Bellabeat Case Study

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Bellabeat Marketing Stragey/Analysis

Project Introduction

This project contains one of two case studies of Google's Data Analytics Professional Certification provided by Google. The requirements for the case study are for the analyst to do data analysis using FitBit Fitness Tracker data to provide high-level marketing strategy recommendations for Bellabeat through the process of Ask, Prepare, Process, Analyst, Share, and Act process.

Bellabeat is a high-tech company that manufactures health-focused innovative products like an app, Leaf (bracelet), Time (watch), and Spring (water bottle). The company also provides subscription services or membership programs for users to have 24/7 access to their fully personalized guidance on nutrition, activity, sleep, health and beauty, and mindfulness-based on their lifestyle and goals.

Business Task

Bellabeat, being a successful small tech company, can become a prominent player in the global smart device market, with smart devices becoming a big part of people's lives. Bellabeat will significantly benefit from the insight of smart devices usage trends to make data-driven decisions for growth and opportunities.

The project goal is to find out how to apply appropriate marketing strategies for Bellabeat's wellness smart devices by analyzing the usage of non-Bellabeat devices. Then, find user's key patterns and relationships, and trends with a final deliverable of high-level marketing recommendations based on critical findings.

Objective

- What are some trends in smart device usage?
- How could these trends apply to Bellabeat customers?
- How could these trends help influence Baellabeat marketing strategy?

Prepare and Process

Where is the data stored?

- The data being used is the Fitbit Fitness Tracker Data (CC0: Public Domain, data set made available through Mobius) stored on Kaggle.

How is the data organized? Is it in long or wide format?

- The 18 data sets that are provided are organized in both long and wide format as a .csv file. The long-formatted data sets will be primarily used.

Are there issues with bias or credibility in this data? Does your data ROCCC (Reliable, Original, Comprehensive, Current, Cited)?

- Reliability: Low - The data sets collected consisted of only 30 individuals who are anonymous with only the assumption that the majority of data collected are of the female gender.
- Originality: Low - The data sets were generated by respondents to a distributed survey via Amazon Mechanical Turk.
- Comprehensive: Medium- The data sets contain daily, hourly, and minutes of calories burned, activity intensity, number of steps, sleep duration, and weight information.
- Current: Medium - The data sets are 5 years old, but significant changes in a person's life may vary depending on a person's life events, habits, or routines. Data are recorded from 2016, March 12th to 2016, May 13th (3 months period).
- Cited: Medium - The data collection and source were well documented.

How are you addressing licensing, privacy, security, and accessibility?

- The data sets are made available through Mobius stored on Kaggle and under the CC0 Public Domain license, which meant that the provider/creator waived their right to their work under the copyright law. As for the surveyor who provided their health data.

How did you verify the data's integrity? * We will be using R programming to check and change if needed for unique ID

Import library needed:

```
#install.packages("tidyverse")
#install.packages("ids")
#install.packages("gridExtra")
library(tidyverse)
library(lubridate)
library(skimr)
library(janitor)
library(ids)
library(gridExtra)
```

CSV files being used:

- dailyActivity_merged.csv
- heartrate_seconds_merged.csv
- sleepDay_merged.csv
- weightLogInfo_merged.csv
- 25.csv
- ACTIVITY_1599810432505.csv
- SLEEP_1599810433552.csv
- HEARTRATE_AUTO_1599810433761.csv

Importing/Read .csv datasets into dataframes:

```
daily_activity = read.csv("~/Case_Study_bellabeat/Fitabase Data 4.12.16-5.12.16/dailyActivity_merged.csv
heart_rate_seconds = read.csv("~/Case_Study_bellabeat/Fitabase Data 4.12.16-5.12.16/heartrate_seconds_me
sleep_day = read.csv("~/Case_Study_bellabeat/Fitabase Data 4.12.16-5.12.16/sleepDay_merged.csv")
weight_log = read.csv("~/Case_Study_bellabeat/Fitabase Data 4.12.16-5.12.16/weightLogInfo_merged.csv")
fitness_trend = read.csv("~/Case_Study_bellabeat/25.csv")
activity_log = read.csv("~/Case_Study_bellabeat/ACTIVITY/ACTIVITY_1599810432505.csv")
sleep_log = read.csv("~/Case_Study_bellabeat/SLEEP/SLEEP_1599810433552.csv")
heartrate_auto_log = read.csv("~/Case_Study_bellabeat/HEARTRATE_AUTO/HEARTRATE_AUTO_1599810433761.csv")
```

Processing/checking Heart Rate Data set

```
#checking data quality of the original
head(heart_rate_seconds)
```

```
##           Id                 Time Value
## 1 2022484408 4/12/2016 7:21:00 AM    97
## 2 2022484408 4/12/2016 7:21:05 AM   102
## 3 2022484408 4/12/2016 7:21:10 AM   105
## 4 2022484408 4/12/2016 7:21:20 AM   103
## 5 2022484408 4/12/2016 7:21:25 AM   101
## 6 2022484408 4/12/2016 7:22:05 AM    95
```

```
skim_without_charts(heart_rate_seconds)
```

Table 1: Data summary

Name	heart_rate_seconds
Number of rows	2483658
Number of columns	3
Column type frequency:	
character	1
numeric	2
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
Time	0	1	19	21	0	961274	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
Id	0	1	5.513765e+09	1950223761.[illegible]	2022484408	4388161847	5553957443	6962181067	8877689391

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
Value	0	1	7.733000e+01	19.4	36	63	73	88	203

```
anyNA(heart_rate_seconds)
```

```
## [1] FALSE
```

```
anyDuplicated(heart_rate_seconds)
```

```
## [1] 0
```

```
#cleaning/confirming data for quality to be place in a dataset that will be used for analysis
heart_rate_sec = heart_rate_seconds %>%
  clean_names() %>%
  distinct() %>%
  mutate(time = parse_date_time(time, "%m/%d/%Y %I:%M:%S %p")) %>%
  separate(col = time,
           into = c("date", "time"), sep = " ") %>%
  mutate(date = as.Date(date),
         time = format(strptime(time, "%H:%M:%S"), "%H")) %>%
  rename(heart_rate = value) %>%
  group_by(id, date, time) %>%
  summarize(heart_rate = mean(heart_rate)) %>%
  arrange(id, date, time)
```

```
## `summarise()` has grouped output by 'id', 'date'. You can override using the `.groups` argument.
```

```
#final quality check
head(heart_rate_sec)
```

```
## # A tibble: 6 x 4
## # Groups:   id, date [1]
##           id date       time  heart_rate
##        <dbl> <date>     <chr>      <dbl>
## 1 2022484408 2016-04-12 07          83.2
## 2 2022484408 2016-04-12 08          68.6
## 3 2022484408 2016-04-12 09          66.4
## 4 2022484408 2016-04-12 10         107.
## 5 2022484408 2016-04-12 11          67.8
## 6 2022484408 2016-04-12 12          66.2
```

```
anyNA(heart_rate_sec)
```

```
## [1] FALSE
```

```
anyDuplicated(heart_rate_sec)
```

```
## [1] 0
```

```
#checking the second heart rate data for quality of the original
head(heartrate_auto_log)
```

```
##      ï..date  time heartRate
## 1 2019-09-13 06:53        80
## 2 2019-09-13 07:23        65
## 3 2019-09-13 09:53        51
## 4 2019-09-13 10:53        87
## 5 2019-09-13 11:23        60
## 6 2019-09-13 12:23        56
```

```
skim_without_charts(heartrate_auto_log)
```

Table 4: Data summary

Name	heartrate_auto_log
Number of rows	2430
Number of columns	3
Column type frequency:	
character	2
numeric	1
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
ï..date	0	1	10	10	0	91	0
time	0	1	5	5	0	1023	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
heartRate	0	1	68.61	20.92	47	54	62	77	150

```
anyNA(heartrate_auto_log)
```

```
## [1] FALSE
```

```
anyDuplicated(heartrate_auto_log)
```

```
## [1] 0
```

```r
#random id generator
set.seed(2430)
activity_id = sort(sample.int(2430,2430))

#cleaning/confirming data for quality to be place in a data set that will be used for analysis
heartrate_auto = heartrate_auto_log %>%
  clean_names() %>%
  distinct() %>%
  rename(date = i_date) %>%
  mutate(date = as.Date(date, "%Y-%m-%d"),
         time = substr(time, 1, 5),
         id = activity_id) %>%
  arrange(id, date, time)

#final quality check
head(heartrate_auto)
```

```
##         date  time heart_rate id
## 1 2019-09-13 06:53         80  1
## 2 2019-09-13 07:23         65  2
## 3 2019-09-13 09:53         51  3
## 4 2019-09-13 10:53         87  4
## 5 2019-09-13 11:23         60  5
## 6 2019-09-13 12:23         56  6
```

```r
anyNA(heartrate_auto)
```

```
## [1] FALSE
```

```r
anyDuplicated(heartrate_auto)
```

```
## [1] 0
```

Processing/checking Sleep Data set

```r
#checking data quality of the original
head(sleep_day)
```

```
##           Id              SleepDay TotalSleepRecords TotalMinutesAsleep
## 1 1503960366 4/12/2016 12:00:00 AM                 1                327
## 2 1503960366 4/13/2016 12:00:00 AM                 2                384
## 3 1503960366 4/15/2016 12:00:00 AM                 1                412
## 4 1503960366 4/16/2016 12:00:00 AM                 2                340
## 5 1503960366 4/17/2016 12:00:00 AM                 1                700
## 6 1503960366 4/19/2016 12:00:00 AM                 1                304
##   TotalTimeInBed
## 1            346
## 2            407
## 3            442
```

```
## 4             367
## 5             712
## 6             320
```

```
skim_without_charts(sleep_day)
```

Table 7: Data summary

Name	sleep_day
Number of rows	413
Number of columns	5
Column type frequency:	
character	1
numeric	4
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
SleepDay	0	1	20	21	0	31	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
Id	0	1	5.000979e+09	2.060360e+09	1503960366	3977333714	4702921684	6962181067	8792009665
TotalSleepRecords	0	1	1.120000e+00	3.450000e-01	1	1	1	1	3
TotalMinutesAsleep	0	1	4.194700e+02	1.183400e+02	58	361	433	490	796
TotalTimeInBed	0	1	4.586400e+02	1.271000e+02	61	403	463	526	961

```
anyNA(sleep_day)
```

```
## [1] FALSE
```

```
anyDuplicated(sleep_day)
```

```
## [1] 162
```

```
#cleaning/confirming data for quality to be place in a data set that will be used for analysis
sleep_d = sleep_day %>%
  distinct() %>%
  clean_names() %>%
  separate(col = sleep_day,
           into = c("sleep_day", "sleep_time"), sep = " ") %>%
```

```r
  mutate(sleep_day = as.Date(sleep_day,"%m/%d/%Y")) %>%
  rename(date = sleep_day) %>%
  mutate(time_awake = total_time_in_bed - total_minutes_asleep) %>%
  arrange(id,date) %>%
  select(-total_sleep_records, -sleep_time)

#final quality check
head(sleep_d)
```

```
##           id       date total_minutes_asleep total_time_in_bed time_awake
## 1 1503960366 2016-04-12                  327               346         19
## 2 1503960366 2016-04-13                  384               407         23
## 3 1503960366 2016-04-15                  412               442         30
## 4 1503960366 2016-04-16                  340               367         27
## 5 1503960366 2016-04-17                  700               712         12
## 6 1503960366 2016-04-19                  304               320         16
```

```r
anyNA(sleep_d)
```

```
## [1] FALSE
```

```r
anyDuplicated(sleep_d)
```

```
## [1] 0
```

```r
#checking the second sleep data for quality of the original
head(sleep_log)
```

```
##      ï..date lastSyncTime deepSleepTime shallowSleepTime wakeTime      start
## 1 2018-09-29   1538285362             0                0        0 1538245800
## 2 2018-09-30   1538396903           141              253        2 1538255880
## 3 2018-10-01   1539148718             0                0        0 1538418600
## 4 2018-10-02   1539148718            80               49        0 1538418180
## 5 2018-10-03   1539148718             0                0        0 1538591400
## 6 2018-10-04   1539148718             0                0        0 1538677800
##         stop
## 1 1538245800
## 2 1538279640
## 3 1538418600
## 4 1538425920
## 5 1538591400
## 6 1538677800
```

```r
skim_without_charts(sleep_log)
```

Table 10: Data summary

Name	sleep_log
Number of rows	538
Number of columns	7
Column type frequency:	
character	1
numeric	6
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
ï..date	0	1	10	10	0	269	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
lastSyncTime	0	1	1.558860e+09	12263513.76	1538285362	1550407001	1565672299	1569240513	1574058669
deepSleepTime	0	1	1.559000e+01	76.66	0	0	0	0	827
shallowSleepTime	0	1	2.371000e+01	94.97	0	0	0	0	878
wakeTime	0	1	1.000000e-02	0.12	0	0	0	0	2
start	0	1	1.557395e+09	12180772.36	1538245800	1546194600	1562351400	1568313000	1574015400
stop	0	1	1.557397e+09	12181880.96	1538245800	1546194600	1562351400	1568313000	1574058660

```r
anyNA(sleep_log)
```

```
## [1] FALSE
```

```r
anyDuplicated(sleep_log)
```

```
## [1] 270
```

```r
#random id generator
set.seed(269)
sleep_id = sort(sample.int(269,269))

#cleaning/confirming data for quality to be place in a dataset that will be used for analysis
sleep_l = sleep_log %>%
  distinct() %>%
  clean_names() %>%
  rename(date = i_date,
         time_awake = wake_time) %>%
  mutate(date = as.Date(date, "%Y-%m-%d"), id = sleep_id,
```

```
         total_minutes_asleep = deep_sleep_time + shallow_sleep_time,
         total_time_in_bed = total_minutes_asleep + time_awake) %>%
  select(id, date, total_minutes_asleep,
         total_time_in_bed, time_awake) %>%
  arrange(id, date)

#final quality check
head(sleep_l)
```

```
##   id       date total_minutes_asleep total_time_in_bed time_awake
## 1  1 2018-09-29                    0                 0          0
## 2  2 2018-09-30                  394               396          2
## 3  3 2018-10-01                    0                 0          0
## 4  4 2018-10-02                  129               129          0
## 5  5 2018-10-03                    0                 0          0
## 6  6 2018-10-04                    0                 0          0
```

```
anyNA(sleep_l)
```

```
## [1] FALSE
```

```
anyDuplicated(sleep_l)
```

```
## [1] 0
```

Processing/checking Weight Log Data set

```
#checking data quality of the original
head(weight_log)
```

```
##           Id                  Date WeightKg WeightPounds Fat   BMI
## 1 1503960366  5/2/2016 11:59:59 PM     52.6     115.9631  22 22.65
## 2 1503960366  5/3/2016 11:59:59 PM     52.6     115.9631  NA 22.65
## 3 1927972279  4/13/2016 1:08:52 AM    133.5     294.3171  NA 47.54
## 4 2873212765 4/21/2016 11:59:59 PM     56.7     125.0021  NA 21.45
## 5 2873212765 5/12/2016 11:59:59 PM     57.3     126.3249  NA 21.69
## 6 4319703577 4/17/2016 11:59:59 PM     72.4     159.6147  25 27.45
##   IsManualReport        LogId
## 1           True 1.462234e+12
## 2           True 1.462320e+12
## 3          False 1.460510e+12
## 4           True 1.461283e+12
## 5           True 1.463098e+12
## 6           True 1.460938e+12
```

```
anyNA(weight_log)
```

```
## [1] TRUE
```

```
anyDuplicated(weight_log)
```

```
## [1] 0
```

```
#cleaning/confirming data for quality to be place in a dataset that will be used for analysis
weight_l = weight_log %>%
  distinct() %>%
  clean_names() %>%
  mutate(date = as.Date(date, "%m/%d/%Y"), height = sqrt(weight_kg/bmi)*100) %>%
  select(-weight_pounds, -log_id, -is_manual_report, -fat) %>%
  arrange(id, date)

#final quality check
head(weight_l)
```

```
##           id       date weight_kg   bmi   height
## 1 1503960366 2016-05-02      52.6 22.65 152.3908
## 2 1503960366 2016-05-03      52.6 22.65 152.3908
## 3 1927972279 2016-04-13     133.5 47.54 167.5757
## 4 2873212765 2016-04-21      56.7 21.45 162.5840
## 5 2873212765 2016-05-12      57.3 21.69 162.5352
## 6 4319703577 2016-04-17      72.4 27.45 162.4045
```

```
anyNA(weight_l)
```

```
## [1] FALSE
```

```
anyDuplicated(weight_l)
```

```
## [1] 0
```

Processing/checking Fitness Trend Data set

```
#checking data quality of the original
head(fitness_trend)
```

```
##         date step_count mood calories_burned hours_of_sleep bool_of_active
## 1 2017-10-06       5464  200             181              5              0
## 2 2017-10-07       6041  100             197              8              0
## 3 2017-10-08         25  100               0              5              0
## 4 2017-10-09       5461  100             174              4              0
## 5 2017-10-10       6915  200             223              5            500
## 6 2017-10-11       4545  100             149              6              0
##   weight_kg
## 1        66
## 2        66
## 3        66
## 4        66
## 5        66
## 6        66
```

```
anyNA(fitness_trend)
```

```
## [1] FALSE
```

```
anyDuplicated(fitness_trend)
```

```
## [1] 0
```

```
#random id generator
set.seed(96)
fitness_id = sort(sample.int(96,96))

#cleaning/confirming data for quality to be place in a dataset that will be used for analysis
fitness_t = fitness_trend %>%
  distinct() %>%
  clean_names() %>%
  rename(total_minutes_asleep = hours_of_sleep, total_steps = step_count) %>%
  mutate(id = fitness_id,
         date = as.Date(date, "%Y-%m-%d"),
         total_minutes_asleep = total_minutes_asleep * 60) %>%
  select(-mood, -bool_of_active) %>%
  arrange(id, date)

fitness_sleep_trend = fitness_t %>%
  select(id, date, total_minutes_asleep)

fitness_weight_trend = fitness_t %>%
  select(id, date, weight_kg)

fitness_activity_trend = fitness_t %>%
  select(id, date, total_steps, calories_burned)

#final quality check
head(fitness_t)
```

```
##         date total_steps calories_burned total_minutes_asleep weight_kg id
## 1 2017-10-06        5464             181                  300        66  1
## 2 2017-10-07        6041             197                  480        66  2
## 3 2017-10-08          25               0                  300        66  3
## 4 2017-10-09        5461             174                  240        66  4
## 5 2017-10-10        6915             223                  300        66  5
## 6 2017-10-11        4545             149                  360        66  6
```

```
head(fitness_activity_trend)
```

```
##   id       date total_steps calories_burned
## 1  1 2017-10-06        5464             181
## 2  2 2017-10-07        6041             197
## 3  3 2017-10-08          25               0
## 4  4 2017-10-09        5461             174
## 5  5 2017-10-10        6915             223
## 6  6 2017-10-11        4545             149
```

```r
head(fitness_sleep_trend)
```

```
##   id       date total_minutes_asleep
## 1  1 2017-10-06                  300
## 2  2 2017-10-07                  480
## 3  3 2017-10-08                  300
## 4  4 2017-10-09                  240
## 5  5 2017-10-10                  300
## 6  6 2017-10-11                  360
```

```r
head(fitness_weight_trend)
```

```
##   id       date weight_kg
## 1  1 2017-10-06        66
## 2  2 2017-10-07        66
## 3  3 2017-10-08        66
## 4  4 2017-10-09        66
## 5  5 2017-10-10        66
## 6  6 2017-10-11        66
```

```r
anyNA(fitness_t)
```

```
## [1] FALSE
```

```r
anyNA(fitness_activity_trend)
```

```
## [1] FALSE
```

```r
anyNA(fitness_sleep_trend)
```

```
## [1] FALSE
```

```r
anyNA(fitness_weight_trend)
```

```
## [1] FALSE
```

```r
anyDuplicated(fitness_t)
```

```
## [1] 0
```

```r
anyDuplicated(fitness_activity_trend)
```

```
## [1] 0
```

```r
anyDuplicated(fitness_sleep_trend)
```

```
## [1] 0
```

```r
anyDuplicated(fitness_weight_trend)
```

```
## [1] 0
```

Processing/checking Activities Data set

```r
#checking data quality of the original
head(daily_activity)
```

```
##           Id ActivityDate TotalSteps TotalDistance TrackerDistance
## 1 1503960366    4/12/2016      13162          8.50            8.50
## 2 1503960366    4/13/2016      10735          6.97            6.97
## 3 1503960366    4/14/2016      10460          6.74            6.74
## 4 1503960366    4/15/2016       9762          6.28            6.28
## 5 1503960366    4/16/2016      12669          8.16            8.16
## 6 1503960366    4/17/2016       9705          6.48            6.48
##   LoggedActivitiesDistance VeryActiveDistance ModeratelyActiveDistance
## 1                        0               1.88                     0.55
## 2                        0               1.57                     0.69
## 3                        0               2.44                     0.40
## 4                        0               2.14                     1.26
## 5                        0               2.71                     0.41
## 6                        0               3.19                     0.78
##   LightActiveDistance SedentaryActiveDistance VeryActiveMinutes
## 1                6.06                       0                25
## 2                4.71                       0                21
## 3                3.91                       0                30
## 4                2.83                       0                29
## 5                5.04                       0                36
## 6                2.51                       0                38
##   FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes Calories
## 1                  13                  328              728     1985
## 2                  19                  217              776     1797
## 3                  11                  181             1218     1776
## 4                  34                  209              726     1745
## 5                  10                  221              773     1863
## 6                  20                  164              539     1728
```

```r
anyNA(daily_activity)
```

```
## [1] FALSE
```

```r
anyDuplicated(daily_activity)
```

```
## [1] 0
```

```r
#cleaning/confirming data for quality to be place in a dataset that will be used for analysis
activity_d = daily_activity %>%
  distinct() %>%
```

```
  clean_names() %>%
  rename(date = activity_date, calories_burned = calories) %>%
  mutate(date = as.Date(date, "%m/%d/%Y")) %>%
  #mutate(avg_active_min = fairly_active_minutes + lightly_active_minutes + sedentary_minutes +
                                 #very_active_minutes) %>%
  select(-tracker_distance, -logged_activities_distance, -moderately_active_distance,
         -light_active_distance, -sedentary_active_distance,
         -fairly_active_minutes, -lightly_active_minutes, -sedentary_minutes, -very_active_minutes) %>%
  arrange(id, date)

#final quality check
head(activity_d)
```

```
##           id       date total_steps total_distance very_active_distance
## 1 1503960366 2016-04-12       13162           8.50                 1.88
## 2 1503960366 2016-04-13       10735           6.97                 1.57
## 3 1503960366 2016-04-14       10460           6.74                 2.44
## 4 1503960366 2016-04-15        9762           6.28                 2.14
## 5 1503960366 2016-04-16       12669           8.16                 2.71
## 6 1503960366 2016-04-17        9705           6.48                 3.19
##   calories_burned
## 1            1985
## 2            1797
## 3            1776
## 4            1745
## 5            1863
## 6            1728
```

```
anyNA(activity_d)
```

```
## [1] FALSE
```

```
anyDuplicated(activity_d)
```

```
## [1] 0
```

```
#checking the second Activity data for quality of the original
head(activity_log)
```

```
##      ï..date lastSyncTime steps distance runDistance calories
## 1 2018-09-29   1538285362  8017     5341          65      157
## 2 2018-09-30   1538396903  4002     2717         127       86
## 3 2018-10-01   1539148718  2379     1484         123       47
## 4 2018-10-02   1539148718     0        0           0        0
## 5 2018-10-03   1539148718  8051     5501         182      165
## 6 2018-10-04   1539148718  6504     4443         195      136
```

```
anyNA(activity_log)
```

```
## [1] FALSE
```

```r
anyDuplicated(activity_log)
```

```
## [1] 270
```

```r
#generating random id number
set.seed(269)
activity_id = sort(sample.int(269, 269))

#cleaning/confirming data for quality to be place in a dataset that will be used for analysis
activity_l = activity_log %>%
  distinct() %>%
  clean_names() %>%
  rename(date = i_date, calories_burned = calories, very_active_distance = run_distance,
         total_steps = steps, total_distance = distance) %>%
  mutate(date = as.Date(date, "%Y-%m-%d"),
         total_distance = total_distance / 1000,
         very_active_distance = very_active_distance / 1000,
         id = c(activity_id)) %>%
  select(-last_sync_time) %>%
  arrange(id, date)

#final quality check
head(activity_l)
```

```
##         date total_steps total_distance very_active_distance calories_burned id
## 1 2018-09-29        8017          5.341                0.065             157  1
## 2 2018-09-30        4002          2.717                0.127              86  2
## 3 2018-10-01        2379          1.484                0.123              47  3
## 4 2018-10-02           0          0.000                0.000               0  4
## 5 2018-10-03        8051          5.501                0.182             165  5
## 6 2018-10-04        6504          4.443                0.195             136  6
```

```r
anyNA(activity_l)
```

```
## [1] FALSE
```

```r
anyDuplicated(activity_l)
```

```
## [1] 0
```

Analyze & Share

Binding all the data set together into activity, sleep, heartrate, weight

```r
activity = bind_rows(activity_d, activity_l, fitness_activity_trend)
sleep = bind_rows(sleep_d, sleep_l, fitness_sleep_trend)
heartrate = rbind(heart_rate_sec, heartrate_auto)
weight = bind_rows(fitness_weight_trend, weight_l)
```

```r
paste("The number of unique IDs in Activity dataset =",n_unique(activity$id))
```

```
## [1] "The number of unique IDs in Activity dataset = 302"
```

```r
paste("The number of unique IDs in Sleep dataset =", n_unique(sleep$id))
```

```
## [1] "The number of unique IDs in Sleep dataset = 293"
```

```r
paste("The number of unique IDs in Heartrate dataset =", n_unique(heartrate$id))
```

```
## [1] "The number of unique IDs in Heartrate dataset = 2444"
```

```r
paste("The number of unique IDs in Weight dataset =", n_unique(weight$id))
```

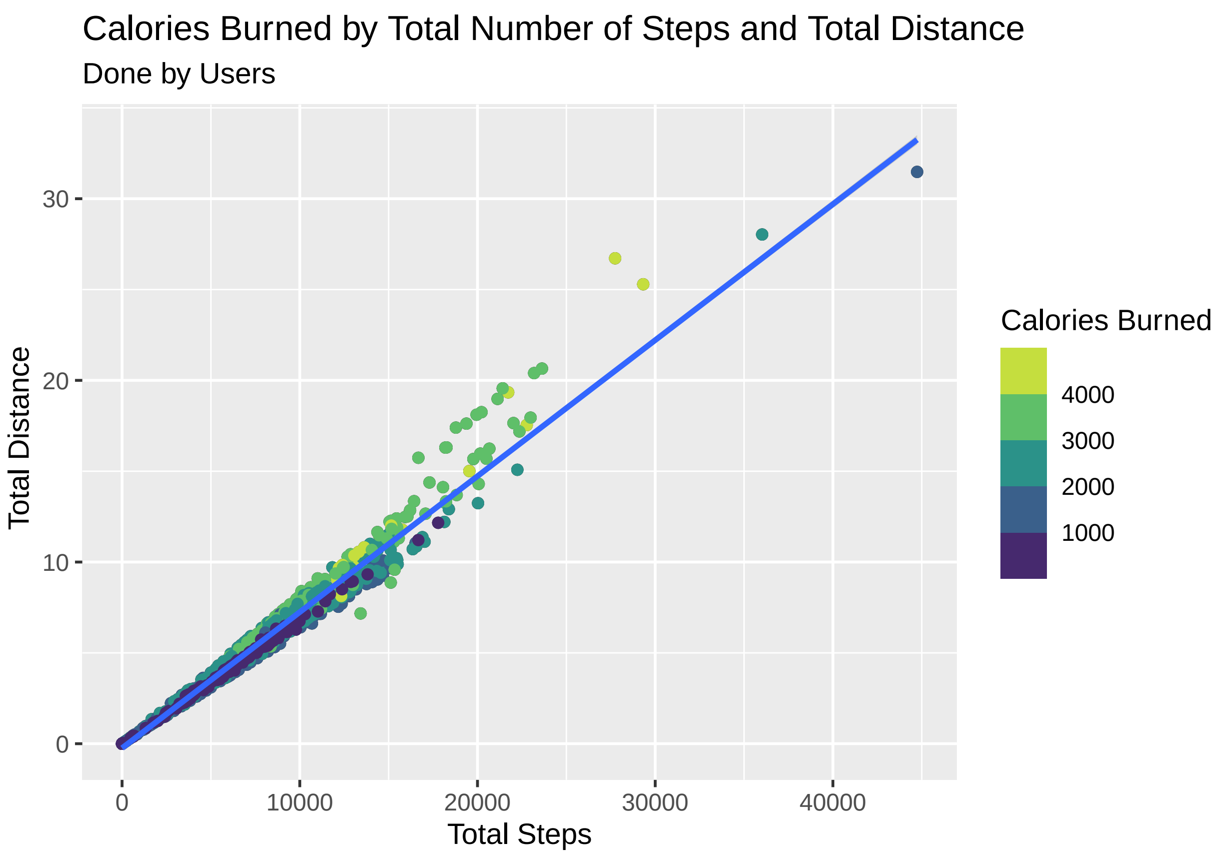
```
## [1] "The number of unique IDs in Weight dataset = 104"
```

Visualization

Calories Burned by Total Number of Steps and Total Distance

```r
ggplot(activity, aes(total_steps, total_distance))+
  geom_jitter() +
  geom_point(aes(color = calories_burned)) +
  scale_color_viridis_b(name = "Calories Burned") +
  stat_smooth(method = lm) +
  labs(title = "Calories Burned by Total Number of Steps and Total Distance",
       subtitle = "Done by Users", x = "Total Steps", y = " Total Distance")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



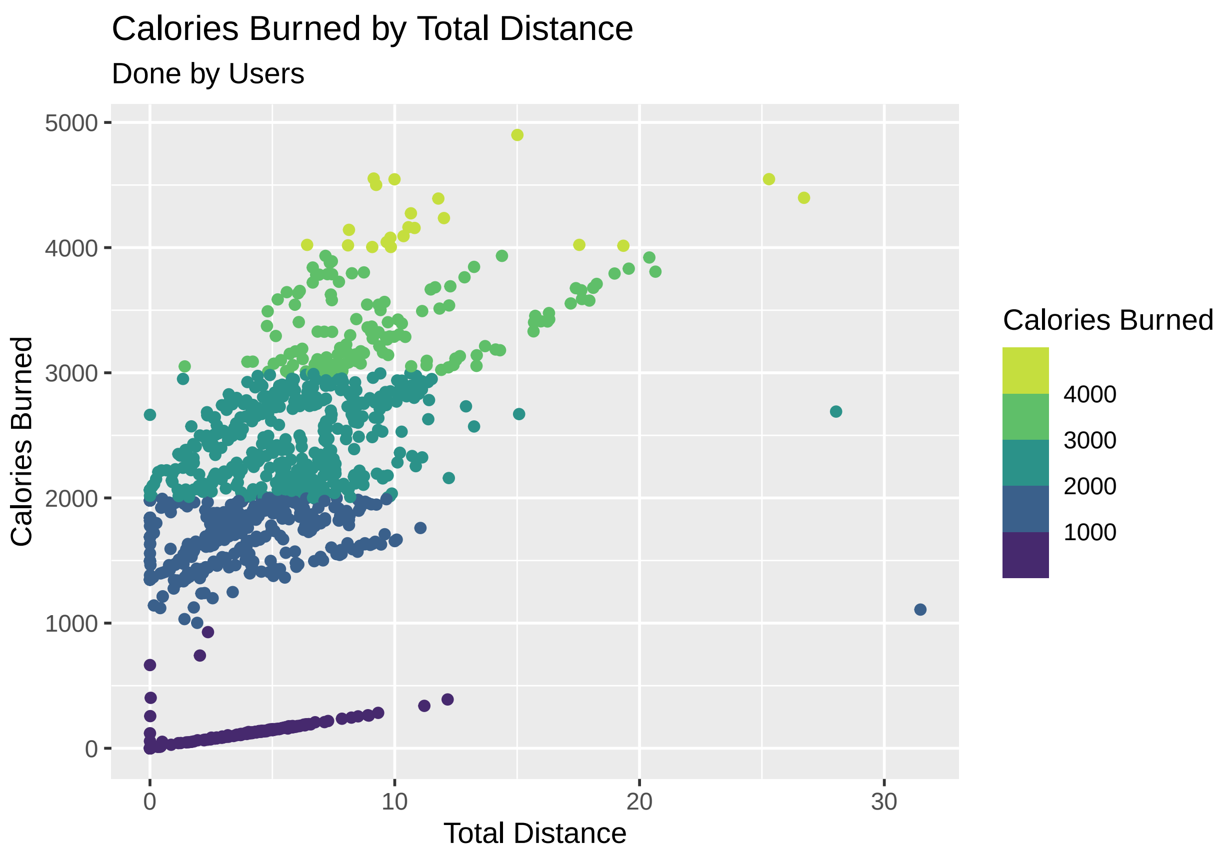

```
ggsave("calories_burned_by_total_steps.png")
```

```
## Saving 6.5 x 4.5 in image
## `geom_smooth()` using formula 'y ~ x'
```

Finding: There is a strong correlation of total steps taken with the total distance taken regarding data relation. Along with calories burned, more steps and distance have been taken.

Total Distance to Calories Burned

```
ggplot(data = activity, aes(x = total_distance, y = calories_burned)) +
  geom_point(aes(color = calories_burned)) +
  scale_color_viridis_b(name = "Calories Burned") +
  labs(title = "Calories Burned by Total Distance", subtitle = "Done by Users",
       x = "Total Distance", y = "Calories Burned")
```




```
ggsave("calories_burned_by_total_distance.png")
```

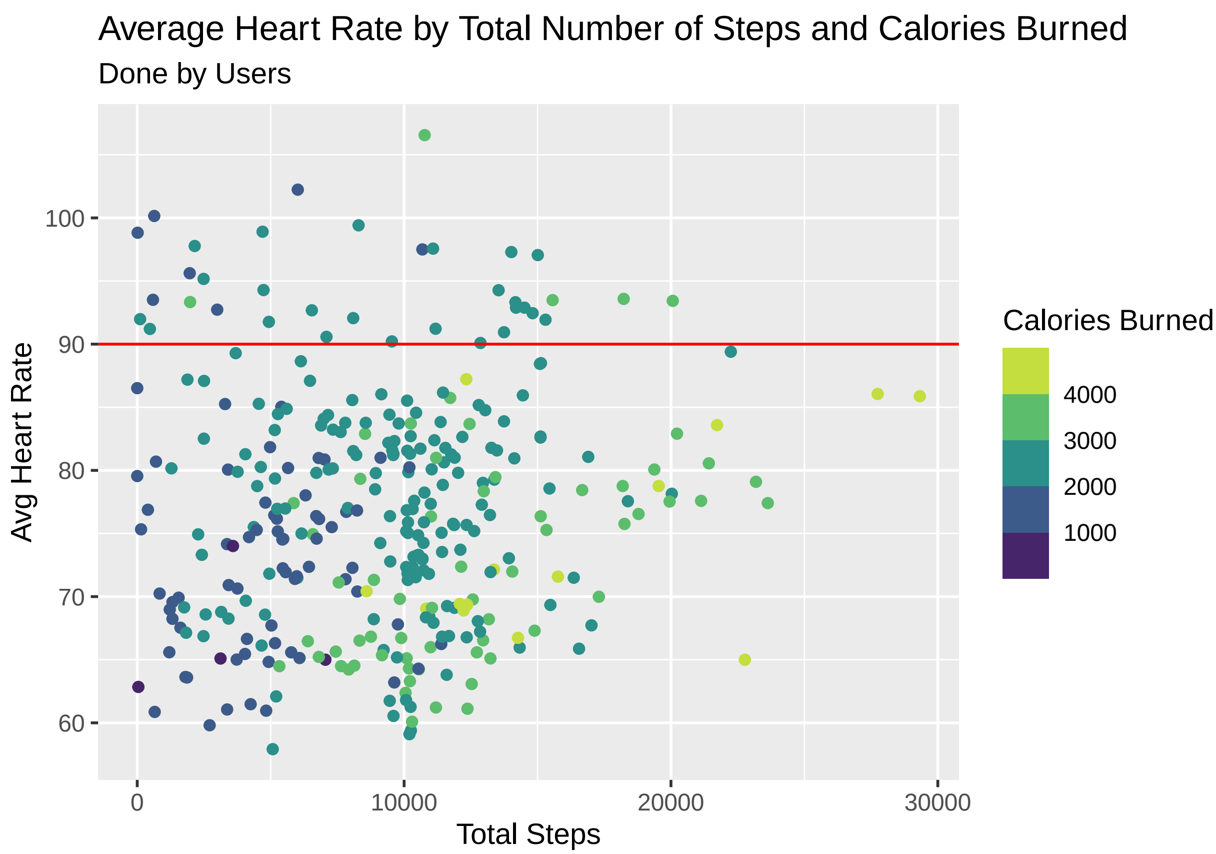
```
## Saving 6.5 x 4.5 in image
```

Finding: Strong indication of two different user base. 1. This user base is a power user who burns calories as intended by the distance taken. 2. This user base takes the most minimal distance to burn calories. However, these two segments are pretty disproportionate.

Average Heart Rate by Total Number of Steps and Calories Burned

```
heartrate %>%
  summarise(avg_heart_rate = mean(heart_rate)) %>%
  merge(activity, all = TRUE) %>%
  drop_na() %>%
  ggplot(aes(x = total_steps, y = avg_heart_rate)) +
  geom_point(aes(color = calories_burned)) +
  geom_hline(aes(yintercept = 90), color = "red") +
  scale_color_viridis_b(name = "Calories Burned") +
  labs(title = "Average Heart Rate by Total Number of Steps and Calories Burned",
       subtitle = "Done by Users", x = "Total Steps", y = "Avg Heart Rate")
```

```
## `summarise()` has grouped output by 'id'. You can override using the `.groups` argument.
```



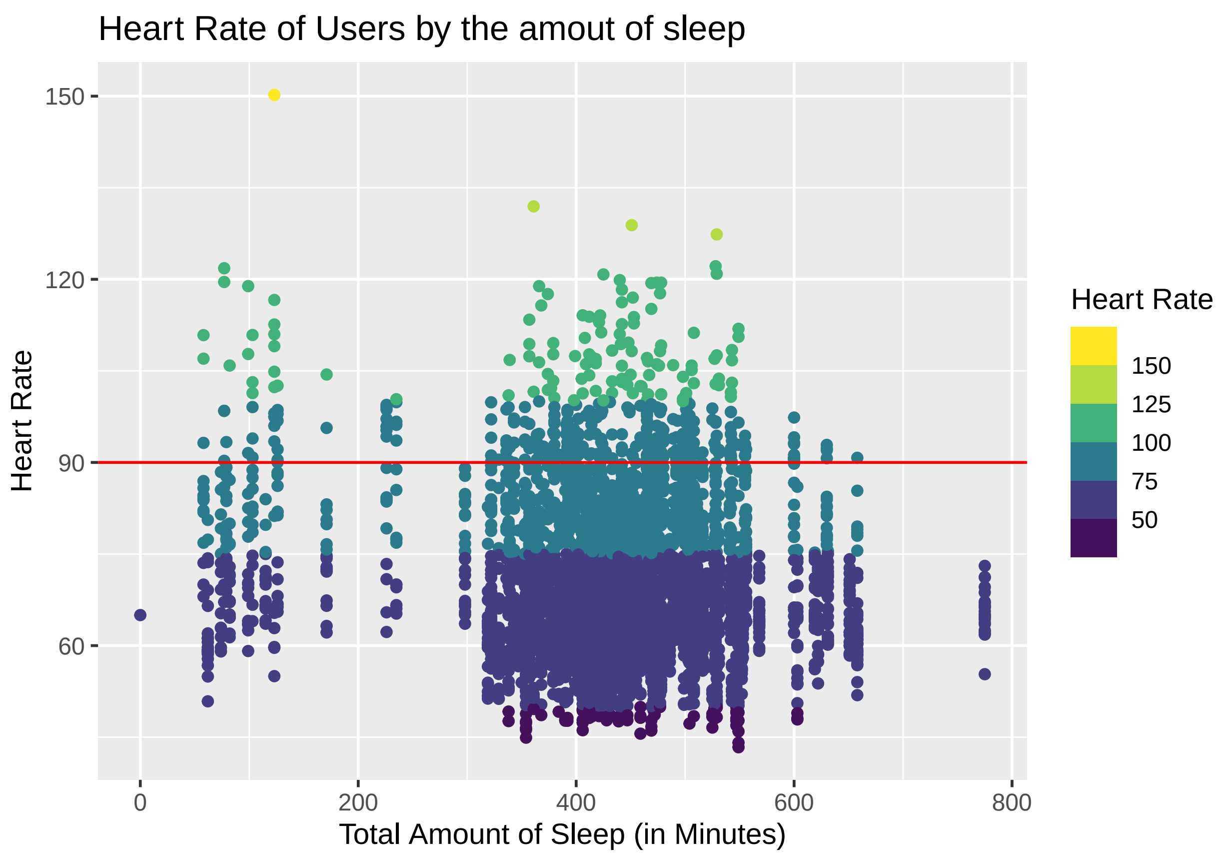

```
ggsave("avg_hear_rate_by_total_steps.png")
```

```
## Saving 6.5 x 4.5 in image
```

Findings: On average, most users' heart rate is not intensely high (below 90) to burn large amounts of calories with many steps.

Heart Rate of Users by the amount of Sleep

```
heartrate %>%
  #summarise(avg_heart_rate = mean(heart_rate)) %>%
  # The above line could be added to look at the average heart rate
  merge(sleep, all = TRUE) %>%
  drop_na() %>%
  ggplot(aes(x = total_minutes_asleep, y = heart_rate)) +
  geom_point(aes(color = heart_rate)) +
  geom_hline(aes(yintercept = 90), color = "red") +
  scale_color_viridis_b(name = "Heart Rate") +
  labs(title = "Heart Rate of Users by the amout of sleep",
       x = "Total Amount of Sleep (in Minutes)", y = "Heart Rate")
```




```
ggsave("heart_rate_by_sleep_amount.png")
```

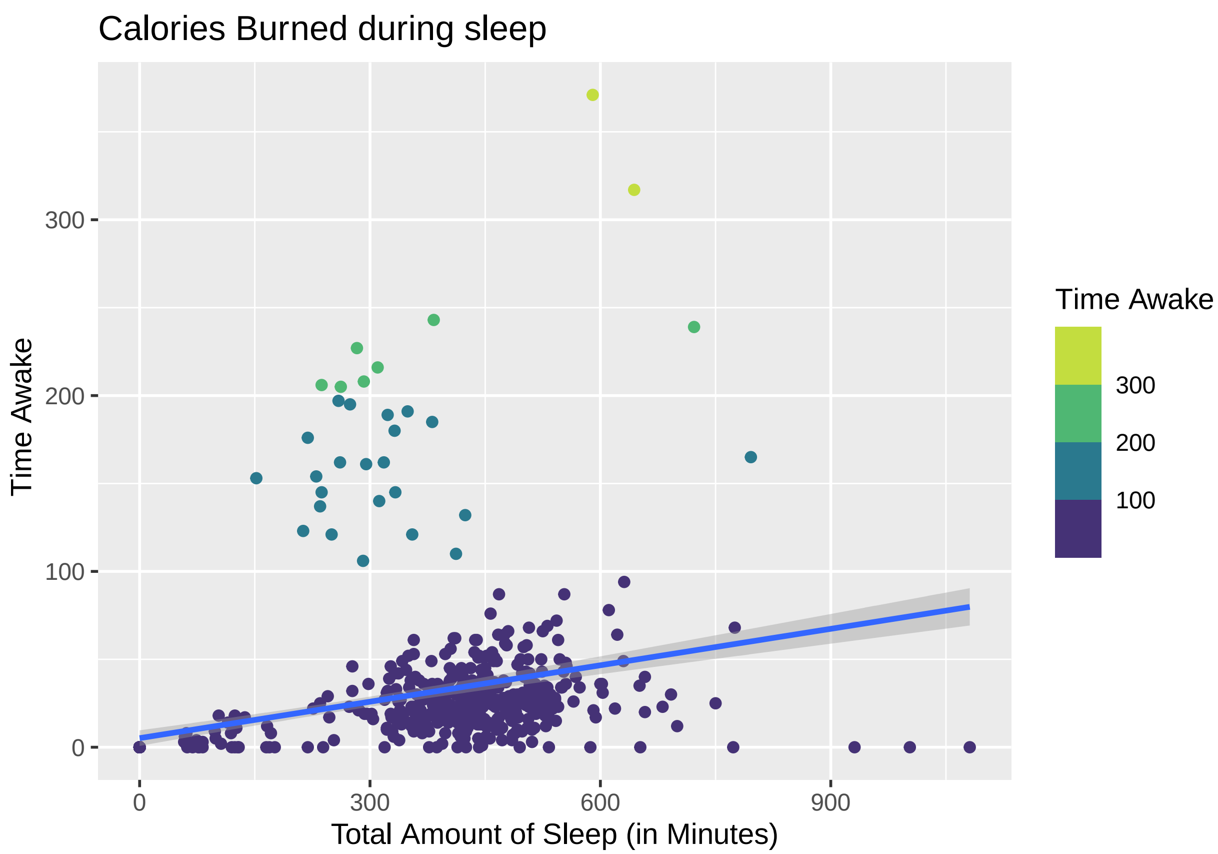
```
## Saving 6.5 x 4.5 in image
```

Finding: Most people who track their sleep data generally have low heart rates as expected but have some outliers with heart rates unusually high, which could be false reading when a tracker is not equipped correctly.

Calories Burned during Sleep

```
ggplot(data = sleep, aes(x = total_minutes_asleep, y = time_awake)) +
  geom_point(aes(color = time_awake)) +
  stat_smooth(method = lm, size = 1) +
  scale_color_viridis_b(name = "Time Awake") +
  labs(title = "Calories Burned during sleep",
       x = "Total Amount of Sleep (in Minutes)", y = " Time Awake")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



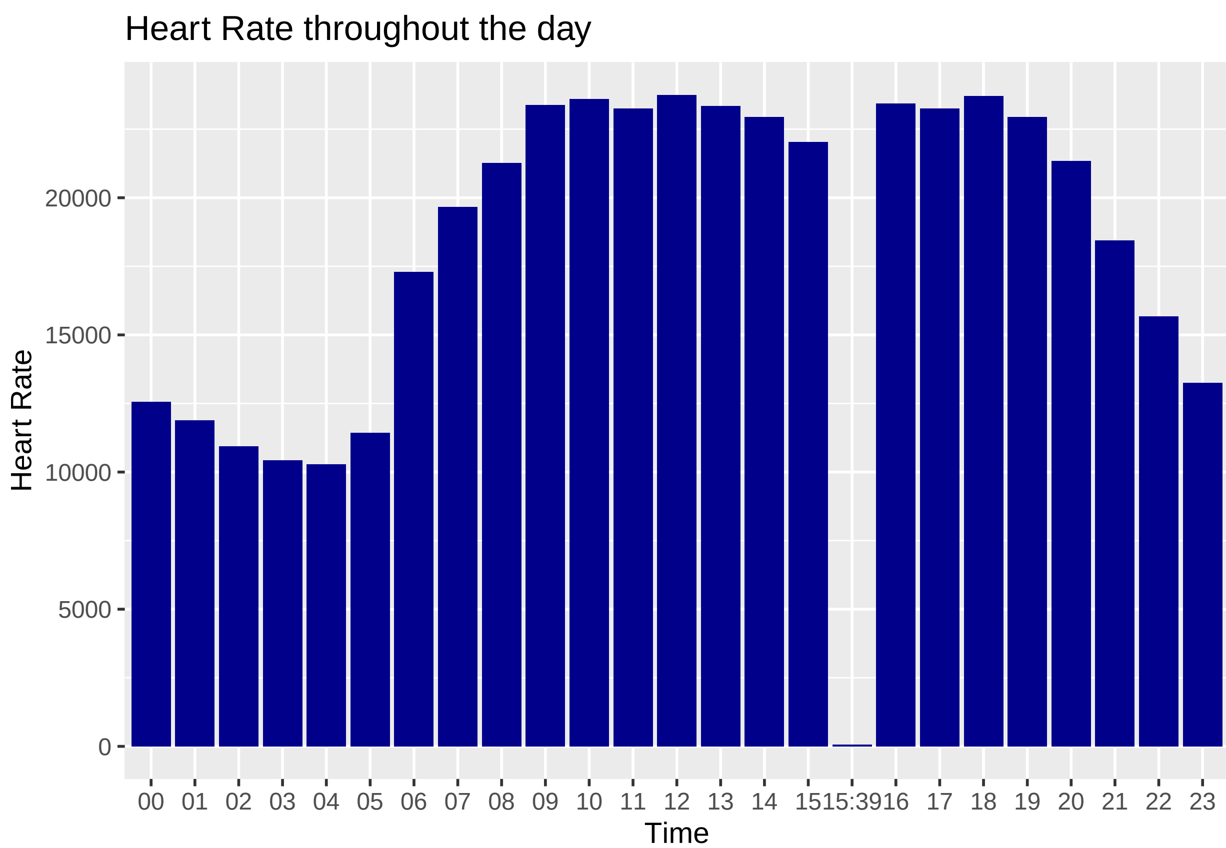

```
ggsave("calories_burned_during_sleep.png")
```

```
## Saving 6.5 x 4.5 in image
## `geom_smooth()` using formula 'y ~ x'
```

Finding: A good indication that people generally stay asleep and do not wake up very much.

Heart Rate throughout the day

```
heartrate %>%
  merge(activity, all = TRUE) %>%
  drop_na() %>%
  ggplot(aes(x = time, y = heart_rate)) +
  geom_col(fill = "darkblue") +
  labs(title = "Heart Rate throughout the day",
       x = "Time", y = "Heart Rate")
```




```
ggsave("heart_rate_in_a_day.png")
```

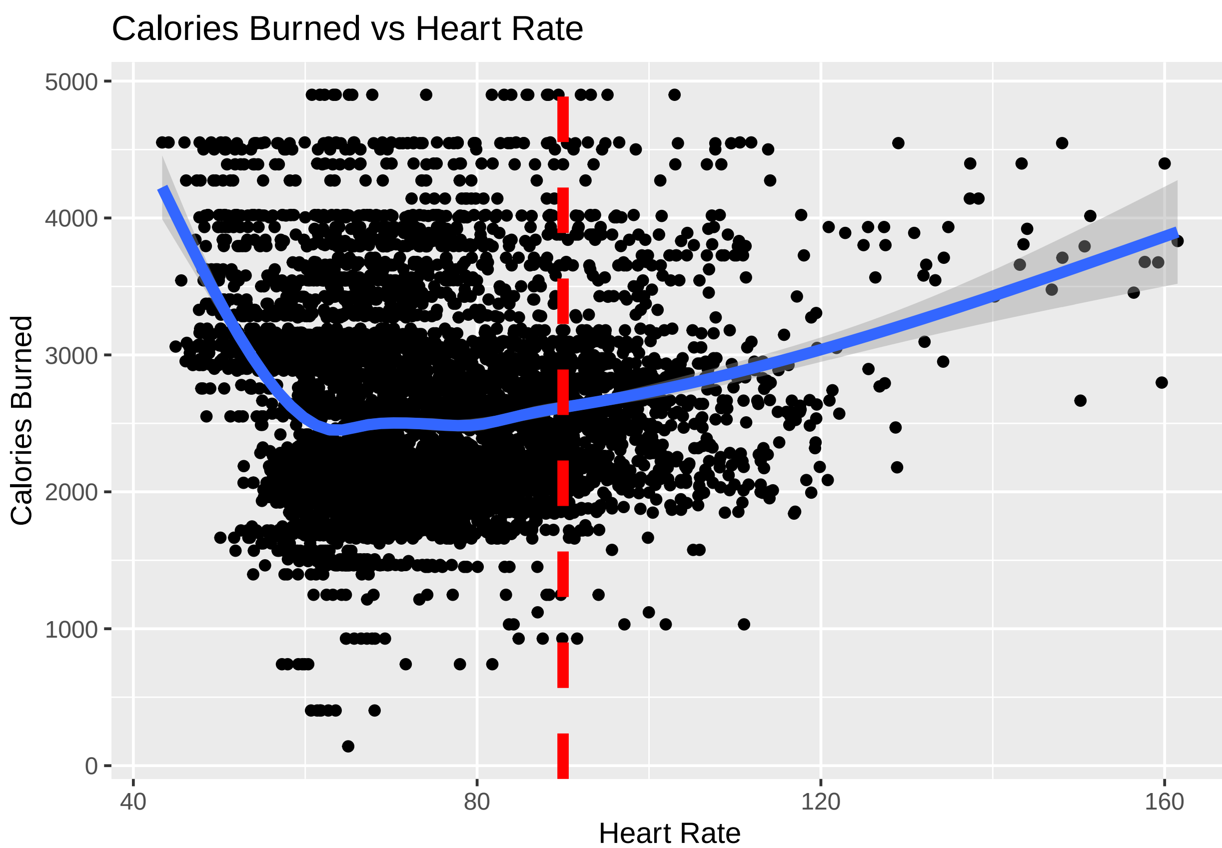
```
## Saving 6.5 x 4.5 in image
```

Finding: People are generally active throughout the day, but one discrepancy the graph inputted a time of 15:39.

Calories Burned vs Heart Rate

```
heartrate %>%
  #summarise(avg_heart_rate = mean(heart_rate)) %>%
  merge(activity, all = TRUE) %>%
  drop_na() %>%
  ggplot(aes(x = heart_rate, y = calories_burned)) +
  geom_point() +
  geom_smooth(size = 2) +
  geom_vline(aes(xintercept = 90), color = "red", size = 2, linetype = "dashed") +
  labs(title = "Calories Burned vs Heart Rate",
       x = "Heart Rate", y = "Calories Burned") +
  theme(legend.position = "none")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```




```
ggsave("calories_burned_vs_heart_rate.png")
```

```
## Saving 6.5 x 4.5 in image
## 'geom_smooth()' using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

Finding: There is an indication that shows that more calories are burned with increased heart rate. However, this also indicates that most users have a heart rate of less than 100 that burns between 2000 to 3000 calories. So it seems like users have moderate activities throughout the day, as previously shown as well.

Other findings:

For starters, not all users are consistent in tracking their daily activities, and some false readings if the health tracking device is not equipped correctly.

Many users do not take enough steps or walked further enough distance to burn significant calories. Users do not generally wear fitness trackers for 24 hours straight.

There is no record of tracking REM sleep other than the basic tracking of the amount of time asleep with a large number of users have relatively low heart rate when asleep.

Most people fall between 5 to 8 hours of sleep range.

Fitbit does not collect hydration data, which Bellabeat water bottle could.

Data shows that people track calories, heart rate, steps taken, and distance taken more than sleep data. Weight is even further less recorded.

An active person has a positive relation to sleep quality with the indication of low heart rate.

Summary:

Many users mainly track their heart rate, steps, distance, and calories burned based on the data collected. Users are burning more calories as their heart rate increases, steps increases, and distance increases as expected with strong correlation. However, there are also strong indications of two different user bases where one shows more activities that are more in line with the high number of steps and distances corresponding to high calories burned. As for the second user base, they do the most minimal activities to burn calories. Furthermore, users generally do less than 20,000 steps averaging a low heart rate, or less than 90, to burn calories. Lastly, keep in mind that the data from Fitbit does not collect hydration data that Bellabeat can leverage on, users do not wear their smart tracking device 24/7, and margin of error of device reading due to the device not being equipped correctly. Overall, base on the data, users do relatively moderate activities to hit their wellness goals that require less than 100 beats per minute heart rate to burn calories with low heart rate during a 5 to 8 hours sleep period.

Act

Limitation

As previously mentioned:

- *Reliability:* **Low** - The data sets collected consisted of only 30 individuals who are anonymous with only the assumption that the majority of data collected are of the female gender.
- *Originality:* **Low** - The data sets were generated by respondents to a distributed survey via Amazon Mechanical Turk.
- *Comprehensive:* **Medium** - The data sets contain daily, hourly, and minutes of calories burned, activity intensity, number of steps, sleep duration, and weight information.
- *Current:* **Medium** - The data sets are 5 years old, but significant changes in a person's life may vary depending on a person's life events, habits, or routines. Data are recorded from 2016, March 12th to 2016, May 13th (3 months period).
- *Cited:* **Medium** - The data collection and source were well documented.
- The data collected do not indicate the user's age in order to indicate what is the appropriate heart rate for the individual as well.

Recommendation

- Bellabeat can include functions in the Bellabeat app to alert users of their in-activity or unusual readings as timely notifications. Even a notification to indicate users to stretch their legs a little for in-activity to maintain wellness goals.
- Offer more or improved customization for users that regularly ask for the user's age, weight, height if the user chooses to input them to recommend users personalized tips to help the user achieve their wellness goals.
- Do a more targeted marketing campaign toward people who are more active, and health-conscious by showing the uniqueness of Bellabeat's products like the Spring (water bottle). For a broader marketing campaign, advertise the connection of each Bellabeat's products with getting enough activities every day, maintaining proper health and hydration, and wellness goals that other competitors can't.
- Points or rewards programs that both subscription and non-subscription-based users can earn for their activity to encourage users to continuously use Bellabeat products that they own while keeping users continue using the product to minimize forgetfulness which could potentially create brand loyalty.

Appendix

Key stakeholders:

- Urska Srsen
- Sando Mur
- Bellabeat Marketing Analytics team

All credits go to Mobius, Arooj, and Parul to provide the data sets used for this project.

Also, credit goes to Google's Data Analytics Professional Certification provided by Google with Coursera for the project/case study layout.

Citation

- Arooj Anwar Khan, "Fitness Trends Dataset." Kaggle, 2018
- Mobius, "FitBit Fitness Tracker Data." Kaggle, 2020
- Parul Garg, "MI FitBit Dataset." Kaggle, 2020, doi: 10.34740/KAGGLE/DSV/1479520.