**Final Project: Assessing Features that Determine Mental Health Treatment**

*Background*

Mental health is an important topic that can be greatly impacted in corporate, high-pressure fields like tech, but is often overlooked or stigmatized. The pace, responsibilities, and stress that people face in the tech industry can take a toll on mental health. However, even when resources are available, people often don’t seek support.

Our group found a Kaggle dataset of a survey on mental health in tech. It includes 27 features related to attitudes towards mental health, access to resources, and the frequency of reported mental health conditions among respondents.

Previous research has applied machine learning models to find behavioral patterns in domains like academia, health, finance, and more. For example, k-means clustering and decision tree models were used to classify students and identify factors that influence academic performance. The results of the models were used to design academic improvement programs (Shovon & Haque, 2012). Similar methods have been used on health datasets to predict diabetes outcomes and group patients by symptom patterns and risk levels (Chen, Zhang, & Wu, 2017). Other forms of machine learning like K-nearest neighbors, random forest, and long short-term memory models have also been used on mental health datasets to predict mental health disorders (Hasan, Theyazn, Aldhyani & Alqarni, 2024). These studies show how machine learning techniques can be used to identify factors linked to mental health outcomes.

*Problem Statement*

The main objective of our project is to classify and predict whether a person sought mental health treatment by building a decision tree model and comparing its results to k-means clusters. The target feature from the dataset is “treatment,” and the models were applied to both the full dataset and a version with selected features.

By training the models on survey data and evaluating their performance, we aim to understand which features are most closely associated with seeking mental health treatment. These insights could support future efforts to improve access to and attitudes towards mental health resources in the tech industry and beyond.

*Proposed Techniques*

**Decision Tree**

This study first used the supervised learning technique, decision tree, to classify the features and understand their significance in choosing treatment or not. This model creates a graphical representation of a hierarchical tree structure where nodes represent features and branches split the data into subsets based on the attribute of the node (GeeksforGeeks, 2025). The model was trained on oversampled, hot-encoded data. The GridSearchCV method was used to evaluate the best parameters through cross-validation. These parameters were selected based on how they affected the tree’s accuracy score, or in other words, overall effectiveness. When applied to the dataset with the intuitively selected features this did not affect the accuracy score. However, when applied to the dataset with all the features, it decreased the score. This is likely due to overfitting. The non-tuned tree was chosen for the full dataset instead.

**K-Means Clustering**

This decision tree model was compared against an unsupervised technique called k-means clustering. This works by grouping the data points into distinct k clusters based on feature similarity (GeeksforGeeks, 2025). This model was trained on hot-encoded, stratified data that retained any missing values as ‘Unknown’. A function was used to determine what size cluster would have the best results for several different metrics including inertia, a measurement of how internally coherent the clusters are, silhouette score, how well each point fits in a cluster, and the dunn index, a measure of the cluster’s compactness and separation (Sankalana, 2023).

When the number of k clusters was plotted against their respective score for each metric, it revealed that the best k in terms of silhouette score was 3 for the intuitively selected features and 2 for the data that included all the features.

*Experimental Data and Results*

The decision tree model performed well overall on both sets of data with the intuitively selected dataset scoring 0.8 in accuracy. The dataset including all features performed best with scores of 0.897 in accuracy, 0.9 for precision, recall, and f1-score in predicting no treatment and 0.89 in predicting there is treatment.

The intuitively selected data’s decision tree revealed age as a strong predictor, with younger employees being more likely to seek treatment. Several nodes also referenced workplace resources for mental health help. When resources were available, employees were more likely to get treatment. In the case where resources were not available, a strong secondary predictor was remote work with those who are not remote being more likely to not get treatment. Similarly, when respondents were unsure if resources were available, the next strong predictor was self-employment, with those who were self-employed being more likely to get treatment. If mental health benefits were not provided at all by the employer, this was a strong predictor that employees would not get treatment.

The full dataset supported the intuitively selected dataset’s findings on age as well as gender with women and younger employees being more likely to seek treatment. The largest and strongest predictor was whether a respondent’s mental health issues interfered with their work, with those not experiencing interference choosing not to get treatment. This tree also included several nodes relating to other’s perception and attitude about mental health in the workplace. For example, whether an employer treats mental health as seriously as physical health or if a respondent felt comfortable sharing about mental health issues with coworkers. Positive and tolerant attitudes were a strong predictor that the employee would get treatment. An unusual finding was the significant predictor of getting treatment if someone worked in Ohio. This node appeared twice in the tree.

The k-means clustering performed very poorly overall with the full dataset having a silhouette score of 0.043 and the intuitively selected dataset performing marginally better at 0.14. Treatment predictions did not form clear and separated clusters.

*Conclusions and Analysis for Results*

The decision tree was a clear winner in comparison to the k-means clustering. It showed main splits along workplace support and resources as well as attitude and tolerance towards mental health issues. Other findings in the tree suggest that tolerance and attitude may play an even bigger role with those working in more isolated environments being more likely to seek treatment.

Expected generational and gender divides as reported by the CDC were also observed giving more legitimacy to other findings (Terlizzi & Norris, 2020). This makes the unusual finding about working in Ohio even more interesting. This needs further study to understand why this prediction occurred and if this would hold true for a larger dataset.

Some nodes contained noisy data with answers like ‘Don’t Know’ or ‘Maybe’. This study could be improved by excluding noisier features so that the decision tree could form a more certain path.

The k-means clustering likely did not perform well because the model is not suited for categorical variables. Because it uses Euclidean distance it assumes that features are numeric and that this distance is meaningful. However, that is not the case with categorical variables that have no inherent order or distance. It would be more beneficial to use a clustering method like k-modes to have more interpretable and meaningful results (Masego 2025).

**References**

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