In [1]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```python
# Load the dataset
df = pd.read_csv('../data/depression_data.csv')
df.head()
```

Out[2]:

	Name	Age	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	
0	Christine Barker	31	Married	Bachelor's Degree	2	Non-smoker	Active	Unemployed	
1	Jacqueline Lewis	55	Married	High School	1	Non-smoker	Sedentary	Employed	
2	Shannon Church	78	Widowed	Master's Degree	1	Non-smoker	Sedentary	Employed	1
3	Charles Jordan	58	Divorced	Master's Degree	3	Non-smoker	Moderate	Unemployed	
4	Michael Rich	18	Single	High School	0	Non-smoker	Sedentary	Unemployed	

In [3]:

```python
# Overview of the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 413768 entries, 0 to 413767
Data columns (total 16 columns):
 #   Column                        Non-Null Count   Dtype  
---  ------                        --------------   -----  
 0   Name                          413768 non-null  object 
 1   Age                           413768 non-null  int64  
 2   Marital Status                413768 non-null  object 
 3   Education Level               413768 non-null  object 
 4   Number of Children            413768 non-null  int64  
 5   Smoking Status                413768 non-null  object 
 6   Physical Activity Level       413768 non-null  object 
 7   Employment Status             413768 non-null  object 
 8   Income                        413768 non-null  float64
 9   Alcohol Consumption           413768 non-null  object 
 10  Dietary Habits                413768 non-null  object 
 11  Sleep Patterns                413768 non-null  object 
 12  History of Mental Illness     413768 non-null  object 
 13  History of Substance Abuse    413768 non-null  object 
 14  Family History of Depression  413768 non-null  object 
 15  Chronic Medical Conditions    413768 non-null  object 
dtypes: float64(1), int64(2), object(13)
memory usage: 50.5+ MB
```

Printing Summary Stats

In [4]:

```python
df.describe()
```

Out[4]:

	Age	Number of Children	Income
count	413768.000000	413768.000000	413768.000000
mean	49.000713	1.298972	50661.707971
std	18.158759	1.237054	40624.100565
min	18.000000	0.000000	0.410000
25%	33.000000	0.000000	21001.030000
50%	49.000000	1.000000	37520.135000
75%	65.000000	2.000000	76616.300000
max	80.000000	4.000000	209995.220000

Checking for missing values

In [5]:

```python
df.isnull().sum()
```

Out[5]:

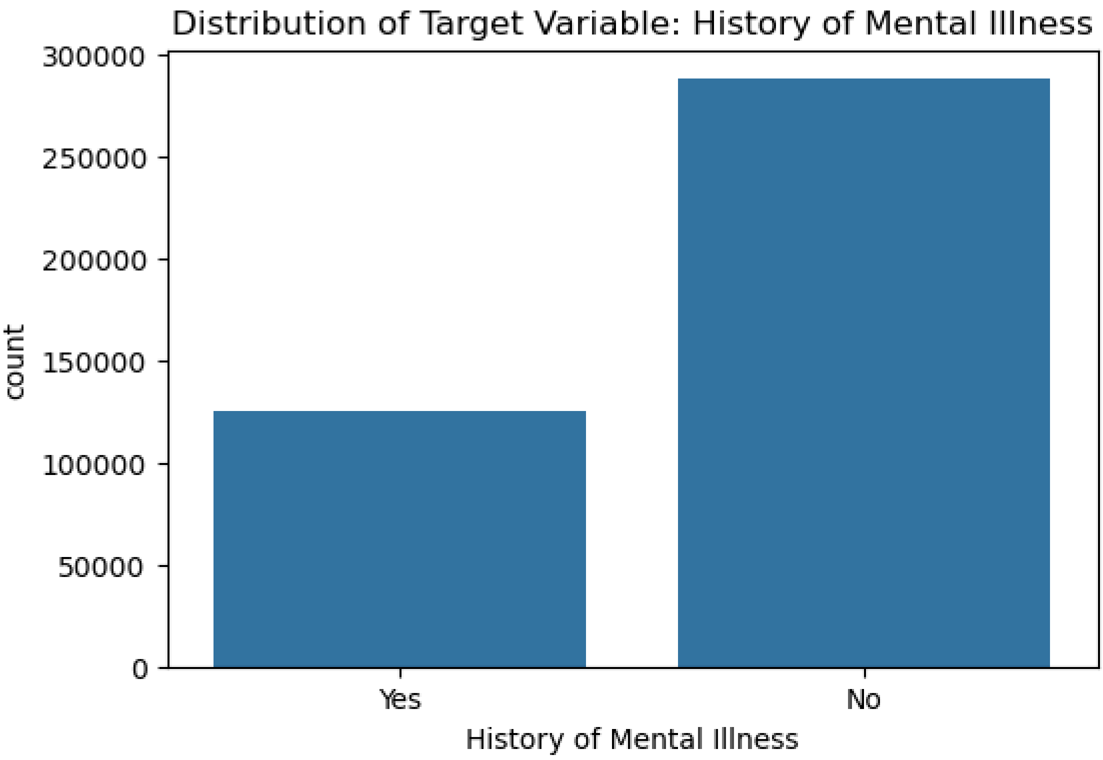
```
Name                            0
Age                             0
Marital Status                  0
Education Level                 0
Number of Children              0
Smoking Status                  0
Physical Activity Level         0
Employment Status               0
Income                          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
dtype: int64
```

There are no missing values in any columns. This indicates that the dataset is complete, and no imputation is required. This is advantageous for model building since we can directly proceed with further analysis without worrying about filling gaps in the data.

Distribution Target Variables (History of Mental Illness)

In [6]:

```python
plt.figure(figsize=(6, 4))
sns.countplot(data=df, x='History of Mental Illness')
plt.title('Distribution of Target Variable: History of Mental Illness')
plt.show()
```

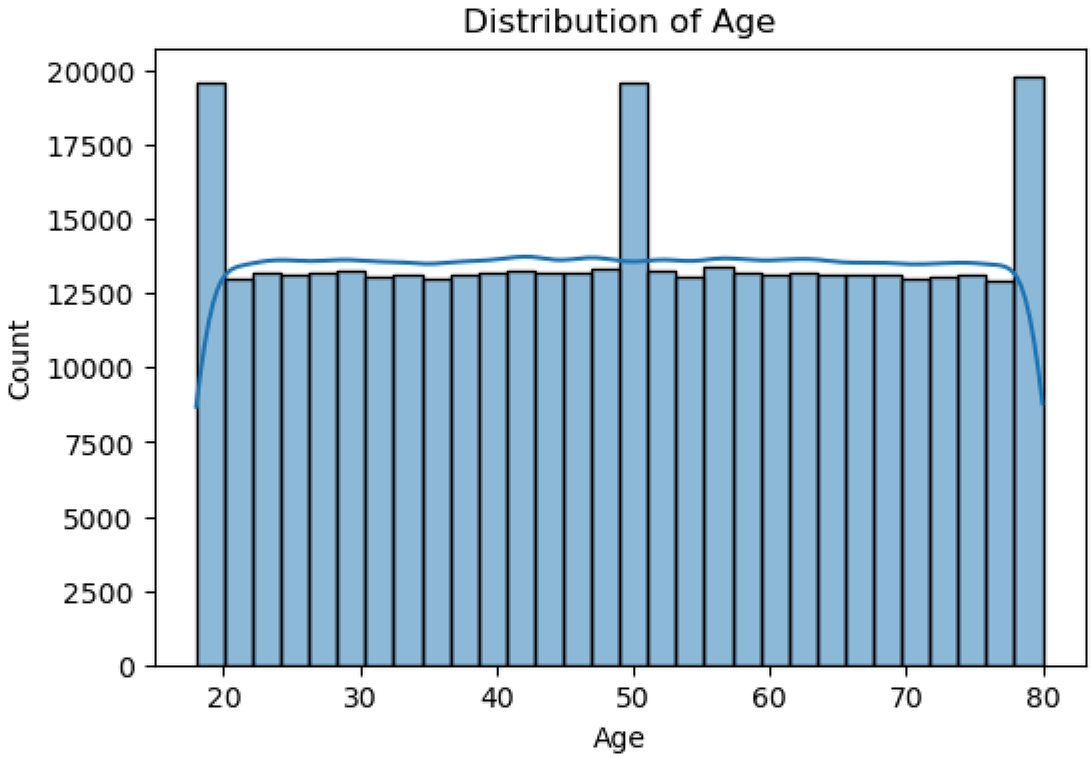


- Observation: The target variable, "History of Mental Illness," shows a clear imbalance, with significantly more individuals having no history of mental illness compared to those who do. The distribution shows that approximately 70% of the data falls under the 'No' category, while only about 30% of the individuals have a history of mental illness.
- Implication: The imbalance in the target class suggests that a resampling technique like SMOTE or class weighting might be needed during model training to avoid bias toward the majority class. This could also affect the evaluation metrics such as accuracy, and metrics like F1-score, precision, and recall may be more appropriate for measuring model performance.

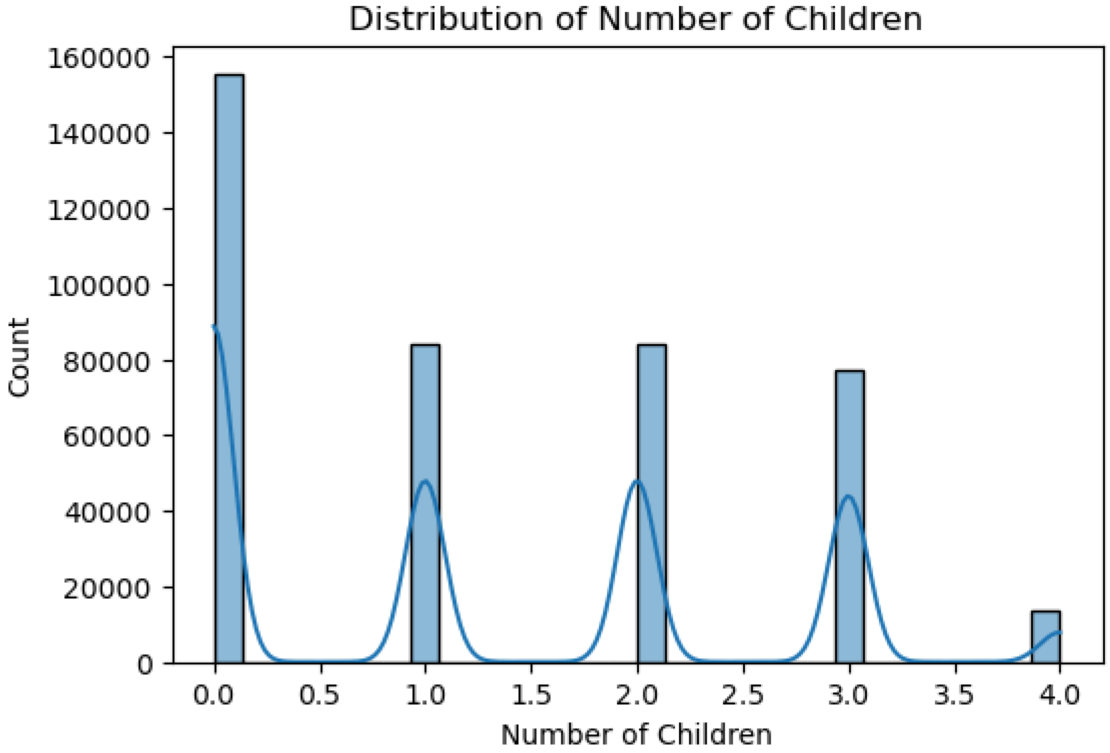
Distribution of Numerical Variables

In [7]:

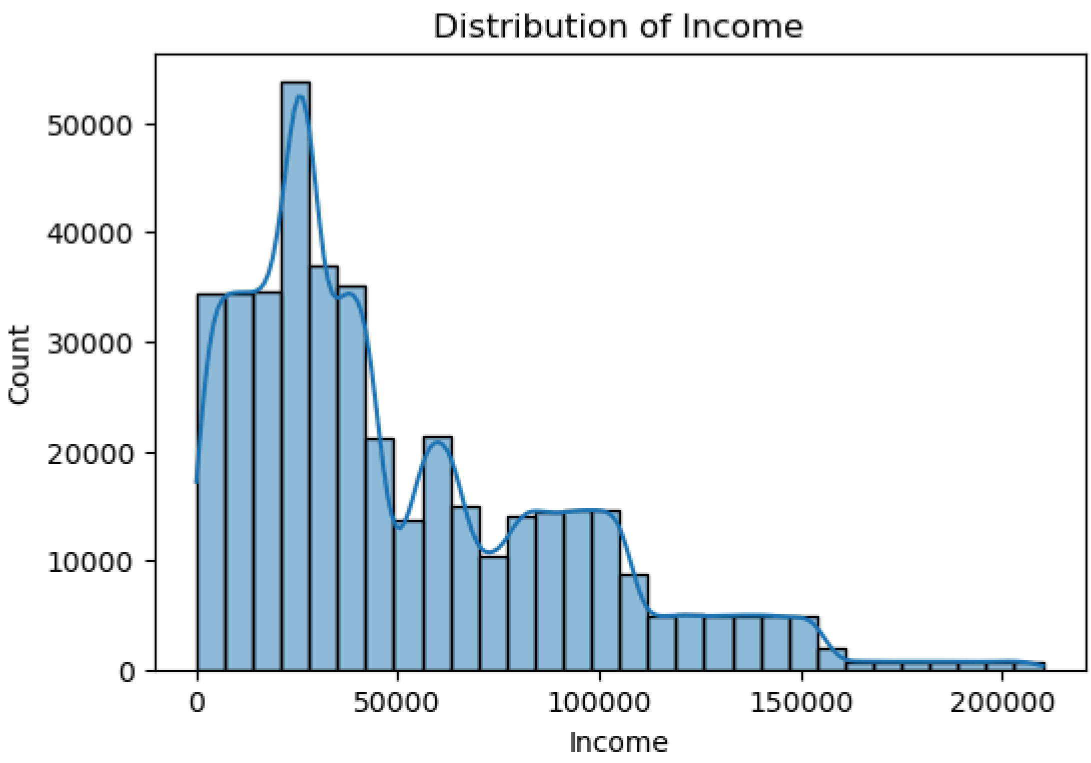
```
numerical_cols = ['Age', 'Number of Children', 'Income']

for col in numerical_cols:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[col], bins=30, kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()
```



Distribution of Age



Distribution of Number of Children

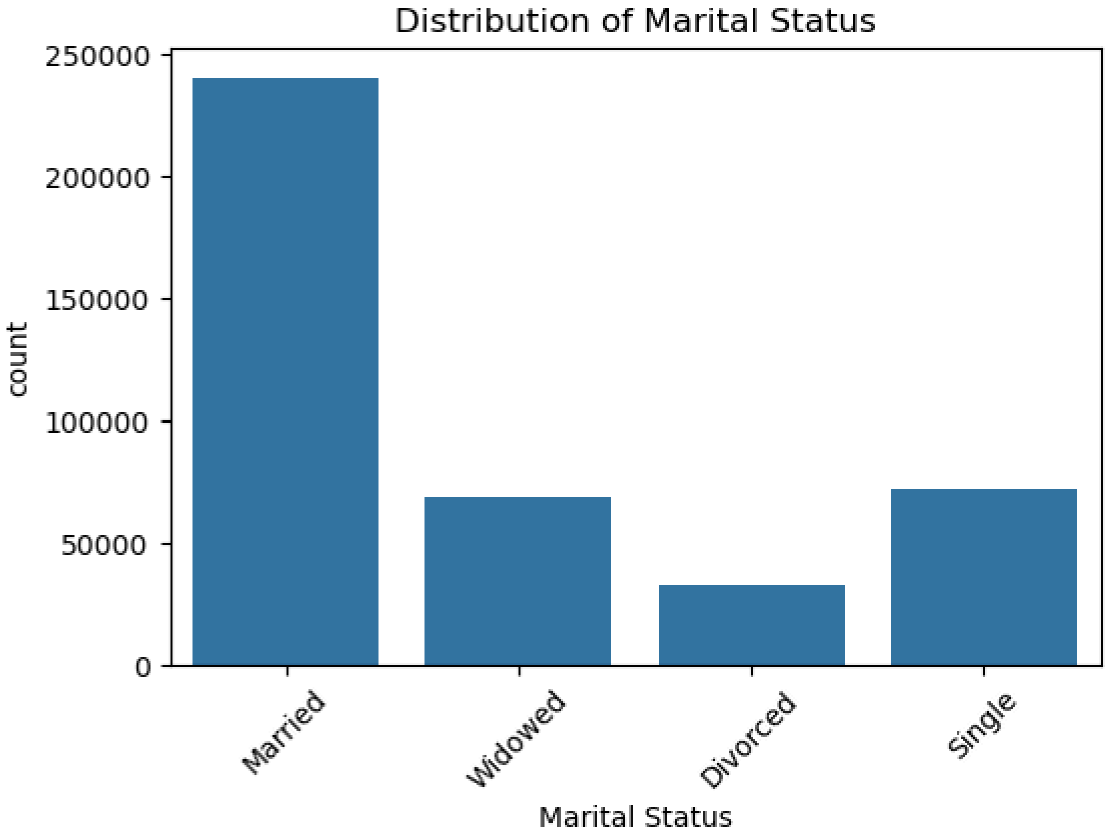


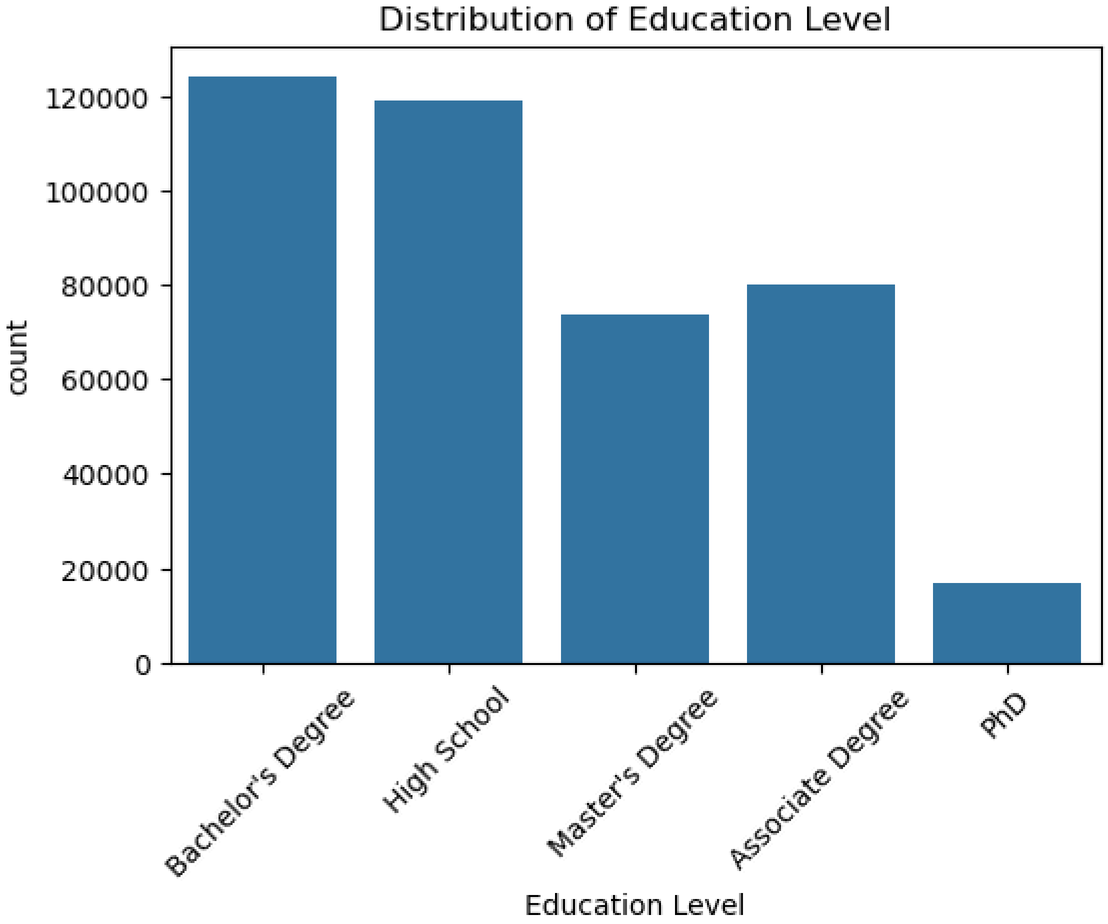
- Age: The age distribution is fairly uniform with some noticeable spikes around certain ages (e.g., 20, 50, and 80). The data covers a wide range of ages, from 18 to 80.
  - Insight: The fairly uniform distribution suggests that the dataset is well-balanced across different age groups. The spikes may indicate sampling artifacts or trends within specific age brackets, possibly tied to life events.
- Income: The income distribution is right-skewed, with most individuals earning between 0 and 50,000. There are a few high-income outliers.
  - Insight: The right-skewed distribution of income indicates that most individuals in the dataset fall under low to moderate income brackets. The presence of outliers (very high incomes) may need to be accounted for during model training, either through transformation (e.g., log scaling) or outlier handling techniques.
- Number of Children: The number of children is also right-skewed, with a majority of individuals having 0 to 2 children.
  - Insight: Most individuals have either no children or 1-2 children. This suggests that large families are rare in this dataset.

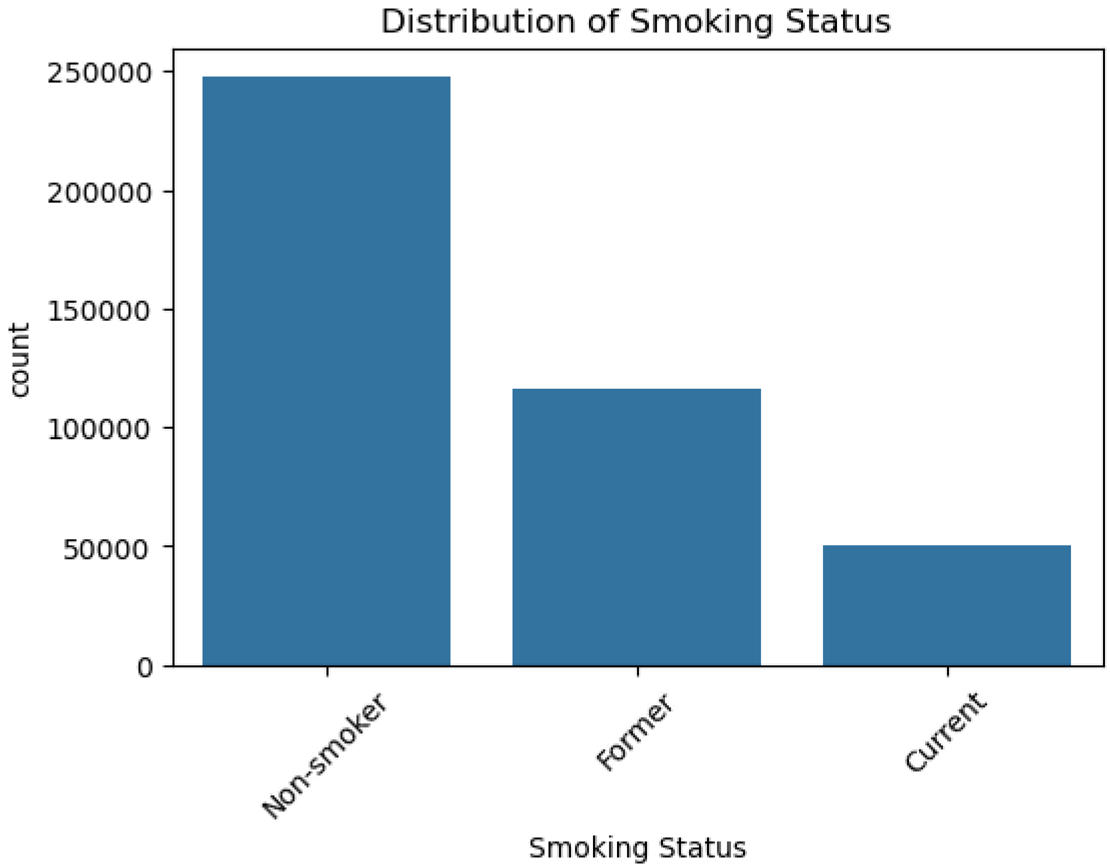
Distribution of Categorical variables

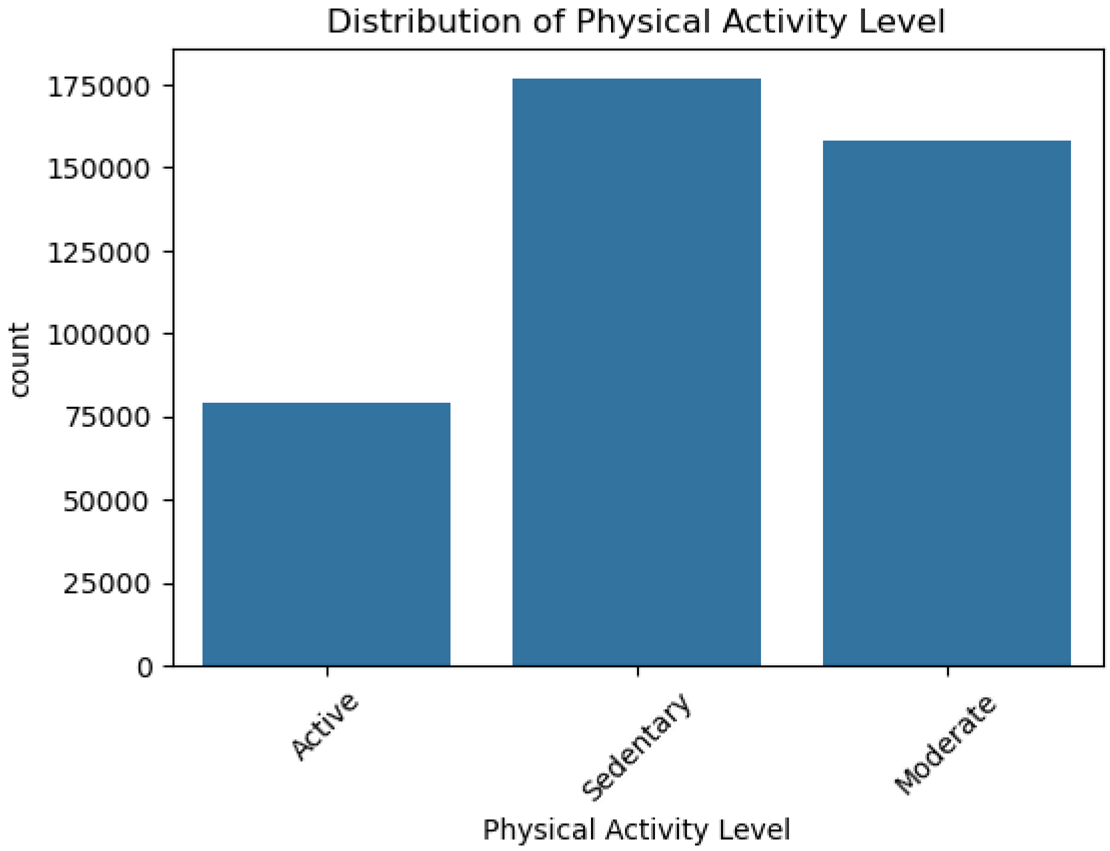
In [8]:

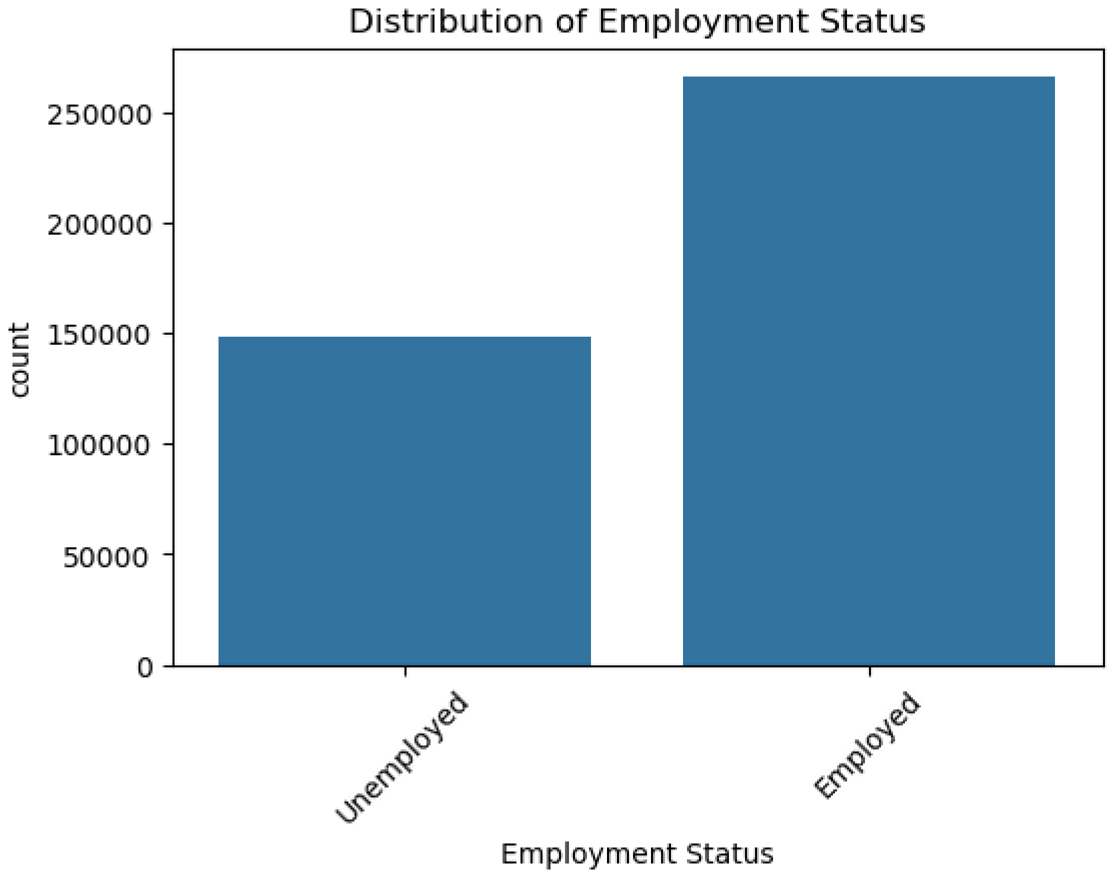
```
categorical_cols = ['Marital Status', 'Education Level', 'Smoking Status', 'Phys
                    'Employment Status', 'Alcohol Consumption', 'Dietary Habits'
                    'History of Substance Abuse', 'Family History of Depression'

# Bar plots for categorical variables
for col in categorical_cols:
    plt.figure(figsize=(6, 4))
    sns.countplot(data=df, x=col)
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.show()
```



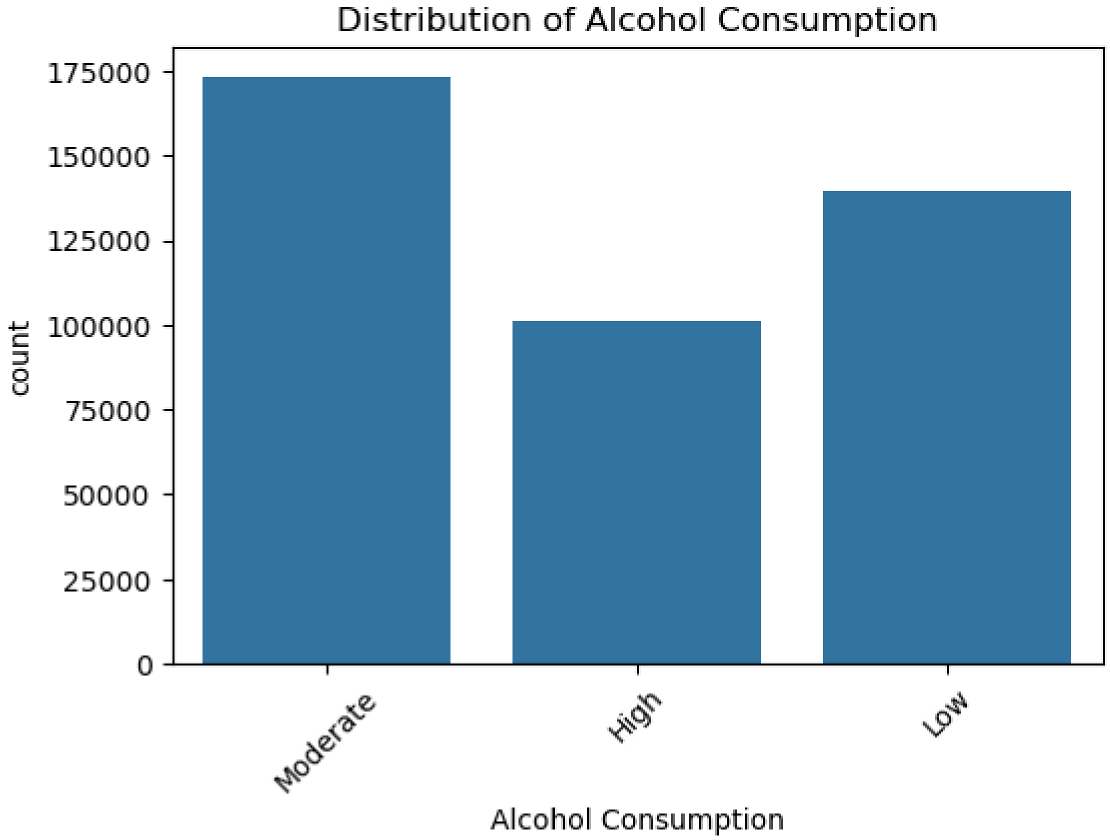



Distribution of Smoking Status
count
250000
200000
150000
100000
50000
0
Non-smoker
Former
Current
Smoking Status

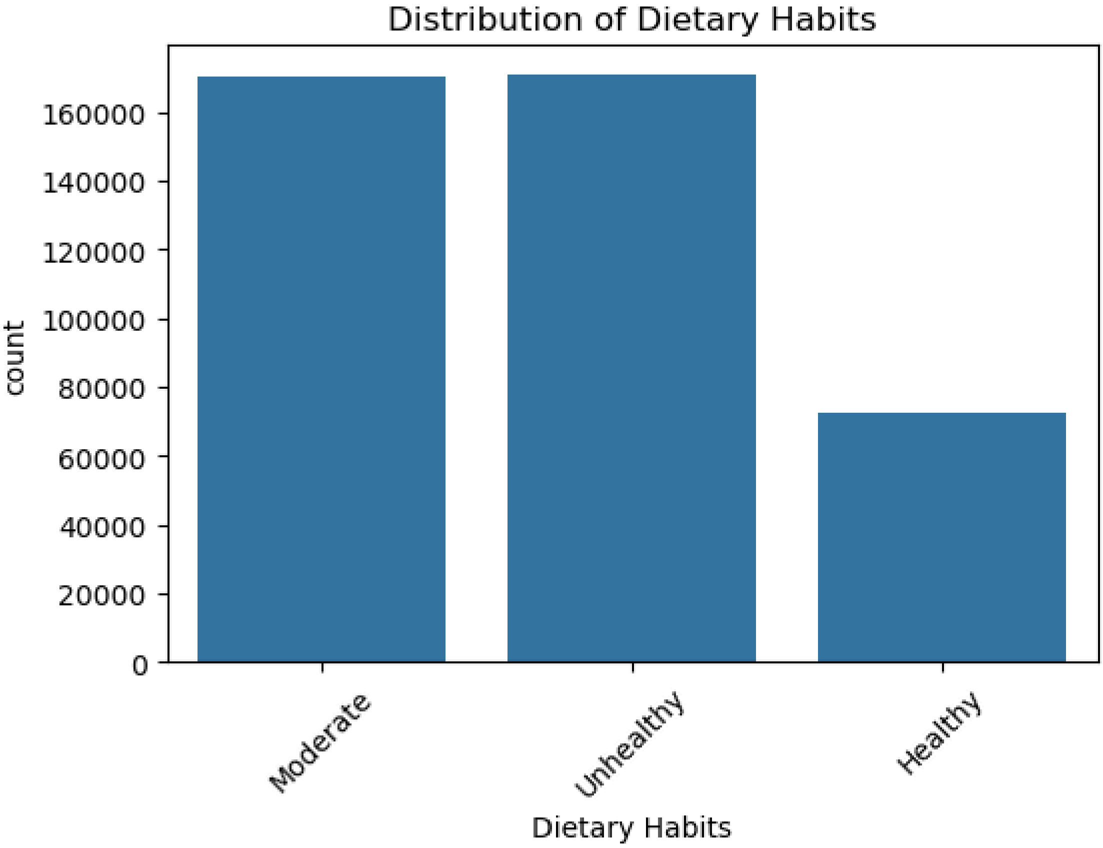

Distribution of Physical Activity Level
count
175000
150000
125000
100000
75000
50000
25000
0
Active
Sedentary
Moderate
Physical Activity Level

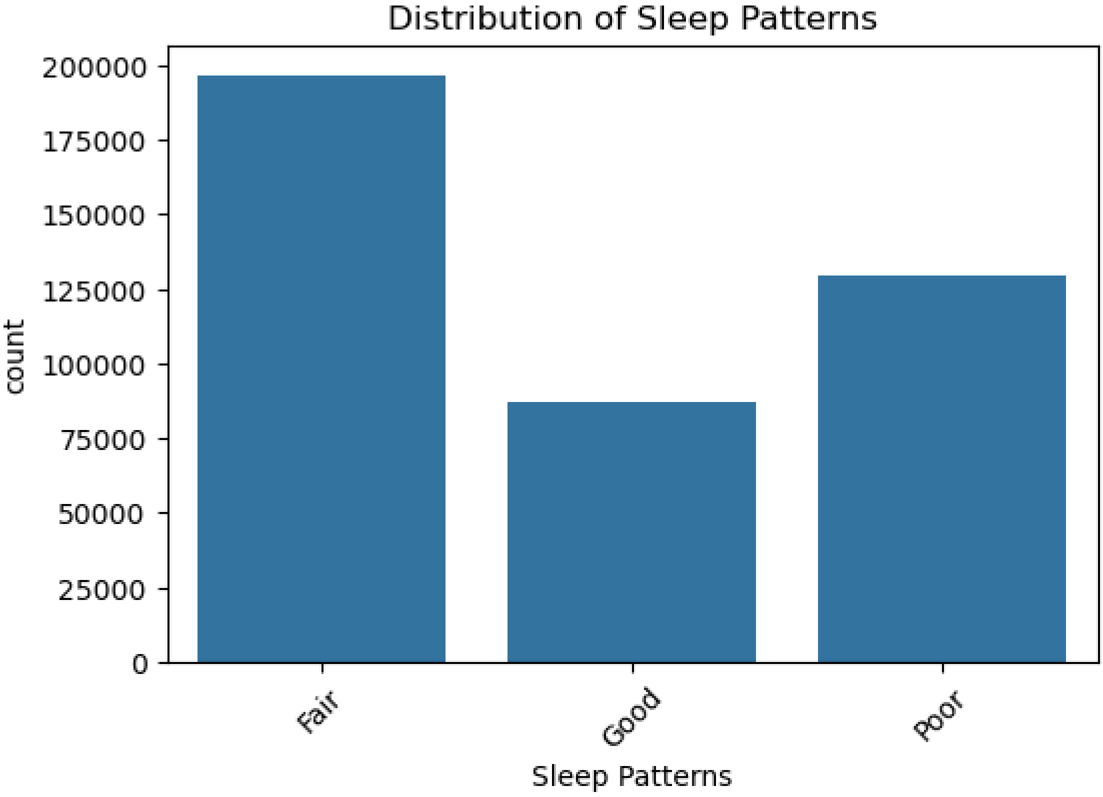


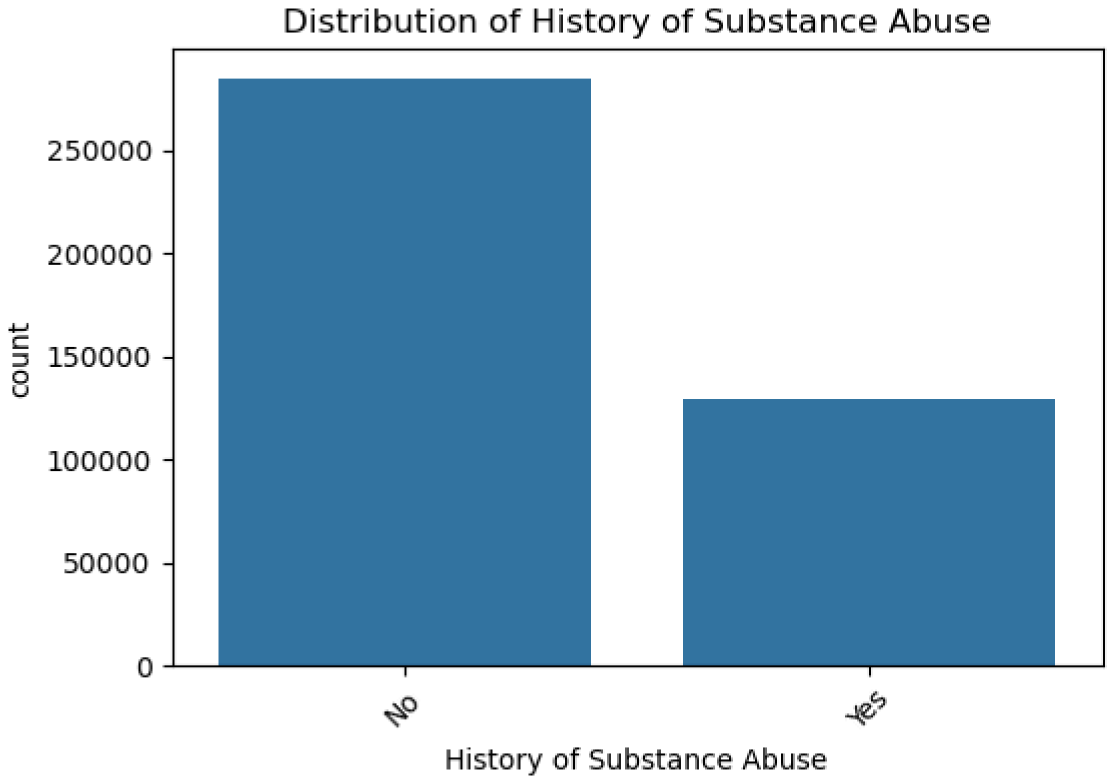
Distribution of Employment Status



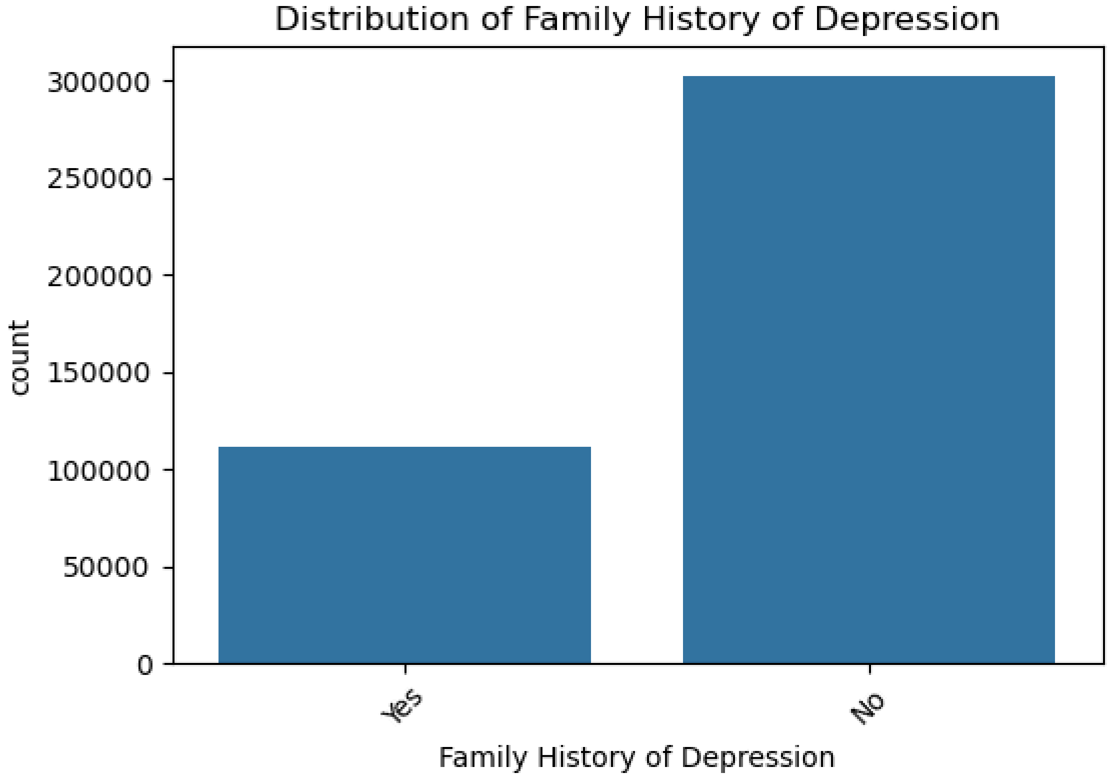
Distribution of Alcohol Consumption


Distribution of Dietary Habits
count
0
20000
40000
60000
80000
100000
120000
140000
160000
Moderate
Unhealthy
Healthy
Dietary Habits

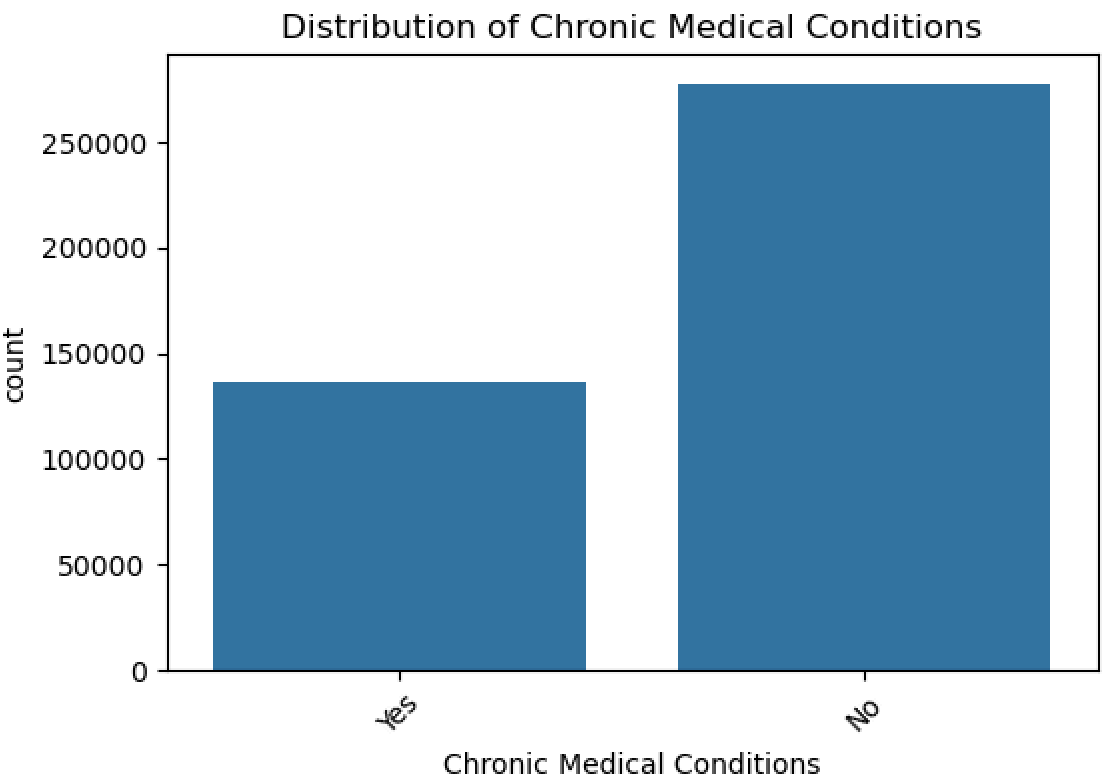

Distribution of Sleep Patterns
count
0
25000
50000
75000
100000
125000
150000
175000
200000
Fair
Good
Poor
Sleep Patterns



Distribution of History of Substance Abuse
count
0
50000
100000
150000
200000
250000
No
Yes
History of Substance Abuse



Distribution of Family History of Depression
count
0
50000
100000
150000
200000
250000
300000
Yes
No
Family History of Depression

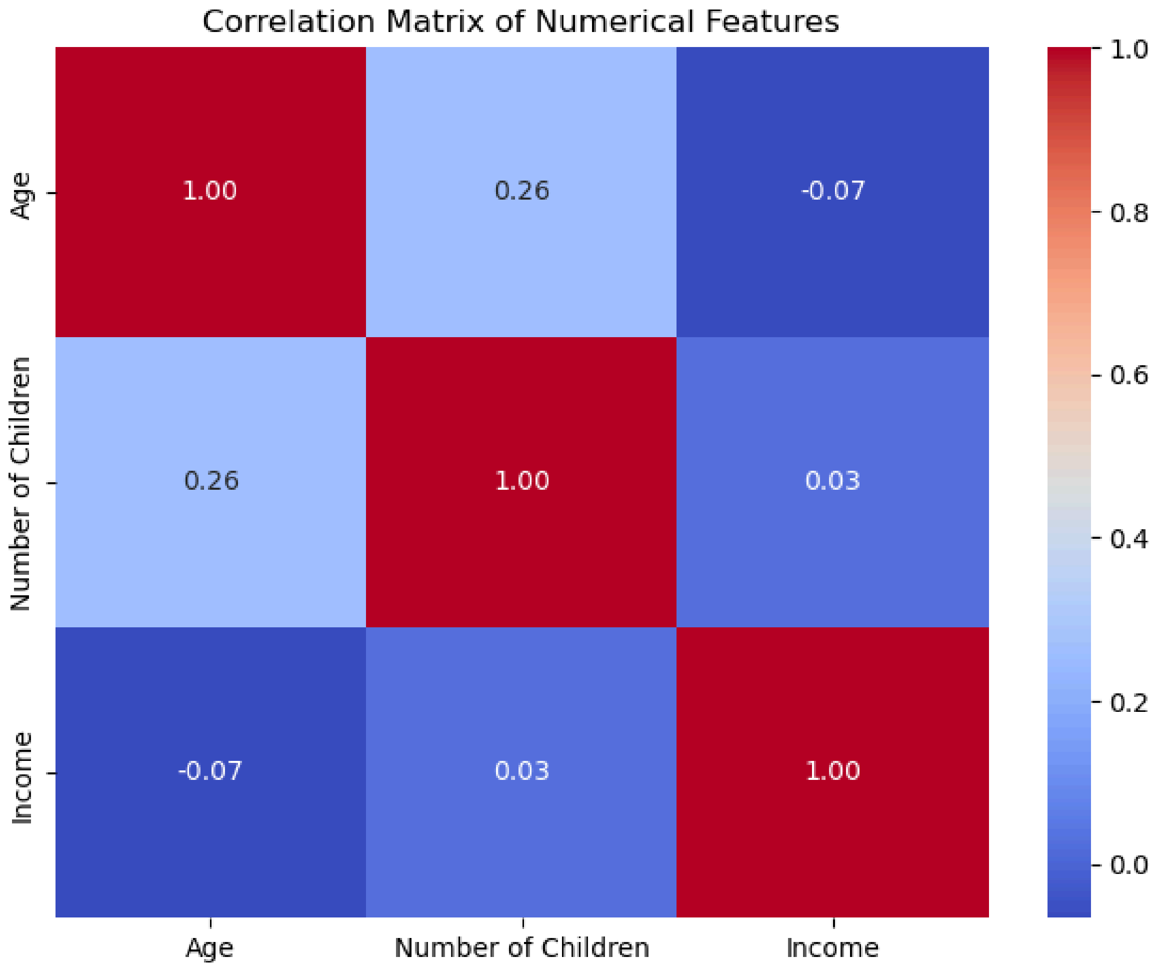


- Marital Status: The dataset is dominated by married individuals, followed by single, widowed, and divorced individuals.
    - Insight: Marital status could be an important factor influencing mental health, as individuals in stable relationships may experience different stressors compared to those who are single, divorced, or widowed.
- Education Level: A significant portion of individuals hold a Bachelor's degree or have completed high school, while fewer hold advanced degrees such as PhDs.
    - Insight: Education may play a role in mental health. For instance, higher education levels could correlate with stress from professional pressures, while lower levels could be tied to socioeconomic challenges.
- Smoking Status: Most individuals in the dataset are non-smokers, while a smaller proportion are former or current smokers.
    - Insight: Smoking status is often associated with mental health. Former or current smokers might experience different mental health challenges compared to non-smokers.
- Employment Status: There is a large portion of employed individuals compared to unemployed.
    - Insight: Employment status may be a strong predictor of mental health, as unemployment is often linked to stress and anxiety.

Correlation of Numerical Features

In [9]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(df[numerical_cols].corr(), annot=True, cmap='coolwarm', fmt='.2f')
```

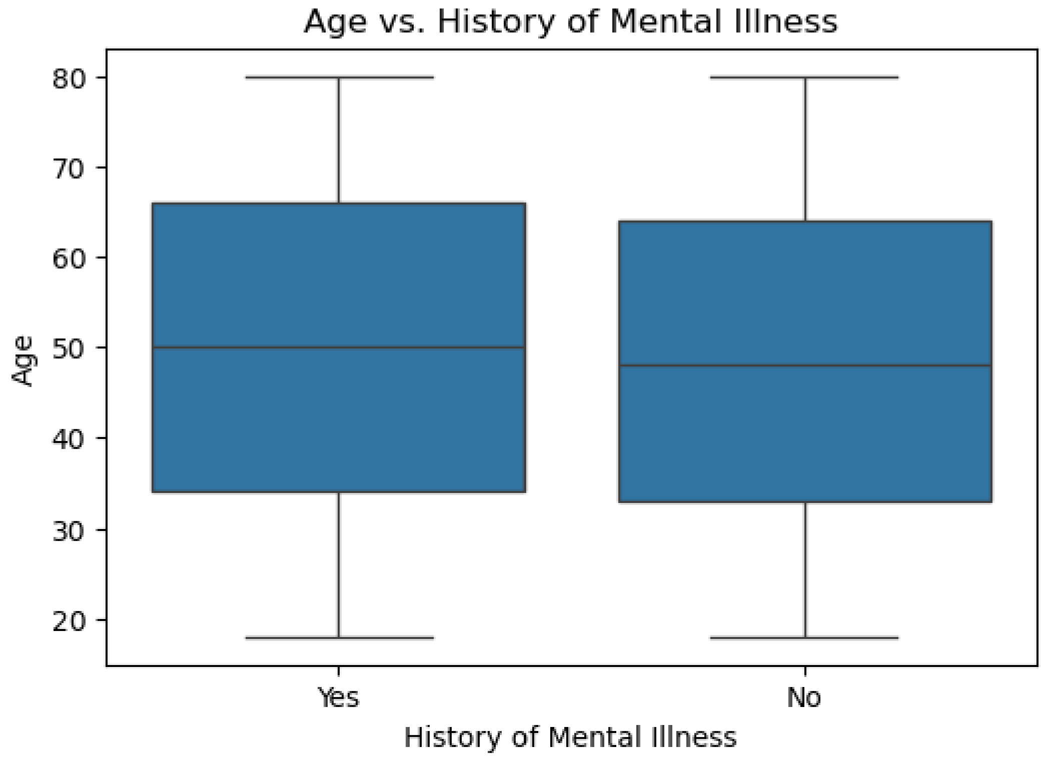
```
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```

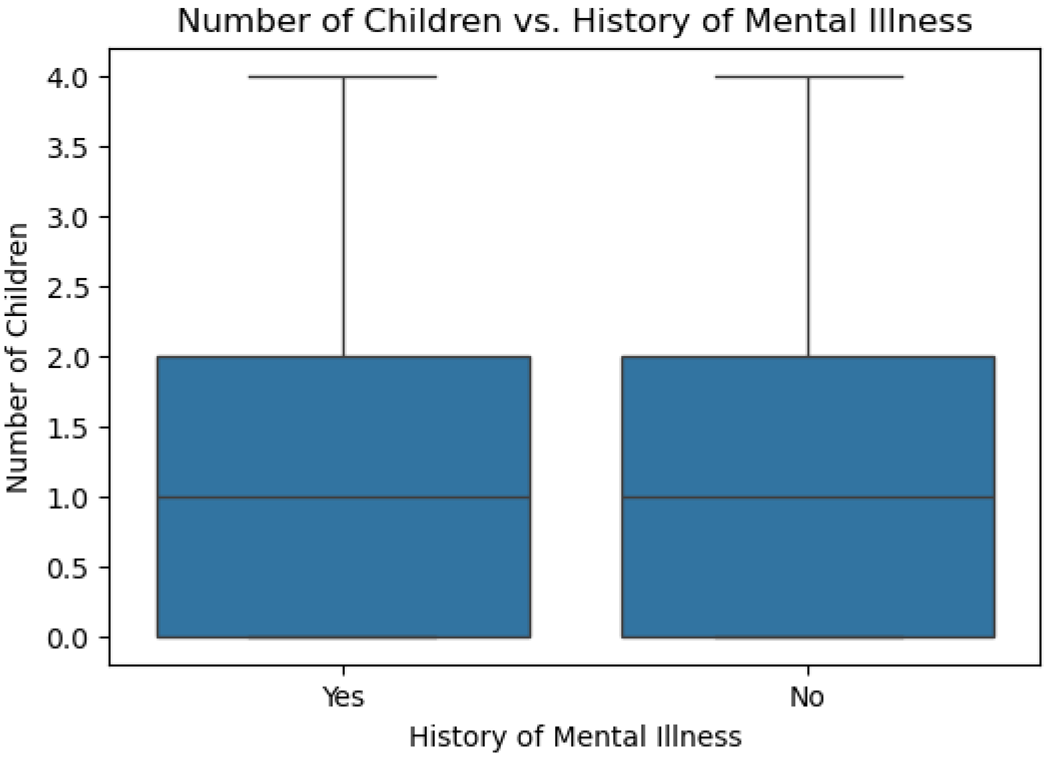


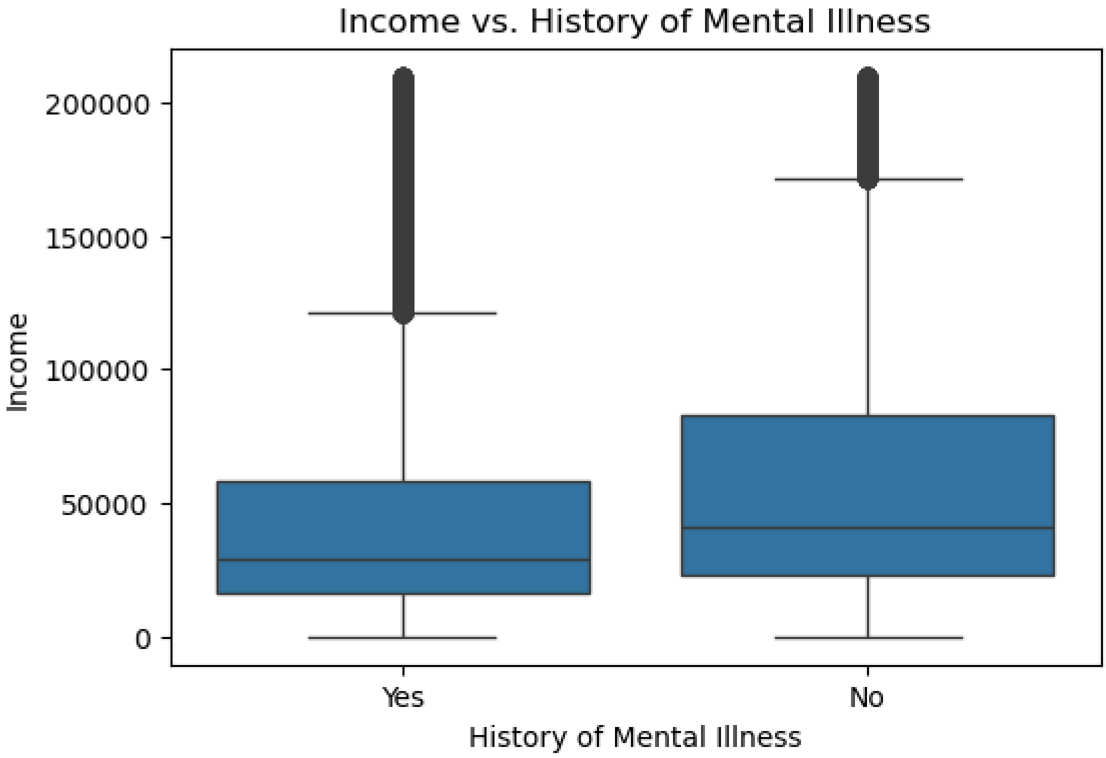
- The correlation heatmap shows minimal correlation between the numerical variables. Age has a slight positive correlation with the number of children, which is expected, as older individuals tend to have more children.
- Implication: Since there is no high correlation between numerical features, multicollinearity should not be an issue in the model.

Analysing relationships between numerical variables and target variables

```
In [10]: for col in numerical_cols:
             plt.figure(figsize=(6, 4))
             sns.boxplot(x='History of Mental Illness', y=col, data=df)
             plt.title(f'{col} vs. History of Mental Illness')
             plt.show()
```


Age vs. History of Mental Illness
Age
80
70
60
50
40
30
20
Yes
No
History of Mental Illness


Number of Children vs. History of Mental Illness
Number of Children
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Yes
No
History of Mental Illness



- Age vs. Mental Illness: There is no clear trend between age and mental illness, as both younger and older individuals are present in both categories.

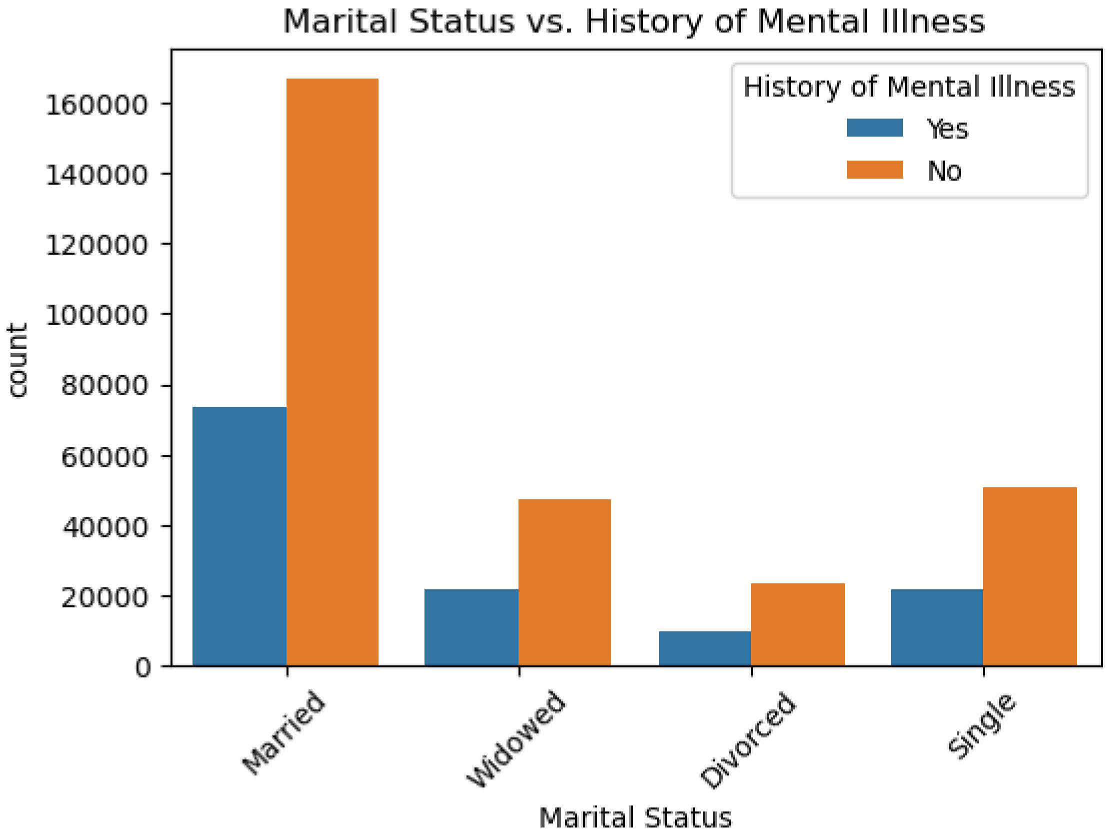
    - Insight: Age alone may not be a strong predictor of mental illness in this dataset. However, interactions with other variables (e.g., employment status or income) could reveal patterns.
- Income vs. Mental Illness: The boxplots suggest that individuals with a history of mental illness tend to have slightly lower incomes than those without. However, the distribution of income is fairly similar for both groups, with outliers present.

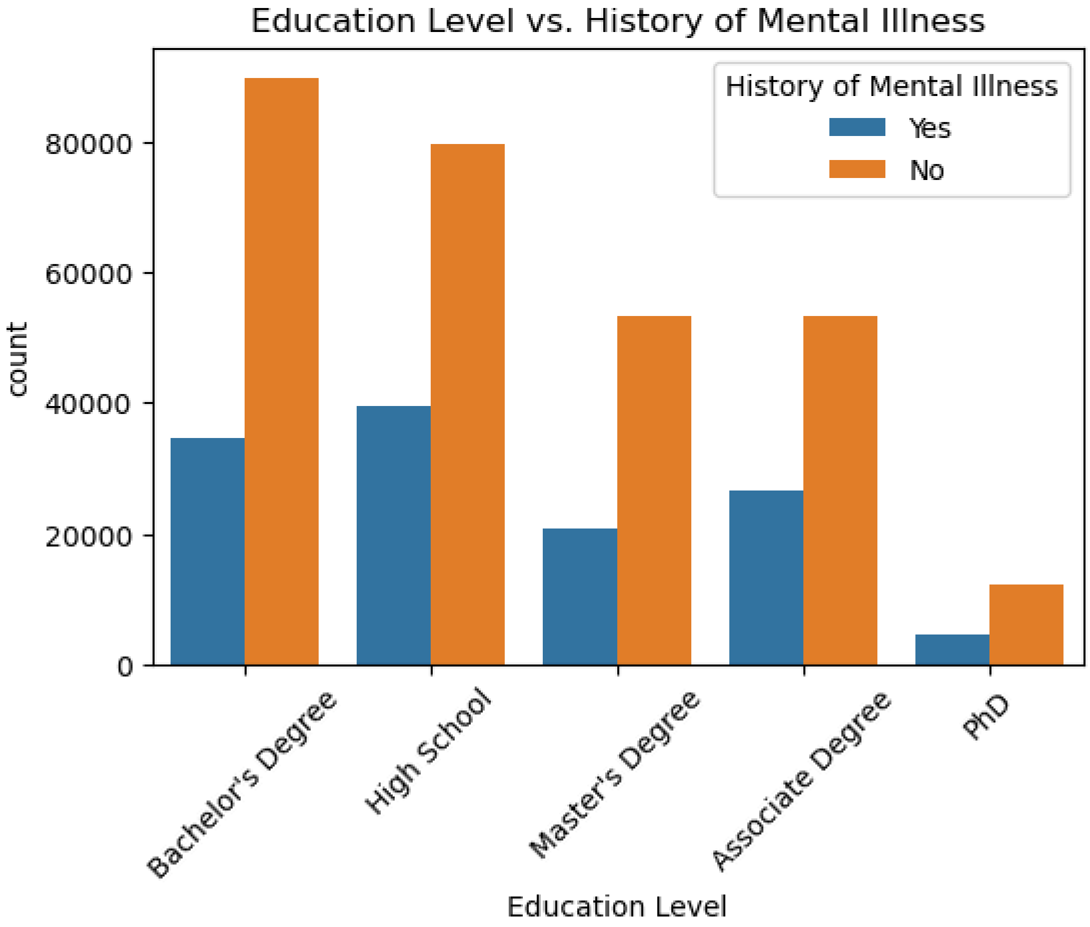
    - Insight: Lower income may be associated with mental health challenges, possibly due to financial stress or limited access to healthcare. The presence of income outliers indicates that high earners are rare in this dataset.
- Number of Children vs. Mental Illness: The number of children appears similar across both groups, suggesting that this feature may not have a strong direct effect on mental illness in this dataset.

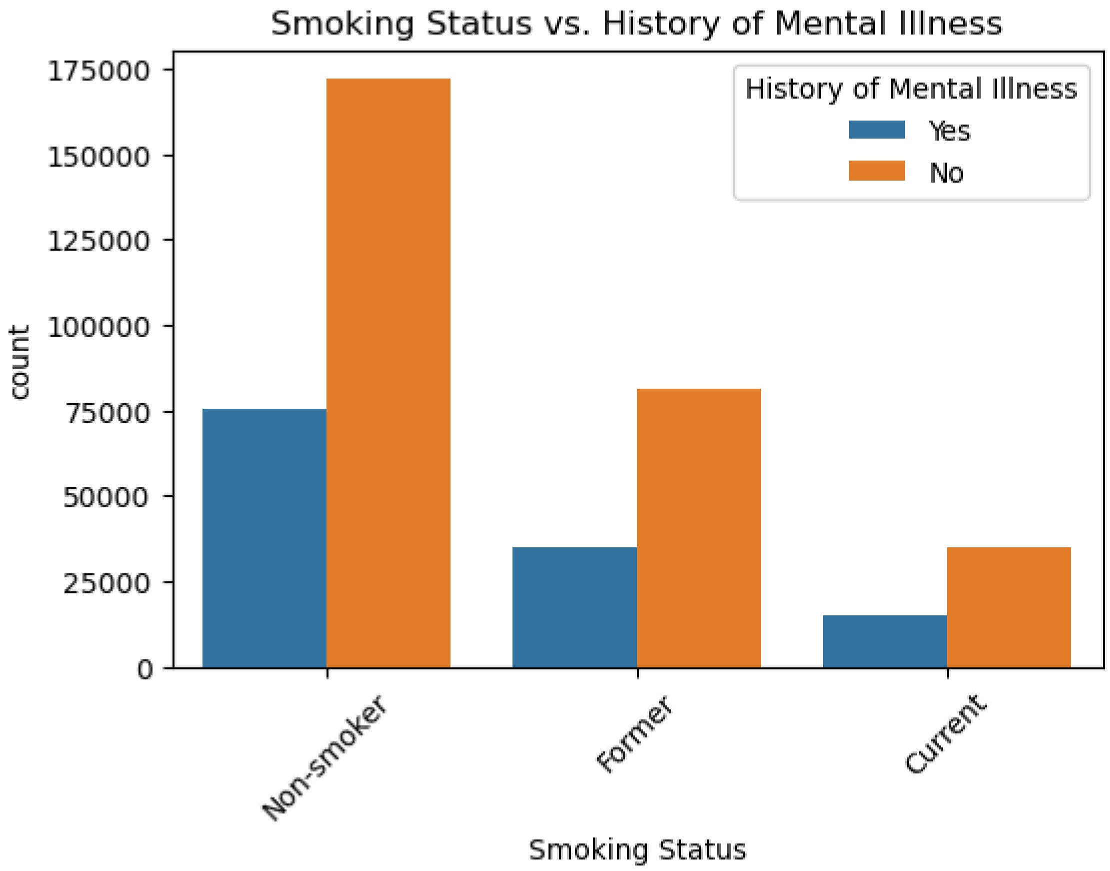
    - Insight: Having more children does not seem to correlate strongly with a history of mental illness.

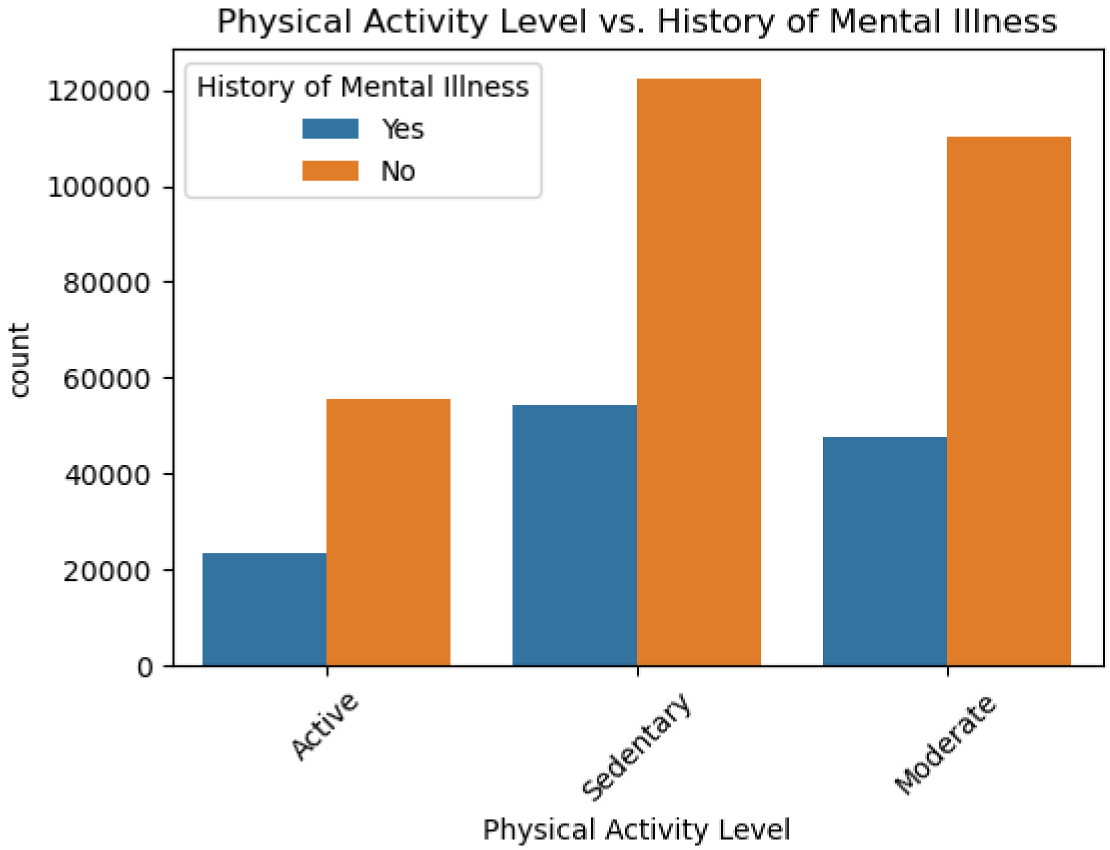
Analysing relationships between categorical variables and target variables

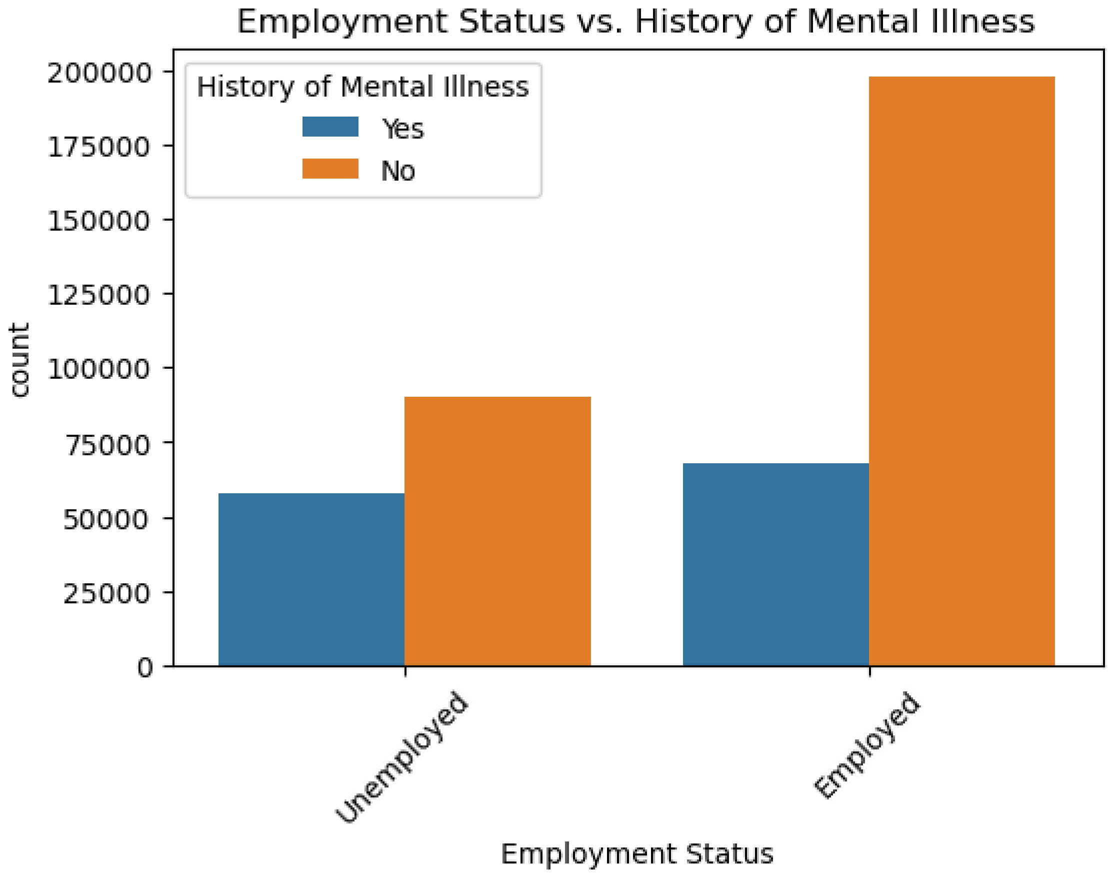
In [11]:
```
for col in categorical_cols:
    plt.figure(figsize=(6, 4))
    sns.countplot(data=df, x=col, hue='History of Mental Illness')
    plt.title(f'{col} vs. History of Mental Illness')
    plt.xticks(rotation=45)
    plt.show()
```

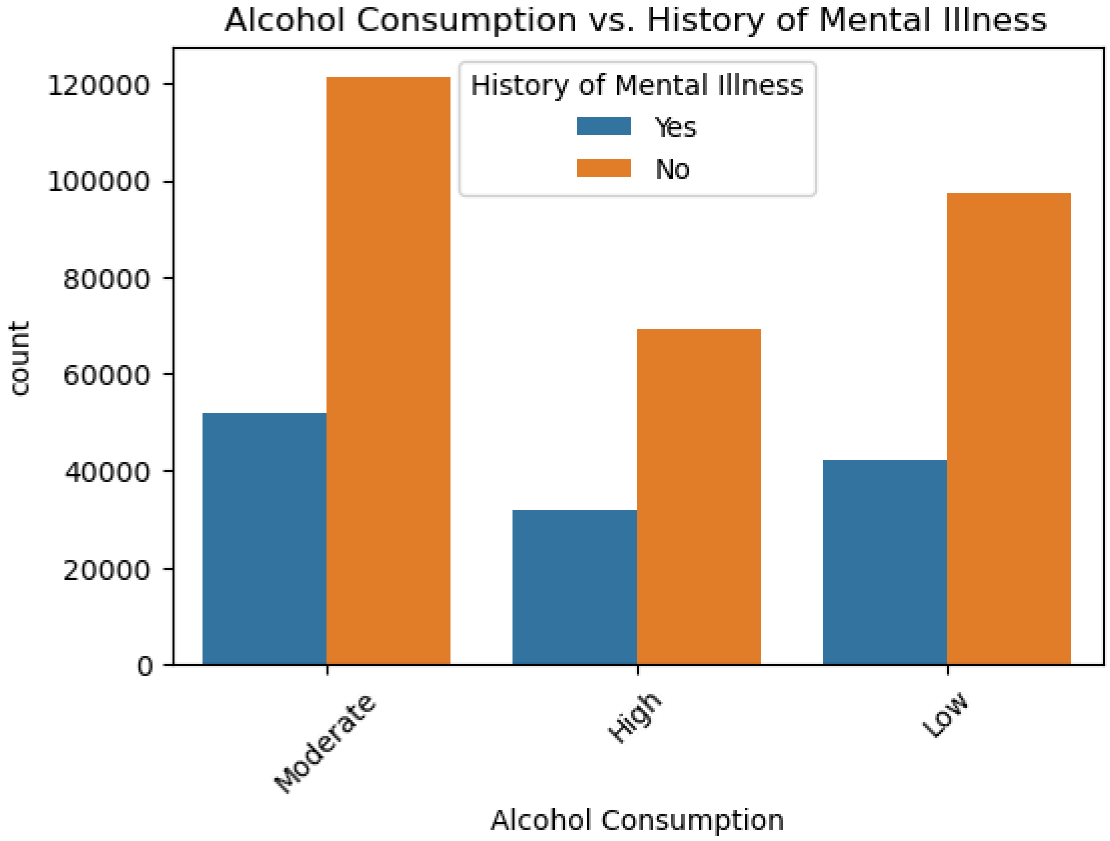

Marital Status vs. History of Mental Illness
History of Mental Illness
Yes
No
count
0
20000
40000
60000
80000
100000
120000
140000
160000
Married
Widowed
Divorced
Single
Marital Status

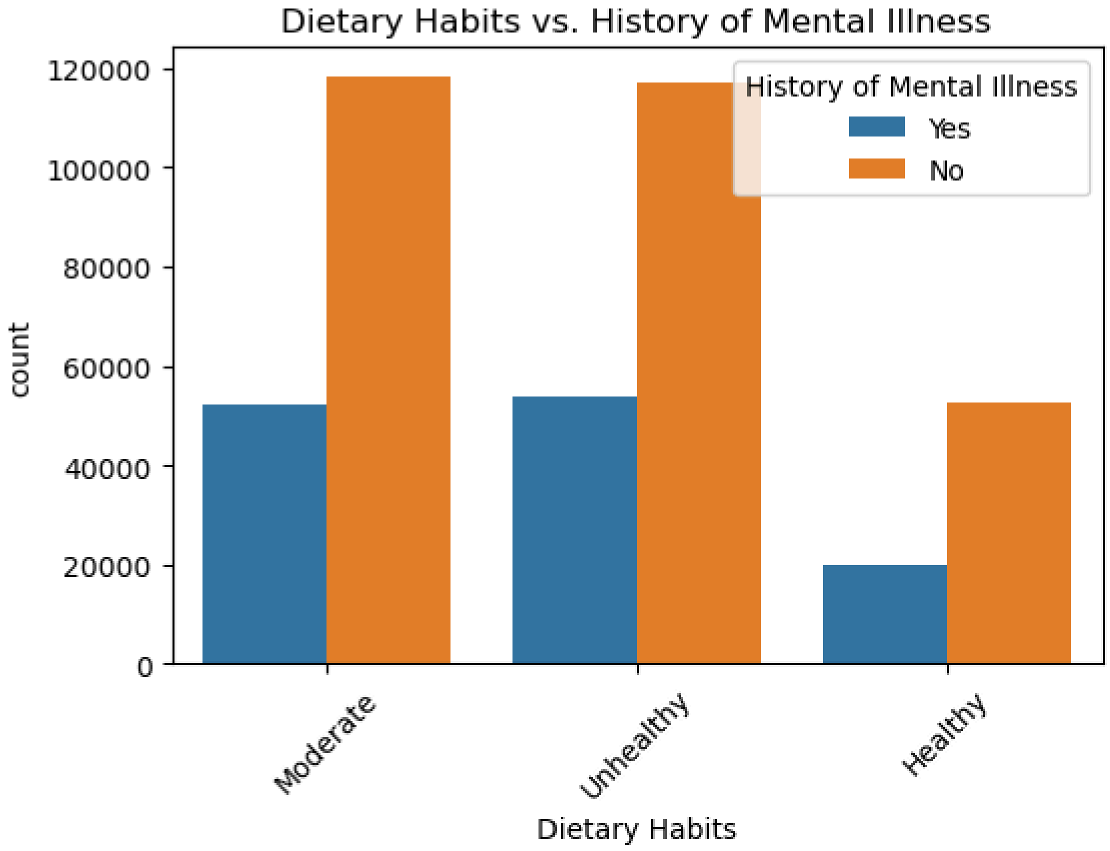

Education Level vs. History of Mental Illness
History of Mental Illness
Yes
No
count
0
20000
40000
60000
80000
Bachelor's Degree
High School
Master's Degree
Associate Degree
PhD
Education Level

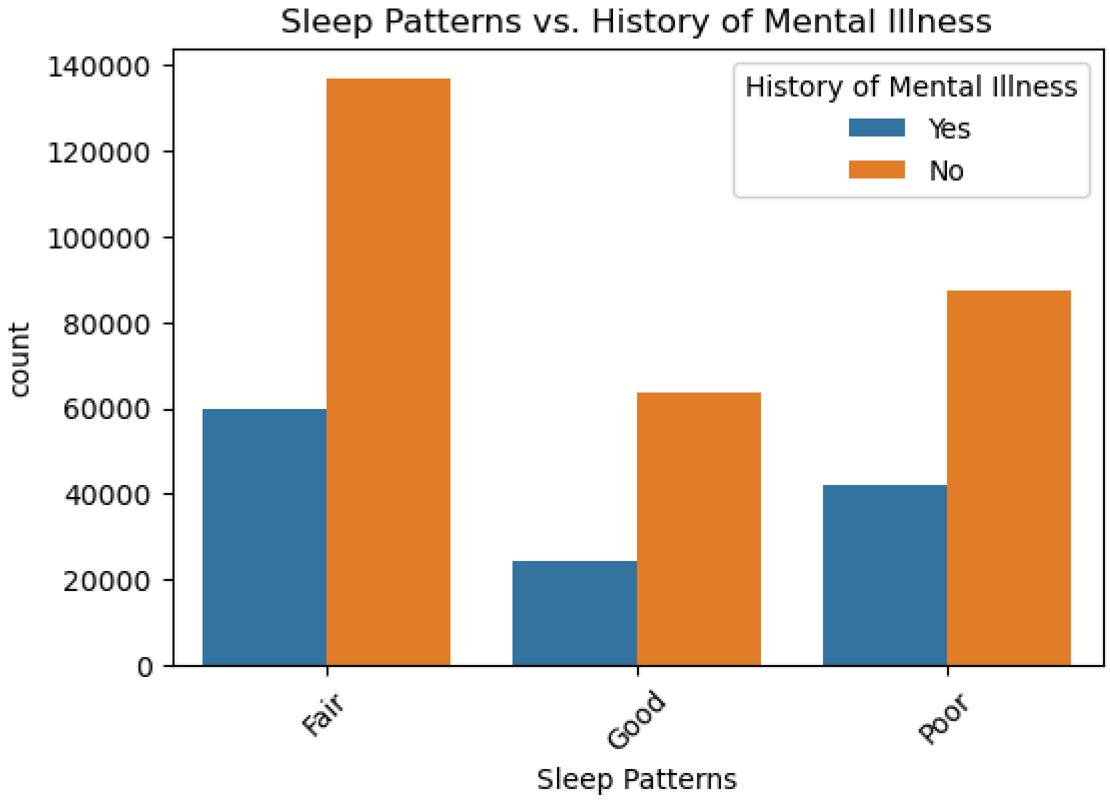

Smoking Status vs. History of Mental Illness
History of Mental Illness
Yes
No
count
175000
150000
125000
100000
75000
50000
25000
0
Non-smoker
Former
Current
Smoking Status

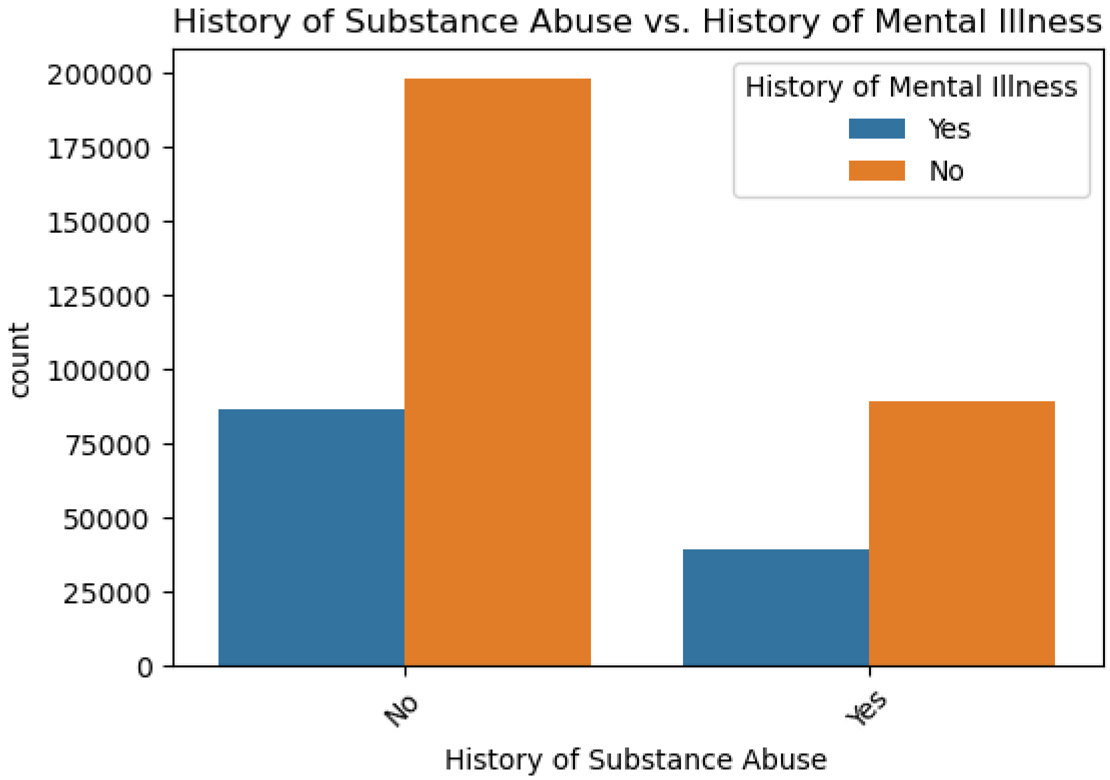

Physical Activity Level vs. History of Mental Illness
History of Mental Illness
Yes
No
count
120000
100000
80000
60000
40000
20000
0
Active
Sedentary
Moderate
Physical Activity Level

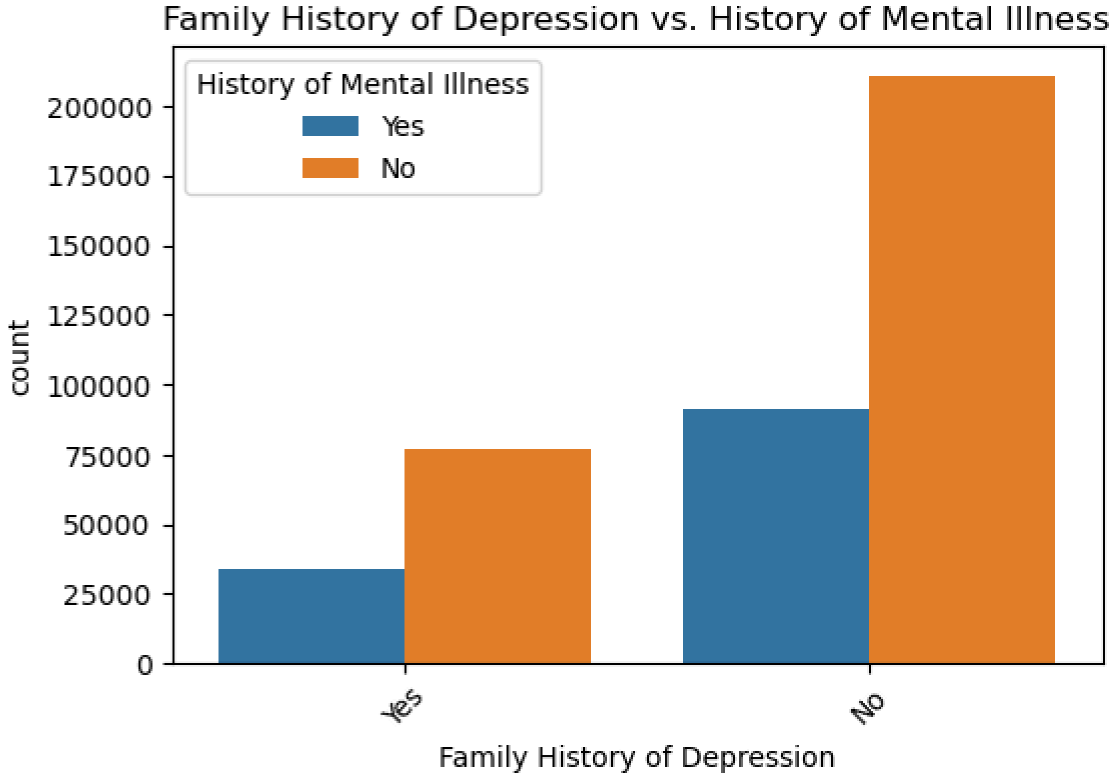

Employment Status vs. History of Mental Illness
History of Mental Illness
Yes
No
count
200000
175000
150000
125000
100000
75000
50000
25000
0
Unemployed
Employed
Employment Status

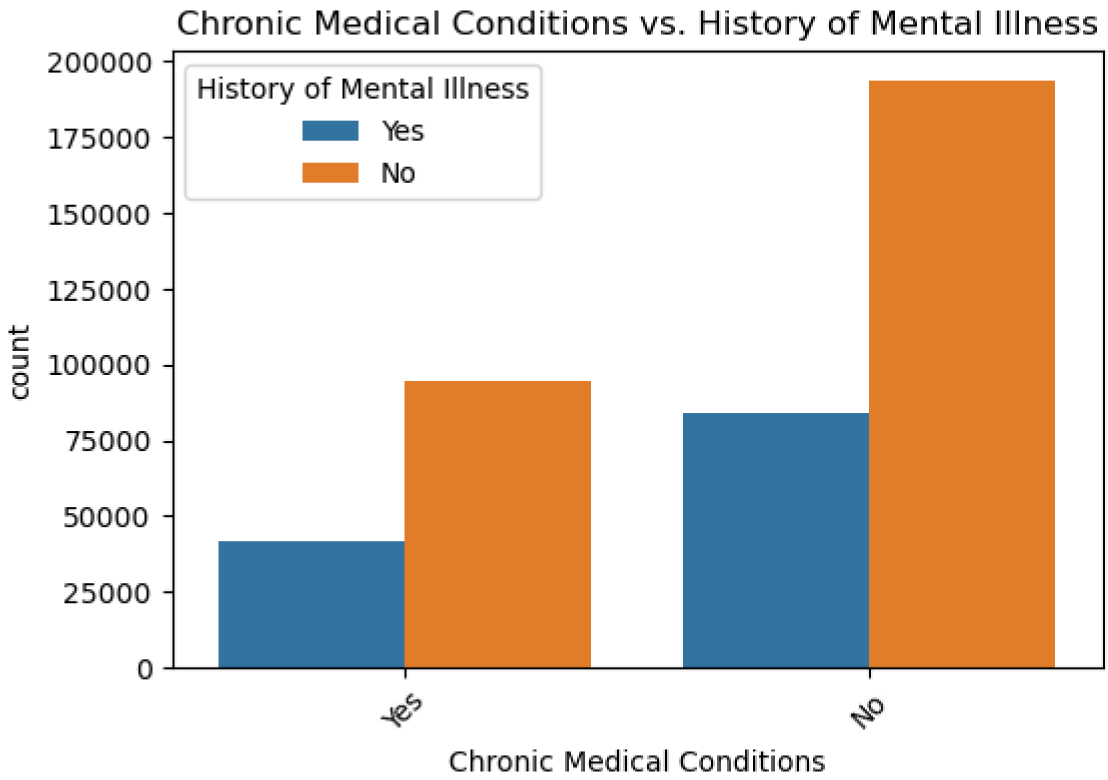

Alcohol Consumption vs. History of Mental Illness
History of Mental Illness
Yes
No
count
120000
100000
80000
60000
40000
20000
0
Moderate
High
Low
Alcohol Consumption


Dietary Habits vs. History of Mental Illness
History of Mental Illness
Yes
No
count
0
20000
40000
60000
80000
100000
120000
Moderate
Unhealthy
Healthy
Dietary Habits


Sleep Patterns vs. History of Mental Illness
History of Mental Illness
Yes
No
count
0
20000
40000
60000
80000
100000
120000
140000
Fair
Good
Poor
Sleep Patterns


History of Substance Abuse vs. History of Mental Illness
History of Mental Illness
Yes
No
count
200000
175000
150000
125000
100000
75000
50000
25000
0
No
Yes
History of Substance Abuse


Family History of Depression vs. History of Mental Illness
History of Mental Illness
Yes
No
count
200000
175000
150000
125000
100000
75000
50000
25000
0
Yes
No
Family History of Depression



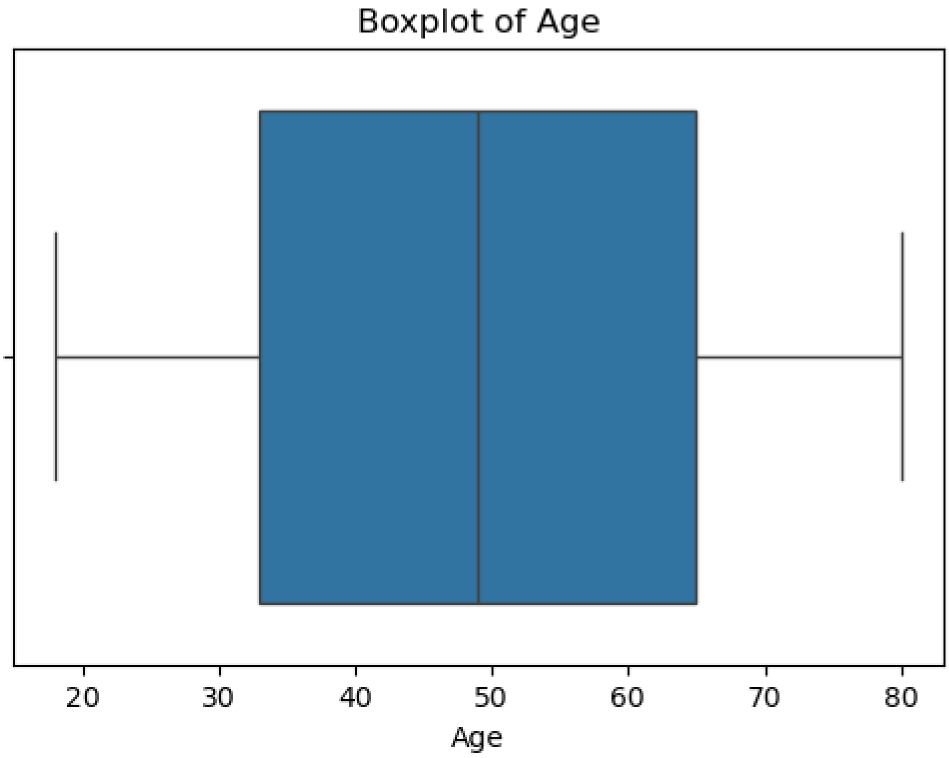
- Marital Status vs. Mental Illness: Married individuals seem to have lower rates of mental illness, while single, divorced, and widowed individuals show higher proportions of mental illness.
    - Insight: Marital status may have a significant impact on mental health. Single, divorced, and widowed individuals might face social isolation or emotional stress that contributes to mental health issues.
- Education Level vs. Mental Illness: There is a higher incidence of mental illness among those with lower education levels (high school and associate degrees) compared to those with higher education (PhDs).
    - Insight: Education level may play a role in mental health, with lower education possibly linked to economic stressors, while higher education may correlate with professional stress.
- Smoking Status vs. Mental Illness: Current and former smokers have higher rates of mental illness compared to non-smokers.
    - Insight: Smoking status could be a key indicator of mental health, as smoking is often used as a coping mechanism for stress.
- Physical Activity vs. Mental Illness: Individuals with sedentary lifestyles show higher rates of mental illness compared to those with active or moderate activity levels.
    - Insight: Physical activity is a known protective factor for mental health, so this variable may be a useful predictor in the model.
- Employment Status vs. Mental Illness: Unemployed individuals are more likely to have a history of mental illness compared to employed individuals.

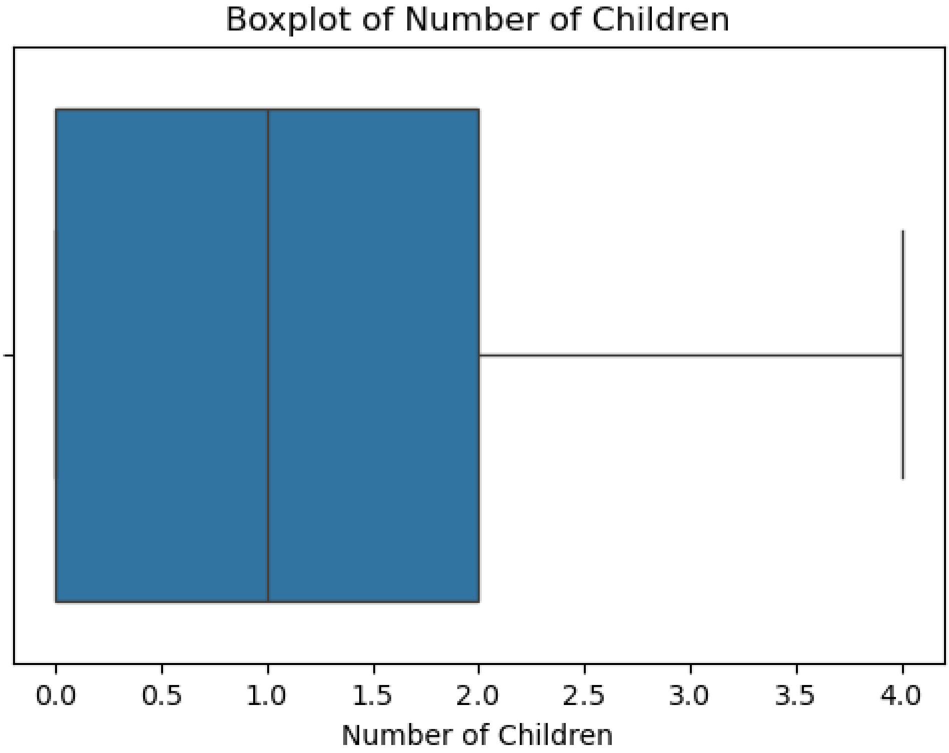
- Insight: Employment may be one of the strongest predictors of mental health in this dataset, as financial security and purpose are often tied to mental well-being.

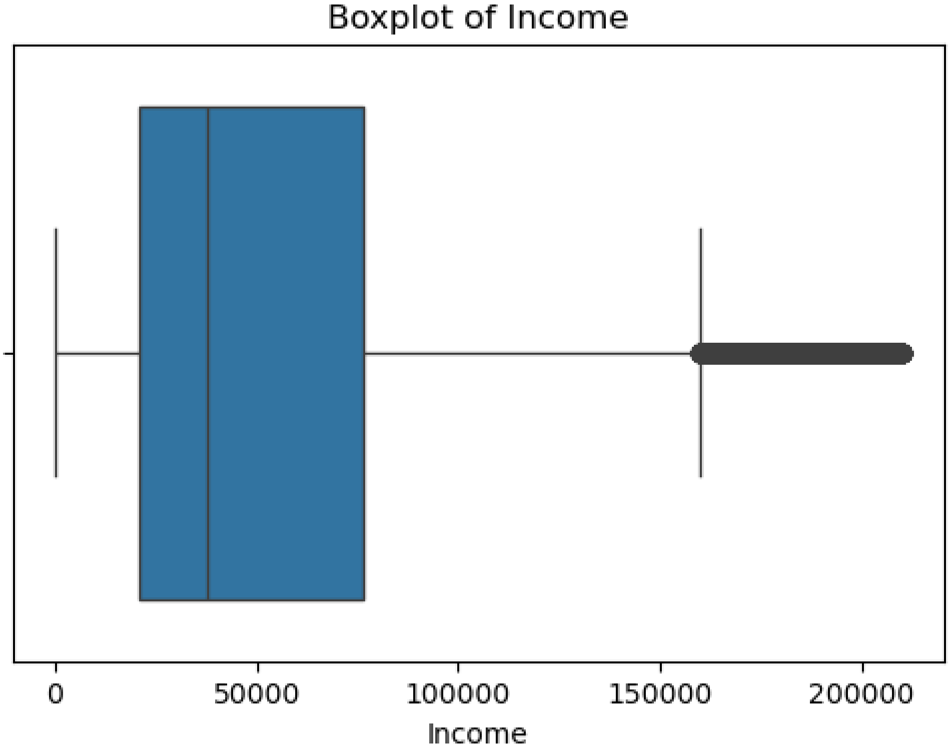
Checking for outliers in numerical variables

In [12]:

```
# 8. Checking for Outliers in Numerical Variables using Boxplot
for col in numerical_cols:
    plt.figure(figsize=(6, 4))
    sns.boxplot(data=df, x=col)
    plt.title(f'Boxplot of {col}')
    plt.show()
```







- Age: There are no significant outliers in the age distribution, with most individuals falling between 20 and 80.
- Income: There are some high-income outliers, with a small number of individuals earning significantly more than the majority. These outliers may need to be considered or removed depending on the model's sensitivity to extreme values.
- Number of Children: There are no significant outliers for the number of children, as the maximum is capped at 4.

Statistical Test to Understand Feature Importances

In [13]:

```
from sklearn.feature_selection import chi2
from sklearn.preprocessing import MinMaxScaler
```

In [14]:

```
from sklearn.feature_selection import chi2
from sklearn.preprocessing import MinMaxScaler
import pandas as pd

# List of categorical columns
categorical_cols = ['Marital Status', 'Education Level', 'Smoking Status', 'Phys
                    'Employment Status', 'Alcohol Consumption', 'Dietary Habits'
                    'History of Substance Abuse', 'Family History of Depression'

# Encoding the target variable
df['History of Mental Illness'] = df['History of Mental Illness'].map({'Yes': 1,

# One-hot encode the categorical columns, excluding the target column
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=False)

# Features (X) and target (y)
X = df_encoded.drop(columns=['Name', 'History of Mental Illness'])  # Dropping i
y = df_encoded['History of Mental Illness']

# Normalizing data for Chi-Square test (Chi-Square test requires non-negative va
X_minmax = MinMaxScaler().fit_transform(X)

# Perform Chi-Square test
chi_scores = chi2(X_minmax, y)

# Display p-values and feature importance
p_values = pd.Series(chi_scores[1], index=X.columns)
important_features = p_values[p_values < 0.05]  # Features significant at p < 0.
print("Important Features based on Chi-Square test:\n", important_features)
```

```
Important Features based on Chi-Square test:
 Age                                   4.827889e-11
Income                               3.229536e-263
Marital Status_Divorced               5.765434e-05
Marital Status_Single                 3.872224e-05
Marital Status_Widowed                2.375366e-08
Education Level_Associate Degree      8.923698e-73
Education Level_Bachelor's Degree     2.545691e-93
Education Level_High School           2.585653e-89
Education Level_Master's Degree       7.878033e-46
Education Level_PhD                   7.261697e-13
Smoking Status_Current                1.103899e-02
Physical Activity Level_Active        7.036633e-05
Physical Activity Level_Sedentary     2.488983e-04
Employment Status_Employed            0.000000e+00
Employment Status_Unemployed          0.000000e+00
Alcohol Consumption_High              6.473697e-14
Alcohol Consumption_Moderate          4.240635e-05
Dietary Habits_Healthy                5.917721e-62
Dietary Habits_Unhealthy              6.081420e-20
Sleep Patterns_Good                   2.675515e-76
Sleep Patterns_Poor                   3.034061e-56
Family History of Depression_Yes      7.185919e-03
Chronic Medical Conditions_No         2.585736e-02
Chronic Medical Conditions_Yes        1.467724e-03
dtype: float64
```

Chi-Square Test Results for Feature Importance:

The Chi-Square test was used to identify features that have a significant relationship with the target variable, "History of Mental Illness." Below are the key insights based on the p-values of each feature:

1. Age and Income:

- **Age** and **Income** both have extremely low p-values, indicating a strong association with the likelihood of mental illness.
- Older individuals and those with different income levels may have different risks or experiences related to mental health, making these variables important to include in the predictive model.

2. Marital Status:

- Significant categories: **Divorced**, **Single**, and **Widowed**.
- Marital status plays an important role in mental health. For instance, individuals who are divorced, single, or widowed are more likely to be associated with a history of mental illness compared to those who are married (used as the reference category).

3. Education Level:

- Significant categories: **Associate Degree**, **Bachelor’s Degree**, **High School**, **Master’s Degree**, **PhD**.
- Education level has a strong relationship with mental illness. Individuals with different levels of education show varying associations with mental health, where higher education levels may correspond with different mental health outcomes compared to individuals with only a high school education.

4. Smoking Status:

- Significant category: **Current smoker**.
- Current smokers show a statistically significant association with mental health issues, supporting known correlations between smoking and mental health risks.

5. Physical Activity Level:

- Significant categories: **Active** and **Sedentary**.
- Physical activity is strongly related to mental health. Sedentary individuals show a higher likelihood of mental health issues, whereas being physically active seems to have protective effects.

6. Employment Status:

- Both **Employed** and **Unemployed** are highly significant.
- Employment status is crucial for mental health, with both employed and unemployed individuals showing significant relationships with mental illness. This could indicate the importance of occupational stress, job security, or lack thereof, in contributing to mental health outcomes.

7. Alcohol Consumption:

- Significant categories: **High** and **Moderate** consumption.

- Higher alcohol consumption is associated with increased mental health risks, which is consistent with literature showing the negative impact of alcohol misuse on mental health.

8. Dietary Habits:

- Significant categories: **Healthy** and **Unhealthy**.
- Both healthy and unhealthy dietary habits are significantly associated with mental illness. This suggests that diet plays an important role in mental health outcomes, likely reflecting nutritional factors that impact mental well-being.

9. Sleep Patterns:

- Significant categories: **Good** and **Poor**.
- Sleep patterns, particularly poor sleep quality, are strongly associated with mental health issues. Good sleep, on the other hand, shows a protective effect.

10. Family History of Depression:

- **Yes** is significant.
- Having a family history of depression significantly increases the likelihood of experiencing mental illness. This aligns with the known hereditary factors in mental health.

11. Chronic Medical Conditions:

- Both **Yes** and **No** are significant.
- The presence or absence of chronic medical conditions shows a significant relationship with mental health. Chronic conditions may exacerbate stress and mental health challenges, while the absence of chronic illness can be a protective factor.

Key Takeaways:

- The Chi-Square test reveals that a wide range of factors, including **socio-demographic variables** (age, marital status, education), **lifestyle choices** (physical activity, smoking, alcohol consumption, dietary habits), and **health-related factors** (sleep patterns, family history of depression, chronic medical conditions), are significantly associated with mental health.
- These findings provide a strong basis for variable selection in model-building efforts, ensuring that the most important and relevant features are included.

In [ ]: