In [1]:
```
# Importing all libraries which we will be using in this project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
import warnings
warnings.filterwarnings('ignore')
```

--> Step 1 - Data Understanding & Cleaning:

View data and checking for Null values or missing values in data

In [2]:
```
# Import .csv data file using pandas
df = pd.read_csv("C:\\Users\\user\\Desktop\\data analytics soft\\Python_Mini_Project_-_Social_Media_Combat\\Stu
dents Social Media Addiction (1).csv")
```

In [3]:
```
# Dataframe count of rows and columns
df.shape
```

Out[3]:
```
(705, 13)
```

In [4]:
```python
df.head()
```

Out[4]:

	Student_ID	Age	Gender	Academic_Level	Country	Avg_Daily_Usage_Hours	Most_Used_Platform	Affects_Academic_Performance	S
0	1	19	Female	Undergraduate	Bangladesh	5.2	Instagram	Yes	
1	2	22	Male	Graduate	India	2.1	Twitter	No	
2	3	20	Female	Undergraduate	USA	6.0	TikTok	Yes	
3	4	18	Male	High School	UK	3.0	YouTube	No	
4	5	21	Male	Graduate	Canada	4.5	Facebook	Yes	

In [5]:
```python
# To view columns, Data types and null values if any in data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 705 entries, 0 to 704
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Student_ID                    705 non-null    int64  
 1   Age                           705 non-null    int64  
 2   Gender                        705 non-null    object 
 3   Academic_Level                705 non-null    object 
 4   Country                       705 non-null    object 
 5   Avg_Daily_Usage_Hours         705 non-null    float64
 6   Most_Used_Platform            705 non-null    object 
 7   Affects_Academic_Performance  705 non-null    object 
 8   Sleep_Hours_Per_Night         705 non-null    float64
 9   Mental_Health_Score           705 non-null    int64  
 10  Relationship_Status           705 non-null    object 
 11  Conflicts_Over_Social_Media   705 non-null    int64  
 12  Addicted_Score                705 non-null    int64  
dtypes: float64(2), int64(5), object(6)
memory usage: 71.7+ KB
```

In [6]:
```
#check for null values in data
df.isnull().sum()
```
Out[6]:
```
Student_ID                      0
Age                             0
Gender                          0
Academic_Level                  0
Country                         0
Avg_Daily_Usage_Hours           0
Most_Used_Platform              0
Affects_Academic_Performance    0
Sleep_Hours_Per_Night           0
Mental_Health_Score             0
Relationship_Status             0
Conflicts_Over_Social_Media     0
Addicted_Score                  0
dtype: int64
```

Check for Duplicate Values in Data and Removing them

In [7]:
```
df.duplicated().sum()                                          # TO find duplicate values found in data
```
Out[7]:
```
0
```

In [8]:
```
df = df.drop_duplicates()                                      # Deleting the duplicate values in dataframe if any
```

In [9]:
```
df.head()
```

Out[9]:

	Student_ID	Age	Gender	Academic_Level	Country	Avg_Daily_Usage_Hours	Most_Used_Platform	Affects_Academic_Performance	S
0	1	19	Female	Undergraduate	Bangladesh	5.2	Instagram	Yes	
1	2	22	Male	Graduate	India	2.1	Twitter	No	
2	3	20	Female	Undergraduate	USA	6.0	TikTok	Yes	
3	4	18	Male	High School	UK	3.0	YouTube	No	
4	5	21	Male	Graduate	Canada	4.5	Facebook	Yes	

Checking Datatypes and changing if needed

In [10]:
```
# To find any incorrect datatypes in data
df.dtypes
```

Out[10]:
```
Student_ID                        int64
Age                               int64
Gender                           object
Academic_Level                   object
Country                          object
Avg_Daily_Usage_Hours           float64
Most_Used_Platform               object
Affects_Academic_Performance     object
Sleep_Hours_Per_Night           float64
Mental_Health_Score               int64
Relationship_Status              object
Conflicts_Over_Social_Media       int64
Addicted_Score                    int64
dtype: object
```

In [11]:
```
# Copy dataframe to a new Dataframe
newdf = df.copy()
newdf.head()
```

Out[11]:

	Student_ID	Age	Gender	Academic_Level	Country	Avg_Daily_Usage_Hours	Most_Used_Platform	Affects_Academic_Performance	S
0	1	19	Female	Undergraduate	Bangladesh	5.2	Instagram	Yes	
1	2	22	Male	Graduate	India	2.1	Twitter	No	
2	3	20	Female	Undergraduate	USA	6.0	TikTok	Yes	
3	4	18	Male	High School	UK	3.0	YouTube	No	
4	5	21	Male	Graduate	Canada	4.5	Facebook	Yes	

In [12]:
```
# defining a function for changing float datatype to hh:mm format in dataframe

def convert_to_Time(data, column_name):

    # Convert float hours to timedelta
    temp_timedelta = pd.to_timedelta(data[column_name], unit='h')

    # changing timedelta in datetime format
    date_time = (pd.Timestamp('1970-01-01') + temp_timedelta)

    # Convert datetime format to HH:MM
    new_column = f"{column_name}_hhmm"
    data[new_column] = date_time.dt.strftime('%H:%M')

    return data
```

In [13]:
```
# applying the above fuction on dataframe columns for changing format
newdf = convert_to_Time(newdf,'Avg_Daily_Usage_Hours')
newdf = convert_to_Time(newdf,'Sleep_Hours_Per_Night')
```

In [14]:
```
# data after cleaning
newdf.head()
```

Out[14]:

	Student_ID	Age	Gender	Academic_Level	Country	Avg_Daily_Usage_Hours	Most_Used_Platform	Affects_Academic_Performance	S
0	1	19	Female	Undergraduate	Bangladesh	5.2	Instagram	Yes	
1	2	22	Male	Graduate	India	2.1	Twitter	No	
2	3	20	Female	Undergraduate	USA	6.0	TikTok	Yes	
3	4	18	Male	High School	UK	3.0	YouTube	No	
4	5	21	Male	Graduate	Canada	4.5	Facebook	Yes	

In [15]:
```
newdf.dtypes
```

Out[15]:
```
Student_ID                       int64
Age                              int64
Gender                          object
Academic_Level                  object
Country                         object
Avg_Daily_Usage_Hours          float64
Most_Used_Platform              object
Affects_Academic_Performance    object
Sleep_Hours_Per_Night          float64
Mental_Health_Score              int64
Relationship_Status             object
Conflicts_Over_Social_Media      int64
Addicted_Score                   int64
Avg_Daily_Usage_Hours_hhmm      object
Sleep_Hours_Per_Night_hhmm      object
dtype: object
```

---> Step 2 : Data Analysis

Summarize data

In [16]:
```
# Columns in data
newdf.columns
```

Out[16]:
```
Index(['Student_ID', 'Age', 'Gender', 'Academic_Level', 'Country',
       'Avg_Daily_Usage_Hours', 'Most_Used_Platform',
       'Affects_Academic_Performance', 'Sleep_Hours_Per_Night',
       'Mental_Health_Score', 'Relationship_Status',
       'Conflicts_Over_Social_Media', 'Addicted_Score',
       'Avg_Daily_Usage_Hours_hhmm', 'Sleep_Hours_Per_Night_hhmm'],
      dtype='object')
```

In [17]:
```
# Using describe() for specific columns with values
newdf[['Avg_Daily_Usage_Hours','Sleep_Hours_Per_Night','Mental_Health_Score',
                            'Conflicts_Over_Social_Media','Addicted_Score']].describe().round(2)
```

Out[17]:

	Avg_Daily_Usage_Hours	Sleep_Hours_Per_Night	Mental_Health_Score	Conflicts_Over_Social_Media	Addicted_Score
count	705.00	705.00	705.00	705.00	705.00
mean	4.92	6.87	6.23	2.85	6.44
std	1.26	1.13	1.11	0.96	1.59
min	1.50	3.80	4.00	0.00	2.00
25%	4.10	6.00	5.00	2.00	5.00
50%	4.80	6.90	6.00	3.00	7.00
75%	5.80	7.70	7.00	4.00	8.00
max	8.50	9.60	9.00	5.00	9.00

Exploratory Data Analysis (EDA)

In [18]:
```
# Total students distribution by age

df[['Age']].value_counts().reset_index()
```

Out[18]:

	Age	0
0	20	165
1	19	163
2	21	156
3	22	147
4	23	34
5	24	26
6	18	14

In [19]:
```
# Students counts by Gender

df[['Gender']].value_counts().reset_index()
```

Out[19]:

	Gender	0
0	Female	353
1	Male	352

In [20]:
```python
# define a function to determine age group based on academic levels
def Age_group(Acad_level):

    acad_level = Acad_level.strip()

    if acad_level == 'High School':
        return "Age_group(18 - 20)"
    elif acad_level == 'Undergraduate':
        return "Age_group(19 - 21)"
    else:
        return "Age_group(21 - 24)"
```

In [21]:
```python
newdf["Age_Group"] = newdf["Academic_Level"].apply(Age_group)
newdf[["Academic_Level", "Age_Group"]].drop_duplicates()
```

Out[21]:

	Academic_Level	Age_Group
0	Undergraduate	Age_group(19 - 21)
1	Graduate	Age_group(21 - 24)
3	High School	Age_group(18 - 20)

In [22]:
```python
# Student in each age group
dfg = newdf.groupby(['Academic_Level',"Age_Group"])['Student_ID'].agg(['count']).reset_index()
dfg.sort_values(by = 'Age_Group')
```

Out[22]:

	Academic_Level	Age_Group	count
1	High School	Age_group(18 - 20)	27
2	Undergraduate	Age_group(19 - 21)	353
0	Graduate	Age_group(21 - 24)	325

Total Daily usage(hours) vs Age

In [23]:
```
grouped1 = newdf.groupby(['Age'])['Avg_Daily_Usage_Hours'].agg('sum','count').reset_index()
grouped1.sort_values(by = 'Avg_Daily_Usage_Hours',ascending = False)
```

Out[23]:

	Age	Avg_Daily_Usage_Hours
1	19	834.6
2	20	813.5
3	21	772.3
4	22	687.4
5	23	153.3
6	24	131.2
0	18	75.4

Avarage daily usage hours vs Gender

In [24]:
```
grouped2 = newdf.groupby('Gender')['Avg_Daily_Usage_Hours'].agg(['sum','mean']).reset_index().round(2)
grouped2.columns = ['Gender','Total_Avg_Usages','Avg_Usage_Per_Person']
grouped2
```

Out[24]:

	Gender	Total_Avg_Usages	Avg_Usage_Per_Person
0	Female	1768.9	5.01
1	Male	1698.8	4.83

Analysis by Age and Gender and daily usage

In [25]:
```
grouped3 = newdf.groupby(['Age', 'Gender'])['Avg_Daily_Usage_Hours'].agg(['count','sum']).reset_index()
grouped3.columns = ['Age','Gender','Student_Count','Total_Avg_Usages']

# Sorting Data and finding top 5 students based on total daily usage
grouped3.sort_values(by = 'Total_Avg_Usages',ascending = False).head()
```

Out[25]:

	Age	Gender	Student_Count	Total_Avg_Usages
4	20	Female	146	716.0
2	19	Female	135	692.4
9	22	Male	134	621.5
7	21	Male	125	616.2
6	21	Female	31	156.1

In [26]:
```
# Total daily usage for female students with age group (19yr to 21 yr)
df[(df['Age'] >= 19) & (df['Age'] <= 21) & (df['Gender'] == 'Female')]['Avg_Daily_Usage_Hours'].sum()
```

Out[26]: 1564.5

In [27]:
```
# Total daily usage for Male students with age group (19yr to 21 yr)
df[(df['Age'] >= 19) & (df['Age'] <= 21) & (df['Gender'] == 'Male')]['Avg_Daily_Usage_Hours'].sum().round(1)
```

Out[27]: 855.9

From above data we can conclude that students with most average daily usage are within age group(19yr to 21 yr) with female students has majority in daily data usage, for average usage per person females have more social media usages compare to males.

Analysis by sleep pattern, Acadmic performance and Social Interactions

In [28]:
```
newdf.columns
```

Out[28]:
```
Index(['Student_ID', 'Age', 'Gender', 'Academic_Level', 'Country',
       'Avg_Daily_Usage_Hours', 'Most_Used_Platform',
       'Affects_Academic_Performance', 'Sleep_Hours_Per_Night',
       'Mental_Health_Score', 'Relationship_Status',
       'Conflicts_Over_Social_Media', 'Addicted_Score',
       'Avg_Daily_Usage_Hours_hhmm', 'Sleep_Hours_Per_Night_hhmm',
       'Age_Group'],
      dtype='object')
```

In [29]:
```
# Gender vs average sleep per night vs social media conflict
grouped4 = newdf.groupby(['Gender'])['Sleep_Hours_Per_Night','Addicted_Score',
                                     'Conflicts_Over_Social_Media'].mean().reset_index().round(2)
grouped4
```

Out[29]:

	Gender	Sleep_Hours_Per_Night	Addicted_Score	Conflicts_Over_Social_Media
0	Female	6.82	6.52	2.93
1	Male	6.92	6.36	2.76

In [30]:
```python
# Relation between Acadmic level vs (avg. sleep, addicted score , mental health)
grouped5 = newdf.groupby(['Academic_Level'])['Sleep_Hours_Per_Night','Addicted_Score',
                                             'Conflicts_Over_Social_Media','Mental_Health_Score'
                                            ].mean().reset_index().round(2)
grouped5
```

Out[30]:

	Academic_Level	Sleep_Hours_Per_Night	Addicted_Score	Conflicts_Over_Social_Media	Mental_Health_Score
0	Graduate	7.03	6.24	2.70	6.37
1	High School	5.46	8.04	3.74	5.11
2	Undergraduate	6.83	6.49	2.92	6.18

In [31]:
```python
# Calculate counts per Gender and Relationship Status
relationship_counts = newdf.groupby('Gender')['Relationship_Status'].value_counts(normalize=True)

# Convert to percentage
relationship_percentages = (relationship_counts * 100).unstack()
relationship_percentages.round()
```

Out[31]:

Relationship_Status	Complicated	In Relationship	Single
Gender			
Female	5.0	39.0	56.0
Male	4.0	43.0	53.0

In [32]:
```
# finding how is the behaviour pattern of students with different relationship status
relationship_data = df.groupby(['Gender','Relationship_Status'])['Addicted_Score','Sleep_Hours_Per_Night',
                                                                 'Mental_Health_Score','Conflicts_Over_Social_M
edia'

                                                                ].mean()
relationship_data.round(2)
```

Out[32]:

Gender	Relationship_Status	Addicted_Score	Sleep_Hours_Per_Night	Mental_Health_Score	Conflicts_Over_Social_Media
Female	**Complicated**	7.47	5.65	5.65	3.35
	In Relationship	6.67	6.56	6.07	2.90
	Single	6.32	7.10	6.29	2.92
Male	**Complicated**	6.53	6.19	6.27	2.67
	In Relationship	6.04	7.08	6.50	2.64
	Single	6.60	6.85	6.10	2.88

In [33]:
```
#total students in each academic level
students = newdf.groupby("Academic_Level")['Student_ID'].count().reset_index()
students
```

Out[33]:

	Academic_Level	Student_ID
0	Graduate	325
1	High School	27
2	Undergraduate	353

In [59]:

```python
# Creating boolean column for performance affected for further calculations
newdf['Performance_Affected'] = newdf['Affects_Academic_Performance'].str.strip().str.lower() == 'yes'

# Total students per Academic_Level and Gender
total_students = newdf.groupby(['Academic_Level', 'Gender'])['Student_ID'].count().reset_index(name='Total_Stud
ents')

# Affected students (Performance_Affected == True)
affected_students = newdf[newdf['Performance_Affected'] == True] \
    .groupby(['Academic_Level', 'Gender'])['Student_ID'].count().reset_index(name='Affected_Students')

merged = pd.merge(total_students, affected_students, on=['Academic_Level', 'Gender'], how='left')

# Calculate percentage
merged['Percentage_Performance_Affected'] = (merged['Affected_Students'] / merged['Total_Students']) * 100
merged.round(2)
```

Out[59]:

	Academic_Level	Gender	Total_Students	Affected_Students	Percentage_Performance_Affected
0	Graduate	Female	48	24	50.00
1	Graduate	Male	277	175	63.18
2	High School	Female	15	15	100.00
3	High School	Male	12	10	83.33
4	Undergraduate	Female	290	192	66.21
5	Undergraduate	Male	63	37	58.73

Classify the Risk Level:

In [35]:
```python
# defining a function for risk levels
def risk_level(hours):
    if hours < 2:
        return 'Low'
    elif hours < 5:
        return 'Medium'
    else:
        return 'High'
```

In [36]:
```python
newdf['Risk_Level'] = df['Avg_Daily_Usage_Hours'].apply(risk_level)
newdf.head()
```

Out[36]:

	Student_ID	Age	Gender	Academic_Level	Country	Avg_Daily_Usage_Hours	Most_Used_Platform	Affects_Academic_Performance	S
0	1	19	Female	Undergraduate	Bangladesh	5.2	Instagram	Yes	
1	2	22	Male	Graduate	India	2.1	Twitter	No	
2	3	20	Female	Undergraduate	USA	6.0	TikTok	Yes	
3	4	18	Male	High School	UK	3.0	YouTube	No	
4	5	21	Male	Graduate	Canada	4.5	Facebook	Yes	

In [37]:
```
# top 5 countries with highest addiction score
country_data = newdf.groupby(["Country","Risk_Level"])['Mental_Health_Score','Addicted_Score','Avg_Daily_Usage_Hours',].mean()
country_data.sort_values(by = 'Addicted_Score',ascending = False).reset_index().head()
```

Out[37]:

	Country	Risk_Level	Mental_Health_Score	Addicted_Score	Avg_Daily_Usage_Hours
0	Czech Republic	High	4.0	9.0	6.1
1	Ecuador	High	5.0	9.0	6.3
2	Lebanon	High	5.0	9.0	5.8
3	Liechtenstein	High	5.0	9.0	5.8
4	Armenia	High	5.0	9.0	5.9

In [38]:
```
#top 5 countries with highest average daily usage
country_data.sort_values(by = 'Avg_Daily_Usage_Hours',ascending = False).reset_index().head().round(2)
```

Out[38]:

	Country	Risk_Level	Mental_Health_Score	Addicted_Score	Avg_Daily_Usage_Hours
0	Australia	High	4.00	9.00	7.20
1	USA	High	4.90	8.60	6.89
2	Russia	High	4.12	8.75	6.79
3	UAE	High	5.00	8.12	6.72
4	India	High	5.12	7.88	6.51

In [39]:
```python
# filtering data based on more than 3 conflicts over social media
newdf[newdf['Conflicts_Over_Social_Media']> 3].mean().reset_index().round()
```

Out[39]:

	index	0
0	Student_ID	371.0
1	Age	20.0
2	Avg_Daily_Usage_Hours	6.0
3	Sleep_Hours_Per_Night	6.0
4	Mental_Health_Score	5.0
5	Conflicts_Over_Social_Media	4.0
6	Addicted_Score	8.0
7	Performance_Affected	1.0

In [40]:
```python
age_mental= newdf.groupby(["Age_Group","Academic_Level"])['Mental_Health_Score'].mean().reset_index()
age_mental.round(2)
```

Out[40]:

	Age_Group	Academic_Level	Mental_Health_Score
0	Age_group(18 - 20)	High School	5.11
1	Age_group(19 - 21)	Undergraduate	6.18
2	Age_group(21 - 24)	Graduate	6.37

From above data we can conclude that the lesser the metal health score, the greater the increase in conflicts over social media, higher risk level and Addicted Score. and students with lower age tends to have lower mental health score.

Aggregation based on risk level

In [41]:
```
# finding max for average daily uses
newdf['Avg_Daily_Usage_Hours'].max()
```

Out[41]: 8.5

In [42]:
```
# finding
newdf['Avg_Daily_Usage_Hours'].min()
```

Out[42]: 1.5

In [43]:
```
round(newdf['Avg_Daily_Usage_Hours'].mean(),2)
```

Out[43]: 4.92

In [44]:
```
# Gender vs risk level vs average addicted score
agg = newdf.groupby(['Gender','Risk_Level'])['Addicted_Score'].mean().reset_index()
agg
```

Out[44]:

	Gender	Risk_Level	Addicted_Score
0	Female	High	7.925926
1	Female	Medium	5.319372
2	Male	High	7.506849
3	Male	Low	2.000000
4	Male	Medium	5.560976

In [45]:
```
agg1 = newdf.groupby(['Academic_Level', 'Risk_Level']).agg(Student_Count=('Student_ID', 'count'),
                                                            Avg_Daily_Usage_Hours=('Avg_Daily_Usage_Hours', 'mea
n'),
                                                            Sleep_Hours_Per_Night=('Sleep_Hours_Per_Night', 'mea
n'),
                                                            Addicted_Score=('Addicted_Score', 'mean')
                                                            ).reset_index()

agg1.round(2)
```

Out[45]:

	Academic_Level	Risk_Level	Student_Count	Avg_Daily_Usage_Hours	Sleep_Hours_Per_Night	Addicted_Score
0	Graduate	High	136	5.94	6.25	7.43
1	Graduate	Low	1	1.50	8.00	2.00
2	Graduate	Medium	188	3.95	7.59	5.41
3	High School	High	25	5.71	5.35	8.32
4	High School	Medium	2	3.50	6.75	4.50
5	Undergraduate	High	147	6.28	5.89	7.90
6	Undergraduate	Medium	206	4.09	7.50	5.49

Students with high risk level are having less sleep hours per night,increase in average daily usage and higher addiction score compare to medium and low risk level students.

Detox Strategy For Students Based on Risk Level

In [46]:

```python
# Defining a function for detox Strategy
def suggest_detox_strategy(df):
    # High Risk Level
    if df['Risk_Level'] == 'High':
        if df['Avg_Daily_Usage_Hours'] >= 7:
            return 'Two weeks social media break and more sleep hours'
        elif df['Sleep_Hours_Per_Night'] < 7 and df['Sleep_Hours_Per_Night'] > 6:
            return 'More sleeping hours and daily screen time limit'
        else:
            return 'Reduce usage gradually and weekly check-ins'

    # Medium Risk level
    elif df['Risk_Level'] == 'Medium':
        if df['Avg_Daily_Usage_Hours'] > 4:
            return 'Encourage offline activities and reduce screen time'
        else:
            return 'Awareness training and Guidance from parents'

    # Low Risk Level
    elif df['Risk_Level'] == 'Low':
        return 'Maintain Good Habits - No Detox Required'

    else:
        return 'No Data'
```

In [47]:
```
# Applying fuction to dataframe
newdf['Detox_Strategy'] = newdf.apply(suggest_detox_strategy, axis=1)

# filtering data to view Risk level and Detox Strategy
newdf[['Student_ID','Risk_Level','Detox_Strategy']].head(10)
```

Out[47]:

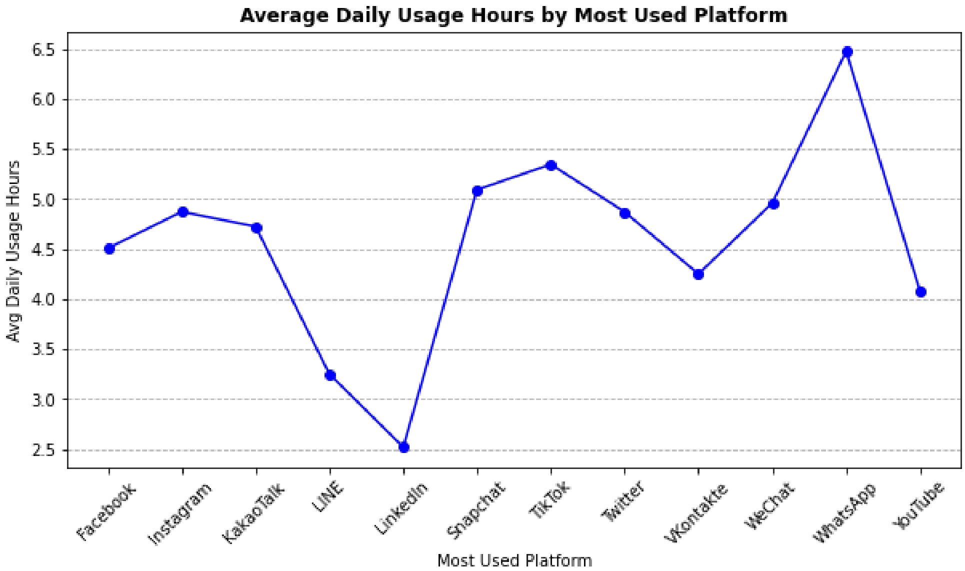
	Student_ID	Risk_Level	Detox_Strategy
0	1	High	More sleeping hours and daily screen time limit
1	2	Medium	Awareness training and Guidance from parents
2	3	High	Reduce usage gradually and weekly check-ins
3	4	Medium	Awareness training and Guidance from parents
4	5	Medium	Encourage offline activities and reduce screen...
5	6	High	Two weeks social media break and more sleep hours
6	7	Low	Maintain Good Habits – No Detox Required
7	8	High	Reduce usage gradually and weekly check-ins
8	9	Medium	Awareness training and Guidance from parents
9	10	Medium	Awareness training and Guidance from parents

Data Visualization using matplotlib and seaborn

Line Chart Visualization for Social Plateform vs Avg daily Usage

In [48]:
```
grouped = newdf.groupby('Most_Used_Platform')['Avg_Daily_Usage_Hours'].mean().reset_index()

x = grouped['Most_Used_Platform']
y = grouped['Avg_Daily_Usage_Hours']
```

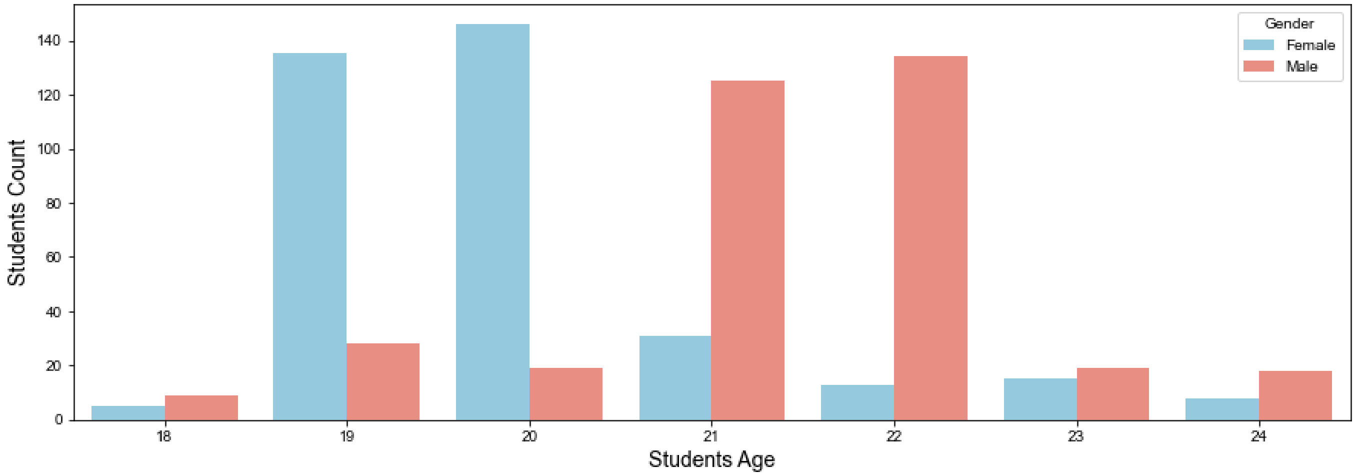
```
plt.figure(figsize=(10, 5))
plt.plot(x, y, marker='o', linestyle='-', color='b')
plt.title('Average Daily Usage Hours by Most Used Platform', fontweight='bold')
plt.xlabel('Most Used Platform')
plt.ylabel('Avg Daily Usage Hours')
plt.xticks(rotation =45)
plt.grid(axis = 'y',linestyle='--')
plt.show()
```



From above we get that on average students spend more time on whatsapp compare to other social media plateforms.

Student Distribution by Age

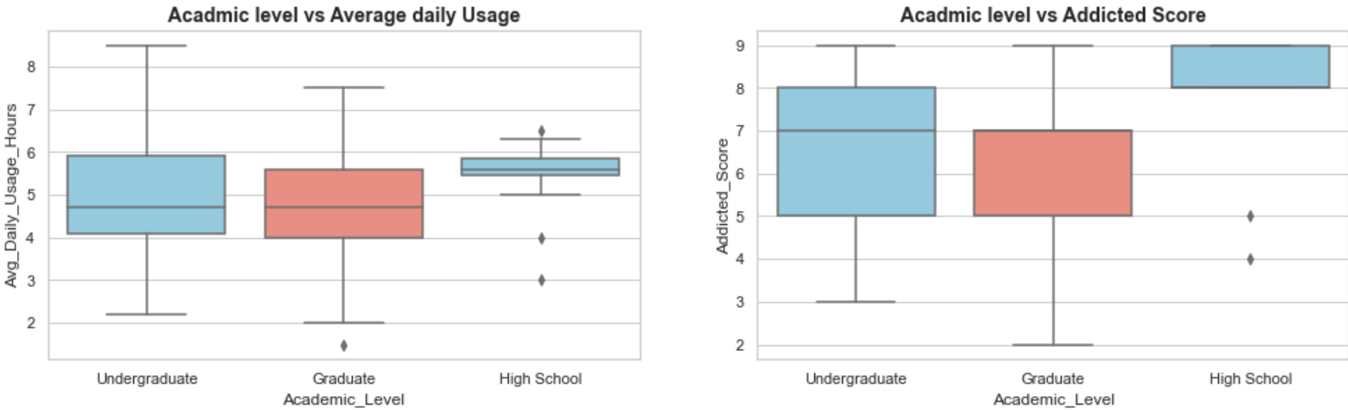
In [49]:
```
# Age Distribution by Gender in Dataframe
fig = plt.figure(figsize = (15,5))
ax = sns.countplot(x='Age', data = newdf,hue = 'Gender',palette = ['skyblue','salmon'])
sns.set(style = "whitegrid")
ax.set_xlabel('Students Age', fontsize = 14)
ax.set_ylabel('Students Count', fontsize = 14)
plt.show()
```



We have female students in majority for age 19 yr & 20 yr and male students in majority for age 21 yr & 22 yr.

Academic level data visualization using Box Plot

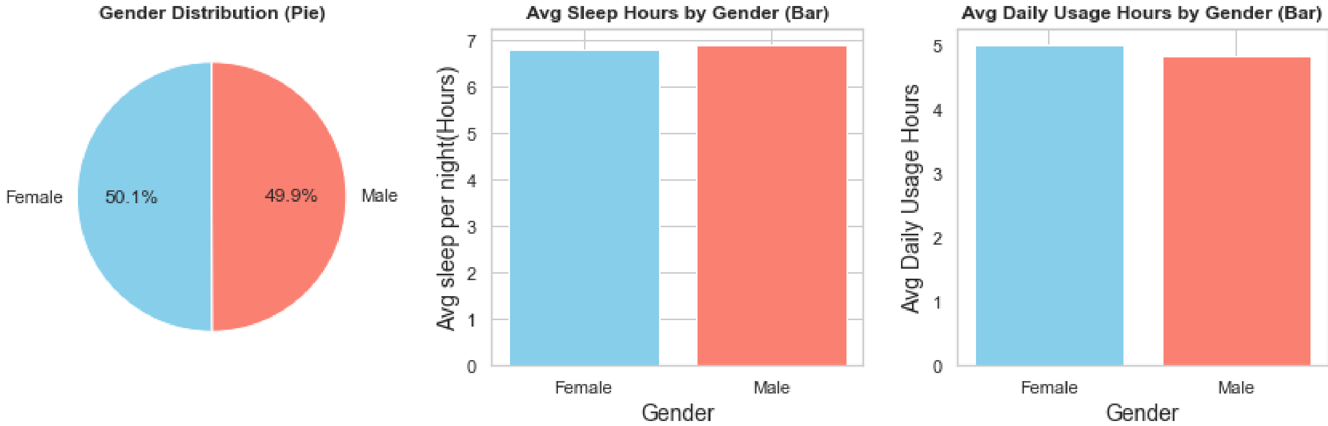
In [50]:
```
plt.figure(figsize = (35,20))
sns.set(style = "whitegrid")
plt.subplot(4,4,1)
sns.boxplot(data = newdf, x = 'Academic_Level', y ='Avg_Daily_Usage_Hours', palette = ['skyblue','salmon'])
plt.title('Acadmic level vs Average daily Usage',fontsize =14,fontweight = 'bold')

plt.subplot(4,4,2)
sns.boxplot(data = newdf, x = 'Academic_Level', y ='Addicted_Score', palette= ['skyblue','salmon'])
plt.title('Acadmic level vs Addicted Score',fontsize =14,fontweight = 'bold')

plt.show()
```



From above box plots we can conclude that high school students have the highest addicted score and as the academic level increases, the average daily usage and addiction score decrease.

Gender based data visualization for daily usages and sleep hours

In [51]:
```
data = newdf.groupby(['Gender'])[['Avg_Daily_Usage_Hours','Student_ID','Sleep_Hours_Per_Night']].agg({'Student_ID':'count',
                                                                                                     'Avg_Daily_Usage_Hours':'mean',
                                                                                                    'Sleep_Hours_Per_Night':'mean'})
data = data.reset_index().round(2)

# Creating subplots
fig, axes = plt.subplots(1,3, figsize=(12,4))

# Gender Distribution
axes[0].pie(data['Student_ID'], labels=data['Gender'], autopct='%1.1f%%', startangle=90, colors = ['skyblue','salmon'])
axes[0].set_title("Gender Distribution (Pie)",fontweight = 'bold')

# gender vs sleep hours per night
axes[1].bar(data['Gender'], data['Sleep_Hours_Per_Night'], color=['skyblue','salmon'])
axes[1].set_title("Avg Sleep Hours by Gender (Bar)",fontweight = 'bold')
axes[1].set_xlabel("Gender",fontsize = 14)
axes[1].set_ylabel("Avg sleep per night(Hours)",fontsize = 14)

# gender vs average daily hour usage
axes[2].bar(data['Gender'], data['Avg_Daily_Usage_Hours'], color=['skyblue','salmon'])
axes[2].set_title("Avg Daily Usage Hours by Gender (Bar)",fontweight = 'bold')
axes[2].set_xlabel("Gender",fontsize = 14)
axes[2].set_ylabel("Avg Daily Usage Hours",fontsize = 14)
axes[2].grid(axis='y', linestyle='--', alpha=0.7)

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

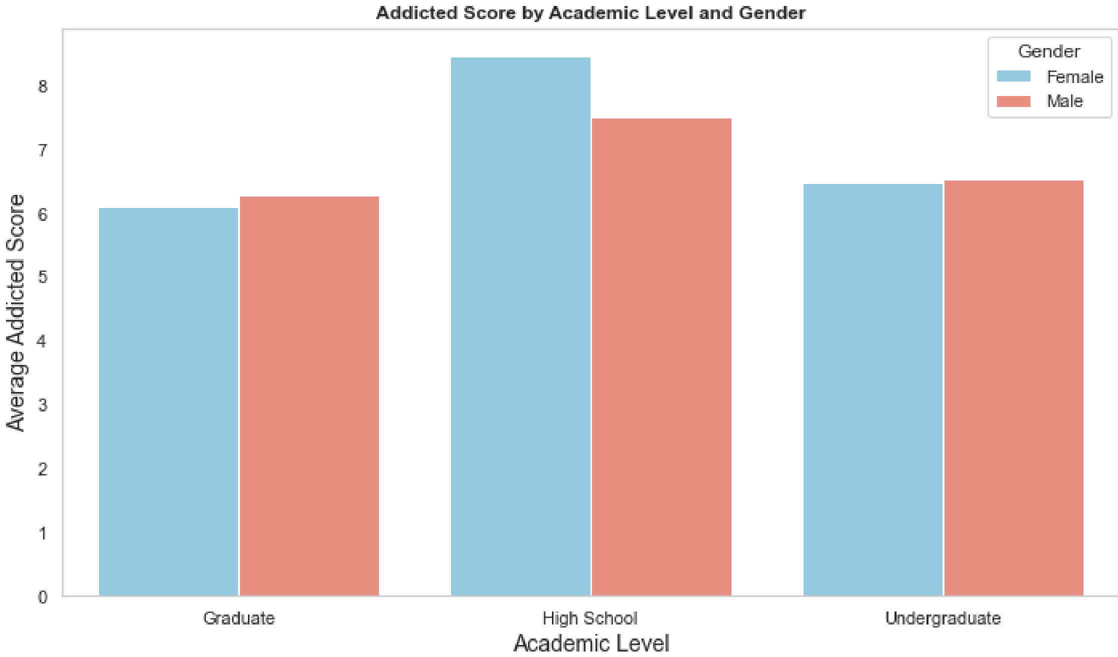


From above we can see that on average girls usually spend more time on social media and have less sleeping hours than boys.

Acadmic Level Vs Social Media Addiction Score

In [52]:

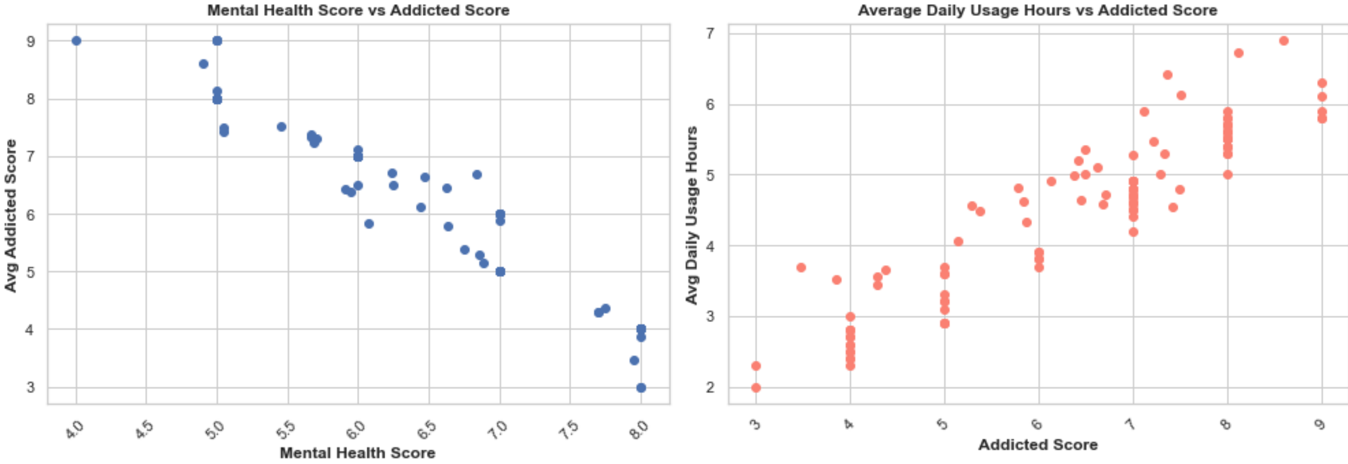
```
# using groupby based on gender and acadmic level
data1 = newdf.groupby(['Gender','Academic_Level'])['Addicted_Score'].mean().reset_index().round(2)

plt.figure(figsize=(10,6))
sns.barplot(data=data1, x ='Academic_Level',y ='Addicted_Score',hue='Gender',palette= ['skyblue','salmon'])
plt.title("Addicted Score by Academic Level and Gender", fontweight='bold')
plt.xlabel("Academic Level",fontsize = 14)
plt.ylabel("Average Addicted Score",fontsize = 14)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



From above we can find that for high school students, females are more addictive to social media and male studends spend more time on social media at undergraduate and graduate levels.

Scatter plot visulization for Average Daily Usage, Mental Health vs Addicted Score

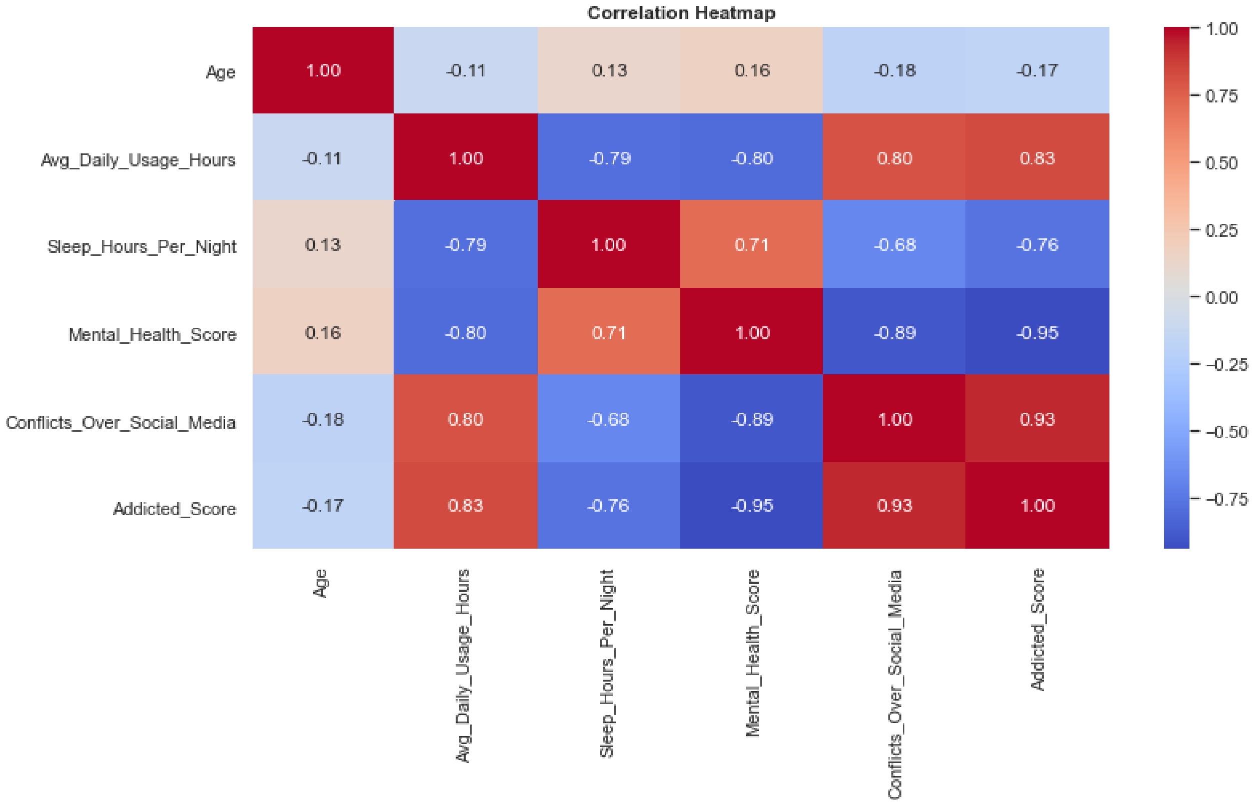
In [53]:
```
data3 = newdf.groupby(["Country"])['Mental_Health_Score','Addicted_Score','Avg_Daily_Usage_Hours',].mean()

# scatter plot

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

axes[0].scatter(data3['Mental_Health_Score'], data3['Addicted_Score'])
axes[0].set_title("Mental Health Score vs Addicted Score", fontweight='bold')
axes[0].set_xlabel("Mental Health Score", fontweight='bold')
axes[0].set_ylabel("Avg Addicted Score", fontweight='bold')
axes[0].tick_params(axis='x', rotation=45)

axes[1].scatter(data3['Addicted_Score'], data3['Avg_Daily_Usage_Hours'], color='salmon')
axes[1].set_title("Average Daily Usage Hours vs Addicted Score", fontweight='bold')
axes[1].set_xlabel("Addicted Score", fontweight='bold')
axes[1].set_ylabel("Avg Daily Usage Hours", fontweight='bold')
axes[1].tick_params(axis='x', rotation=45)

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



From above chart on average we can find that the more time students are spending on social media the more addicted they are getting and mental health degrades when addicted score increases.

In [54]:

```
# Selected numeric columns
numeric_cols = ['Age', 'Avg_Daily_Usage_Hours', 'Sleep_Hours_Per_Night',
                'Mental_Health_Score', 'Conflicts_Over_Social_Media',
                'Addicted_Score']

# correlation matrix
corr = newdf[numeric_cols].corr()

# Plot heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(corr, annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Correlation Heatmap', fontweight='bold')
plt.show()
```


Correlation Heatmap
Age
Avg_Daily_Usage_Hours
Sleep_Hours_Per_Night
Mental_Health_Score
Conflicts_Over_Social_Media
Addicted_Score
1.00 -0.11 0.13 0.16 -0.18 -0.17
-0.11 1.00 -0.79 -0.80 0.80 0.83
0.13 -0.79 1.00 0.71 -0.68 -0.76
0.16 -0.80 0.71 1.00 -0.89 -0.95
-0.18 0.80 -0.68 -0.89 1.00 0.93
-0.17 0.83 -0.76 -0.95 0.93 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

From above heatmap we can conclude these points:

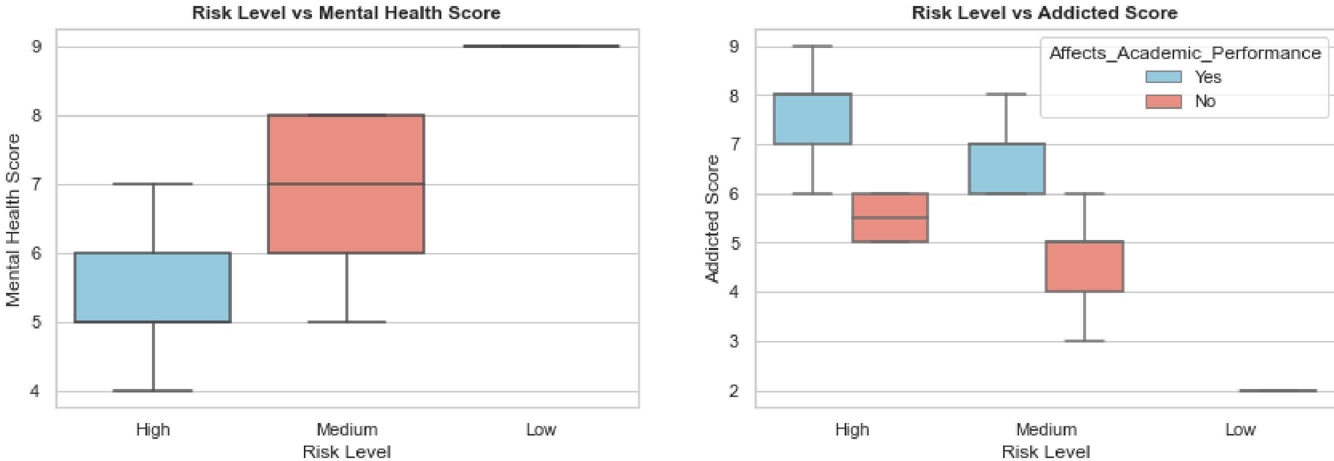
--> The more daily hours spent on social media, we have more conflicts, higher addiction score and lower mental health.

--> Age has minimal effects on other parameters i.e. consistant data pattern across all age group.

--> Less sleep hours per night is associated with higher usage and addiction to social media.

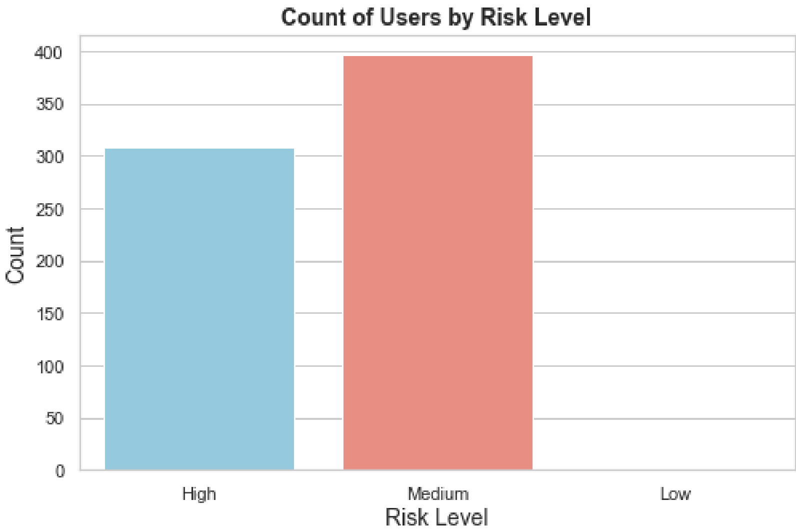
Risk level visualization

In [55]:
```
fig = plt.figure(figsize=(30,20))
plt.subplot(4,4,1)
sns.boxplot(data=newdf, x='Risk_Level', y='Mental_Health_Score', palette=['skyblue','salmon','orange'])
plt.title('Risk Level vs Mental Health Score', fontweight='bold')
plt.xlabel('Risk Level')
plt.ylabel('Mental Health Score')

plt.subplot(4,4,2)
sns.boxplot(data=newdf, x='Risk_Level', y='Addicted_Score',hue = "Affects_Academic_Performance", palette=['skyb
lue','salmon','orange'])
plt.title('Risk Level vs Addicted Score', fontweight='bold')
plt.xlabel('Risk Level')
plt.ylabel('Addicted Score')

plt.show()
```



The students with lower mental score have higher risk level and higher probability to affect thieir academic performance.

In [56]:
```
plt.figure(figsize=(8,5))
sns.countplot(data=newdf, x='Risk_Level', palette=['skyblue','salmon','orange'])
plt.title("Count of Users by Risk Level", fontsize=14, fontweight='bold')
plt.xlabel("Risk Level",fontsize = 14)
plt.ylabel("Count",fontsize = 14)
plt.show()
```



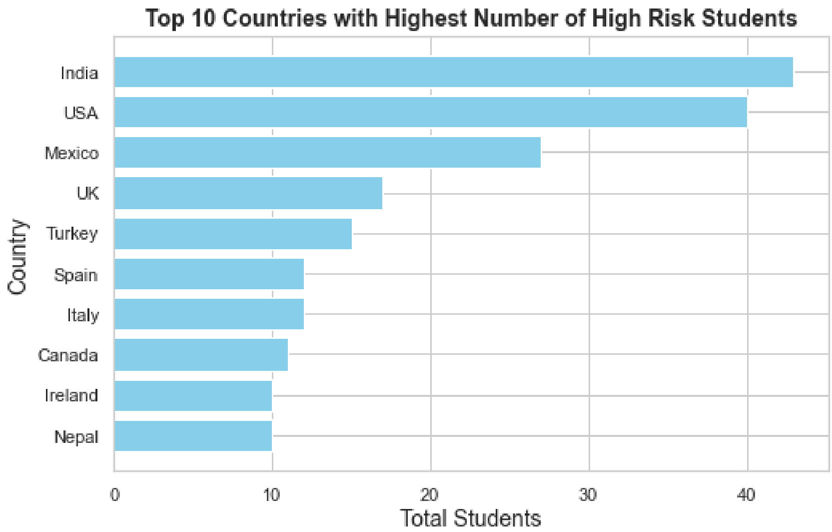
From above we get that most numbers of students belong to medium Risk and then high risk students.

Top 10 Countries based on total High Risk Students

In [57]:

```
# finding contries vs number of high risk students
high_risk_Students_counts = newdf[newdf['Risk_Level'] == 'High'].groupby('Country').agg(Total_Students = ('Student_ID', 'count'))

# Finding top 10 countries
Top_Countries = high_risk_Students_counts.sort_values(by = 'Total_Students',ascending = False).reset_index().head(10)
```

In [58]:
```
plt.figure(figsize=(8,5))

plt.barh(Top_Countries['Country'], Top_Countries['Total_Students'], color='skyblue')
plt.title("Top 10 Countries with Highest Number of High Risk Students",fontsize=14,fontweight='bold')
plt.xlabel("Total Students",fontsize=14)
plt.ylabel("Country",fontsize=14)
plt.gca().invert_yaxis()
plt.show()
```



From above we can conclude that India , USA and Mexico has the highest numbers of High risk Students.

Conclusion:

Key Patterns:

** Students with high usage hours display significantly lower sleep and mental health scores.

** Males show a marginally higher addiction score on average.

** Risk levels increase with younger ages for high school and Undergraduates.

** Most students fall in the medium risk category and then secondly in high-risk category.

** Students with higher addiction score are having low mental health and more numbers of conflicts on social media.

** From boxplot analysis we can find that students with addiction score > 6, are generally having their academic performance affected.

Root Cause:

** The data suggests that higher daily usage of social media negatively affects both academic performance and mental health. Additionally, students who spend more hours online tend to exhibit higher levels of social media addiction.

Recommeded Actions:

** Use of Detox Strategy is most recommended for high-risk and medium risk students.

** To fight addiction in students will also require proactive involvement from educators and parents.

** Institutions can also provide guidance for awareness about social media addiction.

** Students should be encouraged to participate in more offline activities with each others like games,dabates etc.

In [ ]:

```

```