ABC Framework Analysis of Post-Disaster Twitter Dynamics

Student: Debarpita Dash
Roll No: 220328
Team Name: Neuro

Introduction

Social media platforms play a central role in shaping collective responses to disasters. Beyond information sharing, platforms such as Twitter act as real-time social sensors, capturing how people interpret events and express emotions. The continuous, large-scale nature of this data offers a unique lens into the temporal dynamics of collective behavior. Prior research has shown that online discourse systematically shifts after catastrophic events, often moving from situational awareness toward emotional expression and collective action.
An important question therefore is: *Do these observed temporal changes represent organized, non-random responses to disruptive events, or are they merely emergent trends arising from stochastic temporal variation in social media activity?* Addressing this question is crucial for understanding whether online discourse following disasters can be interpreted as a collective response rather than a passive byproduct of heightened attention.
This report applies an ABC (Antecedent–Behavior–Consequence) framework to post-disaster Twitter activity to examine whether disaster onset produces structured, non-random patterns of collective behavior. By treating the disaster as an external antecedent and changes in tweeting behavior as observable responses, the analysis assesses whether shifts in online discourse reflect organized adaptation rather than incidental variation. Combining a behavioral perspective with statistical evaluation, the study provides insight into how collective attention and social response reorganize following disruption, highlighting the potential of social media as a lens for understanding large-scale behavioral dynamics in crisis contexts.

Antecedant

The antecedent condition is defined as the occurrence of a disaster event and the immediate post-impact phase. At this point: **The disaster has already occurred.**
The environment is characterized by uncertainty, urgent information needs, emotional distress, and emerging response efforts. The observation window is restricted to Days 0–7, capturing the acute phase of public reaction. This antecedent creates a powerful situational stimulus that disrupts normal communication patterns and activates large-scale collective sense-making processes.

Behavior

The behavior of interest is the daily distribution of tweet class labels following the disaster. To analyze this, we first compared the proportion of tweets posted immediately after the disaster (the first two days) with those posted during days 3–7. This comparison was visualized using a bar chart, shown in Figure 1.

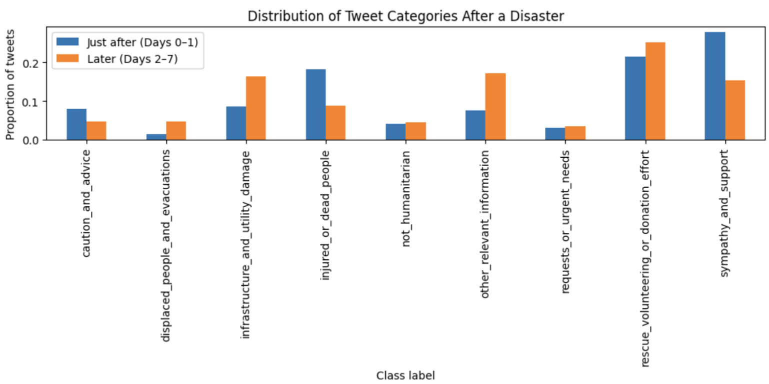

Figure 1: Distribution of tweet class labels in the immediate aftermath (days 1–2) and the later period (days 3–7) following the disaster.

From this analysis, we identify four semantically meaningful categories:

1. `injured_or_dead_people` – reporting casualties and human impact
2. `infrastructure_and_utility_damage` – describing physical destruction and service disruption
3. `sympathy_and_support` – emotional responses, condolences, and expressions of solidarity
4. `rescue_volunteering_or_donation_effort` – mobilization of help and resources

To identify broader linguistic trends across these time periods, we generated word clouds for the two durations (days 1–2 and days 3–7). Before visualization, place names were manually removed by extending the stopword list. The resulting word clouds are shown below.

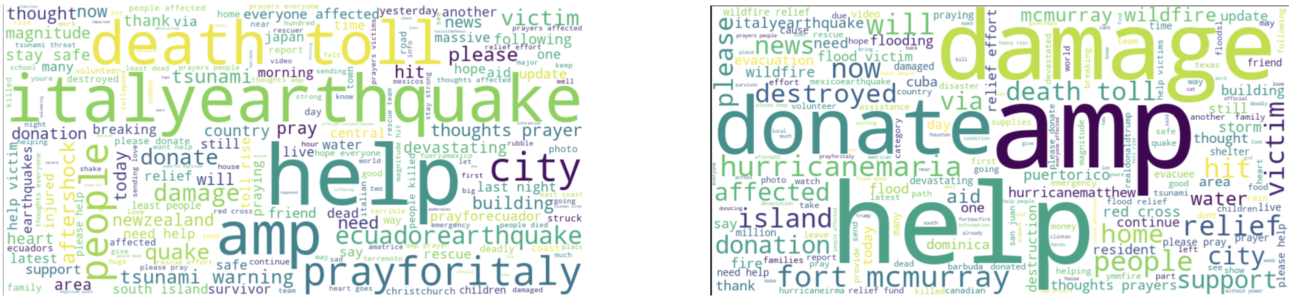

Figure 2: Word clouds for tweets posted (left) in the immediate aftermath (days 1–2) and (right) during the later period (days 3–7).

Following this, we conducted a class-specific analysis by generating word clouds for individual tweet labels in the pre- and post-disaster periods. This analysis was performed to examine whether the linguistic content within each category varied across time. The corresponding word clouds are shown below.

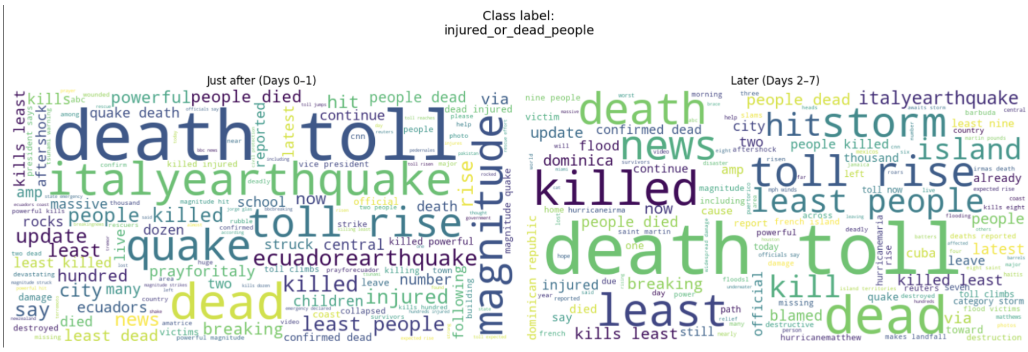

Figure 3: Comparison of word clouds for the label `injured_or_dead_people`.

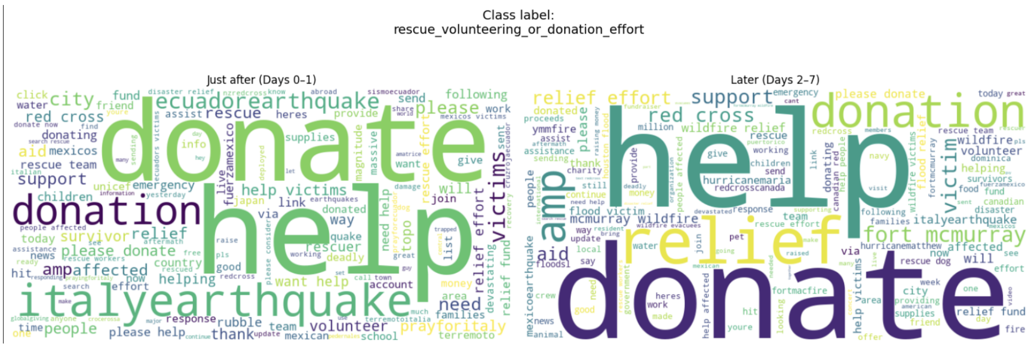

Figure 4: Comparison of word clouds for the label `rescue_volunteering_or_donation_effort`.

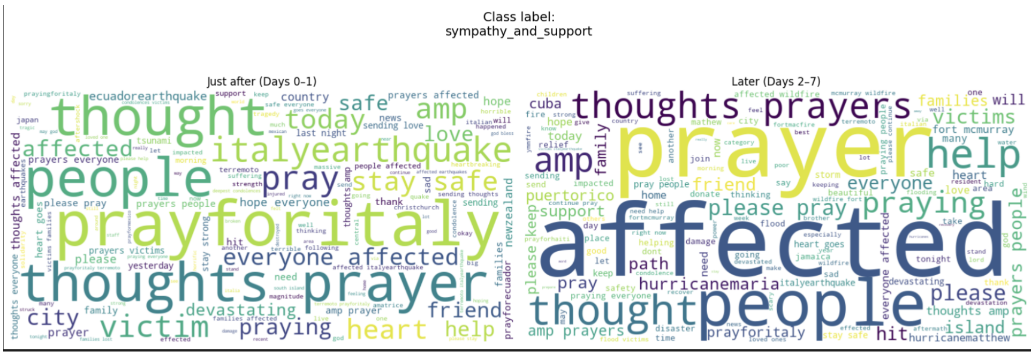

Figure 5: Comparison of word clouds for the label `sympathy_and_support`.

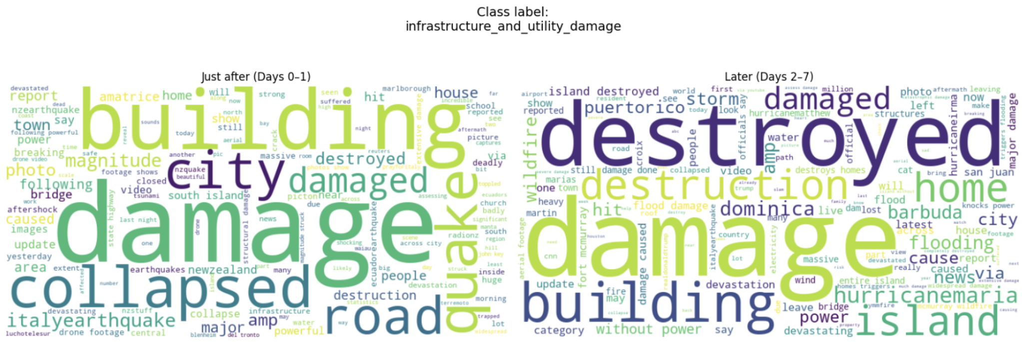

Figure 6: Comparison of word clouds for the label `infrastructure_and_utility_damage`.

To quantitatively assess the similarity between the pre- and post-disaster word usage within each category, we computed the Jaccard similarity between the corresponding word sets. The results are reported in Table 1.

Class Label	**Jaccard Similarity**
`injured_or_dead_people`	0.1937
`rescue_volunteering_or_donation_effort`	0.1926
`infrastructure_and_utility_damage`	0.1745
`sympathy_and_support`	0.1676

Table 1: Jaccard similarity between pre- and post-disaster word sets for each tweet category.

Analysis

The word clouds make the shift in tweeting behavior over time easy to observe.In the immediate aftermath of the disaster (days 1–2), the most prominent words are closely tied to urgency and impact. Terms such as *death toll*, *warning*, *help*, and *hope* appear frequently, along with references to the disaster itself and to rescue and emergency services.This suggests that early tweets focus on understanding what happened, identifying who was affected, and seeking or offering immediate help.During this phase, Twitter largely functions as a channel for rapid situation updates, alerts, and urgent requests.

In contrast, the word cloud for the later period (days 3–7) shows a clear change in emphasis.Although words related to damage and casualties remain present, they are less dominant. Instead, terms such as *donate*, *relief*, *support*, *damage*, and *destroyed* become more visible, indicating a growing focus on recovery and sustained response.At the same time, emotionally supportive language—including *prayers*, *strength*, *together*, and *stay safe*—appears more frequently.

This shift reflects a movement away from immediate shock toward coordination, longer-term assistance, and collective emotional support.Overall, the change in prominent vocabulary across the two periods suggests that tweeting behavior evolves in a structured manner, mirroring the progression from crisis awareness to recovery and solidarity.

The class-specific word clouds further reinforce this temporal pattern. For the `injured_or_dead_people` category, early tweets are dominated by terms such as *magnitude*, *death toll*, and *injured*, reflecting an initial focus on reporting impact and severity. In the later period, words like *killed* and *dead* become more prominent, while references to *injured* largely disappear. This shift suggests a move from immediate reporting toward acknowledging loss and its aftermath.

Within the `rescue_volunteering_or_donation_effort` category, there is overlap in commonly used terms such as *help* and *donate* across both periods.However, the later word cloud introduces more structured and organization-related terms, including *relief* and *Red Cross*, indicating a transition from urgent appeals to more coordinated forms of assistance.

The `sympathy_and_support` category shows relatively stable emotional content over time, though the tone shifts subtly. Early expressions tend to reflect shock and immediate concern, whereas later messages emphasize resilience and shared endurance. This is reflected in the appearance of words such as *affected* in the later period.

For the `infrastructure_and_utility_damage` category, discourse remains broadly consistent across time, with early and later tweets both focusing on physical damage using terms like *school*, *roads*, and *collapsed*, suggesting sustained attention to infrastructure impacts.

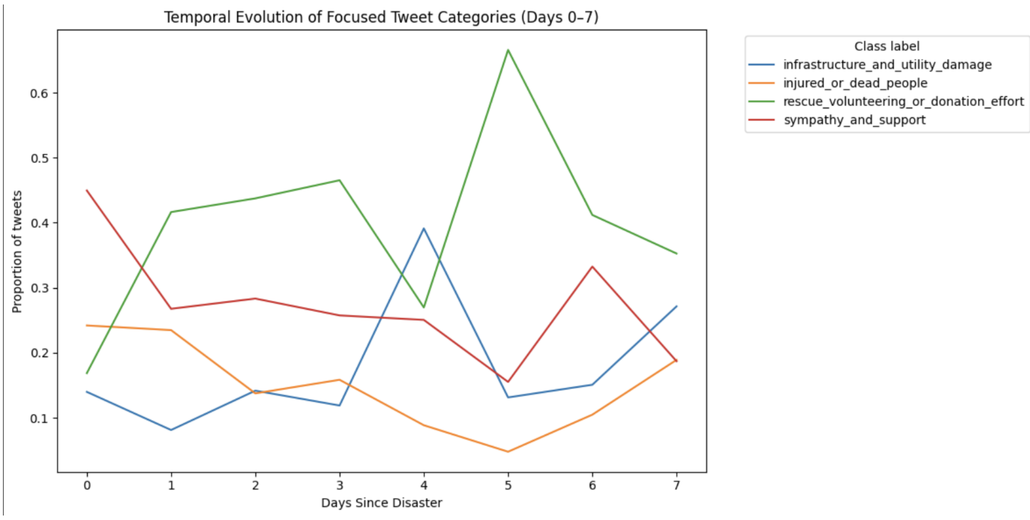

Figure 7: Temporal Evolution of tweet categories

These qualitative patterns align with the Jaccard similarity scores, which are low across all categories. Low similarity values indicate that while the same thematic categories persist, the vocabulary within each category evolves over time. Together, the word clouds and similarity analysis provide clear evidence that post-disaster tweeting behavior is temporally structured and adaptive rather than static.

Consequence

The consequence examined is whether the observed changes in tweet category distributions reflect random temporal fluctuation or a temporally structured collective response to the disaster. To evaluate this, we applied a Monte Carlo permutation test in which tweet timestamps were repeatedly shuffled to generate a null distribution of expected early–later differences under random temporal assignment.

Figure 8 shows the resulting null distributions for each tweet category, along with the observed early–later difference marked by a dashed red line. Across all four categories, the observed differences lie far in the tails of their respective null distributions. The corresponding Monte Carlo p-values are effectively zero for all categories, indicating that such differences are extremely unlikely to occur by chance.

These results provide strong evidence that post-disaster tweeting behavior is not driven by random variation. Instead, the disaster antecedent produces a clear and consistent reorganization of collective attention. Patterns of reporting casualties, discussing infrastructure damage, expressing sympathy, and coordinating rescue or donation efforts all change in systematic ways over time.

Taken together, the permutation results demonstrate that the consequence of the disaster is the emergence of structured, non-random collective dynamics on social media. Rather than fluctuating unpredictably, tweet content evolves in an organized manner, reflecting how public attention shifts from immediate impact and uncertainty toward recovery, support, and coordinated action.

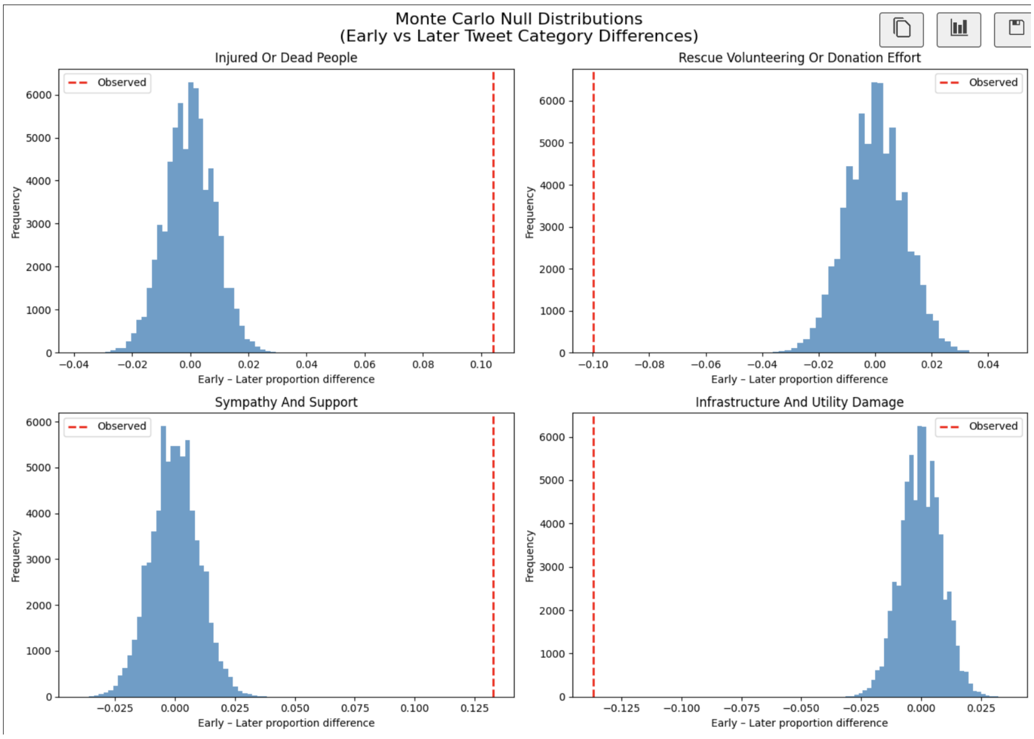

Figure 8: Temporal Evolution of tweet categories

Dastaset

We use the HumAID dataset, a human-annotated collection of disaster-related tweets from Twitter. Each tweet is labeled into predefined humanitarian information categories and includes metadata such as disaster type, location, and timestamp.

Methodology

Jaccard Similarity

To quantify how word usage within each tweet category changes over time, we compute the Jaccard similarity between the sets of unique words appearing in the early (days 1–2) and later (days 3–7) periods. The Jaccard similarity measures the overlap between two sets and is defined as the ratio of the size of their intersection to the size of their union. Lower similarity values indicate greater lexical change between time periods, while higher values suggest more stable vocabulary usage. This measure allows us to assess whether the same categories are discussed using similar or evolving language over time.

Word Cloud Analysis

Word clouds are used as a qualitative tool to visualize the most frequently occurring terms within tweet text. Separate word clouds are generated for different time periods and for individual class labels to highlight shifts in dominant vocabulary. Before generating the word clouds, tweets are lowercased and cleaned, and place names are manually removed by extending the stopword list to avoid location-specific bias. The size of each word reflects its relative frequency, enabling intuitive comparison of linguistic emphasis across time periods and categories.

Monte Carlo Permutation Test

To test whether observed changes in tweet category distributions could arise by chance, we apply a Monte Carlo permutation test. Tweet timestamps are randomly shuffled multiple times to generate a null distribution of early–later proportion differences for each category under random temporal assignment. The observed difference is then compared against this null distribution to compute a p-value. Observed differences that fall in the extreme tails of the null distribution indicate that the temporal patterns are unlikely to be due to random fluctuation, providing evidence of structured collective behavior following the disaster.

Discussion

Framed through the ABC model, the findings show a closed behavioral loop: a disruptive antecedent (disaster onset) triggers observable behavioral change (shifts in tweet categories and language), leading to a measurable consequence (structured collective attention over time).The qualitative analyses reveal how discourse evolves from immediate impact reporting and urgent appeals toward coordinated assistance and emotional support. Importantly, the Monte Carlo permutation test confirms that these shifts are not merely visual trends but reflect statistically robust temporal structure. This suggests that social media platforms function as adaptive collective systems during disasters, organizing attention and communication in response to changing situational demands. Such structure has practical implications for disaster informatics, as temporal patterns in online discourse may help identify emerging needs, coordination phases, and transitions from crisis awareness to recovery.
Several limitations should be noted. The analysis is restricted to a single annotated dataset and a short post-disaster window, and automated classification may introduce labeling noise. Future work could extend this framework across multiple disaster types, longer time spans, and cross-platform data. Overall, by embedding Monte Carlo testing within an ABC behavioral framework, this study demonstrates that post-disaster Twitter activity reflects organized collective dynamics rather than random fluctuation, offering a principled approach for studying large-scale behavioral responses to disruption.

I also conducted a brief analysis of sentiment in tweets following the disaster. The results show that, after a few days, both positive and negative sentiment decrease, while neutral sentiment increases compared to the immediate aftermath, as illustrated in Figure 9.

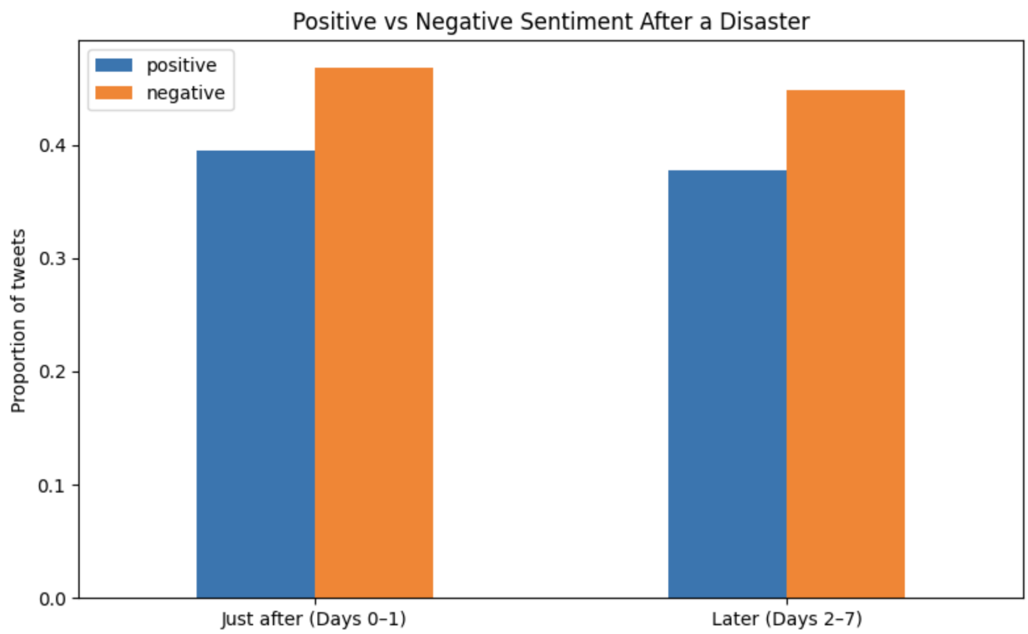

Figure 9: Sentiment across time after disaster

Code

The code used for data processing and analysis is publicly available at: `https://github.com/DebDDash/CGS616_HumanCentredComputing`. The notebook `analysis.ipynb` contains all analysis, visualizations, and statistical tests. The notebook `dataset_gen.ipynb` documents the dataset generation and preprocessing steps.

References

[1] Alam, F., Qazi, U., Imran, M., and Ofli, F. (2021). *HumAID: Human-Annotated Disaster Incidents Data from Twitter*. Proceedings of the International AAAI Conference on Web and Social Media (ICWSM).