

Systematic Review

Cite this article: Panah HR, Madanian S and Yu J (2024). Disaster Health Care and Resiliency: A Systematic Review of the Application of Social Network Data Analytics. *Disaster Medicine and Public Health Preparedness*, **18**, e334, 1–14
<https://doi.org/10.1017/dmp.2024.294>

Received: 14 January 2024
Revised: 19 May 2024
Accepted: 26 September 2024

Keywords:

social network; disaster health care; public health; disaster management; social network analytics

Corresponding author:

Hamidreza Rasouli Panah;
Email: hamid.rasoulipanah@autuni.ac.nz

Disaster Health Care and Resiliency: A Systematic Review of the Application of Social Network Data Analytics

Hamidreza Rasouli Panah , Samaneh Madanian  and Jian Yu 

Auckland University of Technology (AUT), Department of Computer Science and Software Engineering, Auckland, New Zealand

Abstract

Objectives: This systematic literature review explores the applications of social network platforms for disaster health care management and resiliency and investigates their potential to enhance decision-making and policy formulation for public health authorities during such events.

Methods: A comprehensive search across academic databases yielded 90 relevant studies. Utilizing qualitative and thematic analysis, the study identified the primary applications of social network data analytics during disasters, organizing them into 5 key themes: communication, information extraction, disaster Management, Situational Awareness, and Location Identification.

Results: The findings highlight the potential of social networks as an additional tool to enhance decision-making and policymaking for public health authorities in disaster settings, providing a foundation for further research and innovative approaches in this field.

Conclusions: However, analyzing social network data has significant challenges due to the massive volume of information generated and the prevalence of misinformation. Moreover, it is important to point out that social network users do not represent individuals without access to technology, such as some elderly populations. Therefore, relying solely on social network data analytics is insufficient for effective disaster health care management. To ensure efficient disaster management and control, it is necessary to explore alternative sources of information and consider a comprehensive approach.

The growing frequency of disasters is a global concern due to population growth and societal interconnections,¹ which significantly impact more lives and properties.² Additionally, disasters can lead to severe consequences such as death, injury, displacement, and long-term health impacts, and disrupt the economy and social services.³

The Emergency Event Database (EM-DAT) indicates a significant rise in the number of deaths and overall damage from 2015 to 2022.⁴ The number of deaths has risen from 33 000 to 38 000, excluding COVID-19, while the overall damage has surged from 87 million to 225 million USD. The urgency of coping with disasters has led to the implementation of strategies by governments, organizations, and individuals to mitigate their negative impacts and enhance future resilience.⁵ The focus of these strategies and measures is to identify and manage the risks, needs, and vulnerabilities before and after the occurrence of disasters. To reduce disaster impacts, Disaster Management (DM) is a systematic approach, involving mitigation, preparedness, response, and recovery phases.^{6,7} Effective coordination and communication among sectors are crucial for efficient management.⁸

Disasters can significantly impact health and well-being, necessitating the integration of Disaster Health Care Management (DHM) into the disaster management framework.^{9–11} DHM involves improving treatment protocols and mass casualty management to ensure efficient delivery of health services¹² to disaster-affected communities while minimizing risks to health care workers and facilities.¹³ However, to enhance the efficiency of health services and to minimize disaster risks, increasing resilience among societies and health care systems is crucial.¹⁴ Resiliency supports communities in anticipating and adjusting to, and rebounding from disasters, reducing negative impacts.¹⁵ Integrating resilience measures within the DM framework reinforces health care protocols and preparedness.¹⁶ This also requires considering the importance of Situational Awareness (SA) during disasters for effective decision-making and response.¹⁷ SA provides real-time information, enabling authorities to understand conditions, allocate resources efficiently, and adapt strategies, thus enhancing immediate response capabilities and building disaster resilience.^{18,19} Consequently, to enhance SA, identifying and monitoring public health perception and concern is essential in DHM, leading to better resiliency.

Communication and information sharing plays an important role in SA. Effective communication and data exchange among health care professionals, authorities, policy makers, and

© The Author(s), 2025. Published by Cambridge University Press on behalf of Society for Disaster Medicine and Public Health, Inc. This is an Open Access article, distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike licence (<http://creativecommons.org/licenses/by-nc-sa/4.0>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the same Creative Commons licence is used to distribute the re-used or adapted article and the original article is properly cited. The written permission of Cambridge University Press must be obtained prior to any commercial use.



CAMBRIDGE
UNIVERSITY PRESS

public ensures proper consideration of integrated DHM.²⁰ Understanding the community's needs and expectations is important for inclusive, equitable, and responsive DHM.²¹

In this regard, technology advancements and utilization, e.g., Social Network (SN) and Artificial Intelligence (AI), can enhance communication and SA for DHM.²² SN platforms offer vast data on human behavior and communication patterns, enabling authorities to identify patterns, predict occurrences, and optimize response efforts, thereby refining public health systems and increasing community resilience.^{23,24} However, the large SN data volume necessitates the application of AI algorithms, capable of swift and precise processing of huge datasets to reveal complex trends and patterns undetectable to human observation with traditional methods.²⁵

SNs integration with everyday life and activities has transformed social interactions and unveiled opportunities to identify gaps in health care services.²⁶ Platforms like Facebook, Twitter, Instagram, and LinkedIn have revolutionized information sharing and connectivity, encouraging the emergence of social mining, big data analytics, and computational methodologies.²⁷ SNs also serve as channels for individuals to express health-related concerns and experiences, highlighting unrecognized issues²⁸ such as health care accessibility, service quality, and support for those with health needs.

SNs facilitate communication between the public and governmental/non-governmental organizations,^{29,30} providing real-time data for health insights.³¹ This is especially useful during health emergencies,^{32,33} enhancing community resilience and addressing issues during³⁴ or after emergencies.³⁵ Despite SN's applications in DM, their specific roles and benefits in health care are not fully explored. Further investigation could enhance strategies, response, communication, and support before, during, and after disasters and create new collaboration opportunities in DHM.

The interaction that could arise from the partnership of governments, health care organizations, technology companies, and researchers holds immense potential. Each of these stakeholders holds unique expertise and could collectively unravel innovative solutions that capitalize on the strengths of SNs. By developing and implementing strategies that leverage these platforms, DHM could be elevated to new standards. Therefore, this research aims to investigate how SN can serve as a tool to support DHM operations in monitoring situations, enhancing the quality of decisions to increase resiliency in health care system regarding disasters. The study attempts to identify and examine the current literature in SN data analytics methods and approaches, with the goal of extracting insight of their usage in DHM. Specifically, the study intended to discover how SN data analytics can grant DHM authorities to have access to a variety of opinions and perspectives, real-time information, and expertise.

Research Methodology

A Systematic Literature Review (SLR) was conducted to comprehensively review the background of the field. SLR ensures a comprehensive analysis of the existing knowledge to identify the strengths and limitations of utilizing SNs in DHM, finding the trends and suggesting future research directions. SLR and its analysis allowed the study to gain a deeper understanding of the role and applications of SN in DHM and its revolution over the time. The study conducted a thematic³⁶ and qualitative content analysis³⁷ on the retrieved articles. This analysis involved examining the data for themes and patterns that could provide insights towards the study objectives.

This study searched PubMed, CINAHL, Scopus, SpringerLink, Emerald Insight, IEEE Xplore, ACM Digital Computing, and Google Scholar. The selection of these databases was based on AUT library guidelines^{38–40} and considering the multi-disciplinary nature of the research. The main areas of this research were classified into “social network,” “disaster management,” and “health care.” Therefore, the following keywords were considered to construct the search strings:

Social Network: “social media” OR “social network*”

Disaster Management: “disaster management” OR “emergency management” OR “mass emergency”

health care: health care OR “public health” OR medical* OR “health care”

The general search query was: “disaster management” OR “emergency management” OR “mass emergency” AND “social media” OR “social network*” AND health care OR “public health” OR medical* OR “health care”. However, a searching query was optimized for each database (see [Appendix 1](#)).

The study applied inclusion and exclusion criteria ([Table 1](#)) to ensure on relevancy and quality of the studies to be included in this SLR.⁴¹

The initial number of articles retrieved was 9010, which was reduced to 3256 after applying the inclusion and exclusion criteria and removing duplicates. These 3256 articles were then subjected to a detailed screening process based on their relevance to the research questions and objectives. This screening involved a thorough review of titles and abstracts, resulting in the elimination of 3166 studies that did not meet the criteria for inclusion. The remaining 90 studies were selected for an in-depth review. These selected studies were then thoroughly examined to provide a detailed analysis of the research questions and objectives of the present study. [Figure 1](#) illustrates the systematic process of identifying and selecting following the PRISMA guidelines.

Findings and Results

The retrieved articles demonstrate a growing interest in using SN in DHM, particularly since the beginning of the COVID-19 pandemic ([Figure 2](#)).

To identify and visualize the central elements within the studies in the dataset, this study used Network mapping techniques. As illustrated in [Figure 3A](#), “COVID-19,” “Social Media,” and “Twitter” demonstrate the highest number of connections at the core. This can be interpreted as the substantial pandemic's influence and the critical role of digital platform in shaping discussions, spreading information, and accelerating research initiatives. COVID-19 stands as a critical node with direct connections to diverse concepts such as “big data utilization,” “pandemic

Table 1. Inclusion/exclusion criteria

Inclusion criteria	Exclusion criteria
Full text available	Books / organization reports / letters / thesis / abstract
English	Studies with a pure technological focus
2010 (the birth of modern SN platforms) – 2022	Studies with no discussion of SN
Within the scope of SN usage in health care and disaster management	Studies that focus on emergency rather than disaster settings

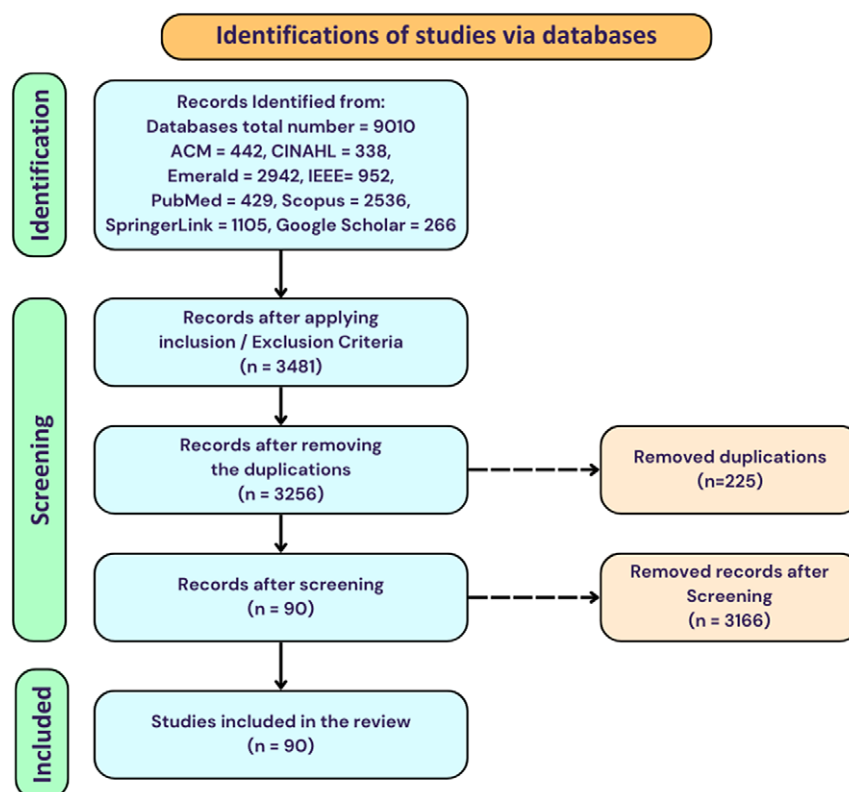


Figure 1. Identification of studies process.

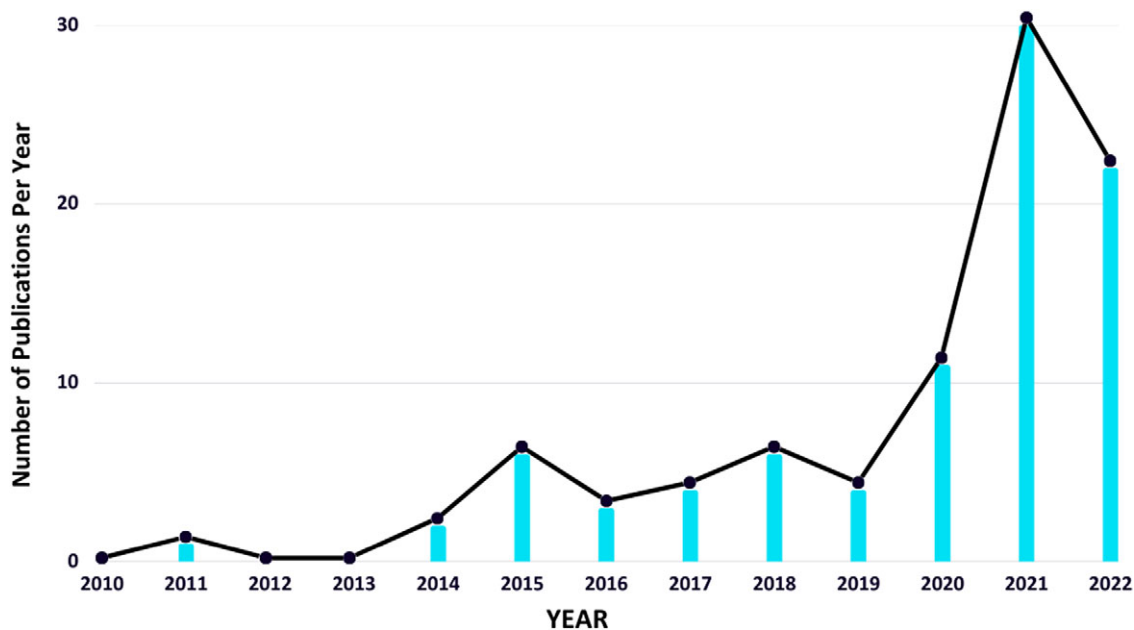


Figure 2. The number of publications per year.

prevention strategies,” “social network analysis,” “data correlation techniques,” “analysis of internet public opinion,” “cooperative governance models,” and “data mining practices.” This shows the multidisciplinary aspect of pandemics, demonstrating the necessity for collaborations among health care, data analytics, public opinion analysis, and governance experts.

Among SN platforms, Twitter acts as a dynamic hub connecting discussions on natural disasters, content analysis, emotions, public sentiment, and behavioral science. This showcases its role in fostering dialogues about disasters and their diverse consequences, including health-related issues. Moreover, direct links include crisis communication techniques, citizen participation through science

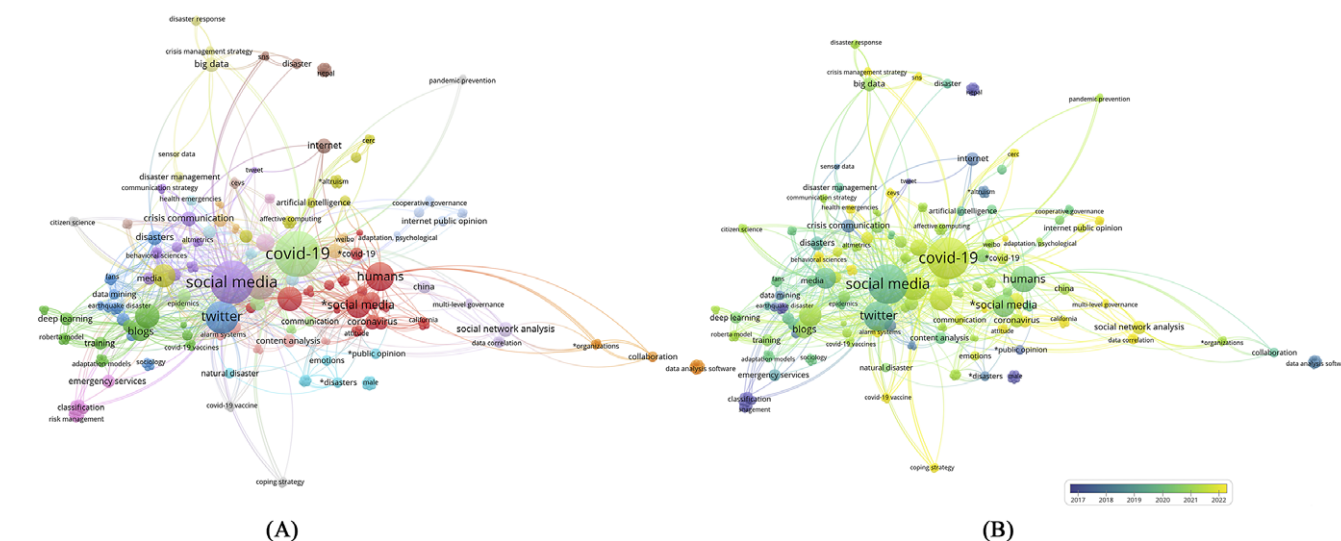


Figure 3. (A) Network mapping, (B) Overlay visualization.

programs, coping strategy design, and communication tactics clarify the role of SN platforms as dynamic hubs for disseminating disaster-related information, engaging the public, and strategizing resilience.

The evolution of study interests is illustrated in Figure 3B using a color spectrum from which the changing landscape of DHM research can be clearly seen. Not surprising, COVID-19 has triggered a noticeable rise in research interest in the field. This reflects a reassessment of disaster preparedness and an increased focus on health care resilience, specifically concerning pandemics. These observations highlight how disasters prompt enhanced information sharing, communication, and collaboration across different disciplines.

Social Network Platforms

Twitter identified as the most frequently used SN platform. This could be rooted in Twitter swift communication, broad user base, and API accessibility facilitating comprehensive data extraction for varied SN investigations, notably in emergency contexts.^{42,43} Weibo, popular in China, serves as a significant avenue for expressing public opinions, while Instagram and Facebook, globally recognized for content sharing, have been extensively employed in disseminating disaster-related information, accumulating substantial daily views.^{44–47} Additionally, WhatsApp's effectiveness in interactive communication during disasters was evident, following by YouTube, WeChat, and Baidu contributed to DHM as leveraged SN platforms.^{48–53}

Among media types analyzed in the out dataset, text emerges as the predominant content form due to its rich information content, ideal for linguistic pattern analysis, sentiment examination, and discourse exploration. Its compatibility with processing and categorization enables large-scale analysis and is readily available on SN platforms accompanied by user-generated captions, comments, and hashtags, offering valuable insights into user behavior and opinions. The abundance and ease of processing of text-based content contribute to its extensive utilization in comprehensive SN dataset studies, facilitating in-depth sentiment analysis and effective topic modelling.

Disaster Types

Different types of disasters were identified in the dataset, with the COVID-19 being the primary focus due to its global impact on health care systems and SN platforms' role in disaster communication.^{47,54–56} The dataset also includes investigations into other infectious disease outbreaks, such as Zika⁵⁷ and Ebola.^{58,59} These studies aim to identify patterns in public concerns and facilitate the dissemination of health-related information to the public. Furthermore, SNs were also instrumental during earthquakes, to gain deeper insights into the situation and to enhance relief operations.^{49,60} Similarly, during hurricanes and flood SN played a crucial role in disseminating information, communicating risks, and analyzing public sentiments to predict public resilience and aid disaster responders effectively.^{61–65} Moreover, SN platforms were utilized to monitor environmental hazards, contributing to increase public awareness.^{66,67} These platforms were also utilized in addressing a spectrum of other disaster types including typhoons, cyclones, water shortages, and petrochemical accidents.^{66,68–70}

Social Network Applications Themes

This study identified 5 primary categories where SNs play a crucial role. These categories and sub-categories are illustrated in Figure 4.

Communication

As expected, communication emerged as the important role of SNs in DM for across all disaster phases. Authorities leveraged SN to disseminate emergency protocols and disaster preparedness guides to a broad audience, fostering public awareness and readiness for disaster response.^{61,62} SNs offer adaptable communication that accommodate to various demographics, ensuring inclusivity and multilingual content, enhancing trust, participation, and collaboration among different groups and organizations in DHM efforts.^{96,109,123} SNs enable coordination among government agencies, emergency response teams, health care organizations, non-profits, and the public in disaster preparedness efforts, increasing resilience and ensuring well-informed populations.¹²¹

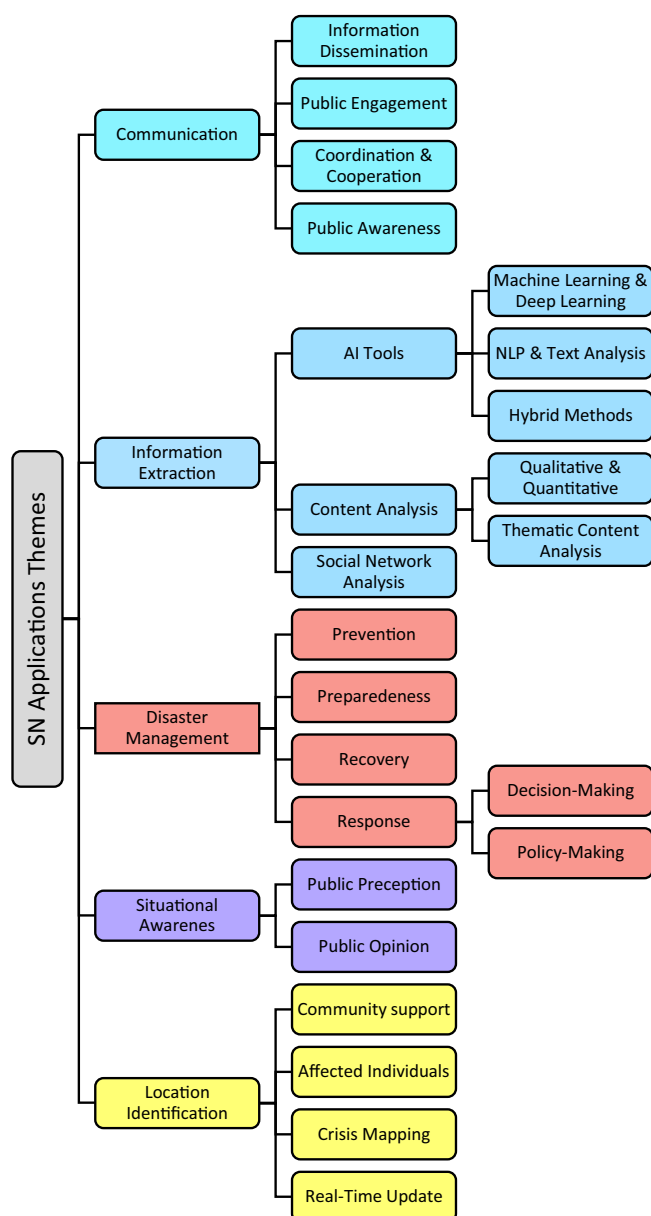


Figure 4. Five main categories of SN applications for DHM.

In disasters, SNs function as critical platforms for immediate, real-time information dissemination.¹²¹ Authorities can use SNs for swift sharing updates including evacuation directives, shelter provisions, and availability of emergency services ensuring timely access and minimizing confusion and misinformation. SNs also enable an interactive, 2-way dialogue.^{50,94} Affected individuals can use SN platforms to seek assistance, report emergencies, and provide firsthand information. This interactive feedback loop proves invaluable for DHM authorities, enabling them to efficiently strategize and allocate resources by using real-time insights and public inputs. This seamless exchange of information facilitates the swift deployment of resources and targeted responses to the pressing needs of affected communities during crises.^{89,95,113}

SNs are also crucial communication tools during recovery efforts. SNs can promote coordination and collaboration among various entities, including government agencies, emergency response teams, health care institutions, and the public.^{114,130} SN

platforms enable community-driven initiatives, such as mobilizing volunteers and the coordination of donation drives, fostering solidarity and resilience in affected communities by empowering individuals to actively participate in the recovery process. Additionally, SNs offer an opportunity for shared content analysis and sentiment tracking, providing valuable insights into public awareness and sentiments following the disaster.^{74,111} By analyzing shared content, authorities gain a deeper understanding of the evolving needs and feelings of the affected population which aids in the formulation of more effective post-disaster communication strategies and developing long-term recovery plans, ensuring targeted, sensitive, and community-aligned efforts.

The role of SNs in DM spans beyond simple information dissemination. It encompasses a spectrum of functions that stimulate public engagement, streamline coordination efforts, and establish feedback mechanisms. This comprehensive involvement significantly amplifies the efficacy of communication strategies throughout all stages of disasters, thereby yielding more efficient and well-coordinated responses and recovery efforts. SN platforms enhance communication strategies during disasters by facilitating rapid dissemination of critical information, encouraging active participation among stakeholders, and facilitating real-time interactions. This enables DHM entities to adapt strategies and allocate resources based on real-time needs and community feedback, increasing resilience and ensuring effective disaster response and recovery initiatives.

Situational Awareness

SA involves the monitoring and comprehension of disasters' impact on public health through SN platforms.^{45,93,122} SNs support real-time understanding of disasters' impact on the public, serving as crucial data sources for constant monitoring of evolving situations.^{115,124} SNs can be centralized spaces for affected individuals to share personal experiences during disasters, enabling immediate communication and identification of emerging health issues.^{81,94} This direct and unfiltered interaction is valuable in swiftly comprehending the evolving health landscape.

Individuals can also use SNs' platforms to share timely updates regarding their status, access to medical facilities, availability of essential supplies, and other relevant information. Moreover, leveraging data mining and analytics techniques is instrumental in recognizing patterns, trends, and potential focal points of health issues.^{63,99,100} This approach significantly improves the capacity and focus of responding to health challenges during disasters.

SNs are influential assets in enhancing disaster SA. These platforms facilitate information sharing among impacted populations, providing crucial insights into health needs and challenges during disasters, enabling responders to adapt effectively.

Information Extraction

Information extraction is the process of gathering and analyzing data to understand disaster impacts, assist communities, and inform governments and agencies for preparedness and public health implications.⁹² SN data analytics can highlight specific problems, such as how disaster relief activities might provoke negative views if they are carried out without a thorough grasp of local cultures.⁶⁰ Also, by investigating the emotional expressions of SN users before, during, and after disasters, it is possible to

determine potential links between DHM activities and disaster impacts.⁷⁷ The analysis helps authorities detect risks, trends, and early warnings; adopt preventative measures; and prepare the public for disasters. Furthermore, during a disaster, it allows authorities to analyze response operations' effectiveness, make required modifications, and assess damages to prepare for recovery.

From the analysis, it is evident that researchers employed diverse methodologies to analyze SN data for DHM, including AI tools, Content Analysis, Social Network Analysis, and other analysis techniques. The discussion over them is provided in the following subsection.

Machine Learning and Deep Learning

There has been an extensive use of Machine Learning (ML) and Deep Learning (DL) techniques, particularly DL architectures, like Long Short-Term Memory networks (LSTM), for analyzing sequential data in SN data during disasters.^{80,113} Stacked LSTM architectures have enabled a more intricate understanding of evolving patterns and sentiments over time, aiding in real-time decision-making.¹⁰¹ Also, the RoBERTa model, a variant of the Bidirectional Encoder Representations from Transformers BERT architecture, excelled in understanding context and semantics within textual data, enabling deeper sentiment analysis and information extraction.^{81,90} Utilizing Multi-task Domain Adversarial Attention Networks (MT-DAAN) enabled simultaneous performance sentiment analysis, entity recognition, and trend identification within SN data.⁸² Traditional Machine Learning algorithms like Support Vector Machines (SVM),^{92,98,116} K-Nearest Neighbours (KNN),^{92,105} Naive Bayes classifiers,^{98,105} and ensemble methods such as Random Forest, Adaboost, and Gradient Boosting have proven effective in classifying sentiments, identifying relevant topics, and forecasting potential trends during disaster events.^{89,98,105,116} For instance, SVM has significantly contributed to sentiment classification, distinguishing between positive and negative sentiments in SN data during and after disasters.

NLP and Text Analysis

Natural Language Processing (NLP) and Text Analysis techniques have been essential in dissecting the linguistic trails in SN data, contributing to DHM research. Again, LSTM-based sentiment analysis has enabled the interpretation of emotional expressions, capturing the sentiments of individuals and communities before, during, and after disaster.⁷⁸ Latent Dirichlet Allocation (LDA) topic modelling has been crucial in uncovering latent themes and prevalent topics within massive volumes of disaster-related textual data.^{50,66,78,97} Additionally, sentiment analysis using Python-based libraries such as NLTK and Snow NLP allows for the extraction of emotions, enabling a deeper understanding of public perceptions and reactions in crisis situations.^{84,86}

Furthermore, BERT, a contextual model understanding, has been leveraged to accurately discern sentiment polarity and emotional expressions. This model is employed with emotion analysis to capture the alterations in public sentiments during different disaster phases.^{84,100} Moreover, Named Entity Recognition (NER) combined with Graph-based clustering effectively identifies and categorizes entities and relationships in SN data.^{100,104} This helps disaster response teams to swiftly identify critical information, locations, and sentiment trends, enabling targeted and efficient intervention strategies.

Hybrid Models

The Hybrid Methods adopted in analyzing SN data for DHM involve combining diverse tools and techniques to gain comprehensive insights. Studies have employed combinations of methodologies such as LDA for topic modelling, sentiment analysis, and correlation analysis to reveal complex perspectives in SN data during disaster events.

The integration of NER, BERT, and Graph-based clustering techniques enable extraction of location-specific information, sentiment trends, and relationship mapping.¹⁰⁰ This integration can support DM authorities in refining response strategies by considering geographic-specific needs and sentiment analysis. Furthermore, employing a combination of Convolutional Neural Network (CNN) and RoBERTa,⁹⁰ Word2Vec, fastText, and LSTM⁹⁹ in a unified pipeline has enabled holistic approaches to analyzing SN data. Combining sentiment analysis, entity recognition, and deep contextual understanding, these methods provide a comprehensive view of SN data during disasters, aiding in informed decision-making by authorities and organizations.

Within the dataset, a spectrum of studies extensively reached into content analysis methodologies to examine SN data in DHM contexts. These studies utilized qualitative and quantitative content analysis approaches to analyze textual information in SN posts during disaster events. Qualitative content analysis delved into subjective aspects of SN discussions, uncovering intensity and emotions^{57,74,75,103} while quantitative content analysis structured sentiments, frequency, and statistical patterns.^{108,109}

Additionally, thematic content analysis emerged as a fundamental tool in categorizing and identifying recurring topics in SN conversations during disasters, offering a comprehensive view of prevalent discussions and priorities.⁵⁶ Psycho-linguistic analysis decoded emotional cues and linguistic patterns in SN communications, revealing insights into individuals' mental and emotional states.¹²⁴ Furthermore, 1 study leveraged SAS text miner, showcasing an automated approach to content analysis, aiding in the extraction, categorization, and summarization of information from extensive volumes of data.⁵⁸

Furthermore, the dataset contains studies that extensively explore Social Network Analysis (SNA) techniques, which are not specifically reliant on AI techniques or qualitative/quantitative methods.¹¹⁴ Researchers used various methods, including specialized software like UCINET, to uncover intricate network structures and dynamics in SN data.⁷¹

Moreover, employing semantic analysis techniques deepened the understanding of underlying meanings conveyed through language in SN discussions related to disaster events.⁹⁶ Dynamic network analysis methods were crucial in tracking changes in network structures over time in SN platforms, offering insights into evolving communication patterns, influence, and interactions. These varied content analysis methodologies provided valuable insights for developing informed DHM strategies without relying on ML techniques.

Location Identification

The utilization of spatiotemporal data derived from SNs significantly enhances the understanding of public health during ongoing disasters. This form of data combines spatial and temporal information, providing a comprehensive view of how health-related issues evolve over both space and time.^{52,80,100} This insight is valuable for assessing the dynamics of a disaster's

impact on public health. For instance, real-time tracking of infection locations and population on SN platforms helps authorities make informed decisions, implement targeted interventions, and provide SA.^{80,99}

Location identification from SN data in disasters is the process of identifying the location of SN posts related to a disaster event. For example, one research utilized DL to categorize disaster-related tweets from impacted areas,⁸⁰ while another employed text analysis to track individuals' positions during disasters.⁵² These methods show how advanced technologies can extract vital location-specific details from SN data. In separate research, a hybrid ML technique was used to identify disaster-related locations.¹⁰⁰ This technique illustrates the interaction between various ML methodologies like NER and advanced models like BERT, to highlight disaster-affected locations.

The utilization of spatiotemporal data from SN platforms aids in understanding health issues' geographical spread and progression during disasters with advanced analyses and tools demonstrating potential for effective public health interventions.

Disaster Management

The analysis of the studies in the review dataset revealed the significant impact of SN platforms across all phases of DM. SN platforms prove invaluable in prevention by spreading essential information, increasing awareness, and enhancing community preparedness.^{53,119} SN platforms aid in the response phase by facilitating communication, coordinating relief efforts, providing real-time updates,^{49,67,72,124} and aiding authorities in decision-making and policy formulation.^{50,64,68,107,123} These networks contribute to SA by extracting information, monitoring initiatives, and detecting hazards and vulnerabilities, crucial for mitigation and preparedness.^{74,119} In relief operations, SN assists in identifying affected areas, connecting aid organizations with communities, and streamlining resource distribution. In the recovery phase, SN remains crucial by helping to allocate resources effectively, identifying vulnerable groups, and assessing evolving community needs and sustainable recovery.^{60,64,124}

Discussion and Conclusion

Studies show SN platforms are crucial for authorities to effectively communicate and share essential information during health emergencies, assessing public awareness and planning responses.⁸⁷ SN platforms foster collaboration and communication between authorities and the public, enhancing disaster risk mitigation and resilience by influencing public perceptions and assessing public awareness and response intentions.^{42,62,120} Moreover, SN improves SA, allowing people, organizations, and governments to monitor and comprehend the effects of disasters and facilitate more effective responses to emerging needs.^{68,122} Through the analysis of SN data, it is possible to address the needs before, during, and after disasters with better efficiency.

AI technologies enable swift implementation of adaptive strategies by analyzing user-generated content on SN platforms, identifying valuable patterns and trends to enhance health care efforts.^{66,68} Employing AI models enables the efficient controlling of health care requirements throughout various stages of disasters to analyzing extensive SN data in real-time. The AI-driven analysis detects frequent patterns, emerging trends, public opinions, and the dynamics of the disasters. Ultimately, this leads to the preservation

of lives and the reduction of disaster-related consequences in communities.^{66,68}

Although, SN platforms have provided new approaches for information sharing and networking, they have also accelerated the generation of massive amounts of information.¹³¹ As a consequence, the rapid pace of information generation has led to information overload, a state where the amount of data overwhelms the capacity to process it effectively.¹³² Additionally, the excessive amount of data can strain cognitive abilities, reduce attention spans, and lead to decision fatigue due to the overwhelming amount of choices or data to process.¹³³

Moreover, the quick spread of false and inaccurate information on SN platforms has raised concerns about potential harm to individuals and society.¹³⁴ False information in DHM can lead to severe consequences, necessitating accurate and timely information for authorities and policy-makers to make informed decisions.¹³⁵ Misleading information can intensify disaster impact, undermine public trust in authorities' response efforts, and contribute to harmful beliefs.¹³⁶ This can result in non-compliance with safety measures that can put people in danger. Therefore, the use of reliable, accurate, and up-to-date information in DHM is crucial to prevent the spread of false information and its negative effects.

Additionally, it is important to recognize that SNs cannot fully represent the entire community's population.¹³⁷ In fact, individuals who use SN may not be the most vulnerable during disasters, potentially distorting understanding of affected populations, especially the elderly and those without technology access. To better understand disaster-affected populations, a comprehensive approach combining SN data with diverse communication methods, community engagement, traditional media, and field assessments is essential to ensure a better understanding of diverse disaster-affected groups.

Furthermore, some types of disasters, such as earthquakes, hurricanes, or cyber-attacks can cripple communication networks, cutting off access to vital channels like SN platforms.¹³⁸ Moreover, displaced individuals might lose their personal technological devices, further limiting their ability to connect via SN.¹³⁹ Disruptions in communication and information dissemination exacerbate challenges in disaster response, highlighting the need for alternative approaches to reach and assist affected communities.

Relying solely on SN for DHM presents a research gap, highlighting the potential for incomplete or inaccurate information due to individuals who are either not active on or lack access to SN platforms. Such oversight can render their concerns and needs invisible within DM frameworks. Future studies should consider the experiences of non-active SN users to fully understand the broader population's perspectives. To address this issue, efforts should be made to collect information from a variety of sources in order to guarantee a thorough grasp of the situation.

Furthermore, while SN platforms are undeniably valuable in emergency situations, they should not serve as the total means to manage disasters. Effective DHM requires coordinating various resources and strategies, planning, robust communication protocols, preparedness measures, and collaboration among stakeholders. It involves thorough preparation by identifying risks, evaluating disaster impacts on health care, and creating flexible emergency response strategies.

It is critical to understand that SN data analytics is only 1 of several ways that should be employed for an effective DHM. Comprehensive DHM mandates integrating diverse methodologies and data sources beyond SN platforms, including traditional data collection, community engagement, expert consultations, and

unpublished data. By embracing a diverse array of resources, DHM efforts can be more resilient and adaptive in addressing the complexities of DM.

It is important to acknowledge that the current study has certain limitations that may be addressed in future research. This study may have overlooked some relevant literature due to selection of keywords and inclusion/exclusion criteria, despite efforts to address these limitations through well-defined research protocols and existing theories. The research underscores the significance of utilizing SNs despite their challenges, paving the way for future research and robust methodologies to enhance disaster decision-making. Future studies should incorporate multiple information sources to improve accuracy and quality, advance scientific knowledge, and aid in informed decision-making processes.

Supplementary material. To view supplementary material for this article, please visit <http://doi.org/10.1017/dmp.2024.294>.

Author contribution. HRP was the main researcher and responsible for data collection and data analysis, all these tasks were conducted under SM supervision. SM contributed to the research method, reflection on research results, and data interpretation. HRP prepared the first draft of the research which was commented on and enhanced by SM. JU commented on the revised version and enhanced the research question. All authors agreed on the final version.

References

- de Ruiter MC, Couasnon A, van den Homberg MJ, et al. Why we can no longer ignore consecutive disasters. *Earth's Future*. 2020;8(3):e2019EF001425.
- Center ADR. Sendai Framework for Disaster Risk Reduction 2015–2030. United Nations Office for Disaster Risk Reduction: Geneva, Switzerland; 2015.
- Moore T, Lakha R. *Tolley's Handbook of Disaster and Emergency Management*. Routledge; 2007.
- EM-DAT. EM-DAT Public. <https://public.emdat.be/>
- Nojavan M, Salehi E, Omidvar B. Conceptual change of disaster management models: a thematic analysis. *Jambá: Journal of Disaster Risk Studies*. 2018;10(1):1–11.
- Noran O. Collaborative disaster management: an interdisciplinary approach. *Comp Ind*. 2014;65(6):1032–1040. doi:<https://doi.org/10.1016/j.compind.2014.04.003>
- Sawalha IH. A contemporary perspective on the disaster management cycle. *Foresight*. 2020;22(4):469–482. doi:[10.1108/FS-11-2019-0097](https://doi.org/10.1108/FS-11-2019-0097)
- Kaynak R, Tuğer AT. Coordination and collaboration functions of disaster coordination centers for humanitarian logistics. *Procedia Soc Behav Sci*. 2014;109:432–437. doi:<https://doi.org/10.1016/j.sbspro.2013.12.486>
- Madanian S, Parry D, Norris T. Healthcare in Disasters and the Role of RFID. *Stud Health Technol Inform*. 2015;216:1008.
- Madanian S, Parry D. Identifying the potential of RFID in disaster health care: an International Delphi Study. *Electronics*. 2021;10(21). doi:[10.3390/electronics10212621](https://doi.org/10.3390/electronics10212621)
- Zhong S, Clark M, Hou X-Y, et al. Progress and challenges of disaster health management in China: a scoping review. *Glob Health Action*. 2014;7(1):24986.
- Norris AC, Martinez S, Labaka L, et al. Disaster E-Health: A New Paradigm for Collaborative Healthcare in Disasters. In: *ISCRAM*. 2015 May.
- Francescutti LH, Sauve M, Prasad AS. *Natural Disasters and Health Care: Lessons to Be Learned*. SAGE Publications; 2017:53–55.
- Biddle L, Wahedi K, Bozorgmehr K. Health system resilience: a literature review of empirical research. *Health Pol Plann*. 2020;35(8):1084–1109. doi:[10.1093/heapol/czaa032](https://doi.org/10.1093/heapol/czaa032)
- Saunders WSA, Becker JS. A discussion of resilience and sustainability: land use planning recovery from the Canterbury earthquake sequence, New Zealand. *Int J Disaster Risk Reduct*. 2015;14:73–81. doi:<https://doi.org/10.1016/j.ijdrr.2015.01.013>
- Haldane V, De Foo C, Abdalla SM, et al. Health systems resilience in managing the COVID-19 pandemic: lessons from 28 countries. *Nat Med*. 2021;27(6):964–980. doi:[10.1038/s41591-021-01381-y](https://doi.org/10.1038/s41591-021-01381-y)
- O'Brien A, Read GJM, Salmon PM. Situation Awareness in multi-agency emergency response: models, methods and applications. *Int J Disaster Risk Reduct*. 2020;48:101634. doi:<https://doi.org/10.1016/j.ijdrr.2020.101634>
- Laurila-Pant M, Pihlajamäki M, Lanki A, et al. A protocol for analysing the role of shared situational awareness and decision-making in cooperative disaster simulations. *Int J Disaster Risk Reduct*. 2023;86:103544. doi:<https://doi.org/10.1016/j.ijdrr.2023.103544>
- Zaman MO, Raihan MMH. Community resilience to natural disasters: a systemic review of contemporary methods and theories. *Nat Haz Res*. 2023;doi:<https://doi.org/10.1016/j.nhres.2023.05.003>
- Altevogt B, Reeve M, Wizemann T. *Engaging the Public in Critical Disaster Planning and Decision Making: Workshop Summary*. National Academies Press; 2013.
- Levine CA, Jansson DR. Concepts and terms for addressing disparities in public health emergencies: accounting for the COVID-19 pandemic and the social determinants of health in the United States. *Disaster Med Public Health Prep*. 2021:1–7.
- Parry D, Madanian S, Norris T. Disaster EHealth-Sustainability in the Extreme. In: *2016 IEEE 14th Intl Conf on Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech)* 2016 (pp. 943–946). IEEE.
- Anson S, Watson H, Wadhwa K, et al. Analysing social media data for disaster preparedness: Understanding the opportunities and barriers faced by humanitarian actors. *Int J Disaster Risk Reduct*. 2017;21:131–139. doi:<https://doi.org/10.1016/j.ijdrr.2016.11.014>
- Acikara T, Xia B, Yigitcanlar T, et al. Contribution of social media analytics to disaster response effectiveness: a systematic review of the literature. *Sustainability*. 2023;15(11):8860.
- Xu Y, Liu X, Cao X, et al. Artificial intelligence: a powerful paradigm for scientific research. *The Innovation*. 2021;2(4):100179. doi:<https://doi.org/10.1016/j.xinn.2021.100179>
- Xie L, Pinto J, Zhong B. Building community resilience on social media to help recover from the COVID-19 pandemic. *Comp Hum Behav*. 2022;134:107294. doi:<https://doi.org/10.1016/j.chb.2022.107294>
- Gupta V, Gupta M. Social media mining: a new framework and literature review. *Int J Bus Anal*. 2016;3(1):58–68.
- Chen Q, Min C, Zhang W, et al. Unpacking the black box: How to promote citizen engagement through government social media during the COVID-19 crisis. *Comp Hum Behav*. 2020;110:106380.
- Dong ZS, Meng L, Christenson L, et al. Social media information sharing for natural disaster response. *Nat Haz*. 2021;107:2077–2104.
- Palen L, Hughes AL. Social Media in Disaster Communication. *Handbook of Disaster Research*. 2018:497–518. Springer. https://doi.org/10.1007/978-3-319-63254-4_24
- Muniz-Rodriguez K, Ofori SK, Bayliss LC, et al. Social media use in emergency response to natural disasters: a systematic review with a public health perspective. *Disaster Med Public Health Prep*. 2020;14(1):139–149.
- Madanian S, Airehrour D, Samsuri NA, et al. Twitter sentiment analysis in Covid-19 Pandemic. *IEEE*. 2021:0399–0405.
- Madanian S, Norris T, Parry D. Disaster eHealth: scoping review. *J Med Internet Res*. 2020;22(10):e18310.
- Yang W, Li Z, Lan Y, et al. A nationwide web-based automated system for outbreak early detection and rapid response in China. *Western Pac Surveill Response J*. 2011;2(1):10.
- Madanian S, Rasoulipannah H, Yu J. Stress detection on social network: public mental health surveillance: public mental health surveillance. *Proceedings of the 2023 Australasian Computer Science Week*. 2023:170–175.
- Clarke V, Braun V. Thematic analysis. *J Pos Psychol*. 2016;12(3):297–298. doi:[10.1080/17439760.2016.126261](https://doi.org/10.1080/17439760.2016.126261)
- Hsieh HF, Shannon SE. Three approaches to qualitative content analysis. *Qual Health Res*. 2005;15(9):1277–88. doi:[10.1177/1049732305276687](https://doi.org/10.1177/1049732305276687)
- Databases: Computer Sciences. Accessed 2022. Auckland University of Technology. <https://aut.ac.nz/libguides.com/az.php?s=43316>.

39. Databases: Disaster & Emergency Management. Accessed 2022. Auckland University of Technology. <https://aut.ac.nz.libguides.com/az.php?s=46637>
40. Databases: Health. Accessed 2022. Auckland University of Technology. <https://aut.ac.nz.libguides.com/az.php?s=43330>
41. Lame G. Systematic literature reviews: an introduction. *Proceedings of the Design Society: International Conference on Engineering Design*. 2019;1(1): 1633–1642. doi:10.1017/dsi.2019.169
42. Mittal R, Ahmed W, Mittal A, et al. Twitter users' coping behaviors during the COVID-19 lockdown: an analysis of tweets using mixed methods. *Inf Disco Deliv*. 2021;49(3):193–202.
43. Seddighi H, Salmani I, Seddighi S. Saving lives and changing minds with Twitter in disasters and pandemics: a literature review. *Journal Media*. 2020;1(1):59–77.
44. Gao H, Guo D, Wu J, et al. Weibo users' emotion and sentiment orientation in Traditional Chinese Medicine (TCM) during the COVID-19 pandemic. *Disaster Med Public Health Prep*. 2022;16(5):1835–1838. doi:10.1017/dmp.2021.259
45. Shan S, Zhao F, Wei Y, Liu M. Disaster management 2.0: a real-time disaster damage assessment model based on mobile social media data—a case study of Weibo (Chinese Twitter). *Saf Sci*. 2019;115:393–413. doi:10.1016/j.ssci.2019.02.029
46. Niknam F, Samadbeik M, Fatehi F, et al. COVID-19 on Instagram: a content analysis of selected accounts. *Health Pol Technol*. 2021;10(1): 165–173. doi:10.1016/j.hlpt.2020.10.016
47. Mori E, Barabaschi B, Cantoni F, et al. Evidences of citizens' engagement from COVID-19 pandemic in Italy. Health care system' Facebook communication. *Int J Public Admin*. 2021;doi:10.1080/01900692.2021.1993906
48. Muswede T, Sithole SL. Social media networking as a coping strategy amid the COVID-19 lockdown: the case of migrant women in Limpopo, South Africa. *South African Review of Sociology*. 2022;52(2):4–19. doi:10.1080/21528586.2022.2068159
49. Basu M, Ghosh S, Jana A, et al. Medical requirements during a natural disaster: a case study on WhatsApp chats among medical personnel during the 2015 Nepal Earthquake. *Disaster Med Public Health Prep*. 2017;11(6): 652–655. doi:10.1017/dmp.2017.8
50. Zhong Z. Internet public opinion evolution in the COVID-19 event and coping strategies. *Disaster Med Public Health Prep*. 2021;15(6):e27–e33. doi:10.1017/dmp.2020.299
51. Park YE. Developing a COVID-19 crisis management strategy using news media and social media in big data analytics. *Soc Sci Comp Rev*. 2022;40(6): 1358–1375. doi:10.1177/08944393211007314
52. Abu-Alsaad HA, Al-Taie RRR. Nlp analysis in social media using big data technologies. *Telkomnika (Telecommunication Computing Electronics and Control)*. 2021;19(6):1840–1846. doi:10.12928/TELKOMNIKA.v19i6.19339
53. Zhuang Y, Zhao T, Shao X. Mechanism of wechat's impact on public risk perception during Covid-19. *Risk Manag Healthc Policy*. 2021;14: 4223–4233. doi:10.2147/RMHP.S328175
54. Chong M, Park HW. COVID-19 in the Twitterverse, from epidemic to pandemic: information-sharing behavior and Twitter as an information carrier. *Scientometrics*. 2021;126(8):6479–6503. doi:10.1007/s11192-021-04054-2
55. Luna S, Guerrero A, Gonzalez K, et al. Social media and pandemic events: challenges for alert-warning systems. In: *2022 17th Annual System of Systems Engineering Conference (SOSE) 2022 Jun 7* (pp. 403–408). IEEE.
56. Durowaye TD, Rice AR, Konkole ATM, et al. Public health perinatal promotion during COVID-19 pandemic: a social media analysis. *BMC Public Health*. 2022;22(1):895. doi:10.1186/s12889-022-13324-4
57. Hagen L, Scharf R, Neely S, et al. Government Social Media Communications During Zika Health Crisis. In: *ACM International Conference Proceeding Series*. 2018.
58. Lazard AJ, Scheinfeld E, Bernhardt JM, et al. Detecting themes of public concern: a text mining analysis of the Centers for Disease Control and Prevention's Ebola live Twitter chat. *Am J Infect Control*. 2015;43(10): 1109–1111. doi:10.1016/j.ajic.2015.05.025
59. Seltzer EK, Jean NS, Kramer-Golinkoff E, et al. The content of social media's shared images about Ebola: a retrospective study. *Public Health*. 2015;129(9):1273–1277. doi:https://doi.org/10.1016/j.puhe.2015.07.025
60. Radiant J, Hiltz SR, Labaka L. An Overview of Public Concerns During the Recovery Period after a Major Earthquake: Nepal Twitter Analysis. The Hawaii International Conference on System Sciences; 2016:136–145.
61. Wang B, Zhuang J. Crisis information distribution on Twitter: a content analysis of tweets during Hurricane Sandy. *Nat Haz*. 2017;89(1):161–181. doi:10.1007/s11069-017-2960-x
62. Wang Y, Hao H, Platt LS. Examining risk and crisis communications of government agencies and stakeholders during early-stages of COVID-19 on Twitter. *Comp Hum Behav*. 2021;114:106568.
63. Chen S, Mao J, Li G. *Spatiotemporal Analysis on Sentiments and Retweet Patterns of Tweets for Disasters*. Springer International Publishing; 2019: 436–443.
64. Bakar UA, Sidi F, Jabar MA, et al. A multistage analysis of predicting public resilience of impactful social media crisis communication in flooding emergencies. *IEEE Access*. 2022;10:57266–57282. doi:10.1109/ACCESS.2022.3176963
65. Rudra K, Goyal P, Ganguly N, et al. Identifying Sub-events and Summarizing Disaster-Related Information from Microblogs. presented at: *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, Ann Arbor, MI, USA; 2018. <https://doi.org/10.1145/3209978.3210030>
66. Xiong J, Hsuen Y, Naslund JA. Digital surveillance for monitoring environmental health threats: a case study capturing public opinion from twitter about the 2019 Chennai water crisis. *Int J Environ Res Public Health*. 2020;17(14):1–15. 5077. doi:10.3390/ijerph17145077
67. Finch KC, Snook KR, Duke CH, et al. Public health implications of social media use during natural disasters, environmental disasters, and other environmental concerns. *Nat Haz*. 2016;83(1):729–760.
68. Saleem S, Mehrotra M. *Emergent Use of Artificial Intelligence and Social Media for Disaster Management*. Springer Singapore; 2022: 195–210.
69. Abbassinia M, Kalatpour O, Motamedzade M, et al. Application of social network analysis to major petrochemical accident: interorganizational collaboration perspective. *Disaster Med Public Health Prep*. 2021;15(5): 631–638. doi:10.1017/dmp.2020.86
70. Asif A, Khatoun S, Hasan MM, et al. Automatic analysis of social media images to identify disaster type and infer appropriate emergency response. *J Big Data*. 2021;8(1):83. doi:10.1186/s40537-021-00471-5
71. Wukich C, Mergel I. Closing the citizen-government communication gap: content, audience, and network analysis of government tweets. *J Homel Secur Emerg Manag*. 2015;12(3):707–735.
72. Alamoodi AH, Zaidan BB, Zaidan AA, et al. Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: a systematic review. *Expert Syst Appl*. 2021;167:114155. doi:10.1016/j.eswa.2020.114155
73. Yum S. Informatics for COVID-19 in New York and California. *Disaster Med Public Health Prep*. 2022;16(5):1775–1779. doi:10.1017/dmp.2021.53
74. Yang Y, Su Y. Public voice via social media: role in cooperative governance during public health emergency. *Int J Environ Res Public Health*. 2020;17(18):1–18. 6840. doi:10.3390/ijerph17186840
75. Pang PCI, Cai Q, Jiang W, et al. Engagement of government social media on facebook during the COVID-19 pandemic in Macao. *Int J Environ Res Public Health*. 2021;18(7):3508. doi:10.3390/ijerph18073508
76. Leibowitz MK, Scudder MR, McCabe M, et al. Emergency medicine influencers' twitter use during the covid-19 pandemic: a mixed-methods analysis. *West J Emerg Med*. 2021;22(3):710–718. doi:10.5811/west-jem.2020.12.49213
77. Garske SI, Elayan S, Sykora M, et al. Space-time dependence of emotions on Twitter after a natural disaster. *Int J Environ Res Public Health*. 2021;18(10):doi:10.3390/ijerph18105292
78. Wang N, Lv X. Research on Emotional Analysis of Netizens and Topic Distribution Under Public Health Emergencies : A Case Study of COVID-19. 2020 International Conference on Public Health and Data Science; 2020:76–80.
79. Woo H, Cho Y, Shim E, et al. Public trauma after the Sewol Ferry Disaster: the role of social media in understanding the public mood. *Int J Environ Res Public Health*. 2015;12(9):10974–10983. doi:10.3390/ijerph120910974

80. Shams S, Goswami S, Lee K. Deep Learning-Based Spatial Analytics for Disaster-Related Tweets: An Experimental Study. *20th IEEE International Conference on Mobile Data Management*; 2019:337–342.
81. Madichetty S, S M. A Neural-Based Approach for Detecting the Situational Information From Twitter During Disaster. *IEEE Trans Comput Soc Syst*. 2021;8(4):870–880. doi:10.1109/TCSS.2021.3064299
82. Krishnan J, Purohit H, Rangwala H. Unsupervised and Interpretable Domain Adaptation to Rapidly Filter Tweets for Emergency Services. *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*; 2020:409–416.
83. Yu S, Eisenman D, Han Z. Temporal dynamics of public emotions during the COVID-19 pandemic at the epicenter of the outbreak: sentiment analysis of Weibo posts from Wuhan. *J Med Internet Res*. 2021;23(3):e27078. doi:10.2196/27078
84. Taeb M, Chi H, Yan J. Applying Machine Learning to Analyze Anti-Vaccination on Tweets. *IEEE International Conference on Big Data*. 2021:4426–4430.
85. Negri V, Scuratti D, Agresti S, et al. Image-Based Social Sensing: Combining AI and the Crowd to Mine Policy-Adherence Indicators from Twitter. In: *Proceedings - International Conference on Software Engineering*; 2021:92–101.
86. Li L, Aldosery A, Vitiugin F, et al. The response of governments and public health agencies to COVID-19 pandemics on social media: a multi-country analysis of Twitter discourse. *Front Public Health*. 2021;9:716333. doi:10.3389/fpubh.2021.716333
87. Han X, Wang J, Zhang M, et al. Using social media to mine and analyze public opinion related to COVID-19 in China. *Int J Environ Res Public Health*. 2020;17(8):doi:10.3390/ijerph17082788
88. Awoyemi T, Ogunniyi KE, Adejumo AV, et al. Emotional analysis of tweets about clinically extremely vulnerable COVID-19 groups. *Cureus*. 2022;14(9):e29323. doi:10.7759/cureus.29323
89. Assery N, Yuan X, Qu X, et al. Identifying Panic Triggers from Disaster-Related Tweets. *IEEE International Conference on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking*; 2020:827–836.
90. Andhale S, Mane P, Vaingankar M, et al. Twitter Sentiment Analysis for COVID-19. In: *2021 International Conference on Communication Information and Computing Technology (ICCICT) 2021 Jun 25* (pp. 1–12). IEEE.
91. Adikari A, Nawaratne R, de Silva D, et al. Emotions of COVID-19: content analysis of self-reported information using artificial intelligence. *J Med Internet Res*. 2021;23(4):e27341. doi:10.2196/27341
92. Adamu H, Jiran MJB, Gan KH, et al. Text Analytics on Twitter Text-based Public Sentiment for Covid-19 Vaccine: A Machine Learning Approach. Kota Kinabalu, Malaysia; 2021:1–6.
93. Onorati T, Diaz P. *Semantic Visualization of Twitter Usage in Emergency and Crisis Situations*. Springer International Publishing; 2015:3–14.
94. Mir AA, Sevukan R. Sentiment analysis of Indian Tweets about Covid-19 vaccines. *J Info Sci*. 2022;doi:10.1177/01655515221118049
95. Li K, Zhou C, Luo XR, et al. Impact of information timeliness and richness on public engagement on social media during COVID-19 pandemic: an empirical investigation based on NLP and machine learning. *Decis Support Syst*. 2022;162:113752. doi:10.1016/j.dss.2022.113752
96. Hoque MU, Lee K, Beyer JL, et al. Analyzing Tweeting patterns and public engagement on Twitter during the recognition period of the COVID-19 pandemic: a study of two U.S. states. *IEEE Access*. 2022;10:72879–72894. doi:10.1109/ACCESS.2022.3189670
97. Havas C, Resch B. Portability of semantic and spatial-temporal machine learning methods to analyse social media for near-real-time disaster monitoring. *Nat Haz*. 2021/09/01 2021;108(3):2939–2969. doi:10.1007/s11069-021-04808-4
98. Ghosh S, Srijith PK, Desarkar MS. Using social media for classifying actionable insights in disaster scenario. *Int J Adv Eng Sci Appl Math*. 2017/12/01 2017;9(4):224–237. doi:10.1007/s12572-017-0197-2
99. Gamal N, Ghoniemy S, Faheem HM, et al. Sentiment-based spatiotemporal prediction framework for pandemic outbreaks awareness using social networks data classification. *IEEE Access*. 2022;10:76434–76469. doi:10.1109/ACCESS.2022.3192417
100. Fan C, Wu F, Mostafavi A. A hybrid machine learning pipeline for automated mapping of events and locations from social media in disasters. *IEEE Access*. 2020;8:10478–10490. doi:10.1109/ACCESS.2020.2965550
101. De Rosi S, Loprete M, Puliga M, et al. The early weeks of the Italian Covid-19 outbreak: sentiment insights from a Twitter analysis. *Article. Health Policy*. 2021;doi:10.1016/j.healthpol.2021.06.006
102. Chipidza W, Akbaripouridibazar E, Gwanzura T, et al. Topic analysis of traditional and social media news coverage of the early COVID-19 pandemic and implications for public health communication. *Disaster Med Public Health Prep*. 2022;16(5):1881–1888. doi:10.1017/dmp.2021.65
103. Machmud M, Irawan B, Karinda K, et al. Analysis of the intensity of communication and coordination of government officials on Twitter social media during the Covid-19 handling in Indonesia. *Acad J Interdiscip Stud*. 2021;10(3):doi:10.36941/ajis-2021-0087
104. Sahoh B, Choksuriwong A. Automatic Semantic Description Extraction from Social Big Data for Emergency Management. *J Syst Sci Syst Eng*. 2020;29(4):412–428. doi:10.1007/s11518-019-5453-5
105. Dalela PK, Sharma S, Kushwaha NK, et al. *Classification of Disaster-Related Tweets Using Supervised Learning: A Case Study on Cyclonic Storm FANI*. Springer Singapore; 2021:169–178.
106. Li Y, Chandra Y, Kapucu N. Crisis coordination and the role of social media in response to COVID-19 in Wuhan, China. *Am Rev Public Admin*. 2020;50(6-7):698–705.
107. Bennett D. Emergency preparedness collaboration on Twitter. *J Emerg Manag*. 2018;16(3):191–202. doi:10.5055/jem.2018.0368
108. Aswani R, Kar AK, Ilavarasan PV. Experience: managing misinformation in social media—insights for policymakers from Twitter analytics. *J Data Informat Qual*. 2019;12(1):Article 6. doi:10.1145/3341107
109. Lachlan KA, Spence PR, Lin X. Expressions of risk awareness and concern through Twitter: On the utility of using the medium as an indication of audience needs. *Comp Hum Behav*. 2014;35:554–559. doi:10.1016/j.chb.2014.02.029
110. Liu L, Tu Y, Zhou X. How local outbreak of COVID-19 affect the risk of internet public opinion: a Chinese social media case study. *Technol Soc*. 2022;71:102113. doi:10.1016/j.techsoc.2022.102113
111. Xing Y, Li Y, Wang FK. How privacy concerns and cultural differences affect public opinion during the COVID-19 pandemic: a case study. *Aslib Journal of Information Management*. 2021;73(4):517–542. doi:10.1108/AJIM-07-2020-0216
112. Fernandez-Luque L, Imran M. Humanitarian health computing using artificial intelligence and social media: a narrative literature review. *Int J Med Inform*. 2018;114:136–142. doi:10.1016/j.ijmedinf.2018.01.015
113. Hasanah NA, Suciati N, Purwitasari D. Identifying degree-of-concern on covid-19 topics with text classification of twitters. *Register: Jurnal Ilmiah Teknologi Sistem Informasi*. 2021;7(1):50–62. doi:10.26594/register.v7i1.2234
114. Yao D, Li J, Chen Y, et al. Interactive governance between and within governmental levels and functions: a social network analysis of China's case against COVID-19. *Am Rev Public Admin*. 2022;52(3):191–205. doi:10.1177/02750740211059534
115. Teague SJ, Shatte ABR, Weller E, et al. Methods and applications of social media monitoring of mental health during disasters: scoping review. *JMIR Mental Health*. 2022;9(2):e33058. doi:10.2196/33058
116. Binsar F, Mauritsius T. Mining of social media on Covid-19 big data infodemic in Indonesia. *J Comp Sci*. 2020;16(11):1598–1609. doi:10.3844/JCSSP.2020.1598.1609
117. Abdulah DM, Saeed MS. Public opinions and conspiracy thinking toward the COVID-19 outbreak in Iraqi Kurdistan. *Disaster Med Public Health Prep*. 2022;16(4):1322–1325. doi:10.1017/dmp.2020.490
118. Arslan M, Roxin AM, Cruz C, et al. A review on applications of big data for disaster management. In: *Proceedings - 13th International Conference on Signal-Image Technology and Internet-Based Systems, SITIS 2017*. 2018:370–375.
119. Dutta B, Peng MH, Chen CC, et al. Role of infodemics on social media in the development of people's readiness to follow COVID-19 preventive

- measures. *Int J Environ Res Public Health*. 2022;19(3)1347. doi:10.3390/ijerph19031347
120. **Alhassan FM, Aldossary SA.** The Saudi Ministry of Health's Twitter communication strategies and public engagement during the COVID-19 pandemic: content analysis study. *JMIR Public Health Surveill*. 2021;7(7):e27942. doi:10.2196/27942
 121. **Fissi S, Gori E, Romolini A.** Social media government communication and stakeholder engagement in the era of Covid-19: evidence from Italy. *Int J Public Sect Manag*. 2022;35(3):276–293. doi:10.1108/IJPSM-06-2021-0145
 122. **Amin I, Pramestri Z, Hodge G,** et al. Social media insights for sustainable development and humanitarian action in Indonesia. In: *Journal of Physics: Conference Series*. 2018.
 123. **Wukich C.** Social media use in emergency management. *J Emerg Manag*. 2015;13(4):281–294. doi:10.5055/jem.2015.0242
 124. **Tommassel A, Diaz-Pace A, Godoy D,** et al. Tracking the evolution of crisis processes and mental health on social media during the COVID-19 pandemic. *Behav Info Technol*. 2021;doi:10.1080/0144929X.2021.1998630
 125. **Yang M, Li Y, Kiang M.** Uncovering social media data for public health surveillance. In: *PACIS 2011 Proceedings*. 2011. <https://aisel.aisnet.org/pacis2011/218>
 126. **Abbas H, Tahoun MM, Aboushady AT,** et al. Usage of social media in epidemic intelligence activities in the WHO, Regional Office for the Eastern Mediterranean. *BMJ Glob Health*. 2022;7(Suppl 4):doi:10.1136/bmjgh-2022-008759
 127. **Alshareef HN, Grigoras D.** Using Twitter and the mobile cloud for delivering medical help in emergencies. Conference paper. *Concurr Comput Pract Exp* 2017;29(24):e4151. doi:10.1002/cpe.4151
 128. **Charles-Smith LE, Reynolds TL, Cameron MA,** et al. Using social media for actionable disease surveillance and outbreak management: a systematic literature review. *PLoS one*. 2015;10(10):e0139701.
 129. **Alshareef HN, Grigoras D.** Using Social Media and the Mobile Cloud to Enhance Emergency and Risk Management. In: *2016 15th International Symposium on Parallel and Distributed Computing (ISPDC) 2016 Jul 8* (pp. 92–99). IEEE.
 130. **Bennett DM.** How do emergency managers use social media platforms? *J Emerg Manag*. 2014;12(4):251–256. doi:10.5055/jem.2014.0178
 131. **Middleton SE, Middleton L, Modafferi S.** Real-time crisis mapping of natural disasters using social media. *IEEE Intelligent Systems*. 2013;29(2):9–17.
 132. **Bermes A.** Information overload and fake news sharing: a transactional stress perspective exploring the mitigating role of consumers' resilience during COVID-19. *J Retail Consum Serv*. 2021;61:102555.
 133. **Cezar BGdS, Maçada ACG.** Cognitive overload, anxiety, cognitive fatigue, avoidance behavior and data literacy in big data environments. *Info Process Manag*. 2023;60(6):103482. doi:<https://doi.org/10.1016/j.ipm.2023.103482>
 134. **Shu K, Sliva A, Wang S,** et al. Fake news detection on social media: a data mining perspective. *ACM SIGKDD Explorations Newsletter*. 2017;19(1):22–36.
 135. **Habib A, Asghar MZ, Khan A,** et al. False information detection in online content and its role in decision making: a systematic literature review. *Soc Netw Anal Min*. 2019;9:1–20.
 136. **Sallam M, Dababseh D, Eid H,** et al. High rates of COVID-19 vaccine hesitancy and its association with conspiracy beliefs: a study in Jordan and Kuwait among other Arab countries. *Vaccines*. 2021;9(1):42.
 137. **Dargin JS, Fan C, Mostafavi A.** Vulnerable populations and social media use in disasters: Uncovering the digital divide in three major U.S. hurricanes. *Int J Disaster Risk Reduct*. 2021;54:102043. doi:<https://doi.org/10.1016/j.ijdrr.2021.102043>
 138. **Wang Q, Li W, Yu Z,** et al. An overview of emergency communication networks. *Remote Sensing*. 2023;15(6). doi:10.3390/rs15061595
 139. **Lokmic-Tomkins Z, Bhandari D, Bain C,** et al. Lessons learned from natural disasters around digital health technologies and delivering quality health care. *Int J Environ Res Public Health*. 2023;20(5):4542.

Appendix

Appendix 1. Modified search queries and the number of the results

Databases	Modified Search Queries
ACM Digital Computing	"disaster management" OR "emergency management" OR "mass emergency" AND "social media" OR "social network*" AND healthcare OR "public health" OR medical* OR "health care"
CINAHL	"disaster management" OR "emergency management" OR "mass emergency" AND "social media" OR "social network*" AND healthcare OR "public health" OR medical* OR "health care"
Emerald Insight	"disaster management" OR "emergency management" OR "mass emergency" AND ("social media" OR "social network*") AND (healthcare OR "public health" OR medical* OR "health care")
IEEE Xplore	("Full Text & Metadata": "disaster management" OR "Full Text & Metadata": "emergency management" OR "Full Text & Metadata": "mass emergency") AND ("Full Text & Metadata": "social media" OR "Full Text & Metadata": "social network*") AND ("Full Text & Metadata": "healthcare OR "Full Text & Metadata": "public health" OR "Full Text & Metadata": "medical*" OR "Full Text & Metadata": "health care")
PubMed	((("disaster management" OR "emergency management" OR "mass emergency" OR disaster* AND ((ft[Filter]) AND (english[Filter])))) AND ("social media" OR "social network*" AND ((ft[Filter]) AND (english[Filter])))) AND (healthcare OR "public health" OR medical* OR "health care" AND ((ft[Filter]) AND (english[Filter])) AND ((ft[Filter]) AND (english[Filter])) Filters: Full text, English
Scopus	(ALL ("disaster management" OR "emergency management" OR "mass emergency") AND ALL (healthcare OR "public health" OR medical* OR "health care") AND ALL ("social media" OR "social network*") AND PUBYEAR > 2009 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp")) AND (LIMIT-TO (LANGUAGE, "English")))
SpringerLink	'healthcare "public health" "health care" & "disaster management" "emergency management" & "social media"
Google Scholar	("disaster management" OR "emergency management" OR "mass emergency") AND ("social media" OR "social network*") AND (healthcare OR "public health" OR "medical*" OR "health care")

Appendix 2. Selected studies for the review

Author(s)	Topic	Platform	Disaster Event
C. Wukich and I. Mergel ⁷¹	Used SN analysis software package UCINET	Twitter	-
H. A. Abu-Alsaad and R. R. K. Al-Taie ⁵²	NLP	Twitter	-
B. Sahoh and A. Choksuriwong ¹⁰⁴	NER	Twitter	-
D. Bennett ¹⁰⁷	Qualitative content analysis	Twitter	-
R. Aswani, A. K. Kar and P. V. Ilavarasan ¹⁰⁸	Quantitative content analysis	Twitter	-
L. Fernandez-Luque and M. Imran ¹¹²	Literature review	-	-
S. J. Teague, A. B. R. Shatte, E. Weller, M. Fuller-Tyszkiewicz and D. M. Hutchinson ¹¹⁵	Scoping review	-	-
M. Arslan, A. M. Roxin, C. Cruz and D. Ginhaç ¹¹⁸	Systematic review	-	-
C. Wukich ¹²³	Qualitative analysis	-	-
M. Yang, Y. Li and M. Kiang ¹²⁵	Qualitative analysis	-	-
H. N. Alshareef and D. Grigoras ¹²⁷	Proposing a system	-	-
H. N. Alshareef and D. Grigoras ¹²⁹	Proposing a system	Twitter	-
F. Niknam, M. Samadbeik, F. Fatehi, M. Shirdel, M. Rezazadeh and P. Bastani ⁴⁶	Content analysis	Instagram	COVID-19
S. Yum ⁷³	Content analysis	Twitter	COVID-19
Y. Yang and Y. Su ⁷⁴	Qualitative analysis	-	COVID-19
P. C. I. Pang, Q. Cai, W. Jiang and K. S. Chan ⁷⁵	Qualitative analysis	Facebook	COVID-19
M. K. Leibowitz, M. R. Scudder, M. McCabe, J. L. Chan, M. R. Klein, N. Seth Trueger, et al. ⁷⁶	Qualitative and quantitative analysis	Twitter	COVID-19
L. Liu, Y. Tu and X. Zhou ⁷⁸	LSTM sentiment analysis, LDA topic modelling	Weibo	COVID-19
Z. Zhong ⁵⁰	Text analysis using a combination of LDA, sentiment analysis, correlation analysis	Baidu	COVID-19
S. Yu, D. Eisenman and Z. Han ⁸³	Sentiment analysis using Python and Snow NLP Python libraries	Weibo	COVID-19
M. Taeb, H. Chi and J. Yan ⁸⁴	NLTK, TF-IDF, LDA, BERT	Twitter	COVID-19
V. Negri, D. Scuratti, S. Agresti, D. Rooein, G. Scalia, A. Ravi Shankar, et al. ⁸⁵	VisualCit, a pipeline for image-based social sensing	Twitter	COVID-19
L. Li, A. Aldosery, F. Vitiugin, N. Nathan, D. Novillo-Ortiz, C. Castillo, et al. ⁸⁶	K-Means, TF-IDF, NLTK	Twitter	COVID-19
X. Han, J. Wang, M. Zhang and X. Wang ⁸⁷	Time series, LDA	Weibo	COVID-19
T. Awoyemi, K. E. Ogunniyi, A. V. Adejumo, U. Ebili, A. Olusanya, E. H. Olojakpoke, et al. ⁸⁸	TF-IDF, LDA, sentiment and emotion analysis	Twitter	COVID-19
S. Andhale, P. Mane, M. Vaingankar, D. Karia and K. T. Talele ⁹⁰	CNN-RoBERTa	Twitter	COVID-19
A. Adikari, R. Nawaratne, D. de Silva, S. Ranasinghe, O. Alahakoon and D. Alahakoon ⁹¹	NLP, word embeddings, markov models	Twitter	COVID-19
H. Adamu, M. J. B. M. Jiran, K. H. Gan and N. H. Samsudin ⁹²	NLP, SVM, KNN	Twitter	COVID-19
Y. E. Park ⁵¹	Semantic network analysis	Twitter - YouTube	COVID-19
A. A. Mir and R. Sevukan ⁹⁴	Sentiment analysis using VADER	Twitter	COVID-19
K. Li, C. Zhou, X. R. Luo, J. Benitez and Q. Liao ⁹⁵	Text mining and NLP	Weibo	COVID-19
M. U. Hoque, K. Lee, J. L. Beyer, S. R. Curran, K. S. Gonser, N. S. N. Lam, et al. ⁹⁶	Sentiment analysis using VADER	Twitter	COVID-19
H. Gao, D. Guo, J. Wu and L. Li ⁴⁴	DLUT-Emotion ontology for sentiment analysis	Weibo	COVID-19

(Continued)

(Continued)

Author(s)	Topic	Platform	Disaster Event
N. Gamal, S. Ghoniemy, H. M. Faheem and N. A. Seada ⁹⁹	Linear classifier, MLP, RNN, and CNN	Twitter	COVID–19
S. De Rosis, M. Lopreite, M. Puliga and M. Vainieri ¹⁰¹	LSTM	Twitter	COVID–19
W. Chipidza, E. Akbaripourdibazar, T. Gwanzura and N. M. Gatto ¹⁰²	LDA	Twitter	COVID–19
M. Machmud, B. Irawan, K. Karinda, J. Susilo and Salahudin ¹⁰³	Qualitative analysis	Twitter	COVID–19
M. Chong and H. W. Park ⁵⁴	Content analysis	Twitter	COVID–19
Y. Li, Y. Chandra and N. Kapucu ¹⁰⁶	LDA	Weibo	COVID–19
E. Mori, B. Barabaschi, F. Cantoni and R. Virtuani ⁴⁷	Qualitative content analysis	Facebook	COVID–19
Y. Wang, H. Hao and L. S. Platt (2021) ⁶²	Dynamic network analysis	Twitter	COVID–19
L. Liu, Y. Tu and X. Zhou ¹¹⁰	AHPSort II, SMAA–2	-	COVID–19
Y. Xing, Y. Li and F. K. Wang ¹¹¹	TF-IDF	Twitter, Weibo	COVID–19
N. A. Hasanah, N. Suciati and D. Purwitasari ¹¹³	Word2Vec, fastText, CNN, RNN and LSTM	Twitter	COVID–19
D. Yao, J. Li, Y. Chen, Q. Gao and W. Yan ¹¹⁴	Social network analysis	-	COVID–19
Y. Zhuang, T. Zhao and X. Shao ⁵³	Qualitative analysis	WeChat	COVID–19
F. Binsar and T. Mauritsius ¹¹⁶	SVM, Random Forest and Naïve Bayes	Twitter	COVID–19
T. D. Durowaye, A. R. Rice, A. T. M. Konkole and K. P. Phillips ⁵⁶	Thematic content analysis	Facebook	COVID–19
D. M. Abdulah and M. S. Saeed ¹¹⁷	Statistical Analysis	Facebook	COVID–19
B. Dutta, M. H. Peng, C. C. Chen and S. L. Sun ¹¹⁹	Delphi Method, NLP	-	COVID–19
F. M. Alhassan and S. A. AlDossary ¹²⁰	Content analysis	Twitter	COVID–19
S. Luna, A. Guerrero, K. Gonzalez and A. Akundi ⁵⁵	NLP, Sentiment Analysis	Twitter	COVID–19
S. Fissi, E. Gori and A. Romolini ¹²¹	CERC	Facebook	COVID–19
I. Amin, Z. Pramestri, G. Hodge and J. G. Lee ¹²²	-	Twitter	COVID–19
T. Muswede and S. L. Sithole ⁴⁸	Qualitative analysis	WhatsApp	COVID–19
A. Tommasel, A. Diaz-Pace, D. Godoy and J. M. Rodriguez ¹²⁴	Psycho-linguistic analysis	Twitter	COVID–19
R. Mittal, W. Ahmed, A. Mittal and I. Aggarwal ⁴²	Sentiment analysis (data extraction), Qualitative analysis	Twitter	COVID–19
Q. Chen, C. Min, W. Zhang, G. Wang, X. Ma and R. Evans ²⁸	Systematic review	Weibo	COVID–19
H. Abbas, M. M. Tahoun, A. T. Aboushady, A. Khalifa, A. Corpuz and P. Nabeth ¹²⁶	-	-	COVID–19
P. K. Dalela, S. Sharma, N. K. Kushwaha, S. Basu, S. Majumdar, A. Yadav, et al. ¹⁰⁵	Linear SVC, logistic regression, multinomial Naive Bayes, Random Forest, XGBoost, KNN	Twitter	Cyclone
S. Madichetty and M. S. ⁸¹	RoBERTa model and feature-based method	Twitter	Different Disaster Scenario
J. Krishnan, H. Purohit and H. Rangwala ⁸²	Multi-task domain adversarial attention network (MT-DAAN)	Twitter	Different Disaster Scenario
J. Radianti, S. R. Hiltz and L. Labaka ⁶⁰	Content analysis	Twitter	Earthquake
T. Onorati and P. Díaz ⁹³	Semantic analysis	Twitter	Earthquake
C. Havas and B. Resch ⁹⁷	LDA	Twitter	Earthquake
K. Rudra, P. Goyal, N. Ganguly, P. Mitra and M. Imran ⁶⁵	Integer linear programming technique	Twitter	Earthquake, Flood, Typhoon
A. Asif, S. Khatoun, M. M. Hasan, M. A. Alshamari, S. Abdou, K. M. Elsayed, et al. ⁷⁰	VGG–16, AHP, CNN	-	Earthquake, Hurricane, and Typhoon

(Continued)

(Continued)

Author(s)	Topic	Platform	Disaster Event
A. J. Lazard, E. Scheinfeld, J. M. Bernhardt, G. B. Wilcox and M. Suran ⁵⁸	SAS text miner	Twitter	Ebola
K. C. Finch, K. R. Snook, C. H. Duke, K.-W. Fu, Z. T. H. Tse, A. Adhikari, et al. ⁶⁷	Scoping review	-	Environmental Disaster
U. A. Bakar, F. Sidi, M. A. Jabar, R. N. H. B. Nor, S. Abdullah and I. Ishak ⁶⁴	ANN, PLS-predict, PLS-SEM	-	Flood
B. Wang and J. Zhuang ⁶¹	Content analysis	Twitter	Hurricane
S. I. Garske, S. Elayan, M. Sykora, T. Edry, L. B. Grabenhenrich, S. Galea, et al. ⁷⁷	Local Indicator of Spatial Association (LISA)	Twitter	Hurricane
S. Shams, S. Goswami and K. Lee ⁸⁰	Deep learning based framework using LLR, Single LSTM, Stacked LSTM, ConvNet	Twitter	Hurricane
N. Assery, X. Yuan, X. Qu, S. Almalki and K. Roy ⁸⁹	TF-IDF, random forest, decision tree	Twitter	Hurricane
C. Fan, F. Wu and A. Mostafavi ¹⁰⁰	A pipeline which integrates Named Entity Recognition (NER), Location Fusion, BERT, Graph-based clustering	Twitter	Hurricane
S. Chen, J. Mao and G. Li ⁶³	Location classification, Time slicing, sentiment classification	Twitter	Hurricane
B. Wang and J. Zhuang ⁶¹	Content analysis	Twitter	Hurricane
K. A. Lachlan, P. R. Spence and X. Lin ¹⁰⁹	Quantitative content analysis	Twitter	Hurricane
S. Saleem and M. Mehrotra ⁶⁸	Literature review	Twitter	Hurricane, Earthquake, Flood, Cyclone
A. H. Alamoodi, B. B. Zaidan, A. A. Zaidan, O. S. Albahri, K. I. Mohammed, R. Q. Malik, et al. ⁷²	Systematic review	-	Infectious Diseases
S. Ghosh, P. K. Srijith and M. S. Desarkar ⁹⁸	Naive bayes classifier, SVM, decision trees, random Forest, Adaboost, gradient boosting	Twitter	Natural Disasters
H. Seddighi, I. Salmani and S. Seddighi ⁴³	Literature review	Twitter	Natural Disasters, Pandemic
M. Basu, S. Ghosh, A. Jana, S. Bandyopadhyay and R. Singh ⁴⁹	-	WhatsApp	Nepal Earthquake
L. E. Charles-Smith, T. L. Reynolds, M. A. Cameron, M. Conway, E. H. Lau, J. M. Olsen, et al. ¹²⁸	Systematic review	-	Outbreak
M. Abbassinia, O. Kalatpour, M. Motamedzade, A. Soltanian and I. Mohammadfam ⁶⁹	Qualitative analysis	-	Petrochemical
H. Woo, Y. Cho, E. Shim, K. Lee and G. Song ⁷⁹	NLP	Twitter	Sewol Ferry Disaster
S. Shan, F. Zhao, Y. Wei and M. Liu ⁴⁵	Qualitative content analysis	Weibo	Typhoon
J. Xiong, Y. Hsuen and J. A. Naslund ⁶⁶	LDA, sentiment analysis	Twitter	Water crisis
L. Hagen, R. Scharf, S. Neely and T. Keller ⁵⁷	Qualitative content analysis	Twitter	Zika