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Leveraging VOSviewer approach for mapping, visualisation, and interpretation of crisis data for disaster management and decision-making

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A R T I C L E I N F O

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A B S T R A C T

Analysing social media data is crucial for crisis management organisations to make timely decisions. Researchers in crisis informatics have devised various methods and systems to process and classify large volumes of crisis-related social media data for effective crisis response and recovery. However, the complexity of previous solutions hampers the timely processing of this data, its visualisation, and its interpretation, which is necessary for effective crisis response. Hence, this study addresses this challenge by employing *visualisation of similarities* to analyse and visualise crisis datasets to aid crisis management and decision-making. The results reveal a "nine-cluster community" of relevant keywords comprising “Green, Brown, Red, Blue, Pink, Purple, Yellow, Orange, and Cyan” colours, in both binary and full count. Specifically, the findings reveal various keywords such as the needs for food, water, shelter, medicine, and electricity. Thereafter, the study discusses the implications of VOSviewer for analysing crisis data theoretically and practically.

1. Introduction

Disasters cause tens of thousands of deaths and economic losses worldwide and events like terrorism or pandemics also contribute to these losses significantly (Boné, Dias, Ferreira and Ribeiro, 2020a). At the outset of a disaster, humanitarian organisations require information for situational awareness to plan and launch relief operations. Also, some of the information shared by affected people during a disaster might elude humanitarian organisations or government agencies due to the large volume of data posted on social media. This information could be useful even after the occurrence of disasters to improve relief operations and manage probable occurrences in the future.

Information for situational awareness includes reports of injured, trapped, or deceased people, information on the urgent needs of victims, and infrastructure damage reports (Alam, Sajjad, Imran and Ofli, 2021b). For example, flooding disasters can wreak havoc on individuals, businesses, and the government, which can impact various sectors, disorganise people, and cause adverse psychological consequences (Charoensukmongkol and Phungsoonthorn, 2020). Gaining insights into this information within the shortest possible time is critical. However, it is challenging because of the large volume of data that has to be analysed or mined. Also, traditional methods like field assessments and surveys waste a significant amount of time (Walaski, 2011; Alam et al., 2021b). In addition, a crisis can emotionally destabilize people due to the fear and uncertainties associated with their experiences. As a result, collecting data using field assessments and surveys could be nearly impossible or difficult to achieve.

On the other hand, as soon as the news of a crisis or disaster is posted on social media, more people become aware of the extent of the disaster. Social media could be used to inform or inquire about crises, making the public and crisis management organisations participate in crisis response through these platforms. Therefore, it is important to implement solutions for effectively collecting and analysing such data. This would assist crisis and humanitarian organisations to plan and launch relief in such time-critical situations. Similarly, this could support the development of disaster resilience strategies after the occurrence of

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disasters.

Microblogging platforms such as X (Twitter), have been extensively utilized to share situational and actionable information. Crisis data obtained from this platform has been used several times in existing studies, which makes parsing and extracting actionable information from crisis datasets challenging (Alam et al., 2021b; Castillo, 2016). On the other hand, the field of crisis informatics, a term that describes the use of social media in crises and disasters (Palen, Vieweg, Liu and Hughes, 2009; Reuter, Ludwig, Kotthaus, Kaufhold, Radziewski and Pipek, 2016; Reuter and Spielhofer, 2017; Reuter and Kaufhold, 2018; Reuter, Kaufhold, Schmid, Spielhofer, Hahne et al., 2019), struggles to develop robust theoretical methods to support sociologically informed development for both technological solutions and policy (Palen et al., 2009; Reuter et al., 2016; Reuter, Kaufhold, Spahr, Spielhofer and Hahne, 2020; Palen, Anderson, Bica, Castillos, Crowley, Díaz, Finn, Grace, Hughes, Imran et al., 2020).

In recent years, there has been a significant increase in research examining and discussing the role and impact of social media on enhancing resilience (Reuter et al., 2019; Reuter and Spielhofer, 2017; Bukar, Jabar, Sidi, Nor, Abdullah and Othman, 2020; Bukar, Jabar, Sidi, Nor and Abdullah, 2021; Bukar, Jabar, Sidi, Nor, Abdullah and Ishak, 2022a; Bukar, Sidi, Jabar, Nor, Abdullah and Ishak, 2022b; Mundottukandi, Jusoh, Pa, Nor, & Bukar, 2024; Cheng, 2018; Paul, Sahoo and Balabantaray, 2023; Li, Yang, Zhang and Zhang, 2019; Malik, Mahmood and Islam, 2023; Oh, Lee and Han, 2021; Yin, Lampert, Cameron, Robinson and Power, 2012; Wu and Kuang, 2021) and the development of computational-based models for extracting actionable information (Alam et al., 2021b; Alam, Qazi, Imran and Ofli, 2021a; Alam, Ofli and Imran, 2019, 2020; Alam, Ahmad, Hasan, Ofli and Imran, 2023; Olteanu, Vieweg and Castillo, 2015; Imran, Castillo, Lucas, Meier and Vieweg, 2014; Boné, Ferreira, Ribeiro and Cadete, 2020b; Boné et al., 2020a; Ponce-López and Spataru, 2022; Ramachandran and Parvathi, 2021; Franceschini, 2023; Imran, Castillo, Diaz and Vieweg, 2015) (also see Fig. 1). The existing computational models include solutions for classifying information, extracting information or data mining systems, summarization, and visualisations. Despite the recent focus of the crisis informatics research community on developing innovative and more robust computational solutions to process and analyse social media data, this study observes several limitations, opening a gap in the current literature. In particular, most of the developed text analysis methods are complex and require knowledge of programming languages to a greater extent (MadhaviLatha and Kumar, 2016; Casas Saez, 2020; Boné et al., 2020b; Ponce-López and Spataru, 2022; Ramachandran and Parvathi, 2021; Franceschini, 2023), which can waste great time in real-time applications such as crisis or disaster response and decision-making scenarios. Second, most of the existing computational models are still being experimented and it is challenging to identify one particular model that is dedicated to analysing crisis response data easily and effectively.

1.1. Motivation of the study

During emergencies, social media becomes a rich source of useful information, as users share a lot of useful information about their conditions, and the needed help, while others share sympathies and opinions. Emergency managers often rely on public information to guide their response (Barner, 2022).

New technologies and intelligence-gathering tools can relay lifesaving information to the public. Such information sometimes provides situational awareness vital for understanding the broader context of emergencies to facilitate informed decision-making (Vieweg, 2012). Therefore, analysing data from social media during disasters is vital in crisis informatics and requires extensive software infrastructures (Casas Saez, 2020). Also, maintaining these systems can be challenging and costly due to the need for rapid query handling and constant computational resources.

One way to address these problems is to extract disaster relief information from social media (Rudra, Ganguly, Goyal and Ghosh, 2018; Castillo, 2016; Avvenuti, Cresci, Del Vigna, Fagni and Tesconi, 2018; Ahadzadeh and Malek, 2021; Garg, Chakraborty and Dandapat, 2023; Hou, Shen, Jia and Xu, 2024; Ghosh, Ghosh, Ganguly, Chakraborty, Jones, Moens and Imran, 2018; Feng, Huang and Sester, 2022). This could provide insights needed to support people urgently in need due to the occurrence of natural disasters. Thus, this paper is targeted at facilitating timely and a relatively simple solution for providing insights into social media data for timely disaster interventions.

1.2. Aim and objectives

This study aims to assess the suitability of the Visualisation of Similarities (VOS) concept available in the popularly known bibliometric analysis software (VOSviewer) (Eck and Waltman, 2007, 2011) to conduct Text Network Analysis (TNA) of social media crisis datasets for disaster response and decision-making. This tool facilitates the production of visualisations, which can assist crisis managers in streamlining their efforts during crisis response and management. With VOSviewer's

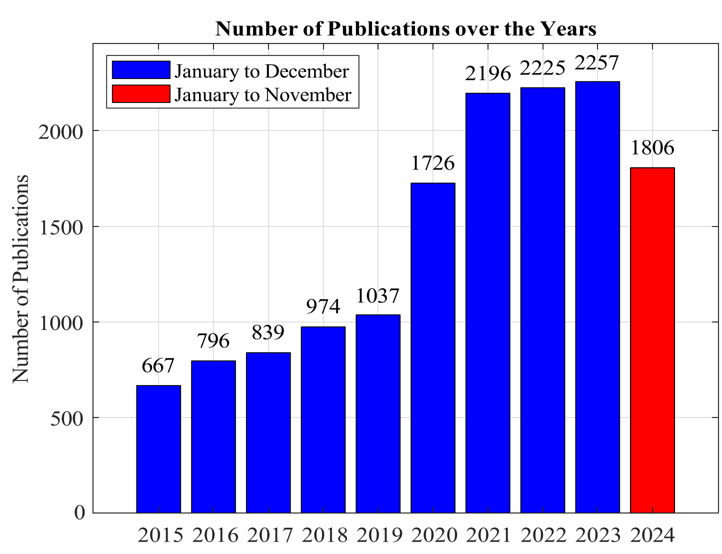

Fig. 1. Publications in Scopus using the search key "Social media" AND disaster OR crisis until November 2024.

capabilities, it is possible to generate, analyse, and explore maps based on any form of network data (Eck and Waltman, 2022). The concept of TNA has been used in studies comparing human-generated and AI-generated content (Kutela, Msechu, Das and Kidando, 2023), while VOSviewer has been used in studies analysing user reactions to the introduction of ChatGPT from LinkedIn data (Bukar, Sayeed, Razak, Yogarayan, Amodu and Raja Mahmood, 2024). Therefore, we applied VOSviewer to analyse the consolidated humanitarian datasets produced by Alam et al. (2021b) to conduct text mining and visualisation of social media crisis response network data. Our rationale for selecting and using the consolidated humanitarian datasets stems from the fact that the dataset is larger, class distribution is better than individual datasets, and enables the proposal of robust computational models that perform better for mapping and visualisation tasks. This can also help us determine the robustness of VOSviewer on such a large social media crisis dataset. Hence, the study intends to address the following objectives:

- Map out attributes for the social media crisis response dataset to meet the requirements of VOSviewer.
- Analyse the social media crisis response dataset to produce visualisation maps and determine the relevance of the keywords.
- Identify the various elements or concerns of relief seeking as identified from the analysis of the crisis dataset.
- Interpret the relationships between these elements and map them to existing humanitarian information types, thereby validating the findings produced by VOSviewer to encourage its usage for crisis data analysis.

1.3. Contribution

This study highlights the importance of simple yet intuitive and timely data analysis of social media crisis data, as these platforms provide immediate insights into disaster impacts and the urgent needs of affected populations. It identifies limitations in existing computational models for crisis informatics and proposes the use of VOSviewer for text network analysis to enhance the analysis of social media crisis datasets. VOSviewer offers a flexible, straightforward, and cost-effective solution, generating valuable information for disaster response and decision-making. Thus, this paper leverages VOSviewer, a tool traditionally designed for bibliometric data analysis, to intuitively process and analyse unstructured social media crisis data. Crisis datasets were sourced from the literature, preprocessed to meet VOSviewer's requirements, and analysed to identify common terms and generate visual maps. This methodological adaptation advances data science research by demonstrating VOSviewer's utility beyond bibliometric datasets, specifically for applications in crisis response. By broadening the tool's applicability, the study provides a replicable framework for leveraging network analysis tools in novel contexts. At the same time, the findings provide a unique perspective to information curated in a typical crisis dataset and illustrate the interconnectedness of public needs and concerns during crises, emphasizing the value of understanding term relationships within social media discourse. By visualising social media crisis data, the study provides a case study that delivers actionable insights for crisis managers, enabling them to prioritise resources, improve response strategies, and make informed decisions. These contributions bridge the gap between unstructured social media data and data-driven strategies, fostering more effective disaster management and enhancing information management during emergencies. Notably, this study highlights the value of interdisciplinary approaches for addressing real-world challenges by advancing both the methodological landscape of data science and the practical field of disaster management.

1.4. Organisation of the paper

The study is structured as follows: Section 2 provides a literature review on using social media text to analyse and support crisis communication; Section 3 explains the methodology applied in conducting the study; Section 4 describes the text mining and visualisation results; Section 5 presents the discussion of the study, including findings on word clusters and relief seeking, comparisons with existing work, recommendations, limitations, and considerations for future research. Finally, the conclusions drawn from this study are covered in Section 6. A detailed structure of this paper is provided in Fig. 2.

2. Literature review

In this section, we review the literature on using social media texts to analyse and support crisis communication and management organisations in planning and launching relief efforts and making decisions. This study examines diverse literature on social media analytics and related topics, carefully selecting relevant papers to study the literature[1]. Given that social media data analysis often requires analytics dashboards, comprehensive data analysis methods, and effective data visualisation techniques (Batrinca and Treleaven, 2015), several studies in crisis informatics literature have similarly contributed systems and techniques to analyse social media crisis data, as presented in Table 1. Section 2.1 briefly discusses the fundamental categories of crisis informatics literature. Section 2.2 reviews and discusses the related studies concerned with analysing and monitoring of social media crisis data. Finally, Section 2.3 discusses the research gap.

2.1. Fundamental categories of crisis informatics literature

The possibility of exploiting social media data for crisis mapping and visualisation has been seen in several works in the current literature. This indicates a rising interest among both scholars and practitioners in various aspects of social media analytics, encompassing data acquisition, management, analysis, and visualisation (Avvenuti, Cresci, Del Vigna and Tesconi, 2016). Neri, Aliprandi, Capeci and Cuadros (2012) outlined six fundamental categories of crisis informatics literature concerned with analysing and monitoring social media data. This thematic category represents the various contributions of existing studies in the crisis informatics discipline involving social media analysis. In the course of this literature review, many existing studies were identified that fall in one or more of the thematic classifications, i.e., focus on individual contribution or in combination. For example, several studies make contributions towards Crawlers to gather documents or database sources. Another focus of the literature is proposing semantic engines to identify relevant knowledge and, therefore detect semantic relations and facts. Moreover, some studies focus on search engines that enable natural language, semantic and semantic-role queries, and others on machine translation engines for the automatic translation of search results. Additionally, there are studies on geo-mapping engines for an interactive geographical representation of documents, as well as several studies on classification engines for clustering of results. Fig. 3 presents the six fundamental categories of the crisis informatics literature.

[1] While this paper primarily focuses on text-based analysis, there are several studies that analyse images or a combination of images and text in crisis informatics (e.g., (da Costa, Meneguette and Ueyama, 2022; Basit, Alam, Fatima and Shaikh, 2023; Giri and Deepak, 2023; Garcia, Rabadi, Abujaber and Seck, 2023; Saleem, Khattar and Mehrotra; Madichetty, 2020; Gupta, Saini, Kundu and Das, 2024; Agarwal, Leekha, Sawhney and Shah, 2020b; Agarwal, Leekha, Sawhney, Ratn Shah, Kumar Yadav and Kumar Vishwakarma, 2020a; Sathyanarayana Murthy, Mohan Krishna Varma, Ravuri, Kishore Babu and Nazeer, 2022; Satyanarayana Murthy, Mohan Krishna Varma, Roy and Nazeer, 2022; de Bruijn, de Moel, Weerts, de Ruiter, Basar, Eilander and Aerts, 2020; Huang, Li, Wang and Ning, 2019; Alam et al., 2020)). These studies, while relevant to the broader field, are outside the scope of this paper, which focuses specifically on text analysis

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Fig. 2. Organisation of this paper.

2.2. Related works

The analysis of social media text for identifying and classifying actionable information in crisis management has garnered substantial research interest in recent years, as evidenced by the diverse range of methodologies and models. Table 1 presents various methods employed for social media text analytics in the literature. These methods can be categorized into six fundamental categories presented in Fig. 3. Specifically, these methods range from machine learning models, natural language processing (NLP), data retrieval and analysis methods, ontology and data management, to visualisation tools. The following section discusses the related literature.

2.2.1. Machine learning techniques

Machine learning (ML) and deep learning (DL) techniques have emerged as crucial approaches for analysing and classifying crisis datasets, as evidenced by their extensive application in the literature. These methods range from traditional ML techniques (e.g., Support Vector Machines, Random Forest) to advanced deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM). Specifically, Cresci, Tesconi, Cimino and Dell'Orletta (2015) developed an infrastructure damage assessment detection model for Italian tweets by employing SVM. This study addresses the challenge of disaster-related tweet classification in a *non-English* language, which is crucial for global disaster management efforts. Similarly, Rudra et al. (2018) developed a two-step methodology for extracting situational information and summarizing disaster tweets in English and Hindi based on SVM classifiers that explore *non-English* tweets to address the challenge of multilingual disaster tweet analysis, particularly in languages like Hindi. Kumar, Singh and Saumya (2019) explored and compared several ML and DL models for classifying informative microblog posts into multicategories. In addition, Hernandez-Suarez, Sanchez-Perez, Toscano-Medina, Perez-Meana, Portillo-Portillo, Sanchez and García Villalba (2019) proposed a Twitter-based sensor for monitoring natural disasters and detecting toponyms in tweets containing event-related information and transforming them into word embeddings for analysis, based on a DL technique known as Bidirectional Long Short-Term Memory (biLSTM) network, trained with pre-labeled embeddings, to analyse sequential data.

Kersten and Klan (2020) introduced a workflow that utilizes agile and flexible analysis methods to provide different views on data and characterize crisis events comprehensively. The study incorporate deep learning (CNN) and ML clustering methods, such as Non-negative Matrix Factorization (NMF), to enable a better understanding and interpretation of crisis data. Furthermore, Avvenuti, Bellomo, Cresci, Nizzoli and Tesconi (2020) introduced HERMES, which leverages a mixed data collection strategy called hybrid sensing and employs both DL and ML techniques (Recurrent CNN, SVM, and max pooling). HERMES increases the amount of damage information available, the density and variety of retrieved geographic information, and the geographic coverage and granularity. Madichetty and Muthukumarasamy (2020) addressed the problem of detecting situational tweets using different deep learning architectures, including CNN, LSTM, biLSTM, and biLSTM attention.

Alam et al. (2021a) developed automatic classification systems using supervised learning approaches with labeled datasets to establish an efficient data collection and sampling pipeline. The authors used CNN in conjunction with FastText embeddings and Amazon Mechanical Turk for model training and dataset labeling, respectively. Similarly, Ramachandran and Parvathi (2021) improved the classification of tweets related to crises by employing deep learning models, including Multilayer Perceptron (MLP), CNN and LSTM. Ahadzadeh and Malek (2021) employed the SVM method to identify damage mentions in text messages on social networks, which allows the creation of a damage map based on damage-related tweets. Chen and Lim (2021) proposed a

Table 1
Related works on the analysis and monitoring of social media crisis covering existing models, features, and categories (refer to Fig. 3 for meanings of CAD, SME, SRE, MTE, GRE, and CLE).

Year	Ref	Models	Other Features	Category
2014	Imran et al. (2014)	AIDR	Customized model	CAD, CLE
2015	Cresci et al. (2015)	SVM	Linguistic and ad-hoc features	SME
2018	Avvenuti et al. (2018)	CrisMap System; embeddings and SVM classifier	Customized web-based dashboard with semantic annotations	CAD, GRE,CLE
	Hernandez-Suarez, Sanchez-Perez, Toscano-Medina, Perez-Meana, Portillo-Portillo and Sanchez (2018)	Supervised classifier, RF	NER, N-gram level, word level	CAD, GRE
	Rudra et al. (2018)	SVM	Bag-of-words, syntactic features, low-level lexi-cal	CLE
2019	Kumar et al. (2019)	RF, KNN, SVM, NB, LSTM, CNN, GRU	TF-IDF, Glove	CLE
	Cheng, Zhang, Su, Gao and Shen (2019)	Normalized affect population index (NAPI)	Assessment approach	SME
	Hernandez-Suarez et al. (2019)	biLSTM, CRF	NER, embeddings	CAD, GRE,CLE
2020	Mircea (2020)	Prototype dashboard, L2 classification layer	Customized dashboard	CAD, SME, GRE,CLE
	Fertier, Montarnal, Barthe-Delanoë, Truptil and Benaben (2020)	Big data 5Vs-based framework	Data management framework	CAD
	Boné et al. (2020a)	CNN	NER. KG, NLP	CAD, SME
	Kersten and Klan (2020)	Non-negative matrix factorization (NMF), CNN, LDA.	Clustering	CAD, SME, CLE
	Boné et al. (2020b)	DIET, DSRM	Natural language understanding (NLU)	SME, GRE,CLE
	Avvenuti et al. (2020)	RCNNs, SVM	Max pooling, word embeddings	GRE
	Madichetty and Muthukumarasamy (2020)	CNN, LSTM, biLSTM, and biLSTM with atten-tion mechanism	GloVe, Word2Ver, crisis word embeddings, BERT embeddings	SRE,CLE
	Priya, Bhanu, Dandapat, Ghosh and Chandra (2020)	TAQE (topic aligned query expansion), Informa-tion retrieval	Latent Dichlet allocation, part of speech	CAD, SME
2021	Alam et al. (2021a)	CNN	FastText (emdeddings), AMT (Amozon Me-chanical Turk)	CAD
	Ramachandran and Parvathi (2021)	MLP, CNN, and LSTM	Vectorization methods (GloVe and Word2Vec)	CLE
	Coche, Rodriguez, Montarnal, Tapia and Benaben (2021)	Metamodol	6Ws	CAD, CLE
	Ahadzadeh and Malek (2021)	SVM		GRE
	Zhang, Shen, Cheng, Su and Zhang (2021)	Demana dictionary, gazetter, biterm topic model	Topic-model based framework	SRE
	Chen and Lim (2021)	Multi-lavel Multi-class classifier (relation classi-fication problem)	Domain specifics libraries, semantic search	CLE
	Madichetty and Sridevi (2021)	SVM, RF, GB, AB, Bagging	Low-level lexical, syntactic, and frequency fea-tures	SRE.CLE
2022	Sadiq et al. (2022)	Fully convolutional network (FCN)	AdamW optimizer	GRE
	Basyurt, Marx, Stieglitz and Mirbabaie (2022)	SMA Dashboard	Customized dashboard	CAD, SME, MTE
	Ponce-López and Spataru (2022)	BERT	LDA, TF-IDF, bag-of-words	MTE
	Scalia et al. (2022)	CIME algorithm	NER	CAD, SME, GRE
	Arathi and Sasikala (2022)	RF	Glove model, metadata features	CLE
	Zheng, Shi, Zhou, Lu and Lin (2022)	Word frequency, trend analysis, semantic analy-sis, keyword-based classification.	Impact analysis	CAD, CLE
2023	Krishna et al. (2023)	Majority-voting ensemble model	TF-IDF, word2vec, GloVe	CLE
	Paul et al. (2023)	CNN, GRU, SkipCNN	Word embeddings, bag of words	CLE
	Garg et al. (2023)	Ontology-based approach		SME, CLE
	Asinthara et al. (2023)	SVM, bi-LSTM	TF-IDF, word2vec	CLE
	Dasari et al. (2023)	Stacking ensemble model	TF-IDF, word2vec, Glove	CLE
	Iparraguirre-Villanueva et al. (2023)	LR, KNN, DT, RF, NB	Bag of words	CAD, CLE
	Sánchez et al. (2023)	Machine Translation (MT), mBERT, BERT, XLM-RoBERT.	MUSE, GloVe, Linquistic features	MTE, CLE
	Razis et al. (2023)	Event mapping framework	Customized framework	CAD, SME, GRE
	Mukhtiar, Rizwan, Habib, Afridi, Hasan and Ahmad (2023)	BERT, RoBERTa, XLNet	Late fusion	CLE
2024	Vassiliades, Stathopoulos-Kampilis, Antzoulatos, Symeoni-dis, Diplaris,	XR4DRAMA		SME, GRE

(continued on next page)

Table 1 (*continued*)

Year	Ref	Models	Other Features	Category
	Vrochidis, Bassiliades and Kompatsiaris (2024)			
	Yan et al. (2024)	SMEGCN (Subsequent multievent graph convolutional network)	Relational and semantic information	SRE
	Mehmood et al. (2024)	BERT, RoBERTa, DistilBERT, and ALBERT	NER, BERTopic library	SME, CLE
	Girsang and Noveta (2024)	SVM	NER, ArcGIS tools	GRE,CLE
	Malik et al. (2024)	BERT classifier, RF, SVM	Fine-tunning of BERT, TF-IDF, word2vec	CLE
	This study	VOSviewer	VOS technique, WPVMF	CLE

semi-supervised model for a comprehensive understanding of social media texts with minimal manual intervention. Their method employed a multi-instance, multi-class classifier to recognize damage reports in social media texts. Madichetty and Sridevi (2021) addressed the issues of infrastructure and human damage by combining the RoBERTa model with feature-based methods to identify situational tweets during disasters.

Moreover, the study by Sadiq, Akhtar, Imran and Ofli (2022) employed a Fully Convolutional Network (FCN) and the AdamW optimizer to process heterogeneous data from four case studies, which improved the accuracy and efficiency of flood extent mapping. Ponce-López and Spataru (2022) utilized ML classifiers based on Deep Belief Neural Networks (DBNN) trained on benchmark datasets of disaster responses and extreme events. Arathi and Sasikala (2022) developed a model based on a random forest model that effectively prioritises tweets based on their relevance and urgency, enhancing the efficiency of crisis response and management efforts.

Krishna, Srinivas and Prasad Reddy (2023) employed ensemble learning, a majority voting-based approach to identify informative tweets by combining the strengths of embedding techniques to improve the accuracy and reliability of tweet classification. Paul et al. (2023) proposed a deep learning-based approach to classifying disaster tweets into binary and multi-class categories by employing CNN, Gated Recurrent Unit (GRU), and SkipCNN models. Asinthara, Jayan and Jacob (2023) proposed a recent multi-class classification approach for disaster tweets based on SVM and biLSTM models, highlighting the significant performance of the SVM model. Dasari, Gorla and PVGD (2023) used a machine learning stacking ensemble model to detect informative tweets collected from crisisNLP dataset. Iparraguirre-Villanueva, Melgarejo-Graciano, Castro-Leon, Olaya-Cotera, John, Epifanía-Huerta, Cabanillas-Carbonell and Zapata-Paulini (2023) classified disaster tweets by exploring several machine learning models, including Naive Bayes (Bernoulli and Multinomial), Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbors (KNN), and RF. Their approach enables efficient classification of disaster-related tweets, facilitating timely analysis and response to crisis events. Sánchez, Sarmiento, Abeliuk, Pérez and Poblete (2023) utilized machine translation techniques and models such as Bidirectional Encoder Representations from Transformers (BERT), Multilingual BERT, and XLM-RoBERTa to automatically classify crisis-related messages.

Yan, Zhou, Zhang, Du and Ren (2024) developed the Subsequent Multievent Graph Convolutional Network (SMEGCN) for predicting events and potential actors using Sina microblog data concerning the Covid-19 pandemic. This model leverages relational and semantic information to predict future events and actors based on multievent graphs extracted from social media data. Mehmood, Zamir, Ayub, Ahmad and Ahmad (2024) proposed a Relevant Classification of Twitter Posts (RCTP) based on a fusion framework merging BERT, RoBERTa, DistilBERT, and ALBERT models for relevant post classification. Similarly, Malik, Younas, Jamjoom and Ignatov (2024) conducted binary and multiclass classification of disaster damage assessment tweets using a BERT classifier, RF, and SVM. They fine-tuned the BERT model on the CrisisMMD dataset and explored transfer learning mechanisms to learn universal contextualized representations, enhancing the accuracy and reliability of disaster damage assessment.

Additionally, it is noted that many ML and DL models were used for geospatial text analysis of crisis data. Some of these approaches were used to extract geographic information Razis, Maroufidis and Anagnostopoulos (2023), Scalia, Francalanci and Pernici (2022) and classification Girsang and Noveta (2024). For example, Razis et al. (2023) developed a text classification framework to deal with noisy data based on several transformers, including BERT, RoBERTa, and XLNet. Their approach utilizes late fusion techniques to differentiate between relevant and non-relevant posts, facilitating more accurate analysis and response to crisis events, while Girsang and Noveta (2024) utilized SVM to classify geospatial natural disaster data. Hence, these models play a pivotal role in analysing and classifying crisis datasets, as demonstrated by various studies (refer to Table 1). Their ability to handle complex, high-dimensional data allows for more accurate predictions and insights in crisis management scenarios.

2.2.2. NLP and semantics engines

Several NLP techniques are widely used across different studies, often in combination with ML models to improve performance and accuracy. Many studies leverage the synergy between ML and NLP, employing techniques such as *n*-grams, GloVe, bag-of-words, and others. Specifically, Cresci et al. (2015) developed a model for Italian tweets

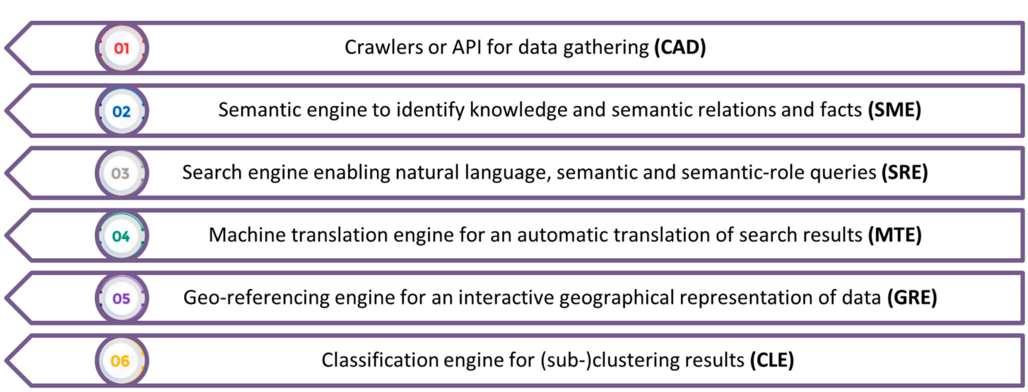

Fig. 3. Categorization of Literature for Crisis Informatics Social Media Analytics.

using a variety of linguistic features. Similarly, Rudra et al. (2018) utilized low-level lexical and syntactic features, while Avvenuti et al. (2018) introduced a Big Data crisis mapping approach that extracts actionable information from tweets using word embeddings and semantic annotators, which enhances the understanding of crisis events and facilitates timely decision-making. Kumar et al. (2019) employed *1*-gram, *2*-gram, and *3*-gram features, along with Term Frequency-Inverse Document Frequency (TF-IDF) for conventional machine learning and GloVe and crisis embeddings for deep learning models.

Moreover, Boné et al. (2020a) developed a data extraction system that utilizes a pipeline of NLP tools, as part of the technique to extract relevant information from social media data, whereas Boné et al. (2020b) leveraged natural language understanding (NLU) to generate responses and update a dynamic knowledge graph (KG) in real-time, enhancing community resilience and decision-making. Madichetty and Muthukumarasamy (2020) utilized GloVe, Word2Vec, crisis word embeddings, and BERT embeddings to enhance tweet classification. Additionally, Priya et al. (2020) improved information retrieval by incorporating Latent Dirichlet Allocation (LDA).

Furthermore, Ramachandran and Parvathi (2021) utilized GloVe and Word2Vec vectorization methods to improve tweet classification accuracy. Madichetty and Sridevi (2021) collectively addressed the issues of infrastructure and human damage from tweets by leveraging on lexicons and TF-IDF features. Chen and Lim (2021) proposed a model that quantifies the severity of damage conveyed in reports by measuring word similarity with known damage-related terms, enabling more efficient analysis of crisis-related social media content. Similarly, Arathi and Sasikala (2022) developed a model for identifying high-priority tweets using GloVe embeddings and metadata features, while Krishna et al. (2023) employed a majority voting-based approach to identify informative tweets using Word2Vec and GloVe models. In addition to word embeddings, Paul et al. (2023) utilized bag-of-words representations to capture semantic information from text. Iparraguirre-Villanueva et al. (2023) also classified disaster tweets with the help of bag-of-words representations.

Moreover, Asinthara et al. (2023) utilizes TF-IDF and Word2Vec features along with ML and DL models for multiclass classification of disaster-related tweets, and Dasari et al. (2023) proposed a classification system for detecting informative tweets using a stacking ensemble model with TF-IDF, Word2Vec, and GloVe feature models. Krishna et al. (2023) employed a majority voting-based approach to identify informative tweets using word2vec, TF-IDF, and the GloVe model. Additionally, Sánchez et al. (2023) proposed a model to automatically classify messages related to crisis events by leveraging cross-language and cross-domain labeled data, incorporating GloVe embeddings and linguistic features to classify messages from different languages and domains.

2.2.3. Data retrieval, analysis and topic modeling approaches

There are various data retrieval, analysis, and topic modeling techniques in the literature. For example, Cheng et al. (2019) proposed an approach to assess the near-real-time intensity of the affected population using social media data. They used the Normalized Affected Population Index (NAPI), which demonstrates a significant ability to indicate the intensity of affected populations during disasters. NAPI offers a novel method for assessing population impact during disasters by leveraging social media data. Priya et al. (2020) utilized an information retrieval approach to assess infrastructure damage tweets based on topic-aligned query expansion, their method improves information retrieval as well as part of speech analysis, thereby facilitating more effective infrastructure damage assessment. Ahadzadeh and Malek (2021) created a damage map based on damage-related tweets and conducted a temporal analysis to understand the timing and distribution of damage-related messages. In addition, Zhang et al. (2021) developed a framework using topic modeling to identify demand for relief supplies distribution via social media data, focusing on the 2013 Typhoon Haiyan. Their study utilized the biterm topic model to identify tweet topics, screen demand-related tweets, and extract demand and location information.

Additionally, Scalia et al. (2022) developed a Contextual Information Maximization for Emergencies (CIME) algorithm to identify and geolocate emergency-related posts useful for mapping, even in the absence of native geocoordinates. Their algorithm leverages geographical references in post metadata, such as text or links, and incorporates indirect information from the post's social network. The study by Sadiq et al. (2022) explored the integration of remote sensing and social sensing data to derive informed flood extent maps through data fusion. Ponce-López and Spataru (2022) analyses behavioural indicators and matches them with climate variables, decoding synoptical records to assess thermal comfort. Zheng et al. (2022) proposed a text mining approach to gather and analyse social media data for early earthquake impact assessment. Their methodology involves collecting disaster-related microblogs from Sina microblogs using crawler technology, followed by data cleaning, hot words analysis, trend analysis of microblog volumes, sentiment analysis, and keyword and rule-based text classification. Also, Mehmood et al. (2024) employed BERTopic library for topic modelling.

2.2.4. Ontology and data management techniques

The literature has shown additional methods and techniques for data management and organisation in crisis informatics research. While many studies rely on ML and NLP synergy, some also employ rule-based or ontology-driven methods. These include techniques leveraging ontology-based approaches, such as knowledge graphs and structured frameworks (Garg et al., 2023; Vassiliades et al., 2024; Boné et al., 2020b), as well as broader data management strategies that enhance organisation and retrieval of crisis information (Fertier et al., 2020; Coche et al., 2021). For example, Garg et al. (2023) developed an ontology-based method for text summarization, which was tested on twelve disaster-related datasets. Their ontology-based approach enables the extraction of key information from disaster-related tweets, facilitating efficient summarization and analysis of crisis events.

Furthermore, the study by Vassiliades et al. (2024) developed XR4DRAMA, a comprehensive tool for media preparation and disaster management. The XR4DRAMA tool incorporates a KG and facilitates the creation/update of Points of Interest (POI) based on user-generated content. This aids in task creation for emergency scenarios. It also featured a mechanism to designate danger zones on maps supported by a Decision Support System (DSS). The KG was used to capture crucial data for crisis handling, including observations, spatio-temporal data, and mitigation/response plans. In addition, Fertier et al. (2020) proposed a framework to enhance situation awareness while considering the 5Vs of Big Data (Volume, Velocity, Variety, Veracity, and Value). This framework provides general principles and a new architecture for implementing effective data management strategies. Coche et al. (2021) introduced an automatic social media information organisation model tailored for decision-makers during crises. Their metamodel organises crucial information using the lens of the 6W's (Who, What, Where, When, Why, and How), enabling efficient information retrieval and analysis. By structuring data around these key dimensions, decision-makers can better understand and respond to crisis events.

2.2.5. Visualisation and AI tools

The review also identifies several visualisation tools and artificial intelligence tools. Specifically, Imran et al. (2014) introduced the "Artificial Intelligence for Disaster Response (AIDR)" model, which facilitates the collection and classification of tweets during disaster events. The model allows users to create classifiers on the fly by annotating incoming data from Twitter. AIDR represents a significant advancement in the automated classification of informative tweets, which enables real-time data collection and classification that offers valuable insights for disaster response and management efforts. Similarly, Mircea (2020) developed a prototype dashboard for classifying, geolocating, and provides interactive visualisation of Covid-19 tweets. This dashboard enables real-time classification and geolocation of tweets, providing valuable insights for monitoring and responding to public health emergencies. Boné et al. (2020b) developed DisBot, a Portuguese chatbot designed to aid citizens and first responders during disasters. Utilizing Design Science Research Methodology (DSRM), DisBot employs a Dual Intent Entity Transformer (DIET) architecture for intent classification and dialogue policies.

Similarly, Basyurt et al. (2022) developed a social media analytics dashboard for a regional government agency. Preliminary results indicate that the system features a user-friendly and responsive design, ensuring secure, flexible, and quick access to information. The dashboard displays regional discussion statistics, sentiment analysis, and emerging topics, empowering decision-makers with valuable insights for crisis management and response. Additionally, Avvenuti et al. (2018) visualised Big Data crisis mapping to enrich tweets in a web-based dashboard. Further, Razis et al. (2023) proposed an Event Mapping framework to identify and extract geographic information directly from official Greek governmental Twitter accounts. Their framework visualises this information on an interactive map, enabling policymakers and responders to understand and respond to crisis events.

2.3. Research gap

Humanitarian organisations have extensively utilized data from social media during disasters (Alam et al., 2021b). Existing studies in the field have focused on diverse approaches, such as machine learning and deep learning models and natural language processing techniques, to extract insights from social media data during crises. These studies typically gather and assess historical or real-time datasets using automated processes. Among the various methods employed, supervised machine learning predominates across different contexts, and classification techniques emerge as the most prevalent, highlighting a lack of unsupervised methods (Okpala, Halse and Kropczynski, 2022). Furthermore, using deep learning and machine learning for producing visualisation maps or word frequency analyses often requires programming skills, such as knowledge of Python (MadhaviLatha and Kumar, 2016; Casas Saez, 2020). Existing visualisation solutions clearly demonstrate the growing role of visualisation tools in decision-making (Mircea, 2020; Avvenuti et al., 2018; Basyurt et al., 2022; Razis et al., 2023). While these methods and tools have demonstrated effectiveness in information extraction, classification, sentiment analysis, and visualisations, the lack of research utilising mapping tool like VOSviewer suggests a missed opportunity to harness their capabilities for visualising the interconnectedness of crisis-related topics and information dissemination networks. It is fascinating how this tool can empower decision-makers; whether analysing tweets or crisis data, the right dashboard can truly make a difference in turning data into actionable insights.

In addition, numerous techniques and systems have been developed to process this data, as illustrated in Table 1. However, despite the extensive exploration of methodologies for analysing crisis-related social media data, there is a need for simple yet robust tools to provide timely and rapid insights into a large amount of information of varying significance on social media. Such tools are needed as ML or DL based tools are too complex, while the Word embedding tools do not provide deep insights into the relationship of the data. While VOSviewer is a powerful tool for bibliometric analysis and network visualisation, and it has primarily been used for scientometric analysis, many studies have demonstrated its application to other datasets and applications different from bibliometric research (Bukar, Sayeed, Razak, Yogarayan, Amodu and Mahmood, 2023a; Bukar et al., 2024; Shah, Lee, Hidayat, Falchook and Muhammad, 2024; Lequeux-Dincă and Teodorescu, 2024; Hajad, Ikhsan, Latif and Saputra, 2024; Rukadikar and Khandelwal, 2024). Examples include datasets obtained from LinkedIn (Bukar et al., 2024), text analysis involving lung cancer (Shah et al., 2024), online newspaper media texts (Lequeux-Dincă and Teodorescu, 2024), political participation of women on Instagram during campaigns (Hajad et al., 2024), and narratives of Chatbot adoption in recruitment (Rukadikar and Khandelwal, 2024). Its application in crisis management and disaster response remains largely unexplored.

Moreover, the hypersensitive and unstable nature of disasters makes an efficient data analysis tool important. For instance, Herovic, Hartten, Walpole, Johnson and Busser (2024) identified several challenges requiring attention in pre- and post-disaster periods, including adequate data representation and streaming collection and analysis of data (Madhavi-Latha and Kumar, 2016; Casas Saez, 2020). Similarly, symbols, irony, ambiguous expressions, and many other aspects of context-aware social media posts (Stieglitz, Dang-Xuan, Bruns and Neuberger, 2014) and user metadata are often nonexistent, with posts linked because creators are socially connected (Tang, Chang and Liu, 2014). While conventional data mining often ignores these aspects, studying tweets in isolation as single statements without considering the monologic or conversational context (Palen and Anderson, 2016). As such, leveraging free, and easily accessible text mining tools such as VOSviewer to crisis data analysis and representation could uncover valuable insights into the structure of crisis-related conversations on social media platforms, identify central themes and context, and map the connection of information during emergency events. Therefore, this study posits the need to explore the text analysis feature of VOSviewer for visualising network structures within crisis datasets.

3. Research method

Data mining methodologies are applied for tasks such as information retrieval, statistical modeling, and machine learning (Injadat, Salo and Nassif, 2016), facilitating the preprocessing, analysis, and interpretation of data. In this study, the methodology for data collection and analysis is delineated into three primary stages. These stages encompass the following: 1) initial data acquisition from existing studies and description of the datasets; 2) preliminary data preprocessing and restructuring to align with the chosen text analysis method; and 3) application of the analysis method to identify the most frequently used terms in social media crisis responses and the generation of visualisation maps. Fig. 4 illustrates the architecture of the proposed method for this research.

3.1. Dataset acquisition

Data-driven digital humanitarian and crisis management is transforming the face of crisis communication and management across various crises (Qadir, Ali, Rasool, Zwitter, Sathiaseelan and Crowcroft, 2016), including natural disasters, refugee crises, terrorist attacks, epidemic crises, civil wars, overcrowding, public violence, and other disaster situations such as industrial accidents, public disorder, and infrastructural failures. Recent strides in crisis damage analysis have produced several datasets aimed at fostering research in this domain (Alam et al., 2021a,b; Reuter et al., 2016). Accessing the requisite data for this research involves navigating diverse platforms and methods and addressing challenges in ensuring data accessibility, quality, and bias (Reuter et al., 2016). To mitigate these challenges, this study leverages crisis datasets available online from Alam et al. (2021b), known as CrisisBench dataset, which had already undergone rigorous scrutiny and validation by several existing studies (Alam et al., 2021a,b; Reuter et al., 2016; Alam et al., 2019, 2020, 2023; Imran et al., 2015). These studies employed diverse data collection methods to ensure a comprehensive representation of social media users discourse during crises. The use of data validated by multiple studies helps mitigate potential ethical issues and biases and enhances the representativeness of the dataset.

Accordingly, when analysing social media data, especially for research purposes, addressing ethical considerations related to privacy and consent is crucial. This study utilises the CrisisBench dataset, which

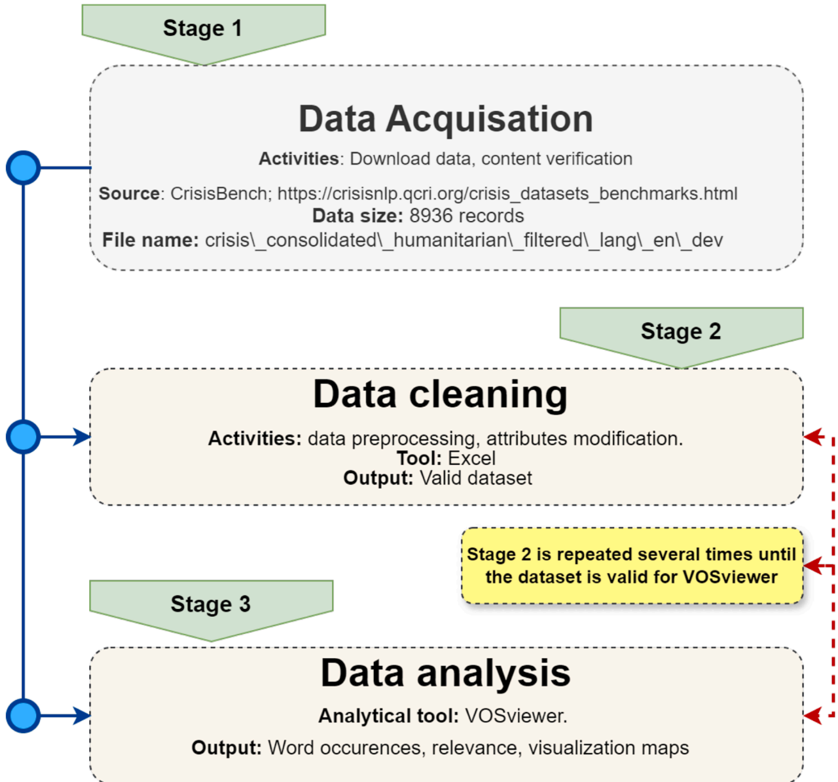

Fig. 4. The Steps of Crisis Mapping Approach.

is publicly available and specifically labelled for damage-related tweets (Alam et al., 2021b). This dataset aligns with prior research efforts that have used similar datasets for training various machine learning and deep learning models (e.g. Alam et al. (2021a, 2019, 2020). As the dataset consists of secondary data obtained from publicly available social media content, it adheres to widely accepted ethical practices for text mining and natural language processing. Therefore, from an ethical perspective, the data used in this study is considered secondary data. Several researchers recognise that information posted on social media is regarded as being in the public domain (Bond and Hewitt-Taylor, 2014; Mikal, Hurst and Conway, 2016; Monks, Cardoso, Papageorgiou, Carolan, Costello and Thomas, 2015; Moreno, Grant, Kacvinsky, Moreno and Fleming, 2012). The initial collection of this data involved content that was publicly accessible on social media platforms (tweets). According to established ethical guidelines, when data is publicly available, informed consent is generally not required for its use in research (Azam, 2018; Gustafson and Woodworth, 2014; Taylor and Pagliari, 2018; Ford, Shepherd, Jones and Hassan, 2021). This approach is based on the principle that data mining represents a form of secondary data analysis conducted on material that is already freely accessible and anonymized (Ford et al., 2021).

The CrisisBench dataset aggregates data from multiple sources, including CrisisLex (CrisisLex26, CrisisLex6), CrisisNLP, SWDM2013, ISCRAM13, Disaster Response Data (DRD), Disasters on Social Media (DSM), CrisisMMD, and data from AIDR. This dataset was curated by crawling user-posted blogs and consolidated from eight datasets, labeled into four disaster types: floods, hurricanes, wildfires, and earthquakes. These labels can be consistently mapped for tasks such as informativeness and humanitarian information type classification. This study focuses on humanitarian type classification, utilizing the "crisis_consolidated_humanitarian_filtered_lang_en_dev" dataset, comprising 8936 records. As this dataset was primarily adopted for use by the VOSviewer application, pre-cleaning is slightly required as discussed in the proceeding section. Focusing on this dataset allows this study to evaluate the current crisis dataset and distinct text analytics method (VOS), as encouraged by Rizza (2023).

3.2. Data preparation

The dataset utilized for this investigation comprises 8936 records written in English, stored in the MS Excel 365 application. To ensure compatibility with the analysis tool, VOSviewer, the dataset was transformed, including attribute addition and modification, to align the data structure with the requirements of VOSviewer. The formatting was conducted to ensure compliance with the analytical tool. This process is pivotal in ensuring that VOSviewer can process the dataset seamlessly, without encountering any errors or inconsistencies. Initially, the crisis dataset's attributes include: 'Id' for identification, 'Event' representing crisis events, 'Source' denoting the origin of data from eight different sources, 'Text' containing posts from social media users, 'Lang' indicating language tags, 'Lang_conf' for language configuration, and 'Class label' for text classification.

However, to have a valid input for analysis using VOSviewer, certain attributes were modified for seamless analysis. For instance, 'Id' remained unchanged, serving as a reliable means of identification to maintain dataset integrity. 'Event' was transformed to 'Title', aligning it more closely with the focal point of this study. Similarly, 'Source' was labeled 'Author', aligning with the syntax of the analytical tool, and providing more clarity on data origins. 'Text' was mapped and transformed to 'Abstract' to streamline the analysis, allowing this study to focus squarely on the core content of the user's social media concerns or reactions. Additionally, attributes like 'Lang' and 'Lang_conf' retained their name, preserving crucial linguistic aspects within our dataset. Finally, 'Class label' was renamed 'Author keyword', reflecting our emphasis on adapting keywords suitable for analysis. By refining these attributes, we have tailored the dataset to closely align with the specifications of VOS software. This strategic adaptation ensures the compatibility of the dataset with VOSviewer, paving the way for more robust and insightful outcomes. The mapping of the attributes of the initial dataset to the attributes adopted for the current analysis using VOS are presented in Table 2.

Following the successful pre-transformation of the dataset, it was uploaded to VOSviewer for analysis, bearing in mind that VOSviewer has been extensively validated by researchers in analysing bibliometric networks (Bukar, Sayeed, Razak, Yogarayan and Amodu, 2023b; Di Vaio, Hassan and Alavoine, 2022; Rialti, Marzi, Ciappei and Busso, 2019; Qian, Du, Liang, Yi, Wang, Tu, Huang, Pei, Ma, Burghardt et al., 2024; Miao, Li, Fan, Ni, Liu, Li and Zhang, 2024; Habil, Srivastav and Thakur, 2024). In other words, its proficiency in visualising and creating text maps based on text data is widely acknowledged (Xu, Ge, Wang and Skare, 2021).

3.3. Data analysis method

Various computational intelligence approaches are employed to assess user opinions, as observed in Section 2. VOSviewer software, developed using Java, is primarily designed for evaluating bibliometric networks (Eck and Waltman, 2022). This tool can generate maps based on text and network data and facilitate their visualisation and exploration. This study leverages VOSviewer for the analysis of crisis datasets. The approach relies on mapping and clustering based on the same fundamental principle, which is a weighted and parameterized variant of modularity-based clustering (Waltman, Eck and Noyons, 2010). This variant was proposed as an alternative to the widely known multidimensional scaling (MDS) technique (Eck and Waltman, 2007; Eck, Waltman, Dekker and Den Berg, 2010). Thus, the VOS clustering method employs this weighted and parameterized variant of the modularity function (WPVMF) (Newman and Girvan, 2004). For a detailed discussion of the mathematical modeling of MDS and WPVMF, refer to Waltman et al. (2010). Thus, the unified VOSviewer clustering technique can be regarded as a weighted variant of modularity-based clustering, featuring a resolution parameter to identify small clusters. The command-line parameters for clustering techniques in the VOSviewer program are detailed in Eck and Waltman (2021, 2022).

According to Eck and Waltman (2007), VOSviewer can show the strengths of participation of terms based on their relationships. This method, known as "visualisation of similarities," graphically locates and arranges each word on the map in the fitting location (Van Eck and Waltman, 2014). The VOSviewer approach offers a variety of resolution factors, making it possible to detect a wide range of clusters. Specifically, the program offers three map renderings: network visualisation, overlay visualisation, and density visualisation, making it an effective knowledge-mapping tool for scientific landscapes (Xu et al., 2021), and produces record frequency and keyword occurrence as collocated frequency measures. Record frequency denotes the total number of records containing the target keyword, while keyword frequency focuses on the keyword's appearance frequency within records. Collocation frequency indicates the number of instances where terms appear closely together. Text clustering, facilitated by VOSviewer's textual clustering method, was employed to identify primary clusters in social media texts, revealing distinct crisis-related themes. The result and discussion of the output generated by the VOSviewer are provided in the result section.

Table 2
Mapping the headings of the Crisis Dataset to conform with VOSviewer input requirements.

S/N	Initial Heading	VOSviewer Head-ing
1	Id	Id
2	Event	Title
3	Source	Author
4	Text	Abstract
5	Lang	Lang
6	Lang_conf	Lang_conf
7	Class label	Author keyword

4. Result of textual analysis

This study analyses the social media crisis dataset, which comprises eight consolidated datasets of different crises, using the text-mining technique feature in VOSviewer 1.6.18 (Eck and Waltman, 2022). Database files that serve as input, accessible through an inbuilt application programming interface (API), were fed to the VOSviewer, which analyses the text from the crisis dataset and generates a map depicting a co-word network based on binary counting and full counting. Specifically, in binary counting, "the occurrences attribute represents the number of records in which a term appears at least once", while in full counting, "the occurrences attribute displays the total number of instances of a term across all records" (Eck and Waltman, 2021). The analysis visualised the terms on a map, depicting a co-word network. The generated map illustrates the distance between terms and indicates the connection between distinct terms. Thus, the smaller the separation between two or more terms (nodes), the greater the importance of the terms connected to those terms (Van Eck and Waltman, 2014). In the following sections, the findings obtained from binary and full counting are discussed.

4.1. Map visualisation in binary counting

Fig. 5 presented the visualisation network and map of text based on binary counting, highlighting the most used terms. The presentation of the terms and their co-occurrence (co-word estimation) illustrates various reactions or concerns of social media users during the crisis. For each of the 372 terms that met the threshold (10 minimum number of occurrences of a term), a relevance score was calculated, and the most relevant terms were selected. Consequently, 60% of the most relevant terms were chosen during binary counting, resulting in 223 terms. Accordingly, the application of colour served to delineate the differences between nine distinct groupings: Green, Brown, Red, Blue, Pink, Purple, Yellow, Orange, and Cyan.

In addition, it is crucial to consider the colour-coding of the phrases that appeared in various clusters. For instance, terms such as "food," "water," "electricity," and "clothing" are grouped, indicating their relatedness and frequency of co-occurrence. This co-occurrence network assigns a numerical value to the extent to which the terms interact in the context of the crisis events. The result shows that the most prominent terms used by several users to demonstrate their concerns during crises are represented in Fig. 5. According to the visualisation map, the most prominent terms were "hagupit," "rubyph," "water," and "food." Findings also show that terms such as "government," "explosion," "supply," "pray," and "rain" appeared quite frequently and were divided based on clusters.

The visualisation shows the relationships between terms, such as "water and supply," "food and supply," and "doctor and medicine," are also significant. Analysing these relationships has the potential to improve crisis management and response in the initial phase and enhance decision-making processes subsequently. The appearance of concerns about relief materials underscores the needs of the affected people during crises. The identification of relief-related terms suggests the most important aspects of citizens' responses when a crisis occurs. For a comprehensive list of all the terms that appeared in binary counting, along with their occurrences and relevance scores, refer to Table A1 in the Appendix.

4.2. Map visualisation in full counting

The terms were put through another test to understand the relative strength of their links with other terms by performing a full counting analysis on the social media crisis dataset. For each of the 379 terms that met the threshold, a relevance score was calculated, and the most relevant terms were selected. Consequently, 60% of these relevant terms were chosen, resulting in 227 terms grouped into nine clusters: Green, Brown, Red, Blue, Pink, Purple, Yellow, Orange, and Cyan. The

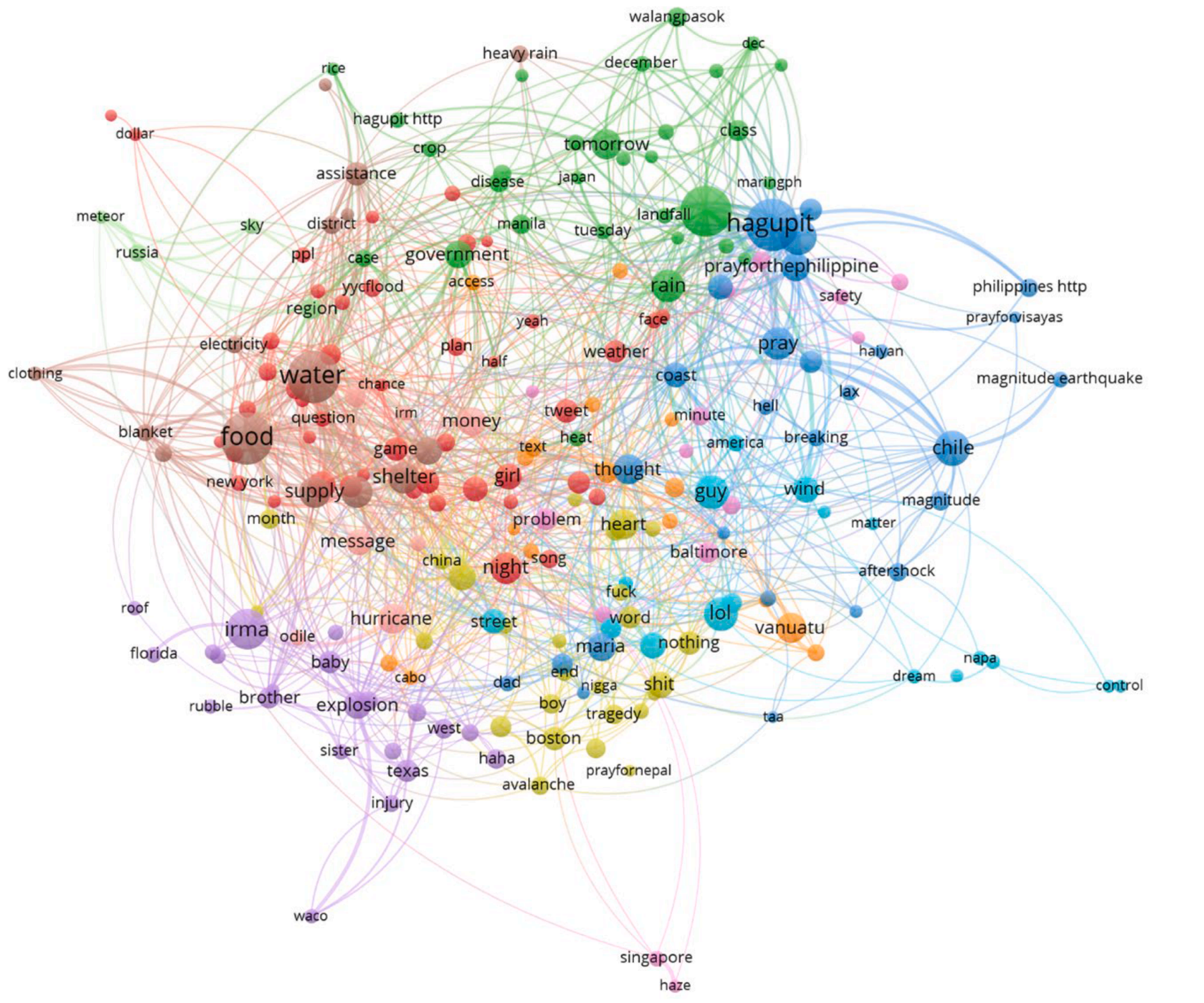

Fig. 5. Co-Occurence Network in Binary Counting.

graphical representation of full counting is presented in Fig. 6. Each cluster illustrates a thematic community with which it is closely related. Hence, the larger the size of the cluster represented by some terms, the more frequently those terms appear in the text. In addition, the distance between the clusters is a good indicator of how strong the relationships are between the clusters. This connection was evidenced by the number of times these words appeared together in the text of various records.

Accordingly, the full counting analysis provides a deeper insight into the structure and dynamics of social media discourse during crises. By considering the total number of instances a term appears across all records, rather than just its presence or absence, full counting offers a more nuanced view of term importance and relationships. Refer to Table A2 (Appendix) for a detailed list of all the terms that appeared in full counting, including their occurrences and relevance scores. Nevertheless, the distinct terms that appeared in both full and binary counting are discussed in the subsequent section, which highlights the importance of employing both counting methods to comprehensively gain insights into the crisis data.

4.3. Binary vs. full counting

The analysis using Vosviewer to examine crisis-related datasets revealed interesting differences between binary and full counting methods. Table 3 compares distinct terms identified using binary and full counting methods in VOSviewer, along with their frequency and relevance scores. The terms identified through binary counting, such as “donate," “vanuatu," and “trump," highlight terms that appear in various records without indicating their frequency within those records. In contrast, full counting terms like “wow," “humanity," and “typhoon pablo" reflect their total instances across all records, providing a more detailed view of term frequency. Interestingly, some terms present in binary counting are absent in full counting and vice versa, such as “donate" and “trump" in binary counting versus “wow" and “humanity" in full counting. This divergence highlights the distinct insights each method offers: binary counting emphasizes the breadth of term occurrence across different records, while full counting focuses on the depth of term frequency within the dataset. This difference is crucial for understanding the unique patterns and relevance of terms depending on the chosen method.

This comparison demonstrates that while both methods identify critical terms, the context and prominence of terms can vary significantly. Such insights can help tailor crisis communication strategies by recognizing key themes and terms prevalent in different counting methods, ensuring a comprehensive understanding of public discourse during crises. Hence, the choice of counting method in text analysis can significantly influence the insights gained from the data. These findings

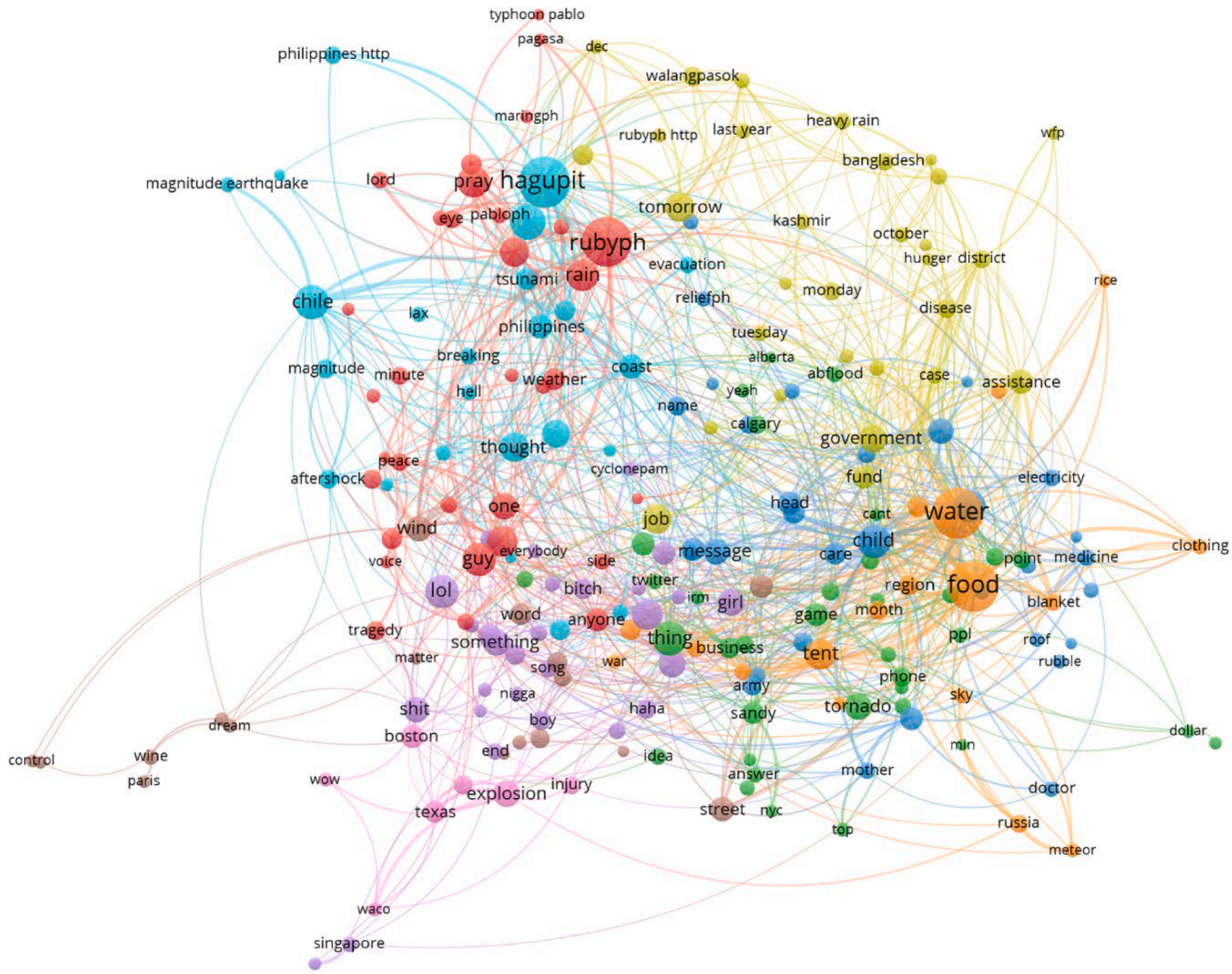

Fig. 6. Co-Occurence Network in Full Counting.

Table 3
Distinct terms between Binary and Full Counting; O: Occurrences; R: Relevance.

Binary counting				Full counting			
S/N	Term	O	R	S/N	Term	O	R
1	donate	17	1.66	1	wow	14	1.67
2	vanuatu	63	1.50	2	humanity	14	1.43
3	trump	17	0.96	3	typhoon pablo	11	1.31
4	money	56	0.78	4	bangladesh	23	1.17
5	hurricane	63	0.76	5	nepalearthquake http	25	1.13
6	cabo	14	0.75	6	job	59	1.07
7	typhoon haiyan	15	0.67	7	percent	11	1.06
8	sister	16	0.62	8	volcano	10	1.01
9	glasgow	13	0.61	9	top	15	0.87
10	brother	29	0.55	10	temporary shelter	10	0.85
11	hurricane odile	21	0.52	11	october	16	0.75
12	landfall	18	0.47	12	evacuation	21	0.63
13	manila	25	0.39	13	fund	36	0.58
14	problem	33	0.26	14	thing	85	0.52
15	need	51	0.25	15	head	39	0.50
16	shelter	64	0.21	16	situation	29	0.37
				17	support	48	0.35
				18	one	52	0.33
				19	child	76	0.31
				20	nation	34	0.28

underscore the importance of selecting an appropriate analysis method based on the research objectives, particularly in crisis communication where both broad and detailed insights are valuable.

5. Discussion and findings

The advent of crises or disasters generates significant public reaction, drawing the attention of crisis management professionals to mine data from social media. This effort has increased the demand for effective social media text analysis. While there are proposed solutions for text analytics, more advanced techniques leverage statistical, machine learning, and linguistic methods (Franceschini, 2023). Common text analytics techniques include word frequency analysis, which measures the most frequently occurring words and phrases in specific conversations. As the application of text analysis continues to grow, this study aims to leverage VOSviewer to identify and evaluate social media crisis datasets. The findings demonstrate VOSviewer's capability to reveal the most frequently occurring words in the dataset, thereby potentially supporting crisis response efforts and decision-making. The use of VOSviewer-based text analytics and word frequency analysis helps determine which terms users mention most often, providing valuable insights for effective crisis management. The findings enrich our understanding of social media discourse during crises by highlighting the frequency and relationships of various keywords. This comprehensive view aids in identifying key concerns, thematic communities, and the strength of their connections, ultimately enhancing crisis management and response efforts.

5.1. Findings

The network visualisations reveal key insights into the dynamics of social media discourse during crises. The identification of frequent and co-occurring terms allows for a better understanding of public sentiment and needs. For example, the terms "hagupit", "yycflood", and cyclonepam are references to specific events or phenomena that significantly impacted public discourse. The frequent mention of "water" and "food" underscores the critical need for these basic necessities during crises. Moreover, the clustering of terms like "government," "explosion," "supply," "pray," and "rain" suggests diverse concerns ranging from governance and infrastructure to emotional and spiritual responses. This diversity in clusters indicates that social media users discuss a broad spectrum of issues, reflecting the complex nature of crises and the multifaceted response required.

The relationships identified, such as between "water and supply" and "food and supply," highlight the interconnected nature of various needs during a crisis. For instance, the need for water and food often correlates with supply chain issues, suggesting that disruptions in one area can significantly impact others. Similarly, the relationship between "doctor and medicine" indicates a focus on healthcare and the critical role of medical professionals and supplies during emergencies. Understanding these relationships and the frequency of specific terms can help crisis managers prioritise resources and actions. By focusing on the most mentioned needs and concerns, such as ensuring the availability of water, food, and medical supplies, crisis response efforts can be more targeted and effective. Additionally, recognizing the importance of terms like "government" and "pray" can guide communication strategies, emphasizing official information and support while acknowledging the emotional and spiritual needs of the affected population. Hence, the visualisation of social media data using VOSviewer provides valuable insights into public discourse, as evident from the crisis dataset. It highlights key concerns, relationships between needs, and the diversity of issues discussed. This information can enhance crisis management strategies, ensuring a more comprehensive and effective response to the complex challenges presented by emergencies.

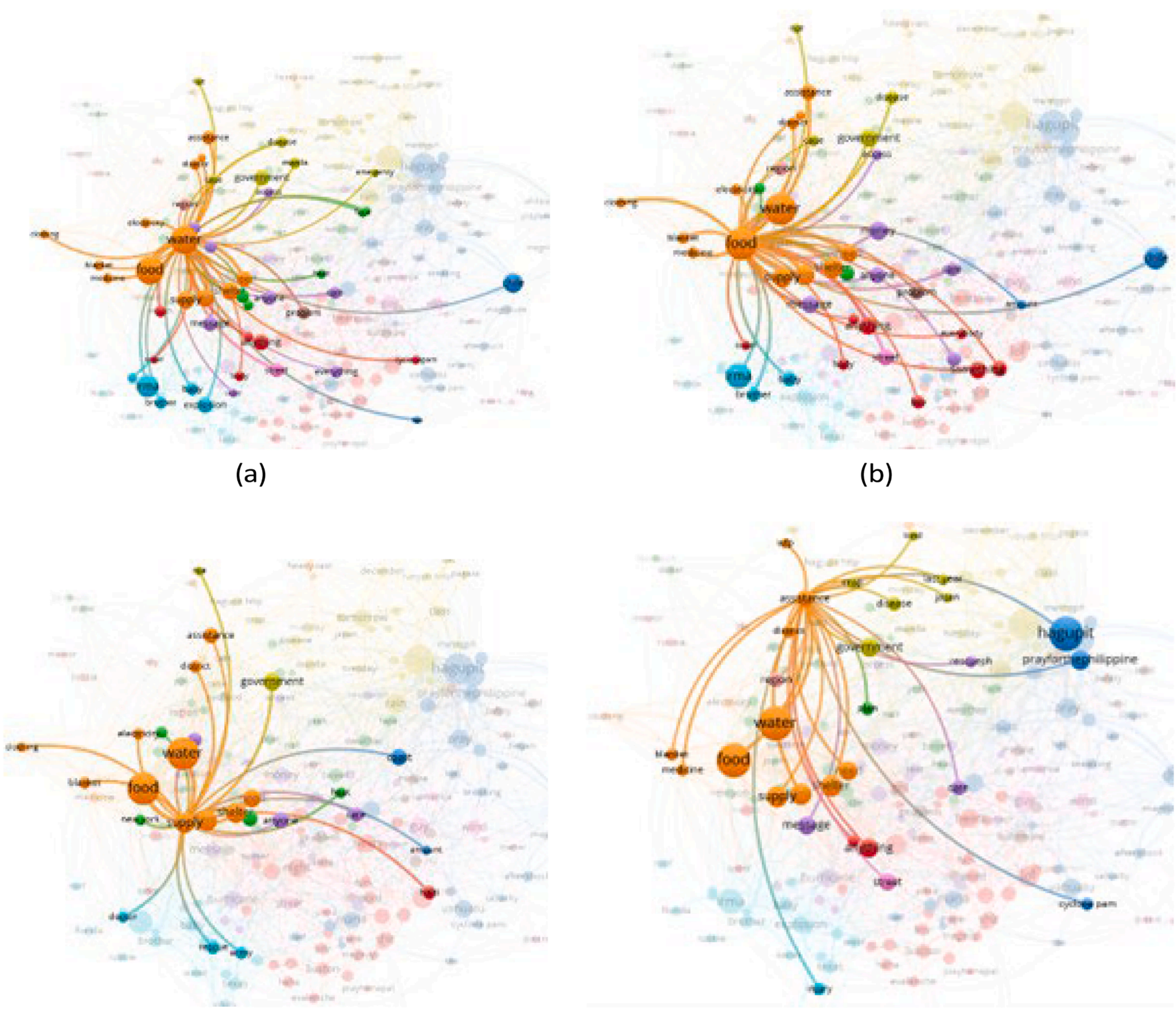

Fig. 7. Relationships of Basic keywords: (a) water, (b) food, (c) supply, and (d) assistance.

5.1.1. Relationships of basic keywords

A co-occurrence network is an undirected graph where nodes represent unique words in a vocabulary, and edges indicate the frequency with which these words co-occur in a dataset (Franceschini, 2023). This study leverages VOSviewer to create a co-occurrence network of social media crisis datasets to visualise and extract information on the relationship between terms in crisis datasets. In this case, four cluster networks are displayed in Fig. 7. In particular, 'water' was considered a focal keyword such that words related to it and their frequencies were obtained, as presented in Fig. 7a. In Fig. 7b, the keyword 'food' was chosen to obtain co-occurrence data. Again, in Fig. 7c, the keyword 'supply' was considered for representation and reasons of visualisation and clarity of the presentation of related terms. Finally, Fig. 7d presents the related words for the 'assistance' cluster.

It was observed that there were some differences among the words that appeared in the corresponding visualisations. For example, in the 'water' cluster, words such as 'emergency,' 'heat,' and 'explosion' appeared. In crises or disasters, the appearance and relation of these words to water could mean a severe water shortage, high temperatures, and the water supply being exploded or damaged. Similarly, 'money' and 'amounts' are a few varied words connected to the 'food' cluster. In disaster situations, the relationship between money and food could mean that there is a lack of money to buy food. In the 'supply' cluster, several words emerged, such as food, water, clothing, electricity, blanket, shelter, etc. Three distinct words emerged, which include 'doctor,' 'rescue,' and 'army.' In crisis situations, the relationship between supply and doctor could suggest a great need for doctors to treat injured people. Finally, in the 'assistance' cluster, several keywords were linked within the cluster. The appearance of these words could suggest the things people are seeking, which indicates consistent keywords such as food, water, and medicine. In addition to these keywords, 'injury' appeared as another distinct keyword in the 'assistance' cluster. This indicates that assistance is needed for injured people.

5.1.2. Relief seeking

In times of crises or disasters, the immediate focus shifts to meeting the basic needs of affected communities. This urgency is palpable as individuals seek relief in the form of food, clothing, shelter, and other essential supplies, which can simply be identified in social media messages. Therefore, understanding these relief-seeking patterns is crucial for effective disaster response and resource allocation. This study harnesses the power of social media data to demonstrate the application of VOSviewer as a valuable tool to gain valuable insights into the specific needs and priorities of affected populations. This is because social media has become a crucial communication tool during crises, which enables real-time information dissemination and quick community mobilization. Hence, analysing social media data with VOSviewer allows us to uncover the needs expressed by individuals directly affected by disasters. Through the outcome of VOS, such as visualisation maps, frequency analysis, and relevance analysis, this study identifies recurring themes and patterns in relief-seeking behavior.

In particular, one of the key observations from visualising the social media crisis datasets is the consistent mention of basic necessities such as food, water, and clothing. When disaster strikes, access to these essentials becomes a top priority for individuals and families grappling with displacement and uncertainty. Visualisations of social media conversations often reveal clusters of posts and hashtags related to requests for food and water aid, donations of clothing, and appeals for temporary shelter. Hence, the prominence of food as a relief-seeking item is particularly notable in visualisation maps generated from the social media data. During crises, access to meals becomes a critical concern, especially for vulnerable populations such as the elderly, children, and those with pre-existing medical conditions. By analysing posts, we can pinpoint a high demand for food assistance and coordinate targeted relief efforts accordingly.

Similarly, clothing emerges as a recurring theme in social media visualisation maps following disasters. Loss of personal belongings due to floods, fires, or other emergencies leaves many individuals without adequate clothing. Visualised maps showing clothing requests help relief organisations tailor their response to meet the diverse needs of affected communities. Beyond food, water, and clothing, the visualisation also highlights the demand for other essential supplies such as electricity, medical assistance, shelter, etc. The identification of keywords associated with these items can help crisis managers identify areas where access to clean water is compromised or where medical facilities are overwhelmed. This information enables responders to prioritise the distribution of critical resources and deploy medical teams to areas with the greatest need.

Moreover, the visualisation can capture the evolving nature of relief-seeking behavior over time. For example, as the immediate impact of a disaster subsides and communities transition from emergency response to recovery, the types of assistance sought may shift. By analysing temporal trends in social media data, crisis management can anticipate changing needs and adapt relief efforts accordingly, ensuring that support reaches those who need it most at each stage of the recovery process. Considering that relief-seeking is a multifaceted phenomenon that manifests in various forms following crises or disasters, in this network visualisation analysis, crisis managers can gain valuable insights into the specific needs and priorities of affected communities. Accordingly, the visualisation maps generated from social media crisis datasets provide a nuanced understanding of relief-seeking behavior, with food, water, clothing, and other essentials emerging as most recurring themes. By leveraging these insights, crisis management can enhance disaster response efforts and better support the resilience and recovery of the affected populations.

5.1.3. Findings of VOSviewer analysis vs. traditional news report

The dataset used in this study comprises datasets consolidated from various types of crisis events, such as earthquakes, floods, fires, and hurricanes (Alam et al., 2019). In this analysis, we identified a range of crisis events that fall into these categories, including Hagupit (Rubyph), YYCFlood, Cyclone Pam, Typhoon Pablo, hurricanes, and tsunamis. Our findings revealed key terms such as "food," "water," "shelter," "medicine," and "clothing." These terms were frequently mentioned in the context of immediate needs and relief efforts during crises. Notably, these findings are consistent with traditional news media reports, which often highlight the urgent need for and supply of these essential items (food, water, shelter, medicine, and clothing) during these disaster response efforts (Admin, 2014; WestPacWx, 2014; B.B.C., 2014, 2015; Ogrodnik, 2013; Guardian, 2015; ReliefWeb, 2013; Pearson and Mullen, 2012; W.H.O., 2012). This consistency between our analysis and traditional news reports serves to validate our findings and under-scores the reliability of the VOSviewer analysis in identifying critical terms related to crisis management.

The use of VOSviewer for term analysis enabled us to systematically identify and visualise the most relevant and frequently mentioned needs during various crisis events. This methodological approach not only corroborates the traditional media's emphasis on these critical needs but also provides a platform for understanding the needs and their relationships. By validating our findings against traditional news reports, we can confidently assert that our analysis accurately reflects the priorities and challenges faced during crisis response and communication. Therefore, the alignment between our VOSviewer analysis and traditional news media reports reinforces the validity of our methodology. This alignment demonstrates the effectiveness of our analytical approach in identifying and prioritizing key terms that are crucial for effective crisis management and response.

5.2. Implication of the findings

This study discusses the implications of the findings for humanitarian information types. First, the analysis reveals various texts corresponding to names of places or countries, crisis types, negative and positive emotions, relief seeking, properties and destruction, stakeholders, periods, etc. Interpreting data and information depends on the context in which it is applied, particularly to crisis management. For example, the names of places in crisis datasets could refer to locations where the crisis or disaster occurred or areas affected by the crisis or disaster. Similarly, terms like food, shelter, and clothing could refer to the relief materials needed by disaster victims. Identifying phrases like boy, baby, and children in crisis datasets could suggest the category of people affected by the crisis. This interpretation is supported by the work of Alam et al. (2019), corresponding to a set of classifications of text, as presented in Fig. 8. The study demonstrates that the identified terms align with the 10 classes of crisis messages for humanitarian information types. This match underscores the effectiveness of the VOSviewer text analysis method in mapping the various aspects of crisis messages, thereby enhancing the ability of humanitarian organisations to address specific needs during disaster response and management.

The findings correspond to the ten (10) humanitarian information types, as discussed below with examples.

- Affected individuals: the visualisations map and analysis show messages corresponding to affected individuals, which contain information about affected people due to a crisis or disaster event, like boy, child, etc.
- Caution and advice: the analysis reveals cautionary and advice kind of messages that report cautions and warnings to advise people in the disaster area. Examples of cautionary and advice messages identify from this analysis include ‘plan’, ‘save everyone’, ‘weather’, ‘talk’, ‘pray’, etc.
- Displaced and evacuations: The visualisations map reveals messages that report about affected people, such as the mention of ‘dad’, ‘mother’, ‘sister’, ‘baby’, ‘brother’ etc. The appearance of these categories of people in a disaster dataset could indicate displaced people or persons needing evacuations due to the disaster event.
- Donation and volunteering: The map shows messages that indicate things that are lacking, e.g., food, water, medicine, shelter, etc., which could lead to requests for donations and volunteering services. The word ‘donates’ also appeared in the co-occurrence network.
- Infrastructure and utility damage: The map indicates the appearance of words such as bridges, roads, electricity, etc. This could mean the messages that report damage to built structures.
- Injured or dead people: In this study, the keyword ‘injury’ was found in the visualisation networks, as well as the appearance of ‘body’ and ‘casualty’. Similarly, the mentioning of keywords such as ‘dad’, ‘mother’, ‘sister’, ‘baby’, ‘brother’ etc could fall under this category. These messages could indicate the report of dead or injured people due to the crisis event.
- Missing and found people: The appearance of keywords such as ‘dad’, ‘mother’, ‘sister’, ‘baby’, ‘brother’ etc. could indicate the category of people in a disaster dataset reported as missing or the found people.
- Requests or needs: the appearance of keywords ‘assistance’ as well as food, water, medicine, clothing, etc. could suggest messages that contain urgent needs or requests of the affected people due to the aftermath of the crisis.
- Response efforts: These are messages that report ongoing response efforts by NGOs, humanitarian organisations, and volunteers. The occurences of these types of keywords could include ’control’, ’plan’, ’evacuation’ ‘save everyone’, etc.
- Sympathy and support: These are messages that convey prayers, sympathy, thoughts, and support to the victims of the crisis. In this study, these types of keywords have appeared in the visualisation map, such as ‘pray’, ‘thought’, ‘prayforvisayas’, ‘prayfornepal’, etc.
- Not informative: These are text that do not fit into any of the predefined categories or lack any useful information. In this study, these types of messages were found, such as ‘haha’, ‘point’, ‘cant’, etc.

5.3. Comparison with existing work

In this section, a comparative analysis is carried out between the visualisation map obtained from this study analysis and existing works.

Firstly, several existing studies propose machine learning, mostly supervised learning methods, to analyse crisis datasets (Krishna et al., 2023; Paul et al., 2023; Garg et al., 2023; Asinthara et al., 2023; Arathi and Sasikala, 2022). Although supervised text mining offers valuable insights into text classification, it falls short of providing comprehensive information about the content of the texts (Kutela, Das and Dadashova, 2022a; Kutela, Magehema, Langa, Steven and Mwekh’iga, 2022b; Kutela, Novat, Adanu, Kidando and Langa, 2022c). Understanding the content is just as crucial as identifying the information source. Therefore, unsupervised text mining was considered essential (Kutela et al., 2023).

Secondly, among the diverse data visualisation techniques, Knowledge Graph and Graph (Boné, Dias, Ferreira, & Ribeiro, 2020a; Coche, Rodriguez, Montarnal, Tapia, & Benaben, 2021) (see Fig. 9) and Word Cloud (Avvenuti et al., 2018; Franceschini, 2023; Kersten and Klan, 2020; Zheng et al., 2022; Ponce-López and Spataru, 2022) (see Fig. 10) visualisations were identified. In this study, VOSviewer was practically applied to mine and process text from social media crisis datasets, which, on the one hand, is different from the most proposed supervised learning methods and, on the other hand, is distinct from other methods used by prior works (Boné et al., 2020a; Coche et al., 2021; Franceschini, 2023; Kersten and Klan, 2020; Ponce-López and Spataru, 2022; Zheng et al., 2022). This study exploits the VOSviewer visualisation technique to show the graphical distribution of crisis textual data, which can be

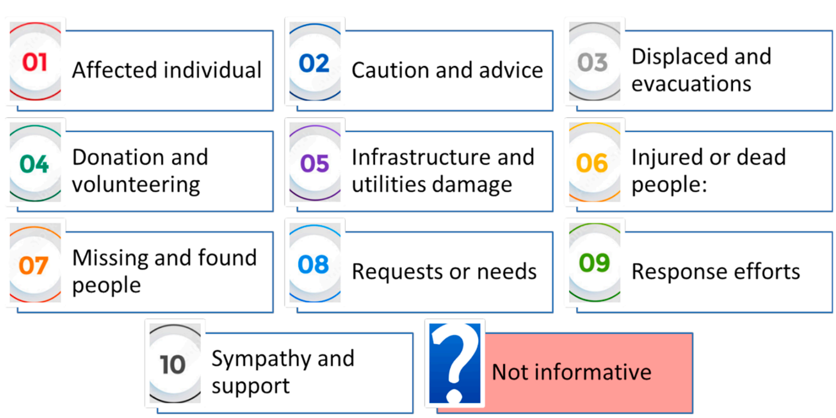

Fig. 8. Classification of crisis messages based on ten (10) humanitarian information types.

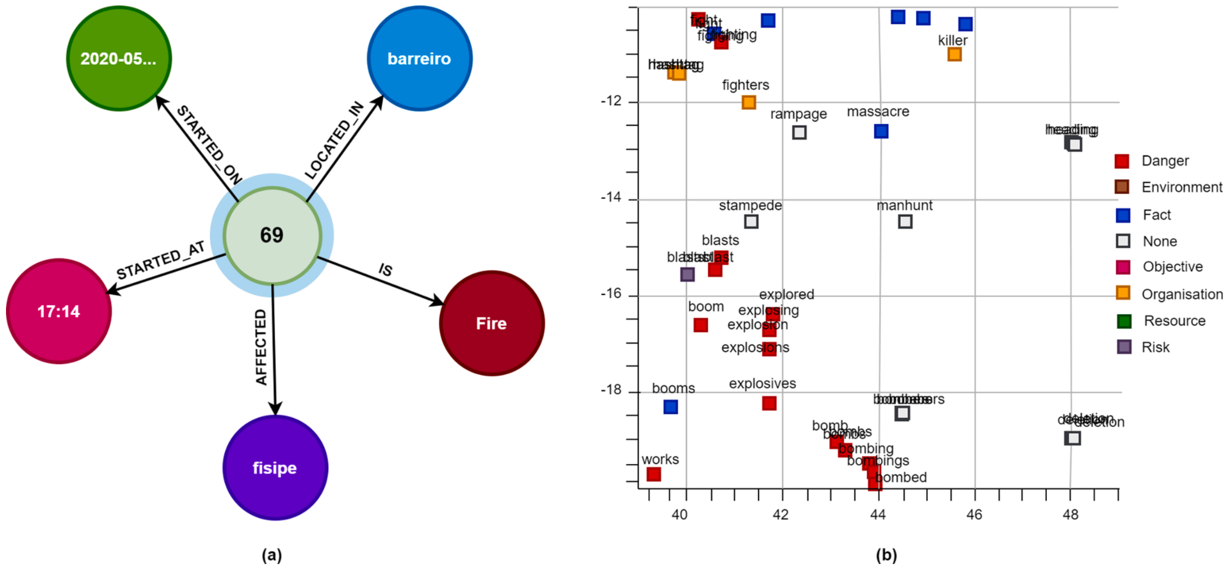

Fig. 9. Visualisation of Prior Work based on Knowledge Graph and Graph, adapted and redrawn from Boné et al. (2020a) (Fig. 9a) and (Coche et al., 2021) (Fig. 9b).

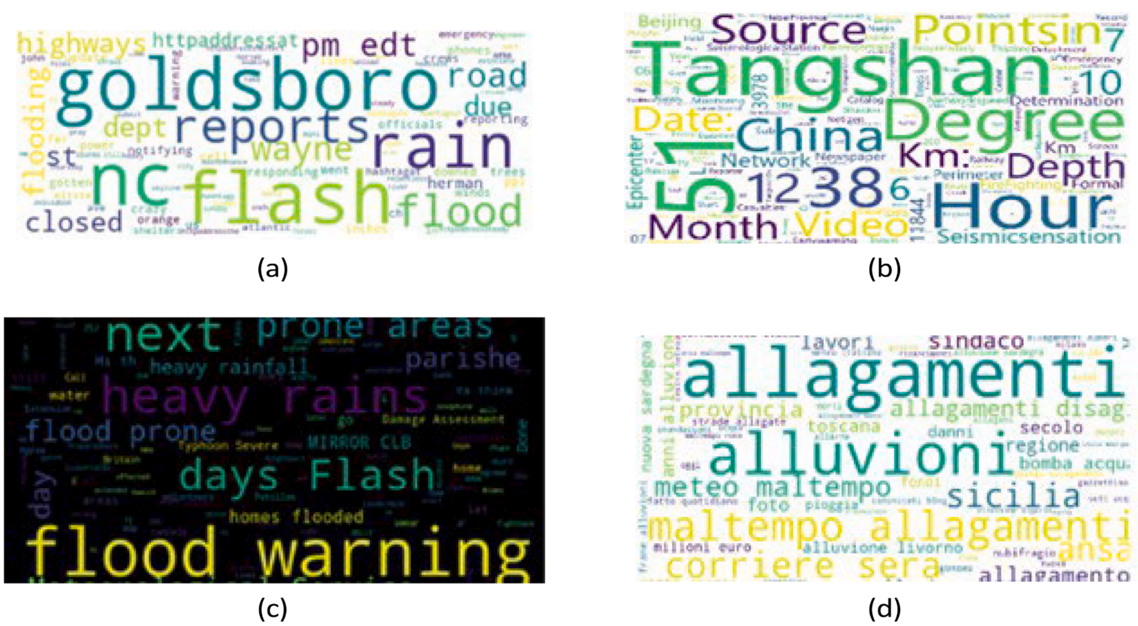

Fig. 10. Visualisations of Prior Works based on Word Cloud: (a) Source: Kersten and Klan (2020), (b) Source: Zheng et al. (2022), (c) Source: Ponce-López and Spataru (2022), and (d) Source: Franceschini (2023).

used in the aftermath of an emergency.

Accordingly, the VOSviewer produces network visualisation of maps based on their occurrence score and relevance score, which contributes to providing a tool that analyses keyword-based data, which is more suited to tracking public engagement and identifying key information (Rachunok, Fan, Lee, Nateghi and Mostafavi, 2022), as well as their relationships. In comparison with existing work, this study noted that Word Cloud is commonly employed to represent text occurrence in social media crisis data analysis. This is evident by its extensive application in the current literature (refer to Fig. 10). As a result, the Word Cloud technique was particularly chosen for comparison with VOSviewer because it was predominantly used in existing works (Franceschini, 2023; Kersten and Klan, 2020; Ponce-López and Spataru, 2022; Zheng et al., 2022), as presented in Table 4. Comparing the two, Word Cloud is best suited for simple and quick visualisations of text data, whereas VOSviewer is more suitable for a deeper analysis and exploration of textual relationships. Moreover, the word cloud serves as a graphical depiction of textual data and is frequently employed to illustrate keyword metadata. This visualisation method portrays the frequency of words within a text by representing them in a weighted list, which is not very helpful for evaluating the impact of disasters and is relatively weak in assisting decision-making in the early stages of a disaster (Zheng et al., 2022).

5.4. Impact of VOSviewer vs. other tools on user understanding and decision-making

This study further evaluates the visualisations produced by VOSviewer and compares them to those produced by other tools in terms of user understanding and decision-making during crisis management. This helps to objectively understand the strengths and limitations of the VOSviewer tool for the analysis of crisis data requiring interpretation.

Table 4
Comparison of between Word Cloud and VOSviewer Visualisations.

Features	Word cloud	VOSviewer
Context	Word Clouds only display individual words without considering their relationships or context within the text.	VOSviewer creates network visualisations that depict relationships between terms based on co-occurrence, providing insights into the structure of textual data.
Text volume	Word cloud may struggle to effectively represent large volumes of text, as common words can overshadow rarer but potentially significant terms.	It offers advanced analysis features such as clustering, density visualisation, and term co-occurrence analysis, allowing for more in-depth exploration of textual data.
Quantitative information	Word Clouds do not provide quantitative information about word frequencies, making it challenging to assess the significance of terms relative to each other.	VOSviewer provides quantitative information about the frequency and strength of relationships between terms, enabling more rigorous analysis and interpretation.

Accordingly, in terms of user understanding and decision-making to aid crisis management, VOSviewer visualisations offer distinct advantages over other tools, particularly word clouds. VOSviewer excels in providing a deeper analysis of textual relationships, which is critical for understanding the complex dynamics during a crisis.

Firstly, unlike word clouds, which only display individual words without context, VOSviewer generates network visualisations that highlight relationships between terms based on their co-occurrence. This could allow crisis managers to grasp not only the frequency of terms but also how they are interconnected, offering a better understanding of the situation to support decision-making. Secondly, our analysis revealed that VOSviewer is also effective in handling large volumes of text through its clustering and density visualisation features, where word clouds might struggle. This suggests that even less frequent terms are not overshadowed by common words, which is crucial for identifying emerging issues or trends in a crisis scenario. Thirdly, VOSviewer provides quantitative data on the frequency and strength of relationships between terms. This enables more in-depth analysis and interpretation, supporting data-driven decision-making during crises. Crisis managers can use these insights to prioritise resources effectively, identify key areas of concern, and develop targeted response strategies.

5.5. Contributions, limitation and future works

The current approach, which focuses on the application of VOSviewer for visualising crisis data, has certain constraints, thus there are areas for future enhancement. Specifically, our study did not involve the direct collection of data, the application of advanced text preprocessing techniques (e.g. *n*-grams, *bi*-grams, *tri*-grams), the development of a new framework for real-time data analysis, or the strong generalizability of the findings. Incorporating *bi*-grams or *tri*-grams in future research could further enrich the analysis by capturing relationships and patterns within the text data that unigrams might miss. Nevertheless, our study emphasizes the need to develop tools that can spontaneously extract data from social media text and structure them in a manner that is compatible with a simple tool such as VoSviewer for very quick insights to be derived from them. In addition, this paper makes several other important contributions to the field and avenues for future research to extend VOSviewer applications.

- Feasibility of VOSviewer in Crisis Data Analysis: The primary contribution of our work lies in demonstrating the feasibility and initial effectiveness of using VOSviewer for analysing social media crisis data. This visualisation tool provides valuable insights into the distribution and relationships of crisis-related terms, which is a novel application in the context of social media crisis data. As such, this study represents an early exploration of applying VOSviewer to analyse consolidated crisis datasets obtained from existing literature, focusing primarily on assessing VOSviewer's feasibility and initial effectiveness. The generalizability of the findings across different types of crises or disasters requires further investigation, particularly by obtaining datasets specific to particular crises. Therefore, the effectiveness of the proposed methodology can only be fully assessed by conducting multiple experiments across various crisis scenarios. Future research will aim to apply this methodology to different types of crises to evaluate its broader applicability and identify any contexts or scenarios where it may be less effective.
- Foundation for Future Frameworks: The data processing and visualisations using VOSviewer were made possible by configuring the crisis dataset to meet VOSviewer requirements. While our study does not include a framework for live data integration or automated data cleaning, it establishes a foundation for such developments. Future research can build on our findings to create comprehensive frameworks that incorporate real-time data retrieval, automated preprocessing, and advanced analysis to address specific crisis management needs. For example, future studies can also improve this concept by adopting and configuring default attributes for crisis datasets for seamless integration into the VOSviewer program, or extending the capabilities of VOSviewer to enable crisis management analyse social media crisis datasets or develop efficient social media crisis data extraction algorithms that produce compatible datasets that can be integrated into the VOSviewer program. Moreover, future studies could benefit from incorporating VOSviewer into their methodological frameworks to analyse data for a holistic understanding of crisis communication dynamics and information flow on social media platforms during emergencies.
- Motivation for GeoLocation Feature for VOSviewer: It is important to note a key limitation of VOSviewer is that it does not include a geolocation function for text, a feature found in other mapping solutions for crisis datasets. In practice, crises such as floods are often confined to specific areas, and relevant information can typically be identified by analysing posts from those particular locations. While the study highlights the importance of co-occurrences of text, it does not address the need for a more targeted, location-aware text parsing approach that could efficiently identify all relevant locations within a dataset. Additionally, the study does not account for the temporal dimension of crisis data, where information and posts increase over time as the situation evolves. The ability of the VOSviewer tool to manage and analyse this temporality remains a weakness, which may limit its effectiveness in real-time crisis management scenarios.
- Hypothesis Generation for Future Research: The study by Reuter et al. (2016) highlighted that verifying social scientific hypotheses solely through data from social media poses challenges (Reuter et al., 2016). However, by visualisations produced in this study, it is feasible to use such data to generate hypotheses that can subsequently be verified using conventional statistics methods. This is made possible since VOSviewer produced output that depicts the relationship among various keywords from crisis data. Therefore, future research could leverage this output to generate hypotheses and validate the relationships depicted in the network map. This approach will help validate the effectiveness of VOSviewer for analysing social media crisis datasets.

6. Conclusion

Due to the significance of managing crises, making decisions, and developing policies, this study leverage and highlights the significant potential of VOSviewer for analysing social media crisis datasets, demonstrating its value in enhancing and supporting disaster response efforts. The findings reveal that VOSviewer effectively identifies and visualises the most frequently occurring terms in social media posts related to crises, offering critical insights into public sentiment and immediate needs during emergencies. In particular, the use of the analytical method enables the creation of co-occurrence networks that provide a clear depiction of how terms are related within the context of a crisis. This facilitates a better understanding of the public's concerns and the resources they require, such as food, water, and medical assistance. By distinguishing these needs, emergency managers can prioritise resource allocation and improve their response strategies. In addition, VOSviewer offers a cost-effective, flexible, and low-maintenance alternative to traditional supervised text mining methods. Unlike word clouds, which merely present word frequency without context, VOSviewer provides a more nuanced analysis by visualising the relationships between terms. This approach enhances the depth of analysis, making it easier to identify key issues and trends in social media discussions during crises. The study underscores the importance of leveraging advanced text analysis tools like VOSviewer in crisis informatics, offering emergency managers the ability to gain rapid insights into unfolding events, thus improving their decision-making processes, as well as the ability to quickly interpret and respond to the public's needs significantly impacting the effectiveness of disaster response efforts.

Moreover, using VOSviewer to explore crisis datasets enhances situational awareness, align with efforts to leverage digital platforms for real-time updates and insights. This contributes to the field of crisis informatics by highlighting the role of social media data in disaster response. In addition, the study extends current social media data analysis methods by identifying frequently discussed topics and showcasing more detailed issues, such as user emotions. This study builds upon existing efforts by deepening our understanding of the actionability of social media content through VOSviewer. By applying VOSviewer to analyse social media content in crises, the study provides insights into how the analytical platforms can deliver relevant and timely information to disaster responders, which can lead to more efficient and effective response efforts, improving outcomes for affected communities. Addressing this gap in the literature, this research provides practical guidance for emergency management practitioners, by showcasing the application of distinct tool and strategies through leveraging VOSviewer to analyse crisis datasets.

CRediT authorship contribution statement

Umar Ali Bukar: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Md Shohel Sayeed:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Funding acquisition. **Oluwatosin Ahmed Amodu:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Siti Fatimah Abdul Razak:** Writing – review & editing, Supervision, Software, Resources, Project administration. **Sumendra Yogarayan:** Writing – review & editing, Visualization, Validation, Software, Project administration, Formal analysis. **Mohamed Othman:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Binary counting: Occurrences and relevance scores of terms
Refer to Table A1.
Full counting: Occurrences and relevance scores of terms
Refer to Table A2.

Table A1
Binary counting result; minimum number of occurrences: 10, 20,863, 372, 60% selected and 223(222); O: Occurrences; R: Relevance.

S/N	Term	O	R	S/N	Term	O	R	S/N	Term	O	R
1	facebook	10	4.48	75	casualty	13	1.05	149	haiyan	15	0.69
2	california wildfire	12	3.35	76	irma	111	1.05	150	kind	13	0.69
3	haze	13	3.35	77	doctor	17	1.05	151	rubyph http	14	0.68
4	control	13	3.16	78	explosion	53	1.04	152	typhoon haiyan	15	0.67
5	wine	15	3.02	79	army	23	1.04	153	point	21	0.67
6	suffolk	13	2.97	80	reliefph	16	1.04	154	philipphines	42	0.66
7	singapore	18	2.69	81	oklahoma	20	1.03	155	safety	17	0.66
8	alberta	10	2.59	82	nyc	12	1.03	156	prayforthephilipphine	57	0.66
9	matter	13	2.17	83	game	36	1.02	157	district	22	0.66
10	prayfornepal	10	2.17	84	avalanche	22	1.01	158	tuesday	18	0.66
11	book	14	2.08	85	class	31	1.01	159	medicine	20	0.64
12	paris	11	2.06	86	boy	27	1.01	160	word	35	0.63
13	meteor	13	2.01	87	text	22	1	161	body	19	0.63
14	waco	15	1.96	88	philippines http	23	1	162	river	24	0.63
15	hair	17	1.92	89	wfp	12	1	163	tomorrow	59	0.63
16	napa	15	1.89	90	port au prince	12	0.98	164	sister	16	0.62
17	magnitude earthquake	16	1.87	91	mom	29	0.97	165	plan	22	0.62
18	russia	19	1.86	92	birthday	19	0.97	166	typhoon	87	0.62
19	cyclone pam	19	1.85	93	trump	17	0.96	167	glasgow	13	0.61
20	dollar	11	1.84	94	japan	12	0.96	168	face	16	0.61
21	florida	16	1.81	95	hell	18	0.96	169	order	13	0.6
22	calgary	24	1.76	96	girl	48	0.96	170	war	15	0.6
23	rubble	14	1.75	97	talk	22	0.95	171	clothing	15	0.59
24	question	17	1.72	98	dec	14	0.95	172	sandy	34	0.59
25	dream	14	1.7	99	sky	18	0.95	173	everybody	15	0.58
26	donate	17	1.66	100	haha	26	0.94	174	case	20	0.57
27	lax	16	1.64	101	maria	55	0.93	175	thought	61	0.56
28	bitch	26	1.64	102	monday	22	0.93	176	brother	29	0.55

(continued on next page)

Table A1 (*continued*)

S/N	Term	O	R	S/N	Term	O	R	S/N	Term	O	R
29	magnitude	26	1.63	103	rescue	25	0.93	177	rice	13	0.54
30	irm	15	1.59	104	chance	13	0.91	178	anyone	40	0.54
31	nigga	13	1.53	105	tornado	49	0.9	179	eye	22	0.54
32	room	16	1.53	106	emergency	13	0.89	180	disease	27	0.53
33	voice	11	1.51	107	bed	15	0.88	181	china	18	0.53
34	fun	15	1.51	108	pagasa	11	0.86	182	helicopter	16	0.53
35	soul	13	1.51	109	new york	17	0.85	183	hurricane odile	21	0.52
36	vanuatu	63	1.5	110	kashmir	16	0.84	184	side	19	0.52
37	pam	35	1.49	111	baby	35	0.84	185	hagupit	180	0.51
38	visit	13	1.47	112	mind	16	0.84	186	pabloph	16	0.51
39	syria	14	1.41	113	heart	63	0.84	187	rubyph	170	0.51
40	balochistan	19	1.39	114	mother	18	0.84	188	something	48	0.49
41	baltimore	30	1.38	115	business	31	0.84	189	hagupit http	16	0.49
42	yycflood	23	1.38	116	earth	19	0.83	190	amount	11	0.48
43	idea	19	1.37	117	snow	12	0.83	191	wind	46	0.48
44	abflood	17	1.36	118	pain	13	0.82	192	blanket	20	0.48
45	min	10	1.34	119	nepal http	25	0.82	193	landfall	18	0.47
46	aftershock	23	1.31	120	bridge	20	0.81	194	roof	15	0.46
47	west	27	1.3	121	nswfire	14	0.8	195	tent	65	0.45
48	boston	38	1.3	122	phone	28	0.8	196	heat	17	0.45
49	yeah	15	1.29	123	hunger	13	0.79	197	pray	69	0.44
50	odile	16	1.23	124	coast	42	0.79	198	message	45	0.44
51	piece	14	1.23	125	lord	19	0.78	199	night	66	0.44
52	tragedy	28	1.23	126	answer	15	0.78	200	street	40	0.43
53	walangpasok	26	1.21	127	money	56	0.78	201	government	51	0.43
54	dad	16	1.2	128	landslide	16	0.78	202	assistance	38	0.42
55	joplin	13	1.19	129	taa	10	0.78	203	heavy rain	20	0.42
56	cyclonepam	14	1.19	130	hurricane	63	0.76	204	month	26	0.42
57	prayforvisayas	10	1.18	131	tweet	36	0.76	205	access	16	0.42
58	chile	81	1.18	132	song	23	0.75	206	name	25	0.42
59	twitter	18	1.18	133	cabo	14	0.75	207	road	38	0.42
60	nepalquakerelief	11	1.15	134	minute	22	0.75	208	food	176	0.4
61	tsunami	35	1.14	135	safe everyone	32	0.73	209	electricity	21	0.4
62	ppl	17	1.13	136	nothing	38	0.73	210	manila	25	0.39
63	half	10	1.12	137	info	19	0.73	211	guy	77	0.39
64	breaking	20	1.12	138	red cross	21	0.73	212	last year	18	0.38
65	cant	12	1.1	139	everything	30	0.73	213	village	31	0.36
66	texas	33	1.1	140	december	16	0.72	214	water	176	0.35
67	peace	23	1.09	141	shit	46	0.72	215	rain	70	0.35
68	america	20	1.09	142	haiti	26	0.71	216	region	31	0.35
69	devastation	16	1.08	143	rescueph	18	0.7	217	supply	68	0.34
70	cat	12	1.08	144	fact	14	0.7	218	care	30	0.31
71	fuck	20	1.07	145	weather	35	0.7	219	anything	51	0.31
72	end	19	1.07	146	moment	30	0.7	220	problem	33	0.26
73	injury	21	1.06	147	crop	18	0.7	221	need	51	0.25
74	maringph	11	1.05	148	lol	78	0.7	222	shelter	64	0.21

Table A2
Full counting result: minimum number of occurrences: 10, 20,863, 379, 60% selected and 227(226); O: Occurrences; R: Relevance.

S/N	Term	O	R	S/N	Term	O	R	S/N	Term	O	R
1	facebook	12	4.45	77	injury	22	1.06	153	eye	22	0.67
2	calfornia wildfire	12	3.57	78	reliefph	16	1.06	154	heart	64	0.67
3	haze	13	3.47	79	monday	22	1.05	155	typhoon	89	0.65
4	wine	18	3.31	80	crop	19	1.04	156	pray	72	0.65
5	control	13	3.3	81	boy	28	1.04	157	tuesday	18	0.65
6	paris	13	3.23	82	dec	15	1.03	158	thought	61	0.64
7	singapore	18	2.82	83	cat	12	1.03	159	coast	42	0.64
8	suffolk	13	2.46	84	pagasa	11	1.02	160	cyclone pam	20	0.64
9	meteor	14	2.39	85	business	31	1.01	161	pabloph	16	0.63
10	prayfornepay	10	2.19	86	volcano	10	1.01	162	word	35	0.63
11	waco	15	2.19	87	chile	84	1.01	163	evacuation	21	0.63
12	voice	13	2.11	88	info	20	1.01	164	hunger	13	0.62
13	russia	22	2.03	89	casualty	13	1	165	side	20	0.62
14	napa	15	1.95	90	mom	31	1	166	point	22	0.62
15	bitch	29	1.83	91	birthday	20	0.99	167	haha	26	0.62
16	alberta	10	1.82	92	class	31	0.98	168	haiyan	30	0.62
17	dollar	12	1.82	93	nepalquakerelief	11	0.98	169	face	16	0.62
18	magnitude earthquake	16	1.81	94	shit	47	0.97	170	new york	17	0.61
19	irm	15	1.75	95	port au prince	13	0.97	171	clothing	16	0.61
20	dream	15	1.72	96	half	10	0.97	172	case	20	0.61
21	lax	16	1.7	97	oklahoma	20	0.97	173	odile	38	0.6

(*continued on next page*)

Table A2 (*continued*)

S/N	Term	O	R	S/N	Term	O	R	S/N	Term	O	R
22	wow	14	1.67	98	tsunami	35	0.95	174	cyclonepam	14	0.6
23	book	14	1.65	99	tornado	50	0.95	175	amount	11	0.6
24	pam	37	1.61	100	pain	16	0.94	176	weather	35	0.6
25	room	16	1.55	101	game	37	0.94	177	lol	80	0.59
26	nigga	14	1.55	102	japan	13	0.94	178	plan	23	0.59
27	america	21	1.54	103	earth	20	0.93	179	everybody	15	0.59
28	question	18	1.54	104	yeah	15	0.93	180	everyone	40	0.58
29	hair	17	1.53	105	peace	23	0.92	181	china	20	0.58
30	florida	17	1.52	106	maria	55	0.91	182	fund	36	0.58
31	matter	13	1.51	107	rescueph	18	0.9	183	heat	17	0.58
32	walangpasok	26	1.45	108	rescue	25	0.89	184	rice	13	0.57
33	dad	16	1.44	109	talk	22	0.88	185	hagupit	181	0.57
34	texas	33	1.43	110	army	24	0.87	186	disease	27	0.55
35	humanity	14	1.43	111	top	15	0.87	187	medicine	21	0.55
36	magnitude	26	1.42	112	tweet	37	0.86	188	wind	46	0.55
37	twitter	18	1.41	113	bridge	20	0.85	189	rubyph	171	0.55
38	piece	14	1.38	114	temporary shelter	10	0.85	190	order	13	0.54
39	min	10	1.37	115	taa	10	0.84	191	river	24	0.54
40	boston	40	1.35	116	kashmir	16	0.84	192	district	23	0.53
41	baltimore	31	1.35	117	mother	20	0.84	193	thing	85	0.52
42	doctor	17	1.34	118	answer	16	0.84	194	blanket	20	0.52
43	yycflood	23	1.33	119	december	16	0.84	195	red cross	22	0.5
44	explosion	53	1.33	120	kind	13	0.84	196	head	39	0.5
45	rubble	14	1.33	121	wfp	13	0.83	197	government	57	0.49
46	fun	15	1.32	122	nepal http	25	0.83	198	helicopter	16	0.49
47	typhoon pablo	11	1.31	123	girl	49	0.83	199	month	26	0.49
48	nyc	12	1.31	124	hell	18	0.83	200	night	66	0.49
49	soul	13	1.3	125	lord	20	0.81	201	something	50	0.46
50	visit	13	1.29	126	emergency	14	0.81	202	region	32	0.46
51	joplin	14	1.29	127	haiti	26	0.81	203	heavy rain	20	0.46
52	maringph	12	1.28	128	baby	37	0.8	204	street	41	0.43
53	west	27	1.27	129	syria	15	0.79	205	access	16	0.43
54	prayforvisayas	10	1.22	130	song	24	0.79	206	last year	18	0.41
55	fuck	20	1.21	131	text	22	0.79	207	assistance	41	0.41
56	aftershock	25	1.21	132	safe everyone	32	0.78	208	guy	77	0.41
57	tragedy	28	1.2	133	phone	28	0.76	209	rain	72	0.41
58	avalanche	22	1.19	134	balochistan	19	0.76	210	tent	66	0.4
59	cant	12	1.19	135	minute	22	0.76	211	food	181	0.39
60	abflood	17	1.19	136	landslide	16	0.76	212	message	47	0.39
61	ppl	18	1.17	137	october	16	0.75	213	roof	15	0.37
62	bangladesh	23	1.17	138	sandy	35	0.74	214	situation	29	0.37
63	sky	18	1.16	139	rubyph http	14	0.74	215	road	39	0.37
64	idea	19	1.14	140	moment	30	0.73	216	water	183	0.36
65	nswfire	14	1.14	141	snow	13	0.73	217	support	48	0.35
66	calgary	24	1.13	142	mind	16	0.73	218	village	31	0.35
67	devastation	16	1.13	143	safety	17	0.72	219	supply	71	0.33
68	nepalearthquake http	25	1.13	144	fact	14	0.71	220	one	52	0.33
69	breaking	20	1.1	145	philippines	42	0.71	221	electricity	21	0.32
70	bed	15	1.09	146	war	15	0.7	222	child	76	0.31
71	end	19	1.08	147	nothing	39	0.7	223	care	34	0.29
72	nepalquake http	10	1.08	148	prayforthephilippine	59	0.7	224	anything	51	0.28
73	philippines http	23	1.08	149	tomorrow	59	0.69	225	nation	34	0.28
74	chance	13	1.08	150	everything	30	0.69	226	name	26	0.27
75	job	59	1.07	151	body	19	0.69				
76	percent	11	1.06	152	hagupit http	16	0.68				

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