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Use of Big Data in Disaster Recovery: An Integrative Literature Review

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Abstract

Objective: Disasters of all varieties have been steadily increasing in frequency. Simultaneously, "big data" has seen explosive growth as a tool in business and private industries while opportunities for robust implementation in disaster management remain nascent. To more explicitly ascertain the current status of big data as applied to disaster recovery, we conducted an integrative literature review.

Methods: Eleven databases were searched using iteratively developed keywords to target big data in a disaster recovery context. All studies were dual-screened by title and abstract followed by dual full-text review to determine if they met inclusion criteria. Articles were included if they focused on big data in a disaster recovery setting and were published in the English-language peer-reviewed literature.

Results: After removing duplicates, 25,417 articles were originally identified. Following dual title/abstract review and full-text review, 18 studies were included in the final analysis. Among those, 44% were United States-based and 39% focused on hurricane recovery. Qualitative themes emerged surrounding geographic information systems (GIS), social media, and mental health.

Conclusions: Big data is an evolving tool for recovery from disasters. More research, particularly in real-time applied disaster recovery settings, is needed to further expand the knowledge base for future applications.

Over the past several decades, 2 separate but emerging trends have converged: an increase in the number of disasters of all varieties and the rise of big data as an analytical tool. In the United States (U.S.) and around the world, disasters have been occurring with increasing frequency.[1–3] A disaster is commonly defined as "a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic, or environmental losses that exceed the community's or society's ability to cope using its own resources."[4] From kinetic natural disasters such as hurricanes and earthquakes, to pandemics such the 2009 H1N1 and coronavirus disease 2019 (COVID-19), and terrorism, the increasing incidence of disasters has created several public health preparedness challenges. Since 2000, more than 1 million people have died globally from natural disasters, with an associated economic impact exceeding $1.7 trillion.[5] In the United States alone, there were 119 major natural disasters between 2010 and 2019 which caused $810.5 billion in expenses and killed 5217 people.[6] While the United States has borne a significant impact from such events, from 1970 to 2008 more than 95% of natural disaster-associated deaths were in developing nations.[5] Climate-related disasters, in particular, have increased nearly 35% since the 1990s.[1]

In the United States, the Federal Emergency Management Agency's (FEMA's) National Response Framework outlines 5 core capabilities within the National Preparedness Goal: prevention, protection, mitigation, response, and recovery.[7] These phases, which comprise the disaster life-cycle, culminate in recovery-phase activities that necessitate addressing longer-term physical health and psychosocial sequelae along with infrastructural impacts.[8–12] These long-term needs form the basis of the recovery phase, in which the goal is to reconstitute the "livelihoods and health, as well as economic, physical, social, cultural and environmental assets, systems and activities, of a disaster-affected community or society."[13] Such recovery efforts are consonant with the United Nations Office for Disaster Risk Reduction's concept of "Build Back Better,"[12] and with FEMA's National Disaster Recovery Framework.[11] As disasters are increasing in frequency and severity, it is critical to recognize that many areas hit by prior disasters are also at higher risk for future disasters, which adds urgency to the need to recover quickly and effectively. Areas still recovering from prior events, or those having not yet adequately addressed physical or social vulnerabilities, may experience even higher morbidity and mortality along with reduced resiliency from disasters.[14]

Against the backdrop of increasingly frequent and severe disasters, the role of "big data" to aid recovery-phase activities requires more explicit ascertainment. In the 21st century, use of data has become a key feature of nearly every industry. While business and private industries, from banking to health care, have made great use of big data for improved efficiency, opportunities exist for enhanced use of big data in disaster management.[15,16] This lag, or lack of use, is often attributed to the highly dynamic, disparate and diverse nature of data in disasters, yet analytic approaches aimed at big data are actually designed to deal with each of these considerations and more.[15] As analytic approaches to big data have been further developed and validated, their use across business, government, and academia have grown.[17]

While the term "big data", and the analytic approaches to manage it, is not always clearly defined, there is general consensus that big data should be defined in terms of Volume, Velocity, and Variety.[17,18] *Volume* refers to the quantity of data, which in a disaster setting may come from established steady-state data sources such as emergency department reporting,[19] responders and other aid workers actively collecting information in the field, Internet of things (IoT) devices,[20] social media,[21,22] industrial equipment, geographic information systems (GIS) technology, overhead imagery, and more. *Velocity* refers to the rate at which data are received or processed. *Variety* refers to the mixed structure and format of the data, especially when a mix of sources are being aggregated in real time.

To date, there have been limited attempts to systematically study and apply the technological advances of big data to disaster management, let alone to recovery-phase efforts therein. Traditionally, most of the limited focus has been placed on response-phase activities in which responders attempt to save lives and property.[23] This focus has extended from more traditional academic literature reviews[23] to startup companies working on machine learning and artificial intelligence to find vulnerable populations during disasters.[24,25] The application of these modern technologies to process big data into usable metrics present promising opportunities for more efficient disaster recovery. As the Volume, Velocity, and Variety of data continue to challenge the disaster management community, and with the pace of disasters increasing globally, enabling adoption and use of big data across all phases of the disaster life cycle, including recovery, is more critical than ever. To that end, here, we present an integrative literature review focusing on big data concepts as applied to the recovery phase of the disaster life cycle.

Methods

To assess the existing knowledge base on disaster recovery using big data, we performed an integrative literature review.[26] The literature search was conducted using search terms developed iteratively *a priori* by the research team. On March 31, 2020, we conducted the final search of PubMed, Embase, CINAHL, LILACS, Web of Science, Scopus, Biosis Citation Index, Compendex, Inspec, NTIS, and GeoBase. All results from each database's inception to the search date were included in the review process. Search terms were developed iteratively *a priori*. Full search terms and scope were adapted for each database and are available in Supplementary Table 1.

Table 1. Inclusion and exclusion criteria for final review

Inclusion criteria	Exclusion criteria
English language text	Non-English text
Full text available	Gray literature, review papers, conference proceedings, non-peer reviewed
Real disaster incident (non-simulation)	Hypothetical or simulations
Big data used: Volume, Velocity, Variety	Non-human health (eg, geology, non-human animals)
Recovery time phase	Non-recovery time phase
	Inadequate study methods (non-rigorous)
	Obvious technical or methodological errors

Using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) Checklist[27] as a guide throughout, all citations were imported into EndNote, a citation management tool (Clarivate Analytics, Philadelphia, PA), and duplicates were removed. The unique records were then imported into Covidence (Veritas Health Innovation, Melbourne, Australia), a systematic review software program for initial title/abstract and follow-on full-text review. At each stage, 2 reviewers screened the articles with a third reviewer resolving conflicts. At the title/abstract phase, each reviewer was blinded to the other reviewer's decision.

Final inclusion and exclusion criteria are listed in Table 1. All articles required, at a minimum, a real-world/nontheoretical disaster research publication during the recovery phase with some implementation of a big data component. Big data can be a nebulous concept, so for the purpose of this research the definitions from Gandomi and Haider[28] were used. Broadly, the tool must include some component of high-volume data, high-velocity data or highly variable data where "traditional data management and analysis technologies (would) [be] inadequate for deriving timely intelligence".[28] Articles were further screened by the reviewers for methodological rigor, including a clearly logical research process, no obvious technical concerns and publications in a peer-reviewed source. Each article included in the final analysis was abstracted for basic features, including the publication data (eg, year, first author), type of disaster (eg, hurricane), study type (eg, case study), and, by consensus, qualitative major themes.

Results

On final search, 51,504 articles were initially identified. After removing duplicates, 25,417 articles remained from the 11 databases used. Blinded dual title/abstract review led to 238 articles being advanced to the full-text review. After full text review, 18 articles[29–46] were ultimately included in the final analysis. Figure 1 displays the final PRISMA[27] diagram.

Geographically, 8/18 (44%) of the included articles focused on disasters impacting the United States, with the remaining including Canada, France, India, Italy, Japan, Pakistan, and Turkey. While there was no left-sided boundary on publication dates, the earliest identified publication was in 2007. Median year of publication was between 2015 and 2016. Overall, disasters studied focused on hurricanes 39% of the time, followed by earthquakes (22%). All but 2 identified studies were classified as a case study or case series (89%), with the outliers being a systematic review and a literature review. Thematically, social media and GIS were

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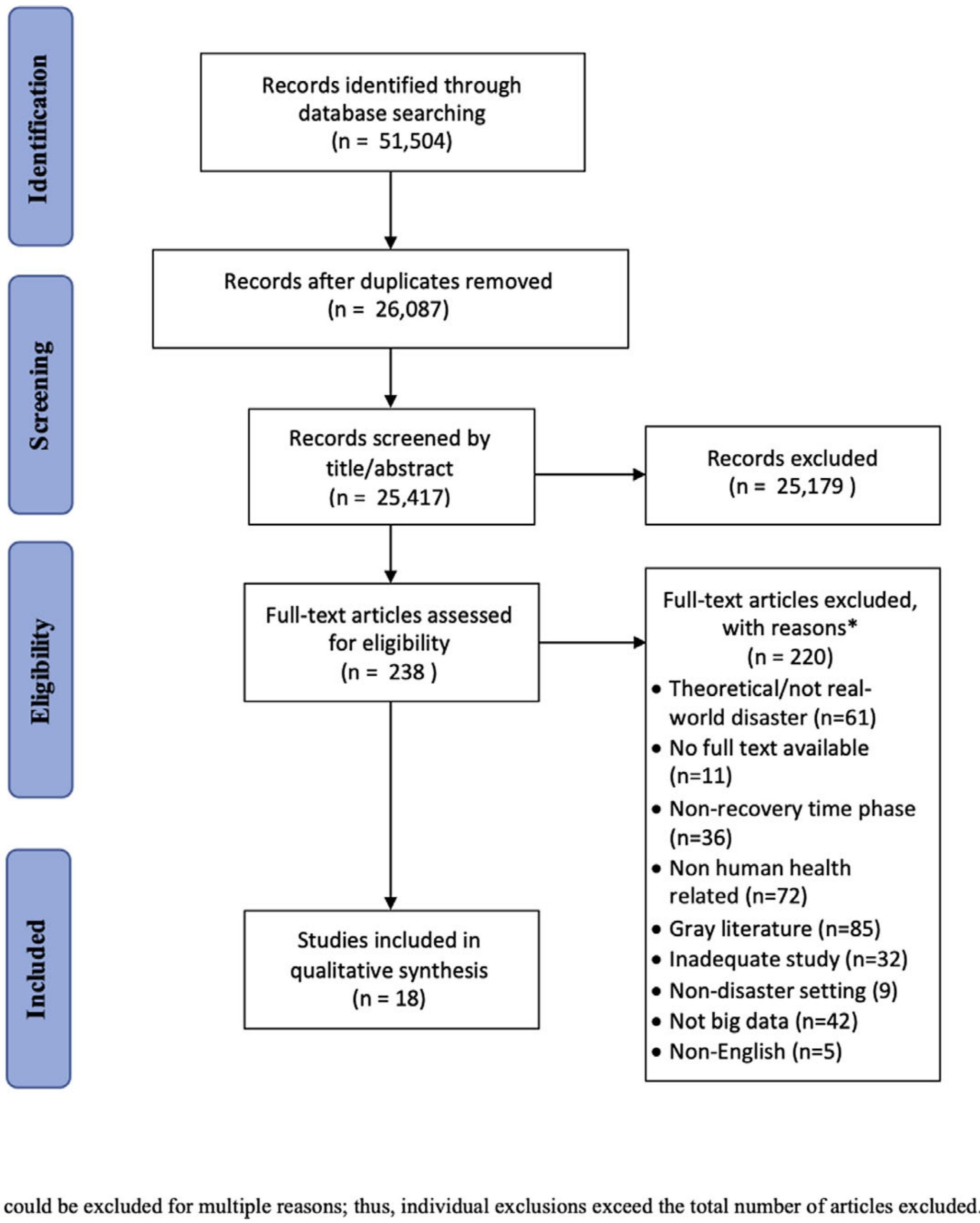

Figure 1. Big Data in Disaster Recovery PRISMA Flow Diagram.

the most commonly identified modalities, at 44% and 33%, respectively. Full results are displayed in Table 2.

GIS

GIS represented the most commonly used tool in the big data disaster recovery landscape. Often used to survey disaster recovery areas, GIS represents a multimodal data stream where different sources of information can readily be merged and superimposed. For example, Aydinoglu and Bilgin[30] developed a model to make GIS data from multiple sources interoperable while focusing on Turkish landslides. GIS was also used in several studies to model human behavior and movement following a disaster. Elliott and Pais[37] used GIS to examine the impact on human displacement and resettlement post disaster in urban versus rural areas. Their key finding was in urban regions, the recovery phase has an effect of dispersing lower socioeconomic status (SES) populations, while in rural areas, long-term recovery concentrates groups of lower SES populations into smaller areas. Contreras et al.[35] assessed post-disaster satisfaction with resettlement by displaced communities as a function of their distance from the center of a natural disaster. In this case study of the L'Aquila earthquake, the authors used spatial variables to indicate the evolution through disaster phases and measure the progression of the recovery process.

Social Media

Social media abstraction is another common method of examining disaster recovery status and community resilience. Combined with surveys and sentiment analysis, social media can provide a

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Table 2. Characteristics of included studies ($n = 18$)

Study	Year	Disaster location	Data source	Disaster type	Topic of interest	Method
Akter[29]	2019	Multiple	Multiple	Multiple	General recovery	Systematic review
Aydinoglu[30]	2015	Turkey	GIS	Landslide	Geographic data modeling	Case study
Boulianne[31]	2018	Canada	Social media	Wildfire	Mental health	Case study
Brandt[32]	2019	United States	Social media	Floods	General recovery	Case study
Buzzelli[33]	2014	Multiple	ICT	Multiple	Communication	Literature review
Cheng[34]	2016	Japan	Social media	Earthquake	Communication	Case study
Contreras[35]	2013	Italy	GIS	Earthquake	Community recovery	Case study
Curtis[36]	2010	United States	GIS/spatial video	Hurricane	Community recovery	Case study
Elliott[37]	2010	United States	GIS/census data	Hurricane	Community recovery	Case study
Fordis[38]	2007	United States	Database website	Hurricane	Communication	Case study
Gruebner[39]	2017	United States	Social media	Hurricane	Mental health	Case study
Huang[40]	2015	United States	Social media	Hurricane	General recovery	Case study
Kimura[41]	2015	Japan	GIS	Earthquake	Life recovery	Case series
Nejat[42]	2019	United States	GIS	Hurricane	Housing recovery	Case series
Ragini[43]	2018	Multiple	Social media	Floods	Sentiment	Case series
Sebek[44]	2014	United States	EHR	Hurricane	Post disaster resources	Case study
Shibuya[45]	2018	Japan	Social media	Earthquake	Socioeconomic recovery	Case study
Wen[46]	2016	France	Social media	Terrorist Attack	Mental health	Case study

Abbreviations: GIS, Geographic Information Systems; ICT, information communication technology; her, electronic health records.

natural data platform for analyzing a community's disaster recovery.[31,32,34,39,40,43,45,46] Notably, due to the rapid ability to share information by means of social media, Twitter in particular was a key driver of disaster information from both regular citizens and government officials, and was used by agencies in the United States[32] and globally.[34] Boulianne et al.[31] found those who followed the Fort McMurray, Alberta wildfire via social media exhibited a statistically significantly higher degree of "caring about others" and increased likelihood of getting involved by means of donations or volunteering. Gruebner et al.[39] took sentiment analysis a step further and proposed using tweets as a supplemental form of syndromic surveillance for disaster-related mental health sequelae. Their research noted a spatial dimension to emotions, prompting a discussion about future efforts to target postdisaster mental health resources at the more granular (eg, neighborhood) level. While more commonly studied in the context of natural disasters, Wen and Lin[46] extrapolated the same concept to the Paris terrorist attacks of 2015. Beyond mental health, indicators of economic recovery, such as used car transactions on Facebook, provided another proxy for community resilience and recovery.[45]

Mental Health

Similarly, given the nature of social media to provide a platform for micro-blogging and real-time expression of thoughts and sentiments, big data provides an opportunity to abstract for mental health sequelae following a disaster. As described above, Gruebner et al.[39] and Wen and Lin[46] trended emotions such as anger, sadness, and fear over both dimensions of time and geographic space for naturally occurring and terrorist disasters, respectively. Boulianne et al.[31] further noted social media could be a prolific source of spreading positive messages about disaster recovery.

Hurricanes

Notably, 7/18 (39%) of the included studies focused on the recovery process after hurricanes. By using big data techniques, the identified studies were able to demonstrate changes in population-level socioeconomic factors (eg, median household income, number of single mother households) along the path of a hurricane.[37] Combined with social media as described above, big data presented the opportunity to trend the disaster process from before the hurricane impacted the community (pre-event phase) through recovery. By aggregating the hurricane damage assessment produced from GIS with the timeline of events, a greater understanding of temporal impact and the pace of the recovery process can be achieved.[40] For example, social media enabled syndromic surveillance for mental health sequelae based on spatial and temporal proximity to the path of the hurricane,[39] and helped determine when the major transition points occurred in the disaster life cycle.[40]

Discussion

In recent years, big data has revolutionized the landscape in many industries, from fraud detection to high-speed financial trading to targeted online advertising. Yet, further opportunities remain for enhanced use of big data to tackle persistent challenges in the disaster management field specifically and throughout the health-care system more broadly.[15,16,47] The disaster life cycle remains a key area of public health emergency management where big data has only begun to permeate.[29] Although the technological and analytical challenges of working with high Volume, Velocity, and Variable data in a disaster recovery setting have traditionally been constrained by technological limitations, novel analytic approaches can help overcome these challenges and enable greater use across the disaster management community. As the real-time accessible volume of data increases (eg, social media) and field technology matures to handle the velocity and variability of the data generated in a recovery environment, new approaches to using big data become accessible. Previous literature reviews have found much broader applications of big data in antecedent phases of the disaster life cycle,[23] but this integrative literature review found the published research on the recovery phase is mostly

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limited to single-incident case studies that leveraged existing big data sources and repurposed them in an *ad hoc* manner. Given the widespread geographic range and reoccurrence of hurricanes and other disasters, big data, including generated through GIS, presents promising opportunities to continuously survey the landscape and trend recovery over extended periods of time and frequently occurring disasters.

A key feature of big data includes the ability to marry multiple data streams in different formats. The findings from our literature review indicate that traditionally disparate data sources can be combined to provide a more comprehensive overview of the recovery process. For example, information obtained from overhead imagery of impacted areas[35] (eg, neighborhood rebuilding, population resettling) can be merged with requests for social services, nutrition,[48] financial support, and economic data,[41,42] along with social media sentiment analysis[29] to provide a more comprehensive perspective of a community's recovery.[8] With the extended timeline of disaster recoveries, these technologies facilitate previously unprecedented assessments of population-level longitudinal physical and mental health, and exacerbations in social inequities.[9] Past research into other phases of the disaster life cycle, such as preparedness, has identified a role for GIS in developing susceptibility tools and early warning indicators.[23]

As the field of big data continues to grow and fully encompass the entire disaster life cycle, additional sources can be added to provide an even greater perspective while cross-validating overlapping data streams. New and increasingly diverse data sources have prompted discussions surrounding adding an additional term to describe big data—Veracity—which refers to the level of trust or accuracy in the data. While not included in most early definitions of big data, veracity has proven to be one of the more critical attributes, often constraining the adoption and use of big data analytics.[49] Despite none of the identified articles having addressed this term explicitly, it has permeated the big data world more broadly, especially in the business community.[17] From senior decision makers to operators in the field, it has been repeatedly noted that trust in the data is a key consideration before adoption of technology in a disaster.[17,49] This is key because, when data sources are not adequately cleaned and integrated with concurrent data streams, there is a real risk of making improper inferences, especially in the context of providing life-saving and life-sustaining services that are the hallmark of a rapidly evolving disaster recovery.[50]

Community Social Well-Being Through Social Media

One area in particular where big data can have a significant impact during a disaster recovery is on community social wellbeing. As previously described, big data has been leveraged to analyze and aggregate various forms of social media independently and in conjunction with other data streams. Given social media's proliferation as a ubiquitous and immediate form of self-expression, big data methods, such as sentiment analysis of Twitter activity, become particularly helpful due to the volume and velocity of new tweets in the wake of a disaster. Ragini et al.[43] explored this issue through a proof-of-concept study using analytical methods to trend the sentiment of social media posts in a disaster region from the response through the recovery. By using machine learning to perform sentiment analysis, the authors were able to demonstrate an ability to separate various needs within an impacted population. While interventions, such as mental health services, are often directed at the individual level, using big data to trend sentiment at the community or neighborhood level longitudinally throughout the recovery can facilitate informatics-driven interventions. Disaster recovery is a complex undertaking, and as areas recovering from disasters are often at risk of future disasters,[51] the public health emergency management community must begin to leverage big data to comprehensively characterize, monitor and improve recovery efforts.

COVID-19 Recovery Opportunities

This integrative literature review was conducted primarily before the impact of COVID-19. Given the once in a generation impact of the COVID-19 pandemic, the recovery process—medically, economically, and psychosocially—is expected to be prolonged and unprecedented in modern times.[10] The scale of COVID-19 led to the adoption of entirely new data systems aimed at collecting and using big data across the national response. For example, the U.S. Department of Health and Human Services (HHS) stood up HHS Protect[52] to integrate hundreds of datasets across government, and the U.S. Department of Defense established Tiberius, a data management platform, to manage informatics around vaccine supply, demand, and distribution.[53] Understanding how these efforts did, or did not, leverage big data analytics effectively throughout the recovery phase, is of immense operational value. Specifically, such understandings present an immediate opportunity for advancing and analyzing new methods to study recovery efforts using big data and to enhance big data's use across academia, government, and industry.

Limitations

As with all literature reviews, this integrative literature review is subject to several limitations. First, the search was developed iteratively using keywords intended to capture major themes. However, it is possible that our search strategy missed a key term and a resulting key item in the literature. Additionally, despite the use of dual reviewers at each stage, it is possible, as with any such review, that human error improperly excluded a key study. As noted above, our literature review was conducted primarily before the impact of COVID-19. However, given current uncertainties surrounding the nature and scope of how big data-related technologies will be applied to the pending full recovery phase post COVID-19, future research will need to explicate COVID-19 specifc recovery-phase big data considerations. Finally, we intentionally limited our search to real-world disasters published in English-language peer-reviewed literature. While this choice is designed to ensure only properly vetted and formally published research was included, worthy examples in gray literature, or in a non-English language, may have been systematically excluded. For example, the plurality of hurricane-related disasters may be a function of a bias in the type of disaster by region of the world and language spoken.

Conclusions

This study examined the existing literature base of past applications of big data to disaster recovery. Our findings revealed limited prior research in this area, largely focused on case studies or series, and specific disasters. Predominantly, the extant literature focuses on the United States, with recurring themes of research assessing the role of big data as applied to GIS, social media, and mental health. This presents a broad opportunity to expand this evolving discipline into the disaster recovery realm. As big data permeates nearly every facet of modern society, while disasters simultaneously increase in frequency, the need and opportunities for further research regarding applications of big data to disaster recovery are timely and highly salient. Particularly in the context of regions experiencing recurring disasters, big data presents opportunities for more efficient monitoring of recovery processes, resources, and ultimately improved human resiliency.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/dmp.2021.332.

Conflict(s) of Interest. The views expressed are those of the authors and do not reflect the official policy or position of any employers or affiliated organizations. The authors have no conflicts of interest to report.

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