UseCase 2: Predicting mental health.

- Download the Depression Dataset (kaggle.com) from https://www.kaggle.com/datasets/anthonytherrien/depression-dataset/data.

Question 1:

Use methods of your choice (e.g. exploratory data analysis, statistical methods, visualisations etc.) to extract useful insights from the data.

Solution 1:

In [ ]:
```
# Import the libraries.
import kagglehub
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

import scipy.stats as stats
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score, precision_score, recall_score, f1_s
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from IPython.display import display
```

```
c:\Users\abhis\AppData\Local\Programs\Python\Python312\Lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress not
found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

a. Data Structure and Overview.

In [ ]:
```
# Dataset path.
datasetpath = 'C:/Users/abhis/OneDrive/Documents/Abhishek_Documents/Professional/AXA/DS_Interview/UseCase_2/Datasets/

# Read and display 3 rows of the dataset.
dataset_df = pd.read_csv(datasetpath)
dataset_df.head(3)
```

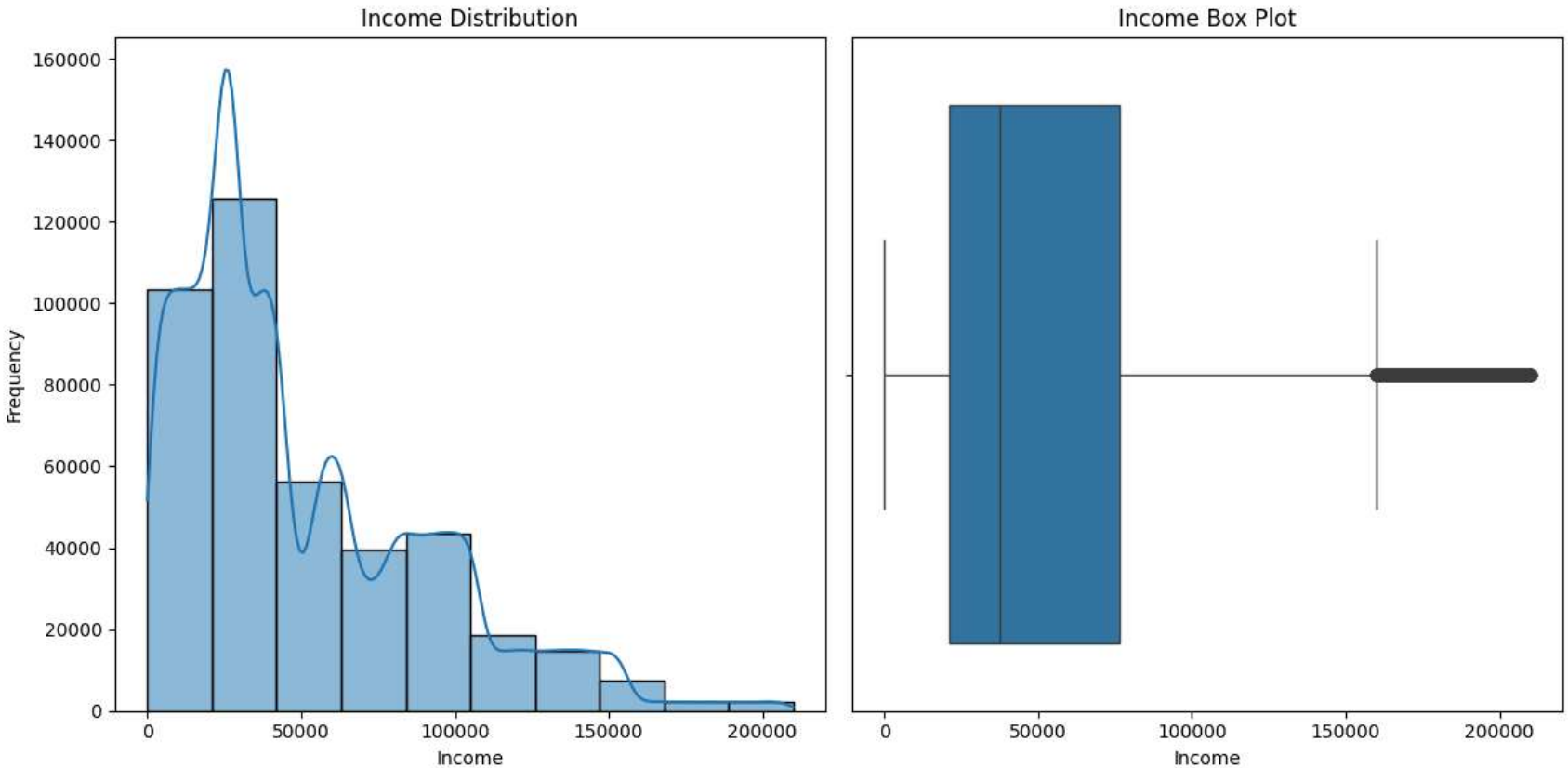
Out[ ]:

	Name	Age	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income	Alcohol Consumption	Dietary Habits	Sl Patte
0	Christine Barker	31	Married	Bachelor's Degree	2	Non-smoker	Active	Unemployed	26265.67	Moderate	Moderate	
1	Jacqueline Lewis	55	Married	High School	1	Non-smoker	Sedentary	Employed	42710.36	High	Unhealthy	
2	Shannon Church	78	Widowed	Master's Degree	1	Non-smoker	Sedentary	Employed	125332.79	Low	Unhealthy	G

a.1) Categorizing the Income and adding a column.

In [ ]:
```
# Step 1: Assess the Income column

# 1.1. Visualize the distribution of Income
plt.figure(figsize=(12, 6))

# Histogram
plt.subplot(1, 2, 1)
sns.histplot(dataset_df['Income'], bins=10, kde=True)
plt.title('Income Distribution')
plt.xlabel('Income')
```

```python
plt.ylabel('Frequency')

# Box Plot
plt.subplot(1, 2, 2)
sns.boxplot(x=dataset_df['Income'])
plt.title('Income Box Plot')

plt.tight_layout()
plt.show()

# 1.2. Calculate summary statistics
income_stats = dataset_df['Income'].describe()
print("Summary Statistics for Income:\n", income_stats)

# Define income categories with hard-coded limits
def categorize_income_hardcoded(income):
    if income < 20000:  # Adjusted threshold for 'Very Low'
        return 'Very Low'
    elif 20000 <= income < 50000:  # Changed to start from 20000 for 'Low'
        return 'Low'
    elif 50000 <= income < 100000:  # Adjusted to make 'Medium' range larger
        return 'Medium'
    elif 100000 <= income < 150000:  # Adjusted to make 'High' range more specific
        return 'High'
    else:
        return 'Very High'  # Everything above 150000 is 'Very High'


# Apply the function to create a new column
dataset_df['Income Category'] = dataset_df['Income'].apply(categorize_income_hardcoded)
```




```
Summary Statistics for Income:
 count    413768.000000
mean      50661.707971
std       40624.100565
min           0.410000
25%       21001.030000
50%       37520.135000
75%       76616.300000
max      209995.220000
Name: Income, dtype: float64
```

a.2) Categorizing the Age column and storing it in a new column.

In [ ]:
```
# Define age categories with hard-coded limits
def categorize_age_hardcoded(age):
    if age < 18:
```

```
        return 'Underage'        # Age less than 18
    elif 18 <= age < 30:
        return 'Young Adult'     # Age from 18 to 29
    elif 30 <= age < 55:
        return 'Adult'           # Age from 30 to 55
    else:
        return 'Senior'          # Age 55 and above

# Apply the categorize function to the Age column
dataset_df['Age Category'] = dataset_df['Age'].apply(categorize_age_hardcoded)
```

In [ ]:
```
# Check for missing values
print('\nCheck for missing values\n\n')
print(dataset_df.isnull().sum())
```

```
Check for missing values


Name                            0
Age                             0
Marital Status                  0
Education Level                 0
Number of Children              0
Smoking Status                  0
Physical Activity Level         0
Employment Status               0
Income                          0
Alcohol Consumption             0
Dietary Habits                  0
Sleep Patterns                  0
History of Mental Illness       0
History of Substance Abuse      0
Family History of Depression    0
Chronic Medical Conditions      0
Income Category                 0
Age Category                    0
dtype: int64
```

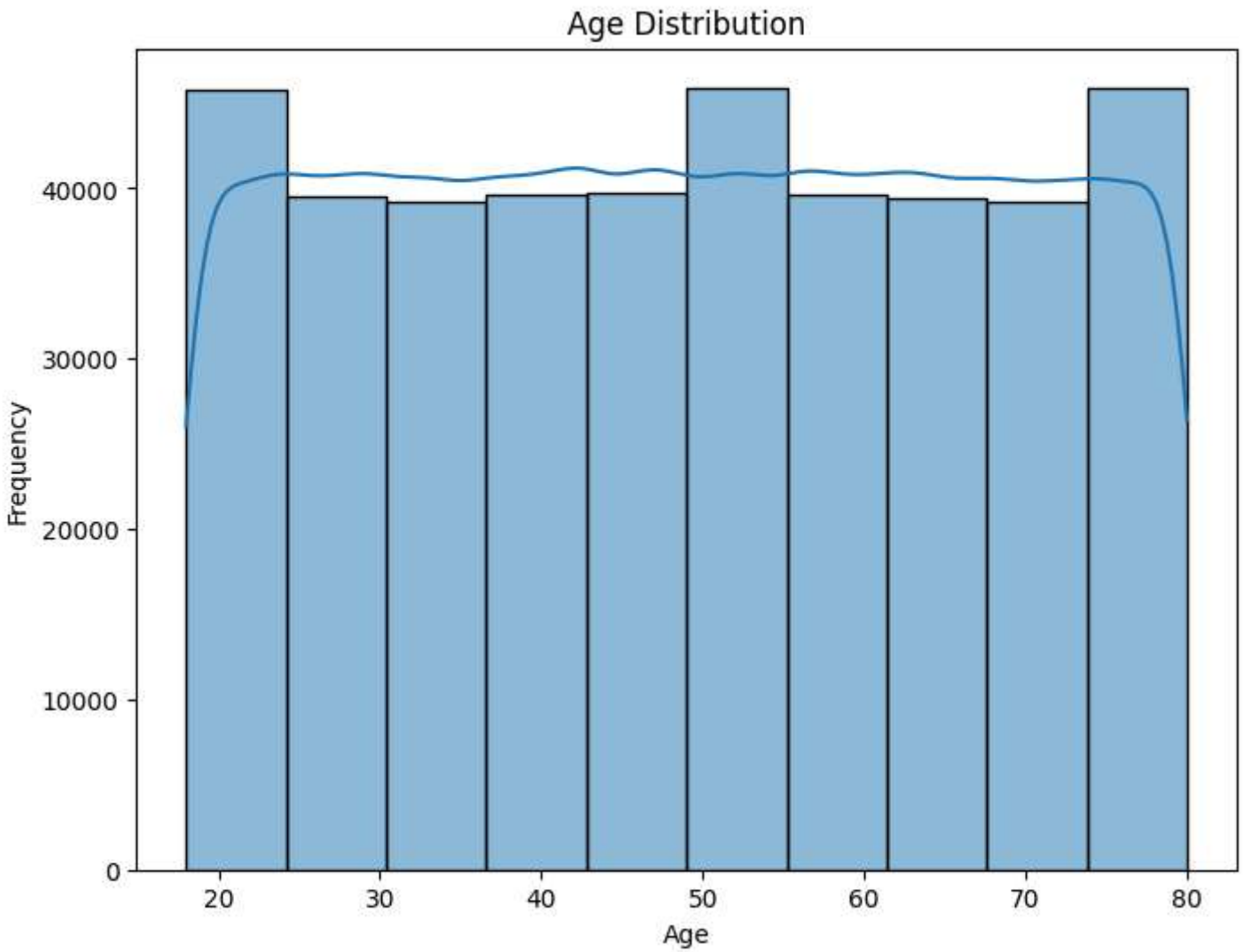
In [ ]:
```
# Data types
print('\nDisplaying the data types of the columns:\n\n')
print(dataset_df.dtypes)
```

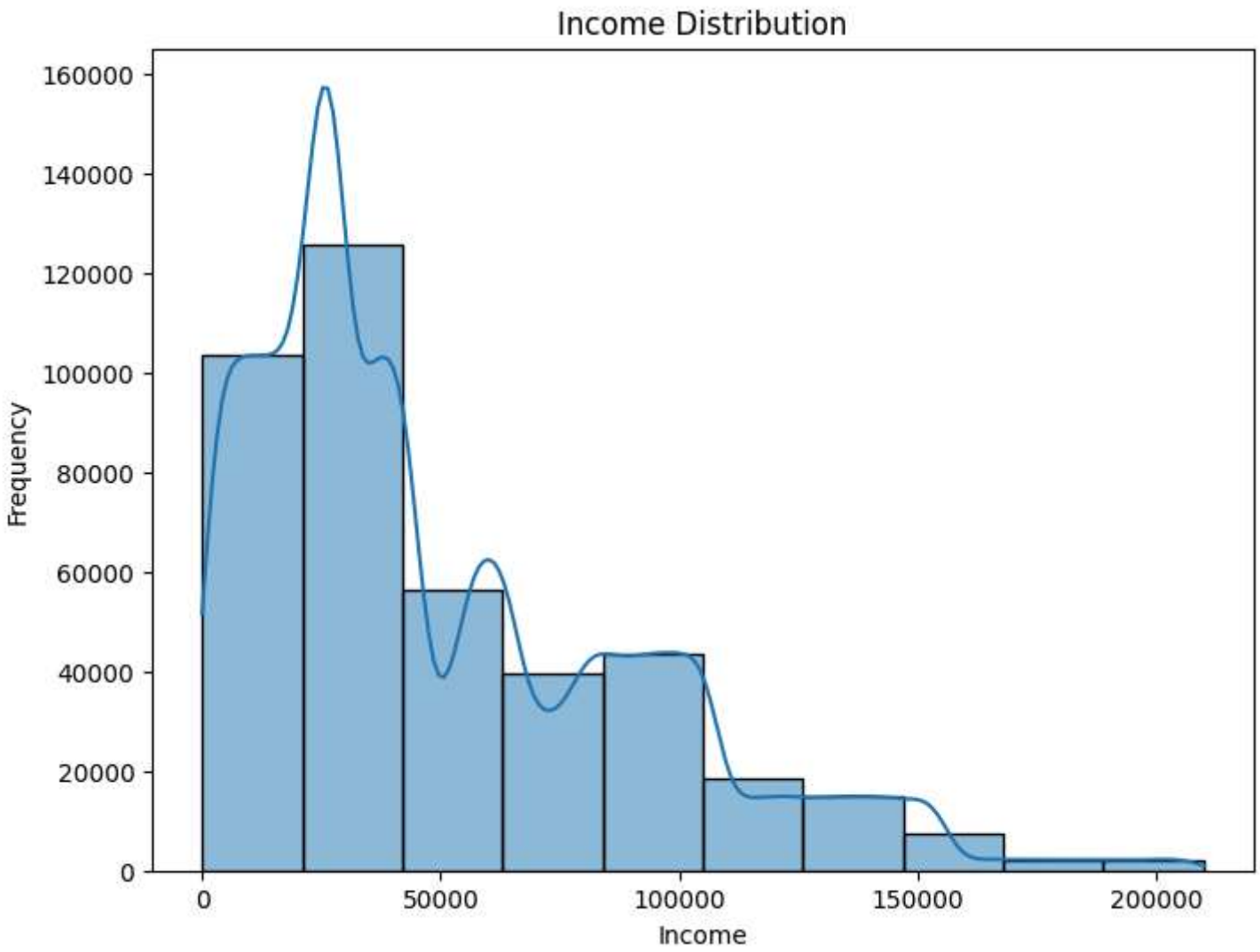
```
Displaying the data types of the columns:


Name                              object
Age                                int64
Marital Status                    object
Education Level                   object
Number of Children                 int64
Smoking Status                    object
Physical Activity Level           object
Employment Status                 object
Income                           float64
Alcohol Consumption               object
Dietary Habits                    object
Sleep Patterns                    object
History of Mental Illness         object
History of Substance Abuse        object
Family History of Depression      object
Chronic Medical Conditions        object
Income Category                   object
Age Category                      object
dtype: object
```

b. Distribution of Age and Income.

In [ ]:

```python
# Distribution of Age
plt.figure(figsize=(8,6))
sns.histplot(dataset_df['Age'], bins=10, kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

# Distribution of Income
plt.figure(figsize=(8,6))
sns.histplot(dataset_df['Income'], bins=10, kde=True)
plt.title('Income Distribution')
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.show()
```

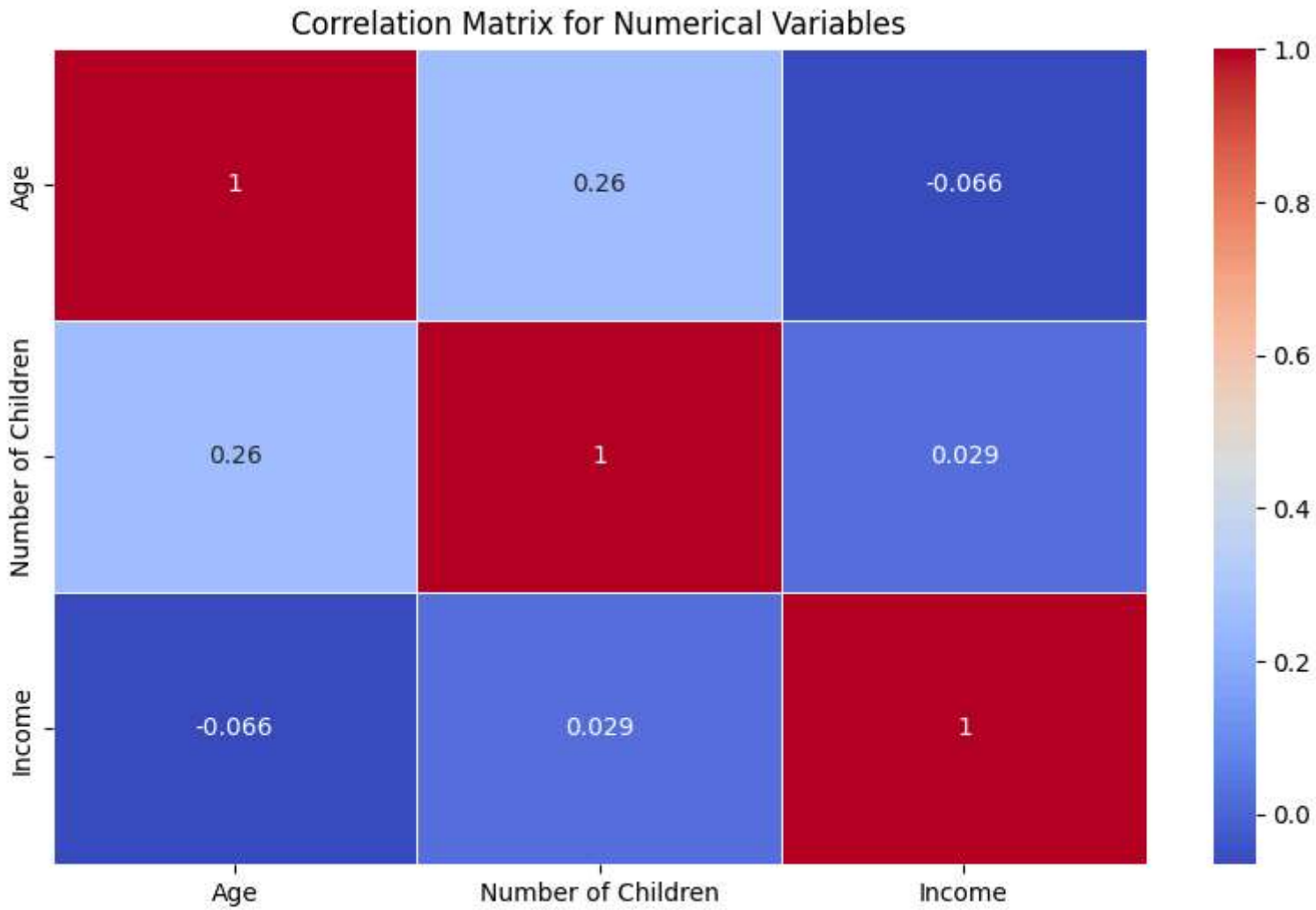

Age Distribution
Frequency
40000
30000
20000
10000
0
20
30
40
50
60
70
80
Age



c. Correlation analysis.

In [ ]:
```
# Select only numerical columns for correlation analysis
numerical_df = dataset_df.select_dtypes(include=['float64', 'int64'])

# Compute the correlation matrix for numerical data
correlation_matrix = numerical_df.corr()
```

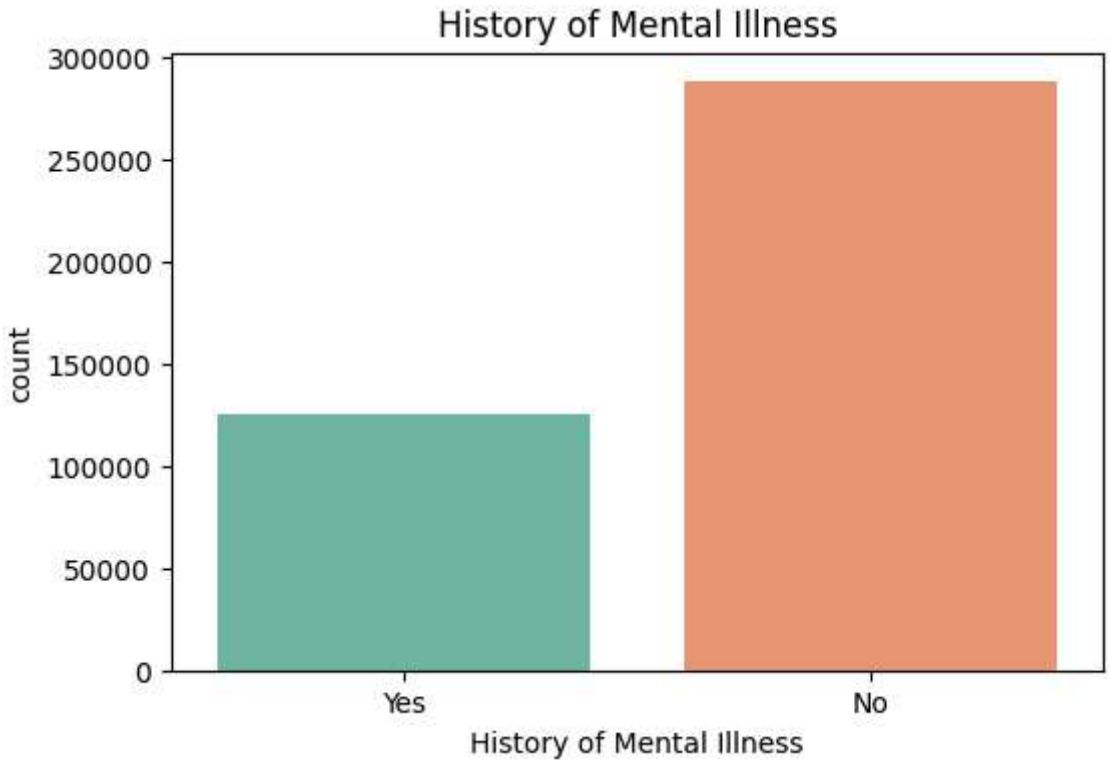
```python
# Plot the heatmap
plt.figure(figsize=(10,6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix for Numerical Variables')
plt.show()
```



d. Cross tabulation and grouped analysis.

In [ ]:
```
# Count plot for History of Mental Illness
plt.figure(figsize=(6,4))
sns.countplot(x='History of Mental Illness', data=dataset_df, palette='Set2')
plt.title('History of Mental Illness')
plt.show()
```

```
C:\Users\abhis\AppData\Local\Temp\ipykernel_29264\1502304843.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `h
ue` and set `legend=False` for the same effect.

  sns.countplot(x='History of Mental Illness', data=dataset_df, palette='Set2')
```



e. Multivariate Analysis: Mental Health and Employment

In [ ]:
```
# Bar plot for variable vs Mental Illness
def multivariate_MentalAnalysis(df, column):
```

```python
# Bool to see if null hypothesis is rejected. later on.
isSignificant = False

# Cross-tabulation for column variable and Mental Illness
print('\n\n')
cross_tab = pd.crosstab(df[column], df['History of Mental Illness'], margins=True)
cross_tab_copy = cross_tab.copy()


# Calculate the ratio of people with Mental Illness = Yes
cross_tab['Mental_Illness_Yes_(%)'] = (cross_tab['Yes'] / cross_tab['All']) * 100

display(cross_tab)
print('\n\n')

# Plot the figure
plt.figure(figsize=(14,4))
sns.countplot(x=column, hue='History of Mental Illness', data=df, palette='Set2')
plt.title(column + ' vs Mental Illness')
plt.show()


# Perform chi-squared analysis and compute p-value.
# Copying the dataset and removing high-cardinality columns like 'Name'
# df = dataset_df.drop(['Name'], axis=1)

# Perform the chi-square test
chi2_stat, p_val, dof, expected = stats.chi2_contingency(cross_tab_copy)

print("Chi-Square Test:")
print(f"Chi-Square Statistic: {chi2_stat}")
print(f"Degrees of Freedom: {dof}")
print(f"P-value: {p_val}")

# Interpretation
alpha = 0.00005  # significance level
if p_val < alpha:
    print("Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null
    isSignificant = True
else:
    print("Result: No significant association (fail to reject null hypothesis)")
```

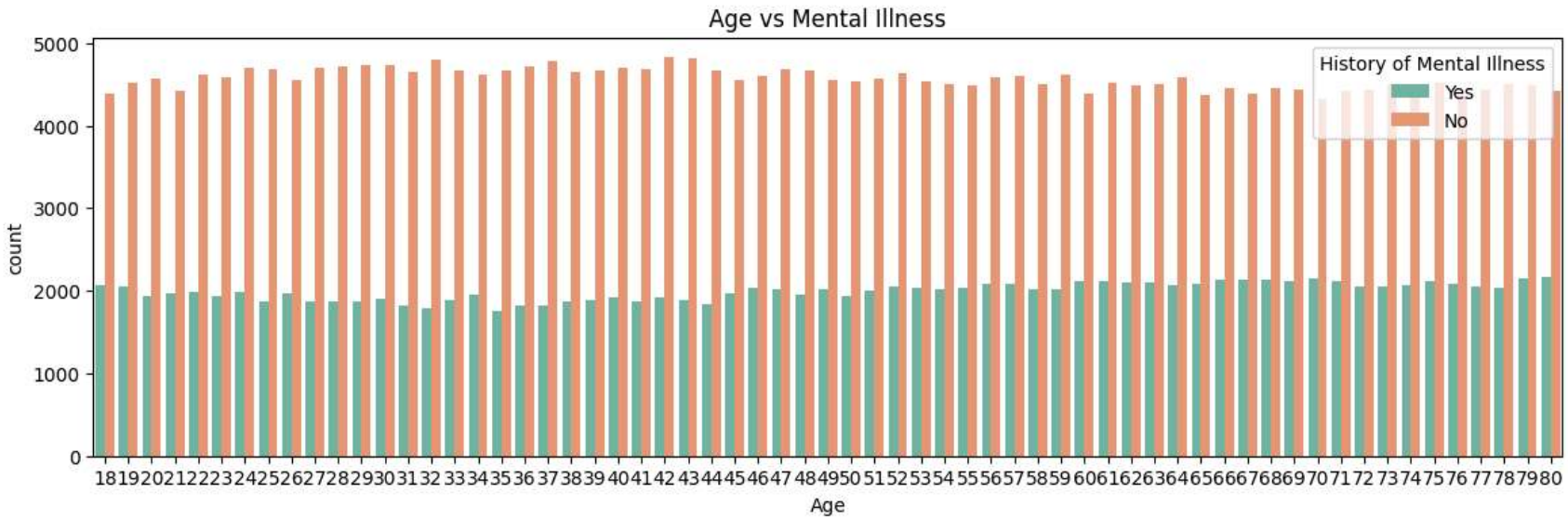
```
    # Return the isSignificant flag.
    return isSignificant
```

In [ ]:
```
# Declaring an empty list to fill with columns with Significant p-values.
isSignificant_list = []

# Looping through the columns and plotting.
for column in dataset_df.columns:

    # Ensuring the Name column doesn't get plotted thereby preventing the total destruction of the RAM this is being
    if column != 'Name' and column != 'Income':

        print('\n\nMulti variate Analysis for the column: ' + column)

        # Making plots and checking if the p-value is significant.
        isSignificant = multivariate_MentalAnalysis(dataset_df, column)

        if isSignificant == True:
            isSignificant_list.append(column)


# Print the sigfnificant list.
print('\n\nList of columns with Significant p-values:\n')
for value in isSignificant_list:
    print(value)
```

```
Multi variate Analysis for the column: Age
```

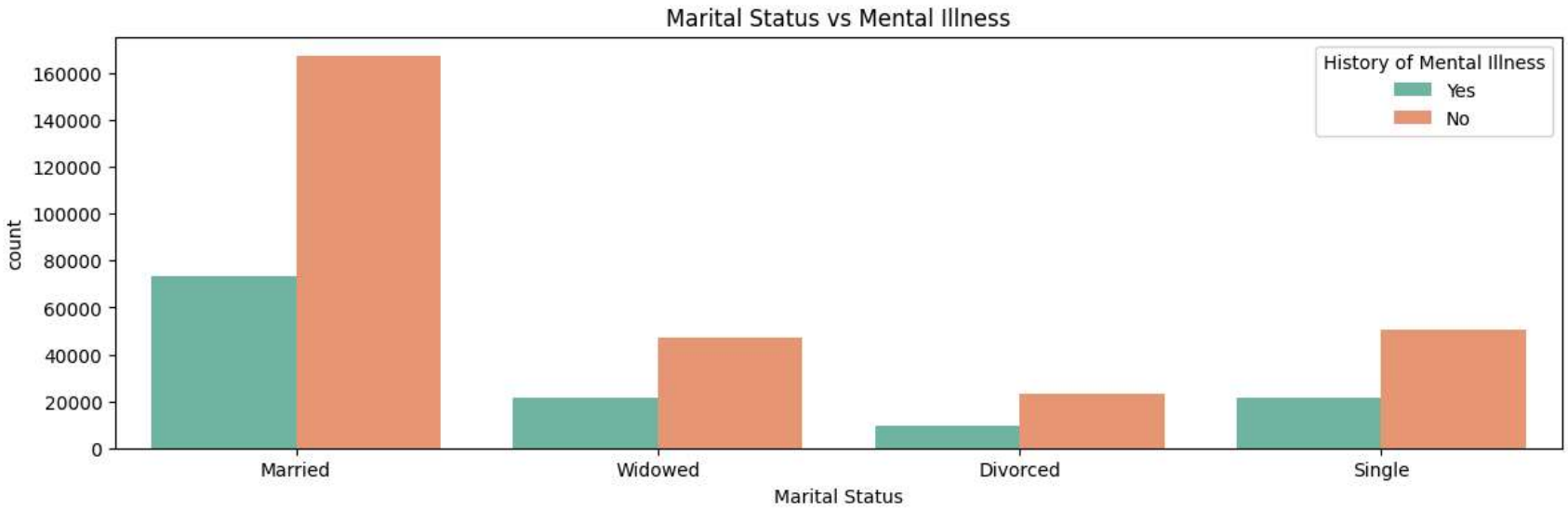
History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Age				
18	4395	2075	6470	32.071097
19	4528	2060	6588	31.268974
20	4572	1938	6510	29.769585
21	4417	1964	6381	30.778875
22	4611	1980	6591	30.040965
...	...	...	...	...
77	4436	2060	6496	31.711823
78	4501	2030	6531	31.082529
79	4493	2144	6637	32.303752
80	4428	2167	6595	32.858226
All	287943	125825	413768	30.409553

64 rows × 4 columns



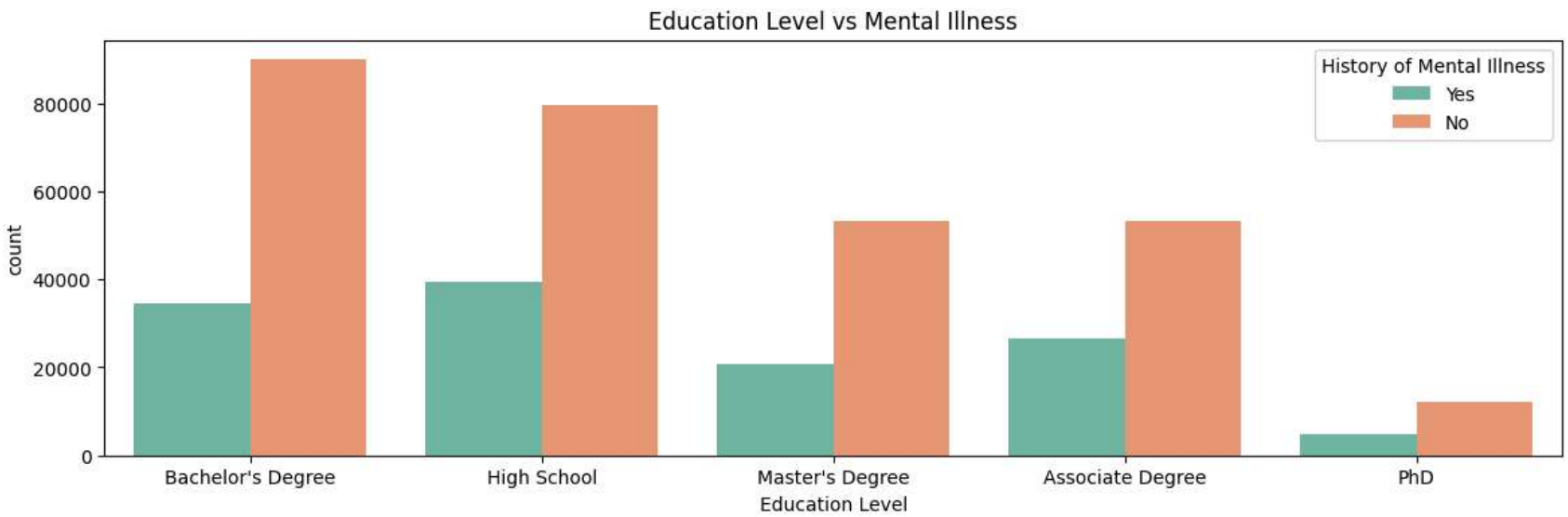

```
Chi-Square Test:
Chi-Square Statistic: 500.67142242076307
Degrees of Freedom: 126
P-value: 4.110946338862388e-46
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Marital Status
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Marital Status				
Divorced	23111	9618	32729	29.386782
Married	167155	73289	240444	30.480694
Single	50690	21420	72110	29.704618
Widowed	46987	21498	68485	31.390816
All	287943	125825	413768	30.409553



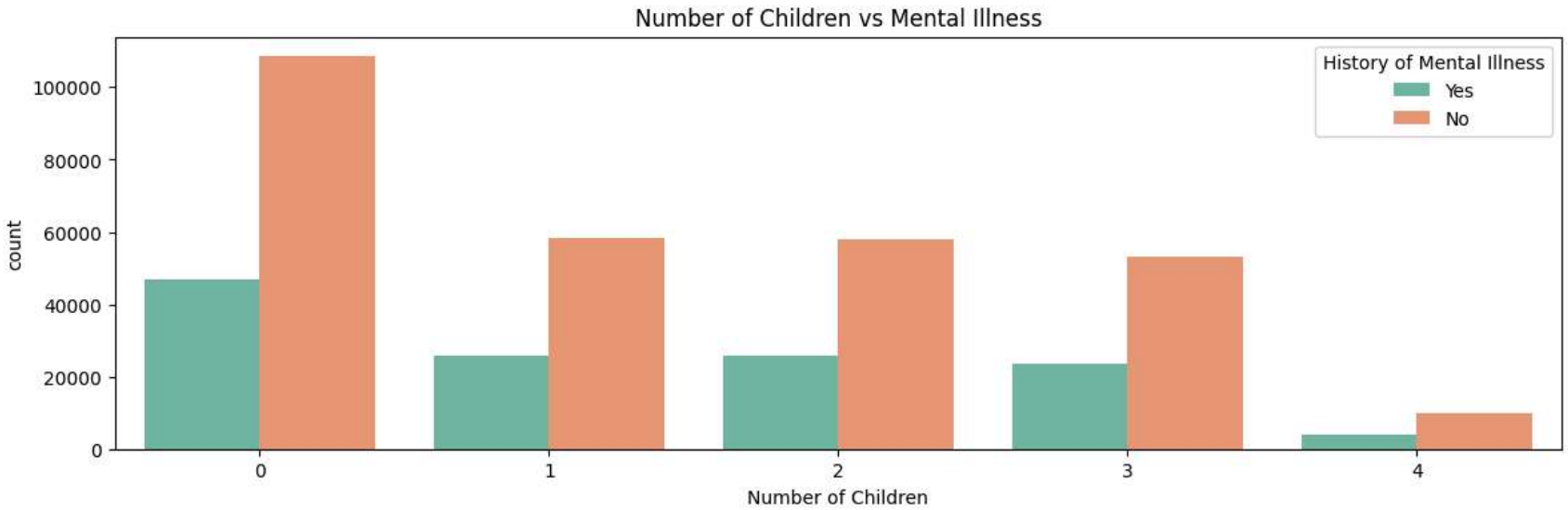

```
Chi-Square Test:
Chi-Square Statistic: 64.84684614908466
Degrees of Freedom: 8
P-value: 5.174587342275629e-11
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Education Level
```

History of Mental Illness Education Level	No	Yes	All	Mental_Illness_Yes_(%)
Associate Degree	53324	26675	79999	33.344167
Bachelor's Degree	89845	34484	124329	27.736087
High School	79583	39344	118927	33.082479
Master's Degree	53111	20657	73768	28.002657
PhD	12080	4665	16745	27.859062
All	287943	125825	413768	30.409553



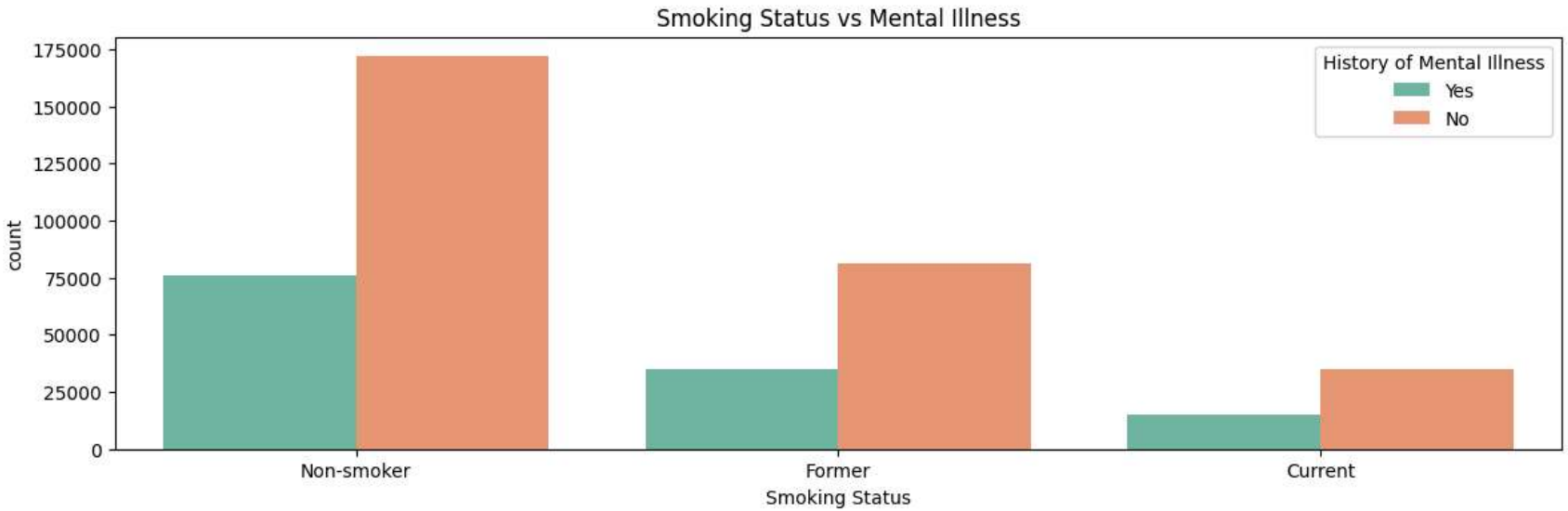
```
Chi-Square Test:
Chi-Square Statistic: 1400.3934320834205
Degrees of Freedom: 10
P-value: 8.157996943827289e-295
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Number of Children
```

History of Mental Illness Number of Children	No	Yes	All	Mental_Illness_Yes_(%)
0	108501	46731	155232	30.103973
1	58304	25621	83925	30.528448
2	58115	25846	83961	30.783340
3	53235	23739	76974	30.840284
4	9788	3888	13676	28.429365
All	287943	125825	413768	30.409553



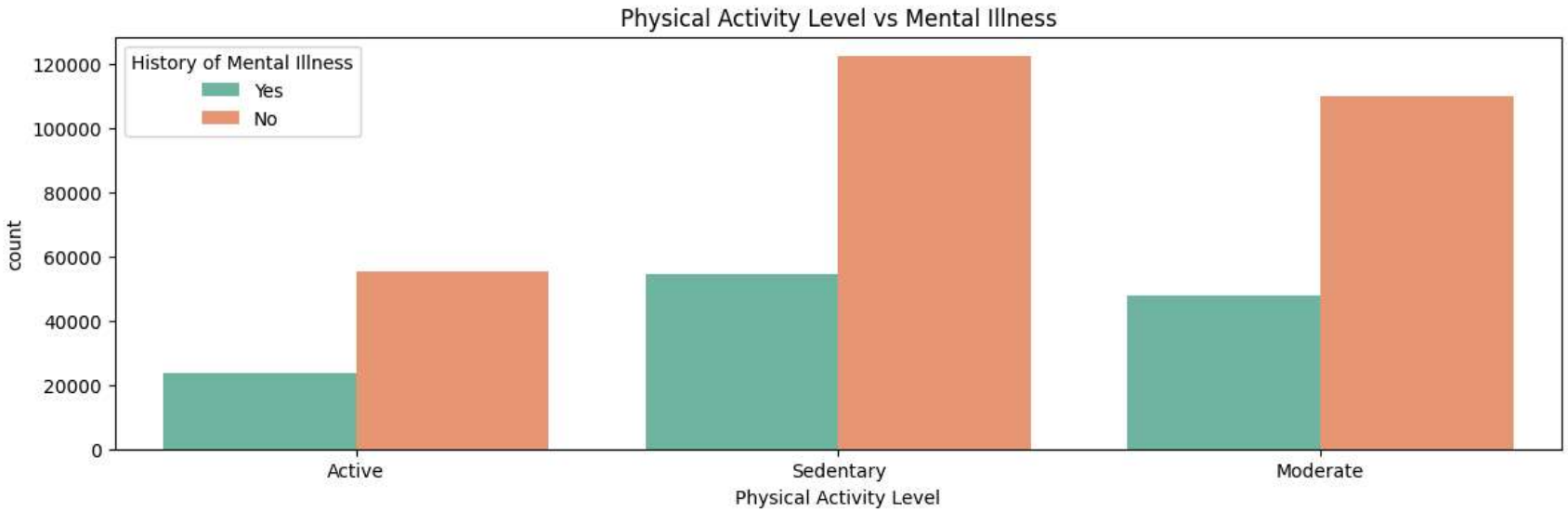

```
Chi-Square Test:
Chi-Square Statistic: 45.04220744816128
Degrees of Freedom: 10
P-value: 2.1369274704913144e-06
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Smoking Status
```

History of Mental Illness Smoking Status	No	Yes	All	Mental_Illness_Yes_(%)
Current	35174	14994	50168	29.887578
Former	81031	35153	116184	30.256318
Non-smoker	171738	75678	247416	30.587351
All	287943	125825	413768	30.409553



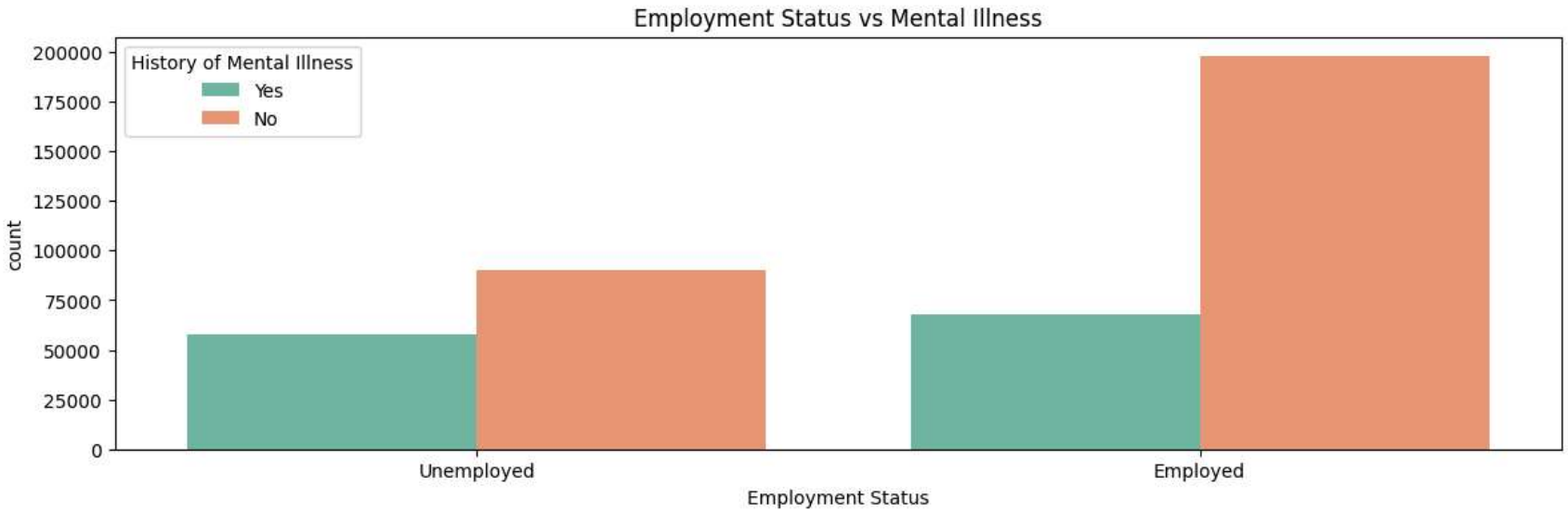

```
Chi-Square Test:
Chi-Square Statistic: 11.444087927498837
Degrees of Freedom: 6
P-value: 0.07558351101869512
Result: No significant association (fail to reject null hypothesis)


Multi variate Analysis for the column: Physical Activity Level
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Physical Activity Level				
Active	55424	23481	78905	29.758570
Moderate	110157	47856	158013	30.286116
Sedentary	122362	54488	176850	30.810291
All	287943	125825	413768	30.409553



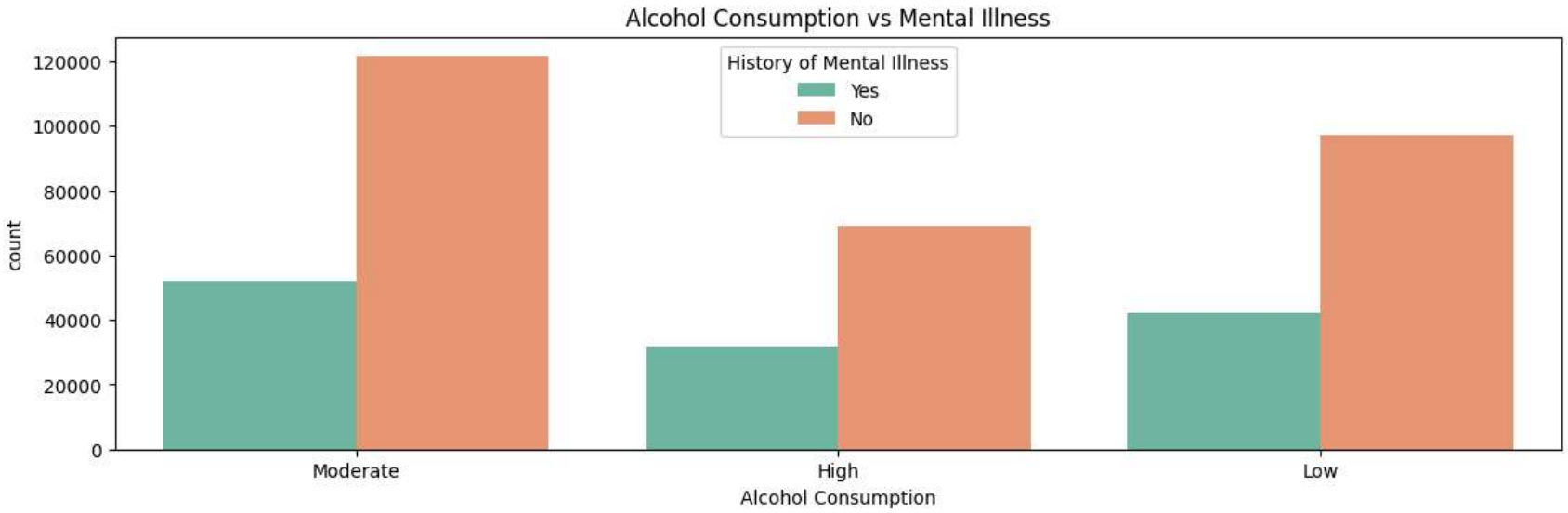

```
Chi-Square Test:
Chi-Square Statistic: 30.359103695976955
Degrees of Freedom: 6
P-value: 3.3586382783323904e-05
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Employment Status
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Employment Status				
Employed	197718	67941	265659	25.574515
Unemployed	90225	57884	148109	39.082027
All	287943	125825	413768	30.409553



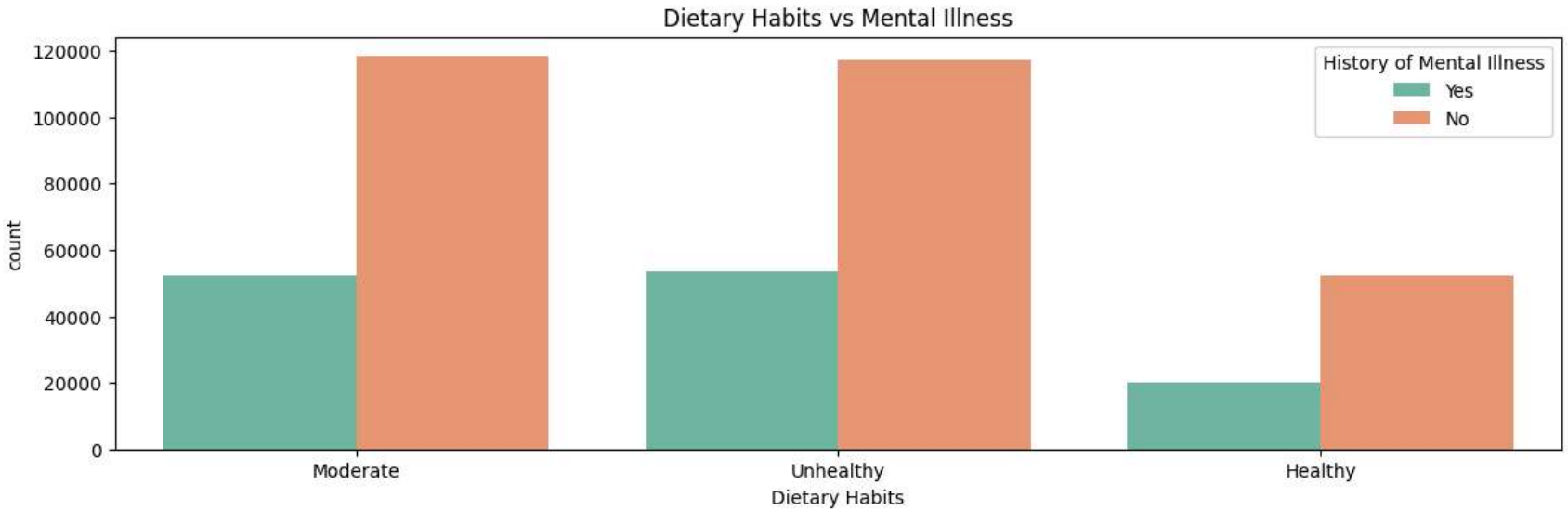

```
Chi-Square Test:
Chi-Square Statistic: 8198.609285236696
Degrees of Freedom: 4
P-value: 0.0
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Alcohol Consumption
```

History of Mental Illness Alcohol Consumption	No	Yes	All	Mental_Illness_Yes_(%)
High	69244	31834	101078	31.494489
Low	97217	42033	139250	30.185278
Moderate	121482	51958	173440	29.957334
All	287943	125825	413768	30.409553



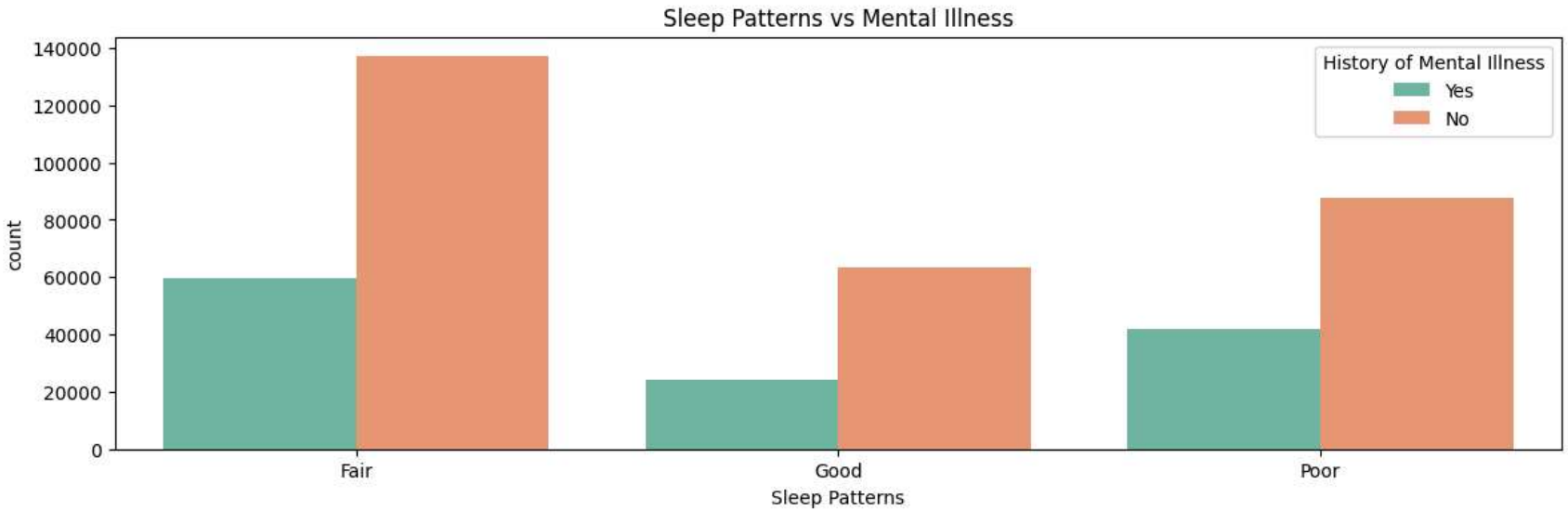

```
Chi-Square Test:
Chi-Square Statistic: 76.2921736165222
Degrees of Freedom: 6
P-value: 2.0796728377428682e-14
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Dietary Habits
```

History of Mental Illness Dietary Habits	No	Yes	All	Mental_Illness_Yes_(%)
Healthy	52514	19991	72505	27.571892
Moderate	118295	52151	170446	30.596787
Unhealthy	117134	53683	170817	31.427200
All	287943	125825	413768	30.409553



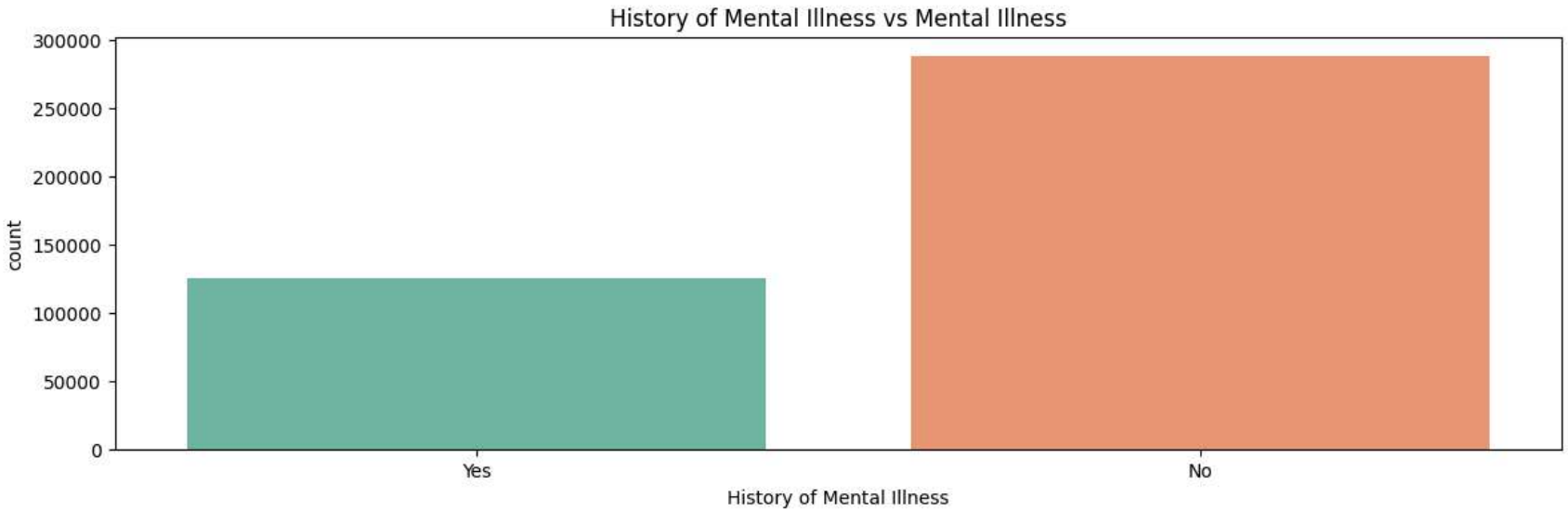

```
Chi-Square Test:
Chi-Square Statistic: 362.3015989567789
Degrees of Freedom: 6
P-value: 3.524135929758325e-75
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: Sleep Patterns
```

History of Mental Illness Sleep Patterns	No	Yes	All	Mental_Illness_Yes_(%)
Fair	137049	59740	196789	30.357388
Good	63334	24063	87397	27.532982
Poor	87560	42022	129582	32.428887
All	287943	125825	413768	30.409553



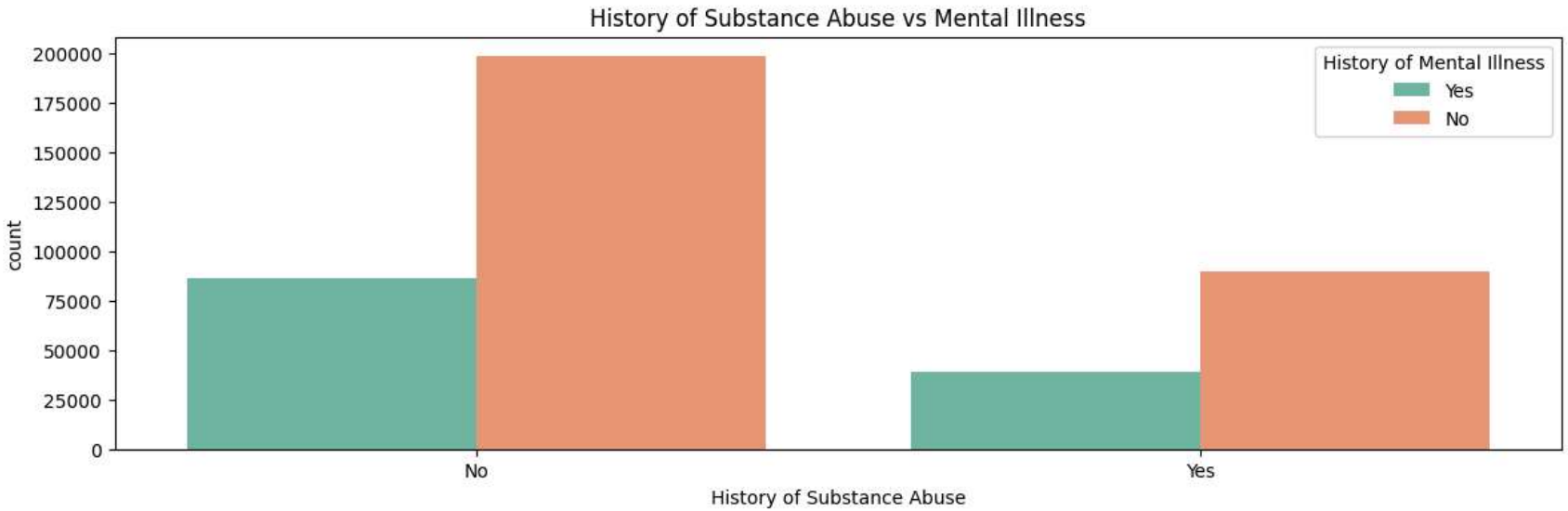

```
Chi-Square Test:
Chi-Square Statistic: 591.6762682229571
Degrees of Freedom: 6
P-value: 1.4559455654713063e-124
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: History of Mental Illness
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
History of Mental Illness				
No	287943	0	287943	0.000000
Yes	0	125825	125825	100.000000
All	287943	125825	413768	30.409553



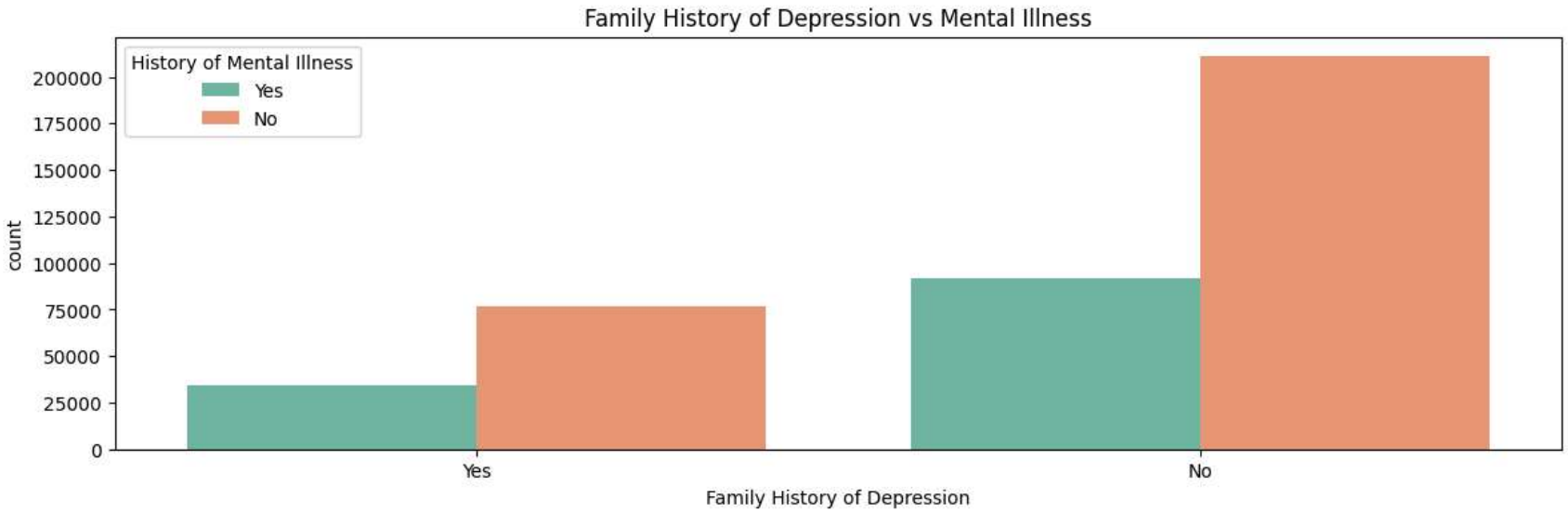

```
Chi-Square Test:
Chi-Square Statistic: 413768.00000000006
Degrees of Freedom: 4
P-value: 0.0
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


Multi variate Analysis for the column: History of Substance Abuse
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
History of Substance Abuse				
No	198402	86478	284880	30.355939
Yes	89541	39347	128888	30.528055
All	287943	125825	413768	30.409553



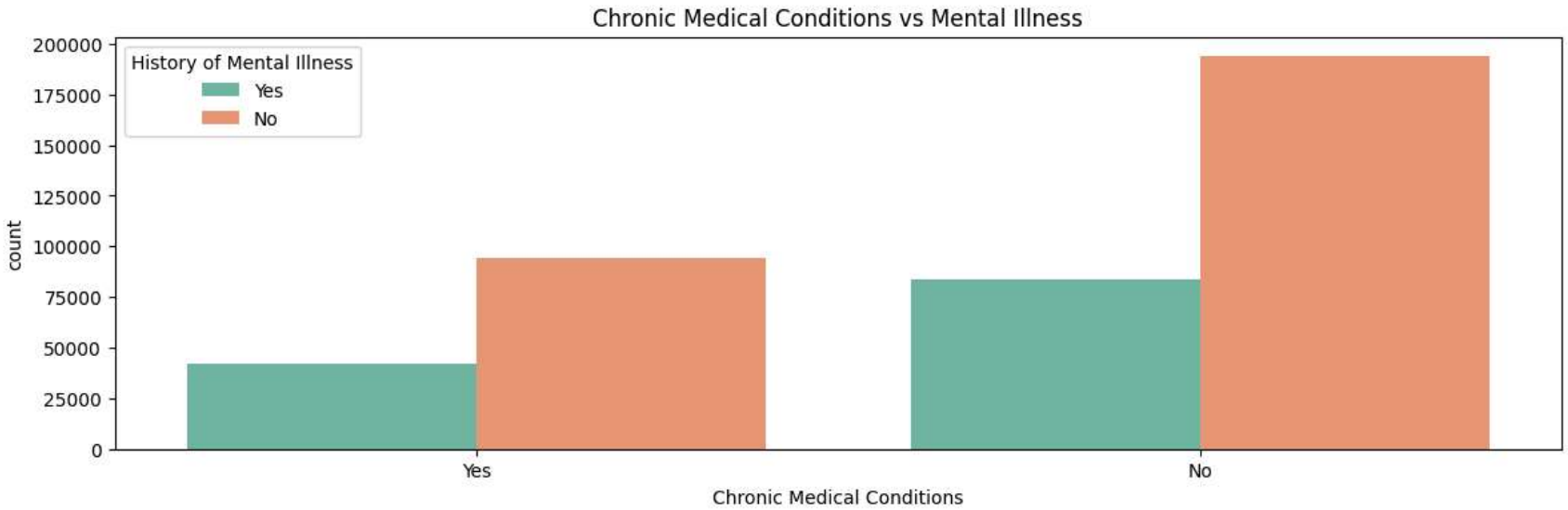

```
Chi-Square Test:
Chi-Square Statistic: 1.2422256323896628
Degrees of Freedom: 4
P-value: 0.8710987098668348
Result: No significant association (fail to reject null hypothesis)


Multi variate Analysis for the column: Family History of Depression
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Family History of Depression				
No	210934	91581	302515	30.273210
Yes	77009	34244	111253	30.780294
All	287943	125825	413768	30.409553



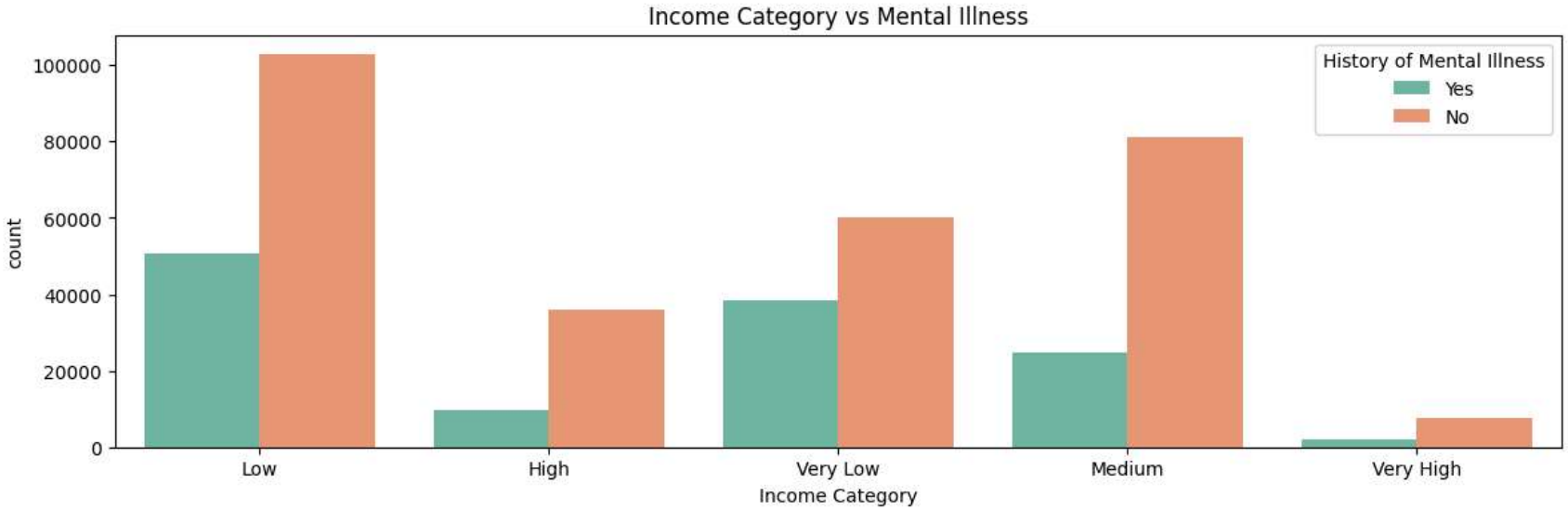

```
Chi-Square Test:
Chi-Square Statistic: 9.88329703237268
Degrees of Freedom: 4
P-value: 0.042440087931455005
Result: No significant association (fail to reject null hypothesis)


Multi variate Analysis for the column: Chronic Medical Conditions
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Chronic Medical Conditions				
No	193696	83865	277561	30.214980
Yes	94247	41960	136207	30.806053
All	287943	125825	413768	30.409553




```
Chi-Square Test:
Chi-Square Statistic: 15.08423291350952
Degrees of Freedom: 4
P-value: 0.004529663381359344
Result: No significant association (fail to reject null hypothesis)


Multi variate Analysis for the column: Income Category
```

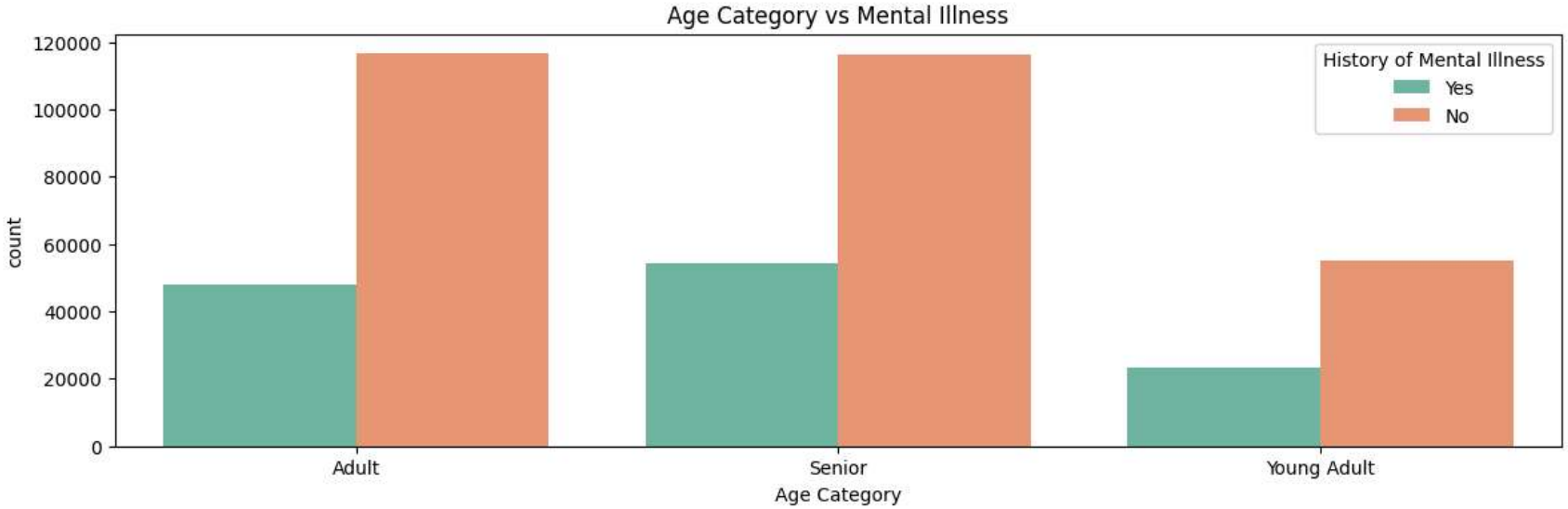
History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Income Category				
High	36108	9714	45822	21.199424
Low	102766	50698	153464	33.035761
Medium	81299	24936	106235	23.472490
Very High	7726	2086	9812	21.259682
Very Low	60044	38391	98435	39.001371
All	287943	125825	413768	30.409553



```
Chi-Square Test:
Chi-Square Statistic: 8574.534918517511
Degrees of Freedom: 10
P-value: 0.0
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)
```

```
Multi variate Analysis for the column: Age Category
```

History of Mental Illness	No	Yes	All	Mental_Illness_Yes_(%)
Age Category				
Adult	116515	47992	164507	29.173227
Senior	116222	54424	170646	31.892925
Young Adult	55206	23409	78615	29.776760
All	287943	125825	413768	30.409553



```
Chi-Square Test:
Chi-Square Statistic: 311.12958252589635
Degrees of Freedom: 6
P-value: 3.368569436572669e-64
Result: Significant association between Alcohol Consumption and History of Mental Illness (reject null hypothesis)


List of columns with Significant p-values:

Age
Marital Status
Education Level
Number of Children
Physical Activity Level
Employment Status
Alcohol Consumption
Dietary Habits
Sleep Patterns
History of Mental Illness
Income Category
Age Category
```

Question 2:

Use suitable models to predict if an individual will suffer mental illness (variable titled “History of Mental Illness”) using all or some of the other variables present in the data.

Your answer should also contain:

- 1. Narratives for including/excluding variables of choice;
- 2. Narrative supporting the model/s of choice,
- 3. An assessment of model performance,
- 4. Assessment of potential model biases.

Solution 2

- 1. Narratives for including/excluding variables of choice:

- Answer: The following variables have been selected based on the cross tabulation analysis where sub classes have shown to have a relatively significant impact on the occurence of mental health illness: (This has also been visualized in the python notebook 'UseCase_2_Code.ipynb'.)
    - Sleep Patterns
    - Education level
    - Dietary Habits
    - Employment Status
    - Income Category
- The following have been selected purely on grounds of common sense and real life observations:
    - Alcohol Consumption
    - Family History of Depression
    - Age Category

- 2. Narrative supporting the model/s of choice:
    - Answer: The following models have been selected (along with the reasoning):
        - Logistic Regression:
            - Provides a fast and linear method to classify.
            - Simple and effective, this is further proven by the resulting confusion matrix, precision, accuracy and f1-scores.
            - It has in-built class balancing features that has been leveraged here to offset the class imbalance in the dataset.
        - Decision Tree:
            - These are non-linear and help model complicated relationships without the need to feature-scale.
            - Provide for a way to class balance.
        - Random Forest:
            - These utilize multiple decision trees and average their predictions.
            - Sometimes much better than decision trees where overfitting can be an issue in Decision-trees.
            - Has in-built class balancing feature.
            - Good model for medium to large datasets.
        - K-Nearest Neighbors:
            - This model is good at identifying patterns.
            - Predictions can be formed based on the clusters it falls under.
        - Extra Trees:

        - Similar to Random Forest, but includes randomness in node splittiong.
        - The added randomness could improve generalization by reducting variance.
        - Class balancing is available.
- 3. An assessment of model performance:
    - Answer: Based on the following table, I conclude the following:

        - If predicting both 'Yes' and 'No' are important. Logisic Regression has a more balanced performance in terms of being suitable at predicting both 'Yes' and 'No' class. This can be inferred by the confusion matrix and the F1-scores.

        - If predicting 'Yes' is more important. The decision trees (all 3 variants) perform similarly and appear to be the best in terms of prediciting the 'Yes' class of the 'History of mental illness'.

        - If predicting 'No; is more important. The KNN model achieves better performance in predicting the 'No' class of the 'History of mental illness'. This can be inferred by the model's F1-Score, precision and recall for the 'No' class.

        - Summary table:

    | Model | Class | Accuracy | Precision | Recall | F1-Score | |----------|-------|----------|----------|----------|----------| | Logistic Regression | No | 0.590747 | 0.752627 | 0.617874 | 0.678626 | | Logistic Regression | Yes | 0.590747 | 0.372520 | 0.527651 | 0.436718 | | Decision Tree | No | 0.568405 | 0.754695 | 0.567210 | 0.647657 | | Decision Tree | Yes | 0.568405 | 0.362012 | 0.571185 | 0.443156 | | Random Forest | No | 0.571528 | 0.753291 | 0.575933 | 0.652780 | | Random Forest | Yes | 0.571528 | 0.362675 | 0.561282 | 0.440633 | | K-Nearest Neighbors | No | 0.642766 | 0.708844 | 0.830163 | 0.764722 | | K-Nearest Neighbors | Yes | 0.642766 | 0.343732 | 0.206900 | 0.258314 | | Extra Trees | No | 0.568434 | 0.754718 | 0.567238 | 0.647684 | | Extra Trees | Yes | 0.568434 | 0.362039 | 0.571217 | 0.443186 |

- 4. Assessment of potential model biases:
    - Answer. The following model biases could potentially affect the outcome:
        - Class Imbalance Bias: Inspite of class balancing, there could possibly be some residual class imbalance issues due to the nature of the dataset.
        - Featue representation bias: Usage of One-hot encoding could potentially introduce over-representation of certain features. This needs to be carefully balanced to avoid skewing predictions.
        - Socioeconomic Bias:
            - Features such as Employment Status, Income Category and Education level could indirectly introduce socioeconomic status. Because they could possibly be related and a consequence of each other.

        - In plain terms, this could train the model to infer that every individual with lower socioeconomic status is predisposed to mental illness, thereby perpetuating untrue sterotypes.
    - Evaluation Bias:
        - Relying on multiple metrics apart from just the accuracy is helpful.
    - Model's inherent Bias:
        - KNN could perform differently based on the data density
        - Logistic Regression might not be considering the complex relationships due to its linear nature.
        - Decision Tree models: These could result in over-fitting due to their sensitivity to features.

a. Run the models and Calculate Confusion Matrix

In [ ]:
```
# Function to calculate and return confusion matrix with y_test and y_pred.
def calculate_confusionMatrix(y_test, y_pred):
    '''
    Function to calculate and return confusion matrix with y_test and y_pred.
    '''

    # total count of y_test
    total_samples = len(y_test)

    # Initialize confusion matrix counters
    true_positive = 0  # Predicted Yes, Actual Yes
    true_negative = 0  # Predicted No, Actual No
    false_positive = 0  # Predicted Yes, Actual No
    false_negative = 0  # Predicted No, Actual Yes

    # Calculate the counts for each cell in the confusion matrix
    for actual, predicted in zip(y_test, y_pred):
        if actual == 'Yes' and predicted == 'Yes':
            true_positive += 1
        elif actual == 'No' and predicted == 'No':
            true_negative += 1
        elif actual == 'No' and predicted == 'Yes':
            false_positive += 1
        elif actual == 'Yes' and predicted == 'No':
            false_negative += 1
```

```
    # Calculate proportions by dividing each count by the total number of samples
    confusion_matrix_total_sample = {
        'Actual Yes': {
            'Predicted Yes': true_positive / total_samples,
            'Predicted No': false_negative / total_samples
        },
        'Actual No': {
            'Predicted Yes': false_positive / total_samples,
            'Predicted No': true_negative / total_samples
        }
    }

    # Convert to a DataFrame for better readability
    confusion_matrix_df = pd.DataFrame(confusion_matrix_total_sample)

    # return the confusion matrix.
    return confusion_matrix_df.round(2)
```

In [ ]:

```
# Assuming your data is in a DataFrame named 'dataset_df'
df = dataset_df.copy()

# Preprocess the data (handle missing values, categorical features, etc.)
# Let's include more relevant columns for prediction

# Define categorical columns for one-hot encoding
categorical_cols = ['Education Level', 'Employment Status', 'Dietary Habits', 'Age Category','Sleep Patterns', 'Alcoh

# One-hot encoding for categorical features
ohe = OneHotEncoder()  # Use sparse=False to get dense output
encoded_features = ohe.fit_transform(df[categorical_cols])

# Create a DataFrame with the one-hot encoded features
encoded_df = pd.DataFrame(encoded_features.toarray(), columns=ohe.get_feature_names_out())

# Concatenate the encoded features with the original DataFrame (excluding the original categorical columns)
df_encoded = pd.concat([df.drop(categorical_cols, axis=1), encoded_df], axis=1)


# columns to keep.
selected_columns = ['Education Level_Associate Degree', "Education Level_Bachelor's Degree",
       'Education Level_High School', "Education Level_Master's Degree",
       'Education Level_PhD', 'Employment Status_Employed',
```

```python
        'Employment Status_Unemployed', 'Dietary Habits_Healthy',
        'Dietary Habits_Moderate', 'Dietary Habits_Unhealthy',
        'Age Category_Adult', 'Age Category_Senior', 'Age Category_Young Adult',
        'Sleep Patterns_Fair', 'Sleep Patterns_Good', 'Sleep Patterns_Poor',
        'Alcohol Consumption_High', 'Alcohol Consumption_Low',
        'Alcohol Consumption_Moderate', 'Family History of Depression_No',
        'Family History of Depression_Yes', 'Income Category_High',
        'Income Category_Low', 'Income Category_Medium',
        'Income Category_Very High', 'Income Category_Very Low']

# Split the updated DataFrame into features (X) and target (y)
# Drop columns that are not in the list
X_encoded = df_encoded[selected_columns]
y = df_encoded['History of Mental Illness']  # Target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.25, random_state=324)

# List of models to compare with class weights for imbalance
models = {
    "Logistic Regression": LogisticRegression(class_weight='balanced', max_iter=1000, random_state=4322),
    "Decision Tree": DecisionTreeClassifier(class_weight='balanced', random_state=1234),
    "Random Forest": RandomForestClassifier(class_weight='balanced', n_estimators=100, random_state=4165),
    "K-Nearest Neighbors": KNeighborsClassifier(),
    "Extra Trees": ExtraTreesClassifier(class_weight='balanced', n_estimators=100, random_state=151617)
}

# DataFrame to store results
results_df = pd.DataFrame(columns=['Model', 'Class', 'Accuracy', 'Precision', 'Recall', 'F1-Score'])

# Loop through models, train, and evaluate
for model_name, model in models.items():
    # Train the model
    model.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = model.predict(X_test)

    # Evaluate the model
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average=None, zero_division=1)  # Separate precision for each class
    recall = recall_score(y_test, y_pred, average=None, zero_division=1)  # Separate recall for each class
```

```python
    f1 = f1_score(y_test, y_pred, average=None, zero_division=1)  # Separate F1 for each class

    # Append the results for class 'No' (first class)
    results_df = pd.concat([results_df, pd.DataFrame({
        'Model': [model_name],
        'Class': ['No'],
        'Accuracy': [accuracy],
        'Precision': [precision[0]],  # Precision for 'No'
        'Recall': [recall[0]],        # Recall for 'No'
        'F1-Score': [f1[0]]           # F1-score for 'No'
    })], ignore_index=True)

    # Append the results for class 'Yes' (second class)
    results_df = pd.concat([results_df, pd.DataFrame({
        'Model': [model_name],
        'Class': ['Yes'],
        'Accuracy': [accuracy],
        'Precision': [precision[1]],  # Precision for 'Yes'
        'Recall': [recall[1]],        # Recall for 'Yes'
        'F1-Score': [f1[1]]           # F1-score for 'Yes'
    })], ignore_index=True)

# Display the results
display(results_df)

print ('\n--------------------------\n--------------------------\n')

for model_name, model in models.items():
    y_pred = model.predict(X_test)
    print('------------------\n')
    print(f"Confusion Matrix for {model_name}:")

    # Calculate the confusion matrix
    print(f"Confusion Matrix Ratios for {model_name} (Proportion of Total Samples):")
    display(calculate_confusionMatrix(y_test, y_pred))
```

```
C:\Users\abhis\AppData\Local\Temp\ipykernel_29264\2529503076.py:70: FutureWarning: The behavior of DataFrame concaten
ation with empty or all-NA entries is deprecated. In a future version, this will no longer exclude empty or all-NA co
lumns when determining the result dtypes. To retain the old behavior, exclude the relevant entries before the concat
operation.
  results_df = pd.concat([results_df, pd.DataFrame({
```

	Model	Class	Accuracy	Precision	Recall	F1-Score
0	Logistic Regression	No	0.590747	0.752627	0.617874	0.678626
1	Logistic Regression	Yes	0.590747	0.372520	0.527651	0.436718
2	Decision Tree	No	0.568405	0.754695	0.567210	0.647657
3	Decision Tree	Yes	0.568405	0.362012	0.571185	0.443156
4	Random Forest	No	0.571528	0.753291	0.575933	0.652780
5	Random Forest	Yes	0.571528	0.362675	0.561282	0.440633
6	K-Nearest Neighbors	No	0.642766	0.708844	0.830163	0.764722
7	K-Nearest Neighbors	Yes	0.642766	0.343732	0.206900	0.258314
8	Extra Trees	No	0.568434	0.754718	0.567238	0.647684
9	Extra Trees	Yes	0.568434	0.362039	0.571217	0.443186

```
--------------------------
--------------------------

------------------

Confusion Matrix for Logistic Regression:
Confusion Matrix Ratios for Logistic Regression (Proportion of Total Samples):
```

	Actual Yes	Actual No
Predicted Yes	0.16	0.27
Predicted No	0.14	0.43

```
------------------

Confusion Matrix for Decision Tree:
Confusion Matrix Ratios for Decision Tree (Proportion of Total Samples):
```

	Actual Yes	Actual No
Predicted Yes	0.17	0.3
Predicted No	0.13	0.4

```
------------------

Confusion Matrix for Random Forest:
Confusion Matrix Ratios for Random Forest (Proportion of Total Samples):
```

	Actual Yes	Actual No
Predicted Yes	0.17	0.3
Predicted No	0.13	0.4

```
------------------

Confusion Matrix for K-Nearest Neighbors:
Confusion Matrix Ratios for K-Nearest Neighbors (Proportion of Total Samples):
```

	Actual Yes	Actual No
Predicted Yes	0.06	0.12
Predicted No	0.24	0.58

```
------------------

Confusion Matrix for Extra Trees:
Confusion Matrix Ratios for Extra Trees (Proportion of Total Samples):
```

	Actual Yes	Actual No
Predicted Yes	0.17	0.3
Predicted No	0.13	0.4

Question 3:

What are the limitations of your chosen approach? How can you improve the performance of your model?

Solution:

The chosen approach could have the following limnitations:

- Socioeconomic and Demographic Bias:
  - Feature selection can be improved by thorough analysis.
  - Utilizing models that are aware of this bias and use methods to reduce or mitigate it.
- Simple Decision Boundaries or Linear models:
  - Decision Trees and Logistic regression often create simple boundaries.
  - They might not be conducive ot capturing complicated relationships in the dataset.
  - Using non-linear models such as neural networks could be a potential solution.
- Feature representation and selection:
  - One-hot encoding could inflate the features with redundant columns, this is noticeable in categorical features that have numerous sub classes.
  - Mitigation is possibl with methods such as target encoding or embeddings.
- OVerfitting risks:
  - Decision tree models usually suffer the risk of overfitting when large on large dataset of onehot encoded features.
  - Cross validation and regulatization can be used for further hyper-parameter tuning and to reduce overfitting.

In [ ]: