BellaBeat Report

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Introduction

Bellabeat is a high-tech company that manufactures health-focused smart products. They offer different smart devices that collect data on **activity**, **sleep**, stress, and reproductive health to empower women with knowledge about their own health and habits.

The main focus of this case is to analyze smart devices fitness data and determine how it could help unlock new growth opportunities for Bellabeat. We will focus on one of Bellabeat's products: Bellabeat app.

The Bellabeat app provides users with health data related to their activity, sleep, stress, menstrual cycle, and mindfulness habits. This data can help users better understand their current habits and make healthy decisions. The Bellabeat app connects to their line of smart wellness products.

1. Business Task

Analyse smart device data usage in order to gain insight into how consumers use non-Bellabeat smart devices and use those insights to guide Bellabeat's marketing strategy.

Objectives(Ask):

- Identify trends on non-Bella Beat smart device usage
- Find ways to connect these trends to BellaBeat produces
- Interpret these trends to make informed decisions for marketing strategies.

Stakeholders:

- Urška Sršen - Bellabeat cofounder and Chief Creative Officer
- Sando Mur - Bellabeat cofounder and key member of Bellabeat executive team
- Bellabeat Marketing Analytics team

Methodology

I used the Google analytics method to complete this case study. This method includes:

- Ask
- Prepare
- Process
- Analysis
- Share
- Act

2. Prepare

2.1 Dataset Used:

The data source used for our case study is FitBit Fitness Tracker Data. This dataset is stored in Kaggle and was made available through Mobius. This dataset can be found here.
It contains 18 CSV files with data provided by thirty three eligible Fitbit users. The users consented to the submission of personal tracker data and made it available to the public.

2.2 Tools Used:

For this case study I chose to use 'R' because of its in-house capabilities to process data and create visual representation within a central hub.

2.3 Data Credibility / Integrity:

Due to the limitation of the size (30 users) and not havbing any demographic information we are likely to encounter a sampling bias. Using ROCCC, we find that:

- **Reliability**: Sources are verified and dataset comes from a verified public dataset.
- **Original**: The data was obtained from 30 FitBit customers who gave their permission for their personal tracker data to be submitted and was created using a distributed poll conducted through Amazon Mechanical Turk.
- **Comprehensive**: This dataset is low on comprehesiveness. It has a small sample of 33 respondents. And from one source alone. It is also over a short period of time; 31 days.

- **Current**: This dataset is outdated and covers only a month in 2016
- **Cited**: The dataset can be found here.

3. Process Phase

Using R, the first phase includes data cleaning. Ensuring that the data we use is void of errors, misspelling, duplicate data, misaligned data types and more.

Here is the changelog for the cleaning process:

- 24/08/2022 - Removed duplicate data
- 24/08/2022 - Removed N/A in datasets
- 25/08/2022 - Clean and rename columns
- 26/08/2022 - Fix consistency of date datatype and time columns in daily_activity and daily_sleep datasets
- 29/08/2022 - Fixed datatype and consistency for hourly_steps dataset
- 29/08/2022- Seperated date and time from one column into two.
- 29/08/2022 - Merged daily_acivity and daily_sleep

4. Analysis Phase AND visualization (share)

In this phase we will do the fun work of analyzing trends of the FitBit users. The information we discover will be later be applied to BellaBeat's marketing strategies. This dataset has 33 respondents which is a small sample in relation to the population that uses health tracking devices.

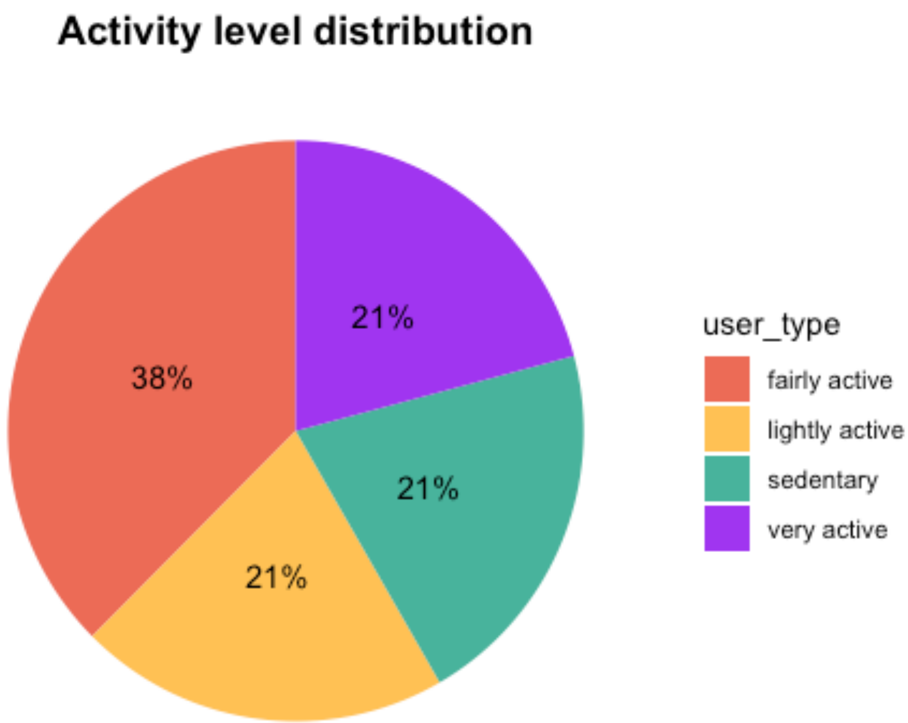

Figure 1

Graph 1 shows how active the users are in our dataset. We created a categorical standard following the 10,000 steps model. The breakdown is as follows:

- Sedentary - Less than 5000 steps a day.
- Lightly Active - Between 5000 and 7499 steps a day.
- Fairly Active - Between 7500 and 9999 steps a day.
- Very Active - More than 10000 steps a day.

The majority (38%) of users are regarded as fairly active. And equally 21% for very active, lightly active, and sedentary. The CDC recommends that users walk closer to 7,500 steps. We can see with this data presented that users on average are well distributed from being consciously active with majority meeting their 7500 steps a day. This does, however, also leave a window of opportunity for BellaBeat. This shows that promotions to help urge users to get more active with their products.

Now that we know users mostly fairly active, we want to know when are they active throughout the week. With that, we also want to know when they sleep more. We will verify, in this step, if each user is getting the recommended amounts of steps (7500) in and the recommended amount of sleep (8 hours).

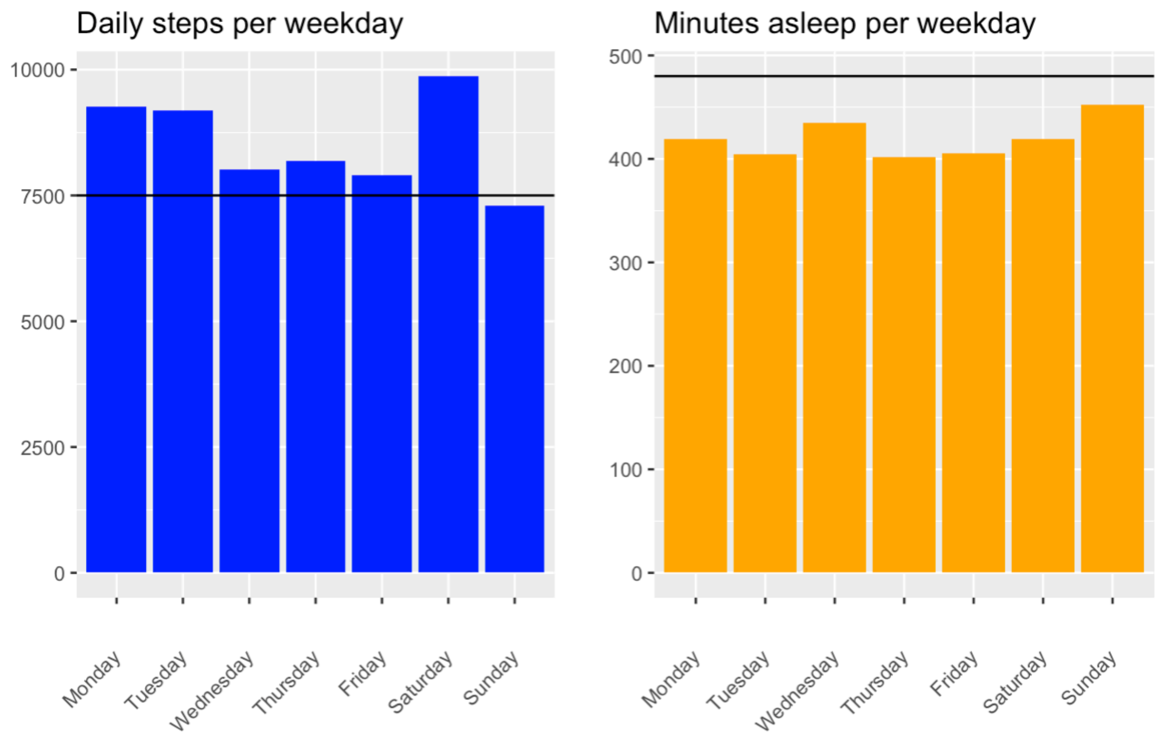

Figure 2

In continuing to understand our users and their data we see further that the users in this dataset are meeting their 7500 every day of the week, except Sundays. This observation makes sense because many use their Sundays to rest while using Saturdays for errands etc. However, none of our users are meeting their recommended sleep.

In diving deeper in our analysis, we want to know when in the day are users mostly active. In understanding the trends of activity throughout our day we are able to get a closer look at users activity routine.

In figure 3, in order to get average steps taken we summarize the steps total for all the user and organize it by the hour.

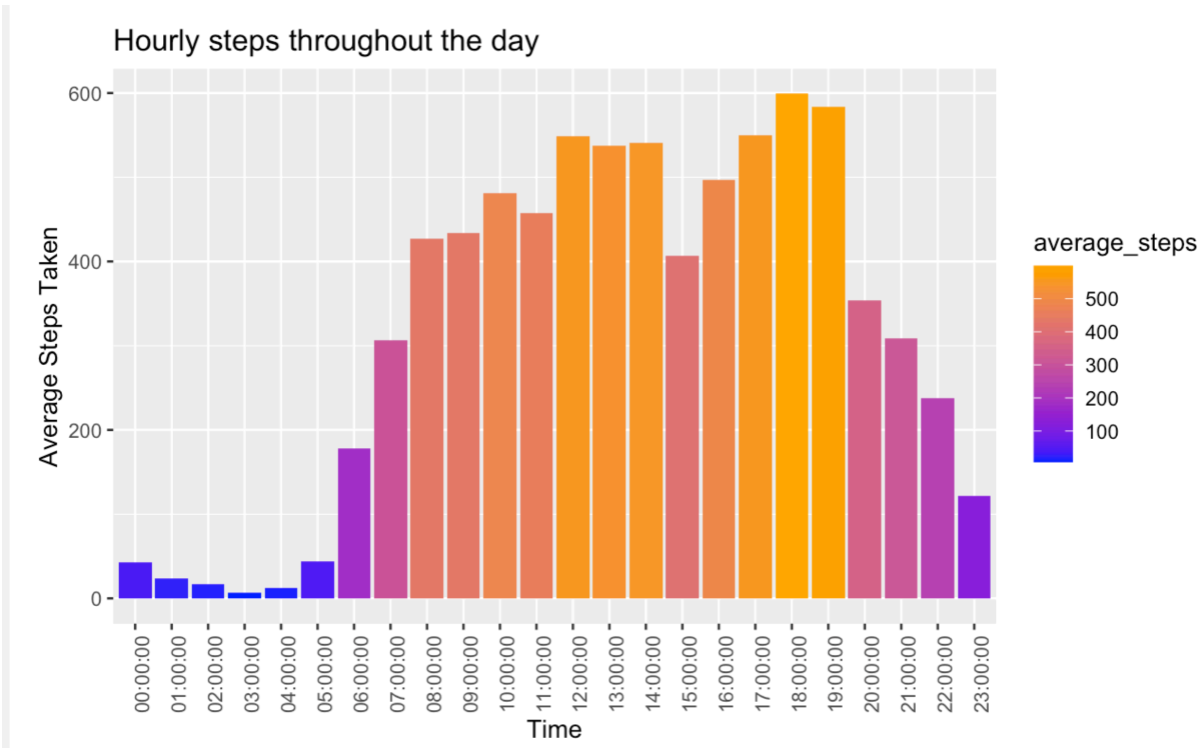

Figure 3

We see here that our users are mostly active in the afternoons between 8am to 7pm. There are peeks in the data between 12pm to 2pm and 5pm to 7pm. This trend could be targeted by BellaBeat through its app.

We have gained insight on user activity, sleep, calories burned and now we want to find out how often do the users actually use their device.

We elected to use a categorical approach based on users using their smart devices on a daily bases. This dataset has data worth up to 31 days, therefore our categories are as follows:

- High Use - Smart Device use between 21 and 31 days.
- Moderate Use - Smart Device use between 10 and 20 days.
- Low Use - Smart Device use between 1 and 10 days.

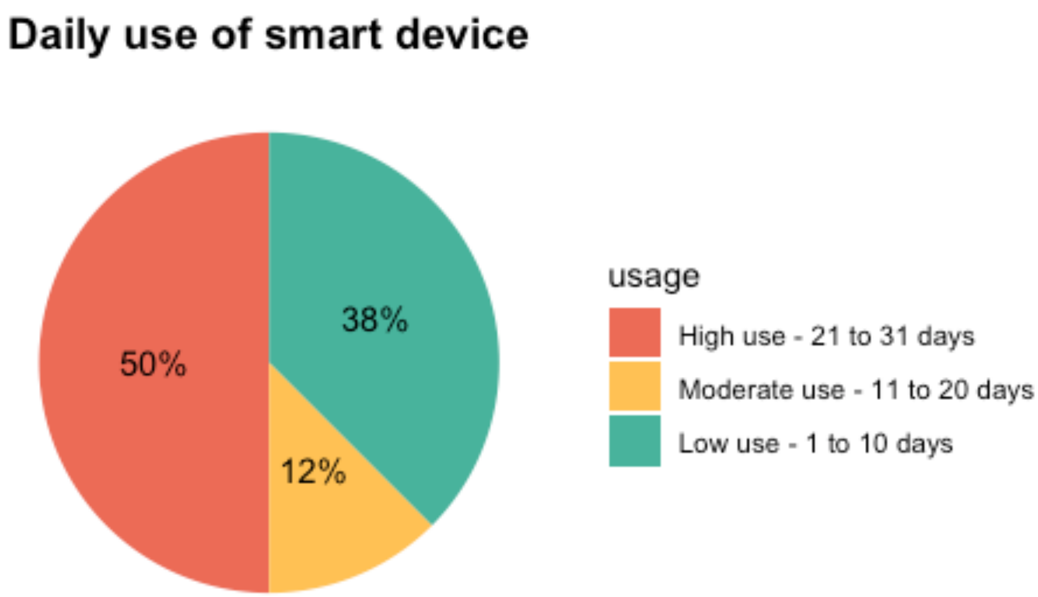

Figure 4

In figure 4 we see a trend where 50% of our users use their smart devices more frequently and more consciously. Together with a moderate usage of 12% we can see that our users perceive value in utilizing their smart devices throughout their day and are fairly conscious of their physical health.

Diving deeper in this analysis, we want to know how much time per day are these users using their devices during a day.

We then chose to calculates the total minutes a user wore their device in a day. Now that we are calculating total minutes a day, we created different categories to understand what our data is telling us.

These are the three categories:

- All day ~ 90% and up of the day
- More than half a day ~ between 50% and 90% of the day
- Less than half a day ~ under 50% of the day

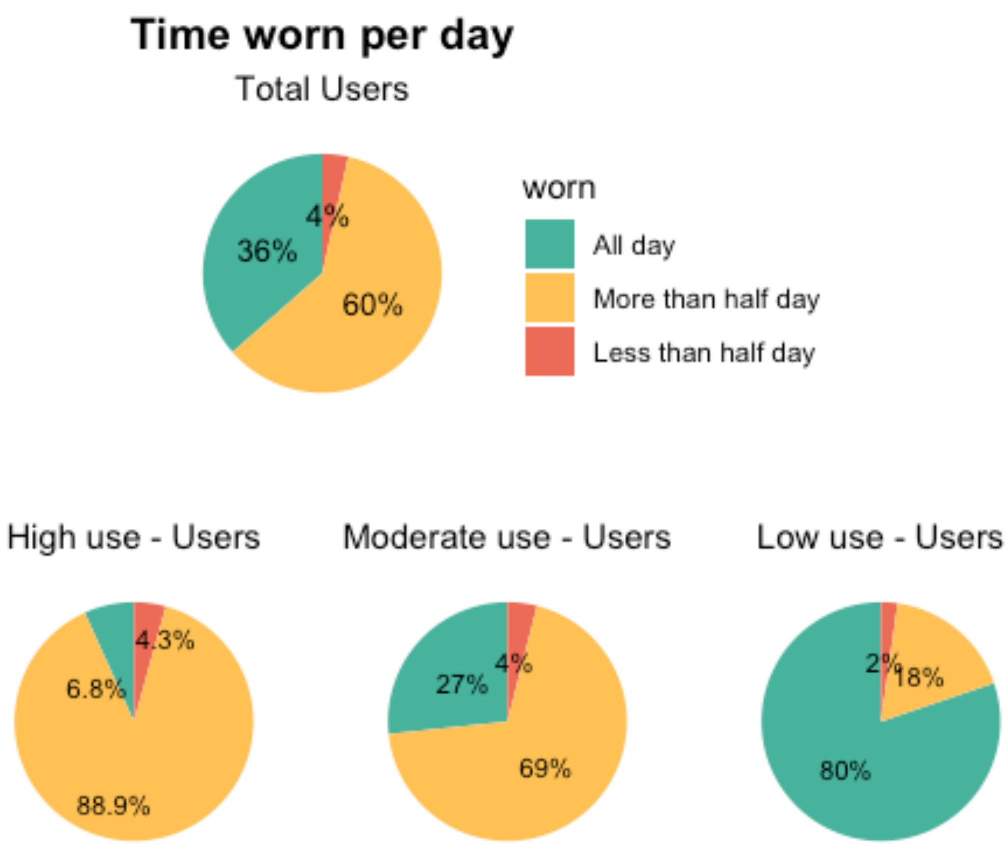

Figure 5

Trends in usage for our users shows that in a day, 36% of our users have their watches on all day. 60% of our total users were their watches for more than half a day and only 4% were it for less than half a day.

This is a positive tell that users not only wear their smart devices for a frequent amount of days but they also will wear them for most of the day.

Figure 5 also shows time worn respective to how frequent users wore their watches in the 31 day frame presented in the dataset. This extra step sheds further light into our previous discovery where we tried to understand how frequent users use their smart devices. We separated them into High usage users (21 to 31 days), Moderate usage users (11 to 20 days) and low usage users (1 to 10 days).

- We found that a majority (88.9%) of our high usage users wear their smart devices for more than half the day.
- 69% of our moderate usage users wear their devices for more than half the day also.
- Surprisingly, of our low usage users, 80% actually wear their watches all day.

This trend shows a high value in wearable technology. BellaBeat can use this angle to promote/invest in more wearable technologies.

5. Act

Bellabeat's target market is women. It would be advisable for Bellabeat to try using their own tracking data for further analysis. This dataset, although insightful, has biased limitations and some demographic details of users aren't available.

The different trends and observations logged can be used to help improve the Bellabeat app.

> 1. Daily notifications on steps and recommended activity: Through our analysis, we found that users are in general fairly active. We can use the app to encourage customers to meet the recommended step count of 7500 and upwards throughout the day. Sending alarms, especially closer to the times they are most active throughout the day: 12 pm to 2 pm and 5 pm to 7 pm.
>
> 2. Reward System: We can encourage users by creating a badge-like system that gradually (over time) increases to encourage users to reach the next level of fitness in their lifestyle. These badges can be arranged by progressive step count/calories burnt through a day or time stamped by month.

In our analysis, we also found that 50% of users are using their devices on a daily basis and that a majority of 96% (36%+60%) are averaging using their devices for most of the day.
This information can help marketing strategies by:

- Ensuring the promotion of Bellabeat WEARABLE products and their long-lasting batteries, comfortability and capabilities with its in house app.
- Since Bellabeat's target audience is women - fashion/elegance is as important.
- Considering Bellabeat's target audience is also young adults avenues of marketing like social media should be heavily utilized.