Journal Pre-proof

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PII: S2212-4209(25)00546-1

DOI: https://doi.org/10.1016/j.ijdrr.2025.105722

Reference: IJDRR 105722

To appear in: *International Journal of Disaster Risk Reduction*

Received Date: 18 October 2024

Revised Date: 20 June 2025

Accepted Date: 22 July 2025

Please cite this article as: L. Alejandra CASTELLANOS, A. EDJOSSAN-SOSSOU, N. KOMENDANTOVA, Evolving Emotions: Tracing Social Media Narratives in the Wake of the Manchester Arena Bombing, *International Journal of Disaster Risk Reduction*, https://doi.org/10.1016/j.ijdrr.2025.105722.

Evolving Emotions

Evolving Emotions: Tracing Social Media Narratives in the Wake of the Manchester Arena Bombing

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We have no known conflict of interest to disclose.

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Abstract:

Individual's behavior and sentiment in online environments have become increasingly reactive to disaster events. Monitoring and analyzing these behaviors and sentiments in the context of manmade disasters provides valuable insights for crisis management professionals. These analytical processes help develop a comprehensive understanding of evolving situations, support effective response strategies, and contribute to societal stability. Employing appropriate methodologies and tools enables the capture and tracking of semantic shifts in social media communications, offering a means to observe their evolution over time.

In this study, we present research conducted on the Manchester Arena Bombing incident in the United Kingdom, which occurred on May 22, 2017, focusing on leveraging data from Twitter (now X). Using Orange, a text-mining analysis software, we explored key discussion topics and their dynamics from messages published immediately after the incident up to a week and a month later. The results demonstrate the evolution of emotional expressions in citizens' messages during each disaster phase analyzed, including the prevalence of negative and positive sentiments during the recovery phase.

Keywords: Social media, Twitter, Semantic analysis, Manmade disasters, Manchester Arena Bombing.

1. Introduction

Social media has revolutionized information sharing and consumption, becoming an essential part of our daily life. Its impact on information distribution is profound, changing communication, news dissemination, and knowledge exchange dynamics (Komendantova, Erokhin, & Albano, 2023). With billions of active users on platforms like Facebook, Twitter, Instagram, TikTok, and LinkedIn, information can cross geographical boundaries and reach a wide audience. News spreads quickly and often in real-time, making social media especially helpful during crises, catastrophes, and breaking news events.

Nowadays, people increasingly turn to social media as their primary information source, leading to a decline in traditional media viewership (Ren et al., 2024). Unlike traditional media, where journalists follow rigorous methods to investigate and communicate accurate information, social media allows any user to create and share content. This transforms users into both senders and receivers in the communication process. Social media platforms enable two-way communication, where recipients can provide feedback by liking, sharing, commenting, and discussing, encouraging interaction and conversation. This interactive feature helps provide context, clarify facts, and debunk myths, making social media a platform for citizen journalism. User-generated content can document distinctive viewpoints and experiences that traditional media may miss. However, these features can also create echo chambers and information bubbles, where misinformation spreads unchecked by alternative sources (Zobeidi, Homayoon, Yazdanpanah, Komendantova, & Warner, 2023).

During crisis events, such as natural and manmade disasters, functions of social media platforms like Twitter (now X), including information dissemination, disaster planning and training, collaborative problem-solving and decision-making, and information gathering, support organizations and first responders in enhancing communications during disaster management phases (Chan, 2013). Given that each disaster management phase requires specific decisions or interventions, the uses of social media by netizens, disaster managers, and authoritative agencies vary across these phases (Kaminska & Rutten, 2014).

Governments and emergency services use social media to inform impacted communities in real-time and issue alerts and warnings. These updates provide advice on evacuation, emergency phone numbers, and security recommendations, assisting individuals in making safety decisions during a crisis. Several digital platforms use social media data to generate crisis maps and visualizations that aid authorities and relief organizations in understanding the situation on the ground. These maps can show affected areas, significant infrastructure damage, and population density, helping allocate resources effectively (Dallo, Elroy, Fallou, Komendantova, & Yosipof, 2023). For example, during the February 2023 Turkey-Syria earthquakes, social media rapidly published crucial information about the event (e.g., location, magnitude) and facilitated response and recovery efforts as many victims trapped under the rubble called for help by posting messages on Twitter (Toraman, Kucukkaya, Ozcelik, & Sahin, 2023). Perez-Figueroa et al. (2024) and Dufty (2016) identified up to 15 and 19 social media disaster communication functions, respectively, including news delivery and consumption, discussion of incident socio-political and scientific causes, disaster mental health support, awareness raising, and fundraising.

Audiences on social media often increase during disasters, enabling the dissemination of information to a large audience (Pew Internet & American Life Project, 2006) (Pereira, Monteiro, Silva, Estima, & Martins, 2020), and maintaining contact with loved ones (Liu, Jin, & Austin, 2013). The rapid and widespread dissemination of information through social media during disasters makes people impressionable and causes their opinions to shift as the event unfolds. People often publish numerous messages and content about the disasters, providing sufficient data for research and a comprehensive picture of the situation before, during and after the event (Phengsuwan *et al*., 2021).

Data analysis technologies, such as data mining, data visualization, machine learning, and AI, are useful tools for studying information flow during disasters on social media. They help understand social perceptions, thoughts, needs, and emotions during all disaster phases, including preparedness, response, and recovery (Meier, 2015) (Ngamassi, Shahriari, Ramakrishnan, & Rahman, 2022) (Adrot, et al., 2022). Analyzing social media information is highly valuable for inferring citizens' behavior in response to a given disaster. Public attitudes, emotions, sentiments, and opinions reflect the state of society to a certain extent. Understanding the state, trend, and evolution of public sentiment can assist rescue agencies in making informed rescue decisions and coordinating emergency management. In recent years, an increasing number of studies have focused on leveraging semantic information from social media data to improve the effectiveness of responses to crisis events due to natural, man-made, or technological disasters, as well as public health emergencies (Zhang & Cheng, 2021).

As social media use during disaster events becomes mainstream, conducting a text analysis of content posted by users can offer valuable insights for policymaking and emergency response. Existing studies on the content analysis of social media messages generally focus on four aspects: text mining (Justicia de la Torre et al., 2018; Alcantara Francia et al., 2022), including topic extraction (Justicia de la Torre *et al.* 2018; Alcantara Francia *et al*., 2022; Djebbi & Ouersighni, 2022; Silva & Santos, 2023; Zadgaonkar & Agrawal, 2024), sentiment analysis (Fitri et al., 2019; Arbane *et al*., 2023), and spatio-temporal analysis of shared content (Zhang & Cheng, 2021; de Carvalho *et al*., 2022); analysis of users' behaviour; social network analysis; and simulation of users' sentiments.
Some studies have examined post-disaster messages on social media (Chae et al., 2014; Radianti et al., 2016; Arora, 2022,) analysing the temporal evolution of people's opinions and sentiments on disasters in cyberspace is a promising research pathway. Other field of research place less emphasis on temporal analysis of social media data (quantity of messages shared over time regarding different periods of the crisis situation, changes in trends of key topics discussed, etc.), resulting in a lack of detailed analysis of topic semantics evolution (Han & Wang, 2022; Zhou *et al.*, 2022), particularly concerning man-made disaster events.

This research aims to analyse the evolution of communication on social media following the Manchester bombing using semantic analysis tools. The goal is to identify recurring topics and patterns of interaction among opinion makers. The terrorist attack on the Manchester Arena was chosen for its unique significance as the deadliest incident in Northwest England's history. The Ariana Grande concert was deliberately targeted to cause maximum societal harm, with many victims being young people. Ariana Grande's global popularity amplified social media attention and media coverage following the attack. On May 22, 2017, Salman Abedi detonated a backpack bomb in the venue's foyer just after Grande's performance, killing 22 mainly young individuals and injuring over a hundred others (Yosipof, Woo, & Komendantova, 2023).

By understanding the dynamics of social media communication in the aftermath of such a significant event, this study aims to contribute to the field of crisis communication and inform strategies for managing public discourse during future crises. The remainder of this paper is organized as follows: Section 2 presents the dataset and methodology, including data collection and analysis techniques, while Section 3 outlines the adopted methodology. The results are presented and discussed in Section 4.

2. Methodology

Text-mining and semantic tools are valuable for extracting quantitative and statistical features from unstructured social media text, enabling the discovery of potentially useful, interesting, or meaningful insights (Ngamassi, Shahriari, Ramakrishnan, & Rahman, 2022) (Yan, Ma, Wu, & Fan, 2022). In the case of disasters, text data is analyzed to deduce the most recurrent topics discussed on social media.

Semantic analysis involves automatically extracting, processing and interpreting textual data to derive relevant information from opinions expressed in messages. It interprets the meaning or polarity of larger text units (sentences, paragraphs, articles) through the semantic composition of smaller elements (Fitri *et al*., 2019). Semantic analysis of tweets during disasters plays a crucial role in understanding public thoughts, identifying key disaster characteristics, and assessing the attitudes and responses of involved actors. This process involves analyzing the textual content of tweets to determine the underlying sentiment and extracting meaning from the composition of smaller semantic elements, such as words and phrases, to interpret the overall message conveyed in the tweets. This helps detect patterns in public emotion, highlight the concerns and priorities of affected communities, and identify potential risks and vulnerabilities.

To analyze public reactions to the Manchester terrorist attack, we examined text published and shared on Twitter using Orange Data Mining (Demsar, et al., 2013), an open-source machine learning, data mining, and visualization software. These semantic approaches enable the analysis of how public reactions evolved in tweets following the Manchester bombing. The analysis aims to shed light on the dynamics of social media communication in the aftermath of the attack.

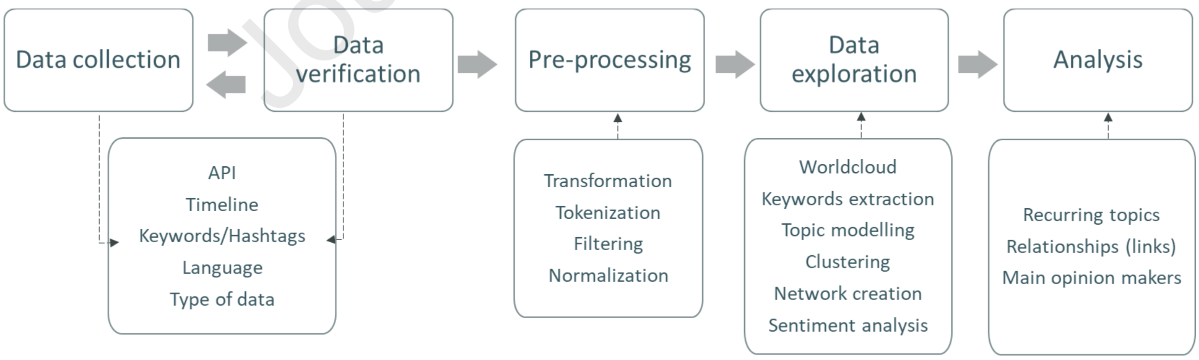

Figure 1- Semantic analysis methodology of Tweets

2.1. Data set

2.1.1. Keywords selection and data verification

Data collection focused on tweets related to the Manchester Arena Bombing. Data was collected using a Twitter Full archive API from 22 May until 8 June 2017 based on the following keywords: “Manchester”, “Ariana Grande”, “terrorist attack”, “terror attack”, “bombing”, “bomb”, “victim”, “police”, “security”, “emergency”, “thoughts and prayers”, “crew”, “ManchesterBombing”.

The selection of keywords used for data collection was informed by a combination of prior academic literature on social media analysis in disaster contexts and practical insights derived from the CORE (sCience and human factOr for Resilient sociEty) project. Specifically, we drew on the findings of Deliverable 2.2, titled "Natural and Manmade Disaster Case Study Identification, Research, and Analysis", which provided a comprehensive overview of terminology and thematic focus areas relevant to disaster-related communication. This dual approach ensured that the keywords reflected both academic framing and real-world discourse, enhancing the dataset's relevance and completeness.

2.1.2. Disaster timeline

Two samples of tweets were analysed based on the timeline of the disaster: i) the response phase from authorities and the public (first week after the attack), and ii) the recovery phase (after the first week of the attack). Details on the timeline are provided in Table 1.

Table 1. Features of Terrorist Attack Twitter database

Database features	**During response**	**During recovery**
Timeline for the analysis	22-28 May 2017	28 May – 8 June 2017
Twitter dataset	148,615	22,461

The first dataset includes tweets and retweets in English during the response phase to the attack. This led to the collection of a database of 148,615 tweets and retweets. On the other hand, the second dataset includes tweets and quote-tweets posted during the recovery phase starting from May 28. Quote tweets are retweets with an additional comment from a user, which expands the dataset and allows for the analysis of more text content. It is important to note that an initial search including tweets and retweets resulted in over 400,000 posts. For storage and processing reasons our search was restricted to tweets and quote-tweets.

The dataset was limited to English-language tweets, which may restrict the generalizability of findings to non-English-speaking populations. Additionally, the dataset was not randomly sampled but filtered based on relevance to the event and keyword matching. Non-English tweets and those lacking textual content were excluded. The final dataset sizes—148,615 for the response phase and 22,461 for the recovery phase—reflect both the natural decline in tweet volume over time and the constraints of data processing. We acknowledge that this imbalance in sample sizes may introduce bias in comparative analyses and have noted this as a limitation in the Discussion section.

The temporal segmentation of the dataset into response and recovery phases was guided by both theoretical and empirical considerations. The response phase was defined as the first seven days following the attack (22–28 May 2017), aligning with standard disaster management frameworks, such as the FEMA National Disaster Recovery Framework (NDRF) of the United States, that characterize the initial week as a period of heightened emergency response, public alertness, and intense media coverage, even though the recovery efforts begin while response is still occurring. This period also coincided with peak Twitter activity in our dataset, reflecting immediate public reaction and information-seeking behaviour. The recovery phase was defined as the period from 28 May to 8 June 2017, beginning after the initial shock had subsided and public discourse began to shift toward themes of mourning, justice, and resilience. The selection of May 28 as the transition point was further supported by the lead-up to the "One Love Manchester" benefit concert on June 4, which served as a symbolic moment of collective healing and solidarity. This division allowed for a meaningful comparison of emotional and thematic shifts in social media narratives across distinct phases of the disaster timeline.

2.1.3. Treatment of Retweets

The initial dataset included both original tweets and retweets. However, for semantic analysis, we excluded retweets without additional commentary (i.e., non-quote retweets). This decision aimed to focus the analysis on unique textual content, offering deeper insights into public discourse and emotional expression. Nonetheless, we acknowledge that retweets, despite lacking original text, play a significant role in amplifying messages and shaping the collective response to a disaster. Although excluded from content analysis, the volume and timing of these retweets were considered in the descriptive analysis of engagement trends. This is acknowledged as a limitation of the study. Future research should more explicitly incorporate retweet dynamics—such as through network analysis or virality metrics—to better capture the full spectrum of public interaction and information dissemination.

In addition, the semantic analysis methodology included a data verification step. This was an iterative process in which the keywords and hashtags, language filters, timeline, and types of tweets collected (e.g., original tweets, retweets, quote tweets) were continuously reviewed and refined. This step was essential to ensure the relevance, consistency, and completeness of the dataset, and to align the data collection process with the evolving understanding of the event's digital footprint.

2.2. Data pre-processing and exploration

To explore the data and extract meaningful insights from tweets, we applied a text transformation and structuring process to remove irrelevant components and retain meaningful content. As part of the preprocessing pipeline, we implemented several steps to enhance data quality and reliability. Non-quote retweets were removed to avoid overrepresentation of repeated content. To reduce noise and filter out automated or low-quality content, we excluded accounts showing indicators of non-organic behavior, such as extremely high posting frequency, low follower-to-following ratios, or highly repetitive content. Tweets containing excessive hashtags or URLs—common markers of spam—were also removed. Furthermore, accounts with disproportionate engagement metrics, such as inflated retweet counts without accompanying comments, were filtered to avoid overemphasis on artificially amplified content. These steps helped ensure the dataset reflected genuine user-generated discourse, improving the accuracy of both semantic and sentiment analyses.

The occurrence of words was analysed using a wordcloud. Additionally, different machine learning algorithms, including hierarchical clustering, network analysis, and sentiment analysis, were employed to investigate the main topics in public debate following the attack and the emotions associated with them. Below we provide a detailed explanation of the various methods and steps using in the framework of this analysis:

- *Wordcloud*: The wordcloud is a visual representation of the most frequently used words in the tweets. It provides an initial overview of the text, helping assess its relevance to the research (Kabir, Karim, Newaz, & Hossain, 2018). Additionally, it offers a preliminar view of discussion trends, with more frequently used words appearing larger in the visualization.
- *Hierarchical clustering*: This method visually groups related words into clusters using a dendrogram, which is generated by hierarchical clustering algorithm. The algorithm creates nested hierarchy of clusters, linking similar terms based on their co-occurrence patterns (Halkidi, 2009).
- *Corpus to network*: Semactic networks were used to visually represent different topics and the strength of their relationships. These networks consist of nodes (words), edges (co-occurrence links between words) and clusters (groups of related terms). The graph structure models semantic relationships, with labeled nodes and edges illustrating how frequently terms appear together in tweets (Drieger, 2013).
  To construct the semantic networks used in this study, term co-occurrence was calculated based on the frequency with which pairs of words appeared within the same tweet. This method assumes that words mentioned together in a single post are likely to be semantically or contextually related. A co-occurrence matrix was then generated, where each cell represented

the number of times two terms co-occurred across the dataset. This matrix serves as the basis for building the network graphs, where nodes represent individual terms and edges represent the strength of their co-occurrence. The thickness of the edges was proportional to the frequency of co-occurrence, enabling the identification of strongly connected thematic clusters.

- *Sentiment analysis*: Natural Language Processing (NLP) was used to determine positivity and negativity of tweets. The sentiment (positive, negative or neutral) of each tweet in English was assessed using the Valence Aware Dictionary and sEntiment Reasoner (VADER) sentiment lexicons model, specifically attuned to sentiments expressed in social media. VADER scores ranges from -1 (most negative) to +1 (most positive), which values closer + 1 indicating stronger positive sentiment.

The timeline of tweet publication was also analyzed, along with the identification of key stakeholders and opinion leaders in the Twitter discourse. This included users who posted the most tweets during the analysis period.

3. Results

The spatial and temporal dynamic of posts by social media users provides a means to follow events in near-real time. In the specific case of manmade disasters, such as a bombing attack, continuously updated information from users helps identify the locations affected by the attack and track its evolution over time. This analysis explores the trend in tweet publications during the first month following the attack, encompassing both the response and recovery phases.

The main results of this study are summarised and discussed as follows. Regarding the kinetics of the posts related to the Manchester Arena bombing, Figure 2.a**Error! Reference source not found.** illustrates a peak in tweet activity immediately after the attack, with around 70,000 messages posted during the first 24 hours (Figure 2.b), followed by a gradual reduction over time. According to the analyzed dataset, the first tweet mentioning the incident was published 6 minutes after the attack, around 10:30 PM, by a user with around 600 followers. The first tweet identified as published by an official/verified account was published by the Daily Mail U.K. (an official media account with more than 739,000 followers) at 10:50 pm.

The number of tweets declined until June 3, when another peak in publication was observed on June 4, with around 5,000 tweets. This spike can be attributed to the benefit concert "One love Manchester", organized by Ariana Grande and British television to pay tribute to the victims of the terrorist attack. This allows conclude that tweets talking about Manchester Arena Bombing were mainly posted during the response period, that means during the first week after the event.

a) During the response phase b) During the first 24 hours after the attack

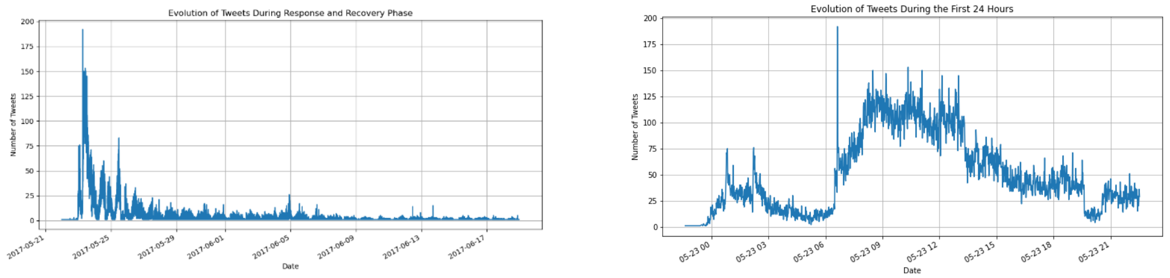

Figure 2. a) Trend of Tweets posted during following the attack and b) during the first 24 hours.

A focus on the tweets posted in the first 24 hours after the event reveals that although the attack happened at around 10:30 pm, it stirred up some attention in the first few hours. Indeed, a first wave of tweets was posted until 03:00 am then a second wave was posted from 06:00 am, peaking around 07:00 am. Early morning is a period during which all kinds of news travel fast, because those who were asleep during the event wake up and discover the news in the traditional media or via their social networks. The attention to the event slowly declined from 01:00 and reached a low point on the evening of May 23 before another slight wave of attention ensued at 08:00 pm. This swing can be explained by the fact that, on the one hand, English people generally dine between 07:00 pm and 08:00 pm and on the other, most evening TV news are broadcast between 05:00 pm and 10:30 pm. Despite turning to social media for collecting information about the event and/or discussing it, people continue to search for more accurate news on traditional channels and react to it on their networks.

3.1. Topics in Twitter database

The most characteristic and frequently used words in the Twitter database during the response and recovery phase were extracted and represented in wordclouds (Figure 3**Error! Reference source not found.**). These wordclouds revealed that during both disaster phases, "victim" was the most used word (Table 2), highlighting the human impact of the attack. Both wordclouds illustrate the attack with words like "police", "bombing", "terror", "arena" and "Ariana" as common dominant terms of the two datasets.

A focus on the first 5 terms in the Top 10 keywords shows that the rate of their occurrences with regard to the total number of tweets in each database are quite similar: the number of tweets with the keyword "victim" represents around 20% in both phases. The results of the 4 other keywords for both phases are the following: 10.87% and 16.27% for "police", 10.37% and 12.56% for "bombing", 11.78% and 12.56% for "terror", and 9.36% and 6.75% for "arena". This means that the term "police" is more discussed during the recovery phase while "arena" has slightly lost Twitter users' attention. During this phase, the location of the incident tends to lose importance. Despite being one of the most frequent terms, the name of the artist "Ariana" appears at the 7th place for both datasets: even if users refer to her in the posted messages, she is not the first concern in the most important topics of discussion during both phases.

The presence of emotionally charged terms such as "love", "heart", "thoughts", and "prayers" in the response phase word cloud underscores the immediate emotional impact and collective mourning. In contrast, the recovery phase word cloud reveals a shift toward institutional and political discourse, with terms like "police", "terrorist", and "Theresa May" gaining prominence. This thematic transition reflects a broader societal processing of the event—from shock and grief to calls for accountability and resilience. The appearance of the bee emoji 🐝, a symbol of Manchester's unity and strength, is particularly noteworthy as it illustrates how local cultural symbols are mobilized in digital spaces to foster solidarity.

a) During the response phase	b) During the recovery phase

Figure 3. Wordcloud of Terrorist attack Twitter database, a) During response phase, and b) During recovery phase.

An analysis of the results summarized in the table below shows that the discussion during the response phase mainly refers to the disaster and the emotion because of the human loses, while the discussion during the recovery phase is mainly dominated by terror-related words (police, bombing, terror, bomber, terrorist).

Table 2. 10 words with higher occurrence in the wordclouds

a) During the response phase		b) During the recovery phase	
Weight	**Word**	**Weight**	**Word**
28,863 (19.48%**)***	victim	4,485 (20.92%)	victim
17,507 (31.29**%)**	terror	3,654 (37.97%)	police
16,157 (42.20**%)**	police	2,822 (51.13%)	bombing
15,409 (52.59**%)**	bombing	2,822 (64.30%)	terror
13,914 (61.98**%)**	arena	1,516 (71.37%)	arena
13,175 (70.88**%)**	thought	1,260 (77.25%)	bomber
11,576 (78.69**%)**	ariana	1,258 (83.12%)	ariana
11,144 (86.21**%)**	family	1,251 (88.95%)	terrorist
10,378 (93.21**%)**	#manchesterbombing	1,232 (94.70%)	man
10,060 (100 %)	people	1,136 (100 %)	arrest

* The values in brackets correspond to the cumulative percentage of the appearance of these Top 10 words relying on the sum of their weights.

More globally, the comparative analysis of the wordclouds reveals both continuity and evolution in the public discourse across the two phases. Indeed, several shared keywords (such as “bombing”, “victim”, “police”, “terror”, “arena”, “Ariana”, “concert”, “Manchester” and “terrorist”) appear prominently across both phases, indicating sustained attention to the nature of the event, the victims, the location and the perpetrator. These recurring keywords suggest a continuous engagement of the Twitter users with the factual and emotional dimensions of the attack. However, the wordclouds show that there exists an emotional and communicative shift over the phases. The response phase is marked by an emotionally charged language which is centered on immediate shock, solidarity and support. Keywords like “thought”, “prayer”, “family” and “everyone” as well as the hashtag #WeStandTogheter reflect collective mourning and unity. Real-time terms like “emergency service”, “incident”, “last night” and “break” highlight the unfolding nature of the event and the urgency of the situation. While the response phase sees a shift toward healing, community support, accountability and rebuilding. Keywords like “support”, “tribute”, “fund”, “donate” and “benefit” emerge for indicating the mobilization of community initiatives and resources. The appearance of other terms such as “investigate”, “MI5”, “officer”, “charge”, “release” and “suspect” reflects a growing of the public interest in justice and protective or security measures. Overall, the transition from the response to the recovery phase is characterized by a clear evolution in public discourse on social media as shown in Table 3. This shift reinforces the importance of temporal framing in social media analysis of disasters and crisis events.

Table 3. Key differences illustrated by the wordclouds

	Response phase	**Recovery phase**
Tone	Emotional, reactive	Reflective, proactive
Key focus	Victims, emergency, unity	Recovery, justice, support
Perpetrator mentions	Low to moderate	High (emergence of his name “Salman Abedi”)
Security terms	Incident, emergency, attack	MI5, investigation

Public actions and initiatives	Prayers, solidarity	Fundraising, support, policy

3.2. Main topics and trends in the Twitter debate

Networks were used to represent the main topics and their associations in the discussion about the Manchester Arena Bombing among Twitter users. In the network, words are represented as nodes, and their associations or links are depicted by edges. This relationship between words depends on their co-occurrence. Finally, the closeness between words is articulated in the form of clusters (groups). In such networks, the sizes of the nodes represent the frequency of terms, and the width of the links depicts the co-occurrence strength between the terms.

The semantic networks illustrate the evolution of discourse. During the response phase, clusters are tightly centered around emotional support and urgent information sharing, such as locating missing persons. The prominence of nodes like “family”, “missing”, and “prayers” reflects the community’s immediate concern for safety and solidarity. In the recovery phase, the emergence of clusters related to “justice”, “terrorist”, and “government” indicates a shift toward political and institutional narratives. The inclusion of public figures and the attacker’s name suggests a growing demand for accountability and policy response. These shifts highlight how emotional narratives evolve into structured public discourse over time. This progression from emotionally driven interactions to politically oriented discourse underscores the dynamic nature of collective communication in the aftermath of a crisis, reinforcing the patterns observed in the wordclouds analysis and offering deeper insights into the evolving priorities and concerns of the netizens over time.

The network of the Twitter database of the response phase displayed 4 main clusters referring to: i) Disaster and victims, ii) Though and prayers to victims, iii) Missing people, and iv) Retweeting to find missing people.

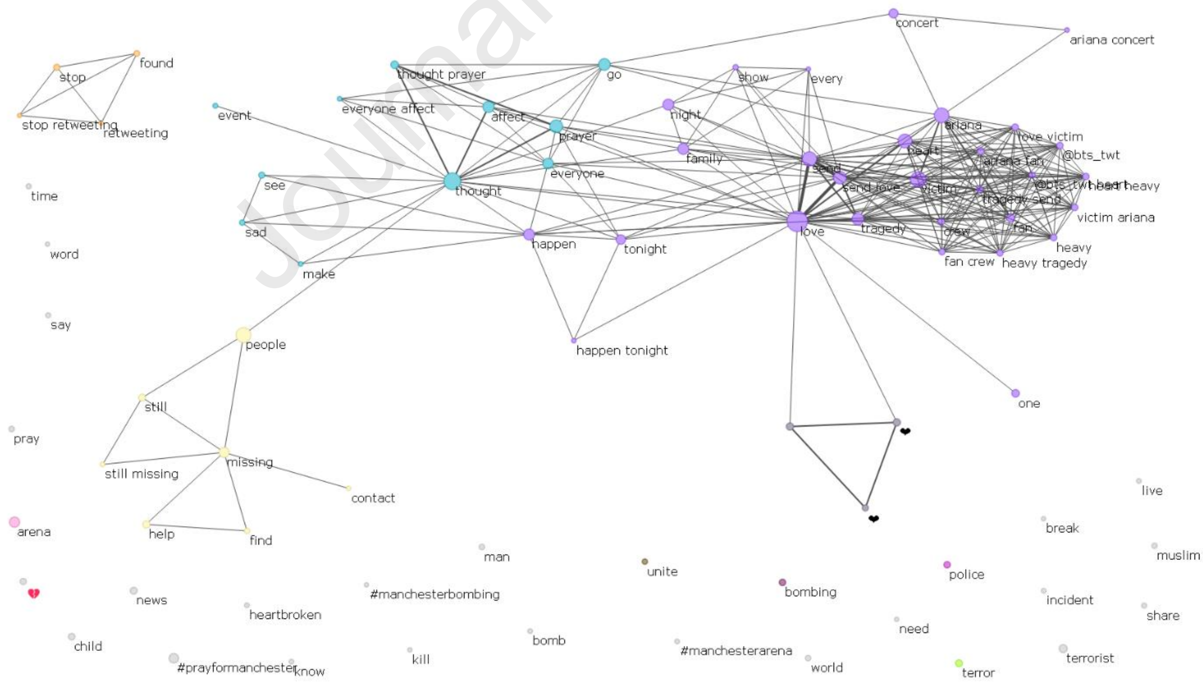

Figure 4. Network of topics in Twitter database during the first week after the attack (response phase). Note: Some labels in the purple cluster may appear small due to visualization constraints. Key terms and their relationships are described in detail in the accompanying text.

The purple cluster in Figure 4, labeled “*Disaster and victims*”, represents the central thematic focus of the response phase. Although some labels in this cluster may appear small due to visualization constraints, the key terms include like “Ariana”, “show”, “victim”, “fan crew”, “family”, “concert”, “tragedy”, “tonight”, etc. These terms collectively reflect the immediate emotional and factual response to the bombing. The cluster is densely connected, indicating a high frequency of co-occurrence among these terms, which underscores the public's focus on the victims and the context of the event. Notably, emotional supportive words such as "love", "send", and "heart" appear prominently, highlighting the widespread expressions of solidarity and compassion. Citizens, including multiple celebrities posted messages of support, for example the south-Korean group BTS:

> "Our hearts are heavy about the tragedy in Manchester. We send our love to all the victims, Ariana, her fans and crew." BTS posted at 8:37 am 23 May of 2017

The second cluster *Though and prayers* (in blue), is exclusively dedicated to the support towards victims after the disaster, as is evident because of the terms in contains: "thought", "prayer", "affect", "everyone".

The third and fourth cluster are *Missing people* (in yellow) and *Retweeting to find missing people* (in orange) respectively. They bring up tweets that were intended to seek news about relatives and/or friends present at the venue and who have not been reported, and the use of the retweeting functionality to disseminate information about these disappearances with disaster managers. In fact, the emergency phone system that operates in Greater Manchester (operated by Vodafone), experienced a catastrophic failure during the attack. This caused families of victims used Twitter and posted photos and information about their relatives to get some news.

The network from the dataset of the recovery phase displayed some new reactions (see Figure 5). The most important cluster *Disaster description* (in red), focused on the description of the attack with different terms from those used in the one-week dataset such as "arena", "terror", "bombing", "terrorist", "explosion", "22", among others. Nonetheless, there are still the following similar nodes "Ariana" and "concert".

The second cluster *Disaster victims* (in brown) could be seen as a mix of the second and the third cluster of the one-week dataset, as it describes the victims and solidarity with them by using terms as "victim", "family", "affect", "victim family", "friend", "though", "though player". In addition to the feeling of solidarity, a new topic appeared on this network, this corresponds to *Tribute to the victims* (in blue) which refers to the messages related to mourning the victims and the different demonstrations of tribute.

The *Disaster management* cluster put emphasis on "police" as the most important node, highlight its role and responsibility during a manmade hazard. Following the attack, Manchester Police constantly updated its Twitter account with crisis communication information. This cluster also stress the name of the terrorist as well as calls for Theresa May's responsibility as Prime Minister at that time. This indicates that Twitter users from Great Britain seem to pay more attention to disaster management in contrary to the group made up of users located worldwide. Clearly, Great Britain citizens are calling for response from the official risk management organizations.

Figure 4 clearly emphasizes the 5 first terms of the Top 10 keywords in both datasets and depicts the links between them. The terms "victim" and "police" are linked through "arena", "bombing" and terror" while the results of the week after the incident do not show links between these words.

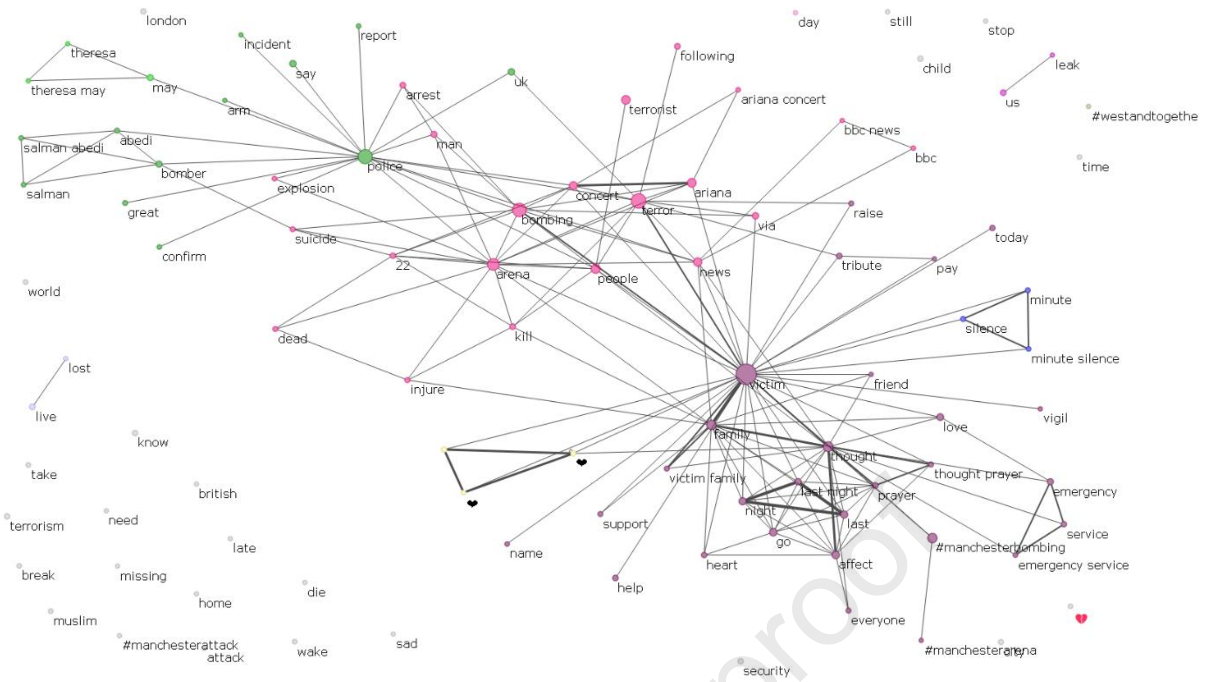

Figure 5. Network of topics in Twitter database during and recovery).

The hierarchical clustering allowed to explore in detail how words and clusters are interconnected. The results indicated the during the response phase, two clusters' topics are prominent, and their content is explained as follows:

- Fist cluster includes emojis (❤), hashtags (manchesterbombing, #manchesterarena, #prayformanchester), as well as tags of Twitter user accounts (@bts_twt)
- Second cluster composed of two main sub-clusters, the first one includes thoughts and players for victims and casualties (thought, player, send love), and ask of aid and help (still missing, people, affect, need help…); and the second cluster relates the details of attack.

The recovery phase has a similar composition that includes more words and details in two main clusters:

- First cluster includes emojis (❤), hashtags (#westandtogether, #manchesterbombing, #manchesterarena, #manchesterattack), number of casualties (22), the city (london) and some first names including that of the victim (Ariana), the assailant (Salman) and the Prime Minister (Teresa).
- Second cluster involves the details of the attack and the tribute to the victims (love, victim, player, thought, minute silence) but it also mentions the action of the authorities, more specifically the policy and the Prime Minister (Teresa May).

The temporal evolution of the most prevalent topics of discussion between the Twitter's users can be observed in the following Figure. Different key words were associated to topics in order to analyze and classify the Tweets. The categories or topics used are:

- **Emotional expression**: Tweets expressing emotions such as sadness, anger, fear, condolences, and support.
- **Help seeking and offering**: Tweets related to seeking or offering help, such as assistance, donations, and volunteering.
- **Emergency alerts and warnings**: Tweets providing urgent information, warnings, or alerts about the situation.
- **Official information and updates**: Tweets containing official statements, updates, and reports from authorities or government bodies.

- **Community and solidarity**: Tweets showing unity, support, and resilience within the community.
- **Condemnation and justice**: Tweets condemning the attack and calling for justice, including mentions of prosecution and punishment.
- **Disaster description**: Tweets describing the event, such as bombing at the Ariana Grande concert.
- **Disaster management**: Tweets related to the management of the disaster, including mentions of police, government officials, and emergency responders.

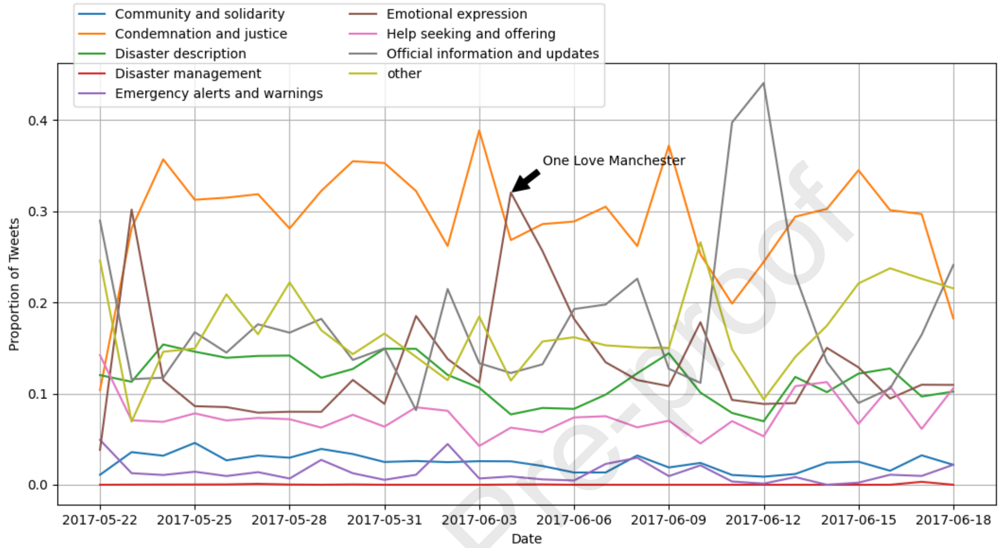

Figure 6. Normalized evolution of tweet publications over category. Values represent the proportion of tweets per category relative to the total tweets per day. A peak in emotional expression is observed around June 4, coinciding with the "One Love Manchester" concert.

To enable clearer comparison of topic dynamics over time, the time-series data were normalized by converting raw tweet counts into proportions relative to the total number of tweets per day. This approach highlights the relative prominence of each topic, independent of fluctuations in overall tweet volume. As shown in Figure 6, which illustrates the temporal dynamics of the defined categories from the occurrence of the bombing on May 22 to June 18, the dominant categories evolve during the period of interest. In the immediate aftermath of the bombing corresponding to the timeslot between May 22 to May 25, four topic categories dominated the public conversation: "condemnation and justice", "disaster description", "official information and updates" and "emotional expression". "Condemnation and justice" messages category (orange line) emerges as the most dominant topic peaking around May 23-24 for reflecting public outrage and demand for accountability. "Disaster description" (green line) and "official information and updates" (grey line) are also highly prevalent indicating netizens' reliance on Twitter as key source of real-time information about the features of the ongoing incident, casualties number as well as crisis and emergency management instructions. In addition, "emotional expression" (brown line) shows a strong peak just after the attack signaling widespread grief, shock and empathy shared by Twitters users globally.

This phase was followed by a transition period ranging from May 25 to June 5 where public discourse shifted towards more sustained engagement with the official information and updates as investigation-related developments emerged. This period was typified by a steady share of messages conveying details about investigation and security measures. Condemnation and justice continued to attract netizens' attention, suggesting their persistent political and security-related concerns. Meanwhile, categories such as "help seeking and offering" (pink line) and "emergency alerts and warnings" (purple line) remained marginal throughout this timeline, probably due to the localized nature and the brief duration of the crisis triggering event; the bombing being a one-time incident rather than a continuously evolving threat.

The collective commemoration expressed through the One Love Manchester tribute concert held on June 4 marked a pivotal shift in the public discourse. Thus, Emotional expressions peaked this day highlighting the symbolic function of this concert as a collective moment of healing and resilience as well as indicating a rerouting of the narrative on Twitter towards unity and emotional recovery, while other categories such as Condemnation and justice showed sustained engagement throughout the recovery phase.

The period after the concert is marked by a rise in attention to the investigative updates and official announcements regarding the Manchester Arena status. Indeed, between June 6 and June 18, the occurrence of several significant developments related to the bombing likely influenced the dominant categories of discussed topics. During the early part of this time (June 5-11), while police raids and evidence collection were still ongoing, frequent updates were shared through official channels and social media. These included statements on public safety (such as the visible patrols by armed police) and updates on arrests as well as coordination between UK and international intelligence agencies. On June 11, Greater Manchester Police announced that all the 22 individuals who were arrested in connection with the attack had been released without charge as investigations suggested that the bomber likely acted solely. On June 14, the Manchester Arena officially announced that it would remain closed for an extended period (until September 2017), leading to the cancellation, the postponement or the relocation of the upcoming events. This development had likely prompted a new wave of public communication related to ticketing, access to the venue and events rescheduling. Messages shared on such developments are part of standard crisis communication intended to ensure that people stay informed in those critical periods. Subsequently, a pronounced increase in the messages of official information and updates category is observed between June 10-12, correlating mainly with official statements from Greater Manchester Police.

The above observations underscore how the temporal dynamics of public discourse on Twitter following a disaster or during a crisis closely align with the occurrence of key developments, reflecting the platform responsiveness to unfolding events and its role as a barometer of public attention and concerns throughout the crisis timeline.

3.3. Sentiment Analysis

The emotion expressed by Twitter users were evaluated through VADER , a lexicon- and rule-based sentiment analysis algorithm, known for its effectiveness in analyzing short, informal, and emotive text typical of social media platforms. VADER accounts for nuances such as capitalization, punctuation, emoticons, and degree modifiers, making it especially effective for analyzing short, informal text like tweets. We selected VADER over other tools such as SentiStrength or machine-learning classifiers because of its accuracy in prior crisis-related studies, low preprocessing requirements, and its suitability for analyzing large datasets without the need for labeled training data.

The results of the analysis indicated an overall negative sentiment with a compound score of -0.357 and -0.274, during the response and recovery phase, respectively. A slight increase in positive sentiment was observed during the recovery phase, suggesting a gradual improvement in public mood. However, overall sentiment remained predominantly negative.

Table 4. Sentiment analysis of Tweets posted after the Manchester Arena Bombing.

During the response phase	During the recovery phase
-0.357	-0.274

To assess whether the observed change in sentiment between the response and recovery phases was statistically significant, we conducted a two-sample t-test on the VADER compound scores. The results indicated a statistically significant difference at the $p < 0.05$ level, suggesting that the increase in positive sentiment during the recovery phase is unlikely to be due to random variation. Confidence intervals for the mean sentiment scores were also calculated and are presented in Figure 7.

The bar chart compares the average positive, negative, and compound sentiment scores across the two phases. While there is a statistically significant increase in the compound sentiment score from the response phase (-0.357) to the recovery phase (-0.274), the overall sentiment remains negative. However, it is important to note that neutral sentiment was the most predominant category in both phases. This suggests that a large portion of tweets were either factual, informational, or emotionally neutral. The persistence of negative sentiment likely reflects both the emotional impact of the attack and the lexical bias introduced by the use of event-specific keywords (e.g., “bombing,” “victim,” “terrorist”). The slight increase in positive sentiment during the recovery phase may be associated with collective healing efforts, such as the “One Love Manchester” concert, but should be interpreted in the context of the overall dominance of neutral sentiment.

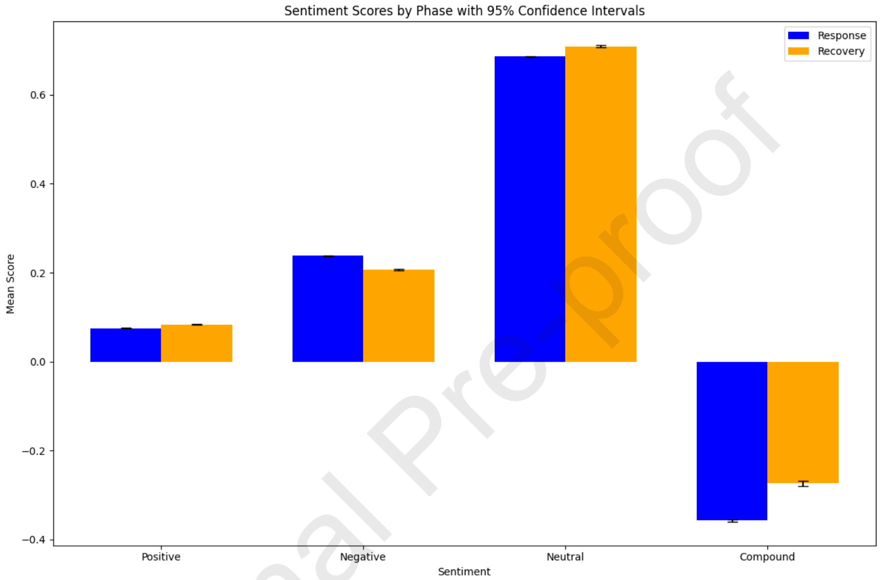

Figure 7. Sentiment scores during the response and recovery phase of the Manchester Arena Bombing.

3.4. Discussion

The temporal evolution of the most prevalent topics of discussion among Twitter users following the Manchester Arena bombing reveals significant insights into public sentiment and behavior during disaster events. The analysis categorized tweets into several key topics: emotional expression, help seeking and offering, emergency alerts and warnings, official information and updates, community and solidarity, condemnation and justice, disaster description, and disaster management.

The results indicate that all topics peaked shortly after the attack on May 23, with varying rates of decline. Notably, there was a significant spike in tweets related to emotional expressions and condemnation and justice during the “One Love Manchester Concert,” which aimed to raise funds for the victims and their families. This event underscores the role of social media in fostering community solidarity and support during crises. Both datasets demonstrated big solidarity with people affected by the event.

Our findings align with previous studies that highlight the critical role of social media in disaster management (Dufty, 2016; Phengsuwan et al., 2021). Similar to the observations by (Adrot, et al., 2022), our analysis demonstrates that social media data can generate diverse insights into emergencies. The presence of tweets about missing people during the response phase, as noted by (Waqas & Imran, 2019), further emphasizes the utility of social media in critical situations.

In the event of a communication failure, such as the Manchester attack, social media platforms were useful for reporting people’s safety or obtaining information about missing individuals. For example, the “Safety Check” feature of Facebook, created to verify people in the affected geographical area of a natural or manmade disaster are alive and well (Titcomb, 2017) , was used by many Facebook users in the venue to notify friends and family that they were safe. On Twitter, several posts shared images of missing people that were widely spread (Craigie-Williams., 2018). Nevertheless, some of these tweets were discredited by hoaxes.

These results highlight the importance of verifying information sources to prevent the spread of misinformation. The presence of hoaxes and rumors, as observed in previous disasters (Cresci, 2017), (Hunt, Agarwal, & Zhuang, 2020), underscores the need for reliable information dissemination during crises. Understanding sentiment trends can help tailor communication strategies to address public concerns more effectively.

In parallel, the results demonstrated that public disclosure on social media varied across the disaster phases. While the average sentiment scores were negative in both the response and recovery phases, the most predominant sentiment category overall was neutral. This suggests that a large proportion of tweets were informational, factual, or emotionally neutral—highlighting Twitter's role as a platform for real-time updates and public discourse rather than purely emotional expression. The persistence of negative sentiment, particularly during the response phase, may be attributed to the immediate emotional shock of the attack, especially given the involvement of children among the victims. During the recovery phase, although sentiment scores showed a statistically significant increase, they remained negative, likely reflecting ongoing grief, public scrutiny of institutional responses, and the lexical bias introduced by keywords such as "bombing" and "victim". This findings align with existing literature suggesting that negative sentiments tend to spread more widely and persist longer on social media than positive ones (Chu *et al*., 2024). Recognizing the predominance of neutral sentiment is essential for interpreting public mood accurately and for designing communication strategies that are responsive to both emotional and informational needs during crises.

Despite the insightful findings, the study has limitations. The timeframe of the datasets differs, making direct comparisons challenging. Future research could focus on a more extended temporal analysis to understand the long-term evolution of public sentiment and behavior. Additionally, exploring the impact of social media algorithms on information dissemination during disasters could provide further insights into managing misinformation.

These findings demonstrate the utility and complexity of social media use during disasters and their significant impact on public behavior. Ensuring the accuracy and reliability of information is crucial for effective disaster management. By understanding the dynamics of social media communication, authorities can better manage public discourse and enhance community resilience during future crises.

4. Conclusions

Social media like Twitter are a very useful channel of communication during sensitive times, such as natural and manmade disasters, because of their wide reach, speed, and easy accessibility. This study aimed to analyze the content shared on social media during some of the disaster management phases following the Manchester arena bombing through the use of semantic approaches.

The results of the semantic analysis allowed the identification of discussion topics in Twitter, in the different phases of the disaster, during the response (first week) and the recovery phase (one month after the attack). The most recurrent topics of discussion claimed "Condemnation and Justice" of the attack and "Emotional expressions" in solidary with the victims. Moreover, the results demonstrated the usability of social media for gathering information about the disaster (type, location, etc.) "Disaster description", or missing people and casualties "Help seeking and offering".

The temporal analysis results show that disasters like the Manchester Arena bombing attract enormous public attention at the moment they occur, which then decreases significantly shortly after. Moreover, the temporal variability of publications implies a significant difference in the Twitter debate during the disaster phase and the recovery phase. The results also show that online discussions were mainly dominated by negative sentiments.

These findings highlight the importance of social media as a tool for disaster management. Authorities can use social media data to monitor public sentiment, gather real-time information, and communicate effectively with the public during crises. Social media platforms can also play a crucial role in disseminating accurate information and debunking misinformation.

Future research could focus on more extended temporal analyses to understand the long-term evolution of public sentiment and behavior. Studies could also explore the impact of social media algorithms on information dissemination during disasters and investigate the role of different social media platforms in various types of disaster events.

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.

Acknowledgments

This research was supported by funding from the Horizon 2020 CORE project (sCience & Human factOr for Resilient sociEty). Additionally, the authors gratefully acknowledge the open access funding provided by the International Institute for Applied Systems Analysis (IIASA) in Laxenburg, Austria.

Authors' individual contributions

These authors contributed to this work: LAC, AED, and NK.

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Declaration of interests

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☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: