# Language and Support in Online Mental Health Communities

Sri Sai Lahari Gandrapu
sgandrap@iu.edu
April 19, 2025

**Abstract**

Peer support plays a crucial role in mental health recovery, and online communities, particularly platforms such as Reddit, have emerged as prominent spaces for these interactions. However, the dynamics that influence engagement and emotional support within such forums remain underexplored. This study analyzes 6,921 posts and 9,885 comments from seven mental health-focused subreddits to investigate how users seek and provide support. A multi-method framework is employed, integrating post-intent classification, emotion analysis, and reply-based network modeling to examine which content styles and user behaviors are associated with high-engagement responses. The findings indicate that emotionally expressive and stylistically clear posts attract more replies, and that a small group of users disproportionately contribute to peer support. These results provide insights into digital empathy and inform the design of community-centered, AI-assisted mental health platforms.

## 1. Introduction

Online mental health communities, such as Reddit's r/mentalhealth and r/depression, serve as important outlets for individuals experiencing psychological distress. These platforms offer anonymity, accessibility, and a unique opportunity for peer-to-peer communication, providing informal spaces for emotional expression, validation, and support, particularly for those who may lack access to formal care.

Despite the growing reliance on these communities, the underlying factors that shape how users engage with and receive support remain insufficiently understood. Previous research has often focused on isolated dimensions, including emotional expression, user activity, or linguistic sentiment, without fully exploring how different communication styles influence community response. Notably, there is limited empirical evidence regarding how post types (e.g., venting, advice-seeking, progress updates) and linguistic tone affect the quantity and quality of peer responses. Furthermore, structural interaction patterns, such as whether support is concentrated among a few highly active users or more evenly distributed, have received relatively little attention in the context of mental health discourse.

To address these gaps, this study adopts a multi-method framework that incorporates fine-tuned BERT-based post classification, sentiment and emotion analysis, and network modeling. This approach enables the examination of how different post styles and emotional tones influence engagement levels and allows for the identification of key users contributing to support. Specifically, the study explores five core questions: (1) What categories of posts (e.g., venting, advice-seeking, progress updates) are most prevalent in online mental health communities? (2) Which linguistic or emotional features are most strongly associated with high-support responses?

(3) How does the tone or stylistic presentation of a post affect the quantity and quality of replies? (4) Which users emerge as the most active or central providers of emotional support? and (5) To what extent is support concentrated among a small number of users versus more evenly distributed across the community? These questions guide the empirical investigation and frame the contributions presented in the sections that follow.

## 2. Literature Review of Related Work

Existing research on emotional support in online mental health platforms has addressed linguistic, affective, and interactional mechanisms. While emotional expression and engagement on social media have been widely studied, fewer works have systematically examined how post intent, tone, and stylistic clarity shape supportive responses in peer-driven environments. Additional research has explored the influence of user behavior and network structure on the distribution of support. Together, these studies underscore both the promise and limitations of automated approaches to studying digital empathy.

Gkotsis et al. [1] applied deep learning techniques to detect psychological distress in social media posts and observed that narratives expressing negative emotions, such as hopelessness or fear, elicited significantly higher levels of engagement. This suggests that emotionally intense disclosures may function as implicit calls for support, a trend also observed in the current dataset.

Guo et al. [2] emphasized the importance of narrative structure, reporting that emotionally rich, story-driven posts tend to elicit more thoughtful and affirming replies. Building on this, the present study classifies posts by intent, such as venting, advice-seeking, or informational, to assess how communicative goals influence response patterns.

From the responder's perspective, Kim et al. [3] demonstrated that empathetic replies are more likely when posts contain somatic or perception-based language (e.g., "I feel stuck"). This study extends that line of inquiry by applying emotion classification to assess affective alignment between posts and their top replies.

Sharma and De Choudhury [4] introduced the concept of linguistic accommodation, showing that users who adapt their tone and vocabulary to community norms tend to receive more supportive responses. This analysis builds on that finding by examining whether tone alignment correlates with engagement metrics such as comment volume and reply sentiment polarity.

Andalibi et al. [5] investigated the impact of emotional openness and message clarity on response dynamics, concluding that well-articulated, emotionally transparent posts receive more substantial support. Informed by this insight, the present study quantifies stylistic clarity using metrics such as word count, subjectivity, and sentiment strength to explore their relationship with reply quality.

While prior studies have explored linguistic, emotional, or behavioral features independently, relatively few have integrated these aspects with structural indicators of social interaction. This research bridges that gap by combining post intent classification, affective modeling, and reply-network analysis to examine how message characteristics and user behavior shape emotional support dynamics in Reddit's mental health communities.

## 3. Data Collection

To analyze peer support dynamics in mental health-related online communities, a custom dataset was constructed using Reddit's public API via the Python Reddit API Wrapper (PRAW). Data were collected from seven support-oriented subreddits: r/mentalhealth, r/depression, r/Anxiety, r/BPD, r/TrueOffMyChest, r/KindVoice, and r/DecidingToBeBetter. For each subreddit, top posts were retrieved along with associated metadata, including post ID, title, author, score, number of comments, selftext, and timestamp. The distribution of posts across subreddits was as follows: r/BPD (1000), r/KindVoice (999), r/Anxiety (996), r/DecidingToBeBetter (996), r/mentalhealth (993), r/depression (970), and r/TrueOffMyChest (967).

To capture interaction structure, the top 10 comments per post were also extracted. Comment trees were flattened using the replace_more(limit=0) function to ensure consistent thread depth across all samples. The final dataset comprises approximately 6,921 posts and 9,885 comments. Posts or comments from deleted accounts or bots (e.g., AutoModerator) were excluded to preserve the integrity of human-to-human interaction. The resulting data were stored in CSV format (reddit_posts.csv and reddit_post_comments.csv) for further analysis.

All data collection procedures complied with Reddit's terms of service and enabled both linguistic and network-level investigation of peer support behavior within online mental health communities.

## 4. Methods

This study adopts a multi-method framework to investigate the linguistic, emotional, and structural characteristics of peer support within Reddit-based mental health communities. The methodology comprises five stages: data collection, preprocessing and feature engineering, post-intent classification, affective analysis, and network-based modeling of user interactions.

### 4.1 Data Collection and Preprocessing

Reddit data were collected using the Python Reddit API Wrapper (PRAW) from seven mental health-focused subreddits: *r/mentalhealth*, *r/depression*, *r/Anxiety*, *r/BPD*, *r/TrueOffMyChest*, *r/KindVoice*, and *r/DecidingToBeBetter*. For each subreddit, the top-ranked posts were retrieved along with their associated top-level comments. Metadata including post ID, title, author, score, number of comments, and timestamps were retained.

To enhance data quality, comments labeled as [deleted] or [removed] were filtered out, and bot-generated accounts were excluded based on username patterns. Titles and selftexts were concatenated into a single text field for each post. Posts lacking textual content were discarded. For each post, the top 10 comments were aggregated into a unified comments_text field.

Additional features were engineered, including character and word counts, image link detection (based on file extensions).

### 4.2 Post Intent and Emotion Classification

To characterize the types of communicative intent expressed in mental health posts and explore the emotional dimensions of engagement, two transformer-based models were employed.

#### Post Intent Classification

A zero-shot classification approach was used to predict the intent of posts without task-specific fine-tuning. The facebook/bart-large-mnli model, accessed via HuggingFace's pipeline("zero-shot-classification"), was applied to a sample of 100 posts. Six candidate labels reflecting common discourse types were predefined: *venting*, *advice-seeking*, *progress update*, *self-reflection*, *gratitude*, and *storytelling*. For each post, the most confident label was selected as the predicted intent. These labels informed further analysis on the prevalence and distribution of post types across the dataset (see Figure 1).

#### Emotion Classification and Engagement

To analyze how emotional content affects engagement, the j-hartmann/emotion-english-distilroberta-base model was used via HuggingFace's emotion classification pipeline. A sample of 500 posts was truncated to approximately 400 characters to meet input constraints. The dominant emotion, i.e., the label with the highest model confidence, was assigned to each post. Average comment count and score were computed for each emotion category to examine correlations between emotional tone and community response (Figure 2). High-arousal emotions, both positive and negative (e.g., *joy*, *disgust*, *fear*), were associated with increased engagement, suggesting that emotional intensity serves as a signal for support mobilization.

### 4.3 Tone, Style, and Engagement Analysis

To assess how stylistic features influence response quality and quantity, sentiment and readability metrics were computed for each post. The VADER (Valence Aware Dictionary for sEntiment Reasoning) analyzer was applied to calculate positive, neutral, negative, and compound sentiment scores for combined title and selftext fields. Additionally, word counts were computed to capture verbosity and structural clarity.

These linguistic features were merged with comment-level engagement metrics, including average reply length, average reply score, and comment count. A Pearson correlation matrix was generated to examine associations between tone/style and support engagement (Figure 3). Results indicated that posts with more positive tone and greater length were associated with longer and higher-quality replies, while negative tone correlated with shorter, lower-scoring responses. This suggests that stylistic clarity and constructive tone enhance peer responsiveness in mental health discourse.

### 4.4 Network-Based Analysis of Support Dynamics

To explore user-level support dynamics, specifically, identifying central support providers and assessing the equity of support distribution, a reply-based user interaction network was constructed.

#### Graph Construction

A directed graph was built where nodes represent users and edges represent reply interactions, with an edge directed from the commenter to the original post author. Users flagged as bots or deleted were excluded, and edges were weighted uniformly.

#### Centrality Analysis and Visualization

Out-degree centrality was computed to identify users most active in providing support. An ego network was visualized for the top contributor (Figure 4), illustrating direct interactions between the central user and their support recipients. The overall distribution of out-degree values (Figure 6) revealed a highly skewed pattern, suggesting that emotional labor is disproportionately shouldered by a small subset of users. A Gini coefficient was computed to quantify inequality in support activity.

In parallel, in-degree centrality was used to identify users who received the most peer engagement. A distribution plot (Figure 7) and corresponding Gini analysis revealed similarly imbalanced patterns of support receipt. A ranked list of top support-receiving users was also generated. These analyses collectively indicate that both giving and receiving support in Reddit mental health communities are structurally concentrated, with implications for emotional equity and community health.

## 5. Findings

This section presents the results of the multi-layered analysis conducted on Reddit mental health communities. The findings are organized around post-level linguistic and emotional features, stylistic influences on engagement, and user-level support dynamics based on network centrality.

### 5.1 Distribution of Post Intent

Figure 1 illustrates the distribution of predicted post categories based on zero-shot classification. Among the sampled posts, **venting** emerged as the most prevalent category, accounting for nearly half (49%) of the dataset. This was followed by **self-reflection** (16%) and **advice-seeking** (14%), while **progress updates**, **gratitude**, and **storytelling** appeared less frequently. These results suggest that users primarily turn to these forums for unfiltered emotional expression and introspective processing, with a moderate focus on seeking guidance.

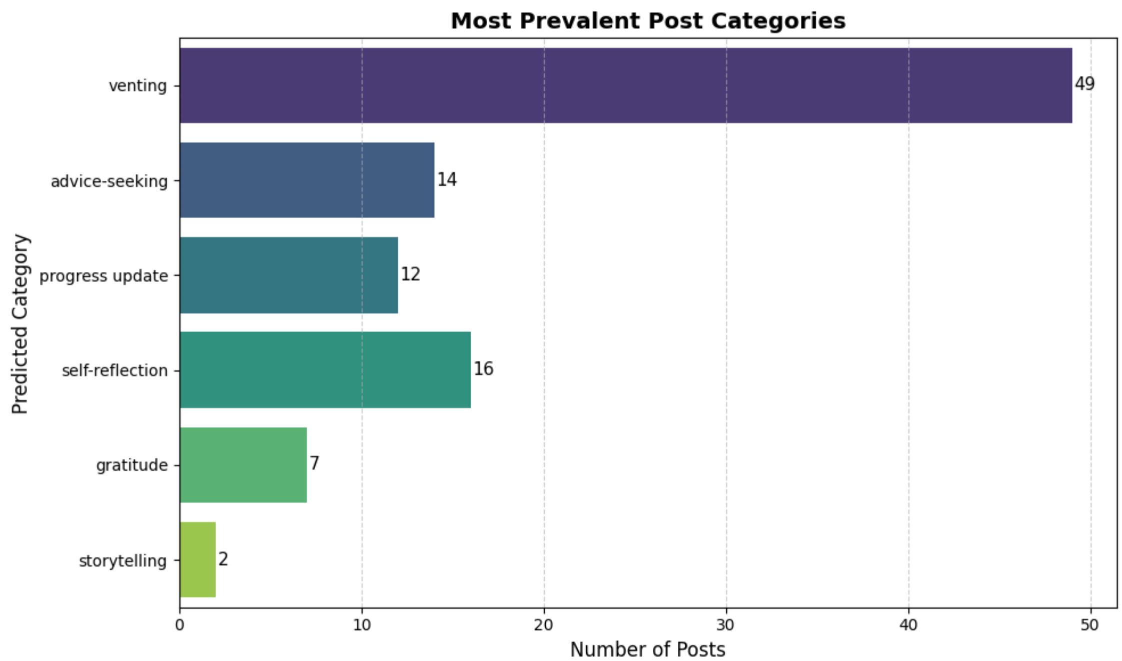


*Figure 1: Most Prevalent Post Categories*

### 5.2 Emotional Engagement Patterns

As shown in Figure 2, posts dominated by disgust, joy, and sadness elicited the highest average upvotes, with disgust slightly leading at 1,186. Posts associated with joy attracted the most comments on average (112), indicating a high degree of interaction. This suggests that both positively and negatively valenced high-arousal emotions are effective in drawing community attention and engagement. Low-arousal emotions, such as neutral or calm states, were correlated with lower engagement levels, reinforcing the hypothesis that emotional salience acts as a signal for support mobilization.

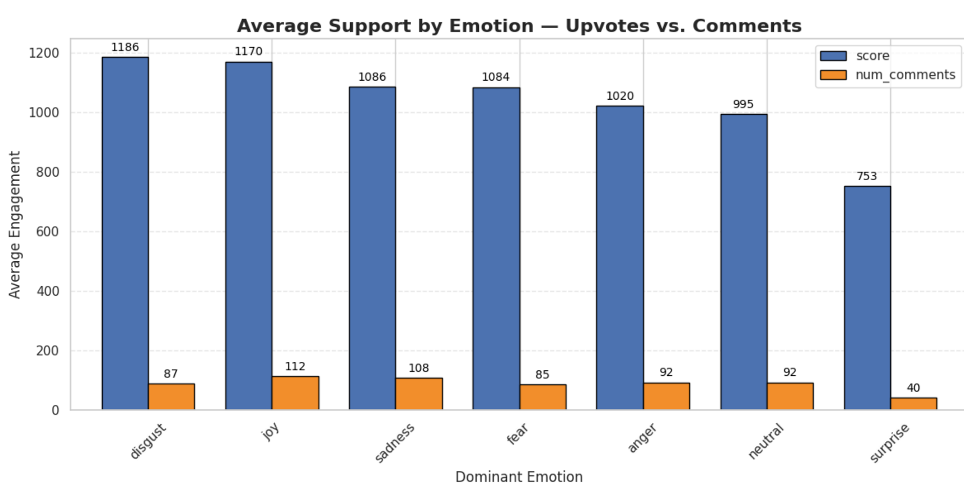


*Figure 2: Average Support by Emotion — Upvotes vs. Comments*

### 5.3 Tone, Style, and Support Quality

Figure 3 presents a Pearson correlation matrix illustrating the relationships between post tone, stylistic clarity, and various indicators of reply engagement. Positive tone exhibited a moderate positive correlation with overall sentiment (r = 0.55), indicating alignment between surface-level tone and aggregate emotional valence. Interestingly, negative tone was positively correlated with average reply length (r = 0.23), suggesting that emotionally intense or negatively framed posts may elicit more elaborate responses, an observation that challenges conventional expectations around negative expression and disengagement.

Post length was moderately correlated with both average reply length (r = 0.40) and, to a lesser extent, average reply score (r = 0.05), implying that more verbose posts are associated with more thoughtful and potentially higher-quality feedback. While the relationship with reply score is weak, the consistent pattern with reply length points toward the importance of message elaboration in triggering sustained peer interaction.

Overall, these findings underscore the influence of both emotional tone and linguistic structure in fostering engaged and supportive discourse within online mental health communities.

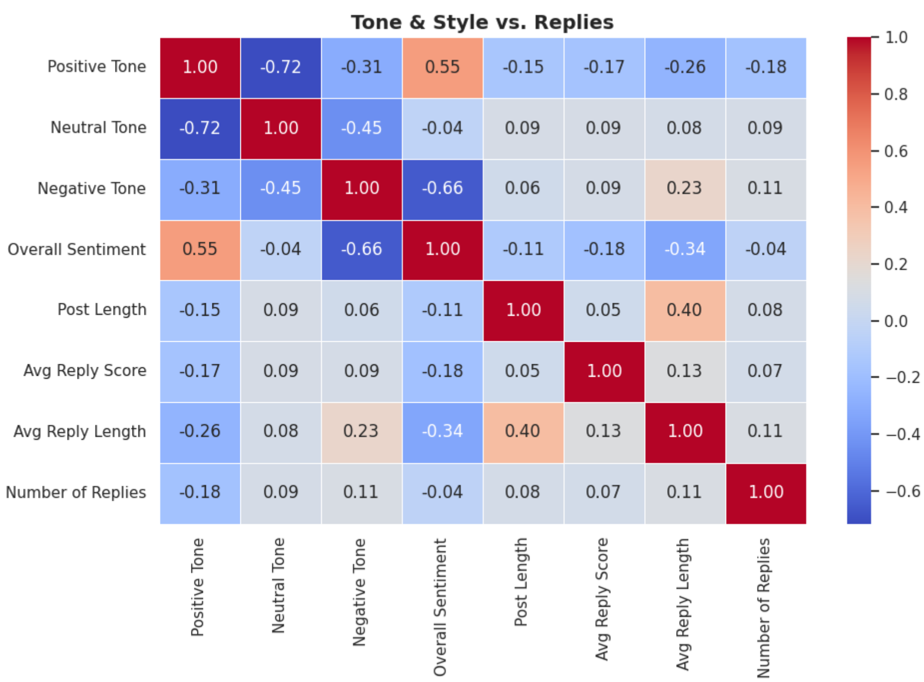


*Figure 3: Tone and Style vs. Reply Characteristics*

### 5.4 Central Users in Support Networks

Figure 4 illustrates the ego network of the top support provider within the Reddit mental health communities. The visualization exhibits a pronounced hub-and-spoke topology, with a single central user ("Sbeast") replying to a diverse set of other users. This structural pattern reflects a high out-degree centrality, indicating the user's significant role in initiating support across multiple threads. The presence of such a central hub underscores the disproportionate emotional labor shouldered by a small group of highly active contributors. This observation is further supported by a ranked list of users based on out-degree centrality, which reveals a concentrated core of support-giving participants within the broader community network.

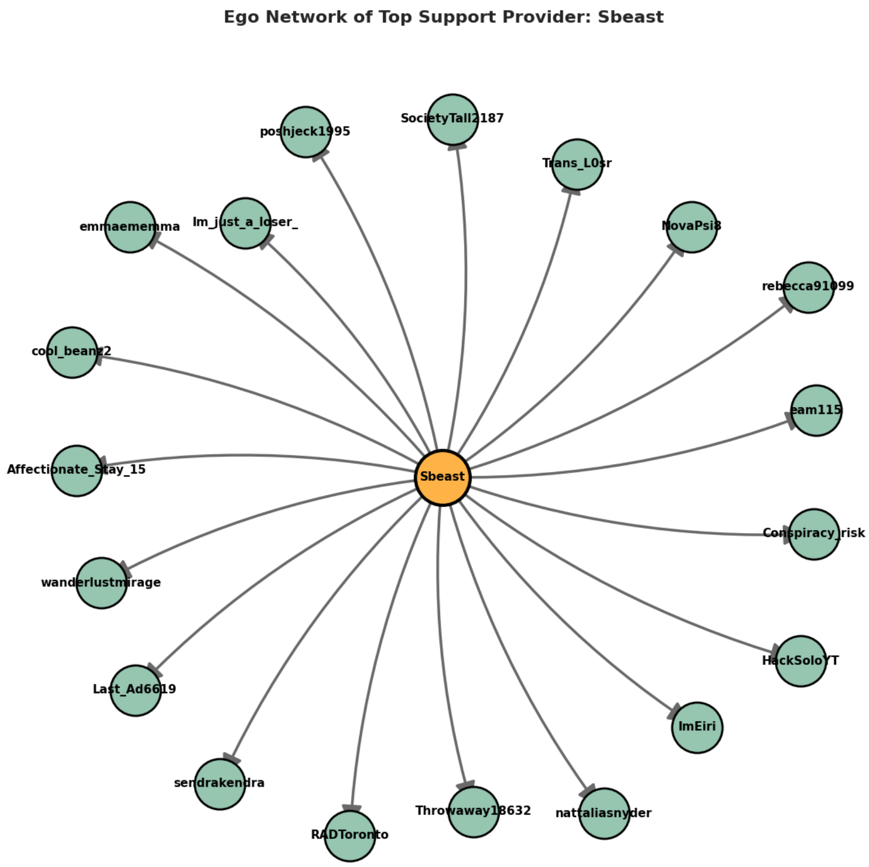


*Figure 4: Ego Network of Top Support Provider*

```
[('Sbeast', 0.003159820389156827),
 ('BRoccoli20', 0.0018293696989855313),
 ('drunky_crowette', 0.0016630633627141194),
 ('taostudent2019', 0.0013304506901712955),
 ('swild89', 0.0011641443538998836),
 ('Vulturette', 0.0011641443538998836),
 ('Fezzverbal', 0.0009978380176284716),
 ('TheAdlerian', 0.0009978380176284716),
 ('LucyLoo152', 0.0009978380176284716),
 ('FiguringItOut--', 0.0009978380176284716)]
```

*Figure 5: Top Support-Giving Users by Out-Degree Centrality*

### 5.5 Inequality in Support Distribution

Figures 6 and 7 display the distributions of out-degree and in-degree centrality, representing support given and support received, respectively. The out-degree distribution exhibits moderate right skew, with a Gini coefficient of **0.22**, suggesting that while some users are more active in providing support, the activity is relatively well distributed across the community. In contrast, the in-degree distribution is heavily right-skewed, with a Gini coefficient of **0.89**, revealing a substantial concentration of support around a small subset of users. These findings indicate that although many users contribute to supporting others, emotional support is primarily received by a select few, highlighting an imbalance in peer engagement dynamics within the community.

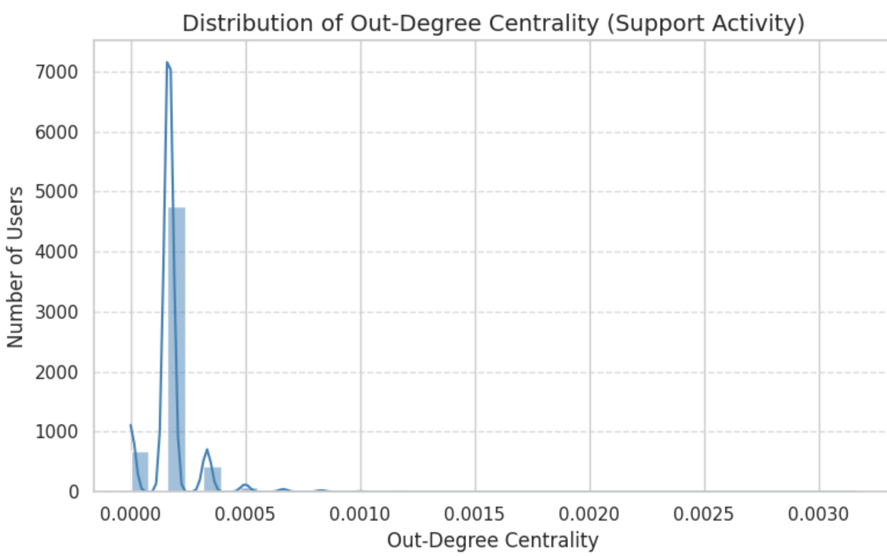


*Figure 6: Distribution of Out-Degree Centrality (Support Activity)*

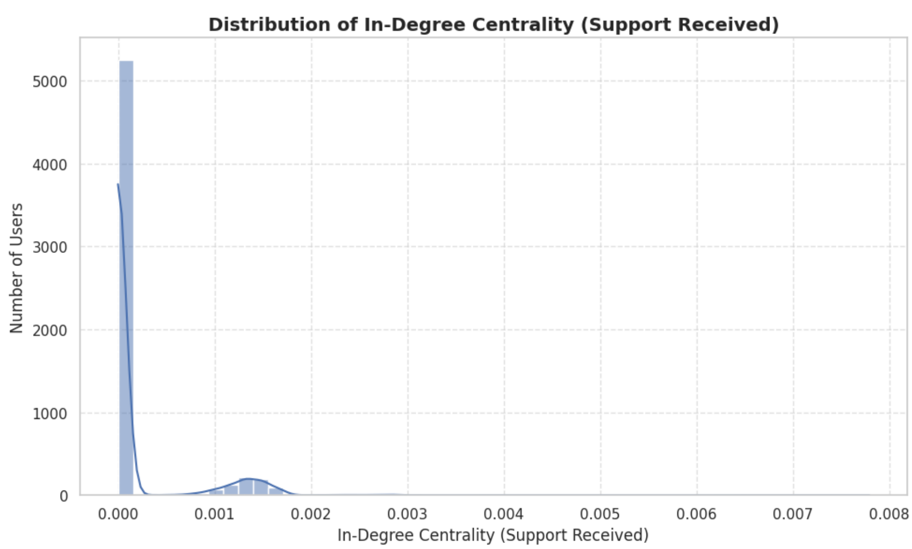


*Figure 7: Distribution of In-Degree Centrality (Support Received)*

## 6. Conclusion

This study presents a multi-faceted analysis of emotional support dynamics within Reddit-based mental health communities by integrating post classification, emotion modeling, linguistic correlation analysis, and social network metrics. The findings underscore that *venting* is the most common communication style, while emotionally expressive and positively toned posts tend to elicit higher-quality peer responses. Emotionally intense disclosures, particularly those conveying *joy*, *sadness*, or *fear*, are associated with elevated engagement, suggesting that emotional salience functions as a cue for support mobilization.

Moreover, the observed correlation between stylistic features such as post length and response characteristics highlights the importance of clarity and expressiveness in fostering meaningful interactions. The network analysis indicates that while support provision is relatively well distributed, support reception remains highly concentrated, pointing to structural imbalances in emotional reciprocity.

Collectively, these insights advance the understanding of how empathy, tone, and engagement are negotiated within digital mental health spaces. They further suggest practical design implications for platform moderators and system developers aiming to build AI-assisted, community-centered support infrastructures that promote inclusive participation and equitable emotional labor.

## 7. Limitations and Future Work

This study presents a comprehensive pipeline for mining emotional support dynamics within Reddit-based mental health communities. However, several limitations warrant consideration.

First, post categorization was conducted using a zero-shot classification model without reference to human-annotated ground truth. While this method supports scalable and domain-agnostic inference, it may introduce classification noise, particularly in cases where posts express multiple overlapping intents (e.g., venting combined with advice-seeking). Future research should incorporate manual annotation or utilize fine-tuned, domain-specific models to improve classification accuracy.

Second, the current framework treats post intent as mutually exclusive. Mental health discourse often reflects multiple simultaneous communicative goals. Adopting a multi-label classification architecture would more accurately capture the semantic richness of user posts.

Additionally, the measurement of support is primarily based on quantitative engagement metrics such as upvotes and comment counts. Although useful as proxies, these indicators do not fully reflect the emotional or empathetic quality of responses. Future work should explore response content using qualitative coding schemes or automated linguistic empathy measures.

Finally, the network analysis is based on a static snapshot of user interactions. A longitudinal approach could uncover how support structures evolve over time, track changes in user centrality, and identify potential signs of emotional fatigue or burnout among frequent contributors.

Addressing these limitations would not only enhance the methodological rigor of future studies but also yield deeper insights into the functioning and sustainability of emotional support within large-scale, peer-driven mental health ecosystems.

## 8. References


[1] G. Gkotsis, A. Oellrich, S. Velupillai, M. Liakata, T. J. P. Hubbard, R. J. B. Dobson, and R. Dutta, "Characterisation of mental health conditions in social media using Informed Deep Learning," *Scientific Reports*, vol. 7, p. 45141, 2017. [Online]. Available: https://doi.org/10.1038/srep45141

[2] Q. Guo, T. Sims, and Y. Yao, "Effects of Support-Seekers' Community Knowledge on Their Expressed Satisfaction with the Received Comments in Mental Health Communities," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–14. [Online]. Available: https://doi.org/10.1145/3411764.3445446

[3] M. Kim, K. Saha, M. De Choudhury, and D. Choi, "Supporters First: Understanding Online Social Support on Mental Health from a Supporter Perspective," *Proceedings of the ACM on Human-Computer Interaction*, vol. 7, no. CSCW1, pp. 92:1–92:28, 2023. [Online]. Available: https://doi.org/10.1145/3579525

[4] E. Sharma and M. De Choudhury, "Mental Health Support and Linguistic Accommodation in Online Communities," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 2018. [Online]. Available: https://dl.acm.org/doi/10.1145/3173574.3174215

[5] N. Andalibi, O. Haimson, L. A. De Choudhury, and A. Forte, "Social Support, Reciprocity, and Anonymity in Responses to Sexual Abuse Disclosures on Social Media," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 25, no. 5, pp. 1–35, 2018. [Online]. Available: https://doi.org/10.1145/3234942

[6] OpenAI, "ChatGPT: GPT-4 Technical Report," OpenAI, San Francisco, CA, USA, 2023. [Online]. Available: https://openai.com/research/gpt-4


## Appendix

### Appendix A. Use of Large Language Models (LLMs)

As part of this project, I consulted GPT-4 (ChatGPT) [6] to assist with model selection, feature design, and data validation. During model selection, I prompted the model with, "What transformer-based models are suitable for classifying Reddit mental health posts into categories such as venting, advice-seeking, or progress updates?” This helped validate the use of bert-base-uncased for fine-tuned multi-class classification.

To resolve issues encountered during training, I asked, “How do I fix the error related to tensor size mismatch when fine-tuning BERT?” The response clarified how to address tokenization and padding mismatches that were leading to dimensional conflicts during model execution.

For feature engineering, I used the prompt, “What linguistic or emotional features should I extract to evaluate the level of support in Reddit comments?” This guided the inclusion of sentiment polarity, subjectivity, word count, and emotional tone as relevant variables in support prediction.

Regarding the construction of the interaction network, I asked, “How can I construct a user-level reply graph from Reddit posts and comments to measure centrality and support distribution?” This informed the use of out-degree and betweenness centrality to identify support-giving users.

When visualizing ego networks, I consulted, “What is the best way to visualize ego networks using Plotly or NetworkX for Reddit user interaction?” The answer supported my decision to use spring layout and top-user labeling to enhance clarity.

Finally, to ensure proper mapping between posts and comments in the scraped data, I used the prompt, “How can I confirm that Reddit comments correctly align with the original posts during data collection?” This assisted in validating post–comment relationships and maintaining data integrity during preprocessing.

### Appendix B. Supplementary Visuals and Data Outputs

This appendix contains selected screenshots of intermediate data outputs and model predictions used throughout the analysis. These visual samples are included to demonstrate the structure and validity of the dataset, the application of transformer-based models, and the distribution of network centrality metrics for identifying key support-giving and support-receiving users.

### Figure B1. Sample Merged Post and Comment Dataset

✅ Loaded 6,921 posts with merged comments.

| | subreddit | id | title | score | author | created_utc | num_comments | selftext | url | post_id | comments_text | text |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | mentalhealth | 8msp9v | Mental Health Awareness Month: I have schizoaf... | 3173 | WarmlyEccentric | 1.527536e+09 | 178 | NaN | https://i.redd.it/rvjzbrtzen011.jpg | 8msp9v | Thank you for posting this, I've failed univer... | Mental Health Awareness Month: I have schizoaf... |
| 1 | mentalhealth | bdk3xt | Not to brag, but instead of laying in bed ALL ... | 2973 | Alyndriel | 1.555356e+09 | 116 | NaN | https://www.reddit.com/r/mentalhealth/comments... | bdk3xt | Honestly, I've found having a shower the most ... | Not to brag, but instead of laying in bed ALL ... |
| 2 | mentalhealth | qssml4 | Thank you to the woman who rang me out at Targ... | 2715 | Crafty_n_depressed44 | 1.636775e+09 | 94 | I went to target and picked out birthday cards... | https://www.reddit.com/r/mentalhealth/comments... | qssml4 | Thank you for for sharing. A reminder: if you ... | Thank you to the woman who rang me out at Targ... |
| 3 | mentalhealth | 1jpt7p8 | My name's Luke and I just got put in a mental ... | 2555 | NaN | 1.743612e+09 | 153 | NaN | https://i.redd.it/48irgwox9gse1.jpeg | 1jpt7p8 | You've got this Luke No yo dont, its ok to be ... | My name's Luke and I just got put in a mental ... |
| 4 | mentalhealth | 6ov5zm | PREACH | 2399 | starrfishandcoffee | 1.500733e+09 | 50 | NaN | https://i.redd.it/z3l4ifx4j5bz.jpg | 6ov5zm | Hmm let me go check what the top comment on th... | PREACH Hmm let me go check what the top comme... |

This screenshot displays the combined Reddit posts and their associated top comments, collected across seven mental health subreddits. Fields include title, selftext, num_comments, and a merged comments_text.

**Figure B2. Zero-Shot Post Intent Classification Output**

| | text | predicted_label | confidence |
|---|---|---|---|
| **0** | Dear mentally stable people: I’m not lazy! I’m... | venting | 0.279619 |
| **1** | I just ordered food by myself! I didn’t even k... | venting | 0.227076 |
| **2** | Feeling weird about some stuff my mom did to m... | self-reflection | 0.242715 |
| **3** | I don’t have BPD I made a post on here a long ... | venting | 0.493856 |
| **4** | Just because I have a job and get out of bed i... | venting | 0.439015 |
| **...** | ... | ... | ... |
| **95** | If you text “Home” to 741741 when feeling sad,... | gratitude | 0.223210 |
| **96** | Do you ever realize how much of a piece of shi... | self-reflection | 0.495941 |
| **97** | I finally found a job After being laid off and... | progress update | 0.405168 |
| **98** | People with a mental illness are not lazy. The... | self-reflection | 0.370534 |
| **99** | I’m an ER nurse and I’m scared Drove home this... | venting | 0.252540 |

A subset of 100 posts was processed using the facebook/bart-large-mnli model to classify post intent. The predicted label and associated confidence scores are shown.

**Figure B3. Average Score and Comments by Dominant Emotion**

| dominant_emotion | score | num_comments |
|---|---|---|
| **disgust** | 1186.500000 | 87.166667 |
| **joy** | 1170.000000 | 111.875000 |
| **sadness** | 1085.888889 | 108.037037 |
| **fear** | 1083.840000 | 85.080000 |
| **anger** | 1020.400000 | 91.600000 |
| **neutral** | 994.695652 | 91.739130 |
| **surprise** | 753.000000 | 40.000000 |

Posts were classified using the j-hartmann/emotion-english-distilroberta-base model. This screenshot shows the mean comment count and upvotes associated with each dominant emotion.

**Figure B4. Sample Outputs from Emotion Classifier**

| | text | predicted_emotion | confidence |
|---|---|---|---|
| **0** | Does anyone else with depression have impaired... | neutral | 0.503 |
| **1** | Found out my daughter is cutting herself I (32... | fear | 0.746 |
| **2** | I just asked to pet someone's dog! I know it s... | fear | 0.940 |
| **3** | [L] [M] [17] My father assaulted me and I cont... | fear | 0.737 |
| **4** | Depression has been hard on my teeth Most days... | fear | 0.326 |
| **...** | ... | ... | ... |
| **495** | [O][27] It’s been a hot minute Hey, there! How... | neutral | 0.741 |
| **496** | If you've declawed your cat or debarked your d... | anger | 0.635 |
| **497** | so much of my childhood was undiagnosed anxiet... | sadness | 0.984 |
| **498** | DAE just wanna go to a psych hospital and be d... | surprise | 0.502 |
| **499** | High-functioning depression: I feel like I'm l... | fear | 0.802 |

500 rows × 3 columns

Text and emotion predictions for 500 sampled posts are displayed, along with model confidence scores, illustrating the diversity of emotional tone in user posts.

**Figure B5. Top Users by In-Degree Centrality (Support Received)**

| | user | in_deg_centrality |
|---|---|---|
| 145 | MrReeRee | 0.779 |
| 718 | FelicityOfficial | 0.696 |
| 2450 | tharsika123 | 0.630 |
| 2495 | milksteakenthusiast1 | 0.398 |
| 1230 | Capybaraontherun | 0.332 |
| 1444 | ArtsyCats | 0.298 |
| 1590 | worstgurl | 0.282 |
| 3458 | GrotiusandPufendorf | 0.282 |
| 1561 | qazsedcft0310 | 0.282 |
| 540 | Ieatoutjelloshots | 0.282 |
| 2052 | trash666_69 | 0.282 |
| 1258 | snowrachell | 0.282 |
| 821 | rebecca91099 | 0.282 |
| 779 | FoxOfficial__ | 0.282 |
| 2517 | Amyshesgotthis | 0.265 |

This screenshot ranks users by their in-degree centrality score, indicating which users received the most replies across the network. These metric highlights structural support dynamics and the concentration of emotional engagement.

These outputs complement the findings discussed in the main body and support transparency in the implementation of the multi-method framework.

**Appendix C. Link to the GitHub repository**

https://github.iu.edu/sgandrap/25SP-ILS-Z639-SMM/tree/main/HW3