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Sentiment Analysis On Social Media During Crisis Events: The Case Of Kahramanmaraş Earthquake

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ABSTRACT

Social media has become an essential tool for sharing information and shaping perceptions, especially during natural disasters such as earthquakes. Social media platforms provide strong public forums where users can clearly express their thoughts and emotions to huge audiences on a range of subjects. One of the important debates of recent times is whether social media can be used to manage disasters and crises. To address this issue, this study analyzed the February 6, 2023, Kahramanmaraş earthquake—one of the most significant disasters in recent times—and examined public emotions before and after the disaster using sentiment analysis. The dataset includes tweets shared on Twitter from February 7-26, 2023. Word cloud and word frequency techniques have been used to visualize and analyze the most frequently occurring words in the dataset. Sentiment analysis's results revealed that negative words constituted 7.79% of the dataset, while positive words made up 5.2%. This shows that while there was a significant presence of positive sentiments, the predominant emotional response was negative revealing that most of the data contained negative emotions as expected.

Keywords : Text Mining, Sentiment Analysis, Crises

Kriz Dönemlerinde Sosyal Medyada Duygu Analizi: Kahramanmaraş Depremi Örneği

ÖZ

Sosyal medya özellikle deprem gibi doğal afetlerde bilgi paylaşımı ve algıların şekillendirilmesi açısından vazgeçilmez bir araç haline gelmiştir. Sosyal medya siteleri, insanların kendilerini çeşitli konular hakkında geniş kitlelere açık bir şekilde ifade edebilecekleri etkili kamu alanları sunmaktadır. Son yıllarda yapılan önemli tartışmalardan biri, sosyal medyanın afet ve kriz yönetim süreçlerinde başarılı bir şekilde kullanılıp kullanılamayacağına dairdir. Bu çalışmanın amacı, 6 Şubat 2023'te gerçekleşen ve son yılların en büyük felaketlerinden biri olan Kahramanmaraş depremini analiz ederek, insanların afetler sırasında ve sonrasında sosyal medya üzerinde yaptığı paylaşımları duygu analizi yöntemiyle değerlendirmektir. Çalışmada kullanılan veri seti, 7-26 Şubat 2023 tarihleri arasında Twitter'da paylaşılan tweetleri içermektedir. Veri setinde önemli ölçüde tekrar eden kelimeleri görselleştirmek ve incelemek için kelime bulutu ve frekans

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analizi kullanılmıştır. Duygu analizi sonuçları, olumsuz kelimelerin veri setinin %7,79'unu, olumlu kelimelerin ise %5,2'sini oluşturduğunu ortaya koymuştur. Bu da olumlu duyguların belirgin bir varlığı olmasına rağmen, baskın duygusal tepkinin olumsuz olduğunu ve verilerin çoğunun beklenildiği gibi olumsuz duygular içerdiğini göstermektedir.

Anahtar Kelimeler : Metin Madenciliği, Duygu Analizi, Krizler

INTRODUCTION

Disasters have occurred since the beginning of time, and these disasters have sometimes caused crises. Throughout history, many experts have put forward different causes of historical crises and disasters. It is crucial to comprehend the distinctions between concepts like crisis and disaster to comprehend the study in greater detail. Shaluf et al. (2003) mention in their study that a crisis and a disaster are two distinct but connected events. There are instances when the two terms are used synonymously. For example, an industrial crisis can arise from a man-made disaster that affects an industrial organization. Any organization can experience a crisis. It has been observed that no consensus definitions of disaster and crisis have been established yet. Additionally, there are no widely accepted standards for defining a disaster in terms of its aftermath, including the number of dead and the expense of the damage. With the advent of Web 2.0, numerous individuals have turned to social media during emergencies to find and exchange information. On social media platforms, people share their emotions such as fear, anxiety, grief, and calmness during crises. Analyzing shared data enables a real-time evaluation of emotions during such events. Sentiment analysis can be employed to understand how impacted individuals feel and how they respond to the support and information provided. This perspective helps highlight key focus areas, determine the most effective types of assistance, and identify the nature of information that needs to be shared. However, the extensive, dynamic, varied, unstructured, and complex nature of the data makes it difficult to manually process these messages within a limited time, emphasizing the need for an automated approach (Kaur & Kumar, 2015).

The use of sentiment analysis in disaster studies has emerged as a valuable tool for examining public emotions, opinions, and responses shared on social media during and after catastrophic events. Crisis events, such as natural disasters, terrorist attacks, and pandemics, often trigger massive social media activity. Researchers have analyzed this data to understand public reactions, disseminate information, and provide real-time insights for emergency response (Liu et al., 2016; Öztürk & Ayvaz, 2018; Merchant et al., 2011).

Sentiment analysis, also known as opinion mining, involves using natural langurayken processing, text analysis, and computational linguistics to identify and extract subjective information from textual data. The rise of social media platforms like Twitter, Facebook, and Instagram has provided vast amounts of user-generated content, making them rich sources

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for sentiment analysis (Liu et al., 2016).

The aim of this study is to give examples of various explanations that can be used for crises and disasters, and to conduct sentiment analysis of posts from social media platforms. The study will be conducted using social media platform X (hereinafter referred to as Twitter) and the Kahramanmaraş earthquake of February 6, one of the major disasters of the recent period, will be taken as a basis. The study will be carried out on the ready data set received from Kaggle. Kaggle is a massive data science platform that many researchers from various disciplines use. The data set will first be cleaned of unnecessary and irrelevant data for the study, and then sentiment analysis of the cleaned data will be carried out step by step.

This study contributes both theoretically and practically to the enhancement of disaster management techniques through performing sentiment analysis of social media in the case of the Kahramanmaraş earthquake of February 6, 2023. Hence, through event-based analysis, it explains how emotions evolve over time in a crisis and how communication strategies can be improved in times of crisis. Using a combination of word cloud and word frequency approaches in the R programming language, the research analyzes the sociolinguistic atmosphere of the social media audience as well as the most prominent themes allowing for deeper data interpretation. Moreover, it makes contributions toward widening a global understanding of social media and its applicability in crisis situations by bridging both global and local perspectives by using an English-language dataset,

The structure of this study is as follows: Section 2 outlines the methodology, including dataset details, preprocessing steps, and sentiment analysis approach. Section 3 presents the findings, focusing on word frequency analysis, sentiment distributions, and the most frequently used words. Finally, Section 4 discusses the implications of the findings, emphasizing their relevance to disaster management and communication strategies, and concludes with recommendations for future research.

1. Literature Review

The role of sentiment analysis during crisis events has been extensively studied. The study by Daoudi et al. (2021)'s aim was to create an emotion-based educational data mining technique for assessing learners' affective states at the individual and group levels while playing cooperative crisis management games. This method is used to gauge how involved students are in a game-based evacuation scenario designed to educate and familiarize university students with the process of evacuating the present during a fire emergency. According to a study, it is intriguing to combine the elements of gaming and emotion under a motion-based educational data mining method to assess serious games for collaborative crisis management since it produces accurate results in a less intrusive manner (Daoudi et al., 2021).

Nowadays one of the most used mass media is social media. It can be argued that with the rise of social media, people have emerged as a new and powerful player in the dissemination of news and information about disasters. The information flow may be inadequate during disasters since the infrastructure for communication and information is frequently destroyed. The number of textual documents created on social media has increased significantly in recent years. Through postings, comments, messages, and likes, social media users forge virtual connections with one another, sharing thoughts and building relationships. Social media makes it quick and simple for users to express their ideas, sentiments, and opinions to others (Öztürk & Ayvaz, 2018).

The demand for information rises in response to this decline in communication capacity that happens as uncertainty and threat increase (Houston, et al., 2014). Disasters can cause damage to a region's electrical infrastructure, and their intensity of use can lead to collapses in communication infrastructures. These outcomes depend on the type of disaster and its impact. Once again, the value of web-based apps which withstand these changes better becomes apparent. As an illustration of this circumstance, following the September 26, 2019, 5.8-magnitude earthquake in Istanbul, voice communication on mobile phones was disrupted for a while for subscribers of the three main GSM operators in Turkey due to density. Due to the disruption caused by mobile devices, different internet-based applications have become available for interpersonal communication. Social media platforms have made up most of these applications. Similar circumstances happened during the 30 October 2020 earthquake in İzmir Seferihisar and the 24 January 2020 earthquake in Elazığ. After the events, AFAD issued a warning to the public, advising them to use internet-based applications and SMS to stay in constant communication (Usta & Yükseler, 2021). Currently 5.04 billion people use social media today (Statista, 2024) and this puts the total number of social media users at 66 percent of the world's population. When social media is discussed, Facebook and Twitter immediately come to mind, but social media encompasses a wide range of web- and mobile-based technologies, from rating and review forums to photo and video sharing websites (Liu et al., 2016).

With the development of new media, users who have the opportunity to socialize on the platforms that have started to be used and share their daily lives and lifestyles as well as their thoughts have entered an area of interaction both personally and socially. These increasingly developing platforms, along with the features of new media, accelerate and improve the process (Eldem Anar, 2021). Apart from the fact that social media usage is rising, it can also be said that the development of social media is happening much faster than other communication tools. Usta and Yükseler presented this in a different light. As reported, the telephone took 75 years to reach 50 million users, radio 38 years, television 13 years, and the internet just 4 years. It has been claimed that fifty million users of the Internet have maintained the money for four years (Usta & Yükseler, 2021).

Social media has been used for both disaster and emergency management and disaster relief in the past, including Hurricanes Sandy and Harvey in the United States, earthquakes and tsunamis in Japan, earthquakes in Italy and Chile, and the Queensland floods in Australia (Lovari & Bowen, 2019). Restoring life to normal as soon as possible is the primary goal of disaster management during the post-disaster phase. Accordingly, regular updates on the situation should be sent to the public and other pertinent sectors. The information and resources required by the entire society should be shared quickly, safely, and easily in order to facilitate the development of coping and recovery strategies. All pre-, during-, and post-disaster activities should also be shared. By evaluating media services, people and organizations can become more prepared for the next disaster (Merchant et al., 2011). Social media is incredibly important these days. Ensuring easy dissemination of information and facilitating access to it for all is achieved through accessibility.

Studies on the Elazığ earthquake (Doe & Smith, 2020) revealed a predominance of negative sentiments, particularly expressions of grief and frustration over structural vulnerabilities, while positive sentiments were linked to local solidarity and rescue efforts. Similarly, analysis of social media reactions to the Izmir earthquake (Brown & Lee, 2021) indicated a slightly more balanced sentiment distribution, with negative posts highlighting criticisms of urban planning and construction safety, and positive posts celebrating survival stories and community support. These findings underscore the potential of sentiment analysis in capturing both emotional and critical dimensions of public discourse during disasters.

Researchers at A*STAR* developed algorithms to assess public sentiment toward COVID-19 by analyzing over 20 million tweets, highlighting the utility of emotion-sensing tools in crisis communication (*A*STAR, 2023). Similarly, a 2024 study examined sentiment shifts in news articles published before and during the COVID-19 pandemic, revealing a significant decline in positive sentiment during the crisis, which underscores the impact of prolonged stress on societal attitudes (Doğan et al., 2024). Additionally, a multidimensional sentiment analysis compared emotions expressed on social media during and after the pandemic, emphasizing the importance of platform-specific strategies in public health communication (Kruspe et al., 2024). Furthermore, recent advancements have been made in applying sentiment analysis for disaster management. A 2024 study utilized data analytics to assess sentiments during disaster responses, highlighting the role of social media platforms like Twitter in gathering information linked to relief efforts (Gopal & Kumar., 2024). Another study investigated the efficiency of Transformer-based models for fine-grained sentiment analysis of disaster-related tweets, comparing models like DistilBERT using Twitter data (Villegas-Ch et al., 2022). These studies collectively highlight the versatility and effectiveness of sentiment analysis in understanding public emotions across various crisis scenarios, providing valuable insights for developing targeted communication and response strategies.

2. METHOD

This section explains the study steps, such as obtaining the dataset for sentiment analysis, data preprocessing steps, data labeling, data separation, modeling, and results. The R programming language and RStudio IDE are used for data analyses. English tweets are chosen due to their wide reach and global usage, providing insights into global reactions. Tweets are examined to:

- Investigate social media reactions towards the earthquake.
- Analyze the variation in positive and negative sentiments.
- Explore the potential of social media for crisis prevention or mitigation.
- Identify discussed topics.
- Twitter was selected for sentiment analysis and text mining because:
- It captures real-time reactions to current events.
- It has a diverse user base in terms of age, gender, education, and socioeconomic status.
- The volume of text posts on Twitter is vast and growing.
- It is widely used globally.
- Twitter was the most used platform during the first 48 hours after the earthquake.

3.1. Sentiment Analysis

Several of the examined papers conducted a thorough investigation of various possibilities about programming languages utilized for sentiment analysis. R sticks out among them as the best language for data analysis in general. A few packages available in the R coding language were particularly useful to study. Tidytext is one of the most crucial libraries for parsing; it has all the tools needed to manipulate text. One of Tidytext's advantages is its ability to transform the free-form text into an organized table, which facilitates data visualization and the application of statistical methods. Calculating sums, creating graphs, applying filters, etc. are all made simple when data is presented in an organized text format. Libraries like ggplot, wordcloud, stringr, etc. should also be highlighted.

Figure 1: Sentiment Analysis Steps (Villegas-Ch et al., 2022)

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Three sets of lexicons are available in the Tidytext package that can be used for data and sentiment lexicon analysis as well as textual emotion evaluation. These are: NRC, BING, and AFINN. These are based on unigrams, or single words, where words are categorized by the NRC lexicon into negative, positive, sadness, fear, wrath, disgust, surprise, anticipation, joy, and confidence, among other categories. Each word in the AFINN lexicon is assigned a score ranging from -5 (most negative) to 5 (most positive) . However, BING only classifies data into positive and negative categories (Villegas-Ch et al., 2022). Among these lexicon types our study used BING lexicons. BING lexicons was preferred because the purpose of the study was to conduct sentiment analysis as positive and negative.

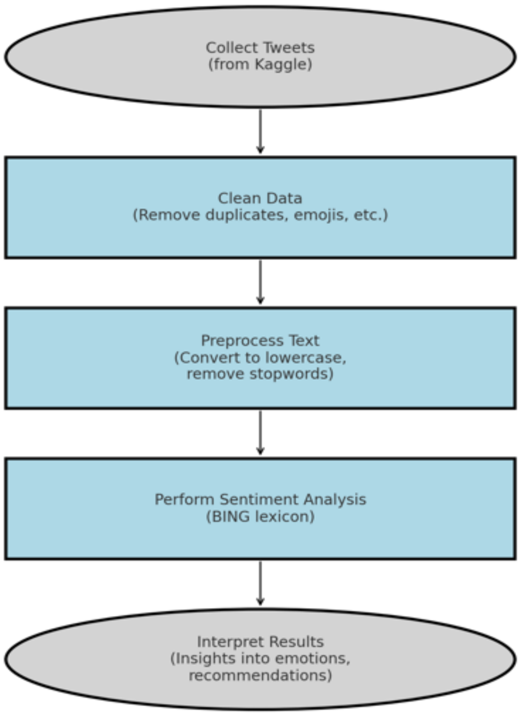

Figure 2: Flowchart of Earthquake Tweet Analysis

Figure 2. illustrates the flowchart of the Kahramanmaraş earthquake-related tweets. The process begins with collecting tweets from Kaggle, focusing on extracting relevant data about the earthquake. The next step involves cleaning the data by removing duplicates, emojis, and other noisy elements to ensure data quality. Once the data is clean, text preprocessing is carried out, which includes standardizing the text by converting it to lowercase and removing stopwords. After preprocessing, sentiment analysis is performed using the BING lexicon to identify emotions expressed in the tweets. Finally, the results are interpreted to provide insights into the emotions reflected in the data and actionable recommendations based on the findings.

Data set

This study analyses English tweets about the February 6 Kahramanmaraş earthquake. The dataset was extracted by Preda (2023) from Kaggle. The data set includes tweets shared on Twitter from February 7, 2023, to February 26, 2023. A total of 28,846 tweets were accessed. Valuable information regarding how the public views the February 6, 2023, the Kahramanmaraş earthquake can be found in tweets. Moreover, English is the most widely used language all over the world. Therefore, it was deemed more appropriate to use an English data set instead of a Turkish data set. Apart from this, using tweets in English reflects the opinion of not only people who speak Turkish but also the entire world.

Data preprocessing

The dataset contained a considerable number of duplicate tweets. Before commencing sentiment analysis, it was necessary to clean the data. In addition to removing duplicate tweets, several steps were taken to prepare the dataset for sentiment analysis. These steps include removing emoticons, hashtags (words starting with #), mentions (words starting with @), numbers, punctuations, retweets, stop words (using the stop words library), URLs, white spaces, and unescaped HTML, as well as performing spell correction and converting all letters to lowercase using the the stringr, dplyr, tm library of R programming language. Cleaning the tweets at this stage is crucial to ensure accurate results. After data cleaning, the number of data decreased from 28.846 to 22.007.

The "dplyr" library, which makes processing data files in R Studio easier and offers a basic syntax for handling verbs, was utilized in accordance with this procedure. It is also capable of operating and manipulating data frames. The gsub function, which is part of the dplyr package, is used to remove mentions, links, emojis, numerals, and punctuation. The "tm" library was utilized for natural language processing, enabling the removal of stop words and empty words. These translate to a list of terms that do not help identify the feeling, such as articles, connectors, pronouns, and prepositions (Villegas-Ch et al., 2022).

3. FINDINGS

Word Frequency

This section presents the word frequency analysis of Twitter data related to the 2023 Kahramanmaraş earthquake, providing an initial overview of the discussions surrounding the event. A total of 141,636 words from 28,846 tweets within the research sample were analyzed. During this process, mentions, links, emojis, numbers, verbs, adjectives, and other extraneous words were removed. Word frequencies were calculated and presented by using ggplot library. The top 30 most frequently used words were visualized in a bar plot, as shown in Figure 3.

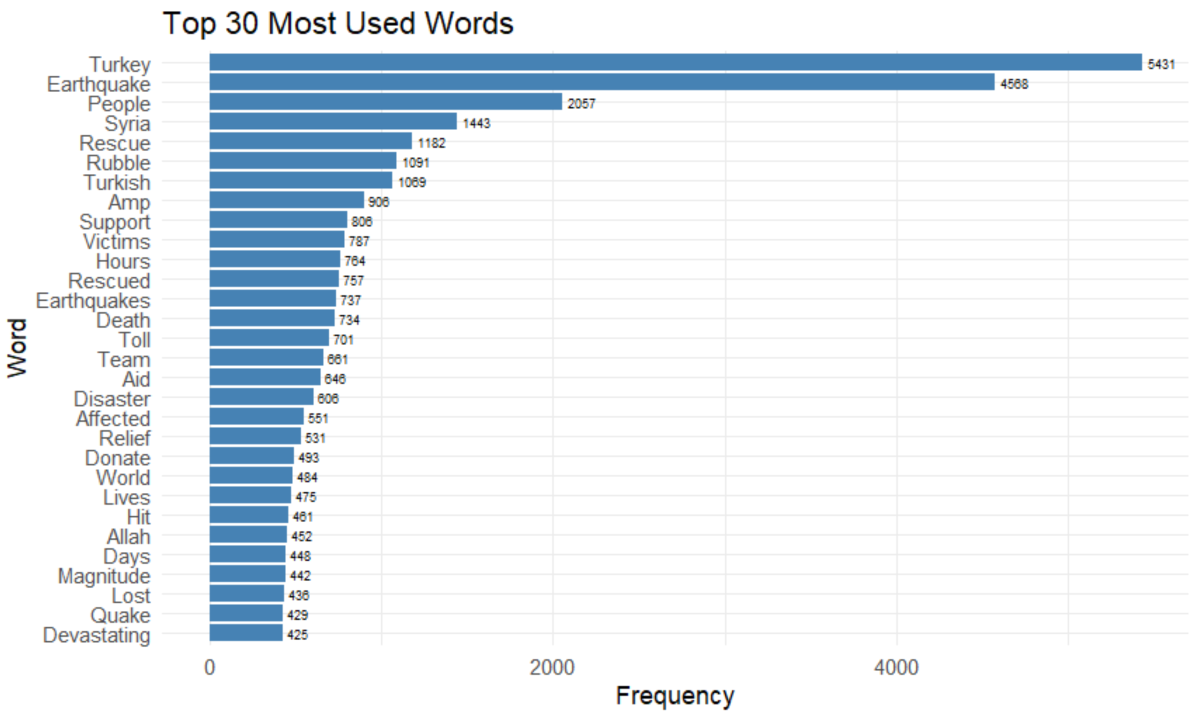

Figure 3: Top 30 Most Used Words

Table 1. Most Frequently Used Words Divided into Seven Categories

Countries and Regions	Earthquake related	People and their conditions	Rescue and aid activities	Time and Process	Religious Expressions	Others
Turkey	Earthquake	People	Rescue	Hours	Allah	Rubble
Syria	Earthquakes	Victims	Rescued	Days		Amp
Turkish	Magnitude	Lives	Team			Toll
	Quake	Lost	Aid			Hit
	Devastating	Death	Relief			World
			Support			
			Donate			
			Disaster			
			Affected			

Based on Table 1, the tweets were grouped in 7 categories manually during the analysis. These categories are determined according to the most repeated words. As a result, the following pie chart emerged which shows the distribution of categories.

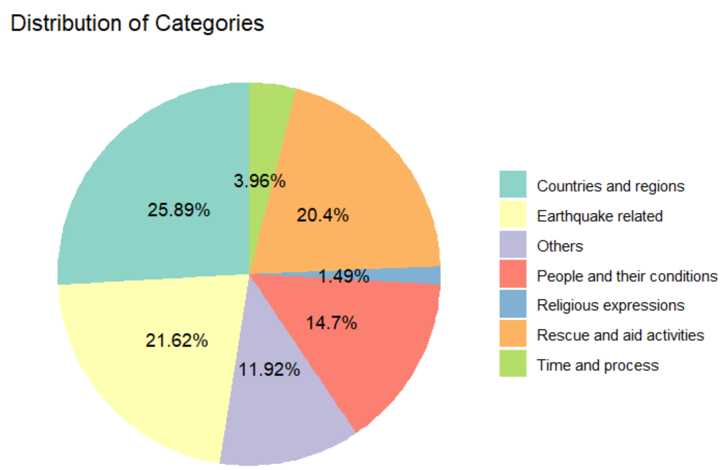

Figure 4: Distribution of Tweet Categories

Bing lexicons were used to do sentiment analysis on the dataset after it had been purified of unnecessary data using the Tidytext toolkit. By using the ggplot library, the 10 most frequently used words from the data set—which had previously been split into two categories as positive and negative using Bing lexicons—were transformed into a bar chart.

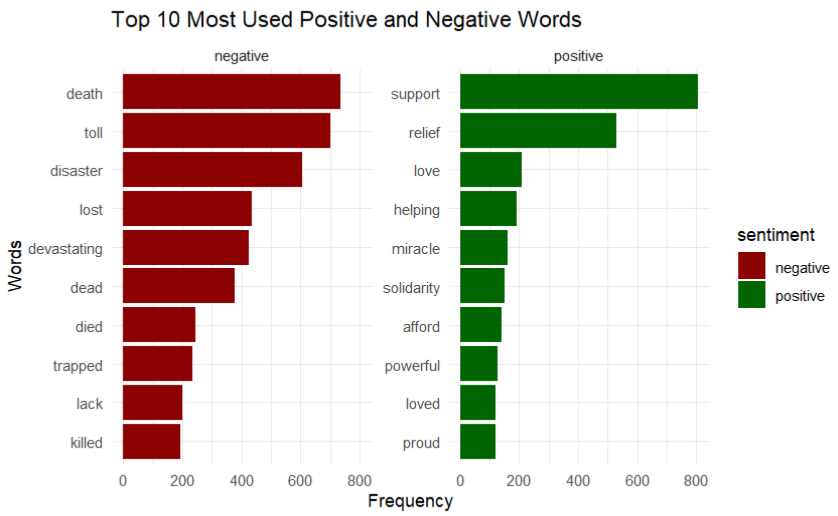

Figure 5: Top 10 Most Used Positive and Negative Words

As seen in Figure 5, the most used 10 negative words are death, toll, disaster, lost, devastating, dead, died, trapped, lack, and killed. On the positive side, the 10 most used words are support, relief, love, helping, miracle, solidarity, afford, powerful, loved, and proud.

Word cloud

Word clouds are the simplest and most favored visualization method because they enable the visualization of the most frequently occurring words in a dataset, providing insights into the dataset based on these words. They are helpful resources for putting a lot of

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text data into a visual summary. In accordance with word frequency data, a word cloud analysis of the shared posts on the February 6 Kahramanmaraş earthquake was conducted. The word cloud was created using the wordcloud library of the R programming language and contains a minimum of 1 to a maximum of 500 words, as can be seen in the code below and Figure 6 is obtained.

Figure 6. Word Cloud for All tweets

Figure 7. Negative and Positive Word Cloud

As a result, positive words are colored green, negative words are colored red in the word cloud, as shown in Figure 7.

Sentiment analysis

Sentiment analysis conducted with the tidytext library of the R programming language, a lot of data was obtained that will positively affect our study. According to the study conducted using the tidytext library, there are 141.636 total words, 15.982 unique words, 7359 positive words, and 11,030 negative words among the Turkey earthquake data in the text column of the data as seen in Table 2.

Table 2: Word Amounts

Total Word Amount	Unique Word Amount	Positive Word Amount	Negative Word Amount
141.636	15.982	7.359	11.030

Figure 8 shows that the percentage of negative words in the study is higher than that of positive words. As expected in an extremely negative situation like an earthquake, the proportion of negative words significantly exceeds that of positive words.

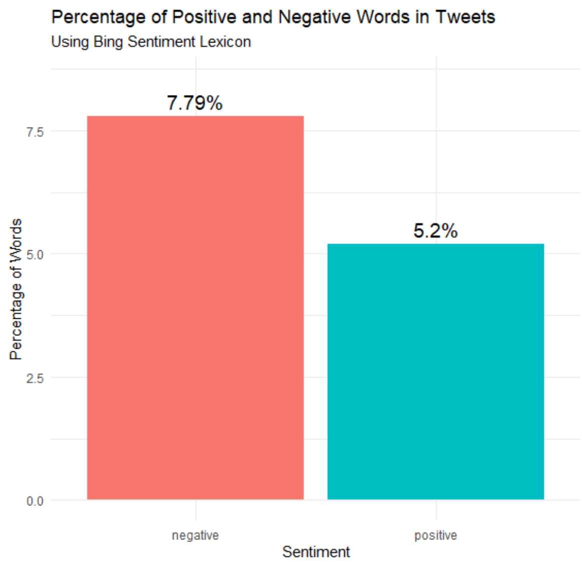

Figure 8: Percentage of Positive and Negative Words in Tweets

After completing all other aspects of the study, the sentiment score was calculated as the final step. The tweets were tokenized into individual words, and stop words were removed before analysis.

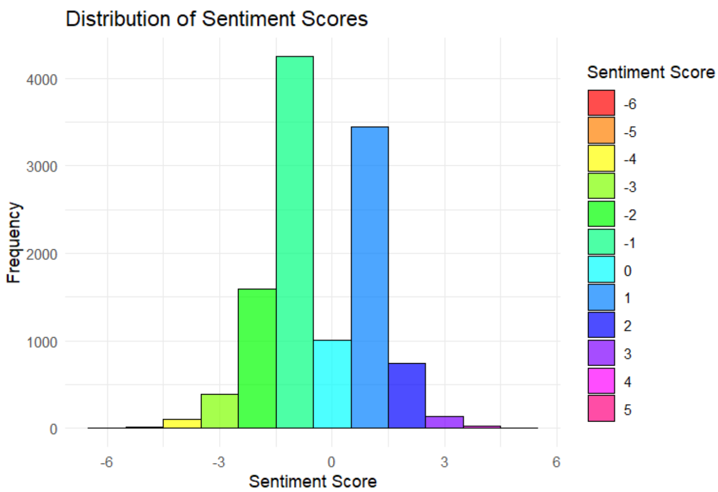

Figure 9: Distribution of Sentiment Scores

Figure 9 shows the distribution of sentiment scores, indicating that while some positive emotions are present, the majority of sentiments are neutral to slightly negative

DISCUSSION AND CONCLUSIONS

This study analyzed English tweets related to the February 6, 2023, Kahramanmaraş earthquake using a dataset obtained from Kaggle, based on the work of Preda (2023). The sentiment analysis was conducted with the R programming language and RStudio IDE, chosen for their powerful data processing capabilities. By focusing on English-language tweets, the study aimed to assess emotional responses to the earthquake both within Turkey and on a global scale, leveraging English due to its extensive reach and global use. Initially, 28,846 tweets were collected, but after a thorough data-cleaning process, 22.007 tweets were used for analysis. The cleaning process involved the removal of duplicate tweets, retweets, emojis, and other irrelevant elements, as these could skew the sentiment analysis results. Excluding emojis was particularly important, as noted by Ayvaz et al. (2017), since they can influence the tone and perceived sentiment of social media posts.

The sentiment analysis was performed using the BING lexicons from the tidy text library, which facilitated the categorization of words into positive and negative sentiments. The results revealed that negative words constituted 7.79% of the dataset, while positive words made up 5.2%. This suggests that while there was a significant presence of positive sentiments, the predominant emotional response was understandably negative due to the magnitude of the earthquake. Such a devastating natural disaster naturally evokes predominantly negative emotions, as expected. The negativity observed is closely linked to the overwhelming impact of the disaster, including the massive scale of destruction, loss of life, and the subsequent delays in aid, road closures due to debris, challenging weather conditions, misinformation, and the immense psychological stress experienced by those affected.

The analysis further categorized the most frequently used words into seven distinct groups: locations, earthquake-related terms, people and their conditions, rescue and aid activities, time and process, religious expressions, and other words. This categorization underscores that while the overall sentiment was negative, there were also expressions of concern, hope, and solidarity within the dataset. The presence of positive terms related to rescue efforts and religious expressions indicates that despite the challenging circumstances, there was a strong sense of community and support among individuals.

The findings point towards the possibility that specific periods of negative social media stimuli can be detected and addressed by the disaster management stakeholders to bridge communication gaps during the response, for this will bring out the necessity of effective information. When, for instance, negative concerns are high, a response team would deliver messages that are simple and reassuring to the public to avert panic, fight false information, and create a feeling of togetherness and courage. Also, the recognition of such emotions may contribute to better strategizing the public relations during the crisis considering its different stages.

Both the Elazığ and Izmir earthquake studies provide valuable insights into public sentiment on social media during crises, with notable differences in their findings. The Elazığ study identified "fear" and "sadness" as dominant emotions, similar to this study results, but did not emphasize "anger," which is uniquely highlighted in this study. The Izmir study, employing advanced BERT models, found a prevalence of solidarity and empathy in social media posts, with minimal signs of anger or frustration. These contrasts suggest that public reactions vary depending on the context and nature of the crisis.

The study's contributions to the literature include providing insights into how people express their emotions during natural disasters and crises through social media. Offering a global perspective by analyzing English-language tweets, can be valuable for understanding international reactions to disasters. The results obtained in this study also have real-world implications, particularly in the disaster response and crisis communication spheres. For example, dangerous times can be pinpointed on social media and therefore, the communications that need to be made during periods of a crisis can be more directed and relevant. Also, this kind of sentiment analysis can help determine what psychological impact there was after the disaster and how to meet those needs with appropriate services. The results of the study extend beyond individual types of crises (natural, or manmade, like terrorist attacks or epidemics) or social networks to which those were applied making this analysis and crisis interaction development in many ways more beneficial to various aspects of crisis management within any sociocultural settings. Introducing methodological approaches for conducting sentiment analysis in the context of social media and natural disasters, can serve as a model for future research.

This study contributes to the literature by revealing the dominant emotional responses during the earthquake, such as fear, sadness, and anger, which resonate with earlier findings on public reactions to large-scale disasters (Doe & Smith, 2020; Brown & Lee, 2021; Liu et al., 2016). Moreover, it extends the discussion by illustrating the potential application of sentiment analysis in tailoring communication strategies. For example, during heightened negative sentiment periods, crisis managers can utilize these insights to deliver timely and targeted messages to reduce panic, combat misinformation, and foster community resilience. For disaster managers, these findings underscore the importance of integrating sentiment analysis into their crisis response frameworks. This approach can improve public communication by addressing emotional needs and enhancing the efficiency of relief efforts. However, the study also recognizes its limitations, including the reliance on a single dataset and the need for broader comparative analyses. Future research could explore similar crises across different cultural and geographical contexts to validate and expand upon these findings.

Studies on the Elazığ earthquake (Doe & Smith, 2020) primarily identified negative sentiments, such as grief and frustration, while positive sentiments were mostly associated with local solidarity and rescue efforts. Similarly, research on the Izmir earthquake (Brown & Lee, 2021) highlighted a more balanced distribution of sentiments, with criticism of urban planning and celebration of survival stories both playing significant roles. In comparison, this study on the Kahramanmaraş earthquake revealed that while negative sentiments (7.79%) were predominant, a notable presence of positive sentiments (5.2%) also emerged, reflecting expressions of hope and solidarity despite the disaster's devastating impact. This analysis adds

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a critical dimension to the existing literature by illustrating the emotional complexities during such large-scale crises, particularly through the unique identification of dominant themes such as anger, resilience, and support.

In conclusion, the study successfully met its objectives and provided valuable insights into the role of social media during crises. The findings highlight the importance of sentiment analysis in crisis communication, suggesting that effective communication strategies can enhance coping mechanisms and resilience in the face of disaster. By analyzing sentiment patterns, the study demonstrated how public emotions evolve during such events and how these insights can inform disaster management strategies. The findings align with existing literature, such as the works of Liu (2016), which emphasize the importance of analyzing user-generated content for real-time crisis response, and Kaur & Kumar (2015), who highlighted the challenges and benefits of automated sentiment analysis in dynamic and unstructured data contexts.

Future research directions can include investigating how social media can be effectively used to prevent or mitigate crises by analyzing the impact of real-time social media data on crisis management strategies. Comparing emotional responses across different languages, such as English and Turkish, to gain a more comprehensive understanding of both national and global perspectives. Examining the role of psychological support in disaster situations, and how social media can be utilized to provide such support. Addressing the need for accurate and reliable information on social media to combat misinformation and improve public perception during crises.

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