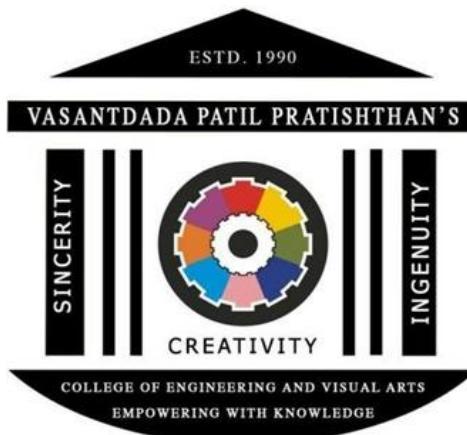


**Data Science using Python
Mini Project Report
On**

Student-Mental & Stress and Coping Mechanisms

PREPARED BY

Kamal Agrahari	VU4F2223028
Rutvik Gondekar	VU4F2223031
Akash Nahak	VU4F2223034
Sahil Deshmukh	VU4F2223020



Class: TE IT-B (Batch -B)
Guided By: Darshana Gajbhiye

Student-Mental & Stress and Coping Mechanisms

Problem Statement:

In today's fast-paced academic environment, students face immense pressure from exams, assignments, social expectations, and future career concerns. This often leads to increased stress, anxiety, and mental health challenges, which can negatively impact their academic performance, personal relationships, and overall well-being.

However, many students lack awareness of effective coping mechanisms and mental health resources. There is a need for a structured approach to help students identify stressors, manage their mental health, and adopt healthy coping strategies. Addressing this issue can lead to improved student productivity, emotional resilience, and overall mental well-being.

About the dataset:

Student_stress.csv (Main dataset for training and analysis):

This dataset contains information about student mental health, stress levels, and coping mechanisms. It can be used for training machine learning models to predict stress levels, identify high-risk students, and recommend coping strategies.

Dataset Use Cases

Predicting Student Stress Levels – Train a model to classify students into low, moderate, or high stress categories.

Clustering Student Mental Health Patterns – Identify groups of students with similar stress levels and behaviors using K-Means clustering.

Anomaly Detection for High-Risk Students – Use Isolation Forest to detect students experiencing extreme stress or unhealthy coping mechanisms.

Coping Mechanism Analysis – Understand which stress management techniques work best for different student groups.

Algorithms used:

Clustering (K-Means) and Anomaly Detection (Isolation Forest) for Student Mental Stress Analysis:

In a **Student Mental Stress and Coping Mechanisms** project, unsupervised learning techniques such as **clustering (K-Means)** and **anomaly detection (Isolation Forest)** provide valuable insights into student stress patterns and unusual mental health conditions.

Clustering (K-Means) for Stress Pattern Identification

Clustering algorithms like K-Means can group students based on their mental health attributes such as academic pressure, social anxiety, sleep hours, exercise frequency, and coping mechanisms. By identifying student clusters, we can:

- Classify students into different stress levels (Low, Moderate, High).
- Identify common stress patterns among students based on their lifestyle and habits.
- Discover distinct coping mechanism groups, such as students who manage stress through exercise vs. those who seek social support.

Example Clusters:

1 Low Stress Group – Students with balanced sleep, regular exercise, and effective coping strategies.

2 Moderate Stress Group – Students with occasional stress but some healthy coping mechanisms.

3 High Stress Group – Students experiencing high academic pressure, poor sleep, and ineffective coping.

By analyzing these clusters, institutions can design targeted stress management programs and recommend personalized coping strategies.

Data Loading and Inspection:

▼ Data Loading and Inspection

```
from google.colab import files
uploaded = files.upload()
import pandas as pd

# Load the dataset
data = pd.read_csv("Student_Mental_Stress_and_Coping_Mechanisms.csv", encoding='latin-1')

# Display basic info
data.info()

# Show the first few rows
data.head()
```

Choose Files Student_M...hanisms.csv

- Student_Mental_Stress_and_Coping_Mechanisms.csv(text/csv) - 57141 bytes, last modified: 3/28/2025 - 100% done

Saving Student_Mental_Stress_and_Coping_Mechanisms.csv to Student_Mental_Stress_and_Coping_Mechanisms (1).csv

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 750 entries, 0 to 750
Data columns (total 20 columns):
```

#	Column	Non-Null Count	Dtype
0	Student ID	750 non-null	object
1	Age	750 non-null	int64
2	Gender	750 non-null	object
3	Academic Performance (GPA)	750 non-null	int64
4	Study Hours Per Week	750 non-null	int64
5	Social Media Usage (Hours per day)	750 non-null	int64
6	Sleep Duration (Hours per night)	750 non-null	int64
7	Physical Exercise (Hours per week)	750 non-null	int64
8	Family Support	750 non-null	int64
9	Financial Stress	750 non-null	int64
10	Peer Pressure	750 non-null	int64
11	Relationship Stress	750 non-null	int64
12	Mental Stress Level	750 non-null	int64
13	Counseling Attendance	750 non-null	int64
14	Diet Quality	750 non-null	int64
15	Stress Coping Mechanisms	750 non-null	int64
16	Cognitive Distortions	750 non-null	int64
17	Family Mental Health History	750 non-null	int64
18	Medical Condition	750 non-null	int64
19	Substance Use	750 non-null	int64

✓ 13s completed at 12:29 AM

	Student ID	Age	Gender	Academic Performance (GPA)	Study Hours Per Week	Social Media Usage (Hours per day)	Sleep Duration (Hours per night)	Physical Exercise (Hours per week)	Family Support	Financial Stress	Peer Pressure	Relationship Stress	Mental Stress Level	Counseling Attendance	Diet Quality	Stress Coping Mechanisms	Cognitive Distortions	Family Mental Health History	Medical Condition	Substance Use
0	802-17-3671	22	Female	2	9	2	12	2	1	1	3	5	9	No	1	Walking or Nature Walks	4	No	Yes	1
1	871-12-8572	25	Female	0	28	0	6	0	1	1	1	2	9	Yes	3	Meditation	2	Yes	No	1
2	495-13-2672	24	Female	0	45	3	12	10	3	3	1	4	9	Yes	5	Reading	1	Yes	Yes	3
3	365-77-2496	20	Male	2	8	7	7	4	1	3	2	5	1	No	1	Social Media Engagement	2	Yes	No	4
4	664-76-5622	28	Male	0	14	6	8	1	2	4	4	2	7	Yes	1	Exercise	1	Yes	No	3

Data Cleaning and Preprocessing

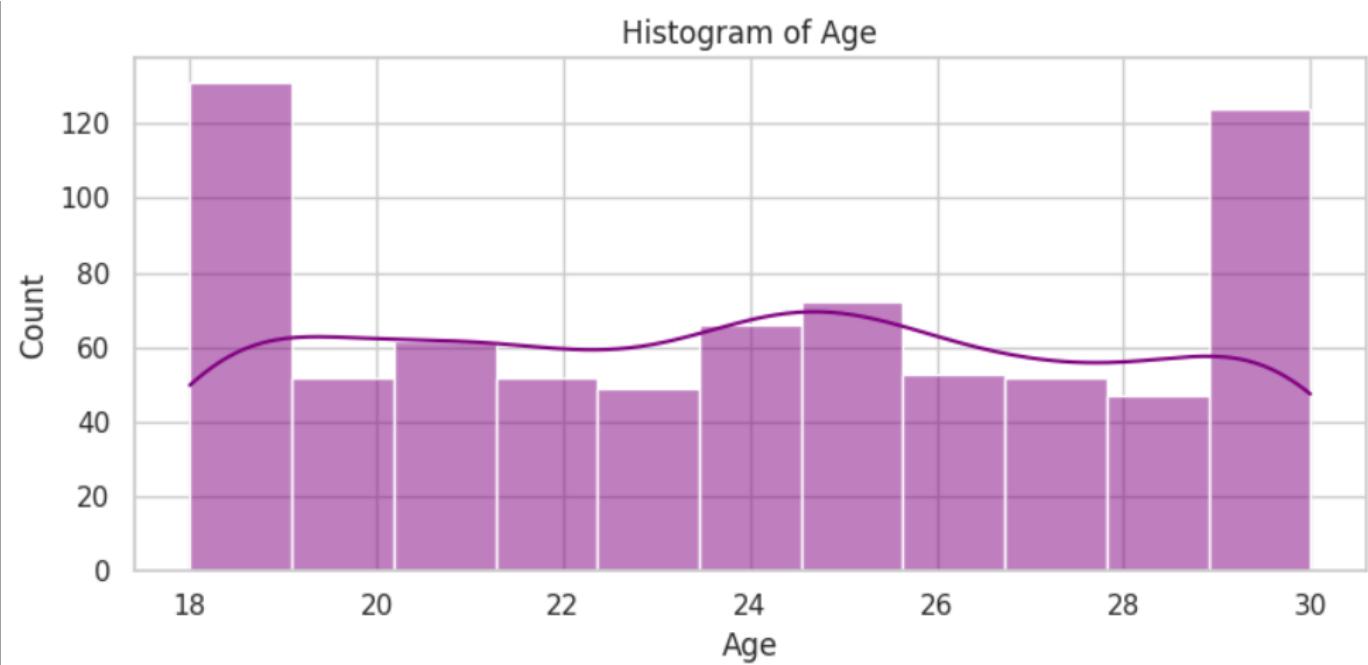
Data columns (total 20 columns):			
#	Column	Non-Null Count	Dtype
0	Student ID	760 non-null	object
1	Age	760 non-null	int64
2	Gender	760 non-null	object
3	Academic Performance (GPA)	760 non-null	int64
4	Study Hours Per Week	760 non-null	int64
5	Social Media Usage (Hours per day)	760 non-null	int64
6	Sleep Duration (Hours per night)	760 non-null	int64
7	Physical Exercise (Hours per week)	760 non-null	int64
8	Family Support	760 non-null	int64
9	Financial Stress	760 non-null	int64
10	Peer Pressure	760 non-null	int64
11	Relationship Stress	760 non-null	int64
12	Mental Stress Level	760 non-null	int64
13	Counseling Attendance	760 non-null	object
14	Diet Quality	760 non-null	int64
15	Stress Coping Mechanisms	760 non-null	object
16	Cognitive Distortions	760 non-null	int64
17	Family Mental Health History	760 non-null	object
18	Medical Condition	760 non-null	object
19	Substance Use	760 non-null	int64

dtypes: int64(14), object(6)
memory usage: 118.9+ KB

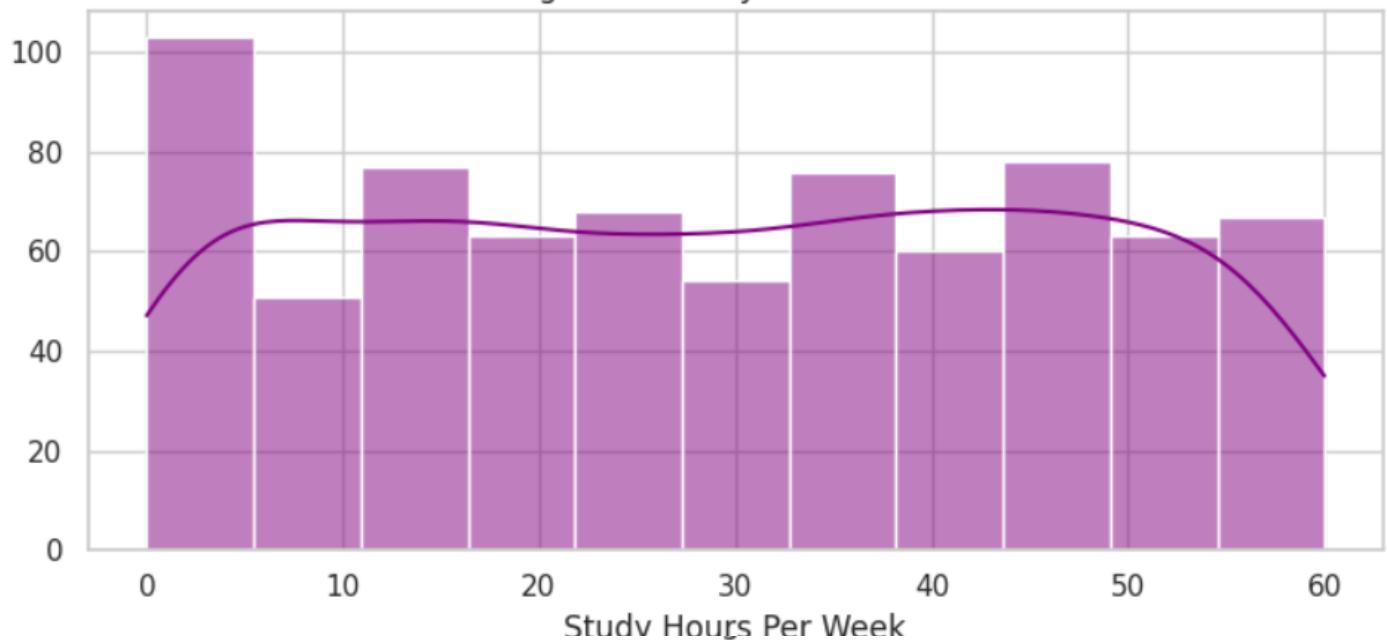
```
Missing values in each column:  
Student ID          0  
Age                 0  
Gender              0  
Academic Performance (GPA) 0  
Study Hours Per Week 0  
Social Media Usage (Hours per day) 0  
Sleep Duration (Hours per night) 0  
Physical Exercise (Hours per week) 0  
Family Support       0  
Financial Stress     0  
Peer Pressure         0  
Relationship Stress   0  
Mental Stress Level   0  
Counseling Attendance 0  
Diet Quality          0  
Stress Coping Mechanisms 0  
Cognitive Distortions 0  
Family Mental Health History 0  
Medical Condition     0  
Substance Use         0  
dtype: int64  
Initial shape: (760, 20), After removing duplicates: (760, 20)  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 760 entries, 0 to 759  
Data columns (total 20 columns):
```

Exploratory Data Analysis:

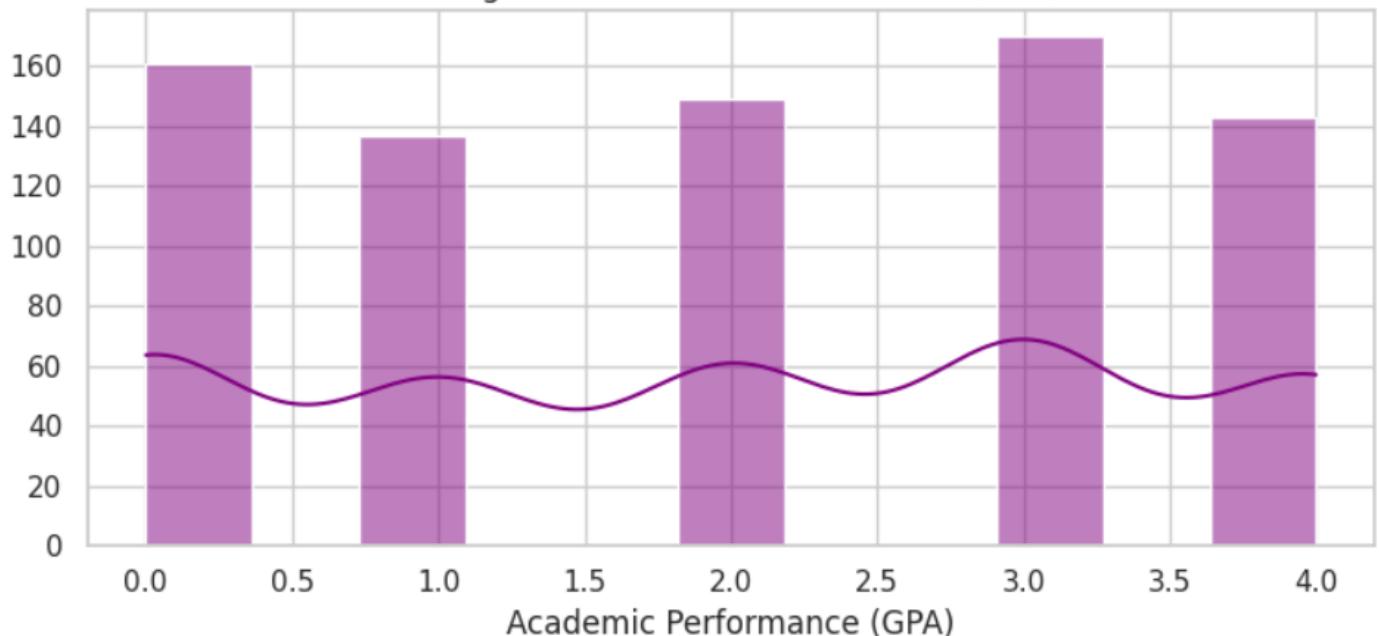
Statistical Summary:															
	Age	Academic Performance (GPA)	Study Hours Per Week	Social Media Usage (Hours per day)	Sleep Duration (Hours per night)	Physical Exercise (Hours per week)	Family Support	Financial Stress	Peer Pressure	Relationship Stress	Mental Stress Level	Diet Quality	Cognitive Distortions	Substance Use	
count	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000	760.000000
mean	23.919737	1.996053	29.130263	4.234211	8.093421	4.934211	2.972368	3.021053	2.982895	2.963158	5.363158	3.042105	3.007895	2.996053	
std	3.819392	1.416535	18.104662	2.565174	2.596838	3.082679	1.413477	1.452662	1.391096	1.369231	2.902856	1.453111	1.432703	1.385502	
min	18.000000	0.000000	0.000000	0.000000	4.000000	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
25%	21.000000	1.000000	13.000000	2.000000	6.000000	2.000000	2.000000	2.000000	2.000000	2.000000	3.000000	2.000000	2.000000	2.000000	2.000000
50%	24.000000	2.000000	29.000000	4.000000	8.000000	5.000000	3.000000	3.000000	3.000000	3.000000	5.000000	3.000000	3.000000	3.000000	3.000000
75%	27.000000	3.000000	45.000000	7.000000	10.000000	8.000000	4.000000	4.000000	4.000000	4.000000	8.000000	4.000000	4.000000	4.000000	4.000000
max	30.000000	4.000000	60.000000	8.000000	12.000000	10.000000	5.000000	5.000000	5.000000	5.000000	10.000000	5.000000	5.000000	5.000000	5.000000

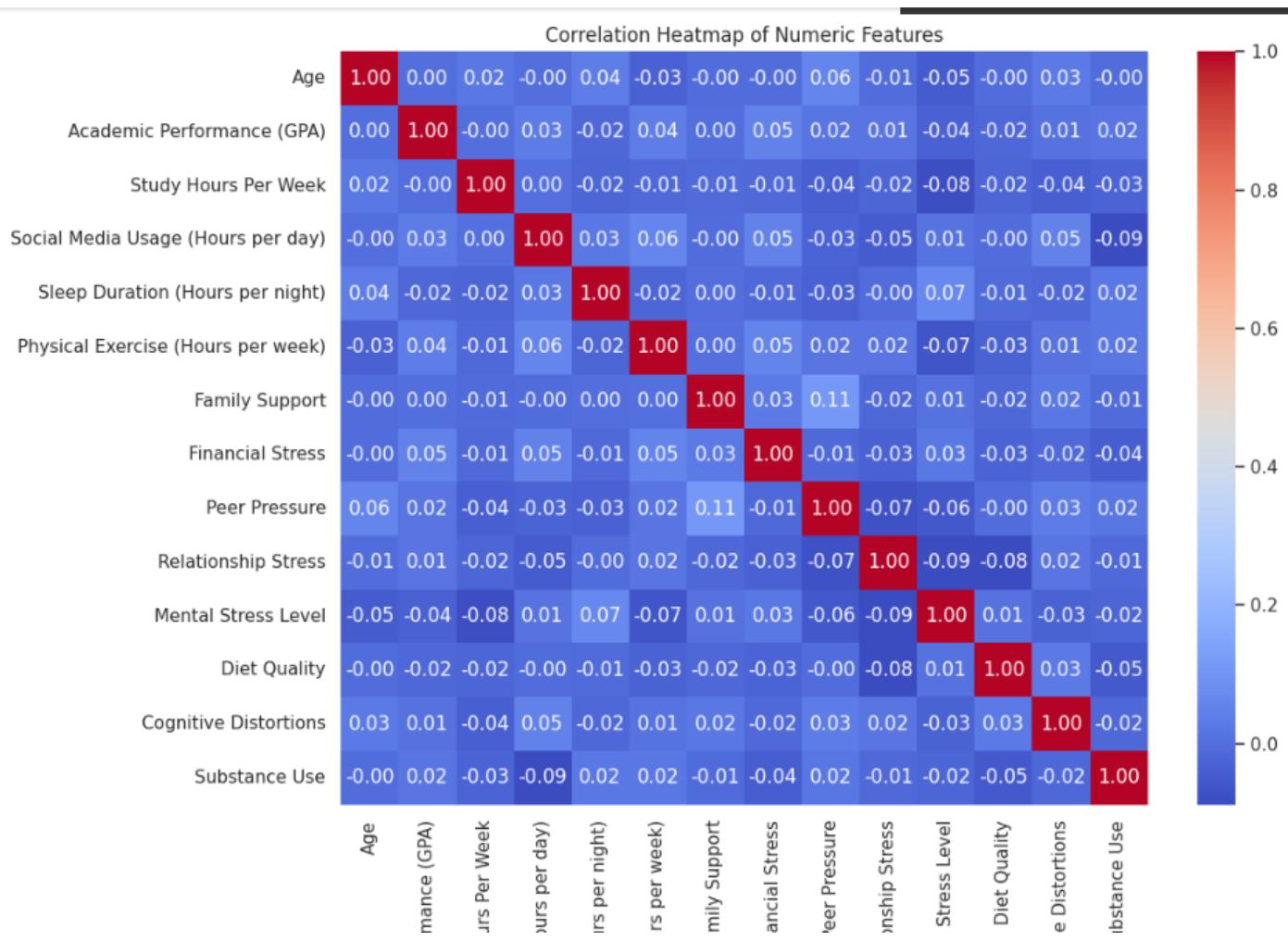
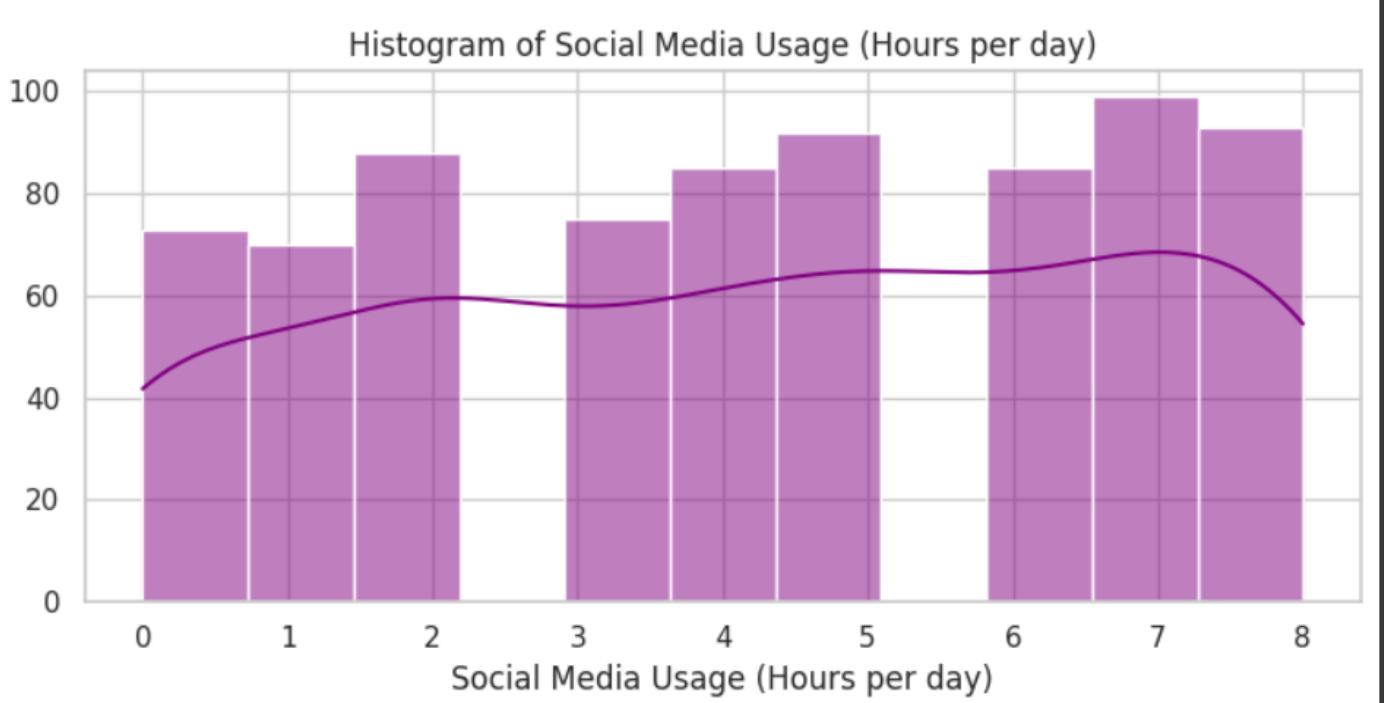


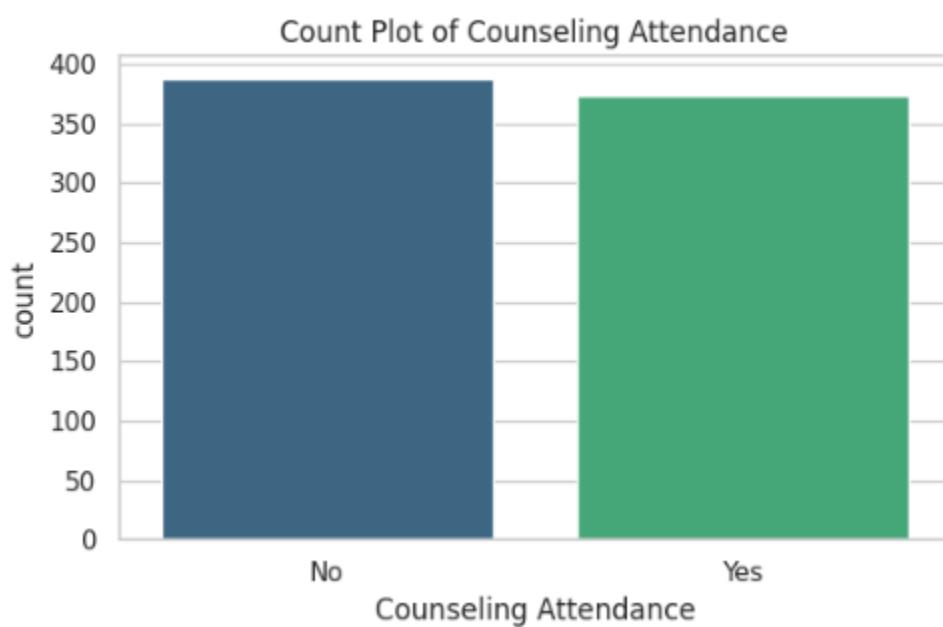
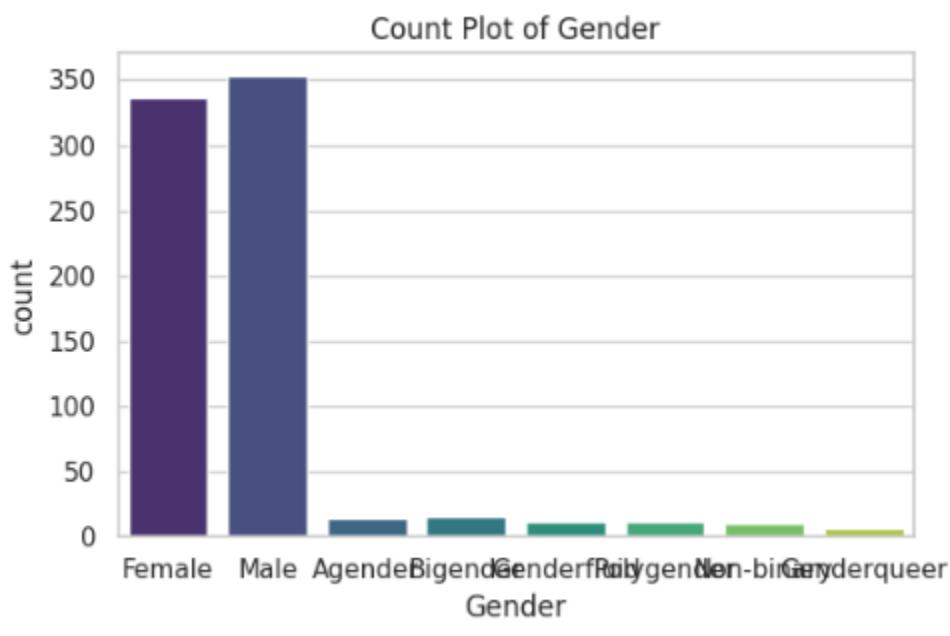
Histogram of Study Hours Per Week



Histogram of Academic Performance (GPA)







Predictive Modeling:

```

mse = mean_squared_error(y_test, y_pred) # Remove squared=False
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
print(f'Random Forest Regressor RMSE: {rmse}')
print(f'Random Forest Regressor R2 Score: {r2}')

```

```

Random Forest Regressor RMSE: 3.054300031792968
Random Forest Regressor R2 Score: -0.08722462469733627

```

Conclusions

The analysis provided a comprehensive overview of the student mental stress dataset. We covered the journey from loading and cleaning the data to exploratory visualization and the development of a predictive model. The Random Forest Regressor, predicting mental stress level using student behavior and support metrics, displayed a particular performance based on the RMSE and R2 scores.

Merits of the approach include:

- Diverse visualization techniques that allow us to gain a multifaceted understanding of the data.
- Step-by-step data cleaning methods to avoid common pitfalls such as missing values and duplicate entries.
- An interpretable modeling approach highlighting feature importance via permutation importance.