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## Mental health signal detection from social media posts

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### Abstract

Social media platforms have become important environments where individuals openly express emotions, stress, and psychological struggles, often before seeking professional support. This study investigates the use of interpretable text analytics techniques for detecting mental health signals, particularly depression and anxiety, from social media posts using SAS Viya Text Miner.

A total of 7,731 anonymized social media posts obtained from publicly available datasets were analyzed through a transparent analytical framework consisting of text preprocessing, text parsing, concept extraction, topic modeling, and rule-based categorization. The findings revealed that depression and anxiety were the most dominant mental health indicators across the dataset. Many posts reflected persistent emotional distress rather than temporary emotional fluctuations. Anxiety-related language frequently involved panic, fear, and repetitive negative thinking, whereas depressive expressions commonly conveyed hopelessness, emotional exhaustion, and social withdrawal. Secondary indicators such as sleep disturbances and unmet emotional needs also emerged as meaningful patterns. In addition, a smaller subset of posts contained severe distress signals, including suicidal ideation.

The results demonstrate that interpretable text mining approaches can effectively identify meaningful psychological patterns from large-scale social media data while maintaining transparency and explainability. Although the proposed framework is not intended for clinical diagnosis, it can support mental health research, population-level monitoring, and early identification of high-risk content within healthcare and public health systems

**Keywords:** Mental Health Analytics; Social Media Analysis; Text Mining; SAS Viya; Depression Detection; Anxiety Detection; Interpretable Analytics; Topic Modeling; Concept Extraction

### Introduction

Mental health conditions such as depression, anxiety, and chronic stress have become increasingly prevalent across global populations. Despite growing awareness of mental health concerns, many individuals continue to delay or avoid seeking professional support because of social stigma, limited access to healthcare services, financial barriers, or insufficient awareness of available resources. During periods of emotional distress, individuals frequently use social media platforms to share thoughts, emotions, and personal experiences. As a result, social media has emerged as a valuable and continuously updated source of information for understanding mental health trends at the population level.

The rapid growth of user-generated online content has created significant challenges for manual analysis. Millions of social media posts are produced daily using informal, unstructured, and highly contextual

language that traditional analytical techniques often struggle to process effectively. Automated text analytics provides a scalable solution for extracting emotional and psychological insights from such data. Recent studies have increasingly applied machine learning and deep learning techniques, including transformer-based models, to identify mental health conditions from online text. Although these approaches frequently achieve high predictive performance, they often lack transparency and interpretability.

Interpretability is particularly important in sensitive domains such as mental health. Researchers, clinicians, and healthcare organizations must understand why specific content is identified as potentially high-risk. Black-box predictions may create ethical concerns, reduce trust, and limit practical adoption in healthcare environments. Consequently, there is growing interest in transparent and explainable text analytics methods capable of identifying emotional distress while maintaining interpretability.

This study applies SAS Viya Text Miner to detect mental health signals from social media posts using interpretable analytical techniques, including text parsing, concept extraction, topic modeling, and rule-based categorization. Rather than diagnosing individuals, the objective is to demonstrate how transparent text mining approaches can support mental health research, large-scale monitoring, and early identification of high-risk content while maintaining ethical accountability and explainability.

The research question of this study is: “How can SAS Viya's interpretable text analytics techniques be used to detect and analyze mental health signals in social media posts?” The research objectives are defined as: the general objective of this study is to detect and analyze mental health indicators in social media posts using interpretable text analytics in SAS Viya. The specific objectives are (1) to preprocess social media text for analysis; (2) to extract mental health concepts using rule-based text mining, and (3) to identify latent mental health themes through topic modeling.

## Literature Review

Social media has become an important digital environment where individuals express emotions, stress, and mental health challenges. Many users disclose feelings associated with depression, anxiety, and emotional distress online before seeking professional assistance, making social media content a valuable source for identifying early psychological signals.

De Choudhury et al. (2013) were among the first researchers to demonstrate that mental health conditions are reflected in online language patterns. Their study found that individuals experiencing depression used more negative emotional language, exhibited greater self-focus, and showed reduced social engagement. These findings established that linguistic behaviors in social media posts can serve as indicators of mental health conditions.

Sentiment and emotion analysis techniques have also been widely applied in mental health analytics. Hutto and Gilbert (2014) introduced the VADER sentiment model, specifically designed for short and informal social media text. Their work demonstrated that rule-based approaches can effectively capture emotional tone while preserving interpretability. Similarly, Mohammad and Turney (2013) developed the NRC Emotion Lexicon, which associates words with emotional categories such as sadness, fear, anger, and joy, enabling more detailed emotional analysis.

Psycholinguistic research further supports the relationship between language and psychological states. Pennebaker et al. (2015), through the Linguistic Inquiry and Word Count (LIWC) framework, demonstrated

that patterns of word usage are strongly associated with anxiety, depression, and cognitive processing. Their findings highlighted the importance of structured and interpretable linguistic analysis in psychological research.

Machine learning approaches have also been extensively explored for mental health detection. Coppersmith et al. (2015) showed that individuals with depression and other psychological conditions exhibit distinct language patterns on social media, enabling automated identification through computational models. More recent deep learning methods have achieved high predictive accuracy; however, they often operate as black-box systems with limited explainability. In healthcare contexts, this lack of transparency may create ethical and practical concerns.

Recent reviews by Shatte et al. (2019) and Liu et al. (2019) emphasized both the opportunities and challenges associated with artificial intelligence in healthcare applications. While advanced machine learning methods can improve predictive performance, transparency and interpretability remain essential for building trust and supporting responsible decision-making.

Recent advances in natural language processing have significantly improved the detection of mental health conditions from social media text through transformer-based models such as BERT and RoBERTa. Although these models often achieve high predictive performance, they generally lack transparency, making it difficult for clinicians and researchers to understand how predictions are generated. Recent explainable AI (XAI) research emphasizes that healthcare applications require models that are interpretable, trustworthy, and ethically accountable. Consequently, there is increasing interest in transparent approaches that combine scalable text analytics with understandable rule-based methods. This study contributes to this direction by applying SAS Viya Text Miner to identify mental health signals through interpretable techniques including text parsing, concept extraction, topic modeling, and rule-based categorization.

### Methodology

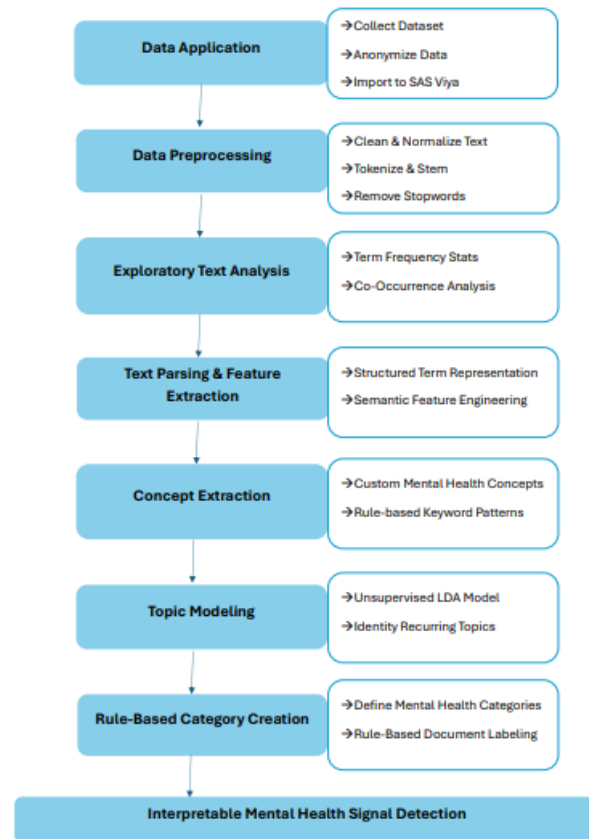
This study employed an interpretable text mining framework using SAS Viya Text Miner to identify mental health signals from social media posts. The methodology consisted of data acquisition, preprocessing, exploratory text analysis, text parsing, concept extraction, topic modeling, and rule-based category analysis. The overall framework was designed to prioritize transparency and explainability throughout the analytical process. (Figure 1)

#### *Data Acquisition*

The information utilized in this research was sourced from publicly accessible Kaggle datasets that include anonymous social media posts gathered from sites like Reddit and Twitter. The specific dataset used in this study was Kaggle data of Stress Detection from Social Media Articles (<https://www.kaggle.com/datasets/mexwell/stress-detection-from-social-media-articles>). These platforms are commonly used by people to convey feelings, personal challenges, and mental health experiences, rendering them appropriate sources for recognizing psychological and emotional indicators. Utilizing anonymized data that is publicly accessible reduces privacy issues while facilitating extensive analysis.

The dataset includes 7,731 social media entries, with each entry reflecting an individual user-generated text. The dataset contains three attributes:

- (1) `clean_text`, which includes the written material of every post following preprocessing;
- (2) `is_depression`, a numerical marker indicating content related to depression; and
- (3) `uniqueid`, which distinctly recognizes each record in the analytical process. The dataset was loaded into SAS Viya for further preprocessing and analysis.



**Figure 1. Methodological framework illustrating the end-to-end text mining process for mental health signal detection.**

## *Data Preprocessing*

Due to the unstructured and casual characteristics of social media text, significant preprocessing was necessary to enhance data quality and analytical dependability.

Initially, duplicate entries and posts lacking text or containing empty content were eliminated to decrease noise. All text was changed to lowercase to maintain uniformity and avoid treating the same word in varying cases as distinct terms. Punctuation, unique symbols, and unnecessary characters were removed.

Subsequently, tokenization was conducted to separate the text into distinct terms. Stopwords were eliminated to concentrate the analysis on semantically significant words. Stemming grouped similar word forms by their common root, enabling variations like depressed, depressing, and depression to be examined

collectively. Part-of-speech tagging was utilized to preserve linguistically important terms, including nouns, verbs, and adjectives, while removing less meaningful tokens.

Following preprocessing, the dataset was converted into a format ready for modeling, ideal for concept extraction, topic modeling, and category analysis. This uniform representation guaranteed uniformity throughout all following analytical stages.

| clean_text                                                                                                                                                                                                                                                                                                                                  | is_depression |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|
| I understand that most people who reply immediately to an op with an invitation to talk privately mean only to help but this type of response usually lead to either disappointment or disaster it usually work out quite differently here than when you say pm me anytime in a casual social context we have huge admiration               | 1             |
| welcome to depression s check in post a place to take a moment and share what is going on and how you are doing if you have an accomplishment you want to talk about these shouldn't be standalone post in the sub a they violate the role model rule but are welcome here or are having a tough time but prefer not to                     | 1             |
| anyone else instead of sleeping more when depressed stay up all night to avoid the next day from coming sooner may be the social anxiety in me but life is so much more peaceful when everyone else is asleep and not expecting thing of you                                                                                                | 1             |
| i ve kind of stuffed around a lot in my life delaying the inevitable of having to work a job and be a responsible adult and i m but the longest i ve ever held a job wa 9 month it was i that i m lazy i wa always doing other thing i enjoy but i know now unemployment ha caused most of my depression recently i just feel utterly       | 1             |
| sleep is my greatest and most comforting escape whenever i wake up these day the literal very first emotion i feel is just misery and reminding myself of all my problem i can t even have a single second to myself it s like waking up everyday is just welcoming yourself back to hell                                                   | 1             |
| i m year old turning soon in a few month i live in constant dread i have no passion no goal no special achievement in my life and never been in a relationship i don t know what i want nor what i m doing in this so called life everything just feel exhausting i cry myself to sleep everyday i also feel extremely disconnected fr      | 1             |
| i live alone and despite me being prone to loneliness i find myself to be emotionally needy i seem to have the urge to cut important people out of my life when i get depressed friend girlfriend i feel easily annoyed and judgmental even if they did nothing wrong i can t explain it maybe by posting here i can find some pe           | 1             |
| i m not looking for sympathy just simply to state why i m done trying to survive i m sitting here in the dark cry my eye out before my birthday knowing it s the last birthday i ll ever have i m tired of fighting for my life every single day sense i wa i ve been fighting i can t do it anymore i m exhausted this illness ha broken m | 1             |
| i don t know how to communicate all of my thought stay inside me instead of telling them to other people like i should my mind simply won t let me i try i really try sometimes and i have so many of them but they get lost my mind is a endless nightmare of thought of despair and hatred towards myself i feel numb and ov              | 1             |
| mom i m sad it hurt in my heart the feeling fall into my stomach i can t stop the fear when they start mom i m sad that i never did anything that i never achieved anything that everything just fell apart i can t get up in the morning i can t focus on anything but the sadness i can t put my clean clothes away i don t have the      | 1             |
| i ve been struggling with depression for a long time now but i just my first severe instance of depersonalization and it scared me so badly i m not even entirely sure why but something about the fact that i just spent over an hour lying on the floor feeling like my body didn t really belong to me and i might not be real is so i   | 1             |

**Figure 2. Cleaned dataset snapshot**

## Exploratory Text Analysis

Prior to utilizing advanced text mining methods, an exploratory text analysis was performed to obtain an initial insight into the dataset. Statistics on term frequency and patterns of term co-occurrence were analyzed to uncover commonly appearing emotional and psychological expressions.

This initial phase uncovered a significant occurrence of terms associated with anxiety, depression, sadness, stress, sleep, and emotional needs, suggesting that the dataset featured considerable mental health-related material. These insights guided the creation of tailored concepts and classifications applied in subsequent phases of analysis.

## Text Parsing and Feature Extraction

Text parsing serves as the basis of the analytical pipeline. Employing the Text Parsing node in SAS Viya, the text that was preprocessed was transformed into a structured representation of terms by documents. This stage allows for recognizing important terms and their connections throughout documents.

The analyzed text reflects both the occurrence and contextual application of emotionally meaningful words. For instance, terms associated with anxiety like anxiety, anxious, panic, and attack are continually recognized and connected, enhancing dependable downstream analysis.

## Concept Extraction

Concept extraction utilized customized rule-based concepts to detect particular signals related to mental health. Concepts were created to encapsulate important psychological conditions, such as anxiety, depression, stress, sadness, sleep issues, suicidal thoughts, and emotional requirements.

Every concept comprises clear linguistic rules that align appropriate terms and expressions within the text. For example, anxiety-related concepts encompass words like anxiety, panic, and attack, whereas sleep-related concepts involve terms such as sleep, hours, and cannot sleep. This method enables straightforward understanding of why a document is linked to a specific mental health indication.

## Topic Modeling

To reveal more extensive hidden themes in the dataset, unsupervised topic modeling was used through the Topics node in SAS Viya. Topic modeling organizes documents by analyzing patterns in word co-occurrence without using pre-established labels.

In this research, sixteen subjects were identified, representing persistent themes in mental health. These subjects encompass persistent emotional suffering, such as ongoing depression and anxiety, as well as sudden emotional emergencies, like panic attacks and intense anxiety. Topic modeling enhances concept extraction by offering an overarching thematic perspective on mental health trends throughout the dataset.

### ***Rule-Based Category Creation***

Besides concepts and topics, rule-based categories were generated to identify organized mental health trends. Fifteen categories were developed, emphasizing themes like time-related anxiety, cognitive processing in depression, sleep issues, uncertainty, sadness, and everyday emotional challenges.

Categories were created based on clear linguistic rules and assessed with diagnostic metrics from SAS Viya. These evaluations measure the uniformity and dependability of category alignments throughout documents. Category analysis allows for a more precise detection of mental health trends than relying solely on topic modeling.

### ***Summary of Methodology Approach***

In summary, the approach combines data collection, preprocessing, exploratory analysis, text analysis, concept identification, topic modeling, and rule-based categories into a cohesive and interpretable analytical framework. By integrating various transparent techniques, this method minimizes dependence on a single approach and facilitates ethical, understandable analysis appropriate for mental health research and decision-support purposes.

## **Results and Analysis**

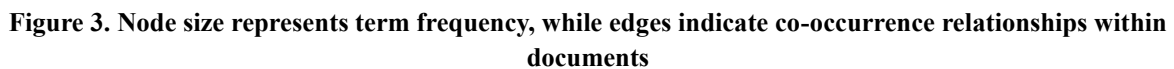
The findings show that indicators of mental health are distinctly present in social media language and can be accurately recognized through interpretable text analysis. Throughout all analytical approaches, depression and anxiety stand out as the primary mental health issues in the dataset.

### ***Text Parsing Analysis Results***

Text parsing outcomes offer understanding of the linguistic framework and contextual application of mental health-related terms in social media content. The analyzed text states that emotionally meaningful words usually generate dense networks of co-occurrence instead of existing alone.

In text related to anxiety, key terms like anxiety and anxious are closely linked to words such as panic, bad, think, and want, indicating ongoing concern and negative emotional assessment. In posts highlighting profound depression, commonly related words include life, mental, assistance, and hospital, suggesting that emotional turmoil is intricately linked to life activities and health-related issues.

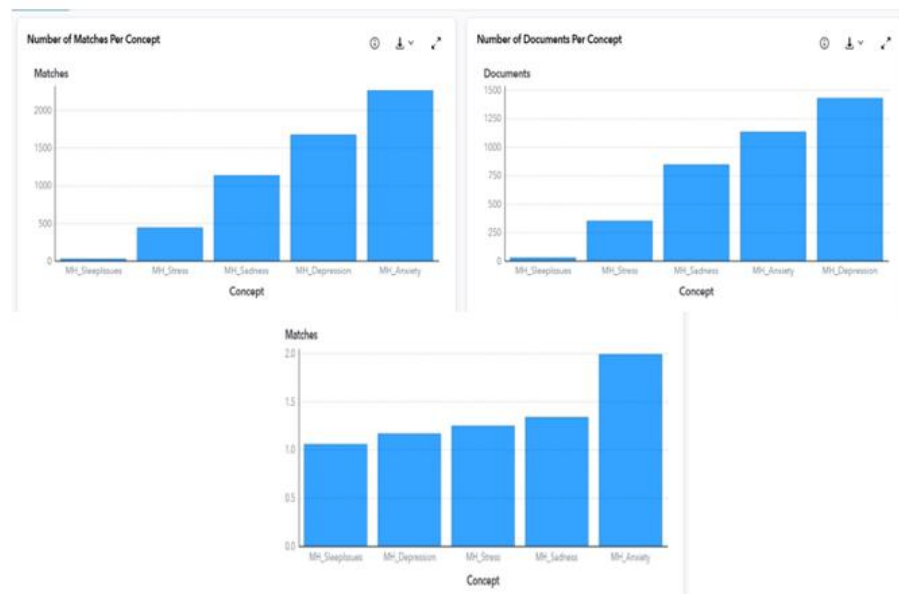
Results from sleep-related parsing emphasize significant links among sleep, night, time, and feelings, indicating inconsistent sleep patterns and ongoing rumination. Expressions indicating high risk for suicide are found within wider cognitive and social frameworks, linked to words like think, want, attempt, and people, reflecting ongoing internal processing instead of mere isolated references.



Concept analysis reveals that anxiety-related terms exhibit the highest average occurrences per document, suggesting that individual posts frequently and repeatedly express concern, panic, and fear. Concepts associated with depression are found in many documents, indicating prevalent emotional turmoil marked by hopelessness, sadness, and emotional fatigue.

### Table 1: Custom Concepts

200



**Figure 4. Mental health concept frequency and document coverage results**

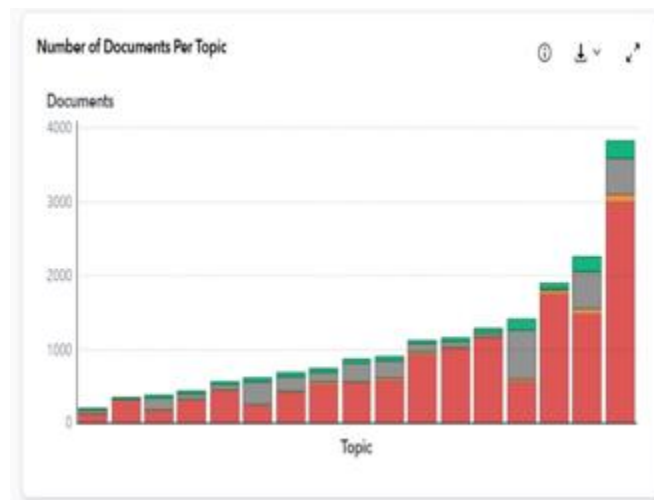
## Topics Modelling Analysis Results

Topic modeling identified sixteen distinct topics representing recurring mental health topics. The top-ranked topics by document count are dominated by chronic depression and anxiety, characterized by persistent negative emotional language and temporal expressions such as never and always.

Other high-frequency topics capture acute anxiety and panic-related distress, as well as uncertainty and life struggles, reflecting varying levels of emotional severity. Smaller topics represent more situational emotional expressions, such as short-term sadness or stress. Overall, the distribution of documents across topics indicates that mental health distress expressed on social media is predominantly chronic rather than situational.

**Table 2: Top topic modeling results showing interpreted topic themes and corresponding document counts**

| Topics                                                         | Number of documents |
|----------------------------------------------------------------|---------------------|
| depression, anxiety, never, low (Chronic Distress)             | 3825                |
| anxiety, panic, attack, anxious, bad (Anxiety & Panic Attacks) | 1897                |
| don't, want, know, just, life (Uncertainty & Life Struggle)    | 754                 |
| sad, wa, oh, sorry, now (Sadness & Emotional Expression)       | 349                 |

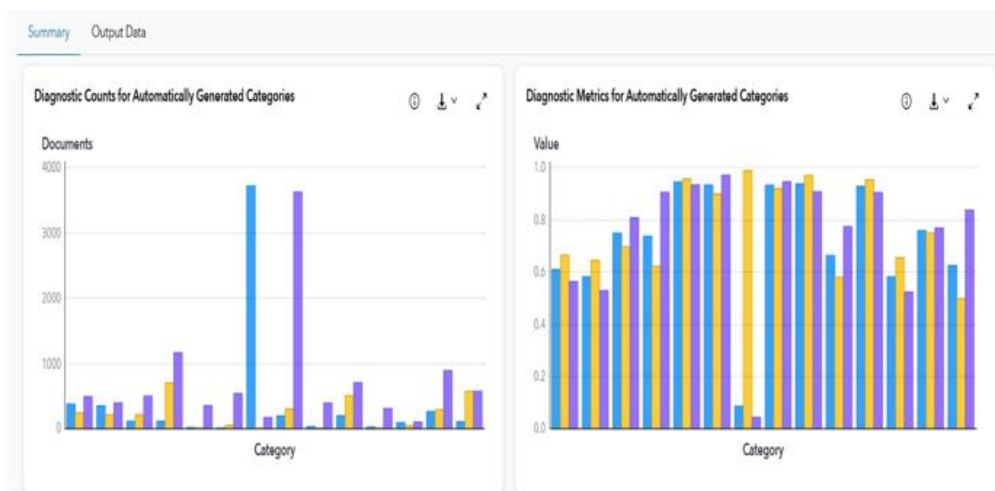


**Figure 5. Distribution of documents across identified topics generated by the topic modeling process**

## *Category Analysis Results*

Category analysis based on rules led to the identification of fifteen understandable categories. Categories associated with anxiety over time and depression through cognitive processing correlated with various documents, signifying ongoing emotional challenges. The sleep-related section emphasizes insomnia and disrupted sleep patterns, strongly associated with anxiety and fatigue.

Categories with fewer match counts reflect more situational distress, like everyday stressors or brief emotional responses. In general, diagnostic metrics suggest that the categories are stable and dependable, validating the efficacy of clear rule-based classification.



**Figure 6. Rule-based category analysis results showing document counts and diagnostic metrics for automatically generated mental health categories**

## Discussion

The findings indicate that social media language contains strong and consistent signals associated with mental health conditions, particularly depression and anxiety. These conditions repeatedly emerged across concepts, topics, and rule-based categories, suggesting that many users experience ongoing emotional distress rather than short-term mood fluctuations.

Anxiety-related language was especially prevalent throughout the dataset. Many posts reflected persistent worry, panic, fear, and repetitive negative thinking. Depression-related expressions frequently conveyed hopelessness, emotional exhaustion, and cognitive rumination, indicating deeper psychological struggles.

Secondary indicators such as sleep disturbances and unmet emotional needs also emerged as meaningful patterns. Discussions related to sleep problems were closely associated with anxiety and fatigue, reinforcing existing evidence regarding the relationship between sleep disruption and mental health conditions. Expressions involving emotional needs often reflected desires for support, understanding, or connection rather than direct requests for professional help.

One of the primary strengths of this study is the use of interpretable text analytics. Unlike black-box machine learning approaches, the proposed framework provides clear explanations regarding how mental health signals are identified through transparent concepts, topics, and linguistic rules. This level of explainability is particularly important in healthcare and mental health applications where ethical responsibility, trust, and accountability are critical.

The study also demonstrates the practical value of SAS Viya Text Miner for large-scale mental health monitoring. By combining concept extraction, topic modeling, and rule-based categorization, the framework enables scalable analysis while preserving interpretability. Such approaches may support healthcare systems and researchers in identifying emerging mental health trends and prioritizing high-risk content when combined with ethical safeguards and professional oversight.

## Conclusion

This study demonstrates that mental health signals such as depression, anxiety, emotional distress, and sleep disturbances are clearly reflected in social media language. Using SAS Viya Text Miner, large volumes of unstructured social media posts were analyzed through interpretable analytical techniques including text parsing, concept extraction, topic modeling, and rule-based categorization.

Across all analytical approaches, depression and anxiety emerged as the most dominant and persistent mental health conditions represented within the dataset. The findings suggest that many individuals use social media platforms to express ongoing emotional struggles and psychological distress.

A major contribution of this research is the emphasis on interpretability. Unlike opaque machine learning systems, the proposed framework enables transparent understanding of how mental health indicators are identified through explicit linguistic rules and thematic patterns. This transparency is essential in sensitive healthcare-related applications where explainability and ethical accountability are necessary.

Although the proposed system is not intended to diagnose individuals, it demonstrates the potential of interpretable text analytics for supporting mental health research, large-scale monitoring, and early identification of high-risk content. Future research may integrate multimodal data sources, real-time monitoring systems, and hybrid machine learning techniques while maintaining transparency and ethical safeguards.

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