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

Abstract:

The behavior and sentiment of individuals in online environments have become increasingly reactive to disaster events. Monitoring and analyzing these behaviors and sentiments in the context of manmade disasters provide valuable insights for crisis management professionals. These analytical processes facilitate a comprehensive understanding of the evolving situation, support the development of effective response strategies, and contribute to maintaining societal stability. Employing appropriate methodologies and tools enables the capture and tracking of the 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 or positive sentiments during the recovery phase.

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

1. Introduction

Social media has revolutionized how information is shared and consumed, becoming an essential part of our everyday lives. 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 turns users into senders 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 lead to echo chambers and information bubbles where misinformation spreads without 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 both 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). Analysing 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) which includes topic extraction (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 background for this work, 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 textual data on social media, allowing for the analysis of texts to uncover potentially useful, interesting, or meaningful knowledge (Ngamassi, Shahriari, Ramakrishnan, & Rahman, 2022) (Yan, Ma, Wu, & Fan, 2022). In the case of disasters, text data are analysed to deduce the most recurrent topics that are published and shared on social media.

Semantic analysis is the process of automatically extracting, processing and understanding textual data to obtain 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. By doing so, patterns in public emotion can be detected, highlighting the concerns and priorities of affected communities, and identify potential risks and vulnerabilities.

In order to analyse the reaction of population regarding the terrorist attack in Manchester, the text published and shared on social media, specifically on Twitter, will be explored through the open-access source machine learning, data mining and visualization software Orange Data Mining (Demsar, et al., 2013). These semantic approaches allow for the investigation of the progression of public reactions and insights from Tweets following the Manchester bombing. The analysis aims to shed light on the dynamics of social media communication in the aftermath of the attack.

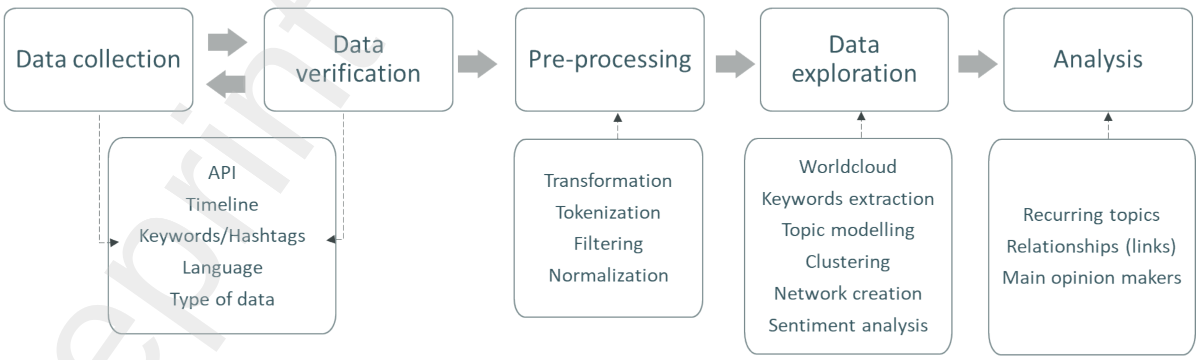

Figure 1- Semantic analysis methodology of Tweets

2.1. Data set

The data collection focused on Tweets posted regarding 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”. Two samples of tweets were analysed based on the timeline of the disaster: i) the response phase from authorities and population (first week from the attack), and ii) the recovery phase (after the first week of the attack). The details of the timeline are detailed 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 re-tweets in English during the response phase to the attack. This led to collect a database of 148,615 tweets and retweets. On the other hand, the second dataset includes the tweets and quote-tweets posted during the recovery phase starting from May 28. Quote tweets are the 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 quota-tweets.

2.2. Semantic analysis

To explore the data and draw a meaning from Tweets, a text transformation and structuring process was carried out to remove unnecessary text components and extract meaningful words. 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 main topics in public debate following the attack and the emotions associated to 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 serves to get an insight of the text analysed, helping to determinate its relevance to the research of the study (Kabir, Karim, Newaz, & Hossain, 2018). Additionally, it allows to gain first insight of trends in the debate, with words of higher frequency appearing bigger in the representation.
- *Hierarchical clustering*: This method visually represents groups of words associated with a topic in the database through a dendrogram, produced by hierarchical clustering algorithm. This algorithm creates a hierarchical series of nested clusters linked between them (Halkidi, 2009).
- *Corpus to network*: The visual representation of different topics and the strength of their relationships were explored through a semantic network, composed of nodes, edges and clusters. Networks model semantic relationships, represented in a graph with labelled nodes and edges (Drieger, 2013). Nodes represent words, edges represent the links or co-occurrence between words, and clusters represent different sets of nodes related to a topic.
- *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. The VADER model score ranges from -1 (negative) to 1 (positive), which scores closer to + 1 indicating higher positivity.
- *Tweet profiler*: According to (Liu, Zhang, & Zhang, 2020), during manmade disasters the role of social media for risk communication is mainly the dissemination of the information and the communication of emotions. In this context, emotions associated to each tweet were deeper analysed using the emotion classification of POMS (Profile of Mood States), which scores emotions of tweets in six categories: depression, anger, fatigue, confusion, tension, and vigour.

The timeline of publication of tweets was also studied as well as stakeholders and opinion makers in the Twitter debate. The later included the user that posted more tweets during the timeframe of analysis.

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.

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

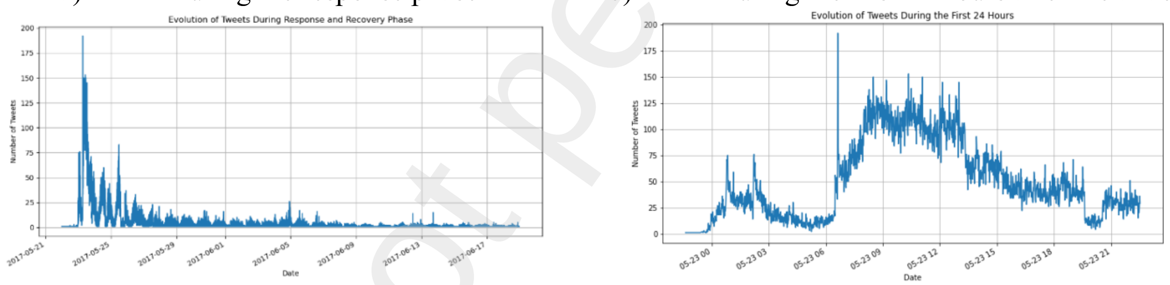

Figure 2. a) Trend of Tweets posted during following the attack and b) during the first 24 hours.

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 were 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 a 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 (**Error! Reference source not found.**). These wordclouds revealed that during both disaster phases, "victim" was the most used word (**Error! Reference source not found.**), 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 worldcloud of the response phase (**Error! Reference source not found.**.a) includes more terms referring to the victims, such as thought, people, family, love, heart, prayer, etc. Additionally, the number of dead victims (22) is prominently mentioned. During the recovery phase (**Error! Reference source not found.**.b), additional details of the disaster commented on by Twitter users can be observed, such as the name of the attacker Salman Abedi, the prime minister at the time, Theresa May, and Ariana Grande, who visited injured fans at the hospital and organized a tribute concert in Manchester for the victims, with all proceeds from the show going toward the “We Love Manchester Emergency Fund”. These details also stand out in the wordcloud. Additionally, after the attack, the Manchester worker bee symbol 🐝, representing Mancunians' hard work during the Industrial Revolution and symbolizing the sense of unity (Manchester City Council, n.d), was widely shared on posts as a representation of hope and 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.

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.

During both periods, emotional expressions and condemnation and justice-related tweets are prominent. Nevertheless, during the response phase, informative messages are largely posted. These messages include emergency alerts and warnings, data about missing friends or relatives, and actions to undertake provided by emergency agencies. On the other hand, during the recovery phase, condemnation and justice messages are more frequently shared. Emotional expression messages go viral during this phase, especially after the number of victims is confirmed, leading to the creation of several tributes to support and offer condolences to the victims.

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.

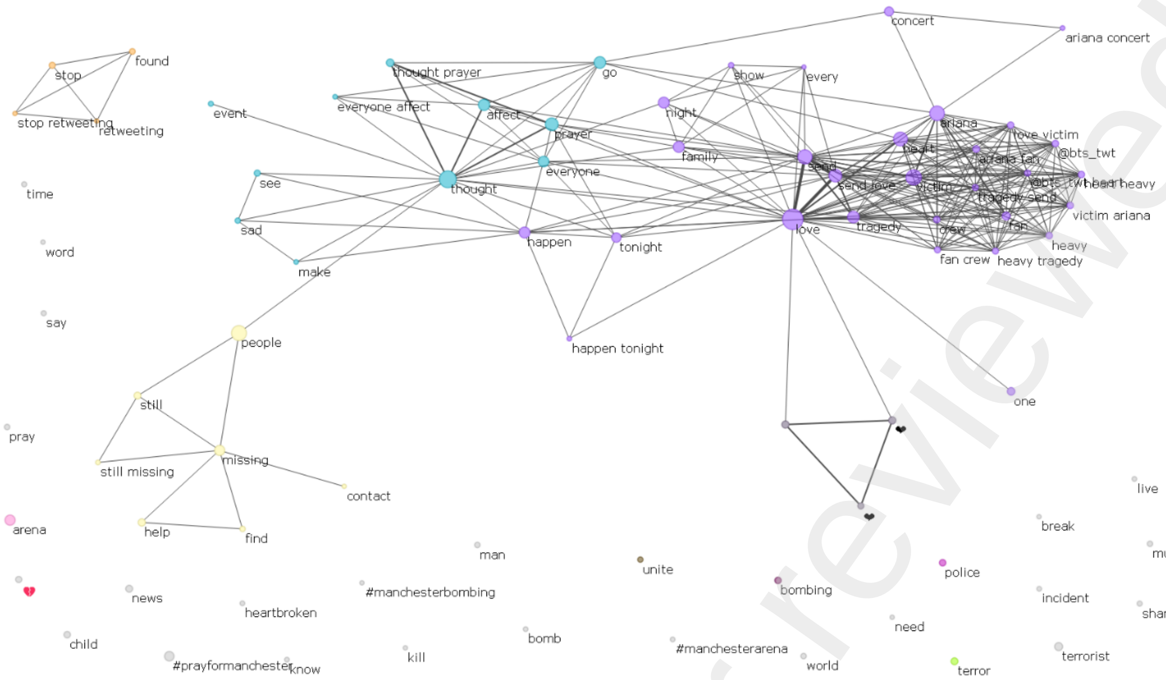

Figure 4. Network of topics in Twitter database during first week after the attack (during the disaster phase)

The cluster *Disaster and victims* (in purple) include words that describe the disaster like "Ariana", "show", "victim", "fan crew", "family", "concert", "tragedy", "tonight", etc. This cluster also stands out at the center of the map, because of a large number of connections, the support towards the victims as there are some terms like "love", "send", "heart". 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 the 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.

The 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.

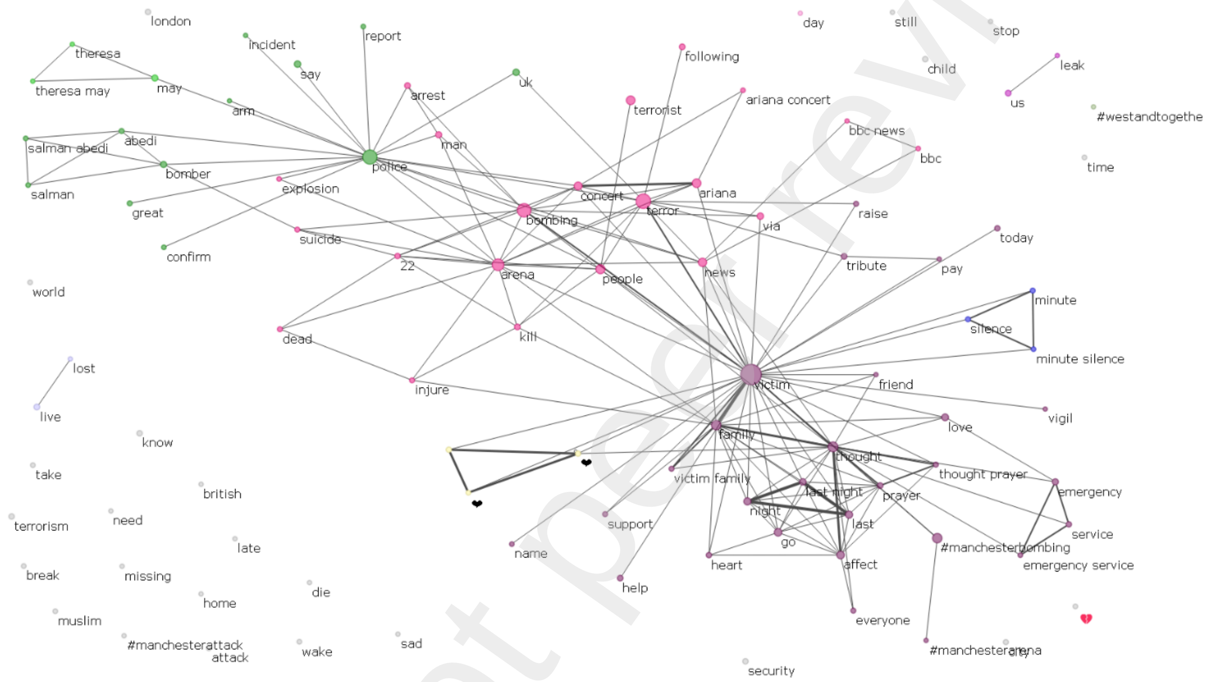

Figure 5. Network of topics in Twitter database during and recovery).

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 worlds 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.

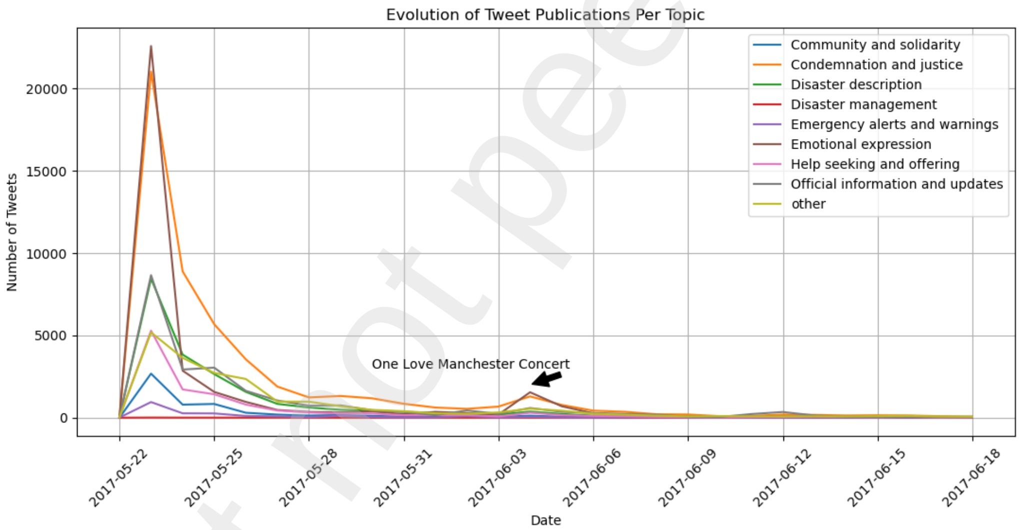

Figure 6. Twitter activity fluctuation per topics after the attack.

In the figure, it is possible to observe all topics peak shortly between May 23, and then decline at varying rates. There is a notable event indicating a spike of in tweet activity with *Emotional expressions* and *Condemnation and justice* messages, due to "One Love Manchester Concert" that aimed to raise funds for the victims and their families, with proceeds going to the We Love Manchester Emergency Fund. It was broadcast live on various platforms and watched by millions worldwide.

3.3. Sentiment Analysis

The emotion of expressed by Twitter' users was evaluated through Vader algorithm. The results indicated an overall negative sentiment with a compound score of -0.357 and -0.274, during the response and recovery phase, respectively. There is a slight increase in positive sentiment during the recovery phase, suggesting a gradual improvement in public mood. Nevertheless, this suggests the sentiment remains negative during the recovery phase.

Table 3. Sentiment analysis of Tweets posted after the Manchester Arena Bombing.

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

The bar chart comparing positive, negative, and compound sentiment scores clearly illustrates the changes in sentiment between the response and recovery phases. There is a slight increase of positive message from response to recovery, but still negative. This suggests the Attack had a significant emotional impact on the public. However, the improvement in sentiment during the recovery phase indicates a gradual return to a more neutral or positive state.

Figure 7. Average 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 the debate in social media varied along the disaster phases. There were more negative words in the database of the response phase (immediately affect the attack). This could be mostly associated with the shocking emotion of the disaster by the public as this involves children's victims. The overall sentiment remains negative during the recovery phase, as there are more clarity of the facts and the human and material losses of the attack, and the performance and failures of first responders (e.g., police) and public organizations (e.g., Prime Minister). The results align with current literature suggesting that negative sentiments are more likely to spread on social media and persist longer than are messages with positive sentiments, as people often express negative emotions online to alleviate their mood in the face of a disaster (Chu *et al*., 2024). The higher the number of messages with negative emotions, the longer the duration of emotional contagion. Additionally, this negative emotion might be due to a deeper knowledge of the attack and its consequences, leading to associating the disaster with negative emotions. Understanding sentiment trends on social media can help in tailoring communication strategies to address public concerns more effectively during different phases of an event.

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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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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