



Depression is a growing global health issue, and early identification of individuals at risk is crucial for effective intervention. In this project, I used **unsupervised learning**, specifically the **K-Means clustering algorithm**, to analyze various factors related to lifestyle, mental health history, and physical habits. The main goal was to identify groups of individuals with similar risk patterns for depression, without any predefined labels or diagnosis data.

By leveraging clustering techniques, I aimed to group people based on their common traits, such as **smoking habits, alcohol consumption, sleep patterns**, and **mental illness history**. This method helps in uncovering hidden patterns in the data, potentially providing insights into which lifestyle combinations are more likely to result in depression. Through this approach, we can better understand at-risk populations, allowing healthcare providers to target interventions more effectively.

This project showcases how unsupervised learning can play a key role in mental health prediction by grouping individuals based on their depression risk factors, even when explicit diagnostic labels are unavailable.

```
In [1]: # Import Libraries
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
pd.set_option("display.max_rows", 500)
```

```
In [2]: # Loading the data from csv file to a Pandas DataFrame
df = pd.read_csv("C:\\Users\\DELL\\OneDrive - Questindustries\\Documents\\Data")
df.head(3)
```

```
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

```
In [3]: # Finding the number of rows and columns
print(df.shape)
```

```
(1000, 16)
```

In this dataset have 50000 rows and 16 columns overall.

```
In [4]: # Getting some information about the dataset
print(df.info())
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Name                                  1000 non-null   object
1   Age                                   1000 non-null   int64
2   Marital Status                       1000 non-null   object
3   Education Level                      1000 non-null   object
4   Number of Children                   1000 non-null   int64
5   Smoking Status                      1000 non-null   object
6   Physical Activity Level              1000 non-null   object
7   Employment Status                   1000 non-null   object
8   Income                              1000 non-null   float64
9   Alcohol Consumption                 1000 non-null   object
10  Dietary Habits                      1000 non-null   object
11  Sleep Patterns                     1000 non-null   object
12  History of Mental Illness           1000 non-null   object
13  History of Substance Abuse          1000 non-null   object
14  Family History of Depression        1000 non-null   object
15  Chronic Medical Conditions          1000 non-null   object
dtypes: float64(1), int64(2), object(13)
memory usage: 125.1+ KB
None

```

I check this dataset data type. Everything is good and there is no any null rows also.

```
In [5]: df.describe()
```

```
Out[5]:
```

	Age	Number of Children	Income
<b>count</b>	1000.000000	1000.000000	1000.000000
<b>mean</b>	49.052000	1.326000	51202.437610
<b>std</b>	17.990357	1.230951	40858.233896
<b>min</b>	18.000000	0.000000	68.900000
<b>25%</b>	33.000000	0.000000	21345.515000
<b>50%</b>	49.500000	1.000000	38576.120000
<b>75%</b>	65.000000	2.000000	76061.160000
<b>max</b>	80.000000	4.000000	209894.250000

```
In [6]: # Checking the missing values
print(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
```

There is no null values in any rows.

```
In [7]: print(df.duplicated().sum())
```

```
0
```

And also there is no any duplicate values.

```
In [8]: print(df.columns)
```

```
Index(['Name', 'Age', 'Marital Status', 'Education Level',
      'Number of Children', 'Smoking Status', 'Physical Activity Level',
      'Employment Status', 'Income', 'Alcohol Consumption', 'Dietary Habits',
      'Sleep Patterns', 'History of Mental Illness',
      'History of Substance Abuse', 'Family History of Depression',
      'Chronic Medical Conditions'],
      dtype='object')
```

There is have these are have the columns so i focused only healthcare related columns.

```
In [9]: df = df.drop(columns='Name',axis=1)
print(df.head(2))
```

	Age	Marital Status	Education Level	Number of Children	Smoking Status	\
0	31	Married	Bachelor's Degree	2	Non-smoker	
1	55	Married	High School	1	Non-smoker	

	Physical Activity Level	Employment Status	Income	Alcohol Consumption	\
0	Active	Unemployed	26265.67	Moderate	
1	Sedentary	Employed	42710.36	High	

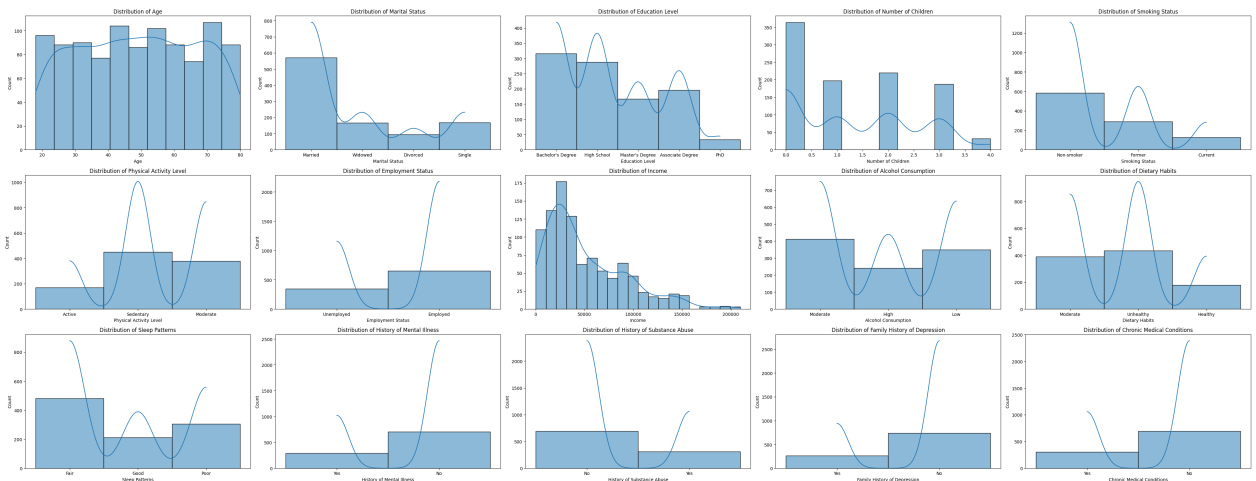
	Dietary Habits	Sleep Patterns	History of Mental Illness	\
0	Moderate	Fair	Yes	
1	Unhealthy	Fair	Yes	

	History of Substance Abuse	Family History of Depression	\
0	No	Yes	
1	No	No	

	Chronic Medical Conditions
0	Yes
1	Yes

I delete name column because for it is unwanted column for this prediction.

```
In [10]: plt.figure(figsize=(40, 25))
for i, feature in enumerate(df.columns, 1):
    plt.subplot(5, 5, i)
    sns.histplot(df[feature], kde=True, legend=df[feature])
    plt.title(f'Distribution of {feature}')
plt.tight_layout()
plt.show()
```



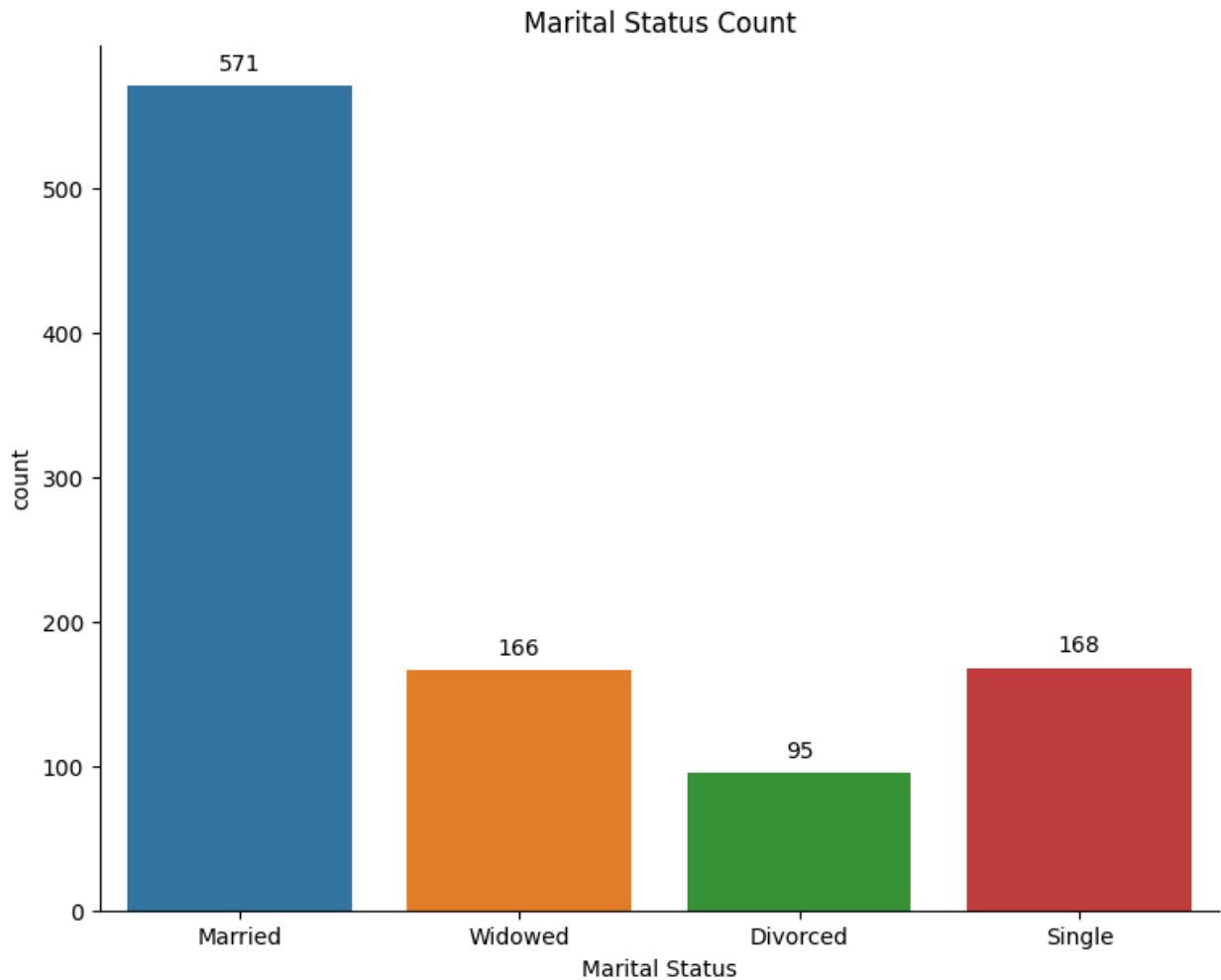
```
In [11]: # Loop through each column in the DataFrame
for col in df:
    if df[col].dtype == 'O': # Check if the column is of object type (category)
        plt.figure(figsize=(9, 7))
        ax = sns.countplot(x=col, data=df, hue=col)

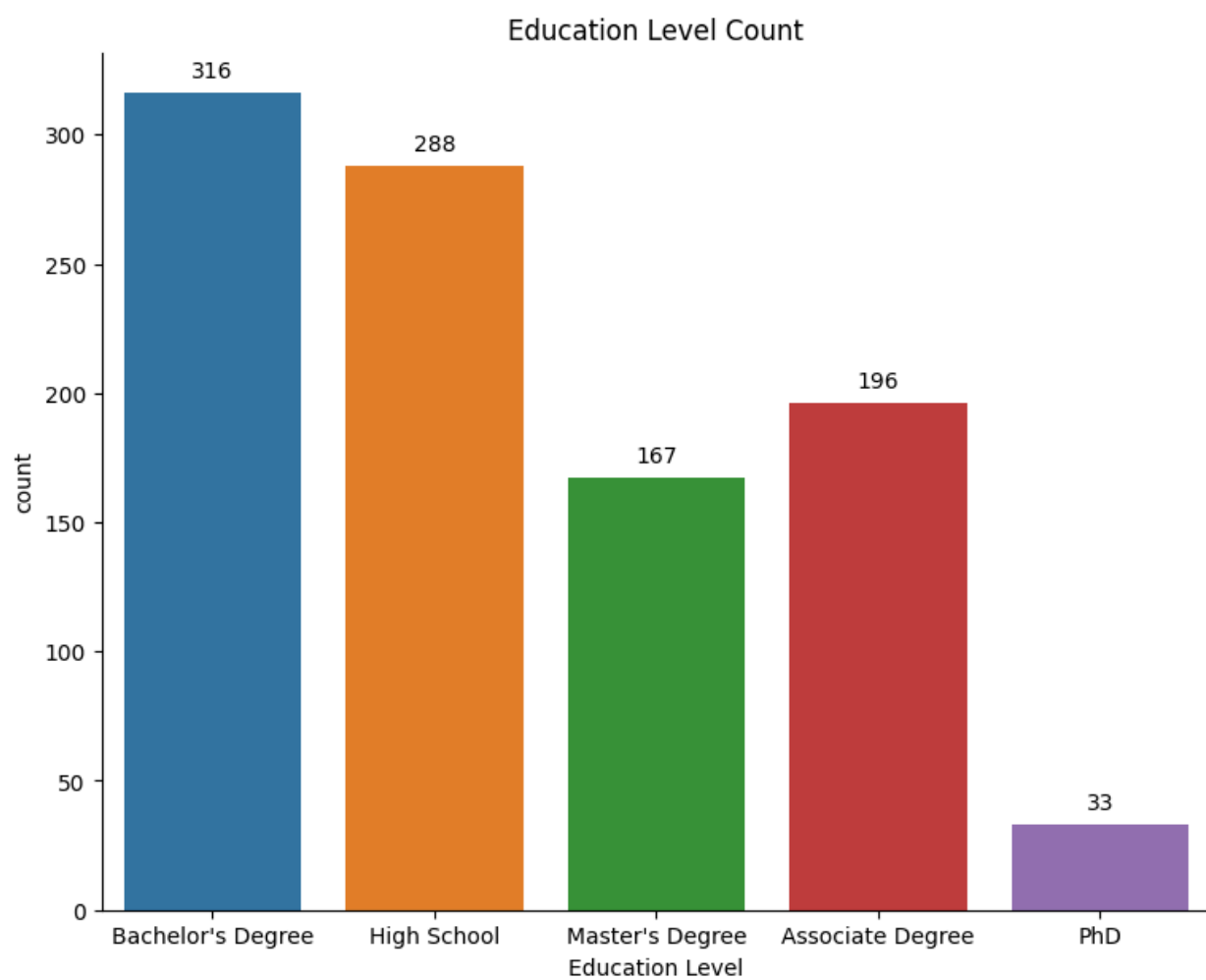
        # Add labels to each bar
        for p in ax.patches:
```

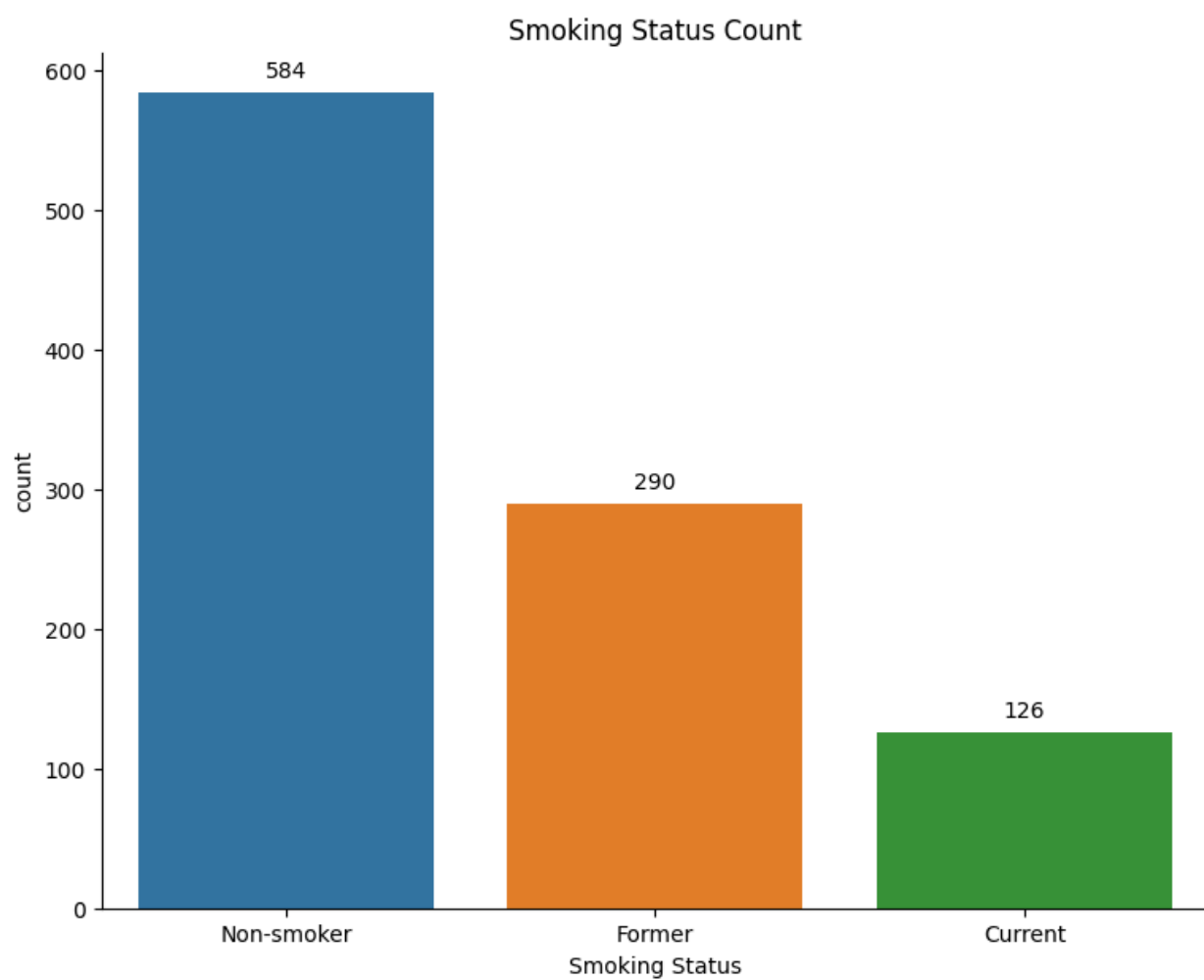
```

ax.annotate(format(p.get_height(), '.0f'),
            (p.get_x() + p.get_width() / 2., p.get_height()),
            ha = 'center', va = 'center',
            xytext = (0, 10),
            textcoords = 'offset points')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.xticks(fontsize=None, ha='center', rotation=None, fontweight=None)
plt.title(f"{col} Count")
plt.show()

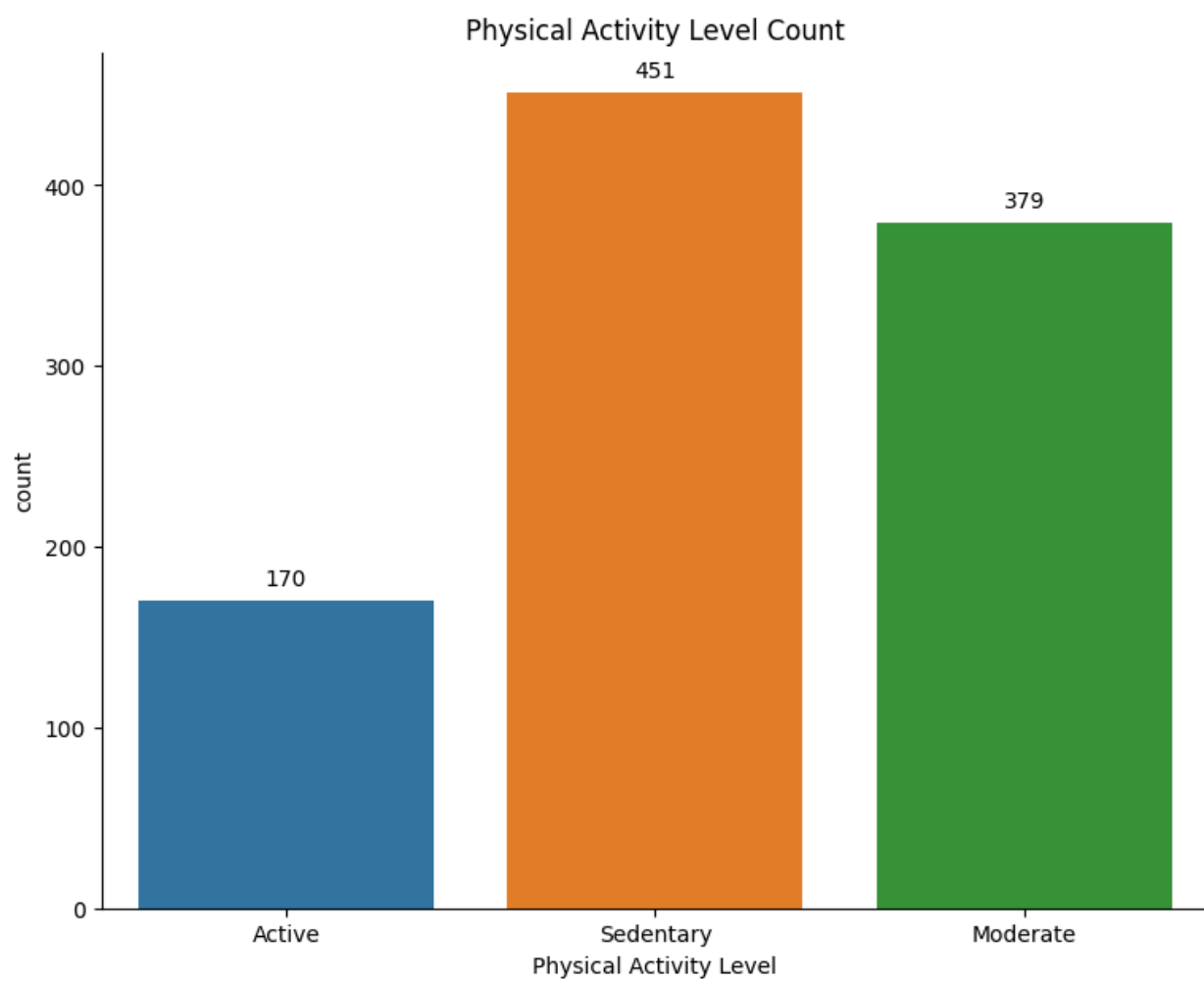
```

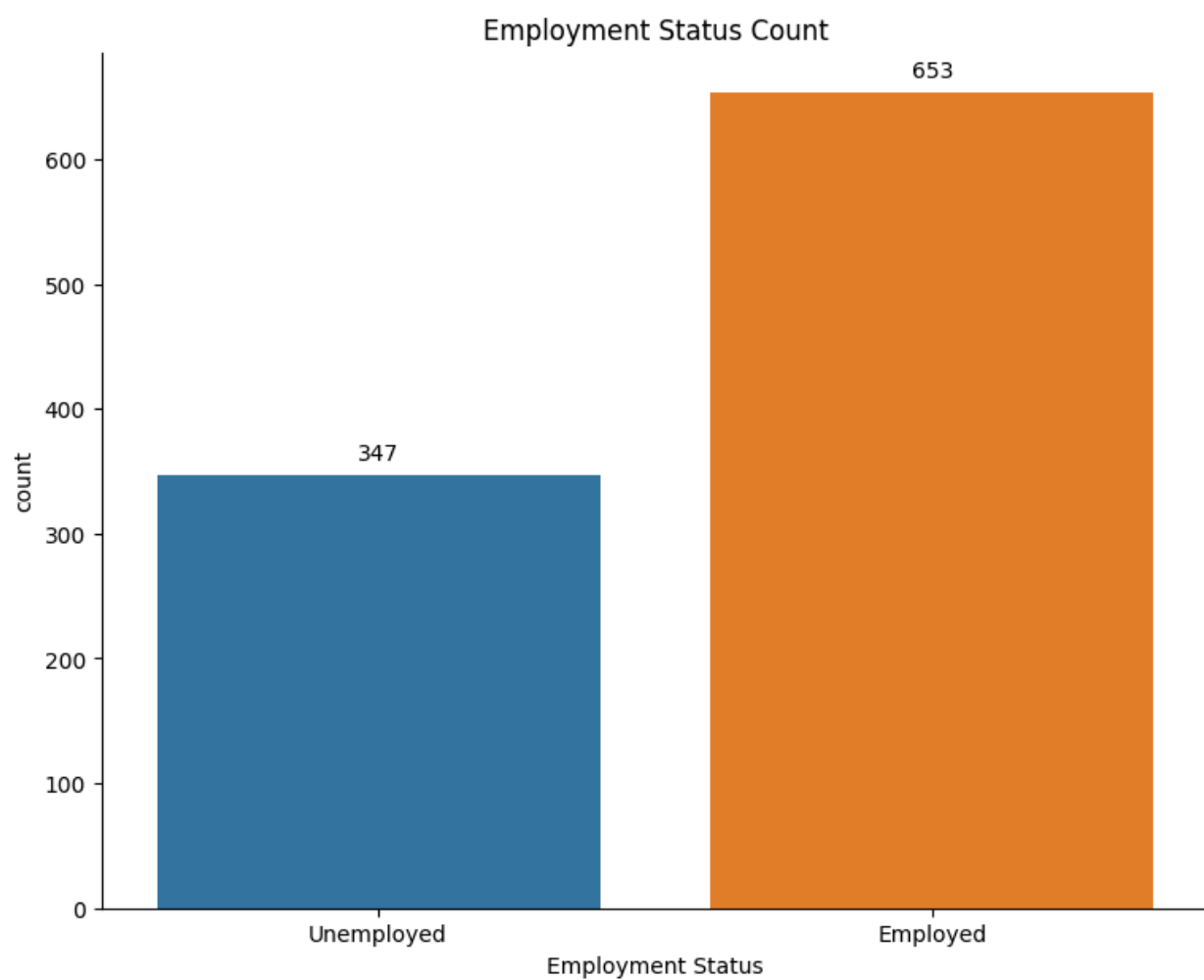


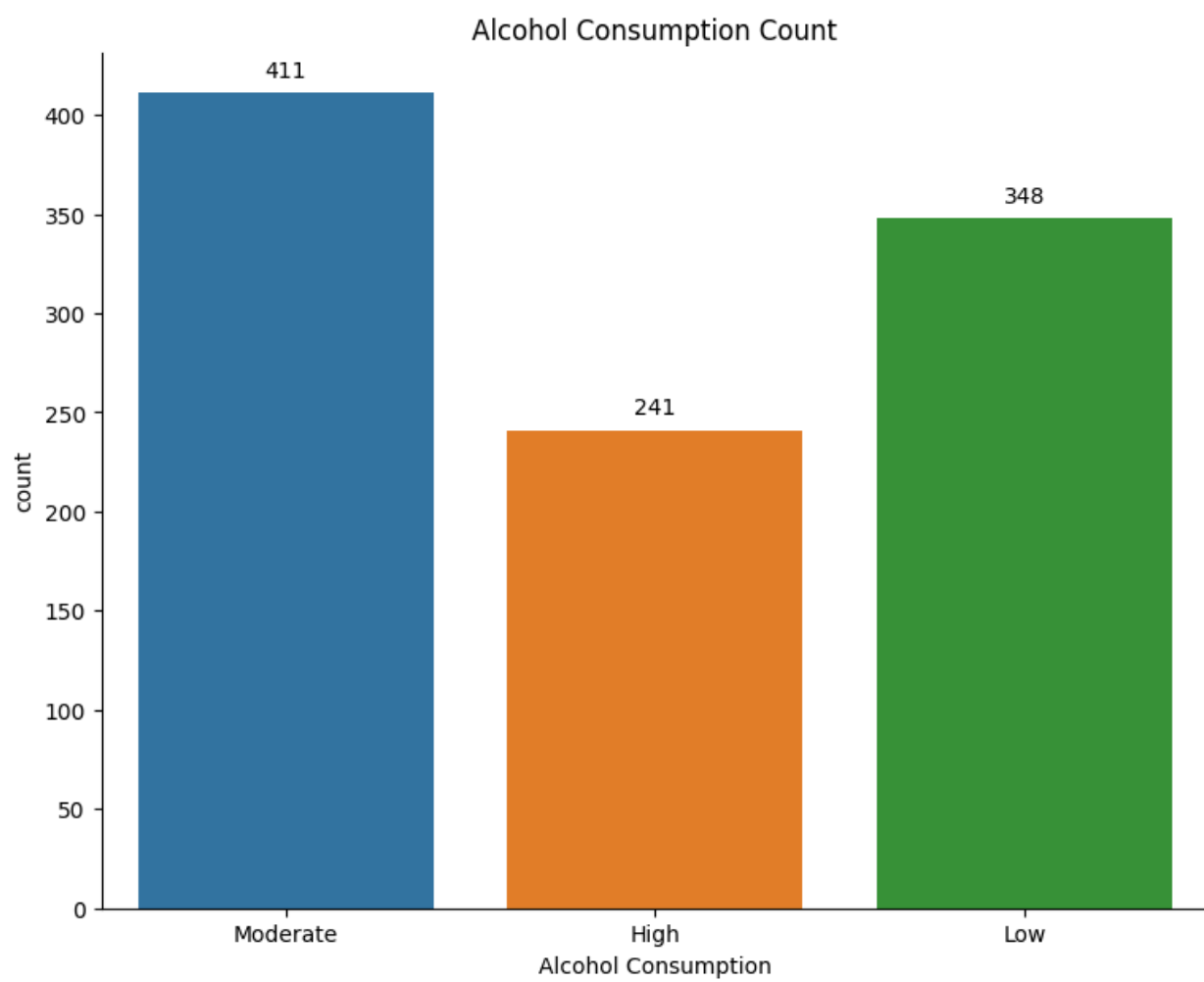


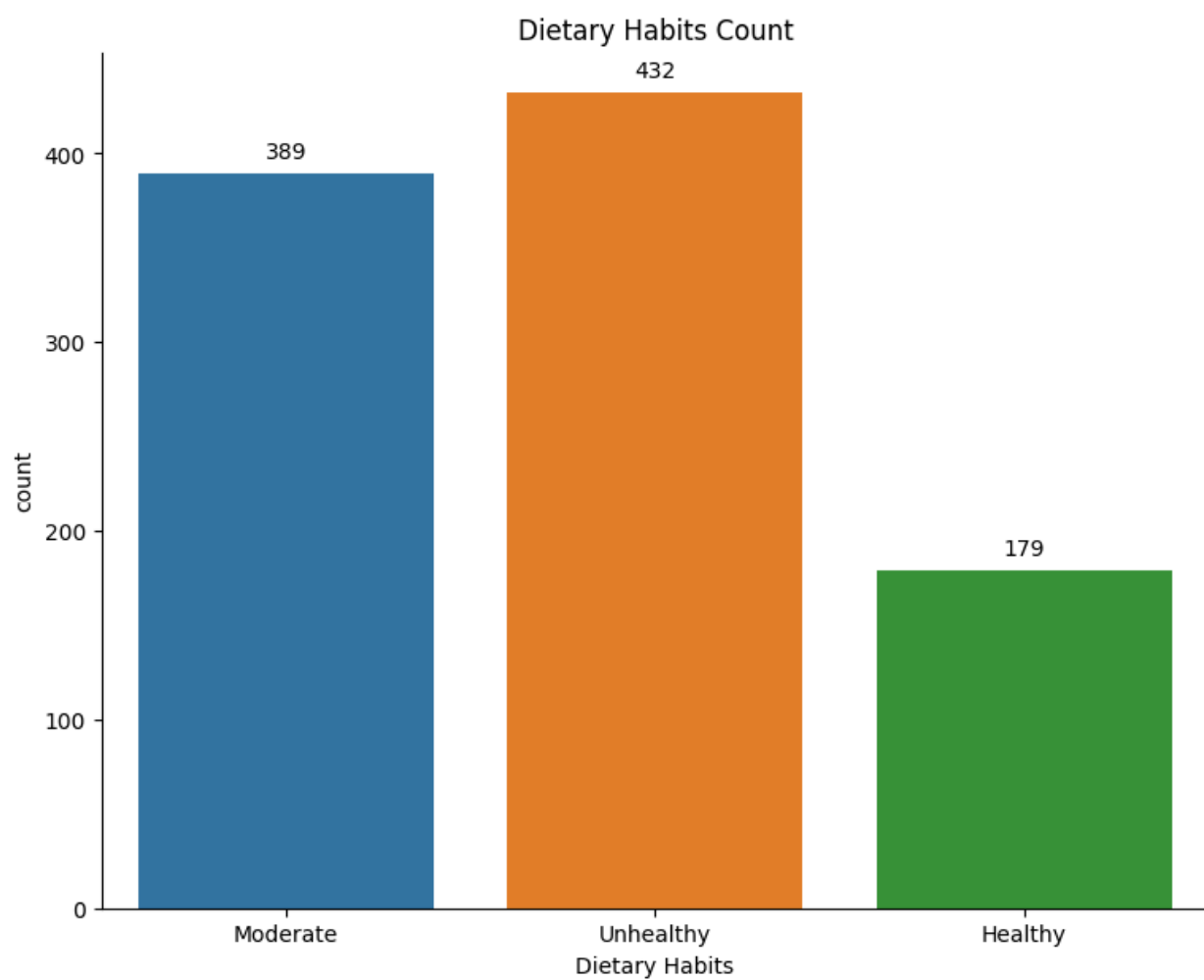


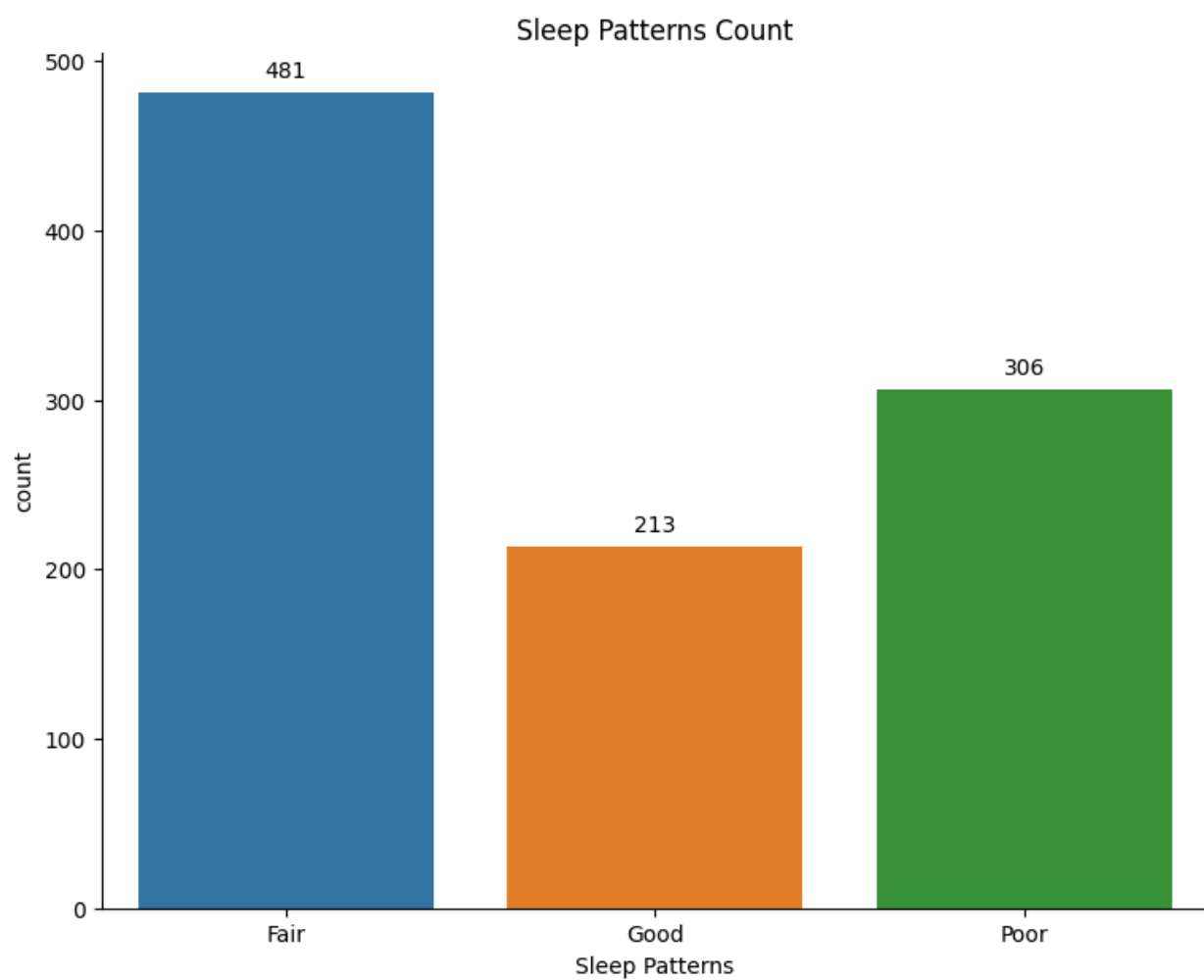


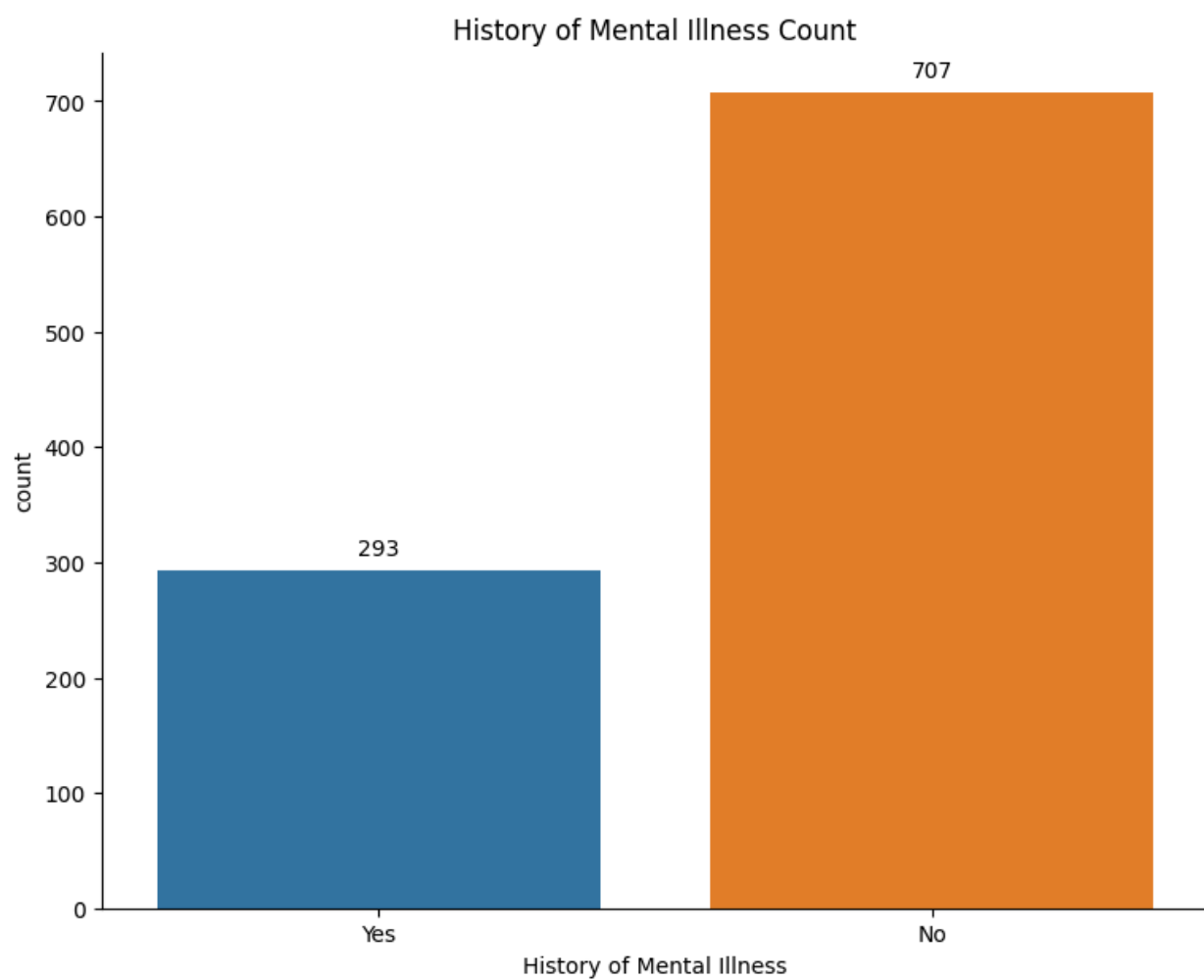


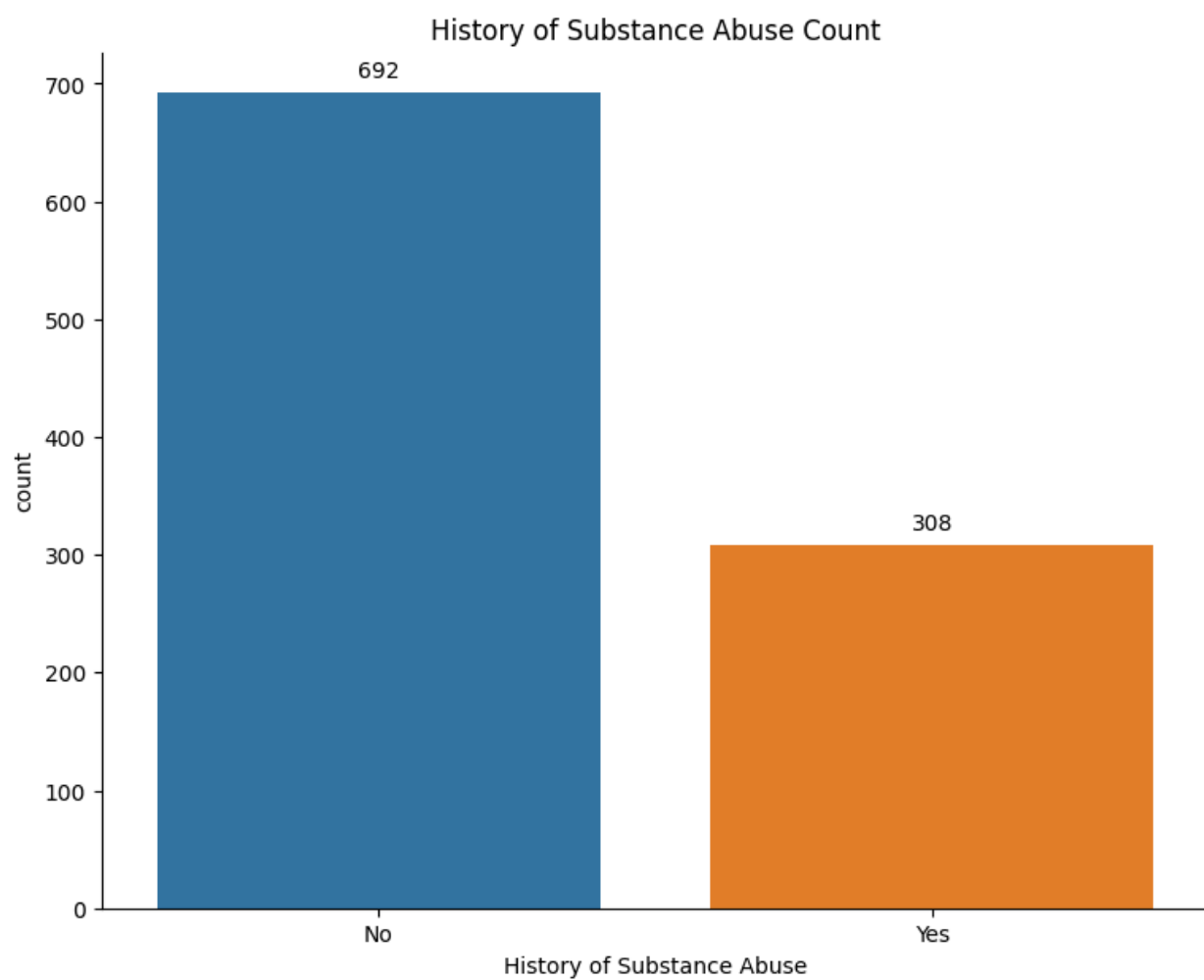


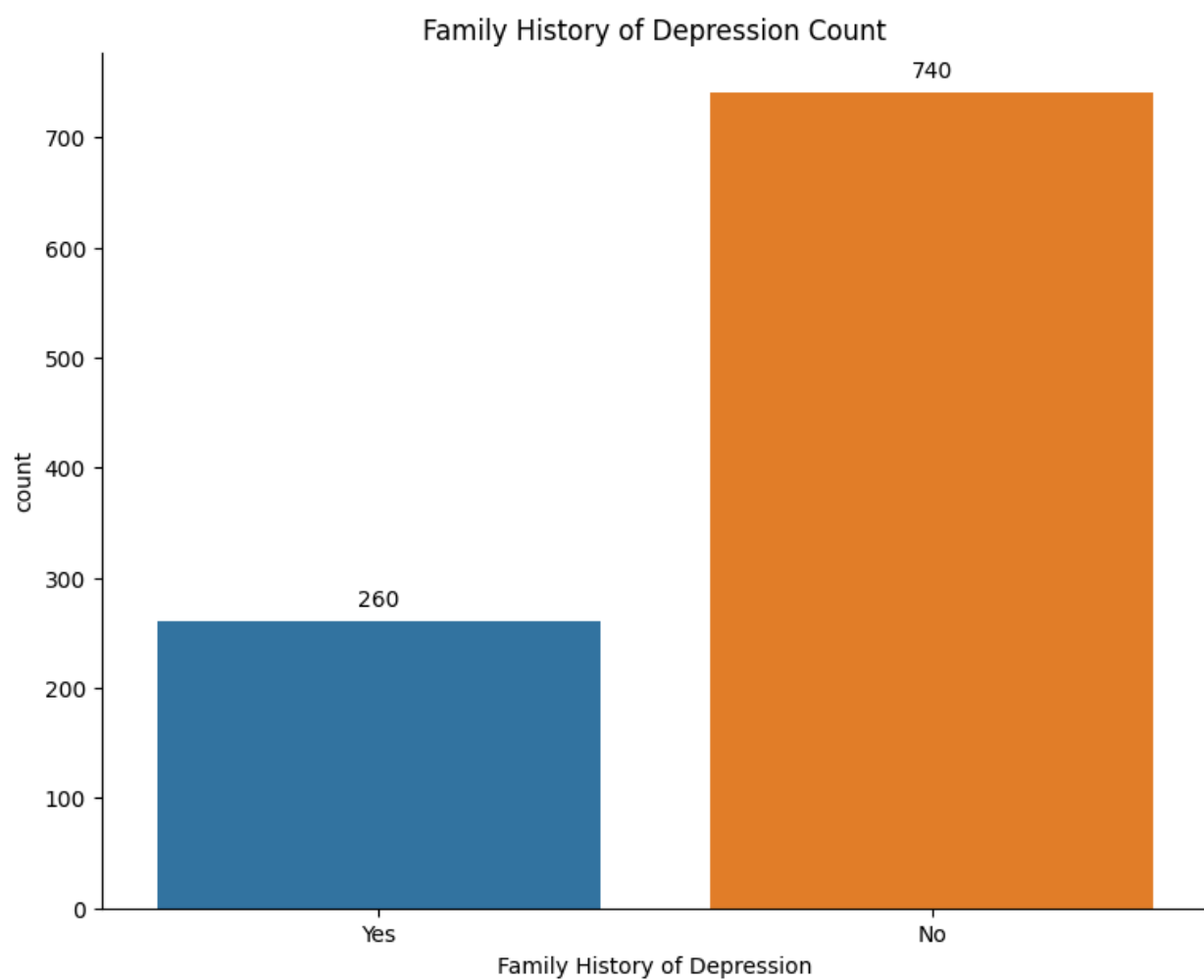




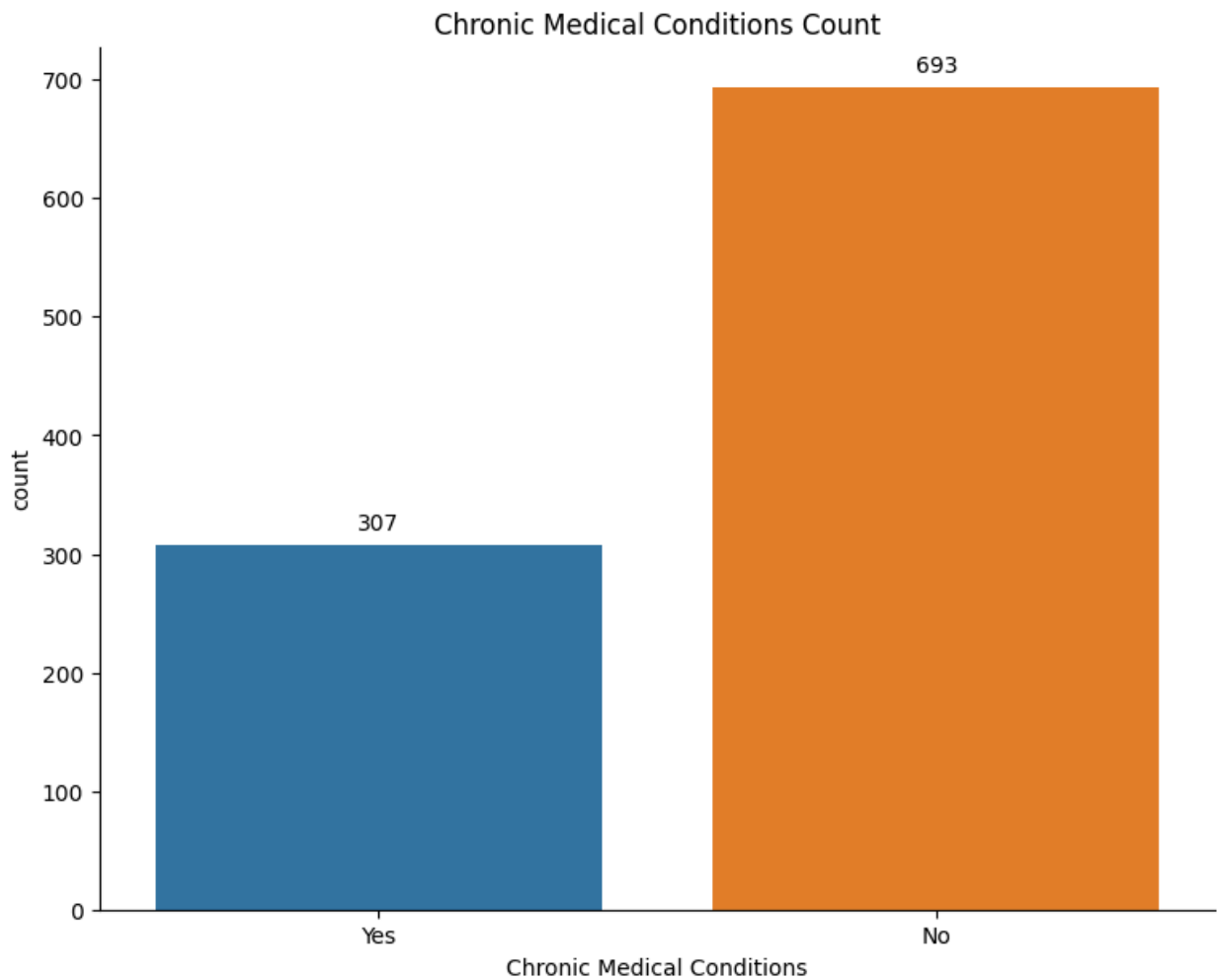












```
In [12]: df.head(2)
```

```
Out[12]:
```

	Age	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income
0	31	Married	Bachelor's Degree	2	Non-smoker	Active	Unemployed	26265.67
1	55	Married	High School	1	Non-smoker	Sedentary	Employed	42710.36

```
In [13]: from sklearn.preprocessing import OrdinalEncoder
```

```
cols_to_encode = [  
    'Marital Status',  
    'Education Level',  
    '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'
]

ordinal_categories = [
    ['Single', 'Married', 'Divorced', 'Widowed'],
    ['High School', "Bachelor's Degree", "Master's Degree", 'Associate Degree'],
    ['Non-smoker', 'Former', 'Current'],
    ['Sedentary', 'Moderate', 'Active'],
    ['Unemployed', 'Employed'],
    ['Low', 'Moderate', 'High'],
    ['Unhealthy', 'Moderate', 'Healthy'],
    ['Poor', 'Good', 'Fair'],
    ['No', 'Yes'],
    ['No', 'Yes'],
    ['No', 'Yes'],
    ['No', 'Yes']
]

encoder = OrdinalEncoder(categories=ordinal_categories)
df[cols_to_encode] = encoder.fit_transform(df[cols_to_encode])

```

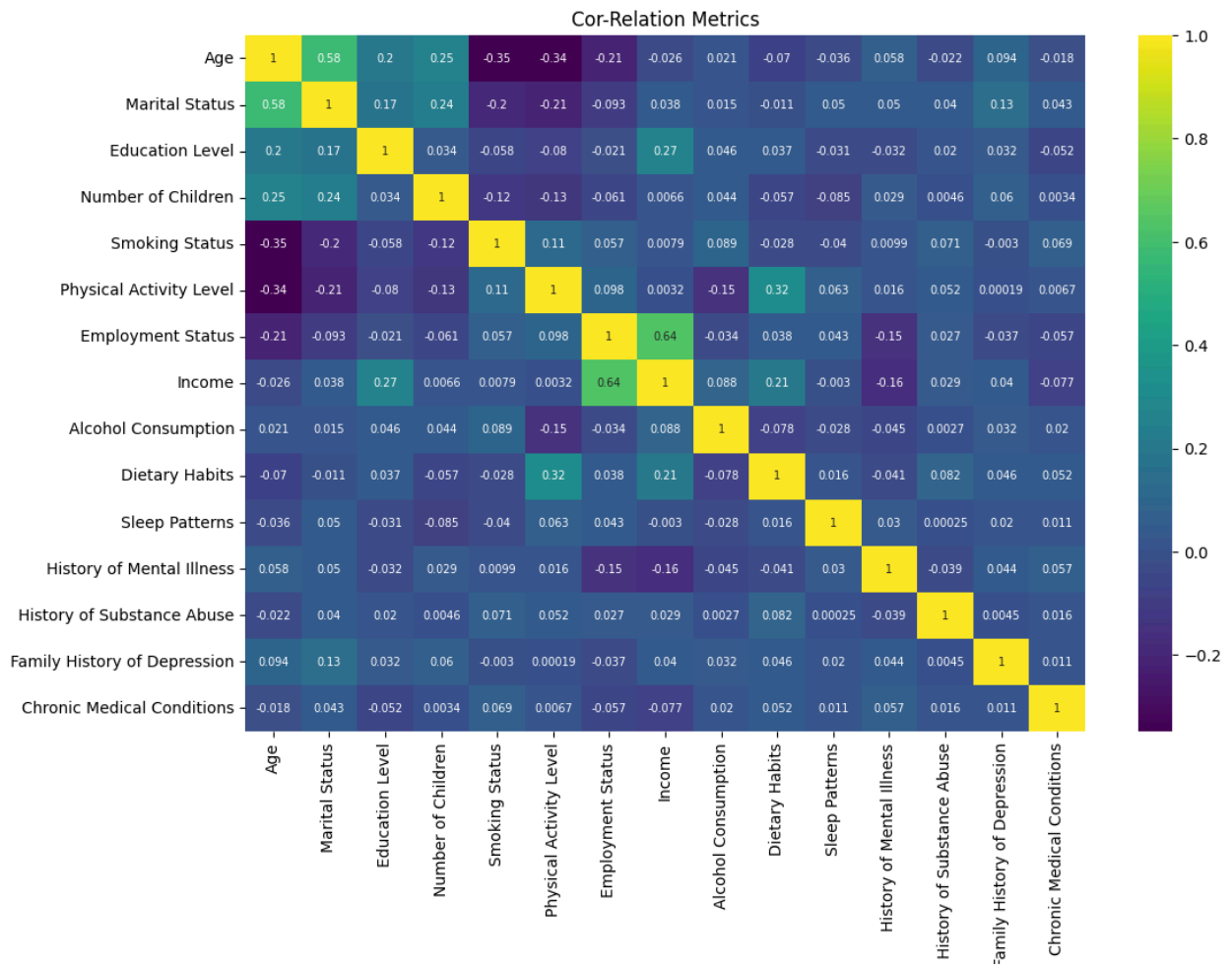
```
In [14]: df[cols_to_encode] = df[cols_to_encode].astype(int)
```

```
In [15]: df.head(2)
```

```
Out[15]:
```

	Age	Marital Status	Education Level	Number of Children	Smoking Status	Physical Activity Level	Employment Status	Income
<b>0</b>	31	1	1	2	0	2	0	26265.67
<b>1</b>	55	1	0	1	0	0	1	42710.36

```
In [16]: fig = plt.figure(figsize=(12,8))
sns.heatmap(df.corr(),annot=True,annot_kws={'size':7}, cmap='viridis')
plt.title("Cor-Relation Metrics")
plt.show()
```



Replace the all the nessesary columns from categeorical to nummerical columns.

```
In [17]: # Visualization for Age and Smoking Status.
age_smoking_bar = px.histogram(df, x=df['Age'], color=df['Smoking Status'],
                                text_auto=True, title='Smoking Status across Di
age_smoking_bar.show()
```

```
In [18]: # Visualization for Physical Activity Level and Chronic Medical Conditions.
age_smoking_bar = px.histogram(df, x=df['Physical Activity Level'], color=df['
                                text_auto=True, title='Physical Activity Level
age_smoking_bar.show()
```

```
In [19]: # Visualization for Income and Education Level.
age_smoking_bar = px.histogram(df, x=df['Income'], color=df['Education Level']
                                text_auto=True, title='Income Distribution acro
age_smoking_bar.show()
```

```
In [20]: # Visualization for Alcohol Consumption and Sleep Patterns.
age_smoking_bar = px.histogram(df, x=df['Alcohol Consumption'], color=df['Slee
                                text_auto=True, title='Alcohol Consumption vs.
age_smoking_bar.show()
```

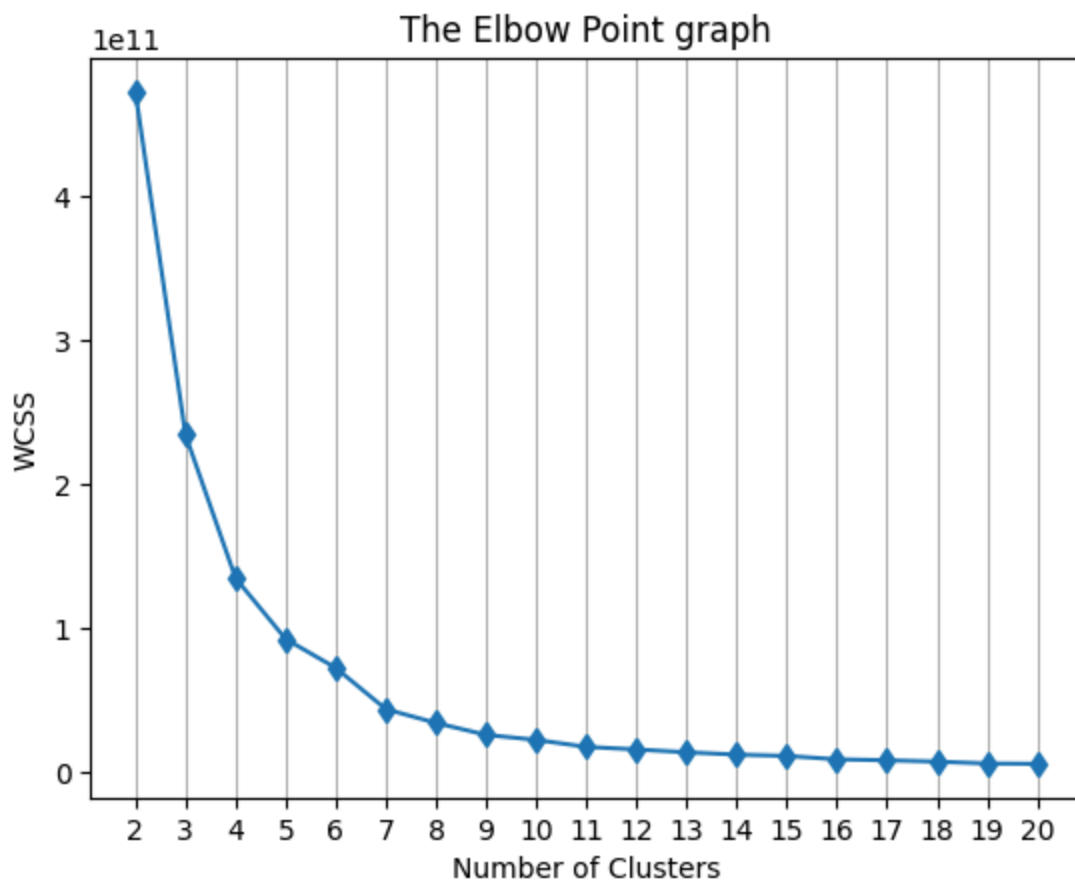
```
In [21]: # Visualization for History of Mental Illness and Employment Status.
age_smoking_bar = px.histogram(df, x=df['History of Mental Illness'], color=df
                                text_auto=True, title='Employment Status based
age_smoking_bar.show()
```

```
In [22]: # Visualization for Family History of Depression and Marital Status.
age_smoking_bar = px.histogram(df, x=df['Family History of Depression'], color
                                text_auto=True, title='Family History of Depres
age_smoking_bar.show()
```

```
In [23]: # Finding wcss value for different number of clusters

wcss = []
for i in range(2, 21):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(df)
    wcss.append(kmeans.inertia_)
```

```
In [24]: # Plot an elbow graph
plt.plot([i for i in range(2, 21)], wcss, marker="d")
plt.xticks([i for i in range(2, 21)])
plt.title("The Elbow Point graph")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS")
plt.grid(axis="x")
plt.show()
```



In [25]: *# Applying KMeans*

```
kmeans = KMeans(n_clusters=3, init="random", n_init="auto")
df['Cluster'] = kmeans.fit_predict(df)
print("Cluster sizes:\n",df['Cluster'].value_counts())
```

Cluster sizes:

```
Cluster
2    611
0    298
1     91
```

Name: count, dtype: int64

In [26]: `silhouette_score(df, kmeans.labels_)`

Out[26]: 0.6413382152891879

```
In [27]: ss = []
no_c = [j for j in range(2,21)]

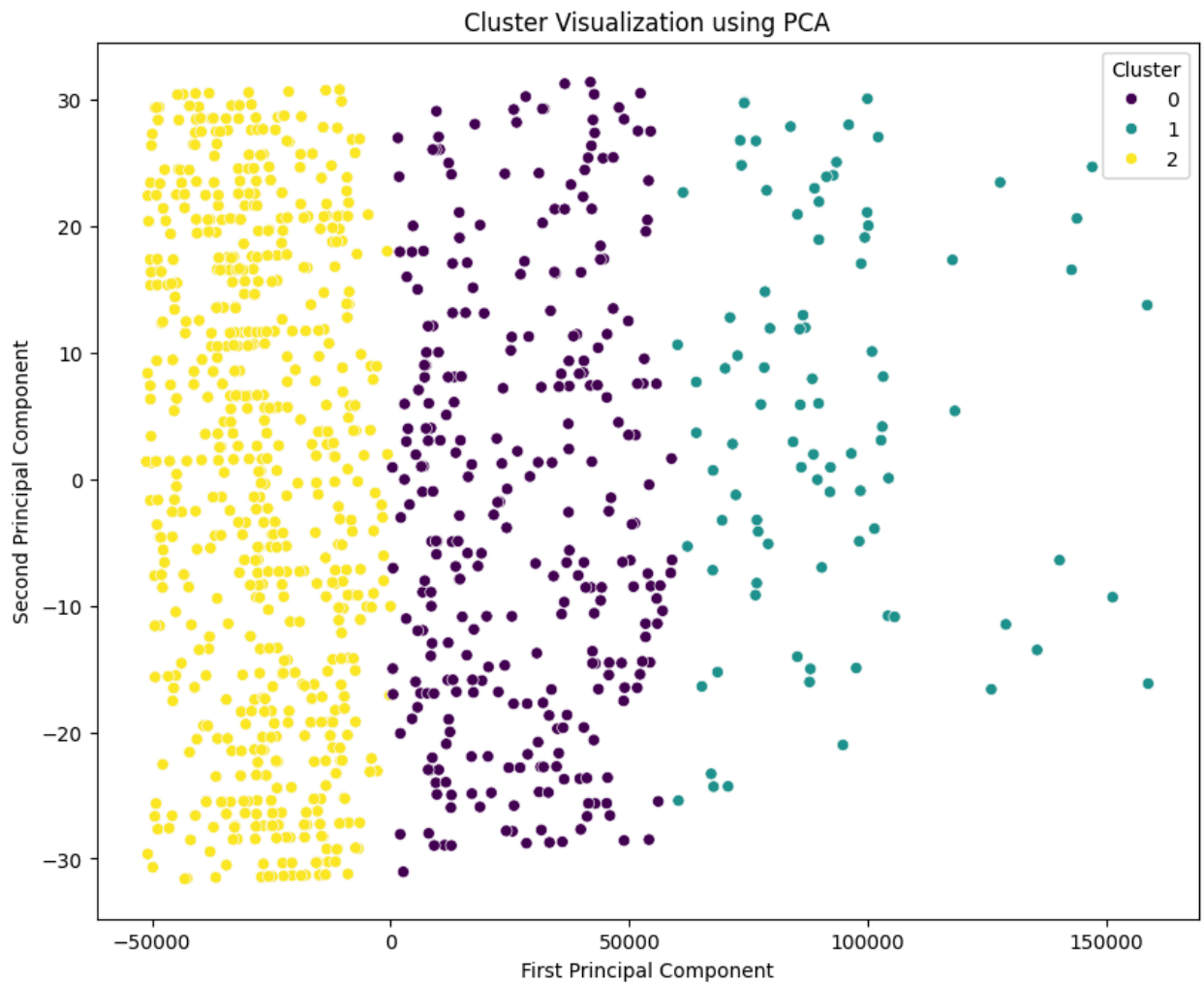
for i in range(2,21):
    km1 = KMeans(n_clusters=i, init="random", n_init="auto")
    km1.fit_predict(df)
    ss.append(silhouette_score(df, km1.labels_))

ss
```

```
Out[27]: [0.666966009013195,  
          0.6413382152891879,  
          0.5864359401564703,  
          0.5562732023563856,  
          0.584765520817268,  
          0.5398568547369123,  
          0.5851271383102905,  
          0.5697185785981921,  
          0.5682634655535632,  
          0.553989633201749,  
          0.5553492734709412,  
          0.559304751099171,  
          0.5582543922002576,  
          0.5520175522608134,  
          0.5497166979919407,  
          0.56681225715333,  
          0.5680188053014582,  
          0.5499295037185933,  
          0.5525334819996408]
```

```
In [28]: # Applying PCA
```

```
pca = PCA(n_components=3)  
X_pca = pca.fit_transform(df)  
plt.figure(figsize=(10, 8))  
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=df['Cluster'], palette='viri  
plt.title('Cluster Visualization using PCA')  
plt.xlabel('First Principal Component')  
plt.ylabel('Second Principal Component')  
plt.show()
```



```
In [29]: score = silhouette_score(df, df['Cluster'])  
print(f'Silhouette Score: {score}')
```

Silhouette Score: 0.6413382152891879

```
In [30]: nfeatures = ['Age', 'Marital Status', 'Education Level', 'Number of Children',  
                    'Smoking Status', 'Physical Activity Level', 'Employment Status',  
                    'Income', 'Alcohol Consumption', 'Dietary Habits', 'Sleep Patterns',  
                    'History of Mental Illness', 'History of Substance Abuse',  
                    'Family History of Depression', 'Chronic Medical Conditions',  
                    'Cluster']
```

```
In [31]: cluster_means = df.groupby('Cluster')[nfeatures].mean()  
print("Cluster means:\n",cluster_means)
```

Cluster means:

	Age	Marital Status	Education Level	Number of Children \
Cluster				
0	46.617450	1.184564	1.483221	1.275168
1	53.197802	1.604396	2.505495	1.461538
2	49.621931	1.243863	1.145663	1.330606

	Smoking Status	Physical Activity Level	Employment Status \
Cluster			
0	0.570470	0.775168	1.000000
1	0.461538	0.615385	1.000000
2	0.540098	0.707038	0.432079

	Income	Alcohol Consumption	Dietary Habits	Sleep Patterns \
Cluster				
0	78543.715705	0.902685	0.993289	1.174497
1	142919.870110	1.076923	1.043956	1.164835
2	24207.368494	0.860884	0.582651	1.176759

	History of Mental Illness	History of Substance Abuse \
Cluster		
0	0.171141	0.328859
1	0.219780	0.340659
2	0.363339	0.292962

	Family History of Depression	Chronic Medical Conditions	Cluster
Cluster			
0	0.265101	0.335570	0.0
1	0.318681	0.164835	1.0
2	0.248773	0.314239	2.0

```
In [32]: cluster_0 = cluster_means.iloc[0]
cluster_1 = cluster_means.iloc[1]
cluster_2 = cluster_means.iloc[2]
print("Cluster Interpretation:")

# Initialize variables
high_risk_cluster = None
average_risk_cluster = None
low_risk_cluster = None

if cluster_0['History of Mental Illness'] > cluster_1['History of Mental Illness']:
    high_risk_cluster = 0
    average_risk_cluster = 1
    low_risk_cluster = 2
elif cluster_1['History of Mental Illness'] > cluster_2['History of Mental Illness']:
    high_risk_cluster = 1
    average_risk_cluster = 2
    low_risk_cluster = 0
else:
    high_risk_cluster = 1
    average_risk_cluster = 2
    low_risk_cluster = 0
```



```
print(f"Cluster {high_risk_cluster} may represent individuals at higher risk of depression.")
print(f"Cluster {average_risk_cluster} may represent individuals at average risk of depression.")
print(f"Cluster {low_risk_cluster} may represent individuals at lower risk of depression.")
```

Cluster Interpretation:

Cluster 1 may represent individuals at higher risk of depression.

Cluster 2 may represent individuals at average risk of depression.

Cluster 0 may represent individuals at lower risk of depression.

```
In [33]: df['Depression_Risk'] = df['Cluster'].map({high_risk_cluster: 'High Risk', average_risk_cluster: 'Average Risk', low_risk_cluster: 'Low Risk'})
```

```
In [34]: print("Sample of results:")
print(df[['Age', 'Income', 'History of Mental Illness', 'Family History of Depression']])
```

Sample of results:

	Age	Income	History of Mental Illness	Family History of Depression	\
674	65	4518.38	1	0	
767	57	47544.24	1	1	
784	20	13382.05	0	0	
336	21	59183.80	0	1	
342	61	209701.03	0	0	
379	73	10539.86	1	0	
950	65	5326.36	0	0	
585	72	2154.82	1	0	
63	71	140015.25	0	1	
26	27	68139.93	0	0	

	Depression_Risk
674	Average Risk
767	Average Risk
784	Average Risk
336	Low Risk
342	High Risk
379	Average Risk
950	Average Risk
585	Average Risk
63	High Risk
26	Low Risk

```
In [35]: df['Depression_Risk'].value_counts()
```

```
Out[35]: Depression_Risk
Average Risk    611
Low Risk       298
High Risk       91
Name: count, dtype: int64
```

```
In [36]: df.to_csv('depression_risk_prediction.csv', index=False)
print("Full results saved to 'depression_risk_prediction.csv'")
```

Full results saved to 'depression\_risk\_prediction.csv'