Data Exploration and Cleaning

In [1]:
```
import pandas
```

Daily Activity

In [2]:
```
daily_activity = pandas.read_csv("dailyActivity_merged.csv")
```

In [3]:
```
daily_activity.head()
```

Out[3]:

	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDi
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	

In [4]:
```
daily_activity.dtypes
```

Out[4]:
```
Id                            int64
ActivityDate                 object
TotalSteps                    int64
TotalDistance               float64
TrackerDistance             float64
LoggedActivitiesDistance    float64
VeryActiveDistance          float64
ModeratelyActiveDistance    float64
LightActiveDistance         float64
SedentaryActiveDistance     float64
VeryActiveMinutes             int64
FairlyActiveMinutes           int64
LightlyActiveMinutes          int64
SedentaryMinutes              int64
Calories                      int64
dtype: object
```

In [5]:
```
daily_activity["ActivityDate"] = pandas.to_datetime(daily_activity["ActivityDate"],
```

In [6]:
```
daily_activity.dtypes
```

Out[6]:
```
Id                                    int64
ActivityDate                 datetime64[ns]
TotalSteps                            int64
TotalDistance                       float64
TrackerDistance                     float64
LoggedActivitiesDistance            float64
VeryActiveDistance                  float64
ModeratelyActiveDistance            float64
LightActiveDistance                 float64
SedentaryActiveDistance             float64
VeryActiveMinutes                     int64
FairlyActiveMinutes                   int64
LightlyActiveMinutes                  int64
SedentaryMinutes                      int64
Calories                              int64
dtype: object
```

In [7]:
```
daily_activity.shape
```

Out[7]:
```
(940, 15)
```

In [8]:
```
len(daily_activity["Id"].unique())
```

Out[8]:
```
33
```

In [9]:
```
daily_activity["Id"].value_counts()
```

```
Out[9]: 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: Id, dtype: int64
```

In [10]:
```
daily_activity.isna().values.any()
```

Out[10]: False

In [11]:
```
daily_activity.duplicated().any()
```

Out[11]: False

In [12]:
```
daily_activity = daily_activity.loc[:, ("Id", "ActivityDate", "TotalSteps", "Sedent
```

In [13]:
```
daily_activity_steps = daily_activity.loc[:, ("Id", "ActivityDate", "TotalSteps")]
daily_activity_steps["ActivityDate"] = daily_activity_steps["ActivityDate"].dt.date
```

Checking the Consistency of Data on Calories

In [14]:
```
daily_activity_calories = daily_activity.copy().loc[:, ("Id", "ActivityDate", "Calo
daily_activity_calories["ActivityDate"] = daily_activity_calories["ActivityDate"].d
```

In [15]:
```
daily_calories = pandas.read_csv("dailyCalories_merged.csv")
```

In [16]:
```
daily_calories["ActivityDay"] = pandas.to_datetime(daily_calories["ActivityDay"], f
```

In [17]:
```
daily_calories["ActivityDay"] = daily_calories["ActivityDay"].dt.date
daily_calories = daily_calories.rename(columns={"Calories": "DailyCalories"})
```

In [18]:
```
hourly_calories = pandas.read_csv("hourlyCalories_merged.csv")
```

In [19]:
```
hourly_calories["ActivityHour"] = pandas.to_datetime(hourly_calories["ActivityHour"
```

In [20]:
```
hourly_calories_added = hourly_calories.copy()
hourly_calories_added["ActivityHour"] = hourly_calories_added["ActivityHour"].dt.da
```

In [21]:
```
hourly_calories_added = hourly_calories_added.groupby(["Id", "ActivityHour"]).sum()
```

In [22]:
```
minute_calories_narrow = pandas.read_csv("minuteCaloriesNarrow_merged.csv")
```

In [23]:
```
minute_calories_narrow["ActivityMinute"] = pandas.to_datetime(minute_calories_narro
```

In [24]:
```
minute_calories_added = minute_calories_narrow.copy()
minute_calories_added["ActivityMinute"] = minute_calories_added["ActivityMinute"].d
```

In [25]:
```
minute_calories_added = minute_calories_added.groupby(["Id", "ActivityMinute"]).sum
```

In [26]:
```
calorie_consistency_test = pandas.merge(daily_activity_calories, daily_calories, le
calorie_consistency_test = pandas.merge(calorie_consistency_test, hourly_calories_a
calorie_consistency_test = pandas.merge(calorie_consistency_test, minute_calories_a
calorie_consistency_test.head()
```

Out[26]:

	Id	ActivityDate	Calories	ActivityDay	DailyCalories	ActivityHour	HourlyCalo
0	1503960366	2016-04-12	1985	2016-04-12	1985	2016-04-12	
1	1503960366	2016-04-13	1797	2016-04-13	1797	2016-04-13	
2	1503960366	2016-04-14	1776	2016-04-14	1776	2016-04-14	
3	1503960366	2016-04-15	1745	2016-04-15	1745	2016-04-15	
4	1503960366	2016-04-16	1863	2016-04-16	1863	2016-04-16	

In [27]:
```
calorie_consistency_test[(calorie_consistency_test["Calories"] == calorie_consisten
                                    (calorie_consistency_test["Calories"] == (calor
```

Out[27]:

	Id	ActivityDate	Calories	ActivityDay	DailyCalories	ActivityHour	HourlyCal
3	1503960366	2016-04-15	1745	2016-04-15	1745	2016-04-15	
15	1503960366	2016-04-27	2159	2016-04-27	2159	2016-04-27	
36	1624580081	2016-04-18	1604	2016-04-18	1604	2016-04-18	
44	1624580081	2016-04-26	1402	2016-04-26	1402	2016-04-26	
50	1624580081	2016-05-02	1497	2016-05-02	1497	2016-05-02	

In [28]:
```
calorie_consistency_test[calorie_consistency_test["Calories"] != calorie_consistenc
```

Out[28]:

	Id	ActivityDate	Calories	ActivityDay	DailyCalories	ActivityHour	HourlyCalo
0	1503960366	2016-04-12	1985	2016-04-12	1985	2016-04-12	
1	1503960366	2016-04-13	1797	2016-04-13	1797	2016-04-13	
4	1503960366	2016-04-16	1863	2016-04-16	1863	2016-04-16	
5	1503960366	2016-04-17	1728	2016-04-17	1728	2016-04-17	
6	1503960366	2016-04-18	1921	2016-04-18	1921	2016-04-18	

In [29]:
```
calorie_consistency_test['MergedToDailyPercentDifference'] = calorie_consistency_te
    lambda row: (abs(row['Calories'] - row['DailyCalories']) / row['DailyCalories']
```

In [30]:
```
calorie_consistency_test['MergedtoHourlyPercentDifference'] = calorie_consistency_t
    lambda row: (abs(row['Calories'] - row['HourlyCaloriesAdded']) / row['HourlyCal
```

In [31]:
```
calorie_consistency_test['MergedtoMinutePercentDifference'] = calorie_consistency_t
    lambda row: (abs(row['Calories'] - row['MinuteCaloriesAdded']) / row['MinuteCal
```

In [32]:
```
calorie_consistency_test.loc[:, ("MergedToDailyPercentDifference", "MergedtoHourlyP
```

Out[32]:

	MergedToDailyPercentDifference	MergedtoHourlyPercentDifference	MergedtoMinute
count	934.0	934.000000	
mean	0.0	0.966506	
std	0.0	6.224956	
min	0.0	0.000000	
25%	0.0	0.040469	
50%	0.0	0.087356	
75%	0.0	0.192725	
max	0.0	107.188161	

In [33]:
```
print(f'Mismatch: {calorie_consistency_test[calorie_consistency_test["MergedtoHourl
print(f'Total: {calorie_consistency_test["Id"].count()}')
```

```
Mismatch: 802
Total: 934
```

765 out of 894 observations contain a mismatch between daily calories, and daily calories calculated from hourly or minute calories. Possible reasons for such discrepancy are rounding error and mistakes during data entry.

In [34]:
```
calorie_consistency_test_droped_high_errors = calorie_consistency_test[(calorie_con
calorie_consistency_test_droped_high_errors.loc[:, ("MergedToDailyPercentDifference
```

Out[34]:

	MergedToDailyPercentDifference	MergedtoHourlyPercentDifference	MergedtoMinute
count	905.0	905.000000	
mean	0.0	0.186183	
std	0.0	0.448649	
min	0.0	0.000000	
25%	0.0	0.039730	
50%	0.0	0.079156	
75%	0.0	0.172513	
max	0.0	4.532677	

In [35]:
```
daily_activity = daily_activity[daily_activity.index.isin(calorie_consistency_test_
```

In [36]:
```
daily_activity.shape
```

Out[36]:
```
(905, 5)
```

Observations with more than 5% difference between daily calories, and calories calculated from hourly or minute calories were removed.

Checking the Consistency of Data on Daily Steps

In [37]:
```
daily_steps = pandas.read_csv("dailySteps_merged.csv")
```

In [38]:
```
daily_steps["ActivityDay"] = pandas.to_datetime(daily_steps["ActivityDay"], format
```

In [39]:
```
daily_steps["ActivityDay"] = daily_steps["ActivityDay"].dt.date
daily_steps = daily_steps.rename(columns={"StepTotal":"DailySteps"})
```

In [40]:
```
hourly_steps_added = pandas.read_csv("hourlySteps_merged.csv")
```

In [41]:
```
hourly_steps_added["ActivityHour"] = pandas.to_datetime(hourly_steps_added["Activit
```

In [42]:
```
hourly_steps_added["ActivityHour"] = hourly_steps_added["ActivityHour"].dt.date
```

In [43]:
```
hourly_steps_added = hourly_steps_added.groupby(["Id", "ActivityHour"]).sum().renam
```

In [44]:
```
minute_steps_added = pandas.read_csv("minuteStepsNarrow_merged.csv")
```

In [45]:
```
minute_steps_added["ActivityMinute"] = pandas.to_datetime(minute_steps_added["Activ
```

In [46]:
```
minute_steps_added["ActivityMinute"] = minute_steps_added["ActivityMinute"].dt.date
```

In [47]:
```
minute_steps_added = minute_steps_added.groupby(["Id", "ActivityMinute"]).sum()
minute_steps_added = minute_steps_added.rename(columns={"Steps":"MinuteStepsAdded"}
minute_steps_added
```

Out[47]:

	Id	ActivityMinute	MinuteStepsAdded
0	1503960366	2016-04-12	13158
1	1503960366	2016-04-13	10735
2	1503960366	2016-04-14	10460
3	1503960366	2016-04-15	9685
4	1503960366	2016-04-16	12669
...	...	...	...
929	8877689391	2016-05-08	10665
930	8877689391	2016-05-09	20156
931	8877689391	2016-05-10	10693
932	8877689391	2016-05-11	21391
933	8877689391	2016-05-12	7120

934 rows × 3 columns

In [48]:
```
step_consistency_test = pandas.merge(daily_activity_steps, daily_steps, left_on=["I
step_consistency_test = pandas.merge(step_consistency_test, hourly_steps_added, lef
step_consistency_test = pandas.merge(step_consistency_test, minute_steps_added, lef
step_consistency_test.head()
```

Out[48]:

	Id	ActivityDate	TotalSteps	ActivityDay	DailySteps	ActivityHour	HourlyStep
0	1503960366	2016-04-12	13162	2016-04-12	13162	2016-04-12	
1	1503960366	2016-04-13	10735	2016-04-13	10735	2016-04-13	
2	1503960366	2016-04-14	10460	2016-04-14	10460	2016-04-14	
3	1503960366	2016-04-15	9762	2016-04-15	9762	2016-04-15	
4	1503960366	2016-04-16	12669	2016-04-16	12669	2016-04-16	

In [49]:
```
step_consistency_test[(step_consistency_test["TotalSteps"] == step_consistency_test
                                   (step_consistency_test["TotalSteps"] == (step_c
```

Out[49]:

	Id	ActivityDate	TotalSteps	ActivityDay	DailySteps	ActivityHour	HourlyStep:
1	1503960366	2016-04-13	10735	2016-04-13	10735	2016-04-13	
2	1503960366	2016-04-14	10460	2016-04-14	10460	2016-04-14	
4	1503960366	2016-04-16	12669	2016-04-16	12669	2016-04-16	
5	1503960366	2016-04-17	9705	2016-04-17	9705	2016-04-17	
6	1503960366	2016-04-18	13019	2016-04-18	13019	2016-04-18	

In [50]:
```
step_consistency_test[(step_consistency_test["TotalSteps"] != step_consistency_test
                                    (step_consistency_test["TotalSteps"] != (step_c
```

Out[50]:

	Id	ActivityDate	TotalSteps	ActivityDay	DailySteps	ActivityHour	HourlySte
0	1503960366	2016-04-12	13162	2016-04-12	13162	2016-04-12	
3	1503960366	2016-04-15	9762	2016-04-15	9762	2016-04-15	
15	1503960366	2016-04-27	18134	2016-04-27	18134	2016-04-27	
16	1503960366	2016-04-28	13154	2016-04-28	13154	2016-04-28	
20	1503960366	2016-05-02	14727	2016-05-02	14727	2016-05-02	

In [51]:
```
step_consistency_test[(step_consistency_test["TotalSteps"] > 0) & (step_consistency
```

Out[51]:

	Id	ActivityDate	TotalSteps	ActivityDay	DailySteps	ActivityHour	HourlySt
379	4319703577	2016-04-12	7753	2016-04-12	7753	2016-04-12	
410	4388161847	2016-04-12	10122	2016-04-12	10122	2016-04-12	
849	8583815059	2016-04-16	5319	2016-04-16	5319	2016-04-16	
850	8583815059	2016-04-17	3008	2016-04-17	3008	2016-04-17	
865	8583815059	2016-05-02	8469	2016-05-02	8469	2016-05-02	

Calculating the % difference between daily steps and daily steps calculated from hourly and minute steps. If daily step count was >0, but daily step count calculated from hourly or minute steps was 0,value of 6% was placed for that row as observations with higher than 5% difference will be filtered out for further analysis.

In [52]:
```
step_consistency_test['MergedToDailyPercentDifference'] = step_consistency_test.app
    lambda row: (abs(row['TotalSteps'] - row['DailySteps']) / row['DailySteps']) *
```

In [53]:
```
step_consistency_test['MergedtoHourlyPercentDifference'] = step_consistency_test.ap
    lambda row: (abs(row['TotalSteps'] - row['HourlyStepsAdded']) / row['HourlyStep
```

In [54]:
```
step_consistency_test['MergedtoMinutePercentDifference'] = step_consistency_test.ap
    lambda row: (abs(row['TotalSteps'] - row['MinuteStepsAdded']) / row['MinuteStep
```

In [55]:
```
step_consistency_test.head()
```

Out[55]:

	Id	ActivityDate	TotalSteps	ActivityDay	DailySteps	ActivityHour	HourlyStep
0	1503960366	2016-04-12	13162	2016-04-12	13162	2016-04-12	
1	1503960366	2016-04-13	10735	2016-04-13	10735	2016-04-13	
2	1503960366	2016-04-14	10460	2016-04-14	10460	2016-04-14	
3	1503960366	2016-04-15	9762	2016-04-15	9762	2016-04-15	
4	1503960366	2016-04-16	12669	2016-04-16	12669	2016-04-16	

In [56]:
```
step_consistency_test.loc[:, ("MergedToDailyPercentDifference", "MergedtoHourlyPerc
```

Out[56]:

	MergedToDailyPercentDifference	MergedtoHourlyPercentDifference	MergedtoMinute
count	934.0	934.000000	
mean	0.0	3.176913	
std	0.0	34.616543	
min	0.0	0.000000	
25%	0.0	0.000000	
50%	0.0	0.000000	
75%	0.0	0.000000	
max	0.0	724.618447	

In [57]:
```
print(f'Mismatch: {step_consistency_test[step_consistency_test["MergedtoHourlyPerce
print(f'Total: {step_consistency_test["Id"].count()}')
```

```
Mismatch: 159
Total: 934
```

159 out of 934 observations contain a mismatch between daily steps, and daily steps calculated from hourly or minute steps. Possible reasons for such discrepancy are rounding error and mistakes during data entry.

In [58]:
```
step_consistency_test_droped_high_errors = step_consistency_test[(step_consistency_
```

In [59]:
```
step_consistency_test_droped_high_errors.loc[:, ("MergedToDailyPercentDifference",
```

Out[59]:

	MergedToDailyPercentDifference	MergedtoHourlyPercentDifference	MergedtoMinute
count	900.0	900.000000	
mean	0.0	0.081552	
std	0.0	0.354611	
min	0.0	0.000000	
25%	0.0	0.000000	
50%	0.0	0.000000	
75%	0.0	0.000000	
max	0.0	4.767442	

In [60]:
```
daily_activity = daily_activity[daily_activity.index.isin(step_consistency_test_dro
```

In [61]:
```
len(daily_activity["Id"].unique())
```

Out[61]: 33

In [62]:
```
(daily_activity["Id"].value_counts() >= 28).sum()
```

Out[62]: 23

Observations with more than 5% difference between daily steps, and daily steps calculated from hourly steps were removed.

Hourly Intensities

In [63]:
```
hourly_intensities = pandas.read_csv("hourlyIntensities_merged.csv")
```

In [64]:
```
hourly_intensities.head()
```

Out[64]:

	Id	ActivityHour	TotalIntensity	AverageIntensity
0	1503960366	4/12/2016 12:00:00 AM	20	0.333333
1	1503960366	4/12/2016 1:00:00 AM	8	0.133333
2	1503960366	4/12/2016 2:00:00 AM	7	0.116667
3	1503960366	4/12/2016 3:00:00 AM	0	0.000000
4	1503960366	4/12/2016 4:00:00 AM	0	0.000000

In [65]:
```
hourly_intensities.dtypes
```

Out[65]:
```
Id                      int64
ActivityHour           object
TotalIntensity          int64
AverageIntensity      float64
dtype: object
```

In [66]:
```
hourly_intensities["ActivityHour"] = pandas.to_datetime(hourly_intensities["Activit
```

In [67]:
```
hourly_intensities.dtypes
```

Out[67]:
```
Id                            int64
ActivityHour         datetime64[ns]
TotalIntensity                int64
AverageIntensity            float64
dtype: object
```

In [68]:
```
hourly_intensities.shape
```

Out[68]: (22099, 4)

In [69]:
```
len(hourly_intensities["Id"].unique())
```

Out[69]: 33

In [70]:
```
hourly_intensities.isna().values.any()
```

Out[70]: False

In [71]:
```
hourly_intensities.duplicated().any()
```

Out[71]: False

Minute MET

In [72]:
```
minute_met = pandas.read_csv("minuteMETsNarrow_merged.csv")
```

In [73]:
```
minute_met.head()
```

Out[73]:

	Id	ActivityMinute	METs
0	1503960366	4/12/2016 12:00:00 AM	10
1	1503960366	4/12/2016 12:01:00 AM	10
2	1503960366	4/12/2016 12:02:00 AM	10
3	1503960366	4/12/2016 12:03:00 AM	10
4	1503960366	4/12/2016 12:04:00 AM	10

In [74]:
```
minute_met.dtypes
```

Out[74]:
```
Id                  int64
ActivityMinute     object
METs                int64
dtype: object
```

In [75]:
```
minute_met["ActivityMinute"] = pandas.to_datetime(minute_met["ActivityMinute"], for
```

In [76]:
```
minute_met.dtypes
```

Out[76]:
```
Id                          int64
ActivityMinute     datetime64[ns]
METs                        int64
dtype: object
```

In [77]:
```
minute_met.shape
```

Out[77]: (1325580, 3)

In [78]:
```
len(minute_met["Id"].unique())
```

Out[78]: 33

In [79]:
```
minute_met.isna().values.any()
```

Out[79]: False

In [80]:
```
minute_met.duplicated().any()
```

Out[80]: False

In [81]:
```
minute_met_min = minute_met.copy()
```

In [82]:
```
minute_met_min["ActivityMinute"] = minute_met_min["ActivityMinute"].dt.strftime("%H
```

In [83]:
```
grouped_met_min = minute_met_min.groupby(["ActivityMinute"])["METs"].describe()
```

In [84]:
```
grouped_met_min[grouped_met_min.index.isin(["00:00:00", "02:00:00", "04:00:00", "6:
```

```
The history saving thread hit an unexpected error (OperationalError('database is loc
ked')).History will not be written to the database.
```

Out[84]:

ActivityMinute	count	mean	std	min	25%	50%	75%	max
00:00:00	934.0	11.688437	9.057299	10.0	10.0	10.0	10.0	133.0
02:00:00	933.0	10.534834	3.888483	10.0	10.0	10.0	10.0	80.0
04:00:00	932.0	10.211373	2.178737	10.0	10.0	10.0	10.0	52.0
08:00:00	931.0	15.264232	11.634348	10.0	10.0	10.0	12.0	96.0
10:00:00	929.0	16.525296	13.646067	10.0	10.0	10.0	13.0	138.0
12:00:00	922.0	17.200651	13.476641	10.0	10.0	11.0	24.0	113.0
14:00:00	918.0	18.245098	15.911281	10.0	10.0	11.0	24.0	129.0
16:00:00	907.0	16.471885	12.949641	10.0	10.0	11.0	13.0	129.0
18:00:00	906.0	18.584989	15.690021	10.0	10.0	11.0	24.0	133.0
20:00:00	906.0	16.835541	13.277177	10.0	10.0	11.0	14.0	125.0
22:00:00	904.0	14.613938	12.037606	10.0	10.0	10.0	12.0	140.0

MET is defined as a rate of energy expended during an activity compared to the rate of energy expended during rest. The summary table above shows that during sleep hours (~midnight to 8 am) there is no difference in MET values between the quartiles, which is expected as energy expenditure of sleeping people is virtually the same. An increase in the MET values is seen in the 50th and 75th percentiles in later hours, which is likely due to the physical activity of more active people. Although these observations are consistent with the context, at rest and sleep, MET is usually around 1, not 10, suggesting that there is an error in data, or a different definition/equation for MET was used in this dataset. As metadata for this dataset not available, an assumption was made that MET values in the dataset were multiplied by 10. To correct this for further analysis, MET values were divided by 10.

In [85]:
```
minute_met_h = minute_met.copy()
```

In [86]:
```
minute_met_h["METs"] = minute_met_h["METs"] / 10
```

In [87]:
```
minute_met_h["ActivityMinute"] = minute_met_h["ActivityMinute"].dt.strftime("%Y-%m-
```

In [88]:
```
minute_met_h = minute_met_h.rename(columns={"ActivityMinute":"Date"})
```

In [89]:
```
minute_met_h.dtypes
```

Out[89]:
```
Id         int64
Date      object
METs     float64
dtype: object
```

In [90]:
```
average_daily_met = minute_met_h.groupby(["Id", "Date"]).mean()
```

In [91]:
```
average_daily_met = average_daily_met.reset_index()
```

In [92]:
```
average_daily_met["Date"] = pandas.to_datetime(average_daily_met["Date"])
```

Daily Sleep

In [93]:
```
daily_sleep = pandas.read_csv("sleepDay_merged.csv")
```

In [94]:
```
daily_sleep.head()
```

Out[94]:

	Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed
0	1503960366	4/12/2016 12:00:00 AM	1	327	346
1	1503960366	4/13/2016 12:00:00 AM	2	384	407
2	1503960366	4/15/2016 12:00:00 AM	1	412	442
3	1503960366	4/16/2016 12:00:00 AM	2	340	367
4	1503960366	4/17/2016 12:00:00 AM	1	700	712

In [95]:
```
daily_sleep.dtypes
```

Out[95]:
```
Id                       int64
SleepDay                object
TotalSleepRecords        int64
TotalMinutesAsleep       int64
TotalTimeInBed           int64
dtype: object
```

In [96]:
```
daily_sleep["SleepDay"] = pandas.to_datetime(daily_sleep["SleepDay"], format = "%m/
```

In [97]:
```
daily_sleep.dtypes
```

Out[97]:
```
Id                               int64
SleepDay                datetime64[ns]
TotalSleepRecords                int64
TotalMinutesAsleep               int64
TotalTimeInBed                   int64
dtype: object
```

In [98]:
```
daily_sleep.shape
```

Out[98]:
```
(413, 5)
```

In [99]:
```
len(daily_sleep["Id"].unique())
```

Out[99]: 24

In [100…
```
daily_sleep["Id"].value_counts()
```

Out[100]:
```
8378563200    32
6962181067    31
5553957443    31
4702921684    28
2026352035    28
3977333714    28
4445114986    28
5577150313    26
4319703577    26
1503960366    25
7086361926    24
4388161847    24
6117666160    18
8792009665    15
2347167796    15
4020332650     8
1927972279     5
4558609924     5
1644430081     4
6775888955     3
8053475328     3
1844505072     3
7007744171     2
2320127002     1
Name: Id, dtype: int64
```

In [101…
```
daily_sleep.isna().values.any()
```

Out[101]: False

In [102…
```
daily_sleep.duplicated().any()
```

Out[102]: True

In [103…
```
daily_sleep[daily_sleep.duplicated(keep=False)]
```

Out[103]:

	Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed
160	4388161847	2016-05-05	1	471	495
161	4388161847	2016-05-05	1	471	495
222	4702921684	2016-05-07	1	520	543
223	4702921684	2016-05-07	1	520	543
379	8378563200	2016-04-25	1	388	402
380	8378563200	2016-04-25	1	388	402

In [104…
```
daily_sleep = daily_sleep.drop_duplicates()
```

In [105…
```
daily_sleep.duplicated().any()
```

Out[105]:
```
False
```

Weight Log

In [106…
```
weight_log = pandas.read_csv("weightLogInfo_merged.csv")
```

In [107…
```
weight_log.head()
```

Out[107]:

	Id	Date	WeightKg	WeightPounds	Fat	BMI	IsManualReport	
0	1503960366	5/2/2016 11:59:59 PM	52.599998	115.963147	22.0	22.650000	True	1
1	1503960366	5/3/2016 11:59:59 PM	52.599998	115.963147	NaN	22.650000	True	1
2	1927972279	4/13/2016 1:08:52 AM	133.500000	294.317120	NaN	47.540001	False	1
3	2873212765	4/21/2016 11:59:59 PM	56.700001	125.002104	NaN	21.450001	True	1
4	2873212765	5/12/2016 11:59:59 PM	57.299999	126.324875	NaN	21.690001	True	1

In [108…
```
weight_log.dtypes
```

Out[108]:
```
Id                  int64
Date               object
WeightKg          float64
WeightPounds      float64
Fat               float64
BMI               float64
IsManualReport       bool
LogId               int64
dtype: object
```

In [109…
```
weight_log["Date"] = pandas.to_datetime(weight_log["Date"], format = "%m/%d/%Y %I:%
```

In [110…
```
weight_log.dtypes
```

Out[110]:
```
Id                           int64
Date                datetime64[ns]
WeightKg                   float64
WeightPounds               float64
Fat                        float64
BMI                        float64
IsManualReport                bool
LogId                        int64
dtype: object
```

In [111…
```
weight_log.shape
```

Out[111]:
```
(67, 8)
```

In [112…
```
len(weight_log["Id"].unique())
```

Out[112]:
```
8
```

In [113…
```
weight_log["Id"].value_counts()
```

Out[113]:
```
6962181067    30
8877689391    24
4558609924     5
1503960366     2
2873212765     2
4319703577     2
1927972279     1
5577150313     1
Name: Id, dtype: int64
```

In [114…
```
weight_log.isna().any()
```

Out[114]:
```
Id                  False
Date                False
WeightKg            False
WeightPounds        False
Fat                  True
BMI                 False
IsManualReport      False
LogId               False
dtype: bool
```

In [115…
```
weight_log[weight_log.isna().any(axis=1)].head()
```

Out[115]:

	Id	Date	WeightKg	WeightPounds	Fat	BMI	IsManualReport	
1	1503960366	2016-05-03 23:59:59	52.599998	115.963147	NaN	22.650000	True	146
2	1927972279	2016-04-13 01:08:52	133.500000	294.317120	NaN	47.540001	False	146
3	2873212765	2016-04-21 23:59:59	56.700001	125.002104	NaN	21.450001	True	146
4	2873212765	2016-05-12 23:59:59	57.299999	126.324875	NaN	21.690001	True	146
6	4319703577	2016-05-04 23:59:59	72.300003	159.394222	NaN	27.379999	True	146

In [116…

```
weight_log[~weight_log.isna().any(axis=1)]
```

Out[116]:

	Id	Date	WeightKg	WeightPounds	Fat	BMI	IsManualReport	
0	1503960366	2016-05-02 23:59:59	52.599998	115.963147	22.0	22.650000	True	1462
5	4319703577	2016-04-17 23:59:59	72.400002	159.614681	25.0	27.450001	True	1460

In [117…

```
weight_log.duplicated().any()
```

Out[117]: False

Exploratory Graphs

In [118…

```
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import f_oneway, ttest_ind
```

Daily Activity and Sleep

Merging Tables

In [119…

```
daily_activity_sleep = pandas.merge(daily_sleep, daily_activity, left_on=["Id", "Sl
```

In [120…
```
daily_activity_sleep = pandas.merge(daily_activity_sleep, average_daily_met, left_o
```

In [121…
```
daily_activity_sleep = daily_activity_sleep.drop(["ActivityDate", "Date"], axis=1)
```

In [122…
```
daily_activity_sleep.rename(columns={"SleepDay":"Date"}, inplace=True)
```

In [123…
```
daily_activity_sleep = daily_activity_sleep.loc[:, ("Id", "TotalMinutesAsleep", "To
daily_activity_sleep.describe()
```

Out[123]:

	Id	TotalMinutesAsleep	TotalSteps	SedentaryMinutes	Calories	
count	3.930000e+02	393.000000	393.000000	393.000000	393.000000	39
mean	5.003939e+09	418.694656	8545.432570	716.277354	2387.908397	
std	2.066512e+09	119.736737	4178.541642	163.129712	757.246898	
min	1.503960e+09	58.000000	42.000000	2.000000	403.000000	
25%	3.977334e+09	361.000000	5183.000000	637.000000	1837.000000	
50%	4.702922e+09	432.000000	8954.000000	720.000000	2196.000000	
75%	6.962181e+09	489.000000	11393.000000	787.000000	2908.000000	
max	8.792010e+09	796.000000	22770.000000	1265.000000	4900.000000	

In [124…
```
len(daily_activity_sleep["Id"].unique())
```

Out[124]: 24

In [125…
```
daily_activity_sleep["Id"].value_counts()
```

```
Out[125]: 6962181067    31
5553957443    31
8378563200    29
3977333714    28
4702921684    27
2026352035    27
4445114986    27
5577150313    25
1503960366    24
7086361926    23
4319703577    23
4388161847    22
6117666160    16
8792009665    15
2347167796    14
4020332650     5
1927972279     5
4558609924     5
1644430081     4
6775888955     3
8053475328     3
1844505072     3
7007744171     2
2320127002     1
Name: Id, dtype: int64
```

In [126…

```
(daily_activity_sleep["Id"].value_counts() >= 14).sum()
```

Out[126]: 15

In [127…

```
(daily_activity_sleep["Id"].value_counts() >= 21).sum()
```

Out[127]: 12

In [128…

```
(daily_activity_sleep["Id"].value_counts() >= 28).sum()
```

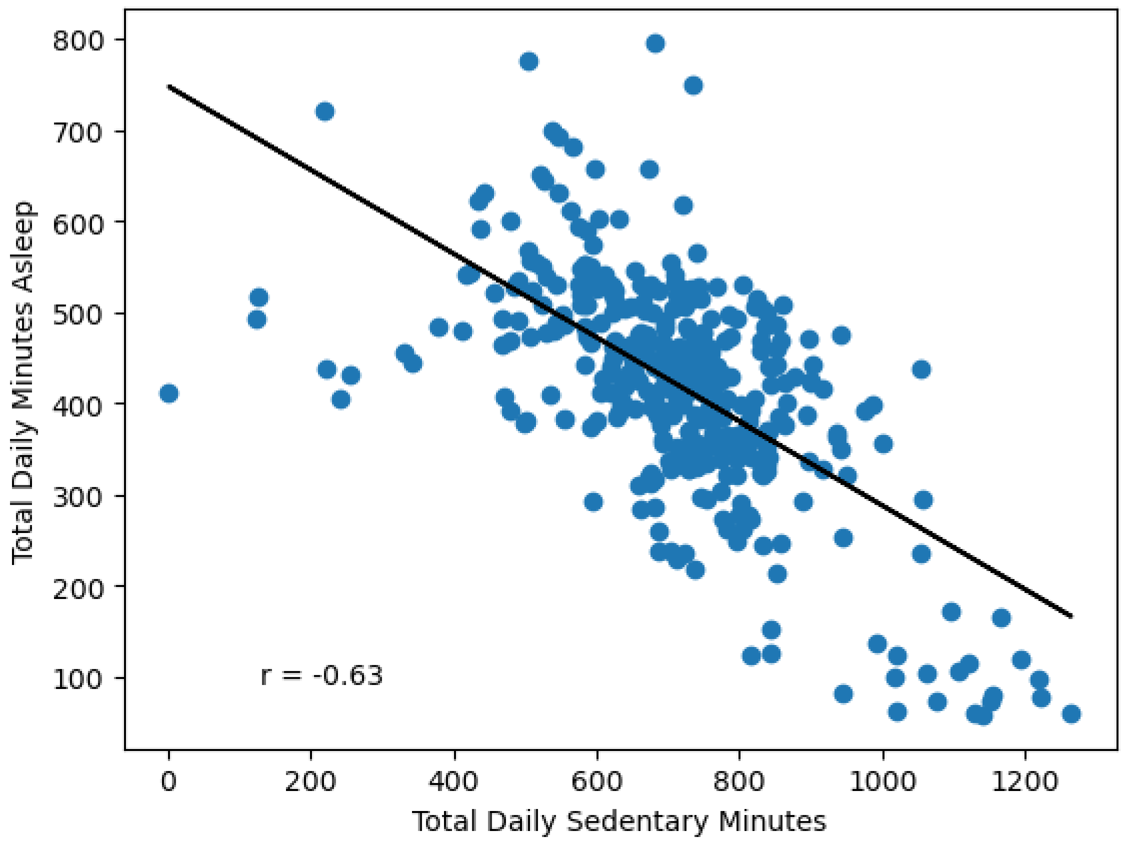
Out[128]: 4

Graphs

In [129…

```
x = daily_activity_sleep["SedentaryMinutes"]
y = daily_activity_sleep["TotalMinutesAsleep"]

plt.scatter(x, y)

coefficients = np.polyfit(x, y, deg=1)
slope = coefficients[0]
intercept = coefficients[1]
regression_line = slope * x + intercept

plt.plot(x, regression_line, color='black')

r_value = np.corrcoef(x, y)[0, 1]
plt.text(0.2, 0.1, f'r = {r_value:.2f}', ha='center', va='center', transform=plt.gc
```

```
plt.xlabel("Total Daily Sedentary Minutes")
plt.ylabel("Total Daily Minutes Asleep")

plt.show()
```



There is a negative correlation between sedentary time and sleep duration, suggesting prolonged sitting negatively affects the duration of sleep.

In [130…

```
daily_activity_sleep.head()
```

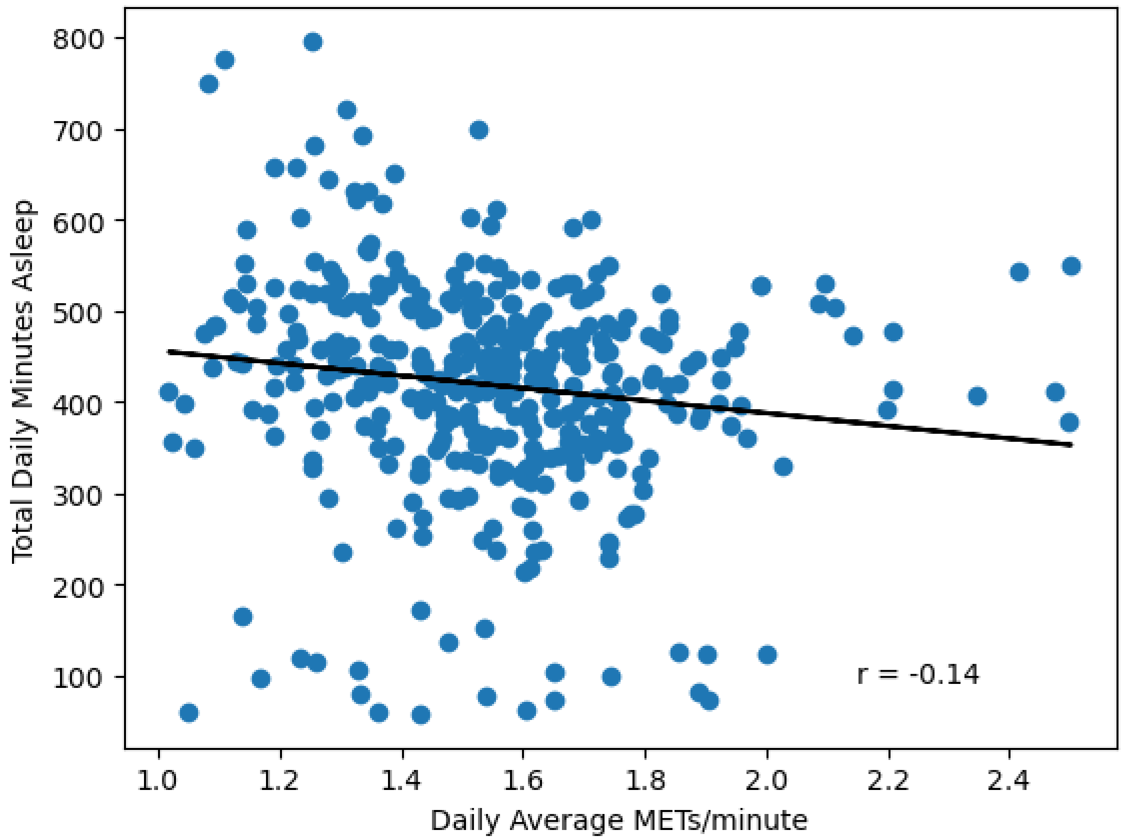
Out[130]:

	Id	TotalMinutesAsleep	TotalSteps	SedentaryMinutes	Calories	METs
0	1503960366	327	13162	728	1985	1.752847
1	1503960366	384	10735	776	1797	1.587431
2	1503960366	412	9762	726	1745	1.540972
3	1503960366	340	12669	773	1863	1.645417
4	1503960366	700	9705	539	1728	1.525833

In [131…

```
x = daily_activity_sleep["METs"]
y = daily_activity_sleep["TotalMinutesAsleep"]

plt.scatter(x, y)

coefficients = np.polyfit(x, y, deg=1)
slope = coefficients[0]
```

```
intercept = coefficients[1]
regression_line = slope * x + intercept

plt.plot(x, regression_line, color='black')

r_value = np.corrcoef(x, y)[0, 1]
plt.text(0.8, 0.1, f'r = {r_value:.2f}', ha='center', va='center', transform=plt.gc

plt.xlabel("Daily Average METs/minute")
plt.ylabel("Total Daily Minutes Asleep")

plt.show()
```



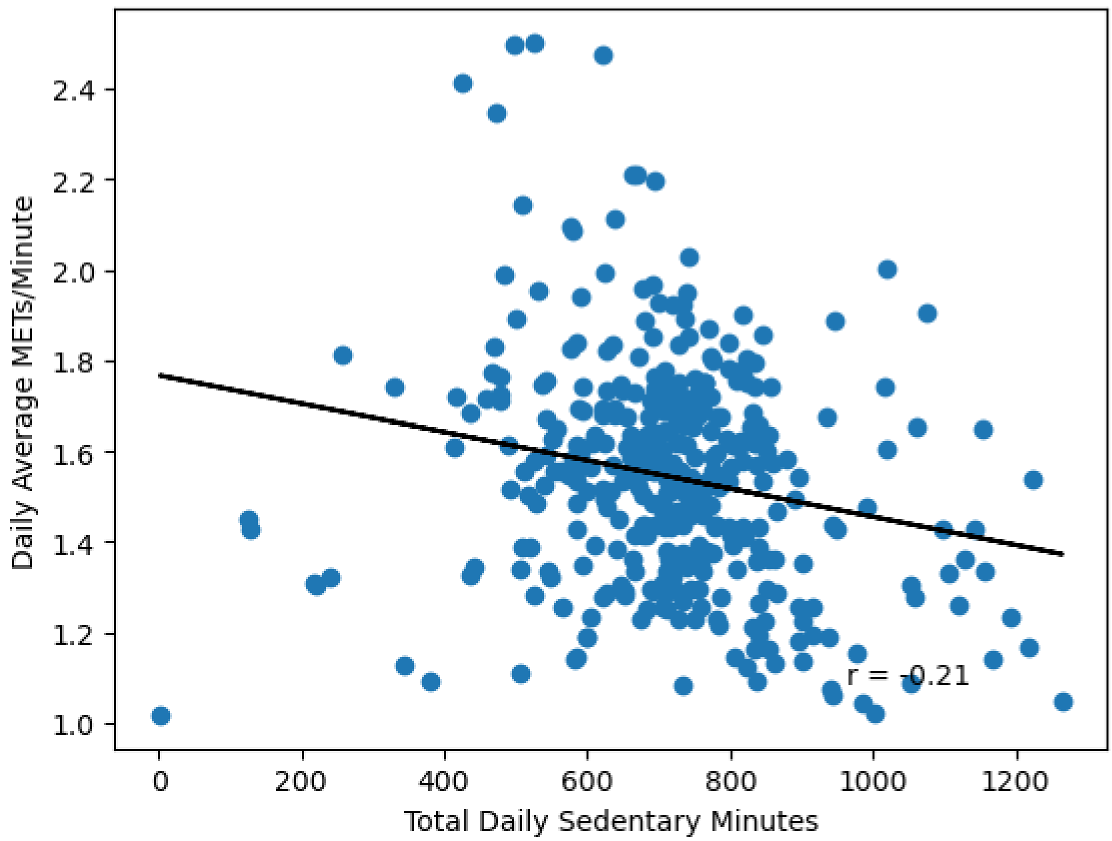
To explore the relationship between physical activity and sleep duration, Metabolic Equivalent Tasks (METs) were used as a physical activity metric. MET is defined as a rate of energy expended during an activity compared to the rate of energy expended during rest. 1 REM is equivalent to a persont resting in a sedentary state, while activities that require MET > 1.5 are generally considered light physical activity (http://dx.doi.org/10.2196/36181).

No obvious relationship is observed between average daily activity expressed in average daily METs and sleep duration. This is in contrast to observations in sedentary time vs sleep duration graph. It is possible that daily sedentary time might not reflect the overall person's physical activity very accurately.

In [132…

```
x = daily_activity_sleep["SedentaryMinutes"]
y = daily_activity_sleep["METs"]
```

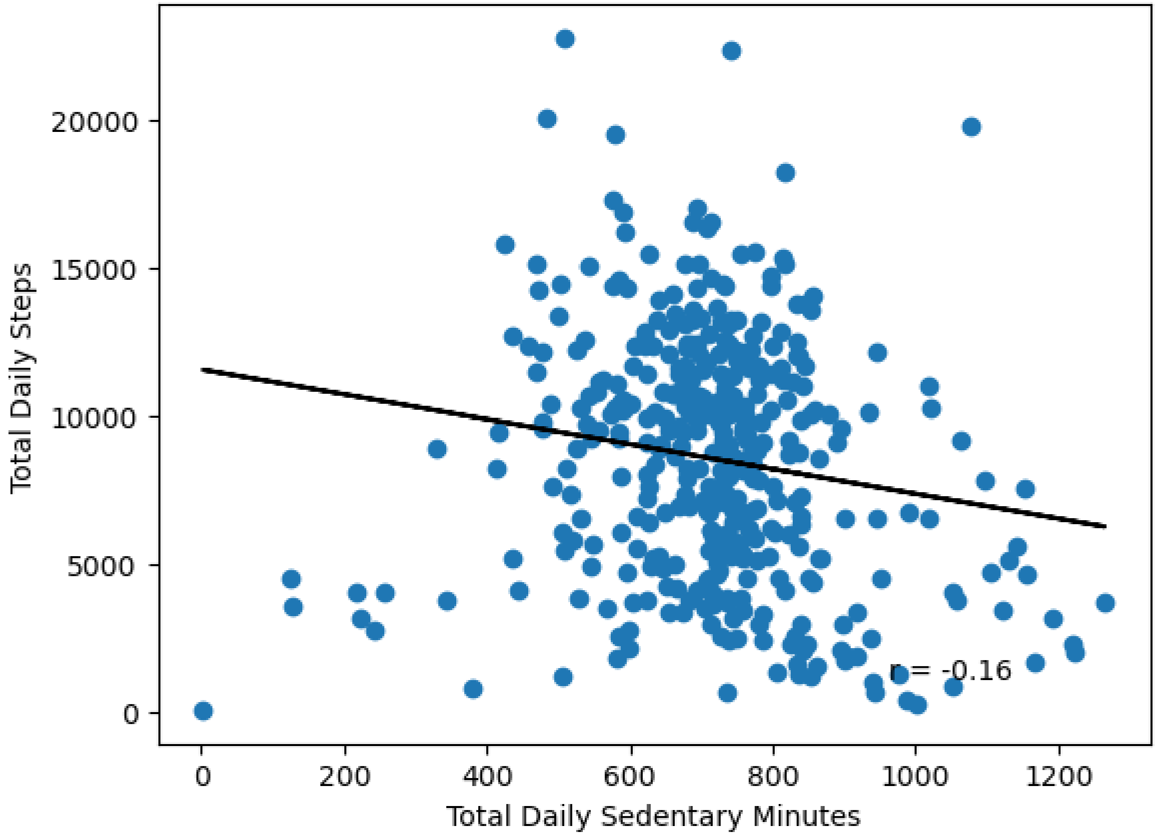
```
plt.scatter(x, y)

coefficients = np.polyfit(x, y, deg=1)
slope = coefficients[0]
intercept = coefficients[1]
regression_line = slope * x + intercept

plt.plot(x, regression_line, color='black')

r_value = np.corrcoef(x, y)[0, 1]
plt.text(0.8, 0.1, f'r = {r_value:.2f}', ha='center', va='center', transform=plt.gc

plt.xlabel("Total Daily Sedentary Minutes")
plt.ylabel("Daily Average METs/Minute")

plt.show()
```



In [133…

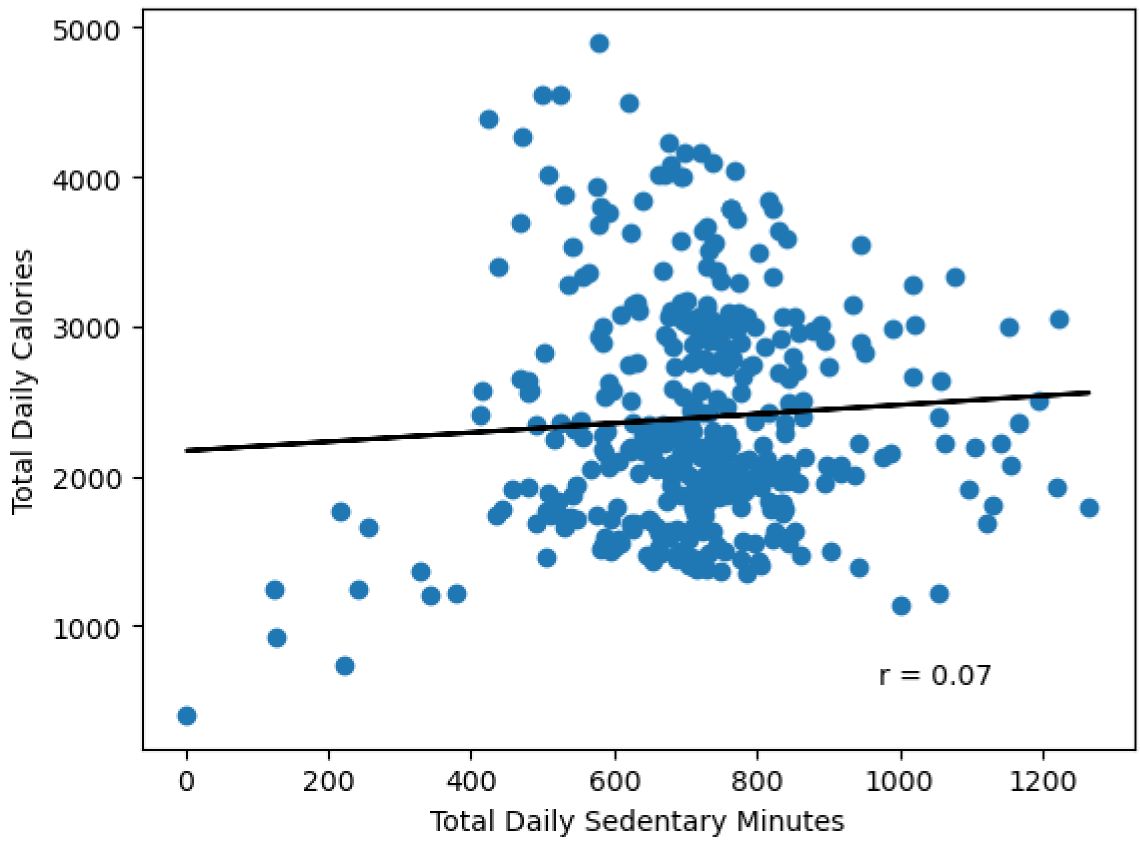
```
x = daily_activity_sleep["SedentaryMinutes"]
y = daily_activity_sleep["TotalSteps"]

plt.scatter(x, y)

coefficients = np.polyfit(x, y, deg=1)
slope = coefficients[0]
intercept = coefficients[1]
regression_line = slope * x + intercept

plt.plot(x, regression_line, color='black')

r_value = np.corrcoef(x, y)[0, 1]
```

```
plt.text(0.8, 0.1, f'r = {r_value:.2f}', ha='center', va='center', transform=plt.gc

plt.xlabel("Total Daily Sedentary Minutes")
plt.ylabel("Total Daily Steps")

plt.show()
```



In [134…

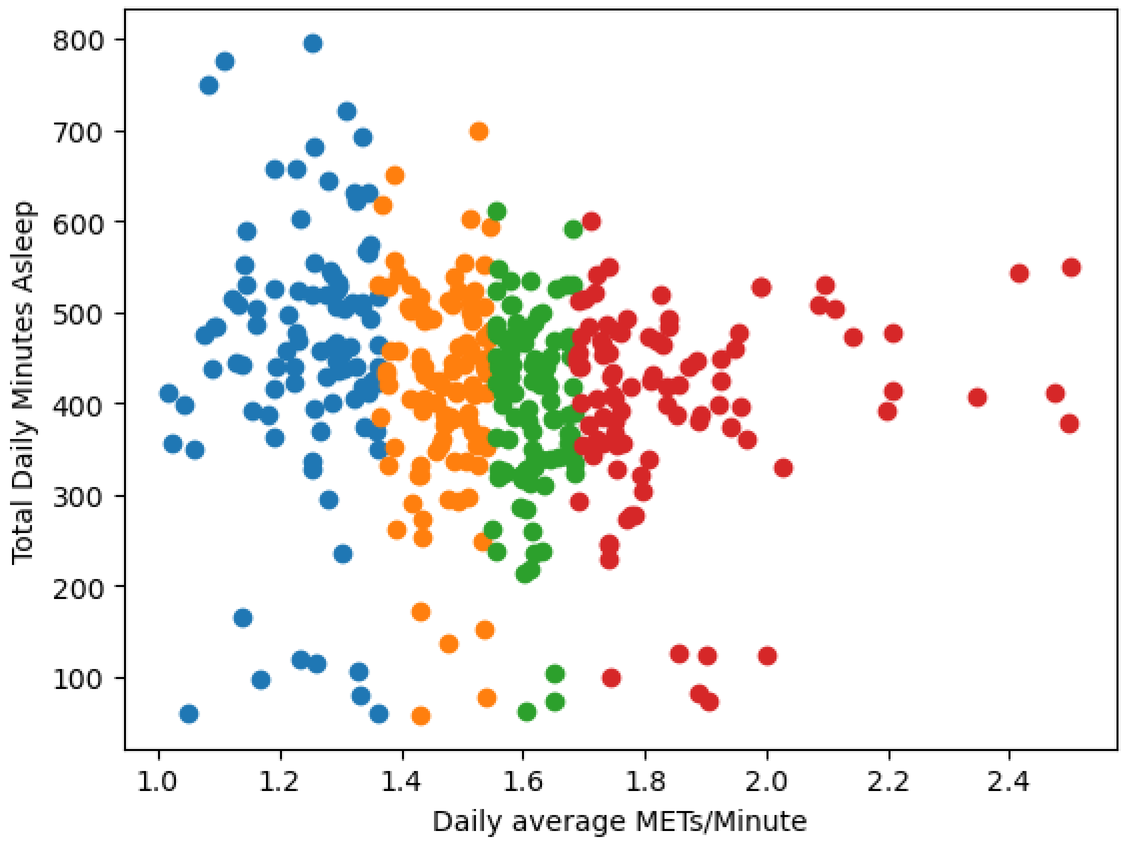
```
x = daily_activity_sleep["SedentaryMinutes"]
y = daily_activity_sleep["Calories"]

plt.scatter(x, y)

coefficients = np.polyfit(x, y, deg=1)
slope = coefficients[0]
intercept = coefficients[1]
regression_line = slope * x + intercept

plt.plot(x, regression_line, color='black')

r_value = np.corrcoef(x, y)[0, 1]
plt.text(0.8, 0.1, f'r = {r_value:.2f}', ha='center', va='center', transform=plt.gc

plt.xlabel("Total Daily Sedentary Minutes")
plt.ylabel("Total Daily Calories")

plt.show()
```



Indeed, it appears that total daily sedentary time is not a great predictor of persons total daily activity (measured as daily average METs/minute or total daily steps) or total daily energy expenditure (total daily calories).

In [135…

```
daily_activity_sleep['METs_Quartile'] = pandas.qcut(daily_activity_sleep['METs'], q
for quartile in ['Q1', 'Q2', 'Q3', 'Q4']:
    plt.scatter(daily_activity_sleep.loc[daily_activity_sleep['METs_Quartile'] == q
                daily_activity_sleep.loc[daily_activity_sleep['METs_Quartile'] == q

plt.xlabel("Daily average METs/Minute")
plt.ylabel("Total Daily Minutes Asleep")
plt.show()
```



Although no upward or downward trends are observed in the average daily MET minutes vs total minutes asleep graph, when data is split into quartiles, data variability seems to decrease as average daily MET minutes increase.

In [136…
```
daily_activity_sleep.groupby("METs_Quartile")["TotalMinutesAsleep"].describe()
```

Out[136]:

METs_Quartile	count	mean	std	min	25%	50%	75%	max
Q1	99.0	457.969697	146.282607	59.0	407.5	463.0	526.00	796.0
Q2	99.0	418.232323	111.491267	58.0	358.0	432.0	495.50	700.0
Q3	98.0	396.102041	100.706114	62.0	338.0	417.0	466.75	611.0
Q4	97.0	401.907216	106.604319	74.0	361.0	418.0	472.00	600.0

In [137…
```
daily_activity_sleep.groupby("METs_Quartile")["METs"].describe()
```

Out[137]:

METs_Quartile	count	mean	std	min	25%	50%	75%	max
Q1	99.0	1.246579	0.091446	1.018056	1.189826	1.276111	1.321001	1.362014
Q2	99.0	1.468878	0.053821	1.363611	1.430764	1.478125	1.515382	1.546875
Q3	98.0	1.612353	0.040929	1.549722	1.577535	1.612500	1.644080	1.685556
Q4	97.0	1.854094	0.187586	1.688542	1.732083	1.777569	1.905486	2.501667

In [138…

```
from scipy.stats import levene
for quartile_1 in ['Q1', 'Q2', 'Q3', 'Q4']:
    for quartile_2 in ['Q1', 'Q2', 'Q3', 'Q4']:
        if quartile_1 != quartile_2:
            statistic, p_value = levene(daily_activity_sleep.loc[daily_activity_sle
            print(f"P-value ({quartile_1} and {quartile_2}): {p_value:.2f}")
```

```
P-value (Q1 and Q2): 0.14
P-value (Q1 and Q3): 0.05
P-value (Q1 and Q4): 0.06
P-value (Q2 and Q1): 0.14
P-value (Q2 and Q3): 0.60
P-value (Q2 and Q4): 0.63
P-value (Q3 and Q1): 0.05
P-value (Q3 and Q2): 0.60
P-value (Q3 and Q4): 0.99
P-value (Q4 and Q1): 0.06
P-value (Q4 and Q2): 0.63
P-value (Q4 and Q3): 0.99
```

Although the average sleep duration is close to the recommended 7 hours, it seems that the standard deviation of data in the first quartile is higher than that in the other quartiles. This suggests, that higher average daily MET minutes might be associated with more consistent nightly sleep duration. This might be important as both under- and oversleeping are known to be detrimental to health.

In [139…

```
daily_activity_sleep['SleepQuality'] = ''
daily_activity_sleep.loc[daily_activity_sleep['TotalMinutesAsleep'] > 480, 'SleepQu
daily_activity_sleep.loc[daily_activity_sleep['TotalMinutesAsleep'] < 360, 'SleepQu
daily_activity_sleep.loc[(daily_activity_sleep['TotalMinutesAsleep'] >= 360) & (dai
```

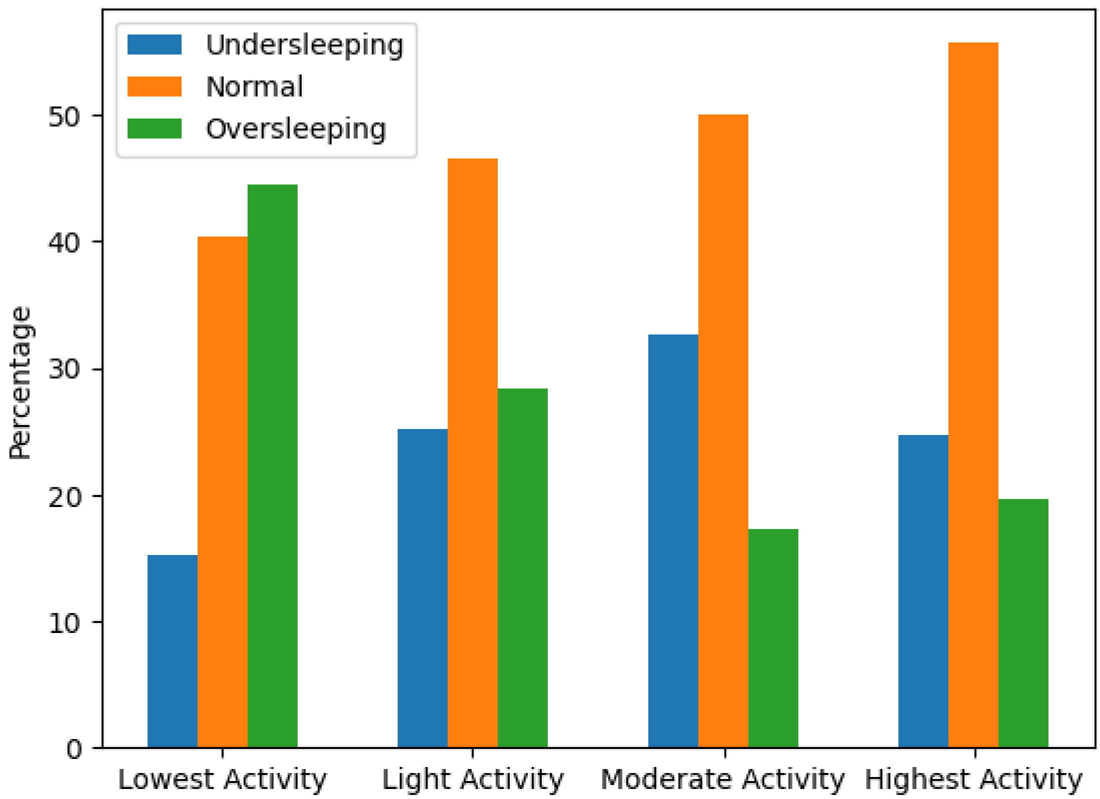
In [140…

```
daily_activity_sleep_grouped = daily_activity_sleep.groupby(["METs_Quartile", "Slee
total = daily_activity_sleep_grouped["normal"] + daily_activity_sleep_grouped["over
daily_activity_sleep_grouped = daily_activity_sleep_grouped.div(total, axis=0) * 10
```

In [141…

```
x_labels = ['Sedentary', 'LightlyActive', 'FairlyActive', 'VeryActive']
bar_width = 0.2

pos_undersleeping = list(range(len(x_labels)))
pos_normal = [pos + bar_width for pos in pos_undersleeping]
pos_oversleeping = [pos + bar_width for pos in pos_normal]
```

```
plt.bar(pos_undersleeping, daily_activity_sleep_grouped['undersleeping'], width=bar
plt.bar(pos_normal, daily_activity_sleep_grouped['normal'], width=bar_width, label=
plt.bar(pos_oversleeping, daily_activity_sleep_grouped['oversleeping'], width=bar_w

plt.ylabel('Percentage')

plt.xticks([pos + bar_width for pos in range(len(x_labels))], ["Lowest Activity", "

plt.legend()

plt.show()
```



Testing if the increase in the proportion of normal duration sleep events in the highest activity quartile is significantly different from the lowest activity quartile

In [142…
```
daily_activity_sleep_stats = daily_activity_sleep.copy()
daily_activity_sleep_stats['SleepQuality'] = ''
daily_activity_sleep_stats.loc[daily_activity_sleep_stats['TotalMinutesAsleep'] > 4
daily_activity_sleep_stats.loc[daily_activity_sleep_stats['TotalMinutesAsleep'] < 3
daily_activity_sleep_stats.loc[(daily_activity_sleep_stats['TotalMinutesAsleep'] >=
```

Normal duration sleep events reclassified as "good", undersleeping and oversleeping events classified as "bad".

In [143…
```
contingency_table = daily_activity_sleep_stats[["METs_Quartile", "SleepQuality"]].g
contingency_table = contingency_table.reset_index()
contingency_table = contingency_table.rename(columns={0:"counts"})
contingency_table = contingency_table.pivot(index='METs_Quartile', columns='SleepQu
```

```
contingency_table = contingency_table.reset_index()
contingency_table
```

Out[143]:

	SleepQuality	METs_Quartile	abnormal	normal
0		Q1	59	40
1		Q2	53	46
2		Q3	49	49
3		Q4	43	54

In [144…

```
import numpy as np
from scipy.stats import chi2_contingency
for quartile_1 in ['Q1', 'Q2', 'Q3', 'Q4']:
    for quartile_2 in ['Q1', 'Q2', 'Q3', 'Q4']:
        if quartile_1 != quartile_2:
            observed_data = contingency_table[contingency_table["METs_Quartile"].is
            chi2, p_value, dof, expected = chi2_contingency(observed_data)
            print(f"P-value ({quartile_1} and {quartile_2}): {p_value:.2f}")
```

```
P-value (Q1 and Q2): 0.47
P-value (Q1 and Q3): 0.23
P-value (Q1 and Q4): 0.05
P-value (Q2 and Q1): 0.47
P-value (Q2 and Q3): 0.72
P-value (Q2 and Q4): 0.25
P-value (Q3 and Q1): 0.23
P-value (Q3 and Q2): 0.72
P-value (Q3 and Q4): 0.52
P-value (Q4 and Q1): 0.05
P-value (Q4 and Q2): 0.25
P-value (Q4 and Q3): 0.52
```

In [145…

```
daily_activity_sleep.groupby("METs_Quartile")["METs"].describe()
```

Out[145]:

METs_Quartile	count	mean	std	min	25%	50%	75%	max
Q1	99.0	1.246579	0.091446	1.018056	1.189826	1.276111	1.321001	1.362014
Q2	99.0	1.468878	0.053821	1.363611	1.430764	1.478125	1.515382	1.546875
Q3	98.0	1.612353	0.040929	1.549722	1.577535	1.612500	1.644080	1.685556
Q4	97.0	1.854094	0.187586	1.688542	1.732083	1.777569	1.905486	2.501667

The MET quartiles were classified as 'Lowest Activity' (1.018056 - 1.364236 average daily MET/minute), 'Light Activity' (1.369375 - 1.546875 average daily MET/minute), 'Moderate Activity' (1.549722 - 1.688889 average daily MET/minute), 'Highest Activity' (1.688542 - 2.501667 average daily MET/minute) categories from the lowest to the highest. Sleep duration was grouped into 'undersleeping' (<6 hrs), 'normal' (6-8 hrs), and 'oversleeping' (>8 hrs). Although it seems that people with the lowest physical activity seem to undersleep less than other groups, it appears to be due to their higher tendency to oversleep. Even light physical activity seems to positively affect the duration of sleep favouring sleep duration within the optimal range.

There is also a tread showing and increase in the fraction of sleep events with normal duration as physical activity increases. The difference between the fraction of normal duration sleep events in the lowest activity and highest activity quartiles did not pass the threshold of statistical significance. However, the p-value was very close to the threshold (p = 0.06), suggesting that the difference between the quartiles might be real. As the power of chi-square test increases with sample size, a higher sample size could be used to verify that the difference between the bottom and top quartiles is real.

daily_activity_sleep.to_csv("activity_sleep_data_cleaned.csv")

Average Hourly Intensities

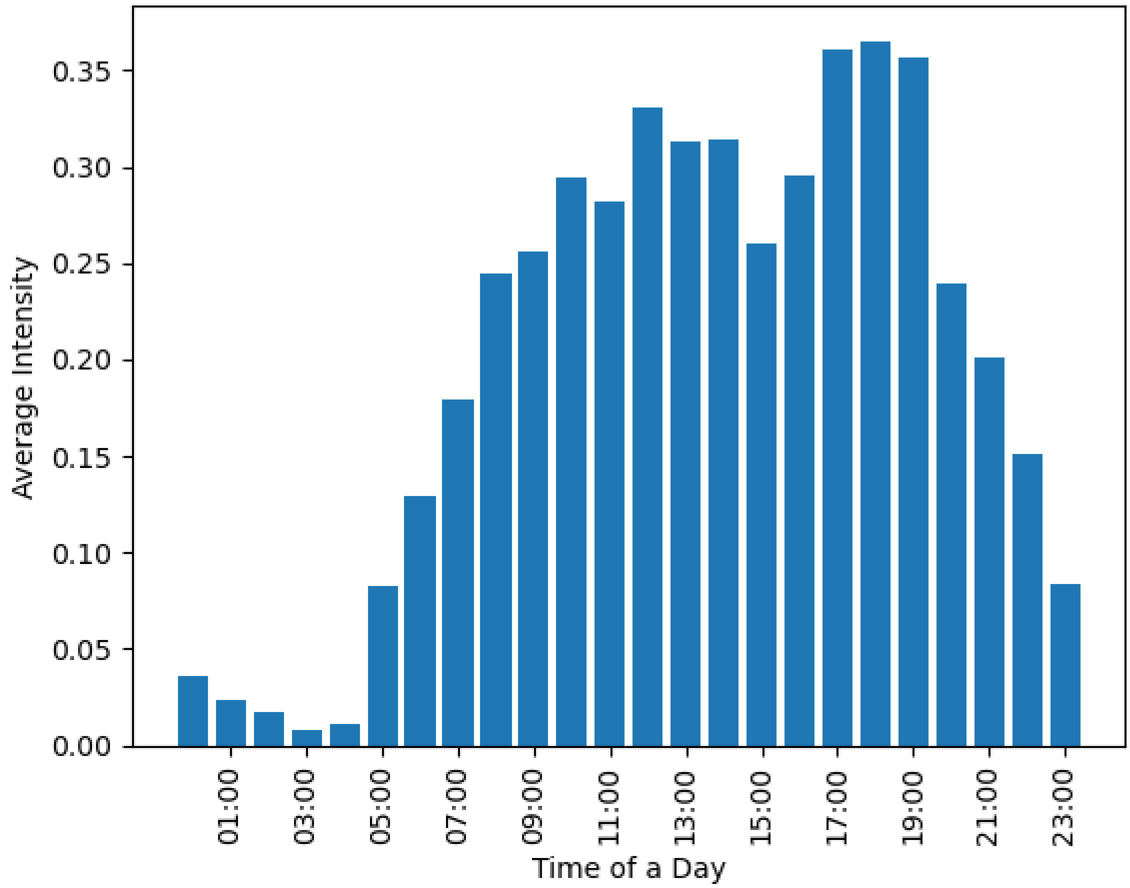
In [146…
```
hourly_intensities["ActivityHour"] = hourly_intensities["ActivityHour"].dt.time
```

In [147…
```
hourly_intensities_grouped = hourly_intensities.groupby("ActivityHour").mean().rese
hourly_intensities_grouped['ActivityHourPlot'] = hourly_intensities_grouped['Activi
hourly_intensities_grouped.dtypes
```

Out[147]:
```
ActivityHour         object
AverageIntensity    float64
ActivityHourPlot      int64
dtype: object
```

In [148…
```
hourly_intensities_grouped["ActivityHour"] = hourly_intensities_grouped["ActivityHo
```

In [149…
```
x = hourly_intensities_grouped["ActivityHourPlot"]
y = hourly_intensities_grouped["AverageIntensity"]

plt.bar(x, y)

plt.xlabel("Time of a Day")
plt.ylabel("Average Intensity")

plt.xticks(hourly_intensities_grouped["ActivityHourPlot"][1::2], hourly_intensities

plt.show()
```



hourly_intensities_grouped.to_csv("hourly_intensities_cleaned.csv")

Calculating the Level of Physical Activity Required to Achieve 1.5 Daily Average METs/minute

In [150…

```
average_daily_met["METs"].describe()
```

Out[150]:

```
count    934.000000
mean       1.466396
std        0.290326
min        1.000000
25%        1.271024
50%        1.469618
75%        1.640677
max        2.577569
Name: METs, dtype: float64
```

In [151…

```
from sympy import *

for MET in [3, 6, 9]:
    x, y = symbols('x y')
    eq1 = Eq((1*x + MET*y)/24, 1.5)
    eq2 = Eq(x + y, 24)
    solution = solve((eq1,eq2), (x, y))
    print(f"{solution[y]:.2f} hours of activity at {MET} METs")
```

```
6.00 hours of activity at 3 METs
2.40 hours of activity at 6 METs
1.50 hours of activity at 9 METs
```

To reach 1.5 daily average METs/minute associated with more consistent sleep duration and more sleep events with a duration that falls within the normal range, people need to accumulate at least 6 hours of light activity, like slow walking, or 2.4 hours of moderate activity, like brisk walking, or 1.5 hours of intense physical activity, like running (https://doi.org/10.1371%2Fjournal.pone.0200701). This seems to be quite feasible as the average daily METs/minute of people who participated in this study is 1.47.