AI Assisted Diagnosis of Mental Health Conditions

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Abstract:

Mental health disorders among adolescents are increasingly prevalent, highlighting the need for accurate diagnoses and effective treatments. This study utilized a neural network to analyze symptom overlap in patients with single versus comorbid mental health diagnoses, aiming to improve diagnostic accuracy. It was conducted using Kaggle's Mental Illness Dataset, which includes demographic data, symptoms, and diagnoses from 3,753 patients. The neural network's performance was evaluated, revealing a difference in effectiveness between the original dataset and the single diagnosis subset. Results indicated that the model performed better with the original dataset, which presented distinct patterns of symptom presentation, facilitating more accurate predictions.This distinction emphasizes the importance of considering the complexity of mental health conditions, as symptoms can vary significantly between patients with single and comorbid diagnoses. However, limitations of subsetting patients include oversimplification of symptoms and reduced sample sizes. Future research should focus on larger datasets and changing factors like symptom severity to deeper understand and improve treatment approaches in mental health care.

Introduction:

Mental health disorders in adolescents are extremely prevalent today. Found in the results of a study from the WHO World Mental Health International College Student project, the top six most common disorders amongst a college population were: major depression, mania/hypomania, generalized anxiety disorder, panic disorder, alcohol use disorder, and substance use disorder (Auerbach et al.). These results were found to have a moderate correlation to numerous variables: older age, female sex, and unmarried-deceased parents (Auerbach et al.). The findings of this study indicated a higher need for mental health services at several colleges (Auerbach et al.).

The authors claim that psychiatric diagnosis can be an unreliable practice and different measures should be taken (Aboraya et al.). They believe that the diagnosis of these patients should not solely rely on clinician validity, as there are numerous factors that could lead them to the wrong diagnosis (Aboraya et al.). This could be a result of the psychiatrists interviewing skills, or simply the validity of the patient’s words (Aboraya et al.). To improve this issue, the authors have proposed an acronym: DR.SED - diagnostic criteria, reference definitions, structuring the interview, clinical experience, and data (Aboraya et al.). To address the unreliability of psychiatric diagnoses, AI models have been developed to improve accuracy by identifying patterns in patient data that clinicians might overlook**,** enhancing both diagnosis and treatment recommendations (Timmons et al.). However, researchers warn that without safeguard to reduce bias, these models could continue social inequities, especially if trained on biased data (Timmons et al.). In my project, I used a neural network to analyze symptom overlap between different mental health diagnoses, aiming to improve diagnostic accuracy. By comparing model performance on single and comorbid datasets, I'm investigating how diagnosis complexity impacts prediction accuracy.

Method:

Dataset:

The dataset used for this analysis can be found from the following address: https://www.kaggle.com/datasets/karanbakshi1/mental-illness-dataset This dataset contains patient information, including demographic data, symptoms, and mental illness diagnoses. The key variables include symptoms (like anxiety, mood changes, or suicidal ideation), diagnoses (such as depression, schizophrenia, or bipolar disorder), and comorbid conditions (e.g., substance abuse). The dataset is designed to facilitate understanding of patterns and relationships between various mental health diagnoses and associated symptoms. There were 3753 patients and 53 symptoms that were recorded in the original dataset.

Identification of top symptoms in single-diagnosis patients:

To prepare the data for analysis, I first filtered the original dataset ('data_original') to create a subset, 'single_diagnosis', which contains patients with only one mental health diagnosis. There were then 394 patients that were found to have a single diagnosis. The remaining patients, with multiple diagnoses or comorbidities, were kept in the original dataset. This filtering allowed for a clearer comparison between patients with a single diagnosis and those with comorbid conditions. Additionally, relevant variables like symptoms were analyzed across these two groups to facilitate the Venn diagram analysis, which compared symptom overlap. The function generates a bar graph to visualize the top 10 symptoms correlated with a specific mental health diagnosis using phi_k. Phi_k is ideal for categorical data: relationships between symptoms and diagnoses. First, the dataset is filtered to include only patients with a single diagnosis, converting symptom columns to boolean values. The phi_k correlation matrix is then calculated. The top 10 symptoms are identified, ranked, and plotted in reverse, with correlation values displayed on a bar plot. The top variables became the most frequently occurring symptoms in each group, and were used to construct the Venn diagrams.

Neural Network:

The neural network starts with an input layer that takes in all the features from the dataset, like symptoms and diagnoses. Then, it has three hidden layers: the first has 128 neurons, the second has 64 neurons, and the third has 32 neurons. These hidden layers help the model find patterns in the data. To make sure it learns the features/patterns, I used the ReLU activation function, which decides when the neurons should pass information forward. At the end, the output layer uses a softmax activation function, which helps the model predict which diagnosis is most likely by turning the results into probabilities.

To assess the performance of the neural network, I used several metrics to check how well the model predicts diagnoses. The metrics include: accuracy, which measures the overall percentage of correct predictions; precision, the ratio of true positive predictions to total predicted positives; hamming loss, the fraction of incorrect labels to total number of labels; jaccard similarity score, gauges the similarity between two sets by comparing their intersection to their union; and exact match ratio, which requires all labels for a sample to be predicted correctly.

Results:

Neural network:

The performance of the neural network was evaluated on both the original dataset and single diagnosis dataset. For the single diagnosis dataset, the model had a mean Hamming loss of 0.034388, a Jaccard similarity score of 0.904641, and an exact match ratio of 0.896624. In contrast, the original dataset had a mean Hamming loss of 0.018047, a Jaccard similarity score of 0.967325, and an exact match ratio of 0.913360.

Hamming Loss: Mean = 0.034388 (95% CI: [0.032909, 0.035868])
Jaccard Similarity Score: Mean = 0.904641 (95% CI: [0.90, 0.909283])
Exact Match Ratio: Mean = 0.896624 (95% CI: [0.892135, 0.901114])

Anxiety:

The Venn diagram comparing the symptoms of patients with a single diagnosis of anxiety versus those with anxiety as part of multiple comorbidities shows overlap (Figure 4). Core symptoms shared by both groups include 6 month duration and sleep disturbance. These symptoms are universally recognized in anxiety disorders, regardless of comorbidity. However, symptoms like irritability and fatigue are more prevalent in patients with multiple comorbid conditions, suggesting that comorbidities may exacerbate or introduce additional symptoms not as commonly seen in isolated anxiety cases.

Depression:

For depression, the analysis highlights the overlap of key symptoms such as persistent sadness, loss of interest or pleasure, and fatigue across both patient groups (Figure 3). While these symptoms are common in all forms of depression, the comorbidity group shows a higher incidence of intrusive memories and suicidal ideation, indicating that patients with multiple mental health issues may experience more severe or diverse depressive symptoms. This may suggest that comorbid conditions intensify the manifestation of depressive symptoms.

Bipolar Disorder:

The Venn diagram for bipolar disorder shows much overlap similar to depression. Shared symptoms like racing thoughts and inflated self-esteem are found in both the single diagnosis and comorbid groups (Figure 1). However, symptoms such as restlessness and recklessness are more common in the comorbidity group, indicating that these patients might have heightened manic episodes when other disorders are present. This suggests that comorbid conditions may influence the intensity or presentation of mania in bipolar disorder patients.

Schizophrenia:

In patients diagnosed with schizophrenia, the analysis highlights core shared symptoms like hallucinations, delusions, and disorganized thinking (Figure 2). These are characteristics of schizophrenia regardless of the presence of comorbid conditions. However, patients with multiple diagnoses exhibited more symptoms of catatonic behavior and diminished emotional expression. This suggests that additional mental health issues could compound the cognitive and emotional challenges faced by individuals with schizophrenia.

Discussion:

Top Features in Single vs. Comorbid datasets:

Catatonia was found to be an enriched symptom in patients with comorbidity status (Figure 2). According to the National Center for Biotechnology Information (NCBI), treatment of catatonia can occur through several distinct interventions (England et al.). These include: benzodiazepines and electroconvulsive therapy (ECT) (England et al.). Benzodiazepines are a type of medication that enhances the effect of a neurotransmitter called GABA, which calms the nervous system and can help alleviate symptoms of catatonia (England et al.). ECT, on the other hand, involves applying controlled electrical currents to the brain to trigger a brief seizure, which can reset abnormal brain activity associated with catatonia (England et al.).

Hallucinations were found to be an enriched symptom in patients with a single diagnosis of anxiety (Figure 4). According to the National Center for Biotechnology Information (NCBI), hallucinations can occur in anxiety disorders, particularly when anxiety is severe or linked to trauma (Chaudhury). Treatment options for hallucinations associated with anxiety include antipsychotic medications and cognitive behavioral therapy (CBT) (Chaudhury). Antipsychotics work by altering dopamine levels in the brain, which helps reduce or eliminate hallucinations (Chaudhury). CBT helps patients address the underlying anxiety that may trigger hallucinations, teaching them strategies to manage stress and anxiety effectively, which in turn can lessen or prevent hallucinatory experiences (Chaudhury).

One of the unique findings of the current approach, subsetting patients based on diagnosis, is that it reveals significant differences in symptom presentation between patients with a single diagnosis and those with comorbidities. For example, I found that hallucinations were more common in single-diagnosis anxiety patients, while symptoms like catatonia were enriched in those with comorbid conditions. This distinction is important because it shows that comorbidity status can significantly impact symptom patterns. With this insight, treatments can be tailored more effectively to address the specific needs of each group. Patients with comorbidities might need more complex treatment plans that address a broader range of symptoms, while those with a single diagnosis can be treated with a more focused approach. This ability to identify unique symptom sets based on comorbidity status can improve treatment outcomes by allowing healthcare providers to apply targeted, individualized interventions.

Neural Network performance: Single vs. Comorbid datasets:

The results indicate that the model performed significantly better with the original dataset compared to the single diagnosis dataset. The original dataset revealed distinct patterns in symptom presentation and relationships between different mental health conditions, which contributed to accuracy and predictability in diagnosis. For example, the model identified overlapping symptoms common to multiple diagnoses, such as anxiety or fatigue, allowing it to recognize shared characteristics and associations. This increased the model's ability to differentiate between conditions, especially in patients with comorbidities. In contrast, the single diagnosis dataset presented challenges that limited the model's effectiveness. It often highlighted generalized symptoms that could be applied to multiple disorders, making it difficult to draw specific conclusions about individual conditions. The lack of variety in symptom patterns in the single diagnosis group led to less accurate predictions, revealing the complexity of diagnosing mental health disorders when only a single diagnosis is considered.

Limits of subsetting patients:

One limitation of subsetting patients based on diagnosis is that it may oversimplify the complexity of mental health conditions. By dividing patients into single diagnosis or comorbidity groups, important variations within each group can be overlooked. Subsetting also reduces the sample size for each group, which may limit the reliability and generalizability of the results. Additionally, the overlap of symptoms in patients with comorbidities can make it difficult to clearly differentiate between conditions, leading to potential errors in classification. This method may also ignore factors like environment or access to care, which can impact symptoms and treatment response. Another limitation is that symptoms might change over time, meaning the initial groupings may not reflect the patient's condition later on. Overall, subsetting gives useful insights but does not fully capture the complexity of mental health disorders. More research is needed to find better ways to account for the complexity of mental health conditions. I would recommend using larger datasets or considering factors that change over time (Ex/ severity of symptoms).

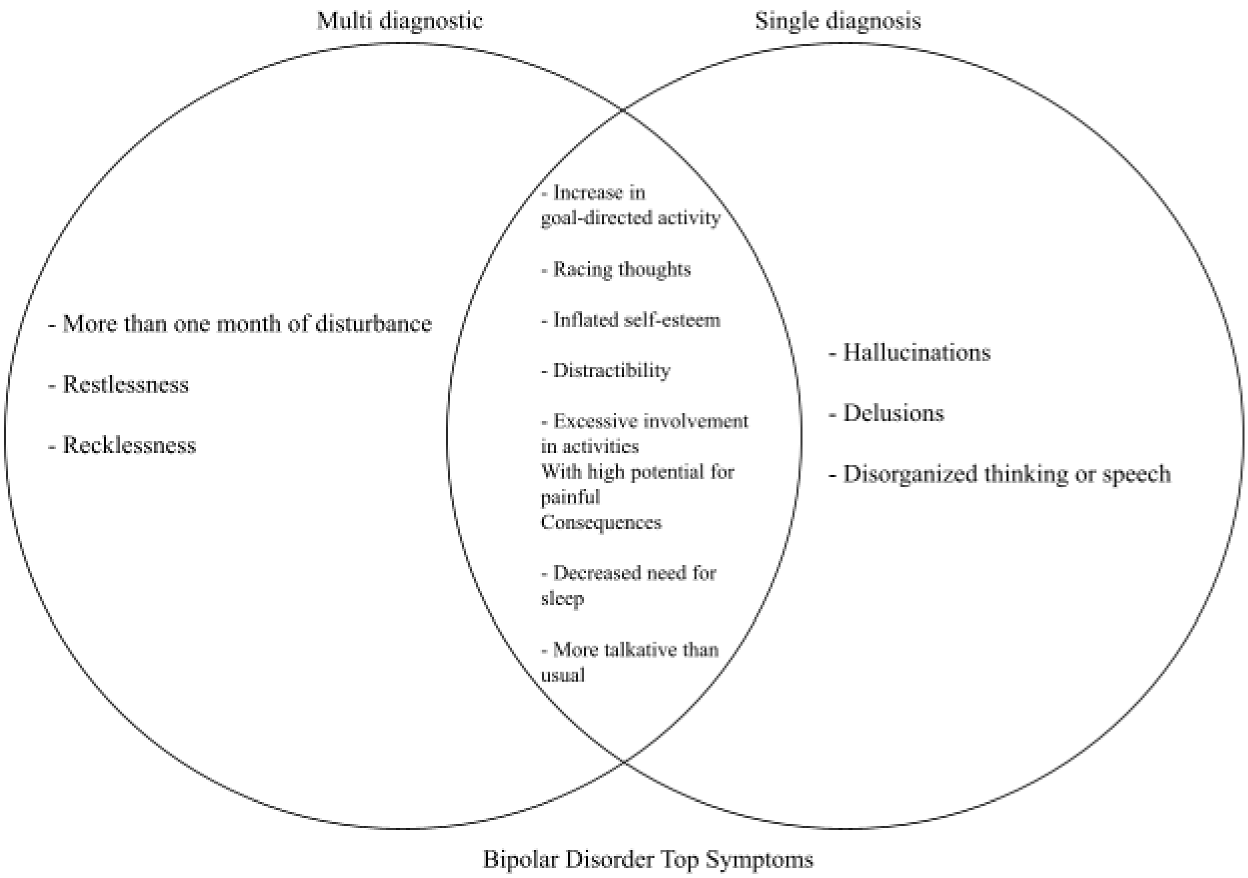

Figure 1: This Venn diagram shows the overlap in symptoms between patients with a single diagnosis of Bipolar Disorder and those with multiple comorbidities. The diagram highlights the shared symptoms as well as those that are unique to each group.

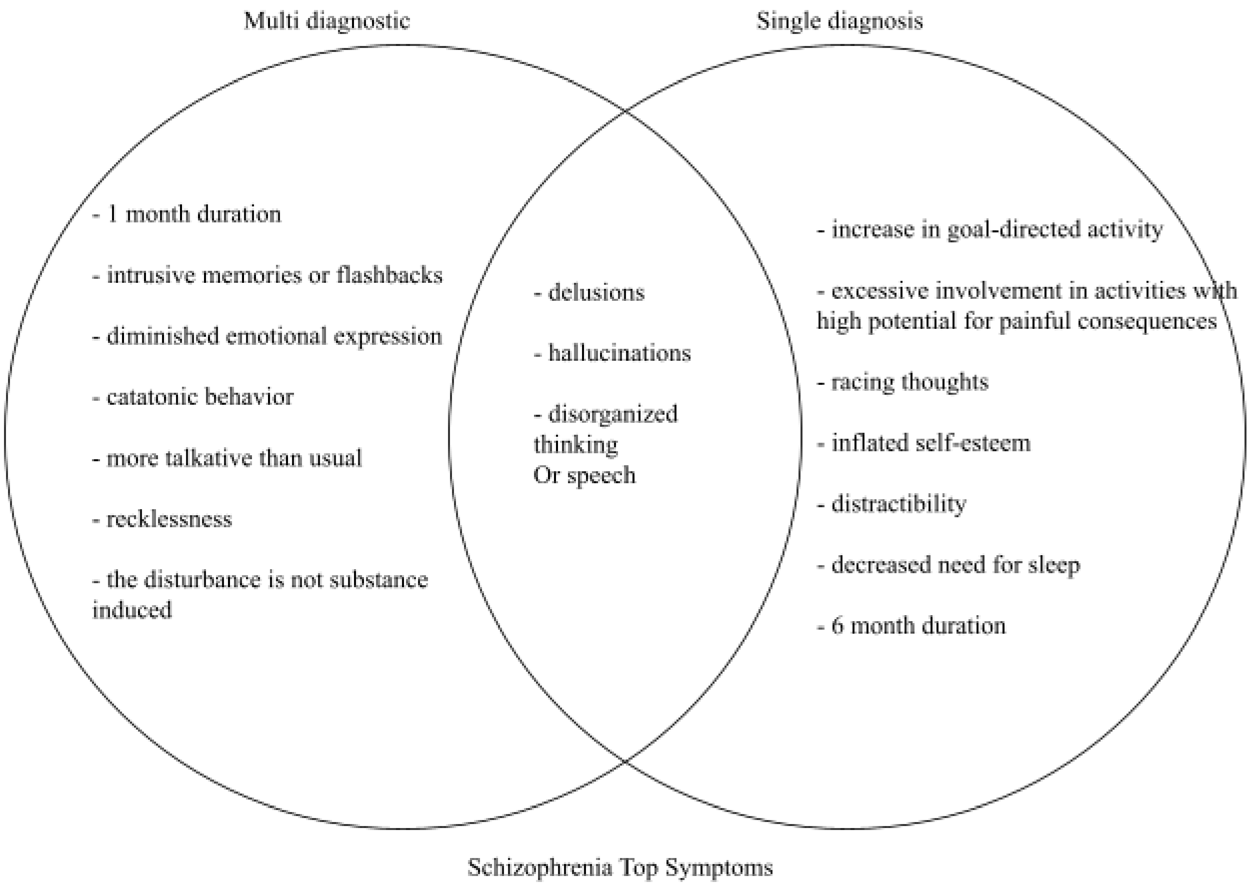

Figure 2: This Venn diagram shows the overlap in symptoms between patients with a single diagnosis of Schizophrenia and those with multiple comorbidities. The diagram highlights the shared symptoms as well as those that are unique to each group.

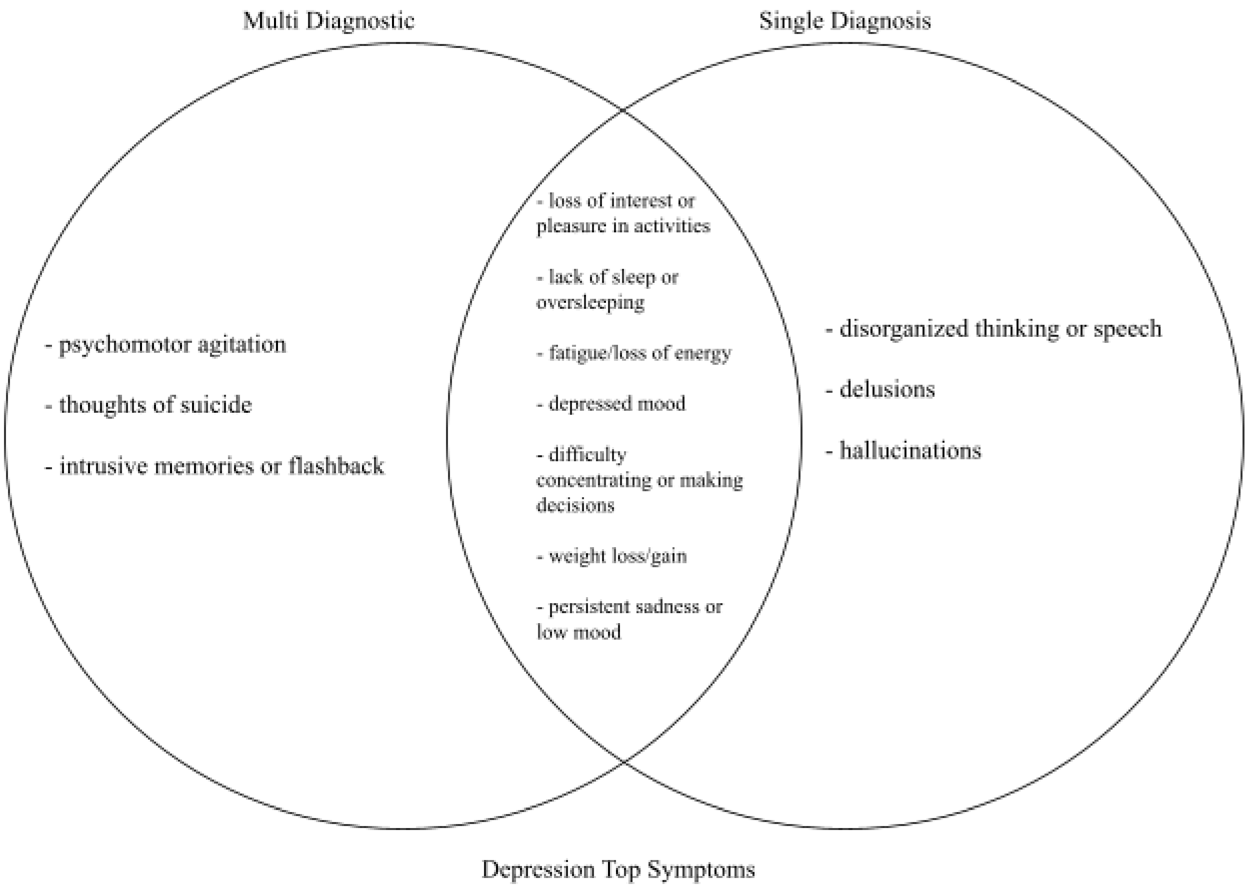

Figure 3: This Venn diagram shows the overlap in symptoms between patients with a single diagnosis of Depression and those with multiple comorbidities. The diagram highlights the shared symptoms as well as those that are unique to each group.

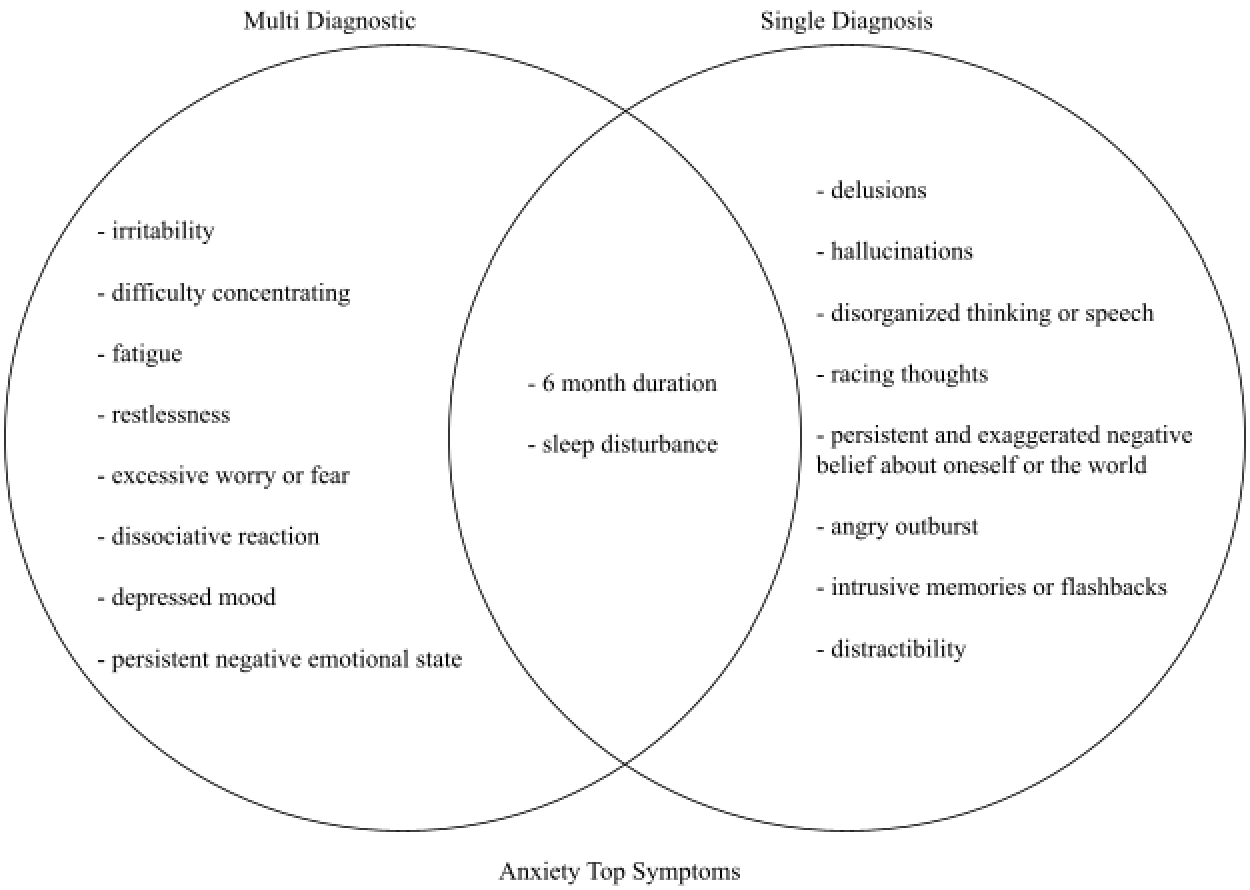

Figure 4: This Venn diagram shows the overlap in symptoms between patients with a single diagnosis of Anxiety and those with multiple comorbidities. The diagram highlights the shared symptoms as well as those that are unique to each group.

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