DEPRESSION

Depression is a common but serious mental health condition that affects how individuals think, feel, and function in daily life. It can lead to emotional and physical problems, and in severe cases, even suicidal thoughts. Among various social classes and demographics, students—especially in secondary and tertiary institutions—are increasingly vulnerable to depression due to academic pressure, social expectations, poor coping mechanisms, and inadequate support systems.

Understanding the patterns and predictors of depression among **students** is critical. It helps in designing timely interventions, shaping school mental health policies, and promoting emotional well-being. This data analysis, identifies key risk factors and target support efforts to the most affected groups, ultimately fostering a healthier learning environment.

DATASET - https://www.kaggle.com/datasets/adilshamim8/student-depression-dataset

```
#import the necessary python libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import geopandas as gpd


#Load the dataset
Depression_data = pd.read_csv('/content/drive/MyDrive/student_depression_dataset.csv')
```

```
Depression_data.head()
```

	id	Gender	Age	City	Profession	Academic Pressure	Work Pressure	CGPA	Study Satisfaction	Job Satisfaction	Sleep Duration	Dietary Habits	Degree	Have ever suitho
0	2	Male	33.0	Visakhapatnam	Student	5.0	0.0	8.97	2.0	0.0	'5-6 hours'	Healthy	B.Pharm	
1	8	Female	24.0	Bangalore	Student	2.0	0.0	5.90	5.0	0.0	'5-6 hours'	Moderate	BSc	
2	26	Male	31.0	Srinagar	Student	3.0	0.0	7.03	5.0	0.0	'Less than 5 hours'	Healthy	BA	
3	30	Female	28.0	Varanasi	Student	3.0	0.0	5.59	2.0	0.0	'7-8 hours'	Moderate	BCA	
4	32	Female	25.0	Jaipur	Student	4.0	0.0	8.13	3.0	0.0	'5-6 hours'	Moderate	M.Tech	

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```
Depression_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27901 entries, 0 to 27900
Data columns (total 18 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   id                                     27901 non-null  int64
 1   Gender                                 27901 non-null  object
 2   Age                                    27901 non-null  float64
 3   City                                   27901 non-null  object
 4   Profession                             27901 non-null  object
 5   Academic Pressure                      27901 non-null  float64
 6   Work Pressure                          27901 non-null  float64
 7   CGPA                                   27901 non-null  float64
 8   Study Satisfaction                     27901 non-null  float64
 9   Job Satisfaction                       27901 non-null  float64
 10  Sleep Duration                         27901 non-null  object
 11  Dietary Habits                         27901 non-null  object
 12  Degree                                 27901 non-null  object
 13  Have you ever had suicidal thoughts ?  27901 non-null  object
 14  Work/Study Hours                       27901 non-null  float64
 15  Financial Stress                       27901 non-null  object
 16  Family History of Mental Illness       27901 non-null  object
 17  Depression                             27901 non-null  int64
dtypes: float64(7), int64(2), object(9)
memory usage: 3.8+ MB
```

```
Depression_data.duplicated().sum()
```

```
np.int64(0)
```

```
Depression_data.describe()
```

	id	Age	Academic Pressure	Work Pressure	CGPA	Study Satisfaction	Job Satisfaction	Work/Study Hours	Depression
count	27901.000000	27901.000000	27901.000000	27901.000000	27901.000000	27901.000000	27901.000000	27901.000000	27901.000000
mean	70442.149421	25.822300	3.141214	0.000430	7.656104	2.943837	0.000681	7.156984	0.585499
std	40641.175216	4.905687	1.381465	0.043992	1.470707	1.361148	0.044394	3.707642	0.492645
min	2.000000	18.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	35039.000000	21.000000	2.000000	0.000000	6.290000	2.000000	0.000000	4.000000	0.000000
50%	70684.000000	25.000000	3.000000	0.000000	7.770000	3.000000	0.000000	8.000000	1.000000
75%	105818.000000	30.000000	4.000000	0.000000	8.920000	4.000000	0.000000	10.000000	1.000000
max	140699.000000	59.000000	5.000000	5.000000	10.000000	5.000000	4.000000	12.000000	1.000000

- Age Ranges from 18-::59 years, with the mean age of ~26 years.
- Majority of respondents are in their early 20s (25% quartile = 21, 75% = 30), typical of **college/university students** or early professionals.
- The CGPA has a maximum value of 10, averaging at 7.66

```
Depression_data.rename(columns={'Have you ever had suicidal thoughts ?': 'Suicidal',
                                'Family History of Mental Illness':'Mental Illness'}, inplace=True)
```

```
sns.set(style="whitegrid")
sns.set_palette("pastel")

plt.figure(figsize=(8, 6))
ax = sns.countplot(data=Depression_data, x='Gender')
ax.set_title('Distribution of Gender')
ax.set_xlabel('Gender')
ax.set_ylabel('Count')

# Add labels to bars
for container in ax.containers:
    ax.bar_label(container, label_type='center')
```


```
Depression_data['Profession'].value_counts()
```

Profession	count
Student	27870
Architect	8
Teacher	6
'Digital Marketer'	3
Chef	2
'Content Writer'	2
Pharmacist	2
Doctor	2
'UX/UI Designer'	1
'Civil Engineer'	1
Manager	1
'Educational Consultant'	1
Lawyer	1
Entrepreneur	1

dtype: int64

The Majority of our target professions are **Students**

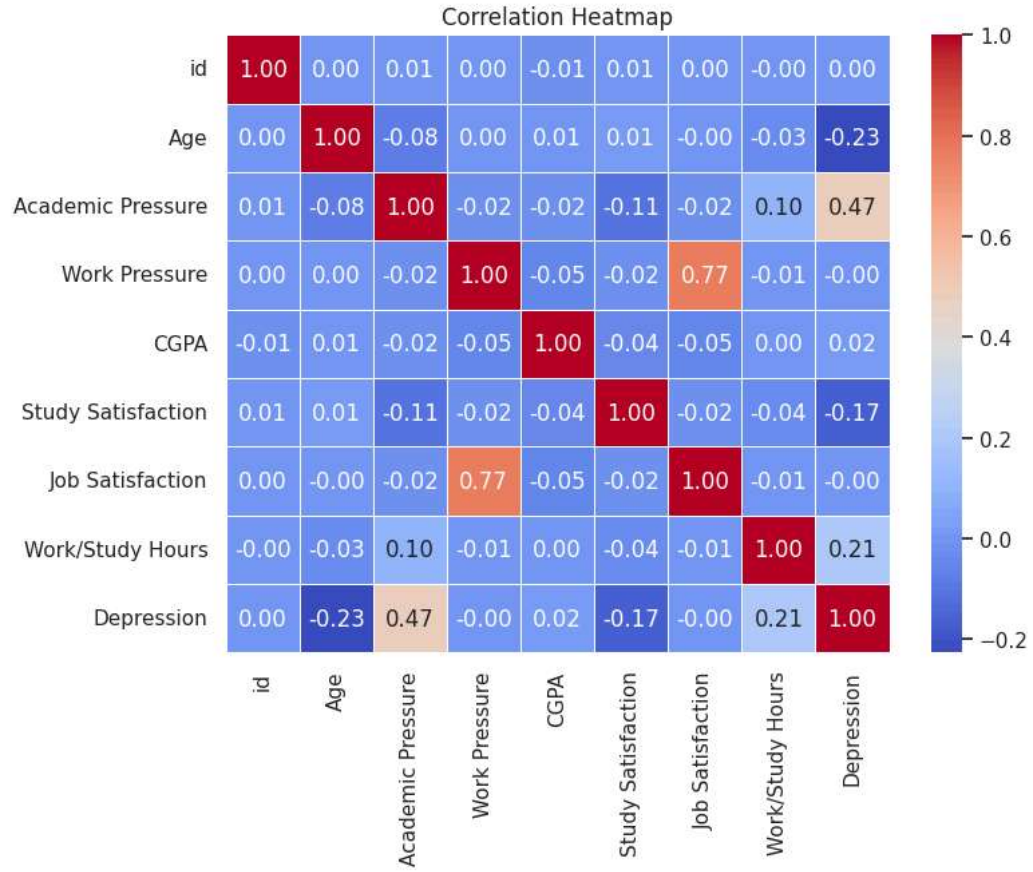
Since **Depression** is our major focus for this analysis, lets identify potential **numeric** predictors of Depression from the dataset.

```
# correlation matrix
corr_Dep = Depression_data.corr(numeric_only=True)

# Plot heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(corr_Dep, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()

# Filter correlations with 'Depression'
depression_corr = corr_Dep['Depression'].drop('Depression').sort_values(key=abs, ascending=False)

# Top correlations
print("Potential correlations with Depression:\n")
print(depression_corr)
```




```
Potential correlations with Depression:

Academic Pressure     0.474835
Age                  -0.226422
Work/Study Hours      0.208563
Study Satisfaction   -0.167971
CGPA                  0.022210
Job Satisfaction     -0.003482
Work Pressure        -0.003351
id                    0.000923
Name: Depression, dtype: float64
```

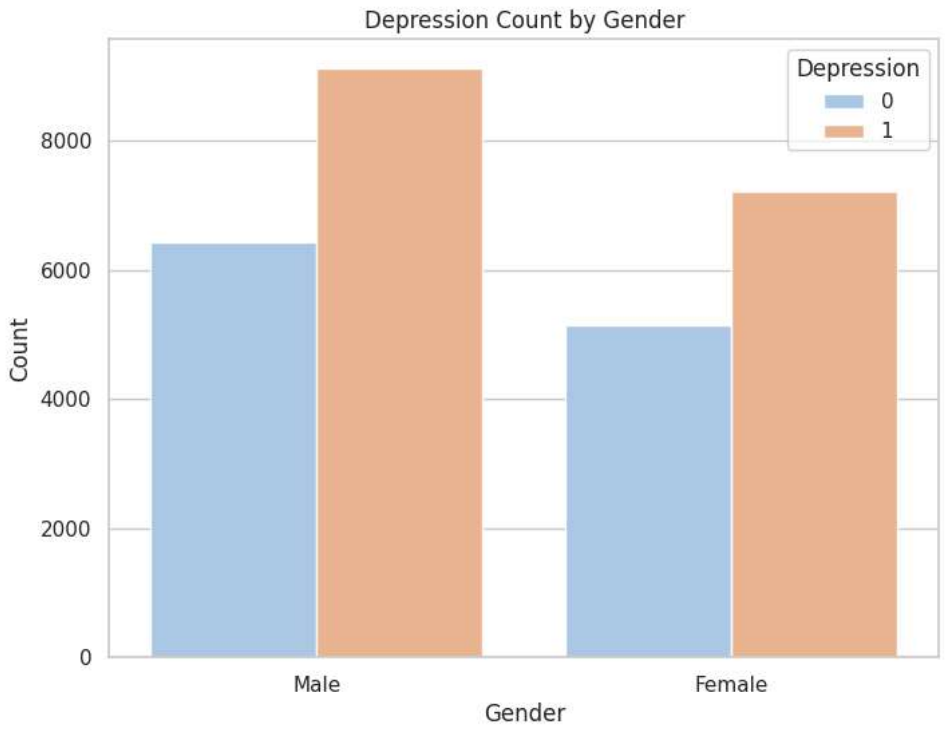
From the result above,

- Academic Pressure and Work/Study Hours are the Major factors that contribute to Depression.
- While, Study Satisfaction contribute the least.

Investigate the relation of Depression to the categorical data

```
# Bar Plot - Gender vs. Depression
plt.figure(figsize=(8, 6))

sns.countplot(data=Depression_data, x='Gender', hue='Depression')
plt.title('Depression Count by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.legend(title='Depression')
plt.show()
```



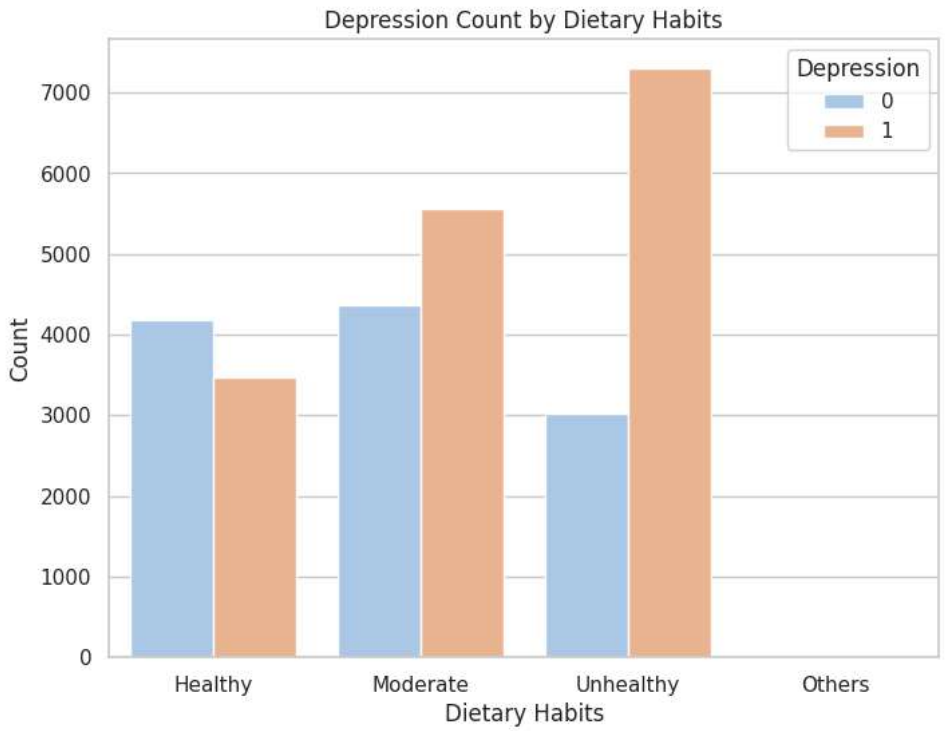
Depression is Prominent amongst the **Male** gender than the Female

```
Depression_data.groupby('Depression')['Dietary Habits'].value_counts().unstack().fillna(0)
```

Dietary Habits	Healthy	Moderate	Others	Unhealthy
Depression				
0	4178	4363	4	3020
1	3473	5558	8	7297

```
# Dietary Habits vs. Depression
plt.figure(figsize=(8, 6))

sns.countplot(data=Depression_data, x='Dietary Habits', hue='Depression')
plt.title('Depression Count by Dietary Habits')
plt.xlabel('Dietary Habits')
plt.ylabel('Count')
plt.legend(title='Depression')
plt.show()
```

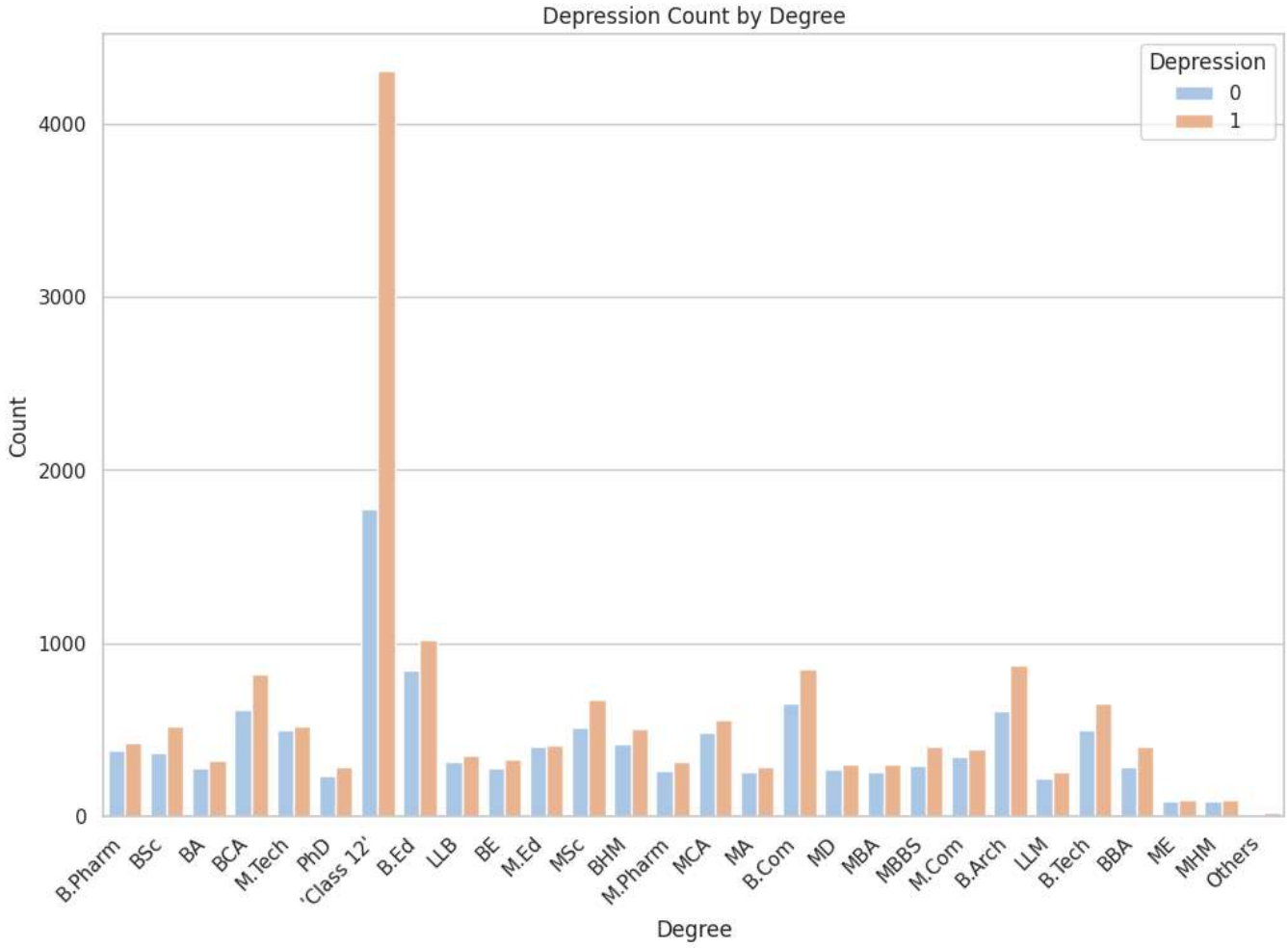


- Individuals with unhealthy dietary habits appear to exhibit higher rates of depression in the data.
- However, it remains unclear whether poor diet contributes directly to depression, or if other factors mediate this relationship.

```
# Degree vs. Depression
plt.figure(figsize=(12, 8))

sns.countplot(data=Depression_data, x='Degree', hue='Depression')
plt.title('Depression Count by Degree')
plt.xlabel('Degree')
plt.ylabel('Count')
plt.legend(title='Depression')

# Rotate x-axis labels
plt.xticks(rotation=45, ha='right')
plt.show()
```

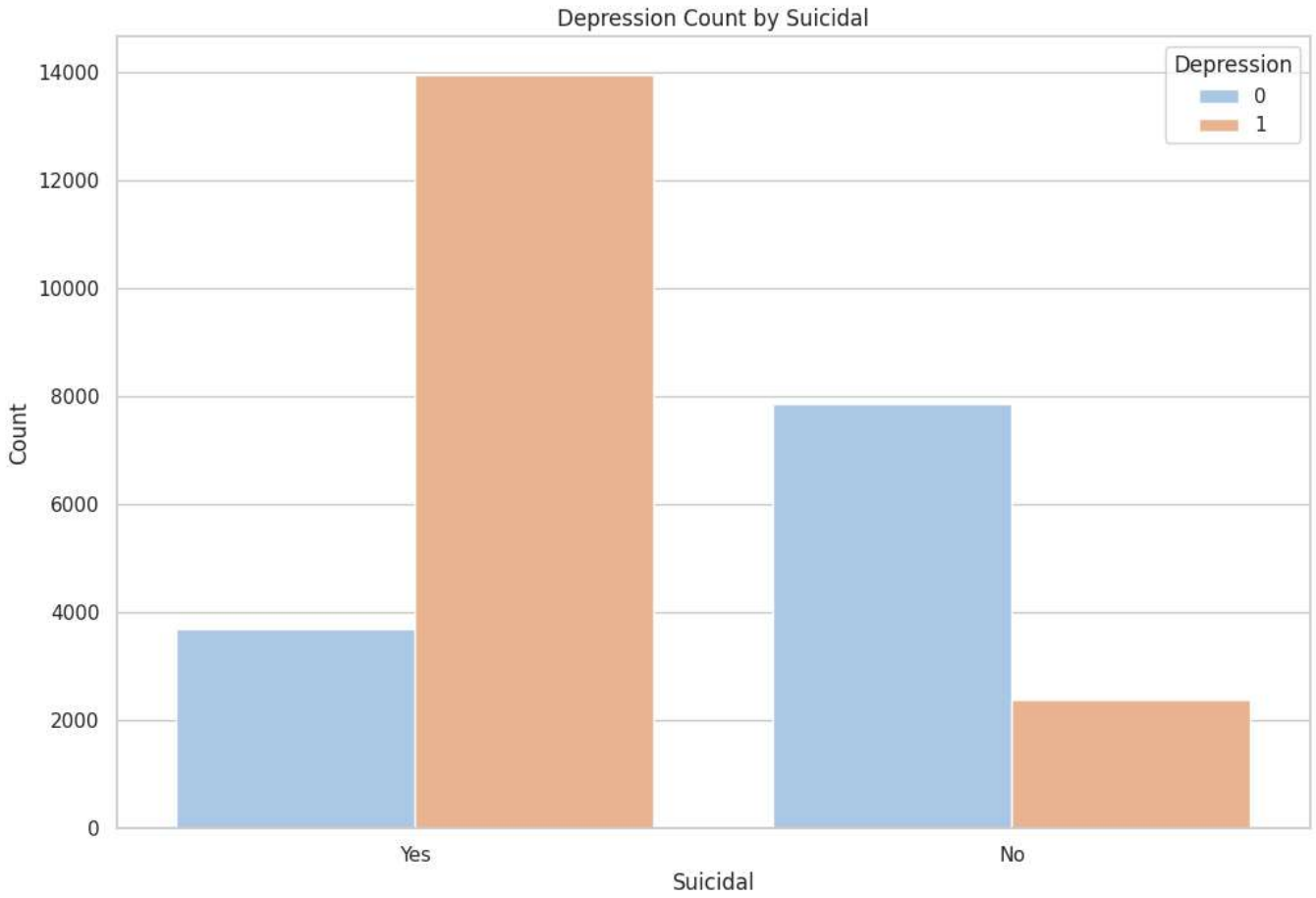


- **'Class 12'** Holders has a significantly higher count of individuals "**4303**" reporting depression compared to all other degree categories.
- The spike in depression cases among "Class 12" holders could suggest a correlation between lower education levels and depression vulnerability. However, correlation is not causation.
- Although, while they are not as significant as Class 12 Degree holder, B.Ed, B.Com, B.Tech, BBA, M.Sc, BCA show considerable depression levels.
- Degrees like B.Ed, B.Com, and BCA may involve competitive job markets or financial stress, potentially contributing to depression.

```
# Degree vs. Suicidal
plt.figure(figsize=(12, 8))

sns.countplot(data=Depression_data, x='Suicidal', hue='Depression')
plt.title('Depression Count by Suicidal')
plt.xlabel('Suicidal')
plt.ylabel('Count')
plt.legend(title='Depression')
```

```
<matplotlib.legend.Legend at 0x7f4cd2f06e10>
```



- The number of people with depression (1) is significantly higher than those without depression (0). Which means, Suicidal ideation appears to be a major indicator or symptom of depression in this dataset.
- However, the number of people without depression (0) is greater than those with depression. This indicates that individuals not experiencing suicidal thoughts are less likely to be depressed.

```
Depression_data.head()
```

	id	Gender	Age	City	Profession	Academic Pressure	Work Pressure	CGPA	Study Satisfaction	Job Satisfaction	Sleep Duration	Dietary Habits	Degree	Sui
0	2	Male	33.0	Visakhapatnam	Student	5.0	0.0	8.97	2.0	0.0	'5-6 hours'	Healthy	B.Pharm	
1	8	Female	24.0	Bangalore	Student	2.0	0.0	5.90	5.0	0.0	'5-6 hours'	Moderate	BSc	
2	26	Male	31.0	Srinagar	Student	3.0	0.0	7.03	5.0	0.0	'Less than 5 hours'	Healthy	BA	
3	30	Female	28.0	Varanasi	Student	3.0	0.0	5.59	2.0	0.0	'7-8 hours'	Moderate	BCA	
4	32	Female	25.0	Jaipur	Student	4.0	0.0	8.13	3.0	0.0	'5-6 hours'	Moderate	M.Tech	

Next steps: Generate code with Depression_data | View recommended plots | New interactive sheet

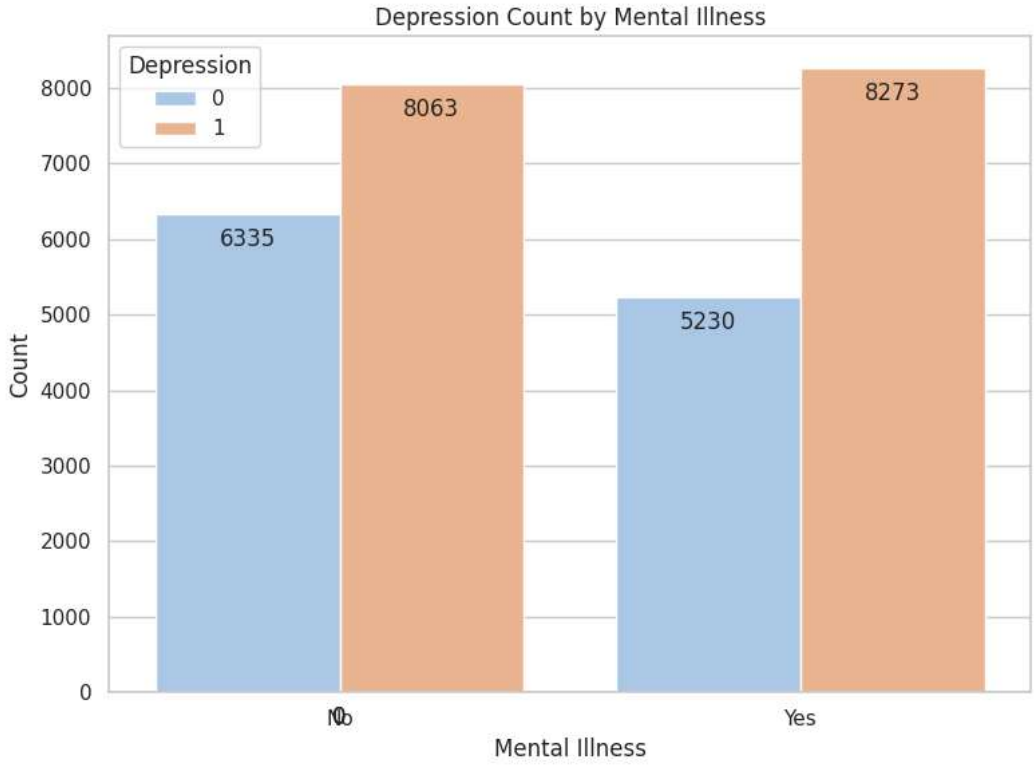
```
plt.figure(figsize=(8, 6))

# Plot
ax = sns.countplot(data=Depression_data, x='Mental Illness', hue='Depression')
plt.title('Depression Count by Mental Illness')
plt.xlabel('Mental Illness')
plt.ylabel('Count')
plt.legend(title='Depression')

# Add bar labels
for p in ax.patches:
    height = p.get_height()
```

```
        ax.text( p.get_x() + p.get_width() / 2, height - 500, f'{height:.0f}', ha='center', va='bottom')

plt.tight_layout()
plt.show()
```

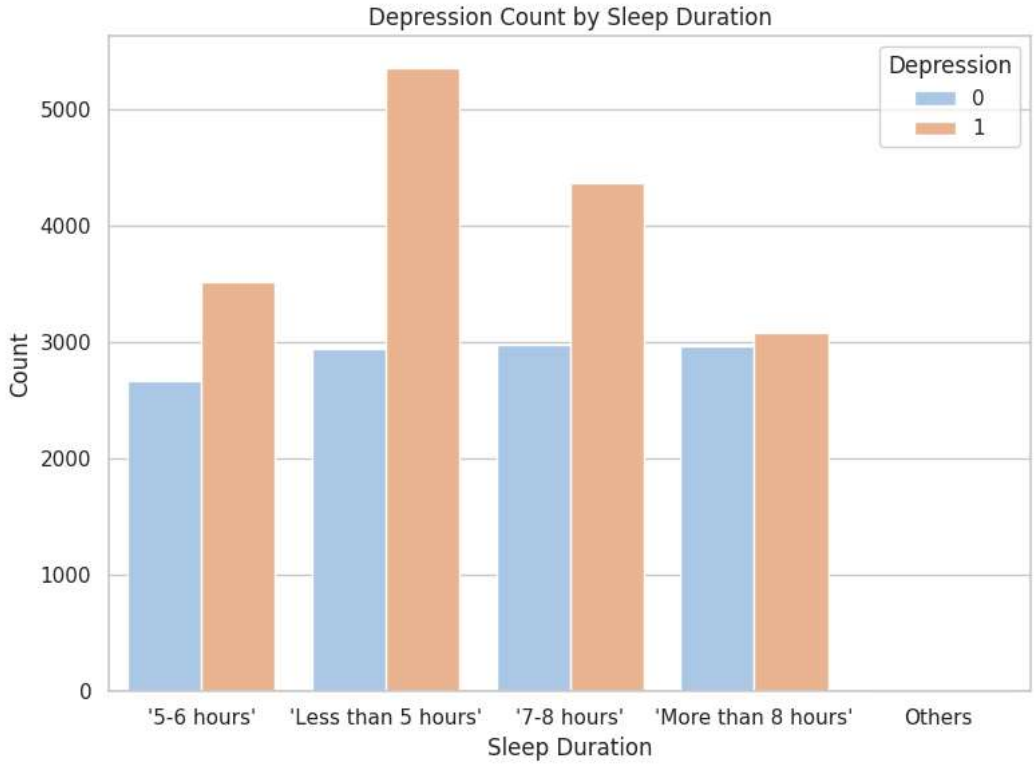


- For individuals with some form of mental illness, a higher proportion also experience depression (8273) compared to those who do not (5230). This suggests a strong correlation between having a mental illness and experiencing depression.
- However, among individuals without any mental illness, there are still a significant number who experience depression (8063), indicating that depression can exist independently of other mental illnesses.
- The data shows that while depression is significantly associated with mental illness, it is not exclusive to individuals with mental illness

```
plt.figure(figsize=(8, 6))

# Plot
ax = sns.countplot(data=Depression_data, x='Sleep Duration', hue='Depression')
plt.title('Depression Count by Sleep Duration')
plt.xlabel('Sleep Duration')
plt.ylabel('Count')
plt.legend(title='Depression')

plt.tight_layout()
plt.show()
```



- Individuals with less sleep (5-6 hours and less than 5 hours) generally see more depression cases compared to those with adequate or excessive sleep.
- Those with no depression are more evenly distributed across sleep durations, which contrasts sharply with the concentrated high depression cases among short-sleeping groups.
- The data suggests a "U-shaped" relationship between sleep duration and depression, where both insufficient sleep and excessive sleep are correlated with higher depression cases, with 7-8 hours being the ideal range.
- Efforts to improve sleep hygiene (Sleeping at the right time) might reduce depression prevalence.

```
Depression_data.head()
```

	id	Gender	Age	City	Profession	Academic Pressure	Work Pressure	CGPA	Study Satisfaction	Job Satisfaction	Sleep Duration	Dietary Habits	Degree	Sui
0	2	Male	33.0	Visakhapatnam	Student	5.0	0.0	8.97	2.0	0.0	'5-6 hours'	Healthy	B.Pharm	
1	8	Female	24.0	Bangalore	Student	2.0	0.0	5.90	5.0	0.0	'5-6 hours'	Moderate	BSc	
2	26	Male	31.0	Srinagar	Student	3.0	0.0	7.03	5.0	0.0	'Less than 5 hours'	Healthy	BA	
3	30	Female	28.0	Varanasi	Student	3.0	0.0	5.59	2.0	0.0	'7-8 hours'	Moderate	BCA	
4	32	Female	25.0	Jaipur	Student	4.0	0.0	8.13	3.0	0.0	'5-6 hours'	Moderate	M.Tech	

Next steps: Generate code with Depression_data | View recommended plots | New interactive sheet

There are some categorical columns that be converted to numerical to investigate their correlation with the target column

```
from sklearn.preprocessing import LabelEncoder

# create a copy of the dataset
D_data = Depression_data.copy()

# convert categorical column to numerical
le = LabelEncoder()
categorical_cols = ['Mental Illness', 'Suicidal', 'Gender', 'Sleep Duration', 'Dietary Habits']
for col in categorical_cols:
    D_data[col] = le.fit_transform(D_data[col])
```

```
D_data.head()
```

	id	Gender	Age	City	Profession	Academic Pressure	Work Pressure	CGPA	Study Satisfaction	Job Satisfaction	Sleep Duration	Dietary Habits	Degree	Suic
0	2	1	33.0	Visakhapatnam	Student	5.0	0.0	8.97	2.0	0.0	0	0	B.Pharm	
1	8	0	24.0	Bangalore	Student	2.0	0.0	5.90	5.0	0.0	0	1	BSc	
2	26	1	31.0	Srinagar	Student	3.0	0.0	7.03	5.0	0.0	2	0	BA	
3	30	0	28.0	Varanasi	Student	3.0	0.0	5.59	2.0	0.0	1	1	BCA	
4	32	0	25.0	Jaipur	Student	4.0	0.0	8.13	3.0	0.0	0	1	M.Tech	

Next steps: Generate code with D_data | View recommended plots | New interactive sheet

```
# correlation matrix
corr_Dep = D_data.corr(numeric_only=True)

# Filter correlations with 'Depression'
depression_corr = corr_Dep['Depression'].drop('Depression').sort_values(key=abs, ascending=False)

# Top correlations
print("Potential correlations with Depression:\n")
print(depression_corr)
```

```
Potential correlations with Depression:

Suicidal              0.546277
Academic Pressure     0.474835
Age                  -0.226422
Work/Study Hours      0.208563
Dietary Habits        0.206605
Study Satisfaction   -0.167971
Mental Illness        0.053430
Sleep Duration       -0.022411
CGPA                  0.022210
Job Satisfaction     -0.003482
Work Pressure        -0.003351
Gender                0.001794
id                    0.000923
Name: Depression, dtype: float64
```

- Turns out Suicidal has a very strong correlation with Depression.
- Suicidal, Academic Pressure and Work/Study Hours are important factors worth considering.

Machine Learning Model Building

```
# import some necessary libraries for machine learning
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score


# Select only numerical columns for X and drop the target column
X = D_data.drop(columns=['Depression', 'id'], errors='ignore')
X = X.select_dtypes(include=['int64', 'float64'])

y = D_data['Depression']



# Split dataset into Train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Scale the dataset
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
#Train the machine learning model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
#model evaluation
y_pred = model.predict(X_test)

print("Random Forest Classification Report:")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```