Bellabeat Case Report

Understanding Smart Device Usage Patterns

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Executive Summary

Using fitness tracking data, I explored how people use smart devices in their daily wellness routines to help inform Bellabeat's marketing strategy. I looked at when and how intensely people exercise, sleep habits, heart rate, and calorie burn patterns. This analysis revealed several key trends that could help Bellabeat better connect with potential customers. My recommendations focus on matching Bellabeat's products to how people use wellness devices daily.

Objective

This analysis aims to harness fitness data from non-Bellabeat devices to gain insights into user behavior. These insights aim to help Bellabeat refine its product offerings and customer engagement strategies. Specifically, this analysis seeks to:

- Identify trends in fitness tracker usage that can influence Bellabeat's product roadmap.
- Provide actionable insights for marketing and customer engagement strategies.
- Recommend new features aligned with user behavior patterns, increasing engagement and retention.

Data Sources

Data for this analysis was sourced from a publicly available Fitbit dataset from Kaggle containing minute-level and daily records of 30 users over two months. The dataset includes:

- Daily and hourly activity data: Step counts by hour and by day.
- Minute-level sleep data: Duration and quality of sleep.
- Minute-level heart rate data: Continuous heart rate readings.
- Hourly calorie expenditure: Caloric burn broken down by hour.
- Hourly intensity metrics: Intensity of physical activity throughout the day.
- User weight logs: Weight records providing context on user fitness and goals.

Data Processing and Cleaning

The following steps were undertaken to ensure the data was fit for analysis.

Data Merging and Formatting

Data from different sources—activity, heart rate, sleep, and intensity—were merged using unique user IDs and timestamps. This involved standardizing date and time formats to ensure proper temporal alignment, which enabled a comprehensive view of each user's daily activity, sleep, and heart rate patterns.

Handling Missing Values

To ensure data integrity, missing or incomplete records were handled carefully. Data points missing in key metrics such as steps, heart rate, or sleep duration were excluded from analyses like user segmentation and correlation studies to maintain accuracy.

Feature Engineering

To enhance the analysis, several new variables were engineered:

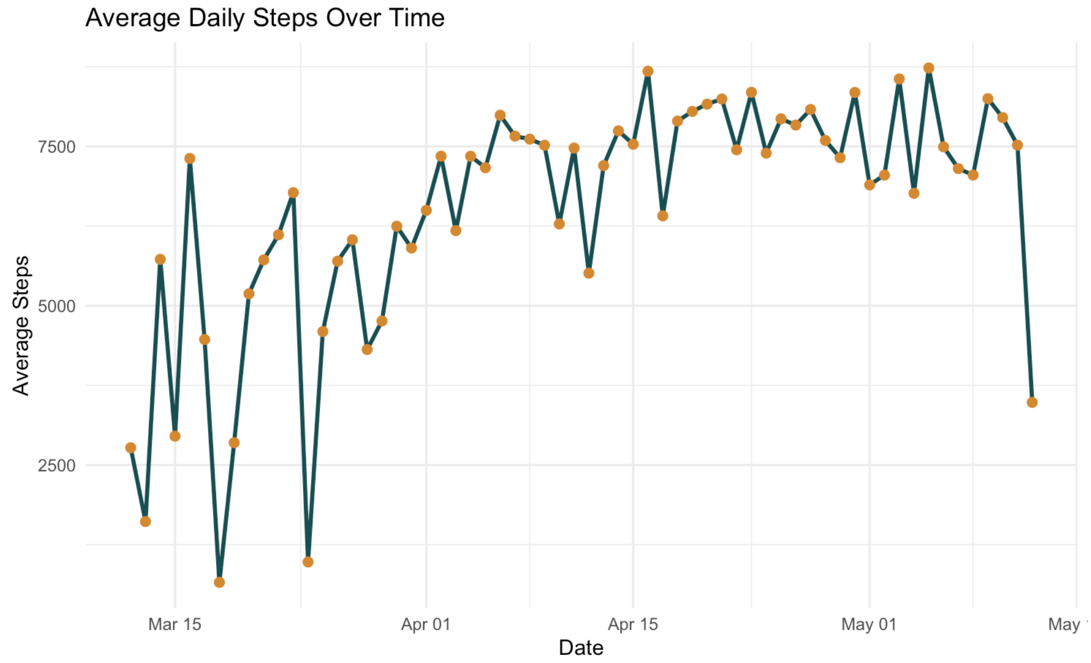
- **Activity Segmentation:** Users were categorized into three activity levels, High Activity, Moderate Activity, and Low Activity, based on their average daily steps.
- **Monthly Aggregations:** Metrics were aggregated by month to detect activity, sleep, and heart rate trends.
- **Day-type Classification:** Activity and sleep data were split into weekday versus weekend patterns to identify behavioral differences.

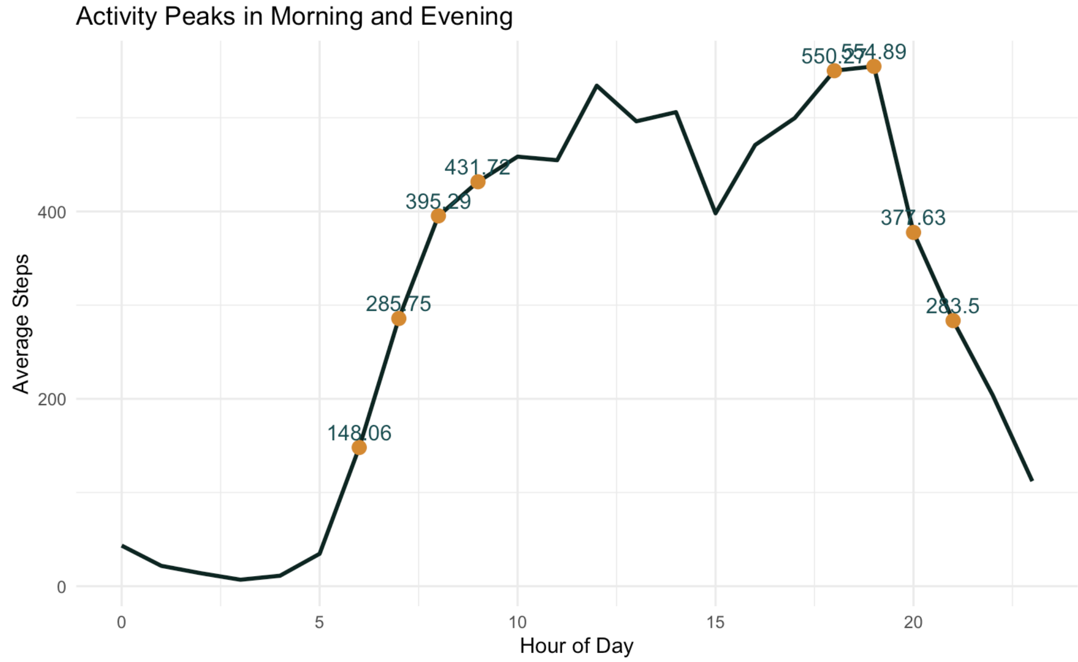
Analysis and Findings

Behavioral Patterns in Activity, Heart Rate, and Sleep

Daily and Hourly Activity Patterns

- **Average Daily Steps:** There is significant variability in daily step counts, with some users walking as few as 500 steps and others exceeding 10,000 steps daily. Peak activity was observed between 7-9 AM and again at 6-8 PM, likely coinciding with commuting and post-work exercise routines.

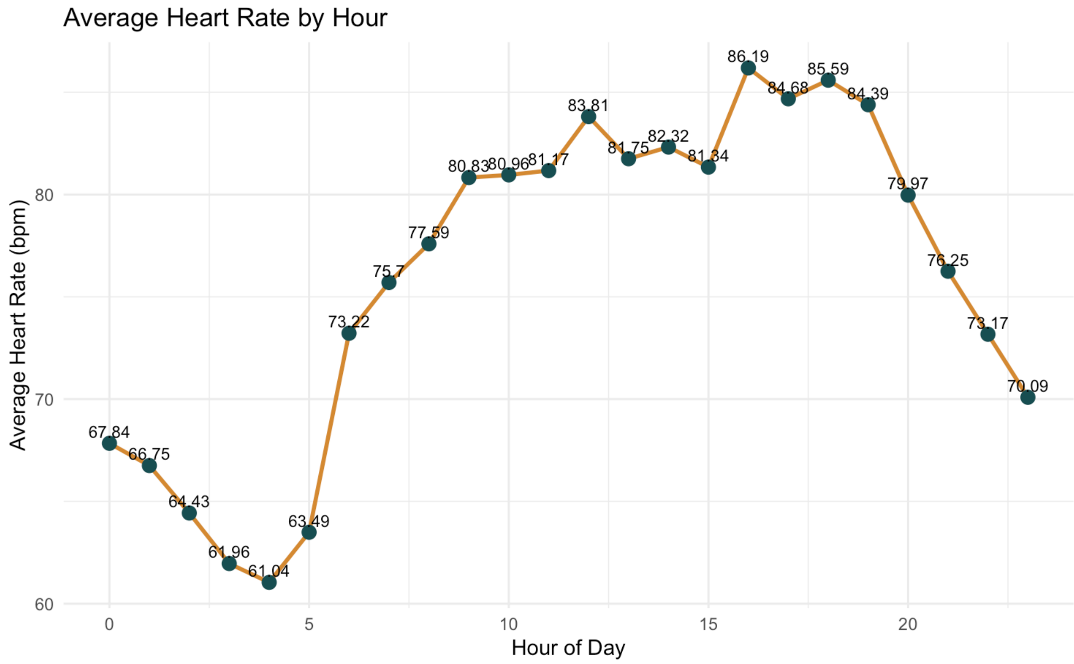




These peak activity periods allow Bellabeat to deliver personalized workout content at these times.

Heart Rate Patterns

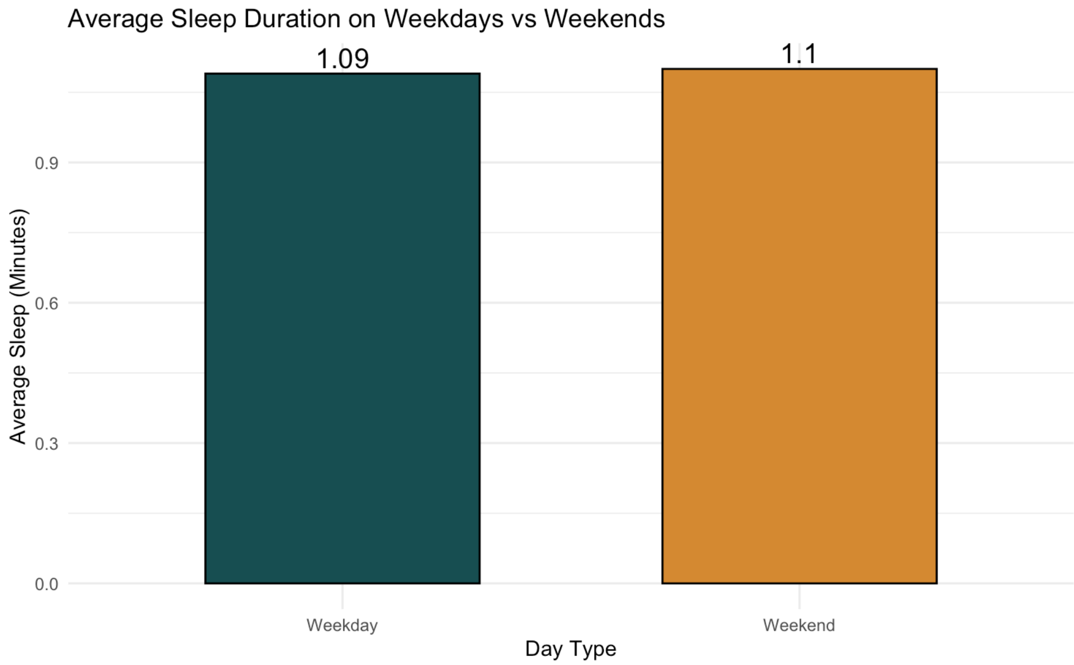
- **Heart Rate by Hour:** Users' average heart rates fluctuate throughout the day. Resting heart rates are around 61.9 bpm and peak at 86.2 bpm during evening exercise. This highlights natural fluctuations between rest and intense activity.



***Bellabeat could focus on heart rate monitoring and stress management tools to help users manage their health during periods of high activity*.**

Sleep Patterns

- **Weekend vs. Weekday Sleep**: Users tend to sleep slightly longer on weekends, averaging 1.1 hours compared to 1.08 hours on weekdays. This suggests users compensate for lost sleep on weekends.



Bellabeat can offer weekend recovery routines to help users improve overall sleep quality.

User Segmentation Based on Multiple Factors

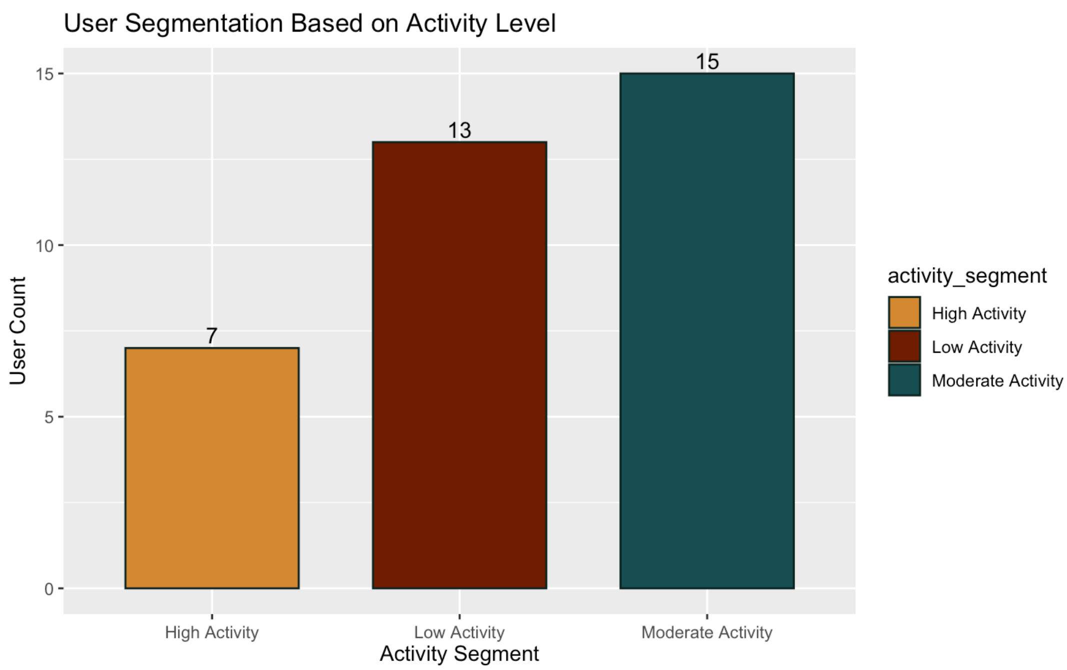
To understand user behavior and provide actionable insights, we performed two types of segmentation: step-based segmentation and K-means clustering using combined fitness metrics such as sleep, heart rate, and physical activity. This approach helps tailor product features and marketing strategies to meet user needs.

Step-Based Segmentation

This method categorized users into three groups based on their average daily steps:

- **High Activity**: Users averaging 10,000+ steps per day (7 users). These individuals are highly active and would respond well to advanced fitness features, such as performance tracking and challenging workout programs.
- **Moderate Activity**: The largest group (15 users) averages 5,000 and 9,999 steps. They maintain moderate activity but could be encouraged to increase it through step challenges, fitness tips, or personalized coaching.
- **Low Activity**: Comprising 13 users, this group averages fewer than 5,000 daily steps. These users could benefit from beginner-friendly content, daily movement reminders, and basic step goals to boost their activity levels.

Key Insight: Most users fall into the Moderate and Low Activity categories, allowing Bellabeat to motivate more significant movement through personalized challenges, rewards, and tips.

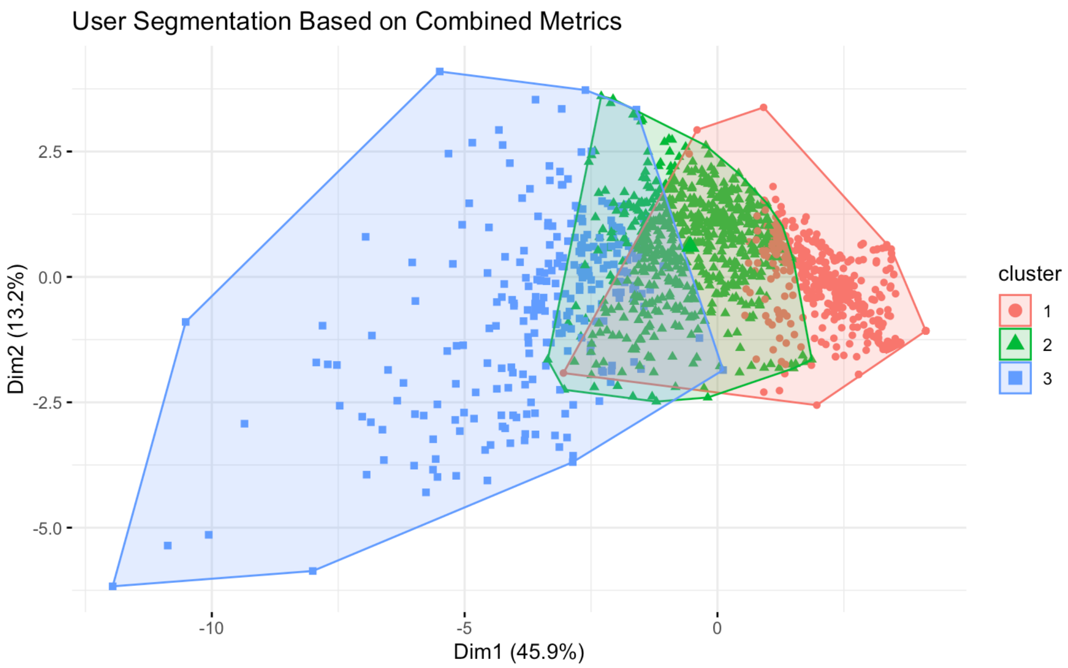


K-means Clustering: Segmentation Based on Combined Metrics

This approach grouped users into three clusters based on a broader range of fitness data, including activity, sleep, and heart rate:

- **Cluster 1 (Low-to-Moderate Activity)**: These users (red circles) exhibit low-to-moderate activity and would benefit from motivational tools like guided workouts and simple fitness challenges.
- **Cluster 2 (Moderate Activity)**: Represented by green triangles, these users are consistently active and could be engaged with more challenging programs and progressive goals.
- **Cluster 3 (Highly Active)**: These highly engaged users (blue squares) show consistently high activity levels and would appreciate advanced features like high-intensity training and detailed performance tracking.

Key Insight: K-means clustering reveals a deeper segmentation of user behavior. Cluster 1 users need motivational tools, while Cluster 3 users are fitness-driven and would respond well to advanced, customizable features.



Intensity Levels and Calorie Burn

Intensity by Time of Day

- Users were most active during the evening, with high-intensity workouts between 6 PM and 8 PM, correlating with increased heart rates and calorie burns.

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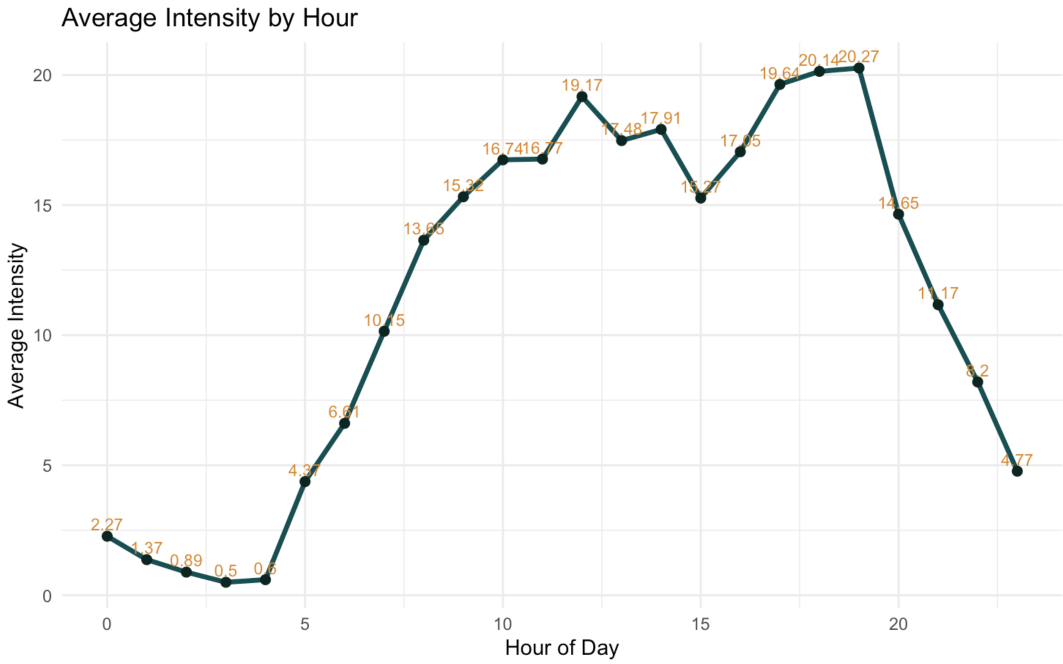

Bellabeat could target these peak hours by offering high-intensity workout content.

Correlation Analysis

A comprehensive correlation analysis explored the relationships between three key variables: average steps, heart rate, and sleep duration. The study used a linear regression model and a correlation matrix, providing insights into how these metrics interact.

Insights from the Regression Model:

The linear regression model was developed to predict average sleep duration based on average steps and heart rate. However, the results revealed that neither average steps nor average heart rate had a statistically significant impact on predicting sleep duration. The model's **R-squared** value was **0.0162**, indicating that only 1.6% of the variance in sleep duration could be explained by steps and heart rate, with an adjusted R-squared of **-0.1806**, further suggesting a weak model fit.

- The **p-values** for both variables were above 0.05, showing no statistical significance:
  - **Steps**: p-value = **0.699**
  - **Heart Rate**: p-value = **0.878**

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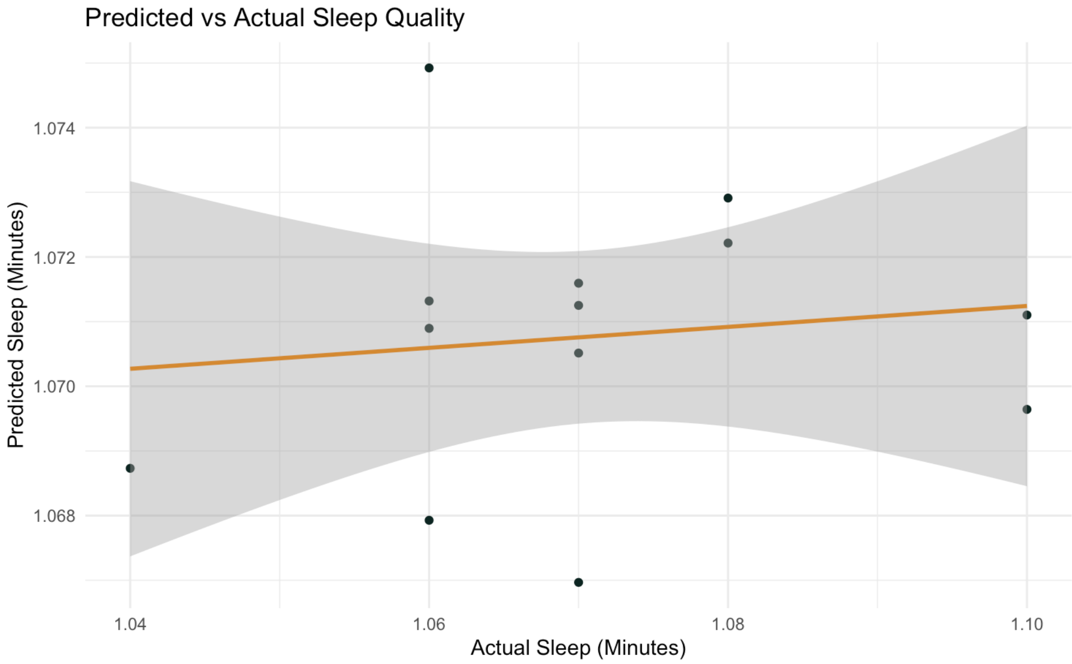


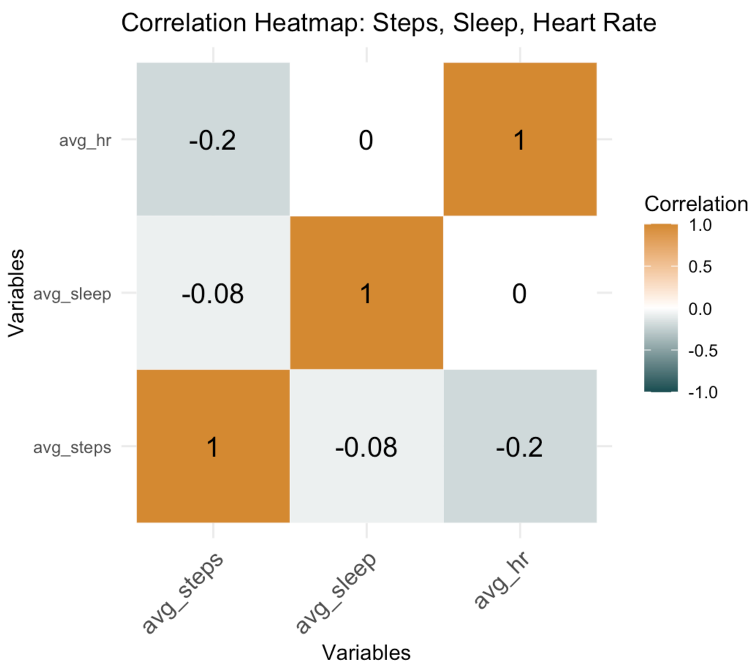
The **Predicted vs. Actual Sleep Quality** plot visualizes this weak relationship. The plot shows a flat line with minimal changes between predicted and actual sleep values, confirming that steps and heart rate contribute little to predicting sleep duration.

Insights from the Correlation Heatmap:

The correlation matrix, visualized in the **Correlation Heatmap**, further confirmed the weak relationships:

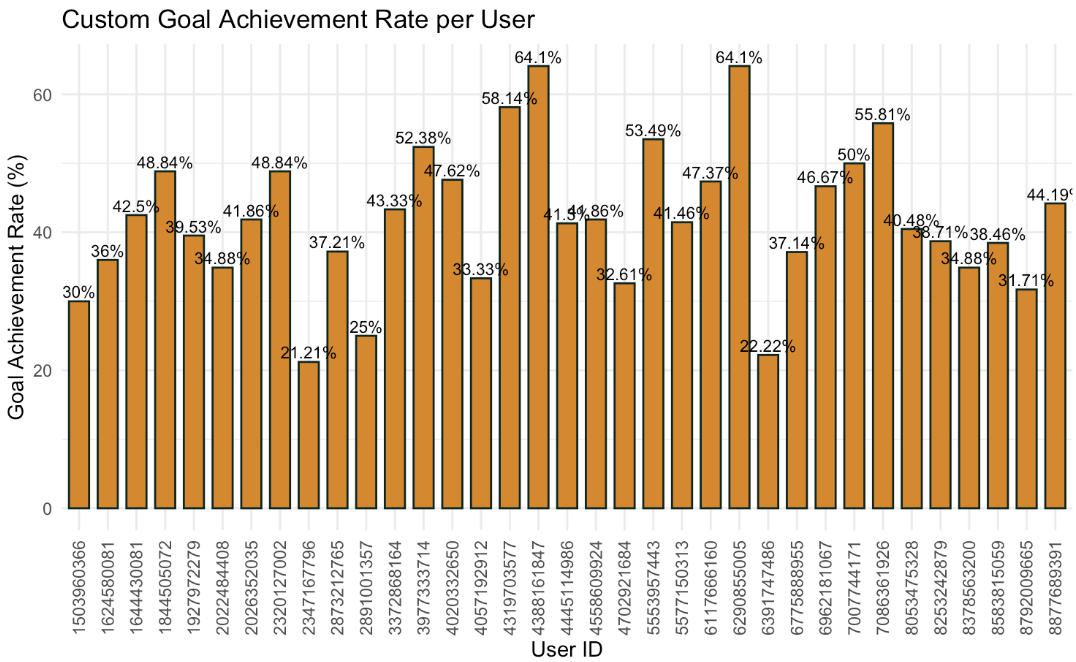
- **Steps vs. Sleep Duration**: A weak negative correlation of **-0.08** suggests that higher physical activity levels (steps) do not significantly influence sleep duration.
- **Heart Rate vs. Sleep Duration**: A moderate negative correlation of **-0.2** indicates a slight tendency for higher resting heart rates to correlate with shorter sleep durations, but the effect is weak.

The heatmap highlights that steps and heart rate are not strong predictors of sleep behavior, and other factors such as stress, nutrition, or external conditions (e.g., environment, daily routine) might need to be considered to understand sleep quality fully.



Goal Achievement Analysis

- **Goal Achievement**: Custom step goals, set at 10% above users' average daily steps, revealed an **average goal achievement rate of 41.7%.** Some users consistently exceeded their targets, while others fell short.



This presents an opportunity for Bellabeat to motivate users with personalized milestone achievements and rewards for goal attainment.

Recommendations

Personalized Insights and Goal Setting

Bellabeat should implement dynamic goal setting that adjusts based on users' past performance. Reward users with badges or notifications for achieving their personalized goals, which can improve engagement and motivation.

- **How**: Track each user's progress and adjust goals accordingly, offering incremental challenges to motivate them.

Stress and Recovery Support

Bellabeat could offer stress management tools for users with high resting heart rates and poor sleep patterns. Features such as mindfulness exercises, relaxation techniques, and sleep improvement tips would help these users manage their health more effectively.

- **How**: Introduce stress-relief notifications and personalized content to reduce stress and improve sleep quality.

Marketing Focus on Weekend Recovery

Users tend to sleep more on weekends, indicating a natural recovery trend. To help users recharge, Bellabeat could promote weekend-specific recovery content, including relaxation, stretching, and mindfulness routines.

- **How**: Develop marketing campaigns focused on weekend recovery, encouraging users to adopt better sleep and recovery habits.

Promoting Evening Exercise Programs

With high levels of activity in the evening, Bellabeat can introduce evening-specific workouts, such as high-intensity interval training (HIIT) programs. These workouts could target users during their most active times.

- **How**: Deliver personalized evening workout suggestions and fitness challenges based on users' past evening activity.

Expanding High-Intensity Training Content

Given the popularity of high-intensity workouts, Bellabeat should expand its interval training programs and offer customizable intensity levels. Users can stay motivated to reach new milestones by introducing progress tracking and real-time feedback.

- **How**: Offer users more customizable HIIT programs with integrated progress tracking and notifications for real-time motivation.

Methodology

The analysis employed several statistical methods:

- **K-means Clustering:** Used to group users based on behavioral similarities, enabling targeted insights for each segment.
- **Correlation Analysis:** Applied to explore relationships between steps, sleep, and heart rate, using correlation matrices to visualize associations.
- **Feature Engineering and Data Transformation:** Features like monthly trends and day-type classifications (weekend vs. weekday) were created to deepen insights into behavioral patterns.

Conclusion

This report highlights diverse user wellness behaviors with identifiable activity, sleep, and intensity trends. By leveraging these insights to deliver personalized recommendations, support stress management, and promote wellness-focused features, Bellabeat can enhance user engagement and establish itself as a leader in the wellness technology space.