Github Collaboration

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Import Data

```
library(readr)
TextMessages <- read_csv("TextMessages.csv") #1-use read_csv (parent df)
#View(TextMessages)
#head(TextMessages)
```

```
kable(head(TextMessages,5), format = "markdown", #
      caption = "Text Message Data Preview",
      table.envir = "table", align = "c")
```

Table 1: Text Message Data Preview

Group	Baseline	Six_months	Participant
1	52	32	1
1	68	48	2
1	85	62	3
1	47	16	4
1	73	63	5

Factorization (Data Wrangling)

```
str(TextMessages)
```

```
## spc_tbl_ [50 x 4] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ Group      : num [1:50] 1 1 1 1 1 1 1 1 1 1 ...
##  $ Baseline   : num [1:50] 52 68 85 47 73 57 63 50 66 60 ...
##  $ Six_months : num [1:50] 32 48 62 16 63 53 59 58 59 57 ...
##  $ Participant: num [1:50] 1 2 3 4 5 6 7 8 9 10 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   Group = col_double(),
##   ..   Baseline = col_double(),
##   ..   Six_months = col_double(),
##   ..   Participant = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

```
#factor a variable en place - risky
make_factor <- function(data, var){
  refactored <- as.factor(data[[var]]) #make factor
  data[[var]] <- refactored #assign factor back to var
  data #return
}

#factor with labels scalably
#!!! to unpack the vectors and setnames to map values to labels
make_factor_scale <- function(data, var, newvarName, fact_num_vect,
                                    fact_char_vect) {
  data[[newvarName]] <- dplyr::recode(data[[var]],
                                      !!!setNames(fact_char_vect,
                                                  fact_num_vect))
  refactored <- as.factor(data[[newvarName]])
  data[[newvarName]] <- refactored
  data
}

#check the groups
unique(TextMessages$Group)
```

```
## [1] 1 2
```

```
TextMessages <- make_factor_scale(TextMessages,
                                      "Group",
                                      "Group_factor", c(1,2),
                                      c("Group 1",
                                        "Group 2"))

TextMessages <- TextMessages %>%
  dplyr::relocate("Group_factor", .after = "Group")
```

Summary Statistics

```
summary_stats_long <- TextMessages %>%
  group_by(Group_factor) %>%
  summarise(
    Baseline_Mean = mean(Baseline, na.rm = TRUE),
    Baseline_SD = sd(Baseline, na.rm = TRUE),
    Baseline_Min = min(Baseline, na.rm = TRUE),
    Baseline_Max = max(Baseline, na.rm = TRUE),
    SixMonths_Mean = mean(Six_months, na.rm = TRUE),
    SixMonths_SD = sd(Six_months, na.rm = TRUE),
    SixMonths_Min = min(Six_months, na.rm = TRUE),
    SixMonths_Max = max(Six_months, na.rm = TRUE)
  ) %>%
  pivot_longer(
    cols = -Group_factor,
    names_to = c("Timepoint", "Statistic"),
    names_sep = "_"
  )
```

Table 2: Statistical Summary for Baseline and Six Months

Group_factor	Timepoint	Statistic	value
Group 1	Baseline	Mean	64.840000
Group 1	Baseline	SD	10.679732
Group 1	Baseline	Min	47.000000
Group 1	Baseline	Max	85.000000
Group 1	SixMonths	Mean	52.960000
Group 1	SixMonths	SD	16.331156
Group 1	SixMonths	Min	9.000000
Group 1	SixMonths	Max	78.000000
Group 2	Baseline	Mean	65.600000
Group 2	Baseline	SD	10.835897
Group 2	Baseline	Min	46.000000
Group 2	Baseline	Max	89.000000
Group 2	SixMonths	Mean	61.840000
Group 2	SixMonths	SD	9.410455
Group 2	SixMonths	Min	46.000000
Group 2	SixMonths	Max	79.000000

Breakdown

At the Baseline (Initial Time Point), participants in Group 1 sent an average of 64.8 text messages, with a standard deviation of 10.7, indicating moderate variability in texting behavior. The minimum number of messages sent was 47, while the maximum was 85. Similarly, participants in Group 2 had a slightly higher mean of 65.6 messages, with a standard deviation of 10.8, suggesting a similar spread of values. The minimum number of messages in this group was 46, and the maximum was 89.

After six months, both groups experienced a decline in the number of messages sent. Group 1 saw a more substantial reduction, with a new mean of 53.0 messages (a decrease of approximately 11.8 messages from baseline). Additionally, the standard deviation increased to 16.3, suggesting that individuals in this group displayed more varied texting behavior over time. The minimum and maximum values were not explicitly provided but are likely within the range of 9 to 78 messages. In contrast, Group 2 maintained a relatively higher number of messages, with a mean of 61.8 messages (a smaller decrease of about 3.8 messages from baseline). The standard deviation was 9.41, indicating that texting behavior remained more consistent within this group. The minimum and maximum values were at least 46 and 79 messages, respectively.

Overall Interpretation

Both groups showed a decline in the number of text messages sent over time. However, Group 1 experienced a greater decrease, suggesting that participants in this group reduced their texting behavior more substantially. Additionally,the increase in standard deviation for Group 1 at six months indicates greater variability in how much texting behavior changed within this group—some participants may have significantly reduced their texting, while others maintained a more consistent level. On the other hand, Group 2 exhibited more stable texting behavior, with a smaller overall decline and less variability over time.

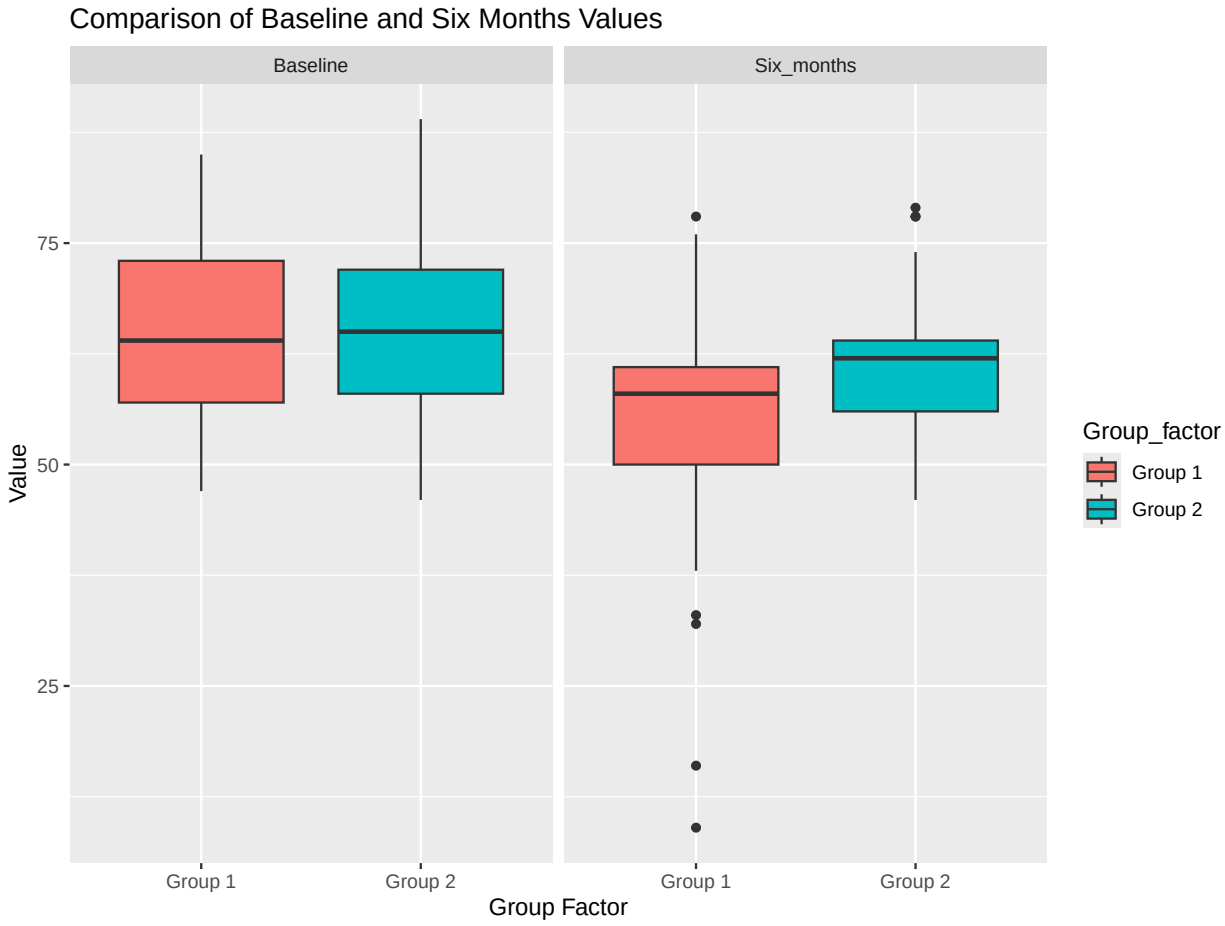
Boxplot Visualization

```
#pivot kaity way
longtext <- gather(TextMessages,Time,Count,Baseline:Six_months, factor_key = TRUE )

#pivot data Tingwei way
TextMessages_long <- TextMessages %>%
  pivot_longer(cols = c(Baseline, Six_months),
               names_to = "Timepoint",
               values_to = "Value")
```

```
#make facet
boxp <- ggplot(TextMessages_long,
              aes(x = Group_factor,
                  y = Value,
                  fill = Group_factor)) +
  geom_boxplot() +
  facet_grid(. ~ Timepoint, scales = "free") +
  labs(x = "Group Factor", y = "Value",
       title = "Comparison of Baseline and Six Months Values")

print(boxp)
```



Box plot Interpretation

There is an observed decrease in the median measure of central tendency which can be extrapolated to the mean and mode of the value being measured. So it means the time frame has an effect on the outcome being analyzed albeit being unable to determine statistical or practical significance.

Secondly, the change in time frame leads to decreased normality of the data as skewness is introduced into both groups at the six month mark. The direction of skewness is not relevant in this brief analysis as this can be done when performing a deeper analysis.

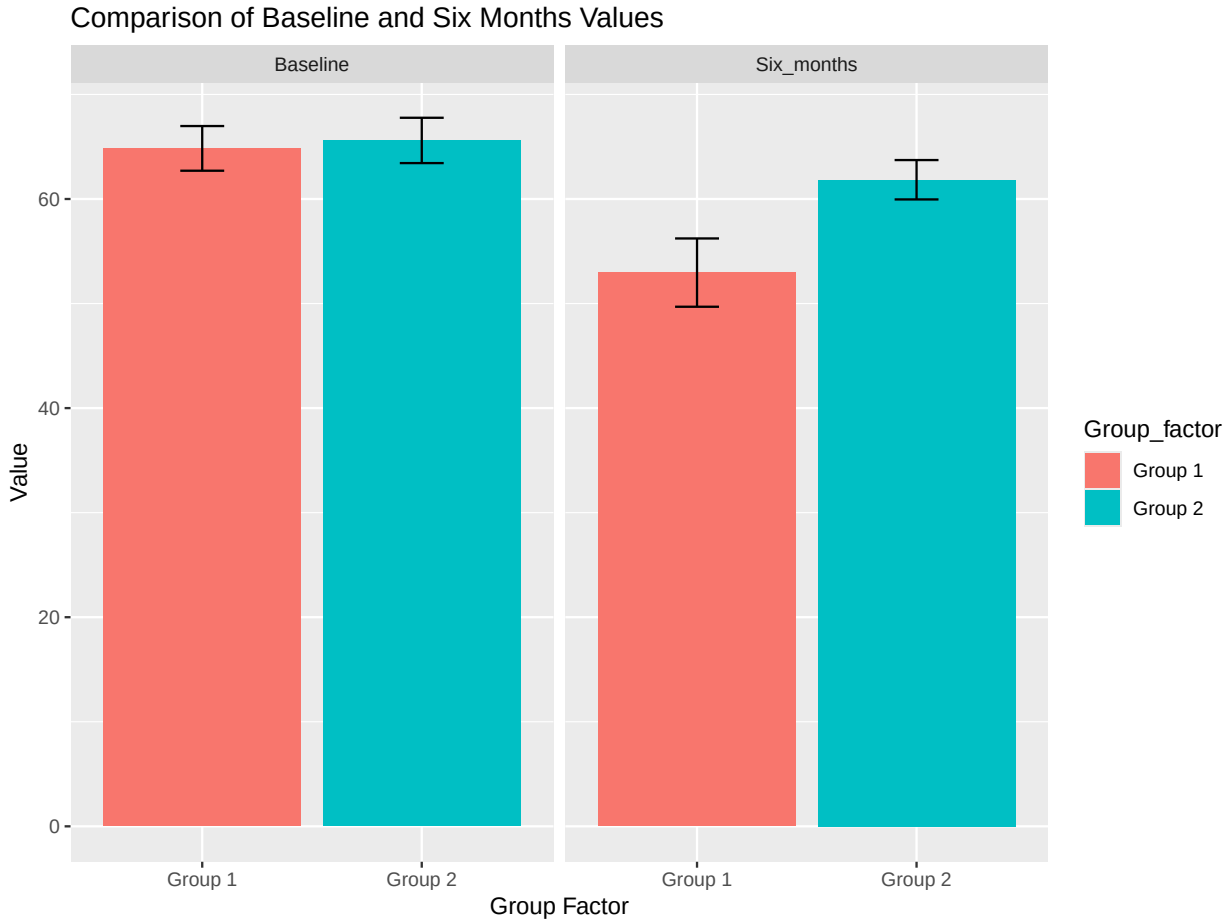
Thirdly, outliers are introduced in the data at the six month mark. This likely indicates that the drivers of the outcome might be introducing some abnormal effects into the groups leading to extreme behaviors of the participants. In Group 1 most outliers deviate towards the low end meaning the effect drivers seem to trigger inhibitory tendencies within some members of this group while the second group seems to exhibit excitatory tendencies from the outcome drivers.

Generally, the longitudinal effect of the study points towards decreased normality of the data and there might be other outcome drivers that trigger extreme behaviors in some study participants.

Barplot Visualization

```
#ideal solution just need to add error bars
barp <- ggplot(TextMessages_long,
               aes(x = Group_factor,
                   y = Value,
                   fill = Group_factor)) +
  stat_summary(fun = "mean", geom = "bar") +
  stat_summary(fun.data =  mean_cl_normal, #"mean_se"
               geom = "errorbar",
               width = .2,
               fun.args = list(mult = 1)) +
  facet_grid(. ~ Timepoint, scales = "free") +
  labs(x = "Group Factor", y = "Value",
       title = "Comparison of Baseline and Six Months Values")

print(barp)
```



Bar plot Interpretation

If we compare the box plots for both groups at baseline, their medians are roughly the same though Group2's is sightly higher by a fractional margin. As indicated previously, the spread of data for the second group is much wider at the upper end, showing that there may be some left tail skewness in their distribution. Looking at the error bar charts, the overlap between both groups shows that there is a chance of no statistical significance in the difference in means between both groups at baseline. If we proceed to the sixth month follow up, there is confirmation that in fact both groups have a decline in text messaging, more so for group 1 than group 2. Group 1 has a much higher degree of outliers and flatness on the left tail. This shows that much of the variability in decreased text messaging for group 1 may be attributed
to a smaller quantity of people. This could also possibly indicate some degree of intervention effect in the the second group at followup since both groups were fairly similar at baseline. If we look at the error bars in the histogram, it is clear that there could be some statistical significance in the difference in means between both groups at the six month follow up.

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Conclusion

This document provides 3 outputs as demanded. The team was able to contribute equally in the generation of this document. There is still a steep learning curve for git and github for all team members but thankfully some of us have a handle on the use of technology to get this project to its complete or mature state.

References

ggplot2 facet : split a plot into a matrix of panels