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The Role of Twitter Sentiment Analysis for Disaster Resilience in a World Class Destination: A Case Study of Ubud, Bali

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Abstract

Accurate, real-time information is crucial for Disaster Resilience efforts, making it essential for prominent international tourist destinations in Bali, such as Ubud, which are vulnerable to hydro-meteorological hazards. This study aims to explore public response patterns to the landslide and flood disaster in Ubud via Twitter (X) data, interpreting the resulting sentiment as a real-time social indicator for crisis management. The methodology adopts the CRISP-DM framework, utilizing a Natural Language Processing (NLP) approach—specifically lexicon-based sentiment analysis and visualization—on Indonesian-language tweet data with the keywords ubud banjir (Ubud flood) and prayforbali following the disaster in October 2022. Key findings reveal an absolute dominance of positive polarity (reaching 98.8%) in public opinion. This significantly high positive sentiment is interpreted as a digital manifestation of strong Social Capital and a collective priority to safeguard Ubud's destination image during the recovery phase, which contrasts with sentiment patterns observed in non-tourism disaster contexts. This analysis contributes to Disaster Informatics by positioning public sentiment as a Real-time Social Indicator. A recommendation that local governments leverage this sentiment data as a strategic asset to enhance crisis communication transparency and reinforce Ubud's image as a resilient and safe international destination.

Keywords *Sentiment Analysis, Natural Language Processing, Twitter, Ubud, Disaster Resilience*

1. INTRODUCTION

Global tourism has entered a crucial recovery phase post-COVID-19 pandemic, highlighting the need for more integrated destination resilience strategies. Specifically, Indonesia's tourism sector shows a significant recovery trend aligned with global patterns. According to data from the Central Statistics Agency (BPS), the number of foreign tourist arrivals in 2022 reached 5.47 million, a sharp increase of

251.28% compared to the previous year, indicating a return of international market interest. Within this recovery context, Bali holds a central role as Indonesia's tourism icon on the world stage, with Ubud being one of the most sought-after premier destinations. Ubud has long been recognized as a unique center of art, spirituality, and culture since 1927, attracting expatriates and tourists seeking the "real Bali" experience (Wirawan et al., 2022). This global reputation is reinforced by international events and its popularity as the setting for the film Eat, Pray, Love (Rahjasa et al., 2024).

However, behind this strong international tourism image, Ubud faces a dual vulnerability that creates the urgency for this research: high economic dependency on tourism (Ariyanti & Ardhana, 2020) and a high risk of hydro-meteorological disasters due to its hilly topography and terraced rice fields. This urgency was demonstrably clear during the disaster incident on October 16-18, 2022, where heavy rain triggered landslides and floods that quickly drew massive attention on social media Twitter (X) and became a Trending Topic. Therefore, this study focuses on Ubud as a crucial case study to understand how to manage information crises and disaster responses quickly and effectively in a highly vulnerable premier tourist location.

In disaster management efforts, accurate and real-time information is a vital component for achieving Disaster Resilience (Dufty, 2012; Yuliana, 2019). Social media platforms, particularly Twitter (X), have proven to be a fast and massive data source for monitoring ground situations, sharing information, and coordinating aid (White, 2012; Rochmaniyah et al., 2023). Various studies have utilized social media data and Natural Language Processing (NLP) approaches, such as sentiment analysis, to assess disaster impacts and identify resource needs. For instance, studies by Zou et al. (2018) and Yuan & Lin (2021) have successfully used Twitter data and NLP to understand disaster response dynamics in broader geographical contexts. The application of NLP methods, specifically lexicon-based sentiment analysis, to evaluate public opinion has also been widely adopted in various domains (Hossain & Rahman, 2022; Hossain et al., 2022).

However, a critical literature gap is identified: the lack of research explicitly linking real-time public opinion data from social media in a premier tourist location (such as Ubud) with the Disaster Resilience theoretical framework as a rapid and effective social indicator for local government. Most existing NLP studies in the disaster domain tend to focus on emergency resource allocation, damage identification, or employ different methods like geospatial mapping. This research seeks to bridge this gap by adopting a lexicon-based NLP approach to analyze public response patterns to the landslide disaster in Ubud. We focus on Twitter (X) text data to identify and categorize public reactions and information needs, which are then connected to the disaster resilience framework.

The main novelty of this study lies in integrating sentiment analysis findings with the Disaster Resilience concept, positioning it as a state-of-the-art approach in crisis information management.

Referring to the definition from the Federal Emergency Management Agency (FEMA, 2006), disaster resilience encompasses a community's ability to "bounce back" quickly. Public opinion and community sentiment, when processed from social media, can function as a crucial real-time social indicator for measuring the level of resilience (recovery situation and public opinions). By processing rapid social media data, this research provides a unique mechanism to accelerate the recovery process and strengthen local government information management strategies in safeguarding vital tourism assets.

Based on the background above, this research aims to:

- Explore and analyze public response patterns from Twitter (X) text data following the disaster in Ubud.
- Determine how the public sentiment response can be utilized as a key aspect in Disaster Resilience management within a tourist region.

This study contributes to two multidisciplinary fields: the field of Information Technology (the application of text mining using NLP) and the field of Disaster Mitigation Management (providing real-time public response insights, visualized for formulating swift and targeted disaster recovery strategies).

Related Work

1. Text Mining and Sentiment Analysis (NLP)

Text Mining is a discipline within Natural Language Processing (NLP) aimed at extracting valuable patterns, information, and knowledge from large, unstructured text data sources (Hermawan & Ismiati, 2020). This process is fundamental because unstructured input requires the application of a structural framework before relevant information can be extracted.

One of the key applications of text mining is Sentiment Analysis. This technique is defined for identifying and evaluating the views, emotions, and attitudes reflected in text, typically categorized as positive, neutral, or negative (Hossain & Rahman, 2022; Hossain et al., 2022). The study by Hossain et al. (2022) confirms the effectiveness of this method in measuring public opinion from textual data. In the disaster context, NLP, particularly through lexicon-based sentiment analysis, becomes a vital tool for quickly processing the immense volume of information generated by social media users.

2. The Utilization of Social Media in Contemporary Disaster Management

Social media, especially Twitter (X), is widely recognized as a crucial source of real-time data in global crisis management. Historically, the role of social media emphasized crisis communication (White, 2012) and building Community Disaster Resilience (Dufty, 2012). In the contemporary context, this role has evolved from a two-way communication tool into a massive data crowdsourcing mechanism, which is essential for enhancing situational awareness (Source 1.7 in the literature). In Indonesia, institutions such as BNBP (National Disaster Management Agency) utilize this platform for mitigation efforts (Rochmaniyah et al., 2023) and disaster communication (Rofiyanti et al., 2023).

The effective use of social media is strongly linked to the concept of social capital. Recent systematic reviews indicate that social capital—including trust, networks, and communication norms within a community—positively influences community disaster resilience processes (Zhao et al., 2024). Social media acts as the primary digital space where this social capital is activated and leveraged during a crisis. Methodologically, studies like Yuan and Lin (2021) have applied social media data and NLP to enhance the understanding of disaster resilience during extreme events, proving the feasibility of using data mining to identify post-disaster needs.

3. The Concept of Disaster Resilience

Disaster Resilience is defined as a community's ability to "bounce back" from the impacts of a disaster through four phases of emergency management: preparedness, response, recovery, and mitigation (Yuliana, 2019). This concept, referenced from the Federal Emergency Management Agency (FEMA, 2006), emphasizes adaptive capacity and functional recovery.

The level of resilience is evaluated through various indicators, where public opinions are recognized as a crucial factor in assessing the recovery and emergency situation (Miller, 2017). Public opinions captured in real-time on social media can function as a fast and reliable social indicator to assess the status of recovery and accelerate strategic decision-making. Therefore, this research positions the results of Twitter sentiment analysis as this public opinion indicator, providing unique insight into the dynamics of disaster resilience within a tourist destination context.

Research Gap

Despite its proven effectiveness in general contexts, there is a lack of research explicitly linking public sentiment analysis in a premier tourist destination (such as Ubud)—which is highly sensitive to image and economic factors (Rahjasa et al., 2024; Ariyanti & Ardhana, 2020)—with the Disaster

Resilience framework. This study will fill this gap by positioning public sentiment as a manifestation of the social capital expressed in digital media and using it as a real-time indicator for disaster management in this vital tourism region.

2. METHODS

This research methodology adopts the industry-standard framework, the CRoss-Industry Standard Process for Data Mining (CRISP-DM). CRISP-DM was selected because it is a flexible and proven effective model for organizing Data Science projects, including text analysis and data mining (Borges et al., 2024). The implementation of CRISP-DM ensures that the data analysis process is conducted systematically and iteratively through the following sequential phases, which are adapted to the research workflow (see Figure 1):

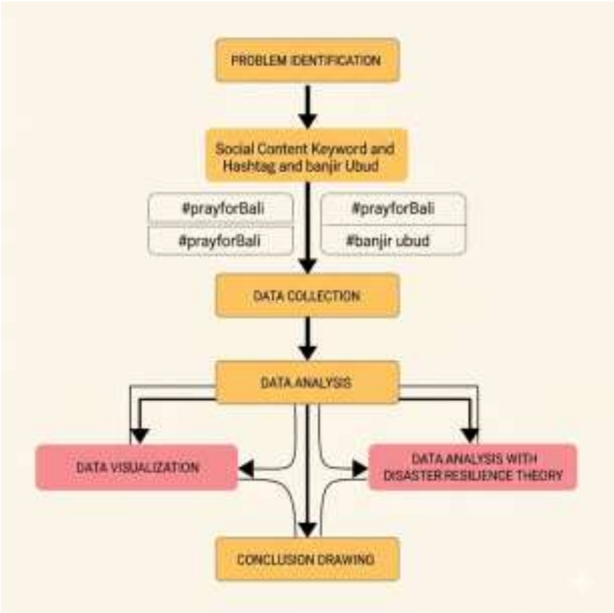

Figure 1. Research Methodology Flowchart

[Source: Researcher]

The research flowchart is adopted from the CRoss-Industry Standard Process for Data Mining (CRISP-DM), a standard framework widely used by data practitioners for Data Science projects. The application of CRISP-DM provides a systematic, staged approach to data analysis. The key phases are outlined below:

a.Business Understanding

This phase involves defining and understanding the research objectives and scope to ensure that the final output aligns with the project goals. In this study, problem identification and scope limitation were executed to specialize the information search towards the research objectives. The primary focus of this phase is detailed as follows:

Objective (Object): To analyze the public response, expressed through opinions on the Twitter (X) social media platform, regarding the hydro-meteorological disaster (flood and landslide) incident in Ubud, Bali, in October 2022.

Goal (Aim): To explore the polarity of public sentiment and determine how this sentiment can be interpreted as a real-time social indicator within the Disaster Resilience framework.

b. Data Understanding

The data for this study consists of unstructured text collected via data scraping from the Twitter (X) social media platform, utilizing a search query based on the R programming language. Keywords (Query): Data was collected using two specific keywords: ubud banjir (Ubud flood) and #prayforbali.

Language Restriction: Data retrieval was restricted exclusively to the Indonesian language (lang="id") to ensure consistency in the Natural Language Processing (NLP) workflow. Data Volume: A total of 3,175 tweets were successfully collected from the two keywords for subsequent analysis.

c. Data Preparation (Preprocessing)

Data preparation, or text preprocessing, is a crucial stage for extracting valuable knowledge from the unstructured text data by eliminating noise and reducing the data's dimensionality (Hermawan & Ismiati, 2020). This process comprises a sequence of steps:

Table 1: Preprocessing Steps

[Source: Hermawan & Ismiati, 2020]

Preprocessing Step	Description and Scientific Purpose
Text Cleaning	Removal of elements irrelevant to sentiment analysis, such as mentions (@), hashtags (#), punctuation, links (http/https), and numerical digits. Purpose: To eliminate noise present in social media data.
Case Folding	Conversion of all textual characters to lowercase. Purpose: To standardize the data format and prevent the system from distinguishing between lexically identical words due to capitalization differences.
Tokenizing	Decomposing sentences into single word units (tokens). Purpose: To prepare the fundamental input (word-by-word data) for subsequent analysis.
Filtering (Stopword Removal)	Elimination of common words (stopwords) that lack contextual significance (e.g., "yang," "dan," "dari"). Purpose: To increase the analytical relevance focused on meaningful keywords.
Stemming	Reducing inflected or derived words to their original root form. Purpose: To ensure lexical consistency within the sentiment dictionary, which is critical for the morphology of the Indonesian language.

```
bahasa <- "id"
tweet <- search_tweets(q = "ubud banjir",
                       n = 10000,
                       include_rts = retweet,
                       type=type,
                       lang=bahasa,
                       retryonratelimit=FALSE,
                       retweet=FALSE)
```

Figure 2. Data Collection

[Source: Researcher]

The image displays a snippet of programming code, most likely written in the R language or a similar syntax utilized within a Data Science environment, documenting the Data Collection phase from Twitter (X). The following provides a description and technical interpretation of the visible code lines:

Table 2: Interpretation of Code Snippet

[Source: Researcher]

Program Code	**Meaning and Goals**
bahasa <- "id"	Setting the language variable to the code "id" (Indonesian), which dictates that the study will exclusively retrieve *tweets* in the Indonesian language.
tweet <- search_tweets(...)	Defining the tweet variable to store the output results generated by the *tweet* search function.
q = "ubud banjir"	Assigning the main search query (q) to the phrase ubud banjir, thereby focusing the data retrieval on the disaster incident in Ubud.
n = 10000	Setting the maximum number of *tweets* (n) to be collected at 10,000.
include_rts = retweet	This line specifies the handling of retweets, with the purpose of controlling their inclusion in the final dataset.
lang = bahasa	Utilizing the pre-established variable ("id") to strictly limit the search query to the Indonesian language.
retryonratelimit = FALSE	Stipulating that the data retrieval process will not automatically retry if the Twitter API *rate limit* is reached.
retweet = FALSE	Establishing that retweets will not be included in the final collected data. This measure ensures that the collected data exclusively comprises original content (non-duplicated entries).

Following the successful data collection, the initial phase according to the planned methodology, Data Understanding, was executed. In this study, using the two selected keywords, 3,175 tweets were obtained for the Pray For Bali keyword, while the Ubud Banjir keyword yielded 86 tweets.

The subsequent phase was Data Preparation (Preprocessing), which aims to extract valuable and relevant knowledge from the unstructured text data (Hermawan & Ismiati, 2020). This process began with text cleaning, which involved removing mentions, hashtags, retweets, links, and numerical characters. Following the cleaning process, case folding was performed to convert all textual characters into lowercase. The third stage was Tokenizing, which transformed sentences into individual word tokens. Finally, Stemming was applied, reducing the extracted words to their original root form.

screen_name	created_at	text	cleaningText	casefoldingText	tokenizingText	stemmingText	polarity
bie103	2022-10-26T06:	@upilitilia @tanyakanrl	Oke thank u Ubud	oke thank u ubud ke	['oke', 'thank', 'u', '	['oke', 'thank', 'u', 'ubu	positive
FitriaHassanah	2022-10-25T17:	@zarazettirazr @detikcor	ubud banjir karen	ubud banjir karena l	['ubud', 'banjir', 'ka	['ubud', 'banjir', 'bany	positive
d2balitour	2022-10-25T01:	@zarazettirazr @detikcor	Mereka belum pe	mereka belum pem	['mereka', 'belum',	['banjir', 'ubud']	positive
Indra2127	2022-10-24T23:	@zarazettirazr @detikcor	ubud banjir karen	ubud banjir karena l	['ubud', 'banjir', 'ka	['ubud', 'banjir', 'bany	positive
daisyyspring	2022-10-23T09:	pdhl mau ke ubud refresl	pdhl mau ke ubud	pdhl mau ke ubud r	['pdhl', 'mau', 'ke', '	['pdhl', 'ubud', 'refresl	positive
AzamSahri	2022-10-20T07:	@TimpalBali ubud-ubud	ubudubud canggu	ubudubud canggukı	['ubudubud', 'cang	['ubudubud', 'canggu',	positive
jakaindra_	2022-10-20T06:	@haekaladzani @dimasb	Ubud banjir parah	ubud banjir parah u	['ubud', 'banjir', 'pa	['ubud', 'banjir', 'parah	positive
bayuadhy	2022-10-20T01:	@Royes__ Kalau daerah k	Kalau daerah kuta	kalau daerah kuta d	['kalau', 'daerah', 'k	['daerah', 'kuta', 'amar	positive
majoritionline	2022-10-20T01:	Antara rakaman keadaan	Antara rakaman kı	antara rakaman kea	['antara', 'rakaman'	['rakaman', 'banjir', 'in	positive
vlorentae2	2022-10-20T01:	@ainicasi @callmesuci_	Iya dimana di dae	iya dimana di daeral	['iya', 'dimana', 'di',	['iya', 'mana', 'daerah',	positive
myeonn16	2022-10-19T23:	aku bersyukur astungkara	aku bersyukur ast	aku bersyukur astur	['aku', 'bersyukur',	['syukur', 'astungkara',	positive
dollhtte	2022-10-19T19:	Banjir di Ubud, sudah suri	Banjir di Ubud suc	banjir di ubud sudal	['banjir', 'di', 'ubud'	['banjir', 'ubud', 'surut	positive

Figure 3. Results of Ubud Banjir Data Preprocessing

[Source: Researcher]

d. Modeling (Sentiment Analysis Approach)

Following the data cleaning process, the analysis proceeded to the modeling phase using the Lexicon-Based Sentiment Analysis method. This method was selected because it enables the rapid classification of tweet polarity into positive, negative, or neutral labels based on a predetermined lexical dictionary. The core steps of the Lexicon-Based process are as follows:

Import Dictionary: Utilizing established Indonesian-language positive and negative sentiment lexicon dictionaries. Score Calculation: Each token within a tweet is matched against the dictionary to determine its sentiment score.

Polarity Classification: The final sentiment is determined based on the total lexical score of the words within the tweet according to the following rules:

$$if\ \sum_k Score\ (k) > 0\ then\ positive \quad \text{.........} \quad (1)$$

$$if\ \sum_k Score\ (k) < 0\ then\ negative \quad \text{.........} \quad (2)$$

$$if\ \sum_k Score\ (k) = 0\ then\ neutral \quad \text{.........} \quad (3$$

e. Evaluation and Visualization

The subsequent step involves visualizing the sentiment analysis results, primarily in the form of a Wordcloud. A Wordcloud is a graphical representation illustrating the frequency of words present within a text corpus; the more frequently a word is used, the larger its size appears in the visualization (Miller, 2017).

3. FINDINGS AND DISCUSSION

3.1. Data Description

The initial sentiment analysis findings for this dataset show that 96.8% of the data yielded a positive sentiment polarity, followed by 1.2% classified as neutral. From these results, it can be inferred that public opinion on the Twitter social media platform regarding the Ubud flood disaster was predominantly positive.

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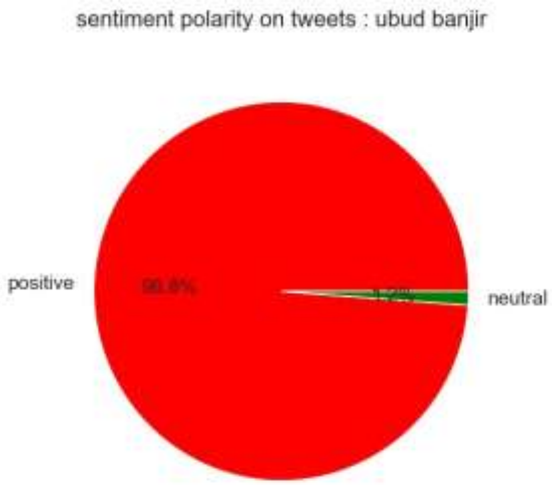

Figure 4. Sentiment Analysis Results

[Source: Researcher]

The pie chart, labeled "sentiment polarity on tweets: ubud banjir," visualizes the results of the sentiment analysis conducted on tweets utilizing the keyword "ubud banjir" (Ubud flood). This diagram quantifies the sentiment polarity (views or emotions) expressed by social media users concerning the flood incident in Ubud.

Visual Data Description

a. Sentiment Dominance: The majority of the data is represented by a large red sector, which symbolizes the Positive polarity.

b.Positive Proportion: Positive sentiment demonstrates an absolute dominance, accounting for 98.8% of the total.

c. Neutral Proportion: Neutral sentiment is represented by a minimal green sector, comprising only 1.2%.

d.Negative Sentiment: Negative polarity is not visibly present in the diagram, indicating its value is negligible or zero.

Figure 5. Results of Sentiment Analysis with the Keyword Ubud Banjir

[Source: Researcher]

Wordcloud of Positive Tweets (Left)

This section illustrates the most frequently occurring words in the tweets classified with Positive sentiment. The dominance of these keywords provides insight into the nature of the positive public response during and after the disaster:

Table 3. Interpretation of Positive Wordcloud Keywords

[Resource: Researcher]

Dominance Keyword	Implications for Disaster Response
ubud (sangat besar), banjir	This confirms the study's geographical and topical focus.
resapan, daerah	It indicates public discussion or awareness regarding the causal factors or technical solutions for the disaster (e.g., concerns related to water absorption/infiltration).
thank (terima kasih), oke, hati	This reflects the presence of emotional support, expressions of gratitude for information or response efforts, or acceptance of a situation ("oke") that was swiftly managed.
ulungsor (longsor)	Disaster keywords appear in a positive context, frequently signifying messages of prayer, hope, or confirmation that the hazard (landslide) has been mitigated.
terabas, rute, jalan	This suggests that the positive discourse centers on access restoration, information regarding passable routes, and post-flood road clearance efforts.

The positive sentiment is not merely confined to emotional support but also encompasses practical discussion regarding recovery and technical management. This demonstrates the function of social media as a crucial information channel for post-disaster recovery and most important thing is the realtime activity that happened in location. For example the words “terabas”, “jalan”, “rute” it might be indicates that some vehicle passing by the flood and others have alternative route in flood area. There was also “hancur” that might be indicate some building destroyed by the flood. If this happened then

BNPB or the local government must be concerned and gave the fast recovery system since Ubud is one of popular tourism destination in the world.

Wordcloud of Neutral Tweets (Right)

This section illustrates the most frequently occurring words in the tweets classified with Neutral sentiment (neither strongly positive nor negative).

Table 4. Interpretation of Neutral Wordcloud Keywords

[Resource: Researcher]

Dominance Keyword	**Implications for Disaster Response**
bisabisanya	This is an expression of surprise or rhetoric, frequently used as an initial reaction without strong accompanying positive or negative sentiment.
ubud, banjir	Once again, this reaffirms the core topic and geographical focus.
dtype, object, casefoldingtext, Name	These words are technical artifacts resulting from the data preprocessing pipeline (e.g., column labels, data types, or residue from the *case folding* step that was not perfectly removed). Their presence in the neutral group indicates that *tweets* containing technical noise often fail to be classified with a pure sentiment value.

Conclusion on Neutral Sentiment

Neutral keywords are predominantly characterized by informative/rhetorical language or technical noise from the data. This composition is consistent with the definition of neutral sentiment (lacking strong emotional loading).

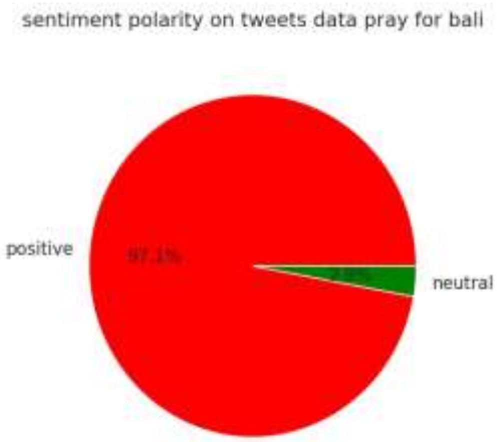

Figure 6. Sentiment Analysis with Keyword Pray For Bali

[Source: Researcher]

This diagram quantifies the distribution of sentiment polarity within the collected data, illustrating the range and proportion of emotional expression among social media users.

Table 5. Pie Chart Interpretation

[Resource: Researcher]

Sentiment Polarity	**Percentage**	**Interpretation**
Positive (Red)	97.10%	Positive Dominance: The results show an absolute dominance of expressions classified as positive. Within the disaster context, such a high percentage reflects a high level of solidarity, empathy, and emotional support originating from the wider public (both local and non-local).
Neutral (Green)	2.90%	Neutral Proportion: This small proportion most likely consists of informative *tweets* lacking emotional load or *tweets* containing technical *noise* that failed to be purely classified.
Negative	0.0% (Not visible)	Negative Absence: The negligible presence of significant negative sentiment confirms that this keyword is predominantly used for psychosocial support and is not utilized for complaints or criticism.

Polarity Conclusion : The results confirm that "Pray For Bali" primarily functions as a hashtag for the mobilization of social support, serving as a digital manifestation of high public Social Capital. This social resource is a vital component of Disaster Resilience during the response and recovery phases.

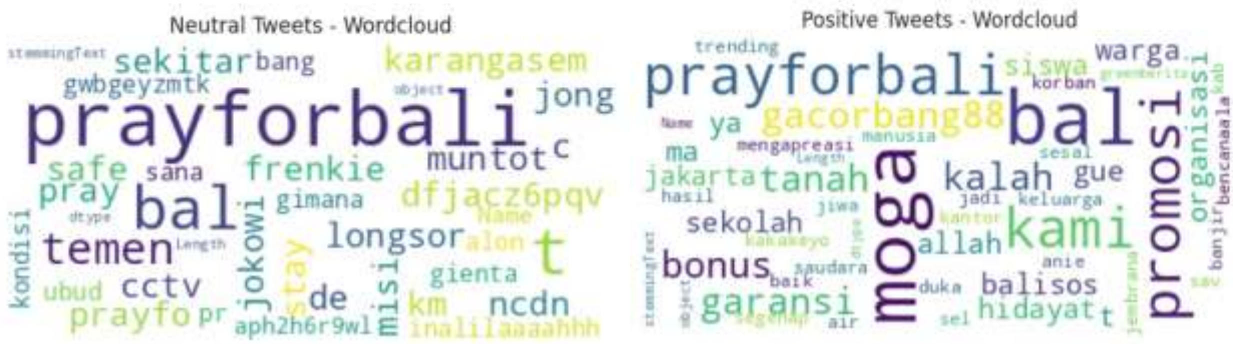

Figure 7. Result of Sentiment Analysis with the Keyword Pray For Bali

(Source: Researcher)

The Wordcloud visualizes the most frequently occurring words within each sentiment group, where word size indicates the frequency of appearance.

Wordcloud of Positive Tweets (Right)

The keywords in this cluster, despite being positive, suggest a notable blending of genuine support and promotional/commercial content.

Table 6. Positive Wordcloud Results and Their Disaster Implications

[Resource: Researcher]

Dominance Keyword	Implications for Disaster Response
prayforbali, kami, kami	Confirms the primary function of the hashtag as a call for solidarity and collective support ("kami" - us/we) from the wider community.
gacor, bangga, bonus, garansi	This is a key finding. Such terms (*gacor* = slang for "excellent" or "cool," *bonus*, *garansi*) are anomalous in a disaster context. This indicates the "hijacking" or opportunistic use of a trending keyword by commercial accounts, spam, or self-promotion efforts to boost their visibility on social media.
tanah, longsor, korban, keluarga	The disaster keywords themselves appear. In a positive context, this signifies that the *tweets* contain specific messages of prayer, hope, or direct support directed towards the victims and their affected families.

Wordcloud of Neutral Tweets (Left)

The keywords in the neutral cluster are predominantly characterized by informative language or words of low relevance, or are residual technical noise from the data cleaning process.

Table 7. Neutral Wordcloud Results and Their Disaster Implications

[Resource: Researcher]

Dominance Keyword	Implications for Disaster Response
prayforbali, bali, sekitar, temen	Contains primary keywords and terms referencing geographical locations or social networks ("temen" - friends/peers). These often represent *tweets* that simply relay factual information or inquire about well-being, lacking strong emotional.
karangasem, jong, muntok	Indicates a presence of a broader geographical discussion or the mention of other potentially affected regions, thereby shifting the focus away from Ubud exclusively.

Implications for Disaster Resilience

The analysis of the "Pray For Bali" keyword provides multi-dimensional insights:

1. Strong Social Indicator: The massive level of positive sentiment (97.1%) serves as an indicator of high Social Capital and Psychosocial Resilience. This suggests the availability of abundant social resources and community readiness to support the recovery effort.

2. Information Management Challenge: The presence of commercial terms (gacor, bonus, promosi) within the positive sentiment indicates a challenge in Disaster Communication. Local authorities must filter this noise to distinguish genuine support messages from spam, which can potentially compromise situational awareness.

3. Recovery Focus: This keyword is effectively used to mobilize moral support and facilitate the transition from the initial shock phase to the Recovery phase through expressions of hope and solidarity.

3.2 Discussion on findings

1. Sentiment Interpretation in Ubud and Comparison with NLP Disaster Studies

The sentiment analysis results, utilizing the Lexicon-Based method, yielded a highly specific finding: an overwhelming dominance of Positive sentiment (98.8%) and minimal Neutral sentiment (1.2%) for the keyword ubud banjir. Although neutral terms like bisabisanya (slang/rhetoric) and technical artifacts were observed, negative sentiment was nearly undetectable.

Comparison of Sentiment Polarity

The exceptionally high positive polarity observed in Ubud stands in stark contrast when compared to NLP sentiment analysis studies focused on broader regional or non-tourism disaster contexts:

Table 8. Comparison of Sentiment Results with Non-tourism Contexts

[Resource: Researcher]

Study Research	Context Focus	Negative/Neutral Sentiment Polarity	Key Interpretation
This Study (Ubud, 2022)	Premier Tourist Destination	Negative ≈ 0%Reflects the dominance of Social Support and Image Recovery efforts (*Reassurance*) as a rapid response.	Reflects the dominance of Social Support and Image Recovery efforts (*Reassurance*) as a rapid response.
Yuan & Lin (2021)	Hurricane Response (US)	Significant Proportion	Focuses on identifying resource allocation, damage, and emergency needs. Negative/neutral sentiment is used to map severity.
Flood Disaster Analysis (Rahayudi, F. F. (2021)	Regional Crisis/Policy	Balanced Positive/Negative (Emergence of debate)	Sentiment is used to map public debate and dissatisfaction regarding government handling or policy.

This contrast demonstrates that:

1. In non-tourism disaster contexts, sentiment is often more evenly distributed or dominated by criticism/requests for aid (negative/neutral), which directly maps physical needs.

2. In Ubud, as a World-Class Destination, the massive positive sentiment (as supported by the wordcloud showing thank and oke) is a digital manifestation of high Social Capital and the collective priority to safeguard the image and reassurance of tourists post-crisis (Zhao et al., 2024).

In the context of Disaster Resilience, public opinion and social media sentiment function as a crucial Real-time Social Indicator (Miller, 2017). The low level of negative sentiment directly indicates a relatively high degree of public trust in the emergency response efforts, thereby facilitating the acceleration of the Recovery phase.

2. The Role of Positive Sentiment in Disaster Resilience and Ubud's Tourism Image

The identified positive sentiment holds dual implications: strengthening Community Disaster Resilience and globally safeguarding Ubud's Tourism Image.

A. Strengthening Disaster Resilience (Public Sector)

Social media, including Twitter, facilitates flexible information exchange (Rochmaniyah et al., 2023), which is crucial for disaster management. Sentiment analysis provides objective, real-time feedback that agencies like BNPB (National Disaster Management Agency) can utilize to achieve the following:

Enhancing Transparency and Communication: The high level of positive sentiment suggests a high degree of public trust (social capital). The government can leverage social media to increase transparency, ensuring accountability, which is highly beneficial for future disaster response planning (Rofiyanti et al., 2023).

Accelerating Response: Through sentiment analysis, the government can filter and prioritize information relevant to recovery efforts. Positive sentiment towards the initial response validates communication strategies and actions, allowing authorities to reinforce disaster mitigation socialization and education in vulnerable regions (Rofiyanti et al., 2023).

B. Safeguarding the Tourism Destination Image (Economic Sector)

Positive sentiment acts as an economic protection mechanism for Ubud, a region heavily reliant on tourism. Public opinion on social media plays a significant role in influencing tourist visitation decisions (Surya et al., 2023).

Post-Crisis Reassurance: The massive positive sentiment, coupled with wordcloud findings showing mixed support, indicates a collective effort, including from commercial accounts, to immediately provide reassurance to potential tourists that Bali/Ubud is safe and capable of a "bounce back" recovery.

Social Proof-Based Marketing: Government bodies and key stakeholders (hotels, travel influencers) can utilize the positive sentiment from disaster handling as powerful social proof in marketing campaigns. Visualizing Ubud's resilience and inherent beauty post-crisis can increase its appeal and visitor numbers, supporting the community's sustainability and welfare.

Thus, positive sentiment on social media is not merely emotional data but a strategic asset used to fortify Ubud's social and economic foundations against disaster vulnerability.

4. CONCLUSION

This research aimed to analyze public response patterns from Twitter data following the landslide disaster in Ubud and position them as a key aspect of disaster resilience management in an international tourist region. Key findings show that the Natural Language Processing lexicon-based sentiment analysis of tweet data (ubud banjir and prayforbali) yielded an absolute dominance of positive polarity (above 97%), with negative sentiment being almost negligible. This high positive polarity is interpreted as a digital manifestation of strong Social Capital, serving as a real-time social indicator to measure the level of Community Disaster Resilience in the dimension of psychosocial recovery and post-crisis image. This finding presents a significant contrast to NLP disaster studies in non-tourism contexts, which tend to be dominated by criticism or requests for resources. Consequently, it is recommended that local government and relevant stakeholders leverage these positive sentiment results as a strategic asset to: (1) Enhance the transparency and accountability of crisis communication through digital platforms (BNPB), and (2) Strengthen Ubud's destination image by integrating positive public support testimonials into reassurance campaigns, thereby mitigating reputational risks and ensuring the sustainability of a resilient tourism sector.

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