Mixed Design Anova

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Happiness Scores

Data Preparation

Upload data + packages

```
f <- "/Users/grantweaver/Dropbox/Grant Weaver/Positive Psychology/Data+Code_Book/ahi-cesd.csv"
ahi_cesd <- read.csv(f, header=TRUE, fill=TRUE, sep = ",")
library(tidyverse)
library(ggplot2)
library(lme4)
library(rstatix)
library(ggpubr)
```

Take a look at the 1st 10 columns + rows

```
ahi_cesd[1:10, ]
ahi_cesd[, 1:10]
```

The data was uploaded correctly. We can continue with the process.

Filter out the subjects who did not complete all tests

```
ahi_cesd <- ahi_cesd %>%
  group_by(id) %>%
  filter(n()==6)
ahi_cesd
```

Anova doesn't deal well with missing subject data, thus we only include subjects who completed all the requirements of the study. The problem is that anova treats each measurement as a separate variable. Anova uses listwise deletion, which means that if one meausrement is missing then the entire case gets dropped. We are not using any techniques to replicate missing data, thus all data must be present from each subject to do the testing.

Load and show one random row by intervention group

```
ahi_cesd %>%
  sample_n_by(intervention, size = 1)
```

This is to check if the data looks as it should; which it does.

Convert id, occasion and intervention into factor variables

```
ahi_cesd <- ahi_cesd %>%
  ungroup(id) %>%
  convert_as_factor(id, occasion, intervention)
```

Converting these 3 variables into factor variables allows us to compute analysis upon them. For when the variables are treated as continuous the analysis doesn't work.

Inspect some random rows of the data by intervention groups

```
set.seed(123)
ahi_cesd %>%
  sample_n_by(intervention, occasion, intervention, size = 1)
```

Everything looks alright.

Here I rename the intervention column

```
ahi_cesd$intervention <- factor(ahi_cesd$intervention,
                                levels = c("1", "2", "3", "4"),
                                labels = c("grat", "good", "streng", "control"))
```

Summary statistics

```
happy_sum <- ahi_cesd %>%
  group_by(intervention, occasion) %>%
  get_summary_stats(ahiTotal, type = "mean_sd") %>%
  print(n=Inf)
```

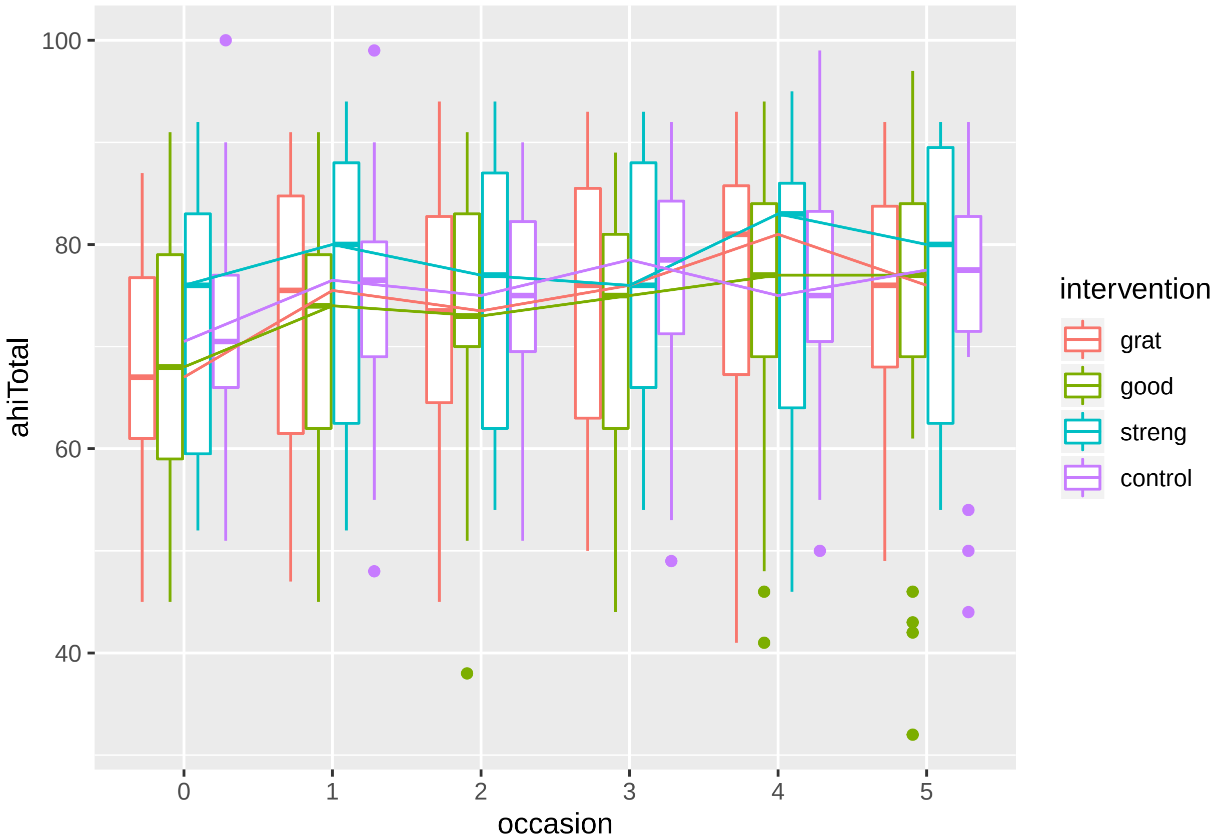
```
## # A tibble: 24 x 6
##    occasion intervention variable     n  mean    sd
##    <fct>    <fct>        <chr>    <dbl> <dbl> <dbl>
##  1 0        grat         ahiTotal    18  67.6  12.2
##  2 1        grat         ahiTotal    18  72    14.8
##  3 2        grat         ahiTotal    18  71.5  14.6
##  4 3        grat         ahiTotal    18  73.8  14.4
##  5 4        grat         ahiTotal    18  75.3  15.0
##  6 5        grat         ahiTotal    18  74.9  13.1
##  7 0        good         ahiTotal    25  69.5  11.8
##  8 1        good         ahiTotal    25  71.5  12.0
##  9 2        good         ahiTotal    25  72.3  12.9
## 10 3        good         ahiTotal    25  71.0  14.0
## 11 4        good         ahiTotal    25  73.2  14.8
## 12 5        good         ahiTotal    25  72.8  16.2
## 13 0        streng       ahiTotal    11  72.5  14.5
## 14 1        streng       ahiTotal    11  75.3  14.7
## 15 2        streng       ahiTotal    11  74.8  14.6
## 16 3        streng       ahiTotal    11  75.9  14.3
## 17 4        streng       ahiTotal    11  75.2  15.8
## 18 5        streng       ahiTotal    11  75.9  15.0
## 19 0        control      ahiTotal    20  71.6  11.9
## 20 1        control      ahiTotal    20  74.2  11.7
## 21 2        control      ahiTotal    20  74.3  11.4
## 22 3        control      ahiTotal    20  75.4  12.3
## 23 4        control      ahiTotal    20  75.6  12.8
## 24 5        control      ahiTotal    20  74.6  12.7
```

Visualization by boxplot

```
bxp <- ggplot(ahi_cesd, aes(occasion, ahiTotal)) +
  geom_boxplot(aes(color=intervention)) +
  stat_summary(fun.y=median, geom = "line",
```

```
                aes(group=factor(intervention), color=intervention), size=.5)

bxp
```



Check assumptions

Check for outliers

```
ahi_cesd %>%
  group_by(intervention, occasion) %>%
  identify_outliers(ahiTotal) %>%
  select(1:2, 49, 51:52)
```

```
## # A tibble: 15 x 5
##    occasion intervention ahiTotal is.outlier is.extreme
##    <fct>    <fct>           <int> <lgl>      <lgl>
##  1 2        good               38 TRUE       FALSE
##  2 4        good               41 TRUE       FALSE
##  3 4        good               46 TRUE       FALSE
##  4 5        good               43 TRUE       FALSE
##  5 5        good               32 TRUE       FALSE
##  6 5        good               42 TRUE       FALSE
##  7 5        good               46 TRUE       FALSE
##  8 0        control           100 TRUE       FALSE
##  9 1        control            48 TRUE       FALSE
## 10 1        control            99 TRUE       FALSE
## 11 3        control            49 TRUE       FALSE
```

```
## 12 4        control              50 TRUE       FALSE
## 13 5        control              44 TRUE       FALSE
## 14 5        control              50 TRUE       FALSE
## 15 5        control              54 TRUE       FALSE
```

Values above Q3 + 1.5xIQR or below Q1 - 1.5xIQR are considered as outliers. Values above Q3 + 3xIQR or below Q1 - 3xIQR are considered extreme outliers.

The outliers don't appear to differ significantly from the mean. In othe words, outliers don't pose a problem in this situation. While there are outliers, there are no extreme outliers that would seem to pose a significant impact on the computation. The outliers are easy to notice from the above boxplot.

Check normality assumption

```
ahi_cesd %>%
  group_by(intervention, occasion) %>%
  shapiro_test(ahiTotal) %>%
  print(n=Inf)
```

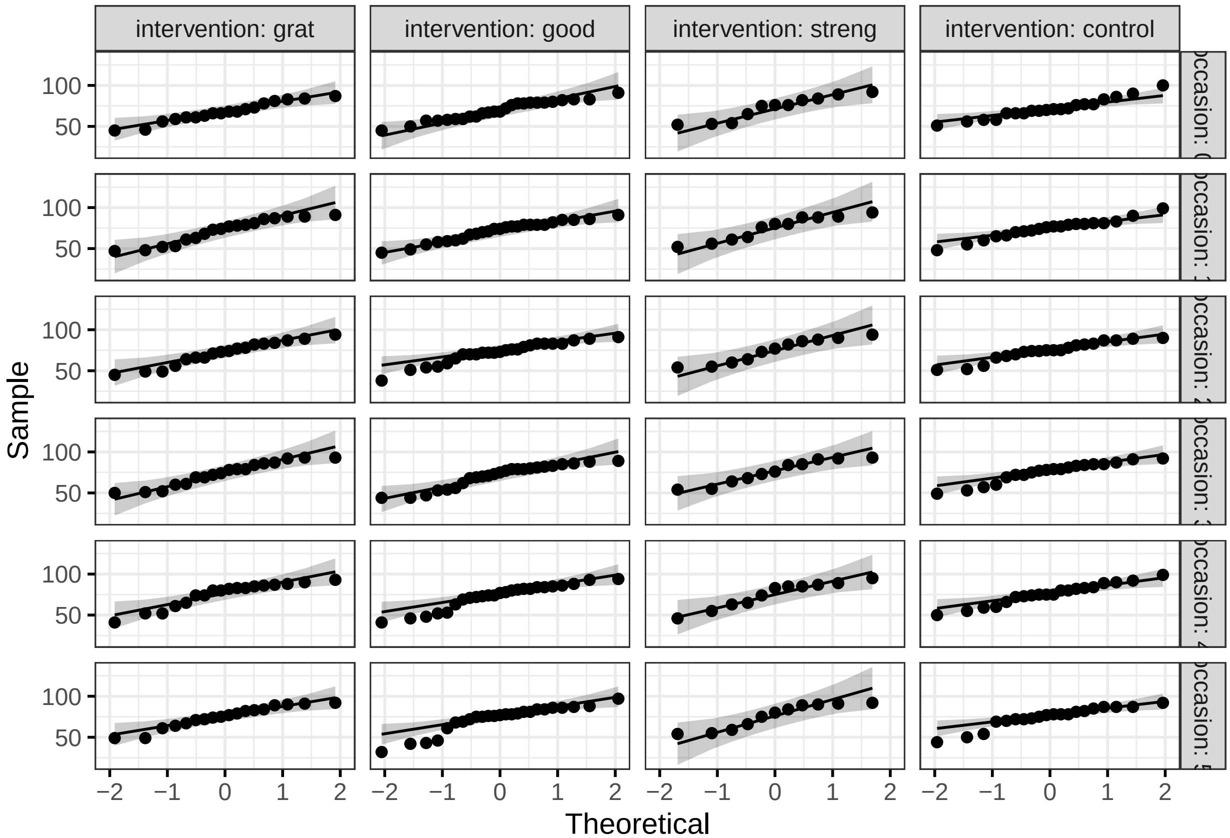
```
## # A tibble: 24 x 5
##    occasion intervention variable statistic       p
##    <fct>    <fct>        <chr>        <dbl>   <dbl>
##  1 0        grat         ahiTotal     0.963 0.661
##  2 1        grat         ahiTotal     0.916 0.111
##  3 2        grat         ahiTotal     0.952 0.453
##  4 3        grat         ahiTotal     0.931 0.206
##  5 4        grat         ahiTotal     0.875 0.0213
##  6 5        grat         ahiTotal     0.934 0.229
##  7 0        good         ahiTotal     0.957 0.359
##  8 1        good         ahiTotal     0.954 0.307
##  9 2        good         ahiTotal     0.932 0.0992
## 10 3        good         ahiTotal     0.904 0.0224
## 11 4        good         ahiTotal     0.910 0.0309
## 12 5        good         ahiTotal     0.861 0.00284
## 13 0        streng       ahiTotal     0.904 0.207
## 14 1        streng       ahiTotal     0.911 0.251
## 15 2        streng       ahiTotal     0.918 0.303
## 16 3        streng       ahiTotal     0.916 0.289
## 17 4        streng       ahiTotal     0.917 0.291
## 18 5        streng       ahiTotal     0.870 0.0767
## 19 0        control      ahiTotal     0.966 0.668
## 20 1        control      ahiTotal     0.968 0.720
## 21 2        control      ahiTotal     0.925 0.124
## 22 3        control      ahiTotal     0.919 0.0952
## 23 4        control      ahiTotal     0.973 0.819
## 24 5        control      ahiTotal     0.892 0.0288
```

The Shapiro-Wilks test for normality is designed to detect all departures from normality. The test rejects the hypothesis of normality when the p-value is <.05. Failing the normality test allows you to state with 95% confidence the data does not fit the normaly distribution. Passing the normality test only allows you to state no significant departure from normality was found. This technique works up to a sample size of 5,000. It works by quantifying the similarity between the observed and normal distributions as a single number: it puts a normal curve over the observed distribution. Then, it computes which percentage of the sample it overlaps with: a similarity percentage. FInally, it computes the probability of finding this observed or more extreme percentage. The null is that the population distribution is normal.

The ahiTotal score was normally distrubted except for 5 cases that had p<.05. We will keep these points in consideration when we move to the QQ plots next.

QQ-Plot

```r
ggqqplot(ahi_cesd, "ahiTotal", ggtheme = theme_bw()) +
  facet_grid(occasion~intervention, labeller = "label_both")
```



QQ plot draws the correlation between the data and the normal distribution.

From the plot above, as all the points fall approximately along the reference line for each cell, we can assume normality.

Homogeneity of variance assumption

```r
ahi_cesd %>%
  group_by(occasion) %>%
  levene_test(ahiTotal ~ intervention)
```

```
## # A tibble: 6 x 5
##   occasion   df1   df2 statistic     p
##   <fct>    <int> <int>     <dbl> <dbl>
## 1 0            3    70     0.306 0.821
## 2 1            3    70     0.804 0.496
## 3 2            3    70     0.788 0.505
## 4 3            3    70     0.399 0.754
## 5 4            3    70     0.187 0.905
## 6 5            3    70     0.316 0.814
```

The homogeneity of variance assumption of the between-subject factor (intervention) can be checked using the Levene's test. The test is performed at each level of occasion based on the mean.

There was homogeneity of variance for there are no p-values<.05.

Homogeneity of covariances assumption

```r
box_m(ahi_cesd[, "ahiTotal", drop = FALSE], ahi_cesd$intervention)
```

```
## # A tibble: 1 x 4
##   statistic p.value parameter method
##       <dbl>   <dbl>     <dbl> <chr>
## 1      3.78   0.286         3 Box's M-test for Homogeneity of Covariance M~
```

The homogeneity of covariances of the between-subject factor (intervention) can be evaluated using the Box's M-test. If this test is statistically significant at p<.001, you do not have equal covariances, but if the test is not statisticaly significant, you have not violated the assumption of homogeneity of covariances.

The p-value>.001 thus there is homogeneity of covariances.

Assumption of sphericity

This assumption is internally calculated in the anova computation below, thus we do not need to worry about this assumption right now.

Turn into data frame

```r
ahi_cesd <- as.data.frame(ahi_cesd)
str(ahi_cesd)
```

Variable selection + modification

```r
ahi_cesd_happy <- ahi_cesd %>%
  select(id, occasion, intervention, ahiTotal) %>%
  mutate(ahiTotal=as.numeric(ahiTotal))
str(ahi_cesd_happy)
```

Computation

```r
res.aov_happy <- anova_test(data = ahi_cesd_happy, dv = ahiTotal,
                      wid = id,
                      between = intervention, within =occasion,
                      detailed = TRUE)
res.aov_happy
```

```
## ANOVA Table (type III tests)
##
## $ANOVA
##                  Effect DFn DFd         SSn      SSd        F        p
## 1           (Intercept)   1  70 2185215.229 63992.38 2390.364 7.54e-56
## 2          intervention   3  70     715.034 63992.38    0.261 8.53e-01
## 3              occasion   5 350     909.655 13162.35    4.838 2.72e-04
## 4 intervention:occasion  15 350     277.994 13162.35    0.493 9.44e-01
##   p<.05   ges
## 1     * 0.966
## 2       0.009
## 3     * 0.012
## 4       0.004
##
## $`Mauchly's Test for Sphericity`
##                  Effect    W        p p<.05
## 1              occasion 0.33 1.95e-10     *
```

```
## 2 intervention:occasion 0.33 1.95e-10     *
##
## $`Sphericity Corrections`
##                  Effect  GGe        DF[GG] p[GG] p[GG]<.05   HFe
## 1              occasion 0.75  3.75, 262.53 0.001         * 0.798
## 2 intervention:occasion 0.75 11.25, 262.53 0.910           0.798
##          DF[HF]   p[HF] p[HF]<.05
## 1  3.99, 279.25 0.00088         *
## 2 11.97, 279.25 0.91800
```

The mixed design method is the blend of within subjects and between subjects design. Within-subjects is the comparisons of the same subjects under different conditions/interventions. Within-subjects is also known as repeated-measures factor since repeated measurements are taken on each subject. Between-subjects is when a different group of subjects is used for each level of the variable. One nice definition I found is "mixed-design anova model tests for mean differences between two or more independent groups while subjecting participants to repeated measures".

In our case the between-subjects factor is intervention and the within-subjects factor is occasion. A 4 x 6 (Intervention x Occasion) mixed-design anova is used.

There are different types of anova tables and it is important to distinguish between the different types. Type 3 anova table is given. In type 3 and type 2 the sums of squares are not sequential, so any order works out fine. Type 3, unlike type 2 have an interaction effect. Type 1 anova the sums of squares are sequential. Type 2 anova does not have an interaction effect. Type 3 anova is best when you are looking for an interaction effect, thus that is why we use type 3 for our computation.

From the results we see that there was a significant main effect for occasion, which means the subjects got happier as the study went on. The intervention X occasion interaction was not significant, which means that the intervention techniques were no better than the placebo. While the intercept is significant, we don't care about about it, for the intercept has no value in this setting.

Post-hoc tests

Comparions for time variable

```
ahi_cesd_happy %>%
  pairwise_t_test(ahiTotal~occasion, paired = TRUE,
                  p.adjust.method = "bonferroni")
```

```
## # A tibble: 15 x 10
##    .y.   group1 group2    n1    n2 statistic    df        p p.adj
##  * <chr> <chr>  <chr>  <int> <int>     <dbl> <dbl>    <dbl> <dbl>
##  1 ahiT~ 0      1         74    74    -3.37     73 1.00e-3 0.018
##  2 ahiT~ 0      2         74    74    -2.92     73 5.00e-3 0.07
##  3 ahiT~ 0      3         74    74    -2.77     73 7.00e-3 0.107
##  4 ahiT~ 0      4         74    74    -3.78     73 3.14e-4 0.005
##  5 ahiT~ 0      5         74    74    -3.47     73 8.65e-4 0.013
##  6 ahiT~ 1      2         74    74    -0.188    73 8.51e-1 1
##  7 ahiT~ 1      3         74    74    -0.879    73 3.82e-1 1
##  8 ahiT~ 1      4         74    74    -1.88     73 6.40e-2 0.968
##  9 ahiT~ 1      5         74    74    -1.36     73 1.77e-1 1
## 10 ahiT~ 2      3         74    74    -0.736    73 4.64e-1 1
## 11 ahiT~ 2      4         74    74    -1.99     73 5.10e-2 0.761
## 12 ahiT~ 2      5         74    74    -1.24     73 2.20e-1 1
## 13 ahiT~ 3      4         74    74    -1.05     73 2.98e-1 1
## 14 ahiT~ 3      5         74    74    -0.591    73 5.56e-1 1
## 15 ahiT~ 4      5         74    74     0.402    73 6.89e-1 1
## # ... with 1 more variable: p.adj.signif <chr>
```

Depression Scores

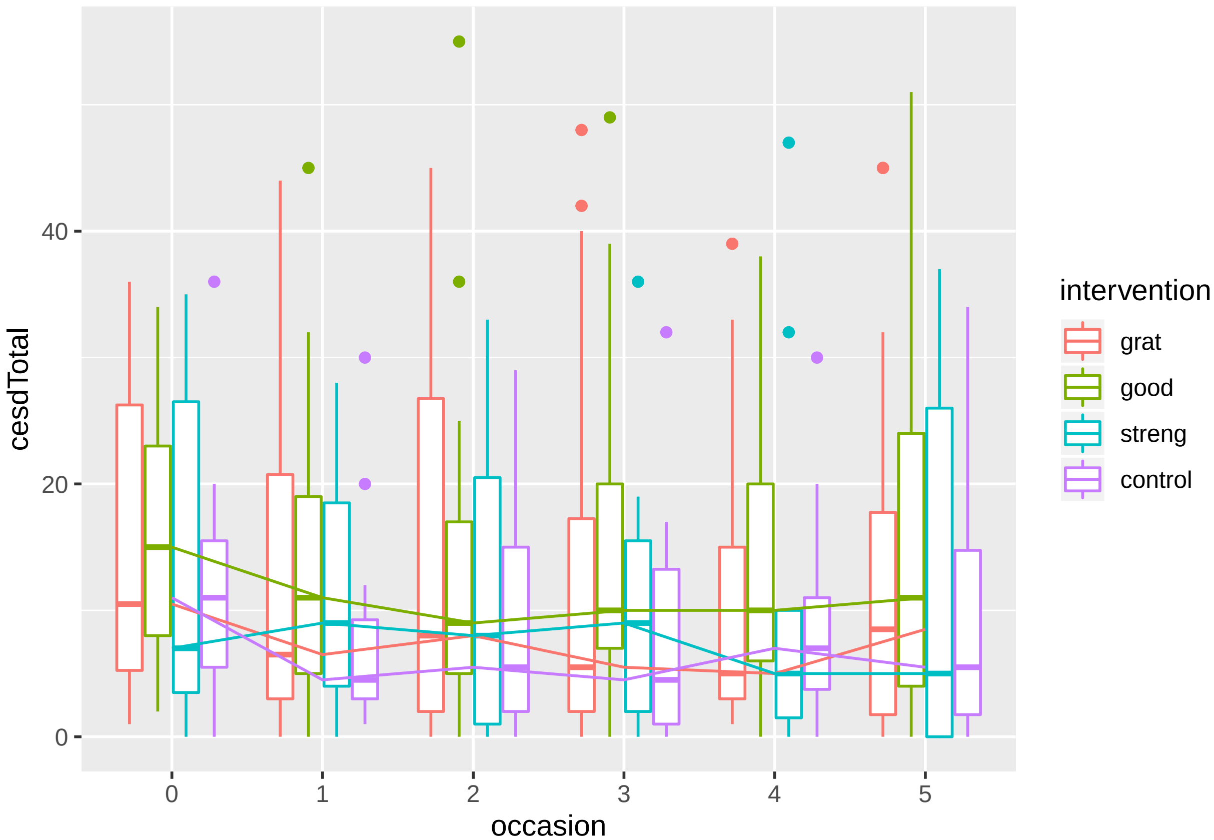
Summary Statistics

```
sad_sum <- ahi_cesd %>%
  group_by(intervention, occasion) %>%
  get_summary_stats(cesdTotal, type = "mean_sd") %>%
  print(n=Inf)
```

```
## # A tibble: 24 x 6
##    occasion intervention variable      n  mean    sd
##    <fct>    <fct>        <chr>     <dbl> <dbl> <dbl>
##  1 0        grat         cesdTotal    18 14.7  12.2 
##  2 1        grat         cesdTotal    18 14.2  15.9 
##  3 2        grat         cesdTotal    18 14.5  15.9 
##  4 3        grat         cesdTotal    18 12.3  15.5 
##  5 4        grat         cesdTotal    18 11.1  12.1 
##  6 5        grat         cesdTotal    18 13.3  14.5 
##  7 0        good         cesdTotal    25 15.1   9.08
##  8 1        good         cesdTotal    25 13.4  11.3 
##  9 2        good         cesdTotal    25 12.7  12.4 
## 10 3        good         cesdTotal    25 13.9  12.5 
## 11 4        good         cesdTotal    25 14.1  11.2 
## 12 5        good         cesdTotal    25 16.6  16.8 
## 13 0        streng       cesdTotal    11 14.2  13.3 
## 14 1        streng       cesdTotal    11 11     9.56
## 15 2        streng       cesdTotal    11 12.1  12.6 
## 16 3        streng       cesdTotal    11 10.4  10.9 
## 17 4        streng       cesdTotal    11 11    15.0 
## 18 5        streng       cesdTotal    11 12.1  14.9 
## 19 0        control      cesdTotal    20 12.0   8.18
## 20 1        control      cesdTotal    20  7.4   6.97
## 21 2        control      cesdTotal    20  9.7   9.40
## 22 3        control      cesdTotal    20  7.55  8.07
## 23 4        control      cesdTotal    20  8.5   7.44
## 24 5        control      cesdTotal    20 10.6  12.0
```

Visulation by boxplot

```
bxp <- ggplot(ahi_cesd, aes(occasion, cesdTotal)) +
  geom_boxplot(aes(color=intervention)) +
  stat_summary(fun.y = median, geom = "line", aes(group=factor(intervention), color=intervention), size=
bxp
```



Check assumptions

Check for outliers

```
ahi_cesd %>%
  group_by(intervention, occasion) %>%
  identify_outliers(cesdTotal) %>%
  select(1:2, 49, 51:52)
```

```
## # A tibble: 17 x 5
##    occasion intervention ahiTotal is.outlier is.extreme
##    <fct>    <fct>           <int> <lgl>      <lgl>
##  1 3        grat               51 TRUE       FALSE
##  2 3        grat               50 TRUE       FALSE
##  3 4        grat               52 TRUE       FALSE
##  4 5        grat               49 TRUE       FALSE
##  5 5        grat               49 TRUE       FALSE
##  6 1        good               45 TRUE       FALSE
##  7 2        good               38 TRUE       TRUE
##  8 2        good               51 TRUE       FALSE
##  9 3        good               44 TRUE       FALSE
## 10 3        streng             55 TRUE       FALSE
## 11 4        streng             55 TRUE       TRUE
## 12 4        streng             46 TRUE       FALSE
## 13 0        control            51 TRUE       FALSE
## 14 1        control            48 TRUE       TRUE
## 15 1        control            60 TRUE       FALSE
## 16 3        control            49 TRUE       FALSE
```

```
## 17 4         control             50 TRUE       FALSE
```

Same formula for outliers as previous. There are some outliers and this time there are a few extreme outliers. We will keep note of these moving forward. The outliers are easy to locate in the previous side-by-side boxplots.

Check normality assumption

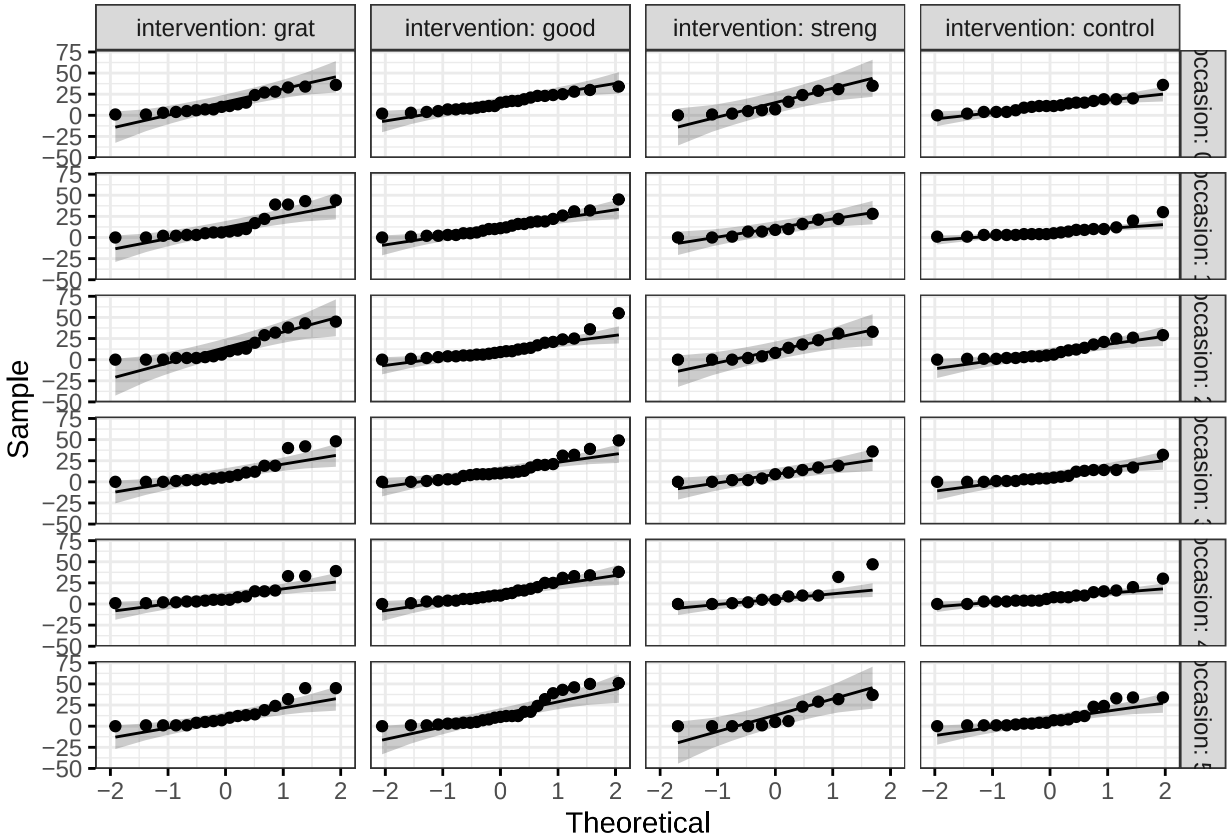
```
ahi_cesd %>%
  group_by(intervention, occasion) %>%
  shapiro_test(cesdTotal) %>%
  print(n=Inf)
```

```
## # A tibble: 24 x 5
##    occasion intervention variable  statistic        p
##    <fct>    <fct>        <chr>         <dbl>    <dbl>
##  1 0        grat         cesdTotal     0.873 0.0197
##  2 1        grat         cesdTotal     0.774 0.000662
##  3 2        grat         cesdTotal     0.826 0.00363
##  4 3        grat         cesdTotal     0.762 0.000469
##  5 4        grat         cesdTotal     0.771 0.000608
##  6 5        grat         cesdTotal     0.820 0.00293
##  7 0        good         cesdTotal     0.952 0.280
##  8 1        good         cesdTotal     0.910 0.0298
##  9 2        good         cesdTotal     0.808 0.000312
## 10 3        good         cesdTotal     0.866 0.00365
## 11 4        good         cesdTotal     0.908 0.0269
## 12 5        good         cesdTotal     0.822 0.000534
## 13 0        streng       cesdTotal     0.866 0.0697
## 14 1        streng       cesdTotal     0.920 0.316
## 15 2        streng       cesdTotal     0.867 0.0703
## 16 3        streng       cesdTotal     0.866 0.0691
## 17 4        streng       cesdTotal     0.729 0.00110
## 18 5        streng       cesdTotal     0.778 0.00482
## 19 0        control      cesdTotal     0.915 0.0784
## 20 1        control      cesdTotal     0.755 0.000201
## 21 2        control      cesdTotal     0.860 0.00787
## 22 3        control      cesdTotal     0.828 0.00231
## 23 4        control      cesdTotal     0.868 0.0109
## 24 5        control      cesdTotal     0.779 0.000434
```

There are 16 cases that have p-value<.05. We will keep these in mind while asseing the QQ plots.

QQ plot

```
ggqqplot(ahi_cesd, "cesdTotal", ggtheme = theme_bw()) +
  facet_grid(occasion~intervention, labeller = "label_both")
```



Unlike when the QQ plots for happy scores, the depression scores aren't all okay. Grat/1, Grat/2, Grat/3, Good/2, Good/5, Streng/4, Control/1 and Control/5 are causes for concern. These are quite a few cases, thus will proceed with caution and take the upcoming results with a grain of salt.

Homogeneity of variance assumption

```
ahi_cesd %>%
  group_by(occasion) %>%
  levene_test(cesdTotal ~ intervention)
```

```
## # A tibble: 6 x 5
##   occasion   df1   df2 statistic     p
##   <fct>    <int> <int>     <dbl> <dbl>
## 1 0            3    70     1.82  0.151
## 2 1            3    70     1.94  0.131
## 3 2            3    70     1.07  0.368
## 4 3            3    70     0.741 0.531
## 5 4            3    70     0.664 0.577
## 6 5            3    70     0.406 0.749
```

There is homogeneity of variance for there are no p-values<.05.

Homogeneity of covariances assumption

```
box_m(ahi_cesd[, "ahiTotal", drop = FALSE], ahi_cesd$intervention)
```

```
## # A tibble: 1 x 4
##   statistic p.value parameter method
##       <dbl>   <dbl>     <dbl> <chr>
```

```
## 1      3.78   0.286         3 Box's M-test for Homogeneity of Covariance M~
```

The p-value<.001 thus there is significant cause for concern on homogeneity of covariances. In other words, we can't conclude homogeneity of covariance.

Assumption of sphericity

This assumption is internally calculated in the anova computation below, thus we do not need to worry about this assumption right now.

Variable selection + modification

```
ahi_cesd_sad <- ahi_cesd %>%
  select(id, occasion, intervention, cesdTotal) %>%
  mutate(cesdTotal=as.numeric(cesdTotal))
str(ahi_cesd_happy)
```

Computation

```
res.aov_sad <- anova_test(data = ahi_cesd_sad, dv = cesdTotal,
                      wid = id,
                      between = intervention, within =occasion,
                      detailed = TRUE)
res.aov_sad
```

```
## ANOVA Table (type III tests)
##
## $ANOVA
##                  Effect DFn DFd       SSn      SSd      F        p p<.05
## 1           (Intercept)   1  70 60246.267 48690.25 86.614 7.26e-14     *
## 2          intervention   3  70  1816.234 48690.25  0.870 4.61e-01
## 3              occasion   5 350   474.780 13544.45  2.454 3.30e-02     *
## 4 intervention:occasion  15 350   344.785 13544.45  0.594 8.80e-01
##     ges
## 1 0.492
## 2 0.028
## 3 0.008
## 4 0.006
##
## $`Mauchly's Test for Sphericity`
##                  Effect     W        p p<.05
## 1              occasion 0.482 6.98e-06     *
## 2 intervention:occasion 0.482 6.98e-06     *
##
## $`Sphericity Corrections`
##                  Effect   GGe        DF[GG]  p[GG] p[GG]<.05   HFe
## 1              occasion 0.754  3.77, 263.85 0.050         * 0.802
## 2 intervention:occasion 0.754 11.31, 263.85 0.837           0.802
##         DF[HF] p[HF] p[HF]<.05
## 1  4.01, 280.74 0.046         *
## 2 12.03, 280.74 0.847
```

As in the happy computation only occasion is signficant as well in the depression instance. People got happier as the study went on. Note that the majority of the impact of time occured from the occasion 0 to occasion 1, after that the effect attenuated off. The interaction term was not significant.

Post-hoc tests

```
ahi_cesd_sad %>%
  pairwise_t_test(cesdTotal~occasion, paired = TRUE,
                  p.adjust.method = "bonferroni")
```

```
## # A tibble: 15 x 10
##     .y.   group1 group2    n1    n2 statistic    df     p p.adj p.adj.signif
##   * <chr> <chr>  <chr>  <int> <int>     <dbl> <dbl> <dbl> <dbl> <chr>
##   1 cesd~ 0      1         74    74     3.15     73 0.002 0.035 *
##   2 cesd~ 0      2         74    74     2.00     73 0.049 0.741 ns
##   3 cesd~ 0      3         74    74     2.79     73 0.007 0.101 ns
##   4 cesd~ 0      4         74    74     2.68     73 0.009 0.137 ns
##   5 cesd~ 0      5         74    74     0.406    73 0.686 1     ns
##   6 cesd~ 1      2         74    74    -0.745    73 0.459 1     ns
##   7 cesd~ 1      3         74    74     0.453    73 0.652 1     ns
##   8 cesd~ 1      4         74    74     0.307    73 0.76  1     ns
##   9 cesd~ 1      5         74    74    -1.62     73 0.11  1     ns
##  10 cesd~ 2      3         74    74     1.13     73 0.261 1     ns
##  11 cesd~ 2      4         74    74     0.832    73 0.408 1     ns
##  12 cesd~ 2      5         74    74    -0.946    73 0.347 1     ns
##  13 cesd~ 3      4         74    74    -0.110    73 0.913 1     ns
##  14 cesd~ 3      5         74    74    -1.85     73 0.068 1     ns
##  15 cesd~ 4      5         74    74    -1.92     73 0.059 0.879 ns
```

Final summary table

```
final_table <- rbind(happy_sum, sad_sum)
```