aerofit-project-1

August 14, 2023

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

[2]:
```
# Importing the dataset and basic df analysis
df = pd.read_csv(r'aerofit_treadmill.csv')
```

[3]:
```
# first few rows of the dataset
df.head()
```

[3]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

[4]:
```
# Shape of dataset
df.shape
```

[4]: (180, 9)

[5]:
```
# basic information about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
```

```
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

[6]:

```python
# statistics of the numerical columns
df.describe(include="all").T.round(1)
```

[6]:

```
              count unique        top freq          mean           std  \
Product         180      3      KP281   80           NaN           NaN
Age           180.0    NaN        NaN  NaN     28.788889      6.943498
Gender          180      2       Male  104           NaN           NaN
Education     180.0    NaN        NaN  NaN     15.572222      1.617055
MaritalStatus   180      2  Partnered  107           NaN           NaN
Usage         180.0    NaN        NaN  NaN      3.455556      1.084797
Fitness       180.0    NaN        NaN  NaN      3.311111      0.958869
Income        180.0    NaN        NaN  NaN  53719.577778  16506.684226
Miles         180.0    NaN        NaN  NaN    103.194444     51.863605

                   min       25%      50%      75%       max
Product            NaN       NaN      NaN      NaN       NaN
Age               18.0      24.0     26.0     33.0      50.0
Gender             NaN       NaN      NaN      NaN       NaN
Education         12.0      14.0     16.0     16.0      21.0
MaritalStatus      NaN       NaN      NaN      NaN       NaN
Usage              2.0       3.0      3.0      4.0       7.0
Fitness            1.0       3.0      3.0      4.0       5.0
Income         29562.0  44058.75  50596.5  58668.0  104581.0
Miles             21.0      66.0     94.0   114.75     360.0
```

[7]:

```python
#
df.describe()
```

[7]:

```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
```

```
min       21.000000
25%       66.000000
50%       94.000000
75%      114.750000
max      360.000000
```

[8]:
```python
df.Education.value_counts()
```

[8]:
```
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64
```

[9]:
```python
df.Age.value_counts()
```

[9]:
```
25    25
23    18
24    12
26    12
28     9
35     8
33     8
30     7
38     7
21     7
22     7
27     7
31     6
34     6
29     6
20     5
40     5
32     4
19     4
48     2
37     2
45     2
47     2
46     1
50     1
18     1
44     1
```

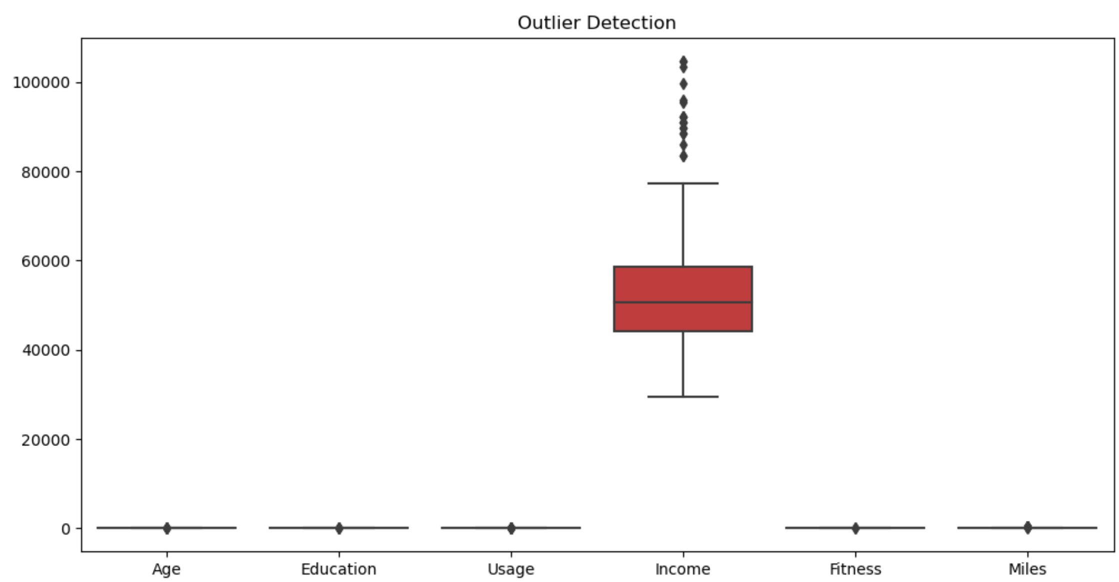
```
43      1
41      1
39      1
36      1
42      1
Name: Age, dtype: int64
```

[10]:
```
df.Product.value_counts()
```

[10]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

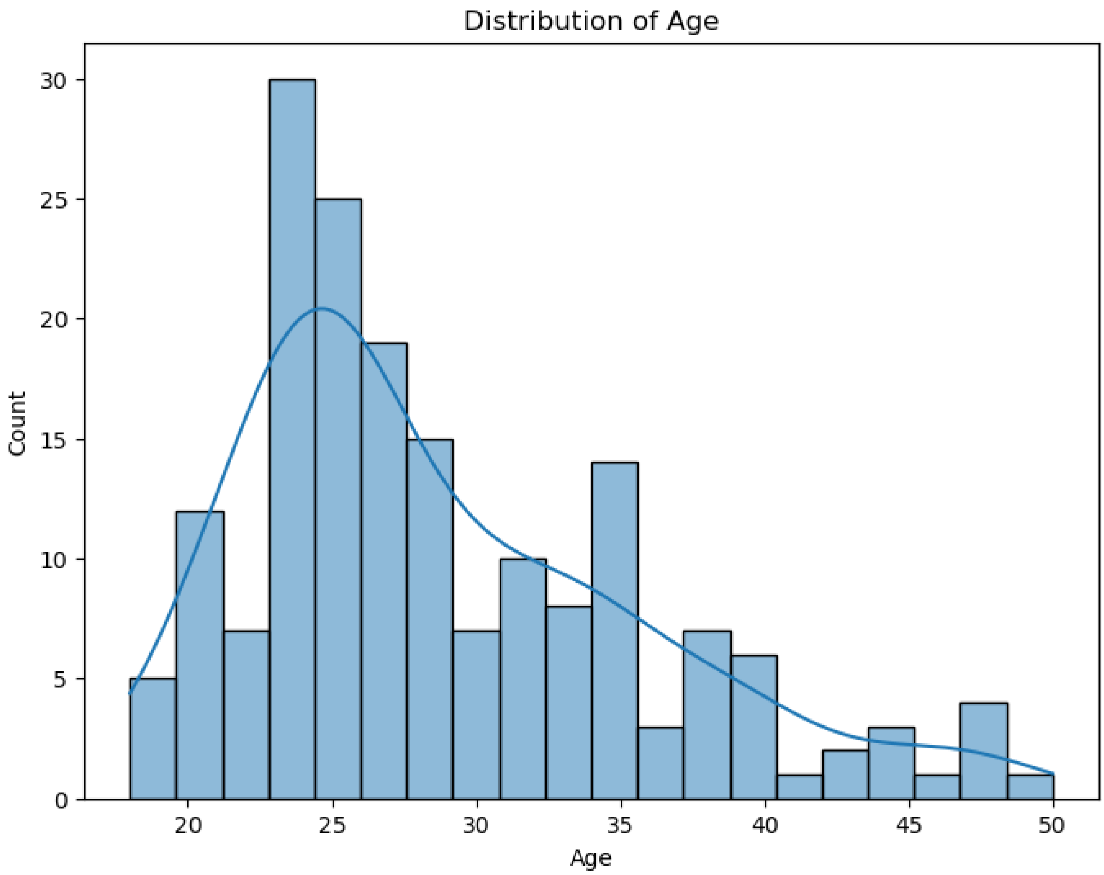
[11]:
```
categorical_cols = ['Product', 'Gender', 'MaritalStatus']
df[categorical_cols] = df[categorical_cols].astype('category')
```

[12]:
```
# Detecting Outliers
# identify and handle outliers using box plots
numeric_cols = ['Age', 'Education', 'Usage', 'Income', 'Fitness', 'Miles']
plt.figure(figsize=(12, 6))
sns.boxplot(data=df[numeric_cols])
plt.title("Outlier Detection")
plt.show()
```

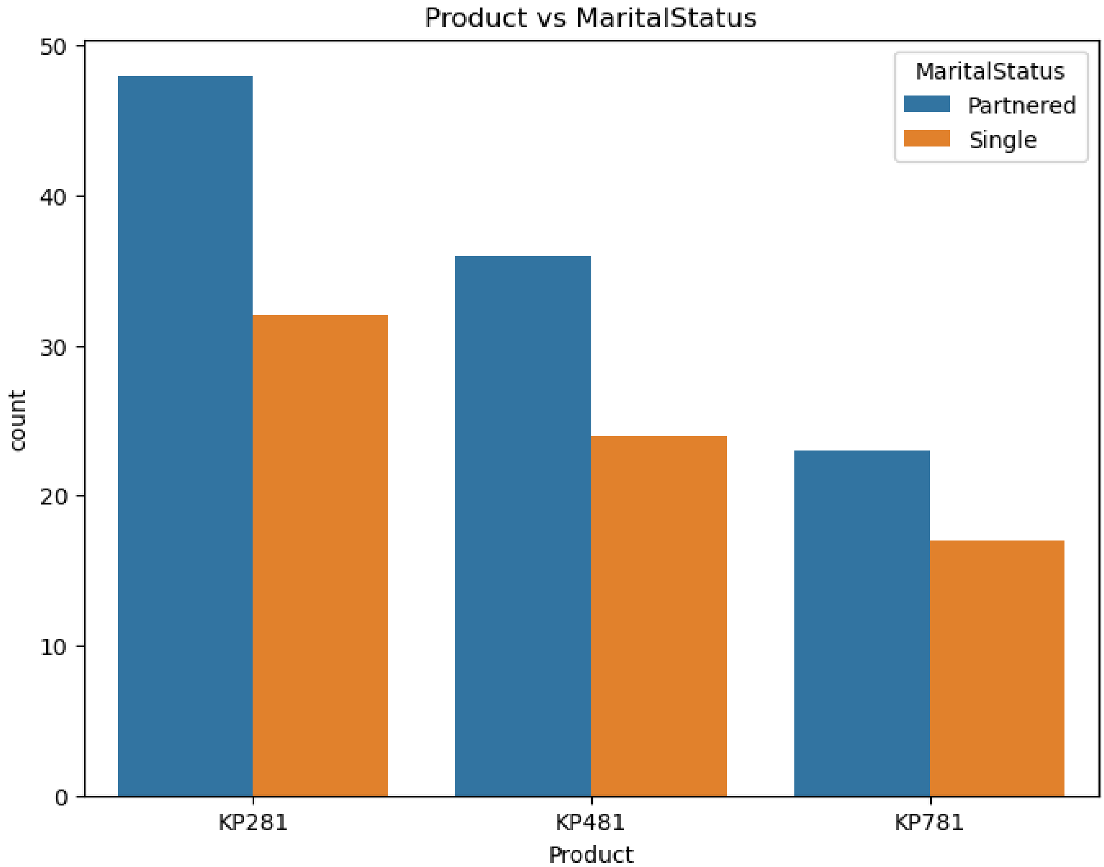


[13]:
```
# Visual Analysis - Univariate & Bivariate
# Histogram of Age
plt.figure(figsize=(8, 6))
```

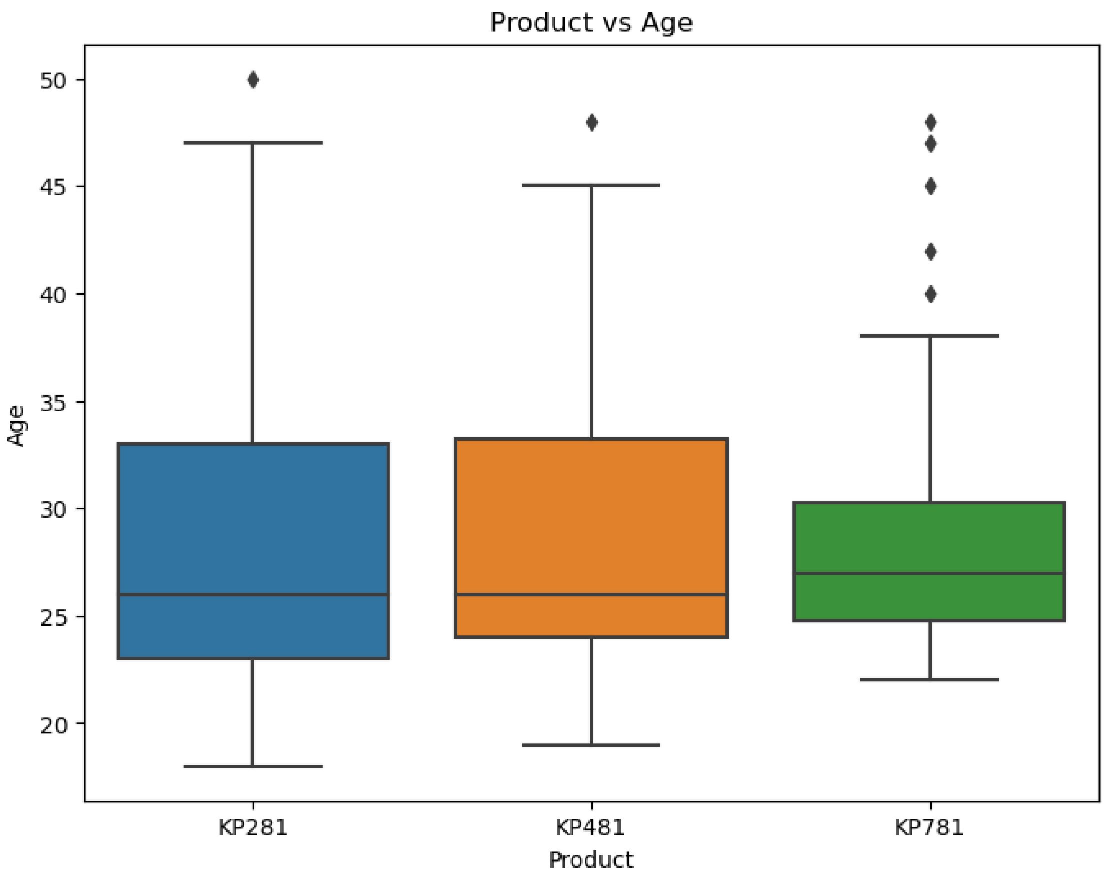
```python
sns.histplot(data=df, x='Age', bins=20, kde=True)
plt.title("Distribution of Age")
plt.show()
```



[14]:
```python
# Countplot for Product vs MaritalStatus
plt.figure(figsize=(8, 6))
sns.countplot(x="Product", hue='MaritalStatus', data=df)
plt.title("Product vs MaritalStatus")
plt.show()
```



[15]:
```
# Boxplot of Product vs Age
plt.figure(figsize=(8, 6))
sns.boxplot(data=df, x='Product', y='Age')
plt.title("Product vs Age")
plt.show()
```



[16]:
```
# Representing marginal probability
# Marginal probabilities of purchasing each product
marginal_prob = pd.crosstab(index=df['Product'], columns='count',␣
↪normalize=True)
print("Marginal Probability:")
print(marginal_prob)
```

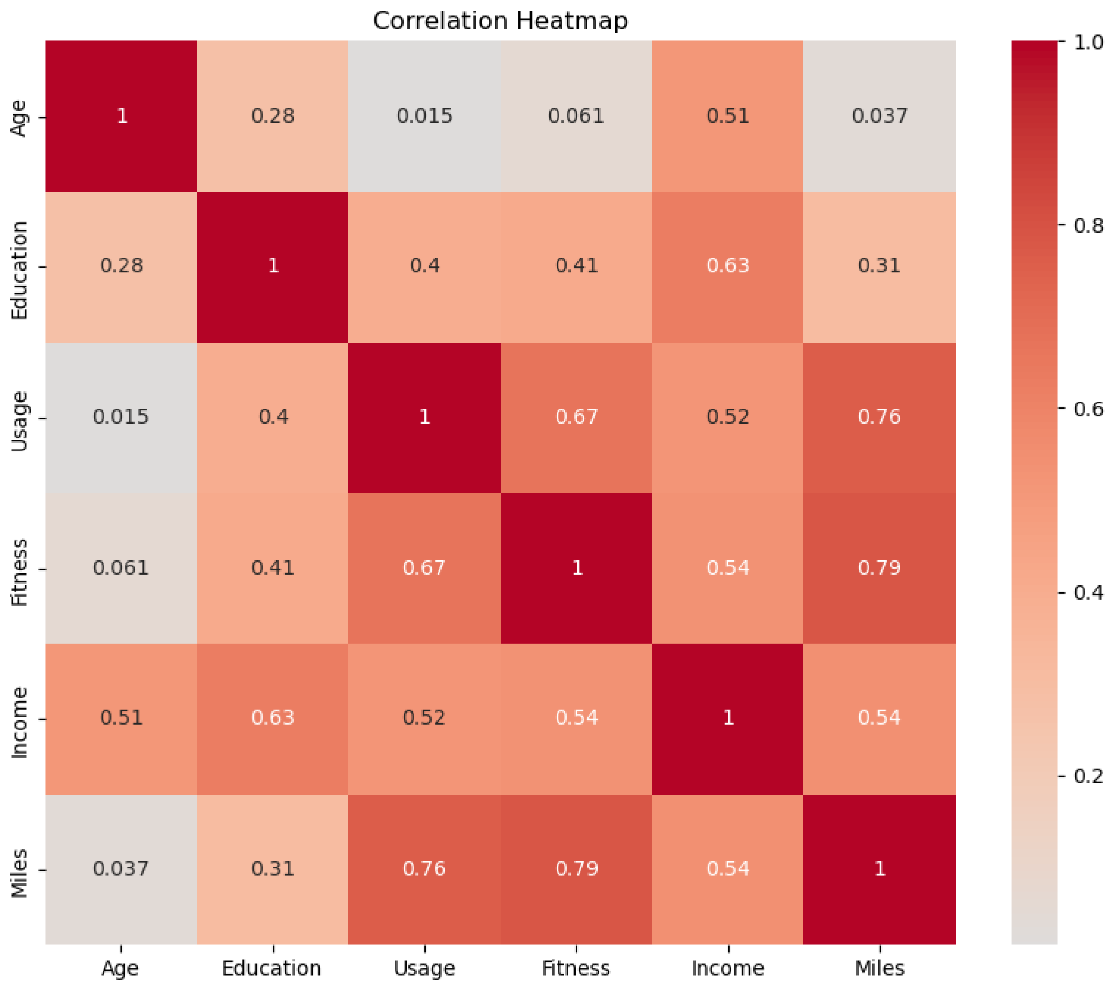
```
Marginal Probability:
col_0        count
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
```

[17]:
```
# Correlation Analysis
# correlation matrix
corr = df.corr()
```

```
C:\Users\rahul\AppData\Local\Temp\ipykernel_10748\2035915871.py:3:
FutureWarning: The default value of numeric_only in DataFrame.corr is
```

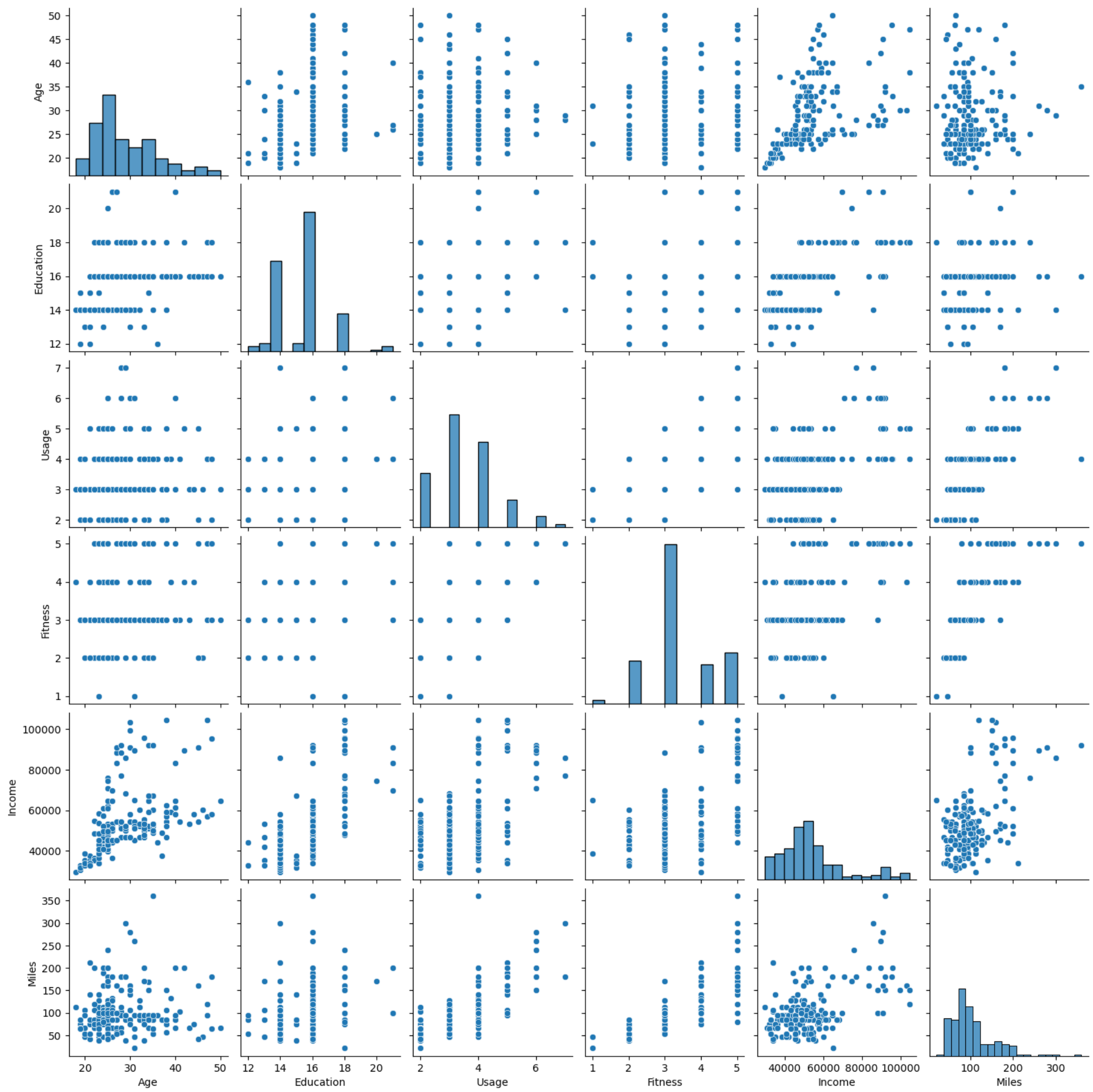
```
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  corr = df.corr()
```

[18]:
```
# Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', center=0)
plt.title("Correlation Heatmap")
plt.show()
```



[19]:
```
# Pairplot
sns.pairplot(df)
```

[19]: <seaborn.axisgrid.PairGrid at 0x18ec25a3d00>



[20]:
```
# Calculating conditional probability
df.std()
```

```
C:\Users\rahul\AppData\Local\Temp\ipykernel_10748\3187971767.py:2:
FutureWarning: The default value of numeric_only in DataFrame.std is deprecated.
In a future version, it will default to False. In addition, specifying
'numeric_only=None' is deprecated. Select only valid columns or specify the
value of numeric_only to silence this warning.
  df.std()
```

[20]:
```
Age            6.943498
Education      1.617055
Usage          1.084797
```

```
Fitness          0.958869
Income       16506.684226
Miles           51.863605
dtype: float64
```

[21]:
```python
# Median
df.median()
```

```
C:\Users\rahul\AppData\Local\Temp\ipykernel_10748\3213049308.py:2:
FutureWarning: The default value of numeric_only in DataFrame.median is
deprecated. In a future version, it will default to False. In addition,
specifying 'numeric_only=None' is deprecated. Select only valid columns or
specify the value of numeric_only to silence this warning.
  df.median()
```

[21]:
```
Age             26.0
Education       16.0
Usage            3.0
Fitness          3.0
Income       50596.5
Miles           94.0
dtype: float64
```

[22]:
```python
# Mean
df.mean()
```

```
C:\Users\rahul\AppData\Local\Temp\ipykernel_10748\2486691740.py:2:
FutureWarning: The default value of numeric_only in DataFrame.mean is
deprecated. In a future version, it will default to False. In addition,
specifying 'numeric_only=None' is deprecated. Select only valid columns or
specify the value of numeric_only to silence this warning.
  df.mean()
```

[22]:
```
Age             28.788889
Education       15.572222
Usage            3.455556
Fitness          3.311111
Income       53719.577778
Miles          103.194444
dtype: float64
```

[23]:
```python
age_diff = df['Age'].mean() - df['Age'].median()
print(f'Difference between mean and median of Age: {age_diff}')
```

```
Difference between mean and median of Age: 2.788888888888888
```

```
[24]: # Gender for each Product
conditional_prob_gender = pd.crosstab(index=df['Product'],␣
  ↪columns=df['Gender'], normalize='index')
print("Conditional Probability (Gender):")
print(conditional_prob_gender)
```

```
Conditional Probability (Gender):
Gender     Female      Male
Product
KP281    0.500000  0.500000
KP481    0.483333  0.516667
KP781    0.175000  0.825000
```

```
[25]: # Customer Profiling - Categorization of users
X = df[['Age', 'Education', 'Usage', 'Income', 'Fitness', 'Miles']]
```

```
[26]: # KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=0)
df['Cluster'] = kmeans.fit_predict(X)
```

```
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\ProgramData\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1382:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

```
[27]: # Generating recommendations and actionable insights
# Customer profiling insights
for cluster in range(3):
    cluster_df = df[df['Cluster'] == cluster]
    print(f"Cluster {cluster} has {len(cluster_df)} customers.")
    print(f"Average age: {cluster_df['Age'].mean():.2f}")
    print(f"Average income: ${cluster_df['Income'].mean():,.2f}")
    print(f"Average fitness rating: {cluster_df['Fitness'].mean():.2f}")
    print()
```

```
Cluster 0 has 22 customers.
Average age: 33.05
Average income: $90,417.00
Average fitness rating: 4.77

Cluster 1 has 85 customers.
Average age: 31.41
Average income: $55,564.86
```

```
Average fitness rating: 3.25

Cluster 2 has 73 customers.
Average age: 24.45
Average income: $40,511.47
Average fitness rating: 2.95
```

[28]:
```python
# Recommendations
recommendations = [
    "Cluster 0 consists of customers with relatively lower age, income, and␣
↪fitness rating.Consider targeting them with entry-level products like KP281.
↪",
    "Cluster 1 comprises customers with higher income and fitness levels. They␣
↪might be interested in advanced treadmills like KP781.",
    "Cluster 2 represents a diverse group. It could be further analyzed to␣
↪identify specific customer segments and tailor marketing strategies␣
↪accordingly."
]

for i, recommendation in enumerate(recommendations):
    print(f"Recommendation {i + 1}: {recommendation}")
```

```
Recommendation 1: Cluster 0 consists of customers with relatively lower age,
income, and fitness rating.Consider targeting them with entry-level products
like KP281.
Recommendation 2: Cluster 1 comprises customers with higher income and fitness
levels. They might be interested in advanced treadmills like KP781.
Recommendation 3: Cluster 2 represents a diverse group. It could be further
analyzed to identify specific customer segments and tailor marketing strategies
accordingly.
```

[ ]: