

Knowledge Mapping for Intelligent Recommendation in Earthquake Disaster Response: A VOSviewer-Based Approach

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Abstract

Effective disaster response requires timely access to relevant information and intelligent tools to interpret it. This study explores the relatively underexplored application of VOSviewer, originally designed for bibliometric analysis, as a knowledge mapping and recommendation tool in the context of earthquake disaster management. Using a dataset of tweets related to the 2023 Turkey–Syria earthquake, the study applies binary and full counting techniques to identify frequently occurring terms, thematic clusters, and key term relationships. The findings reveal dominant concerns such as humanitarian aid, emotional and religious responses, and geopolitical references, along with the notable influence of public figures. By repurposing VOSviewer for crisis-related social media analysis, the research demonstrates its potential as an intelligent analytical and decision-support tool, capable of guiding emergency response strategies. The study contributes to the growing field of crisis informatics by highlighting how knowledge mapping can enhance situational awareness and inform targeted, data-driven disaster response efforts.

Keywords: *Recommender Systems, Earthquake Response, Knowledge Mapping, VOSviewer, Text Mining.*

1. Introduction

Disaster events such as earthquakes and floods continue to pose serious challenges to both industrial resilience and societal well-being. Rapid and informed decision-making during such crises is essential for mitigating impact, coordinating response, and saving lives. In smart cities, recent advancements in the Artificial Intelligence, Internet of Things (IoT), and Big Data are increasingly being integrated into urban emergency management systems [1], offering new pathways for development while enabling the classification and organisation of crisis-related information through intelligent instrumentation and analysis for collective crisis intelligence [2], tools that can not only capture and monitor large-scale data but also analyse it meaningfully to guide action. Traditionally, instrumentation has referred to the use of physical sensors and measurement systems [3]. However, with the rise of data-driven technologies, there is a growing shift toward integrating intelligent

recommender systems that can process data, extract actionable insights, and support emergency decision-making [4], [5], [6], [7], [8]. Social media platforms, in particular, have emerged as critical data sources during disasters [9], [10], [11], [12], offering real-time accounts of public needs, reactions, and developments.

VOSviewer, a tool originally developed for bibliometric and scientific network analysis [13], [14], [15], presents a novel opportunity that can be leverage. While it is primarily used for mapping co-authorships and academic terms, its text mining and co-occurrence analysis capabilities can be repurposed to extract patterns and clusters from any form of network in a large textual dataset [14], including crisis-related social media content [16]. For example, numerous studies have extended the use of VOSviewer beyond traditional bibliometric research, applying it to diverse datasets and contexts [15], [17], [18], [19], [20], [21]. These applications include analysis of online newspaper articles [19], women's political participation on Instagram during election campaigns [20], LinkedIn profiles [17], text data related to lung cancer [18], and the adoption of Chatbots in recruitment narratives [21]. Despite its growing versatility, VOSviewer's use in the domains of crisis management and disaster response remains relatively underexplored [16]. In this regard, VOSviewer can serve as an intelligent knowledge mapping and recommendation tool in data analytics by extracting and visualising relationships among key concerns, sentiments, and needs expressed by the public in unstructured textual sources during disasters.

Therefore, this study proposes a novel adaptation of VOSviewer to analyse social media discourse surrounding the Turkey–Syria earthquake. It aims to explore how VOSviewer can be utilised to uncover thematic clusters and term relationships that reflect public sentiment and urgent needs within the earthquake-related dataset. Accordingly, the study seeks to address the following objectives:

- a. Identify references to victims and humanitarian aid in discussions about the Turkey–Syria earthquake.
- b. Examine emotional expressions and their significance for effective disaster communication on social media.
- c. Reveal the impact of international response and solidarity following the disaster.
- d. Identify major actors or influencers involved in crisis communication, digital volunteering, and donation efforts.

Through this approach, the study contributes to the broader goal of intelligent disaster management by demonstrating how knowledge mapping can support recommendation systems for faster and more effective crisis response. Hence, the structure of this paper is organised as follows. Section 2 details the methodology employed in this study, including the data source, preprocessing steps, and the application of VOSviewer for text mining and knowledge mapping of the Turkey–Syria earthquake dataset. Section 3 presents the results of both binary and full counting analyses, highlighting frequently occurring terms, thematic clusters, and term relationships. Section 4 offers an in-depth discussion of the findings, drawing insights into public sentiment and humanitarian needs during the disaster. It also discusses the implications for disaster response and outlines directions for future research. Finally, Section 5 concludes the study by summarising key contributions

and emphasising the potential of knowledge mapping tools like VOSviewer in enhancing intelligent decision-making for crisis management.

2. Related Works

Recent studies demonstrate the growing role of recommender systems and AI-driven decision support in disaster and emergency management. Early foundational work by Turoff and Hiltz [22] highlighted information overload within professional emergency communities and advocated for social tagging and recommender systems to improve access to relevant “grey literature,” establishing the importance of recommendation technologies in crisis contexts. Building on experiential knowledge, the work by Negre [4] proposed a knowledge-based recommender framework that leverages past crisis actions to guide decision-making in similar future crises, emphasising experience reuse as a core strategy in emergency response.

Several studies focus on decision support and prioritisation using multicriteria and structured decision-making approaches. For example, Kou et al. [23] introduced a “scenario–response” recommender system for post-disaster emergency supply planning by integrating recommender techniques with social tagging and real-time disaster evolution data. Similarly, Kelana et al. [24] applied the Analytical Hierarchy Process (AHP) to prioritise flood disaster management actions across economic, social, and environmental criteria, demonstrating the usefulness of multicriteria decision-making (MCDM) methods for structured prioritisation under constrained resources. Extending this line of work, El Handri et al. [25] proposed an AI-based QoS optimisation approach for post-disaster ad hoc networks, combining machine learning with MCDA to rank communication paths based on QoS attributes, thereby addressing network performance challenges in disaster scenarios.

Another stream of research emphasises knowledge-based, semantic, and ontology-driven recommender systems. Husáková [6] presented an SWRL-based recommendation prototype to support first-aid decision-making for non-professionals, highlighting the importance of rule-based reasoning in time-critical emergencies. In a similar vein, Hu et al. [26] employed knowledge graphs to recommend airport emergency plans by identifying semantically similar cases, significantly improving planning efficiency. More recent works, such as Zhong et al. [27] and Lê et al. [28], further advanced ontology-based and collaborative recommender systems by integrating citizen resources, social technologies, and contextual information to enhance evacuation planning, resource allocation, and stakeholder coordination.

Personalisation and user-centricity are also prominent themes. Li et al. [29] proposed a review-based personalised recommender system that extracts latent user preferences from textual reviews, addressing limitations of traditional rating-based methods in emergency supply distribution. Ahuja et al. [7] integrated a recommender system with an Early Warning System (EWS) using entropy-based similarity measures to prioritise actionable warnings, aiming to improve warning quality and reduce pre-disaster risk. More recently, Karthika et al. [30] developed a semantic-rich recommendation framework for medical emergency response,

demonstrating improved precision and recall in recommending hospitals and coordinating medical resources.

Emerging studies increasingly incorporate advanced AI and generative models. Faiaz and Nawar [31] introduced an AI-driven disaster warning system that combines predictive analytics with large language models (LLMs) to generate contextualised and personalised response guidelines, signalling a shift toward adaptive, user-centred early warning and advisory systems.

2.1. Literature Summary

Overall, the literature, as presented in Table 1, shows a clear evolution from rule-based and experience-driven recommender systems to AI-, ontology-, and LLM-enabled frameworks that support decision-making, resource allocation, and communication in disaster management. However, many studies remain domain-specific (e.g., floods, medical emergencies, airports) or focus on isolated components such as warnings, supplies, or communication networks. This highlights the need for more integrated, scalable, and generalisable recommender frameworks that combine contextual awareness, multicriteria reasoning, and adaptive intelligence across diverse disaster scenarios.

2.2. Research Gap

Despite the growing body of research on social media analytics for disaster management, existing studies largely rely on traditional text mining, sentiment analysis, topic modelling, or machine learning techniques, with limited attention given to knowledge mapping and visual network-based analytical tools. In particular, VOSviewer has been predominantly applied within bibliometric and scientometric domains, while its potential for real-time or near-real-time crisis-related social media analysis remains underexplored. There is a notable gap in understanding how VOSviewer's co-occurrence and clustering mechanisms can be repurposed to support situational awareness, thematic prioritisation, and decision-making during disaster events. This study addresses this gap by leveraging VOSviewer as an intelligent knowledge mapping and recommendation tool for analysing earthquake-related social media data, thereby extending its application beyond bibliometrics into practical disaster response contexts.

Table 1. Contribution and Focus of Related Works

SN	Source	Contribution	Method/Techniques	Crisis Focus
1	[22]	Social tagging and social recommender system features	Data from thirty-four professionals	Health related emergency response
2	[23]	Scenario-response type's poster-disaster emergency suppliers planning	Social tagging and allocation management	Post-disaster recovery
3	[4]	Framework for a recommender system for crisis management	Uses the actions already implemented to manage former crises	Hurricane, tsunami
4	[29]	Review-based personalized recommendation system	Experimental analysis	Generic

5	[6]	SWRL-based prototype for decision making	Prototype	First aid emergency response
6	[24]	Recommendations on priority for flood disaster management	Analytical Hierarchy Process	Flooding
7	[7]	Entropy based Recommender Framework for Early Warning System	Warning web log based on pre-disaster similarity and post-disaster similarity between warning pairs	Flooding
8	[28]	CORec-Cri (Contextulized Ontology-based Recommender system for crisis management)	Collaborative and social technologies	Generic
9	[26]	Content recommendation algorithm based on knowledge representation algorithm and the unified embedded content recommendation algorithm.	Knowledge graph	Airport emergency
10	[25]	Topkws recommendation algorithm	Multicriteria Decision Analysis (MCDA) and ML	Earthquakes,
11	[30]	Semantic-Rich Recommendation System	Experimental analysis	Medical emergencies response
12	[27]	Ontology-based crisis simulation system	Simulation	Generic
13	[31]	AI-powered disaster warning system	Predictive analytics, LLMs, and LangChain framework	Generic

3. Research Method

In line with the framework proposed by Bukar et al. [16], the methodology for data collection and analysis in this study is structured into three major phases. First, data were acquired from an online source, specifically Kaggle (<https://www.kaggle.com/datasets/mrrahulroy/turkey-syria-earthquake-tweets>), and a detailed description of the dataset was provided to establish a clear understanding of its composition and relevance. Second, a series of preprocessing and restructuring procedures were performed on the raw data to ensure compatibility with the selected text analysis technique. This step involved cleaning, normalisation, and preparation of the textual content to enhance the accuracy and reliability of subsequent analyses. Third, the processed data were subjected to a comprehensive text mining process aimed at identifying the most frequently occurring terms within the Turkey-Syria earthquakes. Following this, knowledge maps and network visualisations were generated to uncover thematic patterns and relational structures within the dataset. Hence, the overall architecture of the proposed methodological approach is illustrated in Figure 1, providing a visual summary of the key stages and processes undertaken in this research.

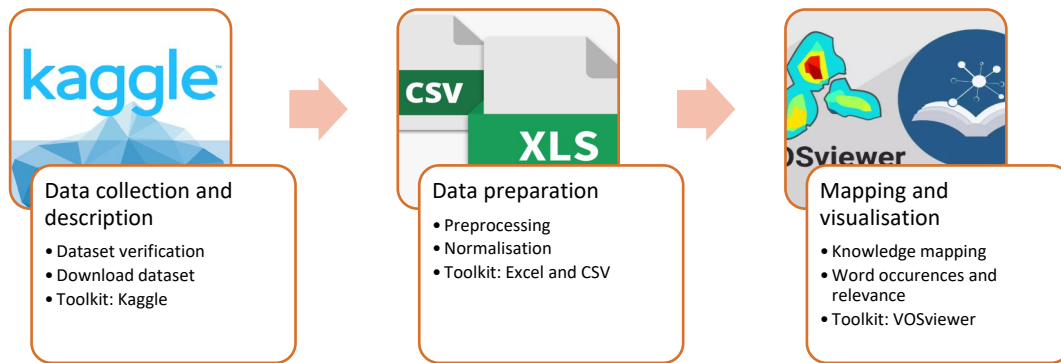


Figure 1. Methodological Approach for Mapping and Visualisation of Disaster Dataset

3.1. Dataset Collection and Description

This study employs a dataset comprising tweets related to the earthquake that affected Turkey and Syria on 6 February 2023. The dataset includes the textual content of each tweet, user profile metadata, timestamps, geographical locations, and interaction metrics such as the number of likes, retweets, and replies. Additionally, it records the hashtags, mentions, and external links associated with each tweet. The dataset provides a snapshot of public discourse concerning the natural disaster and its immediate impact on the affected regions. Analysing this content enables a deeper understanding of public sentiment, information dissemination, and communication patterns during crisis events as reflected on social media platforms. The dataset, comprising 1,000 tweets related to the Turkey–Syria earthquake, was obtained from Kaggle. The tweets were not filtered or pre-selected in any way; they were taken as provided in the dataset to preserve the authenticity and diversity of public discourse.

Moreover, only English-language tweets were used in this study to ensure consistency in the text analysis process and to align with the linguistic capabilities of the VOSviewer analysis tools employed. Regarding data quality, the dataset was downloaded from Kaggle in its original form, as prepared by the original author [32]. Accordingly, the dataset had already undergone preprocessing to remove duplicates, retweets, and bot-generated content. During preliminary review and data cleaning checks, this study found no significant issues related to redundancy or automated content. As such, no additional filtering was applied, and the dataset was analysed as-is to maintain consistency with its original structure and scope. Accordingly, the parameters and settings adopted for the analysis are summarised in Table 2.

Table 1. Dataset and Analysis Parameters

Parameter	Description
Dataset Name	Turkey-Syria Earthquake Tweets
Dataset Source	https://www.kaggle.com/datasets/mrrahulroy/turkey-syria-earthquake-tweets
Number of Tweets	1,000
Date Range of Tweets	6 February 2023 onward

Fields Analysed	Tweet text
Analysis Tool	VOSviewer 1.6.18
Type of Analysis	Co-occurrence and relevance analysis (terms)
Counting Method	Full and Binary counting
Minimum Occurrence Threshold	10 occurrences per term
Cluster Resolution Parameter	1.00
Visualization Type	Network and density visualisations

3.2. Ethical Considerations

Considering the fact that this study involves natural language processing (NLP) and text mining of social media data, it is important to address key ethical considerations. Following the guidance of Ford et al. [33], this study acknowledges the ethical issues around the use of public tweets, particularly concerning user identification and informed consent. The dataset used, publicly available disaster-related tweets, falls between primary and secondary data [34]. To ensure ethical compliance, all data were anonymised to protect user identities [35], as required when dealing with publicly accessible social media content. Many scholars argue that informed consent is not necessary for analysing public online data, provided the data are anonymised and used solely for research purposes [33], [36], [37], [38], [39]. This position aligns with the view that such data falls within the public domain [17], [40], [41], [42]. Therefore, ethical concerns in this study were appropriately addressed through anonymisation and adherence to established guidelines for the use of publicly available social media data.

3.3. Data Size Rationale

This study employs a qualitative approach using text analysis, which prioritises depth of understanding over statistical generalisability. In qualitative research, sample size is often guided by the principle of data saturation, the point at which no new themes or insights emerge during analysis [43], [44], [45]. Rather than relying on fixed numerical thresholds, the adequacy of a sample is determined by its ability to yield rich, meaningful insights relevant to the research questions [46], [47], [48].

In this context, the selection of 1,000 tweets strikes a balance between data richness and manageability. Compared to prior work (e.g., Bukar et al. [17]), which analysed smaller datasets (e.g., 166 comment), this sample offers a broader textual base while remaining practical for qualitative interpretation. Importantly, the dataset was sourced from Kaggle and relates to Syria-Turkey earthquakes, an area where themes often emerge clearly and rapidly, especially in highly focused or event-driven discourses. As Morse [45] noted, simpler or more accessible topics require fewer data points to reach saturation than complex or abstract ones.

Additionally, the use of VOSviewer for visualising and analysing textual data benefits from a dataset of moderate size [17]. Although VOSviewer is a powerful tool, extremely large datasets can hinder interpretability and dilute clarity, especially in early-phase exploratory studies. A sample of 1,000 tweets enables the

tool to generate focused term co-occurrence maps that can reveal core themes and communication trends, without overwhelming the analysis process.

Furthermore, as Boddy [47] and Hennink and Kaiser [49] have shown, qualitative saturation can occur with relatively modest sample sizes when the dataset is thematically concentrated. In many cases, meaningful research has been conducted using fewer than 20 in-depth interviews or even single-case studies, emphasising that adequacy is not a matter of quantity, but of conceptual and thematic completeness [47], [49]. While there is growing interest in setting a priori sample size thresholds [50], many scholars still favour adaptive strategies based on saturation and contextual relevance [43].

Therefore, the justification for using 1,000 tweets also considers feasibility and efficiency. Text analysis of social media content is time-intensive. A dataset of this size allows for thorough engagement with the data while ensuring that key themes related to crisis response and communication are adequately captured. Thus, the chosen sample is justified on the basis of alignment with saturation principles in qualitative research, support from prior literature on adequate sample sizes, practical constraints of visual analysis tools (e.g., VOSviewer), the nature and clarity of the topic under investigation, and the study's aim to offer in-depth insights rather than statistical generalisation.

3.4. Data Preparation

The dataset employed in this study consists of 1,000 English-language records, initially stored using Microsoft Excel 365. To ensure compatibility with the selected analysis tool, VOSviewer, the dataset underwent several formatting and restructuring procedures. Various techniques, including the addition and modification of attributes, were applied to align the data structure with VOSviewer's input requirements. These formatting processes were iteratively refined to guarantee full compliance with the tool's specifications. Specifically, the mapping between the original dataset attributes and those adopted for analysis in VOSviewer is as follows: Id (Id), Date (Date), Username (Author), Content (Abstract), Source (Title), Place (Place), Hashtags (Hashtags), Like Count (Like Count), and Retweet Count (Retweet Count). Upon successful preprocessing, the dataset was prepared and subsequently imported into VOSviewer for further analysis.

3.5. Data Analysis Methodology

VOSviewer has been widely validated for analysing bibliometric networks [51], [52], [53], [54], [55] and is recognised for its capabilities in visualising and constructing text-based maps [56]. Developed in Java, it supports network creation, analysis, and visualisation using a unified mapping and clustering principle [57], positioned as an alternative to traditional multidimensional scaling (MDS) methods [58], [59]. Its clustering relies on a weighted, parameterised modularity function [60]. VOSviewer offers three types of visualisations—network, overlay, and density—making it a powerful tool for knowledge mapping in scientific research [56]. To analyse the Turkey-Syria Earthquake Tweets, VOSviewer is employed to

perform network visualisation analyses. Specifically, a co-occurrence analysis of terms extracted from the tweet content is conducted to identify key themes, emerging topics, and their interrelationships within the crisis communication landscape. VOSviewer's text mining functionality is utilised to preprocess the dataset, including the automatic extraction of relevant terms, synonym merging, and noise reduction. The resulting co-occurrence networks is then visualised to reveal thematic clusters and patterns of discourse. This approach enables the systematic measurement and mapping of public responses, facilitating the identification of dominant concerns, response strategies, and the structure of information flow during the flooding crisis. The findings aim to support intelligent decision-making processes and enhance understanding of social media dynamics in crisis management contexts.

4. Result of Textual Analysis

The Turkey–Syria Earthquake Tweets dataset was analysed using the text-mining functionality of VOSviewer 1.6.18, which enabled the visualisation of terms from the disaster dataset [14]. The analysis produced a co-word network map based on binary and full counting methods. In binary counting, the occurrences attribute reflects the number of records where a term appears at least once, while in full counting, it captures the total frequency of a term across all records [61]. VOSviewer further measures the strength of relationships between terms using a "visualisation of similarities" approach, positioning terms on the map according to their relational proximity [13], [58].

The tool also supports different resolution settings to identify varying cluster densities and has been validated in numerous bibliometric studies [51], [52], [53], [54], [55] and is recognised for its capabilities in visualising and constructing text-based maps [56] as well as analysing datasets other than bibliography [15], [16], [17], [18], [19], [20], [21]. In this approach, the distance between terms represents the strength of their association, the greater the distance, the weaker the link between terms. The subsequent sections present the findings obtained through both binary and full counting analyses.

4.1. Map Visualization in Binary Counting

Figure 2 presents the visualisation network and map of user comments based on binary counting, highlighting the most frequently used terms in the Turkey–Syria earthquake dataset. The co-occurrence (co-word) analysis reveals the various types of responses shared during the disaster. Among 101 terms meeting the threshold, a relevance score was calculated, and 60% of the most relevant terms, 61 terms were selected for the map. The colour coding distinguishes seven distinct clusters (Red, Green, Purple, Orange, Blue, Yellow, and Cyan). Terms such as "survivor," "solidarity," "authority," and "aid" cluster together, reflecting their strong relatedness and frequent co-occurrence during the crisis.

According to the result, the most prominent terms captured in Figure 2 include "magnitude," "devastating," "victim," "donate," and "life." Commonly recurring terms across clusters also include "help," "need," "food," "prayer," and "tent." The

analysis further shows strong relationships between terms such as "victim and tent," "victim and food," and "survivor and aid." These findings suggest that understanding such term relationships could support more effective disaster management and decision-making in the early response phase. The frequent mention of relief-related terms highlights the urgent needs of affected communities, particularly around basic necessities like shelter, food, and aid.

Furthermore, the study noted that several terms appeared in different forms across the texts but conveyed the same meaning. These were merged during the analysis to ensure consistency. Examples include: (Syriaearthquake, turkeyearthquake, Earthquakeinturkey, earthquakeinturkey, Turkiyequake, Major earthquake, Earthquake Syria, Earthquake, Syriaearthquake, Syria earthquake, Quake); (Turkiye Syria, Turkey Syria, Turkey & Syria); (Cristianoronaldo, Cristiano Ronaldo); (Magnitude earthquake, Magnitude); and (Region, Turkey Syria border region, Border). Hence, Table 3 provides a detailed list of all terms identified through binary counting, including their occurrence frequencies and relevance scores. Certain terms were merged due to semantic similarity, and their relevance scores were subsequently recalculated.

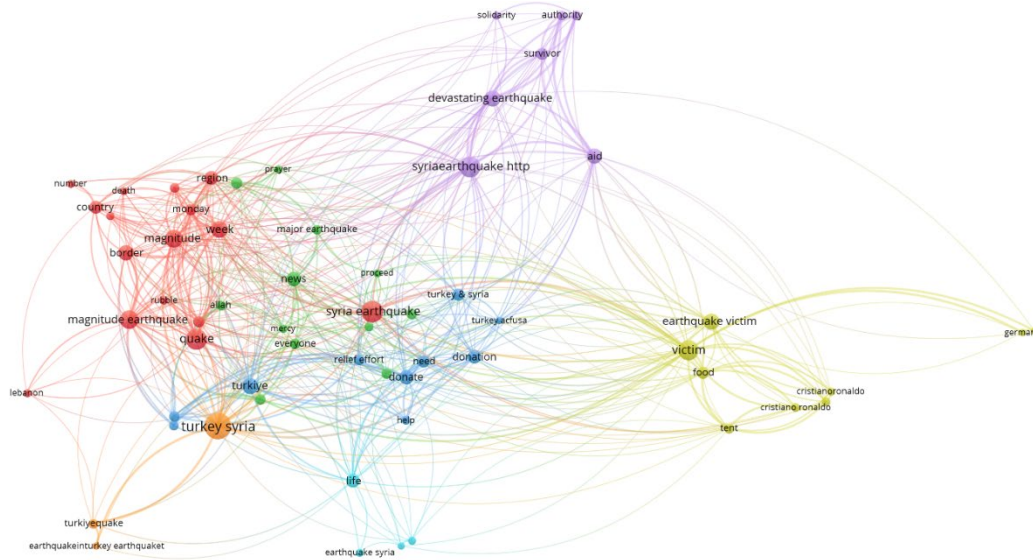


Figure 2. Co-Occurrence Network in Binary Counting

Table 3. Binary counting: Occurrences and relevance scores of terms

SN	Terms	Occurrences	Relevance
1	Syriaearthquake turkeyearthquake	300	11.53
2	Cristiano Ronaldo	25	4.23
3	Turkey Syria	150	2.90
4	Germany	10	2.86
5	Pakistan	10	2.55
6	Plane	13	2.21

7	Number	11	2.06
8	Tent	16	1.86
9	Turkey Syria border region	82	1.73
10	Proceed	11	1.65
11	Kurdistanearthquake,	15	1.56
12	Victim, Earthquake victim	114	1.53
13	Food	24	1.36
14	Authority	16	1.36
15	Solidarity	11	1.24
16	Survivor	24	1.19
17	Sister	16	1.06
18	Country	28	1.00
19	Brother	19	0.98
20	Magnitude earthquake	107	0.95
21	Aftershock	22	0.91
22	Lebanon	11	0.86
23	Help	13	0.84
24	Donate; Donation	67	0.84
25	New earthquake	17	0.79
26	Aid	39	0.78
27	Devastating earthquake	44	0.75
28	May allah	18	0.72
29	Relief effort	18	0.71
30	Mercy	12	0.65
31	Death	11	0.64
32	Turkey acfusa	10	0.64
33	News	34	0.62
34	Allah	15	0.58
35	Prayer	12	0.58
36	Monday	22	0.57
37	Everyone	18	0.55
38	Turkey Syria earthquake appeal	18	0.50
39	Life	31	0.46
40	Week	48	0.44
41	Need	24	0.42
42	Building	23	0.41
43	Rubble	14	0.36
44	Turkiye	41	0.32
45	Way	14	0.25

4.2. Map Visualization in Full Counting

This study also conducted a full counting analysis on the Turkey–Syria earthquake dataset. Among the 103 terms that met the threshold, a relevance score was calculated, and 60% of the most relevant terms, 62 terms were selected and organised into seven clusters: Red, Green, Yellow, Blue, Purple, Orange, and Cyan. The graphical visualisation of the full counting results is shown in Figure 3. Each cluster represents a thematic grouping, reflecting terms that are closely related in meaning and usage. The larger the cluster associated with certain terms, the more frequently those terms appeared in the user comments.

As shown in Figure 3, the proximity between clusters indicates the strength of their interconnections, based on the frequency of co-occurrence across different users' posts. Full counting analysis thus provides a deeper understanding of the structure and dynamics of tweets discourse of the earthquake disaster. By considering the total number of term occurrences, rather than just their presence or absence, this method offers a more detailed view of the importance of terms and their relationships within the dataset.

Furthermore, Table 4 presents a detailed list of all terms identified through full counting, along with their corresponding occurrences and relevance scores. Notably, the unique and overlapping terms from both full and binary counting are examined in the following section, underscoring the value of using both methods to obtain a comprehensive understanding of the crisis-related data.

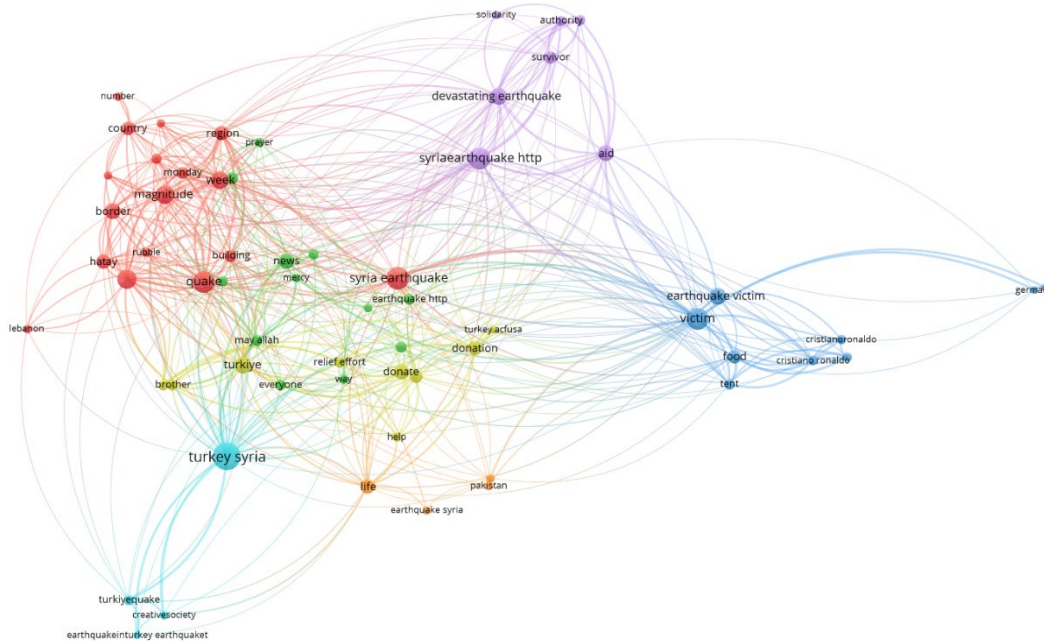


Figure 3. Co-Occurrence Network in Full Counting

Table 4. Full Counting: Occurrences and Relevance Scores of Terms

SN	Term	Occurrences	Relevance
1	Syriaearthquake turkeyearthquake	232	11.55
2	Cristiano Ronaldo	27	3.92
3	Germany	10	2.77
4	Turkey Syria	125	2.69
5	Pakistan	12	2.35
6	Plane	13	2.14
7	Creativesociety	11	1.83
8	Number	11	1.83
9	Tent	16	1.69
10	Turkey syria border region	83	1.69
11	Proceed	11	1.60
12	Kurdistanearthquake	15	1.59
13	Earthquake victim	115	1.59
14	Food	29	1.52
15	Authority	16	1.33
16	Solidarity	11	1.27
17	Survivor	24	1.20
18	Sister	16	0.97
19	Brother	19	0.95
20	Magnitude earthquake	109	0.93
21	Donate; Donation	67	0.91
22	Country	29	0.90
23	Help	13	0.86
24	Aid	41	0.84
25	Aftershock	22	0.83
26	Devastating earthquake	44	0.79
27	Lebanon	12	0.78
28	New earthquake	17	0.77
29	Relief effort	19	0.76
30	Turkey acfusa	10	0.68
31	May allah	18	0.64
32	Prayer	13	0.63
33	Mercy	12	0.60
34	Death	11	0.59
35	Monday	22	0.58
36	News	34	0.57
37	Turkey Syria earthquake appeal	18	0.55
38	Everyone	19	0.54
39	Allah	15	0.54
40	Life	31	0.51
41	Hatay	31	0.50

42	Need	25	0.45
43	Week	48	0.45
44	Rubble	14	0.37
45	Building	23	0.36
46	Turkiye	43	0.31
47	Way	14	0.30

4.3. Binary vs Full Counting

The study run analysis based on binary and full counting and there exist both difference and similarities in the result. Firstly, top terms in both methods are largely consistent, such as "Syriaearthquake turkeyearthquake", "Cristiano Ronaldo", "Turkey Syria", "Victim" / "Earthquake victim", "Tent", "Aid", "Donate", "Magnitude earthquake", etc., have appear prominently in both analyses, indicating high relevance and frequency. It is not noted that both methods group terms that reflect critical concerns and support efforts during the earthquake, such as "Help," "Food," "Relief effort," "Prayer," "Devastating earthquake", etc. Moreover, relevance scores follow a similar descending trend, prioritising highly co-occurring and frequently used terms.

Secondly, the analysis revealed that occurrence values differ due to counting method. This is because binary counting considers whether a term appears in a tweet or not (max 1 per tweet), while full counting considers total frequency of each term across all tweets (including multiple appearances in a single tweet). As a result, some terms show higher total occurrences under full counting. These include "Earthquake victim" 114 (binary) vs. 115 (full) and "Magnitude earthquake" 107 vs. 109. Third, relevance score was adjusted between binary and full counting. In particular, the top terms maintain high relevance in both, the ranking order shifts slightly based on how frequently a term is repeated. Lastly, unique terms were identified from the analysis. For example, "Hatay" and "Creativesociety" appears only in full counting, not in binary.

5. Discussion and Findings

The growing reliance on social media during disasters has opened new avenues for developing intelligent systems to support disaster response and recovery. In line with this, the present study advances the field by applying a VOSviewer-based approach to map knowledge derived from social media discourse following the Turkey–Syria earthquake. Through text mining and co-word analysis, the study identifies key concerns, thematic clusters, and term relationships, offering a structured understanding of public needs and sentiments during the disaster. These findings, as discussed in the following sections, can contribute to building intelligent recommendation systems that can prioritise response efforts based on social media data.

5.1. Findings

The knowledge mapping and term co-occurrence analysis using VOSviewer revealed several prominent thematic clusters within social media discourse during the Turkey–Syria earthquake. These clusters, formed through binary and full counting analyses, reflect key areas of public attention and concern. Their identification offers meaningful insights into how social media can inform disaster response and aid coordination. For instance, the most prominent terms (e.g., "Syriaearthquake turkeyearthquake", "Earthquake victim", "Donate", "Magnitude earthquake") reflect high public concern over the scale, impact, and humanitarian needs resulting from the disaster. These clusters were summarised in Figure 4, and discussed in the sections that follows.



Figure 4. Summary of Findings based on Clusters Generated from VOSviewer

5.1.1. Victims and Humanitarian Aid

One of the most dominant clusters revolves around terms such as Victim, Aid, Food, Relief effort, Tent, and Donate. These terms indicate an overwhelming concern for the immediate well-being of those affected by the earthquake. The frequency and interconnectedness of these words suggest that users were primarily focused on the humanitarian dimensions of the crisis, expressing needs, reporting shortages, and calling for assistance. Accordingly, from a disaster management perspective, the prominence of this cluster highlights the critical role of social media as an indicator of resource gaps and community needs. By identifying which aid-related terms are most frequently used, emergency response teams and humanitarian organisations can better prioritise actions, allocate resources, and respond to the most urgent issues. For example, high co-occurrence between tent and victim points to a strong demand for temporary shelter, which can guide relief agencies in procurement and distribution decisions. Moreover, this cluster demonstrates the potential of intelligent recommendation systems to extract and rank aid needs automatically based on term frequency and relationship strength. Such insights can be instrumental in shaping responsive, needs-based intervention strategies.

5.1.2. Religious and Emotional Expressions

Terms such as May Allah, Prayer, Mercy, and Solidarity form a separate but significant cluster that reflects the emotional and spiritual reactions of users. These terms do not represent physical needs but instead reveal collective mourning, empathy, and hope expressed by communities both within and outside the affected regions. This emotional discourse is crucial for effective disaster communication. Understanding the emotional pulse of the public allows crisis managers to craft culturally sensitive and psychologically supportive messages. Moreover, expressions of solidarity and prayer can also strengthen social cohesion and resilience, which are essential for recovery. Furthermore, recognising this cluster helps inform psychosocial support strategies. As a result, authorities can integrate faith-based messages or collaborate with religious leaders in public communication campaigns to enhance community trust and engagement during relief operations.

5.1.3. Geopolitical References and International Response

Another thematic cluster includes geopolitical terms such as Germany, Pakistan, Lebanon, and Kurdistanearthquake. These terms could often emerge in the context of international solidarity, support offers, and geopolitical relevance. Their inclusion in public discourse demonstrates that the earthquake had not only local but global resonance. From a disaster management standpoint, these mentions may signify opportunities for cross-border collaboration and international aid mobilisation. Monitoring how and where such terms emerge can help response agencies identify external stakeholders willing to assist, track aid pledges, and detect the spread of information or misinformation related to international involvement. Additionally, mentions of specific regions (e.g., Kurdistanearthquake) highlight areas impacted by disaster, suggesting the value of location-specific recommendations for aid allocation and media coverage.

5.1.4. Celebrity Influence on Public Attention

Interestingly, Cristiano Ronaldo appeared consistently among the most frequently mentioned terms. This could demonstrate the role of celebrity figures in shaping public attention and influencing discourse during disasters. In many cases, celebrities act as amplifiers of awareness, fundraising agents, and public advocates [62], which can be used for relief seeking efforts. Therefore, the inclusion of such a term in both binary and full counting analyses highlights the social media amplification effect, where high-profile figures such as Cristiano Ronaldo, catalyse broader engagement with disaster narratives. For disaster management professionals, this could reveal an untapped potential. Hence, leveraging celebrity endorsements or partnerships can boost visibility, accelerate donations, and disseminate critical information. Thus, recognising the influence of celebrities also informs communication strategies and response organisations can collaborate with influential public figures to reach wider audiences, particularly younger demographics, while ensuring message accuracy and integrity during disaster management and communication.

5.2. Reflections and Practical Implications

This section offers reflective insights derived from the textual analysis of tweets related to the Turkey–Syria earthquake. It explores unexpected patterns in the data, identifies notable absences or surprises in the discourse, and discusses how the findings could inform real-world disaster response practices. These reflections aim to bridge the gap between data analysis and actionable knowledge, highlighting the relevance of social media insights for humanitarian communication and crisis management.

5.2.1. Unexpected Patterns in the Data

One surprising finding was the frequent mention of the term "Cristiano Ronaldo" across both binary and full counting analyses. Given that the dataset is focused on a humanitarian crisis, the prominence of a celebrity's name, unrelated to the event's core crisis themes, was unexpected. This reflects how public figures can become focal points in social media discourse during disasters, either due to their involvement in relief efforts or their symbolic role in public empathy and attention. Additionally, the consistency of terms like "tent," "food," "donate," and "aid" across multiple clusters reinforced the importance of basic humanitarian needs during the immediate crisis response, providing validation for disaster communication priorities.

5.2.2. Missing or Unexpected Terms

As noted, the presence of celebrity-related terms (e.g., "Cristiano Ronaldo") was unexpected in a crisis-focused dataset, suggesting the interplay between humanitarian narratives and media visibility. On the other hand, some expected terms were notably absent or underrepresented, such as "rescue operations," "volunteers," "coordination," or "infrastructure damage", terms commonly associated with structured emergency response frameworks. This absence may point to a social media emphasis on emotional expression and immediate needs over institutional responses. It also suggests a potential gap in public discourse that could be important for disaster communication planners to address.

5.2.3. Implications for Disaster Response Practice

These findings offer practical insights for disaster response teams and humanitarian organisations aiming to align their communication strategies with public concerns. The clustering of terms like "survivor," "aid," "food," and "tent" demonstrates the urgency around basic needs, indicating that timely and visible response in these areas can significantly affect public perception and trust. Moreover, the analysis highlights emotional and religious expressions (e.g., "May Allah," "prayer," "mercy"), which suggest that culturally sensitive messaging is essential in regions where spiritual and communal values play a role in coping with trauma. By leveraging term co-occurrence patterns, emergency planners and NGOs can monitor evolving concerns, amplify high-priority needs, and tailor their messaging to better connect with affected populations. The presence of

geographically specific terms (e.g., “Hatay”) also points to the value of geo-targeted communication and resource allocation.

5.2.4. Implications for Intelligent Disaster Management

The identification of these thematic clusters underscores the utility of VOSviewer-based knowledge mapping for intelligent disaster management. Each cluster represents a layer of actionable insight, ranging from material needs to emotional support and international coordination. By systematically analysing co-occurrence patterns and term relevance, disaster response teams can build data-driven recommendation systems that respond to the evolving needs of affected populations. Moreover, the integration of such techniques into crisis informatics enables monitoring of public discourse, helping stakeholders to anticipate shifts in public concern, assess sentiment, and improve response strategies. Ultimately, this approach contributes to more adaptive, responsive, and human-centred disaster management.

5.3. Limitations and Future Work

This study highlights the usefulness of VOSviewer in analysing social media discourse during disasters, several limitations should be acknowledged. VOSviewer primarily excels at visualising term co-occurrence but lacks capabilities for sentiment analysis and temporal tracking, which are essential for understanding the emotional tone and evolution of public discourse over time. As such, it cannot fully capture the dynamic and affective dimensions of crisis communication.

In this study, only English-language tweets were used in this study. While this approach enhances interpretability and avoids translation bias, it inherently limits the cultural and geographical diversity represented in the data. Consequently, the findings may reflect predominantly English-speaking perspectives, which should be taken into account when interpreting the results, particularly in the context of a geographically diverse crisis such as the Turkey–Syria earthquake. Moreover, while the dataset of 1,000 tweets provides valuable insights for exploratory analysis, it represents a relatively small sample size for large-scale social media analytics. Consequently, the generalisability and robustness of the co-occurrence and clustering results may be limited. Thus, future research could address these gaps by incorporating larger and more diverse datasets, including multilingual tweets and content from multiple social media platforms, to better reflect global and culturally diverse perspectives.

Furthermore, another limitation of this study lies in the absence of certain critical terms such as “rescue operations,” “coordination,” and “infrastructure damage” in the analysed dataset. This gap may reflect limitations in the data source or indicate potential platform usage bias, where public discourse on social media may prioritise emotional expression and immediate concerns over operational or infrastructural aspects of disaster response. Consequently, the findings may not fully capture the comprehensive spectrum of disaster management activities, highlighting the need

for future studies to integrate multi-platform or multi-source data to achieve a more holistic understanding of public discourse and response dynamics.

Additionally, combining VOSviewer with advanced natural language processing (NLP) and machine learning techniques could enhance the analytical depth, allowing for more nuanced topic modelling and real-time detection of emerging issues. Finally, a promising direction would be the development of a prototype intelligent recommendation system that integrates VOSviewer for real-time disaster monitoring. This is particularly relevant because the present study utilised a static dataset obtained from Kaggle, rather than through real-time data collection. Therefore, the current framework does not constitute a live monitoring system but serves as a foundational model that could be extended in future research to incorporate real-time data streams and larger datasets for enhanced analytical precision. Such a system could support emergency responders by identifying urgent needs, coordinating resources, and improving decision-making during both the response and recovery phases.

6. Conclusion

This study explored the use of VOSviewer as a text-mining and knowledge mapping tool to analyse social media discourse related to the Turkey–Syria earthquake. By applying both binary and full counting techniques, the research identified key terms, thematic clusters, and term relationships that reflect public concerns, emotional responses, and humanitarian needs during the crisis. The findings demonstrate that VOSviewer can effectively visualise and interpret large-scale social media data, offering actionable insights for disaster response. Clusters related to victims and humanitarian aid, religious and emotional expressions, geopolitical references, and the influence of public figures reveal the multifaceted nature of online communication during emergencies. These insights support the development of intelligent recommendation systems that prioritise real-time needs, improve crisis communication strategies, and enhance resource coordination. The dual application of binary and full counting further underscores the importance of using complementary text analysis methods to capture both breadth and depth in term usage. By doing so, this research contributes to the broader field of crisis informatics and highlights the potential of knowledge mapping tools in supporting data-driven, responsive disaster management systems. Future research may consider expanding the dataset size, incorporating multilingual data, or integrating other machine learning techniques to build more comprehensive and adaptive recommendation models for emergency scenarios.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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