Google Capstone Project: How Can Bellabeat, A Wellness Technology Company Play It Smart?

Step 1: ASK

Bellabeat is a high-tech manufacturer of health-focused products for women, creating awareness for their health and habits. Bellabeat has grown rapidly in recent years and has recognized itself as a tech-driven wellness company for females.

The co-founder and Chief Creative Officer, Urška Sršen is confident that an analysis of non-Bellebeat consumer data (i.e. Fitbit fitness tracker usage data) and analyzing smart device fitness data could help unlock new growth opportunities for the company which will help in improving their user incredibility and to become a larger player in the global smart device market.

Business Task

Analyse consumers' Fitbit fitness tracker usage data to gain insights and trends for improving Bellabeat's marketing strategy.

Objective

- 1. What are some trends in smart device usage?
- 2. How could these trends apply to Bellabeat customers?
- 3. How could these trends help influence Bellabeat's marketing strategy?

Deliverables

- 1. A clear summary of the business task
- 2. A description of all data sources used
- 3. Documentation of any cleaning or manipulation of data
- 4. A summary of your analysis

- 5. Supporting visualizations and key findings
- 6. Your top high-level content recommendations based on your analysis

Key Stakeholders

- Urška Sršen: Bellabeat's co-founder and Chief Creative Officer
- Sando Mur: Mathematician and Bellabeat's cofounder, a key member of the Bellabeat executive team
- Bellabeat marketing analytics team: A team of data analysts responsible for collecting, analyzing, and reporting data that helps guide Bellabeat's marketing strategy.

Step 2: PREPARE

Information on data source

Public data that explores smart device users' daily habits is used. This Kaggle data set contains a personal fitness tracker from thirty Fitbit users. It includes information about daily activity, steps, and heart rate that can be used to explore users' habits. It is stored in 18 CSV files.

Credibility of data

A good data source is ROOCCC which stands for Reliable, **O**riginal, **C**omprehensive, **C**urrent, and **C**ited.

- Reliable: Not reliable because this data only contains 30 individuals which is not a representative sample for the overall population of Fitbit users.
- **Original:** Not original as the dataset was generated by a third party i.e., respondents to a distributed survey via Amazon Mechanical Turk.
- **Comprehensive:** Comprehensive as parameters match most of Bellabeat products' parameters but having more data from more individuals would help with the overall comprehensiveness.
- **Current:** Not current as the data was collected 7 years ago and may not be relevant.
- Cited: Not cited as it is collected by a third party and the source may or may not be reliable.

Overall, the conclusion drawn is that dataset is of bad quality and not reliable. It is not recommended to produce business recommendations based on this data. However, the general insights could still prove to be useful.

Tool

I am using R for data cleaning, transformation, and visualization.

Loading Packages

```
library(tidyverse)
library(ggplot2)
library(dplyr)
library(readr)
library(tidyr)
library(skimr)
library(scales)
library(janitor)
```

Importing Datasets

```
daily_activity<- read.csv("C:\\Users\\user\\Desktop\\Fitabase Data\\
dailyActivity_Merged.csv")
weight<- read.csv("C:\\Users\\user\\Desktop\\Fitabase Data\\
weightLogInfo_merged.csv")
daily_sleep<- read.csv("C:\\Users\\user\\Desktop\\Fitabase Data\\
sleepDay_merged.csv")
```

Step 3: PREPARE

Verifying the data

>head(daily_activity)

2 3 4	1503960366 1503960366 1503960366 1503960366	4/15/2016	13162 10735 10460 9762	TotalDis	8.50 6.97 6.74 6.28	TrackerDis	8.50 6.97 6.74 6.28		/itiesDist	ance 0 0 0 0
_	1503960366	4/16/2016	12669		8.16		8.16			0
6	1503960366	, ,		_ •	6.48		6.48			0
	veryactivel	Distance Moder	ratelyactive		Light	CACTIVEDISI		SedentaryAct	tivebistan	ce
1		1.88		0.55			6.06			0
2		1.57		0.69			4.71			0
3		2.44		0.40			3.91			0
4		2.14		1.26			2.83			0
5		2.71		0.41			5.04			0
6		3.19		0.78			2.51			0
	VeryActive	Minutes Fairly	yActiveMinut	es Light	lyActi	veMinutes	Sedent	taryMinutes	Calories	
1		25		13		328		728	1985	
2		21		19		217		776	1797	
3		30		11		181		1218	1776	
4		29		34		209		726	1745	
5		36		10		221		773	1863	
6		38		20		164		539	1728	

> head(weight)

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

> head(daily_sleep)

Id	sleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed
1 1503960366 4/12/2016	12:00:00 AM	1	327	346
2 1503960366 4/13/2016	12:00:00 AM	2	384	407
3 1503960366 4/15/2016	12:00:00 AM	1	412	442
4 1503960366 4/16/2016	12:00:00 AM	2	340	367
5 1503960366 4/17/2016	12:00:00 AM	1	700	712
6 1503960366 4/19/2016	12:00:00 AM	1	304	320

> glimpse(daily_activity)

```
<db7> 1.88, 1.57, 2.44, 2.14, 2.71, 3.19, 3.25, 3.53, 1.
$ VeryActiveDistance
96, 1.34, 4...
$ ModeratelyActiveDistance <db1> 0.55, 0.69, 0.40, 1.26, 0.41, 0.78, 0.64, 1.32, 0.
48, 0.35, 1...
                           <db7> 6.06, 4.71, 3.91, 2.83, 5.04, 2.51, 4.71, 5.03, 4.
 LightActiveDistance
24, 4.65, 2.
                           $ SedentaryActiveDistance
0, 0, 0, 0,...
                           <int> 25, 21, 30, 29, 36, 38, 42, 50, 28, 19, 66, 41, 39
$ VeryActiveMinutes
 73, 31, 78...
FairlyActiveMinutes
                           <int> 13, 19, 11, 34, 10, 20, 16, 31, 12, 8, 27, 21, 5,
14, 23, 11, ...
$ LightlyActiveMinutes
                           <int> 328, 217, 181, 209, 221, 164, 233, 264, 205, 211,
130, 262, 23...
$ SedentaryMinutes
                           <int> 728, 776, 1218, 726, 773, 539, 1149, 775, 818, 838
, 1217, 732,...
$ Calories
                           <int> 1985, 1797, 1776, 1745, 1863, 1728, 1921, 2035, 17
86, 1775, 18...
```

> glimpse(weight)

```
Rows: 67
Columns: 8
                                                                        <db1> 1503960366, 1503960366, 1927972279, 2873212765, 2873212765,
 $ Id
 4319703577, ...
                                                                        <chr> "5/2/2016 11:59:59 PM", "5/3/2016 11:59:59 PM", "4/13/2016 1
 $ Date
 :08:52 AM", ...
                                                                        <db7> 52.6, 52.6, 133.5, 56.7, 57.3, 72.4, 72.3, 69.7, 70.3, 69.9,
 $ WeightKg
69.2, 69.1,...
$ WeightPounds
                                                                        <db7> 115.9631, 115.9631, 294.3171, 125.0021, 126.3249, 159.6147,
159.3942, 15...
                                                                        $ Fat
NA, NA, NA, ...
 $ BMI
                                                                        <db7> 22.65, 22.65, 47.54, 21.45, 21.69, 27.45, 27.38, 27.25, 27.4
6, 27.32, 27...
$ IsManualReport <chr> "True", "True", "False", "True", "True"
3098e+12, 1....
```

> glimpse(daily_sleep)

There are some records where the step count is zero which means not everyone was consistent in tracking their data each day and some people do not wear it for the whole month.

```
> daily_activity_new<- daily_activity%>%
+ filter(TotalSteps!=0)
> View(daily_activity_new)
```

Removing the zero steps will be a better option to improve the overall analysis.

Separating the date and time

```
> weight_new<- weight%>%
+    separate(Date,into = c("Date","Time"),sep = " ")
warning message:
Expected 2 pieces. Additional pieces discarded in 67 rows [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,
12, 13, 14, 15, 16, 17, 18, 19, 20, ...].
> daily_sleep_new<- daily_sleep%>%
+    separate(SleepDay,into = c("Date","Time"),sep = " ")
warning message:
Expected 2 pieces. Additional pieces discarded in 413 rows [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, ...].

Counting the distinct ID's in each dataset
> n_distinct(daily_activity_new$Id)
[1] 33
> n_distinct(daily_sleep_new$Id)
[1] 24
> n_distinct(weight_new$Id)
[1] 8
```

On analyzing the data we can infer that only 8 people entered their weight, only 24 people entered their sleep data, and also 33 people recorded their daily activity which contradicts the credibility of the data as the data citation says that there are only 30 people in the sample.

Now I will check if there are any duplicate records in the dataset.

```
> nrow(daily_activity_new)
[1] 863
> nrow(daily_sleep_new)
[1] 413
> nrow(weight_new)
[1] 6
> nrow(unique(daily_activity_new))
[1] 863
> nrow(unique(daily_sleep_new))
[1] 410
> nrow(unique(weight_new))
[1] 67
```

To obtain cleaner data duplicate rows should be removed from the sleep data.

```
> daily_sleep_unique <- unique(daily_sleep_new)</pre>
```

Now, the data is ready to be analyzed.

Step 4: ANALYSE

I will analyze, the data and identify the trends, relationships, and patterns in this process. It may include using statistical methods.

Pulling general statistics

8.05e+3 1.11e+4 3.60e+4 5.59e+0 7.90e+0 2.80e+1 5.59e+0 7.88e+0 2.80e+1

> skim_without_charts(daily_activity_new) — Data Summary -**Values** daily_activity_new Name Number of rows 863 Number of columns 15 Column type frequency: character 14 numeric Group variables None — Variable type: character skim_variable n_missing complete_rate min max empty n_unique whitespace 1 ActivityDate 1 8 9 31 — Variable type: numeric n_missing complete_rate sd skim_variable mean p0 p25 0 1 4.86e+9 2.42e+9 150396 <u>0</u>366 <u>2</u>320<u>127</u>002 0 1 8.32e+3 4.74e+3 2 TotalSteps <u>4</u>923 TotalDistance 0 1 5.98e+0 3.72e+0 0 3.37 TrackerDistance 1 5.96e+0 3.70e+0 n 0 3.37 0 1 1.18e-1 6.46e-1 5 LoggedActivitiesDistance 0 1 1.64e+0 2.74e+0 6 VeryActiveDistance 0 0 0 1 6.18e-1 9.05e-1 ModeratelyActiveDistance 0 0 0 1 3.64e+0 1.86e+0 8 LightActiveDistance 0 0 2.34 9 SedentaryActiveDistance 0 1 1.75e-3 7.65e-3 0 n VeryActiveMinutes 1 2.30e+1 3.36e+1 0 0 O FairlyActiveMinutes 1 1.48e+1 2.04e+1 0 11 0 1 2.10e+2 9.68e+1 LightlyActiveMinutes 0 0 146. 13 SedentaryMinutes 0 1 9.56e+2 2.80e+2 0 722. 0 1 2.36e+3 7.03e+2 14 Calories 52 <u>1</u>856. p50 p75 4.45e+9 6.96e+9 8.88e+9

```
5 0
                      4.94e+0
             0
   4.10e-1 2.27e+0 2.19e+1
   3.10e-1 8.65e-1 6.48e+0
   3.58e+0 4.89e+0 1.07e+1
                      1.10e-1
        e+0 3.5 e+1 2.1 e+2
        e+0 2.1 e+1 1.43e+2
12 2.08e+2 2.72e+2 5.18e+2
   1.02e+3 1.19e+3 1.44e+3 2.22e+3 2.83e+3 4.9 e+3
> skim_without_charts(daily_sleep_unique)
- Data Summary -
                                Values
                                daily_sleep_unique
Name
Number of rows
Number of columns
                                410
Column type frequency:
                                2
  character
  numeric
                                4
Group variables
                                None
— Variable type: character
  skim_variable n_missing complete_rate min max empty n_unique whitespace
1 Date
                            0
                                             1
                                                  8
                                                       8
2 Time
                                                              0
                                                                        1
                                                                                      0
— Variable type: numeric –
  skim_variable
                         n_missing complete_rate
                                                                            sd
p0
                           p50
             p25
l Id
                                                   1 <u>4</u>994<u>963</u>041.
                                                                      2.06e+9 <u>1</u>503<u>960</u>
366 <u>3</u>977<u>333</u>714 <u>4</u>702<u>921</u>684
  TotalSleepRecords
                                                                1.12 3.47e-1
1
             1
                           1
  TotalMinutesAsleep
                                  0
                                                   1
                                                              419.
                                                                      1.19e + 2
58
                          432.
            361
  TotalTimeInBed
                                  0
                                                   1
                                                              458.
                                                                      1.27e+2
            404.
                      p100
           p75
  <u>6</u>962<u>181</u>067 <u>8</u>792<u>009</u>665
           490
                        796
                        961
           526
> skim_without_charts(weight_new)
— Data Summary -
                                 Values
                                 weight_new
Number of rows
Number of columns
                                 67
 Column type frequency:
                                 3
   character
   numeric
                                 6
Group variables
                                 None
  - Variable type: character ·
   skim_variable n_missing complete_rate min max empty n_unique whitespace
   Date
                              0
                                                                0
                                               1
                                                         8
 2 Time
                              0
                                                                0
                                                                          26
                                                                                        0
```

I would like to condense each file into only the columns that I want to use for A more focused analysis.

```
> daily_activity_final <- daily_activity_new %>%
+ select(Id, ActivityDate, TotalSteps, VeryActiveMinutes, FairlyActiveMinutes, LightlyActiveMinutes, SedentaryMinutes, Calories) %>%
+ rename(Date = ActivityDate)
> weight_final <- weight_new %>%
+ select(Id, Date, BMI, WeightPounds, IsManualReport)
> daily_sleep_final <- daily_sleep_unique %>%
+ select(Id, Date, TotalMinutesAsleep, TotalTimeInBed)
```

Conclusions Drawn

- The average number of steps logged by users is 8320, which is inadequate. It is recommended to aim a goal of at least 10000 steps per day for weight loss and fitness improvement.
- The average minutes for Very Active is 23.02, for Fairly Active is 14.78, for Lightly Active is 210, and for Sedentary is 955.8.
- On average, users logged 419 minutes of sleep which is approximately
 6.98 hours of sleep which is a good sleep time. It is recommended to sleep for 7-8 hours a day for a healthy mind.
- The average BMI is 25.2, but according to WHO recommendations, the healthy BMI range is 18.5-24.9 which means average users have the nutritional status of pre-obesity.

Note: Due to lack of information regarding the data outliers still exist in the data due to which the above values might be slightly skewed.

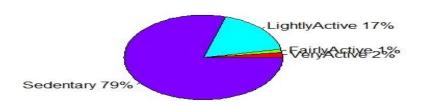
Step 5: SHARE

I will use visualizations to share my insights and important findings.

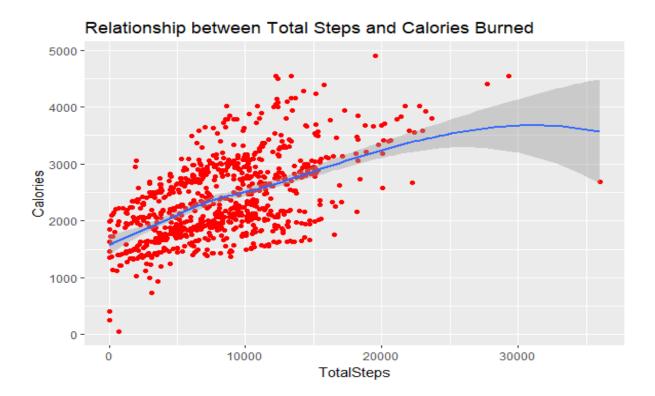
```
> VeryActiveMin <- sum(daily_activity_final$VeryActiveMinutes)
> FairlyActiveMin <- sum(daily_activity_final$FairlyActiveMinutes)
> LightlyActiveMin <- sum(daily_activity_final$LightlyActiveMinutes)
> SedentaryMin <- sum(daily_activity_final$SedentaryMinutes)
> TotalMin <- VeryActiveMin + FairlyActiveMin + LightlyActiveMin + SedentaryMin
> slices <- c(VeryActiveMin,FairlyActiveMin,LightlyActiveMin,SedentaryMin)</pre>
```

```
> lbls <- c("VeryActive","FairlyActive","LightlyActive", "Sedentary")
> pct <- round(slices/sum(slices)*100)
> lbls <- paste(lbls, pct)
> lbls <- paste(lbls, "%", sep="")
> pie(slices, labels = lbls, col = rainbow(length(lbls)), main = "Percenta ge of Activity in Minutes")
```

Percentage of Activity in Minutes



It is visually clear that average users have a sedentary lifestyle as 79% of the activity time is spent sedentary by the average users.



We discovered that it is a positive correlation, and it is obvious that the more steps an individual takes more the calories are burnt. Without more information regarding the person's age, sex, and height, it would be impossible to say exactly how many calories the person needs to burn to lose weight at a healthy rate. However, they are not burning enough weight as the BMI and weight of the individuals who logged those values did not see an improvement over the month of data collection.

```
> combined_data <- merge(daily_activity_new, daily_sleep_unique, by=</pre>
c("Id"))
> combined_data$user_steps <- " "</pre>
> combined_data_grouped <- combined_data %>%
    group_by (Id) %>%
    summarize(average_totalsteps = mean(TotalSteps),
              average_totalcalories = mean(Calories),
              average_totaldistance = mean(TotalDistance),
              average_minutesasleep = mean(TotalMinutesAsleep, na.rm
= TRUE)) %>%
    mutate(user_steps = case_when(
      average_totalsteps >= 10000 ~ "Highly Active/Active",
      average_totalsteps >= 7500 & average_totalsteps < 10000 ~ "Som</pre>
ewhat Active".
      average_totalsteps >= 5000 & average_totalsteps < 7500 ~ "Low</pre>
Active",
      average_totalsteps < 5000 ~ "Sedentary"))</pre>
+
> combined_data <- subset(combined_data, select = -user_steps)</pre>
> combined_data_grouped <- merge(combined_data, combined_data_groupe)</pre>
d, by= c("Id"))
> combined_data_grouped$user_steps <- factor(combined_data_grouped$u</pre>
ser_steps, levels = c("Sedentary", "Low Active", "Somewhat Active",
"Highly Active/Active"))
> ggplot(combined_data_grouped, aes(user_steps, TotalMinutesAsleep))
    geom_boxplot(aes(fill= user_steps))+
    geom_point(alpha = 0.5, aes(size = Calories, color = Calories))+
    labs(title = "Activity Level vs Daily Sleep Minutes", x = "Activ
ity Level", y = "Daily Sleep Minutes", fill= "Activity Level", color
= "Daily Calories Burned", caption= "Data Source:
+ Physical activity for campus employees: a university worksite well
ness program")+
    coord_flip()+
    scale_fill_brewer(palette="PiYG")+
    scale_color_gradient(low= "grey2", high= "red")+
    theme_bw()+
    theme(plot.title = element_text(hjust = 0.5, size = 16))+
    theme(plot.caption = element_text(hjust = 1.75))+
    guides(size = "none",fill ="none")
```



Physical activity for campus employees: a university worksite wellnes:

I assumed that the more sleep an individual had more active they would be but there is no significant correlation between activity level and daily sleep and surprisingly when people slept the most amount of minutes, they became mor e sedentary.

```
> ggplot(combined_data_grouped, aes(user_steps, TotalSteps))+
    geom_boxplot(aes(fill= user_steps))+
    geom_point(alpha = 0.5, aes(size = Calories, color = Calories))+
+
    labs(title = "Activity Level vs Daily Steps", x = "Activity Leve
l", y = "Daily Steps", fill= "Activity Level", size= "", color= "Dai
ly Calories Burned", caption= "Data Source: Physical activity for ca
mpus employees: a university worksite wellness program")+
    coord_flip()+
    scale_fill_brewer(palette="PiYG")+
    scale_color_gradient(low= "grey2", high= "red")+
    theme_bw()+
+
    theme(plot.title = element_text(hjust = 0.5, size = 16))+
+
    theme(plot.caption = element_text(hjust = 1.75))+
+
    guides(size = "none",fill ="none")
```



Data Source: Physical activity for campus employees: a university worksite wellness program

There is a high correlation between daily steps and activity level and also users in more active groups burn more calories per step.

Step 6: ACT

In the final step, we will be delivering our insights and providing recommendations based on our analysis.

Here, we revisit our business questions and share with you our high-level business recommendations.

What are the trends identified?

- The majority of users are using Fitbit to track sedentary activities and not using it for tracking their health habits.
- On average, the average Total Steps per day for the participating individuals was 8053, which is almost 2000 steps below the suggested minimum Total Steps per day.
- There is a high correlation between daily steps and activity level and users in more active groups burn more calories per step.
- There is no significant correlation between activity level and daily sleep and surprisingly when people slept the greatest number of minutes, they became more sedentary.
- The participating individuals did not lose weight, did not improve their BMI or sleep quality, and did not see any overall improvement in their activity levels.

How could these trends help influence Bellabeat's marketing strategy?

- Bellabeat marketing team can encourage users by educating and providing them with knowledge about fitness benefits, suggesting different types of exercise and calorie intake and burnt rate information on the Bellabeat app.
- Bellabeat should introduce a built-in calculator in its products, where the users can enter their details like sex, age, weight, height, and other health information to create precise results.
 - This calculator will notify the user of what their maintenance calories are (and their macros) and how much of a caloric deficit the user needs to be in each day to lose an X amount of lbs each week, based upon their weight goals and time frame.
 - The user would also be notified if they are reaching, have reached, or have passed their daily caloric intake.
- Bellabeat can introduce interesting schemes to motivate users to reach their desired goals. For instance, they can offer free membership to the top 100 most consistent users.
- Bellabeat marketing team can host campaigns and walkathons and introduce how is their product capable of tracking their activities to bring up more awareness towards health among people.