Importing the Dependencies

In [2]:
```
import numpy as np  # used for arrays
import pandas as pd # used for data processing (data loading, data manipulation,
import matplotlib.pyplot as plt # used for plotting graphs
import seaborn as sns
from sklearn.model_selection import train_test_split # used for training and test
from xgboost import XGBRegressor # loading the XGBRegressor
from sklearn import metrics # r2 and mean absolute error
```

Data Collection & Processing

In [3]:
```
# loading the data from csv file to a Pandas DataFrame

calories = pd.read_csv('calories.csv')
```

In [4]:
```
# printing the first 5 rows of the dataframe

calories.head()
```

Out[4]:

	User_ID	Calories
0	14733363	231.0
1	14861698	66.0
2	11179863	26.0
3	16180408	71.0
4	17771927	35.0

In [5]:
```
exercise_data = pd.read_csv('exercise.csv')

# reading the excercise csv into a pandas dataframe
```

In [6]:
```
exercise_data.head()

# printing the first 5 rows of the excercise dataset

# These 2 datasets are connected using the primary key - User_ID
```

Out[6]:

	User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp
0	14733363	male	68	190.0	94.0	29.0	105.0	40.8
1	14861698	female	20	166.0	60.0	14.0	94.0	40.3
2	11179863	male	69	179.0	79.0	5.0	88.0	38.7
3	16180408	female	34	179.0	71.0	13.0	100.0	40.5
4	17771927	female	27	154.0	58.0	10.0	81.0	39.8

Combining the two Dataframes

In [7]:
```
calories_data = pd.concat([exercise_data, calories['Calories']], axis=1)

# adding an extra 'Calories' column to the exercise_data dataframe, axis = 1 indi
```

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

# last column is calories
```

Out[8]:

	User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories
0	14733363	male	68	190.0	94.0	29.0	105.0	40.8	231.0
1	14861698	female	20	166.0	60.0	14.0	94.0	40.3	66.0
2	11179863	male	69	179.0	79.0	5.0	88.0	38.7	26.0
3	16180408	female	34	179.0	71.0	13.0	100.0	40.5	71.0
4	17771927	female	27	154.0	58.0	10.0	81.0	39.8	35.0

In [9]:
```
# number of rows and columns

calories_data.shape
```

Out[9]:
```
(15000, 9)
```

In [10]:
```
#informations about the data

calories_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   User_ID     15000 non-null  int64  
 1   Gender      15000 non-null  object 
 2   Age         15000 non-null  int64  
 3   Height      15000 non-null  float64
 4   Weight      15000 non-null  float64
 5   Duration    15000 non-null  float64
 6   Heart_Rate  15000 non-null  float64
 7   Body_Temp   15000 non-null  float64
 8   Calories    15000 non-null  float64
dtypes: float64(6), int64(2), object(1)
memory usage: 1.0+ MB
```

In [11]:
```
# checking for missing values

calories_data.isnull().sum()
```

Out[11]:
```
User_ID       0
Gender        0
Age           0
Height        0
Weight        0
Duration      0
Heart_Rate    0
Body_Temp     0
Calories      0
dtype: int64
```

Data Analysis

In [12]:
```
# statistical measures about the data

calories_data.describe()
```

Out[12]:

	User_ID	Age	Height	Weight	Duration	Heart_Rate	Bod
count	1.500000e+04	15000.000000	15000.000000	15000.000000	15000.000000	15000.000000	15000
mean	1.497736e+07	42.789800	174.465133	74.966867	15.530600	95.518533	40
std	2.872851e+06	16.980264	14.258114	15.035657	8.319203	9.583328	0
min	1.000116e+07	20.000000	123.000000	36.000000	1.000000	67.000000	37
25%	1.247419e+07	28.000000	164.000000	63.000000	8.000000	88.000000	39
50%	1.499728e+07	39.000000	175.000000	74.000000	16.000000	96.000000	40
75%	1.744928e+07	56.000000	185.000000	87.000000	23.000000	103.000000	40
max	1.999965e+07	79.000000	222.000000	132.000000	30.000000	128.000000	41

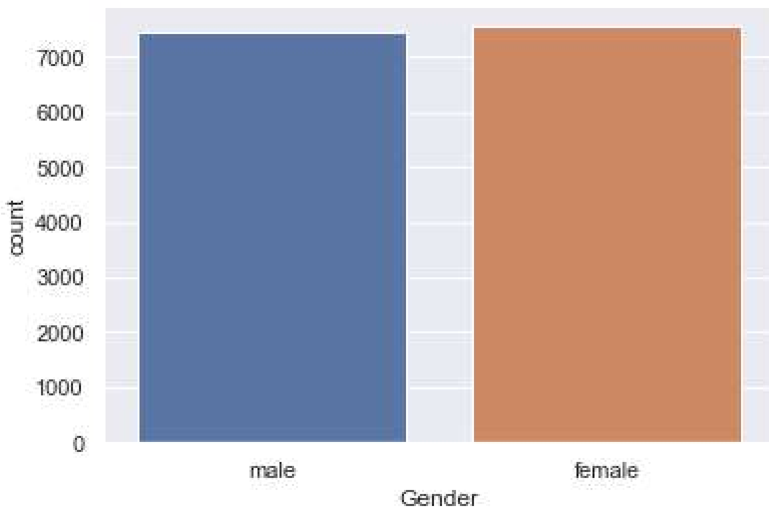
Data Visualization

In [13]:
```
sns.set()
```

In [19]:
```
# plotting the gender column in count plot
sns.countplot(calories_data['Gender'])
# Almost equal, female count exceeds male by a little bit
```

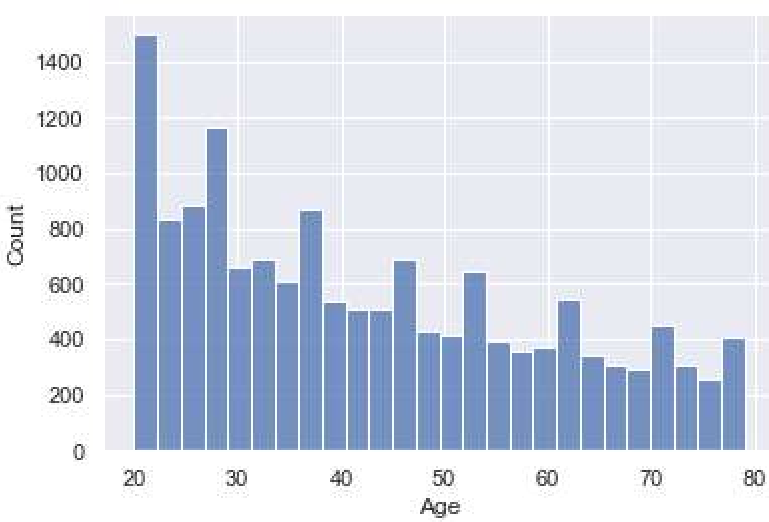
```
C:\Anaconda3\lib\site-packages\seaborn\_decorators.py:43: FutureWarning: Pass t
he following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explic
it keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[19]: <AxesSubplot:xlabel='Gender', ylabel='count'>



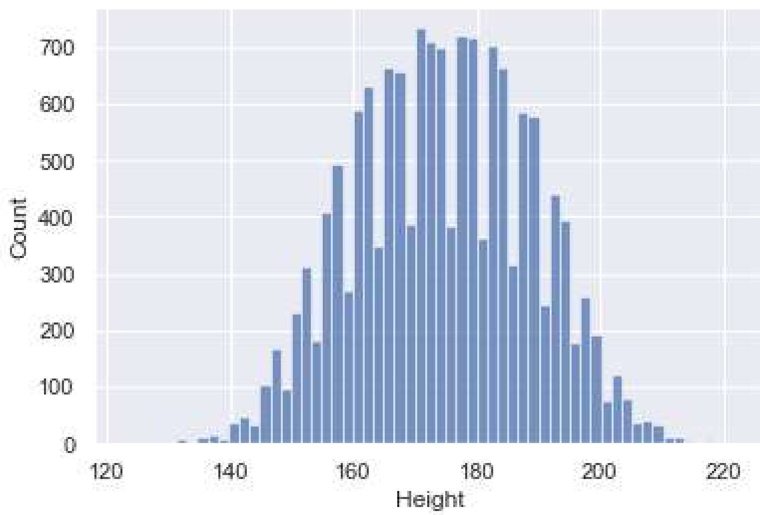
In [23]:
```
# finding the distribution of "Age" column
sns.histplot(calories_data['Age'])

# graph has right skewness, right tail heavier than left.
```

Out[23]: <AxesSubplot:xlabel='Age', ylabel='Count'>



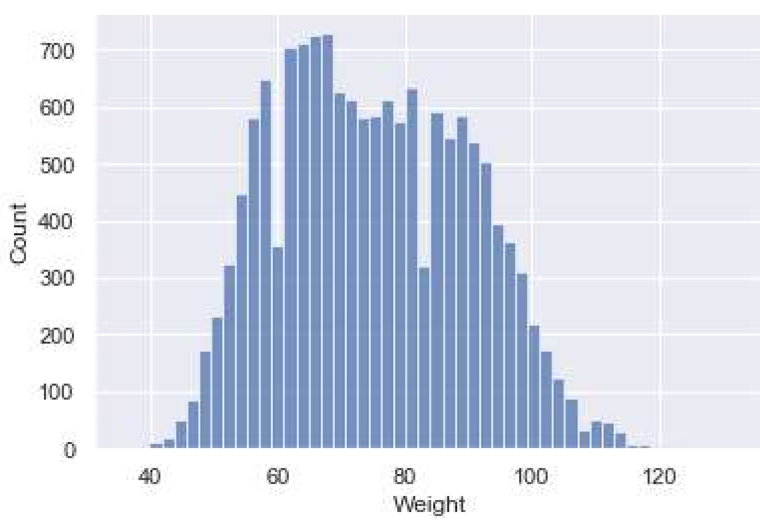
In [24]:
```
# finding the distribution of "Height" column
sns.histplot(calories_data['Height'])

# normal distribution
```

Out[24]: <AxesSubplot:xlabel='Height', ylabel='Count'>



In [25]:
```
# finding the distribution of "Weight" column
sns.histplot(calories_data['Weight'])
```

Out[25]: <AxesSubplot:xlabel='Weight', ylabel='Count'>



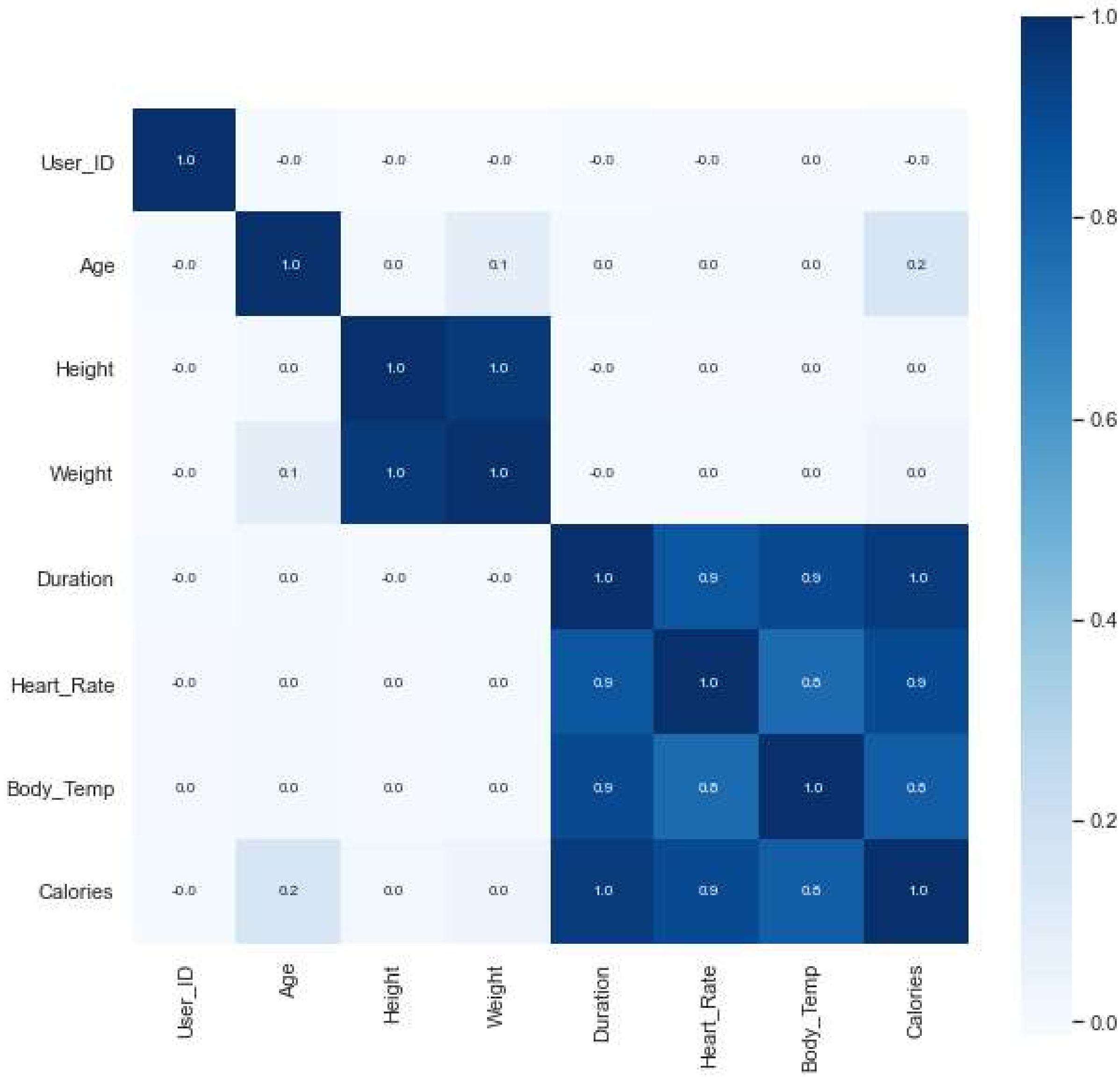
Finding the Correlation in the dataset

1. Positive Correlation
2. Negative Correlation

In [26]:
```
correlation = calories_data.corr()
```

In [27]:
```
# constructing a heatmap to understand the correlation

plt.figure(figsize=(10,10))
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f', annot=True, annot_kws

# Duration, heart_rate, body_temp, calories have the max correlation amoung them
```

Out[27]: <AxesSubplot:>



Converting the text data to numerical values

In [28]:
```
calories_data.replace({"Gender":{'male':0,'female':1}}, inplace=True)

# changing the values of gender as Male -> 0, Female -> 1 for simplicity.
```

In [29]:
```
calories_data.head()

# all values are numerical
```

Out[29]:

	User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories
0	14733363	0	68	190.0	94.0	29.0	105.0	40.8	231.0
1	14861698	1	20	166.0	60.0	14.0	94.0	40.3	66.0
2	11179863	0	69	179.0	79.0	5.0	88.0	38.7	26.0
3	16180408	1	34	179.0	71.0	13.0	100.0	40.5	71.0
4	17771927	1	27	154.0	58.0	10.0	81.0	39.8	35.0

Separating features and Target

In [30]:
```
X = calories_data.drop(columns=['User_ID','Calories'], axis=1)
Y = calories_data['Calories']
```

In [31]:
```
print(X)
```

```
       Gender  Age  Height  Weight  Duration  Heart_Rate  Body_Temp
0           0   68   190.0    94.0      29.0       105.0       40.8
1           1   20   166.0    60.0      14.0        94.0       40.3
2           0   69   179.0    79.0       5.0        88.0       38.7
3           1   34   179.0    71.0      13.0       100.0       40.5
4           1   27   154.0    58.0      10.0        81.0       39.8
...       ...  ...     ...     ...       ...         ...        ...
14995       1   20   193.0    86.0      11.0        92.0       40.4
14996       1   27   165.0    65.0       6.0        85.0       39.2
14997       1   43   159.0    58.0      16.0        90.0       40.1
14998       0   78   193.0    97.0       2.0        84.0       38.3
14999       0   63   173.0    79.0      18.0        92.0       40.5

[15000 rows x 7 columns]
```

In [32]:
```
print(Y)
```

```
0        231.0
1         66.0
2         26.0
3         71.0
4         35.0
         ...  
14995     45.0
14996     23.0
14997     75.0
14998     11.0
14999     98.0
Name: Calories, Length: 15000, dtype: float64
```

Splitting the data into training data and Test data

In [33]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_s
```

In [34]:
```
print(X.shape, X_train.shape, X_test.shape)
```

```
(15000, 7) (12000, 7) (3000, 7)
```

Model Training

XGBoost Regressor

In [35]:
```
# loading the model
model = XGBRegressor()
```

In [36]:
```
# training the model with X_train
model.fit(X_train, Y_train)
```

```
[18:26:31] WARNING: src/objective/regression_obj.cu:152: reg:linear is now depr
ecated in favor of reg:squarederror.
```

Out[36]:
```
XGBRegressor()
```

Evaluation

Prediction on Test Data

In [37]:
```
test_data_prediction = model.predict(X_test)
```

In [38]:
```
print(Y_test)
```

```
7592     127.0
3551     224.0
9698      38.0
3759       6.0
2353     137.0
         ...
8859     177.0
2886      49.0
14357    145.0
9430      24.0
11870     90.0
Name: Calories, Length: 3000, dtype: float64
```

In [39]:
```
print(test_data_prediction)
```

```
[129.06204  223.79721   39.181965 ... 145.59767   22.53474   92.29064 ]
```

Mean Absolute Error

In [40]:
```
mae = metrics.mean_absolute_error(Y_test, test_data_prediction)
```

In [43]:
```
print("Mean Absolute Error = ", mae)
```

```
Mean Absolute Error =  2.7159012502233186
```

In [44]:
```
# R squared Error
error_score = metrics.r2_score(Y_test, test_data_prediction)
print("R squared Error : ", error_score)
```

```
R squared Error :  0.9963065655529431
```

In [45]:
```
plt.scatter(Y_test, test_data_prediction)

# A linear plot amoung Y_test and model
```

Out[45]: <matplotlib.collections.PathCollection at 0x28b5e00d470>