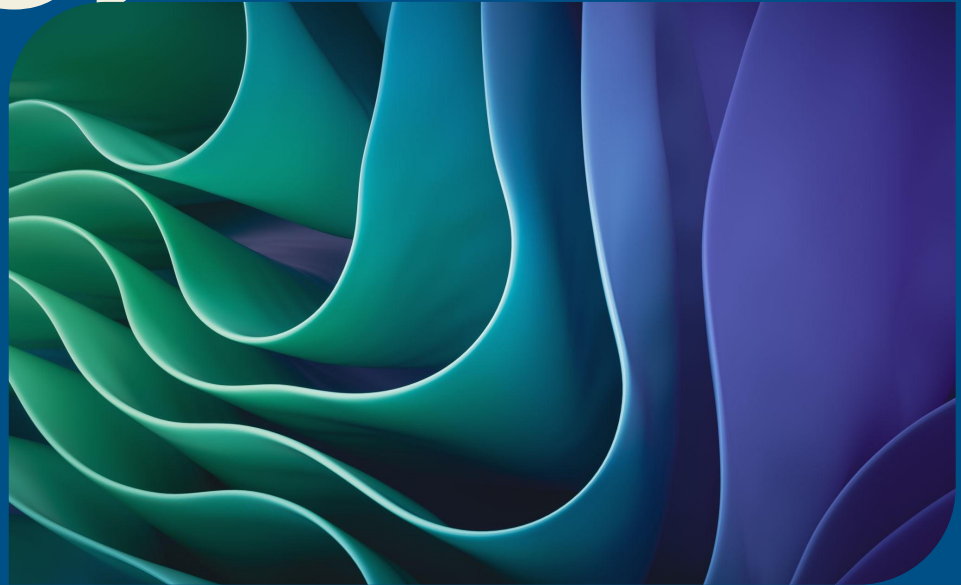


Mental Health In Technology

By Abeezer Babuji



What are the strongest predictors of poor mental health?

- Age
- Gender
- Regions
- Working Conditions
- Mental health and physical health

Background/ Importance

- Mental Health has been a big topic, and affects everyone
- Important to Developers and engineers at risk and companies aiming to support their employees,
- According to Forbes, 23% of remote workers struggle with loneliness

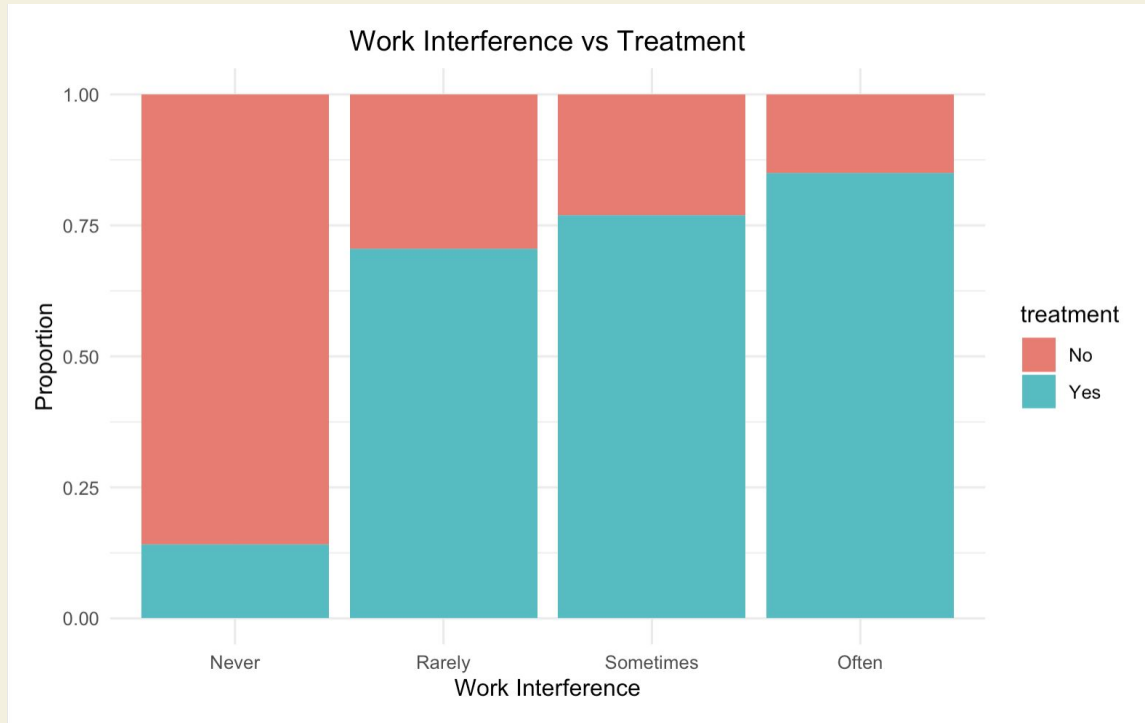


Data Cleaning and Preprocessing

- Datasource from Kaggle (Mental Health Survey in tech workplace from 2014)
- Total of 1259 values and 27 variables
- Removed unnecessary columns, such as Timestamp, state, and comments
- Standardized Country and Gender values to stay consistent
- Fixed age column (people aged from 1 and over 100)
- Removed or cleaned NA values
- Factored categorical values for model use

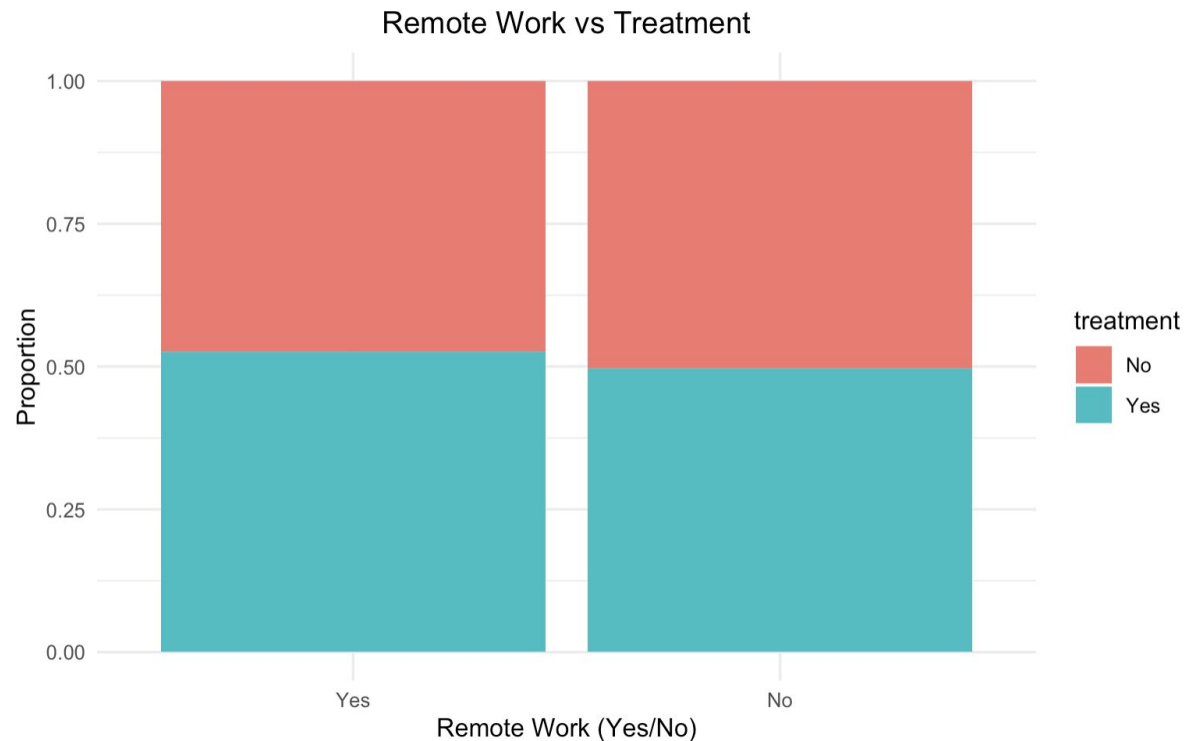


Data Visualization



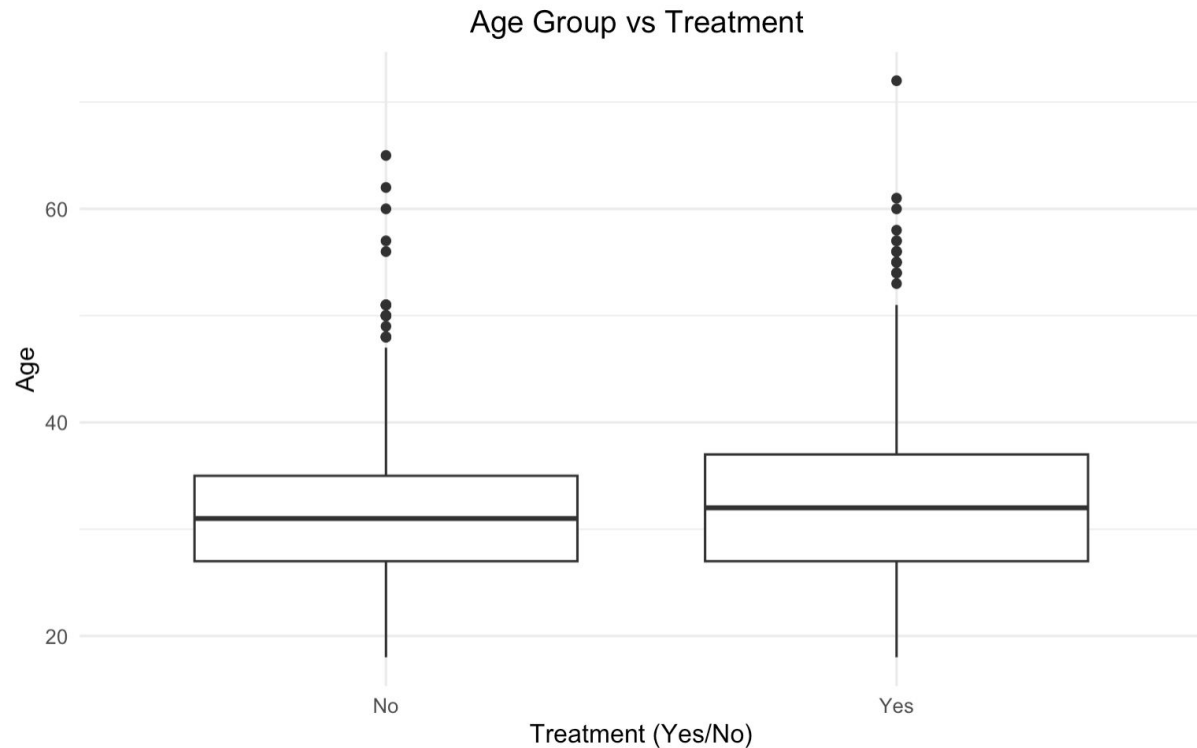
- As work interference rises from Never to Often, the share of employees who seek treatment climbs sharply from around 13 percent to above 75%
- The “Sometimes” and “Often” groups together account for over half of all treatment-seekers, highlighting workload strain as a key driver.

Data Visualization



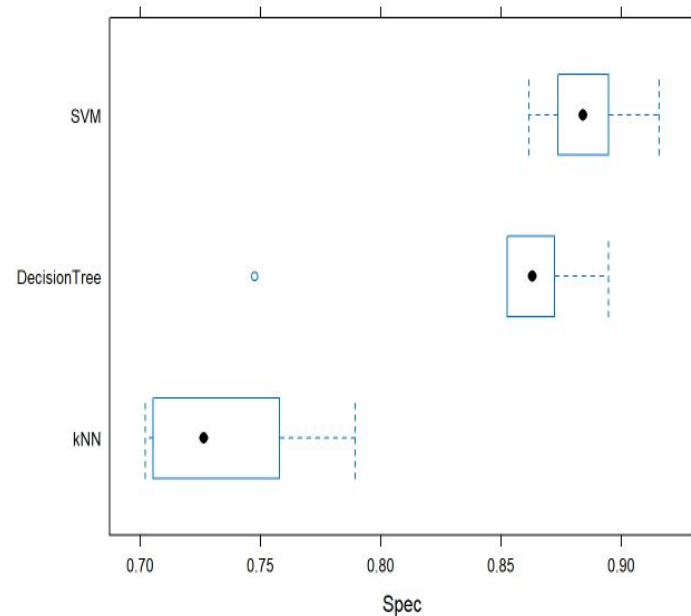
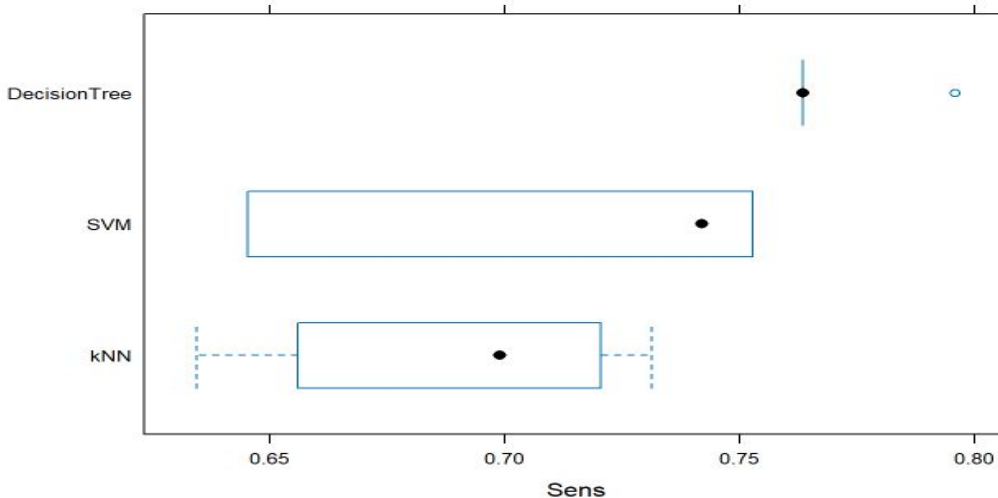
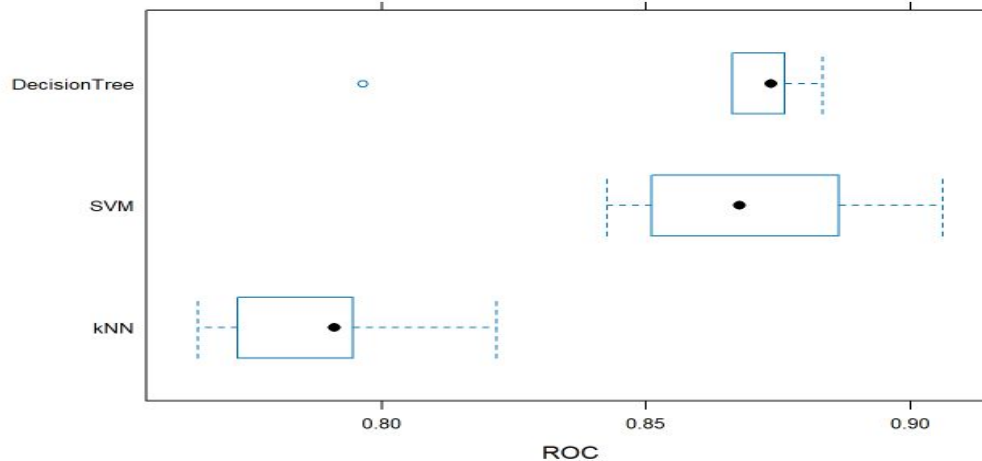
- Remote and Onsite staff show nearly identical rates showing location by itself isn't the decisive factor always.
- This also indicates that support should reach both groups of people instead of just remote workers to achieve better results.

Data Visualization



- Median age of those who seek treatment is a few years higher than non-seekers (mid 30s vs early 30s)
- Age spread is on the wider side but most outliers cluster in the above 60 group amongst those that are actively seeking treatment
- Younger employees are underutilizing treatment/services, so any awareness campaigns can be more effective if younger people are especially targeted.

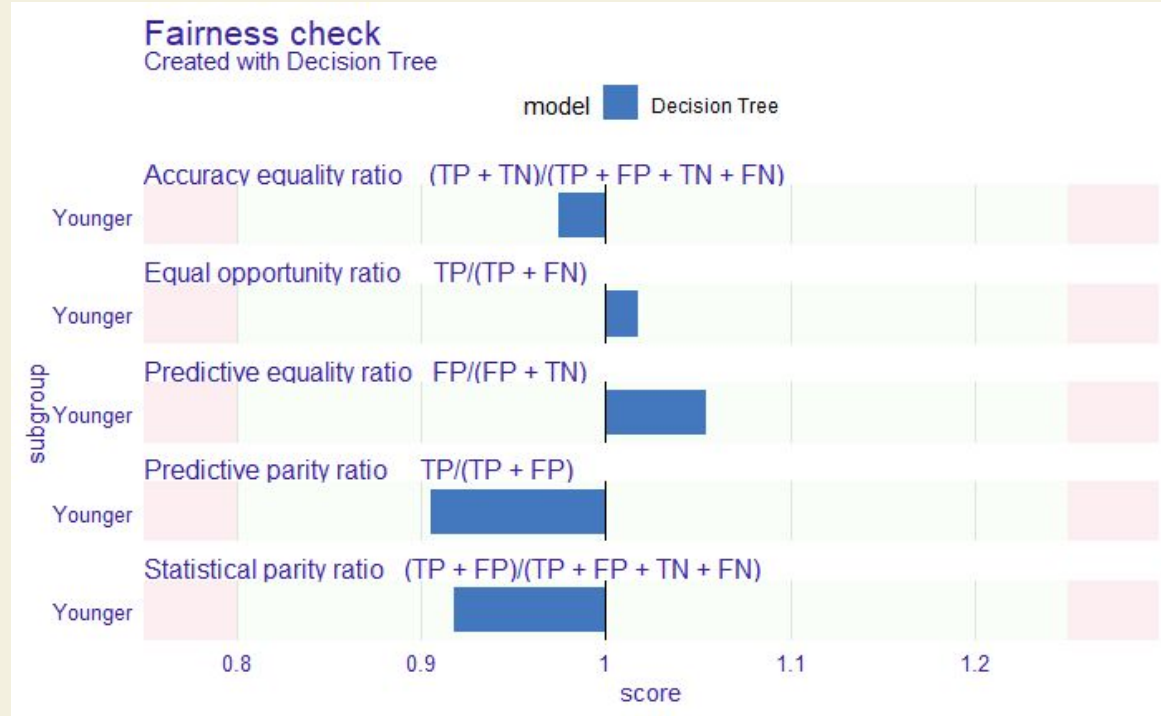
Cross Validation Model Performance



Fairness and Bias Evaluation

Decision Tree:

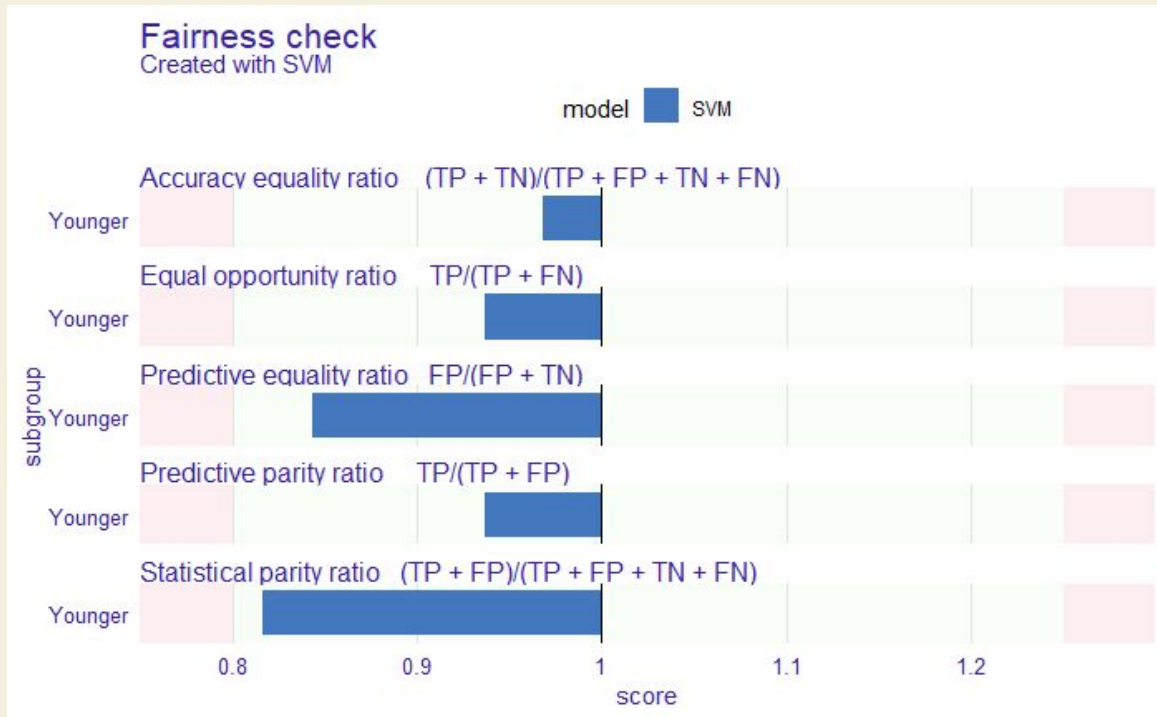
- Total Loss Score: 0.27 (rounded)
- Scored the best out of the three Models
- Passed 5/5 Fairness Metrics
- Most favorable model for Clinical use



Fairness and Bias Evaluation

SVM:

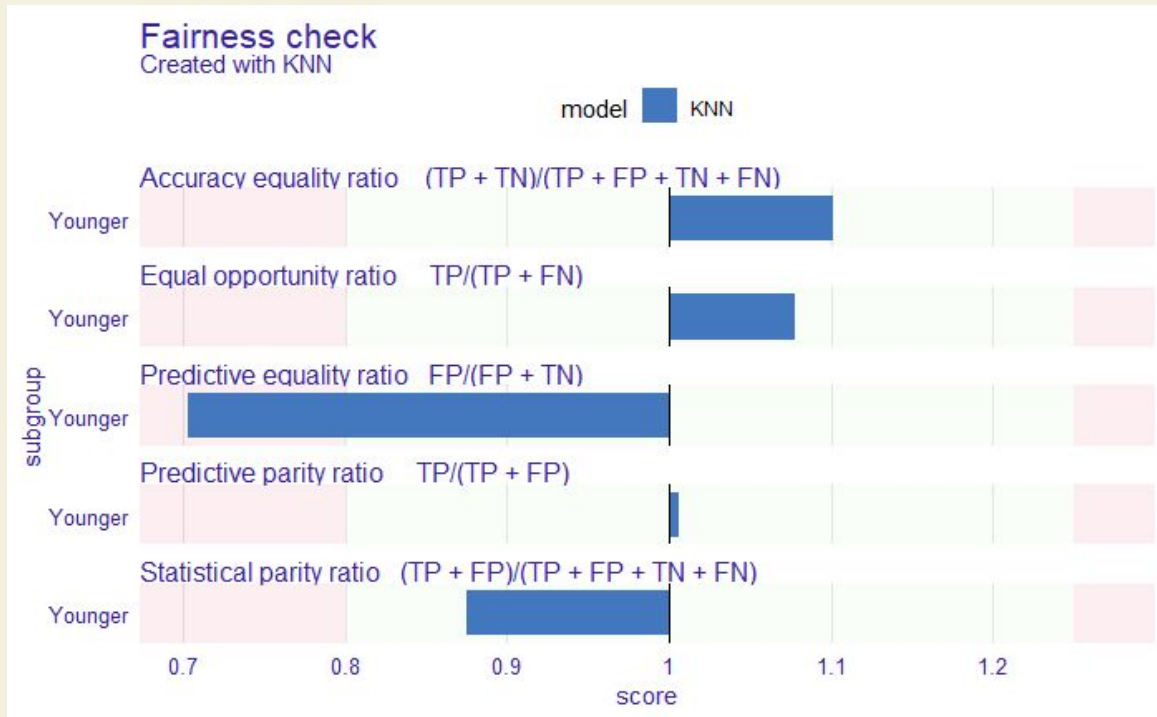
- Total Loss Score: 0.50 (rounded)
- Passed 5/5 Fairness Metrics, but very close to not passing



Fairness and Bias Evaluation

KNN:

- Total Loss Score: 0.61 (rounded)
- Passed 4/5 Fairness Metrics
- Least favorable model for Clinical use



Bias Mitigation

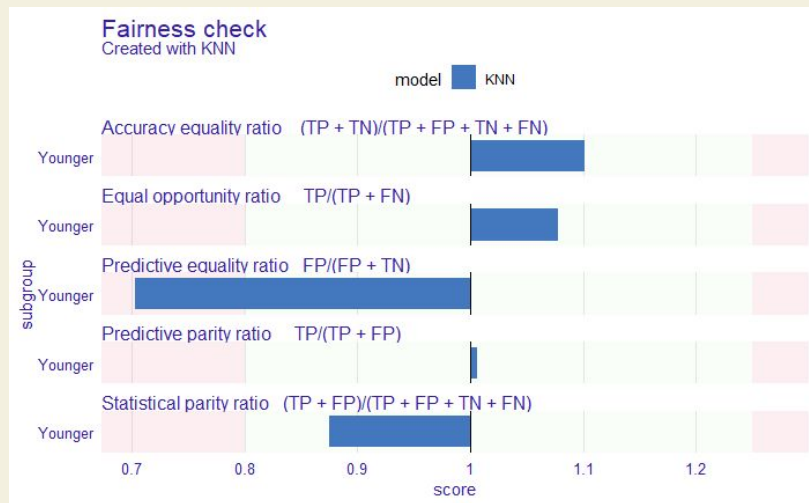
KNN Before:

- Total Loss Score: 0.61 (rounded)
- Passed 4/5 Fairness Metrics
- Least favorable model for Clinical use

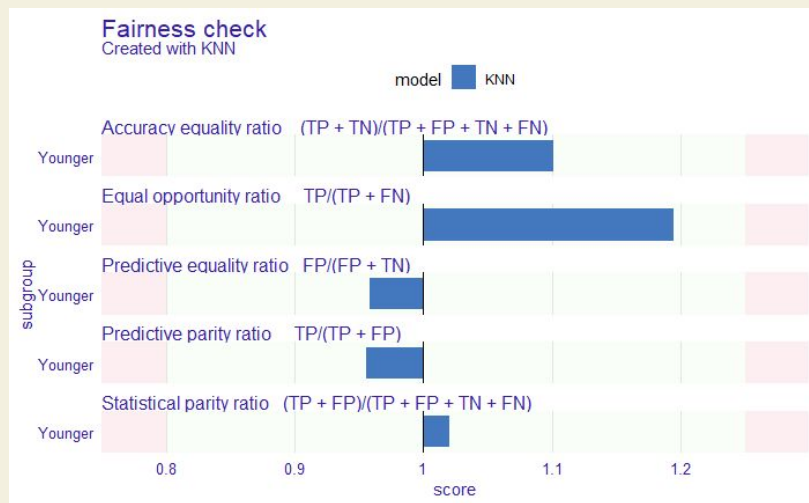
KNN After:

- Total Loss Score: 0.40 (rounded)
- Passed 5/5 Fairness Metrics
- Utilized Threshold Adjustment
- Still not as favorable compared to the Decision Tree

Before Mitigating Bias



After Mitigating Bias



Test Set Evaluation

- SVM & Decision Tree Models performed similarly
- KNN Performed the Worst Overall
- The SVM Model is a more balanced model compared to the Decision Tree



Metric Selection



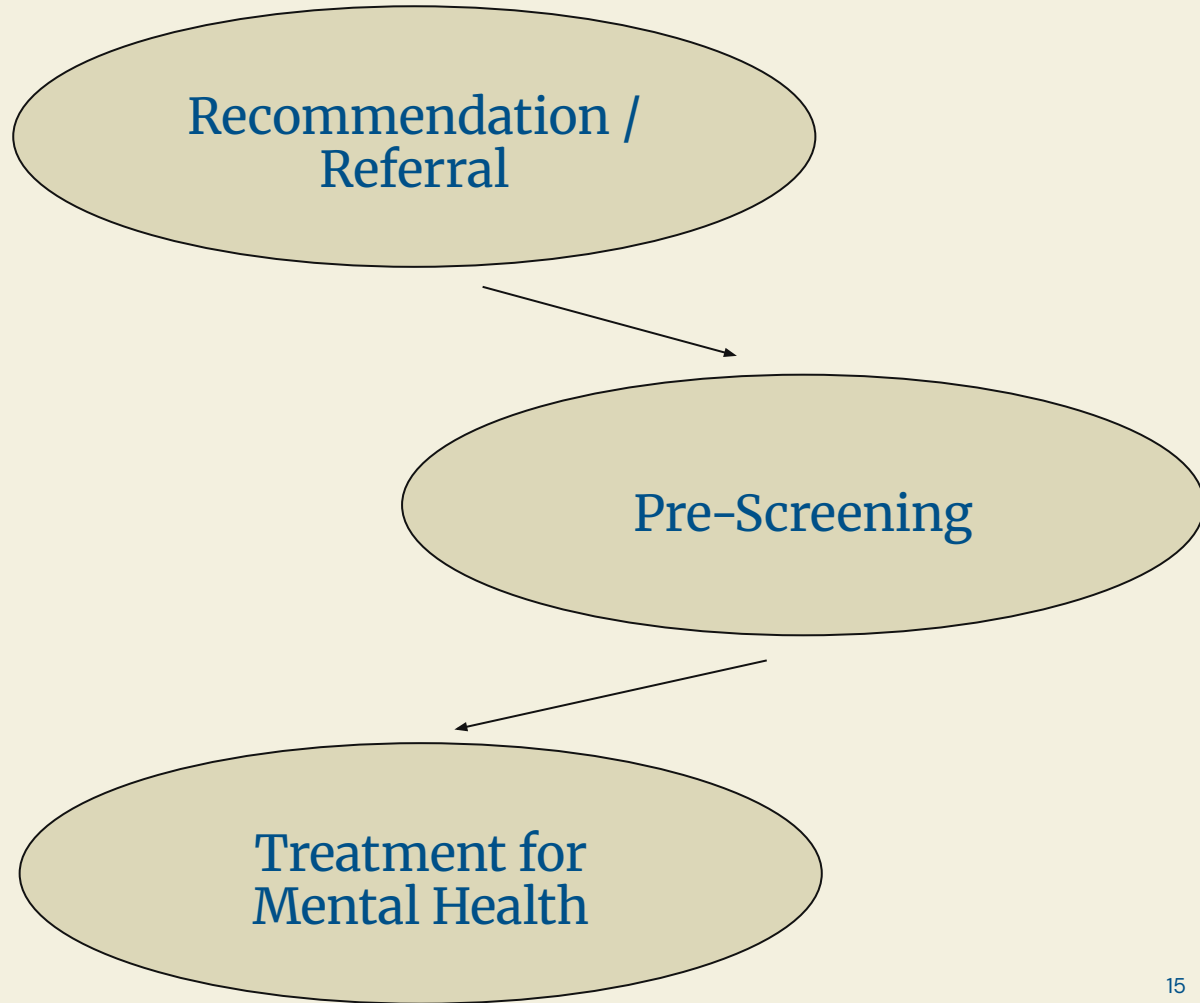
Sensitivity

What we considered:

- Ethically, it's better to over-recommend treatment than under-recommend it
- False negatives are significantly more harmful to a patient
- Untreated mental health issues can escalate and have very severe outcomes

Recommendations to Clinicians

- Utilize the Decision Tree Model
- Primary goal is to get the most amount of people the treatment they need
- Aligns well Ethically
- Create a Pipeline to determine if people truly need help



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Thank you for listening!
Questions?