Information Switching Patterns of Risk Communication in Social Media During Disasters

Khondhaker Al Momin, Arif Mohaimin Sadri, Kristin Olofsson, K.K. Muraleetharan, and Hugh Gladwin

***Abstract*—In an era increasingly affected by natural and human-caused disasters, the role of social media in disaster communication has become ever more critical. Despite substantial research on social media use during crises, a significant gap remains in detecting crisis-related misinformation. Detecting deviations in information is fundamental for identifying and curbing the spread of misinformation. This study introduces a novel *Information Switching Pattern Model* to identify dynamic shifts in perspectives among users who mention each other in crisis-related narratives on social media. These shifts serve as evidence of crisis misinformation affecting user-mention network interactions. The study utilizes advanced natural language processing, network science, and census data to analyze geotagged tweets related to compound disaster events in Oklahoma in 2022. The impact of misinformation is revealed by distinct engagement patterns among various user types, such as bots, private organizations, non-profits, government agencies, and news media throughout different disaster stages. These patterns show how different disasters influence public sentiment, highlight the heightened vulnerability of mobile home communities, and underscore the importance of education and transportation access in crisis response. Understanding these engagement patterns is crucial for detecting misinformation and leveraging social media as an effective tool for risk communication during disasters.**

***Index Terms*—Disaster communication, social media, information-switching, public sentiment, misinformation detection, disaster management.**

I. Introduction and Motivation

THE increasing frequency of natural, human-made, and technological disasters, driven by factors such as climate change and geopolitical shifts, poses ever-greater challenges for emergency management. One of the most critical tasks during such crises is disseminating accurate survival information to the public. This task becomes even more difficult when the crisis involves multiple threats that impact survival requirements differently. In the past, traditional channels like news media, websites, and personal communication networks played a central role in delivering this information [1]. However, in recent years, social media has emerged as a dominant platform for real-time information sharing, bringing with it the dual challenges of rapid information sharing and the risk of misinformation [2]. While scanning and correcting misinformation is a potential approach, the sheer scale of information flow on social media makes this task exceedingly difficult to manage in real time. Consequently, ensuring the dissemination of accurate, reliable information is essential to safeguard public safety, facilitate effective crisis response, and foster trust between communities and authorities [3].

This research introduces a novel methodology for understanding and improving the flow of information during complex crises, particularly when multiple threats impact survival needs differently. It highlights that individuals, in their search for survival information, often engage in various conversations on social media, mentioning or replying to others in different threads. In doing so, they form networks of shared information as they switch between sources to find credible and relevant details. These dynamic shifts in information-seeking behavior can inadvertently spread misinformation. This may lead to confusion, panic, and disruptions in emergency response, potentially worsening the crisis and causing further harm [4]. Understanding these information-switching patterns is therefore critical. It helps enhance emergency communication strategies, mitigate the spread of misinformation, and address the unique challenges posed by modern-day disasters.

The *Information Switching Pattern Model* introduced in this study is designed to detect and analyze dynamic shifts in user behavior during crises. The model differs from existing research on misinformation in several ways. Most prior studies focus on static analysis, identifying and categorizing misinformation only after it has spread, often without considering its evolving nature [5]. In contrast, this model emphasizes real time detection of shifts in user perspectives within a network. By analyzing changes in sentiment and user-mention patterns, this model captures how information deviation evolves and influences user interactions in real time. Additionally, while most existing research has not considered socio-demographic data, our framework integrates geotagged tweets with socioeconomic information from the U.S. Census. This integration enables a more comprehensive understanding of how information switching varies across specific demographic groups and communities.

Received 14 July 2024; revised 27 September 2024; accepted 10 October 2024. Recommended for acceptance by Special Issue On Big Data Analytics in Complex Social Information Networks. *(Corresponding author: Khondhaker Al Momin.)*

Khondhaker Al Momin, Arif Mohaimin Sadri, and K.K. Muraleetharan are with the School of Civil Engineering and Environmental Science, University of Oklahoma, Norman, OK 73019 USA (e-mail: momin@ou.edu).

Kristin Olofsson is with the Department of Political Science, Colorado State University, Fort Collins, CO 80523 USA.

Hugh Gladwin is with the Department of Global and Sociocultural Studies, Florida International University, Miami, FL 33199 USA.

This article has supplementary downloadable material available at https://doi.org/10.1109/TBDATA.2024.3524828, provided by the authors.

Digital Object Identifier 10.1109/TBDATA.2024.3524828

Unlike existing approaches, which often examine misinformation at the level of individual tweets or users [6], our framework utilizes network science to build user-mention networks. This network-based analysis reveals complex patterns of influence and interaction that are not captured by analyzing isolated tweets. Our framework also incorporates topic modeling and temporal analysis to identify distinct patterns of information deviation across various disaster types and peak disaster periods. The temporal dimension provides insights into how misinformation related to different disasters evolves over time. Furthermore, the model's detailed analysis of perspective shifts within user-mention networks provides a comprehensive view of how information switching occurs in the first place. Overall, the proposed framework provides a more dynamic and comprehensive approach to studying information deviation and misinformation, moving beyond the static and isolated perspectives of existing literature. This study specifically addresses the following research questions:

a. *What are the characteristics of online social media actors from diverse groups such as bots, agencies, and individuals who engage in a variety of risk communication topics during disasters?*
b. *How do socio-demographic factors, such as household composition, gender, and race, affect the information-switching patterns of different social media actors during disasters?*
c. *What is the influence mechanism of information switching, and how does network structure shape information-switching patterns within online risk communication networks?*

II. Background and Related Work

Recent studies have highlighted the impact of misinformation on social disruption [7], democracy satisfaction [8], health behaviors [9], trust in information sources [10], vaccine intent [11], credibility judgments [12], and public health responses during crises [13]. For example, during the early months of the COVID-19 pandemic, misinformation was linked to around 6,000 hospitalizations and 800 deaths globally [14]. In one case, a couple in Arizona ingested fish tank cleaner, mistakenly believing it would prevent COVID-19, demonstrating the real dangers of misinformation [15]. The economic toll of misinformation has also been significant, with the stock market and global economy suffering considerable losses [16].

Social media platforms (SMPs) (i.e., Facebook, X (formerly known as Twitter), Instagram, Reddit, and LinkedIn) are virtual spaces where individuals and organizations connect, post and share content. While these platforms are primarily being used to maintain personal connections and promote businesses, they also play a significant role in risk communication [17]. However, automated programs known as bots complicate information flows on these platforms. Bots can be beneficial, disseminating real time information or harmful, spreading misinformation and breaching privacy. For example, Twitter bots can post a high volume of tweets on specific topics, which users may share without verifying the source's accuracy or reliability [18].

Crises inherently create a pressing need for authentic information, which often results in an influx of data from various sources [19]. As individuals and communities try to understand evolving situations, social media platforms are crucial for obtaining up-to-date information and comprehending the changing narrative landscapes. However, this influx can cause information overload and confusion, increasing the risk of misinformation [20]. Thus, to better understand the overall dynamics of information dissemination, it is essential to understand how users transition between different information sources and narratives and how their perspectives change.

As social media has become a dominant form of communication, its potential to both spread authentic information and amplify misinformation is increasingly evident, particularly during crises. SMPs function as a double-edged sword, capable of rapidly disseminating crucial information or, conversely, spreading misinformation, which can lead to confusion, panic, and distrust [21]. Misinformation, in particular, can undermine emergency response efforts and public health measures. As such, understanding how users switch between information sources during crises is critical for improving risk communication. In this study, information switching refers to temporal shifts in perspectives as social media users engage with and spread information across various topics during multiple (compound) hazard events.

Due to their widespread availability and the prevalence of mobile internet access, SMPs are essential tools for risk communication during emergencies [22]. These platforms have transformed how public and private agencies, as well as crisis response teams, interact with local communities during emergencies [23]. However, the dynamic nature of information flow on SMPs marked by the rapid spread of news, rumors, and updates, poses challenges for ensuring accurate and coordinated communication. Misinformation can spread quickly, leading to panic or uncoordinated responses [24]. Moreover, the diverse range of users, from individuals to official organizations, creates varying perceptions and reactions to crisis-related content. To effectively leverage SMPs during crises, it is critical to understand these dynamics and develop strategies for promoting reliable and timely risk communication.

Despite the extensive literature on the role of SMPs in risk communication, research often overlooked detailed analyses of the information switching patterns among users during crises [25], [26], [27]. Previous research has emphasized the general importance of SMPs in crisis management [28], [29], [30], [31], [32], but lacks a comprehensive analysis of how factors such as user types (bot vs. non-bot), disaster context, content type, and socioeconomic variables influence the dynamics of information flow these platforms.

This study addresses this gap by focusing on how social media users engage with, share, and respond to crisis-related information. By analyzing user-mention networks that form around crisis discussions, this study identifies the dynamics of information switching and perspective shifts among social media users. Through a combination of network analysis, topic modeling, sentiment analysis, and regression modeling, this research uncovers the factors driving changes in user engagement and perspective. These insights are crucial for developing effective risk communication strategies.

III. Methodology

This study employs a multi-tiered classification framework for Twitter accounts, including bot detection and differentiation between agency and individual accounts. By integrating machine learning models, natural language processing, and network analysis, we identified information-switching patterns on social media during various disasters.

A. Twitter Account Classification

We implemented a detailed classification process for Twitter users. Initially, we categorized users into bot and non-bot accounts. Non-bot accounts were further classified into agency accounts and individual users. Agency accounts were then divided into four subcategories: government/public entities, private organizations, television or news media channels, and nonprofit organizations. The detailed process for user account classification is provided in the supplementary section, Appendix A, available online.

To gain deeper insights into non-bot accounts on Twitter, we categorized them into two main groups: agency and individual accounts. This classification was based on key features, including profile description, followee-follower ratio, and named entity identification using spaCy's named entity recognition (NER), an open-source natural language processing tool that effectively extracts named entities from text [33]. Agencies typically have formal profile descriptions that detail their work area, services, mission statement, and often include contact information or operating hours. In contrast, individuals tend to have more informal descriptions, reflecting personal details such as interests, hobbies, or location. Agencies generally exhibit a higher follower-to-followee ratio, broadcasting to larger audiences while following fewer accounts [34], whereas individuals typically have a more balanced or lower ratio, engaging in reciprocal interactions by following friends, celebrities, or other accounts of interest.

Further classification of agency accounts was conducted using profile descriptions and tweet content analysis. Agencies were grouped into four categories: government/public, television or news media, private, and non-profit organizations. Well-structured profile descriptions often indicated their affiliation, such as being a government entity, news outlet, private company, or non-profit. Tweet content also played a role in classification; for instance, government agencies primarily post updates on policies, public services, and emergency information, while news agencies focus on sharing articles and breaking news. Private organizations use Twitter to advertise products, share industry insights, or promote customer testimonials, and non-profits typically tweet about their activities, advocacy efforts, or donation appeals [35].

B. Information Switching Pattern Model

We used a multi-step process to examine the dynamics of information switching patterns among social media users during disasters, as outlined in Algorithm 1. This approach combined network analysis, topic modeling, sentiment analysis, and the tracking of sentiment shifts to understand how communication networks evolve in response to ongoing events.

The first step involved collecting a dataset of tweets related to specific disasters. Tweets were selected based on relevant hashtags, keywords, and geotags associated with each event. From this dataset, we constructed a user-mention network [31], where nodes represent individual users and edges indicate mentions between users in tweets. This network was analyzed to identify the largest connected component, ensuring a focus on a coherent subset of users who were interconnected either directly or indirectly. The second step involved topic modeling. Using the tweets from the largest connected component, we applied the Latent Dirichlet Allocation (LDA) algorithm [36] to group tweets into distinct topics based on content similarity, helping to identify the main themes of discussion during the disaster.

Next, we conducted sentiment analysis on the tweets corresponding to each topic. The analysis began with the initial tweet (base tweet) on a given topic and extended to subsequent tweets (follow-up tweets) related to that topic. The goal was to evaluate the sentiment of these tweets and track changes over time. We used the Python package *vaderSentiment* to quantify the sentiment of each tweet, enabling us to observe how user sentiment evolved after the disaster. The central focus of the information-switching pattern analysis was to monitor and measure how users' sentiments and perspectives shifted in response to the disaster. This involved comparing the sentiment of base tweets to follow-up tweets for each topic, identifying users who exhibited changes in sentiment, the magnitude of these changes, and the time intervals when these shifts occurred.

Finally, we analyzed the data to identify patterns of information switching. Statistical and network analysis techniques were used to quantify sentiment shifts and map these changes onto the user-mention network. This analysis helped identify influential users, examine different user types (individuals, agencies, bots), and evaluate demographic and socio-economic characteristics using geotagged locations cross-referenced with census data. This approach provided valuable insights into the mechanisms of information spread and the structure of communication on social networks.

IV. Data Collection

A. Study Area: The State of Oklahoma

This study analyzed geotagged tweets from the state of Oklahoma for the year 2020. According to FEMA's National Risk Index (NRI) [37], Oklahoma faces significant risks from eleven major disasters: tornadoes, heatwaves, droughts, ice storms, hail, strong winds, flooding, flash floods, lightning, hurricanes, earthquakes, and wildfires. Understanding these risks is essential for policymakers and emergency responders in developing effective disaster preparedness and mitigation strategies.

B. Twitter Data

We used the Twitter Academic Application Programming Interface (API) to access Twitter data from January 1 to December

Algorithm 1: Information Switching Pattern Model.

Input: Geo-tagged tweets, U.S. Census data
Output: Information switching patterns, regression and machine learning model results
Begin
Collect geo-tagged tweet data using Twitter API
Perform Data Cleaning:
  - Pre-process and format tweet data
  - Determine sentiment score for each tweet
For each tweet
  Perform reverse geo-coding to identify census tract and county
  Collect socioeconomic information using U.S. Census API
  Map socioeconomic data with each tweet
EndFor
Identify race and gender for each user using race-gender model
Classify users using machine learning models
Classify disaster type for each tweet using BERT model
Create timeseries/temporal plot of tweets
Identify peak periods (weekly) for each disaster type throughout the year
For each disaster type and each peak period
  Perform topic modeling
  Determine the optimum number of topics using coherence scores
  For each optimum topic
    Generate user-mention network (users as nodes, mentions as edges)
    Find all connected component subgraphs of the network
    For each subgraph
      Sort nodes based on timestamp of tweets
      Take the first node as the base node and its sentiment as the base sentiment
      For each other node in the subgraph
        Compute change in sentiment and change in time compared to base node
      EndFor
      Exclude base node and base sentiment score from dataset
    EndFor
  EndFor
EndFor
End

31, 2022 [38]. The data includes tweet content, user information (such as user IDs and screen names), engagement metrics (likes, retweets, and replies), timestamps, geolocation data (when available), and metadata such as hashtags, mentions, and URLs. This extended time frame was chosen to capture the temporal dynamics of social media user behavior during disasters. The API's full-archive search endpoint provided access to the complete historical record of public narratives on Twitter [39].

We used the *point radius* query option with a 25-mile radius, the highest resolution available for this method to capture location-based tweets. Consequently, we divided Oklahoma into a 17.5-mile by 17.5-mile grid (since $17.5\sqrt{2} < 25$ miles) and used the midpoint of each diagonal of the grid squares as the center of a 25-mile radius circle. Through an iterative process, we collected all geotagged tweets from the state. This process generated some duplicate tweets, which were subsequently removed. The final dataset comprised approximately 1.51 million tweets from 42,712 unique users. Fig. 1 shows the distribution of tweets across different counties in Oklahoma. We used the *tweet-preprocessor* Python package to remove noise, i.e., character codes, emojis, stop words, and HTML tags from the tweets to enhance data quality. After removing the noise, all tweets were lemmatized and tokenized. This preprocessing step was essential for subsequent analysis and enabled the identification of various disaster-related tweets.

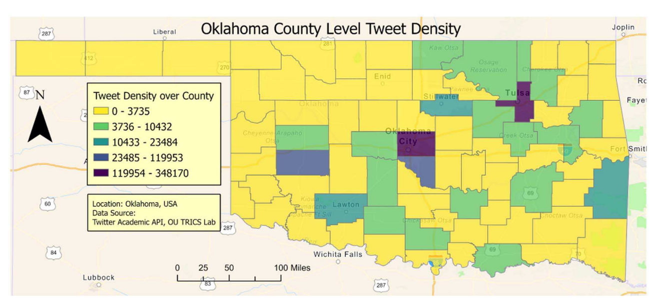


Fig. 1. Tweet density heatmap for different counties in Oklahoma.

C. Socioeconomic and Demographic Data

Race and gender (GR) identification of Twitter users was conducted using the methodology described in [40]. The use of unconventional or *'fancy'* usernames on Twitter often creates challenges in accurately identifying real names. As a result, the GR classification model used in this study included an additional category for unidentified individuals. It is important to note that this GR classification model is not applicable to entities such as organizations, bots, and media outlets like TV stations or newspapers. Geo-tagged tweets provide location information in the form of latitude and longitude coordinates. We applied a reverse geocoding approach to convert these coordinates into census tracts using the Census API, thereby deriving meaningful geographic context. To enrich the analysis, we integrated socioeconomic variables from the Federal Emergency Management Agency (FEMA) Community Resilience Indicator Analysis [41]. This integration allowed us to incorporate detailed socioeconomic context, enhancing our understanding of how demographic and socioeconomic factors influence information-switching patterns during crises.

V. Results

In this section, we present the findings from our study, which cover several key analyses: user account classification, classification and temporal analysis of disaster-related tweets, topic modeling, the information switching pattern model, and linear regression analysis. Each subsection provides insights into user engagement and sentiment evolution in response to disaster-related content on social media, the thematic content of discussions during disaster peaks, and the statistical relationships between user characteristics and sentiment changes. This comprehensive approach sheds light on the multifaceted nature of public interaction with crisis communication on social media platforms.

A. Twitter User Account Classification

We considered six distinct features for bot and non-bot account classification: profile descriptions, average tweeting rate, retweet count, user mention count, followee-follower ratio, and listed count. Using the methodology described in this study, we identified 78 bot accounts among the 42,712 unique users, resulting in 42,634 non-bot accounts. Of these non-bot accounts, 1,714 were classified as agency accounts, while the majority, 40,920 accounts, were classified as individual accounts. We further grouped the 1,714 agency accounts into four categories: government/public agencies, private organizations, news and television channels, and nonprofit organizations. The final distribution is 390 government agencies, 219 news and television channels, 1,088 private organizations, and 17 nonprofit organizations.

B. Classification and Temporal Analysis of Disaster Tweets

Fig. 2.1 to 2.11 shows the number of geotagged tweets classified into each disaster type using a fine-tuned BERT model on our dataset. Strong winds were the most frequently discussed disaster in Oklahoma, with 10,125 mentions (29.57%), while wildfires were the least discussed, with only 52 mentions (0.15%). Each subplot title in the figure includes the total tweet count and the corresponding percentage for each disaster type, using three distinct metrics: count of unique users tweeting about the event, total number of tweets, and the number of users mentioned in tweets related to the event. Significant peaks in the graphs suggest periods of increased tweeting activity, corresponding to actual weather events or heightened public discussion. For example, the tornado graph shows a peak around week 16, and the wildfire graph shows several spikes throughout the year, reflecting multiple hazard events or continued discussion. The hail graph exhibits a regular pattern of peaks, indicating a seasonal nature to hailstorms or related discussions. In contrast, the earthquake graph displays less frequent, sporadic spikes, reflecting the unpredictable nature of earthquakes. Though Oklahoma is not vulnerable to hurricanes, people tend to talk about hurricanes that happened elsewhere.

Fig. 2.12 represents the weekly tweeting activity of different user types across the year. We used Yeo-Johnson transformation [42] on the tweeting frequency to stabilize the variance and make the data more suitable for comparison. This transformation is beneficial for skewed distributions or groups with different variances, as it normalizes the data and makes statistical analysis more robust [43]. Bot accounts show consistent tweet fluctuation, indicated by multiple peaks throughout the year, reflecting automated posting behaviors. Individual users exhibit a volatile tweeting pattern, with several peaks suggesting periods of heightened activity possibly in response to personal interests or major events. Government entities, newspapers, and private agencies show moderate activity with occasional spikes that correlate with public announcements or organizational news. In contrast, nonprofit organizations show the least tweeting activity, maintaining a relatively flat trend line, which implies sporadic engagement on the platform. This graph provides a comparative insight into the tweet frequencies of different types of users, highlighting variations and potential trends in their Twitter use over time.

C. Network Dynamics of User Mentions in Disasters

We analyzed the dynamics of communication within user-mention networks that formed around the disaster-related discussions. A user-mention network is formed by mapping the interactions between users who mention each other in tweets. Each node in the network represents a user, and each edge represents a mention (information flow) from one user to another. The largest component of a user-mention network refers to the most extensive connected subnetwork where any two users are connected directly or indirectly through mentions. We formed this network to understand how information flows and how different types of users engage with each other during disaster events. Analyzing the largest component helps us identify key influencers (described as base nodes in this study) and hubs that drive discussions and disseminate information widely.

The user-mention network shown in Fig. 3(a) represents the dynamics of communication within the largest connected component in tornado related discussions. Central to the graph is a dense cluster of nodes representing key individuals or organizations that play a pivotal role in the dissemination and exchange

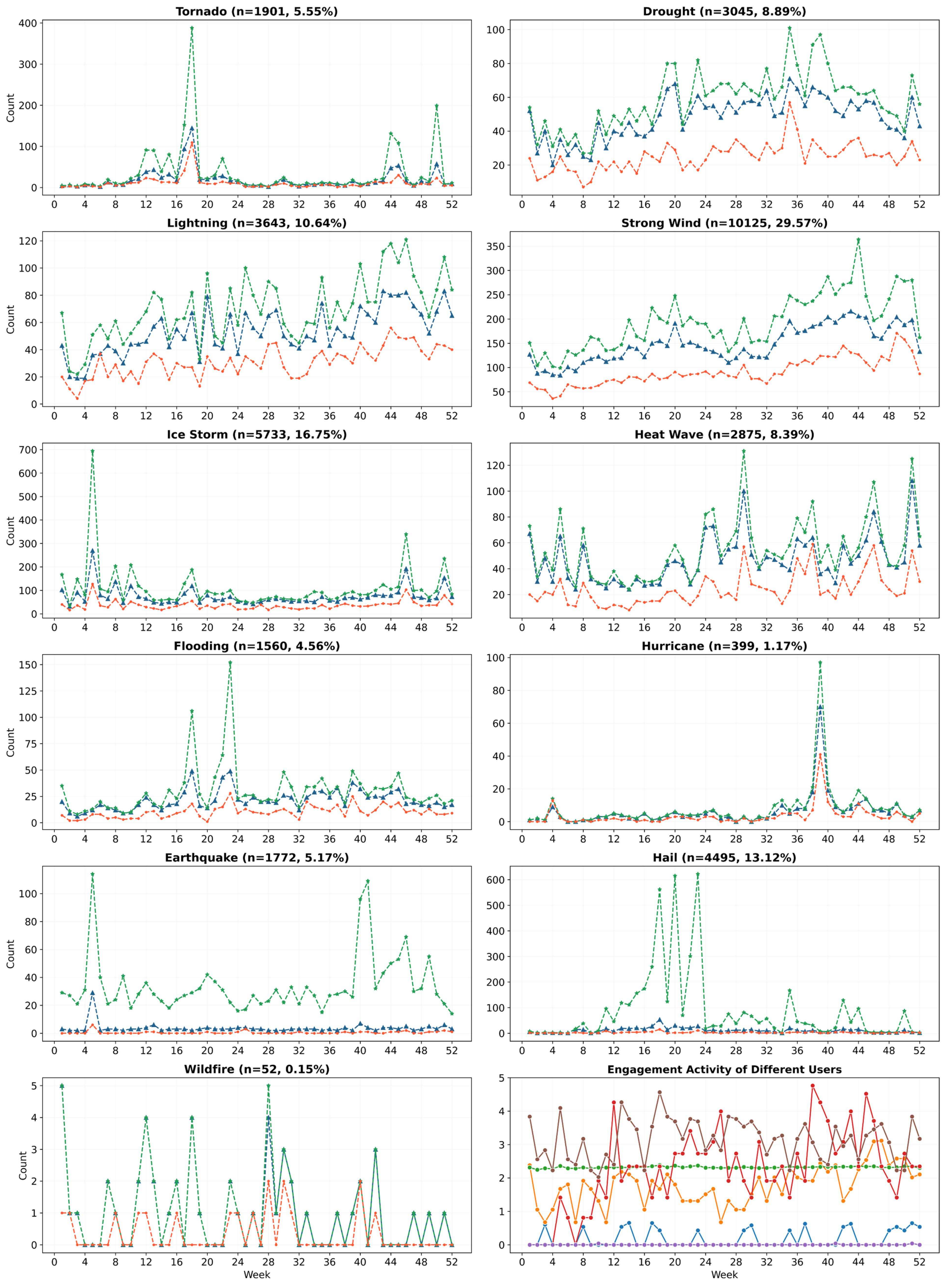
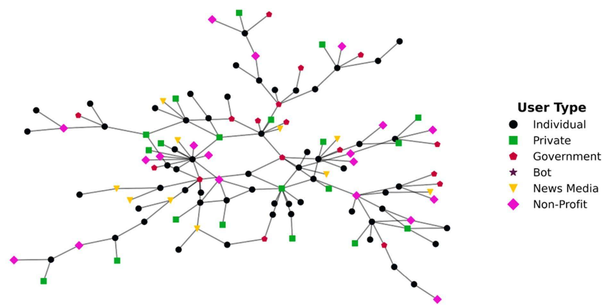
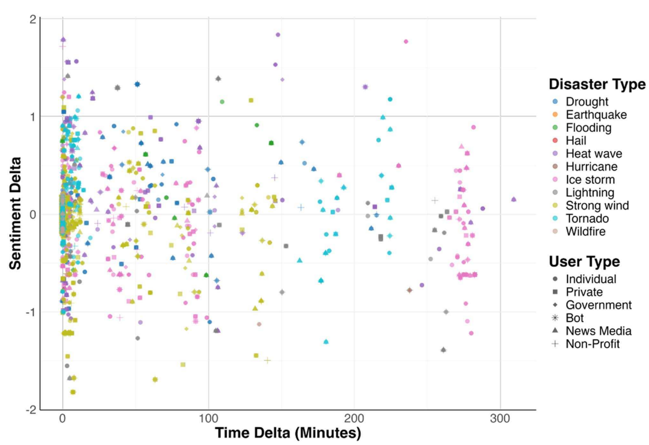


Fig. 2. Weekly Distribution of Tweet Counts. Subfigures 2.1 to 2.11 show tweeting activity for various disasters on a weekly basis, while Subfigure 2.12 illustrates weekly tweeting activity segmented by different user types.



(a) User-Mention Network



(b) Sentiment Variations

Fig. 3. (a) Largest connected component in the Tornado-related user-mention network. (b) Temporal analysis of sentiment changes in response to disaster events.

of information. The color-coded nodes[1]—representing individuals, bots, government, newspapers, and nonprofits—highlight diverse engagement from different entity types. Among these nodes, few stand out due to their higher number of connections (known as degree), signifying their role as influencers or hubs within this network, potentially driving the narrative and flow of information. The descriptive statistics of the user-mention networks discussing various disasters throughout the year are presented in Appendix C, available online.

D. Thematic Content Analysis During Disaster Peaks

This section presents the thematic analysis of tweets, identifying key topics discussed during peak periods of various disasters. The findings from the topic model (presented in Appendix C, available online) reveal a wide range of themes, including water-related concerns, natural calamities, meteorological phenomena, sports, and societal critique. Water-related topics, in particular, cover issues such as water scarcity, the urgency of restoring water resources, and the impact of water on daily life. This emphasizes the significant focus on water availability and management, likely influenced by climate and water-related challenges such as droughts and floods in Oklahoma.

[1]Please note that not all user types are present in this largest component of the tornado related user-mention network

E. Information Switching Pattern Model

Using the comprehensive methodology outlined above, the study generated a dataset consisting of 5,105 observations across 31 variables. These variables include categorical data (e.g., disaster type, month, gender, race) and numerical data (e.g., centrality measures, socioeconomic indicators, sentiment, time deltas). Descriptive statistics for the variables used in this model are provided in Tables I and II. For numerical variables, the tables display the mean, standard deviation, minimum, first quartile (Q1), median (Q2), third quartile (Q3), and maximum values. For categorical variables, the tables show the category values, counts of occurrences, and their percentage of the total.

The dependent variables in the information switching pattern modeling are *Sentiment Delta* (range -2 to 2) and *Time Delta* (range 0 to infinity). The scatter plot in Fig. 3(b) shows the relationship between sentiment changes and the time elapsed since different disaster events. Most sentiment changes occurred within the first 30 minutes, indicating immediate public engagement with disaster-related discussions. This engagement varies by disaster type; for example, hurricanes and floods often lead to positive sentiment changes, whereas droughts and wildfires are associated with negative sentiment changes. This pattern suggests that the nature of a disaster influences public sentiment. Data points are mostly clustered around moderate changes in sentiment, with fewer instances of extreme changes. The distinction between node types is also evident: private organizations display less varied sentiment responses compared to individuals and news outlets. Over time, the frequency of sentiment changes diminishes, indicating a decrease in public engagement or fading intensity of reactions as a disaster becomes less immediate.

Fig. 3(b) can also identify problematic social media users by analyzing their reaction time and sentiment deviation during disaster events. The x-axis in Fig. 3(b) represents Time Delta, indicating how quickly a user reacts, with lower values (closer to the left) showing faster responses. The y-axis represents the Sentiment Delta, which measures changes in sentiment. We focus on users whose sentiment deviations fall outside the moderate range of (-0.5, 0.5), indicating significant deviations from the original sentiment. These users react quickly but exhibit highly unstable or extreme perspective changes within a short amount of time. According to the analysis, the most common problematic users are individuals, with 266 occurrences showing high deviation. This is followed by private entities (110), government organizations (109), newspapers (102), and nonprofits (92).

Several preventive measures can be implemented to address the problematic social media users during disaster events. First, enhancing monitoring and alert systems is crucial; setting up automated tools to track rapid reactions and extreme perspective deviations on social media can enable timely interventions. Targeted communication strategies should also be developed to manage high-risk users, such as individuals and private entities who exhibit significant sentiment deviations. Providing accurate and timely information can mitigate misinformation and reduce sentiment extremes. Educational campaigns can inform users about the impact of their posts, encouraging more responsible communication. Increased moderation efforts on social media

TABLE I
DESCRIPTIVE STATISTICS OF NUMERICAL VARIABLES

Numerical Variable	Mean	Standard Deviation	Minimum	1st Quartile (Q1)	2nd Quartile (Q2)	3rd Quartile (Q3)	Maximum
Sentiment Delta	-0.015	0.379	-1.822	-0.129	-0.002	0.123	1.839
Time Delta	17.858	53.128	0	0.068	0.140	1.845	309.289
Degree Centrality	0.521	0.394	0.008	0.143	0.533	0.667	1
Betweenness Centrality	0.143	0.338	0	0	0.005	0.109	1
Closeness Centrality	0.700	0.063	0	0.667	0.707	0.750	1
Clustering Coefficient	0.005	0.063	0	0	0	0	1
Eigenvector Centrality	0.207	0.267	0	0.050	0.707	0.707	0.707
Average Neighbor Degree	6.098	11.909	1	2	2.5	7	81
Average Degree	1.491	0.355	1	1.333	1.500	1.778	2.571
Network Radius	1.396	1.318	1	1	1	2	6
Network Diameter	2.475	1.589	1	2	2	2	9
Network Density	0.522	0.336	0.018	0.222	0.500	0.667	1
Mobile Homes	70.921	150.823	0	23	83	207	2156
Median Household Income	61843	23249	32045	46978	61146	63750	250001
Unemployed Labor Force	1085	586	70	971	1094	1203	2974
Households with Children	682	446	1	396	639	724	2573
Population 65 and Older (percentile)	18.059	6.916	3	15.851	17.892	20.352	32.963
Black or Hispanic Population (percentile)	6.521	6.015	0	1.418	4.358	7.489	81.593
Single Parent Households (percentile)	17.426	9.266	1	14.918	18.236	19.175	80.793
Married couple Household (percentile)	40.579	15.186	10.933	34.041	41.135	48.548	82.021
Population without Health Insurance (percentile)	19.130	8.033	0.748	12.320	14.054	18.995	31.440
Population without High School Education (percentile)	8.507	4.466	1	3.965	5.853	9.369	26.113
Households without a Vehicle (percentile)	6.479	3.775	0	4.913	7.619	7.692	36
Population Below Poverty Level (percentile)	16.453	9.400	1.041	7.608	15.966	19.694	44.289

TABLE II
DESCRIPTIVE STATISTICS OF CATEGORICAL VARIABLES

Categorical Variable	Value	Count	Percentage	Categorical Variable	Value	Count	Percentage
Disaster Type	Strong Wind	1615	31.64%	Discussion Topic	Wind Warnings	90	1.76%
	Heat Wave	878	17.20%		Election Commentary	55	1.08%
	Ice Storm	707	13.85%		Wildfire Updates	49	0.96%
	Drought	684	13.40%		Oklahoma Flooding	35	0.69%
	Lightning	493	9.66%		Severe Weather Watch	15	0.29%
	Tornado	324	6.35%		Hail Alerts	14	0.27%
	Flooding	208	4.07%		Oklahoma Earthquakes	14	0.27%
	Hurricane	130	2.55%		Severe Flooding Reports	10	0.20%
	Hail	35	0.69%	Gender	Female	1001	19.61%
	Wildfire	17	0.33%		Male	501	9.82%
	Earthquake	14	0.27%		Unidentified	3277	64.19%
Discussion Topic	Tornado Warnings	639	12.52%	Race	Unidentified	3277	64.19%
	Heat Wave Discussions	581	11.38%		White	1587	31.09%
	Wind Conditions	567	11.11%		Asian	148	2.90%
	Weather Reports	497	9.74%		Hispanic	87	1.70%
	Snowfall Reports	389	7.62%		Black	4	0.08%
	Living Cost & Inflation	256	5.02%		American Indian	2	0.04%
	Miscellaneous	292	5.72%	User Type	Individual	2101	41.16%
	Hurricane Concerns	127	2.49%		Private Agencies	819	16.04%
	Water and Daily Needs	223	4.37%		Govt. Agencies	775	15.18%
	Heavy Snow and Ice	183	3.58%		TV & Newspaper	720	14.10%
	Restoring Water Resources	179	3.51%		Non-Profit Organizations	689	13.50%
	Staying Safe in Changing Weather	164	3.22%		Bot	1	0.02%
	Water Concerns	150	2.94%	Base Node Type	Individual	2275	44.56%
	Thunderstorm Discussion	141	2.76%		Non-Profit Organizations	735	14.40%
	Urgent Water Needs	132	2.58%		TV & Newspaper	707	13.87%
	OKC Thunder Games	95	1.86%		Private Agencies	703	13.85%
	Winter Storm Updates	91	1.78%		Govt. Agencies	679	13.30%
					Bot	1	0.02%

platforms are necessary to swiftly address problematic content, with more stringent review processes for posts from users showing high perspective deviations. Collaboration with various organizations, including private entities, government bodies, newspapers, and nonprofits, is essential to ensure coordinated responses and minimize extreme perspective shifts. Finally, establishing feedback mechanisms for users to report problematic content and suggest improvements can enhance the accuracy and stability of information. The information-switching model proposed in this study can be used to identify those problematic users and using the socio-demographic information to find the causes of extreme perspective deviations to refine these preventive measures and improve future response strategies.

In addition to identifying problematic users and implementing preventive measures, analyzing the demographic factors influencing sentiment changes during crises provides further insight into how different groups react under stress. Levene's test [44] indicated that females exhibit greater variance in sentiment change compared to males during crises, with a statistic of 129.06 and p-value less than 0.01, thus rejecting the null hypothesis of equal variances. An ANOVA test showed that minority groups experience more significant sentiment changes during compound hazards compared to other groups. The Race variable had an F-statistic of 6.150 and p-value of 0.002, indicating a statistically significant difference in sentiment changes across racial groups.

1) Results of Linear Regression Analysis: Table III summarizes the results of the linear regression analysis assessing the relationship between various factors—including disaster types, node types, user types, gender, race, network properties, and socioeconomic variables—on sentiment delta and time delta. It provides the regression coefficients and standard errors for each

TABLE III
RESULTS OF THE REGRESSION MODEL

Dependent Variable		**Sentiment Delta**		**Time Delta**	
No. Observations:		5105		5105	
F (32, 5071):		29.24		45.13	
Prob (F-statistic):		0.0000		0.0000	
R-squared:		0.170		0.227	
Adj. R-squared:		0.165		0.222	
Root MSE:		0.248		0.151	
		Sentiment Delta		**Time Delta**	
	Variables	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Disaster Type	Strong Wind	-0.138***	0.025	-0.021**	0.011
	Heat Wave	0.089***	0.029	0.053***	0.013
	Ice Storm	0.063***	0.024	-0.011	0.010
	Drought	0.456***	0.028	-0.030**	0.012
Discussion Topic	Tornado Warnings	0.141***	0.036	0.012	0.016
	Heat Wave Discussions	-0.079**	0.037	-0.071***	0.016
	Wind Conditions	0.218***	0.032	-0.0019	0.014
	Oklahoma Weather Reports	0.178***	0.035	0.012	0.015
	Snowfall Reports	0.052***	0.025	0.0084	0.011
Base Node Type	Individual	0.046***	0.016	0.026***	0.007
	Non-Profit Organizations	0.048***	0.016	-0.012*	0.007
	TV & Newspaper	0.038	0.013	-0.015***	0.006
User Type	Individual	0.005***	0.030	0.032**	0.013
	Private Agencies	-0.022	0.032	-0.039***	0.014
Gender	Female	0.015	0.017	0.018**	0.007
	Male	-0.013	0.024	0.008	0.010
Race	White	-0.042	0.047	0.030	0.020
	Asian	-0.059*	0.036	0.013	0.016
	Other	-0.060*	0.031	-0.007	0.013
Network Properties	Closeness Centrality	0.388***	0.086	-0.030	0.037
	Clustering Coefficient	0.308***	0.096	-0.083**	0.042
	Eigenvector Centrality	-0.500***	0.080	0.076**	0.035
	Average Neighbor Degree	-1.127***	0.056	-0.066***	0.025
	Average Degree	-0.598**	0.196	0.216**	0.085
	Network Diameter	-0.175***	0.052	0.297***	0.023
	Network Density	-0.443***	0.123	0.016	0.054
Socio-Economic	Black or Hispanic Population (percentile)	-0.101	0.065	-0.084***	0.028
	Median Household Income	0.074	0.133	0.023	0.058
	Mobile Homes	0.316***	0.075	0.038	0.032
	Population without Health Insurance (percentile)	0.122**	0.060	-0.029	0.026
	Population without High School Education (percentile)	0.083*	0.046	0.018	0.020
	Households without a Vehicle (percentile)	-0.134**	0.062	-0.067**	0.027
	Population Below Poverty Level (percentile)	-0.064	0.042	0.064***	0.018
Constant		0.526***	0.182	-0.074	0.079

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Sentiment delta was modeled using absolute values.*

independent variable. The table also summarizes the model's overall fit, including the number of observations, the F-statistic and its significance, the R-squared and adjusted R-squared values, and the root mean square error (MSE). The coefficients indicate the average change in the dependent variables (sentiment delta and time delta) associated with each factor, controlling for other variables in the model. Asterisks denote the statistical significance of the coefficients. This table contains outcomes of a thorough regression analysis, including only variables with statistically significant influence. It is the result of multiple iterations and rigorous statistical testing to ensure the reliability of the findings. Factor collapsing was used to combine categories and levels within variables to identify the most significant factors.

2) Disaster Type and Discussion Topic: The analysis of tweets related to different disasters reveals varying effects on sentiment and the rate of sentiment change. Discussions related to strong wind events show a decrease in sentiment variability and a slower rate of sentiment change, indicating a more stable public reaction. Conversely, heat waves significantly increase sentiment variability and the rate of sentiment change, making sentiment more variable over time. Ice storms increase sentiment variability but do not affect the rate of change, reflecting an initial heightened response that stabilizes. In contrast, drought-related discussions increase sentiment variability and show slower rate of change, indicating a diverse and sustained public response.

Tornado warnings increase sentiment variability, suggesting intense public concern, but have minimal impact on the rate of sentiment change, indicating stable reaction timing. Discussions about heat waves also decrease sentiment variability and significantly slow the rate of sentiment change, implying less rapid shifts in sentiment as the heat wave persists. Mentions of wind conditions increase sentiment variability, reflecting diverse reactions, but do not affect the rate of change, indicating consistent emotional responses. General weather reports increase sentiment variability but do not alter the rate of change, suggesting a steady sentiment flow despite initial variability. Finally, snowfall discussions increase sentiment variability, indicating varied emotional responses, but have minimal effect on the rate of change, showing stability in sentiment evolution.

3) Base Node Type and User Type: The base node type, the entity initiating the discussion (e.g., individual, nonprofit organization), affects sentiment and timing differently. Conversations started by individuals significantly increase sentiment variability, showcasing a wide range of personal opinions and reactions. The rate of sentiment change also accelerates, indicating that while initial reactions are diverse, sentiment quickly evolves as the discussion progresses. This highlights the dynamic nature of individual-initiated discussions, marked by varied starting points and rapid sentiment evolution.

Conversations begun by nonprofit organizations also increase sentiment variability, indicating diverse public engagement. However, they show a slight decrease in the rate of sentiment change, suggesting a more gradual evolution of public sentiment following initial responses. Discussions prompted by TV and newspaper entities do not significantly impact sentiment variability but are associated with a notable decrease in the rate of sentiment change. This implies a more stable sentiment trajectory, possibly due to the perceived authority and reliability of these traditional media sources.

4) User-Mention Network Properties: The analysis of network characteristics reveals their varying impacts on sentiment variability and the rate of sentiment change. High closeness centrality within a network correlates with increased sentiment variability, indicating that central users interact with a wider range of people. However, closeness centrality does not significantly influence the rate of sentiment change, suggesting that central users' sentiments vary at a consistent pace. A higher clustering coefficient is associated with increased sentiment variability, indicating that tightly knit clusters contribute to diverse sentiment responses. Conversely, a high clustering coefficient correlates with a decrease in the rate of sentiment change over time, potentially due to the reinforcing effect of closely connected groups maintaining consistent sentiment over longer periods. Greater eigenvector centrality, indicating influential users within the network, is linked to less sentiment variability but an increased rate of sentiment change, suggesting that while influential users have more uniform sentiment responses, their influence leads to quicker shifts in sentiment across the network.

A lower average neighbor degree is tied to less sentiment variability and a slower rate of sentiment change, implying that users with less influential neighbors experience more stable sentiment and less dynamic shifts. Conversely, a lower average degree corresponds with less sentiment variability but a higher rate of sentiment change, indicating that less connected users have more stable sentiment patterns but react more quickly to changes in the network.

A larger network diameter is associated with less sentiment variability, suggesting a dilution of sentiment extremes across larger network paths. However, a larger diameter also correlates with a faster rate of sentiment change, possibly reflecting the delayed but rapid transmission of sentiment across the network. Higher network density results in decreased sentiment variability, indicating more homogenous sentiment in denser networks. However, network density does not significantly influence the rate of sentiment change, suggesting that the density of connections affects the range of sentiment but not the speed of its evolution.

5) Socioeconomic Factors: The analysis of socio-demographic factors reveals their impacts on sentiment variability and the rate of sentiment change. A higher percentile of Black or Hispanic population is associated with decreased sentiment variability, suggesting a more uniform sentiment response within these demographic groups. However, it correlates with an increased rate of sentiment change over time, indicating that while initial responses are uniform, they become more dynamic as situations progress.

Median household income does not significantly influence sentiment variability or the rate of sentiment change, indicating that income levels may not play a decisive role in how sentiment evolves during a crisis within this dataset's context.

The presence of mobile homes in a community is positively associated with sentiment variability, highlighting the potential vulnerability of populations living in mobile homes to sentiment changes during disasters. Communities with significant mobile homes are more likely to experience sentiment shifts. The vulnerability of mobile homes to natural disasters contributes to increased sentiment variability and a higher rate of sentiment change over time.

An increased percentile of the population without health insurance is linked to increased sentiment variability, possibly due to the varied impact of health-related crises on uninsured groups. However, it does not significantly affect the rate of sentiment change over time.

Higher percentages of the population without a high school education are associated with increased sentiment variability, suggesting that educational attainment levels influence how individuals process and react to crisis information. However, there is no significant impact on the rate of sentiment change over time.

Lack of vehicle access within households is negatively associated with sentiment variability, potentially reflecting the impact of transportation access on crisis perception and response capabilities. As vehicle access decreases, sentiment variability also decreases. Households without vehicle access might rely more on local support networks or community resources, leading to a more unified response and less sentiment variability. In contrast, households with vehicle access might have more varied sentiments based on individual choices and perceptions.

The percentile of the population below the poverty level is not significantly associated with sentiment variability but is linked to an increased rate of sentiment change over time. This reflects the precarious nature of the economic conditions of these populations, leading to rapid shifts in sentiment in response to evolving crisis situations.

VI. Conclusion

This study provides a comprehensive analysis of social media user behaviors by categorizing users into six distinct classes and employing various machine learning models to explain their characteristics and behaviors. A novel contribution is the *Information Switching Pattern Model*, which captures changes in public sentiment and their rate during disasters. Supplemented with demographic, socioeconomic, and network property data, this model provides a detailed view of factors driving sentiment variability in crises. The study identifies significant socioeconomic variables and the role of network properties in sentiment dynamics. It reveals the resilience of households without vehicles, the vulnerability of communities living in mobile homes, and the influence of educational attainment and transportation access on crisis response. This research enhances our understanding of social media behavior during disasters and provides valuable insights for policymakers and crisis communicators. Future studies can apply this research design in other contexts to validate the findings. The *Information Switching Pattern Model* can also be used in non-disaster settings, enabling the development of efficient, supportive, and targeted strategies to address challenges in various crisis situations.

With the insights gained from this research, policymakers can better shape responses to build resilience in vulnerable communities. Past work has demonstrated that disaster policy has consistently underserved our most vulnerable populations, and this research is a first step in evidencing additional characteristics of these communities that could inform future policy efforts. In addition, the *Information Switching Pattern Model* highlights the weakness in information dissemination policies during crisis situations. Crisis communicators can use the results here as a basis for tackling this obstacle by modernizing communication structures, which is imperative to improving outcomes for affected communities.

VII. Study Limitations

While this study offers valuable insights, several limitations should be considered when interpreting the results, as they may influence the generalizability and scope of the findings. One of the limitations of our study is the reliance on geotagged tweets, which excludes a significant portion of relevant data that is not geotagged. The spatial specificity provided by geotagged tweets is crucial for linking social media activity with sociodemographic characteristics at the census tract level. Without this geo-information, it would be challenging to accurately correlate tweet content with demographic factors, thus potentially affecting the depth of insights into how different communities are impacted by different disasters. Future research could benefit from exploring methods to incorporate more extensive social media datasets or alternative approaches to enhance the integration of social media data with socio-demographic information. Another challenge involves the classification of misinformation. While the *Information Switching Pattern Model* captures dynamic shifts in sentiment and user interactions, accurately classifying misinformation remains challenging. Not all shifts in public sentiment are necessarily related to misinformation, and distinguishing between legitimate changes in opinion and misinformation-induced behavior requires more robust verification methods.

Acknowledgment

The research presented in this paper was supported by the National Science Foundation under Grant Nos. CAREER-2339100 and OIA-1946093. Any opinions, findings, conclusions, and recommendations expressed are those of the authors and do not necessarily reflect the views of the National Science Foundation. The authors also acknowledge the support provided by the University of Oklahoma Libraries for open access publication.

References

[1] G. Haddow and K. S. Haddow, *Disaster Communications in a Changing Media World*. London, U.K.: Butterworth-Heinemann, 2013.

[2] M. S. Al-Zaman, “Prevalence and source analysis of COVID-19 misinformation in 138 countries,” *IFLA J.*, vol. 48, no. 1, pp. 189–204, 2022.

[3] P. T. Jaeger, B. Shneiderman, K. R. Fleischmann, J. Preece, Y. Qu, and P. F. Wu, “Community response grids: E-government, social networks, and effective emergency management,” *Telecommun. Policy*, vol. 31, no. 10–11, pp. 592–604, 2007.

[4] A. Bernsteiner, T. Schubatzky, and C. Haagen-Schützenhöfer, “Misinformation as a societal problem in times of crisis: A mixed-methods study with future teachers to promote a critical attitude towards information,” *Sustainability*, vol. 15, no. 10, 2023, Art. no. 8161.

[5] S. Lewandowsky, U. K. Ecker, and J. Cook, “Beyond misinformation: Understanding and coping with the “post-truth” era,” *J. Appl. Res. Memory Cogn.*, vol. 6, no. 4, pp. 353–369, 2017.

[6] Y. Wang, R. Han, T. S. Lehman, Q. Lv, and S. Mishra, “Do Twitter users change their behavior after exposure to misinformation? An in-depth analysis,” *Social Netw. Anal. Mining*, vol. 12, no. 1, 2022, Art. no. 167.

[7] R. Iizuka, F. Toriumi, M. Nishiguchi, M. Takano, and M. Yoshida, “Impact of correcting misinformation on social disruption,” *PLoS One*, vol. 17, no. 4, 2022, Art. no. e0265734.

[8] E. C. Nisbet, C. Mortenson, and Q. Li, “The presumed influence of election misinformation on others reduces our own satisfaction with democracy,” *Harvard Kennedy Sch. Misinformation Rev.*, 2021.

[9] V. Suarez-Lledo and J. Alvarez-Galvez, “Prevalence of health misinformation on social media: Systematic review,” *J. Med. Internet Res.*, vol. 23, no. 1, 2021, Art. no. e17187.

[10] S. Chen, L. Xiao, and A. Kumar, “Spread of misinformation on social media: What contributes to it and how to combat it,” *Comput. Hum. Behav.*, vol. 141, 2023.

[11] S. Loomba, A. de Figueiredo, S. Piatek, K. de Graaf, and H. J. Larson, “Measuring the impact of covid-19 vaccine misinformation on vaccination intent in the uk and usa,” *Nat. Hum. Behav.*, vol. 5, no. 3, pp. 337–348, 2021.

[12] J. Zhou, H. Xiang, and B. Xie, “Better safe than sorry: A study on older adults’ credibility judgments and spreading of health misinformation,” *Universal Access Inf. Soc.*, vol. 22, no. 3, pp. 957–966, 2023.

[13] S. K. Chong, S. H. Ali, L. N. Doan, S. S. Yi, C. Trinh-Shevrin, and S. C. Kwon, “Social media use and misinformation among Asian Americans during COVID-19,” *Front. Public Health*, vol. 9, 2022, Art. no. 764681.

[14] M. Spring, “Coronavirus: The human cost of virus misinformation,” 2020. [Online]. Available: https://www.bbc.com/news/stories-52731624

[15] BBC, “Coronavirus: Man dies taking fish tank cleaner as virus drug,” 2020. [Online]. Available: https://www.bbc.com/news/52012242

[16] B. Petrie, “How misinformation became the leading cause of death in the U.S. and what can be done about it,” 2023, Accessed: Aug. 04, 2023.

[17] P. Garg and S. Pahuja, *Social Media: Concept, Role, Categories, Trends, Social Media and AI, Impact on Youth, Careers, Recommendations*. Hershey, PA, USA: IGI Global, 2020, pp. 172–192.

[18] S. Haustein, T. D. Bowman, K. Holmberg, A. Tsou, C. R. Sugimoto, and V. Larivière, "Tweets as impact indicators: Examining the implications of automated bot accounts on twitter," *J. Assoc. Inf. Sci. Technol.*, vol. 67, no. 1, pp. 232–238, 2016.

[19] J. Qadir, A. Ali, R. ur Rasool, A. Zwitter, A. Sathiaseelan, and J. Crowcroft, "Crisis analytics: Big data-driven crisis response," *J. Int. Humanitarian Action*, vol. 1, pp. 1–21, 2016.

[20] M. Mohammed et al., "Assessment of COVID-19 information overload among the general public," *J. Racial Ethnic Health Disparities*, vol. 9, pp. 184–192, 2022.

[21] X. Li, X. Guo, and Z. Shi, "Bright sides and dark sides: Unveiling the double-edged sword effects of social networks," *Social Sci. Med.*, vol. 329, 2023, Art. no. 116035.

[22] R. Ogie, S. James, A. Moore, T. Dilworth, M. Amirghasemi, and J. Whittaker, "Social media use in disaster recovery: A systematic literature review," *Int. J. Disaster Risk Reduction*, vol. 70, 2022, Art. no. 102783.

[23] B. Takahashi, E. C. Tandoc Jr, and C. Carmichael, "Communicating on Twitter during a disaster: An analysis of tweets during typhoon Haiyan in the Philippines," *Comput. Hum. Behav.*, vol. 50, pp. 392–398, 2015.

[24] D. Allington, B. Duffy, S. Wessely, N. Dhavan, and J. Rubin, "Health-protective behaviour, social media usage and conspiracy belief during the COVID-19 public health emergency," *Psychol. Med.*, vol. 51, no. 10, pp. 1763–1769, 2021.

[25] A. M. Sadri et al., "The role of social capital, personal networks, and emergency responders in post-disaster recovery and resilience: A study of rural communities in Indiana," *Natural Hazards*, vol. 90, pp. 1377–1406, 2018.

[26] K. C. Roy, S. Hasan, A. M. Sadri, and M. Cebrian, "Understanding the efficiency of social media based crisis communication during hurricane Sandy," *Int. J. Inf. Manage.*, vol. 52, 2020, Art. no. 102060.

[27] M. W. Graham, E. J. Avery, and S. Park, "The role of social media in local government crisis communications," *Public Relations Rev.*, vol. 41, no. 3, pp. 386–394, 2015.

[28] K. Seneviratne, M. Nadeeshani, S. Senaratne, and S. Perera, "Use of social media in disaster management: Challenges and strategies," *Sustainability*, vol. 16, no. 11, 2024, Art. no. 4824.

[29] A. M. Sadri, S. Hasan, S. V. Ukkusuri, and M. Cebrian, "Crisis communication patterns in social media during hurricane Sandy," *Transp. Res. Rec.*, vol. 2672, no. 1, pp. 125–137, 2018.

[30] X. Han, J. Wang, M. Zhang, and X. Wang, "Using social media to mine and analyze public opinion related to COVID-19 in China," *Int. J. Environ. Res. Public Health*, vol. 17, no. 8, 2020, Art. no. 2788.

[31] K. A. Momin, H. M. I. Kays, and A. M. Sadri, "Identifying crisis response communities in online social networks for compound disasters: The case of hurricane Laura and COVID-19," *Transp. Res. Rec.*, 2023, Art. no. 03611981231168120.

[32] S. V. Ukkusuri, X. Zhan, A. M. Sadri, and Q. Ye, "Use of social media data to explore crisis informatics: Study of 2013 Oklahoma tornado," *Transp. Res. Rec.*, vol. 2459, no. 1, pp. 110–118, 2014.

[33] R. M. Yanti, I. Santoso, and L. H. Suadaa, "Application of named entity recognition via Twitter on spacy in Indonesian (case study: Power failure in the special region of Yogyakarta)," *Indonesian J. Inf. Syst.*, vol. 4, no. 1, pp. 76–86, 2021.

[34] M. Cha, H. Haddadi, F. Benevenuto, and K. Gummadi, "Measuring user influence in Twitter: The million follower fallacy," in *Proc. Int. AAAI Conf. Web Social Media*, 2010, pp. 10–17.

[35] L. Hagen, S. Neely, R. Scharf, and T. E. Keller, "Social media use for crisis and emergency risk communications during the Zika health crisis," *Digit. Government, Res. Pract.*, vol. 1, no. 2, pp. 1–21, 2020.

[36] K. Bastani, H. Namavari, and J. Shaffer, "Latent dirichlet allocation (LDA) for topic modeling of the CFPB consumer complaints," *Expert Syst. Appl.*, vol. 127, pp. 256–271, 2022.

[37] National risk index for natural hazards | FEMA.gov. [Online]. Available: https://www.fema.gov/flood-maps/products-tools/national-risk-index

[38] N. Statt, "Twitter is opening up its full tweet archive to academic researchers for free," *Verge*, Jan 2021. [Online]. Available: https://www.theverge.com/2021/1/26/22250203/twitter-academic-research-publictweet-archive-free-access

[39] T. Adam, "Enabling the future of academic research with the twitter api," *X Developer Platform*, 2021. [Online]. Available: https://developer.x.com/en/blog/product-news/2021/enablingthe-future-of-academic-research-with-the-x-api

[40] K. A. Momin, A. M. Sadri, and M. S. Hasnine, "Leveraging social media data to identify factors influencing public attitude towards accessibility, socioeconomic disparity and public transportation," 2024, *arXiv:2402.01682*.

[41] L. Edgemon, C. Freeman, C. Burdi, J. K. Hutchison, and K. Marsh, "Community resilience indicator analysis: Commonly used indicators from peer-reviewed research," *Argonne Nat. Lab.*, Tech. Rep., Apr. 2023.

[42] S. Weisberg, "Yeo-Johnson power transformations," *Dept. Appl. Statist., Univ. Minnesota*, vol. 1, 2001, Art. no. 2003.

[43] S. A. Othman and H. T. M. Ali, "Improvement of the nonparametric estimation of functional stationary time series using Yeo-Johnson transformation with application to temperature curves," *Adv. Math. Phys.*, vol. 2021, pp. 1–6, 2021.

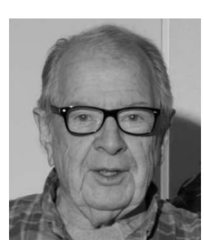
[44] B. B. Schultz, "Levene's test for relative variation," *Systematic Zool.*, vol. 34, no. 4, pp. 449–456, 1985.

Khondhaker Al Momin received the BSc degree in civil engineering and the MSc degree in transportation engineering from the Bangladesh University of Engineering and Technology (BUET). He is currently working toward the PhD degree with the School of Civil Engineering and Environmental Science, the University of Oklahoma. His research focuses on Big Data analytics, network science, natural hazards, and system optimization.

Arif Mohaimin Sadri received the doctoral degree from the Lyles School of Civil Engineering, Purdue University. He is an associate professor with the School of Civil Engineering and Environmental Science, the University of Oklahoma. His research focuses on how transportation systems critically depend on social and other physical systems in the context of natural and human-made hazards. He develops data-driven and network-based solutions to enhance bottom-up resilience in complex, interdependent systems.

Kristin Olofsson received the PhD degree in public affairs from the University of Colorado. She is an assistant professor of political science with Colorado State University. Her research focuses on policy coalitions and networks, particularly in contentious political environments. She employs comparative research designs, survey data, and network analysis to explore public policy, political behavior, and political psychology.

K.K. Muraleetharan is the Kimmell-Bernard chair in Engineering and a David Ross Boyd and a Presidential professor of Civil Engineering and Environmental Science with the University of Oklahoma. He is also a fellow of the American Society of Civil Engineers (ASCE). He is interested in large-scale computer simulations of infrastructure (bridges, roads, levees, port facilities, etc.) subjected to extreme events (earthquakes, ice storms, high winds, etc.), validations of these simulations using small-scale and full-scale testing, and resilience of infrastructure systems following extreme events.



Hugh Gladwin received the PhD degree in cognitive anthropology from Stanford University. He is an associate professor emeritus with Florida International University (FIU). At FIU, he directed the Institute for Public Opinion Research pioneering GIS-based survey design resulting in risk-mapped inferentially-valid random probability design datasets. He is a coauthor of more than 20 publications based on these datasets. He has also studied and published on the intersection of memory models, risk-sharing, and decision-tree modeling.