Case Study 2: How Can a Wellness Technology Company Play It Smart?

Scenario

You are a junior data analyst working on the marketing analyst team at Bellabeat, a high-tech manufacturer of health-focused products for women. Bellabeat is a successful small company, but they have the potential to become a larger player in the global smart device market. Urška Sršen, cofounder and Chief Creative Officer of Bellabeat, believes that analyzing smart device fitness data could help unlock new growth opportunities for the company. You have been asked to 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 you discover will then help guide marketing strategy for the company. You will present your analysis to the Bellabeat executive team along with your high-level recommendations for Bellabeat's marketing strategy.

Ask

Sršen asks you to analyze smart device usage data in order to gain insight into how consumers use non-Bellabeat smart devices. She then wants you to select one Bellabeat product to apply these insights to in your presentation. These questions will guide your analysis:

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 marketing strategy? You will produce a report with the following deliverables:
4. A clear summary of the business task
5. A description of all data sources used
6. Documentation of any cleaning or manipulation of data
7. A summary of your analysis
8. Supporting visualizations and key findings
9. Your top high-level content recommendations based on your analysis

Prepare

Sršen encourages you to use public data that explores smart device users' daily habits. She points you to a specific data set: ● FitBit Fitness Tracker Data (CC0: Public Domain, dataset made available through Mobius): This Kaggle data set contains personal fitness tracker from thirty fitbit users. Thirty eligible Fitbit users consented to the submission of personal tracker data, including minute-level output for physical activity, heart rate, and sleep monitoring. It includes information about daily activity, steps, and heart rate that can be used to explore users' habits. Sršen tells you that this data set might have some limitations, and encourages you to consider adding another data to help address those limitations as you begin to work more with this data.

Process

Case Study Roadmap - Process Guiding questions ● What tools are you choosing and why? ● Have you ensured your data's integrity? ● What steps have you taken to ensure that your data is clean? ● How can you verify that your data is clean and ready to analyze? ● Have you documented your cleaning process so you can review and share those results? Key tasks

1. Check the data for errors.
2. Choose your tools.
3. Transform the data so you can work with it effectively.
4. Document the cleaning process. Deliverable Documentation of any cleaning or manipulation of data

Analyze

Now that your data is stored appropriately and has been prepared for analysis, start putting it to work.

STEP 1: installing packages:

```
install.packages("tidyverse")
install.packages("ggplot2")
```

```
install.packages("plyr")
install.packages("janitor")
install.packages("dplyr")

# library that is going to be needed:
library(tidyverse)
library(ggplot2)
library(readr)
library(plyr)
library(janitor)
library(lubridate)
library(dplyr)
```

```
Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)

Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)

Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)

Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)

Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)

── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
✔ dplyr     1.1.2     ✔ readr     2.1.4
✔ forcats   1.0.0     ✔ stringr   1.5.0
✔ ggplot2   3.4.3     ✔ tibble    3.2.1
✔ lubridate 1.9.2     ✔ tidyr     1.3.0
✔ purrr     1.0.1
── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
------------------------------------------------------------------------------

You have loaded plyr after dplyr - this is likely to cause problems.
If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
library(plyr); library(dplyr)

------------------------------------------------------------------------------


Attaching package: 'plyr'


The following objects are masked from 'package:dplyr':

    arrange, count, desc, failwith, id, mutate, rename, summarise,
    summarize


The following object is masked from 'package:purrr':

    compact



Attaching package: 'janitor'


The following objects are masked from 'package:stats':

    chisq.test, fisher.test
```

STEP 2: collecting data

```
#creating data frame with sleep data
sleep_data <- read.csv("/content/sleepDay_merged.csv")
head(sleep_data)

#creating data frame with acitivity data
daily_activity <- read.csv("/content/dailyActivity_merged.csv")
head(daily_activity)
```

```
#creating data frame with hourly calories
hour_calories <- read.csv("/content/hourlyCalories_merged.csv")
head(hour_calories)
```

A data.frame: 6 × 5

	Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInBed
	<dbl>	<chr>	<int>	<int>	<int>
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

A data

	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveD
	<dbl>	<chr>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	
1	1503960366	4/12/2016	13162	8.50	8.50	0	1.88	
2	1503960366	4/13/2016	10735	6.97	6.97	0	1.57	
3	1503960366	4/14/2016	10460	6.74	6.74	0	2.44	
4	1503960366	4/15/2016	9762	6.28	6.28	0	2.14	
5	1503960366	4/16/2016	12669	8.16	8.16	0	2.71	
6	1503960366	4/17/2016	9705	6.48	6.48	0	3.19	

A data.frame: 6 × 3

	Id	ActivityHour	Calories
	<dbl>	<chr>	<int>
1	1503960366	4/12/2016 12:00:00 AM	81
2	1503960366	4/12/2016 1:00:00 AM	61
3	1503960366	4/12/2016 2:00:00 AM	59
4	1503960366	4/12/2016 3:00:00 AM	47
5	1503960366	4/12/2016 4:00:00 AM	48
6	1503960366	4/12/2016 5:00:00 AM	48

visualizing data

```
print("===>COLUMN NAMES<===")
print(colnames(sleep_data))
print("==============================")
print(colnames(daily_activity))
print("==============================")
print(colnames(hour_calories))
```

```
[1] "===>COLUMN NAMES<==="
[1] "Id"                 "SleepDay"           "TotalSleepRecords"
[4] "TotalMinutesAsleep" "TotalTimeInBed"
[1] "=============================="
 [1] "Id"                       "ActivityDate"
 [3] "TotalSteps"               "TotalDistance"
 [5] "TrackerDistance"          "LoggedActivitiesDistance"
 [7] "VeryActiveDistance"       "ModeratelyActiveDistance"
 [9] "LightActiveDistance"      "SedentaryActiveDistance"
[11] "VeryActiveMinutes"        "FairlyActiveMinutes"
[13] "LightlyActiveMinutes"     "SedentaryMinutes"
[15] "Calories"
[1] "=============================="
[1] "Id"           "ActivityHour" "Calories"
```

STEP 3: Cleaning data

Checking if there is any NA on the data frames or duplicate

```
count(is.na(sleep_data)== TRUE)
count(is.na(daily_activity) == TRUE)
count(is.na(hour_calories) == TRUE)

sum(duplicated(sleep_data))
sum(duplicated(daily_activity))
sum(duplicated(hour_calories))
```

A data.frame: 1 × 6

x.Id	x.SleepDay	x.TotalSleepRecords	x.TotalMinutesAsleep	x.TotalTimeInBed	freq
<lgl>	<lgl>	<lgl>	<lgl>	<lgl>	<int>
FALSE	FALSE	FALSE	FALSE	FALSE	413

x.Id	x.ActivityDate	x.TotalSteps	x.TotalDistance	x.TrackerDistance	x.LoggedActivitiesDistance	x.VeryActiveDistance	x.Moderately
<lgl>	<lgl>	<lgl>	<lgl>	<lgl>	<lgl>	<lgl>	
FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	

A data.frame: 1 × 4

x.Id	x.ActivityHour	x.Calories	freq
<lgl>	<lgl>	<lgl>	<int>
FALSE	FALSE	FALSE	22099

3
0
0

as we can see: there are 3 duplicates in sleep_day we are going to fix that

```
sleep_data <- sleep_data[!duplicated(sleep_data), ]
sum(duplicated(sleep_data))
```

0

now i'm going to change the type of title of the columns

```
sleep_data <- clean_names(sleep_data, case = "snake")
daily_activity <- clean_names(daily_activity, case = "snake")
hour_calories <- clean_names(hour_calories, case = "snake")
```

converting minutes to hours on sleep_day data frame

```
sleep_data <- sleep_data %>%
  mutate(sleeping = total_minutes_asleep/60) %>%
  mutate(in_bed = total_time_in_bed/60)
head(sleep_data)
```

A data.frame: 6 × 7

	id	sleep_day	total_sleep_records	total_minutes_asleep	total_time_in_bed	sleeping	in_bed
	<dbl>	<chr>	<int>	<int>	<int>	<dbl>	<dbl>
1	1503960366	4/12/2016 12:00:00 AM	1	327	346	5.450000	5.766667
2	1503960366	4/13/2016 12:00:00 AM	2	384	407	6.400000	6.783333
3	1503960366	4/15/2016 12:00:00 AM	1	412	442	6.866667	7.366667
4	1503960366	4/16/2016 12:00:00 AM	2	340	367	5.666667	6.116667
5	1503960366	4/17/2016 12:00:00 AM	1	700	712	11.666667	11.866667
6	1503960366	4/19/2016 12:00:00 AM	1	304	320	5.066667	5.333333

converting to datetime hour_calories

```
hour_calories$date <- as.POSIXct(hour_calories$activity_hour, format = "%m/%d/%Y %I:%M:%S %p")
```

let's see if it worked

```
as_tibble(hour_calories)
```

A tibble: 22099 × 4

id	activity_hour	calories	date
<dbl>	<chr>	<int>	<dttm>
1503960366	4/12/2016 12:00:00 AM	81	2016-04-12 00:00:00
1503960366	4/12/2016 1:00:00 AM	61	2016-04-12 01:00:00
1503960366	4/12/2016 2:00:00 AM	59	2016-04-12 02:00:00
1503960366	4/12/2016 3:00:00 AM	47	2016-04-12 03:00:00
1503960366	4/12/2016 4:00:00 AM	48	2016-04-12 04:00:00
1503960366	4/12/2016 5:00:00 AM	48	2016-04-12 05:00:00
1503960366	4/12/2016 6:00:00 AM	48	2016-04-12 06:00:00
1503960366	4/12/2016 7:00:00 AM	47	2016-04-12 07:00:00
1503960366	4/12/2016 8:00:00 AM	68	2016-04-12 08:00:00
1503960366	4/12/2016 9:00:00 AM	141	2016-04-12 09:00:00
1503960366	4/12/2016 10:00:00 AM	99	2016-04-12 10:00:00
1503960366	4/12/2016 11:00:00 AM	76	2016-04-12 11:00:00
1503960366	4/12/2016 12:00:00 PM	73	2016-04-12 12:00:00
1503960366	4/12/2016 1:00:00 PM	66	2016-04-12 13:00:00
1503960366	4/12/2016 2:00:00 PM	110	2016-04-12 14:00:00
1503960366	4/12/2016 3:00:00 PM	151	2016-04-12 15:00:00
1503960366	4/12/2016 4:00:00 PM	76	2016-04-12 16:00:00
1503960366	4/12/2016 5:00:00 PM	83	2016-04-12 17:00:00
1503960366	4/12/2016 6:00:00 PM	124	2016-04-12 18:00:00
1503960366	4/12/2016 7:00:00 PM	104	2016-04-12 19:00:00
1503960366	4/12/2016 8:00:00 PM	132	2016-04-12 20:00:00
1503960366	4/12/2016 9:00:00 PM	100	2016-04-12 21:00:00

transforming to day of week

```
head(hour_calories)
```

A data.frame: 6 × 4

	id	activity_hour	calories	date
	<dbl>	<chr>	<int>	<dttm>
1	1503960366	4/12/2016 12:00:00 AM	81	2016-04-12 00:00:00
2	1503960366	4/12/2016 1:00:00 AM	61	2016-04-12 01:00:00
3	1503960366	4/12/2016 2:00:00 AM	59	2016-04-12 02:00:00
4	1503960366	4/12/2016 3:00:00 AM	47	2016-04-12 03:00:00
5	1503960366	4/12/2016 4:00:00 AM	48	2016-04-12 04:00:00
6	1503960366	4/12/2016 5:00:00 AM	48	2016-04-12 05:00:00

```
#sleep day
sleep_data$date <- mdy_hms(sleep_data$sleep_day)
sleep_data$day_of_week <- weekdays(sleep_data$date)

#daily activity
daily_activity$date <- mdy(daily_activity$activity_date)
daily_activity$day_of_week <- weekdays(daily_activity$date)

#calories
hour_calories$day_of_week <- weekdays(hour_calories$date)
```

before taking the next step, I want to see how many unique IDs we have in each data frame

```
print("Unique sleep_day")
```

```
sleep_data$id <- as.character(sleep_data$id)
unique(sleep_data$id)
length(unique(sleep_data$id))
print("Unique daily_activity")
daily_activity$id <- as.character(daily_activity$id)
unique(daily_activity$id)
length(unique(daily_activity$id))
print("Unique hour_calories")
hour_calories$id <- as.character(hour_calories$id)
unique(hour_calories$id)
length(unique(hour_calories$id))
```

```
[1] "Unique sleep_day"
```
'1503960366' · '1644430081' · '1844505072' · '1927972279' · '2026352035' · '2320127002' · '2347167796' · '3977333714' · '4020332650' · '4319703577' · '4388161847' · '4445114986' · '4558609924' · '4702921684' · '5553957443' · '5577150313' · '6117666160' · '6775888955' · '6962181067' · '7007744171' · '7086361926' · '8053475328' · '8378563200' · '8792009665'
24
```
[1] "Unique daily_activity"
```
'1503960366' · '1624580081' · '1644430081' · '1844505072' · '1927972279' · '2022484408' · '2026352035' · '2320127002' · '2347167796' · '2873212765' · '3372868164' · '3977333714' · '4020332650' · '4057192912' · '4319703577' · '4388161847' · '4445114986' · '4558609924' · '4702921684' · '5553957443' · '5577150313' · '6117666160' · '6290855005' · '6775888955' · '6962181067' · '7007744171' · '7086361926' · '8053475328' · '8253242879' · '8378563200' · '8583815059' · '8792009665' · '8877689391'
33
```
[1] "Unique hour_calories"
```
'1503960366' · '1624580081' · '1644430081' · '1844505072' · '1927972279' · '2022484408' · '2026352035' · '2320127002' · '2347167796' · '2873212765' · '3372868164' · '3977333714' · '4020332650' · '4057192912' · '4319703577' · '4388161847' · '4445114986' · '4558609924' · '4702921684' · '5553957443' · '5577150313' · '6117666160' · '6290855005' · '6775888955' · '6962181067' · '7007744171' · '7086361926' · '8053475328' · '8253242879' · '8378563200' ·
8877689391 5/12/2016 1:00:00 PM 101 2016-05-12 13:00:00

Insights:

- sleep_day = 24 unique ID's
- daily_activity = 33 unique ID's
- hour_calories = 33 unique ID's

they all match except for sleep_day that doesn't all ID's

STEP 4: Analysis

```
cat("The average of sleeping time : ", mean(sleep_data$sleeping),"\n")
cat("The average of time in bed: " ,mean(sleep_data$in_bed),"\n")
cat("The average burning calories/daily: ",mean(daily_activity$calories),"\n")
cat("The average of sedentaty time: ",mean(daily_activity$sedentary_minutes),"\n")
cat("The average of active time: ",mean(daily_activity$very_active_minutes+daily_activity$fairly_active_minutes))
```

```
The average of sleeping time :  6.98622
The average of time in bed:  7.641382
The average burning calories/daily:  2303.61
The average of sedentaty time:  991.2106
The average of active time:  34.72979
```

Insight 1:

- Users spend 1h more in bed then sleeping, that is normal, since people usually takes time to go to sleep because of insomnia or other motives, or likes to spend some time in bed before getting up in the morning.
- The active time and sedentary time it's very worrying, since it's almost 30 times more sedentary time then active.

average of total steps and calories by user

```
aggregate(cbind(total_steps, calories)~id,daily_activity, mean)
```

A data.frame: 33 × 3

id	total_steps	calories
<chr>	<dbl>	<dbl>
1503960366	12116.742	1816.419
1624580081	5743.903	1483.355
1644430081	7282.967	2811.300
1844505072	2580.065	1573.484
1927972279	916.129	2172.806
2022484408	11370.645	2509.968
2026352035	5566.871	1540.645
2320127002	4716.871	1724.161
2347167796	9519.667	2043.444
2873212765	7555.774	1916.968
3372868164	6861.650	1933.100
3977333714	10984.567	1513.667
4020332650	2267.226	2385.806
4057192912	3838.000	1973.750
4319703577	7268.839	2037.677
4388161847	10813.935	3093.871
4445114986	4796.548	2186.194
4558609924	7685.129	2033.258
4702921684	8572.065	2965.548
5553957443	8612.581	1875.677
5577150313	8304.433	3359.633
6117666160	7046.714	2261.143
6290855005	5649.552	2599.621
6775888955	2519.692	2131.769
6962181067	9794.806	1982.032
7007744171	11323.423	2544.000

```
mean(daily_activity$total_steps)
mean(daily_activity$calories)
```

7637.91063829787
2303.60957446809

Insight 2:

- The CDC recommend that most adults aim for 10,000 steps per day.
- As we can see in our analysis only a few reach the recommended steps and users are around 2.500 steps behind the recommendation

Insight 3

- Adults need from 1,600 - 3,000 calories per day
- As we can see the users are burning calories as expected on their daily activities

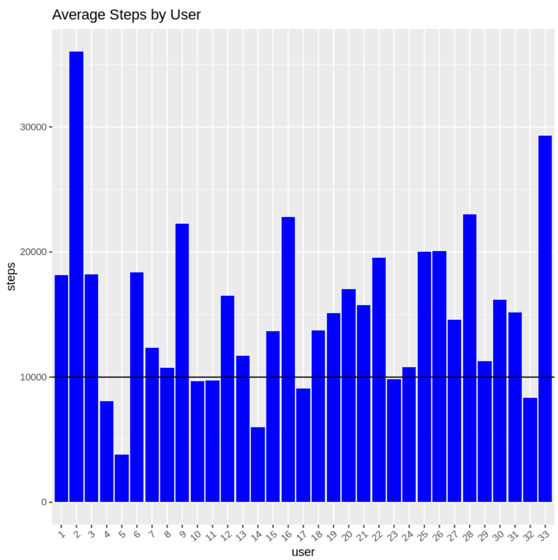
now the average calories thats is burned by hour

```
hour_calories <- hour_calories %>%
  mutate(burning_calories_time = hour(date))

mean(hour_calories$burning_calories_time)
```

11.4157654192497

Now lets see the average steps by user, and if they reach the recommended 10.000 steps

```
# Convert id column to factor
daily_activity$id <- as.factor(daily_activity$id)

# Your ggplot code with changes
ggplot(daily_activity, aes(x = id, y = total_steps)) +
  geom_bar(stat = "identity", fill = "blue", position = position_dodge(width = 0.5)) +
  labs(title = "Average Steps by User", x = "user", y = "steps") +
  geom_hline(yintercept = 10000) +
  theme(axis.text.x = element_text(angle = 40, hjust = 1)) +
  scale_x_discrete(labels = 1:33)
```



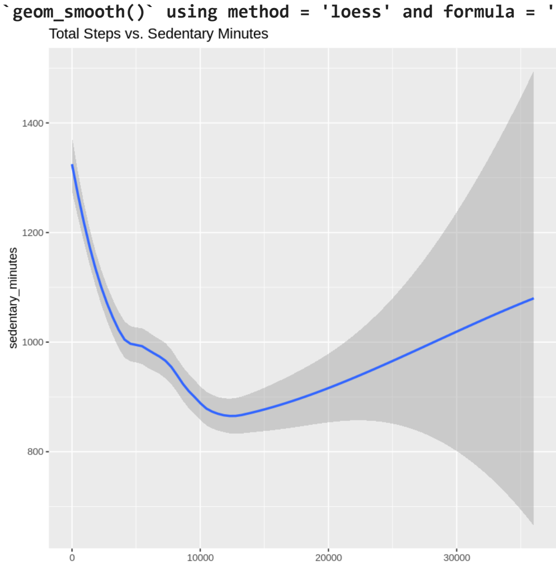
Insight 4:

As the graphic shows us, there are people below the recommended steps and people that reach them and others that go further.

Let's see the relationship between the sendetary minutes and the total steps, to see if our users are more active or sendentarys

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

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



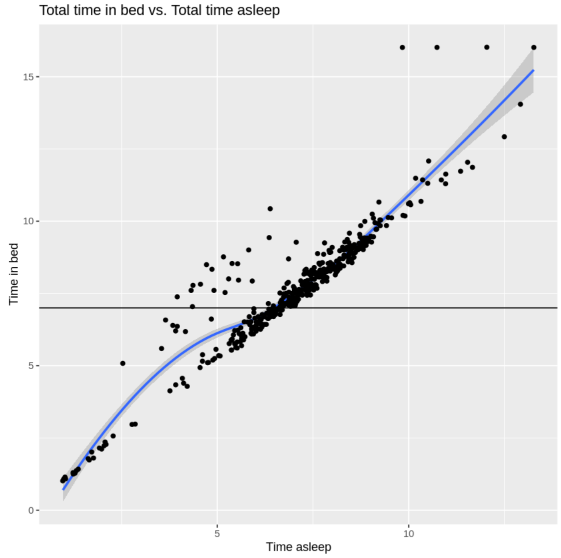
Insight 5:

As mentioned before, when user has more steps, they will likely to have less sedentary minutes. In the other hand, when the user has more sedentary minutes, it's more likely that will have less steps

Now lets see the relationship between time in bed and sleeping

```
ggplot(data=sleep_data, mapping = aes(x=sleeping, y=in_bed)) +
  geom_smooth() +
  geom_jitter() +
  geom_hline(yintercept = 7) +
  labs(title = "Total time in bed vs. Total time asleep", x= "Time asleep", y="Time in bed")
```

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



Insight 6:

Most users are sleeping the 7 hours recommended

Relationship between steps vs. calories

Conclusion:

- As we saw in previous insights the users usually get the recommended 7h sleeps
- They also reach the recommended 10.000 steps per day
- But still they are now having a healthy fitness life, they spend too much sedentary time

Recommendation:

- People like rewards in theis apps, so put a daily goal, weekly and monthly, so when the goal it's achieved, the user gain points and can exchange inside the app. Since the app also sells tangible items, it could sell some smaller items with discounts when using their points, or if the user has the same ammount of points to buy the product, it could exchange the points for the free product only paying the delivery tax.
- Recipies for woman that are looking for loosing weight or maintain a diet, and tips of foods and healthy quick-meals
- Notification when its time to go to bed
- White noise in the app to help users to sleep better
- Control of calories consumption
- Activity tips for inside or outside/gym activities

Target: