Analyzing Mental Health Conversations in Online Forums Through Linguistic Markers and Weather Event Overlays

Rubaiyat Alam Ruhin
a1930497

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Project Area: **LLM**
Project Supervisor: **Dr Indu Bala**

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Abstract

Mental health issues such as depression and anxiety remain among major global challenges and many individuals are increasingly turning to online platforms to share their experiences, seek support and find community. Mental health states are shaped by various components, from which, internal stressors have been widely studied, but the impact of external stressors remains less explored. Weather events are one of such stressors that represent a significant but underexplored domain of inquiry. This work aims to provide insights, through natural language processing, into how online mental health forum discussions reflect early signals of psychological distress and how these signals may be influenced by external stressors such as climate-related disasters. A dataset of more than 40,000 Beyond Blue forum posts and comments combined was created by flattening user interactions into individual text units. Transformer-based models (RoBERTa) were applied to map conversations into a valence–arousal space and extract relevant linguistic markers. Analyses reveal that original posts are skewed toward negative valence and high arousal, dominated by sadness and fear, while comments and replies shift toward neutral or positive tones, reflecting supportive engagement.. In parallel, a dataset of over 300 Australian natural disaster events spanning multiple categories (e.g., bushfires, floods, storms) was curated and cleaned to standardise event types and durations. The next stage of the project will integrate these datasets to explore temporal relationships between disaster events and shifts in emotional expression.

1 Introduction

According to the World Health Organization, in 2019 approximately one in every eight people worldwide around 970 million individuals were living with a mental disorder, with anxiety and depressive disorders being the most common [10]. The COVID-19 pandemic further exacerbated this crisis, with initial estimates in 2020 showing a 26% increase in anxiety disorders and a 28% increase in major depressive disorders in just one year. While evidence-based prevention and treatment options exist, the majority of those experiencing mental health conditions still do not have adequate access to effective care. In response, many individuals increasingly turn to online platforms and forums to share their experiences, seek peer support, and express their struggles in accessible and anonymous ways. These online spaces have thus emerged as important sources of data for understanding patterns of psychological distress.

Much of the existing research has focused on internal stressors such as cognitive biases, personality traits and biological vulnerabilities that shape mental health outcomes. However, external stressors are equally influential and remain comparatively underexplored. The COVID-19 pandemic demonstrated the profound role of external stressors on psychological well-being at a global scale, with heightened social isolation, uncertainty and disruption leading to surges in distress. This raises a critical question: just as a pandemic can trigger widespread mental health challenges, could climate-related disasters such as bushfires, floods or storms also exert significant influence on mental health, particularly as expressed in online communities?

This project aims to provide insights into how external stressors, particularly natural disasters, interact with online mental health signals. It combines two key datasets: (1) a dataset of more than 40,000 Beyond Blue forum posts and comments and (2) a curated dataset of over 300 Australian natural disaster events spanning multiple categories. Using natural language processing (NLP) tools, including transformer-based classifiers (RoBERTa) and psycholinguistic feature extraction, forum discussions are mapped into valence–arousal space and enriched with linguistic markers. The disaster dataset is standardized to ensure consistent event categorization and temporal coverage enabling alignment with forum activity.

1.1 Objectives

The objectives of this project are as follows:

1. Construct suitable datasets for analysis, including (i) Beyond Blue

forum dataset combining posts and comments and (ii) a curated dataset of Australian natural disaster events.

2. Apply transformer-based models and the Circumplex Model of Affect to detect and map emotional and psycholinguistic markers, thereby capturing signals of depressive and anxiety-related symptoms.

3. Examine temporal changes in users' mental states within community interactions, identifying trajectories of deterioration, improvement or stability.

4. Investigate the relationship between natural disaster events and mental health expressions in Beyond Blue posts, including comparative analyses across disaster phases (pre-event, during-event, post-event) and disaster types (e.g., floods, bushfires, storms).

1.2 Scope of This Report

So far, substantial progress has been achieved towards the project objectives. The work completed can be summarised as follows:

1. **Data Acquisition:** A dataset of over 40,000 posts and comments was collected from the Beyond Blue online forum through web scraping[1]. In parallel, a curated dataset of over 300 Australian natural disaster events was created using publicly available information from the Australian Government's Disaster Assist website[2].

2. **Data Cleaning and Preparation:** Both datasets were cleaned, standardised and structured. For Beyond Blue, this involved flattening user interactions (posts and comments) into individual text units, enabling user-level and conversation-level analyses. For the disaster dataset, event types and datetime were standardised to allow future temporal alignment with forum activity.

3. **Exploratory Data Analysis (EDA):** Initial exploration was carried out to understand the structure and distribution of data in both datasets. This included frequency analysis of disaster events, forum activity trends and preliminary inspections of linguistic features.

[1] Beyond Blue Forum. Available at:https://forums.beyondblue.org.au/t5/mental-health-conditions/ct-p/c1-sc2

[2] Australian Government, Disaster Assist. Available at:https://www.disasterassist.gov.au/find-a-disaster/australian-disasters

4. **Feature Extraction and Preliminary Analysis:** Transformer-based models (Twitter RoBERTa) were applied to extract sentiment and emotion features from the Beyond Blue text units. These were further mapped into a valence–arousal space via the Circumplex Model of Affect.

Overall, the first two project objectives—data development and feature extraction—have been substantially achieved, providing a strong foundation for future analyses.

1.3 Preliminary Findings

Preliminary analyses of the Beyond Blue dataset reveal distinct affective patterns across conversational roles. Original posts are predominantly characterised by negative valence and high arousal, dominated by emotions such as sadness and fear, reflecting the disclosure of personal struggles. In contrast, comments from other users shift towards more neutral and positive tones, with higher proportions of supportive or encouraging expressions. Replies from the original poster occupy an intermediate position, balancing ongoing distress with engagement in dialogue. These role-based contrasts highlight the forum's function as both an outlet for distress and a space for community support.

In the disaster dataset, floods and storms emerge as the most frequent event types, followed by bushfires and cyclones. Temporal analysis indicates clear seasonal concentration, with peaks during the Australian summer months (December–February). Average event durations also vary substantially, with bushfires persisting longest while earthquakes, tornadoes, and landslides are short-lived.

Together, these findings provide a strong foundation for subsequent integration of the two datasets, enabling temporal analyses of how disaster timelines may influence emotional expression and mental health signals in online communities.

2 Background

Research on online mental health communities has expanded significantly in recent years, providing insights into how individuals with psychological distress express themselves and interact in digital spaces.

2.1 Related Work

One critical area of interest is the high comorbidity between depression and anxiety, which has been widely observed in clinical populations [5]. This overlap highlights the importance of identifying shared and distinct markers of distress in order to detect "bridge symptoms," such as sleep disturbances or irritability, that connect different conditions. Several studies have focused on the dynamics of user behaviour in online forums. For example, Morini et al. examined how user intentions, such as venting or seeking support, remain stable over time while community responses vary across contexts [8]. In a related study, they found that users' journeys through depression communities on Reddit followed non-linear, spiral-like trajectories, where peer interactions conditioned movement between psychological states [7]. These findings underscore the importance of temporal modelling of conversations in understanding mental health trajectories. Other work has compared different online platforms. Moßburger et al. contrasted a large open forum (Reddit) with a curated environment (Beyond Blue), revealing linguistic and topical differences that reflected moderation and community norms [9]. This comparison is especially relevant here, as our dataset is drawn from Beyond Blue, which provides a moderated space for mental health support. Advances in computational approaches have further improved the ability to detect mental health signals. Uddin et al. demonstrated how recurrent neural networks and deep learning can predict depressive symptoms from large-scale textual data [12]. More recently, Xu et al. evaluated the use of large language models (LLMs) such as GPT-4 and FLAN-T5 for mental health prediction, showing that instruction tuning and prompt design can substantially improve performance [14]. These studies highlight the value of applying state-of-the-art NLP techniques, such as the transformer-based methods adopted in this project. Beyond detection, researchers have also investigated how online interactions may facilitate cognitive change. Gu et al. developed a three-stage textual analysis pipeline to measure changes in cognition among support-seekers, showing that replies often lead to measurable improvements in expressed mental state [3]. This suggests that forum interactions not only reflect but can also shape psychological outcomes.

Together, this body of work establishes the importance of online forums as a resource for understanding and supporting mental health. It also provides methodological guidance, from linguistic analysis and deep learning to temporal modelling and LLM-based approaches, which aligns with the design and implementation of this project.

2.2 Research Gap and Novel Contribution

Although online forums have proven valuable for detecting psychological distress and modelling user trajectories [7, 3], most studies have either focused on clinical populations or open platforms such as Reddit. Comparatively little attention has been given to curated, moderated spaces like Beyond Blue, where community norms and professional oversight shape interactions [9]. Moreover, while the impact of internal stressors and large-scale crises such as the COVID-19 pandemic has been studied extensively [13], the role of other external stressors—particularly natural disasters—remains underexplored.

This project contributes novel insights in two key ways:

1. By developing a large-scale, cleaned dataset of Beyond Blue forum posts and comments alongside a freshly curated dataset of Australian natural disaster events, enabling unique cross-domain analysis.

2. By integrating psycholinguistic and transformer-based feature extraction with temporal alignment of disaster events, this study provides one of the first systematic attempts to examine whether and how, environmental stressors such as natural disasters influence online mental health signals.

2.3 Common Notation and Definitions

To ensure clarity, several key terms, notations, and techniques used throughout this report are defined below:

- **Data Acquisition via Web Scraping:** The Beyond Blue forum dataset was collected using `BeautifulSoup`, a Python library to create the forum post dataset by enabling systematic parsing and extraction of HTML content for large-scale text analysis [1].

- **Valence–Arousal Space:** A two-dimensional model of emotion representation. *Valence* refers to the degree of pleasantness (ranging from negative to positive), while *arousal* indicates the level of activation or intensity (ranging from calm to excited). This structure is derived from the Circumplex Model of Affect and is widely used in affective computing [4].

- **Transformer Models:** A class of deep learning models, such as BERT and RoBERTa, that use self-attention mechanisms to capture contextual meaning in text. In this project, a variant of RoBERTa trained on social media data (HuggingFace Transformers: Twitter RoBERTa) is used for sentiment and emotion classification [2].

- **Temporal Dynamics:** Inspired by prior work on online depression communities [7], temporal analysis is employed to observe how users' mental states shift over time within conversations and across external stressors.

- **Event Phases:** For disaster analysis, each natural disaster is divided into three phases relative to its timeline: *pre-event*, *during-event*, and *post-event*. This allows temporal alignment between disaster events and forum activity.

Overall, the reviewed literature and defined concepts establish a clear foundation for exploring how linguistic patterns and external stressors meets in shaping online mental health discussions.

3 Methods

4 Methods

This project employed a mixed-method pipeline that integrates natural language processing (NLP) with event-based data alignment to investigate links between mental health discourse and external stressors. The methodological framework was designed around two core components: (i) extraction and analysis of linguistic and affective markers from mental health forum texts, and (ii) compilation and integration of structured data on natural disasters. Each step of the pipeline emphasized reproducibility, transparency and scalability, ensuring that the approach could be extended to future datasets and research contexts.

4.1 Dataset

4.1.1 Data Acquisition

Two datasets were constructed for this project: one derived from the Beyond Blue online forums and another from the Australian Government's Disaster Assist website.

Beyond Blue Dataset: Forum data were collected from the Beyond Blue website using an automated Python pipeline combining `Selenium` for browser simulation and `BeautifulSoup` for HTML parsing. The scraper iterated through four categories (*Anxiety*, *Depression*, *PTSD and Trauma*, and *Suicidal Thoughts and Self-Harm*), capturing up to 200 pages per category. Pagination and thread harvesting were managed by the driver loop (Appendix A, Listing 1), while posts and comments were parsed into structured fields (Listings 2–3), with relative timestamps standardised into absolute dates (Listing 4).

For each thread, the following attributes were collected:

- `post_id`, `title`, `author`, `date`, `category`, `preview` and `post_text`;
- `num_comments` and `comments_combined`(up to 40 per thread), stored in JSON format;
- `url` for traceability.

Dates expressed in relative terms (e.g., "yesterday", "2 weeks ago") were normalised into absolute dates using a custom parsing function . Posts prior to January 2019 were excluded to ensure temporal relevance to contemporary climate events.

Natural Disaster Dataset: The disaster dataset was constructed manually in accordance to the beyondblue dataset timeline using publicly available records from the Australian Government's Disaster Assist website. Each entry included:

- `agrn` as the unique identifier for each disaster event;
- `disaster_types` specifying the event category (e.g., bushfire, flood, storm);
- `start_date`, `end_date`, and computed `duration`;
- `state` indicating the affected region.

The dataset was first compiled into a Google Sheet. Event `duration` was calculated automatically using the formula `=end_date - start_date`, and the final version was exported to CSV format for better usability.

4.1.2 Dataset Cleaning

For the Beyond Blue dataset, data integrity checks confirmed there were no missing values or duplicate rows. The `date` column was converted into a standardized `datetime` format, and unnecessary attributes such as `title`, `preview`, and `url` were removed to retain only essential analytical fields. Emojis were stripped from the `post_text` using the `emoji` library to ensure compatibility with NLP tools, and columns were reordered for consistency (`post_id`, `date`, `author`, `post_text`, `category`, `num_comments`, `comments_combined`). After cleaning, the dataset contained 6,753 posts spanning the period 2019–2025, with well-structured metadata and normalized text suitable for analysis.

For the Natural Disaster dataset, cleaning addressed inconsistencies in temporal and categorical features. Start and end dates were parsed into `datetime` objects, and the `duration` field was recalculated directly from these values to correct mismatches with the original entries. Disaster types were normalised into tuples of standardised labels (e.g., `('Storm','Flood')`). Obvious spelling errors (e.g., "Earthqack" → "Earthquake") were corrected, and instantaneous events (e.g., earthquakes, tornadoes, landslides) were assigned a duration of one day. Rows with incomplete date information were dropped, reducing the dataset to 150 records with complete metadata.

4.1.3 Data Processing

The Beyond Blue dataset was originally structured such that each row represented a forum thread, with the original post stored alongside a

JSON field containing up to 40 associated comments. For analytical purposes, this nested format was unsuitable, as both posts and comments needed to be treated as independent text units while preserving conversational context.

To address this, a flattening pipeline was implemented in Python (Appendix B, Listing 5). Each row of the original dataset was expanded into multiple records:

- the `original` post, linked to its `parent_post_id`;
- all replies, tagged as either `commenter` or `op_reply` depending on whether the response was made by the original poster;
- metadata including `user_id`, `date`, and `category`, inherited from the parent thread.

Dates were normalised into `datetime` format, and text fields were cleaned of empty strings and whitespace. The resulting dataset (`df_flat`) consisted of 47,000+ text units, each uniquely identified by a `parent_post_id`–`user_id` pair and sorted chronologically within threads. This flattened structure enabled user-level and temporal analyses across both posts and replies.

4.2 Exploratory Data Analysis (EDA)

4.2.1 Beyond Blue Dataset

Exploratory data analysis was conducted to examine the structural properties, activity trends, and linguistic content of the Beyond Blue dataset. This included:

- Descriptive statistics on dataset size, post lengths, and comment distributions.
- Temporal analysis of posting activity and comment frequency over years.
- Category-wise distribution of posts across *Anxiety*, *Depression*, *PTSD and Trauma*, and *Suicidal Thoughts and Self-Harm*.
- Examination of user participation patterns, identifying highly active contributors and engagement levels.
- Analysis of response latency between posts and comments.
- Textual analysis of post lengths, word frequencies, and sentiment distributions using transformer-based classifiers.

These steps provided both quality checks (e.g., duplicates, missing values) and insights into the dataset's composition, forming the basis for subsequent feature extraction and modelling.

4.2.2 Natural Disaster Dataset

EDA was performed to assess the composition, timing, and regional spread of the natural disaster dataset. This included:

- Descriptive statistics on dataset size (150 events), event types, and durations.
- Temporal analysis of disaster occurrences across years (2020–2025) and seasonal patterns.
- Distribution of events across disaster categories such as *floods*, *storms*, and *bushfires*.
- Analysis of average duration per disaster type, highlighting long-lasting bushfires versus short-term events such as earthquakes.
- State-wise distribution of disasters, identifying hotspots such as Queensland, Western Australia, and New South Wales.

These steps provided both quality checks (e.g., ensuring consistency of dates and duration calculations) and baseline insights into disaster frequency and distribution, forming the foundation for alignment with forum activity in later analyses.

4.3 Feature Extraction

To enable downstream analysis, linguistic and affective features were extracted from the Beyond Blue dataset. The feature extraction process comprised the following components:

4.3.1 Sentiment and Emotion Classification

To capture emotional and psycholinguistic markers in the Beyond Blue dataset, several approaches were explored. Initial trials used lexicon-based tools such as VADER and TextBlob to estimate polarity (valence) and subjectivity (proxy for arousal). However, these methods proved too coarse for the nuanced expressions in mental health data, often failing to capture context-dependent meanings and subtle emotional tones [6].

For these reasons, a transformer-based approach was adopted using pretrained Hugging Face models [2]. Two architectures were integrated for feature extraction:

- `cardiffnlp/twitter-roberta-base-sentiment-latest`, trained on large-scale Twitter data, used for three-way sentiment classification (*negative*, *neutral*, *positive*).
- `j-hartmann/emotion-english-distilroberta-base`, fine-tuned for multi-class emotion detection, covering seven categories: *anger*, *disgust*, *fear*, *joy*, *neutral*, *sadness*, and *surprise*.

Both Hugging Face pipelines and manual implementations were tested. While the pipeline API provided convenience (Appendix C, Listing 6), it lacked flexibility in batching, truncation, and reproducibility. The final implementation therefore used a manual inference function with explicit control over tokenisation, batching, and sequence length (Appendix C, Listing 7). This ensured consistent pre- and post-processing and enabled potential extension to domain-specific fine-tuned models. Computations were executed on Google Colab with GPU acceleration due to the scale of the dataset.

4.3.2 Valence–Arousal Mapping

To project emotional expressions into a continuous affective space, we adopted the Circumplex Model of Affect [11]. Following the computational approach described by Hasan et al. [4], sentiment and emotion classifier outputs were mapped into valence and arousal dimensions.

- **Sentiment-derived valence:** Calculated as the difference between positive and negative sentiment probabilities:

  $$V_s = P(\text{positive}) - P(\text{negative})$$

  where $V_s \in [-1, 1]$ provides a continuous measure of pleasantness. High values indicate positive sentiment, while low values indicate negative sentiment.

- **Emotion-derived valence and arousal:** Each emotion e was assigned fixed coordinates (v_e, a_e) in the valence–arousal space (e.g., joy = high valence, moderate arousal; sadness = low valence, low arousal). Given the probability distribution $P(e)$ from the classifier, weighted averages were computed as:

  $$V_e = \sum_e P(e) \cdot v_e, \quad A_e = \sum_e P(e) \cdot a_e$$

  where V_e and A_e represent continuous emotion-based valence and arousal scores, respectively.

This integration produced both:

- categorical:
  - `sentiment_top`
  - `emotion_top`
- continuous:
  - `valence_s`
  - `valence_e`
  - `arousal_e`

features, along with associated distributions and confidence scores. The enriched dataset therefore contained the following attributes:

- `parent_post_id`
- `user_id`
- `role`
- `text`
- `date`
- `category`
- `sentiment_dist`
- `valence_s`
- `sentiment_top`
- `sentiment_conf`
- `emotion_dist`
- `valence_e`
- `arousal_e`
- `emotion_top`
- `emotion_conf`

These features provided a multi-layered view of psychological expression—capturing both discrete emotion categories and continuous affective dynamics—forming the basis for subsequent temporal, category-level, and role-specific analyses. Code for the valence–arousal mapping implementation is provided in Appendix D.1.

5 Result

5.1 Dataset Overview

5.1.1 Beyond Blue (Unflattened)

The raw Beyond Blue forum dataset (prior to flattening posts and comments) contains **6,753** thread-level posts. Category distribution is shown in Table 1 and illustrated in Appendix 4.

Table 1: Beyond Blue posts by category (unflattened)

Category	**Count**	**Share (%)**
Depression	1,968	29.1
Anxiety	1,951	28.9
Suicidal thoughts and self-harm	1,445	21.4
PTSD and trauma	1,389	20.6
Total	6,753	100.0

Temporal activity. Annual posting volume shows a pronounced rise around 2021, followed by a gradual decline towards 2024–2025 (Appendix 5). Total comment volume exhibits a similar pattern, peaking around 2021 and tapering in later years (Appendix 6). These trends are consistent with pandemic-era engagement spikes and subsequent normalisation.

Engagement distribution. The number of comments per post is *right-skewed* with a long tail (capped at 40 in the collected data): most threads receive a small number of replies, while a minority attract substantial discussion (Appendix 7). This heavy-tailed behaviour motivates robust statistics and careful handling of outliers in downstream analyses.

5.1.2 Beyond Blue Dataset (Flattened)

After flattening posts and comments into a unified structure, the dataset expanded substantially, enabling role-based analyses. In total, the flattened dataset contained **42,961** text entries, composed of original posts, replies by the original poster, and comments by other users. This structure allowed us to investigate conversational dynamics at the thread level. An illustrative sample of the flattened structure is provided in Table 2 excluding the `date` and `category` attribute.

Table 2: Example records from the flattened Beyond Blue dataset. Each row represents a text entry (post, comment, or reply) with associated metadata.

parent_post_id	user_id	role	text (truncated)
1	Toby	original	Hello everyone...
1	Morph	commenter	Hi Toby, ...
1	Audacious	commenter	Hi Toby, ...
1	_Gigi_	commenter	Hello Toby, ...
1	Toby	op_reply	My anxiety ...

Response latency. First-response latency—the time between an original post and the first comment—was highly variable. While the median latency was effectively less than **1 hour** (indicating many posts received an immediate reply on the same day), the distribution exhibited a heavy tail, with some threads showing delays of several days Table 3.

Table 3: Summary statistics of first-response latency (in hours) in the Beyond Blue dataset. Negative values reflect occasional timestamp inconsistencies.

Statistic	Value
Count	6,724
Mean	16.64
Std. Dev.	199.68
Minimum	-888.00
25% Quantile	0.00
Median (50%)	0.00
75% Quantile	24.00
Maximum	14,256.00

Text length by role. Message length distributions differed by role (Appendix 8). Original posts tended to be longer and more detailed, while comments were comparatively shorter. Replies from the original poster (`op_reply`) were the briefest, reflecting follow-up clarifications or acknowledgements. This highlights distinct communication strategies depending on conversational role.

Lexical patterns. Word frequency analysis revealed differences between original posts and comments. Original posts contained more self-referential and problem-focused vocabulary (e.g., "feel", "want", "anxiety"), whereas comments emphasised supportive terms such as "help",

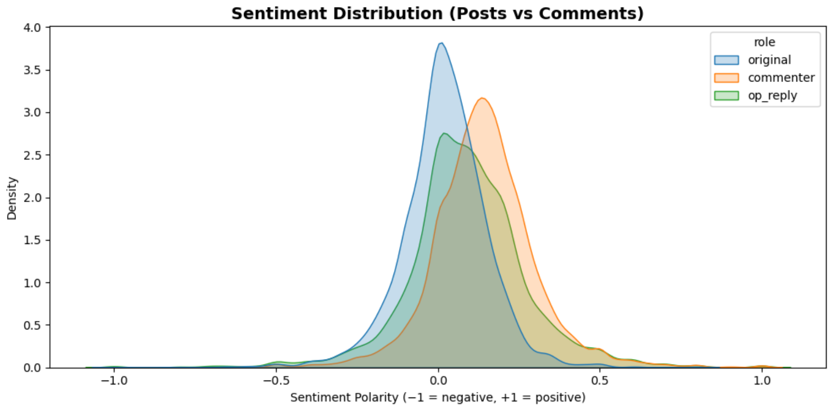

Figure 1: Sentiment polarity distribution by role. Original posts lean negative, while comments shift toward neutral-positive tones.

"support", and "hope" (Appendix 9–11).

Sentiment dynamics. Sentiment distributions, derived from transformer-based embeddings, showed clear contrasts between roles (Figure 1). Original posts were skewed toward the negative spectrum, consistent with users sharing mental health struggles. Comments, in contrast, shifted toward neutral-to-positive tones, reflecting supportive responses. Replies by the original poster lay between these two, balancing ongoing distress with engagement in dialogue.

5.1.3 Natural Disaster Dataset

The cleaned and pre-processed natural disaster dataset allowed exploration of event types, durations, and their temporal distribution.

Disaster types. Floods and storms were the most frequent disaster events, followed by bushfires and cyclones. Less frequent categories included rainfall-related events, tornadoes, earthquakes, and landslides (Table 4).

Event duration. The average duration varied substantially by disaster type (Table 5). Bushfires persisted longest (~ 19.5 days), followed by rainfall events and floods (13–14 days). In contrast, earthquakes, tornadoes, and landslides were short-lived (typically recorded as a single day).

Table 4: Frequency of disaster types in the dataset

Disaster Type	Count
Flood	75
Storm	70
Bushfire	47
Cyclone	13
Rainfall	9
Tornado	4
Earthquake	3
Landslide	1

Table 5: Average duration of disasters by type (in days)

Disaster Type	Avg. Duration (days)
Bushfire	19.49
Rainfall	13.67
Flood	13.37
Cyclone	12.46
Storm	11.96
Earthquake	1.00
Landslide	1.00
Tornado	1.00

Seasonality. Temporal analysis revealed clear seasonal patterns. Disasters were concentrated in the summer months (December–February), peaking sharply in January and February (Appendix 12). When aggregated by season, summer accounted for the majority of events, while winter showed the lowest frequency (Appendix 13). These trends align with Australia's climate, where extreme heat and monsoon activity drive higher incidence of floods, storms, and bushfires.

5.2 Affective Feature Analysis

We now present the results of feature extraction using transformer-based sentiment and emotion classifiers, mapped onto the circumplex model of affect.

Global affective space. Posts were projected into the two-dimensional valence–arousal space (Figure 2). Most observations occupy the negative-to-neutral valence range, with moderate-to-high arousal. This indicates that the forum is predominantly used to express negatively valenced, emotionally charged experiences.

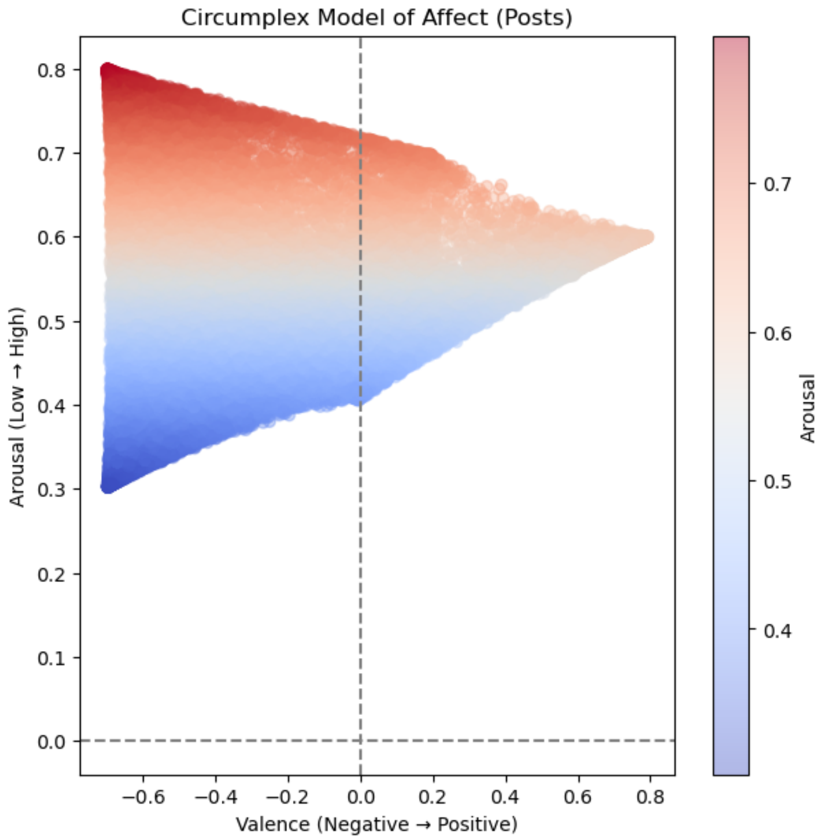

Figure 2: Circumplex projection of Beyond Blue texts: valence (x) vs. arousal (y).

Emotion distribution. Emotion classification further refines this view (Figure 3). Sadness and fear dominate the emotional landscape, followed by neutral and joy, while anger, disgust, and surprise remain marginal. This confirms the clinical relevance of the dataset, with sadness and fear strongly aligned with anxiety, depression, and trauma-related concerns.

Role-based affective differences. To examine conversational dynamics, we compared affect across roles:

- **Valence.** Original posts are the most negative, while comments and `op_reply` entries show a shift toward neutrality and positivity (Appendix 14).
- **Arousal.** Original posts exhibit the highest arousal, consistent with crisis-like disclosure, while comments and replies are lower in arousal (Appendix 15).

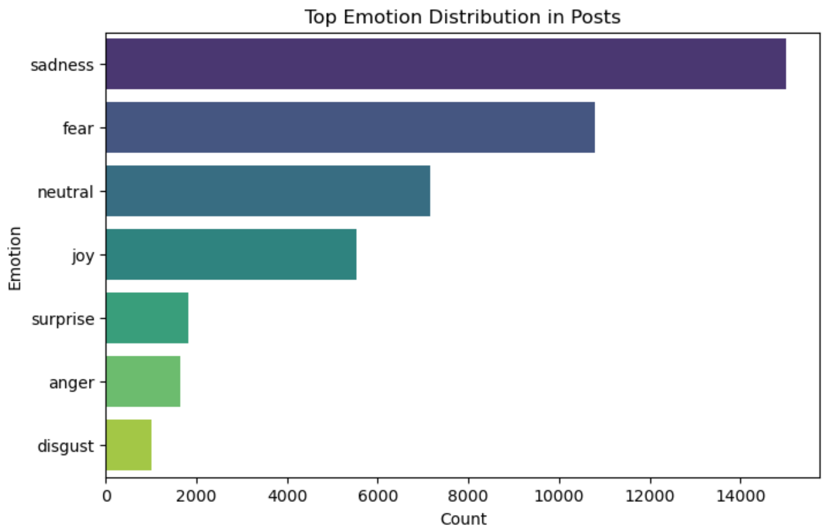

Figure 3: Top emotion distribution for posts.

- **Emotions by role.** A stacked distribution reveals that sadness and fear dominate original posts, whereas comments show relatively higher proportions of neutral and joy, highlighting supportive responses (Appendix 16).

Together, these analyses demonstrate a clear division of affective function: forum users predominantly employ posts to share high-arousal, negatively valenced distress, while responses function as regulating, supportive, and partially positive interventions.

6 Conclusion

This project investigated how online mental health conversations, specifically from the Beyond Blue forum, can be understood through linguistic markers and contextualised against natural disaster events. By constructing and cleaning two substantial datasets—42,000+ flattened forum text units and 150 disaster records—we enabled analyses that combined internal psychological signals with external stressors.

Feature extraction using transformer-based models provided rich affective and psycholinguistic features, projected into valence–arousal space. These analyses revealed distinct role-based communication patterns: original posts carried strong negative valence and high arousal, while comments shifted toward more supportive and positive tones. Such findings underline the forum's function as a peer-support environment. In parallel, the disaster dataset highlighted floods, storms, and bushfires as the most frequent and long-lasting events, establishing a structured baseline for temporal alignment.

The integration of these datasets sets the foundation for the next phase of the project: investigating whether environmental stressors correspond to measurable shifts in mental health expressions online. This work contributes to the growing literature on digital mental health monitoring by emphasising both individual distress markers and collective, external influences.

Future directions include temporal modelling of post–disaster phases, deeper network-based tracking of user trajectories, and identifying bridge symptoms (such as insomnia) that connect anxiety and depression. Ultimately, this line of research supports the potential of computational methods to detect early signals of distress, inform mental health interventions, and enhance preparedness for climate-related challenges.

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Finally, the author acknowledges the use of `ChatGPT` for support in proofreading and grammar refinement.

Appendices

A Scraper Implementation Details

A.1 Pagination and Thread Harvesting

Listing 1: Selenium pagination and thread URL harvesting

```
from selenium import webdriver
from selenium.webdriver.common.by import By
from selenium.webdriver.common.keys import Keys
import time

def harvest_thread_urls(category_url, max_pages=200,
    wait=1.5):
    driver = webdriver.Chrome()
    driver.get(category_url)
    urls = set()
    for _ in range(max_pages):
        # collect thread links on current page
        links = driver.find_elements(By.CSS_SELECTOR,
            "a.message-subject")
        for a in links:
            href = a.get_attribute("href")
            if href:
                urls.add(href)
        # go to next page if available
        next_btn = driver.find_elements(By.
           CSS_SELECTOR, "a.lia-paging-next")
        if not next_btn:
            break
        next_btn[0].click()
        time.sleep(wait)
    driver.quit()
    return sorted(urls)
```

A.2 Thread Parsing (Post + Metadata)

Listing 2: Parsing title, author, date, preview, post_text, num_comments, url

```
from bs4 import BeautifulSoup
import requests

```

```python
def parse_thread(thread_url):
    r = requests.get(thread_url, timeout=15)
    soup = BeautifulSoup(r.text, "html.parser")
    title = soup.select_one("h1.message-subject").get_text(strip=True)
    author = soup.select_one("a.lia-user-name-link").get_text(strip=True)
    date_str = soup.select_one("span.local-date").get_text(strip=True)
    category = soup.select_one("ol.lia-breadcrumb-list li:last-child").get_text(strip=True)

    # main post text and preview
    post_block = soup.select_one("div.lia-message-body-content")
    post_text = post_block.get_text(" ", strip=True) if post_block else ""
    preview = post_text[:300]

    # comments count (fallback to 0 if not found)
    num_comments = 0
    ccount = soup.select_one("span.lia-component-message-view-widget-message-count")
    if ccount:
        try:
            num_comments = int(ccount.get_text(strip=True))
        except:
            pass

    return {
        "title": title, "author": author, "date": date_str, "category": category,
        "preview": preview, "post_text": post_text, "num_comments": num_comments,
        "url": thread_url
    }
```

A.3 Comment Extraction and Packaging

Listing 3: Collecting comments into comments_combined (JSON list)

```python
import json
from datetime import datetime

```

```python
def extract_comments(soup):
    out = []
    blocks = soup.select("li.message-list-item")
    for i, li in enumerate(blocks, start=1):
        ca = li.select_one("a.lia-user-name-link")
        cd = li.select_one("span.local-date")
        cb = li.select_one("div.lia-message-body-
           content")
        if cb:
            out.append({
                "comment_id": str(i),
                "author": ca.get_text(strip=True) if
                   ca else "Unknown",
                "timestamp": cd.get_text(strip=True)
                   if cd else "",
                "comment": cb.get_text(" ", strip=
                   True)
            })
    return json.dumps(out, ensure_ascii=False)
```

A.4 Date Normalisation

Listing 4: Converting relative dates (e.g., 'yesterday', '2 weeks ago') to absolute YYYY-MM-DD

```python
from dateutil.relativedelta import relativedelta
from datetime import datetime, timedelta
import re

def normalise_date(date_str, reference=None):
    """
    Convert relative forum strings to absolute dates.
    If already absolute, return parsed ISO date.
    """
    ref = reference or datetime.today()
    s = date_str.lower().strip()

    # absolute forms first
    for fmt in ("%d %b %Y", "%d %B %Y", "%Y-%m-%d"):
        try:
            return datetime.strptime(s, fmt).date().
               isoformat()
        except:
            pass
```

```

    # relative: 'yesterday', 'today'
    if "yesterday" in s:
        return (ref - timedelta(days=1)).date().isoformat()
    if "today" in s:
        return ref.date().isoformat()

    # 'X day(s)/week(s)/month(s) ago'
    m = re.match(r"(\d+)\s+(day|week|month|year)s?\s+ago", s)
    if m:
        n, unit = int(m.group(1)), m.group(2)
        delta = {"day": {"days": n}, "week": {"weeks": n},
                 "month": {"months": n}, "year": {"years": n}}[unit]
        return (ref - relativedelta(**delta)).date().isoformat()

    # fallback: return as-is
    return s
```

B Flattening Beyond Blue Threads

B.1 Flattening Beyond Blue Threads

Listing 5: Flattening posts and comments into a unified dataset

```
import pandas as pd
import json
import ast

rows = []

for r in df.itertuples(index=False):
    op_author = r.author  # original poster for this thread

    # original post
    rows.append({
        "parent_post_id": r.post_id,
        "user_id":        op_author,
        "role":           "original",
```

```
        "text":            r.post_text,
        "date":            r.date,
        "category":        r.category,
    })

    # comments (inherit parent category)
    raw = getattr(r, "comments_combined", None)
    if pd.notna(raw) and str(raw).strip() not in ("", "[]"):
        parsed = None
        try:
            parsed = json.loads(raw)
        except Exception:
            try:
                parsed = ast.literal_eval(raw)
            except Exception:
                parsed = None
        if isinstance(parsed, (list, tuple)):
            for c in parsed:
                if not isinstance(c, dict):
                    continue
                author_c = c.get("author")
                role_c = "op_reply" if author_c == op_author else "commenter"
                rows.append({
                    "parent_post_id": r.post_id,
                    "user_id":        author_c,
                    "role":           role_c,
                    "text":           c.get("comment"),
                    "date":           c.get("timestamp"),
                    "category":       r.category,
                })

df_flat = pd.DataFrame(
    rows,
    columns=["parent_post_id", "user_id", "role", "text", "date", "category"]
)

# cleanup
df_flat["date"] = pd.to_datetime(df_flat["date"], errors="coerce")
```

```
df_flat["text"] = df_flat["text"].astype(str).str.
    strip()
df_flat = df_flat.dropna(subset=["date"])
df_flat = df_flat[df_flat["text"] != ""]
df_flat = df_flat.sort_values(["parent_post_id", "
    date"]).reset_index(drop=True)
```

C Feature Extraction Implementation

C.1 Pipeline API Example

Listing 6: Using Hugging Face pipeline for sentiment analysis

```
from transformers import pipeline

sentiment_pipe = pipeline(
    task="sentiment-analysis",
    model="cardiffnlp/twitter-roberta-base-sentiment-
       latest",
    framework="pt",
    device=DEVICE
)

emotion_pipe = pipeline(
    task="text-classification",
    model="j-hartmann/emotion-english-distilroberta-
       base",
    framework="pt",
    top_k=None,    # replaces return_all_scores=True
    device=DEVICE
)
```

C.2 Manual Inference Example

Listing 7: Manual inference for reproducible batching and truncation

```
# Sentiment model (NEGATIVE / NEUTRAL / POSITIVE)
sent_tok = AutoTokenizer.from_pretrained("cardiffnlp/
    twitter-roberta-base-sentiment-latest", use_fast=
    True)
sent_model = AutoModelForSequenceClassification.
    from_pretrained("cardiffnlp/twitter-roberta-base-
    sentiment-latest").to(device)
```

```
sent_labels = ["NEGATIVE", "NEUTRAL", "POSITIVE"]

# Emotion model (ANGER, DISGUST, FEAR, JOY, NEUTRAL, SADNESS, SURPRISE)
emo_tok = AutoTokenizer.from_pretrained("j-hartmann/emotion-english-distilroberta-base", use_fast=True)
emo_model = AutoModelForSequenceClassification.from_pretrained("j-hartmann/emotion-english-distilroberta-base").to(device)
emo_labels = ["anger","disgust","fear","joy","neutral","sadness","surprise"]
```

D Implementation Details for Feature Extraction

D.1 Circumplex Projection

Listing 8: Valence–Arousal projection from emotion probabilities

```
import numpy as np

def valence_from_sentiment(dist):
    return dist.get("POSITIVE", 0) - dist.get("NEGATIVE", 0)

emo_to_va = {
    "joy": {"val": 0.8, "aro": 0.6},
    "surprise": {"val": 0.2, "aro": 0.7},
    "neutral": {"val": 0.0, "aro": 0.4},
    "sadness": {"val": -0.7, "aro": 0.3},
    "fear": {"val": -0.7, "aro": 0.8},
    "anger": {"val": -0.7, "aro": 0.8},
    "disgust": {"val": -0.6, "aro": 0.7},
}

def va_from_emotion_dist(dist):
    if not dist: return 0.0, 0.5
    v=a=tot=0
    for emo, p in dist.items():
        if emo in emo_to_va:`
            v += emo_to_va[emo]["val"] * p
            a += emo_to_va[emo]["aro"] * p
```

```
            tot += p
    if tot>0: v/=tot; a/=tot
    return float(v), float(a)

# sentiment
df_flat["sentiment_dist"] = sent_dists
df_flat["valence_s"] = [valence_from_sentiment(d) for
    d in sent_dists]
df_flat["sentiment_top"] = [max(d, key=d.get) if d
   else None for d in sent_dists]
df_flat["sentiment_conf"] = [max(d.values()) if d
   else np.nan for d in sent_dists]

# emotion
df_flat["emotion_dist"] = emo_dists
va_pairs = [va_from_emotion_dist(d) for d in
   emo_dists]
df_flat["valence_e"], df_flat["arousal_e"] = zip(*
   va_pairs)
df_flat["emotion_top"] = [max(d, key=d.get) if d else
    None for d in emo_dists]
df_flat["emotion_conf"] = [max(d.values()) if d else
   np.nan for d in emo_dists]
```

E Additional Figures

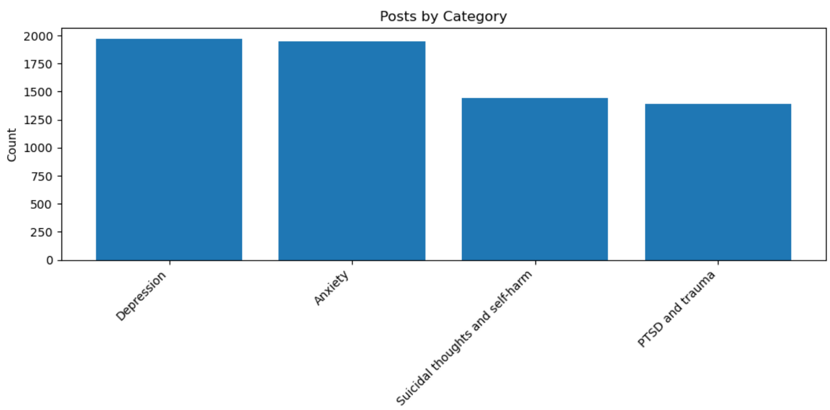

Figure 4: Category-wise distribution of posts across Beyond Blue forum threads.

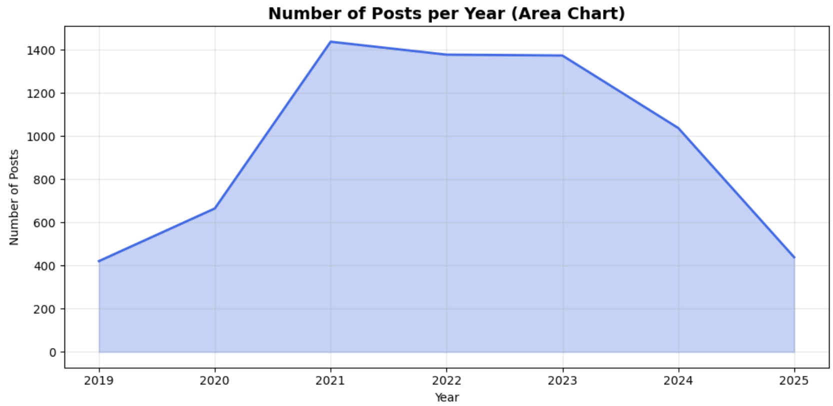

Figure 5: Number of posts per year in the Beyond Blue dataset.

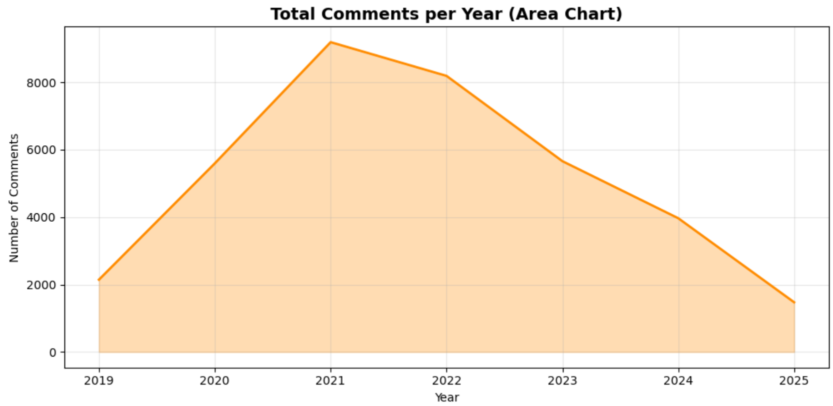

Figure 6: Total number of comments per year in the Beyond Blue dataset, showing peak activity in 2021 followed by gradual decline.

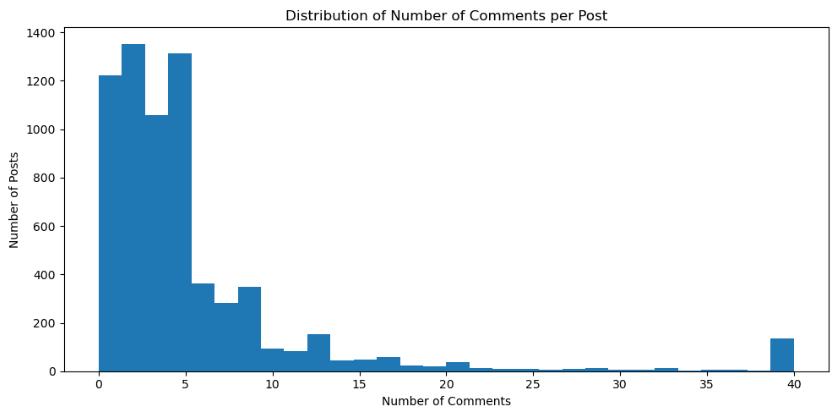

Figure 7: Distribution of number of comments per post in the Beyond Blue dataset. Most posts received fewer than five comments, with a long tail of highly engaged threads.

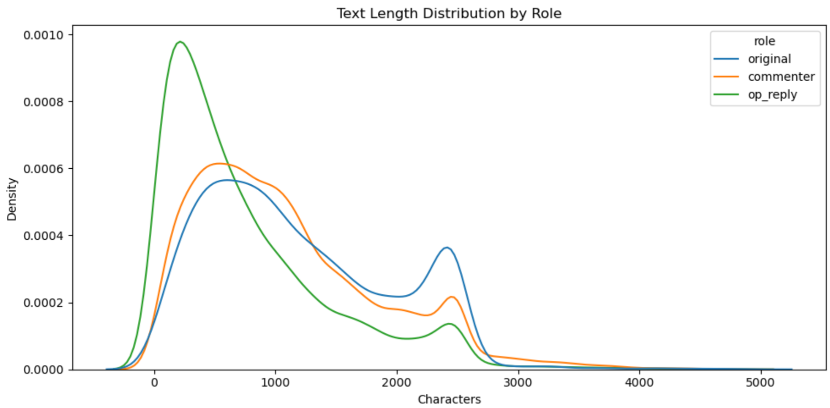

Figure 8: Text length distribution by role. Original posts are generally longer, while comments and replies are shorter.

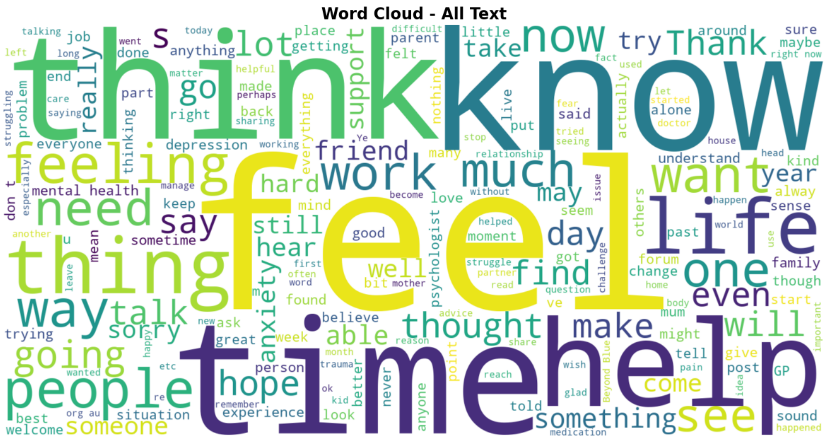

Figure 9: Top words across all text entries in the flattened dataset.

Figure 10: Top words in original posts. Self-referential and problem-focused language is prominent.

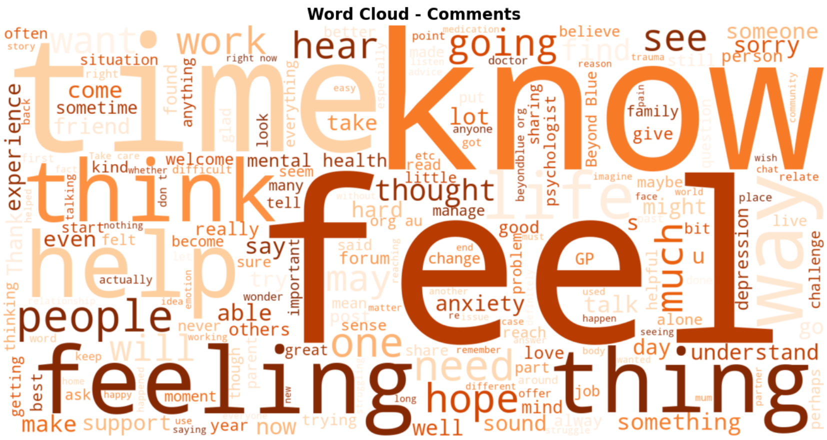

Figure 11: Top words in comments. Supportive and empathetic terms dominate.

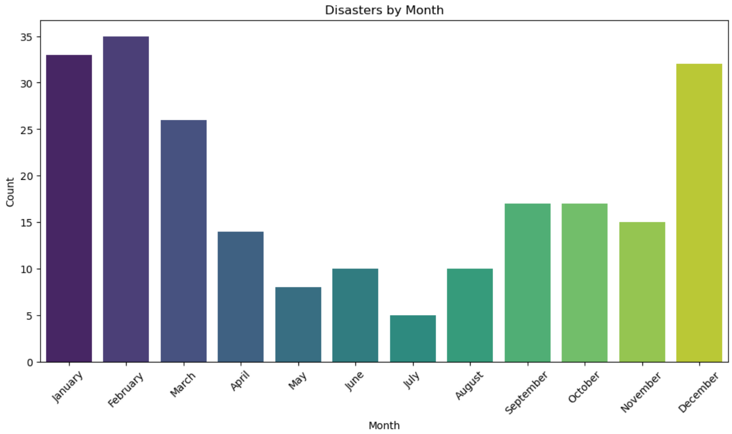

Figure 12: Monthly distribution of disasters. Peaks occur in January and February, with secondary spikes in December.

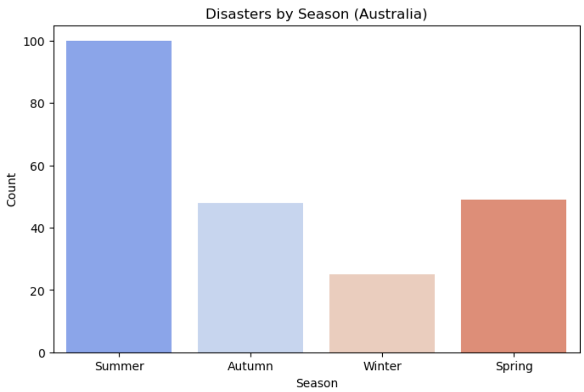

Figure 13: Seasonal distribution of disasters in Australia. Summer dominates with over twice the number of disasters compared to other seasons.

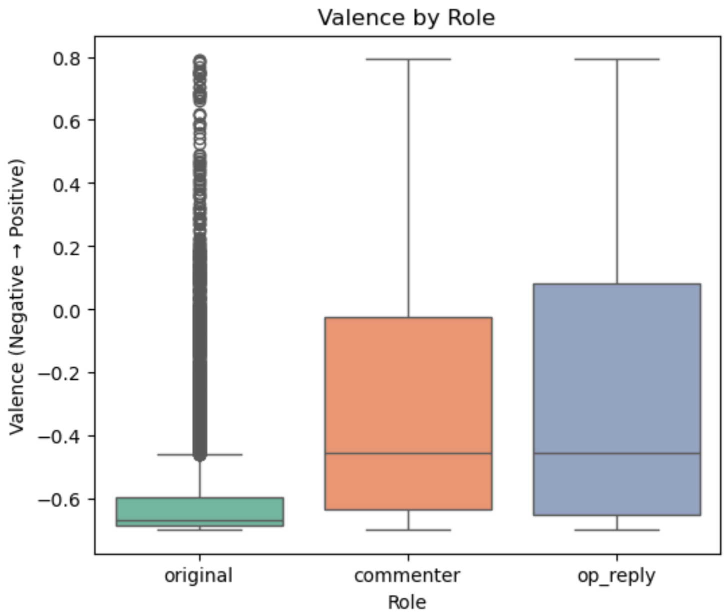

Figure 14: Valence distribution by conversational role (original, commenter, op_reply).

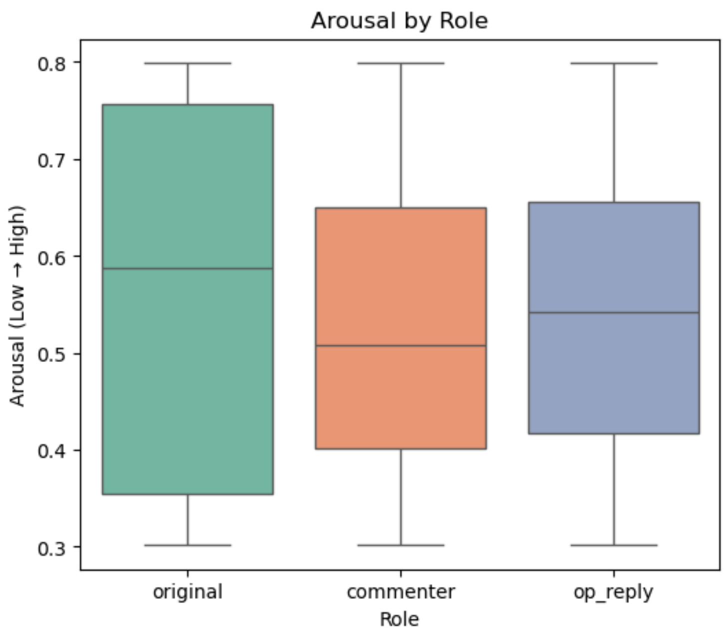

Figure 15: Arousal distribution by conversational role (original, commenter, op_reply).

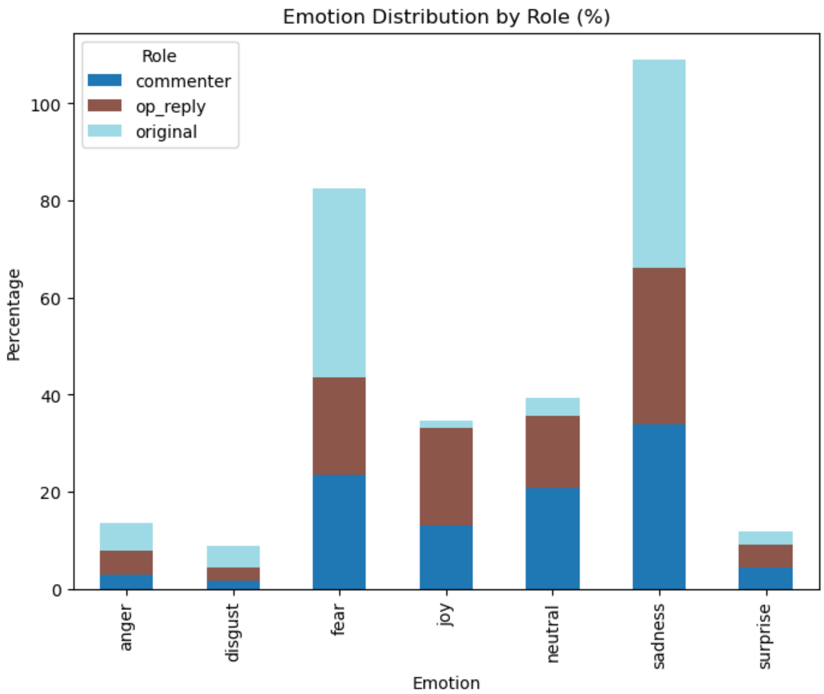

Figure 16: Emotion composition by role (percentage stacked bars).

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