capstonecasestudy

Amadu

2024-08-05

1. SUMMARY

Bellabeat is a women-centric tech and wellness company which develops wearables and accompanying products that monitor biometric and lifestyle data to help women better understand how their bodies work, and as a result, make healthier lifestyle choices.

Together with the Bellabeat app, users are able to gain insights with health data related to their activity, sleep, stress, fitness, heart rate, reproductive health and mindfulness habits.

The goal of the case study is to analyze how non-Bellabeat consumers use their smart fitness devices. With this information, we are to provide high-level recommendations for how these insights can inform Bellabeat's marketing strategy.

Business Approach

Bellabeat emphasizes the integration of wellness and technology, aiming to provide women with tools that empower them to take control of their health. The company's products are designed to be stylish and versatile, allowing users to wear them in various ways that fit their personal style. Bellabeat also focuses on using data analytics to provide personalized health insights and recommendations, enhancing the user experience and promoting overall well-being.

Problem Statement

How can a wellness company play it smart? In this case study, you will perform data analysis for Bellabeat, a high-tech manufacturer of health-focused products for women. You will analyze smart device data to gain insight into how consumers are using their smart devices. Your analysis will help guide future marketing strategies for your team. Along the way, you will perform numerous real-world tasks of a junior data analyst by following the steps of the data analysis process: Ask, Prepare, Process, Analyze, Share, and Act. By the time you are done, you will have a portfolio-ready case study to help you demonstrate your knowledge and skills to potential employers!

2. Ask phase

- Business Task The aim of the case study is to analyze how non-Bellabeat consumers use their smart fitness devices. With this information, we are to provide high-level recommendations for how these insights can inform Bellabeat's marketing strategy around the following questions:
- What are some trends in smart device usage?
- How could these trends apply to Bellabeat customers?
- How could these trends help influence Bellabeat marketing strategy?

3. Prepare Phase

- Dataset used: The FitBit Fitness Tracker dataset (CC0: Public Domain) will be used for this analysis. It is made available on Kaggle by the user, Mobius.

Accessibility and privacy of data:

The data is licensed under CC0: Public Domain, waiving all of his or her rights to the work worldwide under copyright law, including all related and neighboring rights, to the extend by law. The work can be copied, modified, distributed and perform the work, even for commercial purposes, all without asking permission.

Information about our dataset:

The dataset is generated by respondents to a distributed survey via Amazon Mechanical Turk over 31 days between 03.12.2016 - 05.12.2016. Thirty eligible Fitbit users consented to the submission of personal tracker data, including minute-level output for physical activity, heart rate, and sleep monitoring. Variation between output represents use of different types of Fitbit trackers and individual tracking behaviors / preferences.

Data Organization and verification:

The dataset is a collection of 18 .csv files. 15 in long format, 3 in wide format. The datasets consists of wide-ranging information from activity metrics, calories, sleep records, metabolic equivalent of tasks (METs), heart rate and steps; in timeframes of seconds, minutes, hours and days. Several data frames will not be used for the analysis because of the following reasons:

- They are subsets of larger, more complete data frames.
- They are in a minute-level output.
- They are too small of a sample size to provide credible insights.

Data Limitations:

- No Metadata Provided: Information such as location, lifestyle, weather, temperature, humidity etc. would provide a deeper context to the data obtained.
- Missing Demographics: Key demographics data such as gender, age, were not identified. This is a crucial missing information sine Bellabeat creates women-centric products. Insights obtained may not reflect the differences in physiology and activity patterns between different demographic groups. However, we understand such information is under a strict privacy policy.
- Small Sample Size: Thirty users is not an ideal sample size where multiple independent variables are involved. Especially when health and lifestyle data is varied across different facets of society. Insights gained may not apply to all.
- Data Collection Period: 31 days of data between 03.12.2016 - 05.12.2016 is limited in providing high-level recommendations. Seasonal trends impacts heavily on user activity and lifestyle choices. E.g. User's excercise habits differ between summer and winter.

4. Process Phase

Data processing, analysis and visualization will all be done in R Programming with R Studio.

###Installing packages and opening libraries

The following packages will be used for our analysis: 'tidyverse', 'here', 'skimr', 'lubridate', 'janitor', 'viridis', 'ggpubr', 'scales', 'waffles', 'ggrepel', 'ggplot2'.

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## v purrr     1.0.2
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become error
```

```r
library(ggpubr)
library(lubridate)
library(skimr)
library(janitor)
```

```
##
## Attaching package: 'janitor'
##
## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test
```

```r
library(viridis)
```

```
## Loading required package: viridisLite
```

```r
library(scales)
```

```
##
## Attaching package: 'scales'
##
## The following object is masked from 'package:viridis':
##
##     viridis_pal
##
## The following object is masked from 'package:purrr':
##
##     discard
##
## The following object is masked from 'package:readr':
##
##     col_factor
```

```r
library(waffle)
library(ggrepel)
library(ggplot2)
library(RColorBrewer)
```

Importing datasets

- The following tables will be used:
- dailyActivity_merged.csv
- dailyCalories_merged.csv
- dailyIntensities_merged.csv
- sleepDay_merged.csv
- weightLogInfo_merged.csv

Importing data sets

```
daily_activity <- read.csv("dailyActivity_merged.csv")
daily_calories <- read.csv("dailyCalories_merged.csv")
daily_intensities <- read.csv("dailyIntensities_merged.csv")
sleep_day <- read.csv("sleepDay_merged.csv")
weight <- read.csv("weightLogInfo_merged.csv")
```

Exploring Datasets

```
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
```

```
colnames(daily_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(daily_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 ...
```

```r
head(daily_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
```

```r
colnames(daily_calories)
```

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

```r
str(daily_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 ...
```

```r
head(daily_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(daily_intensities)
```

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

```
str(daily_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 ...
```

```
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
```

```
colnames(sleep_day)
```

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

```
str(sleep_day)
```

```
## '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 ...
```

```r
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
```

```r
colnames(weight)
```

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

```r
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" "4/21/2
##  $ 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 ...
```

4. Cleaning and formatting

```r
weight <- weight %>%
  select(-Fat)

daily_calories <- daily_calories %>%
  distinct() %>%
  drop_na()

daily_activity <- daily_activity %>%
  distinct() %>%
  drop_na()

daily_intensities <- daily_intensities %>%
  distinct() %>%
  drop_na()

sleep_day <- sleep_day %>%
  distinct() %>%
  drop_na()
```

```
weight <- weight %>%
  distinct() %>%
  drop_na()
```

```
sleep_day <- clean_names(sleep_day)
daily_activity <- clean_names(daily_activity)
daily_intensities <- clean_names(daily_intensities)
daily_calories <- clean_names(daily_calories)
weight <- clean_names(weight)
```

```
sleep_day <- sleep_day %>%
  rename(sleep_date = sleep_day)
daily_calories <- daily_calories %>%
  rename(activity_date = activity_day)
daily_intensities <- daily_intensities %>%
  rename(activity_date = activity_day)
```

Formatting the datasets:

Fixing formatting dates

I spotted some problems with the timestamp data. So before analysis, I need to convert it to date time format.

```
daily_activity$activity_date=as.POSIXct(daily_activity$activity_date, format="%m/%d/%Y", tz=Sys.timezon
daily_activity$date <- format(daily_activity$activity_date, format = "%m/%d/%y")
daily_activity$activity_date=as.Date(daily_activity$activity_date, format="%m/%d/%Y", tz=Sys.timezone()
daily_activity$date=as.Date(daily_activity$date, format="%m/%d/%Y")

daily_intensities$activity_date=as.Date(daily_intensities$activity_date, format="%m/%d/%Y", tz=Sys.time

sleep_day$sleep_date=as.POSIXct(sleep_day$sleep_date, format="%m/%d/%Y %I:%M:%S %p", tz=Sys.timezone())
sleep_day$date <- format(sleep_day$sleep_date, format = "%m/%d/%y")
sleep_day$date=as.Date(sleep_day$date, "% m/% d/% y")
```

Verification that date and time colums have been formatted

```
class(daily_calories$activity_date)
```

```
## [1] "character"
```

```
class(daily_intensities$activity_date)
```

```
## [1] "Date"
```

```
class(daily_activity$activity_date)
```

```
## [1] "Date"
```

```
class(sleep_day$sleep_date)
```

```
## [1] "POSIXct" "POSIXt"
```

```
class(weight$date)
```

```
## [1] "character"
```

Summerizing the data set (Analyze phase)

```
n_distinct(daily_activity$id)
```

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

```
n_distinct(daily_calories$id)
```

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

```
n_distinct(daily_intensities$id)
```

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

```
n_distinct(sleep_day$id)
```

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

```
n_distinct(weight$id)
```

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

So, there are 33 participants in daily_activity, daily_calories and daily_intensities data sets. 24 participants in the Sleep data. And only 8 participants for the weight data set, 8 participants are not significant to make any recommendations and conclusions based on these dataset. So I will focus my analysis on daily_activity, daily_calories and daily_intensities. although the minimum is 30 participants I will work on the sleep_day data set for practice.

Here are some quick summary statistics about each data frame

- daily_activity summary

```
daily_activity %>%
  select(total_steps,
         total_distance,
         sedentary_minutes, calories) %>%
  summary()
```

```
##   total_steps    total_distance   sedentary_minutes    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:

```
daily_intensities %>%
  select(very_active_minutes, fairly_active_minutes, lightly_active_minutes, sedentary_minutes) %>%
  summary()
```

```
##  very_active_minutes fairly_active_minutes lightly_active_minutes
##  Min.   :  0.00      Min.   :  0.00        Min.   :  0.0
##  1st Qu.:  0.00      1st Qu.:  0.00        1st Qu.:127.0
##  Median :  4.00      Median :  6.00        Median :199.0
##  Mean   : 21.16      Mean   : 13.56        Mean   :192.8
##  3rd Qu.: 32.00      3rd Qu.: 19.00        3rd Qu.:264.0
##  Max.   :210.00      Max.   :143.00        Max.   :518.0
##  sedentary_minutes
```

```
##  Min.   :   0.0
##  1st Qu.: 729.8
##  Median :1057.5
##  Mean   : 991.2
##  3rd Qu.:1229.5
##  Max.   :1440.0
```

- daily_calories dataframe

```r
daily_calories %>%
  select(calories) %>%
  summary()
```

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

- For the sleep record

```r
sleep_day %>%
  select(total_sleep_records, total_minutes_asleep, total_time_in_bed) %>%
  summary()
```

```
##  total_sleep_records total_minutes_asleep total_time_in_bed
##  Min.   :1.00        Min.   : 58.0        Min.   : 61.0
##  1st Qu.:1.00        1st Qu.:361.0        1st Qu.:403.8
##  Median :1.00        Median :432.5        Median :463.0
##  Mean   :1.12        Mean   :419.2        Mean   :458.5
##  3rd Qu.:1.00        3rd Qu.:490.0        3rd Qu.:526.0
##  Max.   :3.00        Max.   :796.0        Max.   :961.0
```

- For the weiht data frame

```r
weight %>%
  select(weight_kg, bmi) %>%
  summary()
```

```
##    weight_kg           bmi
##  Min.   : 52.60   Min.   :21.45
##  1st Qu.: 61.40   1st Qu.:23.96
##  Median : 62.50   Median :24.39
##  Mean   : 72.04   Mean   :25.19
##  3rd Qu.: 85.05   3rd Qu.:25.56
##  Max.   :133.50   Max.   :47.54
```

Key findings from this analysis :

Too Much Sitting: People are sitting for over 16 hours a day on average, which is too high. This indicates a need for strategies to encourage more movement.

Low Physical Activity: Most people are only lightly active, meaning they don't move much beyond basic daily activities. Combined with long sitting periods, this shows they need to be more active.

Average Sleep: On average, people sleep about 7 hours a night, which is generally acceptable but doesn't address physical activity.

Steps per Day: People are walking around 7,638 steps a day. This is less than the CDC's recommendation of 8,000 steps a day, which can significantly lower the risk of health problems. More steps (up to 12,000) are even better for reducing health risks.

Merging some data :

Before beginning to visualize the data, I'm going to merge two data sets : Activity and Sleep data on columns id. Note that there are more participant Ids in the Activity dataset than in the Sleep dataset. So if I use the merge option inner_joint, then I will have the number of participants from the Sleep data set. Take a look:

```
Combined_data_inner <- merge(sleep_day, daily_activity, by="id")
n_distinct(Combined_data_inner$id)
```

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

For analysis, I will consider using 'outer_join' to keep all participants in the dataset. And I can do that by adding in my code chunk the extra argument all=TRUE.

```
Combined_data_outer <- merge(sleep_day, daily_activity, by="id", all = TRUE)
n_distinct(Combined_data_outer$id)
```

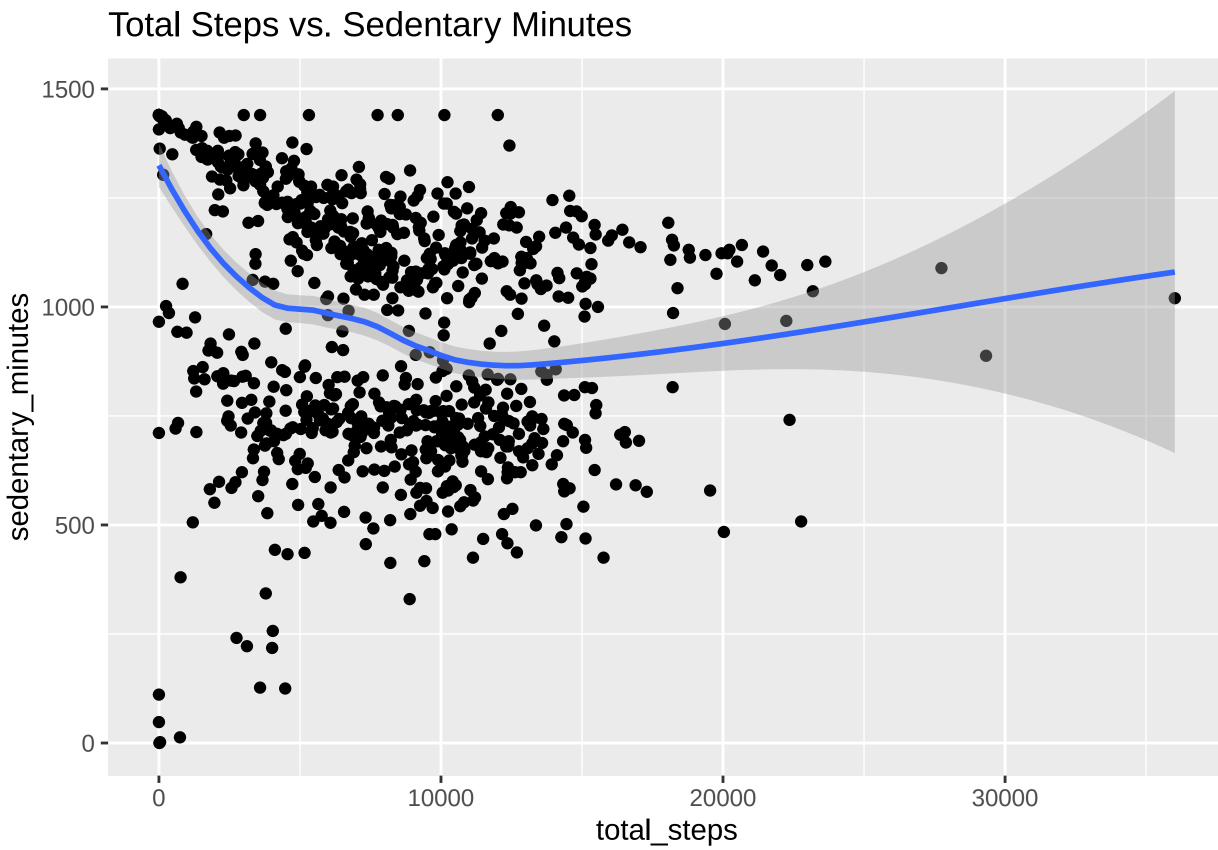
```
## [1] 33
```

Data visualization (Share and Act Phases)

Now let's visualize some key explorations. Relationship between Steps and Sedentary time What's the relationship between steps taken in a day and sedentary minutes?

```
ggplot(data=daily_activity, aes(x=total_steps, y=sedentary_minutes)) + geom_point() + geom_smooth() +
  labs(title = "Total Steps vs. Sedentary Minutes")
```

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



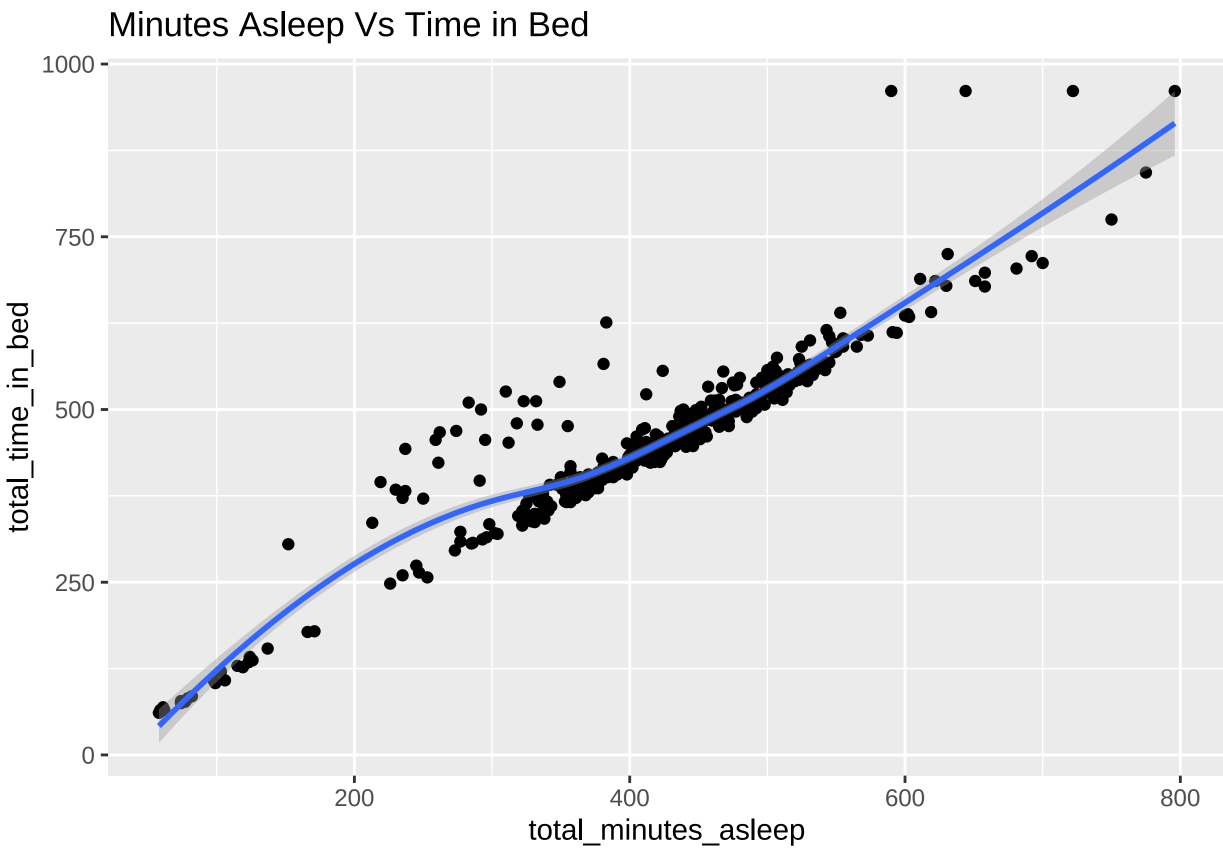
As you can see there is a negative correlation between Steps and Sedentary time. The more Sedentary time you have, the less Steps you're taking during the day. This data shows that the company need to market more to customers with high Sedentary time. And to do that, the company needs to find ways to educate customers about the important of walking more and also incouragethem to set a daily step goal with notification informing them about their progress doing the day.

Relationship between Minutes Asleep and Time in Bed

What's the relationship between minutes asleep and time in bed?

```
ggplot(data=sleep_day, aes(x=total_minutes_asleep, y=total_time_in_bed)) + geom_point() +
  geom_smooth() + labs(title = "Minutes Asleep Vs Time in Bed")
```

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



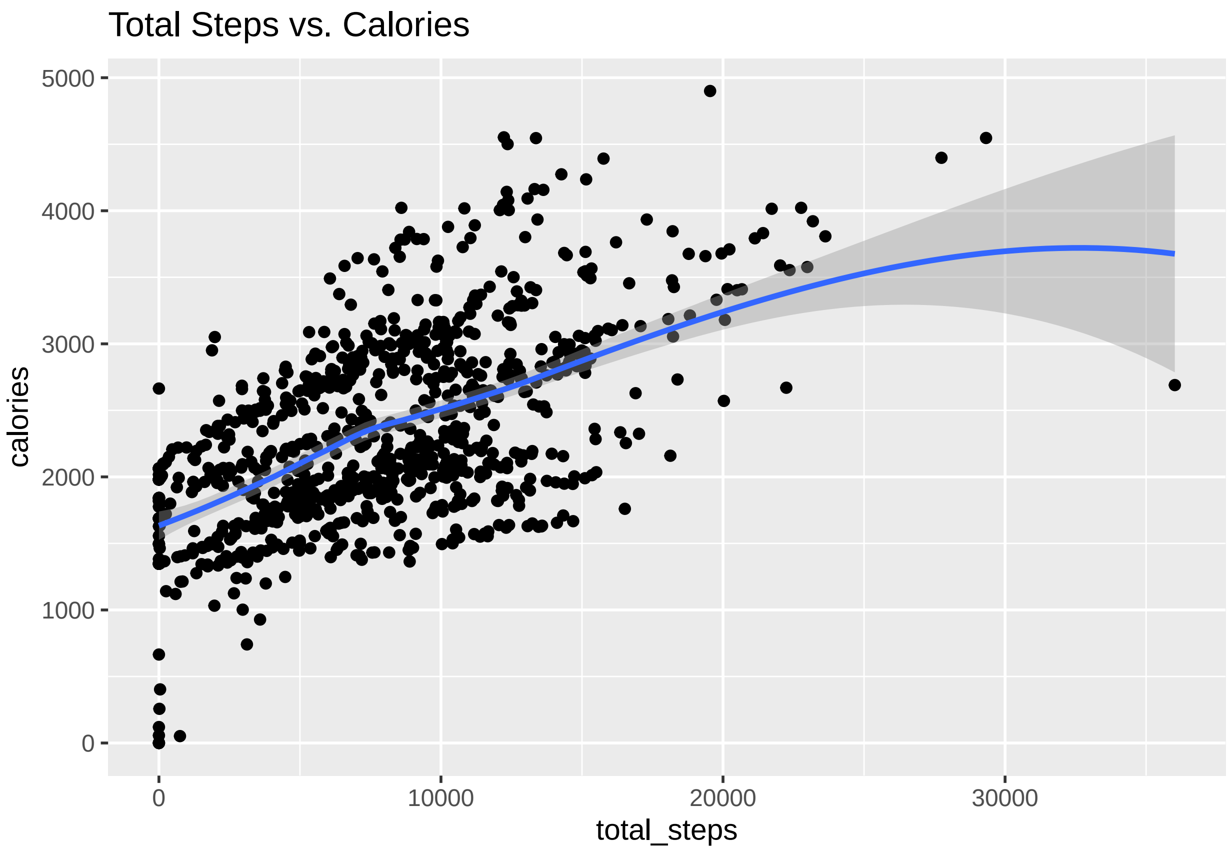
As we might expect, we can see here an almost completely linear trend between Minutes Asleep and Time in Bed. So to help users improve their sleep, the company should consider using notification to go to sleep.

Relationship between Steps and Calories

What's the relationship between steps taken and Calories ?

```
ggplot(data=daily_activity, aes(x=total_steps, y=calories)) +
  geom_point() + geom_smooth() + labs(title="Total Steps vs. Calories")
```

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



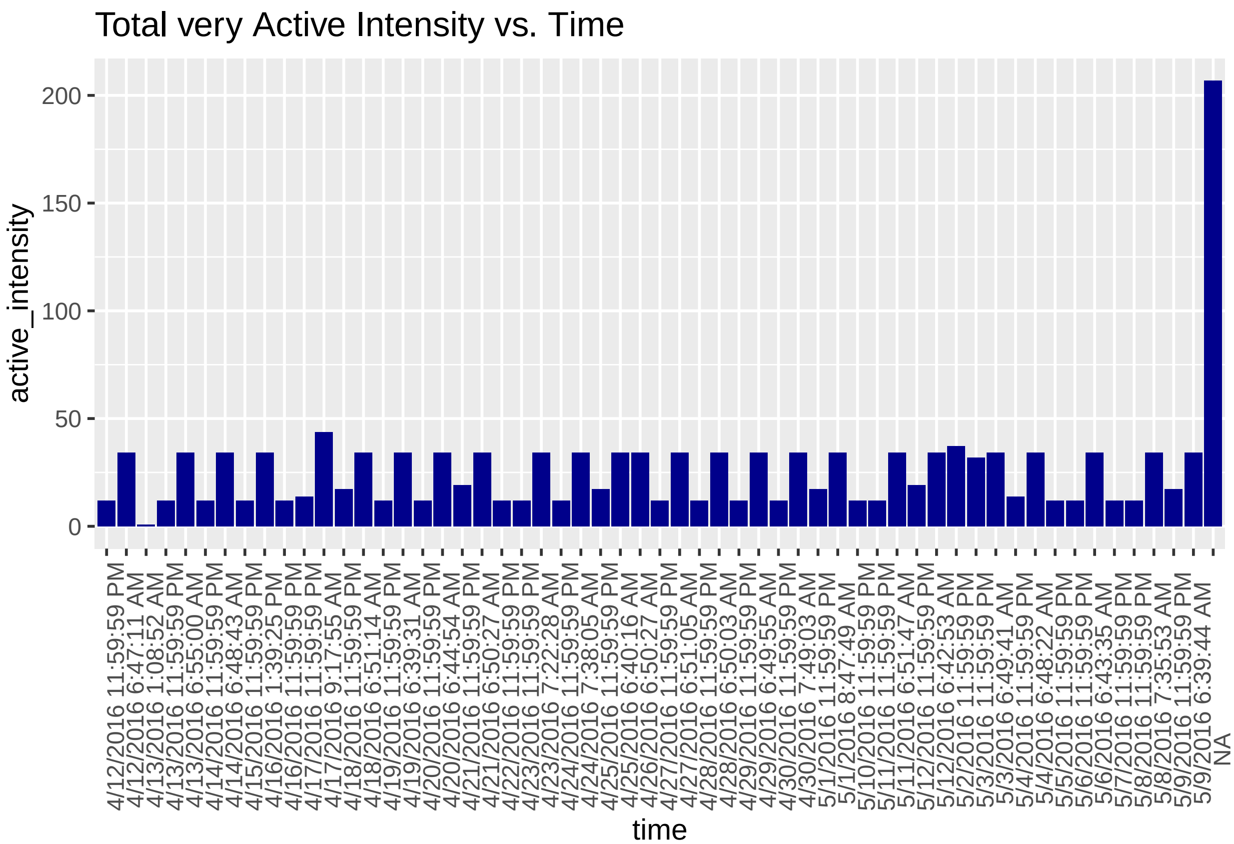
We can see here there's a positive correlation between Total Steps and Calories. The more active we are, the more calories we will burn.

Intensities data

Now, let's look at some Intensities data over time.

```
daily_intensities$active_intensity <- (daily_intensities$very_active_minutes)/60
combined_data <- merge(weight, daily_intensities, by="id", all=TRUE)
combined_data$time <- format(combined_data$date, format = "%H:%M:%S")
```

```
ggplot(data=combined_data, aes(x=time, y=active_intensity)) + geom_col(fill='darkblue')+
  theme(axis.text.x = element_text(angle = 90)) +
  labs(title="Total very Active Intensity vs. Time ")
```



By analyzing some Intensity data over time. The company will have a good idea on how customers are using their product during the day. Most users are active before and after work, I suppose. The company can use this time in the Bellabeat app to remind and motivate users to go for a run or for a walk.

Conclusions & Recommandations for the Business

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, I found some insights that would help influence Bellabeat marketing strategy.

Target Audience:

1. **Profile**
    - **Occupation**: Full-time workers, likely spending significant time at a computer or in an office setting.
    - **Behavior**: Engaged in light physical activity to maintain basic health but not enough to gain more substantial health benefits.

2. **Needs**
    - **Increased Activity**: These individuals need to elevate their daily physical activity to achieve better health outcomes.
    - **Healthy Habits**: They might lack the knowledge or strategies to develop and sustain healthy habits.
    - **Motivation**: There is a need for consistent motivation to keep them engaged in physical activity and health-related practices.

3. **Challenges**

- **Sedentary Lifestyle**: Long hours at the computer and in the office lead to a sedentary lifestyle, increasing the risk of health issues.
- **Time Constraints**: Their busy schedules may make it difficult to incorporate more intensive or frequent physical activities.

4. **Potential Strategies**

- **Educational Content**: Provide users with resources and information on how to develop and maintain healthy habits.
- **Motivational Tools**: Use app features like notifications, reminders, and challenges to keep users motivated and engaged.
- **Tailored Activities**: Recommend simple, effective exercises that can be done in short bursts throughout the day, especially during work breaks.
- **Health Benefits Focus**: Emphasize the long-term health benefits of increasing daily activity beyond light exercise, appealing to their desire to stay in shape and be healthy.

By understanding this target audience, Bellabeat can design marketing campaigns, app features, and content that cater specifically to their needs, helping them to improve their physical activity levels and overall health.

Message to the Company

The Bellabeat app need to be a unique fitness activity app. By becoming a companion guide (like a friend) to its users and customers and help them balance their personal and professional life with healthy habits.

##Recommendations to the Bellabeat Marketing team

1. **High Sedentary Time**

- **Observation**: Users are spending more than 16 hours a day in sedentary activities.
- **Implication**: Excessive sedentary time poses health risks and needs to be addressed.
- **Strategy**:
  - Focus marketing efforts on the customer segment with high sedentary time.
  - Encourage users to start walking more by tracking their daily steps.
  - Implement app notifications to remind users to increase their activity levels.

2. **Average Sleep Duration**

- **Observation**: Users sleep an average of 7 hours per night.
- **Implication**: While 7 hours is within a typical range, improving sleep quality could be beneficial.
- **Strategy**:
  - Use app notifications to remind users to go to bed at an appropriate time.
  - Suggest reducing sedentary time as part of improving overall sleep quality.

3. **Steps Per Day**

- **Observation**: Users are averaging 7,638 steps per day, which is below the CDC's recommendation of 8,000 steps.
- **Implication**: Not reaching the recommended step count can increase health risks.
- **Strategy**:
  - Encourage users to aim for at least 8,000 steps per day.
  - Educate users on the health benefits of reaching 8,000 to 12,000 steps daily, such as significantly lowering the risk of mortality.

4. **Activity Intensity**

- **Observation**: Users are most active before and after work.
- **Implication**: These times are key for encouraging more physical activity.

- **Strategy**:
  - Analyze intensity data to understand user activity patterns throughout the day.
  - Use peak activity times to send motivational reminders via the Bellabeat app, encouraging users to engage in activities like running or walking.

5. **Weight Loss and Calorie Control**

- **Observation**: Some users may be focused on weight loss.
- **Strategy**:
  - Suggest monitoring daily calorie intake as part of weight management.
  - Provide users with ideas for low-calorie, healthy meals, particularly for lunch and dinner, through the Bellabeat app.