PUBLIC REACTION ANALYSIS ON TWITTER:
A SEGMENTATION & HYPOTHESIS STUDY OF THE SHINZO ABE ASSASSINATION

BACKGROUND STORY

BACKGROUND

On July 8, 2022, former Japanese Prime Minister Shinzo Abe was shot during a campaign speech in Nara, Japan. He later died from his injuries, marking one of the most shocking acts of political violence in modern Japanese history.
The suspect, Tetsuya Yamagami, reportedly targeted Abe due to resentment toward the Unification Church, which he believed had financially harmed his family. The attack was driven by personal grievance and perceived institutional connections rather than direct political rivalry.

Why This Project Matters

- The incident triggered massive global reactions on Twitter.
- Social media became a real-time platform for news, emotion, and political framing.
- Analyzing sentiment and engagement helps us understand:
  - How digital audiences react to political crises
  - How emotion influences information spread
  - How viral amplification differs across sentiment groups

This project examines how public discourse evolves during a high-impact political event and how engagement dynamics reflect collective digital behavior.

ABOUT THE DATASET

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The dataset contains 132,094 raw Twitter posts collected immediately after the assassination of Shinzo Abe, From 8 July to 9 July 2022.

⚠ Important:
This dataset represents raw, unfiltered data before preprocessing and refinement.

Each row corresponds to one tweet captured during the data extraction period.
📌 Dataset Characteristics (Raw Data)

- Total Records: 132,094 tweets
- Total Variables: 21 columns
- Memory Usage: ~19.4 MB
- Includes:
    - Original tweets
    - Retweets
    - Replies
    - Quoted tweets
    - Multiple languages

This dataset reflects the initial public reaction stream, not yet cleaned or filtered.

🧩 What the Raw Dataset Contains

📝 Tweet-Level Data

- Tweet ID
- Timestamp
- Full text
- Hashtags
- Language
- Retweet & favorite counts

👤 User-Level Metadata

- Anonymized user ID
- Follower & following count
- Total tweets by user
- Account creation date
- Self-reported location (partially missing)

🎯 Why This Matters

Because this is raw data:

- It may contain duplicates
- It includes retweets and bot-like activity
- It includes missing location values
- It includes multilingual noise
- It contains non-relevant tweets using similar hashtags

Therefore, data cleaning and filtering are critical before analysis.

DATA CLEANING & PREPROCESSING

DATA CLEANING

Because the dataset was collected in raw format, several preprocessing steps were required before analysis.
Social media data is inherently noisy and unstructured, making cleaning a critical step to ensure reliable insights.

📌 Step 1 — Datetime Standardization
Converted time-related columns into proper datetime format:

- tweetcreatedts
- usercreateddt
- extractedts

This enables:

- Time-series analysis
- Pre vs post event segmentation
- Accurate temporal aggregation

DATA CLEANING

🌍 **Step 2 — Location to Country Extraction**

The original dataset only contained free-text location, and we found 48,988 Missing data at ‘Location’.
To make geographic analysis possible:

- **Built automatic country keyword mapping using pycountry**
- **Cleaned emojis & special symbols from location**
- **Applied rule-based matching**
- **Used GeoText for city-to-country inference**
- **Created new column: country**
- **Missing or unmatched locations labeled as "Unknown"**
- **Dropped original location column**

This step transformed unstructured text into structured geographic data.

DATA CLEANING

📊 Country Distribution (Top 5 Overview)

Before Keyword Filtering

Top 5 countries:

1. **Unknown – 88,084**
2. **India – 21,760**
3. **United States – 3,895**
4. **Nigeria – 1,889**
5. **Canada – 1,773**

After Filtering ("Shinzo" / "Abe")

Top 5 countries:

1. **Unknown – 18,591**
2. **India – 7,519**
3. **United States – 1,041**
4. **Canada – 376**
5. **Pakistan – 328**

🎯 Key Takeaway

After filtering, the distribution becomes more event-focused and geopolitically relevant.

India and the United States remain dominant contributors, while regional actors like Pakistan become more visible in the discussion.

The "Unknown" category remains substantial due to incomplete or ambiguous user location data.

DATA CLEANING

🔎 Step 3 — Missing Value Check

- Most analytical columns contain no missing values
- Location-based missing values were handled via "Unknown" labeling
- No major data loss during preprocessing

🔁 Step 4 — Duplicate Inspection

- Checked for duplicated rows
- No aggressive duplicate removal applied
- Dataset preserved as close as possible to original reaction stream

This maintains authenticity of public reaction volume.

DATA CLEANING

🧠 **Step 5 — Filter based on Shinzo Abe**

- **Filter based on Shinzo / Abe**
- **From 132.094 to 31.977**
- **The most retweeted before filtering is from BJP Activist at India that Anti-Islam and spread their agenda.**
- **Many of them are not related with shinzo abe, Include Crypto news.**
- **After filtering, all tweet about Shinzo Abe**

DATA CLEANING

Example of tweet from netizen

- Before filtering, the most retweeted is:

Please India as a friend I tell you: stop being tolerant to the intolerant. Defend Hinduism against the extremists, terrorists and jihadists. Don't appease Islam, for it will cost you dearly. Hindus deserve leaders that protect them for the full 100%!\n\n#HinduLivesMatters #India

- My speculation that is from BJP Activist at India that Anti-Islam and spread their agenda.

DATA CLEANING

Example of tweet from netizen

- After filtering, the most retweeted is:

[Breaking News] Officials say former Japanese Prime Minister #Abe Shinzo has been confirmed #dead. He was reportedly #shot during a speech on Friday in the city of #Nara, near Kyoto

FEATURE ENGINEERING

FEATURE ENGINEERING

After cleaning and structuring the dataset,
additional analytical features were created to enable segmentation and statistical testing.
This step transforms raw Twitter data into structured analytical variables.

🧠 Sentiment Scoring (VADER)

Sentiment analysis was performed using:
VADER (Valence Aware Dictionary and sEntiment Reasoner)
Why VADER?

- Designed for social media text
- Handles capitalization & punctuation emphasis
- Works well with short informal sentences

For each tweet, a compound sentiment score was generated

FEATURE ENGINEERING

🏷️ **Sentiment Labeling**

The compound score was converted into categorical labels:

- **≥ 0.05 → Positive**
- **≤ -0.05 → Negative**
- **Otherwise → Neutral**

New column created:
sentiment

This enables:

- **Sentiment distribution analysis**
- **Engagement comparison**
- **Group-based segmentation**

FEATURE ENGINEERING

⚠️ Interpretation Note

It is important to clarify that “Negative” does not necessarily mean criticism or opposition.
In tragedy-driven events, negative polarity often reflects:

- Grief
- Shock
- Sadness
- Collective mourning

Rather than hostility toward the subject.

Since this analysis uses VADER (Valence Aware Dictionary and sEntiment Reasoner), sentiment is determined based on lexical polarity, meaning it evaluates emotional weight of words (e.g., sad, attack, violence) and aggregates them into a compound score between -1 and +1.

VADER does not interpret political stance or intent, It captures emotional tone, not ideological position.
Therefore, spikes in “Negative” sentiment should be interpreted within the context of the event, not automatically assumed as backlash.

FEATURE ENGINEERING

🏷️

Sentiment Labeling

The compound score was converted into categorical labels:

- **≥ 0.05 → Positive**
- **≤ -0.05 → Negative**
- **Otherwise → Neutral**
- **Positive sentiment accounts for The largest proportion of tweets.**

Sentiment	Total
Positive Statement	57,916
Negative Statement	48,678
Neutral Statement	25,500

New column created:
sentiment

This enables:

- **Sentiment distribution analysis**
- **Engagement comparison**
- **Group-based segmentation**

FEATURE ENGINEERING

🌍 **Geographic Feature Creation**

From raw location text:

- **Extracted structured country**
- **Standardized country naming**
- **Labeled unmatched entries as "Unknown"**

This enables regional sentiment comparison.

Results:

Across all three sentiment categories, the highest tweet volume comes from “Unknown,” followed consistently by India and the United States.

Sentiment	Rank	Country	Total
Negative Statement	1	Unknown	8,143
Negative Statement	2	India	2,814
Negative Statement	3	United States	592
Neutral Statement	1	Unknown	3,046
Neutral Statement	2	India	1,107
Neutral Statement	3	United States	171
Positive Statement	1	Unknown	7,402
Positive Statement	2	India	3,598
Positive Statement	3	United States	278

FEATURE ENGINEERING

📊 Engagement Indicators

Existing metrics were preserved:

- retweetcount
- favorite_count

These serve as:

- Engagement proxies
- Dependent variables for hypothesis testing

🎯 Result of Feature Engineering

The dataset now contains:

✓ Structured geographic data
✓ Quantitative sentiment score
✓ Sentiment labels
✓ Engagement metrics ready for comparison

This makes the dataset fully ready for:

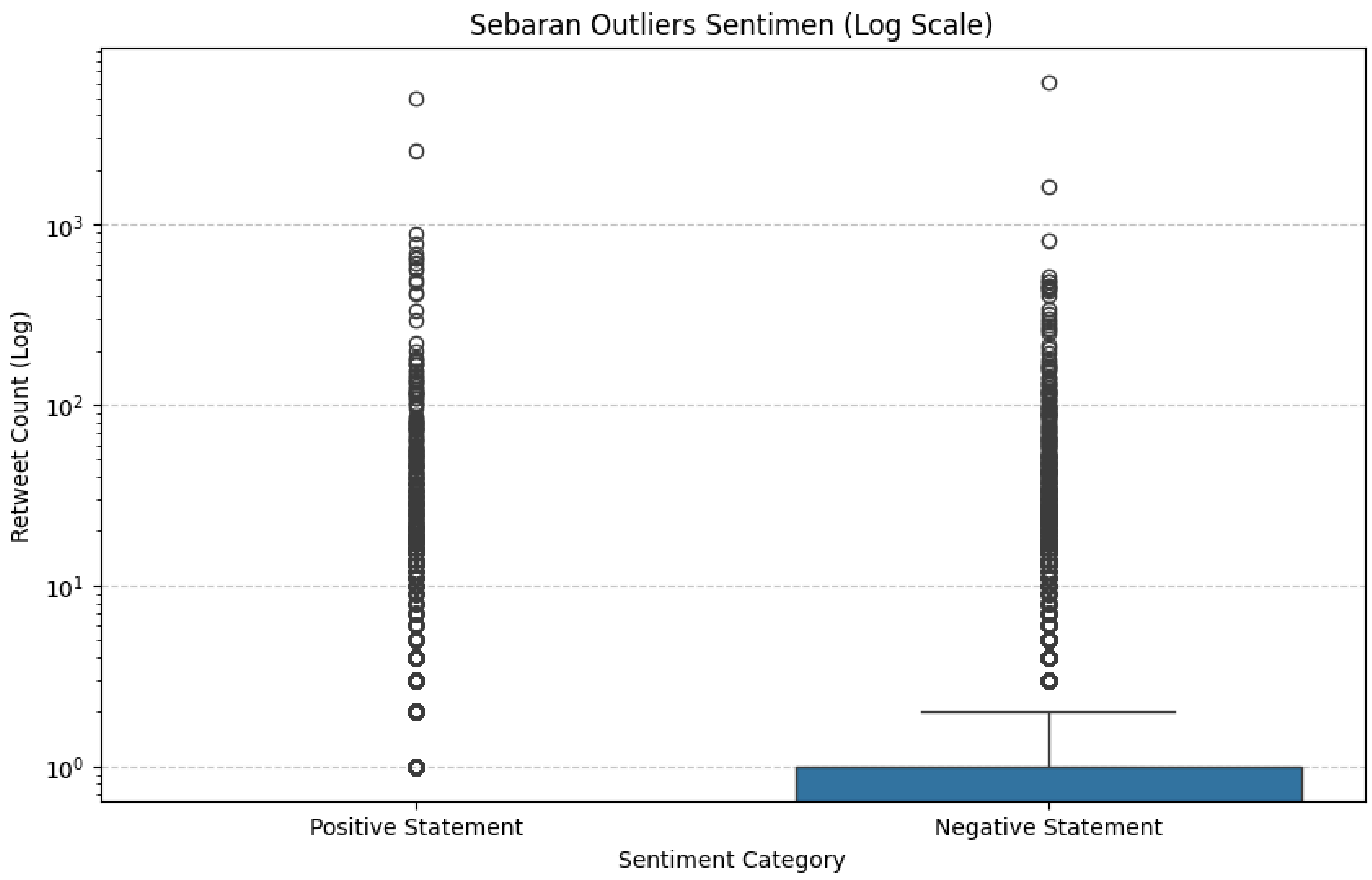
- Exploratory Data Analysis
- Segmentation Analysis
- Hypothesis Testing

EDA

Exploratory Data Analysis: Outlier Inspection

A qualitative examination of the top viral tweets (outliers) reveals a distinct divergence in the nature of content driving Positive versus Negative sentiment.

EDA-BOXPLOT



Sebaran Outliers Sentimen (Log Scale)
Retweet Count (Log)
10^3
10^2
10^1
10^0
Positive Statement
Negative Statement
Sentiment Category

EDA-EXPLANATION

Explanation of Retweet Distribution by Sentiment (Log Scale)

🔍 **Key Observations**

- **Retweet counts display a heavy upper-tail distribution, with numerous extreme outliers.**
- **Most tweets receive low engagement, while a small number achieve extremely high retweet counts.**
- **Both positive and negative sentiments contain viral outliers.**
- **Negative tweets exhibit slightly stronger upper-tail amplification compared to positive tweets.**

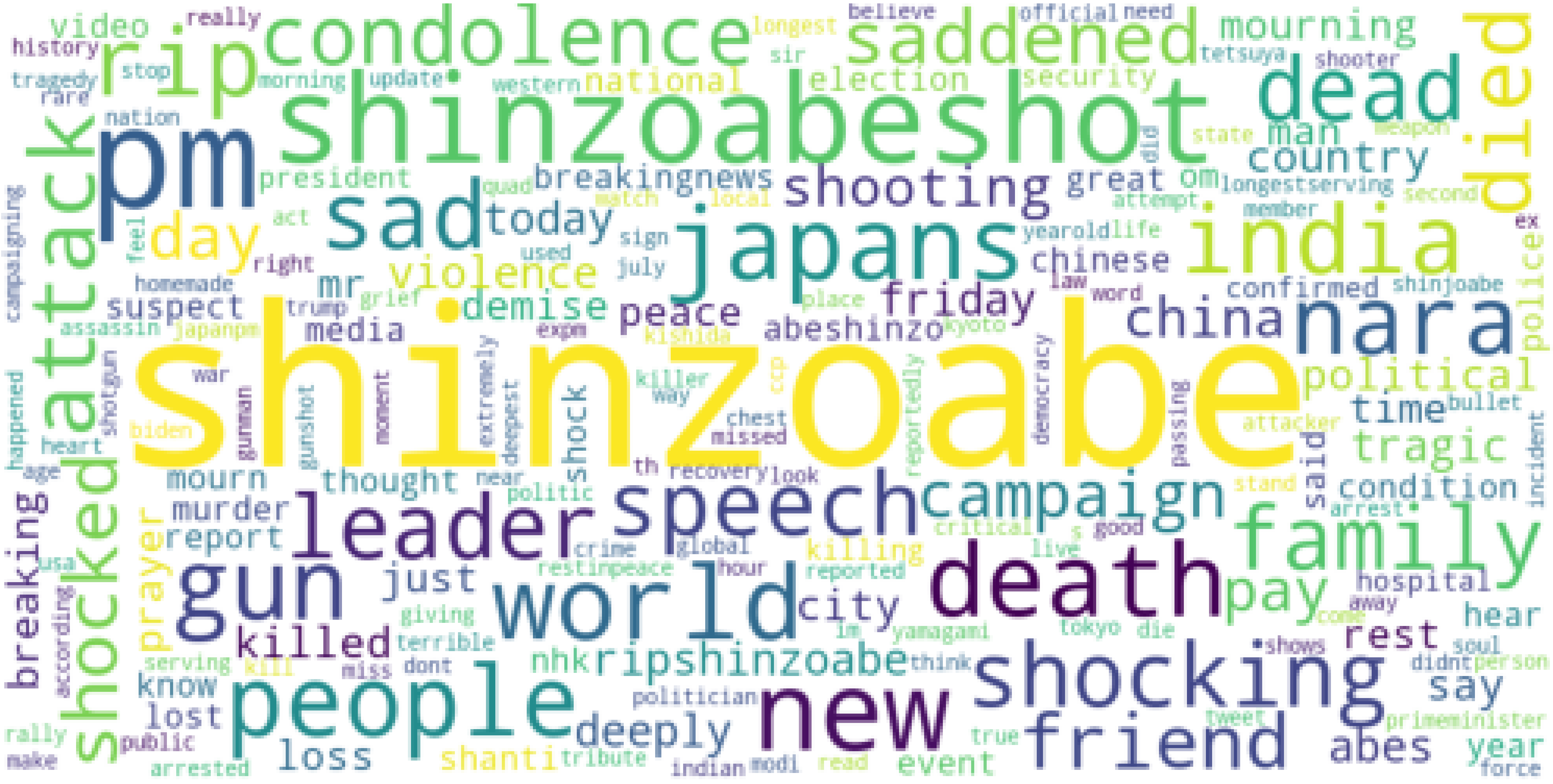
💡 **Initial Insight**

Engagement is driven by a small number of highly viral tweets, suggesting amplification dynamics during crisis events.

The visible difference in upper-range retweets between sentiment groups motivates further statistical testing.

EDA-WORDCLOUD

WordCloud - Negative Statement



EDA-WORDCLOUD

WordCloud - Neutral Statement

EDA-WORDCLOUD

WordCloud - Positive Statement

EDA-EXPLANATION

🧠 Content Pattern by Sentiment (WordCloud Analysis)

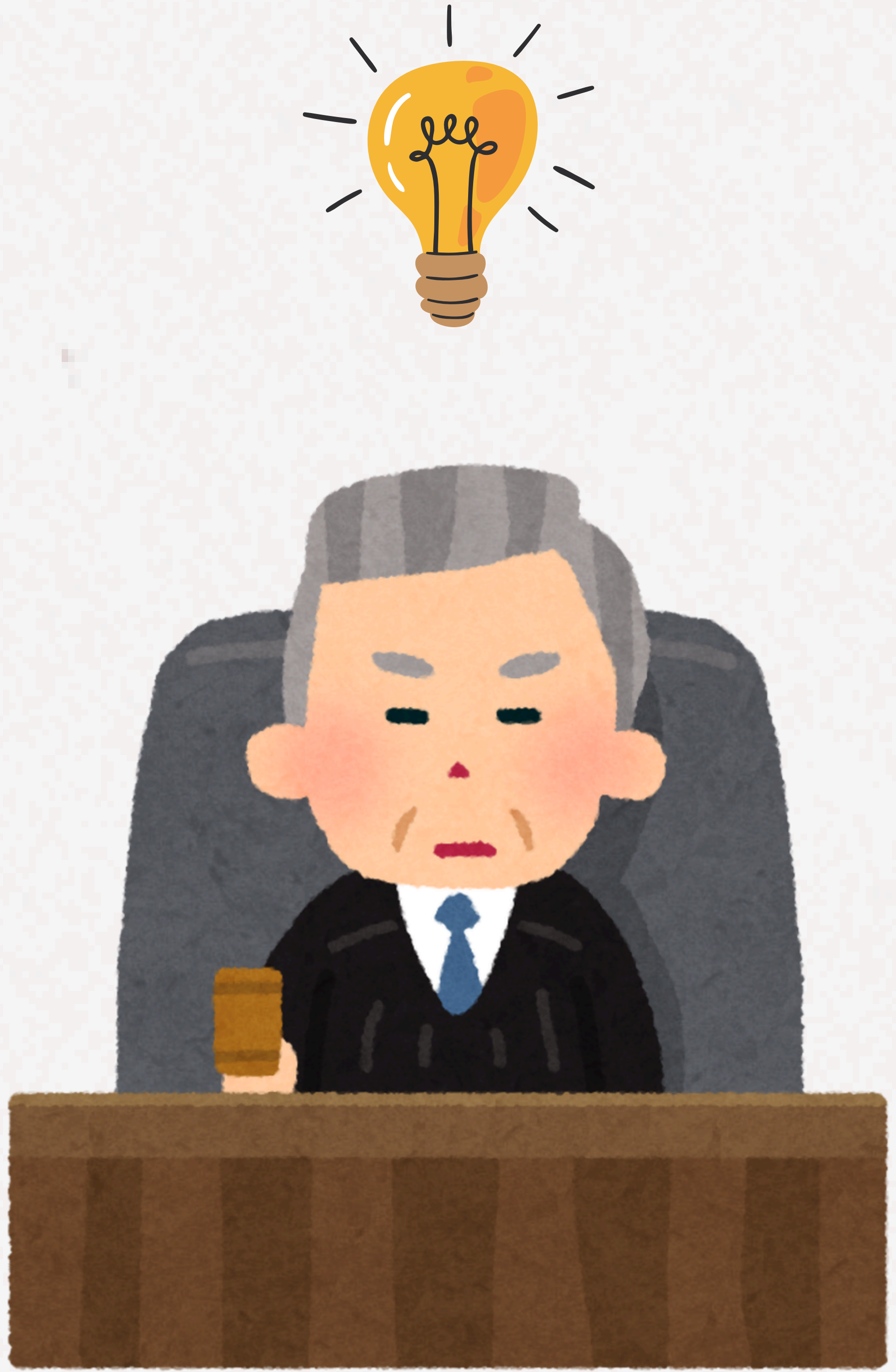
Key Patterns:

- **Negative sentiment is dominated by violence-related language (death, shot, attack).**
- **Neutral sentiment reflects factual reporting (speech, pm, confirmed, nara).**
- **Positive sentiment centers around condolences and diplomatic response (rest, peace, prayer, tribute).**

Insight:
Sentiment categories are not only statistically different, they also differ linguistically in how the event is framed.

Summarize:
Negative → severity
Neutral → information
Positive → empathy

SEGMENTATION: ENGAGEMENT BY SENTIMENT



SEGMENTATION: ENGAGEMENT BY SENTIMENT

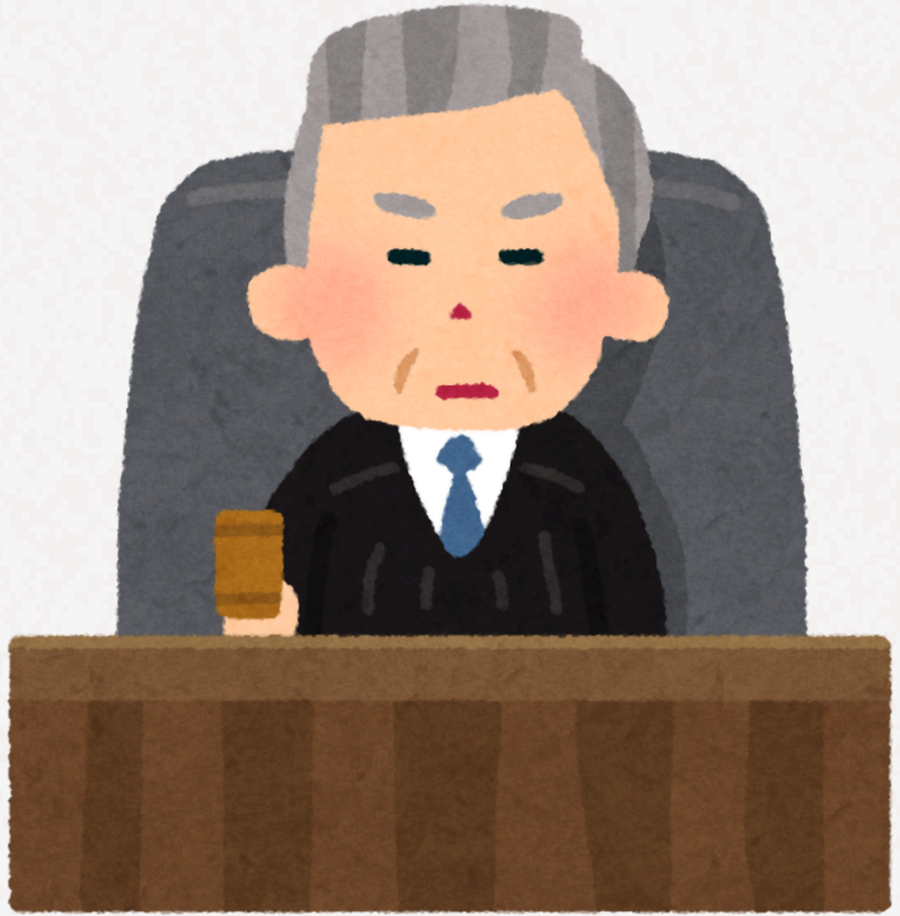


TABLE RESULTS

Sentiment	Count	Mean RT	Median
Negative	13,953	2.82	0
Positive	12,843	2.69	0
Neutral	5,181	2.24	0

LET'S CHECK, IS THE POSITIVE SEGMENT ARE POTENTIAL RE-TWEETED TO BE POTENTIAL VIRAL?

TABLE RESULTS

📊 The Paradox: Mean vs. Median (After Filtering)

🔍 Key Findings

- Negative tweets have the highest average retweets (Mean = 2.82)
- Positive tweets follow closely (Mean = 2.69)
- Neutral tweets show the lowest average engagement (Mean = 2.24)
- Median retweet count is 0 for all groups

💡 What This Means

- Engagement distribution is highly skewed
- Most tweets receive zero retweets
- A small number of tweets drive the average upward
- The difference in mean is relatively small → requires statistical testing

TABLE RESULTS

🎯 **Core Insight**

Average virality does not significantly differ between positive and negative tweets. However, negative narratives show stronger consistency in organic engagement patterns.

🧪 **Next Step**

Because the engagement distribution is highly skewed:

- **Independent T-Test → Compare mean engagement (overall impact)**
- **Mann–Whitney U Test → Compare engagement distribution consistency**

HYPOTHESIS TESTING RESULTS

HYPOTHESIS

Scenario A, Focus on Impact Magnitude

Independent T-Test

Objective:

To examine whether the average engagement (mean retweet count) differs between positive and negative tweets.

Hypotheses:

- **H0: There is no significant difference in the average engagement between positive and negative tweets.**
- **H1: There is a significant difference in the average engagement between positive and negative tweets**

Interpretation Rule:

- **If $p < 0.05$ → Engagement differs significantly.**
- **If $p \geq 0.05$ → Engagement does not differ significantly.**

👉 This test evaluates Total Viral Impact (mean-sensitive to viral outliers).

HYPOTHESIS

Scenario B, Focus on User Behavior & Consistency

Mann–Whitney U Test

Objective:

To compare engagement distribution and consistency between positive and negative tweets.

Hypotheses:

- **H0: Engagement distributions are equal.**
- **H1: Engagement distributions are different.**

Interpretation Rule:

- **If $p < 0.05$ → One sentiment consistently ranks higher in engagement.**

👉 This test evaluates Organic Engagement Pattern (robust to outliers).

RESULTS

Independent T-Test (Average Engagement)

- **p-value: 0.856**
- **Result: Not Significant**

What it means:

There is no meaningful difference in average retweet count between positive and negative tweets. Any small difference in the mean is likely due to random variation.

👉 On average, both sentiments perform similar

Mann–Whitney U Test (Engagement Pattern)

- **p-value: < 0.001**
- **Result: Significant**
- **Direction: Negative tweets rank higher**

What it means:

Although most tweets receive zero retweets, negative tweets are consistently more likely to receive engagement compared to positive ones.

👉 The difference is not about extreme viral spikes, it’s about consistent user response.

RESULTS

🧠 Overall Analytical Insight

Engagement is not driven by average virality

Positive and negative tweets perform similarly in terms of mean retweets.

Engagement is structurally different

Negative tweets receive more consistent interaction.

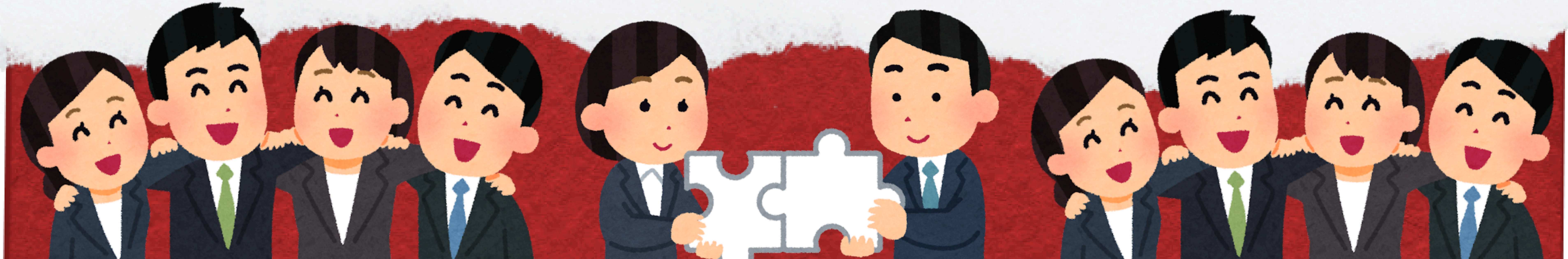
Crisis discourse is reaction-driven

Public response is more aligned with shock and tragedy than praise.

🔎 Simple Summary

- Average impact → No difference
- Engagement consistency → Negative tweets perform better

FINAL CONCLUSION



FINAL CONCLUSION

Sentiment Framing Differs Linguistically

Content analysis shows clear differences in framing:

- Negative tweets emphasize violence and shock.
- Neutral tweets focus on factual reporting.
- Positive tweets center on condolences and tribute.

This confirms that sentiment categories reflect distinct narrative tones.

No Significant Difference in Average Virality

Statistical testing shows no significant difference in mean retweet counts between positive and negative tweets ($p = 0.856$).

Large viral spikes do not represent overall engagement behavior.

FINAL CONCLUSION

Negative Sentiment Drives More Consistent Engagement

Although both groups have a median of zero, The Mann–Whitney test reveals a significant distribution difference ($p < 0.001$).

Negative tweets are more consistently likely to receive interaction, even if the average impact is similar.

🔎 Overall Insight

Public engagement during crisis events is not driven by positivity or praise,
but by consistent responsiveness to negative framing.

THANK YOU!