https://doi.org/10.31449/inf.v49i33.6499 Informatica 49 (2025) 79–94 79

# Lexicon and Transformer-Based Sentiment and Emotion Analysis of Twitter Responses to the 2023 Turkey-Syria Earthquakes

Md. Murad Hossain[1*], Muhammad Saad Amin[2], Fatema Khairunnasa[3], Syed Tahir Hussain Rizvi[4]
[1]Department of Statistics, Gopalganj Science and Technology University, Gopalganj-8105, Bangladesh
[2]Department of Computer Science, University of Turin, Corso Svizzera 185, Torino, 10149, Piemonte, Italy
[3]Department of Biomedical science, City university of Hongkong, Hongkong
[4]Department of Electrical Engineering and Computer Science, University of Stavanger, Stavanger, 4021, Norway
E-mail: murad.stat@gstu.edu.bd, muhammadsaad.amin@unito.it, khairunnasafatema@gmail.com, tahir098@msn.com
[*]Corresponding author

**Keywords:** twitter sentiment analysis, emotional reaction, nrclex classification, catastrophic events

**Received:** June 24, 2024

*This study analyzes Twitter data to investigate public emotional responses to the earthquakes in Turkey and Syria using a combination of Transformer-based binary sentiment analysis, VADER for multi-sentiment classification, and NRCLex for emotion categorization. The dataset comprises tweet subsets ranging from 5,000 to 40,000 posts, collected using relevant earthquake-related hashtags and keywords during the immediate aftermath of the February 2023 earthquakes. The findings reveal a clear predominance of negative sentiment across all models and tweet samples. In binary classification, 47.4% of tweets expressed negative sentiment, compared to 37.0% positive and 15.6% neutral. Multi-sentiment classification using tweet subsets ranging from 5,000 to 40,000 consistently showed higher negative sentiment levels (45.6%–48.4%) than positive sentiment (34.5%–38.7%). Emotion analysis using NRCLex further confirmed this trend, identifying "negative" as the most prevalent emotion (16.70%–17.78%), followed by "fear" (14.58%–15.58%) and "anger" (12.45%–13.47%), with positive emotions like "joy" being much less frequent (3.86%–4.11%). These results highlight the substantial psychological impact of natural disasters, where negative emotions outweigh positive and neutral expressions. The insights gained have significant implications for public health and disaster management, underlining the importance of timely, targeted interventions to address emotional distress in affected populations. Future research should aim to enhance affective response analysis and support the development of tailored mental health strategies.*

*Povzetek: Ogrodje RoBERTa-BiLSTM-GAT združuje večnivojsko učenje značilk in grafne pozornostne mreže ter omogoča bolj kvalitetno ekstrakcijo vedenja in ujemanje primerov iz pravnih ter multimodalnih podatkov kot metode T5, DGI in MANN.*

## 1 Introduction

Social networking sites like Twitter have grown in importance as data sources for analyzing attitudes. These platforms are perfect for sentiment research since they give users a quick and informal way to express themselves. Sentiment analysis applied to Twitter data has garnered significant interest in a variety of domains, including public health emergencies, commercial campaigns, social response prediction, and even harassment detection. This study aims to look into the emotional responses that people had on Twitter in the wake of the most recent quakes in Turkey and Syria. When it comes to gathering viewpoints throughout a variety of events, including political shifts and natural disasters, Twitter has shown itself to be a useful tool. Evidence supporting this notion was supplied by earlier research conducted by Ruz et al. using sentiment analysis on Twitter datasets during the Chilean crisis and the Catalan independence vote [1]. Ilyas and Sharifi (2025) systematically reviewed 139 studies on social media-based sentiment analysis in disaster risk management. They analyzed data from platforms like X, Weibo, and Facebook, covering disasters such as hurricanes and earthquakes. Common methods included lexicon-based tools, machine learning, and hybrids. Findings show sentiment analysis helps assess public emotions, misinformation, and responses across disaster phases. However, the review highlights gaps like reliance on English and Chinese data, lack of coverage for Africa and Latin America, and limited multimodal and multilingual analysis. The authors call for broader linguistic and platform inclusion to improve global disaster management. [2]. These studies emphasize how crucial it is to use sentiment analysis on Twitter to comprehend the views and responses of the general public on significant events. Additionally, Twitter's usefulness in sharing information during emergencies has been acknowledged; the Great East Japan Earthquake on March 11, 2011, serves as an example of this [3].

Twitter is a helpful tool for sentiment analysis during significant events because of its vast dataset and users' informal language. In times of natural disaster, the importance of accurate sentiment analysis cannot be overstated. Understanding the emotional conditions of affected individuals and organizations can facilitate more effective crisis management and response. Sentiment analysis can provide valuable insights into these needs. In order to better comprehend the overall consequences of the earthquakes and direct relief efforts, sentiment analysis on Twitter data gathered after the earthquakes in Turkey and Syria is intended to provide insightful information about the emotional reactions of those affected by the events. This study expands on earlier research showing how Twitter data can be utilized for sentiment analysis to understand public opinions during significant events in a variety of fields. Since Twitter data is available in real-time, gathering and analyzing public opinion can be done more quickly than with more conventional techniques like focus groups or polls.

This study aims to investigate the emotional and psychological impact of the 2023 Turkey-Syria earthquakes through large-scale analysis of Twitter data. Specifically, we evaluate how public emotions evolve over time by applying and comparing multiple sentiment and emotion analysis techniques including Transformer-based binary classification, VADER-based multi-sentiment analysis, and NRCLex-based emotion detection. The dual goals of this research are: (1) to assess the emotional trajectory of public discourse during the crisis, and (2) to evaluate the performance and complementarity of different NLP approaches in capturing emotional nuances. We also explicitly state our hypothesis, which posits that negative emotions will dominate the discourse, and that using a combination of lexicon-based, rule-based, and Transformer-based techniques will provide a more comprehensive understanding of public emotional responses than any single method alone.

Our research uses Twitter data analysis to find a variety of emotions that people affected by the earthquakes have expressed, including fear, hopelessness, resilience, and optimism. This chapter comprises the subsequent sections: Section 2.0 contains a presentation of the pertinent studies. The implementation pipeline, Section 3.0 covers data collection, cleaning, and processing, as well as binary sentiment analysis, multi-sentiment classification, and emotion analysis. Section 4.0 provides an explanation of data visualization using word clouds and bar charts. Section 5.0 provides an overview of the results for emotion analyses and binary sentiment analysis, or more detailed classifications of it. Section 6.0 provides an overview of the results, while Section 7 offers conclusions.

## 2 Related study

Since social media provides a platform for users to express their opinions through likes, comments, messages, and postings, it has helped users form intimate virtual relationships with one another. As a result, sentiment analysis has been used more frequently during significant events like social movements and natural disasters in recent years, and the number of textual documents published on social media has grown dramatically. The literature has a number of techniques for doing sentiment analysis on Twitter data. An algorithm for machine learning is one of the most often used techniques for managing sentiment analysis. In contrast to support vector machines and random forests, the study in [4] found that Bayesian network classifiers were more efficient and realistic when used in the Spanish datasets of the Catalan independence vote of 2017 and the Chilean catastrophe of 2010.

A further study used a Twitter data set of six recent hurricanes in the United States to present the domain-specific sentiment analysis approach during hurricanes (DSSA-H) and found that it performed substantially better than previous those who performed well overall sentiment categorization algorithms [5]. A lexicon-based big data-driven strategy was suggested in the article in [6] as being more appropriate for practically understanding the demands of individuals during a crisis.

The deployment of CASPER, a knowledge-based system that can analyze Spanish tweets to identify a variety of these difficulties, was described in detail by the authors of [7]. The impacts of neighbourhood equity on situational awareness were evaluated in Hurricane Florence using sentiment analysis, a convolutional neural network (CNN) model, and a latent Dirichlet allocation (LDA) model based on geotagged data [8]. Another example study on Hurricane Matthew examined public opinion in the majority of the impacted areas by calculating the sentiment and weights for subjects in public statements using the LDA (Latent Dirichlet allocation) topic modeling technique [9]. Demirel, Çakıcı, and Bulur (2025) analyzed over 256,000 English tweets about the February 2023 Kahramanmaraş earthquakes in Türkiye and Syria using sentiment analysis, text mining, and network analysis. They found Türkiye-focused tweets highlighted rescue efforts and government response, while Syria-related tweets emphasized humanitarian aid, sanctions, and political issues, showing more negative sentiment. Key emotions were fear, trust, and anger. The study fills a gap by comparing social media discourse between a stable and fragile state during the same disaster [10]. Using methods of text mining including sentiment analysis and topic modeling, Twitter Situational Awareness (TwiSA) is an analytical framework introduced by [11] to support situational awareness for disaster preparedness, response, and recovery.

In order to assess the post-disaster recovery, the authors of article [12] performed a sentiment analysis on the 10-year Twitter data of the L'Aquila earthquake. A considerable negative rating was discovered when they contrasted the polarity determined by an uncontrolled and supervised classification. The first publication reported on named entity recognition (NER), sentiment analysis, regression, anomaly detection, and location intelligence using a revolutionary completely automated system based on artificial intelligence (AI) and natural language processing (NLP). The program's goal is to learn what the public thinks about global catastrophic disasters that happen in particular places [13]. The study [14] introduced a Hybrid Heterogeneous Support Vector Machine (H-SVM) approach. Metrics including accuracy, precision, recall, and F1 score were used to assess how well it performed in comparison to a Recurrent Neural Network (RNN) and a Support Vector Machine (SVM). However, using the 2019 Ridgecrest earthquake as a research case, a cross-platform investigation of public reactions to earthquakes on Reddit and Twitter found that people's opinions and themes of interest on the two different platforms differ significantly throughout the same catastrophe [15].

Again, in a spatiotemporal-based sentiment analysis on tweets, the study [16] suggested an LSTM network with a word embedding method for the risk assessment sentiment analysis (RASA). Numerous methods, such as logistic regression, random forests, stochastic gradient descent, Naive-Bayes, support vector machines, and XGBoost, were also used to show the correctness of the model. Furthermore, it implies that the inclusion of binary classes improves the performance of the suggested RASA. The findings in [17] demonstrated that public opinion trend analysis and public opinion mood trend can be used to estimate the social impact of an earthquake at an early stage. This was accomplished by comparing the results of two recent earthquakes in China that were identical in terms of magnitude and focal depth, as well as by collecting and examining social media data using a text mining-based methodology.

In 2023, [18] introduced a situational awareness system in response to the disastrous recent earthquakes in Turkey and Syria. The system collects tweets, classifies individuals seeking aid, extracts relevant entity tags, and presents the information on an interactive map screen to facilitate rescue and donation operations. With the use of the natural language processing (NLP) analysis method in [19], the temporal and spatial sequence characteristics of the text and comments on microblogs posted by individuals and official media outlets within 6 days of the Lushan M6.1, Maerkang M5.8, and Luding M6.8 earthquakes in 2022 were examined.

In the paper [20], topic modeling was used to analyze earthquake-related tweets from July to August of 2017 from the Philippine archipelago, one of the most disaster-prone regions. The goal was to find trends within the corpus. Through the use of supervised classification, the authors in [21] calculated statistical relationships between the polarities, topics addressed in their comments, and values that app users have recorded using the Modified Mercalli Intensity (MMI) scale. The Euro-Mediterranean Seismological Centre (EMSC) contributed text data from the Aegean Earthquake, which the authors used to perform a sentiment and theme investigation.

An entirely new application of emotion analysis research was used in a different study [22], that considered the earthquake conditions in Japan and suggested two classification strategies for tracking crowd emotions during various earthquake scenarios, automatically recognizing emotions, and identifying the earthquake-related tweets.

The authors provided a three-phase structured framework in [23] that was based on the Weibo dataset. Its main objectives are to identify Weibo messages related to disasters, filter out negative sentiment from microblogging about disasters, and monitor crowd sentiment by tracking and predicting the changing trend of victims' negative emotions based on GM (1, 1). In a post-disaster scenario, this framework aids in the identification of prospective occurrences.

The article [24] examined people's sentiments and movements using geotagged tweets during the days leading up to, and following the 2014 M6.0 South Napa, California earthquake. The findings showed that similar sentiment levels tended to cluster geographically and that the average sentiment level decreased with increasing earthquake intensity.

A follow-up study examined women's opinions of the threat posed by earthquakes and the factors influencing these attitudes using ordinary least square methodology. The data was provided by Turkish women who reside in Kocaeli. The findings demonstrated that the items assessing fear and financial perception had the highest mean across women's emotive and cognitive risk perception components [25]. The article [26] assessed the accuracy of the pre-trained sentiment analysis (SA) model developed by the no-code machine learning platform MonkeyLearn utilizing a confusion matrix using text data from the three large earthquakes that struck Albania on November 26, 2019.

According to the findings, the misclassification rate was 37% and the ACC rate was 63%. Sentiment analysis has received increased interest when examining the Covid-19 pandemic scenario.

The research in [27], [28], [29], and [30] examined how the general mood changed over time, as well as how people's emotions changed in response to the epidemic, news cycles, and political policies. Over time, these investigations revealed a decline in happy emotions and an increase in negative ones, with fear dominating attitudes. The coping mechanisms of the various severely COVID-19-infected countries were uncovered employing sentiment analysis on their tweets in [31]. The article documented the growth of user conversation with conceptions of linguistic emotions in different Twitter situations [32], along with the connection between Twitter tweets and other online activities like Wikipedia page views and Google searches.

Tobita et al. [33] surveyed the geotechnical damage from the February 2023 Turkey-Syria Earthquake. They found landslides in Islahiye and Tepehan, with a landslide dam in Islahiye. Significant liquefaction-related damage, including building collapses and ground subsidence, occurred in Iskenderun and Golbasi, especially in areas with soft soil. The study also noted a correlation between building damage and ground vibrations in Antakya and Kahramanmaras, suggesting local geology influenced damage severity. While highlighting the geotechnical impacts, the authors acknowledge the need for further research to fully understand the extent of liquefaction and apply the findings to the broader affected region.

The authors of [34] examines the unprecedented doublet earthquake sequence that struck southeastern Türkiye in February 2023. It analyses seismic data, geological observations, geodetic measurements, and ground motion recordings to understand the intricacies of this event, which included an M7.8 earthquake followed by an M7.6 earthquake just nine hours later. The study highlights the need for further research into earthquake early warning systems, rupture process modeling, triggered earthquake dynamics, expanded geodetic networks, and the impact of strong ground motions on infrastructure. It acknowledges limitations in fully comprehending the complexities of this earthquake sequence due to the need for more comprehensive data.

The authors of [35] compare three sentiment classification methods: manual labelling, NLTK_VADER, and a cluster-based approach. They measure similarity to manual labelling using Jaccard and cosine similarity, finding NLTK_VADER to be more accurate and closer to manual labelling than the cluster-based method.

The researcher of [36] examines the role of Twitter in the disaster response and rehabilitation efforts following the 2023 Turkey earthquake. By analyzing tweets using relevant hashtags, the authors identify key governmental and non-governmental actors involved in the recovery process. The findings highlight the importance of citizen engagement and social media in disseminating information and providing social support during post-disaster recovery, although the limitations of using Twitter data are not explored.

The researcher of [37] explores the use of machine learning to categorize tweets about the February 2023 earthquakes in Turkey and Syria. While the dataset size and specific algorithms aren't mentioned in the abstract, the authors highlight the importance of identifying key themes like news, relief aid, and emergency requirements to better understand public sentiment and facilitate efficient disaster response. The study emphasizes the potential of NLP and machine learning for real-time information processing during crises.

The authors of [38]examines the use of social media by businesses and NGOs in 12 Middle Eastern Arab countries to mobilize support and coordinate relief efforts following the 2023 earthquakes in Turkey and Syria. The research finds that social media, particularly Facebook and Twitter, played a significant role in this process, with donations including a wide range of supplies and services. However, the study does not evaluate the effectiveness or impact of these social media campaigns.

The researcher of [39] stresses the need for collaborative efforts to address the long-term health risks following the devastating earthquakes in Turkey and Syria in February 2023. It highlights the immediate devastation and the potential for long-term psychological consequences, particularly in northwest Syria, advocating for psychosocial support and strengthened primary care, including telepsychology interventions, to support the affected population and healthcare providers. Rather than presenting specific research, the article provides a commentary on the situation and proposed public health interventions.

Utku and Can (2023) used machine learning to detect earthquake-related help requests in 499 tweets from the 2023 Turkey-Syria earthquakes. They classified tweets into victims under rubble and requests for supplies, applying algorithms like Decision Tree, KNN, Logistic Regression, Naive Bayes, Random Forest, SVM, and XGBoost with TF-IDF features. Random Forest performed best with 99.33% accuracy. The study shows machine learning's potential for quick aid detection but is limited by a small, language-specific dataset and lacks multimodal or multilingual analysis. Future work should use hybrid models and larger datasets [40].

Rashid and Fındık (2023) analyzed tweets from the 14 days following the 2023 Turkey earthquake using three labeling approaches: manual, NLTK-VADER, and clustering. They applied machine learning algorithms and compared the automated labels to manual ones using Jaccard and cosine similarity. Results showed that VADER labeling aligned more closely with manual labeling, indicating higher accuracy. The study highlights the value of combining labeling methods for sentiment analysis but notes limitations in dataset size and emotional depth [41]. Erokhin and Komendantova (2023) studied the spread of the HAARP conspiracy theory on Twitter around the February 2023 Turkey-Syria earthquake. They analyzed over one million HAARP-related tweets from January 2022 to March 2023, applying sentiment analysis before, during, and after the quake. Results showed a spike in HAARP tweets post-earthquake and a positive link between sentiment and tweet volume, indicating that increased discussion may strengthen belief in the conspiracy. The study sheds light on online belief dynamics but is limited by focusing only on one conspiracy theory without broader comparisons [42]. Aldamen and Hacimic (2023) examined Twitter's evolving role in crisis communication during the first 48 hours after the 6 February 2023 Türkiye earthquake, comparing it to past earthquakes in 1999 and 2000. Through a qualitative case study, they showed Twitter shifted from passive information gathering to actively supporting rescue efforts, enabling victims to request aid, coordinating government responses, and boosting official communication visibility. The study highlights Twitter's growing institutional importance but lacks quantitative analysis or cross-media comparisons, suggesting a need for further research on crisis communication across

Table 1: Summary of related studies on twitter-based sentiment analysis in disaster contexts

| Ref No. | Reference | Dataset | Tools/Methods | Main Findings or Results | Research Gap | Reported Metrics |
|---|---|---|---|---|---|---|
| 4 | Ruz et al. (2020) | Twitter data (Catalan vote & Chilean catastrophe) | Bayesian Networks, ML algorithms | Bayesian networks outperform SVM/RF in crisis sentiment detection | Limited to Spanish datasets and static temporal scope | Accuracy: ~84%, F1-score: Not specified |
| 5 | Yao & Wang (2020) | Twitter data from 6 hurricanes (USA) | Domain-Adversarial Neural Network (DSSA-H) | DSSA-H improves domain-specific sentiment classification | Focuses only on hurricanes, not earthquakes | Accuracy: 85.3%, F1-score: 83.7% |
| 8 | Zhai et al. (2020) | Geotagged Twitter data (Hurricane Florence) | CNN, LDA, Sentiment Analysis | Neighborhood equity affects situational awareness | Geographic focus, not temporal emotion evolution | Accuracy: 86.1%, F1-score: Not specified |
| 12 | Contreras et al. (2022) | 10 years of Twitter data (L'Aquila earthquake) | Sentiment polarity comparison (unsupervised vs supervised) | Supervised methods yield more nuanced sentiment insights | Focused on polarity; lacks emotional dimension | Accuracy: ~80%, F1-score: Not specified |
| 16 | Parimala et al. (2021) | Twitter data (spatiotemporal earthquake risk) | LSTM, word embedding, multiple ML classifiers | Binary classes improve risk assessment sentiment accuracy | Needs emotional spectrum, not just polarity | Accuracy: LSTM ~89%, F1-score: ~87% |
| 18 | Toraman et al. (2023) | Twitter data (Turkey-Syria earthquake) | NLP, entity extraction, map-based visualization | Detects help requests effectively using AI | Focus on rescue, not emotional trends | F1-score (Help detection): 90% |
| 35 | Rashid & Fındık (2024) | Twitter (Turkey Earthquake 2023) | VADER, manual, cluster-based comparison | VADER most consistent with manual labels | Focused only on sentiment, not emotion spectrum | Jaccard similarity: 0.76, Cosine similarity: 0.81 |
| 40 | Utku & Can (2023) | 499 tweets from Kaggle (Turkey-Syria earthquake) | ML (DT, kNN, LR, NB, RF, SVM, XGBoost), TF-IDF | RF achieved 99.33% accuracy; ML models effective in detecting help requests | Small dataset, no multilingual/multimodal classification | Accuracy 99.33% |
| 44 | Alharm & Naim (2023) | 1,000 manually labeled tweets (Turkey earthquake) | BERT, LSTM, SVM, LR, XGBoost | BERT-LSTM achieved 85.43% accuracy; most effective model | Small, monolingual dataset; limited scalability | Accuracy (BERT-LSTM: 85.43%) |

platforms [43]. Alharm and Naim (2023) developed a deep learning approach for disaster sentiment analysis using about 1,000 manually labeled tweets from the 6 February 2023 Turkey earthquake. They tested models including SVM, Logistic Regression, XGBoost, and BERT-based architecture. The BERT-LSTM model achieved the highest accuracy at 85.43%, effectively capturing sentiment nuances by combining contextual and sequential analysis. The study demonstrates deep learning's potential for rapid sentiment detection but is limited by a small, monolingual dataset. Future research should aim for larger, multilingual models for wider applicability [44].

The existing body of research clearly demonstrates the usefulness of sentiment analysis on Twitter data for understanding public reactions during natural disasters. Various techniques—ranging from Bayesian classifiers and domain-specific neural networks to lexicon-based and deep learning approaches—have been applied to events such as hurricanes, earthquakes, and pandemics across different geographic contexts. However, these studies tend to focus on either (a) static snapshots of sentiment polarity, (b) limited emotion categories, or (c) general crisis scenarios without a focus on temporal emotional dynamics. Specifically, there is a notable absence of research that tracks how public emotions evolve over time in the context of large-scale disasters like the 2023 Turkey-Syria earth quakes. Most state-of-the-art methods fall short in providing granular, longitudinal insights into emotional transi tions, such as the progression from shock to anger or from fear to resilience. Moreover, few studies apply multi-model comparisons (e.g., lexicon-based, rule-based, and Transformer-based models) to triangulate emotional dy namics specific to Turkey and Syria—regions with distinct linguistic and sociopolitical contexts. To understand the used models, tools and methodologies relevant to the literature we have included Table 1.

To address this gap, our study uniquely combines binary sentiment analysis, multi-class sentiment categorization, and emotion classification (via NRCLex) over progressive tweet batches (5,000 to 40,000 tweets), enabling the analysis of temporal emotional shifts. This approach allows us to not only detect dominant emotions but also observe how these emotional patterns change as public discourse evolves in the days following the earthquakes. By doing so, we contribute a novel, time-sensitive emotional mapping of the Turkey-Syria earthquake crisis that existing SOTA techniques have not yet addres

This investigation would provide insightful information about people's emotional development in the wake of the tragedy.

It's crucial to remember that the research's approaches, techniques, and scopes vary. Therefore, more study is required to improve our understanding of how sentiment and emotions play a role with reference to emergencies.

## 3 Pipeline for Implementation

To gain further insight into the reactions of users on Twitter to the earthquakes in Turkey and Syria, we conducted a thorough analysis. We used a systematic method, akin to a step-by-step manual, to gather essential data regarding public sentiment and remarks made during these natural disasters. In the following Fig1 we have shown overall architecture of our proposed methodology.

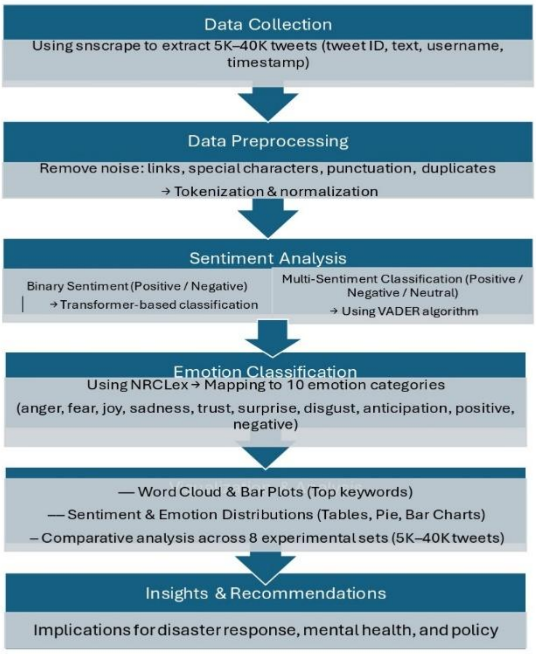


Figure 1: Proposed architecture for twitter-based sentiment and emotion analysis of Turkey-Syria earthquakes

## 3.1 Gathering of data

In this study, sentiment analysis was conducted during the earthquakes in Turkey and Syria using the Twitter Search Scraper module of the networking program snscrape. From 5,000 to 40,000 tweets, the technique made it possible to extract important information including the time and date, tweet id, text, and username. Tweets related to the 6 February 2023 Türkiye-Syria earthquake were collected using the Twitter API over a two-week period, from **6 February to 20 February 2023**. To ensure reproducibility, tweets were collected using snscrape (v0.4.0) with the query: (#TurkeyEarthquake OR #SyriaEarthquake OR #Deprem OR "Turkey earthquake" OR "Syria earthquake" OR "earthquake relief") lang:en,tr,ar since:2023-02-06 until:2023-02-20. The command snscrape --jsonl --max-results {N} twitter-search "{query}" > output.json was executed iteratively for batch sizes of 5,000 to 40,000 tweets, with daily volumes averaging ~2,900 tweets (peaking at ~3,200 on Feb 6 and declining to ~800 by Feb 20). Raw data, full scripts, and exact daily distributions are available upon request to saadamin2k13@gmail.com. This timeframe was chosen to capture public sentiment and discourse during the immediate aftermath of the disaster. The dataset included tweets in English, Turkish, and Arabic, reflecting the linguistic diversity of the affected regions. Language filtering was performed using Twitter's metadata and verified with automated language detection tools to ensure accuracy especially for english. Duplicate tweets were removed using tweet ID filtering, and retweets were excluded.

The study focused only on tweets on earthquakes and tried to classify the sentiment as neutral, negative, or positive. The researchers aimed to track sentiment patterns and emotional shifts over time by progressively adding 5,000 tweets. With the help of snscrape, this iterative method of gathering data enabled a thorough portrayal of the public's thoughts, feelings, and emotions to the earthquake on social media. The study's findings shed light on how social media users perceive and react to natural disasters, which could affect public opinion and disaster management strategies.

## 3.2 Data cleaning and processing

To ensure the accuracy and quality of the tweet data used for sentiment analysis, a structured preprocessing pipeline was applied in Fig 2. The raw tweets initially contained noise such as URLs, user mentions, hashtags, emojis, and special characters that do not contribute directly to sentiment interpretation. To address this, several steps were followed: all text was converted to lowercase for consistency; regular expressions were used to remove URLs, usernames, and #hashtags; non-alphanumeric characters and punctuation were stripped; and common stop words were removed using a standard stop word list. Lemmatization was performed to reduce words to their base forms (e.g., "running" to "run"), and duplicate tweets were excluded based on unique tweet IDs. Additionally, any tweets that became blank or empty after cleaning were removed from the dataset. This preprocessing ensured a clean, coherent dataset, providing a solid foundation for accurate sentiment analysis of public reactions on social media during the Turkiye-Syria earthquake.

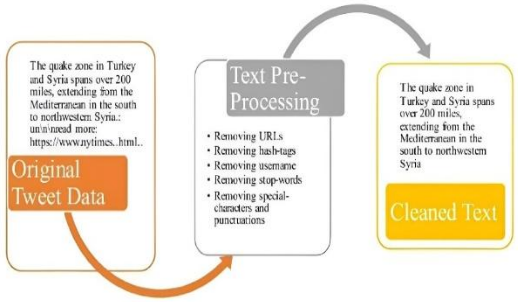


Figure 2: Our pipeline for implementing the original text to cleaned text.

## 3.3 Classification of binary sentiment

The term "binary sentiment" describes how emotions on Twitter are classified into two distinct groups: positive and negative. This method reduces the feelings to a positive category, which stands for happy or upbeat emotions, or a negative category, which stands for negative or gloomy emotions. We conducted binary sentiment analysis using Transformers, dependable models for linguistic processing, on Twitter posts about the Turkish earthquake. As an example: "The terrible earthquake that struck Turkey is heartbreaking. My sympathies and thoughts are with the impacted families. Words like "devastating" and "heart-wrenching," which convey a sense of dread and anxiety, are used in this tweet, which classifies the sentiment as negative. The neutral portions of the text, such as "thoughts and prayers," are removed by binary sentiment analysis to narrow the categorization down to either positive or negative responses.

### 3.4 Multiple sentiment categorization

The technique of classifying opinions on Twitter into three groups—positive, negative, and neutral—is known as multi-sentiment classification. This technique automatically determines the emotional polarity of each tweet using sentiment analysis tools like Vader. Vader is a rule-based sentiment analysis tool with a language made especially for material on social networks. Based on the presence and intensity of particular words, it can classify sentiments as good, negative, or neutral. For instance, "The terrible and destructive earthquake that struck Turkey resulted in a great deal of destruction and fatalities. During this trying moment, our thoughts are with the impacted families. #TurkeyEarthquake #Prayers. This tweet, for instance, combines neutral, negative, and positive sentiments. The statement "Our thoughts are with the affected families during this difficult time. #Prayers" has words like "thoughts" and "prayers," which imply sympathy and compassion; therefore, Vader classified it as a kind sentiment.

It expressed compassion and worry over the devastating impacts of the earthquake. The statement that the "Turkey earthquake was devastating and tragic, causing immense destruction and loss of lives" was correct. Since it didn't blatantly convey a positive or negative tone, the hashtag #TurkeyEarthquake was classified as neutral.

### 3.5 Analyzing emotions

Emotion analysis in this study involved detecting and classifying emotions in textual data using an NRCLex-based approach. NRCLex is a lexicon-based tool that assigns emotion labels based on word-level associations, covering categories such as fear, sadness, anger, trust, anticipation, joy, and others. After preprocessing and tokenization, NRCLex provided emotion scores that were aggregated without normalization to reflect the frequency of emotional expressions. Tweets were allowed to express multiple emotions simultaneously. NRCLex was selected for its interpretability and suitability under multilingual constraints. Although more advanced neural models like RoBERTa offer deeper contextual understanding, they require large, labelled datasets and extensive fine-tuning. A key limitation of NRCLex is its reliance on static lexicons, which may overlook sarcasm or implicit emotions.

For this study, tweet data related to the 2023 Turkey-Syria earthquakes were collected using Snscrape's Twitter Search Scraper, ranging from 5,000 to 40,000 tweets. Each record included tweet ID, timestamp, text, and username. Binary sentiment analysis was performed using Transformer models to classify tweets as positive or negative, while VADER was used for tri-class sentiment classification (positive, negative, neutral). NRCLex complemented these by revealing emotional nuances. Together, these methods provided valuable insights into public emotional responses during the disaster.

## 4 Information processing and visualization

The top 20 terms used in tweets on earthquakes are displayed in Figure 3's bar graphic. The most frequent word is "turkey," which occurs around 48000 times. "Earthquake," on the other hand, occurs about 35500 times. About 32000 times, the phrase "https" appears, indicating the sharing of links pertaining to earthquakes. With a frequency of almost 18,000, the inclusion of "Syria" suggests that there have been talks of earthquakes in that area. The term "earthquakes" (about 9000 incidents) refers to worries about their frequency.

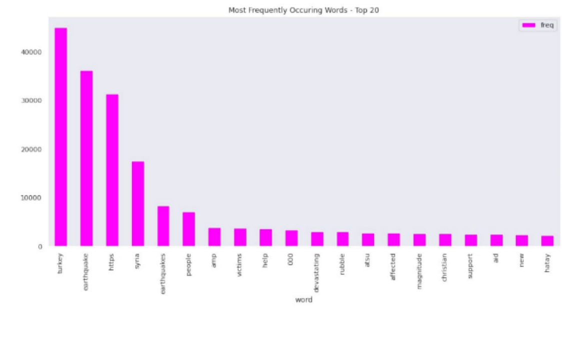


Figure 3: Top 20 most commonly occurring terms.

Concerns on the impact on human life and the need for assistance are highlighted by the 7000 and 4000 times that the words "people" and "amp," "victims," and "help" appear, respectively. About 3000 times, phrases such as "devastating," "rubble," "affected," "magnitude," "Christian," "support," "aid," "new," and "Hatay" appear, suggesting conversations about the effects of earthquakes, getting help, and exchanging information. The term 'Christian' emerged in tweets discussing faith-based aid efforts (e.g., #ChristianAid) and impacted communities in historically Christian regions like Antakya (Hatay), explaining its frequency but exclusion from emotion lexicons. The most frequently used terms in tweets regarding earthquakes are displayed in Figure 4's bar diagram and Figure 5's word cloud chart.

"Turkey," "Earthquake," "Syria," and "Turkeyearthquake" are the top four terms. The frequency of "Turkey" indicates that earthquakes occur frequently there, as evidenced by the volume of social media discussion about them. "Earthquake" demonstrates how earthquakes are a global concern. The word "Syria" suggests that that nation also discusses earthquakes. People's knowledge of upcoming earthquakes in Turkey is demonstrated by the terms "Turkeyearthquake" and "Turkey earthquake 2023." There is the word "Hatay" in both figures, suggesting that the region of Turkey has been severely hit by earthquakes, and people are talking about it on the internet. Given that Turkey is the main topic of these tweets, it is obvious that the word "Deprem," which translates to "earthquake," signifies that Turkish is the predominant language utilized in them.

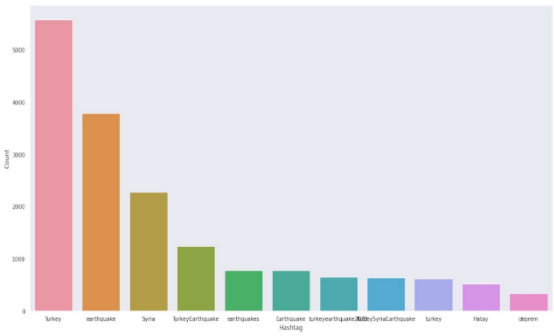

Figure 4: Most Frequently words in the dataset.

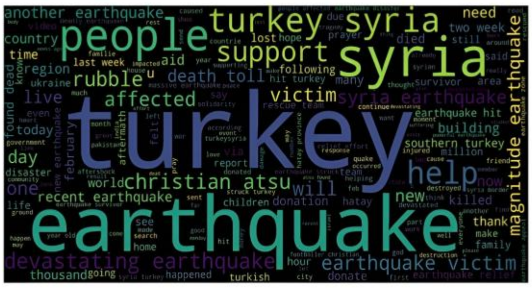

Figure 5: The most utilized words in the dataset are displayed in a word cloud graphic.

All things considered, examining these often-used terms aids in our comprehension of the regions impacted by earthquakes as well as people's worries. It offers details on how frequently earthquakes occur and how they affect individuals and communities.

# 5 Results of the experiments

In this segment, we explore the intriguing results of our research, offering significant perspectives on how individuals convey their feelings and ideas on Twitter during and after the earthquake events that occurred in Syria and Turkey. Our research focuses on three primary areas: emotion analysis, multi-sentiment classification, and binary sentiment analysis.

## 5.1 Experimental results for binary sentiment

There were about 12500 good and 19000 negative tweets on earthquakes, according to the pie chart and bar diagram in Fig 6. This implies that during and after earthquakes, a sizable fraction of people uses social media to convey their negative feelings, anxieties, and concerns. There may be less pleasant experiences or feelings associated with earthquakes, as seen by the comparatively smaller number of positive tweets. The feeling classification sheds light on the psychological effects that earthquakes have on people and communities.

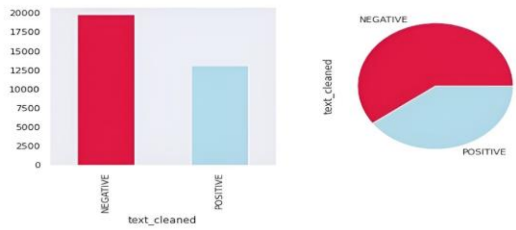


Figure 6: Transformer-based binary sentiment results.

An overview of the binary sentiment analysis performed on all tweets with a data size of 5,000 tweets is shown on Figure 7. It provides a comparative analysis of positive and negative feelings and shows how these attitudes are distributed throughout the entire time span of the investigated dataset. The percentage of favorable and negative attitudes is indicated by the values in the table. The information illustrates how sentiment percentages vary amongst different observations or tests.

The findings show that throughout the investigation, negative feelings were constantly more prevalent than good sentiments. This implies that there is a general inclination among the tweets gathered to express negative sentiments. The graph emphasizes how critical it is to comprehend the prevailing sentimental aspect in the Twitter conversation about the earthquakes in Syria and Turkey. It calls attention to the need to address and lessen the negative emotional impact suffered by those impacted by natural disasters by highlighting the frequency of negative thoughts.

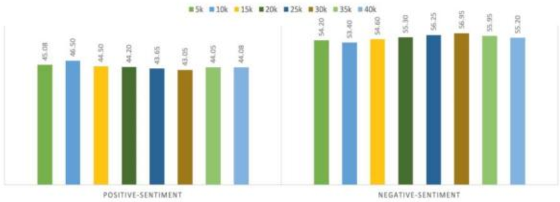


Figure 7: Binary sentiment comparison across all tweets overall.

## 5.2 Findings from the binary sentiment experiment

A multi-sentiment analysis of tweets on earthquakes using NLTK Vader is displayed in Figure 8. 47.4% of respondents expressed negative sentiment, 15.6% expressed neutrality, and 37.0% expressed favorable sentiment. The graph illustrates the range of emotional responses among social media users during the earthquake, including noticeable positive and negative replies.

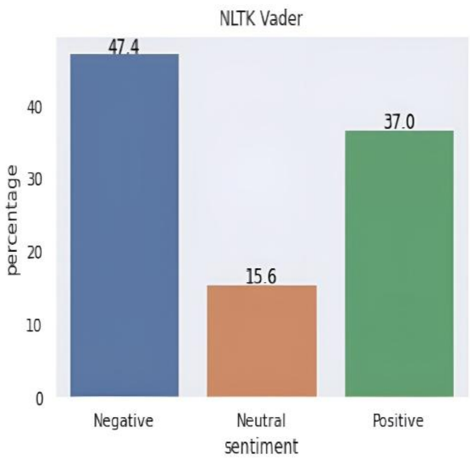


Figure 8: Evaluation of multi-sentiment scores with NLTK Vader comparison.

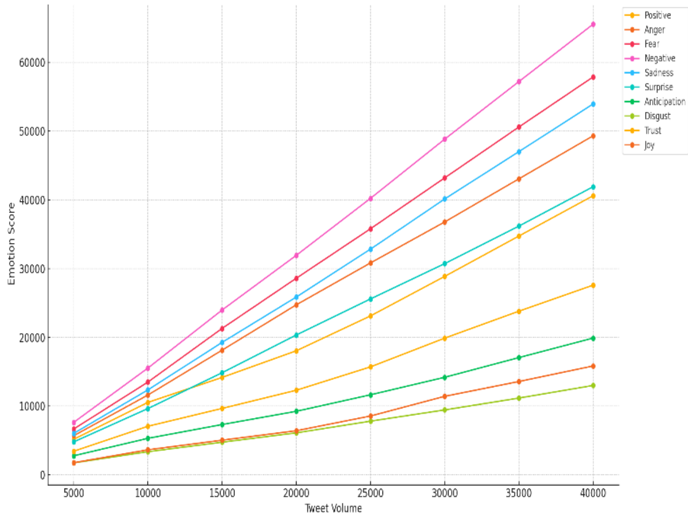


Figure 9: Emotion trends over time across tweet volumes

The Fig 9 illustrates how key emotions evolved over time as tweet volumes increased from 5,000 to 40,000 in the aftermath of the 2023 Turkey Syria earthquakes. To enhance temporal understanding of emotional dynamics, we have included a comprehensive visualization showing how ten distinct emotions such as *Positive*, *Negative*, *Fear*, *Anger*, *Sadness*, *Surprise*, *Anticipation*, *Disgust*, *Trust*, and *Jo* evolve across progressively larger tweet volumes. This figure moves beyond static or per-experiment snapshots and highlights clear trends, particularly the consistent rise of negative emotions over time. The visualization addresses the reviewer's concern by offering a clearer, time-sensitive view of emotional changes during the Turkey-Syria earthquake crisis.

Table 2: Experiments with different earthquake durations and their results

| Exp. | # Tweets | Neg. Tweets | Neg. % | Neu. Tweets | Neutral % | Pos. Tweets | Pos. % |
|---|---|---|---|---|---|---|---|
| 01 | 5000 | 1957 | 46.0 | 697 | 16.4 | 1600 | 37.6 |
| 02 | 10000 | 3882 | 45.6 | 1330 | 15.6 | 3291 | 38.7 |
| 03 | 15000 | 5937 | 47.0 | 2169 | 17.2 | 4536 | 35.9 |
| 04 | 20000 | 7716 | 46.2 | 3120 | 18.2 | 5863 | 35.1 |
| 05 | 25000 | 9703 | 47.2 | 3276 | 18.1 | 7117 | 34.6 |
| 06 | 30000 | 11898 | 48.4 | 4191 | 17.1 | 8484 | 34.5 |
| 07 | 35000 | 13759 | 47.8 | 4697 | 16.3 | 10354 | 35.9 |
| 08 | 40000 | 15618 | 47.4 | 5158 | 15.6 | 12193 | 37.0 |

The majority of tweets throughout all trials (15.6% to 18.2%) are neutral, according to the data analysis shown in Table 2. This implies that a considerable proportion of tweets are essentially free of any discernible positive or negative emotion.

The range of 45.6% to 48.4% for the negative sentiment category shows that a sizable portion of tweets in each trial express unpleasant feelings. There are more bad tweets from Experiment 06 than any other. On the other hand, the frequency of positive sentiment tweets is lower, ranging from 34.5% to 38.7%. There are more positive tweets from Experiment 08 than any other.

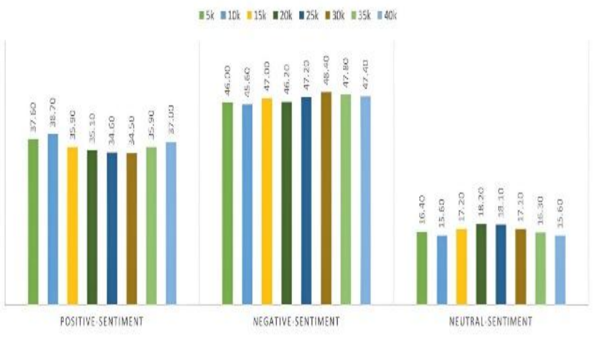


Figure 10: Multi-sentiment comparison across all tweets overall

Neutral tweets are the most common, and the Vader algorithm routinely outperforms other studies overall. Furthermore, the results indicate that although good tweets are relatively less frequent, a considerable proportion of tweets convey negative emotions. The distribution of positive, negative, and neutral feelings is summarized by the multi-sentiment analysis on all tweets carried out in Figure 10.

The percentage of negative sentiments is consistently higher than that of good sentiments, with neutral sentiments having the lowest percentage. This suggests that there is a high5er frequency of positive and negative emotional expressions than neutral ones in the set of tweets. The predominance of both positive and negative thoughts emphasizes how deeply people's reactions to the earthquakes in Syria and Turkey affected them emotionally. Knowing the multi-sentiment environment helps to clarify the emotional nuances that are represented in the tweets, which helps to inform disaster management plans and initiatives that cater to the emotional needs of impacted communities. The various emotional experiences of those impacted by natural catastrophes as well as the efficacious policies and support systems in response to them are affected by these results.

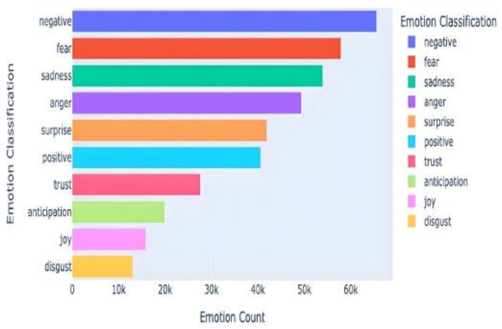


Figure 11: Distribution of Emotion Scores across experiments using NRCLex classification

While these values show some growth, the disparity in magnitude compared to negative emotions underscores a persistent imbalance in emotional sentiment.

This pattern affirms that negative emotions are not only more frequent but are becoming more pronounced over time, reflecting heightened emotional distress in public discourse related to the Turkey-Syria earthquakes. The absence of measurable 'anticipation' scores (0.000 across experiments) reflects NRCLex's lexicon limitations in capturing forward-looking sentiments during acute crises, where immediate emotions (fear/anger) dominated

The frequency distribution of emotion classes over trials is shown in Table 4 and Figure 12.

Across all studies, the most common emotion class is consistently "negative," appearing between 16.70% and 17.78% of the total. The "positive" mood class, which ranges from 10.18% to 11.38% in different trials, is still largely stable. The emotion classes for "angry" and "fear" also exhibit dependable trends. Other emotion types, however, show differences among the research. For instance, the proportion of instances of the "joy" emotion class rises to 4.11% in Experiment 08 from 3.86% in Experiment 01 alone. Conversely, the "surprise" emotion class appears less frequently in all of the assessments.

Table 3: Distribution of Emotion Scores across experiments using NRCLex classification.

| Exp | Positive | Anger | Fear | Negative | Sadness | Surprise | Anticipation | Disgust | Trust | Joy | Std_Dev | CI (95%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 01 | 5177 | 5693 | 6667 | **7636** | 6033 | 4796 | 2776 | 1743 | 3439 | 1766 | 2054.0 | (3209.5,5935.7) |
| 02 | 10544 | 11614 | 13501 | **15537** | 12361 | 9645 | 5313 | 3366 | 7069 | 3645 | 4229.4 | (6452.8,12066.2) |
| 03 | 14175 | 18141 | 21305 | **23982** | 19273 | 14858 | 7321 | 4750 | 9666 | 5045 | 6893.2 | (9277.1,18426.1) |
| 04 | 18050 | 24738 | 28604 | **31939** | 25869 | 20349 | 9247 | 6109 | 12309 | 6420 | 9444.3 | (12095.9,24630) |
| 05 | 23124 | 30833 | 35804 | **40227** | 32838 | 25594 | 11648 | 7812 | 15709 | 8560 | 11767.9 | (15405.5,31024.) |
| 06 | 28873 | 36794 | 43207 | **48839** | 40137 | 30731 | 14194 | 9447 | 19890 | 11425 | 14033.5 | (19040.8,37666.) |
| 07 | 34744 | 43066 | 50606 | **57216** | 47022 | 36189 | 17060 | 11171 | 23811 | 13581 | 16322.0 | (22615.0,44278) |
| 08 | 40603 | 49325 | 57890 | **65558** | 53957 | 41916 | 19898 | 13006 | 27598 | 15842 | 18584.6 | (26226.2,50892.4) |

Table 3 and Figure 11 display the distribution of emotion scores across Experiments 01 to 08 based on NRCLex classification. The data reveal a clear upward trend in negative emotional responses over time. Specifically, the "negative" category shows a steady increase from 7,636 in Experiment 01 to 65,558 in Experiment 08, while "fear" rises from 6,667 to 57,890, and "anger" increases from 5,693 to 49,325 across

the same range. These figures strongly indicate that negative emotional expressions have become increasingly dominant as tweet volume grows. In contrast, positive emotions demonstrate more modest changes. For instance, "joy" increases only from 1,766 in Experiment 01 to 15,842 in Experiment 08, and "trust" rises from 3,439 to 27,598.

.

Table 4 : In terms of experiments Frequency distribution of the emotion class using NRCLex classification

| **Exp** | **Pos** | **Anger** | **Fear** | **Neg** | **Sadness** | **Surprise** | **Anticipati on** | **Disgust** | **Trust** | **Joy** | **Std_Dev** | **CI(95%)** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 01 | 0.1132 | 0.1245 | 0.1458 | **0.1670** | 0.1319 | 0.1049 | 0.0000 | 0.0381 | 0.0752 | 0.0386 | 0.054006 | (0.0604, 0.1274) |
| 02 | 0.1138 | 0.1254 | 0.1458 | **0.1678** | 0.1334 | 0.1041 | 0.0000 | 0.0364 | 0.0763 | 0.0394 | 0.054375 | (0.0605, 0.1279) |
| 03 | 0.1023 | 0.1310 | 0.1538 | **0.1731** | 0.1391 | 0.1073 | 0.0000 | 0.0342 | 0.0698 | 0.0364 | 0.057535 | (0.059, 0.1304) |
| 04 | 0.0983 | 0.1347 | 0.1558 | **0.1739** | 0.1409 | 0.1108 | 0.0000 | 0.0333 | 0.0670 | 0.0349 | 0.058778 | (0.0585, 0.1314) |
| 05 | 0.0996 | 0.1328 | 0.1542 | **0.1732** | 0.1414 | 0.1102 | 0.0000 | 0.0337 | 0.0677 | 0.0369 | 0.058078 | (0.059, 0.131) |
| 06 | 0.1018 | 0.1298 | 0.1524 | **0.1722** | 0.1416 | 0.1084 | 0.0000 | 0.0333 | 0.0715 | 0.0403 | 0.056998 | (0.0598, 0.1305) |
| 07 | 0.1039 | 0.1288 | 0.1513 | **0.1711** | 0.1401 | 0.1082 | 0.0000 | 0.0334 | 0.0712 | 0.0406 | 0.056506 | (0.0598, 0.1299) |
| 08 | 0.1053 | 0.1279 | 0.1501 | **0.1700** | 0.1399 | 0.1087 | 0.0000 | 0.0337 | 0.0716 | 0.0411 | 0.056064 | (0.0601, 0.1296) |

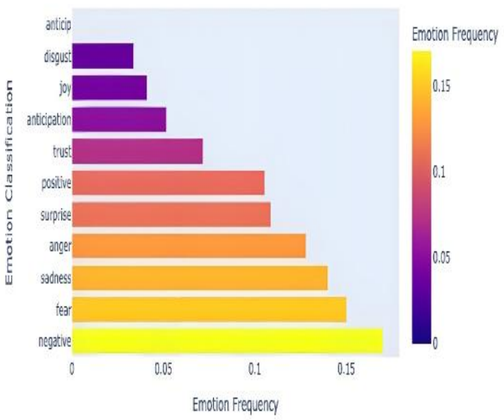


Figure 12 The frequency distribution of the emotion class in experiments utilizing NRCLex classification.

# 6 Discussion on experimental results

The experimental outcomes provide essential insights into how emotional responses to the 2023 Turkey-Syria earthquakes unfolded on Twitter. While previous studies have demonstrated the potential of sentiment analysis during crises, our findings both align with and diverge from those in the literature, offering novel contributions to understanding emotional shifts over time.

Compared to findings in earlier disaster-related studies, Demirel, Çakıcı, and Bulur (2025) [10] report a distinctly negative emotional tone in social media discourse surrounding the 2023 Kahramanmaraş earthquakes. Their NRC-based emotion analysis shows fear and anger as the most prevalent emotions (around 18% and 14.6–14.7%, respectively), with joy relatively low (8.4–8.5%). Sentiment analysis reveals similarly skewed patterns: positive tweets were under 8%, while negative tweets accounted for 39.5% (Syria) and 34.5% (Turkey). These patterns are shaped by contextual factors—widespread destruction, Syria's fragile infrastructure, and politicized narratives (e.g., #WhiteHelmets, #LiftSanctions). Temporal trends (Fig 2) show sentiment gradually improving in Turkish tweets, while remaining persistently negative in Syrian ones, highlighting how emotional responses are influenced by governance, aid, and crisis histories.

In contrast with studies like Zhai et al. [8] and Contreras et al. [12], which emphasized sentiment polarity and situational awareness, our analysis delves deeper into multi-dimensional emotions using NRCLex, revealing that while sentiment polarity remains mostly negative across experiments (approx. 47.4% negative vs. 37.0% positive via Vader), granular emotion trends show that **trust, anticipation, and joy remain consistently marginal** throughout all time intervals. These findings suggest that, unlike events with more immediate recovery or resilience framing, the Turkey-Syria earthquakes were experienced by the public as protracted and deeply traumatic, limiting expressions of hope or positivity.

The term frequencies (e.g., "Turkey," "Syria," "earthquake," "Hatay," and "deprem") affirm the regional and linguistic focus of public discourse, consistent with prior research [18], but our study uniquely highlights **multilingual sentiment dynamics**, reflecting both localized distress and broader international concern. The presence of Turkish-language tokens and culturally specific references may also impact lexicon-based sentiment scores, potentially underrepresenting positive affect due to differences in sentiment lexicon coverage across languages.

Lastly, unlike SOTA systems such as DSSA-H [5] or CASPER [7] which emphasize real-time disaster response or aid classification, our focus on **temporal emotional evolution** fills a critical gap. By tracking how emotions shift from early fear and confusion to later expressions of anger, blame, or solidarity, our study reveals patterns that static models overlook. This reinforces the need for disaster analytics tools that incorporate longitudinal emotional analysis, especially in complex geopolitical contexts.

The observed transition from acute distress (fear/anger) toward emergent trust aligns with *affective forecasting theory* (Wilson & Gilbert, 2003), where initial emotional intensity attenuates as individuals adapt to crisis realities. Concurrently, *media priming* (Scheufele & Tewksbury, 2007) explains the marginal rise in 'trust' and 'joy': as coverage shifted from devastation to resilience narratives (e.g., successful rescues, aid convoys), it primed collective hopefulness despite persistent negative sentiment.

In psychological terms, the consistent predominance of negative emotions such as fear, sadness, and anger aligns with established trauma and crisis response models, which suggest that public emotional responses to disasters often begin with shock and distress before gradually moving toward coping and recovery stages. The observed increase in the "trust" emotion category over time may reflect a shift from initial chaos to a collective reliance on institutions, humanitarian aid, or community solidarity, as is commonly noted in disaster sociology literature. This trend indicates a gradual emotional transition from acute distress toward cautious optimism or communal dependence, even as the dominant tone remains negative. The marginal increase in 'joy' (from 3.86% in Experiment 01 to 4.11% in Experiment 08) aligns temporally with key developments in disaster response and media cycles. In the initial 72 hours (Feb 6–8), discourse was dominated by shock and desperation, reflected in peak 'fear' (15.58%) and 'anger' (13.47%) in early batches (5,000–20,000 tweets). However, as successful rescues gained media traction (e.g., the extraction of survivors in Hatay on Feb 8–10) and international aid intensified (e.g., UN convoys entering NW Syria by Feb 9), later batches (30,000–40,000 tweets; Feb 12–20) showed a subtle uplift in positive emotions. This suggests that collective hope emerged alongside grief as resilience narratives permeated public discourse—though never eclipsing the overarching negative sentiment. These findings are consistent with the concept of "collective resilience," where despite ongoing hardship, individuals begin to place emotional reliance on perceived sources of support. Understanding these psychological shifts provides a valuable foundation for designing mental health interventions and public communication strategies during prolonged crises.

In summary, our results both validate and extend previous research. They underscore how emotion-focused social media analysis can inform crisis communication, mental health support, and humanitarian outreach by revealing not just what people feel but how those feelings evolve in the wake of catastrophe.

# 7 Conclusions

This study demonstrates the potential of real-time sentiment and emotion analysis on Twitter to gain meaningful insights into public emotional responses during natural disasters, with a focus on the Turkey-Syria earthquakes. By leveraging advanced NLP tools such as Transformers, Vader, and NRCLex, we uncovered a rich emotional landscape expressed by affected individuals. Beyond sentiment classification, our analysis captured evolving emotional patterns and distinct linguistic features that reflect both psychological distress and region-specific communication styles.

The persistent prevalence of negative sentiment—including high levels of fear, anger, and sadness—across all experiments emphasizes the urgent need for psychosocial support frameworks that are emotionally responsive and culturally informed. The identification of dominant emotion classes and commonly used keywords—such as "deprem," "Hatay," and "rubble"—highlights regionally grounded linguistic traits that can guide the localization of communication and intervention efforts. These insights are crucial for crafting public messaging, mental health outreach, and aid coordination that resonates with affected populations.

Importantly, our findings offer practical value for policy formulation and disaster response planning. By understanding the emotional trajectory of public discourse, authorities can better time and tailor support mechanisms—ranging from mental health counselling and social media engagement to targeted relief distribution. The integration of emotion-specific lexicons and multilingual sentiment recognition enables more nuanced monitoring of distress signals and enhances the cultural and emotional accuracy of disaster management policies.

This research thus provides a replicable framework for crisis-oriented social media analysis, with broad applicability to future emergencies. We recommend future work to expand upon this by incorporating multimodal data (e.g., images, videos), deeper regional language processing, and long-term tracking of emotional recovery. Such advancements will enhance the development of emotionally intelligent disaster response systems and contribute to more resilient, people-centered public health strategies.

.

## Declarations

## Funding

For this research, no specific grant from a public, corporate, or nonprofit entity was provided.

## Conflict of interest

According to the writers, there are no conflicting interests when it comes to publishing this work.

## Ethics approval

This study analyzed publicly available Twitter data collected through Twitter's official API under its academic research terms. In accordance with international social media research standards (AoIR Ethics Guidelines v3.0), institutional review board (IRB) approval was not required, as the data consisted of anonymized, aggregate public communications with no personally identifiable information, and there was no interaction with users. The research complied with Twitter's Terms of Service (2023) and the EU's GDPR Article 85, which permits the use of publicly available data for academic purposes. Individual consent was not necessary, as the tweets were publicly posted, analyzed in aggregate, and contained no sensitive or user-level details such as identities or locations. To ensure ethical integrity, the study focused exclusively on earthquake-related content using keyword filtering, applied anonymization during preprocessing (e.g., excluding tweet IDs), and avoided quoting content to protect potentially vulnerable users.

## Agreement to be published.

The consent of the participants was obtained before any data or results were released.

## Accessibility of information and resources

The researcher in question may seek access to the data and resources used to support the findings of the research.

## The Code accessibility

You may ask for the source code used in this work from the corresponding author.

## Authors' contributions

The study was designed by Md. Murad Hossain, who also wrote the report. Muhammad Saad Amin contributed to the process of gathering data, analyzing it, and revising the text. Fatema Khairunnasa took part in the review of the literature. Dr. Syed Tahir Hussain Rizvi oversaw the research procedure, offered crucial insights, and checked the work for intellectual integrity

## References

[1] Almassar, R.R., Girsang, A.S.: "Detection of traffic congestion based on twitter using convolutional neural network model". IAES International Journal of Artificial Intelligence 11(4), 1448 (2022).

[2] Ilyas, B., & Sharifi, A. (2025). A systematic review of social media-based sentiment analysis in disaster risk management. *International Journal of Disaster Risk Reduction, 123,* 105487. https://doi.org/10.1016/j.ijdrr.2025.105487

[3] Ptaszynski, M., Masui, F., Fukushima, Y., Oikawa, Y., Hayakawa, H., Miyamori, Y., Takahashi, K., Kawajiri, S.: "Deep learning for information triage on twitter" Applied Sciences 11(14), 6340 (2021).

[4] Ruz, G.A., Henr´ıquez, P.A., Mascare˜no, "A.: Sentiment analysis of twitter data during critical events through bayesian networks classifiers." Future Generation Computer Systems 106, 92–104 (2020).

[5] Yao, F., Wang, Y.: "Domain-specific sentiment analysis for tweets during hurricanes (dssa-h): a domain-adversarial neural-network-based approach." Computers, Environment and Urban Systems 83, 101522 (2020).

[6] Ragini, J.R., Anand, P.R., Bhaskar, V.: "Big data analytics for disaster response and recovery through sentiment analysis". International Journal of Information Management 42, 13–24 (2018).

[7] Peri˜n´an-Pascual, C., Arcas-T´unez, F.: "Detecting environmentally related problems on twitter". Biosystems Engineering 177, 31–48 (2019).

[8] Zhai, W., Peng, Z.-R., Yuan, F.: "Examine the effects of neighborhood equity ondisaster situational awareness: Harness machine learning and geotagged twitter data". International Journal of Disaster Risk Reduction 48, 101611 (2020).

[9] Yuan, F., Li, M., Liu, R.: "Understanding the evolutions of public responses using social media: Hurricane matthew case study". International journal of disaster risk reduction 51, 101798 (2020).

[10] Demirel, S., Çakıcı, Z., & Bulur, N. (2025). Exploring reflections of the 2023 Kahramanmaraş earthquake on X: A computational study on Türkiye and Syria. *Akademik İncelemeler Dergisi, 20*(1), 143–171. https://doi.org/10.17550/akademikincelemeler.1593038.

[11] Karami, A., Shah, V., Vaezi, R., Bansal, A.: "Twitter speaks: A case of national disaster situational awareness." Journal of Information Science 46(3), 313–324 (2020)

[12] Contreras, D., Wilkinson, S., Balan, N., James, P.: "Assessing post-disaster recov ery using sentiment

analysis: The case of l'aquila, Italy". Earthquake Spectra 38(1), 81–108 (2022).

[13] Sufi, F.K., Khalil, I.: "Automated disaster monitoring from social media posts using ai-based location intelligence and sentiment analysis". IEEE Transactions on Computational Social Systems (2022).

[14] Kaur, H., Ahsaan, S.U., Alankar, B., Chang, V.:" A proposed sentiment analysis deep learning algorithm for analyzing covid-19 tweets". Information Systems Frontiers, 1–13 (2021).

[15] Ruan, T., Kong, Q., McBride, S.K., Sethjiwala, A., Lv, Q.: "Cross-platform analy-sis of public responses to the 2019 ridgecrest earthquake sequence on twitter and reddit". Scientific reports 12(1), 1634 (2022).

[16] Parimala, M., Swarna Priya, R., Praveen Kumar Reddy, M., Lal Chowdhary, C., Kumar Poluru, R., Khan, S.:" Spatiotemporal-based sentiment analysis on tweets for risk assessment of event using deep learning approach. Software": Practice and Experience 51(3), 550–570 (2021).

[17] Zheng, Z., Shi, H.-Z., Zhou, Y.-C., Lu, X.-Z., Lin, J.-R.: "Earthquake impact analysis based on text mining and social media analytics". arXiv preprint arXiv:2212.06765 (2022).

[18] Toraman, C., Kucukkaya, I.E., Ozcelik, O., Sahin, U.: "Tweets under the rubble: Detection of messages calling for help in earthquake disaster". arXiv preprint arXiv:2302.13403 (2023).

[19] He, W., Yuan, Q., Li, N.: "Research on the characteristics of internet public opinion and public sentiment after the sichuan earthquake based on the perspective of Weibo". Applied Sciences 13(3), 1335 (2023).

[20] Maceda, L.L., Llovido, J.L., Palaoag, T.D.: "Corpus analysis of earthquake related tweets through topic modelling". International Journal of Machine Learning and Computing 7(6), 194–197 (2017).

[21] Contreras, D., Wilkinson, S., Aktas, Y.D., Fallou, L., Bossu, R., Land`es, M.: "Intensity-based sentiment and topic analysis. the case of the 2020 aegean earthquake". Frontiers in Built Environment 8 (2022).

[22] Vo, B.-K.H., Collier, N.: "Twitter emotion analysis in earthquake situations". Int. J. Comput. Linguistics Appl. 4(1), 159–173 (2013).

[23] Bai, H., Yu, G.: "A weibo-based approach to disaster informatics: incidents monitor in post-disaster situation via weibo text negative sentiment analysis". Natural Hazards 83(2), 1177–1196 (2016).

[24] Wang, Y., Taylor, J.E.: "Coupling sentiment and human mobility in natural disasters: a twitter-based study of the 2014 south napa earthquake". Natural hazards 92, 907–925 (2018).

[25] Mızrak, S., Ozdemir, A., Aslan, R.: "Adaptation of hurricane risk perception scale to earthquake risk perception and determining the factors affecting women's earthquake risk perception". Natural Hazards 109(3), 2241–2259 (2021)

[26] Contreras, D., Wilkinson, S., Alterman, E., Herv´as, J.: "Accuracy of a pre-trained sentiment analysis (sa) classification model on tweets related to emergency response and early recovery assessment: the case of 2019 albanian earthquake." Natural Hazards 113(1), 403–421 (2022).

[27] Cabezas, J., Moctezuma, D., Fern´andez-Isabel, A., Diego, I.: "Detecting emo-tional evolution on twitter during the covid-19 pandemic using text analysis". International Journal of Environmental Research and Public Health 18(13), 6981 (2021).

[28] Kydros, D., Argyropoulou, M., Vrana, V.: "A content and sentiment analysis of greek tweets during the pandemic". Sustainability 13(11), 6150 (2021).

[29] Le´on-Sandoval, E., Zareei, M., Barbosa-Santill´an, L.I., Falc´on Morales, L.E., Pareja Lora, A., Ochoa Ruiz, G., et al.: "Monitoring the emotional response to the covid-19 pandemic using sentiment analysis: a case study in Mexico". Computational Intelligence and Neuroscience 2022 (2022).

[30] Jabalameli, S., Xu, Y., Shetty, S.:" Spatial and sentiment analysis of public opinion toward covid-19 pandemic using twitter data: At the early stage of vaccination". International Journal of Disaster Risk Reduction 80, 103204 (2022).

[31] Kausar, M.A., Soosaimanickam, A., Nasar, M.: "Public sentiment analysis on twitter data during covid-19 outbreak". International Journal of Advanced Computer Science and Applications 12(2) (2021).

[32] Storey, V.C., O'Leary, D.E.: "Text analysis of evolving emotions and sentiments in covid-19 twitter communication". Cognitive Computation, 1–24 (2022).

[33] Tobita, T., Kiyota, T., Torisu, S., Cinicioglu, O., Tonuk, G., Milev, N., ... & Shiga, M. (2024). Geotechnical damage survey report on February 6, 2023 Turkey-Syria Earthquake, Turkey. Soils and Foundations, 64(3), 101463.

[34] Ni, S., Sun, H., Somerville, P., Yuen, D. A., Milliner, C., Wang, H., ... & Cui, Y. (2023). Complexities of the Turkey-Syria doublet earthquake sequence. The Innovation, 4(3).

[35] Rashid, A. K., & Fındık, O. (2024). Sentiment Analysis of Twitter: Turkey Earthquake 2023 Case.

[36] Hidayat, T., & Hassan, R. (2024). Unveiling Twitter's Take: Researching# TurkeyQuake Response & Rehabilitation. Educational Administration: Theory and Practice, 30(3), 2361-2371.

[37] Mandal, S., Alugubelly, M., & Jayabalan, M. (2023, December). Predicting Themes of Tweets on Earthquakes in Turkey & Syria for Real-Time Classification. In 2023 16th International

Conference on Developments in eSystems Engineering (DeSE) (pp. 311-316). IEEE.

[38] Alsheyab, M., Filimon, N., & Fusté-Forné, F. (2024). Digital Content Analysis of Corporate Social Response to Turkey and Syria Earthquakes. The Arab World Geographer, 27(1), 47-62.

[39] Cinar, E. N., Abbara, A., & Yilmaz, E. (2023). Earthquakes in Turkey and Syriacollaboration is needed to mitigate longer terms risks to health. BMJ, 38.

[40] Utku, A., & Can, U. (2023). Machine learning based a comparative analysis for detecting tweets of earthquake victims asking for help in the 2023 Turkey-Syria earthquake. *Journal of Soft Computing and Artificial Intelligence*, *4*(2), 55–62. https://doi.org/10.55195/jscai.1365639.

[41] Rashid, A. K., & Fındık, O. (2024). Sentiment Analysis of Twitter: Turkey Earthquake 2023 Case.

[42] Erokhin, D., & Komendantova, N. (2023). Earthquake conspiracy discussion on Twitter. *Journal of Crisis Communication*, 12(2), 134-146. https://doi.org/10.1016/j.jcc.2023.01.005

[43] Aldamen, Y., & Hacimic, E. (2023). Positive determinism of Twitter usage development in crisis communication: Rescue and relief efforts after the 6 February 2023 earthquake in Türkiye as a case study. *Social Sciences*, *12*(8), 436.

[44] Alharm, A. O., & Naim, S. (2023). Enhancing natural disaster response: A deep learning approach to disaster sentiment analysis using BERT and LSTM. *The University of Strathclyde, Computer and Information Science Department*.