Bellabeat Case Study - Divyansh Negi

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INTRODUCTION

Welcome to the Bellabeat data analysis case study! In this case study, we will perform many real-world tasks of a junior data analyst. In order to answer the key business questions, we will follow the steps of the data analysis process: **ask, prepare, process, analyze, share, and act**.

Scenario

In this study, we will focus on one of Bellabeat's products and analyze smart device data to gain insight into how consumers are using their smart devices. The insights we discover will then help guide marketing strategy for the company. We will be presenting our analysis to the Bellabeat executive team along with our recommendations for Bellabeat's marketing strategy.

About the Company Bellabeat

Urška Sršen and Sando Mur founded Bellabeat, a high-tech company that manufactures health-focused smart products. Sršen used her background as an artist to develop beautifully designed technology that informs and inspires women around the world. Collecting data on activity, sleep, stress, and reproductive health has allowed Bellabeat to empower women with knowledge about their own health and habits. Since it was founded in 2013, Bellabeat has grown rapidly and quickly positioned itself as a tech-driven wellness company for women.

ASK phase

Identifying the business task:-

- **What are some trends in smart device usage? How could these trends help influence Bellabeat marketing strategy ?**

The company need to better target their marketing efforts into their customer's needs based on their usage of their fitness smart devices. And then, make high-level recommendations for how these trends can inform Bellabeat marketing strategy.

- **Who are the main stakeholders ?**

The main stakeholders are Urška Sršen, Bellabeat's co-founder and Chief Creative Officer; Sando Mur, Mathematician and Bellabeat's cofounder; And also, we need to think about and work with the rest of the Bellabeat marketing analytics team.

PREPARE Phase

In this phase, we will download and Import the dataset. Then make sure all the data is organized, credible, sorted and filtered.

Downloading the data

We will be using public data that explores smart device users' daily habits from FitBit Fitness Tracker Data. FitBit Fitness Tracker Data from Kaggle.

FitBit Fitness Tracker Data : https://www.kaggle.com/datasets/arashnic/fitbit

Uploading the data

We'll be manually uploading all the data on Rstudio for the analysis in the working directory.

Loading the packages

Now we'll load all the necessary packages that will help us in the analysis. And in the code we'll be using message=FALSE and warning=FALSE, to save space. And to prevent printing of the execution of the R code generated and the warning messages.

```
# Installing packages
install.packages("tidyverse")
install.packages("lubridate")
install.packages("dplyr")
install.packages("ggplot2")
install.packages("tidyr")
```

Now we'll load the packages.

```
# Loading packages
library(tidyverse)
library(lubridate)
library(dplyr)
library(ggplot2)
library(tidyr)
```

Importing the data

After uploading we'll be importing all dataset. Then we'll VIEW, CLEAN, FORMAT, and ORGANIZE the data for the analysis.

- **dailyActivity_merged.csv**

```
# Importing Activity dataset :

Activity <- read.csv("dailyActivity_merged.csv")
head(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
```

```
colnames(Activity)
```

```
##  [1] "Id"                       "ActivityDate"
##  [3] "TotalSteps"               "TotalDistance"
##  [5] "TrackerDistance"          "LoggedActivitiesDistance"
##  [7] "VeryActiveDistance"       "ModeratelyActiveDistance"
##  [9] "LightActiveDistance"      "SedentaryActiveDistance"
## [11] "VeryActiveMinutes"        "FairlyActiveMinutes"
## [13] "LightlyActiveMinutes"     "SedentaryMinutes"
## [15] "Calories"
```

```
str(Activity)
```

```
## 'data.frame':    940 obs. of  15 variables:
##  $ Id                       : num  1.5e+09 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
##  $ ActivityDate             : chr  "4/12/2016" "4/13/2016" "4/14/2016" "4/15/2016" ...
##  $ TotalSteps               : int  13162 10735 10460 9762 12669 9705 13019 15506 10544 9819 ...
##  $ TotalDistance            : num  8.5 6.97 6.74 6.28 8.16 ...
##  $ TrackerDistance          : num  8.5 6.97 6.74 6.28 8.16 ...
##  $ LoggedActivitiesDistance: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ VeryActiveDistance       : num  1.88 1.57 2.44 2.14 2.71 ...
##  $ ModeratelyActiveDistance: num  0.55 0.69 0.4 1.26 0.41 ...
##  $ LightActiveDistance      : num  6.06 4.71 3.91 2.83 5.04 ...
##  $ SedentaryActiveDistance : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ VeryActiveMinutes        : int  25 21 30 29 36 38 42 50 28 19 ...
##  $ FairlyActiveMinutes      : int  13 19 11 34 10 20 16 31 12 8 ...
##  $ LightlyActiveMinutes     : int  328 217 181 209 221 164 233 264 205 211 ...
##  $ SedentaryMinutes         : int  728 776 1218 726 773 539 1149 775 818 838 ...
##  $ Calories                 : int  1985 1797 1776 1745 1863 1728 1921 2035 1786 1775 ...
```

- **dailyCalories_merged.csv**

```
# Importing Calories dataset :
Calories <- read.csv("dailyCalories_merged.csv")
head(Calories)
```

```
##           Id ActivityDay Calories
## 1 1503960366   4/12/2016     1985
## 2 1503960366   4/13/2016     1797
## 3 1503960366   4/14/2016     1776
## 4 1503960366   4/15/2016     1745
## 5 1503960366   4/16/2016     1863
## 6 1503960366   4/17/2016     1728
```

```
colnames(Calories)
```

```
## [1] "Id"          "ActivityDay" "Calories"
```

```
str(Calories)
```

```
## 'data.frame':    940 obs. of  3 variables:
##  $ Id         : num  1.5e+09 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
##  $ ActivityDay: chr  "4/12/2016" "4/13/2016" "4/14/2016" "4/15/2016" ...
##  $ Calories   : int  1985 1797 1776 1745 1863 1728 1921 2035 1786 1775 ...
```

- **dailyIntensities_merged.csv**

```
# Importing Intensities dataset :
Intensities <- read.csv("dailyIntensities_merged.csv")
head(Intensities)
```

```
##           Id ActivityDay SedentaryMinutes LightlyActiveMinutes
## 1 1503960366   4/12/2016              728                  328
## 2 1503960366   4/13/2016              776                  217
## 3 1503960366   4/14/2016             1218                  181
## 4 1503960366   4/15/2016              726                  209
## 5 1503960366   4/16/2016              773                  221
## 6 1503960366   4/17/2016              539                  164
##   FairlyActiveMinutes VeryActiveMinutes SedentaryActiveDistance
## 1                  13                25                       0
## 2                  19                21                       0
## 3                  11                30                       0
## 4                  34                29                       0
## 5                  10                36                       0
## 6                  20                38                       0
##   LightActiveDistance ModeratelyActiveDistance VeryActiveDistance
## 1                6.06                     0.55               1.88
## 2                4.71                     0.69               1.57
## 3                3.91                     0.40               2.44
## 4                2.83                     1.26               2.14
## 5                5.04                     0.41               2.71
## 6                2.51                     0.78               3.19
```

```
colnames(Intensities)
```

```
##  [1] "Id"                       "ActivityDay"
##  [3] "SedentaryMinutes"         "LightlyActiveMinutes"
##  [5] "FairlyActiveMinutes"      "VeryActiveMinutes"
##  [7] "SedentaryActiveDistance"  "LightActiveDistance"
##  [9] "ModeratelyActiveDistance" "VeryActiveDistance"
```

```
str(Intensities)
```

```
## 'data.frame':    940 obs. of  10 variables:
##  $ Id                       : num  1.5e+09 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
##  $ ActivityDay              : chr  "4/12/2016" "4/13/2016" "4/14/2016" "4/15/2016" ...
##  $ SedentaryMinutes         : int  728 776 1218 726 773 539 1149 775 818 838 ...
##  $ LightlyActiveMinutes     : int  328 217 181 209 221 164 233 264 205 211 ...
##  $ FairlyActiveMinutes      : int  13 19 11 34 10 20 16 31 12 8 ...
##  $ VeryActiveMinutes        : int  25 21 30 29 36 38 42 50 28 19 ...
##  $ SedentaryActiveDistance  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ LightActiveDistance      : num  6.06 4.71 3.91 2.83 5.04 ...
```

```
##  $ ModeratelyActiveDistance: num  0.55 0.69 0.4 1.26 0.41 ...
##  $ VeryActiveDistance      : num  1.88 1.57 2.44 2.14 2.71 ...
```

- **heartrate_seconds_merged.csv**

```
# Importing Heartrate dataset :
Heartrate <- read.csv("heartrate_seconds_merged.csv")
head(Heartrate)
```

```
##           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
```

```
colnames(Heartrate)
```

```
## [1] "Id"    "Time"  "Value"
```

```
str(Heartrate)
```

```
## 'data.frame':    2483658 obs. of  3 variables:
##  $ Id   : num  2.02e+09 2.02e+09 2.02e+09 2.02e+09 2.02e+09 ...
##  $ Time : chr  "4/12/2016 7:21:00 AM" "4/12/2016 7:21:05 AM" "4/12/2016 7:21:10 AM" "4/12/2016 7:21:1
##  $ Value: int  97 102 105 103 101 95 91 93 94 93 ...
```

- **sleepDay_merged.csv**

```
# Importing Sleep dataset :
Sleep <- read.csv("sleepDay_merged.csv")
head(Sleep)
```

```
##           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
```

```
colnames(Sleep)
```

```
## [1] "Id"                 "SleepDay"           "TotalSleepRecords"
## [4] "TotalMinutesAsleep" "TotalTimeInBed"
```

```
str(Sleep)
```

```
## 'data.frame':    413 obs. of  5 variables:
##  $ Id                : num  1.5e+09 1.5e+09 1.5e+09 1.5e+09 1.5e+09 ...
##  $ SleepDay          : chr  "4/12/2016 12:00:00 AM" "4/13/2016 12:00:00 AM" "4/15/2016 12:00:00 AM" "
##  $ TotalSleepRecords : int  1 2 1 2 1 1 1 1 1 1 ...
```

```
##  $ TotalMinutesAsleep: int  327 384 412 340 700 304 360 325 361 430 ...
##  $ TotalTimeInBed    : int  346 407 442 367 712 320 377 364 384 449 ...
```

- **weightLogInfo_merged.csv**

```
# Importing Weight dataset :
Weight <- read.csv("weightLogInfo_merged.csv")
head(Weight)
```

```
##           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
```

```
colnames(Weight)
```

```
## [1] "Id"             "Date"           "WeightKg"       "WeightPounds"
## [5] "Fat"            "BMI"            "IsManualReport" "LogId"
```

```
str(Weight)
```

```
## 'data.frame':    67 obs. of  8 variables:
##  $ Id            : num  1.50e+09 1.50e+09 1.93e+09 2.87e+09 2.87e+09 ...
##  $ Date          : chr  "5/2/2016 11:59:59 PM" "5/3/2016 11:59:59 PM" "4/13/2016 1:08:52 AM" "4/21/20
##  $ WeightKg      : num  52.6 52.6 133.5 56.7 57.3 ...
##  $ WeightPounds  : num  116 116 294 125 126 ...
##  $ Fat           : int  22 NA NA NA NA 25 NA NA NA NA ...
##  $ BMI           : num  22.6 22.6 47.5 21.5 21.7 ...
##  $ IsManualReport: chr  "True" "True" "False" "True" ...
##  $ LogId         : num  1.46e+12 1.46e+12 1.46e+12 1.46e+12 1.46e+12 ...
```

All datasets have been improrted.

Process Phase

Cleaning

Now, we'll Process, Clean and Organize the dataset for analysis.

We'll install and load the packages for cleaning:

```
# Installing package
install.packages("tidyverse")
library(janitor)
```

We'll clean the names of the data using clean_names().

```
clean_names(Activity)
clean_names(Calories)
clean_names(Weight)
```

```
clean_names(Heartrate)
clean_names(Intensities)
clean_names(Sleep)
```

And some other cleaning steps we performed with the data :

- For Dataset (Activity, Calories and Intensities): No Spelling errors, Misfiled values, Missing values, Extra and blank space, no duplicated were found.
- For Sleep data : 3 duplicates were found and removed.
- For Weight data : too many missing values were found in one column. So we removed that column.

ANALYSE Phase

After storing all the data and preparing it for analysis. We can start the analysis.

Let's look at the total number of participants in each data sets:

```
n_distinct(Activity$Id)
```

```
## [1] 33
```

```
n_distinct(Calories$Id)
```

```
## [1] 33
```

```
n_distinct(Intensities$Id)
```

```
## [1] 33
```

```
n_distinct(Heartrate$Id)
```

```
## [1] 14
```

```
n_distinct(Sleep$Id)
```

```
## [1] 24
```

```
n_distinct(Weight$Id)
```

```
## [1] 8
```

So, there are 33 participants in the activity, calories and intensities data sets. 24 participants in the Sleep data. And only 14 participants for Heartrate, and only 8 in the weight data set. 8 and 14 participants are not significant to make any recommendations and conclusions based on these dataset.

So I will focus on these datasets for my analysis: Activity, Calories, Intensities and Sleep.

Here are some quick summary statistics about each data frame.

For the Activity dataframe:

```
# Activity
Activity %>%
  select(TotalSteps,
         TotalDistance,
         SedentaryMinutes, Calories) %>%
  summary()
```

```
##    TotalSteps    TotalDistance    SedentaryMinutes    Calories
##  Min.   :    0   Min.   : 0.000   Min.   :   0.0   Min.   :   0
##  1st Qu.: 3790   1st Qu.: 2.620   1st Qu.: 729.8   1st Qu.:1828
```

```
##  Median : 7406   Median : 5.245   Median :1057.5   Median :2134
##  Mean   : 7638   Mean   : 5.490   Mean   : 991.2   Mean   :2304
##  3rd Qu.:10727   3rd Qu.: 7.713   3rd Qu.:1229.5   3rd Qu.:2793
##  Max.   :36019   Max.   :28.030   Max.   :1440.0   Max.   :4900
```

Exploring the number of Intense active participants :

```
# Explore number of active minutes per category
Intensities %>%
  select(VeryActiveMinutes, FairlyActiveMinutes, LightlyActiveMinutes, SedentaryMinutes) %>%
  summary()
```

```
##  VeryActiveMinutes FairlyActiveMinutes LightlyActiveMinutes SedentaryMinutes
##  Min.   :  0.00    Min.   :  0.00      Min.   :  0.0        Min.   :   0.0
##  1st Qu.:  0.00    1st Qu.:  0.00      1st Qu.:127.0        1st Qu.: 729.8
##  Median :  4.00    Median :  6.00      Median :199.0        Median :1057.5
##  Mean   : 21.16    Mean   : 13.56      Mean   :192.8        Mean   : 991.2
##  3rd Qu.: 32.00    3rd Qu.: 19.00      3rd Qu.:264.0        3rd Qu.:1229.5
##  Max.   :210.00    Max.   :143.00      Max.   :518.0        Max.   :1440.0
```

For the Calories dataframe:

```
# Calories
Calories %>%
  select(Calories) %>%
  summary()
```

```
##     Calories
##  Min.   :   0
##  1st Qu.:1828
##  Median :2134
##  Mean   :2304
##  3rd Qu.:2793
##  Max.   :4900
```

For the Sleep dataframe:

```
# Sleep
Sleep %>%
  select(TotalSleepRecords, TotalMinutesAsleep, TotalTimeInBed) %>%
  summary()
```

```
##  TotalSleepRecords TotalMinutesAsleep TotalTimeInBed
##  Min.   :1.000     Min.   : 58.0      Min.   : 61.0
##  1st Qu.:1.000     1st Qu.:361.0      1st Qu.:403.0
##  Median :1.000     Median :433.0      Median :463.0
##  Mean   :1.119     Mean   :419.5      Mean   :458.6
##  3rd Qu.:1.000     3rd Qu.:490.0      3rd Qu.:526.0
##  Max.   :3.000     Max.   :796.0      Max.   :961.0
```

For the Weight dataframe:

```
# Weight
Weight %>%
  select(WeightKg, Fat) %>%
  summary()
```

```
##     WeightKg           Fat
##  Min.   : 52.60   Min.   :22.00
```

```
##  1st Qu.: 61.40   1st Qu.:22.75
##  Median : 62.50   Median :23.50
##  Mean   : 72.04   Mean   :23.50
##  3rd Qu.: 85.05   3rd Qu.:24.25
##  Max.   :133.50   Max.   :25.00
##                   NA's   :65
```

Findings:

- The average sedentary time is too high (more than 16 hours). Which can be reduced with a good marketing strategy.
- The majority of the participants are lightly active. With a high sedentary time.
- Participants sleep 1 time for an average of 7 hours.
- Average total steps per day (which is 7638) is a little bit less than recommended by the CDC. According to the CDC research, taking 8,000 steps per day was associated with a 51% lower risk for all-cause mortality (or death from all causes). And taking 12,000 steps per day was associated with a 65% lower risk compared with taking 4,000 steps.

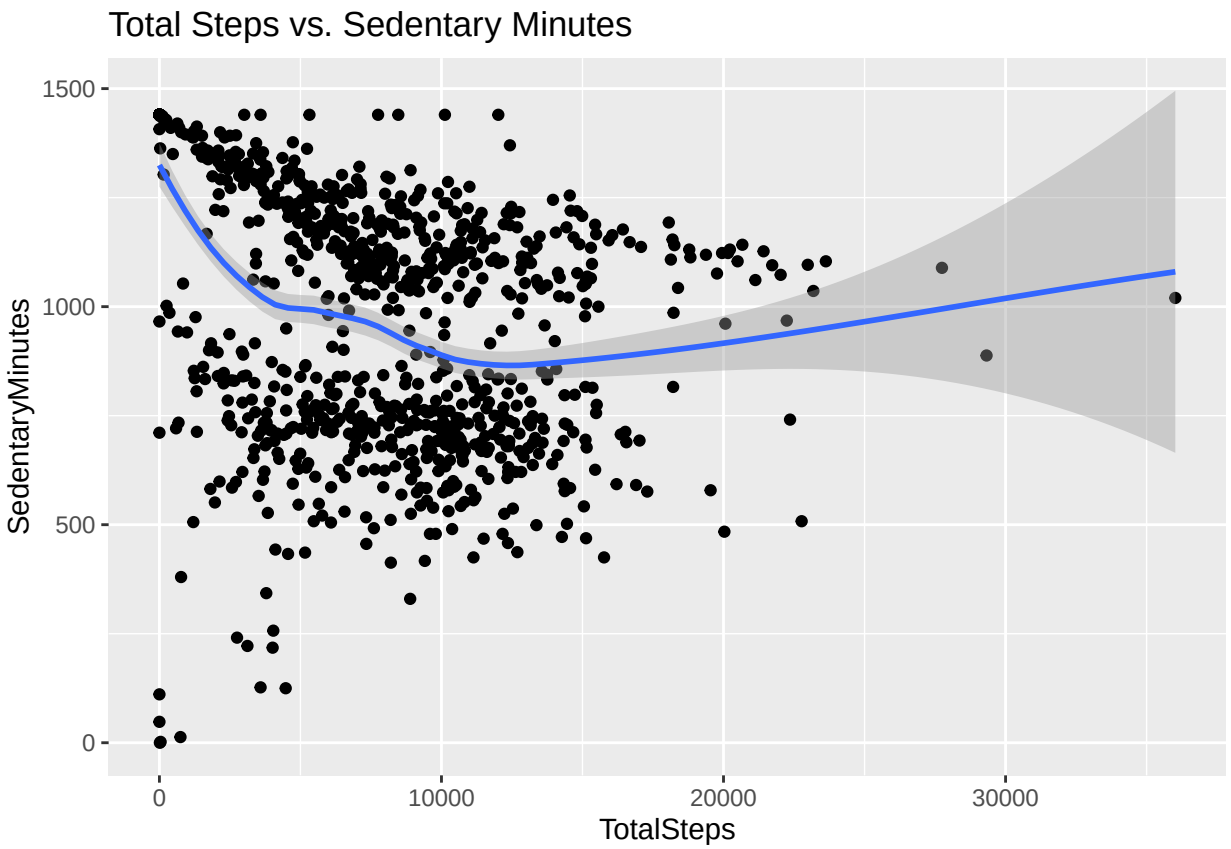
SHARE and ACT Phases

Now we'll visualize some findings.

* Relationship between Steps and Sedentary time

```
ggplot(data=Activity, aes(x=TotalSteps, y=SedentaryMinutes)) + geom_point() + geom_smooth() + labs(titl
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



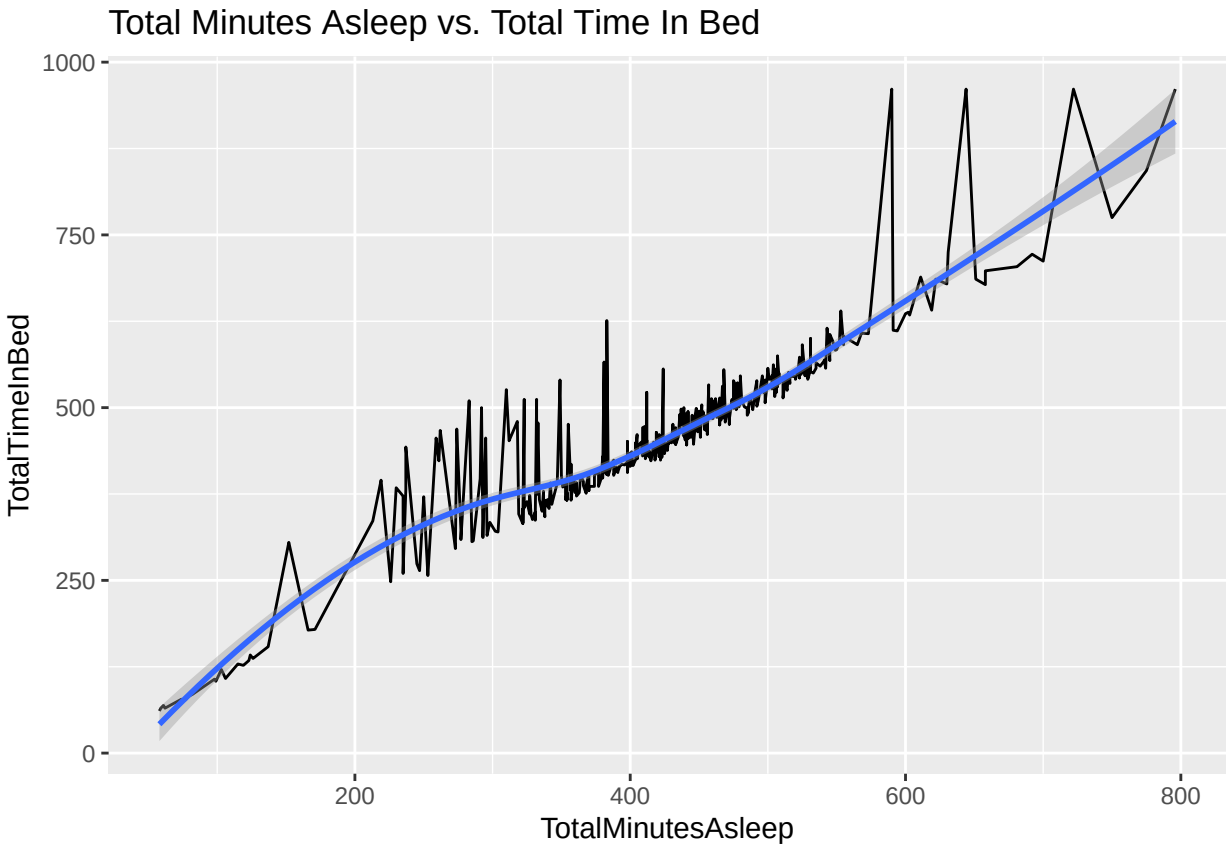
We can see a negative correlation between Steps and Sedentary time. The more Sedentary time you have, the

less Steps you're taking during the day. This data shows that the company need to market more the customer segments with high Sedentary time. And to do that, the company needs to find ways to get customers get started in walking more and also measure their daily steps.

*** Relationship between Minutes Asleep and Time in Bed**

```
ggplot(data=Sleep, aes(x=TotalMinutesAsleep, y=TotalTimeInBed)) + geom_line() +geom_smooth() + labs(tit
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

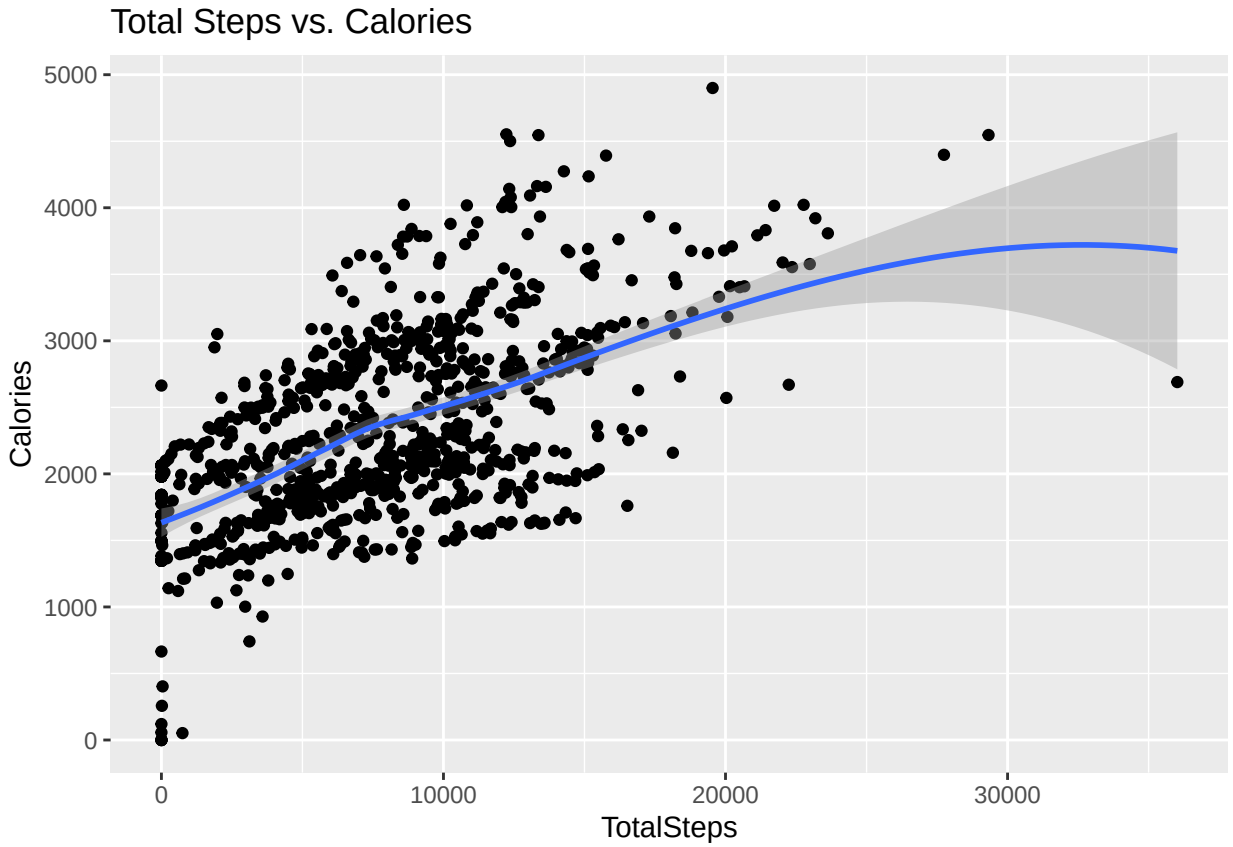


We can see here an almost completely linear trend between Minutes Asleep and Time in Bed. So to help users improve their sleep, the company should consider using notification to go to sleep.

*** Relationship between Steps and Calories**

```
ggplot(data=Activity, aes(x=TotalSteps, y=Calories)) + geom_point() + geom_smooth() + labs(title="Total
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



We can see here a positive correlation between Total Steps and Calories. The more active we are, the more calories we will burn.

Conclusions & Recommandations

So, collecting data on activity, sleep, stress, etc. will allow the company Bellabeat to empower the customers with knowledge about their own health and daily habits. The company Bellabeat is growing rapidly and quickly positioned itself as a tech-driven wellness company for their customers.

By analyzing the FitBit Fitness Tracker Data set, We have found some insights that would help influence Bellabeat marketing strategy.

- The average sedentary time is too high for the users of the app (more than 16 hours). And definitely needs to be reduced with a good marketing strategy. So, the data shows that the company need to market more to the customer segment with a high Sedentary time. And to do that, the company needs to find ways to get customers started in walking more by measuring their daily steps (+ notifications).
- Participants sleep 1 time for an average of 7 hours. To help users improve their sleep, Bellabeat should consider using app notifications to go to bed.
- The average total steps per day (which is 7638) is a little bit less than recommended by the CDC. According to the CDC research, taking 8,000 steps per day was associated with a 51% lower risk for all-cause mortality (or death from all causes). And taking 12,000 steps per day was associated with a 65% lower risk compared with taking 4,000 steps. So, Bellabeat can encourage people to take at least 8,000 steps per day by explaining the healthy benefits of doing that.
- For customers who want to lose weight, it can be a good idea to control daily calorie consumption. And Bellabeat can suggest some ideas for low-calorie healthy food.

Hence, the case study has been concluded.