Current mental health discussions on Reddit: a computational analysis of support communities

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Abstract

Online platforms have become important places for young people and adults to talk about sensitive topics like mental health, offering dedicated spaces. This research analyses posts and comments taken from Reddit communities related to mental health with the goal to give an overall perspective on the current mental health discussions on the platform. To do so, posts and relative comments have been taken from five Reddit communities in the span of around 7 weeks. Different techniques have been applied in order to understand different elements of the discussion (community description, text features, topics, sentiment).

keywords: mental health - reddit - text analysis - topic modeling - sentiment analysis

1 Introduction

Online platforms provide opportunities to discuss a wide range of topics. The vast amount of user-generated content allows researchers to analyze and extract valuable insights from these discussions. Mental health is a very delicate topic of discussion and users of online platforms like Reddit have been organizing spaces in which to talk freely about it. Reddit is organized into communities called subreddits, each one dedicated to a specific topic, with some of them created to discuss about mental health. This paper employed a combination of techniques such as topic modeling and sentiment analysis in order to examine the discussions in these communities, to better understand their emotional tone and thematic content.

The code can be consulted at the link: https://github.com/SamC-dev/mental-health-in-reddit

2 Literature review

2.1 State of the art

Research applying computational methods on Reddit communities related to mental health have its foundation in 2014, when a first comprehensive analysis was published with the title *"Mental Health Discourse on Reddit: Self-Disclosure, Social Support, and Anonymity"* [1]. The study focused on three key aspects:

- The linguistic attributes associated to self disclosure.

- The factors which drive social support on posts and and the various forms it takes.
- The role of anonimity (via throwaway accounts) in sharing mental health information.

The data, categorized in the form of posts and comments, have been taken from different subreddits across a two months period, and an adequate set of computational techniques have been implemented to address the research questions.

The first analysis is linguistical and performed with the use of the psycholinguistic lexicon liwc to quantify emotional, cognitive, and psychological indicators in text (e.g: pronoun use); LDA is used to build thematic clusters to identify types of social support; a negative binomial regression analysis is performed to investigate whether the attributes of posts are predictors of the extent of support received in the comments; a simple word matching has been used to find throwaway accounts.

The investigation of an underexplored area using a combination of computational methods and giving the foundations of further research is the main strength of this paper, nevertheless the authors acknowledge limitations regarding the lack of a mixed method (quantitative and qualitative) to assess users' mental health conditions.

Park et al. (2018)[2] extracted the main themes expressed in three popular subreddits, investigating similarities and differences between them through k-means clustering, an unsupervised learning algorithms grouping topics into clusters. These clusters were then compared by visually looking at overlapping themes showed in a Venn diagram and then by computing similarity scores. The results showed that the three communities shared topics related to sleep issues, work related discussions, gratitude and positive emotions sharing, but each of them had unique themes (e.g: overthinking more discussed in the anxiety subreddit).

The study conducted a well detailed community comparison, explaining the results in a clear way thorugh the use of multiple visualizations. The main limitation is given by the little variety of data analyzed. With a research question focused on communities comparison, taking only 3 subreddits limits generalizability. This limitation is acknowledged by the authors, who invite future studies to address other online communities, also outside of Reddit.

Kamarudin et al. (2021) [3]addressed four key questions about the reliability of online mental health discussions, sentiment distribution, negativity assumption, and topic variation across communities. 52 subreddits data were collected and categorized into five communities following prior related work. Using VADER for sentiment analysis and LDA for topic modeling, the authors found out that 4 out of 5 communities show more positivity than negativity, only the one related to trauma and abuse showed more negative sentiment. Topics were finally extracted and assigned to each of them.

The extensive data collection and following categorization are the strengths of this analysis, but the sentiment analysis, primarily reliant on a basic tool such as VADER, could have been more in depth and extended in order to ["...further investigate the construction for sentiment lexicon for mental health or extract the relation of drug to mental health."].

Fraga et al. (2018) [4] investigated user activities, interactions and the discourse pattern analysis of posts and comments across four popular subreddits, resulting in three key findings:

- Interactions are centered on content and they are independent from the authors who published the post. These interactions were modeled using weighted directed graphs G where nodes represent users and edges the comments.

- Using discussion trees the authors found out that the posts with the deepest trees of comments are request of help.

- The four subreddits share a common language, including encouragements words. A relationship modeling network (RMN), a recursive neural network, is used for this task.

The collection involved a huge amount of data and the authors conducted topic modeling with a novel approach (RMN) instead of employing the traditional LDA, but the paper is not clear about the period of collection and analysis. It seems data belongs to a span of 8 years (2011-2017) but, apart from analyzing the growth of these subreddits over time, the main analysis is conducted only on 2017 data, resulting in what seems a limitation.

2.2 Research questions

In light of the previous works this paper aims at giving details about the current discussion on mental health related subreddits, In particular formulating and answering to three questions:

- Q.1: What are the dominant topics of discussion in mental health related Reddit communities?

- Q.2: What is the prevailing emotional tone of discussions (as captured by general sentiment analysis), and how does this sentiment vary across posts and comments, and among the different mental health communities?

- Q.3: How do domain-specific emotional categories manifest within the identified topics, and how do they vary between posts and comments and across topics?

3 Research methodology

This study adopts a suitable methodological framework to address the proposed research questions.

3.1 Data collection

The dataset contains posts and comments taken from 5 different communities in Reddit, a popular online platform known for its user driven communities called subreddits. Reddit's favors discussion through a free of expression and a structure characterized by posts and nested comments.

The 5 subreddits have been identified through a snowball approach. The initial subreddit has been identified by typing in the search bar the keyword mental health and selecting the most followed one (r/mentalhealth). From here the communities "r/depression" and "r/Anxiety" were retrieved by looking at the suggested ones, these two suggested the last ones.

For each subreddit posts and comments have been retrieved in reverse chronological order in a span of around 7 weeks (07/05 - 22/06) using the popular wrapper library praw.

Reddit Api put stricter limitations in data scraping, limiting to 1000 posts per subreddit the maximum amount. The raw datasets, containing 4822 posts and 11310 comments, were anyway sufficient to capture the recent discussion and provided a robust foundation to conduct the research.

3.2 Preprocessing and cleaning

The raw datasets have been preprocessed to facilitate and improve the next analyses:

- Text cleaning: punctuation, urls and special characters have been removed. text have been converted into lowercase. Stop words have been downloaded from the nltk library for english words, to which specific words were added (e.g: common, bot generated or irrelevant words).
- Handling content: content marked as [removed] and [deleted], duplicates and low effort content (less than 5 words) have been removed.
- Language identification: all non english posts and comments have been removed.
- Tokenization.

the final data folder included two cleaned datasets for each of the subreddits (one for posts and one for comments), and two additional aggregated datasets with all posts and comments. Each step of this research separates posts and comments. This choice is justified by their different nature: posts are longer and support seeking, comments are shorter and reactive.

3.3 Descriptive statistics

For each dataset different metrics of engagement have been computed:

- Origin: which dataset (subreddit or combination).
- Average, median and standard deviation of number of comments.
- Maximum number of upvotes.
- Maximum number of comments.
- Unique users.
- Average text length.

Across all subreddits, engagement doesn't seem high, with a median of 2 comments for each post. The average text length is quite balanced, around 200 words for each post, making them suitable for topic modeling and sentiment analysis. Some posts received a high number of upvotes and comments, sign that these posts created a debate around it.

3.4 Ethical considerations

Given the sensitive nature of mental health discussions, ethical considerations were a top priority throughout this research, and the approach in collection and analysis of data was guided by the principle of respect of users' privacy, considering that despite being a public space, users have a skewed expectation of privacy driven by failure in understanding permanence and reach of data, and failure in understanding the big data computational tools which could be used to analyze those data (Benton et al., 2017)[5]. This study complies with article 9 of GDPR [6] in the processing of special categories of data, and adopts the following procedure to protect users' privacy:

- Storage limitation: personal data are kept only for the necessary amount of time to complete the research, then permanently deleted.
- Data minimization: only the necessary data is collected.
- The collected data are not shared with anyone.

- Anonimity is granted to all the users and their identification from processed data is not possible to perform.
- Data are analyzed in their aggregated form.

4 Results

4.1 Q.1

To extract the main themes of discussion, prior studies in the literature commonly employed Latent Dirichlet Allocation (LDA), which has become a standard technique for topic modeling in textual analysis. This study aligns with that approach but extends it by incorporating BERTopic, a more recent method that leverages Transformer-based embeddings and clustering algorithms to capture semantic context. While LDA relies on word frequency and treats words as independent (i.e., ignoring their contextual meaning), BERTopic uses pre-trained language models (e.g., BERT) to generate dense vector representations of documents, allowing it to identify semantically coherent clusters. Both models were applied separately to posts and comments, a choice justified by their different nature, being posts generally longer and support seeking, while comments generally shorter and reactive.To evaluate the semantic coherence of the generated topics, we used the c_v coherence score, which ranges from 0 (no coherence) to 1 (high coherence).

LDA RESULTS:
The LDA model produced ten topics each for posts and comments.

- **Posts analysis:** Five of the ten topics were directly related to common mental health concerns such as anxiety and depression. This aligns with expectations given the subreddit contexts. In these topics include frequent terms like "sleep", "medication", "panick attack" , "therapy" and "help". The remaining topics were less interpretable. The average coherence score was moderate, around 0.42.
- **Comments analysis:** opics generated from comments were more coherent overall, with an average coherence score of 0.62. Several topics overlapped conceptually with those derived from posts, indicating thematic consistency across different types of discourse.

Figure 1: Posts topic example

BERTopic:
By applying the second method, topics resulted more consistent, with an overall clear context in each of them. Coherence scores were similar to LDA, with a drop to 0.53 in comments. In both posts and comments, the majority of the topics were very specific, including discussions around anxiety during flights, drinking problems, recent war episodes, feeling of being lonely.

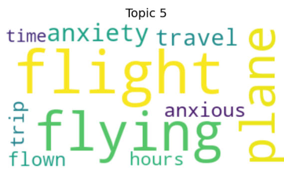

Figure 2: Posts topic example

4.2 Q.2

The second research question has been addressed by implementing VADER, a popular sentiment analysis technique, usually implemented in social media data. VADER assigns a sentiment score to each text instance (in this case to each post and comment) on a scale between -1 and +1, where the two extremes respectively represent a negative tone and a positive one, with 0 representing complete neutrality. VADER was applied to all the selected subreddits. The results revealed notable differences in sentiment distribution between posts and comments:

- Posts showed a relatively balanced sentiment distribution, but with slightly higher frequency of negative sentiment. The sentiment scores were dispersed across the spectrum, with peaks toward both positive and negative extremes.

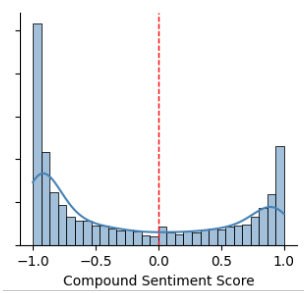

Figure 3: Posts sentiment distribution

- Comments, in contrast, exhibited a stronger skew toward positive sentiment.

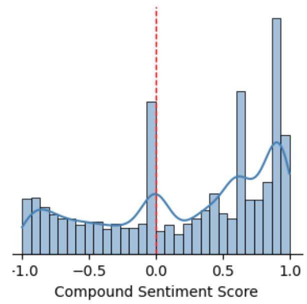

Figure 4: Comments sentiment distribution

The difference in posts and comments likely reflects the different roles of posts and comments. Posts are often written by users seeking emotional support, typically describing distressing or negative personal experiences, while comments tend to offer this support through encouragement or advise, resulting in a positive tone. This pattern is especially valid in support communities (r/depressionhelp, r/Anxietyhelp), which give the highest contribution to the overall positive sentiment.

4.3 Q.3

Previous work in sentiment analysis has typically relied on tools like VADER or generic emotion lexicons (e.g., the NRC Emotion Lexicon). While useful, these approaches often fail to capture the nuanced emotional landscape of discussions within the mental health domain, leading to limited analytical depth. This study advances beyond that by incorporating a customized mental health lexicon through the use of Empath, a lexicon-based text analysis tool used to detect and quantify psychological, emotional, and topical categories in text. Empath scans a body of text and scores it across predefined semantic categories (200 total), each represented by a set of words which are expanded using deep learning models trained on word embeddings (e.g: word2vec). For this study, key categories—such as anxiety crisis—were further refined using unigrams and bigrams extracted from subreddit posts and comments, allowing for greater contextual relevance. Analyses were performed separately for posts and comments, and stratified by previously identified topics, offering more in depth results. Key findings:

- Posts exhibit a high frequency of emotionally negative language. Categories like nervousness (4.1%), shame (3.0%), pain (3.6%), suffering (2.6%), and violence (3.0%) show a combined presence of over 16%, though overlap is possible. In contrast, positive emotional language appears in only 2.6% of the content, indicating an overall negative emotional tone.

--- Overall Average Empath Category Proportions (Posts) ---

Empath_negative_emotion	0.050488
Empath_nervousness	0.040871
Empath_pain	0.036423
Empath_health	0.030691
Empath_violence	0.030449
Empath_shame	0.029892
Empath_sadness	0.028945
Empath_positive_emotion	0.026252
Empath_suffering	0.025989
Empath_fear	0.024726

Figure 5: Posts domain specific sentiment

- The previously mentioned positivity of comments and their supportive nature is confirmed by categories like optimism (2%), speaking and communication (4.7%), with positive emotional language slightly superior (3%). Previous categories, like nervousness and pain, reduced their presence compared to posts.

--- Overall Average Empath Category Proportions (Comments) ---

Empath_health	0.035375
Empath_negative_emotion	0.031815
Empath_nervousness	0.030248
Empath_positive_emotion	0.029661
Empath_communication	0.027856
Empath_sadness	0.024319
Empath_fear	0.021822
Empath_pain	0.021689
Empath_optimism	0.020404
Empath_speaking	0.020205

Figure 6: Comments domain specific sentiment

- Topic-level analysis reveals consistent patterns, particularly with nervousness, which remains consistent across contexts, peaking in those topics related to air traveling and alcohol (respectively 7.8% and 5.7%). Some topics extracted from the comments show notably high share of positive tone (up to 20%), further supporting their supportive role in discourse.

5 Conclusions

This study explored mental health related discussions on Reddit by analyzing posts and comments collected from a span of around 7 weeks. Through the application of two topic modeling techniques and both general and domain specific sentiment analysis, serveral meaningful patterns emerged:

1. Both LDA and BERTopic successfully identified a wide range of themes discussed across subreddits. Topics reflected common mental health concerns such as anxiety, depression, medication use, and therapy, as well as more context-specific issues like air travel-related anxiety and substance use. The use of BERTopic was fundamental to capture the complexities of online mental health discussions.

2. Sentiment analysis using VADER showed a clear distinction in emotional tone between posts and comments. Posts tended to be more negative, consistent with their support seeking function. In contrast, comments were more positive, often providing encouragement, advice, or empathy. This dual dynamic reinforces Reddit's role as a space for both self-disclosure and peer support.

3. To address limitations of generic sentiment tools, the study implemented a customized mental health lexicon using Empath, improving emotional granularity. This approach revealed underexplored prevalent tones, such as nervousness, pain and shame in posts, and greater optimism and communication in comments. The refinement of Empath categories with subreddit-specific unigrams and bigrams enabled more accurate contextual representation of emotions, particularly highlighting topic-level emotional variation.

The study confirms Reddit as a valuable platform for understanding contemporary mental health discourse. It demonstrates the need for context-aware analytical tools to accurately capture emotional and thematic nuances. The separation of posts and comments in the analysis provided a clearer picture of the platform's function of meeting point between people in seek of support and people who give it. While this study offers important insights, it's limited to data collected in a short period of time, and small in dimensions. Future research should expand both the time period and the amount of data. Further development or even fine tuning of models could enrich the understanding of the discussions. In conclusion, this research gives a contribution to a deeper, more precise understanding of mental health discussions on Reddit and underscores the importance of tailoring analytical methods to the domain's unique linguistic and emotional characteristics.

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