FitBit Tracker Data

Keyah Taneja

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About the Company

Bellabeat is a high-tech manufacturer of health-focused products for women. Bellabeat is a successful small company, but they have the potential to become a larger player in the global smart device market. Urška Sršen, cofounder and Chief Creative Officer of Bellabeat, believes that analyzing smart device fitness data could help unlock new growth opportunities for the company.

Services offered by Bellabeat

1. 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.
2. Leaf: Bellabeat's classic wellness tracker can be worn as a bracelet, necklace, or clip. The Leaf tracker connects to the Bellabeat app to track activity, sleep, and stress.
3. Time: This wellness watch combines the timeless look of a classic timepiece with smart technology to track user activity, sleep, and stress. The Time watch connects to the Bellabeat app to provide you with insights into your daily wellness.
4. Spring: This is a water bottle that tracks daily water intake using smart technology to ensure that you are appropriately hydrated throughout the day. The Spring bottle connects to the Bellabeat app to track your hydration levels.
5. Bellabeat membership: Bellabeat also offers a subscription-based membership program for users. Membership gives users 24/7 access to fully personalized guidance on nutrition, activity, sleep, health and beauty, and mindfulness based on their lifestyle and goals.

The dataset provided is not representative of all the services offered by Bellabeat devices and is limited in its scope. However, it will help us gain an understanding of features that promote active use of similar devices and guide marketing and product designing strategies for Bellabeat.

These datasets were generated by respondents to a distributed survey via Amazon Mechanical Turk between 03.12.2016-05.12.2016. Thirty eligible Fitbit users consented to the submission of personal tracker data, including minute-level output for physical activity, heart rate, and sleep monitoring. Limitations such as the size of data sample and the fact that not knowing key information such as participants' demographic characteristics, lifestyle, time location, weather indicators, activity tracker usage , unfortunately, would limit the scope of analysis that can be performed.

Questions for Analysis: 1. What are some trends in smart device usage? 2. How could these trends apply to Bellabeat customers? 3. How could these trends help influence Bellabeat marketing strategy?

Business Task:

Identify potential opportunities for growth and recommendations for the Bellabeat marketing strategy improvement based on trends in smart device usage.

This project will analyze FitBit Fitness Tracker Data available on kaggle (https://www.kaggle.com/datasets/arashnic/fitbit/data). Through the analysis of this open source data, we can get insights into factors influencing the usage of such fitness tracking devices which can help our stakeholders design new devices or update existing devices accordingly.

Approach

Initially, I will do EDA to observe any trends, patterns and associations between variables. Since we have dates for when the data was collected, the number of days will account for higher or lower usage of fitness devices.

The main focus will be on what features are used the most.

For the purpose of this analysis, I will be focusing on hourly data and disregarding the minute level data.

Loading Packages

```
#install.packages("tidyverse")
#install.packages("dplyr")
#install.packages("ggplot2")
#install.packages("readr")
#install.packages("VennDiagram")
#install.packages("lubridate")
#install.packages("DataExplorer")
#install.packages("janitor")
#install.packages("tidyr")
#install.packages("gridExtra")
#install.packages("UpSetR")
#install.packages("ggridges")
#install.packages("plotly")
#install.packages("openair")
#install.packages("formattable")
#install.packages("plotrix")
#install.packages("viridis")
#install.packages("GGally")
#install.packages("RColorBrewer")
#install.packages("ggbeeswarm")
#install.packages("corrplot")



# loading

library(tidyverse)
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✔ dplyr     1.1.4     ✔ readr     2.1.5
## ✔ forcats   1.0.0     ✔ stringr   1.5.1
## ✔ ggplot2   3.5.1     ✔ tibble    3.2.1
## ✔ lubridate 1.9.3     ✔ tidyr     1.3.1
## ✔ purrr     1.0.2
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

```
library(dplyr)
library(ggplot2)
library(readr)
library(VennDiagram)
```

```
## Loading required package: grid
## Loading required package: futile.logger
```

```
library(lubridate)
#library(DataExplorer)
library(janitor)
```

```
##
## Attaching package: 'janitor'
##
## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test
```

```
library(tidyr)
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
library(grid)
library(UpSetR)
library(ggridges)
library(openair)
library(plotly)
```

```
##
## Attaching package: 'plotly'
##
## The following object is masked from 'package:ggplot2':
##
##     last_plot
##
## The following object is masked from 'package:stats':
##
##     filter
##
## The following object is masked from 'package:graphics':
##
##     layout
```

```
library(formattable)
```

```
##
## Attaching package: 'formattable'
##
## The following object is masked from 'package:plotly':
##
##     style
```

```
library(viridis)
```

```
## Loading required package: viridisLite
```

```
library(plotrix)
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

```
library(RColorBrewer)
library(ggbeeswarm)
library(corrplot)
```

```
## corrplot 0.94 loaded
```

```
setwd("C:/Users/keyah/OneDrive/Documents/Google Certificate Data Analysis/Capstone/FitBit Data/F
itabase Data 4.12.16-5.12.16")
```

Reading data files

```
daily_activity <- read.csv("dailyActivity_merged.csv")
hourly_calories <- read.csv("hourlyCalories_merged.csv")
hourly_intensities <- read.csv("hourlyIntensities_merged.csv")
hourly_steps <- read.csv("hourlySteps_merged.csv")
sleep_day <- read.csv("sleepDay_merged.csv")
heart_rate <- read.csv("heartrate_seconds_merged.csv")
weightLog <- read.csv("weightLogInfo_merged.csv")

# looking at the first few rows of each dataset
head(daily_activity)
```

	Id <dbl>	ActivityDate <chr>	TotalSteps <int>	TotalDistance <dbl>	TrackerDistance <dbl>	LoggedActivities
1	1503960366	4/12/2016	13162	8.50	8.50	
2	1503960366	4/13/2016	10735	6.97	6.97	
3	1503960366	4/14/2016	10460	6.74	6.74	
4	1503960366	4/15/2016	9762	6.28	6.28	
5	1503960366	4/16/2016	12669	8.16	8.16	
6	1503960366	4/17/2016	9705	6.48	6.48	

6 rows | 1-7 of 16 columns

```
head(hourly_calories)
```

	Id <dbl>	ActivityHour <chr>	Calories <int>
1	1503960366	4/12/2016 12:00:00 AM	81
2	1503960366	4/12/2016 1:00:00 AM	61
3	1503960366	4/12/2016 2:00:00 AM	59
4	1503960366	4/12/2016 3:00:00 AM	47
5	1503960366	4/12/2016 4:00:00 AM	48
6	1503960366	4/12/2016 5:00:00 AM	48

6 rows

```
head(hourly_intensities)
```

	Id	ActivityHour	TotalIntensity	AverageIntensity
	<dbl>	<chr>	<int>	<dbl>
1	1503960366	4/12/2016 12:00:00 AM	20	0.333333
2	1503960366	4/12/2016 1:00:00 AM	8	0.133333
3	1503960366	4/12/2016 2:00:00 AM	7	0.116667
4	1503960366	4/12/2016 3:00:00 AM	0	0.000000
5	1503960366	4/12/2016 4:00:00 AM	0	0.000000
6	1503960366	4/12/2016 5:00:00 AM	0	0.000000

6 rows

```
head(hourly_steps)
```

	Id	ActivityHour	StepTotal
	<dbl>	<chr>	<int>
1	1503960366	4/12/2016 12:00:00 AM	373
2	1503960366	4/12/2016 1:00:00 AM	160
3	1503960366	4/12/2016 2:00:00 AM	151
4	1503960366	4/12/2016 3:00:00 AM	0
5	1503960366	4/12/2016 4:00:00 AM	0
6	1503960366	4/12/2016 5:00:00 AM	0

6 rows

```
head(sleep_day)
```

	Id	SleepDay	TotalSleepRecords	TotalMinutesAsleep	TotalTimeInI
	<dbl>	<chr>	<int>	<int>	<
1	1503960366	4/12/2016 12:00:00 AM	1	327	
2	1503960366	4/13/2016 12:00:00 AM	2	384	
3	1503960366	4/15/2016 12:00:00 AM	1	412	
4	1503960366	4/16/2016 12:00:00 AM	2	340	
5	1503960366	4/17/2016 12:00:00 AM	1	700	
6	1503960366	4/19/2016 12:00:00 AM	1	304	

6 rows

```
head(heart_rate)
```

	Id	Time	Value
	<dbl>	<chr>	<int>
1	2022484408	4/12/2016 7:21:00 AM	97
2	2022484408	4/12/2016 7:21:05 AM	102
3	2022484408	4/12/2016 7:21:10 AM	105
4	2022484408	4/12/2016 7:21:20 AM	103
5	2022484408	4/12/2016 7:21:25 AM	101
6	2022484408	4/12/2016 7:22:05 AM	95

6 rows

```
head(weightLog)
```

	Id	Date	Weight…	WeightPounds	F..	BMI	IsManualReport	
	<dbl>	<chr>	<dbl>	<dbl>	<int>	<dbl>	<chr>	
1	1503960366	5/2/2016 11:59:59 PM	52.6	115.9631	22	22.65	True	1.4
2	1503960366	5/3/2016 11:59:59 PM	52.6	115.9631	*NA*	22.65	True	1.4
3	1927972279	4/13/2016 1:08:52 AM	133.5	294.3171	*NA*	47.54	False	1.4
4	2873212765	4/21/2016 11:59:59 PM	56.7	125.0021	*NA*	21.45	True	1.4
5	2873212765	5/12/2016 11:59:59 PM	57.3	126.3249	*NA*	21.69	True	1.4
6	4319703577	4/17/2016 11:59:59 PM	72.4	159.6147	25	27.45	True	1.4

6 rows

We can see all datasets have IDs as the primary key which can be used to combine them.

First, we will begin by cleaning and formatting the datasets.

```
# Checking if the data contains any missing values

sum(is.na(daily_activity))
```

```
## [1] 0
```

```
sum(is.na(hourly_calories))
```

```
## [1] 0
```

```
sum(is.na(hourly_intensities))
```

```
## [1] 0
```

```
sum(is.na(hourly_steps))
```

```
## [1] 0
```

```
sum(is.na(sleep_day))
```

```
## [1] 0
```

```
sum(is.na(heart_rate))
```

```
## [1] 0
```

```
sum(is.na(weightLog))
```

```
## [1] 65
```

As we can see there are 65 missing values in the weightLog dataset, however, further analysis reveals we won't be using this dataset, therefore, these values are not replaced.

Starting by cleaning the column names

```
daily <- daily_activity %>%
  clean_names() %>%
  mutate(date = mdy(daily_activity$ActivityDate), day_week=weekdays(date)) %>%
  select(1,16,17,3,15,4,11:14)

head(daily)
```

	id <dbl>	date <date>	day_week <chr>	total_steps <int>	calories <int>	total_distance <dbl>	very_active_mir
1	1503960366	2016-04-12	Tuesday	13162	1985	8.50	
2	1503960366	2016-04-13	Wednesday	10735	1797	6.97	
3	1503960366	2016-04-14	Thursday	10460	1776	6.74	
4	1503960366	2016-04-15	Friday	9762	1745	6.28	
5	1503960366	2016-04-16	Saturday	12669	1863	8.16	
6	1503960366	2016-04-17	Sunday	9705	1728	6.48	

Cleaning and combining the hourly datasets

```
hourly_activity <- hourly_calories %>%
  left_join(hourly_intensities, by = c("Id","ActivityHour")) %>%
  left_join(hourly_steps, by= c("Id","ActivityHour")) %>%
  clean_names() %>%
  mutate(act_hour = mdy_hms(activity_hour), day_week=weekdays(act_hour)) %>%
  separate(act_hour, into=c("date", "time"), sep= " ") %>%
  mutate(date = ymd(date)) %>% #keeping date format same as daily activity
  select(-average_intensity) %>% #removing since we have total intensity
  select (1,6,7,8,3:5)
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 934 rows [1, 25, 49, 73,
## 97, 121, 145, 169, 193, 217, 241, 265, 289, 313, 337, 361, 385, 409, 433, 457,
## ...].
```

```
head(hourly_activity)
```

	id <dbl>	date <date>	time <chr>	day_week <chr>	calories <int>	total_intensity <int>	step_total <int>
1	1503960366	2016-04-12	NA	Tuesday	81	20	373
2	1503960366	2016-04-12	01:00:00	Tuesday	61	8	160
3	1503960366	2016-04-12	02:00:00	Tuesday	59	7	151
4	1503960366	2016-04-12	03:00:00	Tuesday	47	0	0
5	1503960366	2016-04-12	04:00:00	Tuesday	48	0	0
6	1503960366	2016-04-12	05:00:00	Tuesday	48	0	0

6 rows

Preparing the sleep day table

```
sleep <- sleep_day %>%
  clean_names() %>%
  separate(sleep_day, into= c("date","time"), sep=" ") %>%
  mutate(date = mdy(date), day_week = weekdays(date)) %>%
  select (-time) %>%
  select(1,2,6,3:5)
```

```
## Warning: Expected 2 pieces. Additional pieces discarded in 413 rows [1, 2, 3, 4, 5, 6,
## 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, ...].
```

Preparing heartrate data

```
heartrate <- heart_rate %>%
  clean_names() %>%
  rename("rate_time" = "time") %>%
  mutate(rate_time = mdy_hms(rate_time), day_week = weekdays(rate_time) ) %>%
  separate(rate_time, into=c("date", "time"), sep= " ")
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 112 rows [163348, 172616,
## 181769, 200361, 209351, 233670, 242959, 270506, 280034, 289057, 306914, 309278,
## 355636, 369794, 594739, 610339, 619544, 645115, 654389, 663605, ...].
```

```
  #select(-c(time, value)) %>%
  #group_by(id,date) %>%
  #summarise(.groups = "drop")

head(heartrate)
```

	id <dbl>	date <chr>	time <chr>	value <int>	day_week <chr>
1	2022484408	2016-04-12	07:21:00	97	Tuesday
2	2022484408	2016-04-12	07:21:05	102	Tuesday
3	2022484408	2016-04-12	07:21:10	105	Tuesday
4	2022484408	2016-04-12	07:21:20	103	Tuesday
5	2022484408	2016-04-12	07:21:25	101	Tuesday
6	2022484408	2016-04-12	07:22:05	95	Tuesday

6 rows

Preparing weight log data

```
weight_log <- weightLog %>%
  clean_names() %>%
  mutate(date = mdy_hms(date), day_week = weekdays(date) ) %>%
  separate(col = date, into = c("date", "time"), sep = " ") %>%
  select(1,2,3,10,4,6,7)

head(weight_log)
```

	id <dbl>	date <chr>	time <chr>	day_week <chr>	weight_kg <dbl>	fat <int>	bmi <dbl>
1	1503960366	2016-05-02	23:59:59	Monday	52.6	22	22.65
2	1503960366	2016-05-03	23:59:59	Tuesday	52.6	NA	22.65
3	1927972279	2016-04-13	01:08:52	Wednesday	133.5	NA	47.54

	id	date	time	day_week	weight_kg	fat	bmi
	<dbl>	<chr>	<chr>	<chr>	<dbl>	<int>	<dbl>
4	2873212765	2016-04-21	23:59:59	Thursday	56.7	NA	21.45
5	2873212765	2016-05-12	23:59:59	Thursday	57.3	NA	21.69
6	4319703577	2016-04-17	23:59:59	Sunday	72.4	25	27.45

6 rows

Checking the number of unique ids for each dataset

```
length(unique(daily$id))
```

```
## [1] 33
```

```
length(unique(hourly_activity$id))
```

```
## [1] 33
```

```
length(unique(sleep$id))
```

```
## [1] 24
```

```
length(unique(heartrate$id))
```

```
## [1] 14
```

```
length(unique(weight_log$id))
```

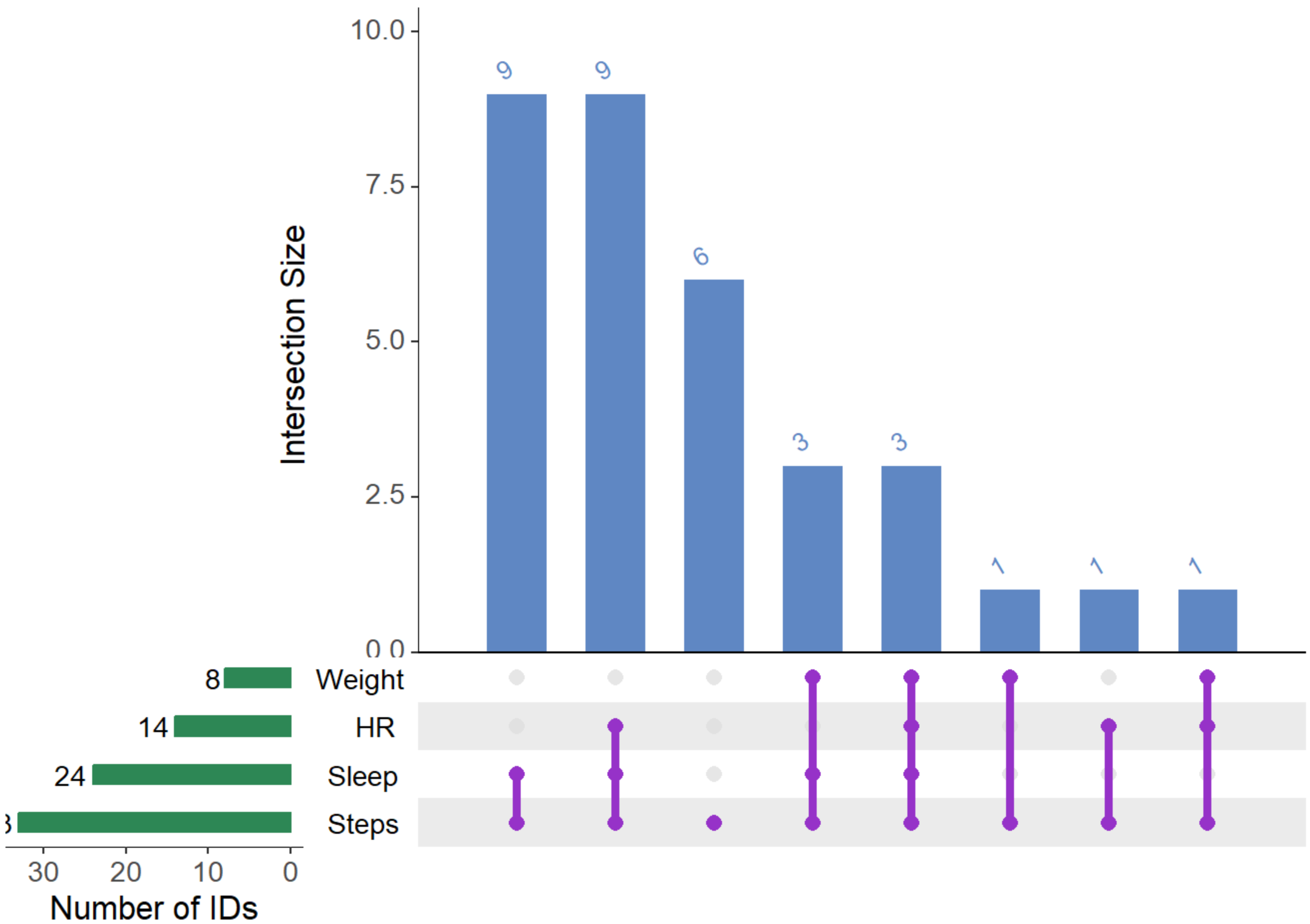
```
## [1] 8
```

Since the number of unique ids differs a lot for each dataset, we will visualize the intersection between these datasets. Hourly and daily users are

```
identical(unique(daily$id),unique(hourly_activity$id)) #it shows that ids for hourly acitivty an
d daily acitivty are same and hence the daily activity data is a generalized summary of the hour
ly recorded data
```

```
## [1] TRUE
```

```
step_ids <- unique(daily$id)
sleep_ids <- unique(sleep$id)
heartrate_ids <- unique(heartrate$id)
weight_ids <- unique(weight_log$id)

data_list <- list(Steps=step_ids, Sleep=sleep_ids, HR=heartrate_ids, Weight=weight_ids)
upset_data <- fromList(data_list)
upset(upset_data,  order.by = "freq",
  main.bar.color = '#6189C5',
  sets.bar.color = "seagreen",
  sets.x.label = "Number of IDs",
  text.scale = 1.5,
  point.size = 2.5,
  line.size = 1.5,
  matrix.color = "darkorchid",
  mainbar.y.label = "Intersection Size",
  number.angles = 30,
  shade.color = "gray",
  show.numbers = "yes",
  set_size.show = TRUE)
```



```
#ggsave("reduced_upset_plot.png", plot = upset_plot, width = 8, height = 6, dpi = 300)



#plot(upset_plot)
```

As we can see, there are only 3 Ids using all four features.

Single-feature records or users:

18% (6 Ids) have only STEPS count records (no other features being used)

Duo-feature users:

27% (9 Ids) have only duo-feature of STEPS - SLEEP records (This subgroup is the closest one to that of Bellabeat's Leaf users as purely recorded Steps - Sleep)

1 id has only the duo feature of STEPS - WEIGHT record

1 id has duo feature of STEPS - HEARTRATE record

Trio_feature users:

27% (9 ids) used 3 features of STEPS - SLEEP - HEARTRATE

9% (3 ids) used 3 features of STEPS - SLEEP - WEIGHT

1 id used trio-feature STEPS - HEARTRATE - WEIGHT

Since the dataframe closest to the BellaBeat device is too small (only 9 Ids), we will be using the Sleep-Step Dataset, who may or may not be using other features.

```
# Checking which ids have both STEP and SLEEP

length(sleep_ids[sleep_ids %in% step_ids])
```

```
## [1] 24
```

Joining the 2 datasets

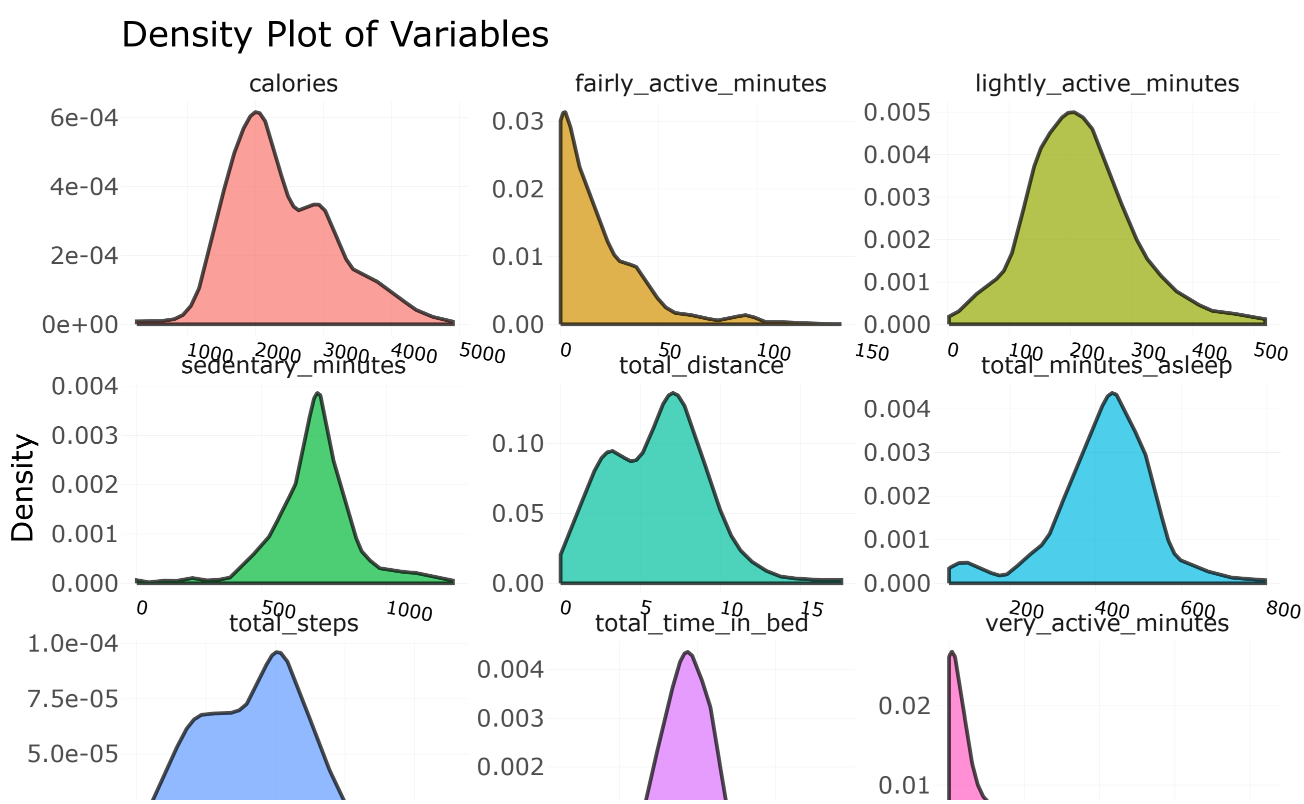
```
step_sleep <- daily %>%
  inner_join(sleep, by = c("id","date","day_week"))

step_sleep <- step_sleep[!duplicated(step_sleep), ] #removing duplicates

head(step_sleep)
```

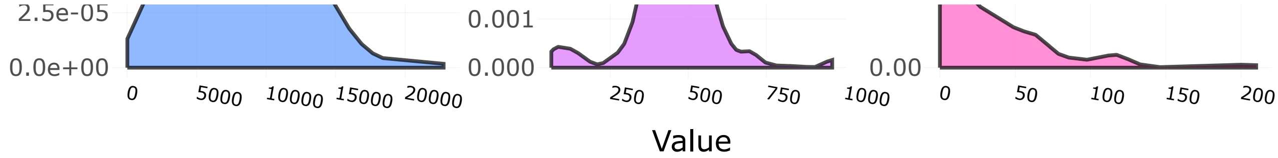
	id <dbl>	date <date>	day_week <chr>	total_steps <int>	calories <int>	total_distance <dbl>	very_active_mir
1	1503960366	2016-04-12	Tuesday	13162	1985	8.50	

	id	date	day_week	total_steps	calories	total_distance	very_active_mir
	<dbl>	<date>	<chr>	<int>	<int>	<dbl>	
2	1503960366	2016-04-13	Wednesday	10735	1797	6.97	
3	1503960366	2016-04-15	Friday	9762	1745	6.28	
4	1503960366	2016-04-16	Saturday	12669	1863	8.16	
5	1503960366	2016-04-17	Sunday	9705	1728	6.48	
6	1503960366	2016-04-19	Tuesday	15506	2035	9.88	

```
step_sleep_lf <- step_sleep %>%
  select(-c(id,date,day_week, total_sleep_records)) %>%
  pivot_longer(cols = total_steps:total_time_in_bed, names_to = "variable", values_to = "value")
```

```
p <- ggplot(step_sleep_lf, aes(x = value, fill = variable)) +
  geom_density(alpha = 0.7) +
  labs(title = "Density Plot of Variables", x = "Value", y = "Density") +
  theme_minimal() +
  theme(legend.position = "none") +
  #theme(axis.text.x = element_text( hjust = 1, vjust = 1))
  theme(axis.text.x = element_text(size = 7, angle = 350, vjust = -1, color = "black"))+
  theme(panel.spacing = unit(1, "lines")) +
  facet_wrap(~ variable, scales = "free")

ggplotly(p)
```

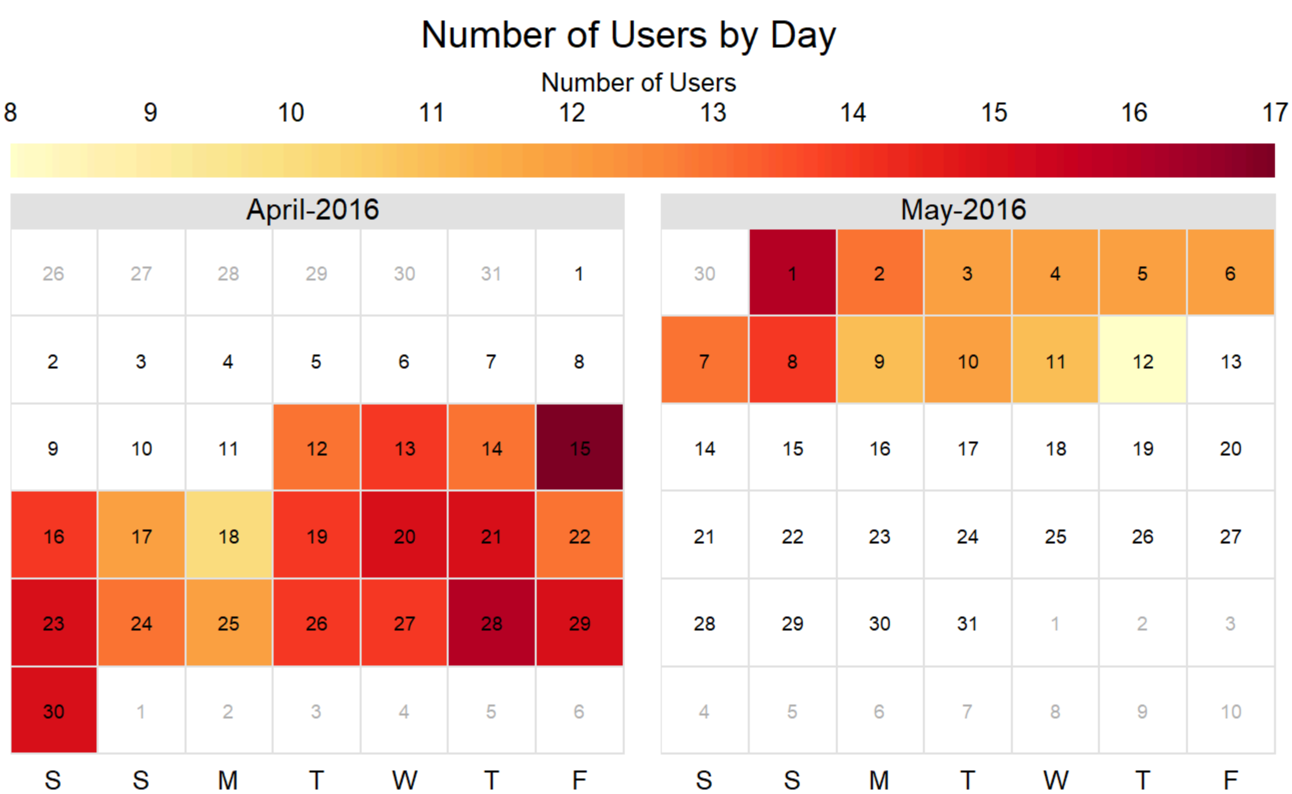




The “Total steps” variable shows a peak with the majority of the distribution concentrated in the middle, while a few values extend into the right tail. This indicates that the data points are not normally distributed. Additionally, the plot reveals a few extreme values on the lower right end, which could suggest measurement errors (e.g., false steps recorded due to wrist movements) or instances when users engaged in extra exercise on those particular days.

The “Very active minutes” and “Fairly active minutes” variables are positively skewed, with most data points clustered on the left side, primarily around zero. This could indicate a technical error, such as the device not syncing with the user’s phone app—a common tracking issue reported in the Fitbit Community. Alternatively, it could mean that users did not engage in any exercise on those days. There are also a few outliers on the right, with values exceeding 100 minutes.

```
# Get number of users used their devices each day:
no_users <- step_sleep %>%
  group_by(date) %>%
  summarise(user_perday = sum(n()), .groups = "drop")
#Plot a calendar heat map on total steps by day
calendarPlot(no_users, pollutant = "user_perday",year=2016, month = 1:5, main = "Number of Users by Day", cols="heat", key.header = "Number of Users", key.position = "top")
```



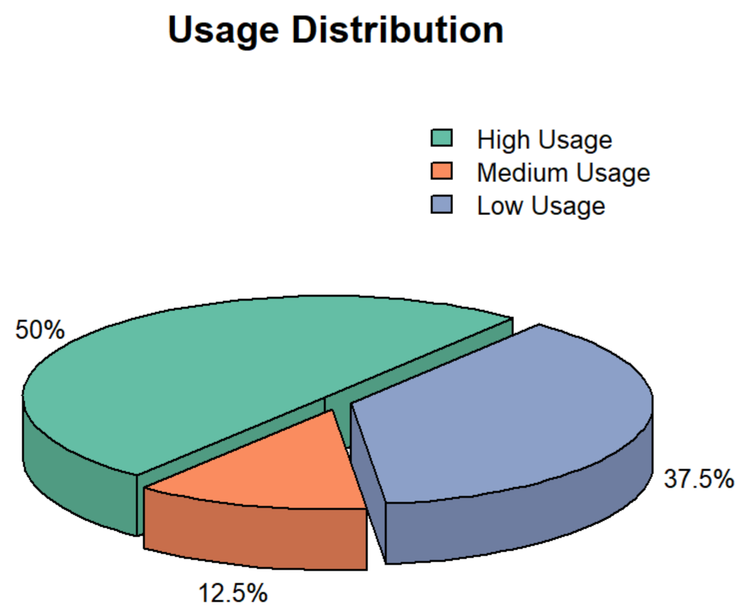
```
options(repr.plot.width = 14, repr.plot.height = 10)
```

The visualization shows the 30 days the data is collected, days with darker colors indicate more users tracked data on that day whereas lighter color indicates less tracked data. Highest number of data was collected on April 15 whereas the least was collected on May 12.

Creating subsets of low, medium and high users

based on the number of days they are active.

```
obs_days <- step_sleep %>% group_by(id) %>%
  summarise(num_dayuse = sum(n())) %>%
  arrange(-num_dayuse)


# Dividing ids into different usage categories
usage <- obs_days %>%
  mutate(group = case_when(
    between(num_dayuse, 1, 10) ~ "Low Usage",
    between(num_dayuse, 11, 20) ~ "Medium Usage",
    between(num_dayuse, 21, 31) ~ "High Usage",
    TRUE ~ NA_character_
    ))

# df with new usage classification
usage_df <- step_sleep %>%
  left_join(usage, by = "id")

sum_usage <- usage %>%
  mutate(group = fct_relevel(group, c("High Usage", "Medium Usage", "Low Usage"))) %>%
  group_by(group) %>%
  summarise(num_users = n()) %>%  #counting each observation vs sum is used to aggregate
  mutate(percent = num_users/sum(num_users)*100)


colors <- brewer.pal(length(sum_usage$group), "Set2")

# Create a 3D pie chart
pie3D(
  x = sum_usage$num_users,
  labels = paste0(sum_usage$percent, "%"),
  explode = 0.05 ,   # Adds space between slices
  main = "Usage Distribution",
  col = colors,
  labelcex = 0.8,  # Adjust label size
  radius = 1,  # Adjust radius size
  start = 0.9
  )

par(xpd = TRUE)  # Allow plotting outside the plot area
legend("topright", legend = sum_usage$group, fill = colors, bty = "n", cex = 0.8)
```



As we can see majority of users are high users whereas medium usage lowers are the least.

High users are those who use their devices for atleast 21 days. medium users use the devices for 11 to 20 days in a month and less than 10 days usage is classified as low usage.

Creating a dataframe with data for each user of three usage levels for each day:

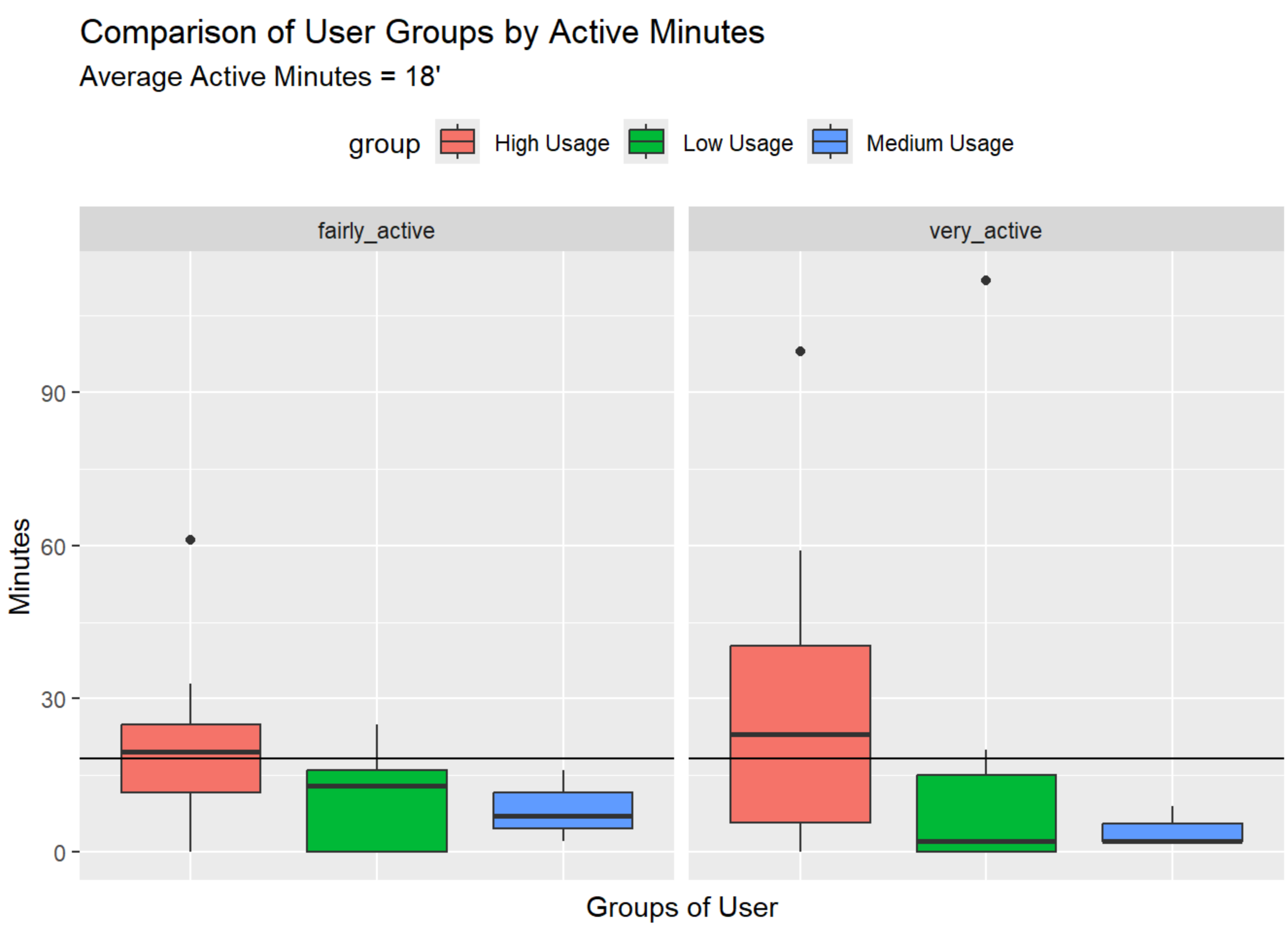
```
usage_hr <- usage_df %>% group_by(group, date, id, day_week) %>%
  mutate(total_mins = sum(very_active_minutes, fairly_active_minutes, lightly_active_minutes, to
tal_time_in_bed)) %>%
  summarise(steps = round(mean(total_steps),0),
            distance = round(mean(total_distance),0),
    very_active = round(mean(very_active_minutes),0),
            fairly_active = round(mean(fairly_active_minutes),0),
            lightly_active = round(mean(lightly_active_minutes),0),
            sedentary_hr = round(mean(sedentary_minutes)/60,2), #dividing by 60 since we data in
minutes and converting to hr
            bed_hr = round(mean(total_time_in_bed)/60,2),
            asleep_hr = round(mean(total_minutes_asleep)/60,2),
            avg_hr = round(sum(very_active, fairly_active, lightly_active, sedentary_minutes, to
tal_time_in_bed/60,2)))
```

```
## `summarise()` has grouped output by 'group', 'date', 'id'. You can override
## using the `.groups` argument.
```

This creates our main dataset that is divided: 1. usage levels 2. date/days of the week 3. id

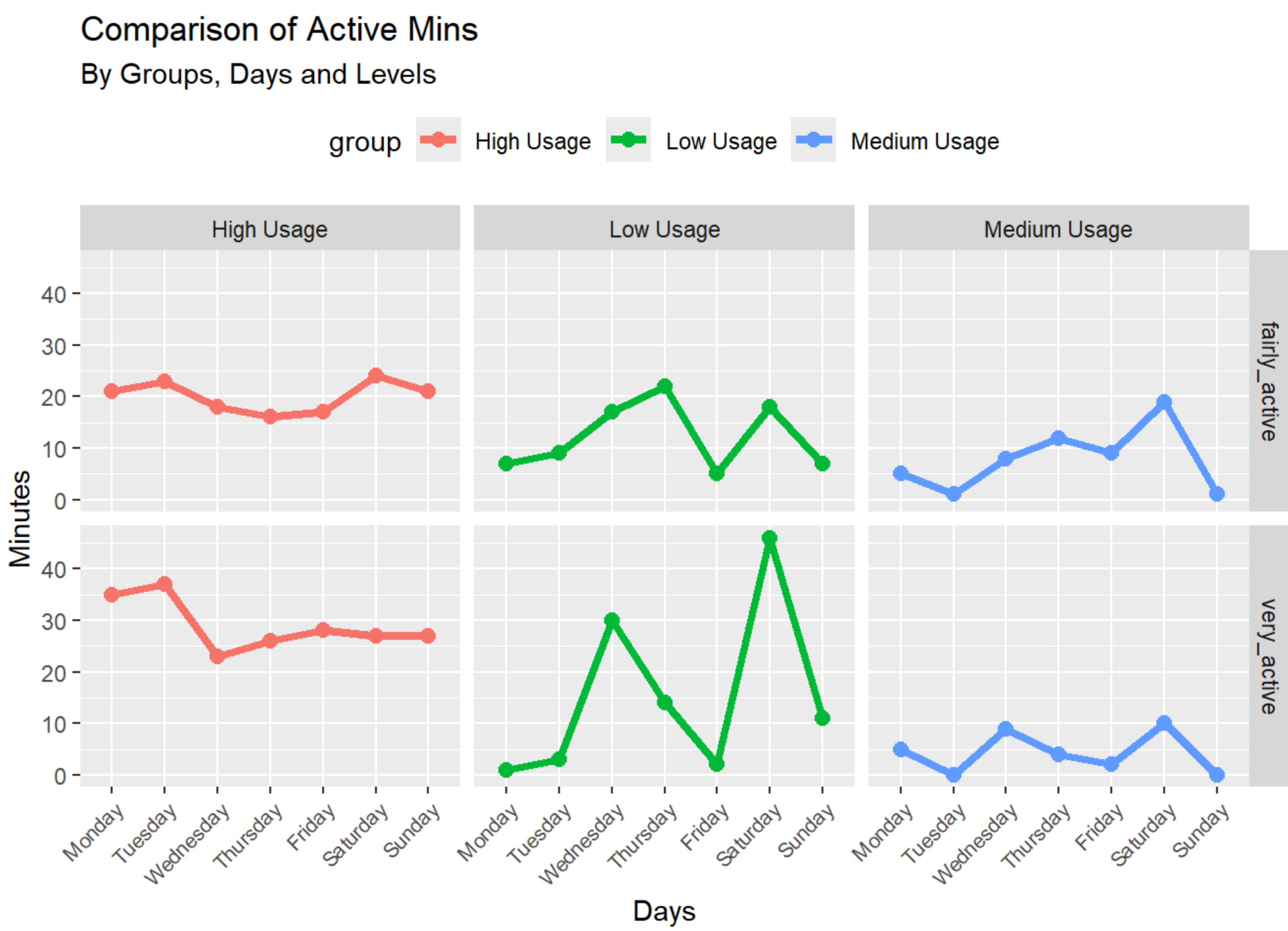
Each id may be repeated on different days, unique ids = 24

```
# Compare user groups by their average very active minutes
# Summarise Active minutes by groups
active <- usage_hr %>%
  group_by(group, id) %>%
  summarise(very_active = round(mean(very_active),0),
            fairly_active = round(mean(fairly_active),0),
            .groups = "drop")
# Reshape data
active_long <- gather(data = active, key = "variables", value = "value", -c(group, id))
# PLot data
ggplot(active_long, aes(group, value, fill=group))+
  geom_boxplot(show.legend = TRUE)+
  geom_hline(yintercept = mean(active_long$value), color = "black")+
  xlab("Groups of User") + ylab("Minutes") +
  ggtitle("Comparison of User Groups by Active Minutes", "Average Active Minutes = 18'")+
  theme(axis.text.x=element_blank(), axis.ticks.x=element_blank())+
  theme(legend.position = "top")+
facet_wrap(~variables)
```



With average activity of 18 mins, in both intensity levels, the higher usage group has the most activity, whereas the medium activity group has the least active minutes.High and low users have outliers with extremely high amount of time. High usage group has a wide range of time spent being very active whereas the moderate usage group has very less minutes spent in fairly active or very active instensities.

```
active2 <- usage_df %>%
  group_by(day_week, group) %>%
  summarise(very_active = round(mean(very_active_minutes),0),
            fairly_active = round(mean(fairly_active_minutes),0),.groups = "drop")
# Reshape data
active2_long <- gather(data = active2, key = "variables", value = "value", -c(group,day_week))
# Plot data
active2_long %>% mutate(day_week = fct_relevel(day_week,c("Monday", "Tuesday", "Wednesday", "Thu
rsday", "Friday", "Saturday","Sunday"))) %>%


 ggplot(aes(x= day_week, y=value, color=group, group = interaction(variables, group)))+
  geom_line(linewidth = 1.5)+
  geom_point(size =2.5) +
  theme(axis.text.x = element_text(size = 8, angle = 45, hjust = 1, vjust = 1))+
  theme(legend.position = "top")+
  labs(x="Days" , y="Minutes")+
  ggtitle("Comparison of Active Mins", "By Groups, Days and Levels")+
  facet_grid(variables~group)
```



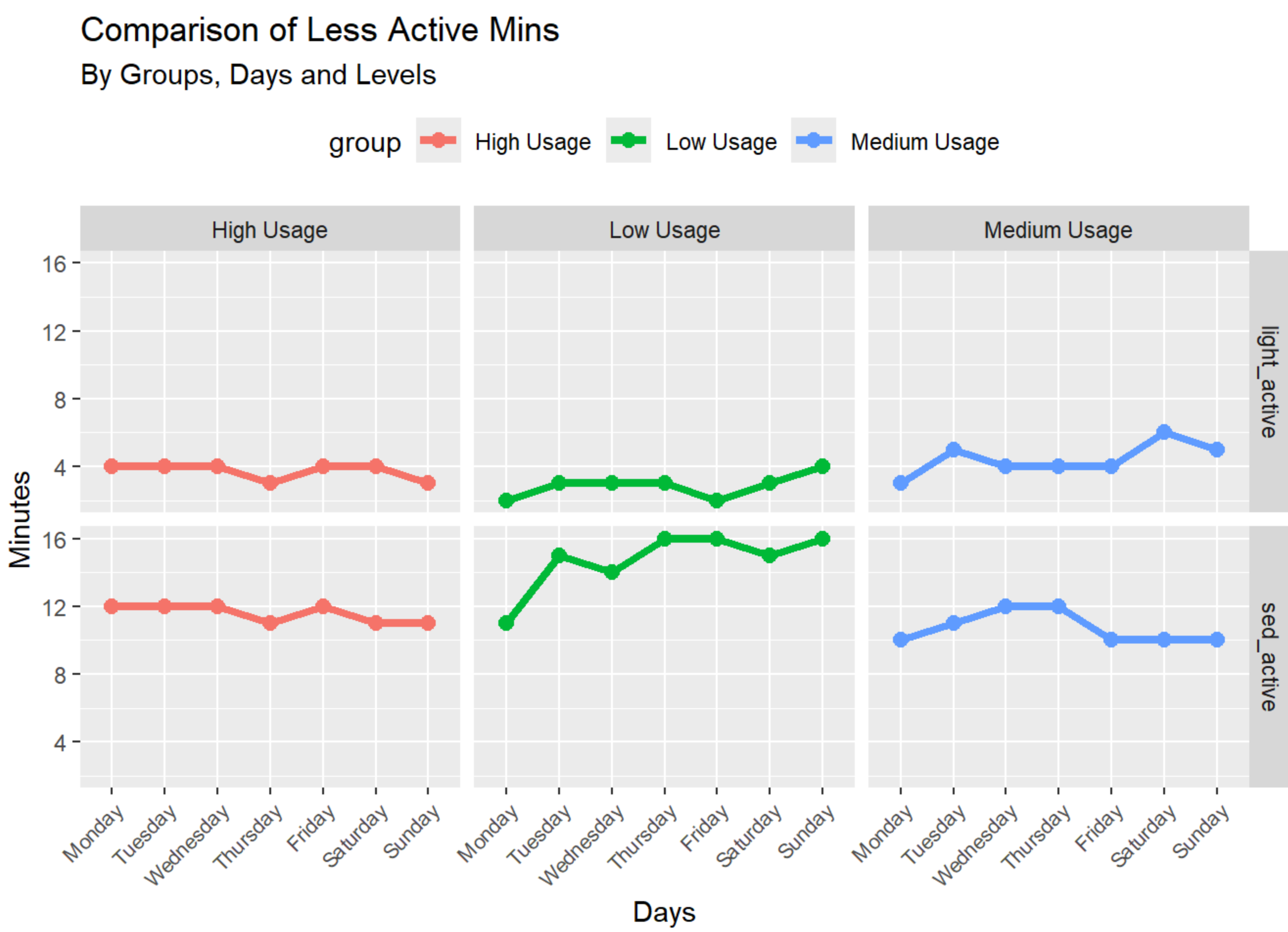
As we can see high usage users are active throughout the week with no particular trend, whereas low users are very active on Wednesdays and saturday but there seems to be no significant trend. Medium usage users also lack any patterns and are consistently low in their active minutes.

Comparing lightly active and sedentary groups

```
low_usage <- usage_hr %>%
  group_by(group, id) %>%
   summarise(lightly_hr = round(mean(lightly_active)/60,2),
            sedentary_hr = round(mean(sedentary_hr),0), .groups = "drop")

# Reshape data
low_usage_long <- gather(data = low_usage, key = "variables", value = "value", -c(group, id))


ggplot(low_usage_long, aes(group, value, fill=group))+
  geom_boxplot(show.legend = TRUE)+
  xlab("Groups of User") + ylab("Minutes") +
  ggtitle("Comparison of User Groups by Active Minutes")+
  theme(axis.text.x=element_blank(), axis.ticks.x=element_blank())+
  theme(legend.position = "top")+
facet_wrap(~variables)
```

All groups tend to spend similar amount of time in light activities, however low users tend to spend the most amount of time in sedentary.

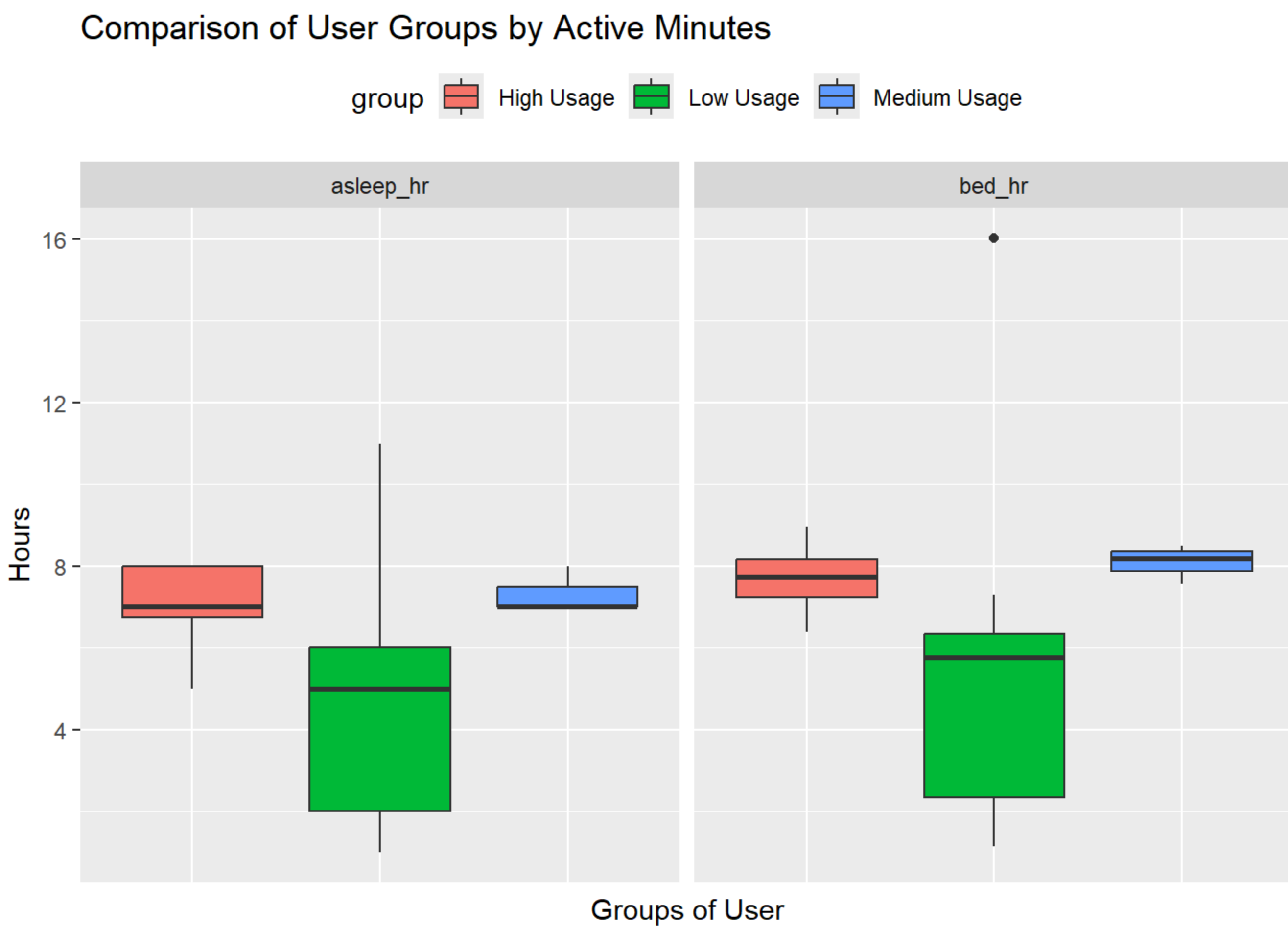
```
light2 <- usage_df %>%
  group_by(day_week, group) %>%
  summarise(light_active = round(mean(lightly_active_minutes)/60,0),
            sed_active = round(mean(sedentary_minutes)/60,0),.groups = "drop")
# Reshape data
light2_long <- gather(data = light2, key = "variables", value = "value", -c(group,day_week))
# Plot data
light2_long %>% mutate(day_week = fct_relevel(day_week,c("Monday", "Tuesday", "Wednesday", "Thur
sday", "Friday", "Saturday","Sunday"))) %>%

  ggplot(aes(x= day_week, y=value, color=group, group = interaction(variables, group)))+
  geom_line(linewidth = 1.5)+
  geom_point(size =2.5) +
  theme(axis.text.x = element_text(size = 8, angle = 45, hjust = 1, vjust = 1))+
  theme(legend.position = "top")+
  labs(x="Days" , y="Minutes")+
  ggtitle("Comparison of Less Active Mins", "By Groups, Days and Levels")+
  facet_grid(variables~group)
```



Similar to the previous visualization, low users have the highest minutes in sedentary activties and the lowest in light activities. High usage users have fairly consistent amount of time in light and sedentary activities.

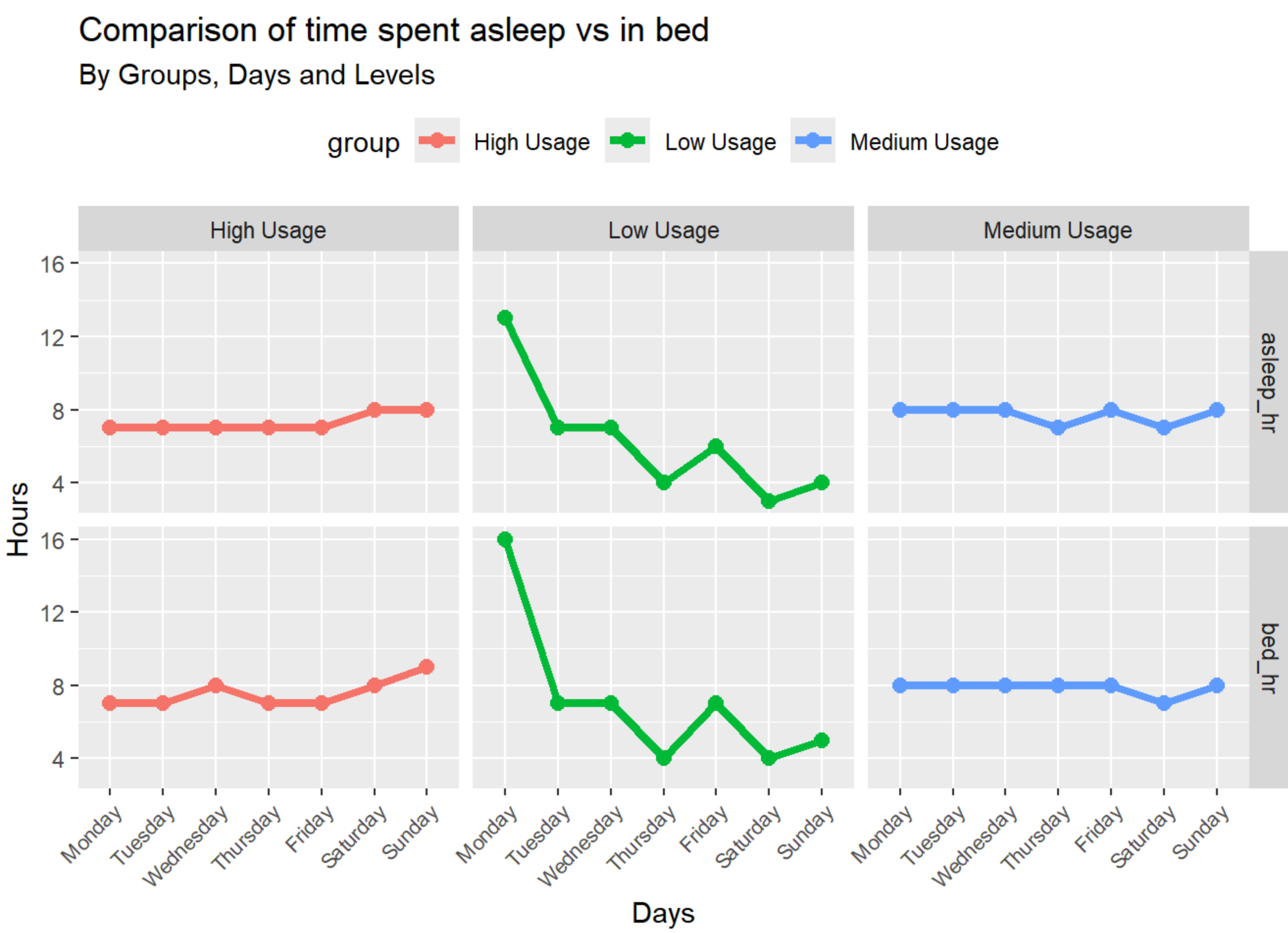
Comparison of hours in bed vs hours asleep for high medium and low usage groups

```
bed_usage <- usage_hr %>%
  group_by(group, id) %>%
   summarise(bed_hr = round(mean(bed_hr),2),
            asleep_hr = round(mean(asleep_hr),0), .groups = "drop")

# Reshape data
bed_usage_long <- gather(data = bed_usage, key = "variables", value = "value", -c(group, id))

ggplot(bed_usage_long, aes(group, value, fill=group))+
  geom_boxplot(show.legend = TRUE)+
  xlab("Groups of User") + ylab("Hours") +
  ggtitle("Comparison of User Groups by Active Minutes")+
  theme(axis.text.x=element_blank(), axis.ticks.x=element_blank())+
  theme(legend.position = "top")+
facet_wrap(~variables)
```



The low usage group have their sleep hours and rest hours varied the most (between 2-6 hour) and tend to have insufficient sleep while the high and moderate usage groups steadily stuck with their bed routine and had sufficient sleep.

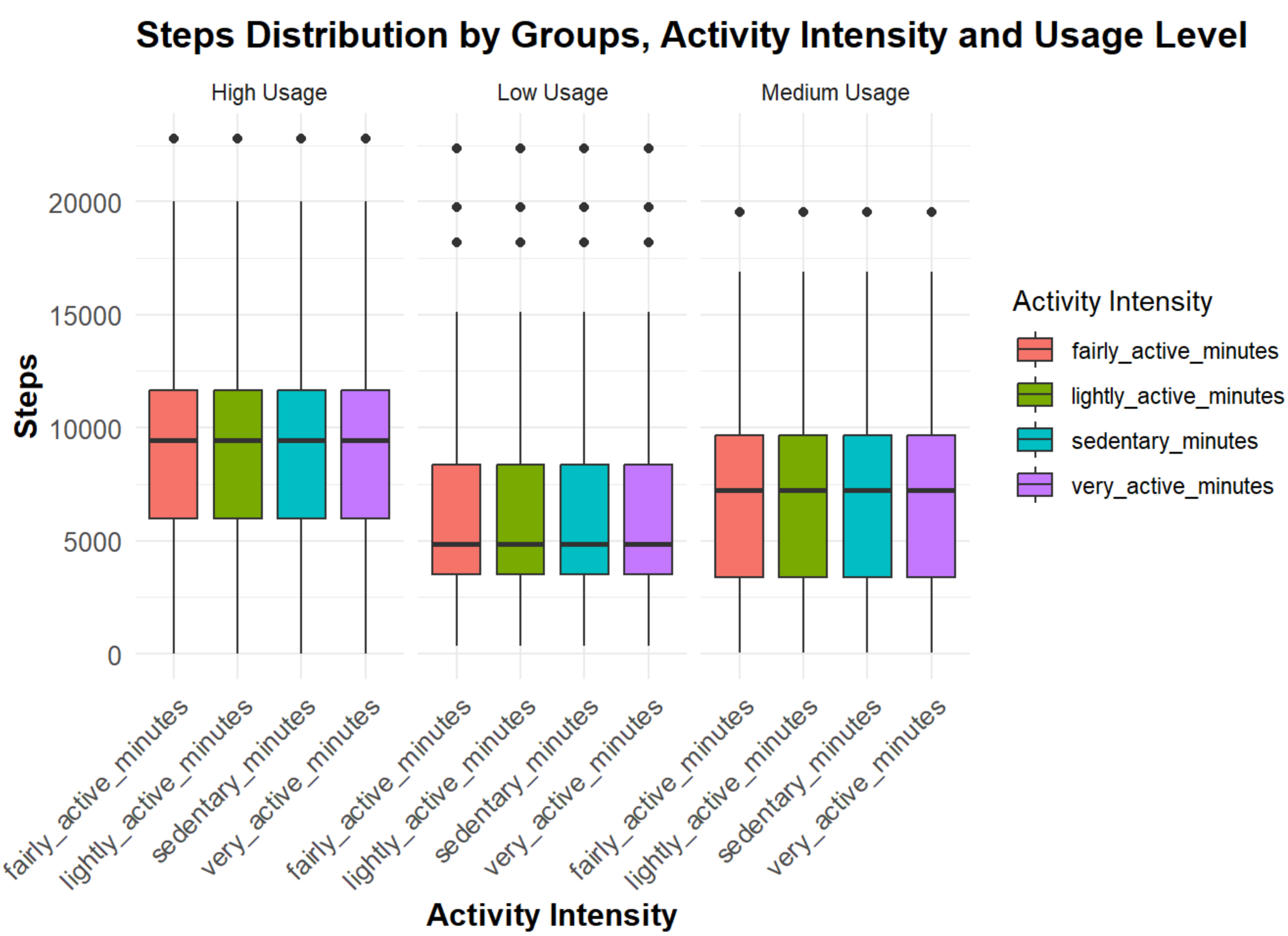
```
bed2 <- usage_df %>%
  group_by(day_week, group) %>%
  summarise(bed_hr = round(mean(total_time_in_bed)/60,0),
            asleep_hr = round(mean(total_minutes_asleep)/60,0),.groups = "drop")
# Reshape data
bed2_long <- gather(data = bed2, key = "variables", value = "value", -c(group,day_week))
# Plot data
bed2_long %>% mutate(day_week = fct_relevel(day_week,c("Monday", "Tuesday", "Wednesday", "Thursd
ay", "Friday", "Saturday","Sunday"))) %>%

  ggplot(aes(x= day_week, y=value, color=group, group = interaction(variables, group)))+
  geom_line(linewidth = 1.5)+
  geom_point(size =2.5) +
  theme(axis.text.x = element_text(size = 8, angle = 45, hjust = 1, vjust = 1))+
  theme(legend.position = "top")+
  labs(x="Days" , y="Hours")+
  ggtitle("Comparison of time spent asleep vs in bed", "By Groups, Days and Levels")+
  facet_grid(variables~group)
```



Users in high and medium usage have a fairly consistent sleeping patterns and time spend in bed, whereas low usage users have the most inconsistent sleep schedule with most amount of sleep recorded at the starting of the week.

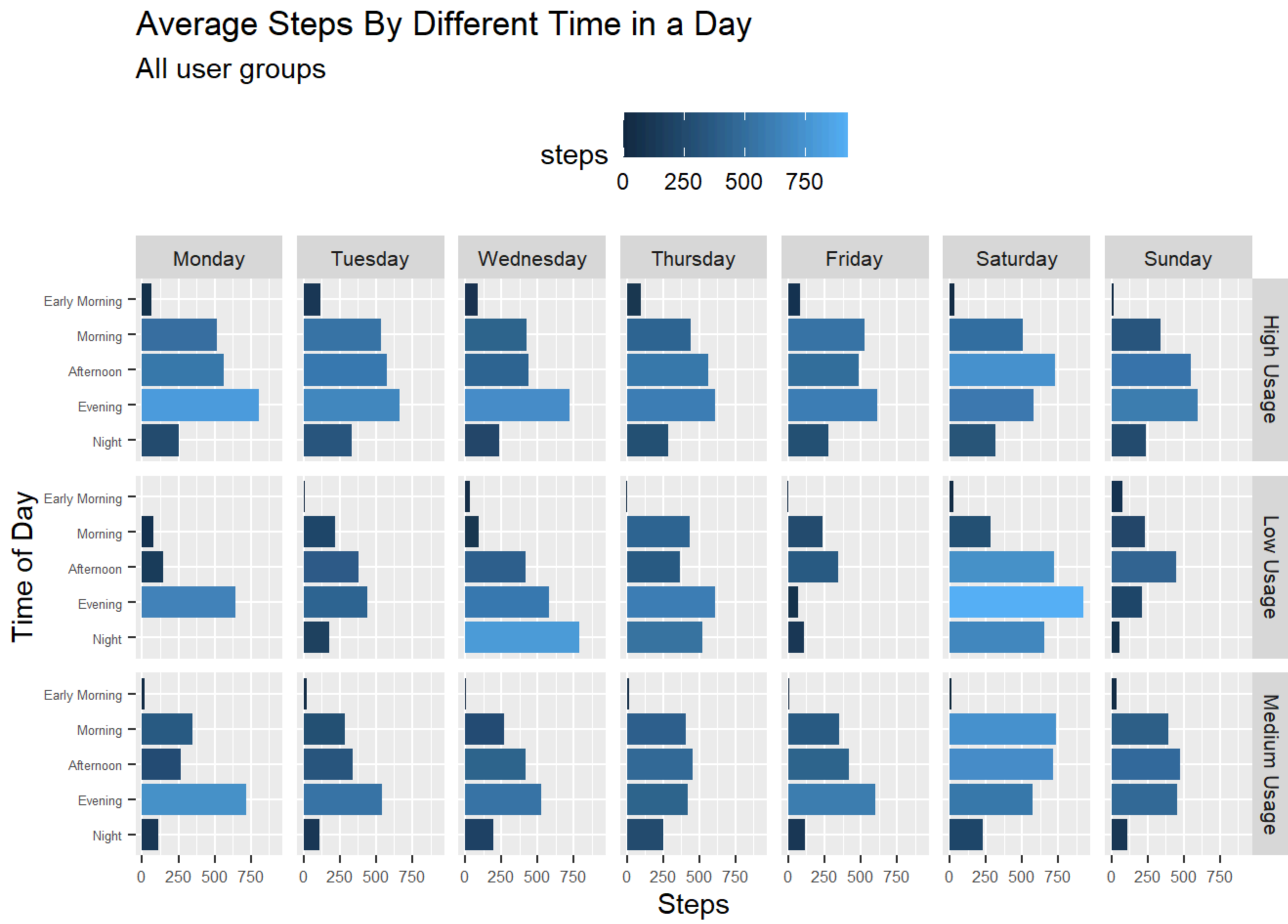
The difference between time spend in bed vs asleep is also the biggest in low usage group, indicating the users spend a lot of time in bed where they are not actually asleep, specially on Mondays.

```
usage_long <- usage_df %>%
  gather(key = "activity_type", value = "minutes",
         very_active_minutes, fairly_active_minutes, sedentary_minutes, lightly_active_minutes)


ggplot(usage_long, aes(x = activity_type, y = total_steps, fill = activity_type)) +
  geom_boxplot() +
  facet_wrap(~ group) +
  labs(title = "Steps Distribution by Groups, Activity Intensity and Usage Level",
       x = "Activity Intensity",
       y = "Steps",
       fill = "Activity Intensity")+
  theme_minimal() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),  # Adjust x-axis text
    axis.text = element_text(size = 10),  # Adjust axis text size
    axis.title = element_text(size = 12, face = "bold"),  # Adjust axis title size
    plot.title = element_text(size = 14, face = "bold")  # Adjust plot title size
  )
```



As visualized, high users log more number of average steps, in all intensity levels and low usage user have lesser number of steps logged, however they also have more outliers with increased number of steps, implying that these users might be more active but are not using the device.

```
distri_hr <- merge(hourly_activity, usage_df, by = c("id", "date", "day_week"))
distri_hr <- distri_hr[!duplicated(distri_hr), ] %>% #removing any duplicate rows
  na.omit() %>%
 mutate(hr= format(parse_date_time(as.character(time), "HMS"), format = "%H:%M"),
  hour_numeric = as.numeric(substr(hr, 1, 2)),
  replace_na(list(hour_numeric = 24)),
  time_of_day = case_when(
    between(hour_numeric, 0, 6 ) ~ "Early Morning",
    between(hour_numeric, 7, 11) ~ "Morning",
    between(hour_numeric, 12, 16) ~ "Afternoon",
    between(hour_numeric, 17, 20) ~ "Evening",
    between(hour_numeric, 21, 24) ~ "Night"
    )) %>%
mutate(time_of_day = fct_relevel(time_of_day, c("Night", "Evening",  "Afternoon", "Morning","Ear
ly Morning")),
       day_week = fct_relevel(day_week, c("Monday", "Tuesday", "Wednesday", "Thursday", "Frida
y", "Saturday","Sunday"))) %>%
  group_by(time_of_day,day_week, group) %>%
  summarise(
    steps = mean(step_total),
    .groups = "drop"
  )



ggplot(distri_hr, aes(x=time_of_day, y=steps, fill = steps))+
  #scale_fill_gradient(low = "green", high = "red")+
  geom_bar(stat = 'identity', show.legend = TRUE) +
  coord_flip() +
  ggtitle("Average Steps By Different Time in a Day", "All user groups") +
  xlab("Time of Day") + ylab("Steps") +
  theme(axis.text.x = element_text(size=6), axis.text.y = element_text(size=5))+
  theme(legend.position = "top")+
  facet_grid(group~day_week) +
  theme(strip.text = element_text(size = 8))
```



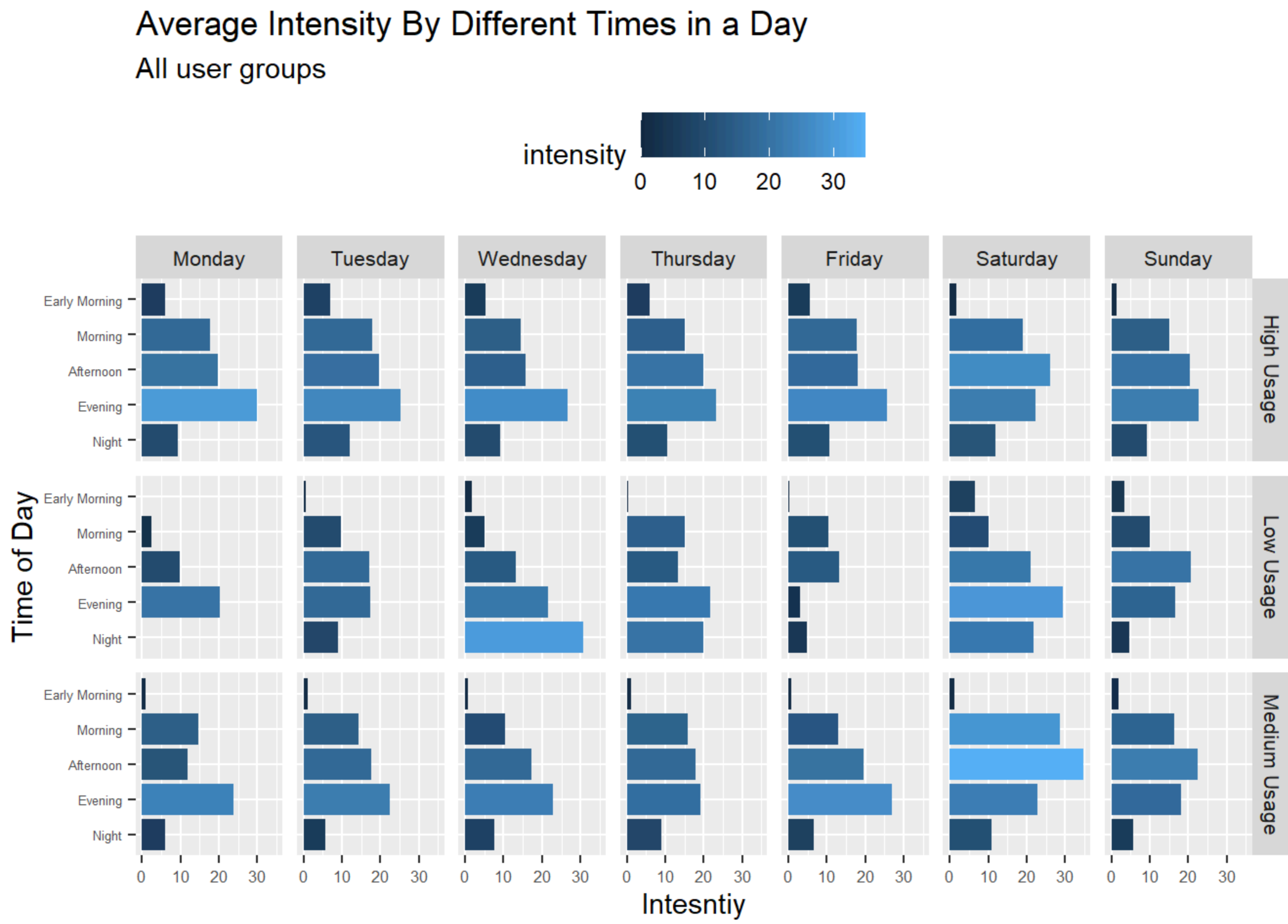
-High Usage group tends to have the highest number of steps taken consistently throughout the week, with a preference for evening steps. Majority of the steps were taken in the evening hours ie between 5:00 to 8:00 pm. The second most active time of the day was around lunch.

-For low usage group, there was no consistent routine in walking, there were some days with very high number of steps like saturday evening and wednesday night but there was no pattern.

-Medium usage group do walk daily but the time of the day is not consistent, it varies from morning to evening, with least amount of steps at night.

-In all groups, Saturday and Monday evening seems to be the most active duration where most steps are recorded.

```
distri_inte <- merge(hourly_activity, usage_df, by = c("id", "date", "day_week" ))
distri_inte <- distri_inte[!duplicated(distri_inte), ] %>% #removing any duplicate rows
  na.omit() %>%
 mutate(hr= format(parse_date_time(as.character(time), "HMS"), format = "%H:%M"),
  hour_numeric = as.numeric(substr(hr, 1, 2)),
    replace_na(list(hour_numeric = 24)),
  time_of_day = case_when(
    between(hour_numeric, 0, 6 ) ~ "Early Morning",
    between(hour_numeric, 7, 11) ~ "Morning",
    between(hour_numeric, 12, 16) ~ "Afternoon",
    between(hour_numeric, 17, 20) ~ "Evening",
    between(hour_numeric, 21, 24) ~ "Night"
    )) %>%
mutate(time_of_day = fct_relevel(time_of_day, c("Night", "Evening",  "Afternoon", "Morning","Ear
ly Morning")),
       day_week = fct_relevel(day_week, c("Monday", "Tuesday", "Wednesday", "Thursday", "Frida
y", "Saturday","Sunday"))) %>%
  group_by(time_of_day,day_week, group) %>%
  summarise(
    intensity = mean(total_intensity),
    .groups = "drop"
  )

ggplot(distri_inte, aes(x=time_of_day, y=intensity, fill = intensity))+
  #scale_fill_gradient(low = "green", high = "red")+
  geom_bar(stat = 'identity', show.legend = TRUE) +
  coord_flip() +
  ggtitle("Average Intensity By Different Times in a Day", "All user groups") +
  xlab("Time of Day") + ylab("Intesntiy") +
  theme(axis.text.x = element_text(size=6), axis.text.y = element_text(size=5))+
  theme(legend.position = "top")+
  facet_grid(group~day_week) +
  theme(strip.text = element_text(size = 8))
```



As observed in the previous graph, highest intensity is during evening for all groups which is when majority steps were also recorded.

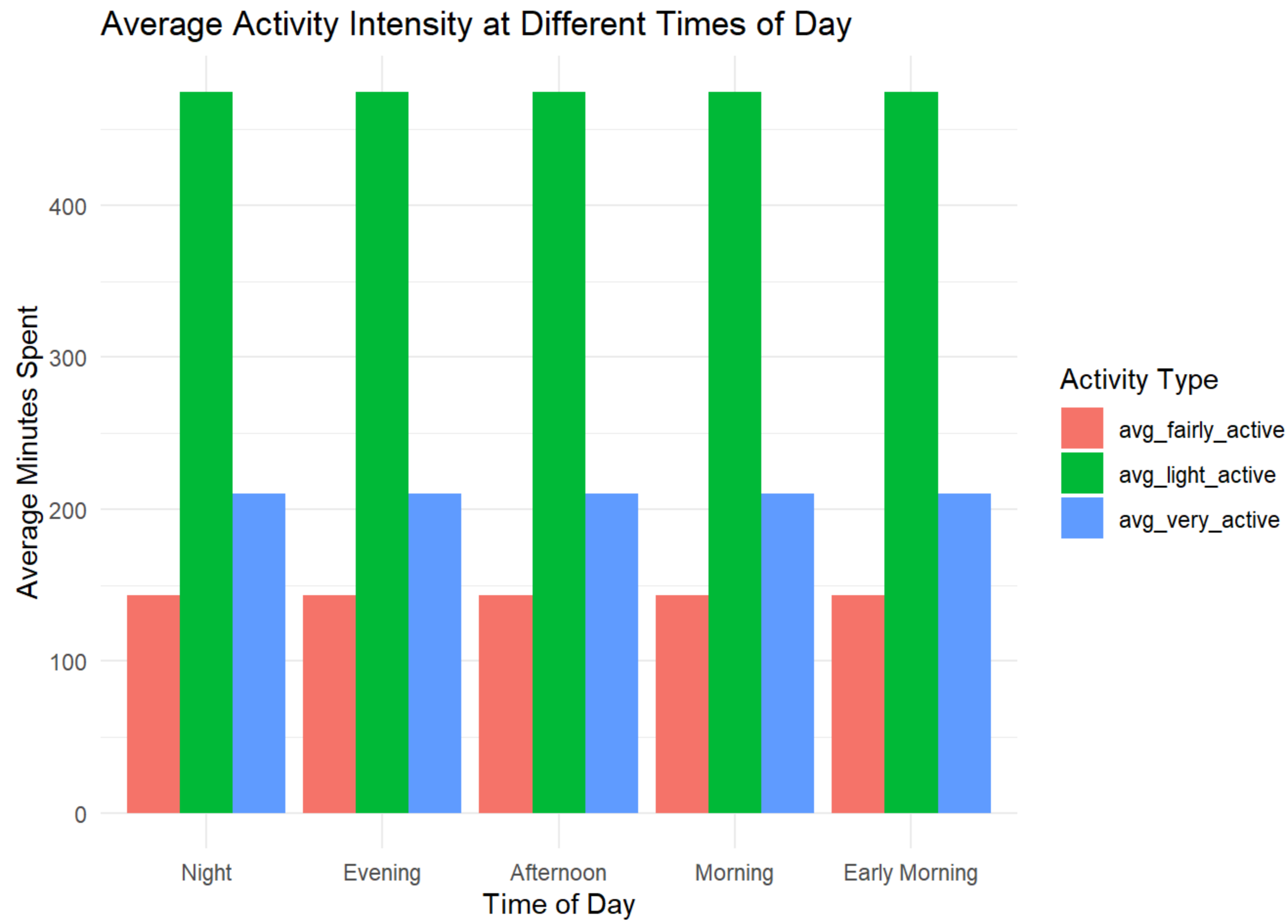
It is interesting to note that high usage group had high intensity through out the week during evening hours, and moderate intensity at other times of the day, whereas low or moderate usage group did not have a consistent pattern in intensities.

Visualizing the levels of intensity by high usage group at different times of the day

```
hour_int_high <- full_join(usage_hr, hourly_activity, by =c( "id", "day_week", "date"))
hour_int_high <- subset(hour_int_high, group=="High Usage")  %>%
 mutate(hr= format(parse_date_time(as.character(time), "HMS"), format = "%H:%M"),
  hour_numeric = as.numeric(substr(hr, 1, 2)),
  hour_numeric = replace_na(hour_numeric, 24),
  time_of_day = case_when(
    between(hour_numeric, 0, 6 ) ~ "Early Morning",
    between(hour_numeric, 7, 11) ~ "Morning",
    between(hour_numeric, 12, 16) ~ "Afternoon",
    between(hour_numeric, 17, 20) ~ "Evening",
    between(hour_numeric, 21, 24) ~ "Night"
    )) %>%
  mutate(time_of_day = fct_relevel(time_of_day, c("Night", "Evening",  "Afternoon", "Morning","E
arly Morning")),
      day_week = fct_relevel(day_week, c("Monday", "Tuesday", "Wednesday", "Thursday", "Frida
y", "Saturday","Sunday")),

  avg_very_active = mean(very_active),
  avg_fairly_active = mean(fairly_active),
  avg_light_active = mean(lightly_active)) %>%
  #select(3:5, 6:8, 19:23) %>%
  pivot_longer(
    cols = c("avg_very_active", "avg_fairly_active", "avg_light_active"),
    names_to = "activity_type",
    values_to = "minutes"
  )
```

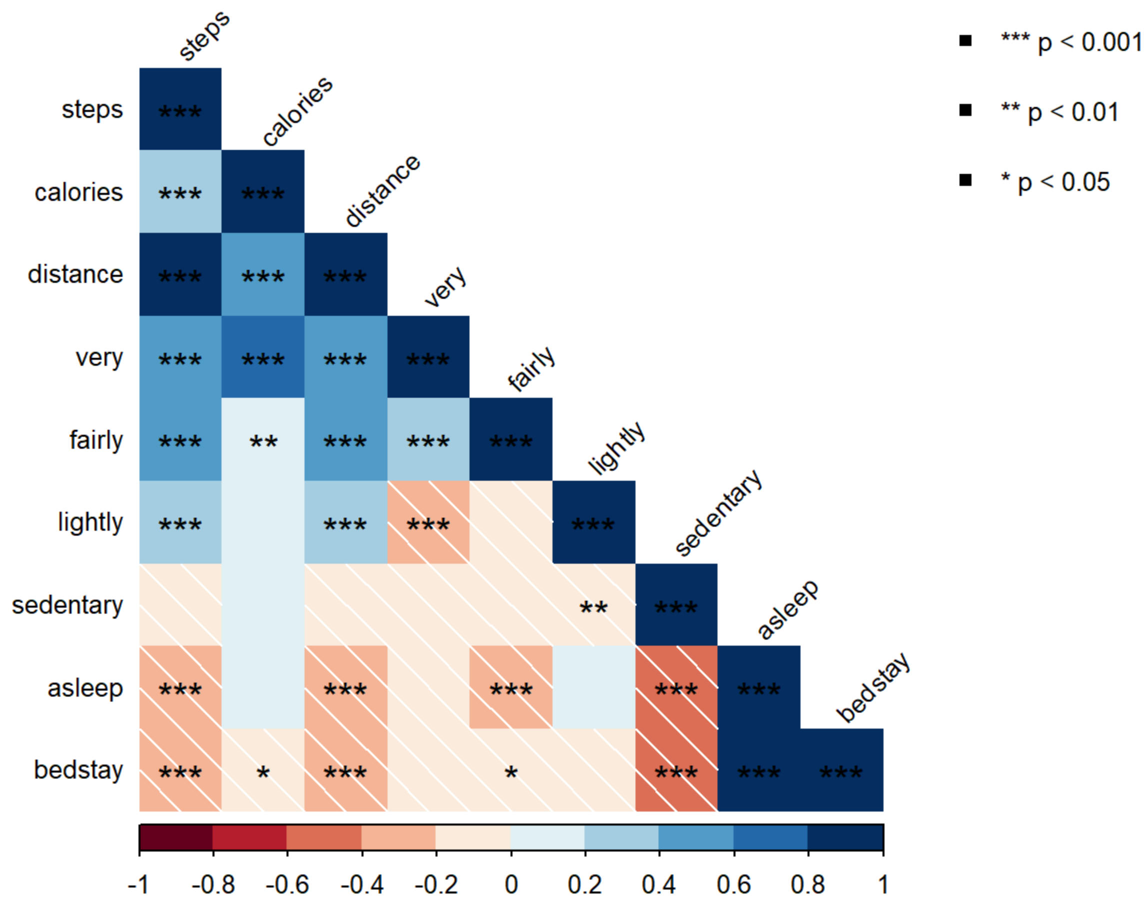
```
## Warning: There were 337 warnings in `mutate()`.
## The first warning was:
## ℹ In argument: `time_of_day = fct_relevel(...)`.
## ℹ In group 317: `group = "High Usage"`, `date = 2016-05-11`, `id = 5577150313`.
## Caused by warning:
## ! 2 unknown levels in `f`: Evening and Afternoon
## ℹ Run `dplyr::last_dplyr_warnings()` to see the 336 remaining warnings.
```

```
ggplot(hour_int_high, aes(x = time_of_day, y = minutes, fill = activity_type)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Average Activity Intensity at Different Times of Day",
      x = "Time of Day", y = "Average Minutes Spent",
      fill = "Activity Type") +
  theme_minimal()
```



Checking which features are strongly correlated with more number of steps in the high usage group.

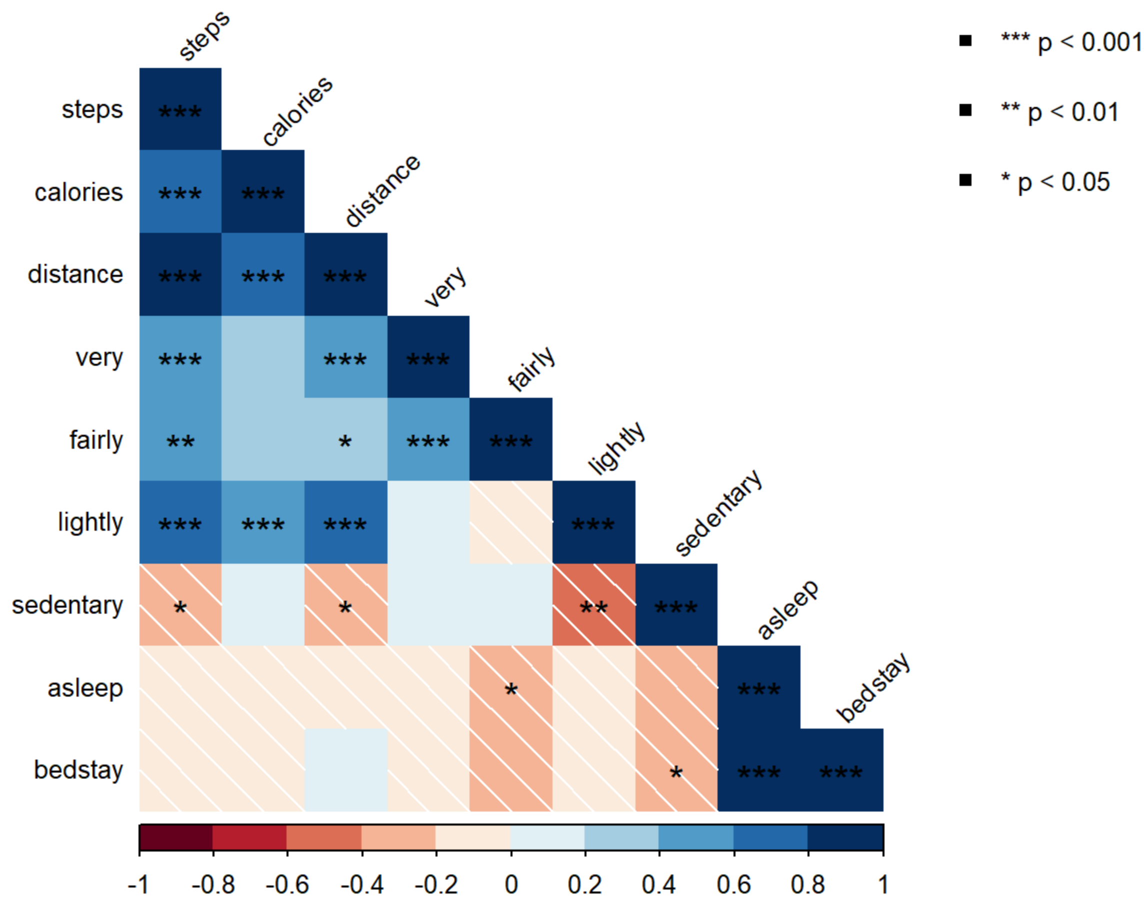
```
high_usage <- subset(usage_df, group=="High Usage")
high_corr <- high_usage %>% select(-c(1:3, 11, 14, 15)) %>%
rename(steps = total_steps,
    distance = total_distance,
    fairly = fairly_active_minutes,
    very = very_active_minutes,
    lightly = lightly_active_minutes,
    sedentary = sedentary_minutes,
    asleep = total_minutes_asleep,
    bedstay = total_time_in_bed)

high_corr_mat <- cor(high_corr)
p_matrix <- cor.mtest(high_corr)$p


signif_levels <- c(0.001, 0.01, 0.05)
signif_symbols <- c("***", "**", "*")


par(mar = c(10, 4, 4, 8))

corrplot(high_corr_mat,
         method = "shade",        # Visualization method ('color', 'circle', 'square', etc.)
         type = "lower",          # Show only upper triangle ('full', 'upper', 'lower')
         #order = "hclust",        # Hierarchical clustering order
         p.mat = p_matrix,        # Matrix of p-values
         sig.level = signif_levels, # Significance levels
         insig = "label_sig",     # How to handle insignificant correlations
         pch.cex = 1.2,           # Size of the significance symbols
         pch.col = "black",       # Color of the significance symbols
         cl.pos = "b",            # Position of color legend ('n' for none)
         col = COL2("RdBu", 10),  # Color palette
         tl.col = "black",        # Text label color
         tl.srt = 45,
         tl.cex = 0.8
         )

legend("topright", legend = c("*** p < 0.001", "** p < 0.01", "* p < 0.05"),
       col = "black", pch = 15, bty = "n", cex = 0.8, xpd= TRUE)
```



As seen in the correlation plot, high usage group tends to take the number of steps logged is positively correlated with higher intensity levels and is also correlated with time spend asleep. However, calories burnt does not have a strong correlation with number of steps taken, impying users might be opting for different forms of physical activities. Steps in this group are correlated with higher intensity levels.

Checking which features are strongly correlated with more number of steps in the medium usage group.

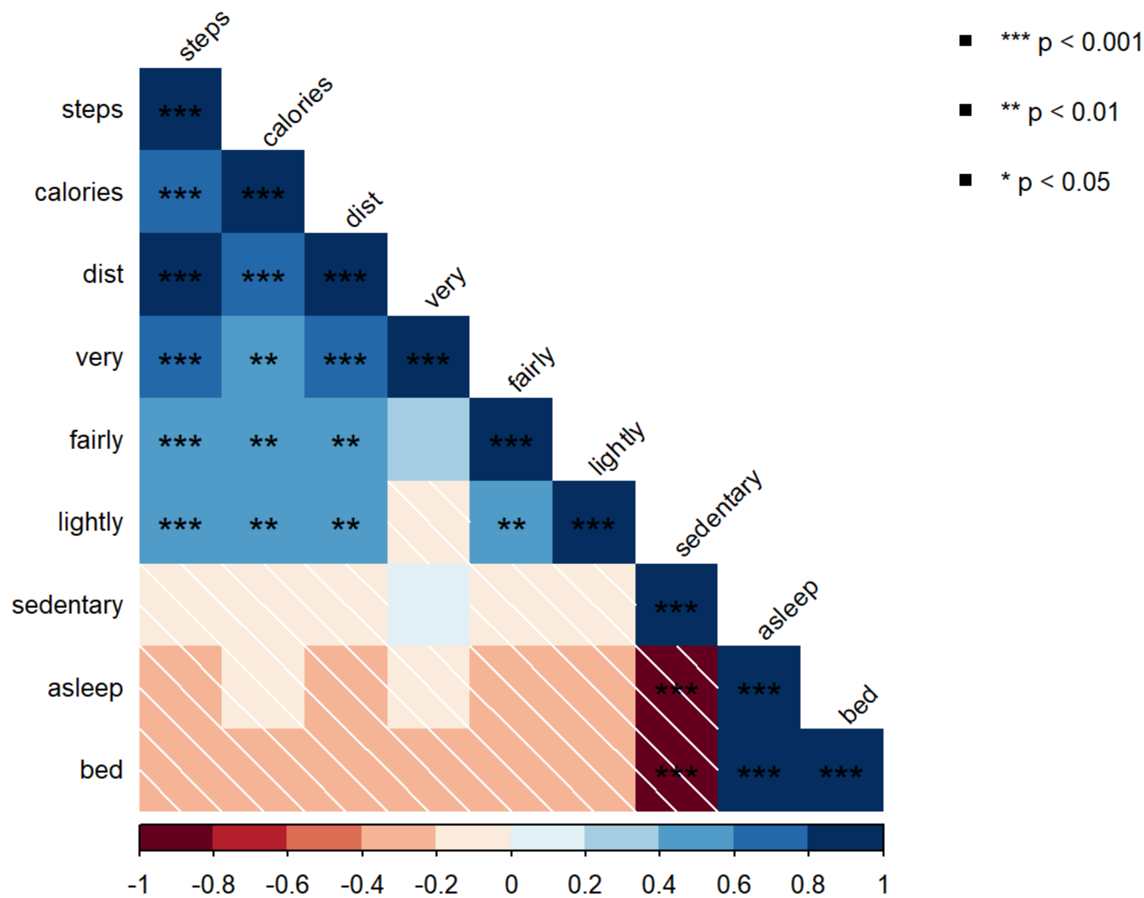
```
med_usage <- subset(usage_df, group=="Medium Usage")
med_corr <- med_usage %>% select(-c(1:3, 11, 14, 15)) %>%
rename(steps = total_steps,
    distance = total_distance,
    fairly = fairly_active_minutes,
    very = very_active_minutes,
    lightly = lightly_active_minutes,
    sedentary = sedentary_minutes,
    asleep = total_minutes_asleep,
    bedstay = total_time_in_bed)

med_corr_mat <- cor(med_corr)
p_med_matrix <- cor.mtest(med_corr)$p


par(mar = c(10, 4, 4, 8))

corrplot(med_corr_mat,
         method = "shade",        # Visualization method ('color', 'circle', 'square', etc.)
         type = "lower",          # Show only upper triangle ('full', 'upper', 'lower')
         p.mat = p_med_matrix,        # Matrix of p-values
         sig.level = signif_levels, # Significance levels
         insig = "label_sig",     # How to handle insignificant correlations
         pch.cex = 1.2,           # Size of the significance symbols
         pch.col = "black",       # Color of the significance symbols
         cl.pos = "b",            # Position of color legend ('n' for none)
         col = COL2("RdBu", 10),  # Color palette
         tl.col = "black",        # Text label color
         tl.srt = 45,
         tl.cex = 0.8
         )

legend("topright", legend = c("*** p < 0.001", "** p < 0.01", "* p < 0.05"),
       col = "black", pch = 15, bty = "n", cex = 0.8, xpd= TRUE)
```



In the medium usage group, the correlation between steps and higher intensity of physical activity is not that high, number of steps taken increases with lower intesnity levels and longer distances, which might be casual walks to school or markets, which is also when more calories are burnt in this group. There is also a small negative correlation between time spent in bed and asleep with the number of steps taken; if the user rests lesser, the number of steps taken also reduces.

Checking which features are strongly correlated with more number of steps in the low usage group.

```
low_usage <- subset(usage_df, group=="Low Usage")
low_corr <- low_usage %>% select(-c(1:3, 11, 14, 15)) %>%
rename(steps = total_steps,
    dist = total_distance,
    fairly = fairly_active_minutes,
    very = very_active_minutes,
    lightly = lightly_active_minutes,
    sedentary = sedentary_minutes,
    asleep = total_minutes_asleep,
    bed = total_time_in_bed)

low_corr_mat <- cor(low_corr)
p_low_matrix <- cor.mtest(low_corr)$p

par(mar = c(10, 4, 4, 8))

corrplot(low_corr_mat,
         method = "shade",        # Visualization method ('color', 'circle', 'square', etc.)
         type = "lower",          # Show only upper triangle ('full', 'upper', 'lower')
         p.mat = p_low_matrix,        # Matrix of p-values
         sig.level = signif_levels, # Significance levels
         insig = "label_sig",     # How to handle insignificant correlations
         pch.cex = 1.2,           # Size of the significance symbols
         pch.col = "black",       # Color of the significance symbols
         cl.pos = "b",            # Position of color legend ('n' for none)
         col = COL2("RdBu", 10),  # Color palette
         tl.col = "black",        # Text label color
         tl.srt = 45,
         tl.cex = 0.8
         )

legend("topright", legend = c("*** p < 0.001", "** p < 0.01", "* p < 0.05"),
       col = "black", pch = 15, bty = "n", cex = 0.8, xpd= TRUE)
```



For the users with the least recorded data, higher number of steps is associated with rigourous forms of activity and most calories are burnt when distance is higher, implying longer duration of intense exercise.

Discussion

Though our data set was limited, it gave us some useful insights about consumer usage of fitness devices. The given users were divided into 3 categories based off the number of days they wore devices:

-High Usage (21-30 Days):

```
Since these users wore their devices the most, it can be presumed that they are health conscious
and have tendency to record their daily activities. They are likely diligent about syncing their
data regularly. These are the everyday users who follow a clear and consistent schedule to achie
ve their daily goals.

  **Weekly Schedule**: The group tends to have a consistent schedule throughout the week, incldu
ing weekends where during morning, afternoon and evening, some physical activity is recorded, wi
th evening having the most active time of the day. Their sleeping patterns are also fairly consi
stent and they get around 8 hours of sleep daily.

  **Exercise Type**: These users tend to engage in all kinds of physical activites throughout th
e day, and remain fairly more active even during working hours. Most of the calories burned by u
sers in this group came from vigorous exercises. Similarly, the majority of steps were accumulat
ed during exercises of high or moderate intensity. However, the number of calories burned is not
necessarily proportional to the number of steps taken, suggesting that frequent users may have e
ngaged in other forms of physical activity.
```

-Medium Usage (11-20 Days):

```
These users wore their devices for lesser number of days, implying that they are interested in b
eing more health conscious but can lack motivation to be consistent. They exercised less compare
d to the other two groups, these participants took fewer steps during weekdays and compensated f
or this on weekends. While their hourly step pattern may be somewhat similar to the high usage g
roup, their activity levels remained much less intense, even lower than those in the low usage g
roup.

**Weekly Schedule**: There seems to be no consistent pattern in the form or schedule of phyiscal
activity followed by this group but they recorded sufficient time spent in bed and asleep hours.
Most of the activity is spent in lesser intensities such as commuitng and shopping, whereas time
recorded for higher intesnity levels is very low. Compared to high intensity group, not much act
ivity is observed during evening, higher intensity levels are recorded on weekends, specially Sa
turday.

**Exercise Type**: Lighter forms of activity are more prevelant in this group, for example: comm
uting between places or shopping, where they spend most of their time.
```

-Low Usage (0-10 Days):

```
Though the group had the least amount of recorded data, it was observed that whenever possible t
he users kept themselves active, they are flexible in their timings and schedule.

** Weekly Schedule**: The group does not have a concsitent pattern of workout but Saturday seems
to be the most active day. The users tend to spend a lot of time in bed, even when they are not
asleep. The group also has the most number of outliers in terms of minutes in different activity
levels, indicating that these users might be more active but are not recording their activities.

**Exercise Type**: Higher calories are burnt in higher intensity exercises with higher number of
steps, indicating that they might be engaging in intense walking activities.
```

Limitations

1. Small Dataset: The dataset provided is very small, and the sample similar to Bellabeat users is even smaller, limiting the generalization of the observations.

a. Technical issues:50% of the users did not use their device or tracked their data for the whole month which furhter limits the analysis.

2. Lack of Background Information: The data has been collected anonymously and there is no information provided about the participants like their sex, occupation, age which can severely impact the data and hence, it limits the scope of application.

Recommendations

1. Increasing Product Integration:

   It is important to make the customers more interested in the product and fitness. Fitness devices are common to own but very few actually utilize them due to the lack of information about their features and benefits.

   Therefore, a mobile-based application which provides insight on the features available and shares real-time feedback, by comparing activity on active days, can work as a motivational factor to help users.

2. Convenient Product Usage:

The product can be integrated with a mobile application which can record steps, even when someone forgets the fitness tracker at home. As seen in the low usage users, there might be chances of users simply not using the fitness tracker, therefore applications recording steps can serve as motivation to use the device which will provide more insights. The app can also track water consumption, weight and calories consumed, further integrating it into overall health score for a day.

3. Customized Notifications:

Through the app, users can be reminded about working out, depending on the time of the day when they workout; They can also be notified about bed time. Furthermore, users can indicate whether they want to loose weight or build muscle, and health notifications with food and workout ideas can be shared with the user.

4. Targeting the Interested Population:

Health conscious people are more likely to record their activities and engage with the app, therefore it can be promoted to already active people like hikers, cyclists or other athletes.

To attract new customers, promotions can be made inside gyms or nutritional websites.

5. Rewards and Sharing:

To make the experience more rewarding, a badge system can be offered in the app, where users earn badges for hitting certain milestones. Further, sharing updates with family or friends can also serve as a motivational factor.