Exploring Cognitive Sustainability Concerns in Public Responses to Extreme Weather Events: An NLP Analysis of Twitter Data

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Abstract

The United States has a long history of experiencing extreme weather events. Hurricanes are among the most devastating natural disasters that have significant economic and physical impacts on the country. By applying Natural Language Processing (NLP) to Twitter data for sentiment analysis, emotion detection, and topic modelling, this study provides a more thorough understanding of public response and concerns during five study cases of hurricanes that hit the United States: Harvey, Irma, Maria, Ida, and Ian. The findings on sentiment analysis revealed that 64.75% of the tweets were classified as Negative and 35.25% as Positive. For emotion detection, the predominant emotion was anger, with 39.91%. These results were centred around the main public concerns shown by the topic modelling: hurricane management, donation and support, and disaster impacts. Our future work will focus on understanding people's responses to extreme weather events through the evolving concept of Cognitive Sustainability.

1. Introduction

Extreme weather events (EWE), characterized by their increasing intensity and frequency, clearly indicate the impact of climate change (*Fischer, Knutti, 2015*). These disasters are defined as events in which some meteorological variables, such as strong wind speeds (e.g., hurricanes), reach extreme values that can lead to tragedies, resulting in serious physical and financial damages, with significant impacts on healthcare systems (*Stephenson, Diaz, Murnane, 2008; Ebi, Bowen, 2016*). The United States (U.S.) has a longstanding history of experiencing EWE, as evidenced by 355 weather-related and climatic disasters since 1980. These events have resulted in substantial losses and costs exceeding $2.540 trillion, demonstrating their significant economic impact on the country. Among the most devastating EWEs are hurricanes, which claim a high number of lives while destroying the infrastructure and damaging the healthcare system on numerous levels (*Waddell et al., 2021*). For example, Hurricane Harvey in 2017, the second-costliest natural disaster in U.S. history after Hurricane Katrina, accounted for $152.5B and more than 75 total deaths (*Oluyomi et al., 2021, NOAA National Centers for Environmental Information 2023*).

Similarly, Hurricane Ian, which impacted Florida in 2022, being the third costliest hurricane in U.S. history, accounted for $114.0B in economic losses and 148 reported deaths in mid-January. The severe consequences of these hurricanes extend beyond economic losses. The most tragic outcome is the loss of lives, often resulting from drowning, electrocution, or bodily

injury, which is the most severe acute result of a hurricane. Mental health issues, on the other hand, are a critical aspect of public concerns and can be severely amplified or result in hurricane disasters (*Ebi et al., 2021*). Major effects of Hurricane Katrina included increases in unhealthy behaviours, post-traumatic stress disorder (PTSD), anxiety, and elevated relapse rates for pre-existing health conditions. More than 50% of evacuees with persistent and severe psychological effects are less likely to receive treatment contact from healthcare providers (*Mills, Edmondson, Park, 2007*).

Moreover, hurricanes can cause significant damage to infrastructure systems, affecting mostly vulnerable populations and working-class communities that struggle in the long term to recover (*Dash et al., 2007*). Electric power outages, in particular, can be very disruptive and affect other critical infrastructures on a high level, such as transportation and healthcare services (*Mitsova et al., 2019*). For instance, the major impact of Hurricane Maria on Puerto Rico was the electric power outage that initially affected the island and lasted more than ten months. The island's orography, logistical constraints, and the severity of the destruction all had a significant role in the exceedingly delayed restoration process that resulted in the island's power grid having very low resilience (*Kwasinski et al., 2019*). During these disasters, the public responds in various ways to cope with the potential damages. Emergency preparedness, evacuation, and migration become a priority, leading people to relocate to safer areas and create emergency plans by seeking timely and accurate information from local authorities and disaster management agencies and relying on community networks to share resources and support (*Sutton, Tierney, 2006*). This collective response reflects the importance of effective communication during emergencies in sharing resources, providing support, and disseminating critical updates (*Lu, Yang, 2011*).

Sustainability refers to the ability to meet the needs of the present without compromising the ability of future generations to meet their own needs. It involves making choices and implementing practices considering the long-term health of the environment, society, and the economy. Sustainability aims to balance social, economic, and environmental factors to ensure that resources are used in a way that preserves and protects them for the benefit of current and future generations. In this article, several levels of sustainability are considered. Cognitive sustainability is not a widely recognized term within the mainstream discussion on sustainability. However, it can be inferred to relate to maintaining cognitive well-being and resilience, particularly in the context of the challenges posed by the modern information age. Social sustainability could be defined as the ability of a society or community to develop in a way that meets the needs of the present without compromising the ability of future generations to meet their own needs. It focuses on fostering social well-being, equity, and justice. Physical sustainability could refer to individuals' or communities' long-term health and well-being. The physical aspects of sustainable development focus on the built environment and infrastructure. This might include the design and construction of buildings, transportation systems, and urban spaces that minimize environmental impact, use resources efficiently, and contribute to the overall resilience of communities. Emotional sustainability could also be the sustainability of interpersonal relationships and social connections. This might include fostering healthy relationships, effective communication, and community support. Building and maintaining positive social connections is essential.

Understanding this intricate web of responses through the lens of cognitive sustainability reveals the deeper cognitive processes at play. The prioritization of safety and the collaborative efforts to gather and disseminate information showcase the cognitive adaptability of individuals and communities in the face of environmental crisis, aligning with the main characteristics of cognitive sustainability. The ability to collectively navigate challenges and optimize human value creation during extreme weather events reflects a sustainable cognitive approach to social, emotional, and the implication of sustainability levels, harmonizing artificial and biological cognitive systems with the broader goal of enhancing resilience and well-being (*Zoldy et al., 2022*). In this context, and with the increasing number of natural disasters, traditional methods for analyzing public concerns, such as surveys, have become constrained, expensive, and time-consuming (*Karami et al., 2020*). However, the emergence of social media has revolutionized how we track and understand people's concerns, offering unique and efficient ways of capturing real-time public sentiment and reactions. By gathering tweets from those who were impacted by Hurricanes Maria, Harvey, Irma, Ida, and Ian and using Natural Language Processing (NLP) techniques to analyze the textual data, we can examine people's responses, with the Twitter platform being a valuable source of real-time data due to its wide user base and potential for capturing diverse perspectives.

In 2023, Twitter will have 353.9 million users (please note that in April 2023, Twitter merged with X.), offering real-time feedback and using a timestamp to update users on conversations. As a result, Twitter has the potential to be a trustworthy and pertinent data source and offers a special chance to comprehend users' issues and contribute to enhancing situational awareness with a low waiting time access to data. Twitter has diverse applications, from finance to politics and health. However, because of problems with deception, attention-grabbing content, performance measurement, dependability, and the inability to independently check both the poster and the content they publish, using microblogging feeds as information sources during a significant event is still challenging (*Neppalli et al., 2017*). Still, research has been conducted to encourage outcomes. For example, a framework and Web-based system called Twitcident was developed by *Abel et al. (2012)* to monitor and filter information from social media streams, notably Twitter. Also, the extraction, processing, and classification of Twitter feeds have advanced significantly thanks to machine learning and natural language processing. A study on using this platform in public health and disasters shows that people are likely to communicate their feelings and thoughts about disasters on social

media sites (*Vieweg et al., 2010*). Consequently, crisis response managers can benefit from social media by better knowing how the public reacts to disasters and analyzing their sentiments and expressions (*Yuan, Li, Liu, 2020*).

The EWE we worked on occurred when communities had access to vast amounts of data, which presented an opportunity to advance public health systems using cutting-edge tools like data-driven artificial intelligence (AI). Natural language processing (NLP) is a subset of AI technologies with significant promise in pinpointing trends and sentiments related to particular themes (*Al-Garadi, Yang, Sarker, 2022*). When tweets are gathered using Twitter's Academic API, the major goal is to determine the sentiment of each one by defining positive and negative polarity, detecting emotions, and extracting different related topics with topic modelling. Compared to surveys or questionnaires, this can be a simpler method of retrieving user's opinions and thoughts. Numerous research studies have used NLP to address public response and community vulnerabilities during disasters using sentiment and topic modelling approaches (*Albahli et al., 2021*). For instance, during Hurricane Laura in 2020, research proposed a supervised approach from NLP models with a Latent Dirichlet Allocation (LDA) workflow to investigate temporal latent topics from tweets to retrieve real-time situational awareness (SA) (*Zhou et al., 2023*).

This work fills this gap by thoroughly examining the public response during extreme weather events, taking into account the study case hurricanes that occurred between 2017 and 2022 in the USA. With this prolonged time frame, evaluating how people's concerns have evolved, noting shifting dynamics, and spotting patterns or trends in susceptibility is possible. This work, framed within the exploration of cognitive sustainability in public responses to extreme weather events, offers a more comprehensive knowledge of the effects of extreme weather events on individuals by looking at a sequence of events rather than isolated incidents, especially with the adoption of a novel strategy with Twitter being a rich source of real-time information. We aim to provide a more thorough and nuanced understanding of these concerns in such contexts by applying NLP analysis to Twitter data and looking at the voices and emotions of people directly or indirectly affected by these extreme weather events.

2. Data and methods

2.1 Extreme weather events

In this study, we aim to understand the public response during EWE through the lens of cognitive sustainability. We selected five hurricanes that took place between 2017 and 2022. These events include Hurricane Maria, Hurricane Harvey, Hurricane Irma, Hurricane Ida, and Hurricane Ian. Collecting tweets, we delve into people's cognitive, social, physical, and emotional sustainability concerns and responses to these disasters, examining their sentiments and expressions. Our selection of the hurricanes was mainly based on their severity as determined by their attributes. We first focused on hurricanes from the past ten years. By narrowing our scope to recent events between 2017 and 2022, the selection of certain hurricanes was determined by their effects on finances and mortality, with a concentration on hurricanes that caused large losses in property and lives. We focused on hurricanes that were at least Saffir-Simpson Category 4 in severity and escalated to Category 5 in some cases.

2.2 Twitter data

In this study, 113,475 tweets were collected from 2017 to 2022 and were stored in Twitter's Search API, which was used for collecting tweets in this research. Twitter's Standard Search API returns tweets from the previous seven days based on user-specified search criteria. In this study, we conducted keyword- and hashtag-based research for data collection using the "search/tweets" endpoint of the Twitter API. A set of carefully selected queries was used to achieve this, which could be combined using logical operators such as 'OR' and 'NOT'. This approach allowed for precise filtering of tweets, ensuring that the collected data pertained to the selected hurricanes and encompassed keywords related to hurricane impacts. We specified different queries for each timeline event and removed the replies and retweets. Then, we fetched the corresponding tweets located in the USA from specific time ranges. The collection was done over a 7 to 10-day period for each hurricane, which allowed the capture of reactions from the beginning to the end of the hurricane event during the preparation and impact phases. This is particularly useful as it allows us to collect many tweets containing relevant keywords in a single request. The endpoint supports pagination, which means we can retrieve up to 500 tweets per request. Another reason why this method was chosen is its flexibility and precision. Table I provides a summary of the Twitter data used in our study.

Table 1. Twitter data summary

Hurricane Name	Collection / start_time	Collection/ End_time	Number of tweets collected
Ian	2022-09-22	2022-10-02	12 860
Ida	2021-08-26	2021-09-05	9 680
Harvey	2017-08-23	2017-09-02	16 204
Irma	2017-08-03	2017-08-12	20 638
Maria	2017-09-30	2017-10-10	54 093

Source: own compilation

2.3 Data cleaning

For the preprocessing stage of our study, we cleaned the collected Twitter dataset (only English data were considered) to meet the specific requirements of BERT and BERTopic *Fig. 1* illustrates the steps followed (see chapter 2.4). The cleaning process involved removing noise by removing special characters, numbers, and emojis from the tweets to concentrate on the textual content. It also removed HTML, different mentions (i.e., words starting with '@' and '#'), symbols, flags, Unicode characters, and punctuation. In addition, particular user references and linkages were removed from remarks and URLs. The text was changed to lowercase for consistency, and any leading or trailing whitespace was removed. To guarantee a unique dataset for analysis, duplicate tweets were also found and eliminated. The total number of tweets dropped from 113,475 to 68,373 after cleaning, creating a more accurate dataset that can be used for BERT model training and evaluation. We refrained from employing conventional text preprocessing techniques like lemmatization and stemming. This decision was underpinned by our use of BERT, a cutting-edge transformer-based model, which inherently captures contextual meaning and ensures the preservation of the text's richness and nuance.
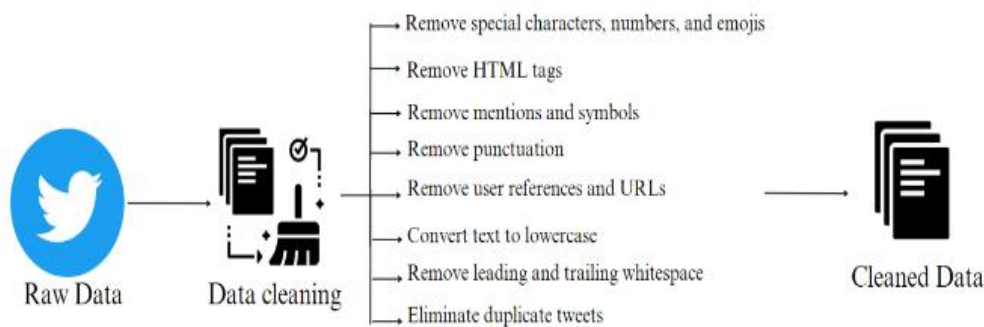

Fig. 1. Data cleaning process

2.4 Bert Model

This study used BERT for sentiment analysis, emotion detection, and topic modelling. BERT is a multi-layered structure of Bidirectional Transformer encoder layers based on the architecture of the transformer (*Nguyen et al., 2020*). The main benefit of BERT is the application of two-dimensional transformer training techniques. BERT combines how to look at a text string from 2 dimensions. This technique can significantly increase the retention of word representations in sentences. BERT models are an effective tool for sentiment analysis for binary and multiclass classification (*Catelli, Pelosi, Esposito, 2022*).

Additionally, BERT is also suitable for emotion detection; it can successfully categorize text into particular emotional categories by being trained on datasets that include various emotions (*Acheampong, Nunoo-Mensah, Chen 2021*). Our study used two pre-trained Bert-based models: The roBERTa-based model from Hugging Face for sentiment analysis and the BERT-base uncased emotion model for emotion detection. These models were chosen based on their established performance and suitability for our study. The RoBERTa-based model from Hugging Face is a state-of-the-art model that performs three tasks:

(i) sentiment analysis,
(ii) hate speech detection, and
(iii) offensive language identification.

The model is trained on approximately 58 million tweets using the TweetEval benchmark. The sentiment analysis task aims to recognize if a tweet is positive, negative, or neutral. The training set comprised 45,389 tweets, the validation set included 2,000 tweets, and the testing set consisted of 11,906 tweets from the Semeval2017 dataset. The macro recall score for the testing performance was 68.5 (*Barbieri et al., 2020*).

Similarly, the BERT-base uncased emotion model is a popular and widely used model designed for emotion analysis tasks. It was trained on a diverse range of emotions and fine-tuned using PyTorch Lightning, providing a validation accuracy (val_acc) of 0.931. It has demonstrated excellent performance in various benchmark datasets. It has proven effective in accurately predicting emotions and their suitability with the specific emotions we aimed to analyze in our study.

For Topic modelling, we used BERTopic. This model has emerged as a promising alternative for topic modelling techniques like Probabilistic Latent Semantic Analysis and Latent Dirichlet Allocation. BERTopic offers several benefits over these traditional methods, frequently requiring complex changes and morpheme analysis for the best outcomes. Other models frequently ignore the semantic connections between words, but this model does not. BERTopic creates accurate and coherent topic expressions using the clustering technique and TF-IDF's class-based transformation. It incorporates BERT-based embedding and c-TF-IDF word weights during the text embedding stage to improve the quality of topic representations. Using text clustering, BERTopic also excels at locating pertinent subjects throughout various domains (*Sun et al., 2023*).

Applying topic modelling techniques helps to uncover hidden themes and "topics" within our dataset. Analyzing the words in the dataset, we identified patterns and connections that revealed certain topics discussed. We used BERTopic, simplifying the topic modelling process by employing various embedding techniques and c-TF-IDF to create dense clusters. Our approach involved extracting the 40 most common topics from the dataset. We then manually selected the most relevant topics and grouped them together based on the similarity between their keywords. For instance, we observed that 'topic 2' was characterized by keywords such as "donation," "fundraiser," "proceeds," and "donating," while 'topic 14' featured keywords such as "donation," "donate," "collecting," and "fundraising." Recognizing the similarity between these keywords, we grouped these topics under the same category: "hurricane and healthcare management." We plotted an inter-topic distance map to extract even more relevant topics, allowing us to observe clusters of closely related topics.

3. Results

3.1 General analysis

The dataset contains 113 475 tweets. We analyzed the average number of tweets during the day and night periods, provided in Table 2. We observed that the number of tweets during the day (from 5 am to 8 pm) exceeded those during the night (from 8 pm to 5 am). However, the number of night tweets remains high compared to the total number of Tweets in the dataset, emphasizing the ongoing discussion of disaster-related topics even during late hours. This highlights individuals' significant engagement and interest in addressing and sharing information about hurricanes throughout the day, including nighttime.

Table 2. Hurricane Twitter Activity Analysis

Hurricane	Total tweets	Day tweets	Night tweets	The average number of tweets per whole day
Ian	12860	8551	4309	459.28
Ida	9680	5938	3742	312.25
Harvey	16204	10022	6182	540.13
Irma	20638	11748	8890	665.74
Maria	54093	30660	23433	1865.27

Source: Own compilation

3.2 Word Cloud & Frequency Analysis

In order to address public concerns, we conducted a thorough analysis of the dataset, focusing on word frequency and Word cloud visualization techniques. The Word cloud analysis aimed to filter out irrelevant words in the first step, including political references and random speech-related terms. The second step consisted of excluding hurricane-related terms, such as the names of specific hurricanes. We aimed to highlight the key terms and concepts about people's responses and concerns. This approach allowed us to gain valuable insights into the predominant discussions during extreme weather events. Table 3 provides the most frequently used words shown by the Word cloud.

Table 3: Most common Word cloud terms

Extracted terms	Frequency
emergency	19,269
evacuation	8,531
help	5,218
relief	3,821
disaster response	2,962
hospital	2,405

Source: own compilation

The word cloud in Fig. 2 provided valuable insights into the prevalent topics among the tweets collected. Several recurring emergency terms were frequently mentioned. Words such as "affected" highlight the widespread impact of these hurricanes on different areas of the USA. Other terms such as 'family', 'home', and 'shelter' emerged as key concerns. Medical assistance and healthcare facilities were represented by "emergency" and "hospital" words. Other terms worth noting are "victim" and "death", which suggest the occurrence of an unfortunate loss of life and the potential emotional impact on individuals and families. On a more positive note, the mention of "donate" and "relief" indicates the existence of a spirit of generosity and a willingness among people to contribute and support relief efforts. It may indicate the need for support and donations during the emergency crisis, especially with the presence of phrases such as "mandatory evacuation", "help", and "supply resources" that signify the importance and urgency of evacuation measures for the affected areas and the challenges encountered to rebuild and provide essential aid and resources. This comprehensive analysis offers a glimpse into the cognitive concerns, needs, and actions of individuals, local government authorities, and healthcare providers, underscoring the importance of effective disaster response strategies and the strength of community support systems.

Fig. 2. Word cloud

3.3 Temporal analysis

For a temporal analysis, the study examined the temporal distribution of tweets for each of the five hurricanes. Specifically, we present Fig. 3 for Ida tweets distribution, which was the most representative as it captured the trend from the landfall to the dissipation of the hurricane over time. The collection of Ida-related tweets ranged from August 26, 2021, to September 5, 2021, covering the initial stages and the dissipation of the hurricane. On September 1st and 2nd, 2021, Hurricane Ida significantly impacted the Northeastern United States, becoming an extratropical cyclone. This resulted in catastrophic river and flash flooding, particularly affecting regions like Louisiana (*Shultz et al., 2022*). The histogram presented in Fig. 3 highlights a sharp increase in tweets one day after the disaster, reflecting the immediate aftermath and the public response to the event. The slight delay in the burst of tweets can be attributed to the progressive nature of the hurricane. As time progressed and the hurricane dissipated, the number of tweets per day gradually decreased, as depicted in the figure. This observation suggests public attention and discussion around the hurricane waned over time.
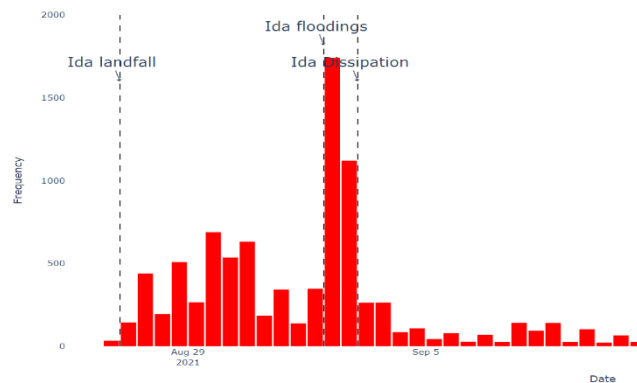
Fig. 3. Hurricane Ida Tweet's distribution

3.4 Sentiment analysis

In our study, we conducted the sentiment analysis for tweets using a pre-trained Roberta-base model from Hugging Face. We ran the model for the sentiment task. The sentiment analysis aims to recognize if a tweet is positive, negative or neutral. Noteworthy outcomes were found for the five hurricane cases. The model predicted a distribution of sentiments, with 64.75% classified as Negative, 35.25% as Positive, and 0.0% as Neutral. The sentiment analysis provided a binary classification for negative and positive sentiments, so our analysis will focus on this binary framework. We discovered distinct temporal patterns in the sentiments expressed, closely aligned with the real-life situations experienced during the hurricanes. The percentage of negative tweets indicating hurricane-related sentiments (64.75%) exhibited similar patterns across all five hurricanes. In each case, the number of tweets sharply increased as the hurricane approached and peaked, corresponding to the hurricane's intensity and impact on affected areas, such as floods and heavy rains. The hurricanes profoundly impacted people and the environment, as reflected in the sustained social media discussions.

We selected Hurricane Harvey and Irma as representative examples to explore the temporal patterns of sentiment predictions and their relationship with hurricane paths. Fig. 4 displays the sentiment distribution during the occurrence of Irma and Harvey. As Hurricane Harvey moved closer and made landfall in Texas, sentiments became more negative, indicated by the prevalence of negative terms, as shown in Fig. 4. This shift in sentiment likely resulted from the heavy rains and damage caused by the storm across Texas and Louisiana.

Following the dissipation of Harvey, Hurricane Irma, reaching Category 5 on September 4, 2017, emerged as the subsequent hurricane of interest. Irma inflicted widespread and catastrophic damage, particularly in the northeastern Caribbean and the Florida Keys. The predicted sentiments align with the temporal trends of hurricane landfall and intensity, evidenced by the substantial gap between positive and negative sentiments. As the relief efforts were initiated, evacuation procedures were implemented, disaster response management came into play, and the gap between sentiments gradually narrowed. These findings highlight the dynamic interplay between hurricane occurrences and the sentiments expressed on social media. They also underscore the crucial aspect of non-physical sustainability at the social and emotional levels. This dimension of sustainability is particularly evident in the evolving sentiments and nuanced temporal patterns observed during the occurrence and aftermath of hurricanes like Harvey and Irma. The emotional sustainability aspect becomes pronounced as the community navigates through the challenges posed by extreme weather events. It accentuates the vital role of relief efforts and emergency response measures in fostering emotional resilience and social cohesion. Thus, our analysis contributes to understanding sentiment dynamics and sheds light on the inherent sustainability challenges and coping mechanisms at the non-physical levels.
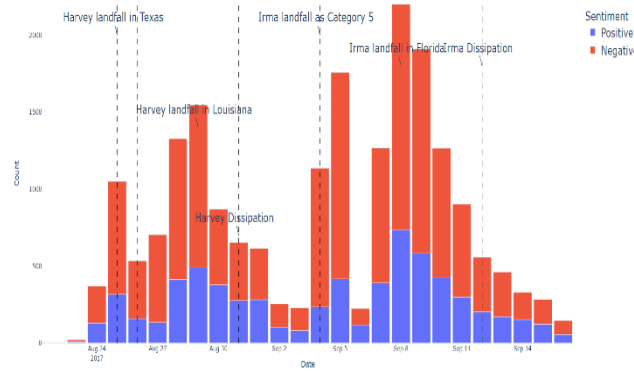
Fig. 4. Sentiment distribution during hurricanes: Irma and Harvey

3.5 Emotional analysis

We used the pre-trained BERT-based " bert-base-uncased-emotion " model from Hugging Face for the emotion detection analysis. This model was further fine-tuned on an emotion dataset using PyTorch Lightning. The selected model can predict six emotions: Anger, Fear, Sadness, Joy, Surprise, and Love. These emotions were deemed suitable for our study case, allowing us to capture a broad range of emotional responses. The choice of the model was based on the number of users and the evaluation parameters, and it has exhibited accurate results. Fig. 5 provides the emotion percentages in the dataset.
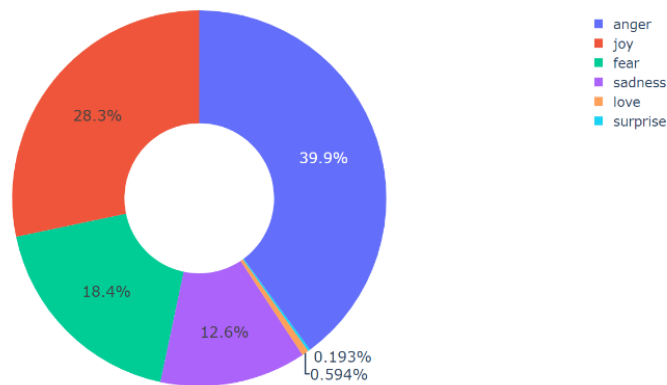

Fig. 5. Emotions distribution during all hurricanes

The results for emotion analysis revealed a notable distribution, with anger comprising the highest percentage at 39.91%, followed by joy at 28.30%. Fear and sadness accounted for 18.38% and 12.63%, respectively, while Love and Surprise had minimal representation, with percentages of 0.59% and 0.19%, respectively. For further analysis, we will concentrate on the four primary emotions: anger, joy, fear, and sadness. These emotions encompass a wide range of reactions and discussions surrounding hurricanes. To gain deeper insights into the main topics associated with each emotion, we have generated a word cloud, depicted in Fig. 6, which visually represents the most frequently occurring words about the four emotions considered in our study. To get a coherent analysis of emotions, we grouped them into Negative and Positive emotions. The negative emotions, which include anger, fear, and sadness, accounted for a total percentage of 70.92%, while the positive emotions were represented by joy (28.30%), which is consistent with our expectations.

3.5.1 Negative emotions

The dominant emotion observed in our dataset was anger, with a percentage of 39.91%. This finding reflects the discontent and frustration expressed by individuals during the occurrence of the hurricanes. The word cloud associated with anger reveals the presence of mandatory evacuation, emergency, power outage, and infrastructure protection, indicating dissatisfaction with healthcare services, disaster management preparedness, and infrastructure. These observations indicate that a significant number of users expressed their anger towards these aspects of the hurricanes. The fear detected in our dataset exhibited similar concerns to those associated with anger, as evidenced by the shared terms in the word cloud. These terms revolve around disaster management and emergency operations, reflecting the unease experienced by individuals during the hurricanes. Sadness reveals the level of intensity of the disasters, emphasizing the unfortunate loss of lives and the extent of devastation caused. Words

such as death, devastation, and damage are prevalent in the Sadness word cloud, highlighting the profound impact of the hurricanes on affected communities.

3.5.2 Positive Emotions

The Joy emotion accounted for 28.30% of the emotions detected. It can be attributed to relief efforts, assistance, and individual resilience. Words associated with joy in the word cloud include relief, help, life, and family, indicating a glimmer of positivity towards the challenges faced during the hurricanes.

Fig. 6. Word cloud for Anger, Joy, Sadness, and Fear (dominant) emotions

We also employed a temporal analysis approach to investigate the normalized emotion distribution over time presented in Fig. 7 to examine the evolving emotions detected during hurricane events. Among the hurricanes studied, Hurricane Ida emerged as the most representative case for our analysis. During the progression of Hurricane Ida, we observed distinct patterns in the emotions detected. Prior to the landfall of the hurricane, there was a noticeable increase in emotions such as fear and anger. These emotions peaked one day before and during the hurricane's landfall and the day of flooding caused by the disaster. This aligns with our expectations, as the heightened fear and anger can be attributed to the anticipation and direct impact of the hurricane, as well as the uncertainties and potential threats associated with the flooding. This finding suggests a prevailing sense of dissatisfaction and insecurity.

Furthermore, the emotion of sadness showed a continuous upward trend throughout the hurricane event. This observation corresponds to the increasing intensity of the disaster, reflecting the accumulation of devastating impacts and the loss of lives. The rising trend in sadness emotions can potentially indicate individuals directly affected by the hurricane and experiencing profound emotional distress. It seems the patterns of anger and fear are significantly different. Fear practically ceases when the worst happens, but anger is maintained even after that, though diminishingly.

On a contrasting note, the emotion of joy increased, particularly after the dissipation of the hurricane. This highlights the presence of individuals who have been relieved from the immediate impacts of the hurricane or have been successfully rescued and saved. The growing joy can be attributed to relief and gratitude among those spared from the hurricane's direct consequences.
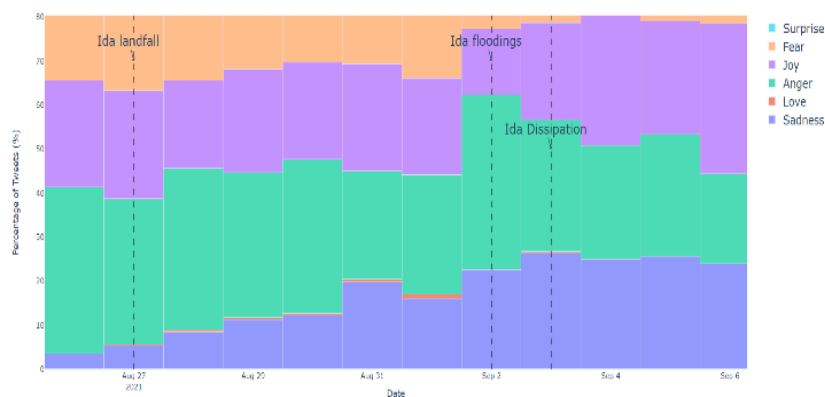
Fig. 7 Emotion distribution during Hurricane Ida

3.6 Topic Modeling

Through this analysis, we identified three main topics from the dataset provided in Table 4. that highlighted the most people's concerns during hurricane occurrence. Analyzing the generated topics shows that the public's response to hurricanes primarily revolved around hurricanes and healthcare management. The first topic highlighted the public's concerns about evacuation efforts, disaster response, and infrastructure preparedness to cope with such disasters effectively. Individuals seek viable strategies for ensuring their safety and minimizing potential damage. Another prominently discussed topic revolved around support and donations. Within this theme, individuals proposed and sought assistance through various means, including collecting 'help', 'fundraising' initiatives, and 'donations'.

Furthermore, hurricane intensity and forecasting emerged as a significant area of interest for the public. People actively sought information regarding hurricane evolution, intensity levels, and ways to disseminate this information to others. Keywords such as 'shortage' and 'death' emphasized the seriousness of the situation, indicating the public's awareness of the human and resource implications caused by hurricanes.

Table 4. Most discussed topics

Topic groups	Related keywords
Hurricane/healthcare management	'kit','Irma','operation','monitoring', 'management','center','prepared', 'evacuation','mandatory','underprepared', 'preparedness','response','hospital', 'patient', 'infrastructure
Support and donation	'donation','fundraiser','proceeds','donating', 'donate','collecting', 'fundraising', 'victim', 'help', 'affected', 'helping'
Hurricane intensity and forecasting	'toll', 'death', 'rise', 'serious', 'shortage', 'category','strengthens','declares', 'intensifies''become','rapidly','expected', 'intensify'

Source: Own compilation

4. Discussion

This study aims to examine and understand the public's response during extreme weather events by exploring cognitive sustainability concerns. The study approach was based on collecting Twitter data using healthcare/hurricane-related keywords for each of the five study cases and applying NLP models for sentiment, emotion, and topic analysis. A first noteworthy observation is the prevailing culture of social media engagement, even during disasters and at all hours of the day, which was emphasized by the significant number of tweets collected during the night. The word cloud and frequency analysis findings unveiled a notable presence of words related to disaster response, infrastructure, and help-seeking, where people were deeply concerned about their safety and the need to relocate to safer areas when faced with the imminent threat of extreme weather. This response reflects the urgency and importance of evacuation measures in protecting lives and mitigating potential damages. Emotional aspects, when talking about home and family, highlight the impact of EWE on the personal and mental health of individuals and communities. People's concerns centred on protecting their lives, homes, and loved ones, underlining the sense of vulnerability and the need for effective disaster preparedness plans.

Another aspect worth noting is the discussions related to providing and seeking help, which is compelling evidence of a robust information-spreading culture. It showcases the public's heightened awareness and proactive approach towards disaster preparedness, reflecting how individuals use communication channels to share critical information, warn others, and offer support during extreme weather events. These findings were supported by the outcomes of the topic modelling analysis that provided a concise and informative summary of what we classified as the main three concerns expressed by the public during EWE. The identified concerns and active engagement observed in the public response to hurricanes are deeply connected to the cognitive sustainability concept. The first prominent concern centred around emphasizing hurricane management, reflecting the need for extended sustainability where decision-makers actively manage various aspects and dimensions of the disaster. This involves responding to the immediate impact and strategically planning for infrastructure preparedness and evacuation, ensuring a comprehensive and sustainable disaster response. The second topic, revolving around donation and support, resonates with the principle of inter-cognitive sustainability. The community actively engages in collective efforts, such as fundraising and donations, showcasing a collaborative response that transcends individual cognition to support the broader affected community. The third topic, focusing on hurricane intensity and forecasting, emphasizes a shared understanding and concern for the evolving situation, with information dissemination playing a crucial role. The temporal analysis, which represented a pattern from the initial stages of the hurricane until its dissipation, further highlights this cognitive sustainability aspect, showcasing the

community's active participation in sharing real-time updates and urgent messages and experiences with social media being a way to stay informed and connected, promoting a collective and informed response.

As the hurricane intensifies, the frequency of tweets increases as people express their sentiments, emotions, and concerns about the unfolding situation. In this context, sentiment analysis results indicated a higher prevalence of negative sentiment than positive sentiment. Neutral sentiments were not detected, which may be caused by imbalanced training data and potential limitations in the training process of the pre-trained model we applied. With the dominance of the negative sentiment, it becomes evident that the overall public opinion, as reflected in the word cloud, is negative. Further analysis revealed that anger was the predominant negative sentiment extracted from emotion detection, indicating a significant dissatisfaction among citizens with disaster response and emergency efforts. This finding was corroborated by the word cloud associated with anger, highlighting the presence of these topics.

Additionally, the continuous increase in the emotions of fear and sadness, as shown in the normalized emotion distribution for Hurricane Ida, suggests a failure in effectively managing the hurricane disaster. This is particularly evident in the persistence of sadness, even after the dissipation of Hurricane Ida, reflecting the long-lasting impacts generally associated with the physical, mental, and financial difficulties faced by those directly or indirectly affected by the disaster. These findings align with our expectations for a topic focused on disasters and emergencies, with the expression of love being understandably diminished during such events. Additionally, the absence of surprise can be attributed to the availability of advanced forecasting systems that inform individuals of the hurricane's occurrence in advance. By examining the temporal aspects of our sentiment and emotion detection findings, we can investigate how fast people's responses evolve during extreme weather events. While negative sentiment was consistently prevalent, the gap between negative and positive sentiments, as shown in the daily sentiment distribution for hurricanes Irma and Harvey, rapidly decreased during hurricane dissipation and in the following days. This finding aligns with the emotion distribution of Hurricane Ida, where the emotion of joy increased the day after the hurricane's dissipation, likely attributed to relief efforts, as indicated by the word cloud associated with the joy emotion. This suggests a positively fast change in people's emotions that effective disaster response and emergency interventions can explain. However, the parallel increase in the emotion of sadness in the same graph raises questions about which populations received more assistance during the hurricanes. This leads us to one of the study's limitations: our dataset's absence of geographical indications.

This study was the first attempt to examine the public response during disasters. However, it is important to acknowledge several limitations that should be considered for future work. First, the dataset was imbalanced for each hurricane. This discrepancy in the number of tweets collected makes it challenging to compare the study case events directly. Additionally, the absence of geolocation information associated with the tweets limited our ability to capture the areas most affected by hurricanes. Moreover, good evaluation parameters for pre-trained models do not necessarily mean better performance or accurate results. This was evident in the case of the RoBERTa model, where the absence of neutral tweets in our dataset affected the model's ability to classify news-related content accurately.

We propose training an NLP model on a well-labelled and balanced dataset for future work. Additionally, we suggest the use of geo-located tweets in order to capture disparities. Also, inspired by the topic modelling results that revealed evacuation and disaster response as predominant concerns, we can work on assessing emergency management and healthcare system vulnerability during EWE, which will facilitate the development of targeted interventions to strengthen disaster response capabilities for cognitive sustainability and propose alternatives with a focus on exploring the role that E-health and telemedicine as innovative solutions.

5. Conclusion

In conclusion, this study explored the public's response during EWE by analyzing Twitter data and highlighting the concept of cognitive sustainability. The analysis revealed three key concerns: hurricane management, donation and support, and disaster impacts. We provided insight into how people react to these topics by applying NLP techniques for sentiment and emotional analysis. However, it is essential to acknowledge the limitations of this study. The imbalanced data collection and lack of geographical indications in the dataset may have influenced the representation of certain areas and topics, potentially impacting the overall findings.

For future work, it is recommended to address the limitations by ensuring a more balanced data collection and incorporating geographical parameters. Moreover, further research could focus on refining sentiment and emotion analysis by training NLP models rather than relying on pre-trained ones to capture the nuances of public responses more accurately. Exploring other social media platforms and languages could provide a more comprehensive understanding of the public's response during EWE. Finally, this study lays the groundwork for better understanding the public's concerns and responses during extreme weather events, offering valuable insights for disaster management and emergency preparedness efforts.

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