CBT-App Report

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1 Introduction

The data available at https://uoepsy.github.io/data/dapr1_assessed_report_2223.csv from 60 participants selected via a random sample. A researcher has developed a cognitive behavioural therapy (CBT) based on a smartphone app, and is testing how effective it is in helping people to exercise more. The researcher recorded the average number of minutes of exercise per day per participant. Out of the 60 participants, thirty were randomly selected and were given the app. They were asked every time they did not feel like exercising to open the app and complete a five-minute task. There are two numeric variables recording the exercise time in minutes for each subject at the beginning (exercise_pday_start) and after a month (exercise_pday_1month) of the experiment running. A categorical variable (app_group) representing which subjects got the app and the ones that didn't. These are the variables that we used for our investigation. The subject number is denoted by a nominal variable (sub_nr). There are no impossible or missing values.

All 60 participants were followed up a month later. For each subject, the average number of exercise minutes per day (over a week) was recorded.

2 Analysis

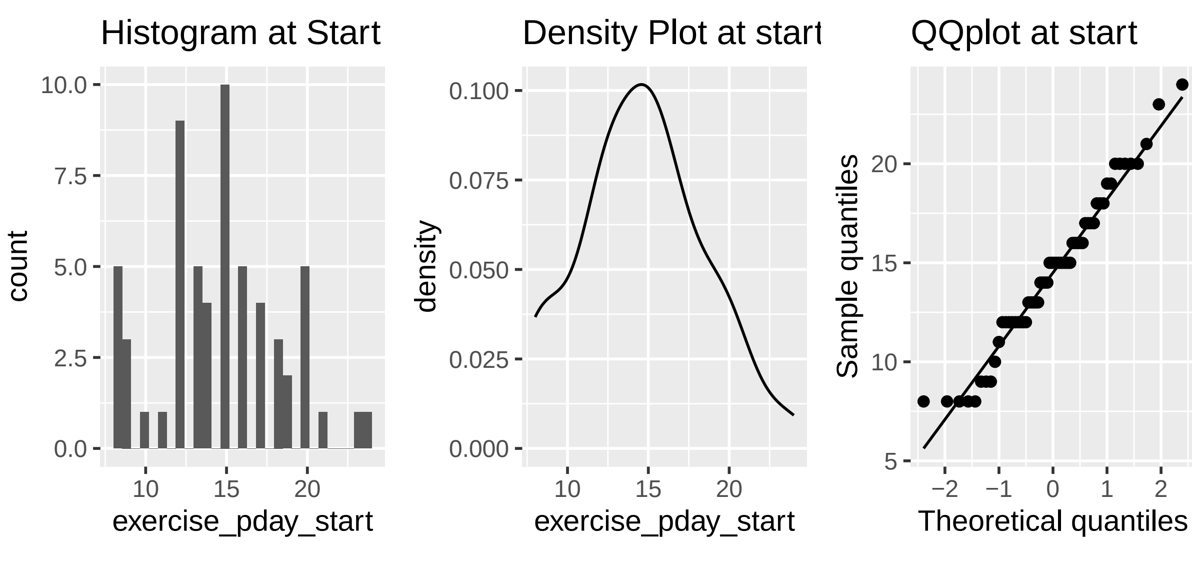


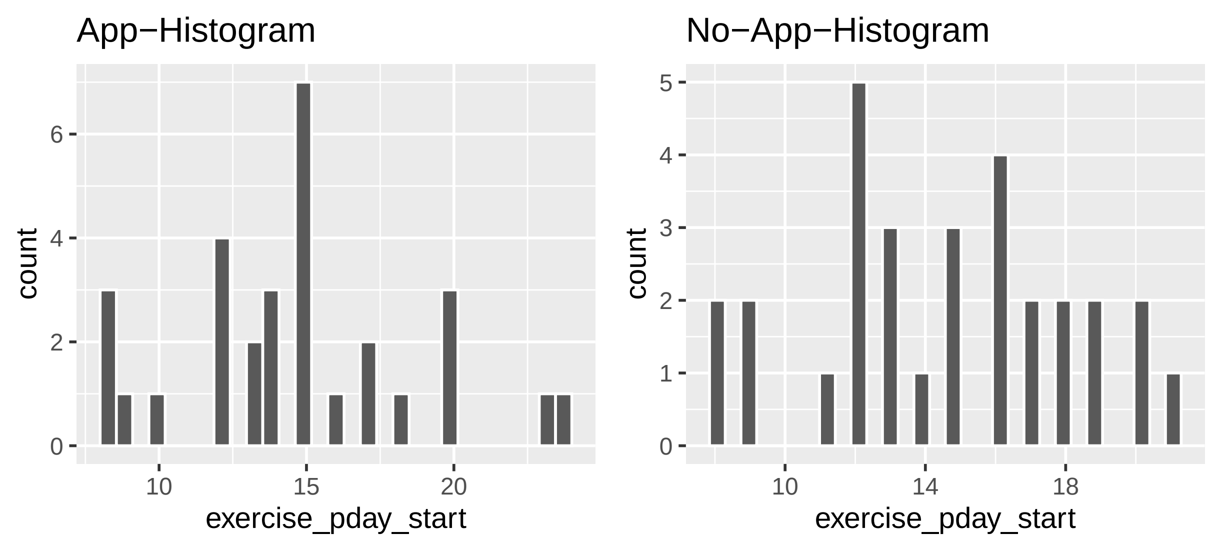
Figure 1: Graphs

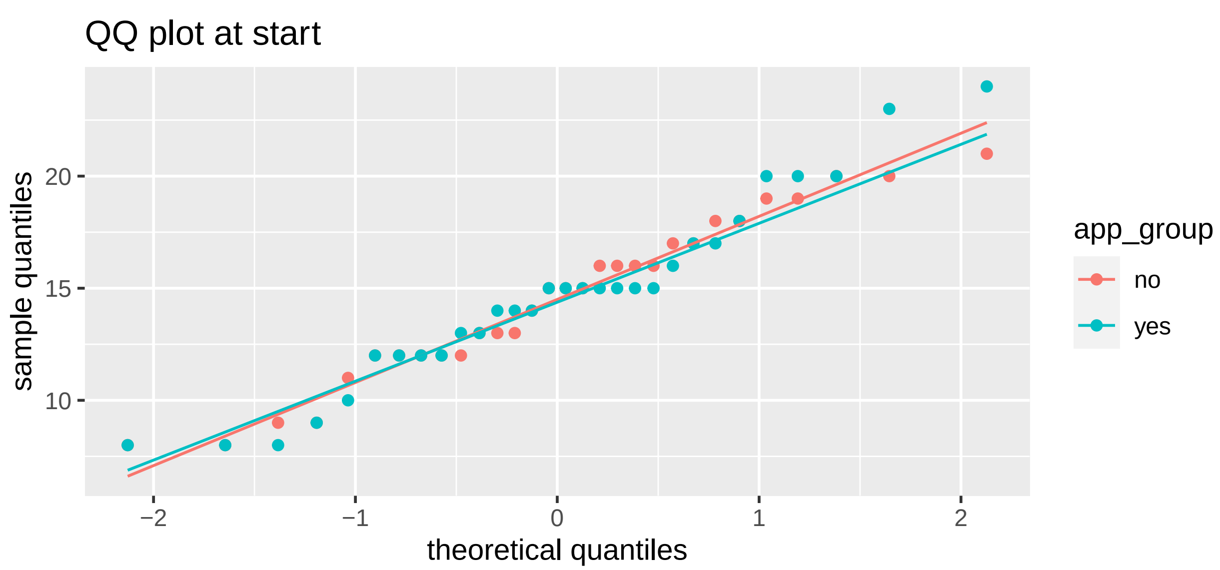
Throughout the entire report we used a significance level $\alpha = 0.05$.

Independence of observations can be assumed based on the experiment design.

A one sample t-test was conducted to determine if there was a statistically significant difference between the population mean exercise time and the 15 minutes per day of 60 participants. Although the sample of 60 participants had a slightly lower exercise time at the start of the month (14.58) than 15 minutes a day, this difference was not statistically significant ($t(59) = -0.83$, $p > 0.05$, two-tailed).

The assumption of normality was visually assessed (via histograms, density plots, and a QQplot) as well as statistically via a ShapiroWilks test. Whilst the QQplot did show some deviation from the diagonal line, the Shapiro-Wilks test suggested that the sample came from a population that was normally distributed ($W = 0.97$, $p = 0.17$). This was inline with the histogram and density plot, which suggested that the data for the exercise at the start was normally distributed (and where skew < 1). The size of the effect was found to be small = 0.11 [-0.36, 0.15].





To investigate whether the average number of exercise minutes per day of those in the non-app group condition (n=30) and the app group condition (n=30) significantly differed, we performed an independent samples t-test with a 95% confidence interval for the population difference in mean exercise time at the point of recruitment between the two app groups. There wasn't a significant difference between the group that didn't use the app (Mean = 14.53, SD = 3.65) and the group that did (Mean = 14.63, SD = 4.11) ($t(29) =$

-0.1, p = 0.92, two-sided). Thus, the exercise time at the point of recruitment doesn't differ much for the two groups.

The assumption of normality was visually assessed (via histograms, density plots, and a QQplot) as well as statistically via a Shapiro-Wilks test. The QQplots showed slight but not much deviation from the diagonal line in either group, and the Shapiro-Wilks test for both groups with the app (W =0.95, p=0.23) and without (W=0.96, p=0.42) suggested that the samples came from a population that was normally distributed. This was inline with the histogram for both groups, which suggested that the exercise time was normally distributed (and where skew < 1). Based on the results of our F-test, there was no significant difference between the two population variances (F(29,29)=0.78, p=0.526). The size of the effect was found to be small or weak (0.03).

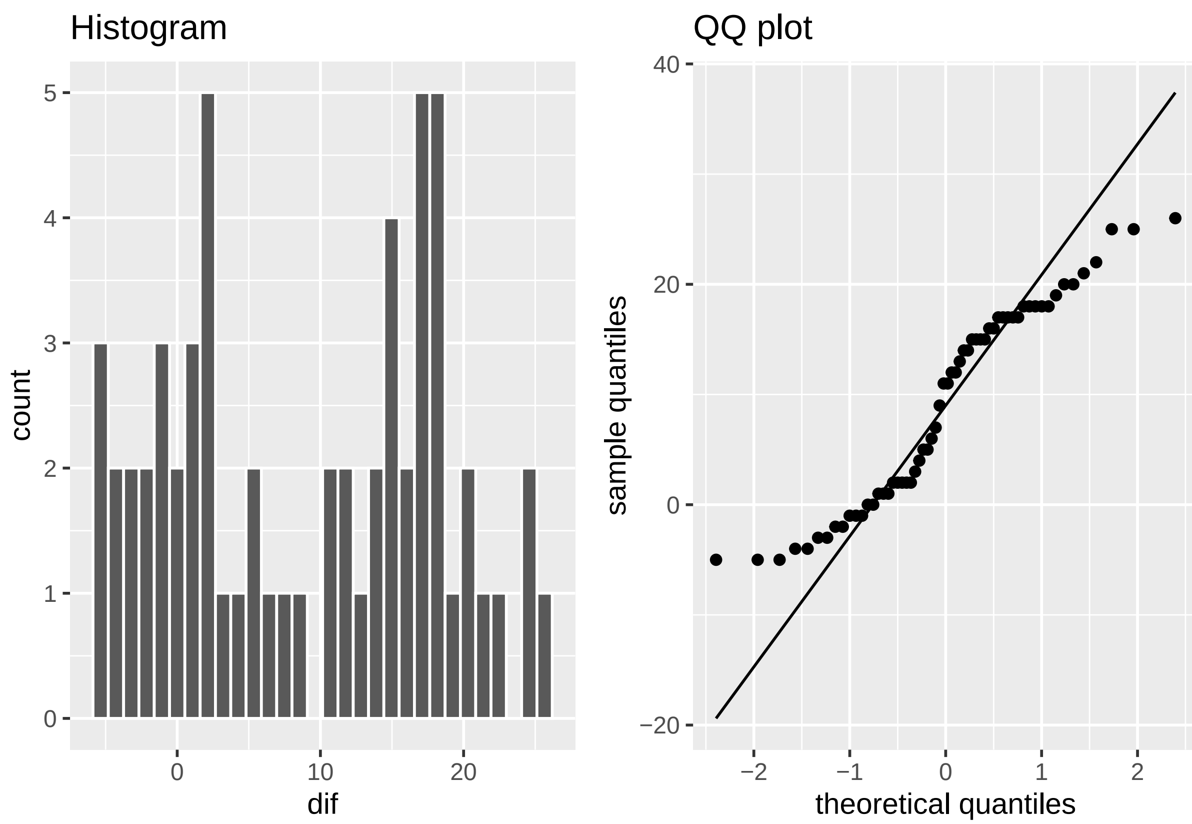


Figure 2: Histogram

A paired-sample t-test was conducted in order to determine ($\alpha = 0.05$) if a statistically significant mean difference in exercise time before and after the one month period for the group receiving the app was present. The no-app group mean score was lower (Mean = 14.63, 4.1) by a margin compared to the group who got the app (Mean = 31.9, 4.37). The difference was statistically significant. We are 99% confident that the exercise time before receiving the app was between 18.7 and 15.8 points lower than the exercise time after receiving the app. Thus, we reject the null hypothesis of no difference.

Data comprised comparing the exercise time after receiving the app and before. The assumption of normality was visually assessed (via histograms and a QQplot) as well as statistically via a Shapiro-Wilks test. The QQplot did not show much deviation from the diagonal line apart from the ends, and the Shapiro-Wilks test suggested that the difference scores were normally distributed (W = 0.92, p = .001) . This was inline with the histogram, which suggested that the difference in scores between the two assessment times was normally distributed (and where skew < 1). The size of the effect was found to be weak. (-0.1)

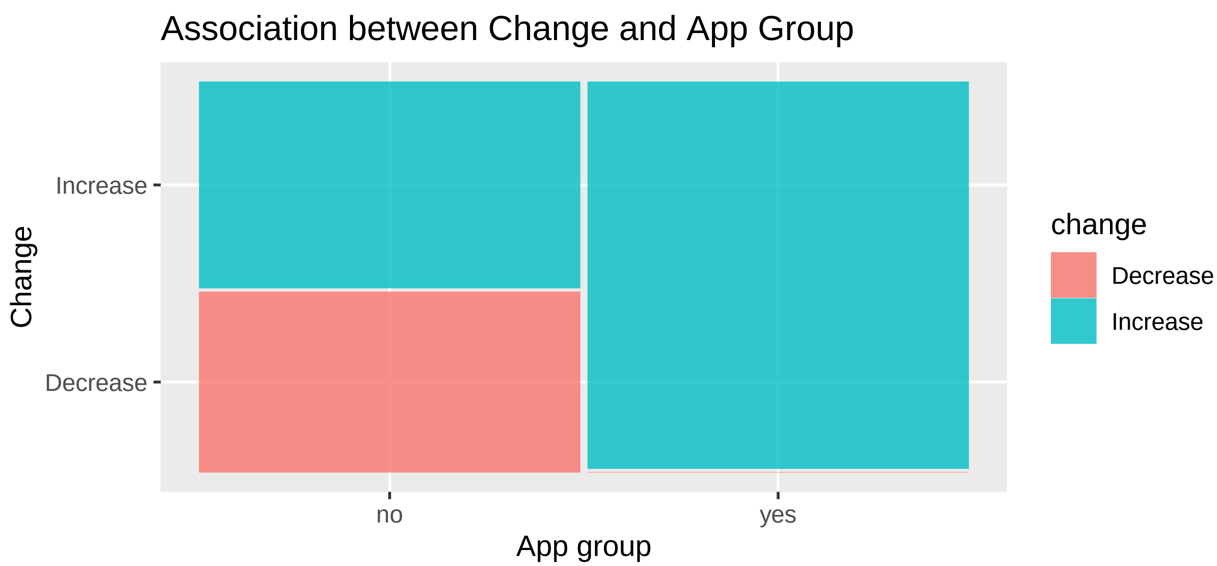


Figure 3: MosaicPlot

A Chi-Squared Test of Independence showed that there was a significant association between the participants who were given the app and increased times of exercise.(Chi-Square (df=1, n=60)=15.74, p=7.247e-05 (large effect)). The participants who were given the app did have a significant increase in exercise time. Additionally, the group who didn't receive the app didn't have a significant increase in exercise time. From the Pearson's residual test, we also infer the same, that the group with the app did have an increase in exercise time.

Just as the previous times, the data remains to be normal.(W=0.97, p=0.17) The graphs indicate the same.

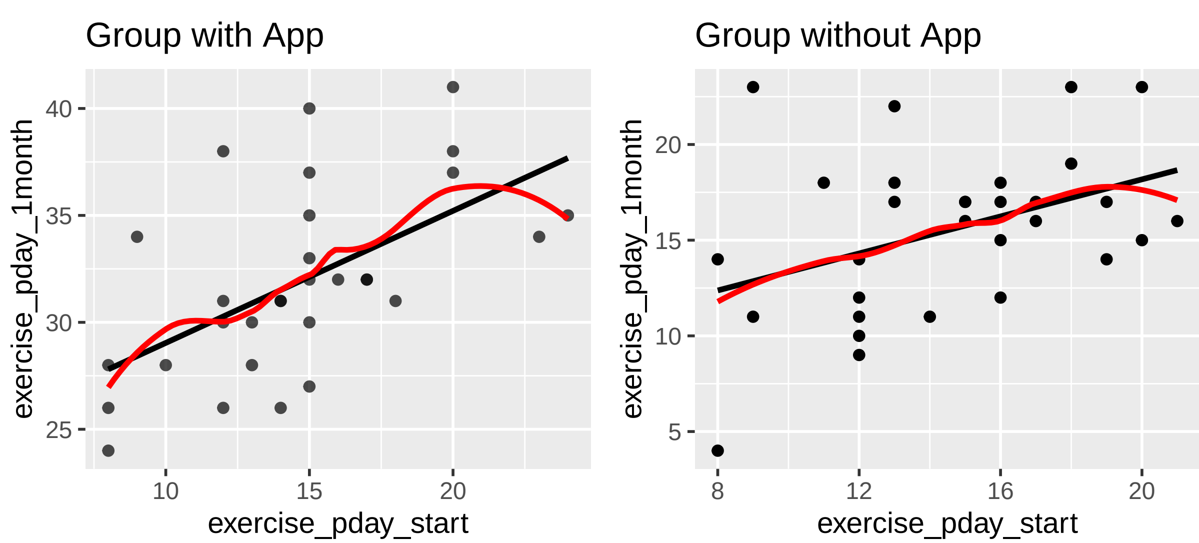


Figure 4: ScatterPlots

From the scatterplots we can see that the loess line for the group that didn't recieve the app doesn't deviate from the main line and remains consistent, implying that there wasn't much change in the exercise time of the participants who weren't given the app-based CBT. On the other hand, the loess line for the group with the app isn't exactly constricted to the main line and at points shows variability and increase.

From the correlation test, we can see that the group with the app has a strong association (cor = 0.58). The group which didn't recieve the app based CBT however has about a moderate association (cor = 0.40) but from all the previous analyses, not enough to conclude a correlation.

3 Discussion

The report analyzed the findings of a researcher who has developed a cognitive behavioural therapy (CBT) based on a smartphone app, and is testing how effective it is in helping people to exercise more.

The analysis indicates that at the point of recruitment, the population mean exercise time does not significantly differ from 15 minutes. Implying that our participants at an average did 15 minutes of exercise per day at the point of recruitment.

From our independent-sample test analysis, we infer that the population exercise mean time doesn't differ significantly between the group who got the app and the one that didn't. This lays out a base for us to know that both the groups in fact exercised the same amount prior to the experiment being conducted.

From the analysis, we can indeed say that the group recieving the app-based CBT had a significant increase in exercise time after a month of the experiment being conducted.The direction of increase supports our directional hypothesis and indicates that the app does help subjects increase their exercise time.

Once again, from the analysis we can conclude the fact that increased exercise time is indeed associated with recieving the app-based CBT. Which is the main purpose of this experiment.

In conclusion, we see that the group who did recieve the app-based CBT did infact have an increase in exercise time and the group that did not, didn't have a significant increase. Thus, the study concludes that using the CBT app is indeed effective in helping people to exercise more when compared to no use of the app.

4 Appendix B: R code

```
knitr::opts_chunk$set(echo = FALSE, message = FALSE, warning = FALSE)
library(tidyverse)
library(patchwork)
library(kableExtra)
library(psych)
library(effectsize)
library(ggmosaic)
#Week 1

cbt_data <- read_csv("https://uoepsy.github.io/data/dapr1_assessed_report_2223.csv")

head(cbt_data)
str(cbt_data)
glimpse(cbt_data)
summary(cbt_data)

#sub_nr -> nominal
#exercise_pday_start -> numerical
#exercise_pday_1month -> numerical
#app_group -> categorical
```

```r
h_viz <- ggplot(cbt_data, aes(x = exercise_pday_start)) +
geom_histogram() +
labs(title = "Histogram at Start")

h_viz

d_viz <- ggplot(cbt_data, aes(x= exercise_pday_start)) +
geom_density() +
labs(title = "Density Plot at start")

descTable <- cbt_data %>%
    summarise(
              n = n(),
              Min = min(exercise_pday_start),
              Max = max(exercise_pday_start),
              M = mean(exercise_pday_start),
              SD = sd(exercise_pday_start))
descTable

h_viz | d_viz

cbt_viz <- describe(cbt_data$exercise_pday_start)

cbt_viz

#one sample t-test
t.test(cbt_data$exercise_pday_start, mu = 15, alternative = "two.sided")

cbt_skew <- cbt_data %>%
summarise(viz_skew = round(skew(exercise_pday_start), 2))
cbt_skew

###qq plot
q_viz <- ggplot(cbt_data, aes(sample = exercise_pday_start)) +
geom_qq() +
geom_qq_line() +
labs(title = "QQplot at start", x= "Theoretical quantiles", y = "Sample quantiles")

q_viz

shapiro.test(cbt_data$exercise_pday_start)

cohens_d(cbt_data$exercise_pday_start, mu = 15, alternative = "two.sided")
#Week 2

summary(cbt_data$app_group)

summaryTable <- cbt_data %>%
    group_by(app_group)%>%
    summarise(
              Min = min(exercise_pday_start),
              Max = max(exercise_pday_start),
              M = mean(exercise_pday_start),
```

```
              SD = sd(exercise_pday_start),
              n = n())%>%
      kable(digits = 2)%>%
      kable_styling(full_width = FALSE)

summaryTable

t.test(cbt_data$exercise_pday_start ~ cbt_data$app_group,
       alternative = "two.sided",
       var.equal = TRUE)

#Normality
skew_pday_start <- cbt_data%>%
                        group_by(app_group)%>%
                          summarise(
                            skew = round(skew(exercise_pday_start), 2))

hist1 <- cbt_data%>%
  filter(app_group=="yes")%>%
  ggplot(., aes(x = exercise_pday_start)) +
  geom_histogram(color = 'white')+
  labs(title = "App-Histogram")

hist2 <- cbt_data%>%
  filter(app_group=="no")%>%
  ggplot(., aes(x = exercise_pday_start)) +
  geom_histogram(color = 'white')+
  labs(title = "No-App-Histogram")
hist1 | hist2

q_start <- ggplot(data = cbt_data,
                    aes(sample = exercise_pday_start, colour = app_group))+
                geom_qq()+
                geom_qq_line()+
                  labs(title ="QQ plot at start", x= "theoretical quantiles", y= "sample quantiles")
q_start


shapiro_app <- cbt_data%>%
  filter(app_group=="yes")%>%
  pull(exercise_pday_start)%>%
  shapiro.test()


shapiro_noapp <- cbt_data%>%
  filter(app_group=="no")%>%
  pull(exercise_pday_start)%>%
  shapiro.test()

shapiro_app
shapiro_noapp

#skew = -0.09 for no, 0.34 for yes
```

```
#QQplot shows slight deviation from diagonal line
#w1=0.95 a=0.05 w>a
#w2=0.96 a=0.05 w>a

#Homogeneity of variance
var.test(cbt_data$exercise_pday_start~cbt_data$app_group,ratio=1)
#p-value = 0.526 p-value > a

#size effect
cohens_d(cbt_data$exercise_pday_start~cbt_data$app_group)


#-2.1  1.9 95% CI
#Week3

Table<- cbt_data%>%
  group_by(app_group)%>%
  mutate(dif= exercise_pday_1month-exercise_pday_start)%>%
  summarise(
    dbar= mean(dif),
    SD=sd(dif),
    mu=0,
    n=n())%>%
   kable(digits = 2)%>%
      kable_styling(full_width = FALSE)
Table

cbt_app <- cbt_data %>% filter(app_group == "yes")

cbt_pairedt <- t.test(cbt_app$exercise_pday_start, cbt_app$exercise_pday_1month,
paired = TRUE,
mu = 0,
alternative = "two.sided",
conf.level = 0.95)

cbt_pairedt

#normality
norm_data<- cbt_data%>%
  mutate(dif= exercise_pday_1month-exercise_pday_start)

hist_norm <- ggplot(norm_data, aes(x = dif)) +
    geom_histogram(color = 'white')+
  labs(title = "Histogram")


q_viz3 <- ggplot(norm_data,
                aes(sample = dif))+
                geom_qq()+
                geom_qq_line()+
                  labs(title ="QQ plot", x= "theoretical quantiles", y= "sample quantiles")
q_viz3
```

```
norm_data%>%
  summarise(skew=round(skew(dif),2))

shapiro.test(norm_data$dif)

cohens_d(norm_data$exercise_pday_start, norm_data$exercise_pday_1month,
paired = TRUE,
mu = 0,
alternative = "two.sided",
ci = 0.95)
#Week4
cbt_incdec <- cbt_data %>%
    mutate(change = ifelse(exercise_pday_1month > exercise_pday_start, 'Increase', 'Decrease'))

table(cbt_incdec$change)

freq_tbl <- table(cbt_incdec$change, cbt_incdec$app_group)
freq_tbl

mos_plot <- ggplot(cbt_incdec) +
    geom_mosaic(aes(x = product(change, app_group), fill = change)) +
    labs(title = "Association between Change and App Group", x = "App group", y = "Change")
mos_plot

chitest <- chisq.test(cbt_incdec$change, cbt_incdec$app_group)
chitest

chitest$residuals

phi(chitest)

#normality
skewchi <- cbt_incdec %>%
                summarise(
                  skew = round(skew(exercise_pday_start),2)
                )
skewchi

startQQ1<-ggplot(data = cbt_data, aes(sample=cbt_incdec$exercise_pday_start))+
                geom_qq()+
                geom_qq_line()+
   labs(title ="QQ plot for start exercise per day", x= "theoretical quantiles", y= "sample quantiles")
startQQ1
shapiro.test(cbt_incdec$exercise_pday_start)

#Week5
cbt_app <- cbt_data %>% filter(app_group == "yes")
cbt_no_app <- cbt_data %>% filter(app_group == "no")

scplot_app <- ggplot(cbt_app, aes(exercise_pday_start, exercise_pday_1month)) + geom_point(alpha=0.7) +
geom_smooth(method = 'lm', colour = 'black', se = F) +
geom_smooth(method = 'loess', colour = 'red', se = F) +
  labs(title ="Group with App")
```

```r
scplot_no_app <- ggplot(cbt_no_app, aes(exercise_pday_start, exercise_pday_1month)) + geom_point() +
geom_smooth(method = 'lm', colour = 'black', se = F) +
geom_smooth(method = 'loess', colour = 'red', se = F) +
  labs(title ="Group without App")

(scplot_app | scplot_no_app)

cortest_app<- cor.test(cbt_app$exercise_pday_start, cbt_app$exercise_pday_1month)
cortest_app

# cor > 0.5 Strong association

cortest_no_app<- cor.test(cbt_no_app$exercise_pday_start, cbt_no_app$exercise_pday_1month)
cortest_no_app
h_viz | d_viz | q_viz
hist1 | hist2

q_start
hist_norm | q_viz3
mos_plot

scplot_app | scplot_no_app
```