# Bellabeat Case Study

## Growth Opportunities in Wellness Tech: Data-Driven Strategies

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# Company Overview

Bellabeat is a wellness company delivering health-focused solutions for women.

**The company has five products:**

- **Bellabeat app** - Tracks activity, sleep, stress, menstrual cycle, and mindfulness habits
- **Leaf** - Wellness Tracker worn as a bracelet, necklace, or clip, tracking activity, sleep, and stress
- **Time** - Wellness Watch that tracks activity, sleep, and stress
- **Spring** - Water Bottle tracks daily water intake
- **Bellabeat Membership** - Subscription service offering personalized guidance on nutrition, activity, sleep, health, beauty, and mindfulness

# Business Task

- Identify consumer behavior trends and actionable insights from public data of non-Bellabeat smart devices
- Recommend strategies from these findings that can guide Bellabeat’s marketing strategy and support growth

# Key Questions

- What are the emerging trends in consumer behavior related to smart device usage?
    - Who uses them?
    - How do they use them?
    - When do they use them?
- How can Bellabeat leverage these trends to enhance the customer experience and meet their needs?
- How can Bellabeat refine its marketing strategy and expand its presence using these insights?

# Data Overview

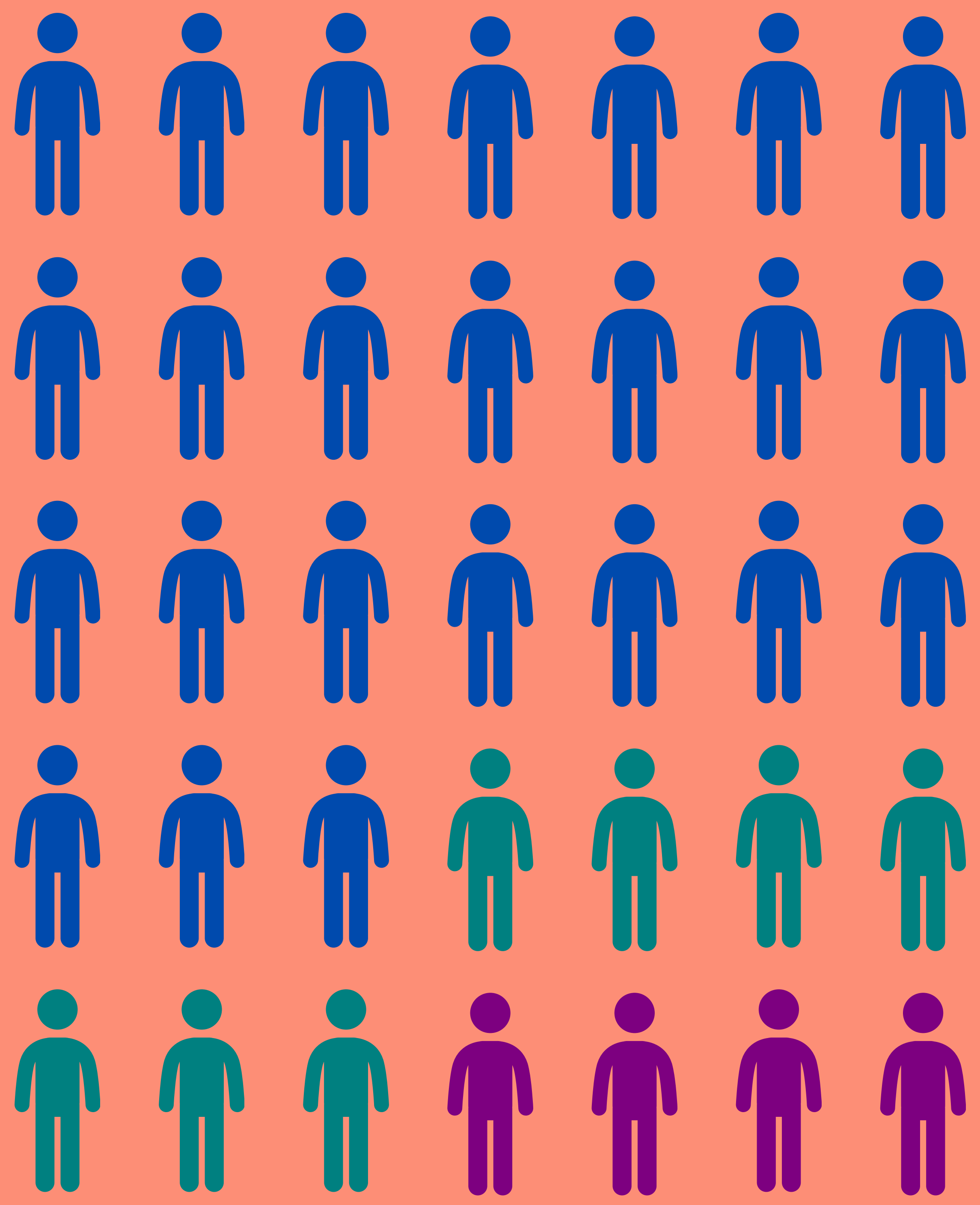
- Public personal dataset of 35 unique FitBit trackers
- Collected from 03/12/2016 to 05/12/2016
- Output for daily activity, calories, sleep, steps, and weight
- *Source: FitBit Fitness Tracker Data*

## Tools Used

- R programming for data cleaning, analysis, and visualizations

# Tracking Behavior

- 100% of Users tracked their activity
- Of those:
  - 69% tracked **Sleep**
  - 20% tracked **Sleep + Weight**
  - 11% tracked **Weight**

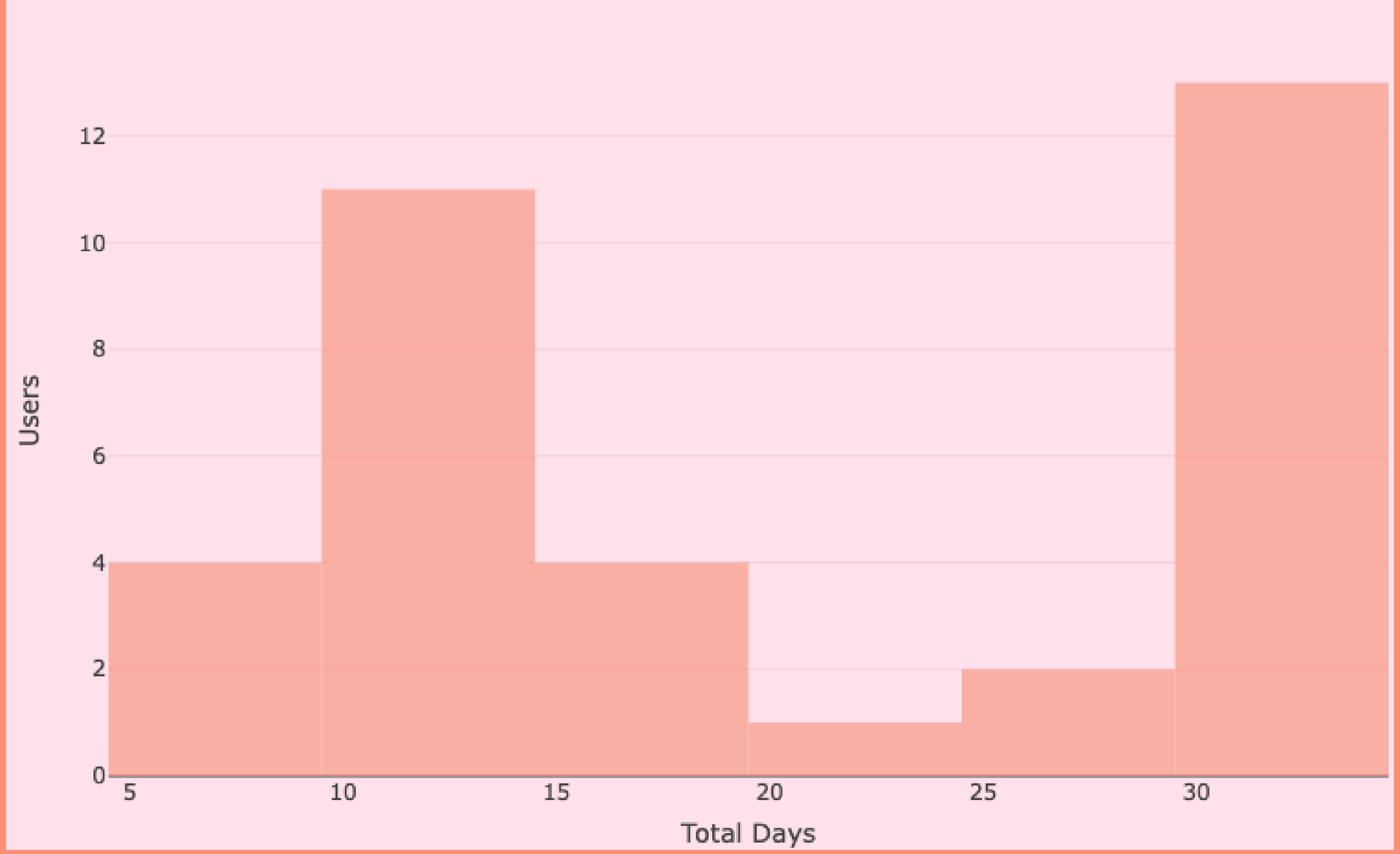


# Engagement

- How many days did they use it?

- 37% (13/35) tracked consistently for 30–34 days
- 54% (19/35) tracked for less than 20 days
- Less frequent engagement may be due to:
  - novelty
  - forgetting to use the device
  - finding it less relevant over time

- **Opportunity:** Increase frequency of low engagement Users by understanding the motivation of consistent Users

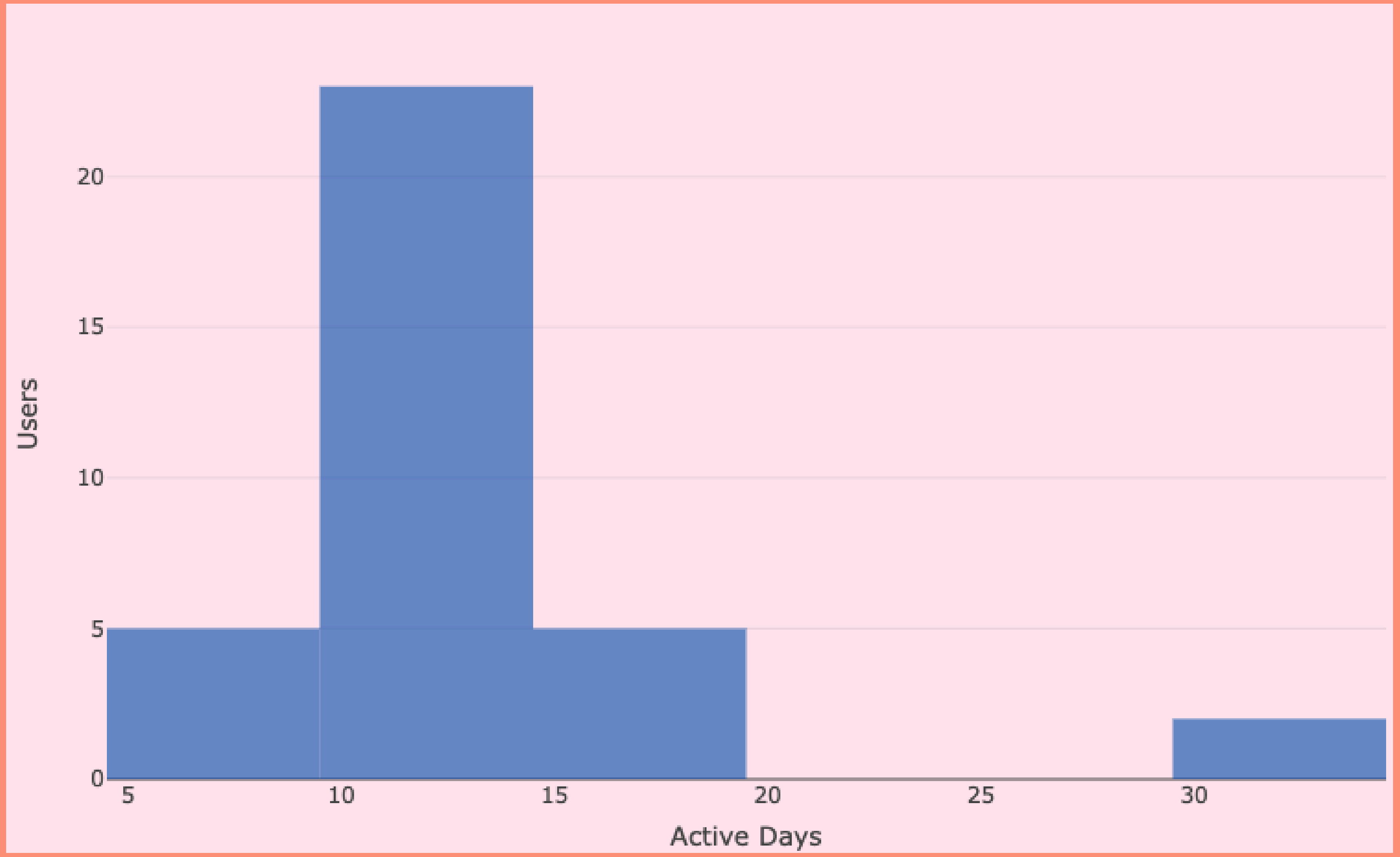


# Activity

- How many days did they track activity?

- 66% (23/35) tracked for 10–14 days
- 28% (10/35) tracked for 5–9 and 15–20 days
- 6% (2/35) tracked for 30–34 days
- No tracking observed between 20–30 days
- This distribution suggests that most Users are not active everyday

- **Opportunity:** Increase frequency of daily activity

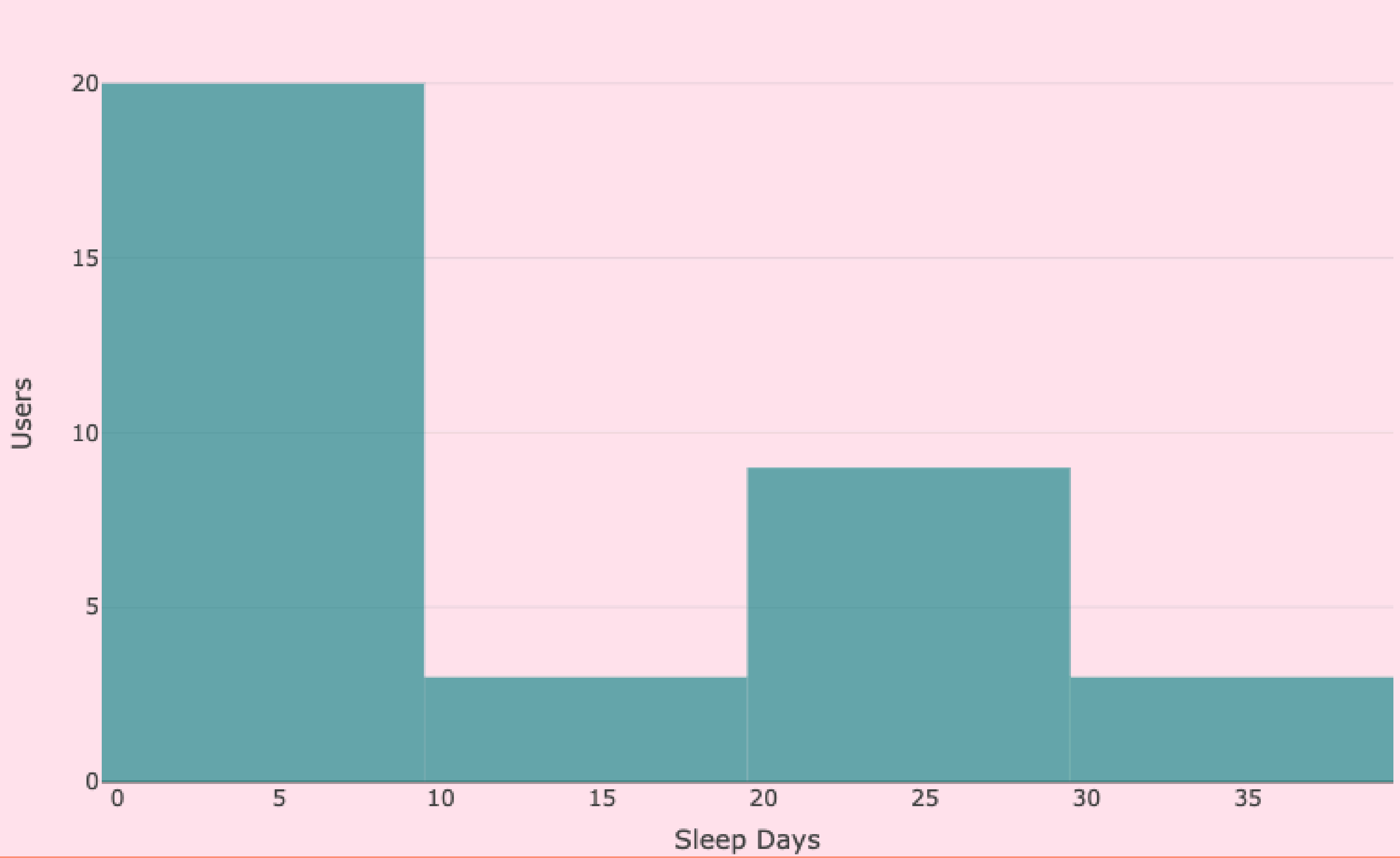


# Sleep

- How many days did they track sleep?

- 57% (20/35) tracked for 0-9 days
- 9% (3/35) tracked for 10-19 days
- 26% (9/35) tracked for 20-29 days
- 9% (3/35) tracked for 30-39 days

- **Opportunity:** Encourage consistent sleep tracking by understanding disengagement (i.e., comfort of wearing device at night, battery life)



# Weight

- How many days did they track weight?

- Small sample size: lack of data makes it difficult for meaningful conclusions
  - Two Users accounted for 73% of the entries
- Forecast Errors: The short data for the two Users of 9 and 15 days creates large forecast errors
- Data Inconsistencies: Non-syncronous entries inhibits effective cross-sectional analysis

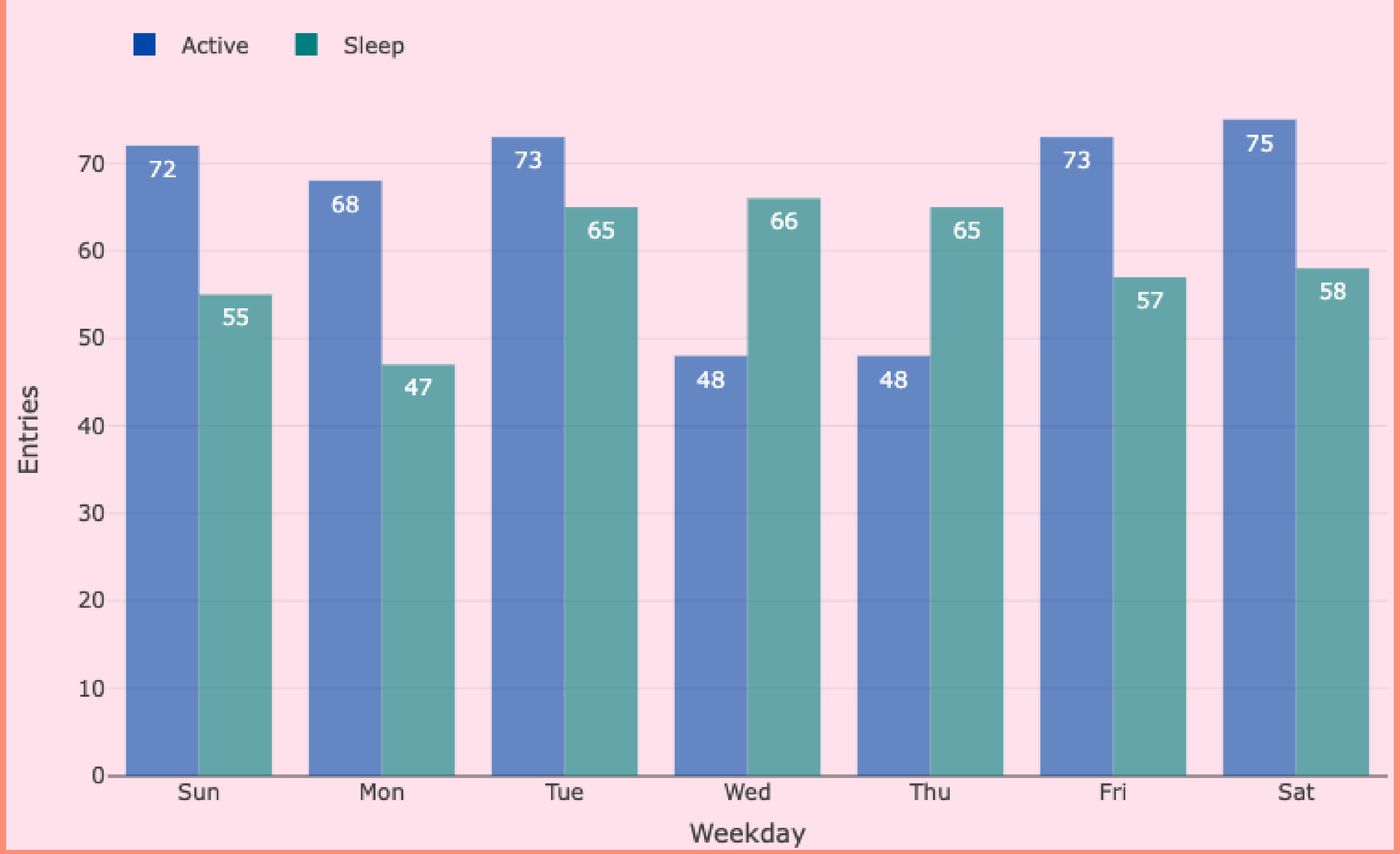
- **Opportunity:** Conduct further research to understand why Users didn’t track weight

# Weekdays

- Does the day of the week change behavior?

- Weekend Activity tracking peaks: Saturday and Sunday show consistent high levels of tracking, suggesting time availability is a major driver for activity routine
- Weekday peaks for Sleep tracking: Midweek (Tuesday–Thursday) shows higher sleep tracking routine than on the weekends

- **Opportunity:** Encourage consistent use by understanding why weekday behavior changes

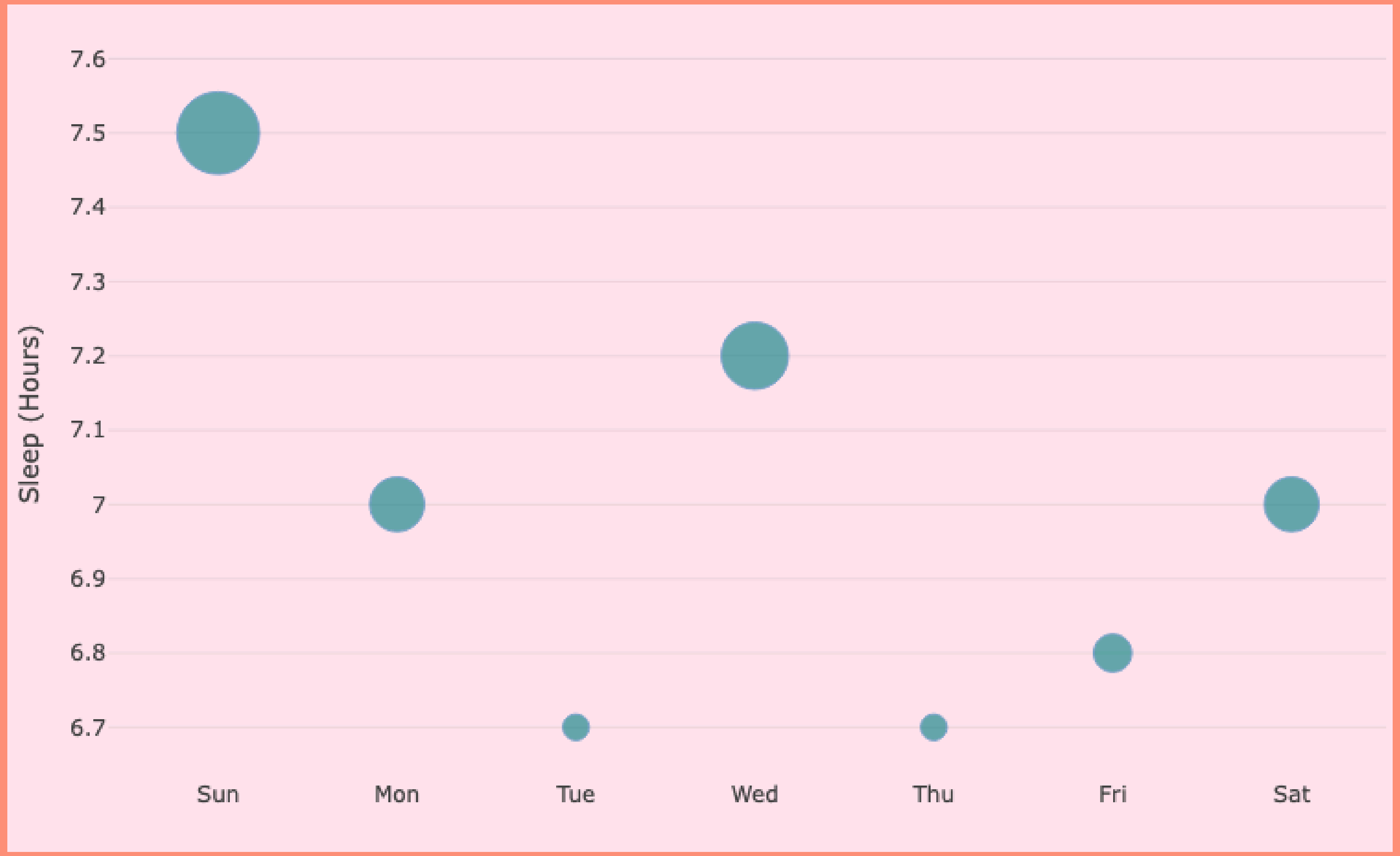


# Sleep

- Do sleep patterns change during the week?

- Midweek: Users sleep less on Tuesday and Thursday (6.7 hours), yet track more frequently
  - routines or responsibilities may be disrupting their sleep
- Weekend: Sunday sleep is highest (7.5 hours)
  - Users may be catching up on sleep

- **Opportunity:** Improve sleep consistency by understanding why patterns change

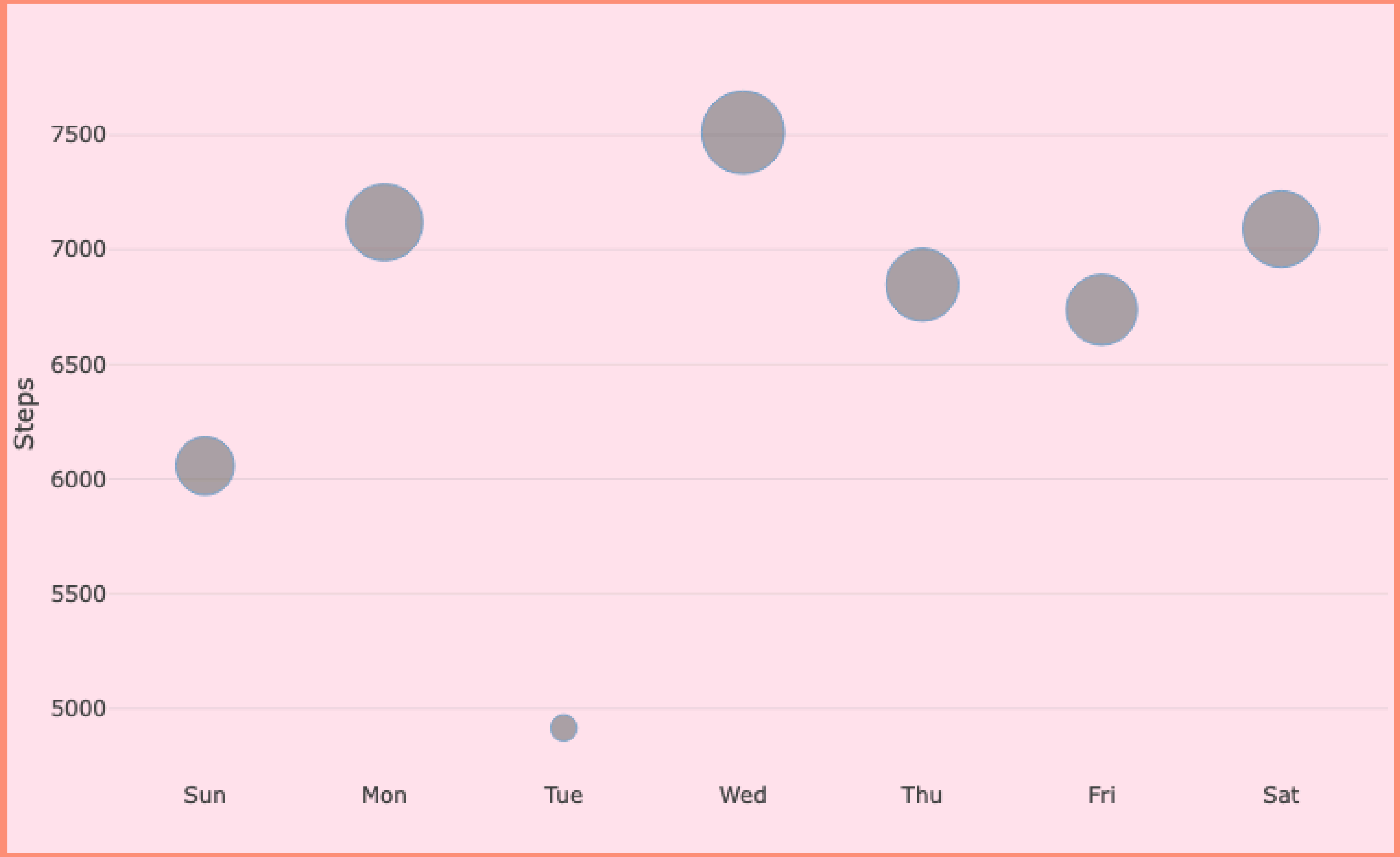


# Steps

- Do activity patterns change during the week?

- High step count on Wednesday (7,500+) could align with Users midweek routines
- Dip on Sunday (~6,000): Users might be winding down or resting after Saturday
- Tuesday's low step count (-5,000) could reflect an adjustment to the workweek

- **Opportunity:** Increase activity on Sundays and Tuesdays with app notifications or reminders to motivate Users

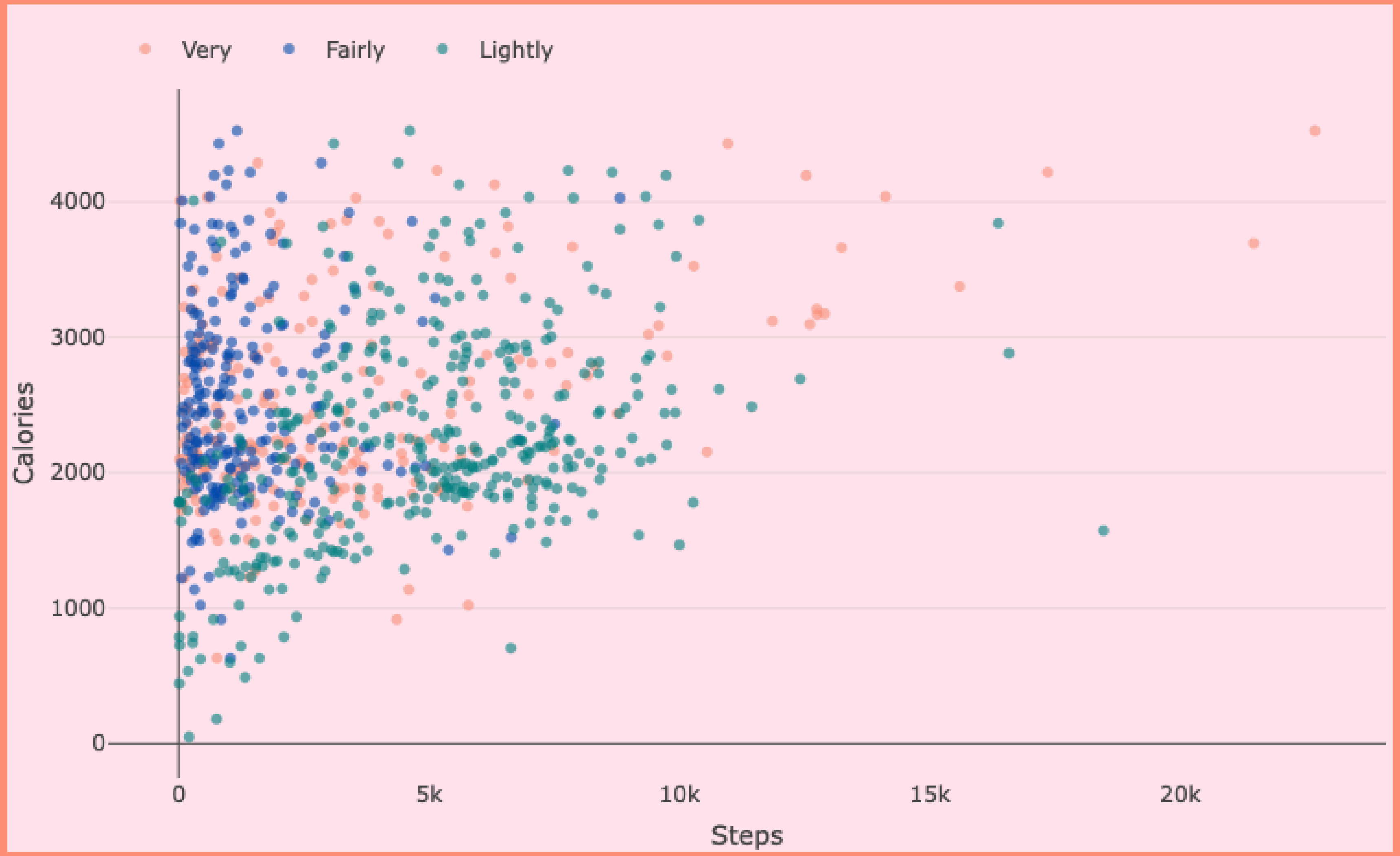


# Steps & Calories

- Are Steps and Calories related?

- Positive correlation of steps and calories
- High variability at low step counts (under 5,000) may result from:
  - metabolic rate
  - non-tracked activities not reflected in steps
- A few Very Active Users burn a high number of calories (above 4,000) with step counts exceeding 15,000–20,000 steps

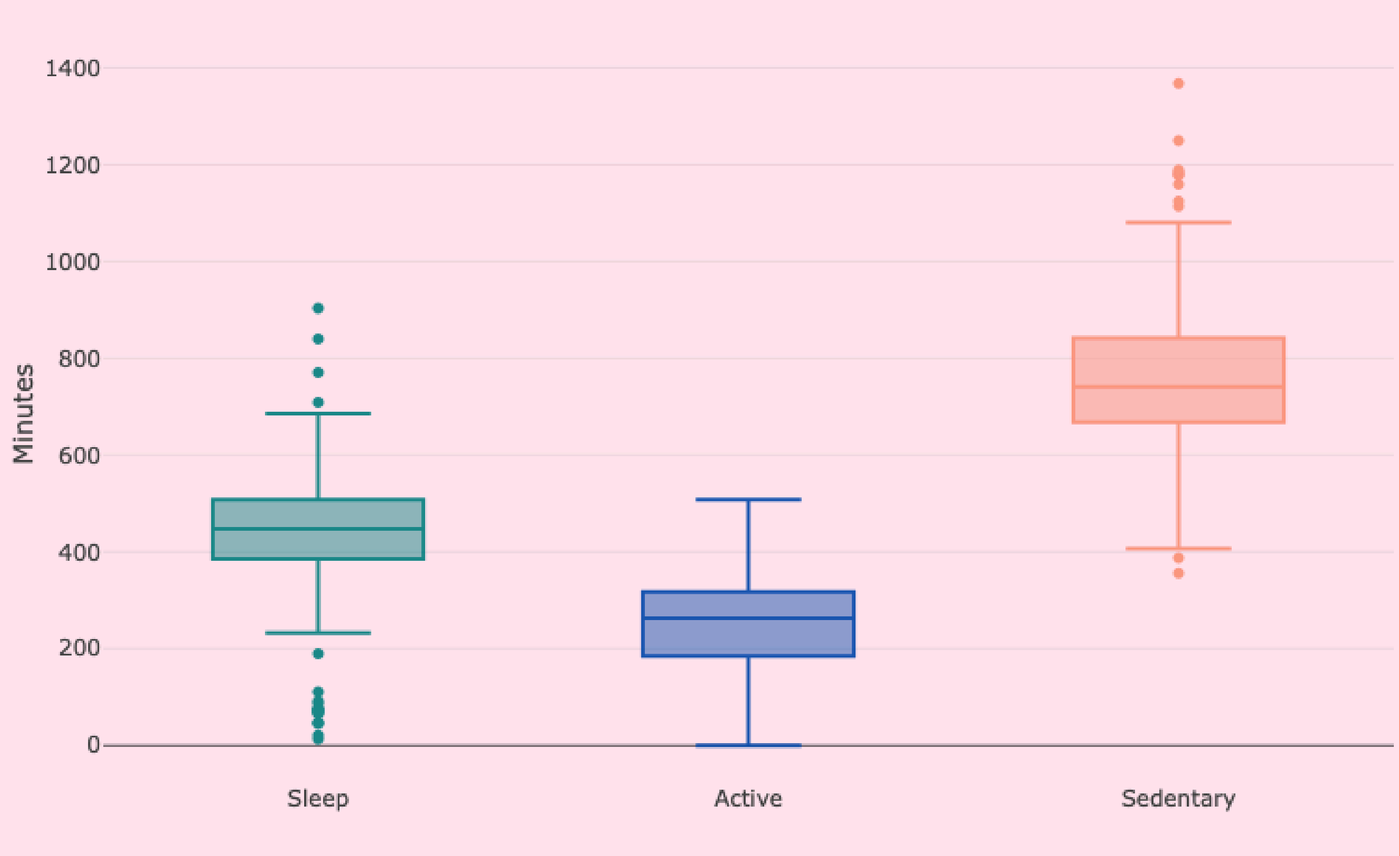
- **Opportunity:** Increase step counts by understanding usage constraints



# Daily Behavior

- How do Users spend their time each day?

- **Active:** Median time is 260 minutes (~4 hours)
  - Active time is variable from zero to 7 hours
- **Sleep:** Median time is 450 minutes (~7.5 hours), aligning with the recommended time
  - Outliers exist for low and high sleep times
- **Sedentary:** Median time is the highest at 740 minutes (~12.5 hours)
  - Sedentary behavior dominates Users' time
  - Outliers exist for highly sedentary Users




**Opportunity:** Increase sleep accuracy and decrease sedentary minutes

# Recommendations

**Marketing Segmentation:** Deliver personalized and impactful marketing messages by User behavior

| User Segment | Action |
|---|---|
| **Highly Engaged (30+ days)** | Brand advocates and a source of behavioral insights |
| **Short-Term (5-19 days)** | Target these Users with personalized nudges and gamified experiences to increase retention |
| **Weekend Warriors** | Promote weekday activity habits and recovery awareness |
| **Low Sleep, High Activity** | Provide recovery-focused education and encourage balance between movement and rest |
| **Sedentary Risk** | Deliver in-app reminder notifications and challenges to reduce long sedentary periods |
| **New Users** | Focus messaging on onboarding, emphasizing easy wins and setting wellness goals |

# Recommendations

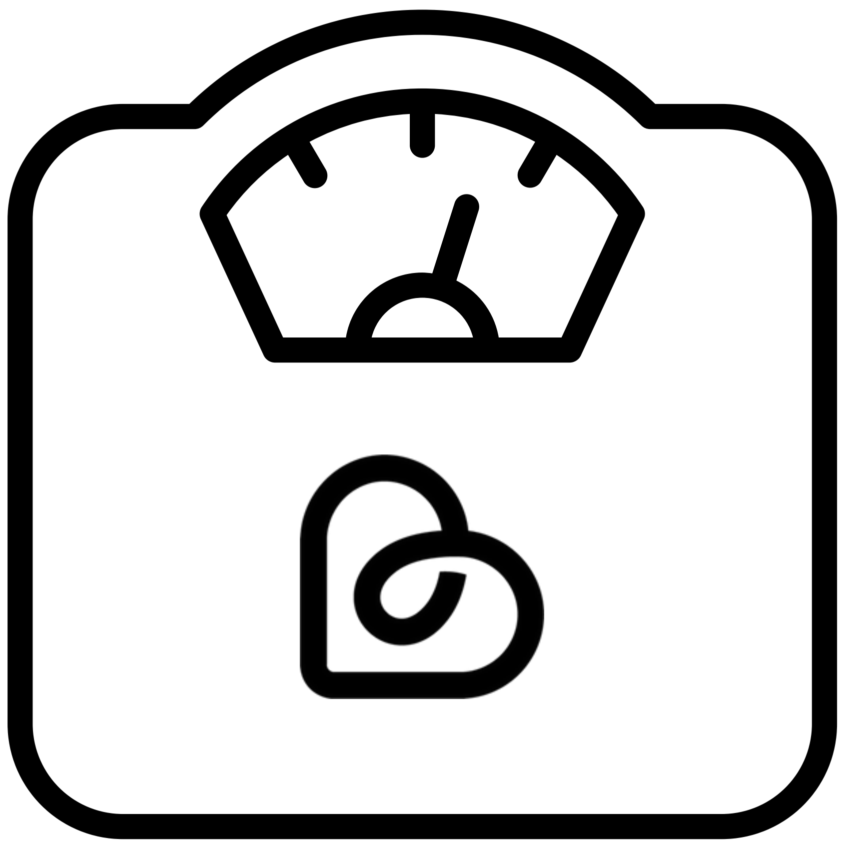
## Engagement & Retention

| Engagement | Retention |
|---|---|
| • Target mid-range Users (10–19 days of tracking) with nudges, rewards, or gamification to encourage consistency and develop long-term tracking habits<br>• Use streak-based incentives to increase engagement, especially on low-engagement days (e.g., Tuesday and Thursday)<br>• Investigate whether the same Users tracking on weekends are disengaged on weekdays. Tailored nudges could help maintain consistency<br>• Promote Sleep and Activity Balance: Educate Users on the importance of balancing high activity levels (e.g., on weekends) with adequate sleep for recovery | • Implement a Loyalty Program that rewards Users for consistent engagement with the app<br>• Address midweek sleep dips by sharing tips for improving rest during busy workdays<br>• Leverage Weekend Peaks: Capitalize on naturally high weekend activity levels (Saturday and Sunday) with fitness challenges, group activities, or marketing campaigns tailored to weekend routines<br>• Create a Referral Program rewarding Users for inviting friends to join Bellabeat's platform |

# Recommendations

**Product Expansion & Enhancements**

- Automate Weight Tracking:
  - Develop a Smart Scale or integration that automatically uploads weight data to the Bellabeat app. This could involve syncing with smart scales or partnering with manufacturers to enhance the app's functionality
    - Benefit: Streamlines the tracking process, reduces User friction, and encourages consistent engagement
- Enhanced User Analytics: Provide deeper insights into sleep, activity, and calorie data to personalize User experiences further



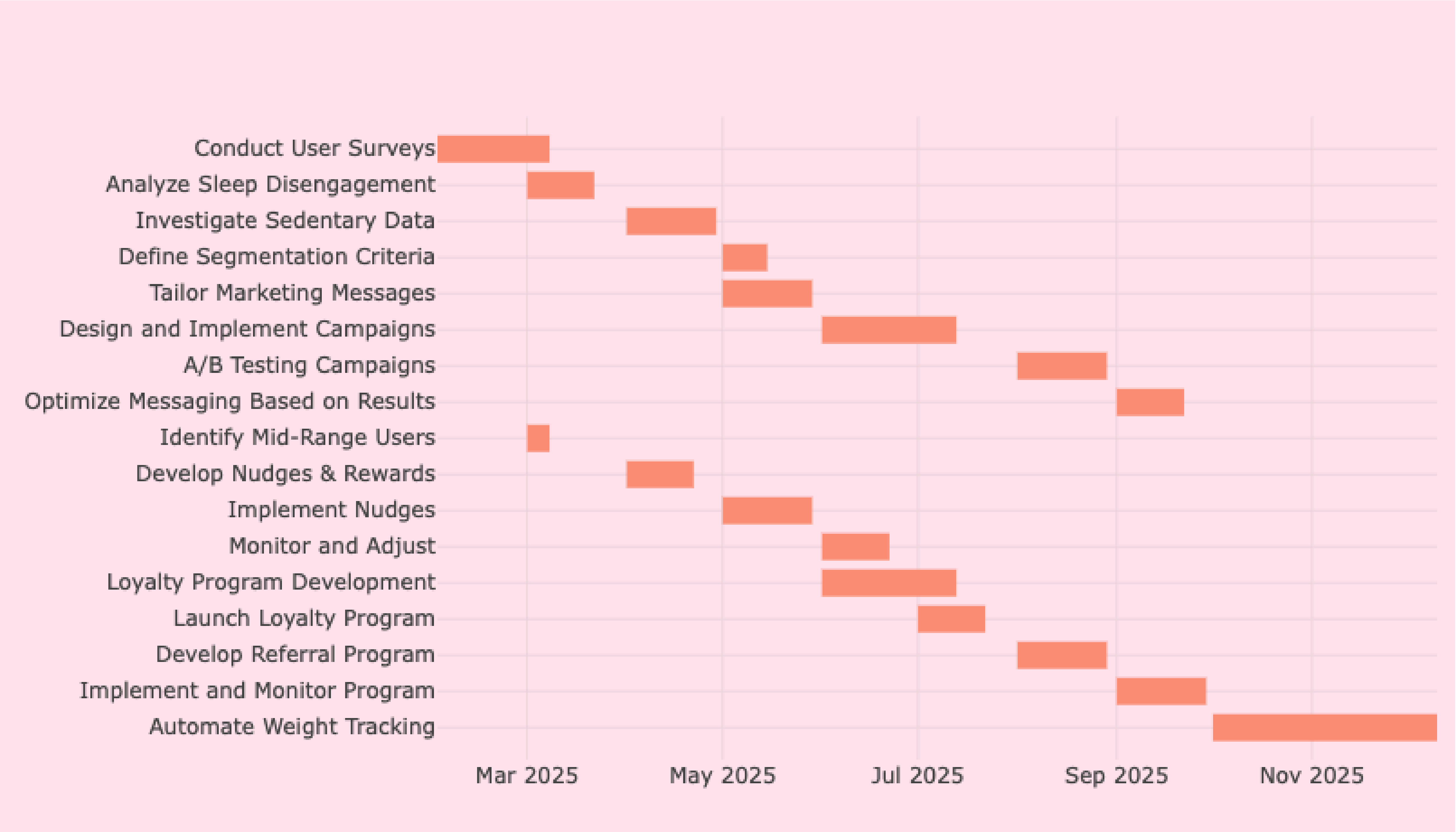
# Recommendations

**Deeper Analysis Opportunities**

- Conduct Qualitative Research, such as surveys or interviews, to understand why Users disengage with tracking after short periods or prioritize activity tracking over sleep and weight tracking
- Investigate disengagement of sleep trackers after less than 10 days (i.e., discomfort of wearing device at night, battery life)
- Analyze outliers in sleep and sedentary data to design personalized features or insights for Users with extreme habits

# Timeline

- This sample Gantt Chart provides a high-level view of tasks starting in February 2025. Total Duration is dependent on parallel task execution and resource availability



# Conclusion

The combination of targeted marketing, engagement and retention strategies, personalized insights, and product expansion positions Bellabeat for significant growth. By leveraging User data more effectively and addressing behavior trends with innovative solutions, Bellabeat can enhance both its product and User experience.

# Appendix

### Data Limitations

- Small Sample Size: The dataset contains a limited number of entries
- Demographic Information: The dataset lacks age and gender information. Since Bellabeat products are designed for women, this data may not reflect the broader customer base or represent the average Bellabeat User
- Participant Data Inconsistencies: The number of recorded entries varies significantly among participants, impacting the consistency and comparability of the data
- Lack of Metadata Descriptions: Key attribute definitions (e.g., sedentary, lightly active, fairly active, and very active minutes) are not provided, limiting the ability to interpret these variables more accurately
- Overlapping Categories: The data does not clearly differentiate between Sedentary Minutes and Sleep Minutes, potentially skewing activity-related insights

# Appendix

**R was used to prepare, process and analyze the data**

- Long and wide formats used
- Data was cleaned of duplicates and null values
- Fields reformatted for consistency, e.g., Date
- Removed extreme outlier and invalid values
- The tracker does not accurately distinguish between Sedentary minutes and Sleep minutes

**Activity Data:**

- Total of 35 unique IDs
- 411 total entries
- Inconsistent User particpation

# Appendix

**Sleep Data:**

- 24 unique IDs
- 413 total entries - indicates inconsistent User participation

**Weight Data:**

- 33 total entries from 11 unique IDs, sample size too small
- Two IDs account for 24 entries
  - For these two IDs with time-series data, the data length of 9 and 15 days create large forecast errors because of the insufficient data
- Non-syncronous entries inhibits effective cross-sectional analysis