities, countries, research methodology, research area, and disaster phase.

3.1 Classification by authors

The shortlisted articles are summarized by authors to identify the researchers with the greatest impact. More than 150 authors have contributed to the body of knowledge through 76 papers published in 66 journals. Significant contributors include Carley, K.M., Kowalchuck, M., Landwehr, P.M., Ye, X and Abdul Samad, S. Figure 2 shows the top five researchers (out of a total of 159), based on their publications.

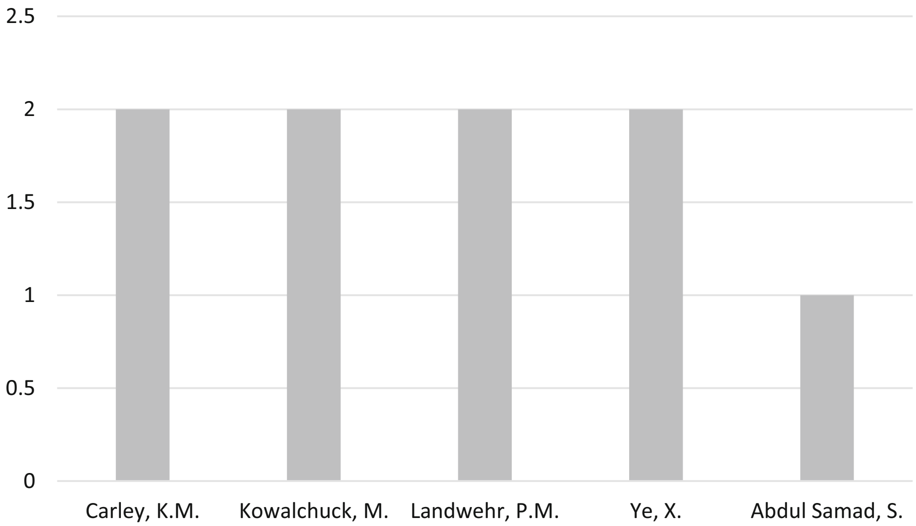

Fig. 2 Distribution of shortlisted articles by authors

3.2 Classification by universities

Through our literature review, we realized that a total of 143 universities and institutes have contributed to the area of big data in DM. Such outstanding number may be attributed to the fact that minimizing disasters and their impact have become the pressing need of the hour. Figure 3 shows the top ten universities contributing to this area of research. The majority of articles have been published by the authors from the Wuhan University (3), followed by those from the Collaborative Innovative Center of Geospatial Technology (2), the National Disaster Management Research Institute (2), the Pennsylvania State University (2) and the Arizona State University (2).

3.3 Classification by countries

Our literature review reveals that the contributors are from 30 different countries. Contributions from the United States of America constitute 80% of the publications. Other significant contributors include China, Australia, Japan, the United Kingdom and France. In fact, this observation is consistent with the previous analysis based on universities as most of them are located in China, South Korea, and the United States of America. Figure 4 presents the top ten contributors in this area of research.

3.4 Classification by subject areas

According to the method chosen for the review, the papers were scrutinized to bring out the major subject areas. In this regard, each paper was examined critically in order to identify the areas where research was performed (see Fig. 5). The results indicate that the application of big data in the disaster context has expanded into a broad spectrum of subject areas, including engineering, computer science, social science, medicine, environmental science, etc. It can be seen that out of 76 articles, 24 came from engineering, 23 studies dealt with computer science and social science, 14 studies with medicine and 12 with environmental issues. From

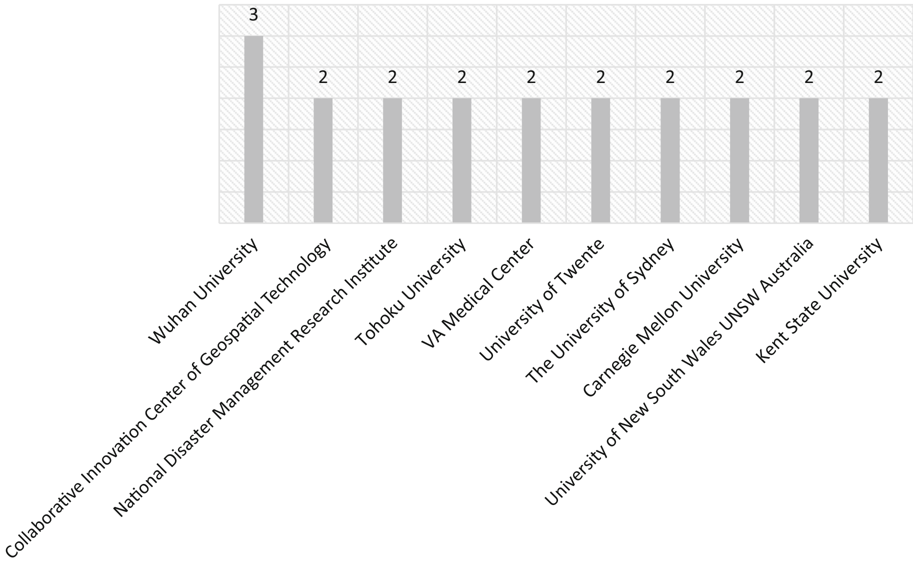

Fig. 3 Distribution of shortlisted articles by top universities

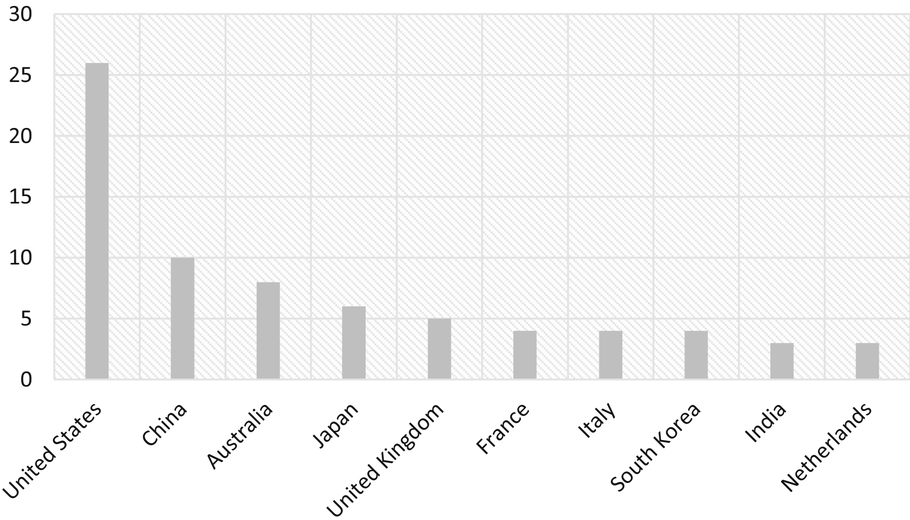

Fig. 4 Distribution of shortlisted articles by top countries

the analysis being made, we have observed that more work are still needed in the areas of mathematics, decision sciences and pharmacology.

3.5 Classification by research methodology

The distribution of reviewed studies with respect to the research methodologies are shown in Fig. 6. It clearly appears that the majority of articles being reviewed use analytical models. These studies focus on how to solve problems in relation to post-earthquake emergency

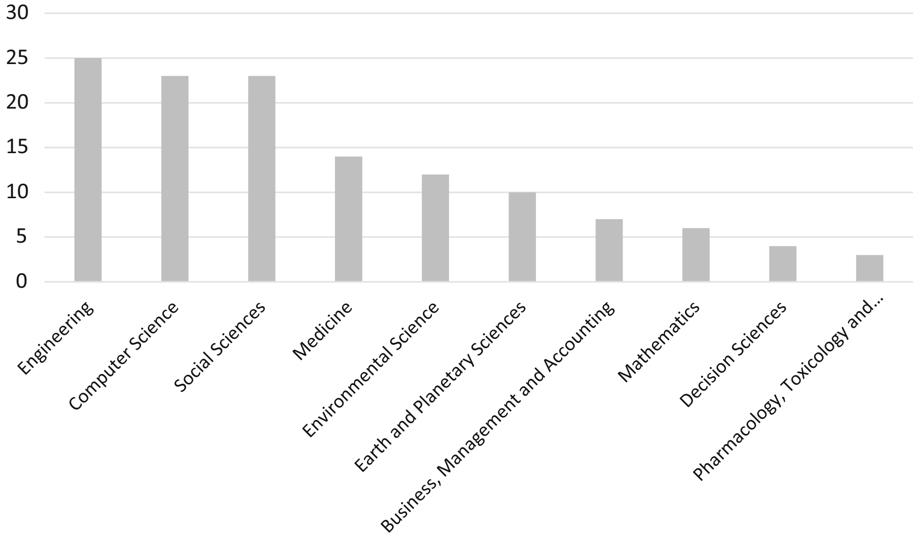

Fig. 5 Distribution of shortlisted articles by subject areas

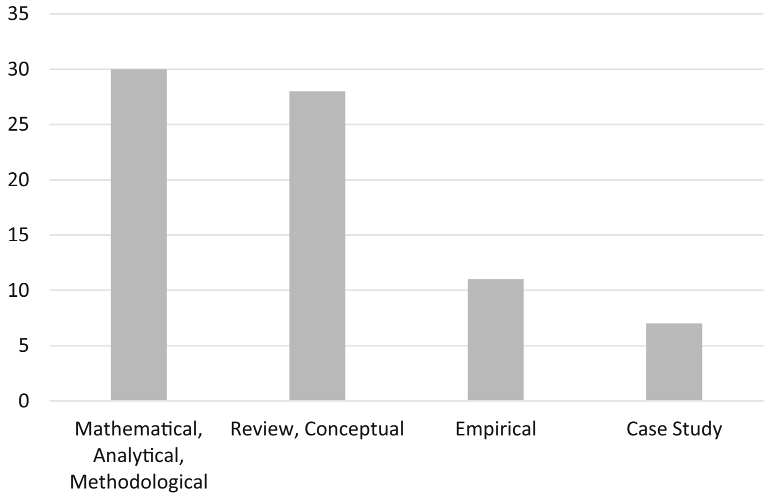

Fig. 6 Distribution of shortlisted articles by research methodologies

response (Ghosh and Gosavi 2017), early warning system for biodiversity (Rovero and Ahumada 2017), welfare impacts of urban disasters (Grinberger and Felsenstein 2016), etc. This includes the use of semi-Markov model, cloud-based architecture, agent-based models, and P2P cloud network services (Chung and Park 2016). We also note that an equivalent number of review and conceptual studies have been done on DM. On the other hand, we found only a few case studies. This can be explained by the fact that case study research is not well utilized in operations management research (Hassini et al. 2012). Moreover, big data applications in DM area is a relatively new research field, and researchers need to carry out more case studies as it would help in understanding the real issues and problems, something that the case study methodology is well suited for Rowely (2002).

3.6 Classification by disaster phases

In the literature, the emergency response efforts have been classified into two stages: pre-event and post-event response (Tufekci and Wallace 1998; Altay and Green 2006). The first stage includes tasks related to prediction and analyses of potential risk and preparedness for mitigation. As for the second stage, it starts while the disaster is still in progress. During this stage, it is very challenging to allocate, coordinate and manage resources.

In the context of DM, the United States emergency management identified four different phases: mitigation, preparedness, response, and recovery (Green and McGinnis 2002; Waugh 2000; Altay and Green 2006), commonly known as DM lifecycle stages. During the mitigation phase, the chances of the disaster happening are prevented and its impacts once it occurs re minimized. The preparedness phase prepares the community or users to react and respond at the time of disaster. This phase involves allocation of resources and emergency procedures in order to safeguard life, property, environment, and the socio-economic and political structure of the community. In the recovery phase, actions are taken with a long-term goal to stabilize the community and restore normalcy after the immediate impact of the disaster.

We have categorized the shortlisted articles based on the four phases of DM lifecycle (see Table 1). It can be seen that about 36.8% of all the articles address the mitigation issue. In these articles, various mitigation strategies and tools, such as power grid disaster prevention and dispatch system (Wang et al. 2016a, b, c), hybrid decision support system (Drosio and Stanek 2016), global flood detection system and global flood awareness system, have been proposed to deal with disasters. We note that the response phase follows mitigation in a context of research productivity, with 28.9% of articles published in this area. However, there are relatively fewer articles (22.5%) focussing on the preparedness phase of DM lifecycle. But the phase that clearly needs much attention is disaster recovery, as we obtained only 2 articles (2.6%) in this category. Moreover, we note that 2 articles (2.6%) focussed on general disaster management without specifying any particular phase of disaster while 5 articles (6.6%) targeted all the four phases of disaster.

3.7 Classification by data clustering

To identify the major research clusters of this field, the Louvain algorithm was applied to 235 node network using Gephi. We observed that the value of modularity index was 0.15, which indicates a strong bond among the nodes of any particular cluster. In other words, the papers which are cited together share the same area of interest. Table 1 shows the top publications of each cluster based on PageRank. Based on a careful examination of contents and research areas of the leading papers, the authors of this study identified four research clusters that could be valuable domains for conducting big data research in the disaster context.

The literature classification presented in Table 2 exhibits that researchers in cluster 1 were mainly concerned about the role played by social media platforms, such as Twitter, in times of distress. As people turn to these sites to broadcast their needs and gather timely-relevant information, new software platforms are being deployed to analyze the incoming data from social media. These tweets are also investigated to detect possible seismic events, to compare and contrast the behavior of people during emergency and in relation to national security, and extract information using information extraction (IE) techniques. Although social media is a potential source of information for crisis management, information from other sources must

Table 1 Distribution of articles based on the disaster phase

Disaster phase	Publications
Mitigation	Wang et al. (2016a, b, c), Cinnamon et al. (2016); Chang and Lo (2016), Zeydan et al. (2016), Drosio and Stanek (2016), Ang and Seng (2016), Jianping et al. (2016), Koshimura (2016), Janke et al. (2016), Moreira et al. (2015), Shakir et al. (2014), Cooper et al. (2011), De Albuquerque et al. (2015), Revilla-Romero et al. (2015), Venkatesan et al. (2015), Lee et al. (2015), Villena-Román et al. (2014), Araz (2014), Krasuski and Wasilewski (2013), Miranda et al. (2013), Granell and Ostermann (2016), Cherichi and Faiz (2016)
Preparedness	Liaqat et al. (2017), Rovero and Ahumada (2017), Carley et al. (2016), Goff and Cain (2016), Wang et al. (2016a, b, c), Keon et al. (2015), Johal (2015), Ram et al. (2015), Haworth and Bruce (2015), Li et al. (2015), Radianti et al. (2015), Schultz (2012), Prewitt (2013), Fosso Wamba et al. (2015)
Response	Ghosh and Gosavi (2017), Hultquist and Cervone (2017), Papadopoulos et al. (2017), Erdelj et al. (2017), Palmieri et al. (2016), Tan et al. (2016), Grabowski et al. (2016), Collins et al. (2016), Alamdar et al. (2016), Haug et al. (2016), Lee et al. (2015), Li et al. (2015), Bostenaru Dan and Armas (2015), Miura et al. (2015), Hara and Kuwahara (2015), Tomaszewski et al. (2015), Scott and Batchelor (2013), Bruns and Liang (2012), Winquist et al. (2014)
Recovery	Grinberger and Felsenstein (2016), Chung and Park (2016)
No specified disaster phase	Cutts et al. (2015), Murayama and Burton (2015)
Target all disaster phases	Landwehr et al. (2016), Dufty (2016), Huang and Xiao (2015), Goswami et al. (2016), Huang et al. (2015)

also be taken into account. Recent disasters, such as the Southern California Wildfire of 2007 and the Sichuan Earthquake of 2008, have shown that information provided by eye-witnesses through social networking outlets (e.g., Twitter, Instagram, Flickr, and others) can greatly improve situational awareness. Therefore, our cluster 2 studied the potential of Volunteered Geographic Information (VGI), that is, the spatial information collected by volunteers from the public and shared over the Internet. For instance, Kent and Capello (2013) compared the spatial distribution of wildfire and non-wildfire specific user generated content to confirm the presence of a social networking user base that contributed to situational awareness. Poser and Dransch (2010) discussed the opportunities and challenges faced when using VGI for disaster management, specifically focussing on the response and recovery phases.

Realizing the fact that location is an important factor in disaster messages (Gelernter and Mushegian 2011; Qian et al. 2013), cluster 3 moved ahead with the technique of spatial data mining that refers to the discovery of interesting relationships and characteristics existing implicitly in spatial databases. The researchers in this cluster mainly focussed on proposing effective and efficient clustering techniques for spatial data mining, but also a novel join-less approach for efficient co-location pattern mining (Yoo and Shekhar 2006). In addition, researchers in this cluster explored the behaviour of Twitter users under an emergency situation (Mendoza et al. 2010; Mandel et al. 2012) and developed systems that capture the information received from Twitter that helps in avoiding and monitoring emergency situations, like earthquakes (Robinson et al. 2013). The works in cluster 4 contributed to the applications of data mining techniques, electronic commerce, and RFID. For instance,

Table 2 Distribution of shortlisted articles based on clustering

Cluster 1 (Social media's roles)	Cluster 2 (Volunteered geographic information)	Cluster 3 (Spatial data mining)	Cluster 4 (Applications of data mining)
Vieweg et al. (2010)	Shelton et al. (2014)	Mendoza et al. (2010)	Boyd and Crawford (2012)
Earle et al. (2010)	De Albuquerque et al. (2015)	Mandel et al. (2012)	Reddi et al. (2011)
Hughes and Palen (2009)	Craglia et al. (2012)	Robinson et al. (2013)	Ponserre et al. (2012)
Zook et al. (2010)	De Longueville et al. (2010)	Gelernter and Mushegian (2011)	Ngai et al. (2012)
Kitchin (2014)	Bengtsson et al. (2011)	Yoo and Shekhar (2006)	Ngai et al. (2009)
Landwehr and Carley (2014)	Poser and Dransch (2010)	Özyer et al. (2007)	Ngai et al. (2009)
Starbird and Palen (2010)	Crawford and Finn (2015)	Ng and Han (2002)	Ngai et al. (2008)
Schnebele and Waters (2014)	Kent and Capello (2013)	Penurkar and Deshpande (2014)	Ngai and Wat (2002)
Vieweg (2010)	Liang et al. (2013)	Qian et al. (2013)	Ngai and Gunasekaran (2007)
Gao et al. (2011)	Crooks et al. (2013)	Mukherjee et al. (2015)	

Ngai et al. (2009) applied data mining tools to study customer relationship management, as extracting and identifying useful information and knowledge from customer databases leads to customer value maximization and to the acquisition and retention of potential customers. Ngai and Gunasekaran (2007) and Ngai and Wat (2002) reviewed the literature on electronic and mobile commerce, and provided useful insights into these topics. In addition, RFID has been used to improve garment manufacturing processes (Ngai et al. 2012) and healthcare industries (Ngai et al. 2009).

4 Discussion and research agenda

While the use of big data helps in predicting disasters and preparing safety measures, there are a few challenges that need to be addressed before reaping the benefits from it. The extant literature argues that decision-makers need to address various challenges, such as crisis analytics platform, data governance, data quality, analytics capabilities and evidence-based findings. From our analysis, we found that there are only a few studies that are based on theories. By "theory" we mean "connections among phenomena, a story about why acts, events, structure and thoughts occur" (Sutton and Staw 1995, p. 378). Therefore, more theory-based research is required to identify the applications of big data in DM. In the following sections, we shed light on various challenges and opportunities of big data research in DM with theoretical insights.

The development of big data-driven crisis analytics platform has many applications that can enhance disaster response. Often, disaster has cascading effects (e.g., Tsunami followed by earthquake) which requires that a real-time analytics platform be developed to prioritize urgent issues, prevent follow-up hazards, coordinate aid organizations and arrange first responders. Thus, it is critical to ensure a crisis analytics platform that is highly disaster-tolerant, reliable, available and secured. The extant literature has largely focused on descriptive (i.e., what happened) or diagnostic analytics (i.e., why did it happen), the big data-driven crisis analytics platform has opened up the opportunity to apply predictive analytics (what will happen).

Emergency services grapple with the massive amount of data arriving through multiple channels, such as first responders, sensors, satellite networks or social media. Therefore, the biggest challenge is to develop a data integration protocol that ensures proper data gathering, modelling and notification systems (Agarwal and Dhar 2014; Miller 2013). Emergency services are empowered more than ever before to develop a preemptive disaster management system based on big data. For example, mobile phones, satellites and social media have an enormous amount of location-specific data, the challenge is to know how emergency service and disaster relief agencies can usher in big data to provide real-time services using the right channel. In addition, it is also important to develop an emergency communication system and informational hub using text, images, speech, video, maps, crowdsourced data, and formal reports. During a crisis situation, it can help people locate emergency accommodation, food and water, evacuation route, or missing people.

Data quality is the key for developing pre-emptive disaster management in big data environment (Kiron et al. 2014). Poor quality data makes it difficult to assess and use for emergency services (Beath et al. 2012). The potential of big data can be capitalized by addressing the risks of inaccurate and redundant data. Decision-making based on such data might jeopardize the whole rescue operations because mass unfiltered data might threaten privacy (e.g., names and addresses, social security numbers). Overall, the current state of big data remains informal and poorly structured; therefore, it needs to be addressed adequately to ensure data quality.

Big data analytics capability (BDAC) in disaster management refers to the competence to provide solid crisis insights using data management, infrastructure (technology) and talent (personnel) capability to take real-time decisions (Kiron et al. 2014). It remains a critical challenge for emergency and disaster relief agencies to manage all these capabilities equally to leverage big data. Using an entanglement view of sociomaterialism, we argue that the BDAC dimensions do not act in isolation; rather, they act together. They are also constitutively entangled (Orlikowski 2007) and mutually supportive (Barton and Court 2012). In this case, Akter et al. (2016) found support for 11 subdimensions (i.e., BDA planning, investment, coordination, control, connectivity, compatibility, modularity, technical knowledge, technology management knowledge, business knowledge, and relational knowledge) under three primary dimensions (i.e., management capability, infrastructure capability and talent capability). These factors can be taken into account when developing a BDAC model emergency service system.

When big data integrates with cloud computing, it can tackle various real time challenges to provide critical recovery services in disasters. However, there are some challenges in implementing big data in private or public cloud which includes protecting ownership of data, privacy, security and data loss. Thus, first, it is important to establish data ownership to protect unauthorized sharing. Second, regulatory compliance frameworks should be established and relevant laws (regional, national or international) are required to be met. Finally, to better manage big data, both private and public clouds should come up with contingency or back up plans in the context of data loss by hazards, such as, hacking, fire, flood, and earthquake or power failure (Chang 2015).

It is important to articulate a solid and compelling emergency service operation case using big data in disaster management. Both in academia and in practice, the extant literature reports a fascinating case that illuminates an emergency service context and applies the methodology, such as defining the problem, reviewing the literature, developing the model by selecting the variables, collecting and analyzing the data and making time critical emergency service and disaster relief decisions. It is known that case study-based research is scarce in the operations management literature. Similarly, as shown in Fig. 6, we found only 7 case studies that address the issue of disasters. As we stressed in our results, we believe it is important that case studies be more strongly emphasized. Overall, there are lots of avenues to present non-trivial research questions in this stream and we offer some examples in Table 3 using management theories. According to Starr and Wassenhove (2014, p. 934), "Big data analysis brings new insights. It is much easier today to predict some disasters as well as their impact by using greatly improved forecasting methods, for example, in the case of hurricanes…. Big data analysis based on social media traffic will have deep impacts on our knowledge and understanding of behavior in disaster situations".

5 Limitations and conclusions

In this study we conducted a review of the literature on the role of big data in resolving disaster-related problems. We identified 76 papers published between 2010 and January 2017 that were relevant to our review. This review enabled us to identify the trend and to determine the research gaps in the literature. In conclusion, we report the strengths and limitations related to our review technique. About the strengths, we adopted a clear and rigorous approach; each author performed the data collection independently and then discussed it with co-authors, thus

Table 3 Future research questions relating to big data in disaster management

Disaster management research streams	Relevant theories	Future research questions for big data in disaster management
Crisis analytics platform	Big data analytics theories (Akter et al. 2016; Davenport et al. 2012; Davenport 2013a, b; Schläfke et al. 2013)	How can organizations provide real-time analytics, multimodal informatics, disaster tolerance and context awareness?
		How to develop predictive models rather than descriptive or diagnostic ones?
		How to provide context aware personalized crisis information using AI, machine learning, GPS with smartphones?
Strategic management	Organizational ambidexterity (O'Reilly and Tushman 2008) and resource based view (Barney 1991)	How to develop a holistic analytics culture across various functional divisions to leverage big data?
		How to establish a fit among big data analytics capabilities, strategic alignment, agility and firm performance?
Operations management	Process level, firm level, supply chain level, and societal level decision making (Wamba et al. 2017)	Is there any impact of big data analytics on continuous quality improvement?
		How to use big data analytics to improve processes and logistics?
		Does big data analytics influence security, privacy and the ethics of mass data collection?
		Is there any impact of big data on internal and externa processes and relationships?

Table 3 continued

Disaster management research streams	Relevant theories	Future research questions for big data in disaster management
Information systems	IT capability theories (Kim et al. 2012)	What factors influence reliability, visualization, governance, security, and privacy in using big data for emergency service operations?
		How can an emergency agency use omni-channels to establish big data analytics protocol?
		What are the big data capability dimensions for emergency and disaster relief agencies?
		How can a firm leverage big data sources and cloud-based architecture to produce solid insight on accommodation, food and water?
Organizational agility	Dynamic capability theory (Teece and Leih 2016)	How to develop dynamic analytics capabilities in disaster management to address risk and deep uncertainty?
		How can organization develop a robust HR policy to retain and nurture data scientists in disaster management?
		What types of resource allocations are needed to improve the technical, statistical and managerial capabilities to deal with big data?
		How can managers in emergency organizations build agility to sense, seize and transform?

Table 3 continued

Disaster management research streams	Relevant theories	Future research questions for big data in disaster management
Big data system in private or public cloud	Cloud computing theories (Chang 2015)	How to protect ownership and privacy of data in private cloud?
		Is there any contingency plan for big data in private or public cloud to minimize risks in the contexts of disasters?
		Is private cloud approach better than public cloud in the context of data loss by blackout, earthquake, fire, flood, hacking or by other causes.
Productivity and value	Value and productivity (Akter et al. 2016; Ji-fan Ren et al. 2017)	To what extent transactional costs can be reduced using big data analytics in disaster management?
		How to leverage strategic and transformative business values from big data analytics to develop preemptive disaster management policies?

obtaining an accurate database. We also included all the articles, in order to capture different aspects and behaviors of DM research. Moreover, we believe that the search of papers in title, abstract and keywords fields rather than just searching in key words is a asset, because it avoids the risk of discarding significant papers. Regarding the limitations, we considered only papers that satisfied some specific criteria and with subjects we considered coherent and inherent with DM. For instance, we did not include unpublished works, book chapters and conference proceedings. These decisions could lead to the exclusion of relevant studies and to the limitation of creativity and innovations. This review deployed the SCOPUS database. While aiming for a comprehensive coverage by following rigorous, systematic review and synthesis procedures, the database selection and filtering processes may have omitted some relevant research works. We noted that the majority of articles focused on the mitigation and response phase, and a good number on the preparedness phase, while only two articles targeted disaster recovery. More research is thus needed on how communities should recover from the aftermath of disaster.

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