Import required packages for EDA, statistical analysis and Visualization

```
import warnings
warnings.filterwarnings('ignore')
import os
os.chdir('/Users/admin/Desktop/AXA')
import pandas as pd
import numpy as np
from pandas import Series,DataFrame
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
from wolta.data_tools import col_types
from wolta.data_tools import make_numerics
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from catboost import CatBoostClassifier
from xgboost import XGBClassifier
```

upload dataset provided by AXA Health

```
df=pd.read_csv('depression_data.csv')
```

This is a use case of class imbalance, as there are 69.6% of the total population representing to people with "No Mental Illness" whereas only 30.4% represneting to pouplation with "Mental Illness"

```
df['History of Mental Illness'].value_counts()

History of Mental Illness
No     287943
Yes    125825
Name: count, dtype: int64
```

```
Target_column_mapping = {'Yes': 1, 'No': 0}
df['History of Mental Illness'] = df['History of Mental Illness'].map(Target_column_mapping)
```

No duplicate rows in the dataset

```
df.duplicated().sum()
```

```
0
```

No null values in the dataset

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

```
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
```

This is a use case of class imbalance, as there are 69.6% of the total population representing to people with "No Mental Illness" whereas only 30.4% represneting to pouplation with "Mental Illness"

Mapping the target column for easier interpretation(History of Mental Illness) as Yes to 1 (have history of mental illnness) and No:1(no history of mental illness)

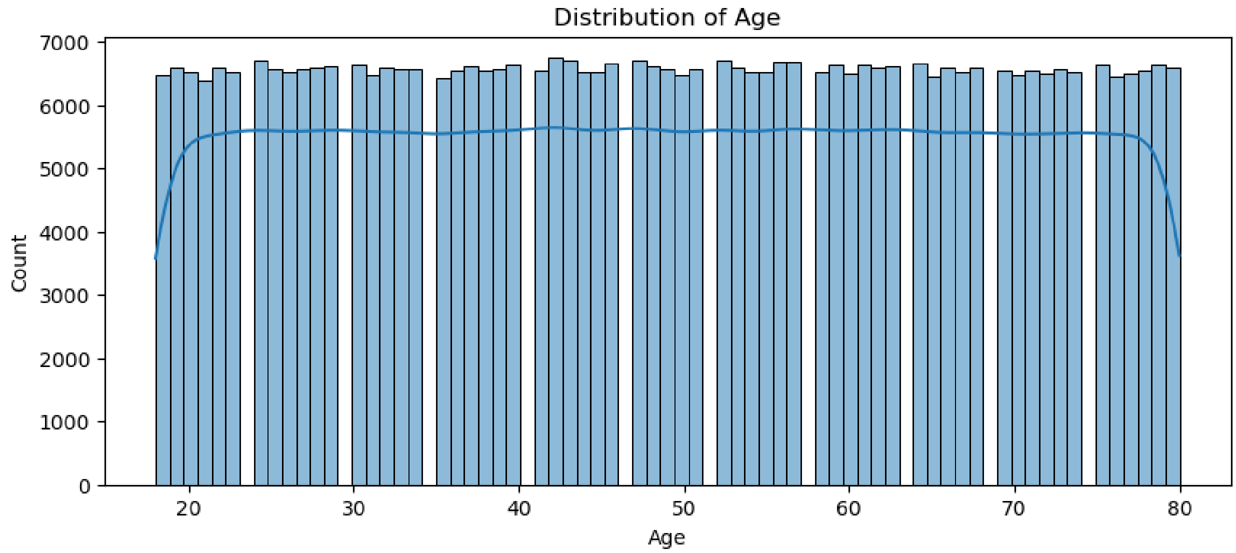
```
Target_column_mapping = {'Yes': 1, 'No': 0}
df['History of Mental Illness'] = df['History of Mental 
Illness'].map(Target_column_mapping)
```

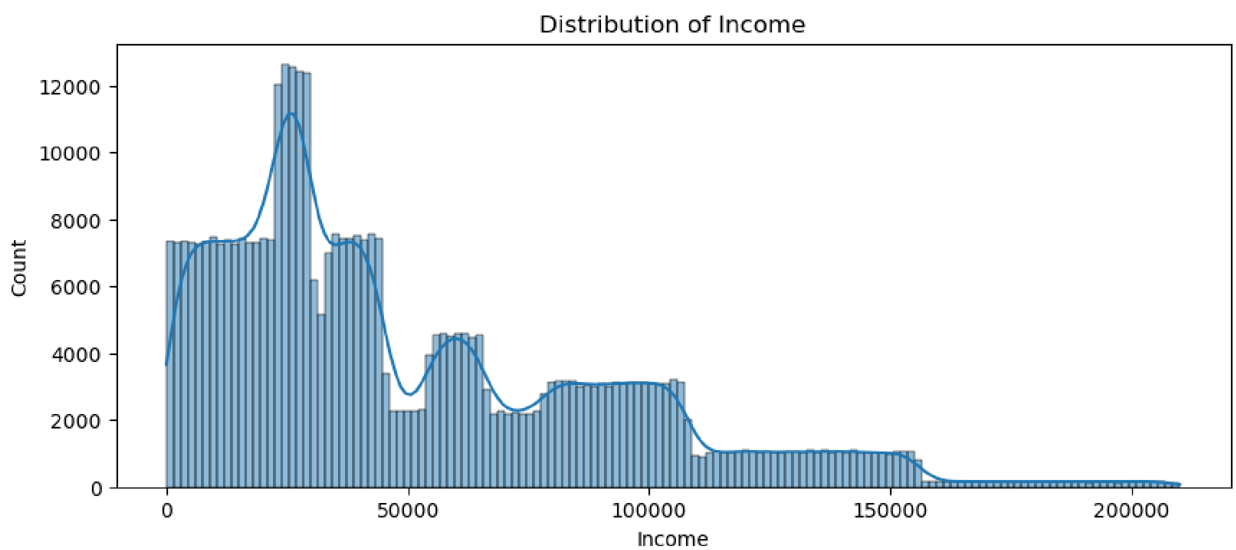
Univariate feature analysis on Age and Income to see if there is any outliers based on the kernel density estimate

Based on the distribution of Age this looks like age feature distribution doesn't contain outliers while Income feature shows there is outliers based on kernel density estimate more towards very high income of 170,000+

```
numerical_features = ['Age','Income']
for feature in numerical_features:
    plt.figure(figsize=(10, 4))
    sns.histplot(data=df, x=feature, kde=True)
```

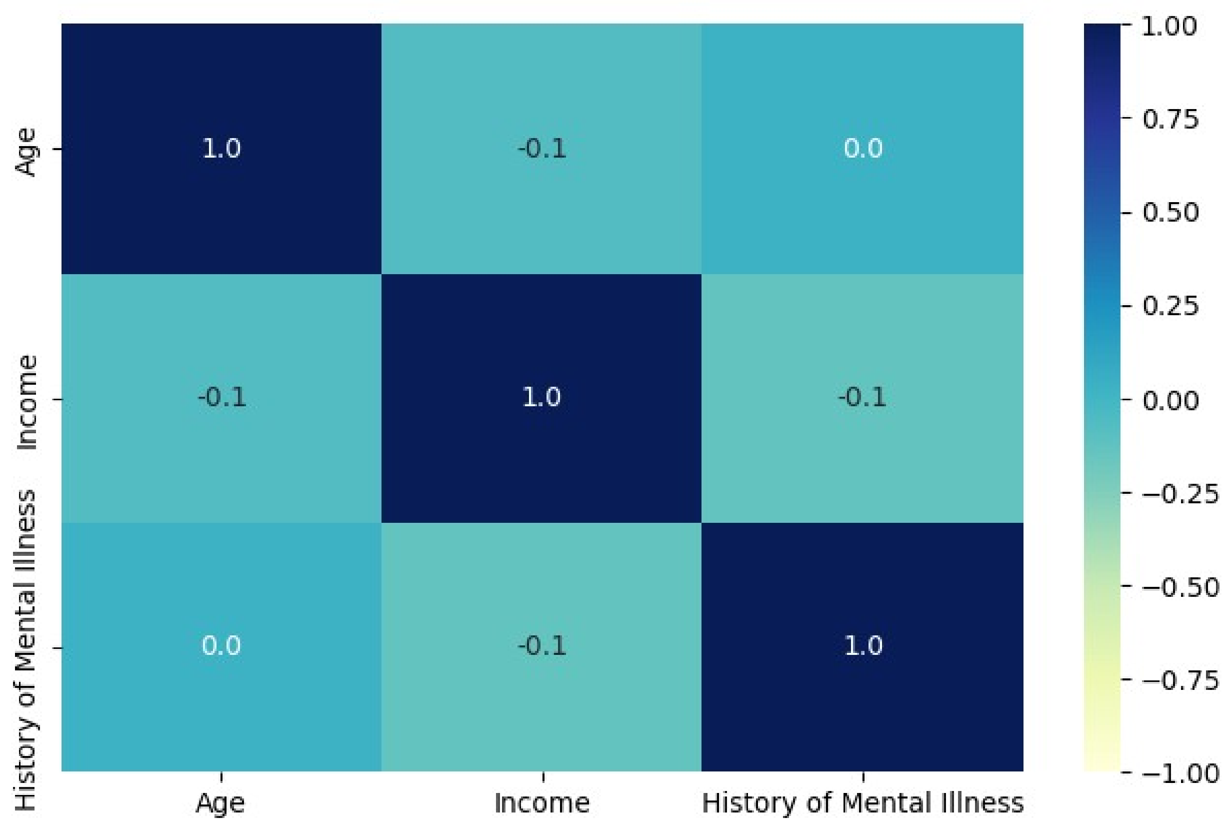
```
    plt.title('Distribution of ' + feature)
    plt.show()
```





To check pearson coorelation firstly the distribution has to normal distribuition (bell shaped curve). Based on the heatmap below this looks like there is no positive, no negative relationship between the numerical features vs Target("History of Mental Illness")

```
feature_list = ['Age', 'Income', 'History of Mental Illness']
fig_dims = (8,5)
fig, ax = plt.subplots(figsize=fig_dims)
sns.heatmap(df[feature_list].corr(method='pearson'),cmap="YlGnBu",vmin
=-1,annot=True,fmt='.1f',ax=ax)

<Axes: >
```

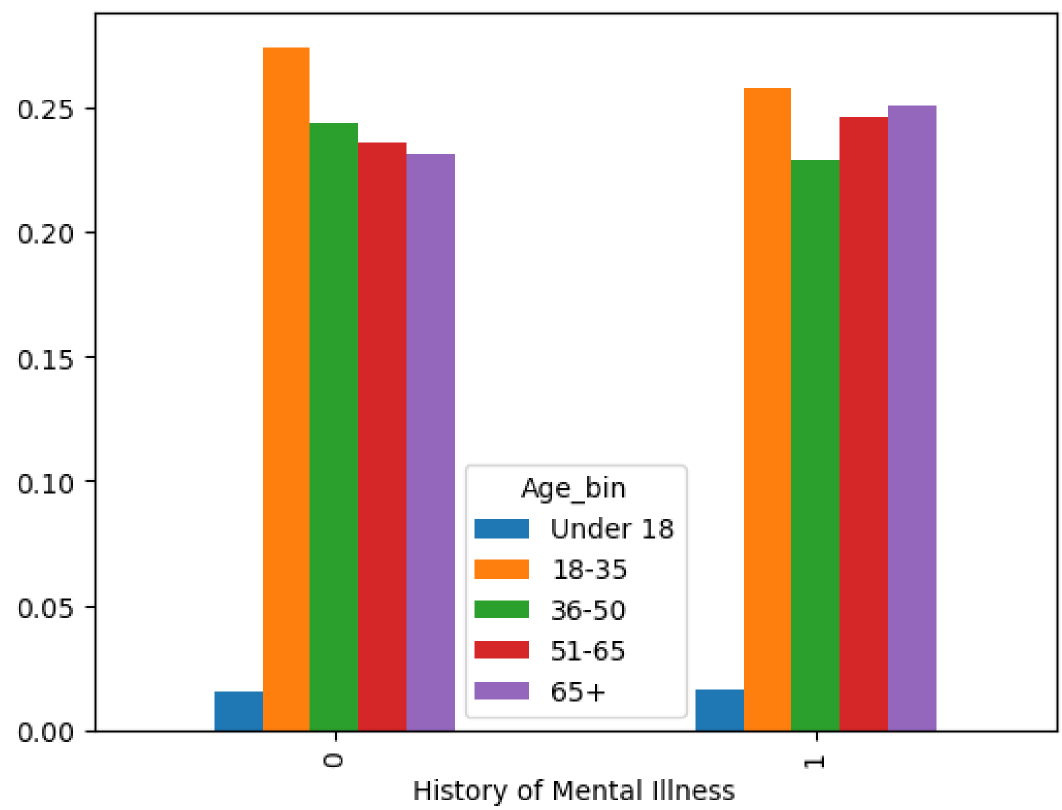


(Feature engineering)-In order to reduce the number of unique values of a variable binning is the best option . This converts continuos variables to discrete bins. As this helps to capture non-linear relationships between a feature and Target . Furthermore, this will result in creating two new additional features i.e. Income_Range and Age_bin. This will further simplify the complex transformations and improve model performance.

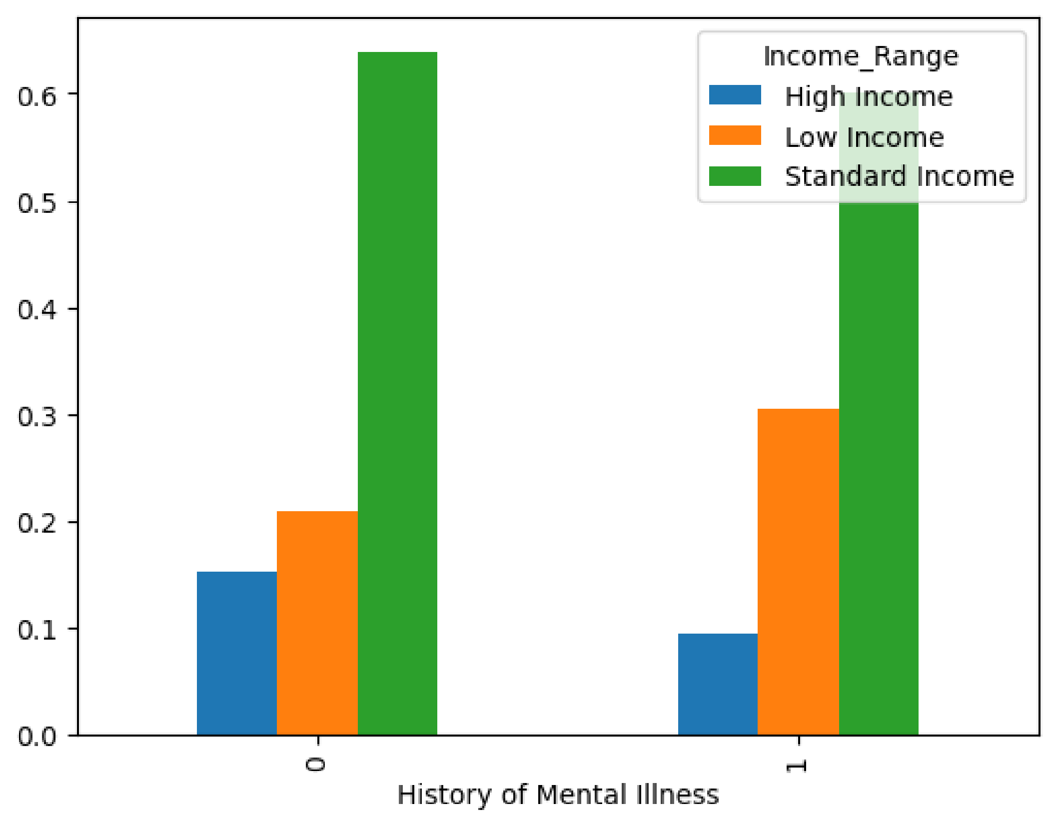
```
def income_range(Income):
    if Income<20000:
        return 'Low Income'
    elif (Income > 20000) & (Income<100000):
        return 'Standard Income'
    elif Income >100000:
        return 'High Income'
df['Income_Range']=df['Income'].apply(income_range)
df['Age_bin'] = pd.cut(df['Age'], bins=[-np.inf, 18, 35, 50, 65,
np.inf], labels=['Under 18', '18-35', '36-50', '51-65', '65+'])
```

Name column is dropped mainly as this is a privacy concern and its not relevant for model interpretation

```
df.drop(columns=["Name"],inplace=True)

# Bivariate Analysis
SS = pd.crosstab(df['History of Mental Illness'],df['Age_bin'])
SS.div(SS.sum(1),axis=0).plot(kind='bar',stacked=False)

SS = pd.crosstab(df['History of Mental Illness'],df['Income_Range'])
SS.div(SS.sum(1),axis=0).plot(kind='bar',stacked=False)

<Axes: xlabel='History of Mental Illness'>
```

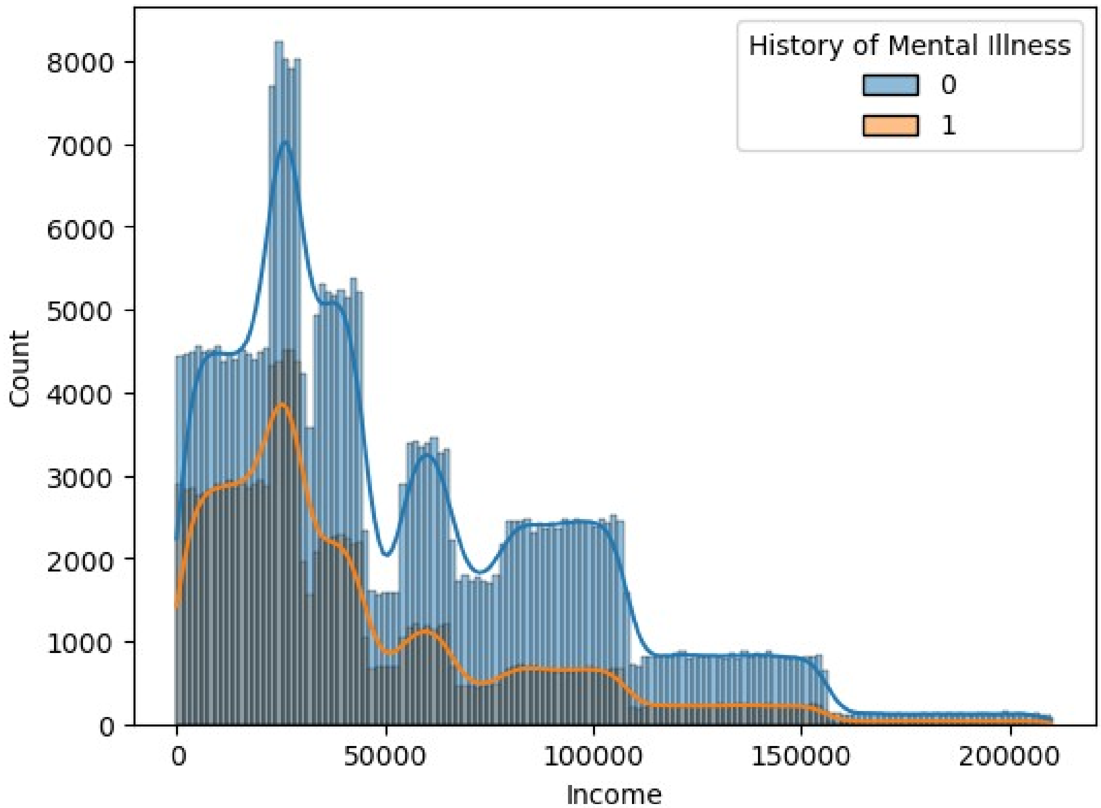


Age_bin
Under 18
18-35
36-50
51-65
65+
0.25
0.20
0.15
0.10
0.05
0.00
0
1
History of Mental Illness

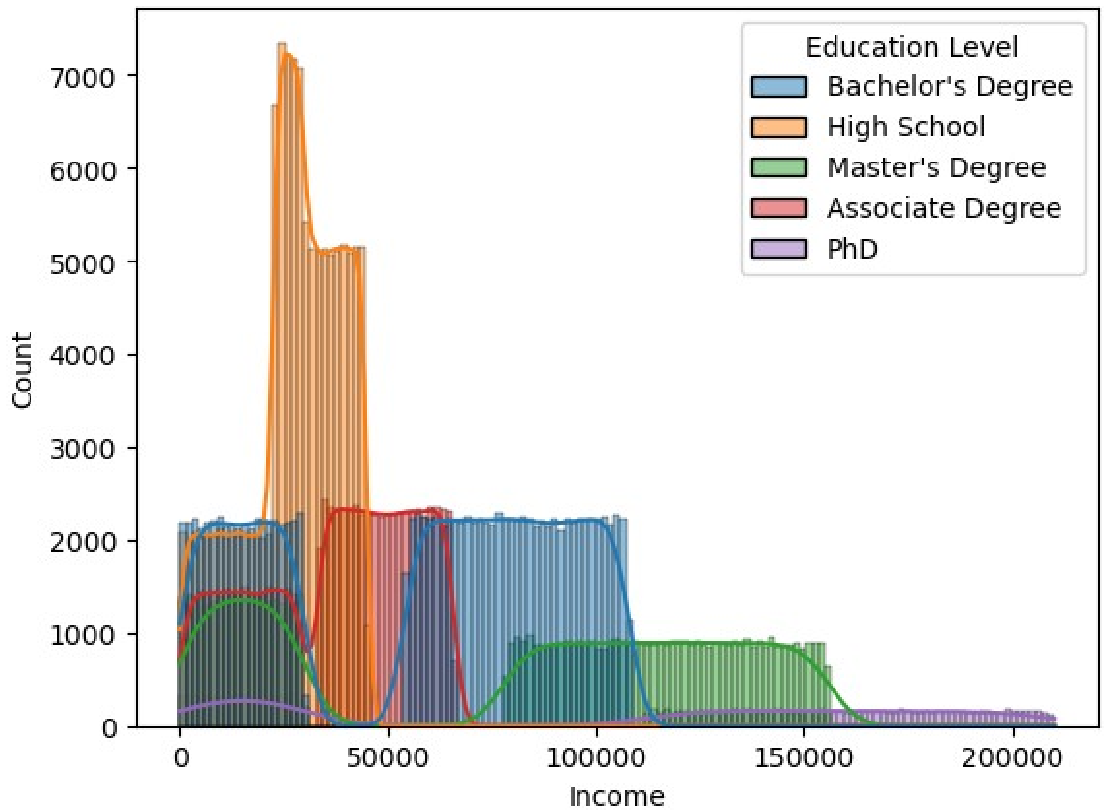


Income_Range
High Income
Low Income
Standard Income
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
1
History of Mental Illness

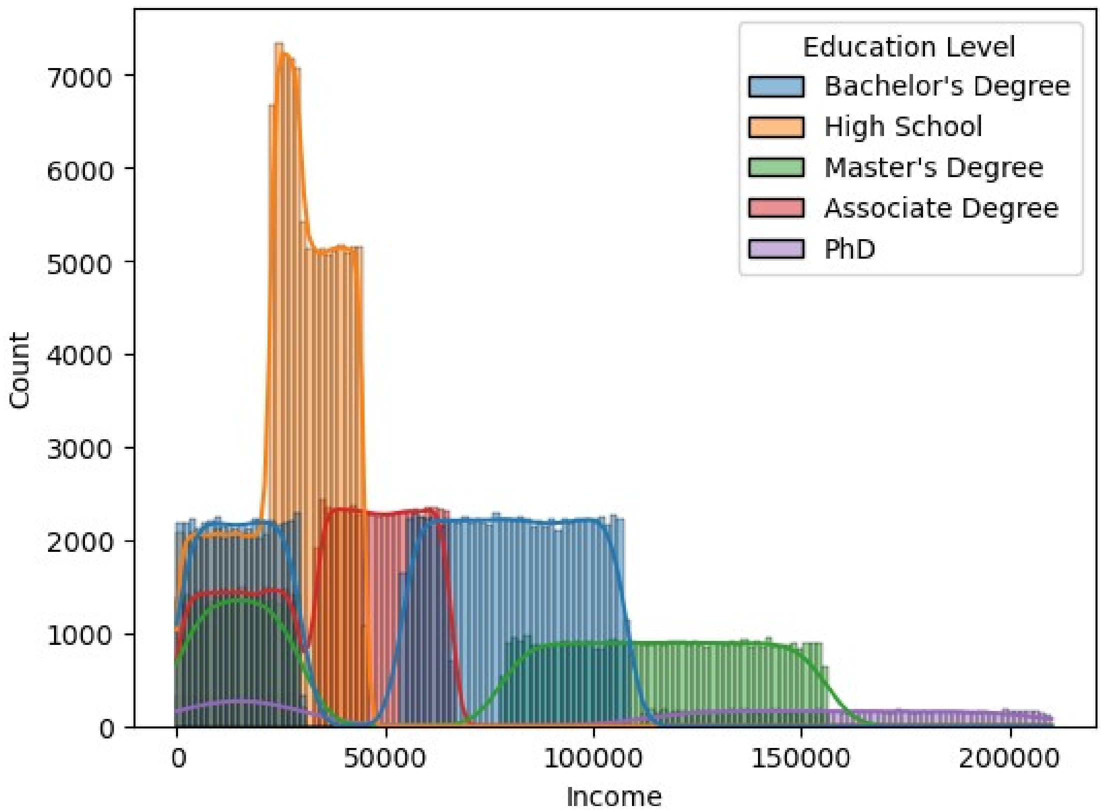
```python
sns.histplot(data = df, x = "Income", kde = True, hue = "History of
Mental Illness");
```



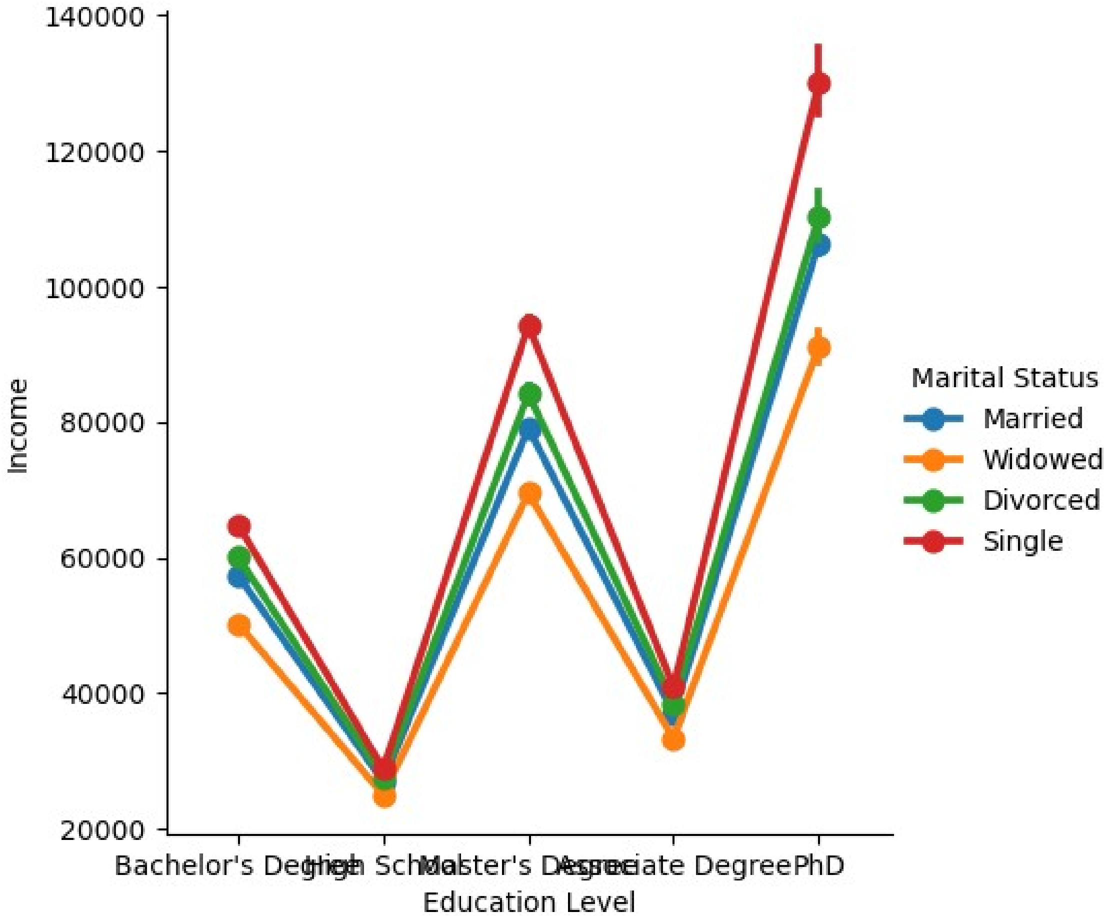

```python
sns.histplot(data = df, x = "Income", kde = True, hue = "Education
Level");
```




```
sns.histplot(data = df, x = "Income", kde = True, hue = "Education
Level");
```

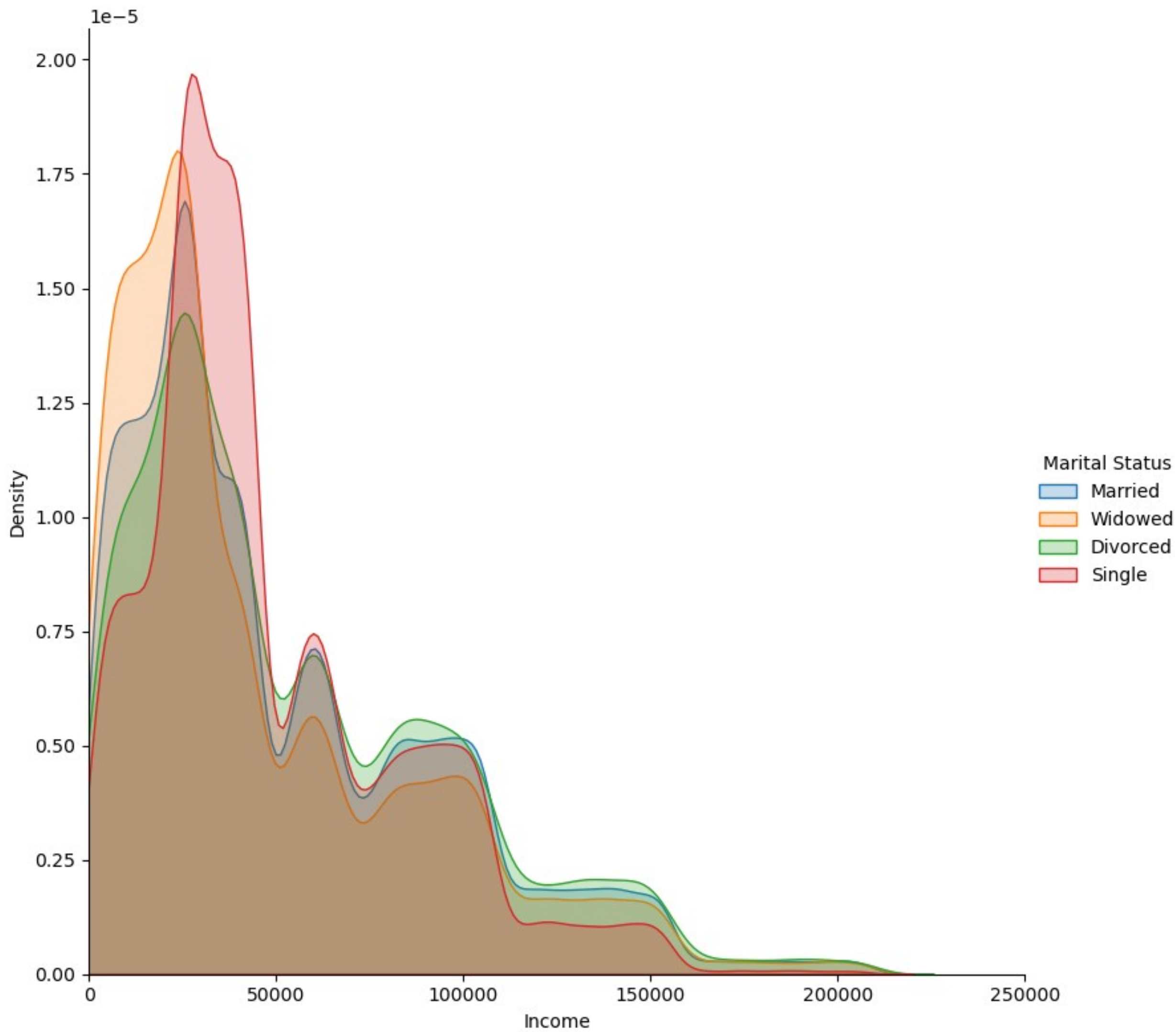



```
sns.catplot(data = df, x = "Education Level", y = "Income", hue =
"Marital Status", kind = "point");
```

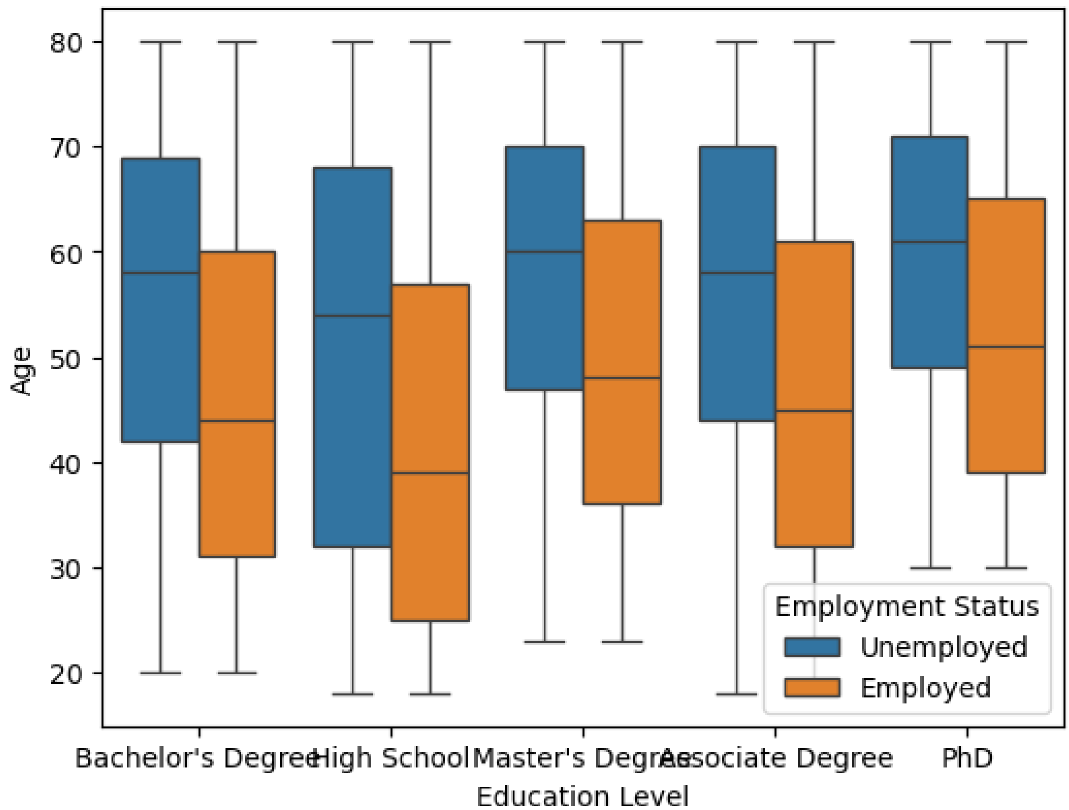


KDE plot between Income and Mariatal Status

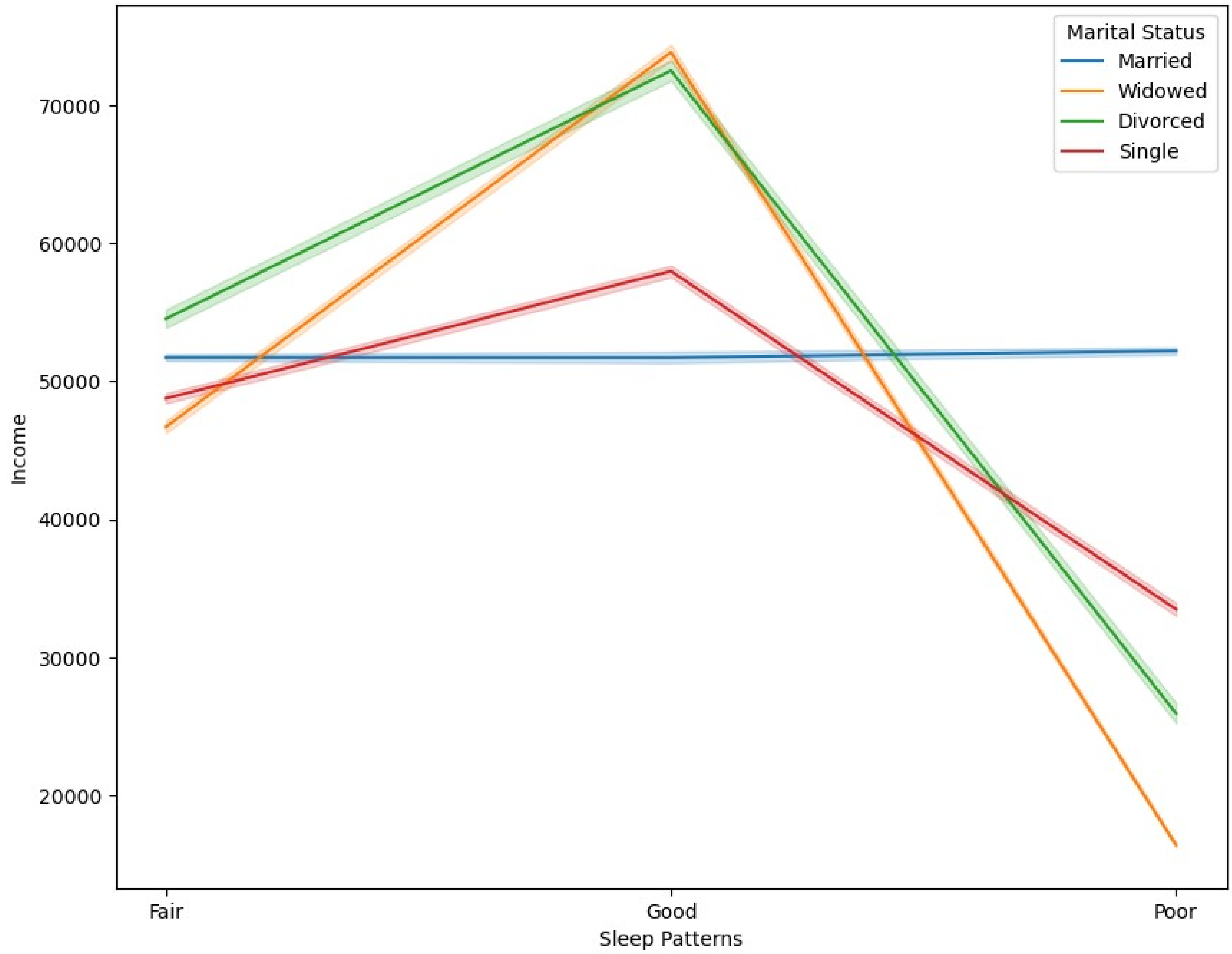
```
sns.FacetGrid(data = df,
              hue = "Marital Status",
              height = 8,
              xlim = (0, 250000)).map(sns.kdeplot, "Income", fill =
True).add_legend();
```



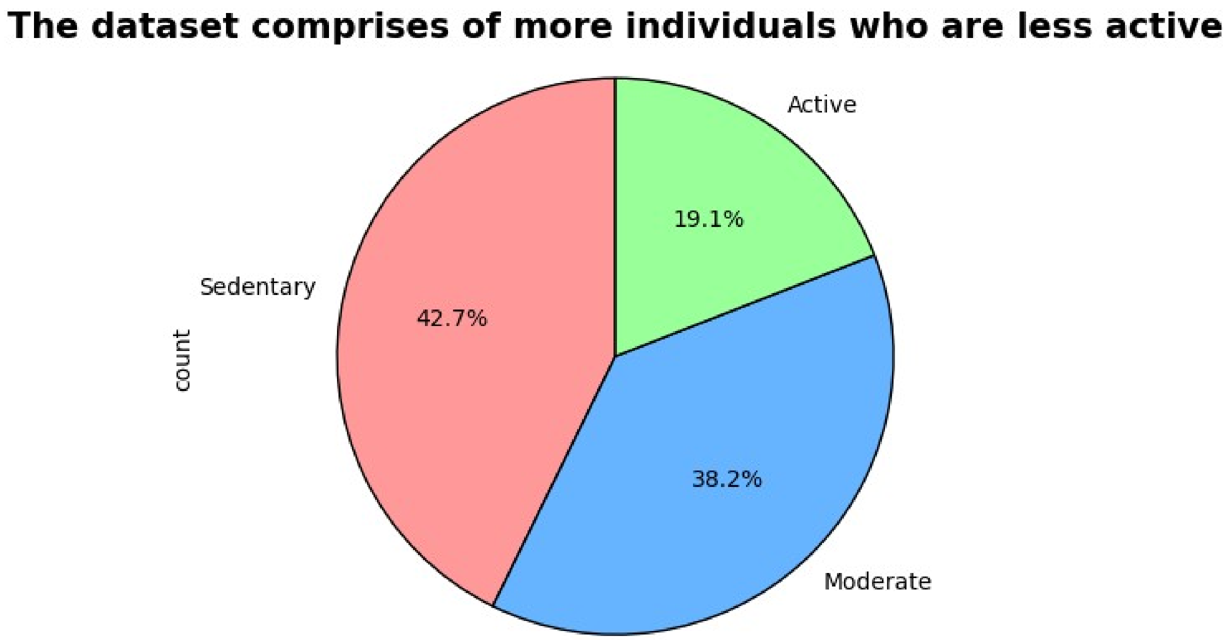

```
sns.boxplot(data = df,
            x = "Education Level",
            y = "Age",
            hue = "Employment Status");
```




```
plt.figure(figsize = (10, 8))
sns.lineplot(data = df,
             x = "Sleep Patterns",
             y = "Income",
             hue = "Marital Status");
```

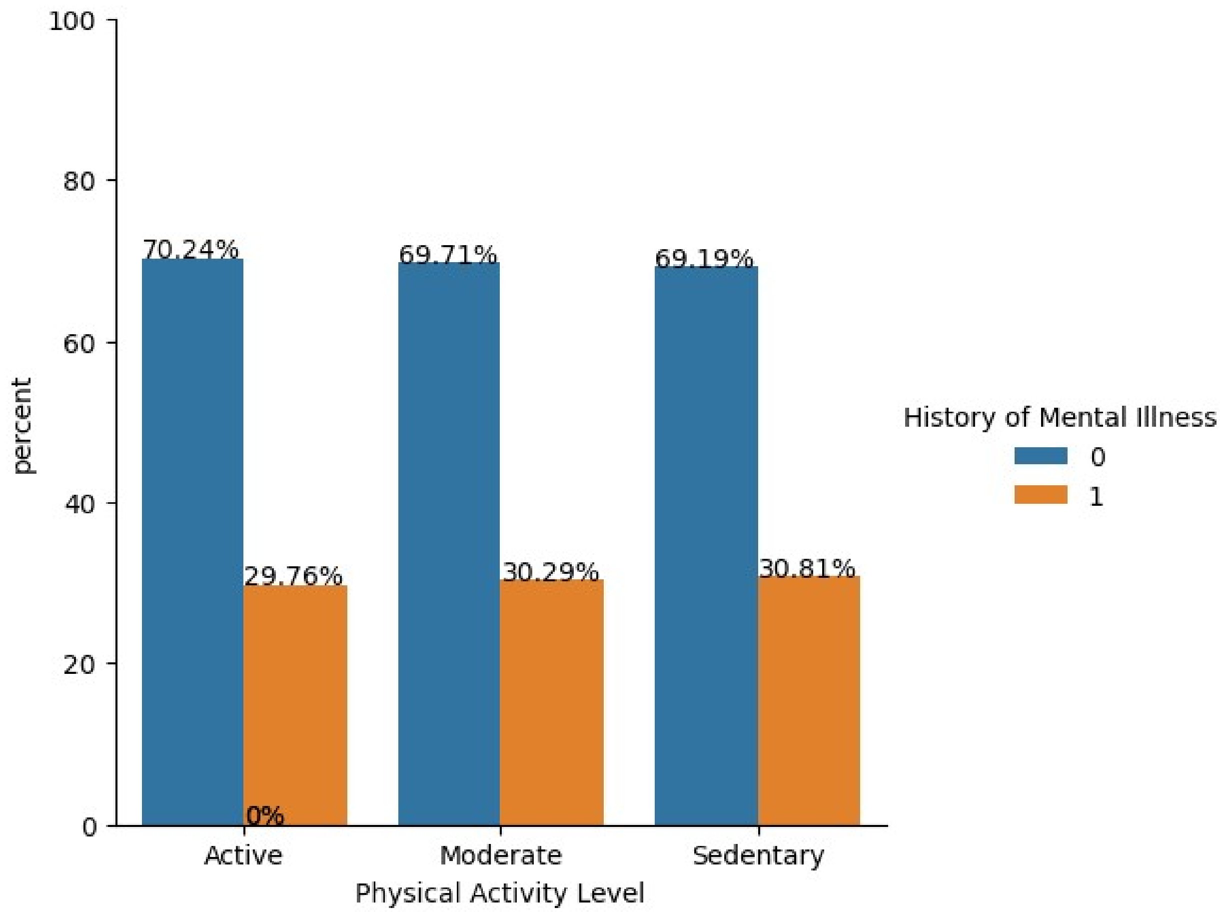



```
df['Physical Activity Level'].value_counts().plot(kind = 'pie' ,
autopct= '%0.1f%%',

colors=['#ff9999','#66b3ff','#99ff99','#ffcc99'],

shadow=False,startangle=90, wedgeprops={'edgecolor': 'black'} )
plt.title('The dataset comprises of more individuals who are less
active',fontsize=15,weight='bold')
plt.axis('equal')
plt.show()
```



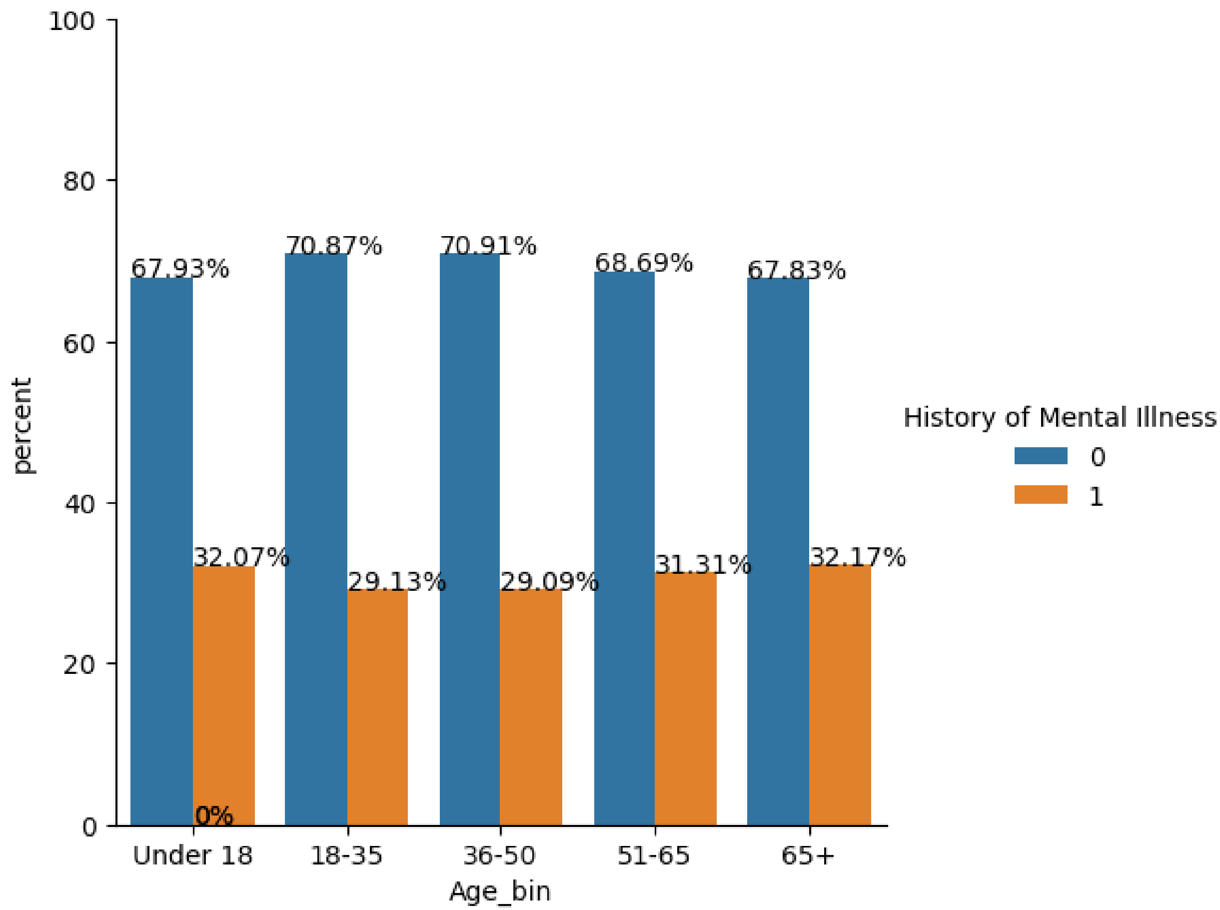
Sedentary to Moderate activity level individuals have the risk of having mental illness

```
x,y = 'Physical Activity Level', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



Under 18 and 65+ age group individual are likely to mental illness

```
x,y = 'Age_bin', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```

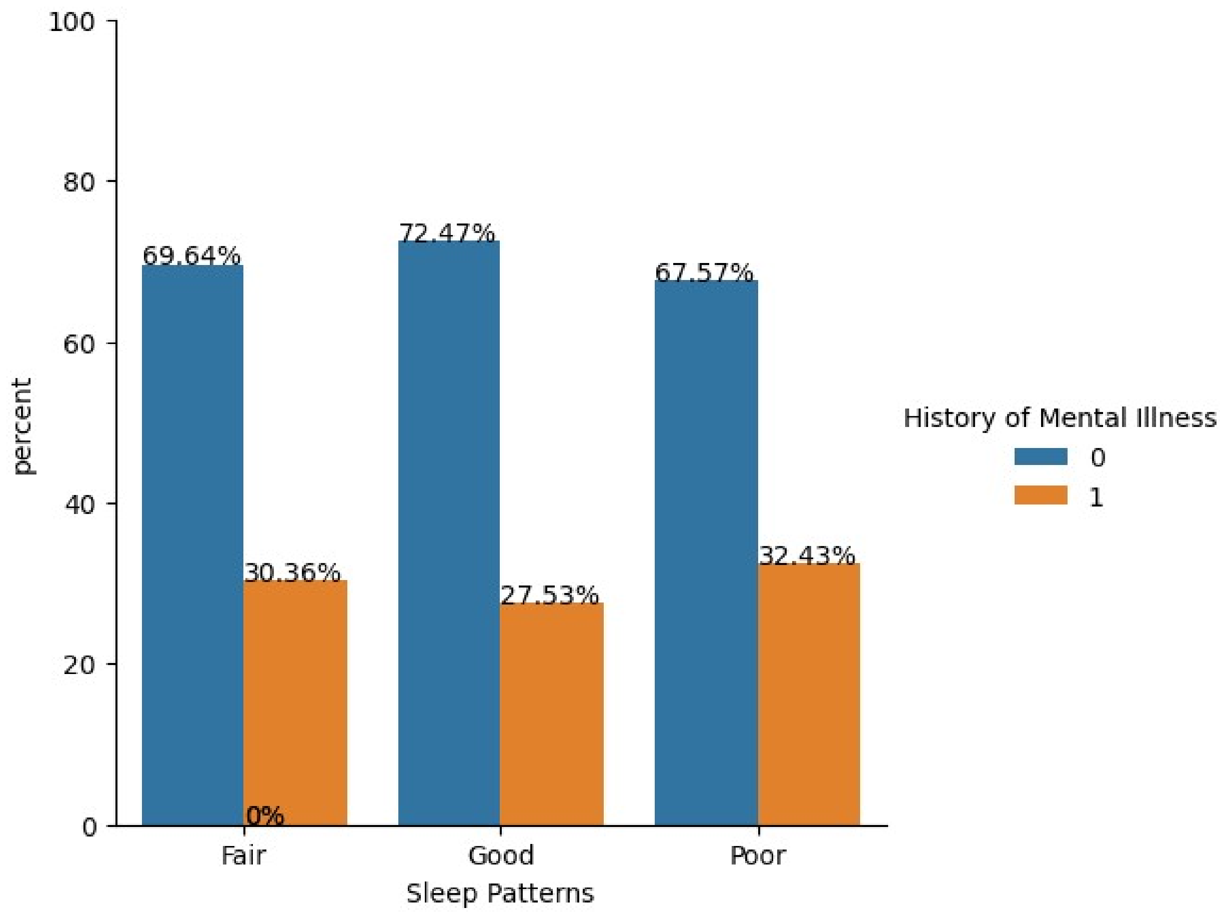



```
sns.countplot(data = df,
              x = "Smoking Status",
              hue = "Smoking Status",
              order = df["Smoking Status


              value_counts().index,
              palette = "Set1").set_title("Non-Smokers are more than
Current and former smokers",weight='bold');
```

Poor sleep cycle can be a good indicator of having mental illness

```
x,y = 'Sleep Patterns', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()
```

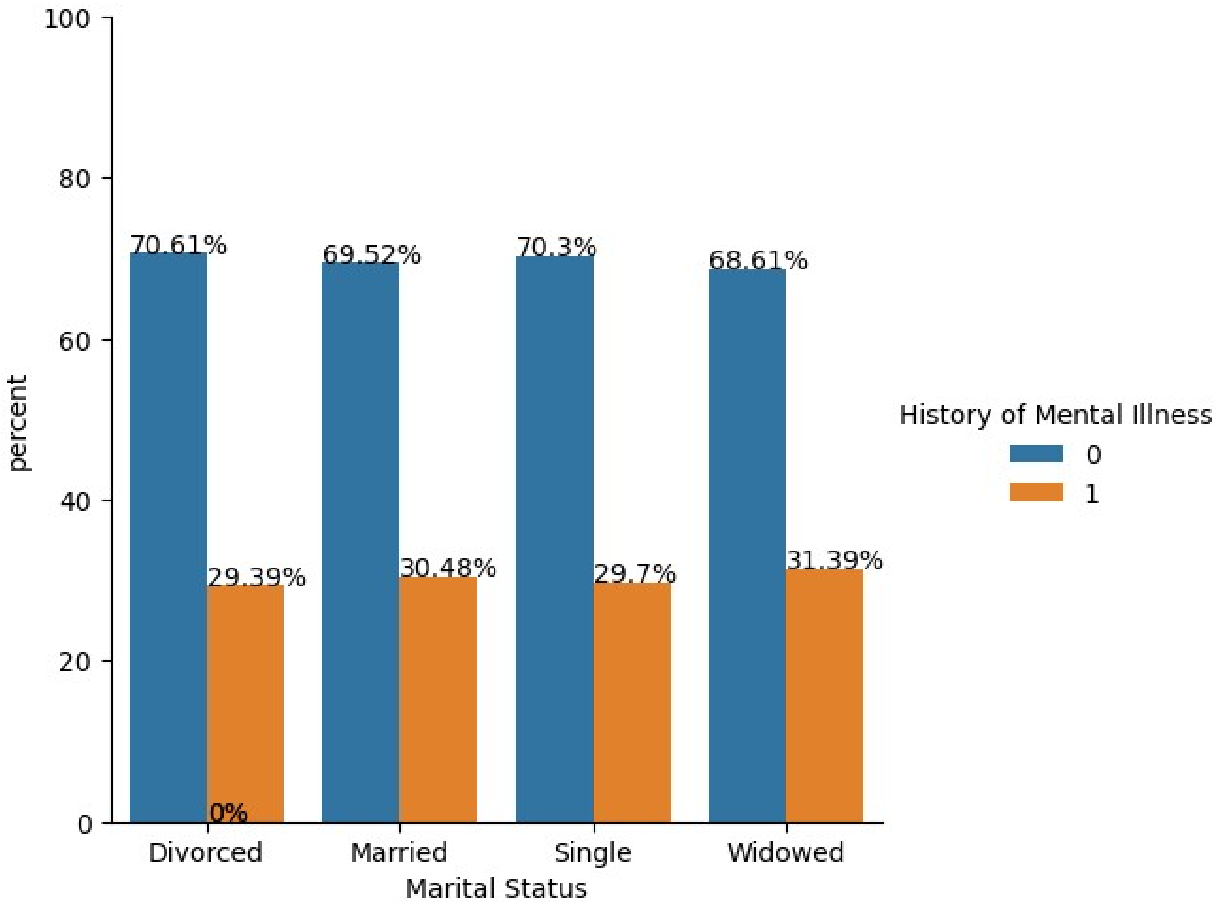
```
g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



Widowed individuals are more likely to have more chances of Mental illness

```
x,y = 'Marital Status', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
```

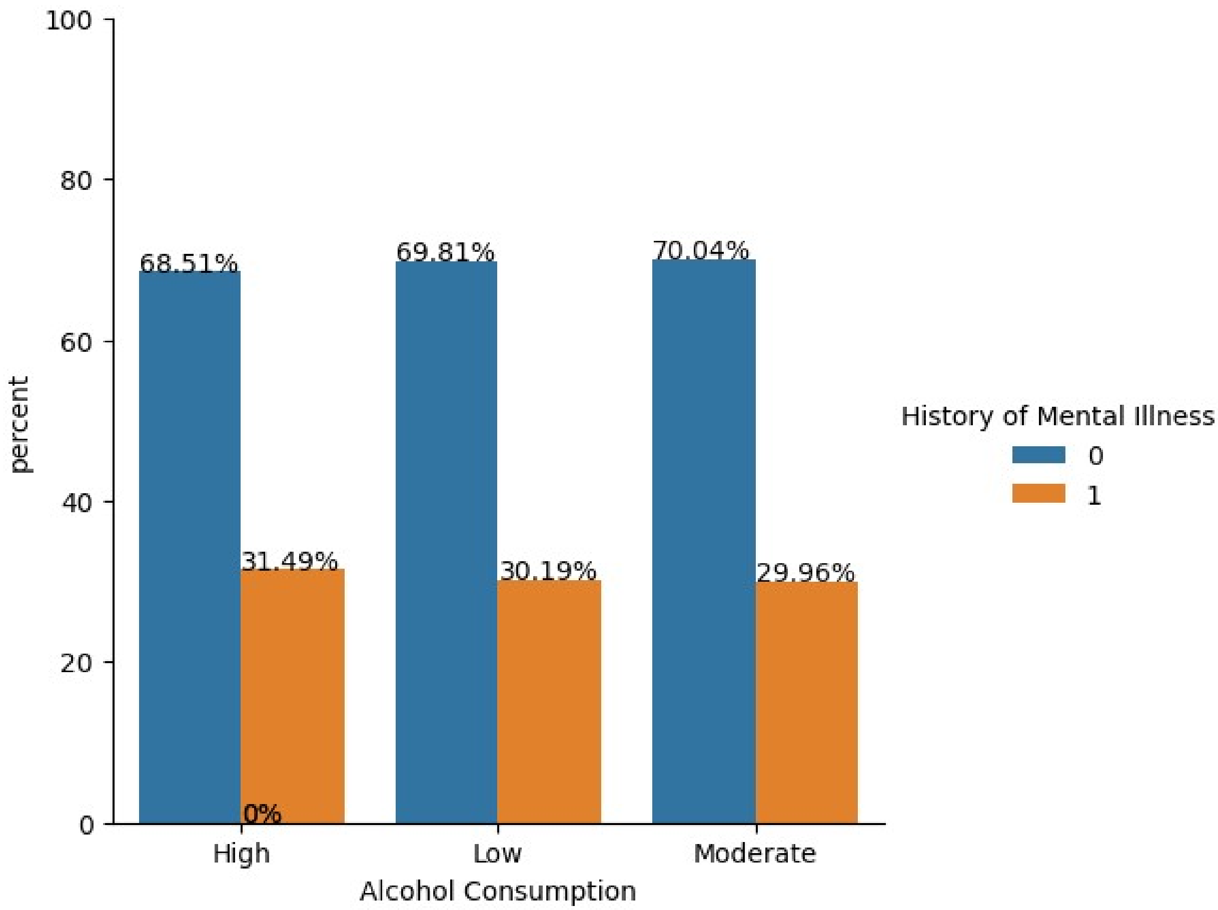
```
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



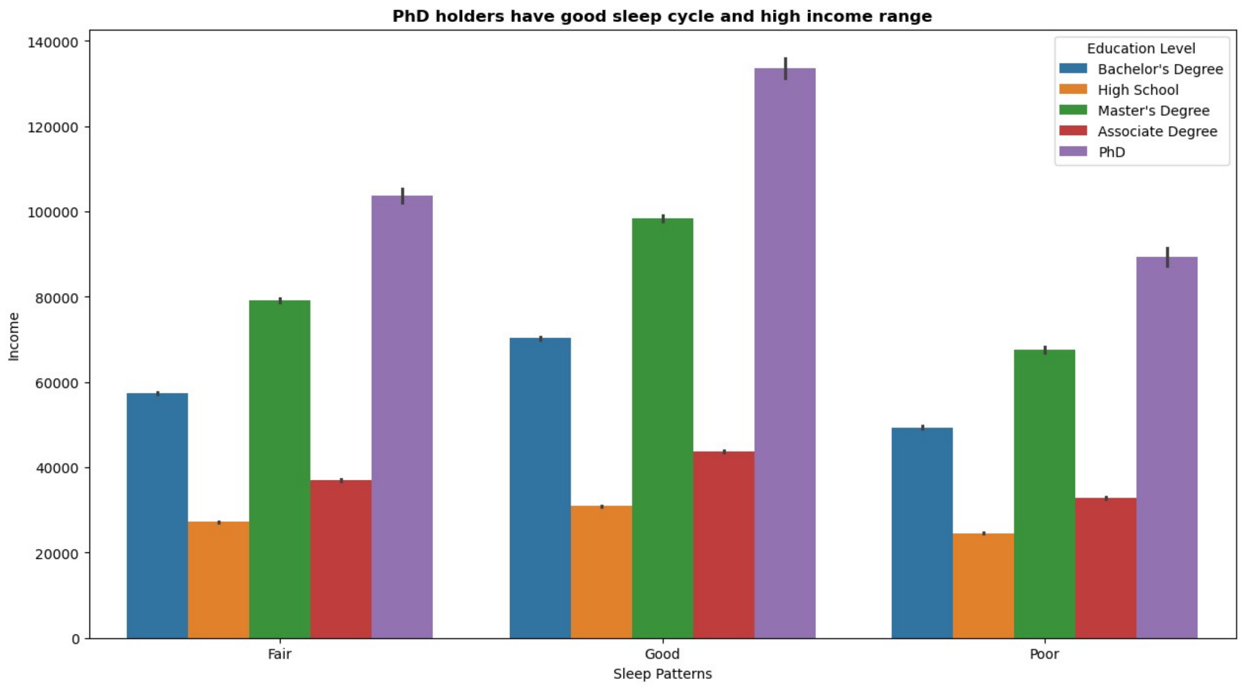
People with high alcohol intake are more likely to have Mental illness

```
x,y = 'Alcohol Consumption', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)
```

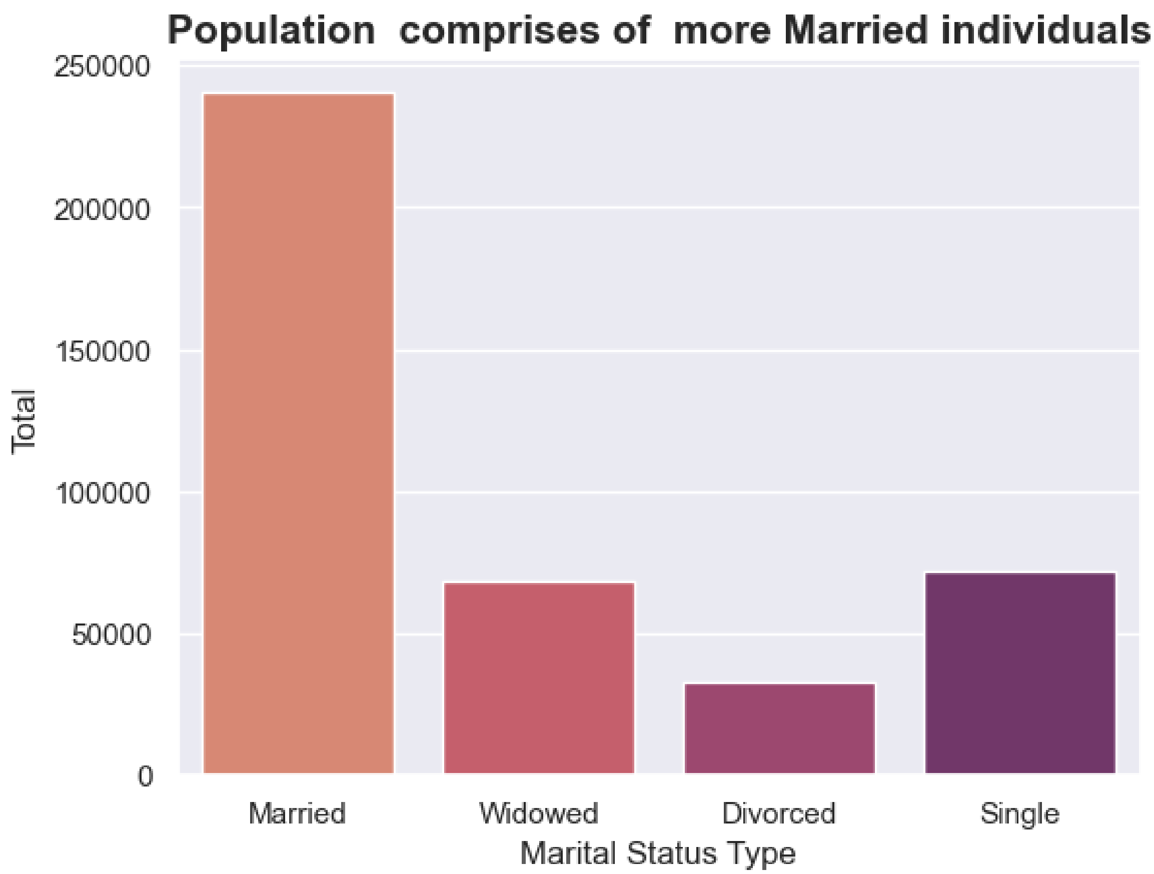
```
for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```




```
plt.figure(figsize = (15, 8))
sns.barplot(data = df,
            x = "Sleep Patterns",
            y = "Income",
            hue = "Education Level").set_title("PhD holders have good
sleep cycle and high income range",weight='bold');
```




```
sns.set_theme(style="darkgrid")
sns.countplot(x="Marital Status", data=df, palette="flare")
plt.xlabel('Marital Status Type')
plt.ylabel('Total')
plt.title('Population  comprises of  more Married 
individuals',fontsize=15,weight='bold')
plt.show()
```

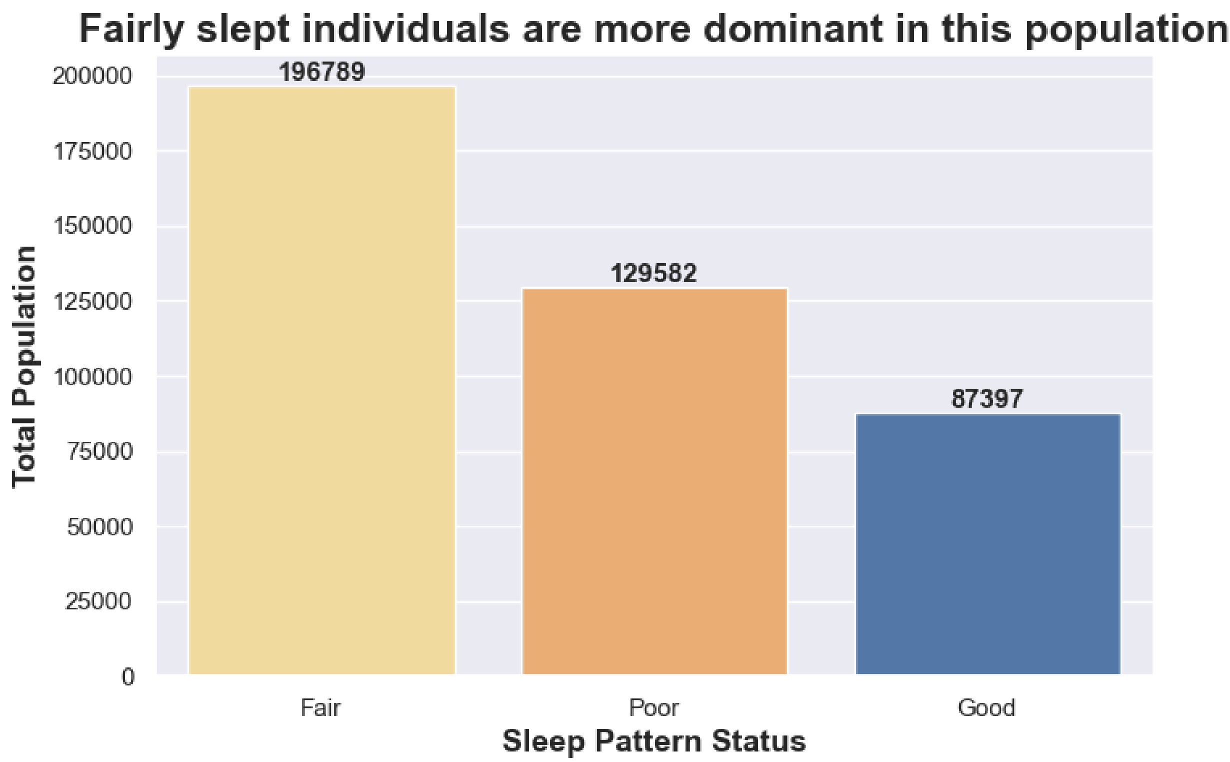



```
Sleep_Patterns_status=pd.DataFrame(df['Sleep
Patterns'].value_counts())
Sleep_Patterns_status.rename_axis('Sleep Patterns',inplace=True)
Sleep_Patterns_status.columns=['Total Count']
Sleep_Patterns_status=Sleep_Patterns_status.reset_index()
Sleep_Patterns_status
```

	Sleep Patterns	Total Count
0	Fair	196789
1	Poor	129582
2	Good	87397

```
plt.figure(figsize=(8,5))
palette = ["#fee090", "#fdae61", "#4575b4", "#313695"]
bar=sns.barplot(x='Sleep Patterns',y='Total
Count',data=Sleep_Patterns_status,palette=palette)

plt.title('Fairly slept individuals are more dominant in this
population',fontsize=18,weight='bold')
plt.xlabel('Sleep Pattern Status',fontsize=14,weight='bold')
plt.ylabel('Total Population',fontsize=14,weight='bold')

for i in range(len(Sleep_Patterns_status)):
```

```
    plt.text(i,Sleep_Patterns_status['Total Count']
[i] ,Sleep_Patterns_status['Total Count'][i],
             ha='center', va='bottom', fontsize=12, fontweight='bold')

plt.show()
```




```
Alcohol_Consumption=pd.DataFrame(df['Alcohol
Consumption'].value_counts())
Alcohol_Consumption.rename_axis('Alcohol Consumption',inplace=True)
Alcohol_Consumption.columns=['Total Count']
Alcohol_Consumption=Alcohol_Consumption.reset_index()
Alcohol_Consumption
```

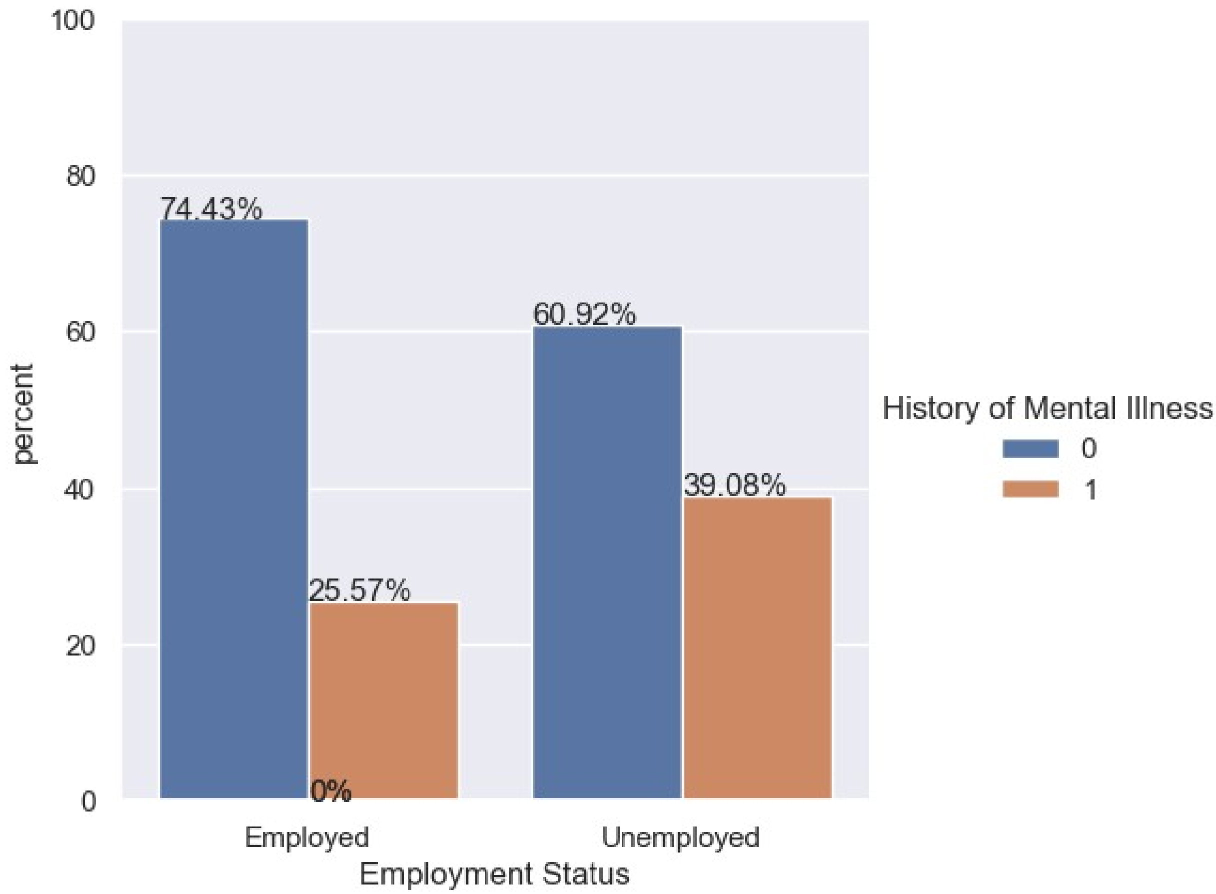
	Alcohol Consumption	Total Count
0	Moderate	173440
1	Low	139250
2	High	101078

```
Employment_Status=pd.DataFrame(df['Employment Status'].value_counts())
Employment_Status.rename_axis('Employment Status',inplace=True)
Employment_Status.columns=['Total Count']
Employment_Status=Employment_Status.reset_index()
Employment_Status
```

```
  Employment Status  Total Count
0          Employed       265659
1        Unemployed       148109
```

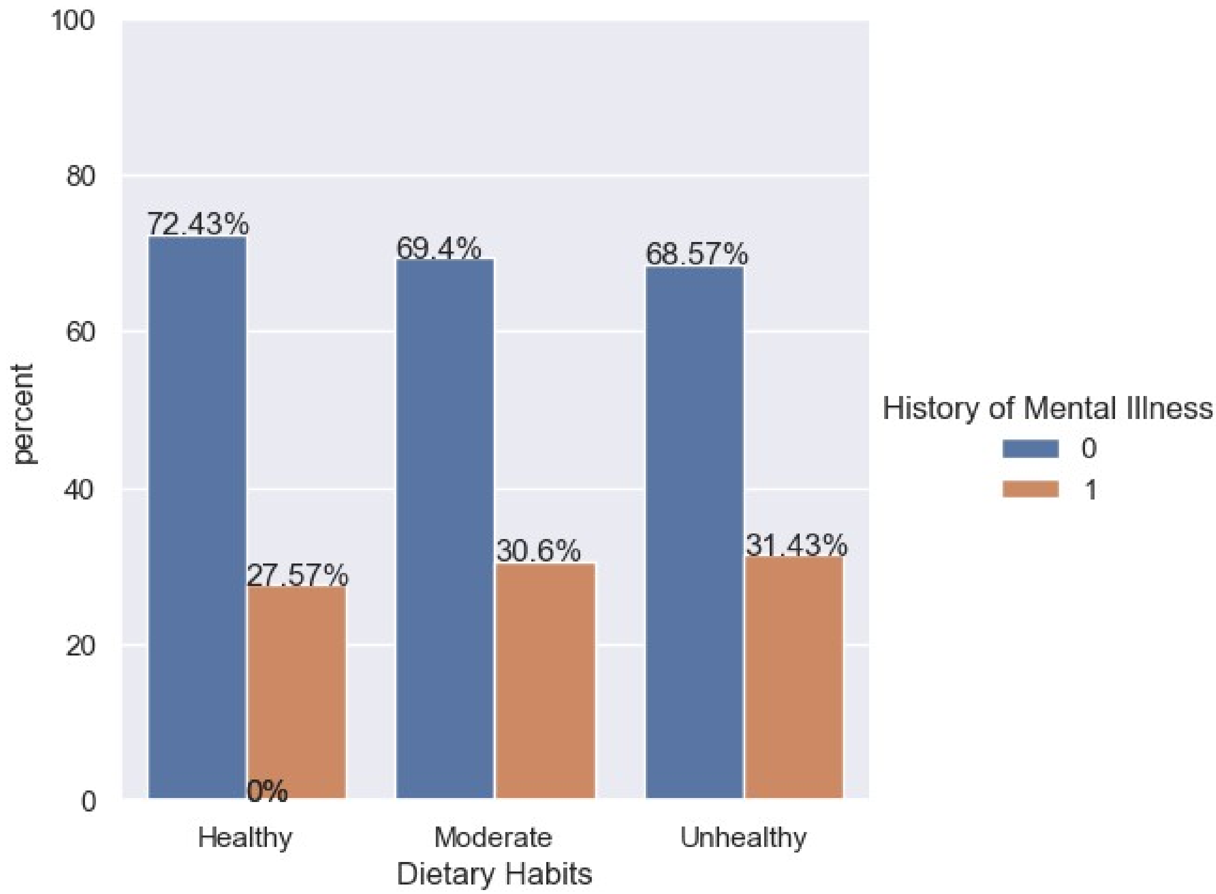
Unemployement can be a cause of mental illness

```
x,y = 'Employment Status', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



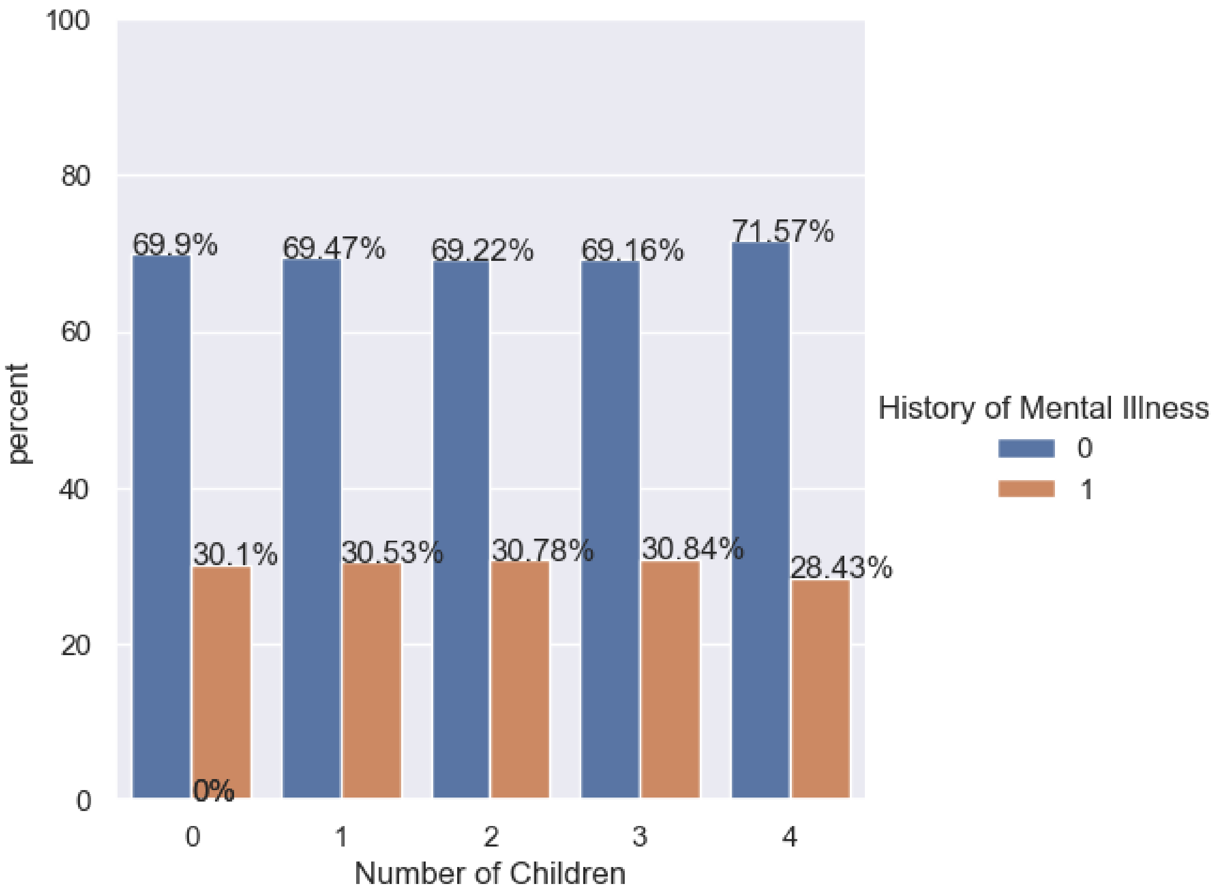
Poor diet can lead to mental illness

```
x,y = 'Dietary Habits', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



People with less than 4 children have higher chances of having mental illness

```
x,y = 'Number of Children', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```




```
smoking_status=pd.DataFrame(df['Smoking Status'].value_counts())
smoking_status.rename_axis('Smoking Status',inplace=True)
smoking_status.columns=['Total Count']
smoking_status= smoking_status.reset_index()
smoking_status
```

	Smoking Status	Total Count
0	Non-smoker	247416
1	Former	116184
2	Current	50168

The population comprises of more individuals with no children than others

```
Number_of_Children=pd.DataFrame(df['Number of
Children'].value_counts())
Number_of_Children.rename_axis('Number of Children', inplace=True)
Number_of_Children.columns = ['Father or Mother ']
```

```
Number_of_Children= Number_of_Children.reset_index()
Number_of_Children
```

	Number of Children	Father or Mother
0	0	155232
1	2	83961
2	1	83925
3	3	76974
4	4	13676

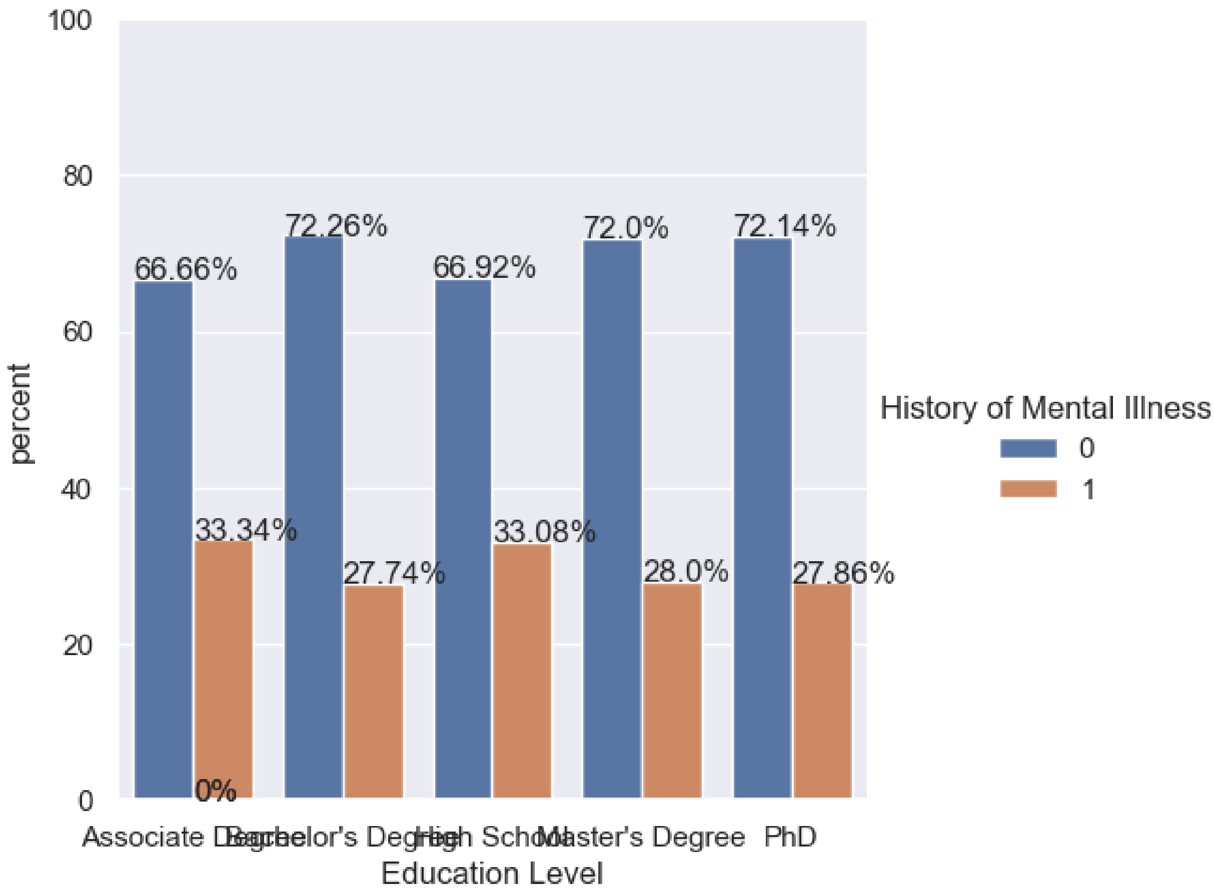
We have more data points where education level is Bachelor's Degree and High school

```
Education_Level=pd.DataFrame(df['Education Level'].value_counts())
Education_Level.rename_axis('Education Level',inplace=True)
Education_Level.columns=['Total Count']
Education_Level=Education_Level.reset_index()
Education_Level
```

	Education Level	Total Count
0	Bachelor's Degree	124329
1	High School	118927
2	Associate Degree	79999
3	Master's Degree	73768
4	PhD	16745

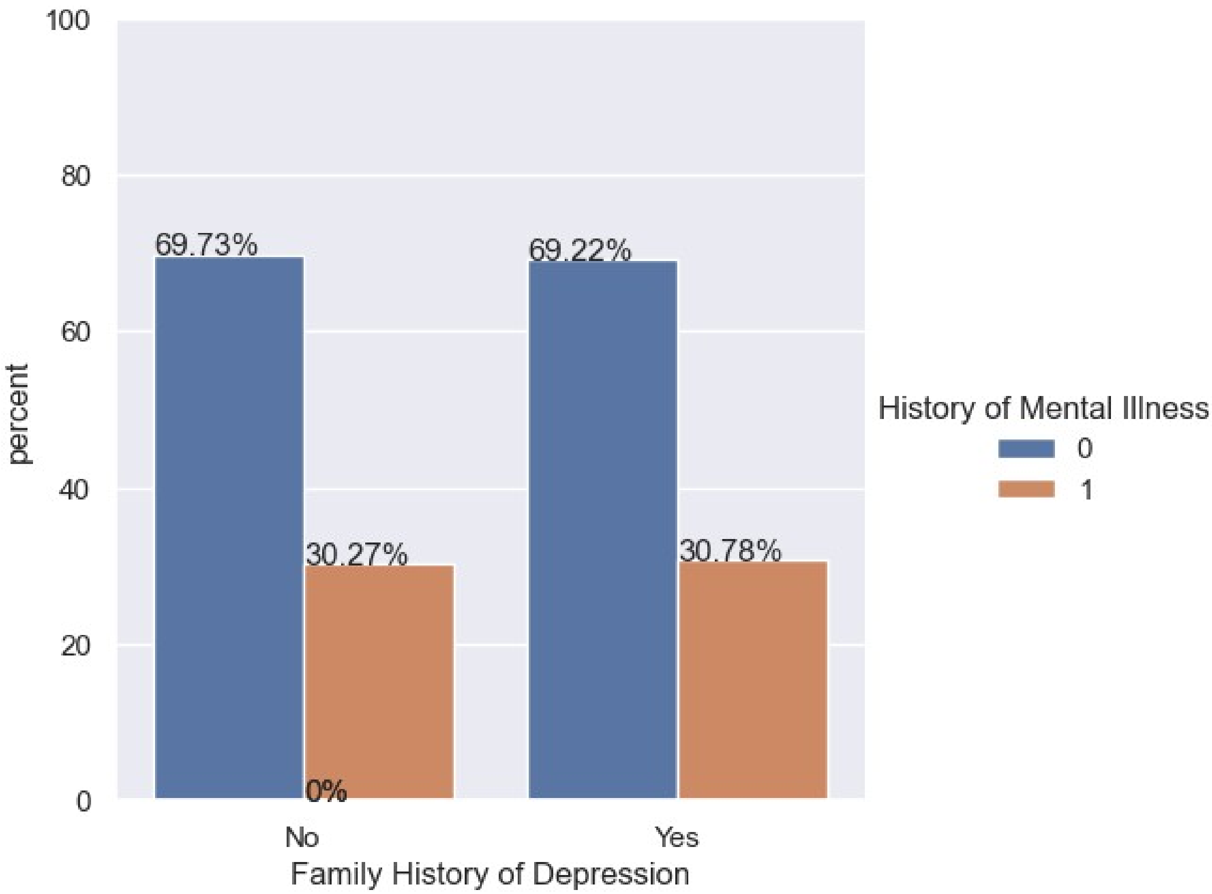
Associate degree individuals are more likely to have mental illness

```
x,y = 'Education Level', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



People with history of depression seems like no direct relationship to hving mental illness

```
x,y = 'Family History of Depression', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```



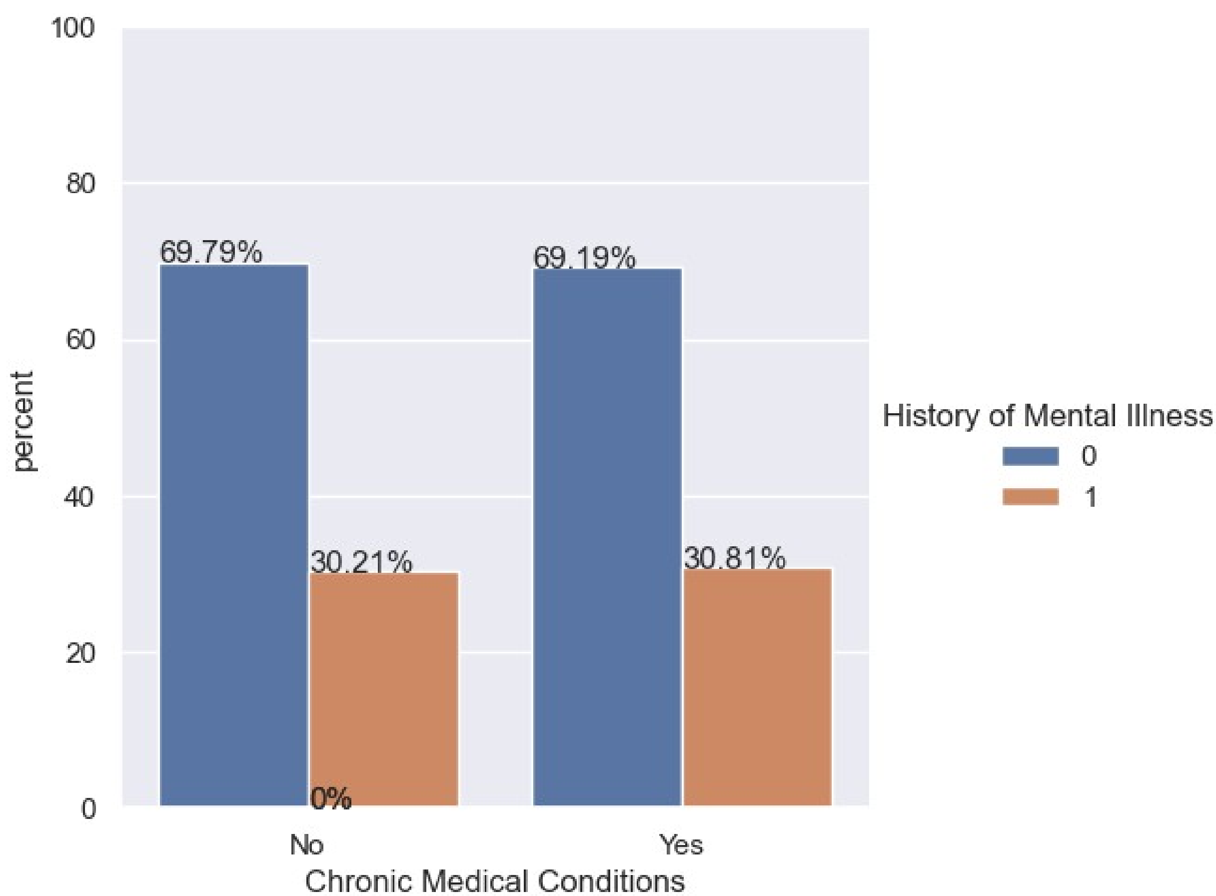
Total count of People not having chronic medical conditions is twice that of having chronic medical condition

```
Medical_condition=pd.DataFrame(df['Chronic Medical
Conditions'].value_counts())
Medical_condition.rename_axis('Chronic Medical
Conditions',inplace=True)
Medical_condition.columns=['Total Count']
Medical_condition=Medical_condition.reset_index()
Medical_condition
```

	Chronic Medical Conditions	Total Count
0	No	277561
1	Yes	136207

Chronic medical condition may not be the right feature to predict mental illness

```
x,y = 'Chronic Medical Conditions', 'History of Mental Illness'

df1 = df.groupby(x)[y].value_counts(normalize=True)
df1 = df1.mul(100)
df1 = df1.rename('percent').reset_index()

g = sns.catplot(x=x,y='percent',hue=y,kind='bar',data=df1)
g.ax.set_ylim(0,100)

for p in g.ax.patches:
    txt = str(round(p.get_height(),2)) + '%'
    txt_x = p.get_x()
    txt_y = p.get_height()
    g.ax.text(txt_x,txt_y,txt)
```

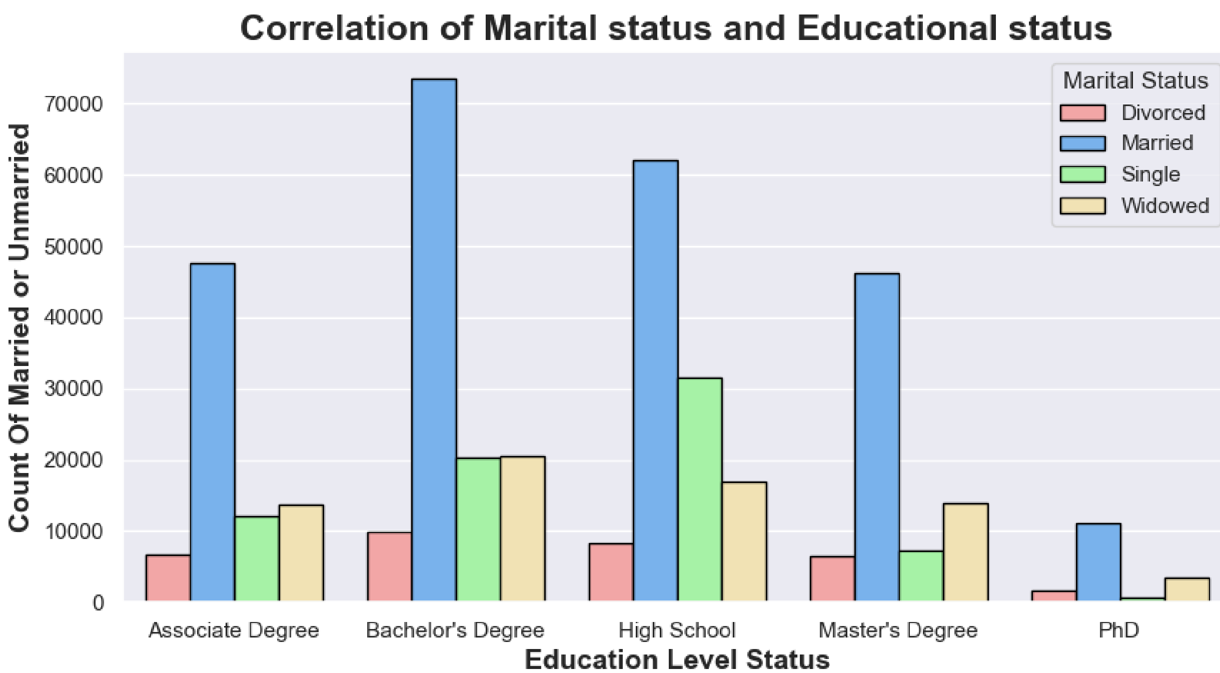



```
Married_Education = df.groupby(['Marital Status','Education Level'])
['Marital Status'].count().reset_index(name =
```

```
'Count Of Married or Unmarried')
Married_Education
```

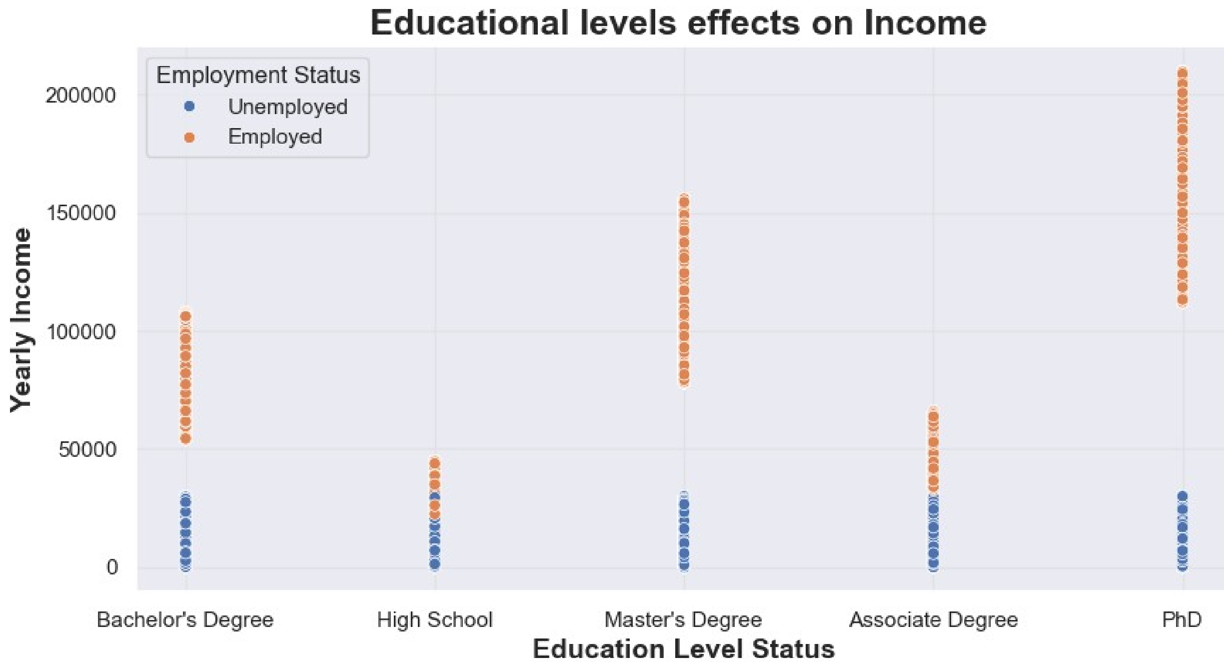
	Marital Status	Education Level	Count Of Married or Unmarried
0	Divorced	Associate Degree	6661
1	Divorced	Bachelor's Degree	9812
2	Divorced	High School	8193
3	Divorced	Master's Degree	6455
4	Divorced	PhD	1608
5	Married	Associate Degree	47535
6	Married	Bachelor's Degree	73573
7	Married	High School	62126
8	Married	Master's Degree	46194
9	Married	PhD	11016
10	Single	Associate Degree	12109
11	Single	Bachelor's Degree	20345
12	Single	High School	31651
13	Single	Master's Degree	7314
14	Single	PhD	691
15	Widowed	Associate Degree	13694
16	Widowed	Bachelor's Degree	20599
17	Widowed	High School	16957
18	Widowed	Master's Degree	13805
19	Widowed	PhD	3430

```
fig, ax = plt.subplots(figsize= (10,5))
sns.barplot(x = 'Education Level', y = 'Count Of Married or Unmarried',data = Married_Education,palette=
            ['#FF9999', '#66B2FF', '#99FF99','#fbe7aa'], edgecolor='black',
 hue = 'Marital Status')
plt.title('Correlation of Marital status and Educational status',fontsize=18,weight='bold')
plt.xlabel('Education Level Status',fontsize=14,weight='bold')
plt.ylabel('Count Of Married or Unmarried',fontsize=14,weight='bold')
plt.show()
```



People with higher education can have potential to earn more

```
fig, ax = plt.subplots(figsize= (10,5))
sns.scatterplot(x = 'Education Level',y = 'Income',data =
df.sort_values(by = []), hue = 'Employment Status' )
plt.title('Educational levels effects on Income
',fontsize=18,weight='bold')
plt.xlabel('Education Level Status',fontsize=14,weight='bold')
plt.ylabel('Yearly Income',fontsize=14,weight='bold')
plt.grid(color='#e2e2e6')
plt.show()
```



Label Encoding all categorical columns values to unique numerical identifier

```
from wolta.data_tools import col_types
from wolta.data_tools import make_numerics
types = col_types(df, print_columns=True)
types = col_types(df)
loc = 0
for col in df.columns:
    if types[loc] == 'str':
        df[col] = make_numerics(df[col])
    loc += 1
```

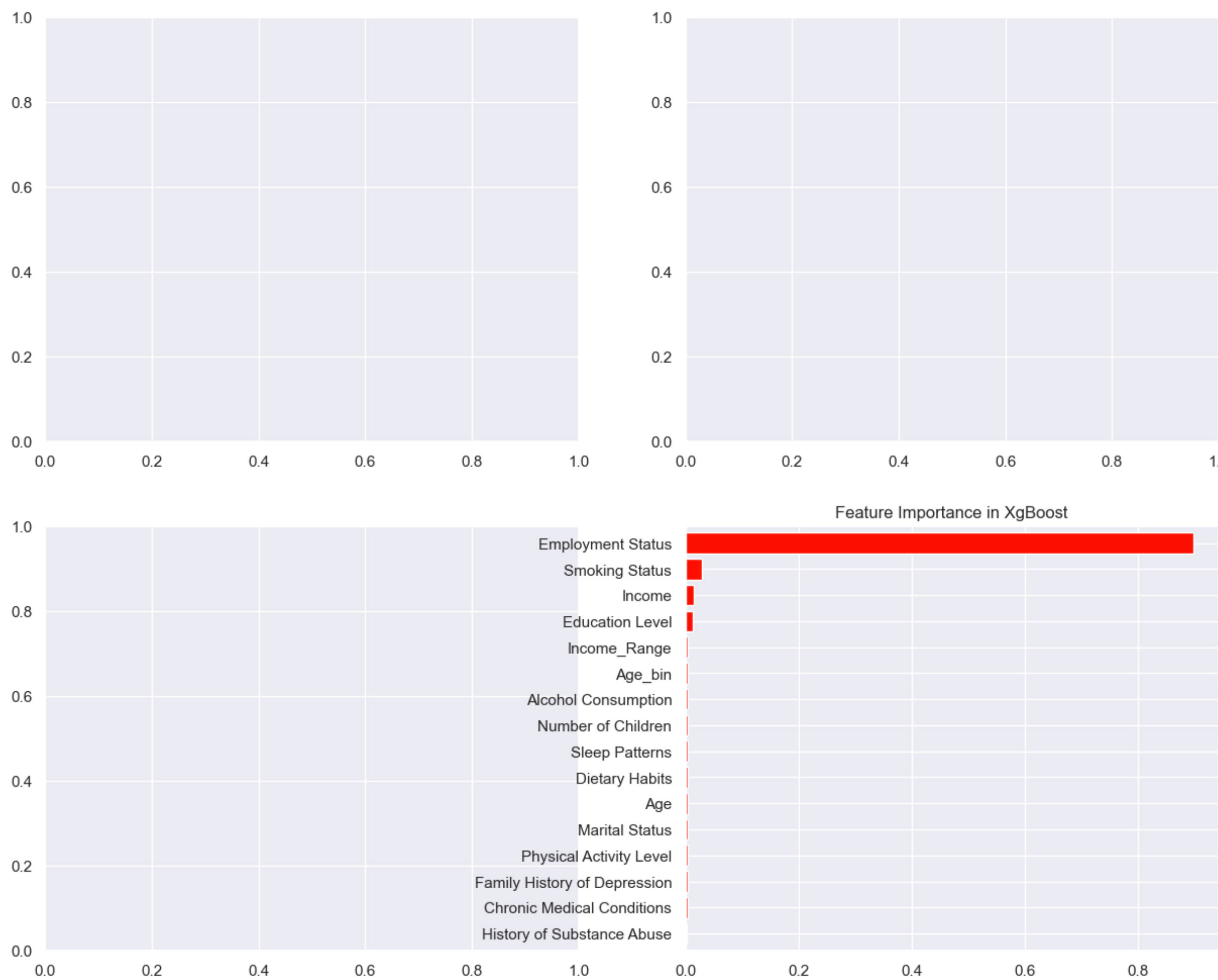
```
Age: int64
Marital Status: str
Education Level: str
Number of Children: int64
Smoking Status: str
Physical Activity Level: str
Employment Status: str
Income: float64
Alcohol Consumption: str
Dietary Habits: str
Sleep Patterns: str
History of Mental Illness: int64
History of Substance Abuse: str
Family History of Depression: str
```

```
Chronic Medical Conditions: str
Income_Range: str
Age_bin: str
```

Convert categorical column datatypes to category and encoding its values

```
df[['Marital Status','Education Level','Number of Children','Smoking 
Status','Physical Activity Level','Employment Status',
    'Alcohol Consumption','Dietary Habits','Sleep Patterns','History 
of Mental Illness','History of Substance Abuse',
  'Family History of Depression', 'Chronic Medical Conditions', 
'Income_Range','Age_bin']].apply(lambda x: x.astype('category'))

types = col_types(df, print_columns=False)
types = col_types(df)
loc = 0
for col in df.columns:
    if types[loc] == 'str':
        df[col] = make_numerics(df[col])
    loc += 1

X = df.drop('History of Mental Illness', axis=1)
Y = df['History of Mental Illness']
f,ax=plt.subplots(2,2,figsize=(15,12))
model=RandomForestClassifier(n_estimators=100,random_state=0)
model.fit(X,Y)
pd.Series(model.feature_importances_,X.columns).sort_values(ascending=
True).plot.barh(width=0.8,ax=ax[0,0])
ax[0,0].set_title('Feature Importance in Random Forests')
model=AdaBoostClassifier(n_estimators=100,learning_rate=0.05,random_st
ate=0)
model.fit(X,Y)
pd.Series(model.feature_importances_,X.columns).sort_values(ascending=
True).plot.barh(width=0.8,ax=ax[0,1],color='#ddff11')
ax[0,1].set_title('Feature Importance in AdaBoost')
model=GradientBoostingClassifier(n_estimators=100,learning_rate=0.1,ra
ndom_state=0)
model.fit(X,Y)
pd.Series(model.feature_importances_,X.columns).sort_values(ascending=
True).plot.barh(width=0.8,ax=ax[1,0],cmap='RdYlGn_r')
ax[1,0].set_title('Feature Importance in Gradient Boosting')

model=XGBClassifier(n_estimators=100,learning_rate=0.1,enable_categori
cal=True)
model.fit(X,Y)
pd.Series(model.feature_importances_,X.columns).sort_values(ascending=
```

```
True).plot.barh(width=0.8,ax=ax[1,1],color='#FD0F00')
ax[1,1].set_title('Feature Importance in XgBoost')
plt.show()


X = df.drop('History of Mental Illness', axis=1)
Y = df['History of Mental Illness']
f,ax=plt.subplots(2,2,figsize=(15,12))
model=XGBClassifier(n_estimators=100,learning_rate=0.1,enable_categori
cal=True)
model.fit(X,Y)
pd.Series(model.feature_importances_,X.columns).sort_values(ascending=
True).plot.barh(width=0.8,ax=ax[1,1],color='#FD0F00')
ax[1,1].set_title('Feature Importance in XgBoost')
plt.show()
```



The difference between these two features Income and Age is statistically significant

```
from scipy.stats import spearmanr
#calculate Spearman Rank correlation and corresponding p-value(should be less than 0.05 to be statistically significant)
rho, p = spearmanr(df['Income'], df['Age'])
#print Spearman rank correlation and p-value
print('spearman relationship score:',rho)
print('The p value is:',p)
```

```
spearman relationship score: -0.12088665129874963
The p value is: 0.0
```