Fitbit and Exercise Data Study

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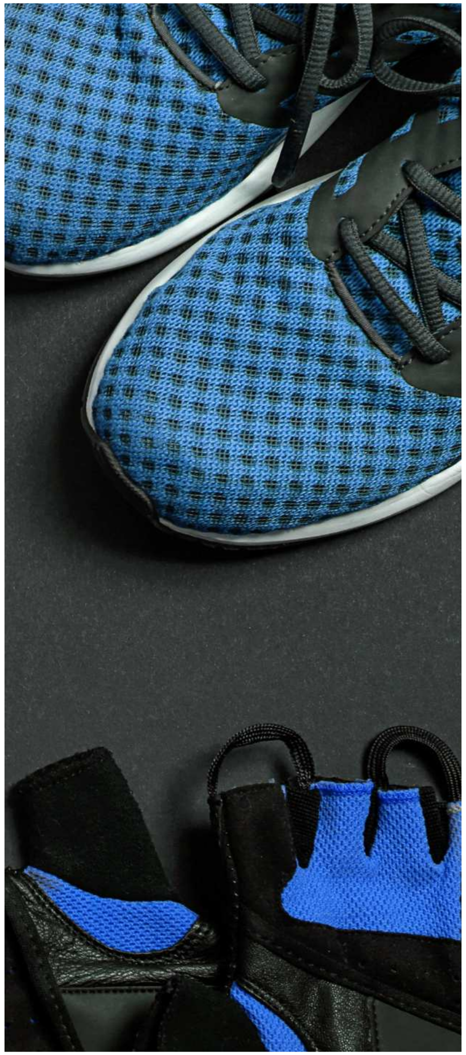
INTRODUCTION

- This study involves looking at 2 separate datasets:

1) Activity/ sleep metrics for 33 participants over 31 days measured using a Fitbit wearable device.
2) Exercise lab data for an individual exercise session: calories burned during the session was recorded along with activity and demographic information for each participant.

GENERAL QUESTIONS/ PROBLEM STATEMENT

- Can any insights be gained into app or hardware features that Fitbit might be able to incorporate in future iterations of their technology?
- What are the minimum metrics that Fitbit needs to obtain to calculate the daily calorie burn of users (demographic information + metrics obtained from wearable)?
- Does regular logging of activity correlate to improved fitness?



FURTHER QUESTIONS

Dataset 1: Month activity and sleep - Fitbit

- What is the average Fitbit user's pattern of activity and sleep – looking at daily and weekly timeframes?
- Can we find a relationship between users' pattern of activity and daily calorie burn/ Basal Metabolic Rate?
- How regularly do users log their activity over the month?
  - Is there a relationship between frequency of logged activity and daily calorie burn, or other health metrics?

Dataset 2: Individual exercise session – Exercise lab

- For an individual exercise session, what are the most important metrics that can be used to predict calorie burn?
- Using metrics that could normally be obtained from a Fitbit wearable, what is the most accurate model we can build to predict Calorie burn for the exercise session?

THE DATA:

Dataset 1 – Fitbit

- Public domain data obtained from Kaggle (uploaded by user Mobius):
  - https://www.kaggle.com/datasets/arashnic/fitbit
- Data was collected from 33 participants over a period of 31 days (12.04.2016-12.05.2016). Participants had to opt in to having their information collected via a survey form distributed online through Amazon.

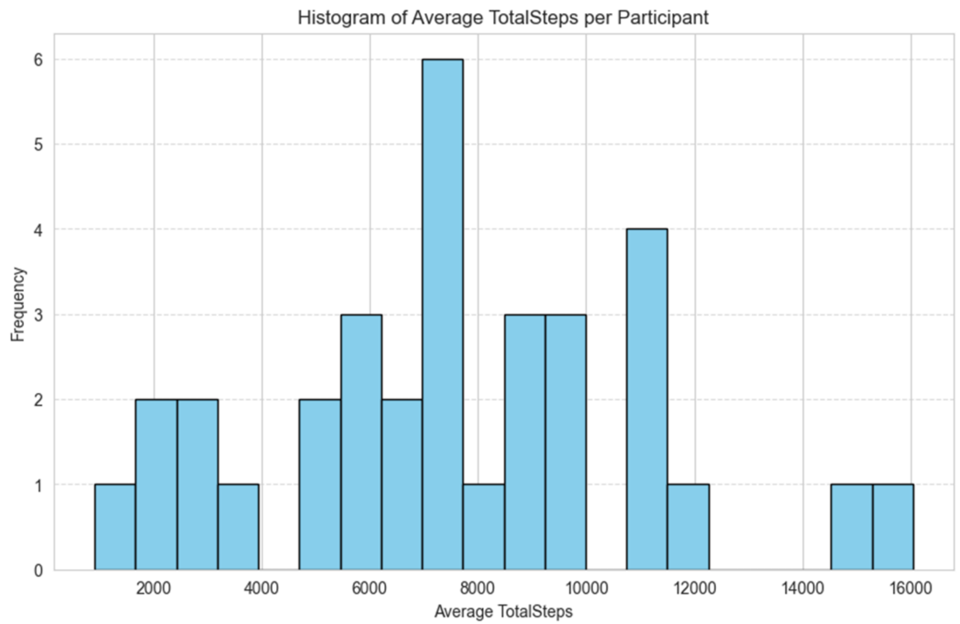
- **Features considered:**
  - **Id** – Unique participant id
  - **ActivityDate** – Date of activity recorded (for daily activities)
  - **ActivityHour** – Datetime for hourly granularity
  - **Measures of distance:**
    - TotalSteps, TotalDistance
    - Distance broken down by activity intensity:
      - VeryActiveDistance, FairlyActiveDistance, LightlyActiveDistance, SedentaryDistance
  - **Time breakdown of activity:**
    - VeryActiveMinutes, FairlyActiveMinutes, LightlyActiveMinutes, SedentaryMinutes
  - **Calories** – The calories burned during the time interval considered (day/hour)

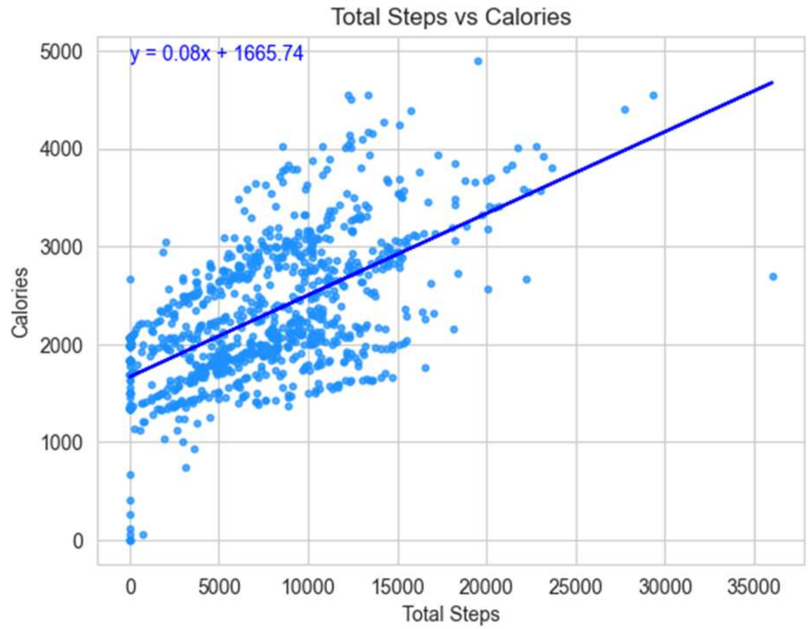
Dataset 2 – Exercise Lab

- Exercise physiology lab data collected from clinics across the USA in 2017, collated by Graeme Malcolm, Data and AI Content Development Manager at Microsoft, Redmond Washington. Data was initially posted as materials for a Microsoft Azure machine learning training course ("Microsoft DAT263x Introduction to Artificial Intelligence (AI)" - https://www.youtube.com/watch?v=21nsGTBFE4M). Data was reposted to Kaggle by user Fernando Fernandez in 2018: https://www.kaggle.com/datasets/fmendes/fmendesdat263xdemos/data?select=exercise.csv
- 15000 individuals from across USA, representing multiple age groups and an even division of male and female participants
- Feature columns:
  - **User_ID** – unique participant identifier
  - **Demographic/ personal information**
    - Gender, Age, Height, Weight
  - **Exercise metrics**
    - Duration – (length of exercise session in minutes)
    - Heart_Rate (bpm)
    - Body_Temp – (skin surface temperature in ˚C)

HYPOTHESES

- Dataset 1 – Fitbit
  - There is a positive correlation between the frequency with which Fitbit users record fitness metrics via their wearable, and exercise outcomes. Logging frequency would correlate positively with daily Calories burned and general health metrics like Basal Metabolic Rate (BMR). Logging frequency could be used as a predictor to calculate Calories and BMR.
- Dataset 2 – Exercise Lab
  - For an individual exercise session, there is a significant relationship between Calories burned and at least some of the following predictors:
    - <u>Exercise metrics:</u> Duration of exercise, Heart Rate, Skin Surface Temperature
    - <u>Demographic information:</u> Age, Gender, Height, Weight



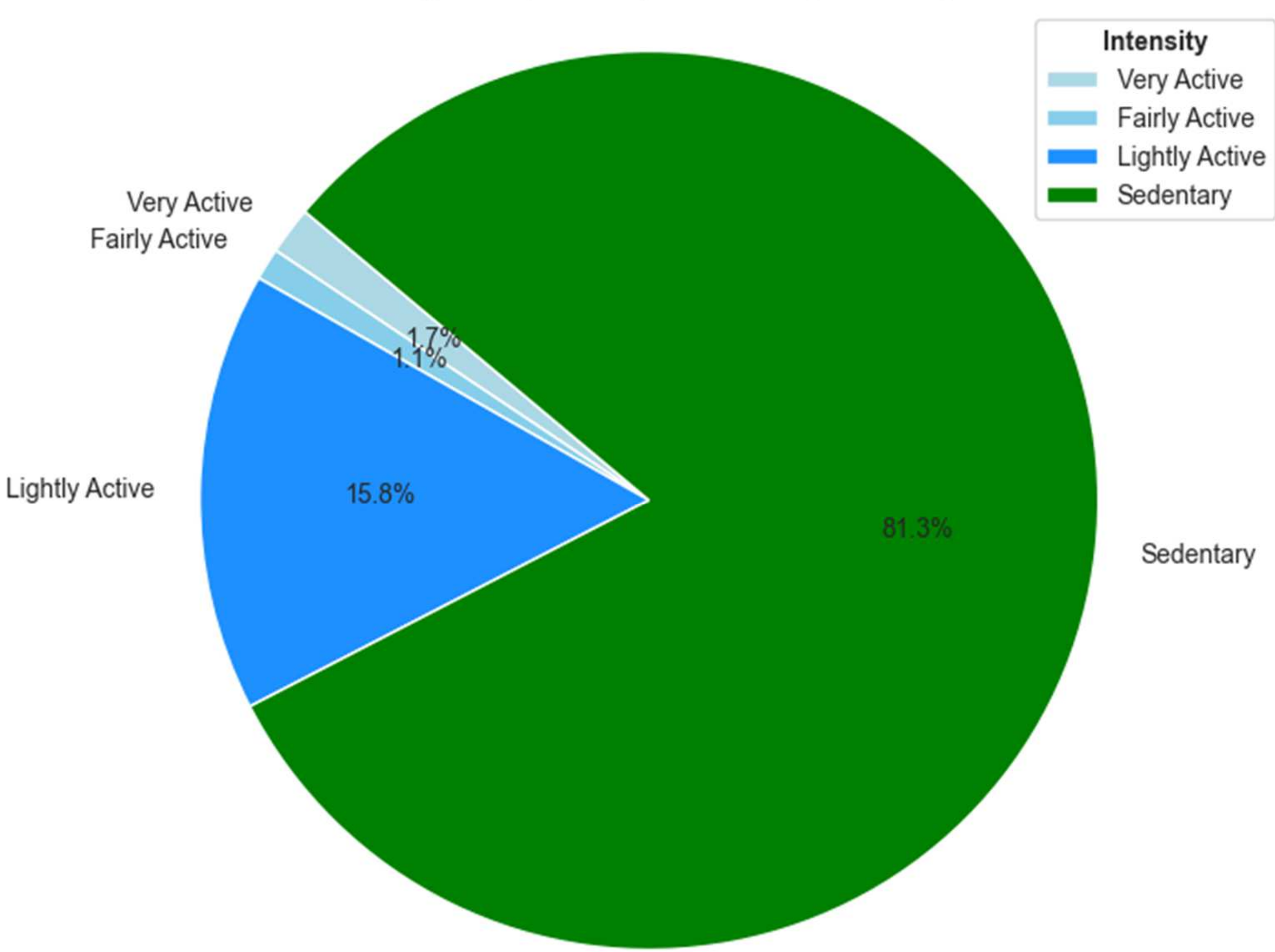


ANALYSIS

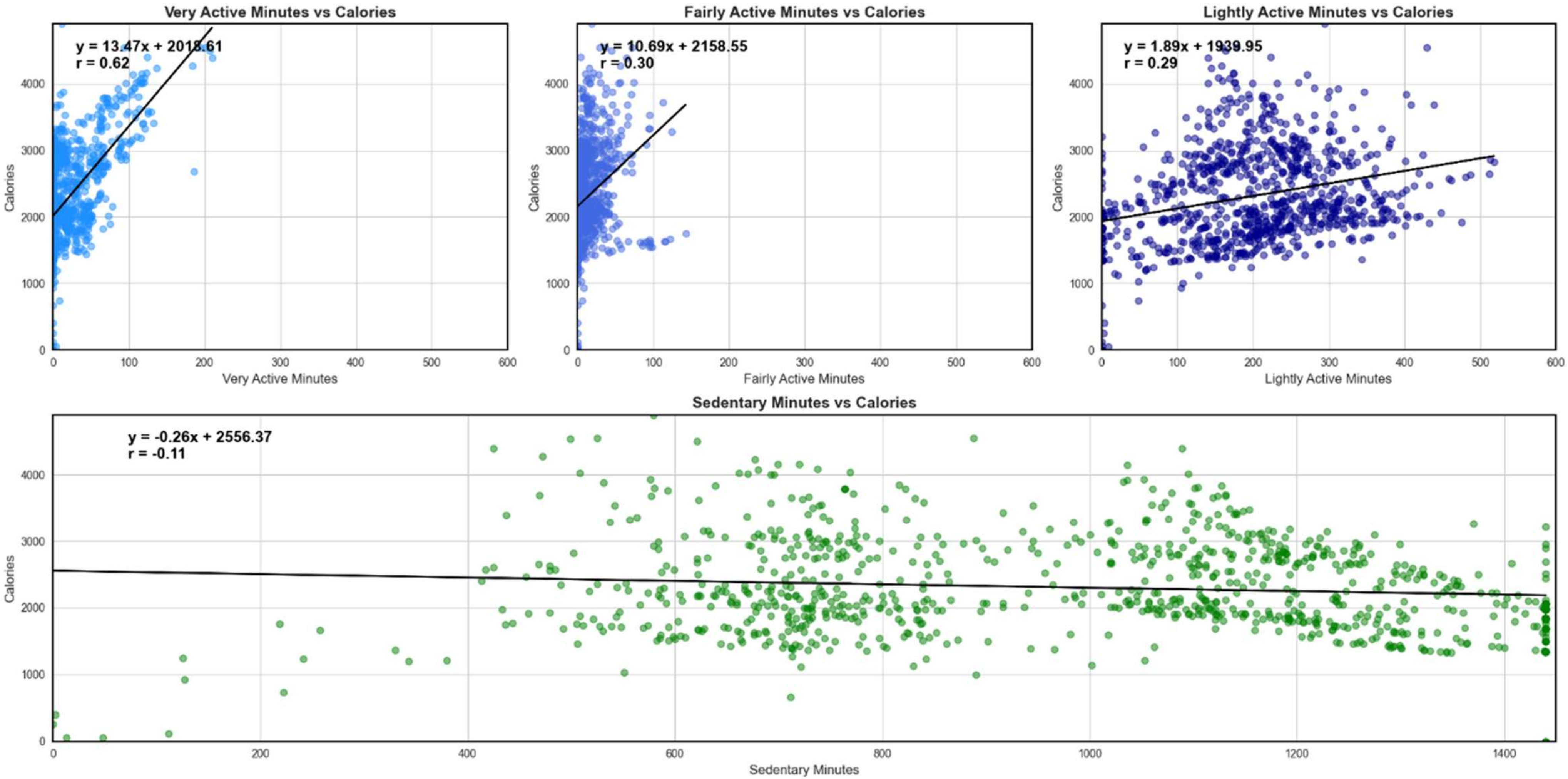
- Initial analysis confirmed that TotalSteps, ActiveDistance, and ActiveMinutes metrics correlated positively with daily Calorie burn, as expected. Higher activity = more energy expenditure.

ACTIVE MINUTES

- People spent most of their day (81%) sedentary, with more vigorous activities forming smaller share of time during the day.
- Fitbit users undertook more light exercise (15.8%) than vigorous exercise (VeryActive = 1.7%, FairlyActive = 1.1%).
- Mean total steps per day was ~7600 - below the recommended 10000, for improved fitness.
- While the Fitbit app includes activity reminders, potentially the Fitbit could be doing more to promote movement during the day.
- Distribution of SedentaryMinutes had a lower standard deviation than ActiveMinutes - values bunching up around the mean (around 16.5 hours sedentary time) suggest that people like to get a certain amount of sedentary time per day without much variation.

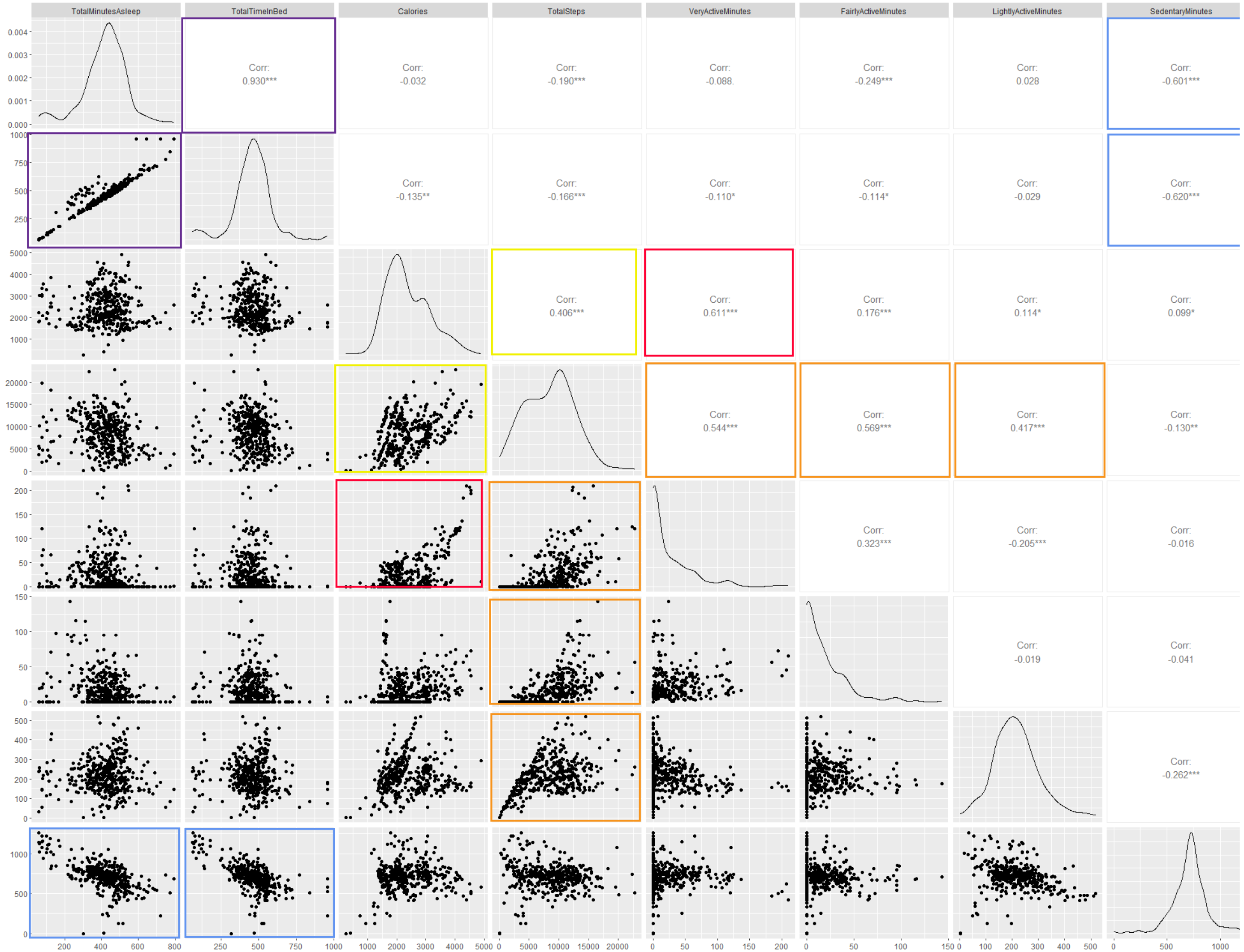


ACTIVE MINUTES VS CALORIES – 4 DIFFERENT INTENSITY LEVELS



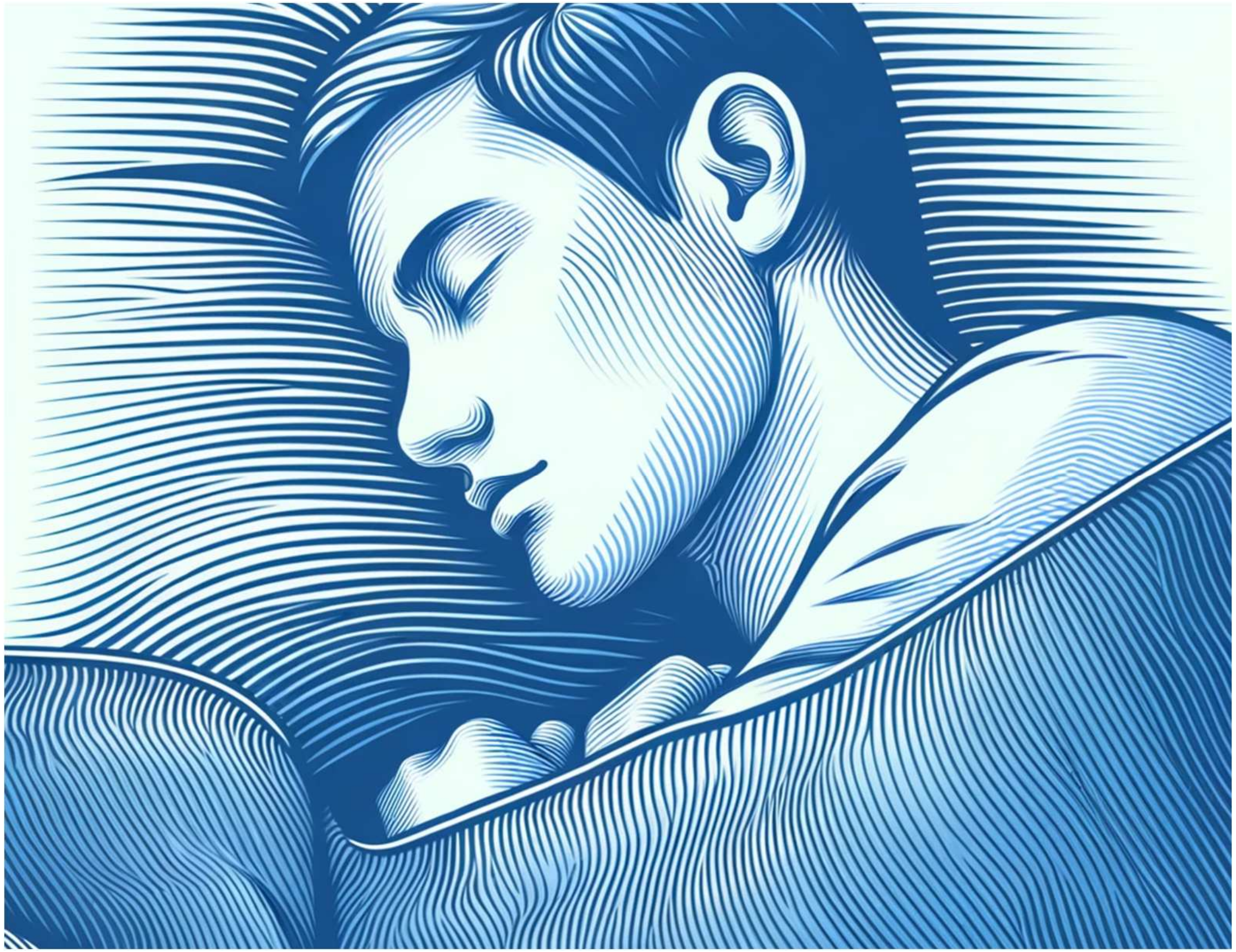
CORRELATIONS: ACTIVITY AND SLEEP

- Pairs plot, activity and sleep metrics, showing scatter matrix of the various features and correlations.



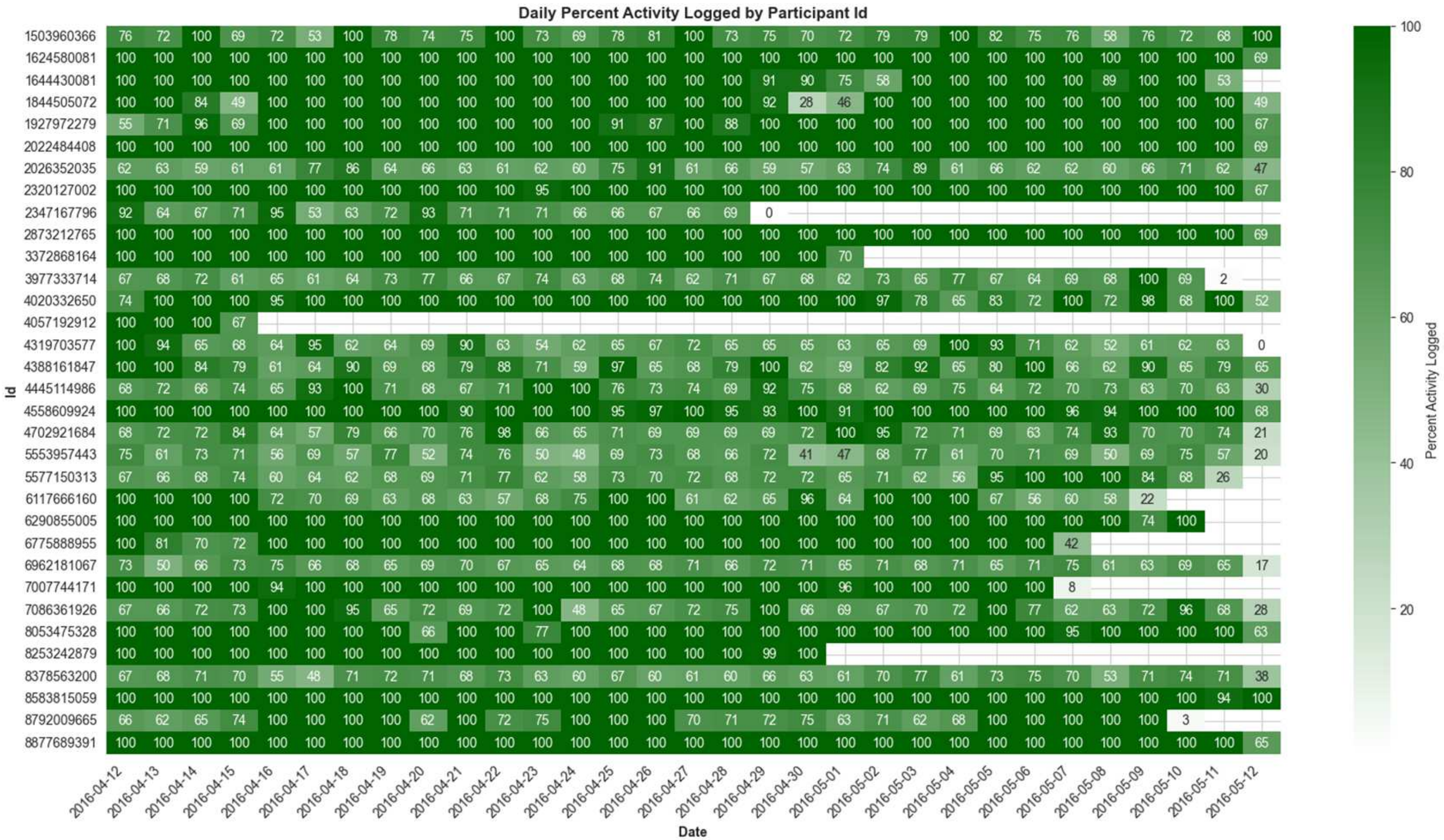
SLEEP

- There was a strong negative correlation between total time spent asleep and sedentary minutes during the day.
- Individuals that slept better were less sedentary during the day.
- However, most people were getting slightly less that the recommended 7 hours of sleep.
- On average, individuals slept more on a Sunday, but otherwise slept relatively consistently during the week.



ACTIVITY LOGGING BEHAVIOUR

- While a lot of participants were diligent with using their wearable to log activity, logging a large proportion of 100% days, nobody logged activity for all minutes of the month.
- This is understandable since the wearable needs to be taken off to charge, isn't generally worn to shower or for prolonged water-based activities.
- The average % minutes logged per person across the month was 77%.
- This is a good result, indicating that Fitbit owners are committed to using their device.
- Pattern of logging across individuals suggests that motivation was a big factor contributing to logging frequency.

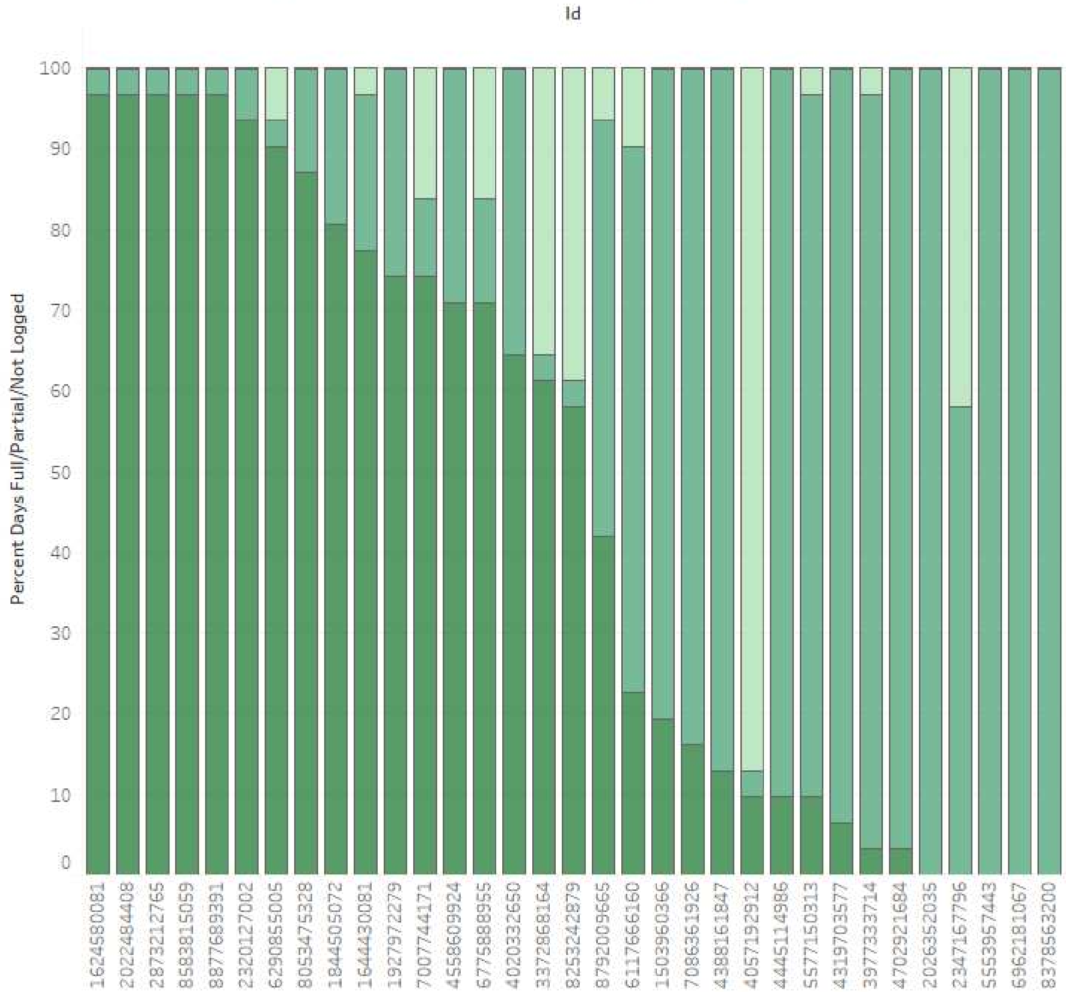


Users that logged partial days ended up logging a lot of partial days in total, whereas there was a group of users that were very committed to logging full days. The motivation to log full days seemed to come and go in blocks. There would be a run of partially logged days, then a block of 1 or 2 full days, then another block of partial days.

ACTIVITY LOGGING BEHAVIOUR

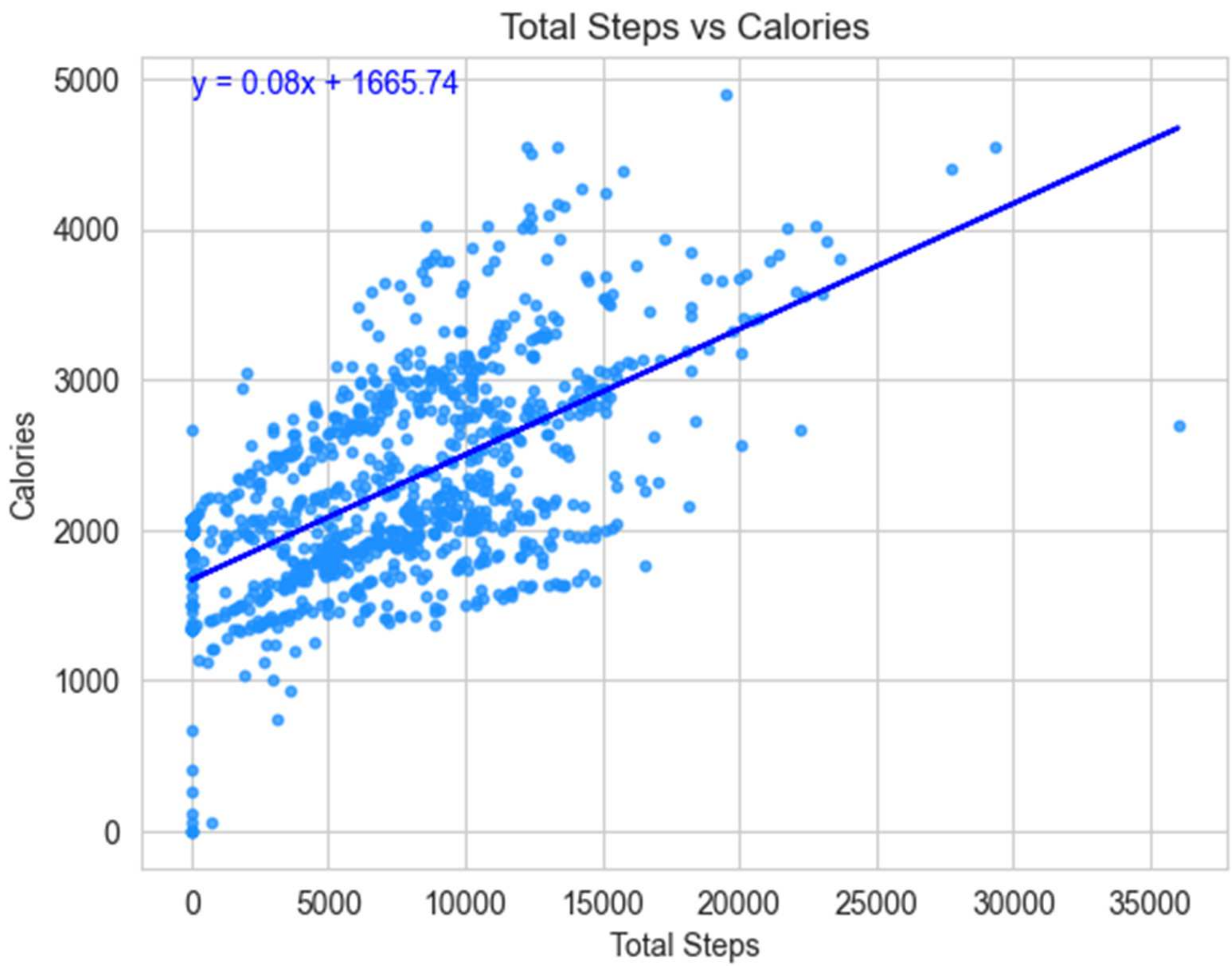
- Potentially the Fitbit app could address these motivational issues more effectively through reminders/ incentives to wear the device.
- On-device reminders can only be viewed with the Fitbit is worn, but perhaps more emphasis could be put on phone reminders for less motivated users.

Breakdown of %Days (Full/ Partial/ Not Logged) by Id

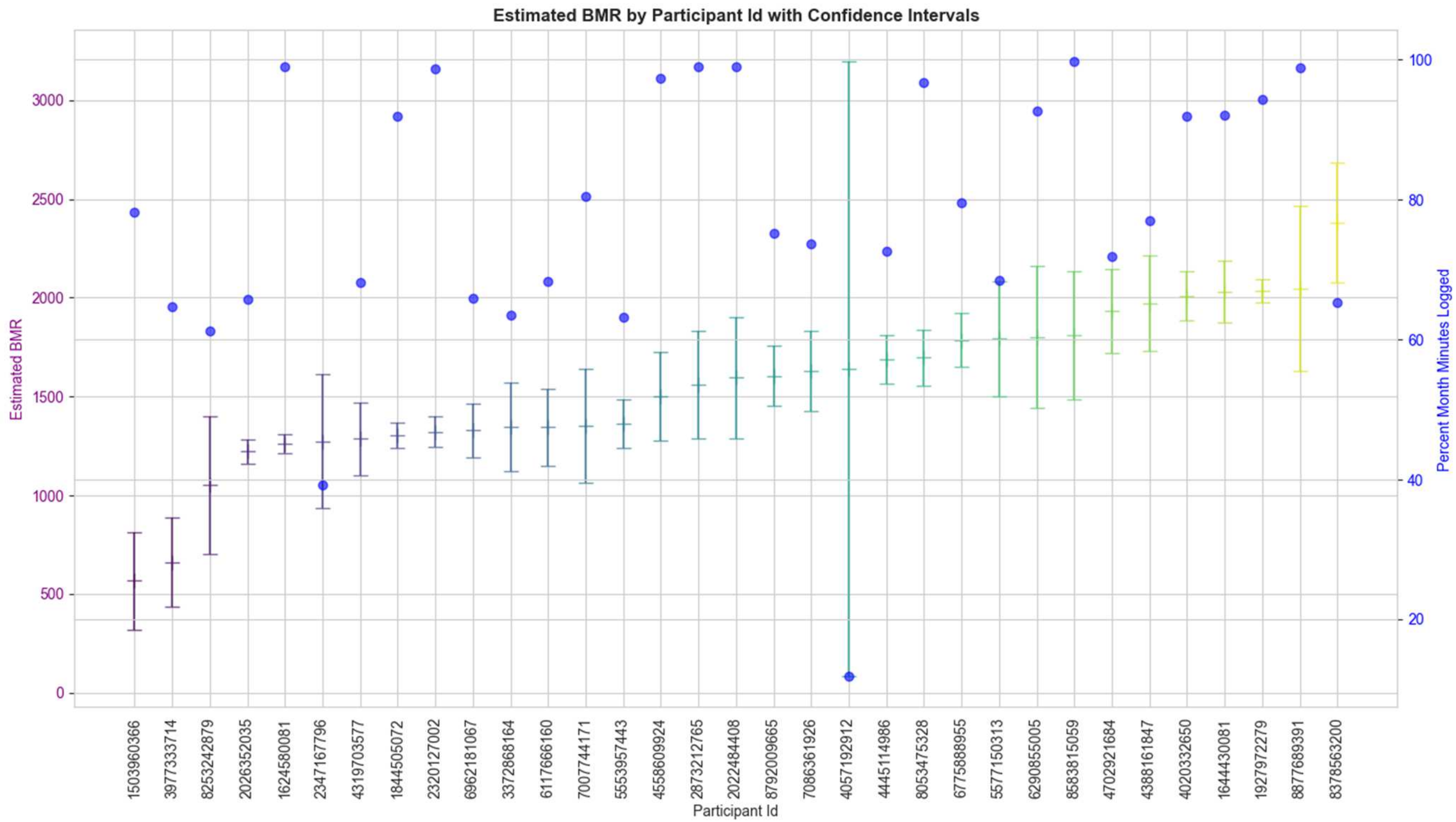


BMR

- Basal Metabolic Rate (BMR) is the energy the body uses to maintain basic functions while at rest.
- Higher BMR is considered to be a measure of physical fitness.
- This was estimated using a simple linear regression of Calories on TotalSteps.
- BMR was the intercept of the fit line.
- This demonstrates how many features innate to an individual participant may be inferred just from activity metrics, even when demographic information is not available.

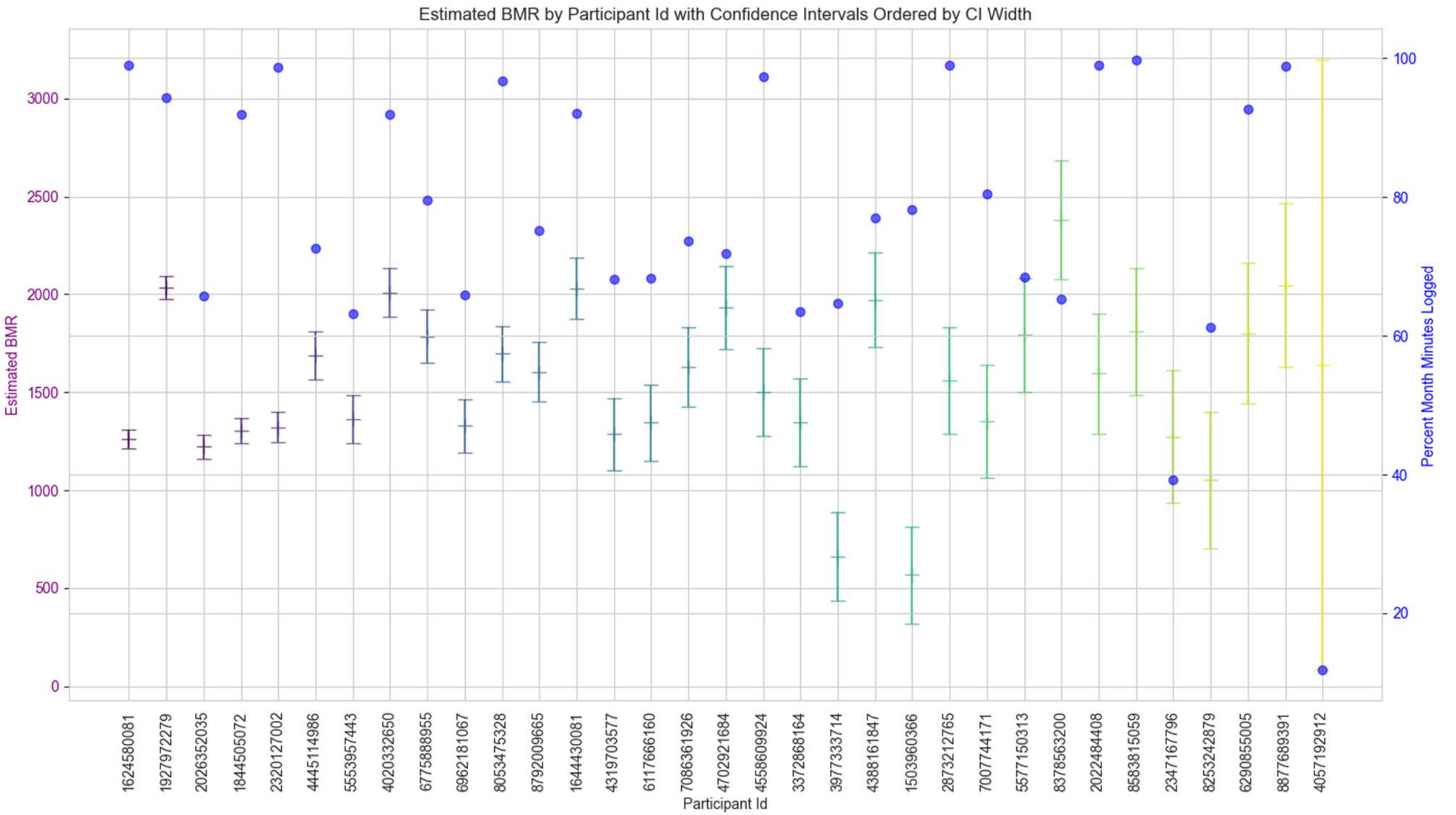


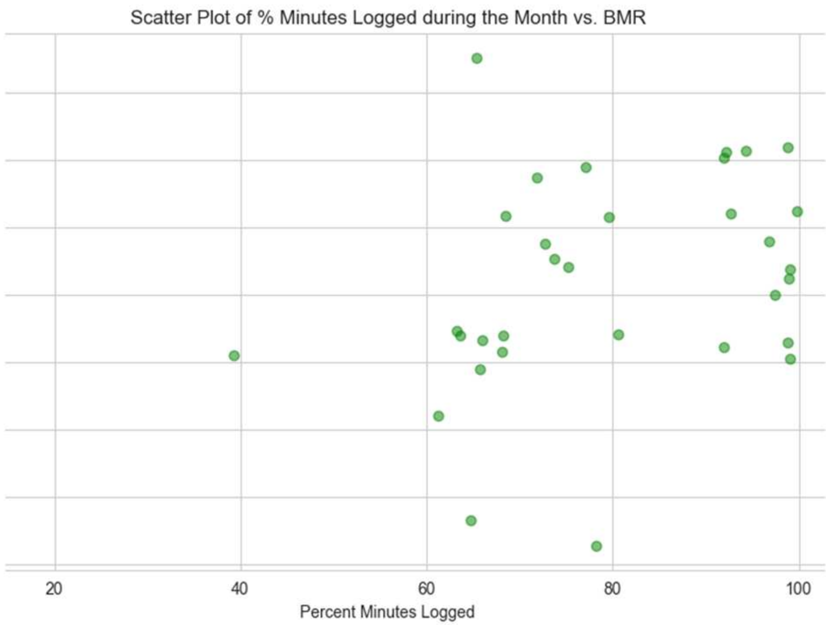
BMR

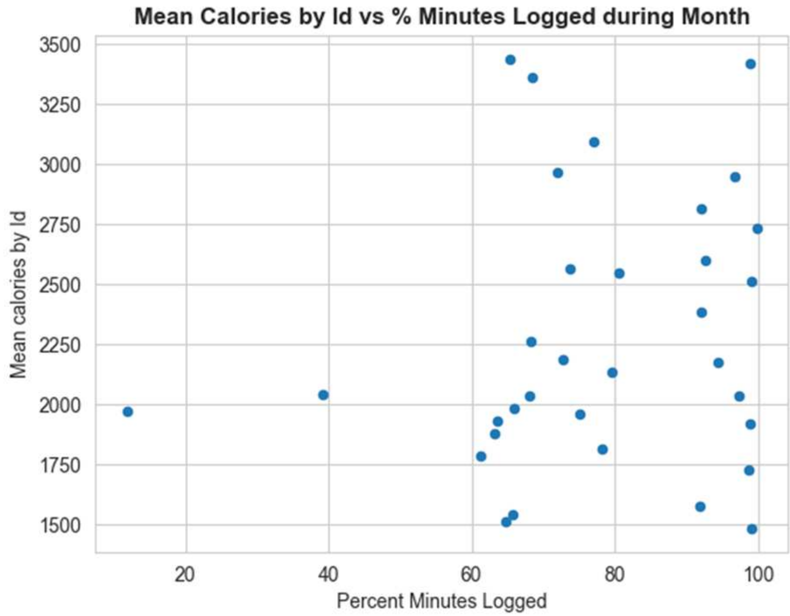


Estimated BMR by Participant Id with Confidence Intervals
Estimated BMR
0
500
1000
1500
2000
2500
3000
Percent Month Minutes Logged
20
40
60
80
100
Participant Id
1503960366
3977333714
8253242879
2026352035
1624580081
2347167796
4319703577
1844505072
2320127002
6962181067
3372868164
6117666160
7007744171
5553957443
4558609924
2873212765
2022484408
8792009665
7086361926
4057192912
4445114986
8053475328
6775888955
5577150313
6290855005
8583815059
4702921684
4388161847
4020332650
1644430081
1927972279
8877689391
8378563200

BMR


Estimated BMR by Participant Id with Confidence Intervals Ordered by CI Width
Estimated BMR
Percent Month Minutes Logged
Participant Id
0
500
1000
1500
2000
2500
3000
20
40
60
80
100
1624580081
1927972279
2026352035
1844505072
2320127002
4445114986
5553957443
4020332650
6775888955
6962181067
8053475328
8792009665
1644430081
4319703577
6117666160
7086361926
4702921684
4558609924
3372868164
3977333714
4388161847
1503960366
2873212765
7007744171
5577150313
8378563200
2022484408
8583815059
2347167796
8253242879
6290855005
8877689391
4057192912





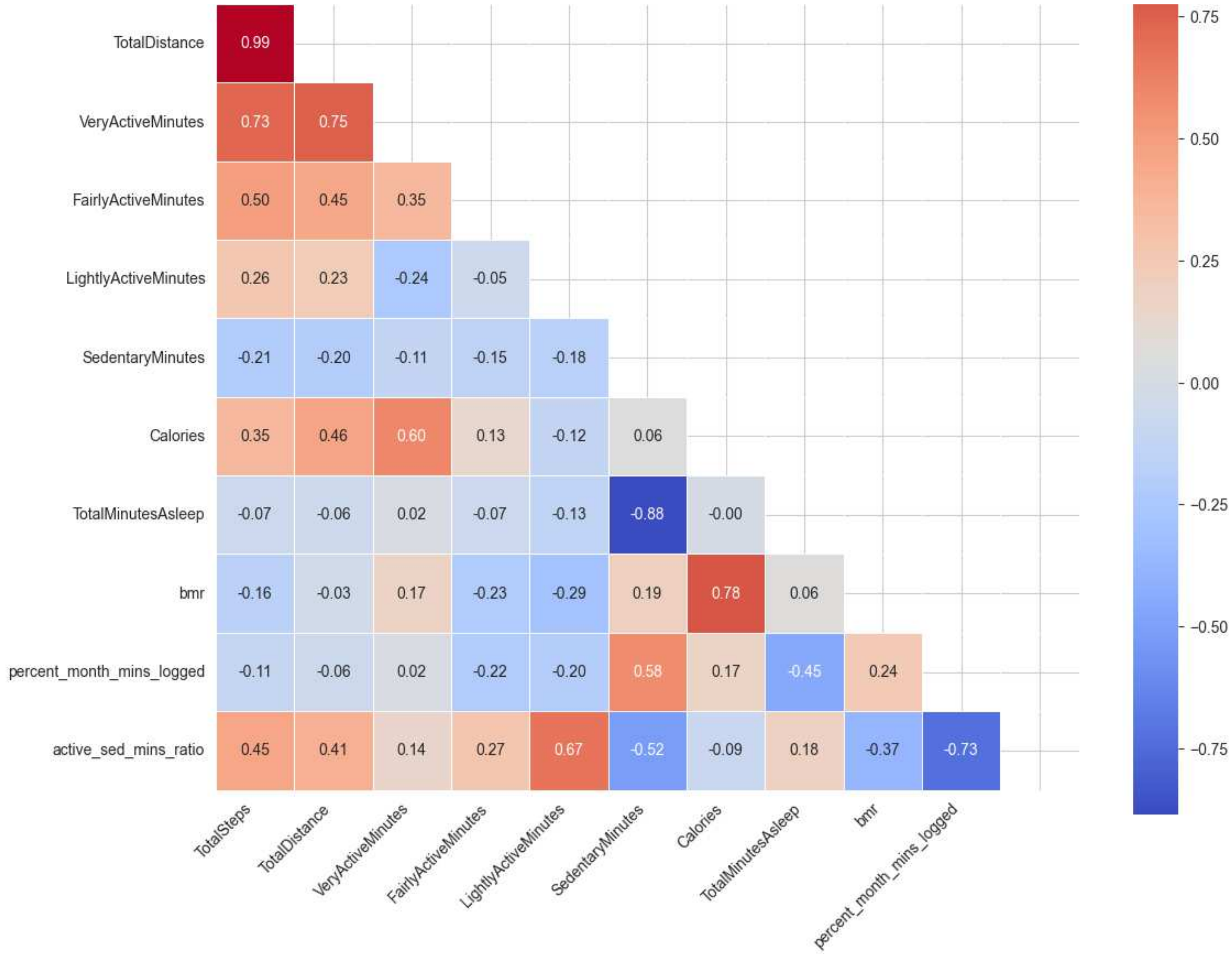
LOGGING FREQUENCY → CALORIES BURNED/ BMR

- Increased frequency of logging activity/ sleep metrics did not correlate to increased daily calories burned, nor did it correlate to improved health metrics such as BMR.
- People the that logged more total minutes of metrics during the month were mostly logging sedentary minutes.
- They were just logging more time while they were inactive. More research needs to be done on how to encourage movement when the Fitbit is worn.

CORRELATIONS

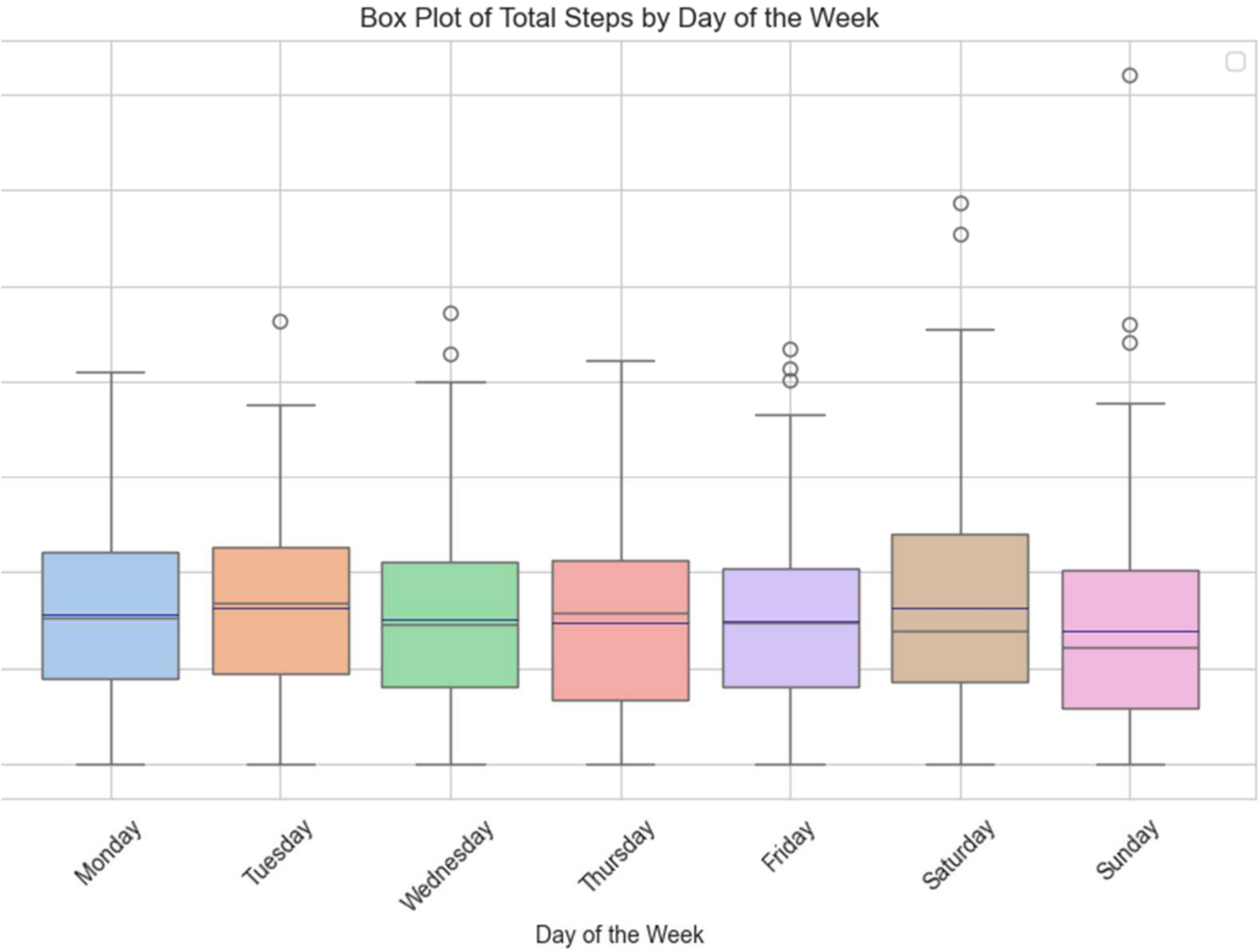
- INCLUDING LOGGING FREQUENCY AND BMR

- A strong correlation between logging frequency and Calories burned, or logging frequency and BMR, was not observed.
- Consequently, logging metrics could not be utilized as a predictive basis for Calories burned as initially anticipated.
- In fact, most of the features strongly correlated with calories were auto-correlated by an existing mathematical relationship.
- For example, Steps and ActiveDistance metrics are used by the Fitbit algorithm to calculate daily Calories burned. Hence, these metrics correlate with calories in the analysis, but there is no point using them in a new model to predict Calories - it doesn't reveal anything new.



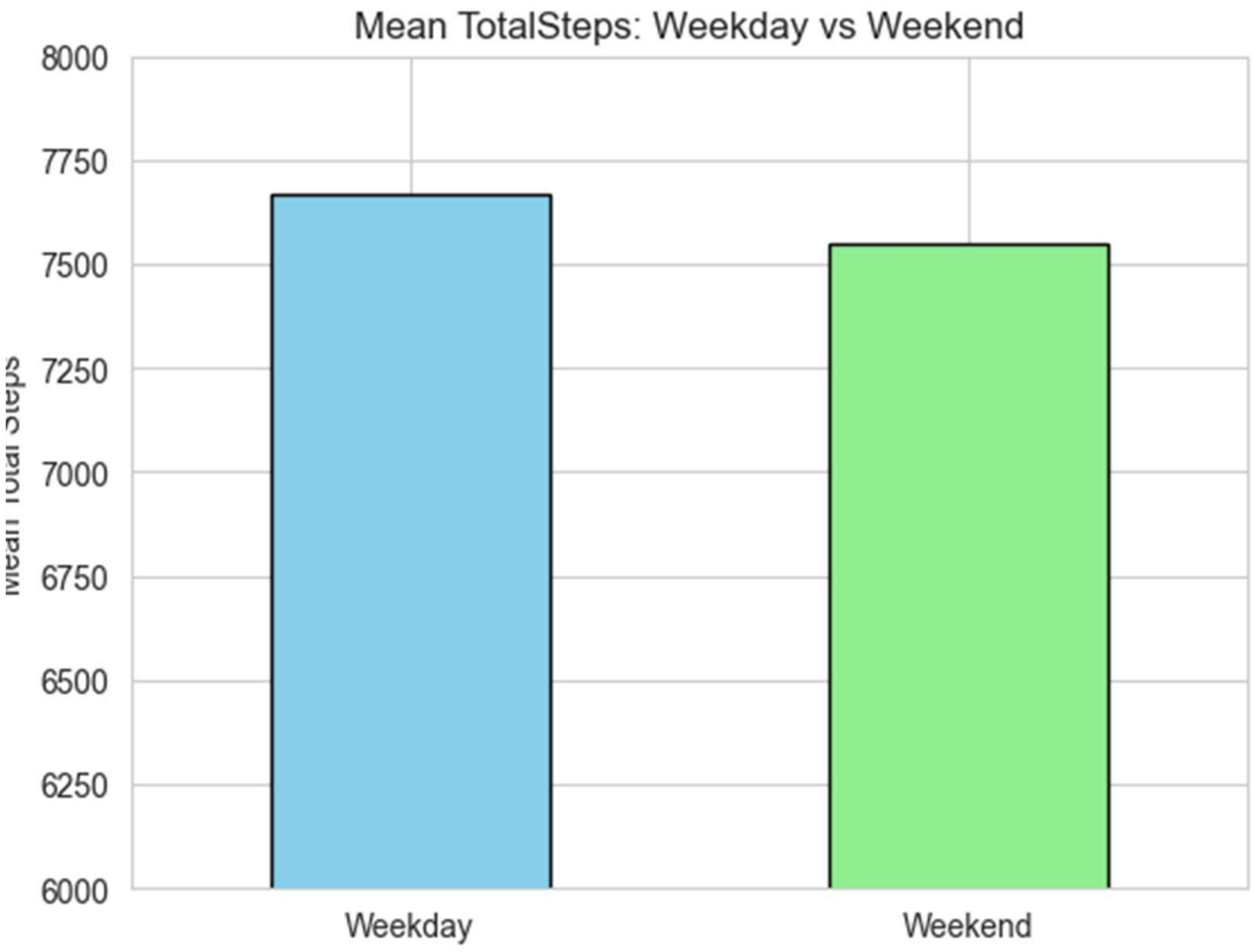
ACTIVITY ACROSS THE WEEK

- There were no strong patterns in activity/ sleep across the week. Highest Mean TotalSteps was on Saturday, but low on Sunday.



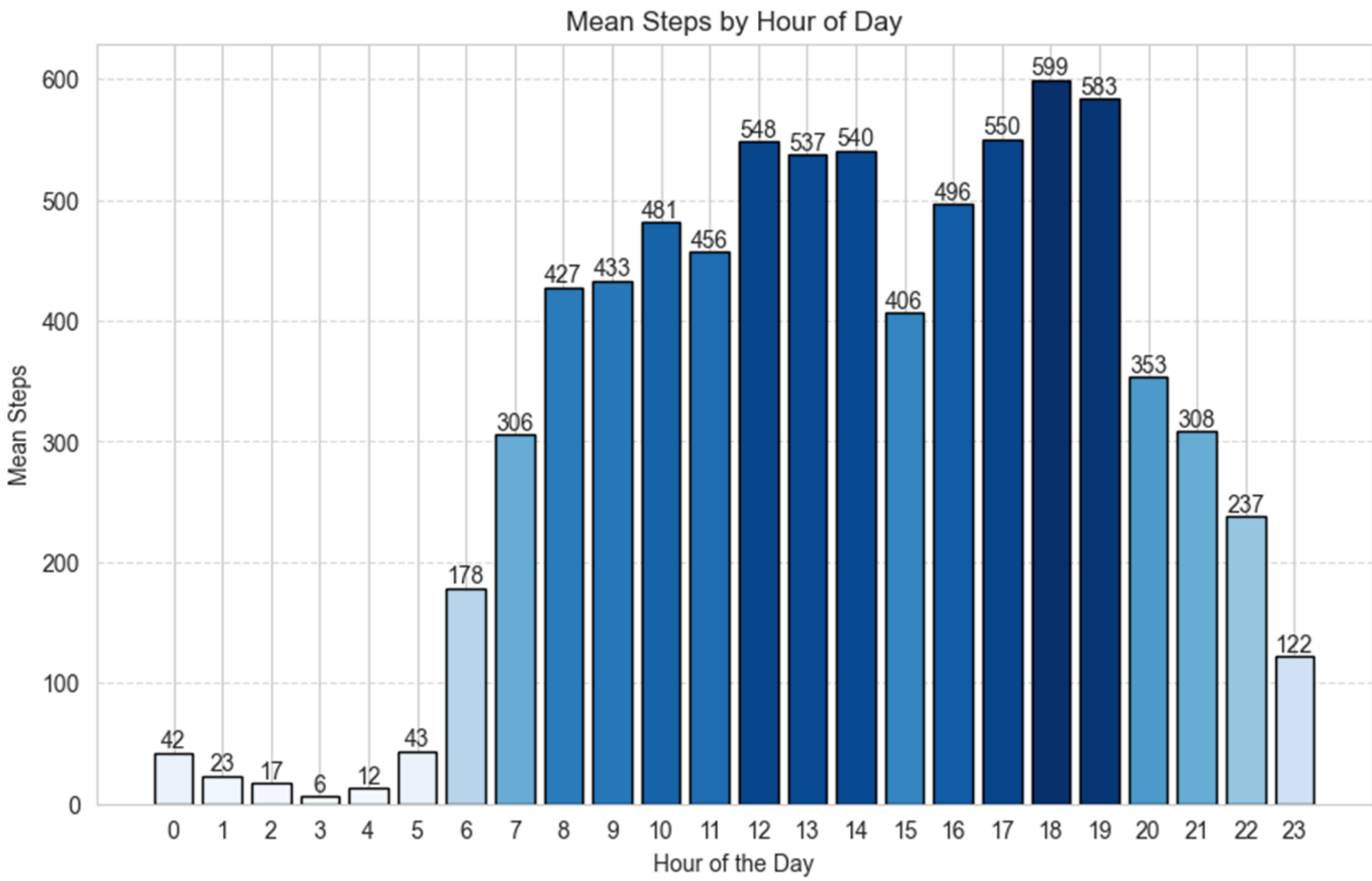
ACTIVITY ACROSS THE WEEK

- Overall, Mean TotalSteps was higher on an average weekday than on the weekend.

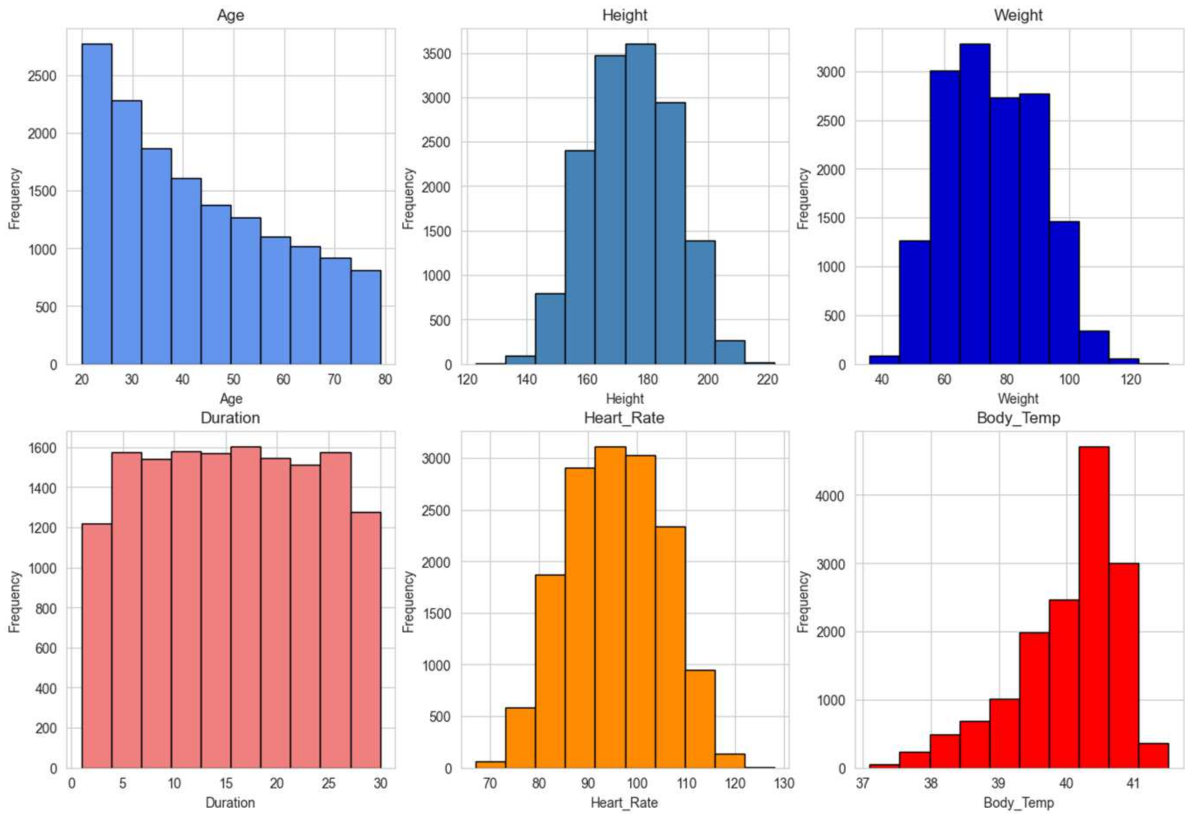


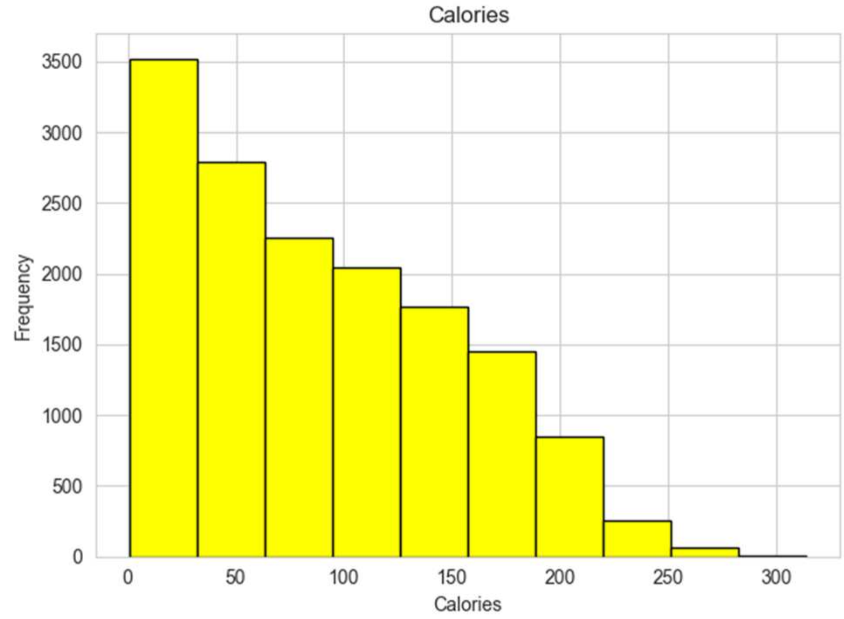
ACTIVITY ACROSS HOURS OF THE DAY

- The most active hours of the day:
- Activity (mean steps/ hour) increased from 6am, reaching peaks around lunchtime (from 12-2pm ~540 steps) and after work (5-7pm 550-599 steps), before dropping sharply at 8pm and continuing to decrease.
- There was a small amount of activity after midnight that may be attributed to restlessness/ getting out of bed. The lowest activity was at 3am.



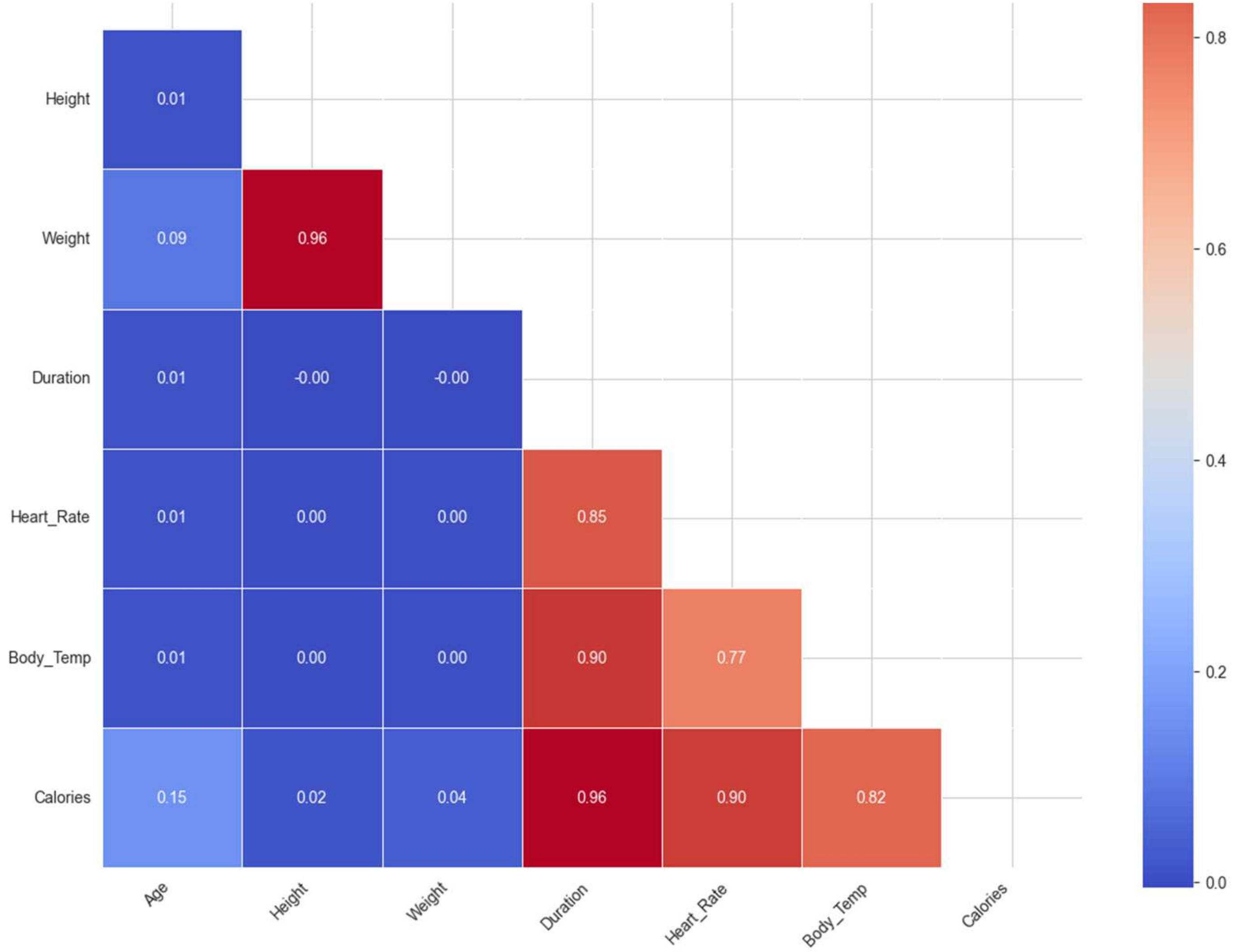
DATASET 2: DISTRIBUTIONS





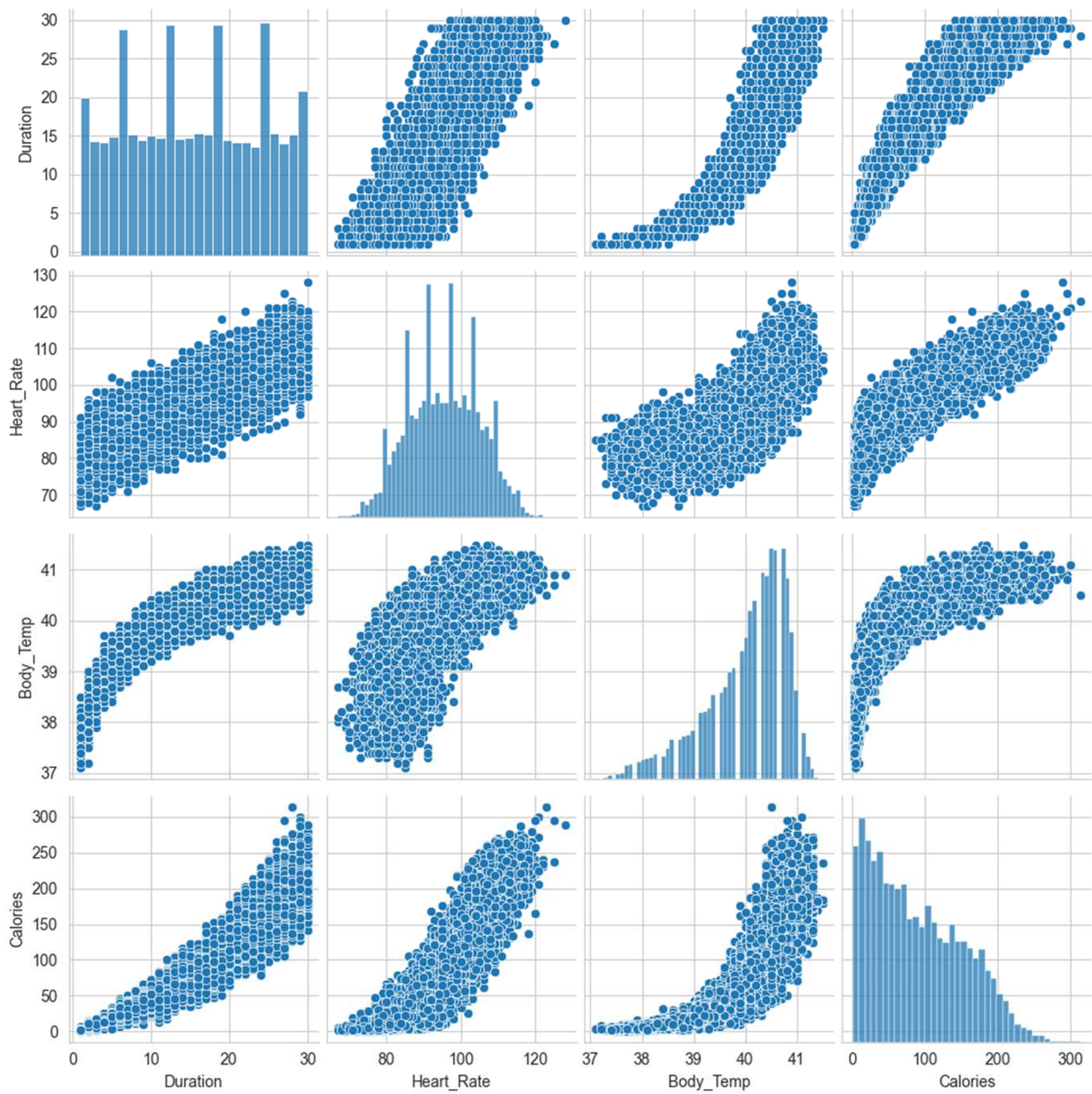
DATASET 2: EXERCISE LAB
- CORRELATIONS

- The most important metrics for predicting calories using the Exercise Lab data were:
  - **Duration** of exercise (mins)
  - skin surface **Temperature** (degrees Celsius)
  - average **Heart Rate** during exercise session(bpm).
- The other predictors (Age, Gender, Height, Weight) had significantly less impact on calculating Calories burned in an individual exercise session.



DATASET 2: EXERCISE LAB

- SCATTER MATRIX



DATASET 2: REGRESSION MODELS

- Ultimately a **polynomial model** was favoured, including all predictors but focusing on the main trio (**Duration, Body_Temp, HR**).
- **Interaction** between highly correlated variables **Height** and **Weight** was accounted for.

(Model 1) Linear model with limited features
Calories ~ Duration, Heart_Rate, Body_Temp

$$Calories = 470.35 + 6.641 \times Duration + 1.991 \times HeartRate - 16.843 \times BodyTemp$$

DATASET 2: REGRESSION MODELS

(Model 2) – Linear model with all features

Calories ~ Duration, Heart_Rate, Body_Temp, Height, Weight, Age, Gender

$$
\begin{aligned}
Calories = 463.57 + 6.640 \times Duration + 1.990 \times HeartRate - 16.982 \times BodyTemp \\
- 0.183 \times Height + 0.301 \times Weight + 0.501 \times Age - 1.268 \times Gender
\end{aligned}
$$

(Model 3) – Polynomial model with all features, and interaction between main predictors

Calories ~ Duration, Heart_Rate, Body_Temp, Height, Weight, Age, Gender

Term	Coeff
Intercept	58058.67077
Duration	494.2601214
Heart_Rate	65.93890501
Body_Temp	-4630.655015
Duration^2	0.861890428
Duration*Heart_Rate	0.305197875
Duration*Body_Temp	-25.81705582
Heart_Rate^2	-0.207564439
Heart_Rate*Body_Temp	-2.493708847
Body_Temp^2	121.9341689
Duration^3	-0.000156231
Duration^2	0.000168001
Duration^2*Body_Temp	-0.021323592
Duration*Heart_Rate^2	-0.000441785
Duration*Heart_Rate*Body_Temp	-0.002635485
Duration*Body_Temp^2	0.330006237
Heart_Rate^3	0.000132234
Heart_Rate^2*Body_Temp	0.004423207
Heart_Rate*Body_Temp^2	0.022600493
Body_Temp^3	-1.062405974
Height	-0.197387327
Weight	0.313585191
Age	0.493846064
Gender	-1.267649976

```
Calories = 58058
+494.260*D +65.939*H -4630.655*B -0.19738*H +0.31358*W +0.49384*A -1.2676*G        [linear terms]
+0.86189*D^2 +121.934B^2 -0.20756*H^2                                               [quadratic terms]
-0.00015623*D^3 -1.0624*B^3 +0.00013223*H^3                                         [cubic terms]
+0.30520*D*H -25.817*D*B -2.4937*H*B                                                [two-way interactions]
+0.00016800*D^2*H -0.021324*D^2*B -0.00044179*D*H^2 +0.33001*D*B^2 +0.0044232*H^2*B + 0.022600*H*B^2
-0.0026354*D*H*B                                                                    [three-way interaction]
```

DATASET 2: REGRESSION MODELS

(Model 4) – Simplified linear regression with limited interaction
Calories ~(Heart_rate)^3, (Duration)^2, (Body_Temp)^2, Height, Weight, Age, Gender, Height*Weight

$$\begin{aligned} Calories = & -54.9368 + 7.7773 \times 10^{-5} \times HeartRate^3 + 1.4446 \times Duration^2 \\ & + 0.079416 \times BodyTemp^2 - 0.7427 \times Height - 1.5321 \times Weight \\ & + 0.0092282 \times Height \times Weight \end{aligned}$$

- **This is the preferred model:**

model_number	RMSE	r-squared
null	61.86	
1	14.57	0.946
2	11.29	0.967
3	8.21	
4	8.92	0.980

RECOMMENDATIONS FOR FITBIT:

1. Enhance User Engagement and Motivation

- To address the high levels of sedentary behaviour, Fitbit could introduce more personalized, dynamic reminders and motivational challenges that encourage users to move more throughout the day. This could be enhanced through gamification or community challenges that leverage social motivation.
- Implement features that reward users for consistent logging and achieving daily and weekly activity goals, potentially integrating with wellness programs that offer real-world incentives.

2. Sleep and Activity Insight Integration

- Given the correlation between sleep and activity levels, Fitbit could develop more integrated insights that help users understand how improving one could beneficially impact the other. This could involve personalized advice or programs that aim to enhance both sleep quality and daily activity.

3. Advanced Feature Development

- Considering the importance of exercise duration, heart rate, and skin temperature in predicting calorie burn, future iterations of Fitbit devices should continue to refine these sensors and algorithms for even more accurate tracking.
- Invest in enhancing skin temperature tracking capabilities across all device tiers to make this feature a standard offering, given its relevance to overall health insights and calorie burn estimation.

4. Research and Development Focus

- Ongoing research into user behaviour patterns and health outcomes can inform the development of new features or improvements to existing ones. This includes exploring ways to encourage more active and less sedentary lifestyles among users.
- Collaboration with health professionals and institutions to validate the effectiveness of Fitbit's tracking capabilities and health insight recommendations.

LIMITATIONS AND FUTURE DATA COLLECTION STRATEGIES

Dataset 1 analysis was severely limited by cohort size (33) and missing demographic data. It was disappointing that the weight_log and heart rate components of this data were so incomplete, as these would have provided a stronger basis to explore the relationships of metrics with general health. BMI could have been an interesting response variable to explore and HR would have been a good predictor for Calories. It would have been interesting to study these metrics in granular data over the course of a month.

Dataset 2 was limited by lack of documentation. While demographic data on participants was available, there was not much information on how the Exercise Lab metrics were collected from participants: e.g. types of activity, lab environment, exact date of collection. This makes it difficult to generalise conclusion to different types of exercise (anaerobic vs aerobic). Given that the data was curated for education purposes, there is some uncertainty about how the model will perform on out of sample data, given the variability of unprocessed real-world data.

In future, I would opt for larger scale Fitbit studies such as LifeSnaps for more comprehensive data collection.
https://www.nature.com/articles/s41597-022-01764-x

Keep in mind that Fitbit has been acquired by Google, and thus is expected to leverage Google's resources to innovate and possibly increase its market presence.

By addressing these areas, Fitbit can improve its product offerings, engage users more effectively, and enhance its position as a leader in personalized health and fitness tracking