Behavioural Pattern Analysis

Tasks:

1. Trends in Smart Devices Using Fitbit Data:

The primary objective of this analysis is to uncover and understand the prevailing trends within the realm of smart devices, as evidenced by the Fitbit dataset. By analyzing minute-level data on physical activity, heart rate, and sleep patterns, we aim to identify patterns and insights that shed light on how users engage with their smart devices, particularly Fitbit.

2. Application to Our Customers:

With the insights gleaned from this dataset, we can draw parallels between the observed trends and our customer base. By understanding how users interact with their Fitbit devices and engage in physical activity and monitoring, we can align these trends with the preferences and behaviors of our own customers. This alignment allows us to better tailor our products and services to meet their needs and expectations.

3. Influence on Marketing Strategy:

The trends unearthed from the Fitbit data can serve as a compass guiding our marketing strategy. By identifying key patterns such as peak activity times, popular activity types, and engagement durations, we can strategically time our marketing campaigns and promotions to coincide with these periods of heightened user engagement. This strategic alignment enhances the relevance of our marketing efforts and increases the likelihood of resonating with our target audience.

Data Sources:

The data for this study is sourced from the publicly available Fitbit dataset, accessible at https://www.kaggle.com/arashnic/fitbit. The dataset encompasses a comprehensive collection of minute-level records encompassing physical activity, heart rate, and sleep monitoring. Thirty Fitbit users have consented to the utilization of their data for this analysis, offering a robust representation of user behaviors.

Data Cleaning and Manipulation:

Prior to analysis, the dataset underwent rigorous cleaning and manipulation processes. This included converting date and time fields into appropriate formats, handling missing values, and categorizing activity intensities. Additionally, data sources were merged to facilitate cross-domain analysis, ensuring a holistic view of user behavior.

Summary of Analysis:

Through a combination of exploratory data analysis (EDA) and advanced visualization techniques, we unearthed valuable insights into user behaviours and preferences. These insights encompass peak activity times, distribution of activity intensities, heart rate trends, and sleep patterns. These findings serve as the foundation for the subsequent content recommendations and strategic considerations.

Supporting Visualizations and Key Findings:

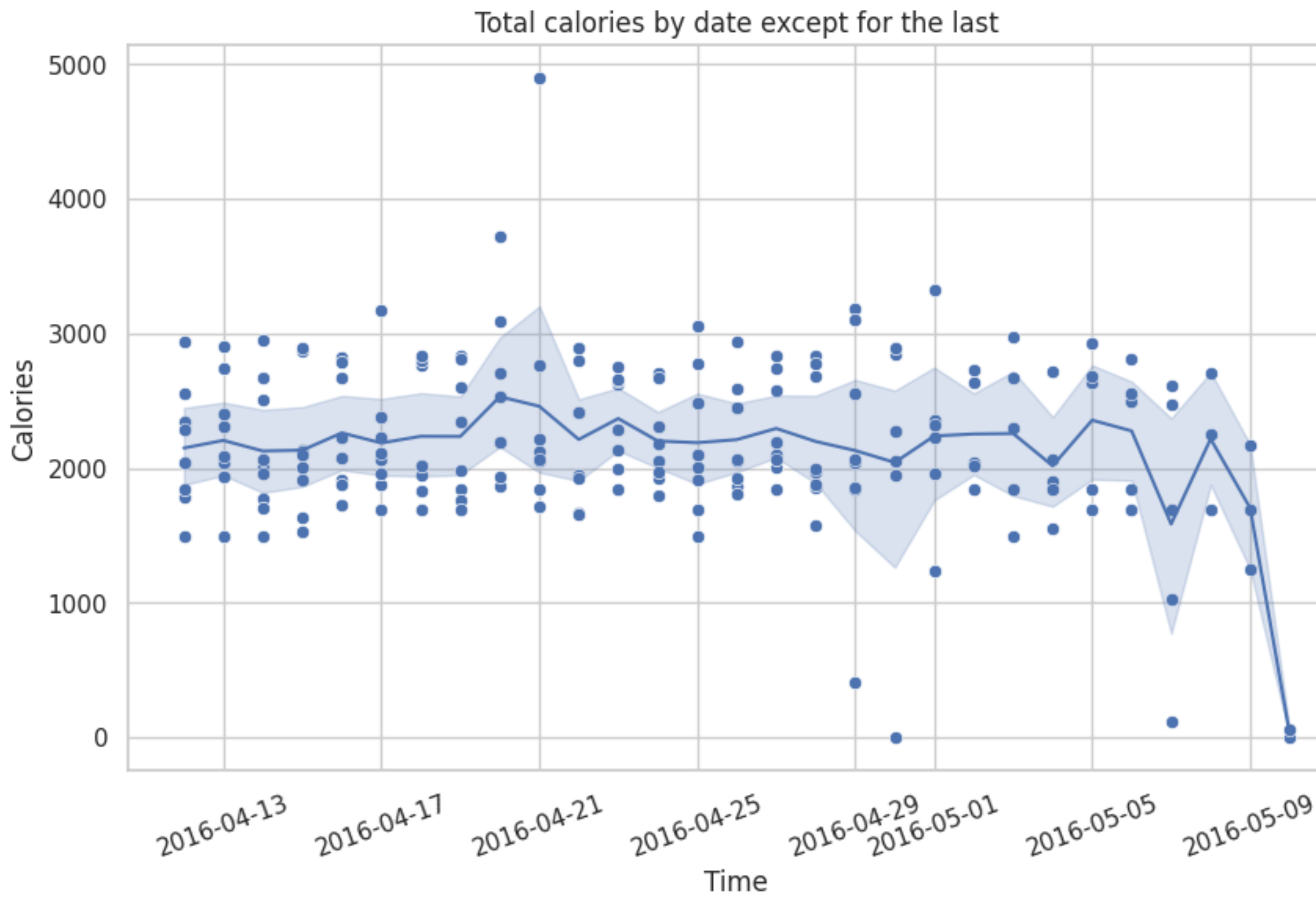
Our visualizations include time series plots showcasing calorie expenditure, intensity distributions, and heart rate trends. We've also developed bar plots to illustrate daily step counts for active and non-active users. Additionally, histograms display activity intensities, aiding in understanding engagement levels.

The dataset employed for this comprehensive case study is sourced from the publicly accessible repository at https://www.kaggle.com/arashnic/fitbit. This dataset comprises minute-level records pertaining to physical activity, heart rate, and sleep patterns. The data originates from a pool of 30 qualified Fitbit users who have willingly provided their consent for its utilization in this study. Through an exploration of this dataset, we endeavour to gain deeper insights into the patterns and trends within the recorded parameters.

Calorie vs Time:

Looking at the average calorie burn over time, it seems that people are burning fewer calories over the period. This might suggest a decrease in exercise. However, something interesting happens on the last day – everyone burns fewer calories. This could be due to data collection quirks or external factors like holidays.

To get a clearer picture, let's reanalyze the data without the last day. This will help us understand the calorie trend more accurately and provide better insights for decision-making.

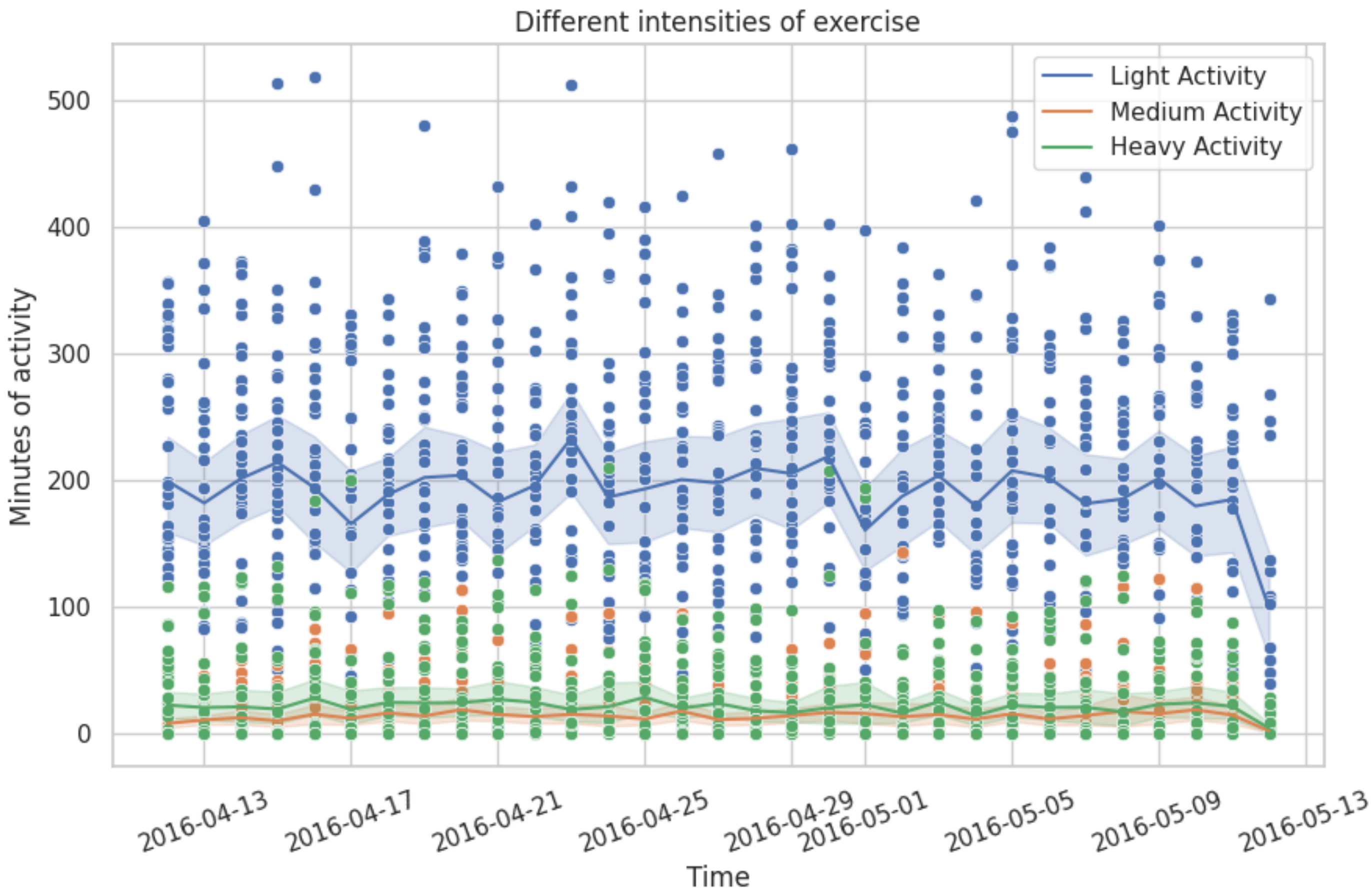


Upon closer examination, we observe that the apparent drop in calorie expenditure towards the end of the period isn't a consistent trend. It's primarily influenced by the last day's data, which is not truly indicative of a pattern.

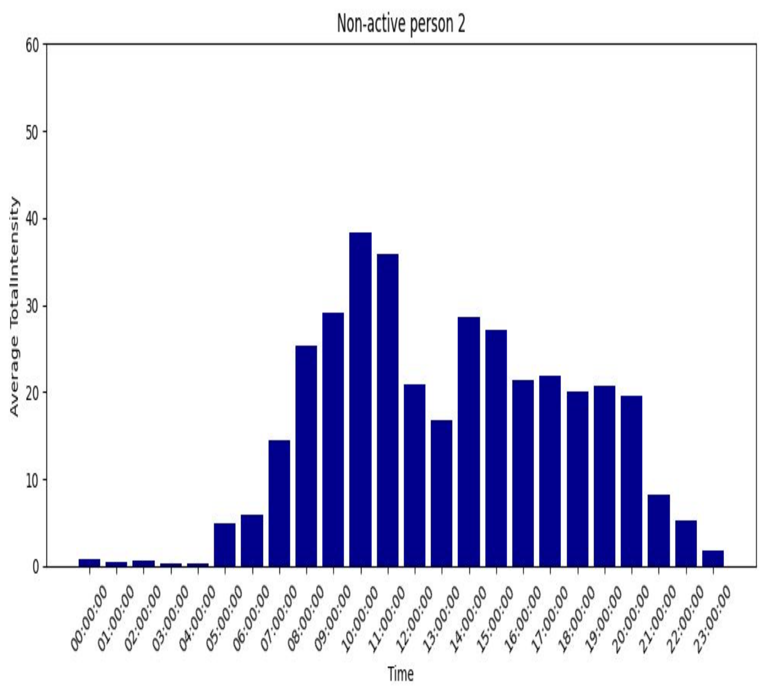
Additionally, it's valuable to explore activity intensity by comparing variables like Lightly Active Minutes, Fairly Active Minutes, and Very Active Minutes. Analyzing the distribution of these intensities could reveal the most engaged group of individuals who might be interested in Fitbit products. Understanding the preferred activity levels of potential customers can inform marketing strategies and product targeting.

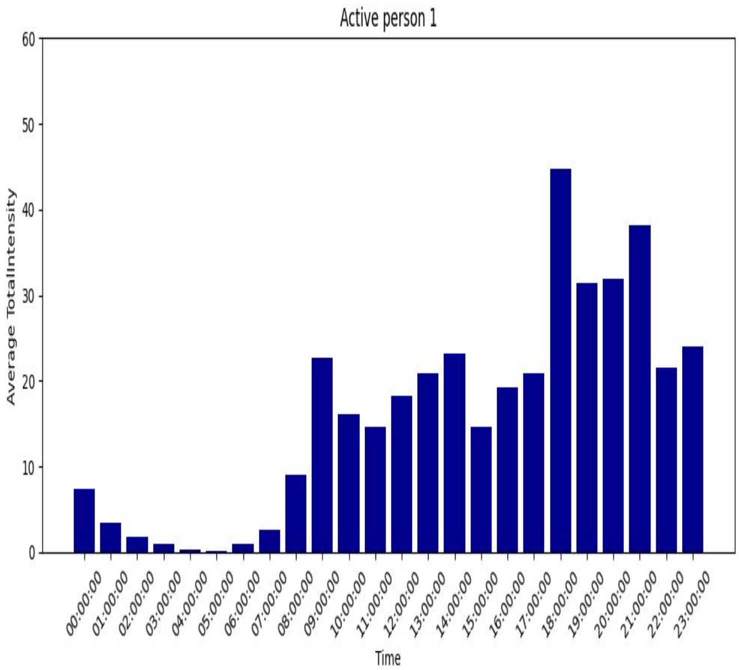
Intensities vs Time:

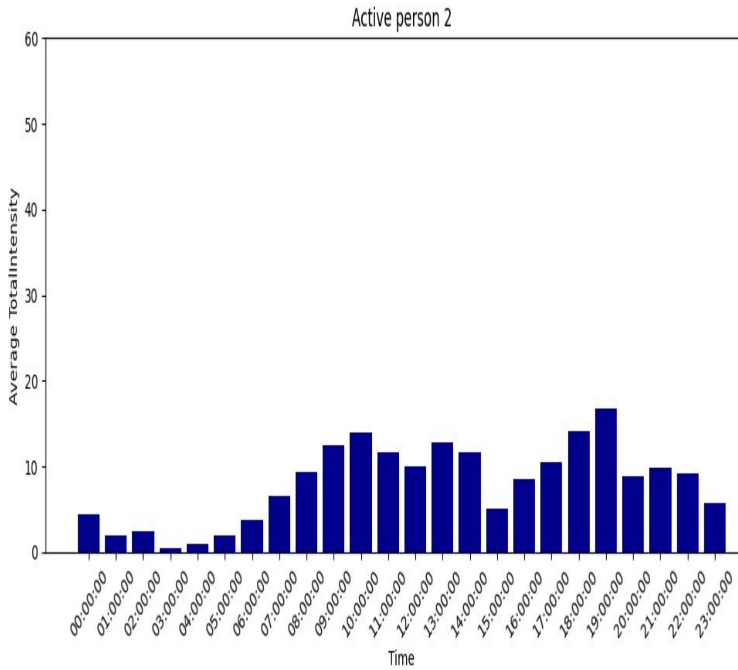
Exploring individual data by utilizing the 'Id' variable offers us an opportunity to delve into specific patterns among users. This will allow us to gain a more nuanced understanding of activity preferences and tailor marketing strategies and product offerings to different customer segments.

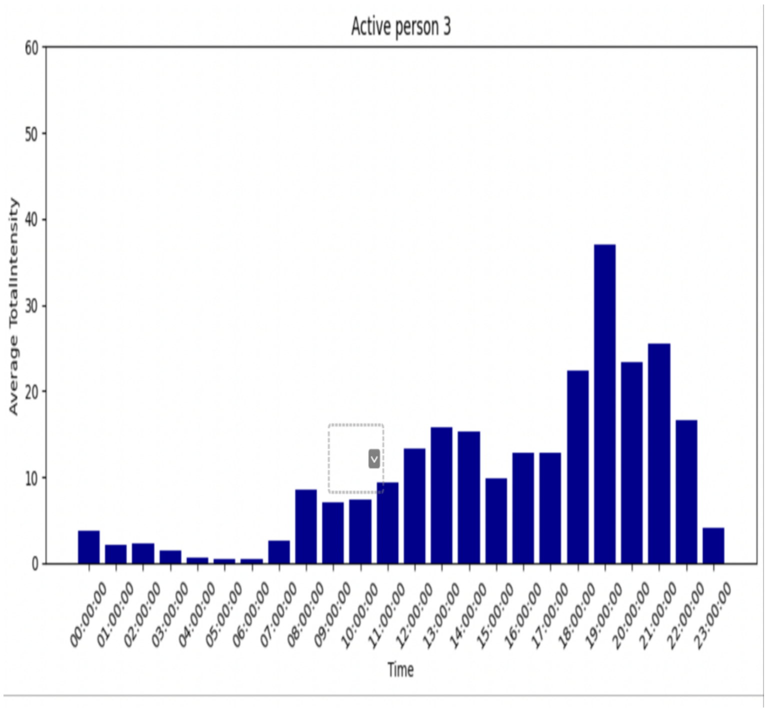


The distribution plot of activity intensity indicates that a significant portion of individuals engage in light activity. However, it's important to note that the dominance of light activity minutes might overshadow the influence of medium and heavy activities when examining average data. This implies that the combined average might not accurately reflect the impact of these higher intensity activities.

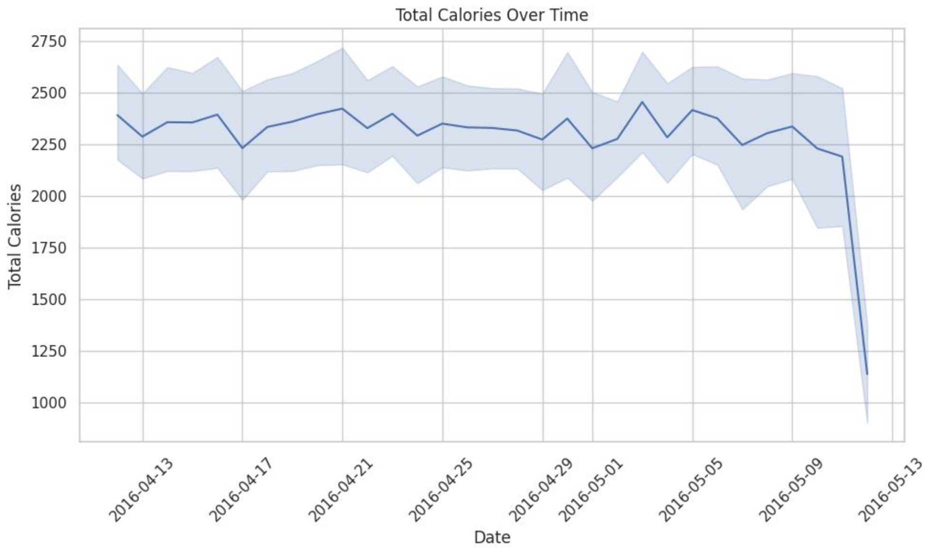






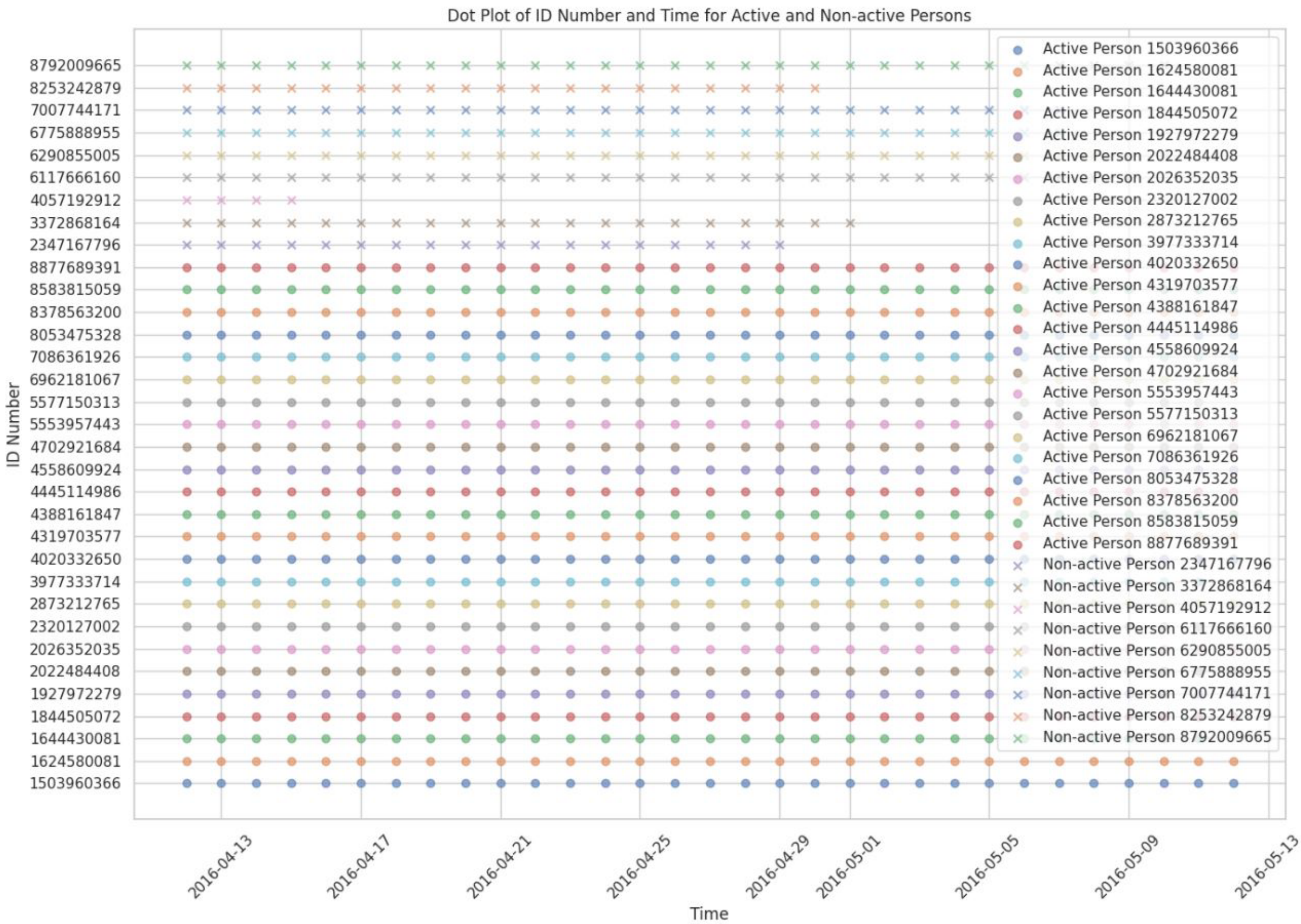


Upon analyzing this data, I haven't identified a discernible pattern that reliably distinguishes individuals more prone to dropping out. However, it's evident that, in line with the previous visualizations, a majority of individuals refrain from exercising between 23:00 and 04:00. Nonetheless, it's important to note that this trend doesn't apply universally to all individuals."

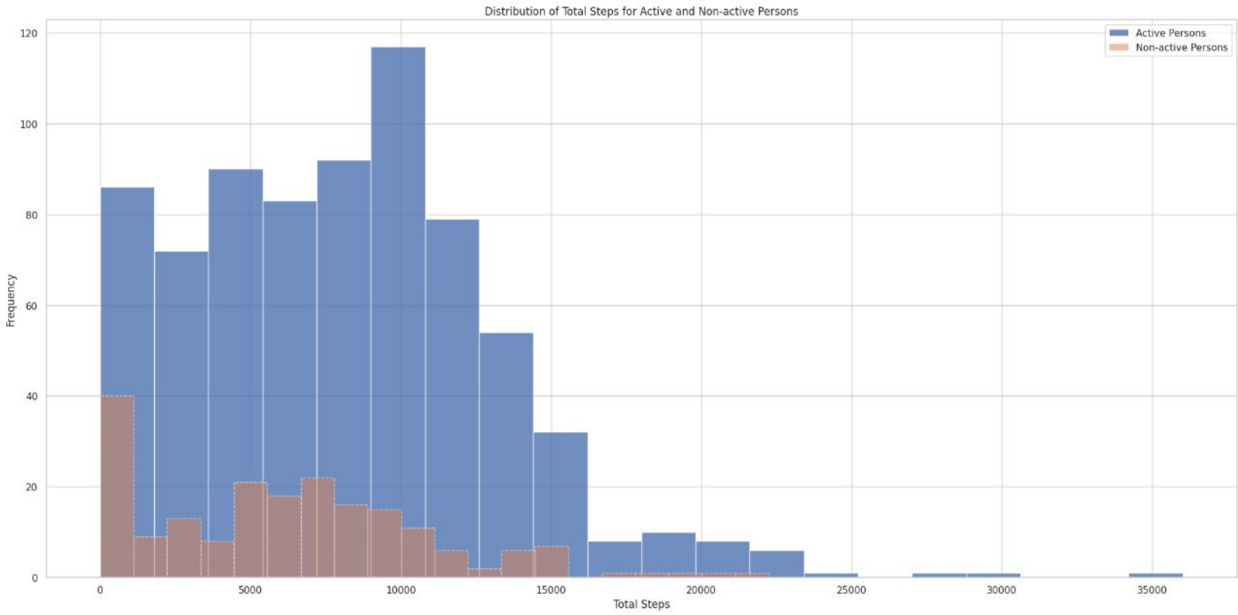


This shows us that actually, there is no drop in the Calories over time, but we can see the sudden decrease on the last day only .

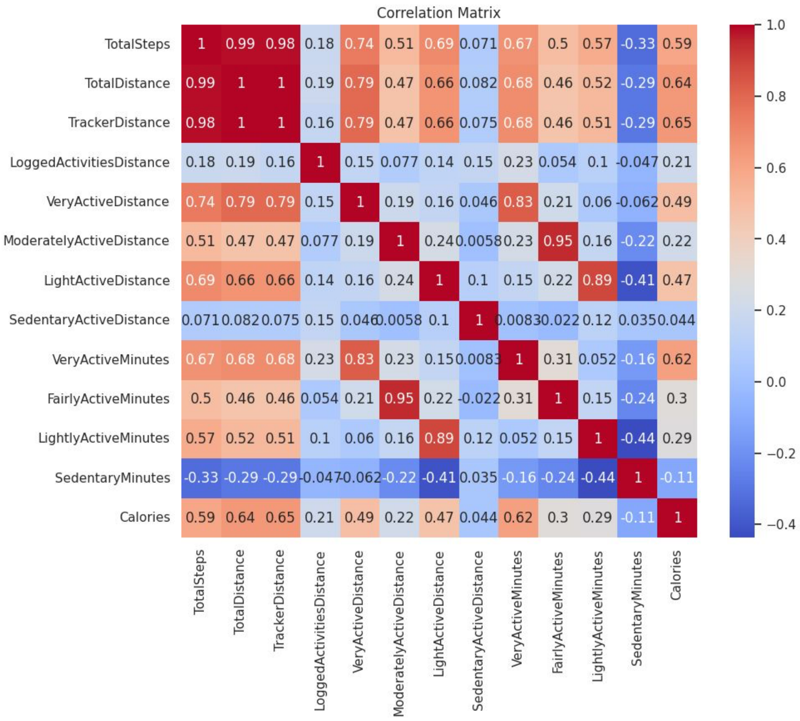
Active and Non -Active persons Activities



This is informative because it shows that out of the 33 people 9 people have not been wearing their device until the end. This is also a potential indicator that people lose interested after some time.



Above plot reveals that there is noteworthy contrast between the count of active and non-active individuals. However, there appears to be minimal disparity in the step counts taken by individuals categorized as active or non-active.



The correlation matrix clearly suggest the influence of one index among other indices with varying between -1 to 1 (-1 being completely opposite correlation and +1 being true correlation), for example total steps influences total distance and tracker distance directly with correlation indices of 0.99 and 0.98 respectively. Indices that represent exercise and workout relates positively with active times and active distance, whereas same indices relates negatively with sedentary and non-active times.

Conclusion drawn from our analysis:

Visualisation of data indicates a clear trend among the users, motivation for exercise (especially heavy exercise) reduces with the time being. A small portion of users even skipped their routine.

Sedentary activities constitute a significant portion, 81%, of users' daily active minutes. On average, users spend 12 hours in sedentary minutes, 4 hours in light activity, and only around half an hour in fairly or very active pursuits.

Saturday stands out with users taking more steps, burning more calories, and having reduced sedentary time. In contrast, Sunday emerges as the most inactive day for users.

Among users who logged sleep data, 54% spent approximately 55 minutes awake in bed before falling asleep.

Peak step activity occurs between 5 PM and 7 PM. Sedentary users take minimal steps, burning 1500 to 2500 calories, while more active users take more steps and burn similar calories.

Marketing suggestions

Few customers used the weight log feature, so it's not a strong selling point. Instead, focus on promoting features like activity, sleep, and steps tracking. Also, explore ways to enhance the appeal of the weight log feature.

Our data reveals that participants engaged most in "light" activity and had fewer "very active" minutes each day. Consider adding a "level up" feature where users earn points for active time, encouraging more engagement.

Sundays have about a 1000-step drop compared to other days. Sending Sunday morning notifications with step goals and rewarding 7-day streaks could boost usage on all days.

Peak usage occurs around 6pm, indicating users are active after work. Target working adults with ads emphasizing easy step tracking during busy days. Reminders at 12pm and 8pm could promote activity during breaks.

Participants averaged less sleep than recommended. Market the sleep tracking feature, possibly alongside a meditation app or habit tracker, for users seeking sleep insights.