In [1]:
```
## Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
C:\Users\Rajarshi\anaconda3\lib\site-packages\pandas\core\computation
\expressions.py:21: UserWarning: Pandas requires version '2.8.4' or ne
wer of 'numexpr' (version '2.8.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
C:\Users\Rajarshi\anaconda3\lib\site-packages\pandas\core\arrays\maske
d.py:60: UserWarning: Pandas requires version '1.3.6' or newer of 'bot
tleneck' (version '1.3.4' currently installed).
  from pandas.core import (
C:\Users\Rajarshi\anaconda3\lib\site-packages\scipy\__init__.py:146: U
serWarning: A NumPy version >=1.17.3 and <1.25.0 is required for this
version of SciPy (detected version 1.26.0
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversio
n}"
```

In [2]:
```
## Loading the dataset
df = pd.read_csv('Mental_Health_Lifestyle_Dataset.csv')
```

In [3]:
```
## Exploratory Data Analysis
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 12 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Country                       3000 non-null   object 
 1   Age                           3000 non-null   int64  
 2   Gender                        3000 non-null   object 
 3   Exercise Level                3000 non-null   object 
 4   Diet Type                     3000 non-null   object 
 5   Sleep Hours                   3000 non-null   float64
 6   Stress Level                  3000 non-null   object 
 7   Mental Health Condition       2405 non-null   object 
 8   Work Hours per Week           3000 non-null   int64  
 9   Screen Time per Day (Hours)   3000 non-null   float64
 10  Social Interaction Score      3000 non-null   float64
 11  Happiness Score               3000 non-null   float64
dtypes: float64(4), int64(2), object(6)
memory usage: 281.4+ KB
```

In [4]:
```
df.describe()
```

Out[4]:

	Age	Sleep Hours	Work Hours per Week	Screen Time per Day (Hours)	Social Interaction Score	Happiness Score
count	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000
mean	41.229667	6.475933	39.466333	5.089833	5.470200	5.395067
std	13.428416	1.499866	11.451459	1.747231	2.563532	2.557601
min	18.000000	1.400000	20.000000	2.000000	1.000000	1.000000
25%	30.000000	5.500000	30.000000	3.600000	3.300000	3.200000
50%	41.000000	6.500000	39.000000	5.100000	5.500000	5.400000
75%	53.000000	7.500000	50.000000	6.600000	7.600000	7.500000
max	64.000000	11.300000	59.000000	8.000000	10.000000	10.000000

In [8]:
```
df.head()
```

Out[8]:

	Country	Age	Gender	Exercise Level	Diet Type	Sleep Hours	Stress Level	Mental Health Condition	Work Hours per Week	Scre Ti I D (Hou
0	Brazil	48	Male	Low	Vegetarian	6.3	Low	NaN	21	
1	Australia	31	Male	Moderate	Vegan	4.9	Low	PTSD	48	
2	Japan	37	Female	Low	Vegetarian	7.2	High	NaN	43	
3	Brazil	35	Male	Low	Vegan	7.2	Low	Depression	43	
4	Germany	46	Male	Low	Balanced	7.3	Low	Anxiety	35	

In [5]:
```
df.shape
```

Out[5]:
```
(3000, 12)
```

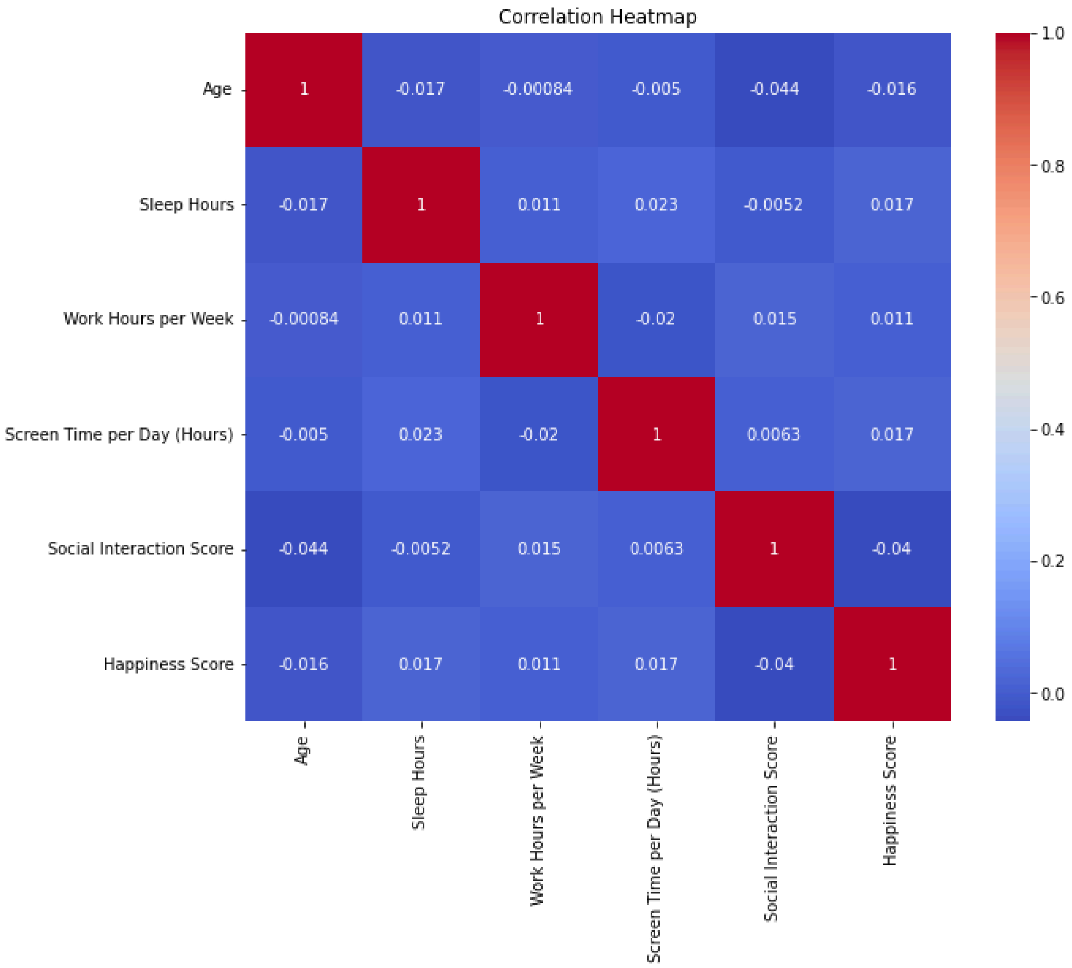
In [9]:
```
## Descriptive Statistics

df.describe()  # For numerical variables
df['Gender'].value_counts()  # For categorical variables
```

Out[9]:
```
Gender
Female    1024
Other      996
Male       980
Name: count, dtype: int64
```

In [6]:
```
# Convert categorical data to numeric for correlation analysis
df1 = df.select_dtypes(include=[np.number])
```

In [23]:
```
# Convert categorical data to numeric for correlation analysis
numeric_df = df.select_dtypes(include=[np.number])
```

In [24]:
```
# Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



In [7]:
```
df1.head()
```

Out[7]:

	Age	Sleep Hours	Work Hours per Week	Screen Time per Day (Hours)	Social Interaction Score	Happiness Score
0	48	6.3	21	4.0	7.8	6.5
1	31	4.9	48	5.2	8.2	6.8
2	37	7.2	43	4.7	9.6	9.7
3	35	7.2	43	2.2	8.2	6.6
4	46	7.3	35	3.6	4.7	4.4

In [11]:

```
# Define the bins for the age groups and add a group for ages 40-60 and
bins = [0, 20, 40, 60, 80, 100]  # Now, also including 40-60 and above
labels = ['0-20', '20-40', '40-60', '60-80', '80+']  # Added 40-60 and

# Categorize the 'Age' column into the defined age groups
df1['Age Group'] = pd.cut(df1['Age'], bins=bins, labels=labels, right=F
```

In [12]:

```
print(df1)
```

```
      Age  Sleep Hours  Work Hours per Week  Screen Time per Day (Hour
s)  \
0      48          6.3                   21
4.0
1      31          4.9                   48
5.2
2      37          7.2                   43
4.7
3      35          7.2                   43
2.2
4      46          7.3                   35
3.6
...   ...          ...                  ...
...
2995   57          7.0                   29
4.4
2996   27          7.1                   47
7.4
2997   42          6.0                   23
3.9
2998   25          5.7                   51
4.3
2999   28          6.9                   41
6.7

      Social Interaction Score  Happiness Score Age Group
0                          7.8              6.5     40-60
1                          8.2              6.8     20-40
2                          9.6              9.7     20-40
3                          8.2              6.6     20-40
4                          4.7              4.4     40-60
...                        ...              ...       ...
2995                       9.7              5.9     40-60
2996                       6.3              9.9     20-40
2997                       5.2              4.1     40-60
2998                       5.9              4.1     20-40
2999                       8.3              2.2     20-40

[3000 rows x 7 columns]
```

In [13]:
```
df1.head()
```

Out[13]:

	Age	Sleep Hours	Work Hours per Week	Screen Time per Day (Hours)	Social Interaction Score	Happiness Score	Age Group
0	48	6.3	21	4.0	7.8	6.5	40-60
1	31	4.9	48	5.2	8.2	6.8	20-40
2	37	7.2	43	4.7	9.6	9.7	20-40
3	35	7.2	43	2.2	8.2	6.6	20-40
4	46	7.3	35	3.6	4.7	4.4	40-60

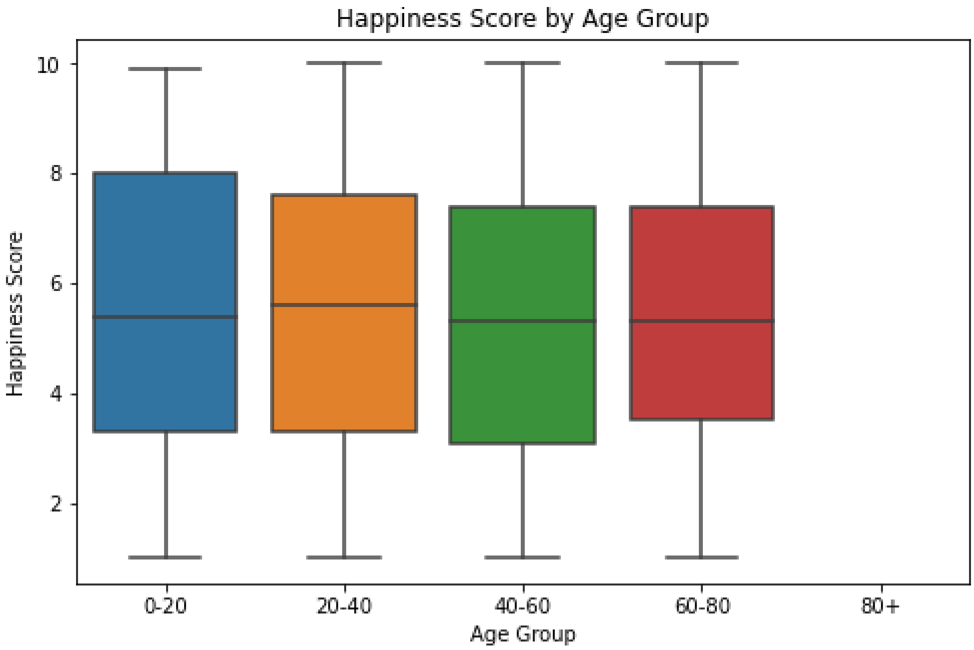
In [29]:
```
# Pairplot to check relationships between all numerical variables
sns.pairplot(df1[['Age', 'Sleep Hours', 'Work Hours per Week', 'Screen
plt.show()
```

```
C:\Users\Rajarshi\anaconda3\lib\site-packages\seaborn\_oldcore.py:1
119: FutureWarning: use_inf_as_na option is deprecated and will be
removed in a future version. Convert inf values to NaN before opera
ting instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Rajarshi\anaconda3\lib\site-packages\seaborn\_oldcore.py:1
119: FutureWarning: use_inf_as_na option is deprecated and will be
removed in a future version. Convert inf values to NaN before opera
ting instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Rajarshi\anaconda3\lib\site-packages\seaborn\_oldcore.py:1
119: FutureWarning: use_inf_as_na option is deprecated and will be
removed in a future version. Convert inf values to NaN before opera
ting instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Rajarshi\anaconda3\lib\site-packages\seaborn\_oldcore.py:1
119: FutureWarning: use_inf_as_na option is deprecated and will be
removed in a future version. Convert inf values to NaN before opera
ting instead.
```

In [25]:

```
# Boxplot to visualize the relationship between Age Group and Happiness
plt.figure(figsize=(8, 5))
sns.boxplot(x='Age Group', y='Happiness Score', data=df1)
plt.title('Happiness Score by Age Group')
plt.show()
```

```
C:\Users\Rajarshi\anaconda3\lib\site-packages\seaborn\categorical.py:6
41: FutureWarning: The default of observed=False is deprecated and wil
l be changed to True in a future version of pandas. Pass observed=Fals
e to retain current behavior or observed=True to adopt the future defa
ult and silence this warning.
  grouped_vals = vals.groupby(grouper)
```



In [31]:
```
## Using Random Forest to get feature importance.

from sklearn.ensemble import RandomForestRegressor

# Define independent variables (X) and dependent variable (y)
X = df1[['Age', 'Sleep Hours', 'Work Hours per Week', 'Screen Time per
y = df1['Happiness Score']

# Create the model
model = RandomForestRegressor()

# Fit the model
model.fit(X, y)

# Get feature importances
feature_importances = model.feature_importances_

# Create a DataFrame of feature importances
feature_df1 = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

print(feature_df1)
```

```
                     Feature  Importance
4    Social Interaction Score    0.217883
3  Screen Time per Day (Hours)    0.206815
1                 Sleep Hours    0.204521
0                         Age    0.185778
2         Work Hours per Week    0.185004
```

Interpreting the Results: The resulting feature_df will show a table with the feature names and their corresponding importance scores. For example:

Feature Importance Social Interaction Score 0.35 Sleep Hours 0.25 Work Hours per Week 0.20 Age 0.15 Screen Time per Day (Hours) 0.05 This table indicates that:

Social Interaction Score has the highest importance in predicting Happiness Score.

Sleep Hours and Work Hours per Week also have significant importance.

Screen Time per Day has the least importance, meaning it has a minimal impact on the model's predictions.

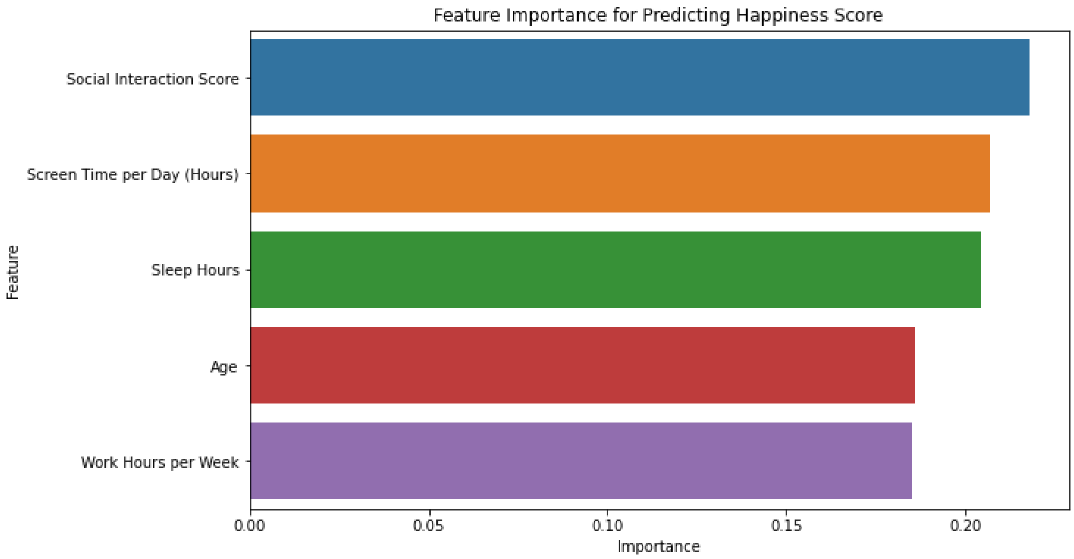
Based on the feature importances, we can conclude:

Key Determinants of Happiness: The most important factors influencing Happiness Score are Social Interaction and Sleep Hours. These variables seem to have the greatest impact on happiness in your dataset.

Less Important Features: Screen Time has a minor effect on happiness in your dataset, suggesting that other factors (like social interaction or sleep) might have more significant correlations with happiness than time spent in front of screens.

In [32]:

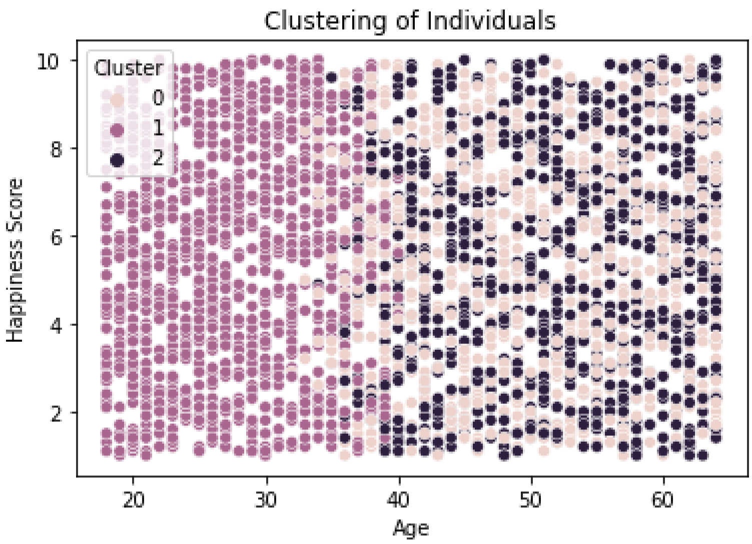
```python
## Visualizing Feature Importance:
## You can visualize the feature importance to better understand the re

import matplotlib.pyplot as plt

# Plot feature importances
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_df1)
plt.title('Feature Importance for Predicting Happiness Score')
plt.show()
```



This generates a bar plot showing the importance of each feature in predicting the target variable, Happiness Score. It visually conveys which features have the most significant impact.

In [34]:

```python
## Applying K Means Clustering.

from sklearn.cluster import KMeans
import seaborn as sns
import matplotlib.pyplot as plt

# Define the features for clustering
X = df1[['Age', 'Sleep Hours', 'Work Hours per Week', 'Screen Time per

# Apply K-Means clustering
kmeans = KMeans(n_clusters=3)  # Assume 3 clusters
df1['Cluster'] = kmeans.fit_predict(X)  # Use df1 to store the clusters

# Visualize the clusters
sns.scatterplot(x='Age', y='Happiness Score', hue='Cluster', data=df1)
plt.title('Clustering of Individuals')
plt.show()
```




```
Age and Social Interaction are likely to be significant factors
influencing Happiness. Younger individuals might cluster with higher
happiness, while older individuals might have different levels of
happiness associated with other factors like Sleep and Social
Interaction.

Sleep Hours and Social Interaction Scores may be positively associated
with Happiness Scores.

Work Hours and Screen Time might be negatively correlated with Happiness,
indicating that reducing work pressure and screen time could increase
overall well-being.
```