

fitbit-analysis-part1-1

February 2, 2024

1 FITBIT DATA ANALYSIS PROJECT (DIPEN PRADHAN & ROSHANI SINGH)

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import altair as alt
```

```
[2]: ! pip install altair
```

```
Requirement already satisfied: altair in c:\users\avili\anaconda3\lib\site-
packages (5.2.0)
Requirement already satisfied: jinja2 in c:\users\avili\anaconda3\lib\site-
packages (from altair) (3.1.2)
Requirement already satisfied: jsonschema>=3.0 in
c:\users\avili\anaconda3\lib\site-packages (from altair) (4.17.3)
Requirement already satisfied: numpy in c:\users\avili\anaconda3\lib\site-
packages (from altair) (1.24.3)
Requirement already satisfied: packaging in c:\users\avili\anaconda3\lib\site-
packages (from altair) (23.1)
Requirement already satisfied: pandas>=0.25 in
c:\users\avili\anaconda3\lib\site-packages (from altair) (2.0.3)
Requirement already satisfied: toolz in c:\users\avili\anaconda3\lib\site-
packages (from altair) (0.12.0)
Requirement already satisfied: attrs>=17.4.0 in
c:\users\avili\anaconda3\lib\site-packages (from jsonschema>=3.0->altair)
(22.1.0)
Requirement already satisfied: pyparsing!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in
c:\users\avili\anaconda3\lib\site-packages (from jsonschema>=3.0->altair)
(0.18.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\avili\anaconda3\lib\site-packages (from pandas>=0.25->altair) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
c:\users\avili\anaconda3\lib\site-packages (from pandas>=0.25->altair)
(2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in
```

c:\users\avili\anaconda3\lib\site-packages (from pandas>=0.25->altair) (2023.3)
Requirement already satisfied: MarkupSafe>=2.0 in
c:\users\avili\anaconda3\lib\site-packages (from jinja2->altair) (2.1.1)
Requirement already satisfied: six>=1.5 in c:\users\avili\anaconda3\lib\site-
packages (from python-dateutil>=2.8.2->pandas>=0.25->altair) (1.16.0)

```
[3]: dailyActivity = pd.read_csv("C:\\Users\\avili\\Downloads\\dailyActivity_merged.
    ↪csv")
dailycalories = pd.read_csv("C:\\Users\\avili\\Downloads\\dailyCalories_merged.
    ↪csv")
dailyIntensities = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\dailyIntensities_merged.csv")
dailySteps = pd.read_csv("C:\\Users\\avili\\Downloads\\dailySteps_merged.csv")
heartrate_seconds = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\heartrate_seconds_merged (1).csv")
hourlyCalories = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\hourlyCalories_merged.csv")
hourlyIntensities = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\hourlyIntensities_merged.csv")
hourlySteps = pd.read_csv("C:\\Users\\avili\\Downloads\\hourlySteps_merged.csv")
minuteCaloriesNarrow = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteCaloriesNarrow_merged (2).csv")
minuteCaloriesWide = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteCaloriesWide_merged.csv")
minuteIntensitiesNarrow = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteIntensitiesNarrow_merged.csv")
minuteIntensitiesWide = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteIntensitiesWide_merged.csv")
minuteMETsNarrow = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteMETsNarrow_merged.csv")
minuteSleep = pd.read_csv("C:\\Users\\avili\\Downloads\\minuteSleep_merged.csv")
minuteStepsNarrow = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteStepsNarrow_merged.csv")
minuteStepsWide = pd.read_csv("C:
    ↪\\Users\\avili\\Downloads\\minuteStepsWide_merged.csv")
sleepDay = pd.read_csv("C:\\Users\\avili\\Downloads\\sleepDay_merged (1).csv")
weightLogInfo = pd.read_csv("C:\\Users\\avili\\Downloads\\weightLogInfo_merged_
    ↪(1).csv")
```

```
[4]: sleepDay.head()
```

```
[4]:
```

	Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	\
0	1503960366	4/12/2016 12:00:00 AM	1	327	
1	1503960366	4/13/2016 12:00:00 AM	2	384	
2	1503960366	4/15/2016 12:00:00 AM	1	412	
3	1503960366	4/16/2016 12:00:00 AM	2	340	

4 1503960366 4/17/2016 12:00:00 AM 1 700

```
TotalTimeInBed
0          346
1          407
2          442
3          367
4          712
```

```
[5]: sleepDay['Id'].unique()
```

```
[5]: array([1503960366, 1644430081, 1844505072, 1927972279, 2026352035,
          2320127002, 2347167796, 3977333714, 4020332650, 4319703577,
          4388161847, 4445114986, 4558609924, 4702921684, 5553957443,
          5577150313, 6117666160, 6775888955, 6962181067, 7007744171,
          7086361926, 8053475328, 8378563200, 8792009665], dtype=int64)
```

```
[6]: weightLogInfo.head(30)
```

```
[6]:
```

	Id	Date	WeightKg	WeightPounds	Fat	\
0	1503960366	5/2/2016 11:59:59 PM	52.599998	115.963147	22.0	
1	1503960366	5/3/2016 11:59:59 PM	52.599998	115.963147	NaN	
2	1927972279	4/13/2016 1:08:52 AM	133.500000	294.317120	NaN	
3	2873212765	4/21/2016 11:59:59 PM	56.700001	125.002104	NaN	
4	2873212765	5/12/2016 11:59:59 PM	57.299999	126.324875	NaN	
5	4319703577	4/17/2016 11:59:59 PM	72.400002	159.614681	25.0	
6	4319703577	5/4/2016 11:59:59 PM	72.300003	159.394222	NaN	
7	4558609924	4/18/2016 11:59:59 PM	69.699997	153.662190	NaN	
8	4558609924	4/25/2016 11:59:59 PM	70.300003	154.984977	NaN	
9	4558609924	5/1/2016 11:59:59 PM	69.900002	154.103125	NaN	
10	4558609924	5/2/2016 11:59:59 PM	69.199997	152.559879	NaN	
11	4558609924	5/9/2016 11:59:59 PM	69.099998	152.339420	NaN	
12	5577150313	4/17/2016 9:17:55 AM	90.699997	199.959265	NaN	
13	6962181067	4/12/2016 11:59:59 PM	62.500000	137.788914	NaN	
14	6962181067	4/13/2016 11:59:59 PM	62.099998	136.907061	NaN	
15	6962181067	4/14/2016 11:59:59 PM	61.700001	136.025217	NaN	
16	6962181067	4/15/2016 11:59:59 PM	61.500000	135.584291	NaN	
17	6962181067	4/16/2016 11:59:59 PM	62.000000	136.686603	NaN	
18	6962181067	4/17/2016 11:59:59 PM	61.400002	135.363832	NaN	
19	6962181067	4/18/2016 11:59:59 PM	61.200001	134.922906	NaN	
20	6962181067	4/19/2016 11:59:59 PM	61.400002	135.363832	NaN	
21	6962181067	4/20/2016 11:59:59 PM	61.700001	136.025217	NaN	
22	6962181067	4/21/2016 11:59:59 PM	61.400002	135.363832	NaN	
23	6962181067	4/22/2016 11:59:59 PM	61.400002	135.363832	NaN	
24	6962181067	4/23/2016 11:59:59 PM	61.500000	135.584291	NaN	
25	6962181067	4/24/2016 11:59:59 PM	61.500000	135.584291	NaN	
26	6962181067	4/25/2016 11:59:59 PM	61.700001	136.025217	NaN	

27	6962181067	4/27/2016 11:59:59 PM	61.200001	134.922906	NaN
28	6962181067	4/28/2016 11:59:59 PM	61.200001	134.922906	NaN
29	6962181067	4/29/2016 11:59:59 PM	61.400002	135.363832	NaN

	BMI	IsManualReport	LogId
0	22.650000	True	1462233599000
1	22.650000	True	1462319999000
2	47.540001	False	1460509732000
3	21.450001	True	1461283199000
4	21.690001	True	1463097599000
5	27.450001	True	1460937599000
6	27.379999	True	1462406399000
7	27.250000	True	1461023999000
8	27.459999	True	1461628799000
9	27.320000	True	1462147199000
10	27.040001	True	1462233599000
11	27.000000	True	1462838399000
12	28.000000	False	1460884675000
13	24.389999	True	1460505599000
14	24.240000	True	1460591999000
15	24.100000	True	1460678399000
16	24.000000	True	1460764799000
17	24.209999	True	1460851199000
18	23.959999	True	1460937599000
19	23.889999	True	1461023999000
20	23.959999	True	1461110399000
21	24.100000	True	1461196799000
22	23.959999	True	1461283199000
23	23.959999	True	1461369599000
24	24.000000	True	1461455999000
25	24.000000	True	1461542399000
26	24.100000	True	1461628799000
27	23.889999	True	1461801599000
28	23.889999	True	1461887999000
29	23.959999	True	1461974399000

```
[7]: weightLogInfo.shape
```

```
[7]: (67, 8)
```

```
[8]: weightLogInfo['Id'].value_counts()
```

```
[8]: Id
6962181067    30
8877689391    24
4558609924     5
1503960366     2
```

```
2873212765    2
4319703577    2
1927972279    1
5577150313    1
Name: count, dtype: int64
```

```
[9]: # to find out how many records are manual reporting
weightLogInfo['IsManualReport'].value_counts()
```

```
[9]: IsManualReport
True    41
False   26
Name: count, dtype: int64
```

```
[10]: #Out of 67 records, 41 records were manually reported. It means the fitness
      ↪ tracker is not automatically tracking the weight for all the users.
      #It depends on what kind of Fitness tracker is being used. Weight is a
      ↪ essential metrics for a healthy body,
      #and we can track the weight of the participants using a smart device connected
      ↪ to the user's account.
```

```
[11]: weightLogInfo['Id'].dtype
```

```
[11]: dtype('int64')
```

```
[12]: weightLogInfo['Id'].astype('object')
```

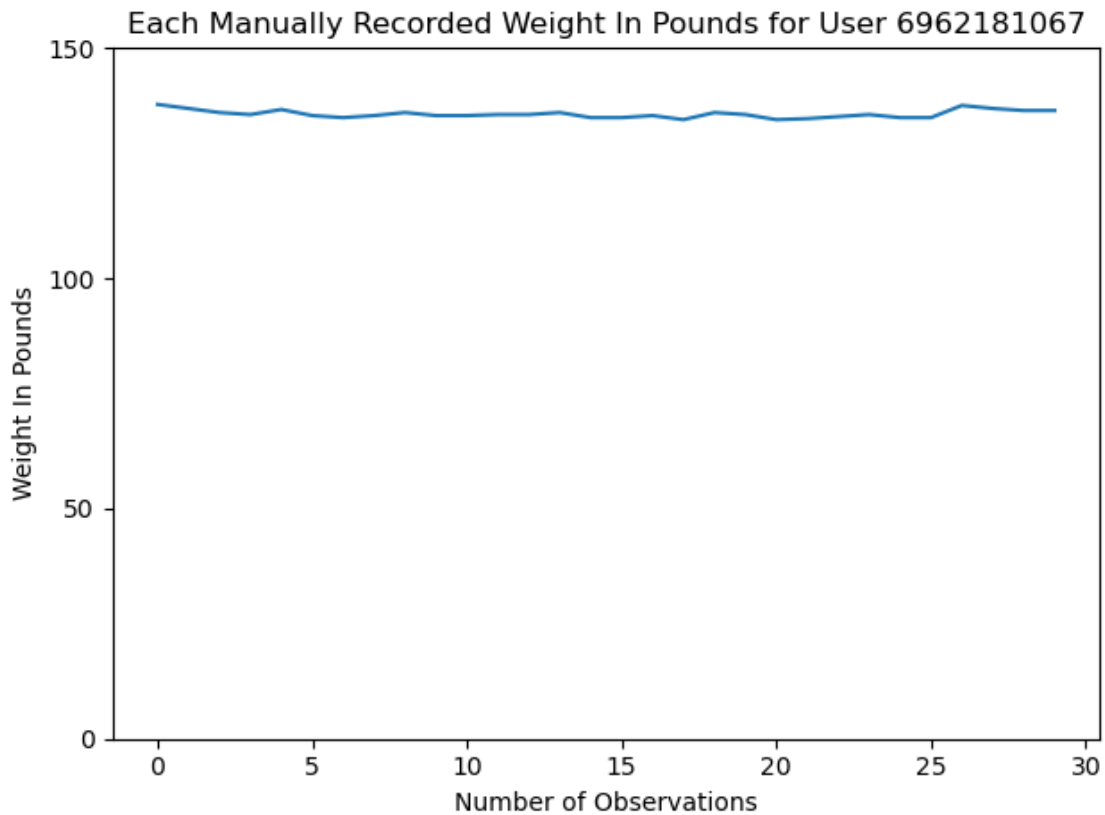
```
[12]: 0    1503960366
      1    1503960366
      2    1927972279
      3    2873212765
      4    2873212765
      ...
      62    8877689391
      63    8877689391
      64    8877689391
      65    8877689391
      66    8877689391
      Name: Id, Length: 67, dtype: object
```

```
[13]: weightLogInfo['Fat'].isnull().sum()
```

```
[13]: 65
```

```
[14]: # let's check the weight records for one particular id who has 30 records to
      ↪ see how the data is.
weightLogInfo1 = weightLogInfo[weightLogInfo['Id']==6962181067].reset_index()
```

```
weightLogInfo1['WeightPounds'].plot(kind='line')
plt.yticks(ticks=range(0,160,50),labels=range(0,160,50))
plt.title('Each Manually Recorded Weight In Pounds for User 6962181067')
plt.xlabel('Number of Observations')
plt.ylabel('Weight In Pounds')
plt.tight_layout()
```



```
[15]: # Finding the average weight of each user from the dataset in ascending order
      ↳ by WeightPounds with their respective average BMI
df1 = weightLogInfo.groupby('Id')[['WeightPounds', 'BMI']].mean().
      ↳ sort_values(by='WeightPounds').reset_index()
df1
```

```
[15]:
```

	Id	WeightPounds	BMI
0	1503960366	115.963147	22.650000
1	2873212765	125.663489	21.570001
2	6962181067	135.701872	24.028000
3	4558609924	153.529918	27.214000
4	4319703577	159.504452	27.415000
5	8877689391	187.714432	25.487083

```
6 5577150313    199.959265  28.000000
7 1927972279    294.317120  47.540001
```

```
[16]: # Calculate the BMI range
#BMI Range to measure Overall Health
# Underweight (Below 18.5)
#Healthy Weight (18.5 - 24.9)#
#Overweight (25.0 - 29.9)
#Obesity (30.0 and Above)
for i in df1.index:
    if (df1.loc[i, 'BMI']>24.9):
        df1.loc[i, 'Overweight'] = 'Yes'
    else:
        df1.loc[i, 'Overweight'] = 'No'
# to check the new column and the data
df1
```

```
[16]:
```

	Id	WeightPounds	BMI	Overweight
0	1503960366	115.963147	22.650000	No
1	2873212765	125.663489	21.570001	No
2	6962181067	135.701872	24.028000	No
3	4558609924	153.529918	27.214000	Yes
4	4319703577	159.504452	27.415000	Yes
5	8877689391	187.714432	25.487083	Yes
6	5577150313	199.959265	28.000000	Yes
7	1927972279	294.317120	47.540001	Yes

```
[17]: # the Id(1927972279) hs the highest weight pound which is overweight it should
↳ be Analysis
```

```
[18]: # Checking the average sleeptime and average total time in bed of the id with
↳ heaviest weight and highest BMI
new_df = sleepDay[sleepDay['Id']==1927972279]
new_df.groupby('Id')[['TotalMinutesAsleep', 'TotalTimeInBed']].mean()
```

```
[18]:
```

	Id	TotalMinutesAsleep	TotalTimeInBed
	1927972279	417.0	437.8

```
[19]: dailyActivity.head()
```

```
[19]:
```

	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	\
0	1503960366	4/12/2016	13162	8.50	8.50	
1	1503960366	4/13/2016	10735	6.97	6.97	
2	1503960366	4/14/2016	10460	6.74	6.74	
3	1503960366	4/15/2016	9762	6.28	6.28	
4	1503960366	4/16/2016	12669	8.16	8.16	

	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	\
0	0.0	1.88	0.55	
1	0.0	1.57	0.69	
2	0.0	2.44	0.40	
3	0.0	2.14	1.26	
4	0.0	2.71	0.41	

	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	\
0	6.06	0.0	25	
1	4.71	0.0	21	
2	3.91	0.0	30	
3	2.83	0.0	29	
4	5.04	0.0	36	

	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	Calories
0	13	328	728	1985
1	19	217	776	1797
2	11	181	1218	1776
3	34	209	726	1745
4	10	221	773	1863

```
[20]: dailycalories.head()
```

```
[20]:
```

	Id	ActivityDay	Calories
0	1503960366	4/12/2016	1985
1	1503960366	4/13/2016	1797
2	1503960366	4/14/2016	1776
3	1503960366	4/15/2016	1745
4	1503960366	4/16/2016	1863

```
[21]: dailyActivity['Id'].value_counts()
```

```
[21]: Id
```

1503960366	31
4319703577	31
8583815059	31
8378563200	31
8053475328	31
7086361926	31
6962181067	31
5553957443	31
4702921684	31
4558609924	31
1624580081	31
4388161847	31
4445114986	31

8877689391	31
1927972279	31
2873212765	31
2320127002	31
4020332650	31
2026352035	31
1844505072	31
2022484408	31
3977333714	30
1644430081	30
5577150313	30
8792009665	29
6290855005	29
6117666160	28
6775888955	26
7007744171	26
3372868164	20
8253242879	19
2347167796	18
4057192912	4

Name: count, dtype: int64

```
[22]: dailycalories['Id'].value_counts()
```

```
[22]: Id
1503960366    31
4319703577    31
8583815059    31
8378563200    31
8053475328    31
7086361926    31
6962181067    31
5553957443    31
4702921684    31
4558609924    31
1624580081    31
4388161847    31
4445114986    31
8877689391    31
1927972279    31
2873212765    31
2320127002    31
4020332650    31
2026352035    31
1844505072    31
2022484408    31
3977333714    30
```

```

1644430081    30
5577150313    30
8792009665    29
6290855005    29
6117666160    28
6775888955    26
7007744171    26
3372868164    20
8253242879    19
2347167796    18
4057192912     4
Name: count, dtype: int64

```

```

[23]: activitycalorymerged = dailyActivity.
      ↪groupby('Id')[['TotalSteps', 'TotalDistance', 'TrackerDistance', 'LoggedActivitiesDistance', 'V
      ↪
      ↪ModeratelyActiveDistance', 'LightActiveDistance', 'SedentaryActiveDistance', 'VeryActiveMinut
      ↪
      ↪FairlyActiveMinutes', 'LightlyActiveMinutes', 'SedentaryMinutes', 'Calories']].
      ↪mean().reset_index()

```

```

[24]: activitycalorymerged

```

```

[24]:
      Id  TotalSteps  TotalDistance  TrackerDistance  \
0  1503960366  12116.741935      7.809677      7.809677
1  1624580081   5743.903226      3.914839      3.914839
2  1644430081   7282.966667      5.295333      5.295333
3  1844505072   2580.064516      1.706129      1.706129
4  1927972279    916.129032      0.634516      0.634516
5  2022484408  11370.645161      8.084193      8.084193
6  2026352035   5566.870968      3.454839      3.454839
7  2320127002   4716.870968      3.187742      3.187742
8  2347167796   9519.666667      6.355556      6.355556
9  2873212765   7555.774194      5.101613      5.101613
10 3372868164   6861.650000      4.707000      4.707000
11 3977333714  10984.566667      7.517000      7.517000
12 4020332650   2267.225806      1.626129      1.626129
13 4057192912   3838.000000      2.862500      2.862500
14 4319703577   7268.838710      4.892258      4.892258
15 4388161847  10813.935484      8.393226      8.393226
16 4445114986   4796.548387      3.245806      3.245806
17 4558609924   7685.129032      5.080645      5.080645
18 4702921684   8572.064516      6.955161      6.955161
19 5553957443   8612.580645      5.639677      5.639677
20 5577150313   8304.433333      6.213333      6.213333
21 6117666160   7046.714286      5.342143      5.342143
22 6290855005   5649.551724      4.272414      4.272414

```

23	6775888955	2519.692308	1.813462	1.813462
24	6962181067	9794.806452	6.585806	6.519355
25	7007744171	11323.423077	8.015385	7.575769
26	7086361926	9371.774194	6.388065	6.388065
27	8053475328	14763.290323	11.475161	11.475161
28	8253242879	6482.157895	4.667368	4.667368
29	8378563200	8717.709677	6.913548	6.913548
30	8583815059	7198.516129	5.615484	5.615484
31	8792009665	1853.724138	1.186552	1.186552
32	8877689391	16040.032258	13.212903	13.212903

	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	\
0	0.000000	2.858387	0.794194	
1	0.000000	0.939355	0.360645	
2	0.000000	0.730000	0.951000	
3	0.000000	0.008387	0.049032	
4	0.000000	0.095806	0.031290	
5	0.000000	2.421613	0.720000	
6	0.000000	0.006129	0.011290	
7	0.000000	0.106774	0.097742	
8	0.000000	1.059444	1.075000	
9	0.000000	0.676129	0.276129	
10	0.000000	0.629500	0.153000	
11	0.000000	1.615000	2.751000	
12	0.000000	0.142258	0.129677	
13	0.000000	0.052500	0.065000	
14	0.000000	0.278065	0.502258	
15	0.000000	1.719355	0.901935	
16	0.000000	0.523226	0.075484	
17	0.000000	0.549355	0.682258	
18	0.000000	0.417419	1.304839	
19	0.000000	1.464194	0.669032	
20	0.000000	3.113667	0.658000	
21	0.000000	0.128214	0.083929	
22	0.000000	0.085517	0.128276	
23	0.075369	0.709231	0.384231	
24	0.323700	1.616452	0.960000	
25	2.118673	2.415000	0.738462	
26	0.000000	2.781290	0.773226	
27	0.000000	8.514839	0.423871	
28	0.000000	2.214210	0.695789	
29	1.116158	2.503548	0.519032	
30	0.000000	0.798065	1.020645	
31	0.000000	0.024828	0.058276	
32	0.000000	6.637419	0.337742	

LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	\
---------------------	-------------------------	-------------------	---

0	4.152903	0.000000	38.709677
1	2.606774	0.006129	8.677419
2	3.609000	0.004000	9.566667
3	1.647419	0.000000	0.129032
4	0.507097	0.000000	1.322581
5	4.942581	0.000000	36.290323
6	3.436129	0.000000	0.096774
7	2.980323	0.000000	1.354839
8	4.221667	0.000000	13.500000
9	4.143548	0.005161	14.096774
10	3.910000	0.011000	9.150000
11	3.134333	0.000000	18.900000
12	1.308387	0.005484	5.193548
13	2.687500	0.000000	0.750000
14	3.768710	0.000000	3.580645
15	5.396129	0.000000	23.161290
16	2.644839	0.000000	6.612903
17	3.847742	0.000000	10.387097
18	5.225484	0.000000	5.129032
19	3.504516	0.000000	23.419355
20	2.428000	0.000000	87.333333
21	4.843214	0.000000	1.571429
22	4.048621	0.008621	2.758621
23	0.711538	0.000000	11.000000
24	4.001613	0.006774	22.806452
25	4.861538	0.000769	31.038462
26	2.818710	0.000000	42.580645
27	2.533871	0.000000	85.161290
28	1.754737	0.000526	20.526316
29	3.889355	0.000000	58.677419
30	2.617419	0.000000	9.677419
31	1.103448	0.000000	0.965517
32	6.188710	0.005161	66.064516

	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	Calories
0	19.161290	219.935484	848.161290	1816.419355
1	5.806452	153.483871	1257.741935	1483.354839
2	21.366667	178.466667	1161.866667	2811.300000
3	1.290323	115.451613	1206.612903	1573.483871
4	0.774194	38.580645	1317.419355	2172.806452
5	19.354839	257.451613	1112.580645	2509.967742
6	0.258065	256.645161	689.419355	1540.645161
7	2.580645	198.193548	1220.096774	1724.161290
8	20.555556	252.500000	687.166667	2043.444444
9	6.129032	308.000000	1097.193548	1916.967742
10	4.100000	327.900000	1077.550000	1933.100000
11	61.266667	174.766667	707.533333	1513.666667

12	5.354839	76.935484	1237.258065	2385.806452
13	1.500000	103.000000	1217.250000	1973.750000
14	12.322581	228.774194	735.806452	2037.677419
15	20.354839	229.354839	836.677419	3093.870968
16	1.741935	209.096774	829.903226	2186.193548
17	13.709677	284.967742	1093.612903	2033.258065
18	26.032258	237.483871	766.419355	2965.548387
19	13.000000	206.193548	668.354839	1875.677419
20	29.833333	147.933333	754.433333	3359.633333
21	2.035714	288.357143	796.285714	2261.142857
22	3.793103	227.448276	1193.034483	2599.620690
23	14.807692	40.153846	1299.423077	2131.769231
24	18.516129	245.806452	662.322581	1982.032258
25	16.269231	280.730769	1055.346154	2544.000000
26	25.354839	143.838710	850.451613	2566.354839
27	9.580645	150.967742	1148.000000	2945.806452
28	14.315789	116.894737	1287.368421	1788.000000
29	10.258065	156.096774	716.129032	3436.580645
30	22.193548	138.290323	1267.225806	2732.032258
31	4.034483	91.793103	1060.482759	1962.310345
32	9.935484	234.709677	1112.870968	3420.258065

```
[25]: dailyIntensities.head()
```

```
[25]:
```

	Id	ActivityDay	SedentaryMinutes	LightlyActiveMinutes	\
0	1503960366	4/12/2016	728	328	
1	1503960366	4/13/2016	776	217	
2	1503960366	4/14/2016	1218	181	
3	1503960366	4/15/2016	726	209	
4	1503960366	4/16/2016	773	221	

	FairlyActiveMinutes	VeryActiveMinutes	SedentaryActiveDistance	\
0	13	25	0.0	
1	19	21	0.0	
2	11	30	0.0	
3	34	29	0.0	
4	10	36	0.0	

	LightActiveDistance	ModeratelyActiveDistance	VeryActiveDistance
0	6.06	0.55	1.88
1	4.71	0.69	1.57
2	3.91	0.40	2.44
3	2.83	1.26	2.14
4	5.04	0.41	2.71

```
[26]: activitycalorymerged.describe()
```

[26]:

	Id	TotalSteps	TotalDistance	TrackerDistance	\
count	3.300000e+01	33.000000	33.000000	33.000000	
mean	4.857201e+09	7519.272678	5.398953	5.383618	
std	2.433765e+09	3576.340125	2.772293	2.759479	
min	1.503960e+09	916.129032	0.634516	0.634516	
25%	2.347168e+09	5566.870968	3.454839	3.454839	
50%	4.445115e+09	7282.966667	5.295333	5.295333	
75%	6.962181e+09	9519.666667	6.913548	6.913548	
max	8.877689e+09	16040.032258	13.212903	13.212903	

	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	\
count	33.000000	33.000000	33.000000	
mean	0.110118	1.449551	0.557039	
std	0.412496	1.866091	0.537638	
min	0.000000	0.006129	0.011290	
25%	0.000000	0.142258	0.128276	
50%	0.000000	0.730000	0.502258	
75%	0.000000	2.214210	0.773226	
max	2.118673	8.514839	2.751000	

	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	\
count	33.000000	33.000000	33.000000	
mean	3.317450	0.001625	20.308769	
std	1.375683	0.003020	23.803214	
min	0.507097	0.000000	0.096774	
25%	2.606774	0.000000	3.580645	
50%	3.504516	0.000000	10.387097	
75%	4.143548	0.000769	23.419355	
max	6.188710	0.011000	87.333333	

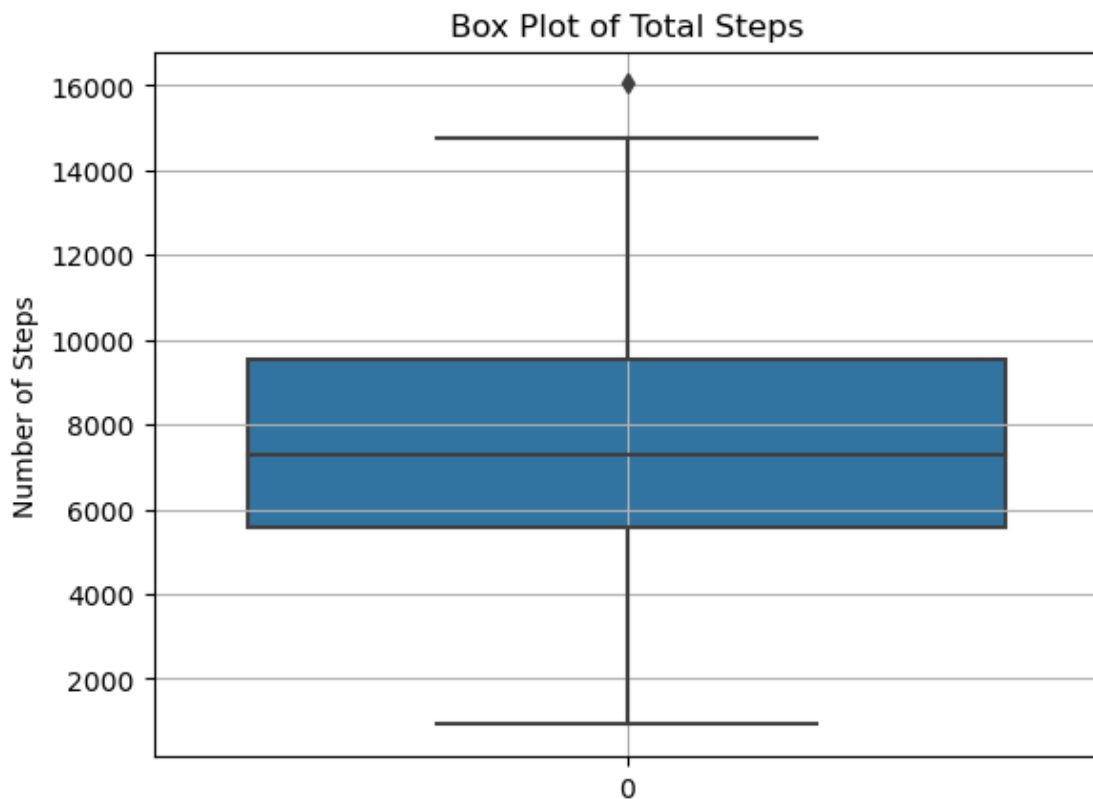
	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	\
count	33.000000	33.000000	33.000000	
mean	13.260240	191.521291	999.151475	
std	12.108217	75.689747	227.678526	
min	0.258065	38.580645	662.322581	
25%	4.034483	143.838710	766.419355	
50%	12.322581	206.193548	1077.550000	
75%	19.354839	245.806452	1206.612903	
max	61.266667	327.900000	1317.419355	

	Calories
count	33.000000
mean	2282.443660
std	562.761632
min	1483.354839
25%	1916.967742
50%	2131.769231

75% 2599.620690
max 3436.580645

```
[27]: #The average number of daily total steps of the participants are 7,519, which  
      ↪ is less  
      # the CDC recommended 8,000 steps. The maximum number of Total Steps is  
      ↪ 16040, is very unusual and may be outlier data.  
      #We can remove or replace outlier data to clean the data for better analysis
```

```
[28]: sns.boxplot(data=activitycalorymerged['TotalSteps'])  
      plt.grid(True)  
      plt.ylabel('Number of Steps')  
      plt.title('Box Plot of Total Steps')  
      plt.show()
```



```
[29]: q3 = activitycalorymerged['TotalSteps'].quantile(0.75)  
      q1 = activitycalorymerged['TotalSteps'].quantile(0.25)  
      # now, i will calculate the inter quartile range  
      iqr = q3-q1  
      # now i will calculate the max value of the data, anything away from the max is  
      ↪ considered outliers value
```

```
outliers = q3 + (1.5* iqr)
```

```
[30]: len(activitycalorymerged[activitycalorymerged['TotalSteps']>outliers])
```

```
[30]: 1
```

```
[31]: len(activitycalorymerged['TotalSteps'])
```

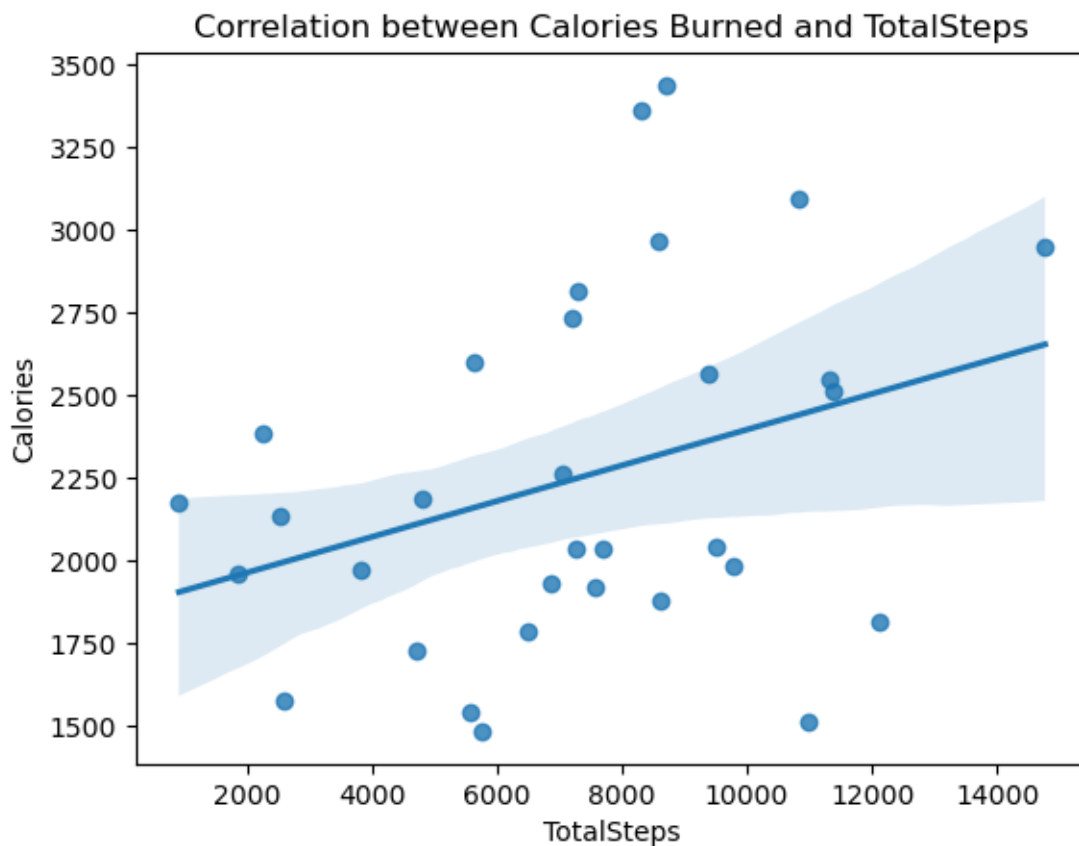
```
[31]: 33
```

```
[32]: activitycalorymerged.  
      ↪drop(activitycalorymerged[activitycalorymerged['TotalSteps']>outliers].  
      ↪index,inplace=True)
```

```
[33]: len(activitycalorymerged['TotalSteps'])
```

```
[33]: 32
```

```
[34]: sns.regplot(data=activitycalorymerged,y='Calories',x='TotalSteps')  
      plt.title('Correlation between Calories Burned and TotalSteps')  
      plt.show()
```




```
[35]: #The scatterplot shows us there is a direct proportional relationship between
      ↪Calories burned and Total daily steps.
      #The more number of daily steps led to more calories burned.
```

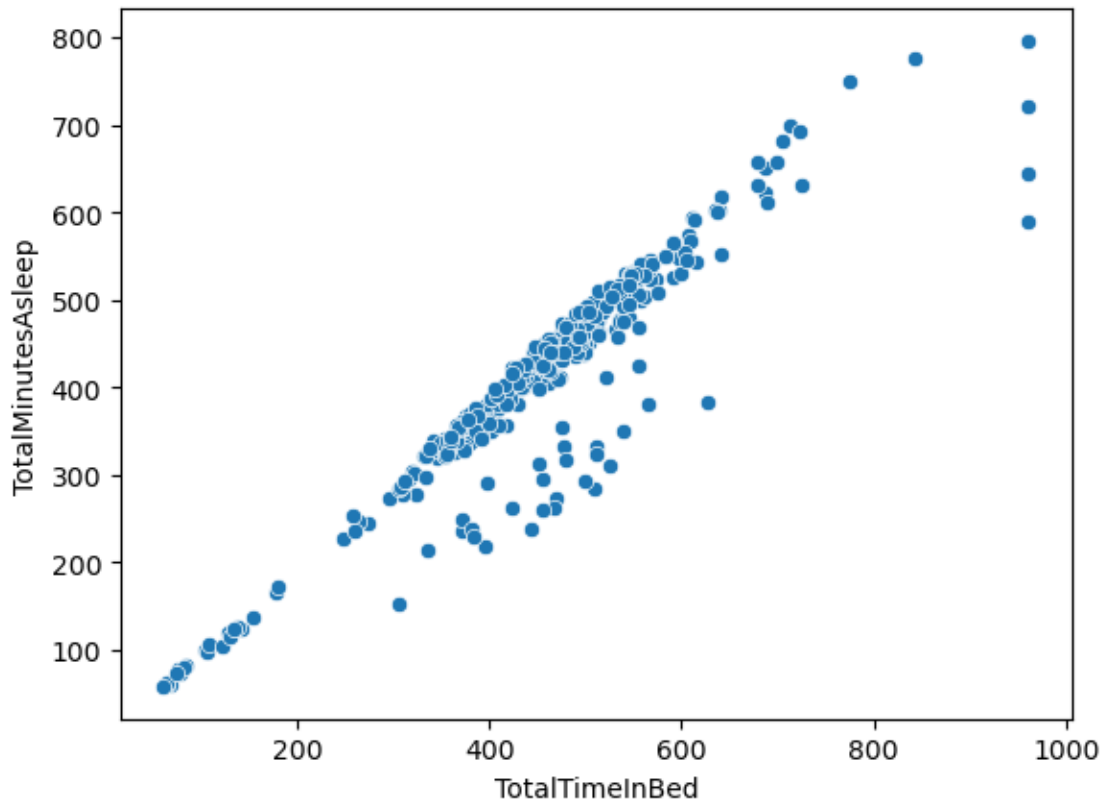
```
[36]: #Checking statistical Analysis for sleepday dataset
      sleepDay.describe()
```

```
[36]:
```

	Id	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed
count	4.130000e+02	413.000000	413.000000	413.000000
mean	5.000979e+09	1.118644	419.467312	458.639225
std	2.060360e+09	0.345521	118.344679	127.101607
min	1.503960e+09	1.000000	58.000000	61.000000
25%	3.977334e+09	1.000000	361.000000	403.000000
50%	4.702922e+09	1.000000	433.000000	463.000000
75%	6.962181e+09	1.000000	490.000000	526.000000
max	8.792010e+09	3.000000	796.000000	961.000000

```
[37]: sns.scatterplot(data=sleepDay, x="TotalTimeInBed", y="TotalMinutesAsleep")
      plt
```

```
[37]: <module 'matplotlib.pyplot' from 'C:\\Users\\avili\\anaconda3\\Lib\\site-
      packages\\matplotlib\\pyplot.py'>
```



```
[38]: df_sleeptime = sleepDay.groupby('Id')[['TotalMinutesAsleep', 'TotalTimeInBed']].
      ↪mean().sort_values(by='TotalMinutesAsleep').reset_index()
df_sleeptime.head()
```

```
[38]:
```

	Id	TotalMinutesAsleep	TotalTimeInBed
0	2320127002	61.000000	69.000000
1	7007744171	68.500000	71.500000
2	4558609924	127.600000	140.000000
3	3977333714	293.642857	461.142857
4	1644430081	294.000000	346.000000

```
[39]: # Create a new column Overweight to find if a user is Overweight or not.
for i in df_sleeptime.index:
    if (df_sleeptime.loc[i, 'TotalMinutesAsleep'] < 480):
        df_sleeptime.loc[i, 'lack_of_sleep'] = 'Yes'
    else:
        df_sleeptime.loc[i, 'lack_of_sleep'] = 'No'
df_sleeptime.head()
```

```
[39]:
```

	Id	TotalMinutesAsleep	TotalTimeInBed	lack_of_sleep
0	2320127002	61.000000	69.000000	Yes

1	7007744171	68.500000	71.500000	Yes
2	4558609924	127.600000	140.000000	Yes
3	3977333714	293.642857	461.142857	Yes
4	1644430081	294.000000	346.000000	Yes

```
[40]: df_sleeptime['lack_of_sleep'].value_counts()
```

```
[40]: lack_of_sleep
Yes    22
No      2
Name: count, dtype: int64
```

```
[41]: df_sleep_weightmerge = df1.merge(df_sleeptime,on='Id',how="left")
df_sleep_weightmerge
```

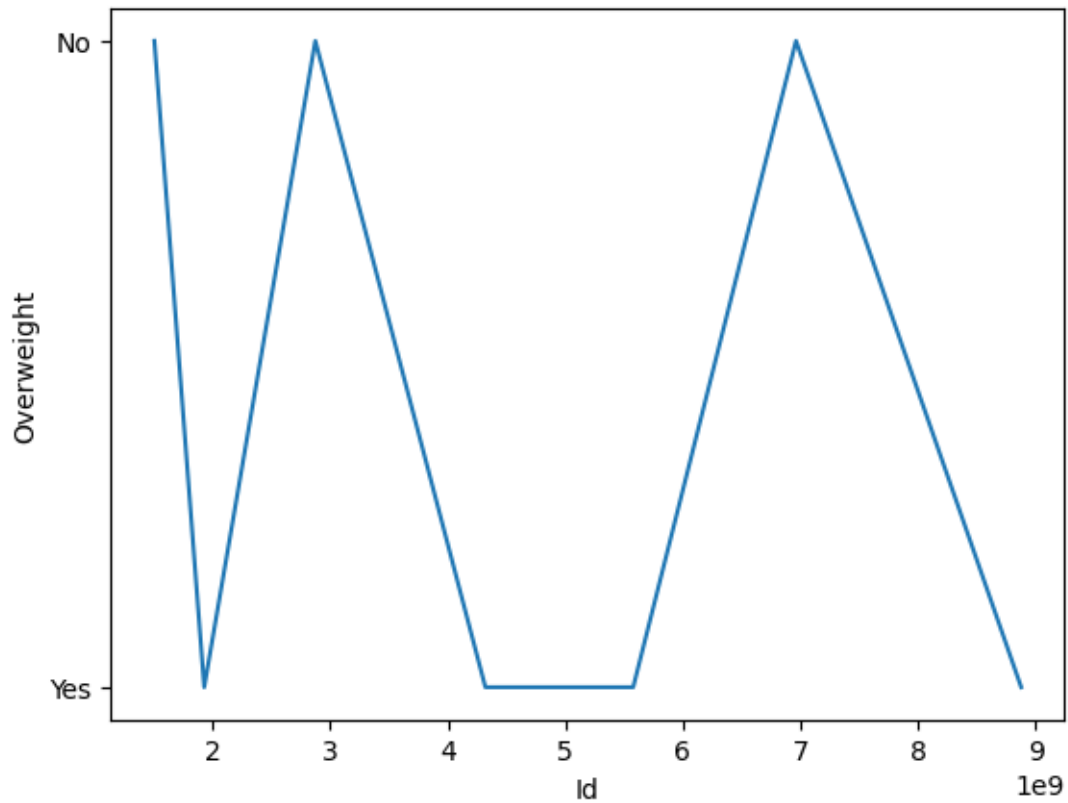
```
[41]:
```

	Id	WeightPounds	BMI	Overweight	TotalMinutesAsleep \
0	1503960366	115.963147	22.650000	No	360.280000
1	2873212765	125.663489	21.570001	No	NaN
2	6962181067	135.701872	24.028000	No	448.000000
3	4558609924	153.529918	27.214000	Yes	127.600000
4	4319703577	159.504452	27.415000	Yes	476.653846
5	8877689391	187.714432	25.487083	Yes	NaN
6	5577150313	199.959265	28.000000	Yes	432.000000
7	1927972279	294.317120	47.540001	Yes	417.000000

	TotalTimeInBed	lack_of_sleep
0	383.200000	Yes
1	NaN	NaN
2	466.129032	Yes
3	140.000000	Yes
4	501.961538	Yes
5	NaN	NaN
6	460.615385	Yes
7	437.800000	Yes

```
[42]: sns.lineplot(data=df_sleep_weightmerge, x="Id", y="Overweight")
```

```
[42]: <Axes: xlabel='Id', ylabel='Overweight'>
```



```
[43]: # Join the grouped id_sleep_weightmerge dataframe and activitycalorymerged
      ↪ dataframe
df_sleepweight_calories = df_sleep_weightmerge.
      ↪ merge(activitycalorymerged,on='Id',how="left")
df_sleepweight_calories
```

```
[43]:
```

	Id	WeightPounds	BMI	Overweight	TotalMinutesAsleep	\
0	1503960366	115.963147	22.650000	No	360.280000	
1	2873212765	125.663489	21.570001	No	NaN	
2	6962181067	135.701872	24.028000	No	448.000000	
3	4558609924	153.529918	27.214000	Yes	127.600000	
4	4319703577	159.504452	27.415000	Yes	476.653846	
5	8877689391	187.714432	25.487083	Yes	NaN	
6	5577150313	199.959265	28.000000	Yes	432.000000	
7	1927972279	294.317120	47.540001	Yes	417.000000	

	TotalTimeInBed	lack_of_sleep	TotalSteps	TotalDistance	TrackerDistance	\
0	383.200000	Yes	12116.741935	7.809677	7.809677	
1	NaN	NaN	7555.774194	5.101613	5.101613	
2	466.129032	Yes	9794.806452	6.585806	6.519355	
3	140.000000	Yes	7685.129032	5.080645	5.080645	

4	501.961538	Yes	7268.838710	4.892258	4.892258
5	NaN	NaN	NaN	NaN	NaN
6	460.615385	Yes	8304.433333	6.213333	6.213333
7	437.800000	Yes	916.129032	0.634516	0.634516

	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	\
0	0.0000	2.858387	0.794194	
1	0.0000	0.676129	0.276129	
2	0.3237	1.616452	0.960000	
3	0.0000	0.549355	0.682258	
4	0.0000	0.278065	0.502258	
5	NaN	NaN	NaN	
6	0.0000	3.113667	0.658000	
7	0.0000	0.095806	0.031290	

	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	\
0	4.152903	0.000000	38.709677	
1	4.143548	0.005161	14.096774	
2	4.001613	0.006774	22.806452	
3	3.847742	0.000000	10.387097	
4	3.768710	0.000000	3.580645	
5	NaN	NaN	NaN	
6	2.428000	0.000000	87.333333	
7	0.507097	0.000000	1.322581	

	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	Calories
0	19.161290	219.935484	848.161290	1816.419355
1	6.129032	308.000000	1097.193548	1916.967742
2	18.516129	245.806452	662.322581	1982.032258
3	13.709677	284.967742	1093.612903	2033.258065
4	12.322581	228.774194	735.806452	2037.677419
5	NaN	NaN	NaN	NaN
6	29.833333	147.933333	754.433333	3359.633333
7	0.774194	38.580645	1317.419355	2172.806452

```
[44]: df_sleepweight_calories.describe()
```

```
[44]:
```

	Id	WeightPounds	BMI	TotalMinutesAsleep	\
count	8.000000e+00	8.000000	8.000000	6.000000	
mean	4.575060e+09	171.544212	27.988011	376.922308	
std	2.524611e+09	57.433835	8.236066	128.122419	
min	1.503960e+09	115.963147	21.570001	127.600000	
25%	2.636903e+09	133.192276	23.683500	374.460000	
50%	4.439157e+09	156.517185	26.350542	424.500000	
75%	5.923408e+09	190.775641	27.561250	444.000000	
max	8.877689e+09	294.317120	47.540001	476.653846	

	TotalTimeInBed	TotalSteps	TotalDistance	TrackerDistance \
count	6.000000	7.000000	7.000000	7.000000
mean	398.284326	7663.121813	5.188264	5.178771
std	132.466485	3427.328178	2.262706	2.255995
min	140.000000	916.129032	0.634516	0.634516
25%	396.850000	7412.306452	4.986452	4.986452
50%	449.207692	7685.129032	5.101613	5.101613
75%	464.750620	9049.619892	6.399570	6.366344
max	501.961538	12116.741935	7.809677	7.809677

	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance \
count	7.000000	7.000000	7.000000
mean	0.046243	1.312551	0.557733
std	0.122347	1.242586	0.316968
min	0.000000	0.095806	0.031290
25%	0.000000	0.413710	0.389194
50%	0.000000	0.676129	0.658000
75%	0.000000	2.237419	0.738226
max	0.323700	3.113667	0.960000

	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes \
count	7.000000	7.000000	7.000000
mean	3.264230	0.001705	25.462366
std	1.354174	0.002949	30.079176
min	0.507097	0.000000	1.322581
25%	3.098355	0.000000	6.983871
50%	3.847742	0.000000	14.096774
75%	4.072581	0.002581	30.758065
max	4.152903	0.006774	87.333333

	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes \
count	7.000000	7.000000	7.000000
mean	14.349462	210.571121	929.849923
std	9.457325	91.462225	242.108800
min	0.774194	38.580645	662.322581
25%	9.225806	183.934409	745.119892
50%	13.709677	228.774194	848.161290
75%	18.838710	265.387097	1095.403226
max	29.833333	308.000000	1317.419355

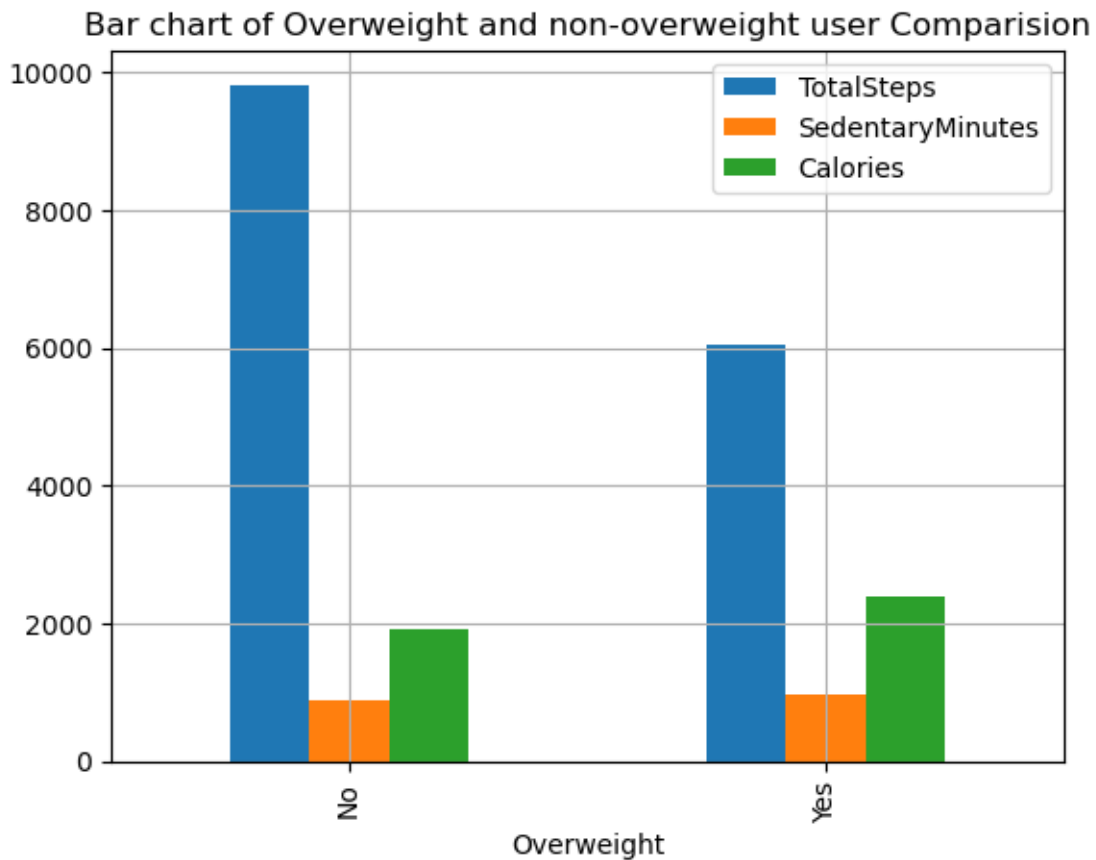
	Calories
count	7.000000
mean	2188.399232
std	528.117681
min	1816.419355
25%	1949.500000
50%	2033.258065

```
75%    2105.241935
max     3359.633333
```

```
[45]: # let's group the joined dataframe data into by overweight yes or no to show
      ↪ TotalSteps, SedentaryMinutes and Calories.
df_overweight_group = df_sleepweight_calories.
      ↪ groupby('Overweight')[['TotalSteps', 'SedentaryMinutes', 'Calories']].mean()
```

```
[46]: plt.figure(figsize=(10,10))
df_overweight_group.plot(kind='bar',grid=True)
plt.title('Bar chart of Overweight and non-overweight user Comparision')
plt.show()
```

<Figure size 1000x1000 with 0 Axes>



```
[47]: #Bar chart shows us that the Overweight user's take less steps which means less
      ↪ movement,
      #more sedentary time, and more weight gain. Although the calories burned for
      ↪ overweight is more than non-overweight users,
```

#a overweight person needs to burn more calories than other people depending on ↵
↪ their present body weight.