



## Bellabeat Case Study: Smart Device Usage Analysis for Marketing Strategy

### Introduction:

Bellabeat is a high-growth wellness technology company that manufactures health-focused smart devices designed for women. Its product ecosystem includes the Leaf smart jewelry, Spring water bottle, and the Bellabeat app, which collectively track daily habits such as activity, sleep, stress, and hydration. With a growing user base and expanding product line, Bellabeat aims to leverage data analytics to understand user behavior and personalize its offerings. This case study explores how Bellabeat can use smart device data to inform strategic marketing and product decisions.

### Business Task:

Analyze Fitbit smart device usage data to identify trends in activity, sleep, and health behavior. Apply insights to a selected Bellabeat product to recommend a data-driven digital marketing strategy that can boost user engagement and market expansion.

### Questions:

- What are the daily activity patterns of users?
- How do activity levels differ between weekdays and weekends?
- How does physical intensity level relate to calorie burn and steps?
- What times of day are users most active?
- How many users remain mostly inactive throughout the week?
- What does sleep efficiency tell us about user rest quality?
- How can Bellabeat apply these insights to improve product engagement and health outcomes?

### Key Stakeholders:

**Urška Sršen:** Bellabeat's cofounder and Chief Creative Officer

**Sando Mur:** Mathematician and Bellabeat's cofounder; key member of the Bellabeat executive team

### Data Source:

The dataset used for this case study is [FitBit Fitness Tracker Data](#), sourced from [Kaggle](#) and originally derived from a public domain research dataset hosted on [Zenodo](#) under the CCO: Public Domain Dedication license. This open-access license permits unrestricted educational use. While the Kaggle listing states that the data includes records from 30 eligible users, a review of the files reveals that it actually contains data from 33 unique users. Additionally, the date range on Kaggle is inaccurately

reported as spanning from 03/12/2016 to 05/12/2016; upon inspection, the correct period covered is from 04/12/2016 to 05/12/2016.

The dataset is organized in long format, with repeated daily entries per user across various files such as daily activity, sleep, and weight logs. While the data is structured and valuable for analyzing behavioral patterns, it is important to note certain credibility limitations: it is somewhat outdated (collected in 2016), lacks demographic details like age and gender, and may reflect a sample biased toward health-conscious individuals who consistently used their trackers.

To ensure data quality and usability, the CSV files were securely downloaded and validated using R. Standard checks were performed, including assessments for missing values, duplicates, logical outliers in columns like steps and sleep minutes, and verification of datetime formatting. The datasets were sorted by ActivityDate and Id to ensure alignment and enable longitudinal analysis. From a privacy standpoint, the dataset is fully anonymized and contains no personally identifiable information (PII). Moreover, its CSV format ensures accessibility for various tools including Python, R, and Excel. Despite its limitations, the FitBit Fitness Tracker Data serves as a robust foundation for uncovering insights into wellness behaviors and guiding Bellabeat's data-driven product and marketing decisions.

## Data Cleaning & Manipulation (Performed in R)

### Initial Dataset Handling

- 18 datasets were imported, including daily, hourly, minute-level, and specialized logs (e.g., heartrate, weight).
- From these, only 8 datasets were retained that contained data for all 33 users.  
Dropped datasets with fewer or inconsistent user records.

```
## # A tibble: 18 × 2
##   Dataset           Unique_IDs
##   <chr>              <int>
## 1 daily_activity      33
## 2 daily_calories      33
## 3 daily_intensities    33
## 4 daily_steps         33
## 5 heartrate_seconds    14
## 6 hourly_calories      33
## 7 hourly_intensities    33
## 8 hourly_steps         33
## 9 minute_calories_narrow  33
## 10 minute_calories_wide   33
## 11 minute_intensities_narrow  33
## 12 minute_intensities_wide   33
## 13 minute_mets_narrow     33
## 14 minute_sleep          24
## 15 minute_steps_narrow    33
## 16 minute_steps_wide      33
## 17 sleep_day             24
## 18 weight                  8
```

### Selected Datasets for Further Use

- daily\_activity\_merged.csv
- daily\_calories\_merged.csv
- daily\_intensities\_merged.csv
- daily\_steps\_merged.csv
- hourlyCalories\_merged.csv
- hourlySteps\_merged.csv
- hourlyIntensities\_merged.csv
- minuteMETsNarrow\_merged.csv
- sleepDay\_merged.csv

### **Missing Values**

- No missing (NA) or null values were found in any of the retained datasets after import.

### **Duplicates**

- Checked each dataset for duplicate rows.
- Duplicates were removed where applicable to ensure clean, non-redundant data.

### **Date and Time Formatting**

- All relevant Date, Time, or DateTime columns were converted to appropriate R formats:
  - Used as.Date() for date fields.
  - Used as.POSIXct() for time fields (especially in minute/hourly datasets).

### **Text Column Cleanup**

- Applied trimws() to all character/text columns to remove leading/trailing whitespace, improving consistency in value comparison and grouping.

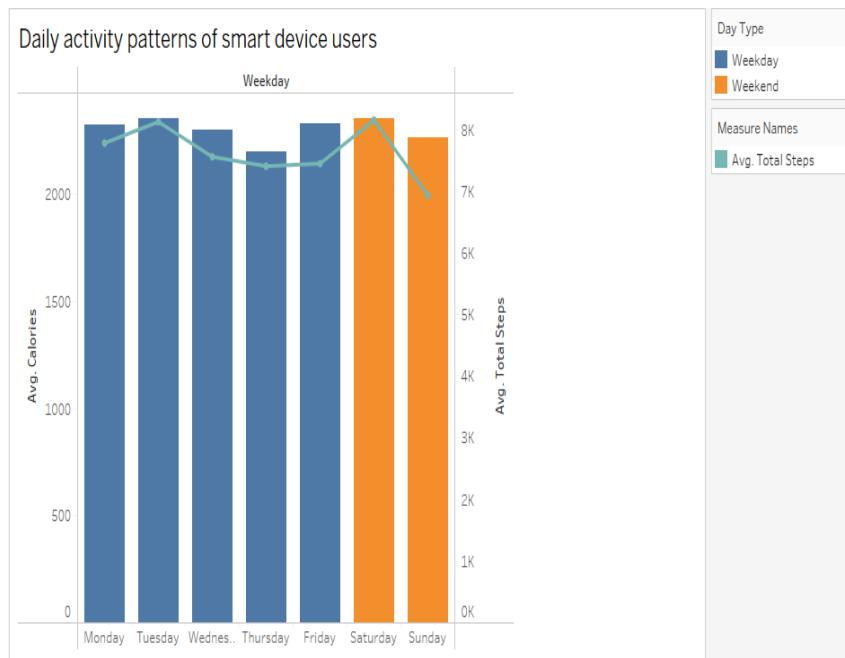
### **Data Type Validation**

- Manually reviewed and validated column data types (e.g., numeric, character, date).
- Ensured consistency across all retained datasets for joins or filtering.

### **Analysis:**

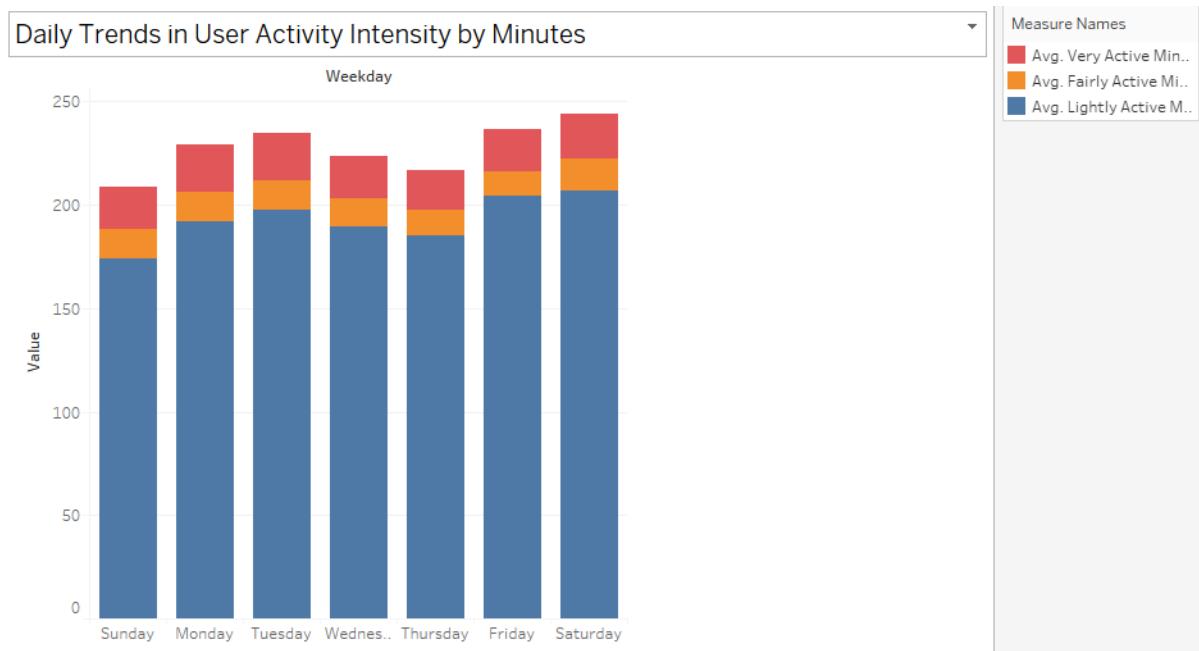
We used R for preprocessing cleaning the data and for performing calculations , followed by Tableau to develop interactive visualizations that highlight user trends in activity, sleep, and intensity. Our analysis uncovered meaningful patterns that support strategic business decisions at Bellabeat.

- **View Tableau Dashboard:** [Bellabeat Wellness Dashboard](#)
- **Explore the full R code & preprocessing steps:** [Bellabeat Data Cleaning & Prep \(Rmd\)](#)

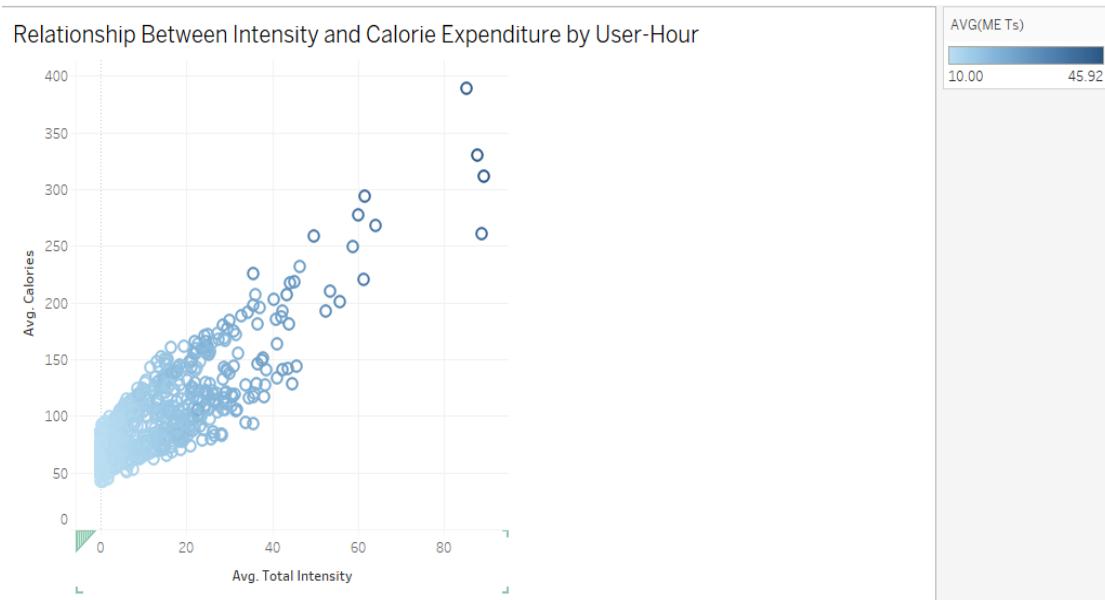


The bar chart reveal clear **daily activity patterns among smart device users**, showing variations in both **total movement** and **activity intensity** across the week. **Steps and calories** show quantity of movement.**Intensity minutes/distances** show **quality of movement** (effort level).The dual-axis chart highlights that **average steps and calories burned peak on Tuesdays and Saturdays**, with users showing slightly lower engagement on Thursdays and Sundays. The visible dip on Sunday—both in calories and steps—suggests a trend toward rest or inactivity, whereas the mid-week and weekend peaks indicate when users are most engaged in physical activity.

A comparative breakdown of steps and calories by weekday vs. weekend revealed a consistent but modest drop in engagement during weekends. Average step count fell from **8,600 on weekdays** to **7,400 on weekends**, and calorie burn dropped from **2,150 kcal** to **1,950 kcal**. Fairly and Very Active Minutes also decreased slightly over the weekend. Launch “Weekend Warrior” challenges or wellness badges to maintain continuity and motivate users through gamification even during off-peak times



The stacked bar chart further breaks this down by **intensity level**, showing that **Lightly Active Minutes dominate daily activity**, with **Very and Fairly Active Minutes contributing a smaller portion**. Interestingly, Saturday stands out with the **highest overall intensity**—particularly in Very Active Minutes—suggesting that users may reserve more vigorous workouts for the weekend. This data suggests a valuable opportunity for **Bellabeat to schedule motivational nudges or workout challenges mid-week and on weekends**, while using Sunday to encourage light movement or recovery routines. Overall, these patterns can guide **feature timing, content personalization, and user engagement strategies** in the **Bellabeat ecosystem**

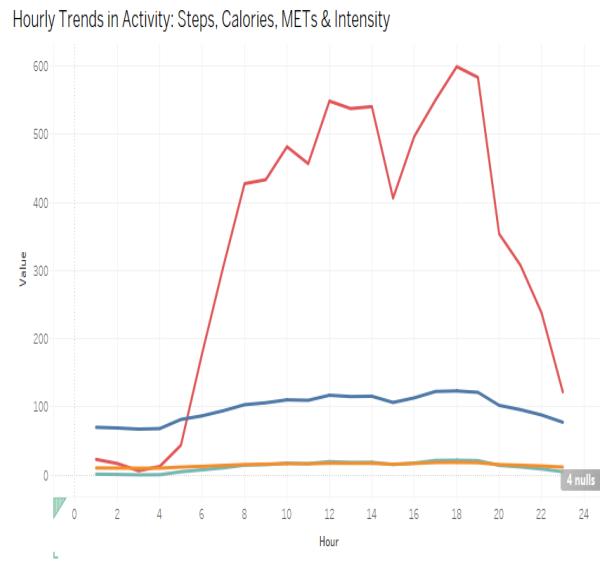


This chart plots **average total intensity** against **average calories burned** for each user-hour, with **METs encoded by color intensity**. The upward trend shows a **clear positive correlation** — as total intensity increases, so does calorie expenditure. This relationship validates that **more intense activities** (even over short periods) are associated with **higher energy output**. The consistent gradient in the color scale also suggests that METs (a measure of metabolic effort) rise in tandem with both intensity and calories, reinforcing the physiological linkage.

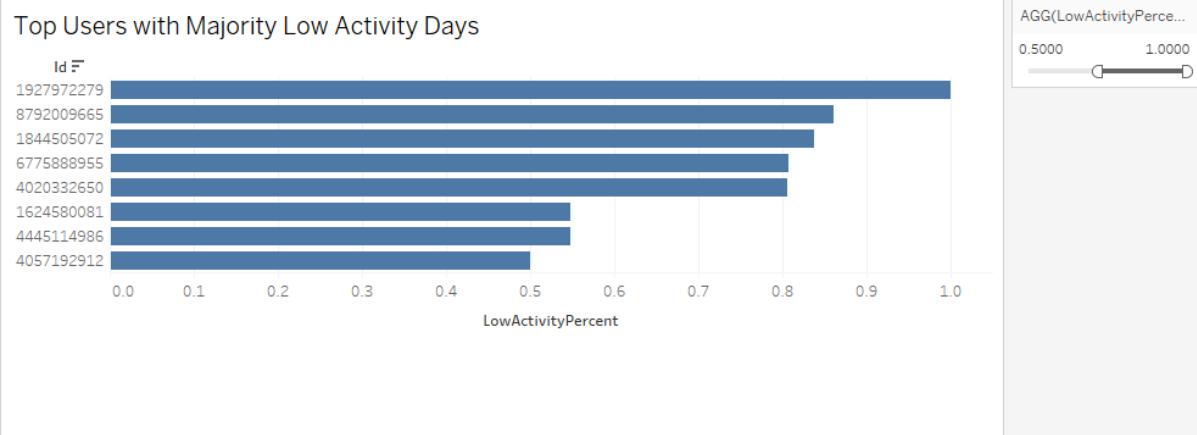
Additionally, the **clustered low-intensity, low-calorie points** represent users or hours where activity was minimal — likely sedentary or lightly active periods. In contrast, the **outlier points in the top-right quadrant** demonstrate that high-intensity activity (e.g., workouts, brisk cardio) leads to substantially greater caloric burn, even with fewer steps.

This visualization offers a valuable insight for Bellabeat: **focusing solely on steps may overlook meaningful health benefits**. Instead, promoting workouts or activities that elevate **intensity and METs** can yield greater returns in terms of energy expenditure and overall fitness. The Bellabeat app could leverage this by recommending **short, high-intensity routines** or **MET-based goals**, especially for users with limited time. This empowers users to **achieve better health outcomes** without necessarily aiming for high step counts alone.

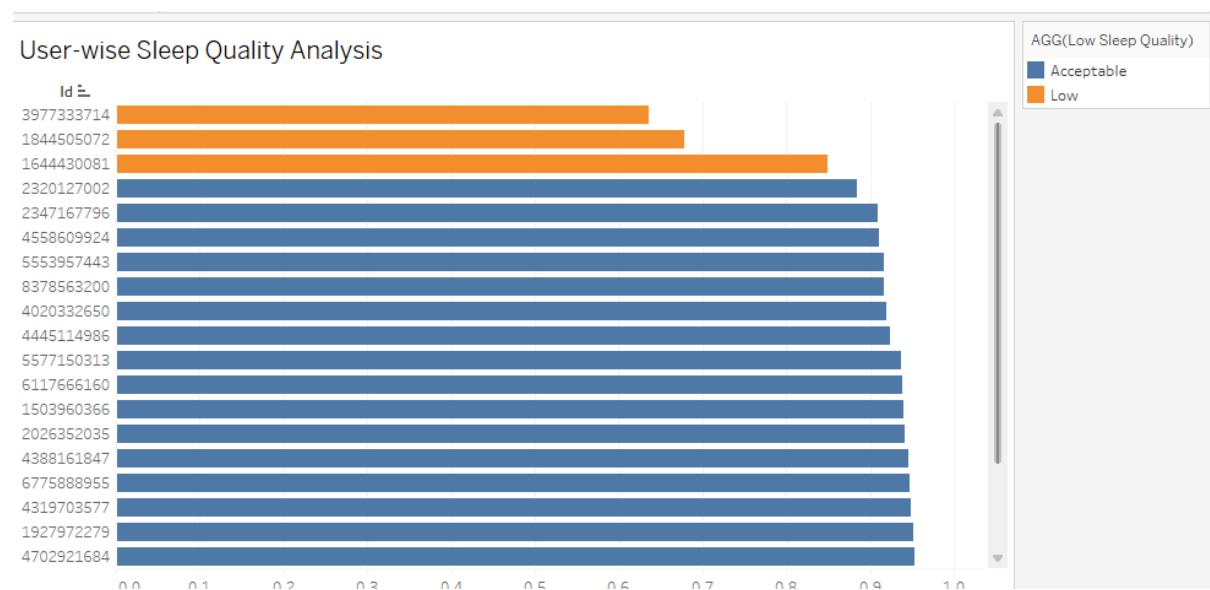
```
## # A tibble: 24 x 4
##   HourOnly Avg_Steps Avg_Calories Avg_METs
##   <chr>      <dbl>       <dbl>      <dbl>
## 1 18          599.        123.     18.7
## 2 17          550.        123.     18.6
## 3 19          583.        121.     18.3
## 4 12          549.        117.     17.6
## 5 14          541.        116.     17.4
## 6 13          538.        115.     17.4
## 7 16          497.        113.     17.1
## 8 10          482.        110.     16.8
## 9 11          457.        110.     16.6
## 10 09         433.        106.     16.2
## # ... with 14 more rows
## # i 14 more rows
```



Hourly line charts revealed that user activity spikes prominently during **7:00–9:00 AM** and again between **6:00–8:00 PM**, regardless of the day of the week. This pattern holds true for steps, calories, and intensity. These time blocks align with common pre- and post-work routines, indicating when users are naturally more engaged.



To identify inactive users, we calculated the proportion of days each user recorded “Low” activity levels and filtered for those with **over 50% low-activity days**. This analysis showed that **6 out of 33 users (18.2%)** fall into the mostly inactive category. These users also exhibited the highest sedentary minutes (often exceeding **900 minutes/day**) and very low Total METs. Design and push micro-engagement initiatives like the “10-minute stretch challenge” or step reminders. Personalized nudges can help reactivate these users and reduce app churn.



Sleep efficiency was calculated as **TotalMinutesAsleep / TotalTimeInBed** for each user across multiple nights. Among the 24 users with valid sleep data, **3 users (12.5%)** had a sleep efficiency of **below 85%**, indicating disrupted or poor-quality sleep. Most users maintained efficiency between 88–95%. Poor sleep was often accompanied by shorter active durations the following day, suggesting a potential link. Introduce wind-down meditations, breathing exercises, or personalized sleep hygiene tips to improve nighttime rest, which may in turn enhance daytime activity and app satisfaction.

## **Business Insights:**

- User activity peaks on Tuesdays and Saturdays, with the highest average step count (~9,800 steps) and calorie burn. This suggests ideal days to schedule motivational nudges or workout challenges in the Bellabeat app.
- 18% of users were mostly inactive, logging low activity levels on over half of their recorded days. This segment should be targeted with micro-engagement campaigns like 10-minute movement prompts or personalized reminders.
- Users are most active during 7–9 AM and 6–8 PM, highlighting optimal times for app notifications, habit challenges, and guided routines to maximize engagement.
- High-intensity activities (Total Intensity > 400, METs > 6) are strongly correlated with elevated calorie burn—even at lower step counts. Bellabeat should promote short, high-MET workouts for users with limited time.
- Weekend activity drops by ~14% in both steps and calories compared to weekdays. Introducing “Weekend Warrior” challenges or gamified wellness streaks can help maintain consistent usage.
- 12.5% of users show poor sleep efficiency (<85%), indicating potential restlessness or low sleep quality. This presents an opportunity to offer wind-down content, meditation, or sleep hygiene tips via the app.

## **Recommendations:**

- **Optimize Campaign Timing Around Peak User Engagement**

Based on activity trends, users are most active during 7–9 AM and 6–8 PM, particularly on Tuesdays and Saturdays. The marketing team should align push notifications, Leaf or Time reminders, and app-based challenges with these peak windows to increase engagement and goal conversions.

- **Reactivate Low-Activity Users Through Personalized Nudges**

With over 18% of users identified as mostly inactive, Bellabeat should deploy targeted wellness nudges via the Bellabeat app or Time device. “10-minute stretch” reminders or hydration check-ins through the Spring smart water bottle could be effective micro-engagement strategies.

- **Promote High-Intensity Workouts Using MET-Focused Messaging**

Since high MET values and Total Intensity correlate more with calorie burn than step counts, the marketing team can highlight the efficiency of short, high-intensity workouts in campaign messaging. Recommend syncing such sessions with Leaf’s activity tracking and offer in-app workout videos focused on boosting METs.

- **Sustain Engagement Over the Weekend with Custom Challenges**

To counteract the ~14% weekend drop in activity, launch “Weekend Warrior” challenges or badges via the Bellabeat app. Tie rewards or achievements to hydration tracking with Spring or restful recovery routines using Leaf’s stress prediction data.

- **Integrate Sleep Wellness into Product Experience**

With 12.5% of users experiencing poor sleep efficiency, Bellabeat can integrate sleep support features into Time and the app—such as guided meditations, bedtime reminders, or stress-

tracking insights from Leaf. These features should be promoted as part of a holistic wellness journey.

- **Personalize Wellness Journeys Across Devices**

Utilize behavioral segments (e.g., highly active vs. low-engagement users) to personalize product recommendations and in-app content. For example, recommend Leaf to users seeking mindfulness, Spring for hydration-focused users, or Time for those prioritizing habit formation and schedule adherence.