Social Phobia Experiments by Eleanor Leigh. PE analyses by Argyris

Argyris Stringaris

09/07/2022

Overview

This is an analysis of data that Eleanor sent me yesterday (08/07/2022). They are based on her experiment described here: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7909699/

It is a within-subject experiment where adolescents with high and low social anxiety were asked to take part in a conversations with stooges (psychology students). They were instructed–in a counter-balanced fashion–to either focus on themselves and to use safety behaviours (denoted "with" in EL's data), or not to (denoted "without"in EL's data).

The key variables are the following:

- Prediction1Rating_Study2 -> Belief in original prediction Study 2 (0-100). For the purposes of analyses I have relabelled it as expectation in code chunks below.
- Anxiety_with_Study2 -> How anxious did you feel during the WITH conversation (0-100)
- Belief_With_Study2 -> How much did your feared prediction happen (0-100) WITH
- Anxiety_WithOUT_Study2 -> How anxious did you feel during the WITHOUT conversation (0-100)
- Belief_WithOUT_Study2 -> How much did your feared prediction happen (0-100) WITHOUT

These also allow us to build prediction errors with and without safety behaviours.

A short **Executive Summary** follows here before the analyses

1. *Prediction error* is minimally related to anxiety. **This makes it very unlikely that PE is a mediator of the relationship between experimental condition and anxiety as an outcome.**
2. *Belief* is fairly strongly related to anxiety in both experimental conditions. **Thierefore belief may a possible mediator of the relationship between experimental condition and anxiety** Although, because belief and anxiety are measured at the same time (and may be hard to measure separately from each other), it may be hard to exclude the possibility of reverse causality, or of a common third factor(s).
3. *Expectation*, that is, how people think at the beginning of the experiment about the outcome seems to play an important for the outcomes of both anxiety and belief. **The higher the expectation about the outcome, the higher the change in both the outcomes across both conditions**.

Load data

```r
el_soph_exp_pe <- read.csv("~/argyris_code/Wellcom_Application_Active_Ingredients/Aim1.Database Stage 2
View(el_soph_exp_pe)
```

Keep only Study 2 as per Eleanor's instruction, create a PE variable, and keep necessary columns

```r
el_soph_exp_pe <- el_soph_exp_pe %>%
filter(Study ==2) %>%
mutate (pe_with = Belief_With_Study2 - Prediction1Rating_Study2,
pe_without = Belief_WithOUT_Study2 - Prediction1Rating_Study2)
```

Check effect of order (this was a within person cross-over experiment)

```r
# el_soph_exp_pe %>%
# group_by(ConditionOrder_2) %>%
#   summarise_at(c("Prediction1Rating_Study2", "Anxiety_with_Study2", "Anxiety_WithOUT_Study2", "Belief
```

*Question to EL: I don't know how condition is coded. There seems to be some effect on the predictions

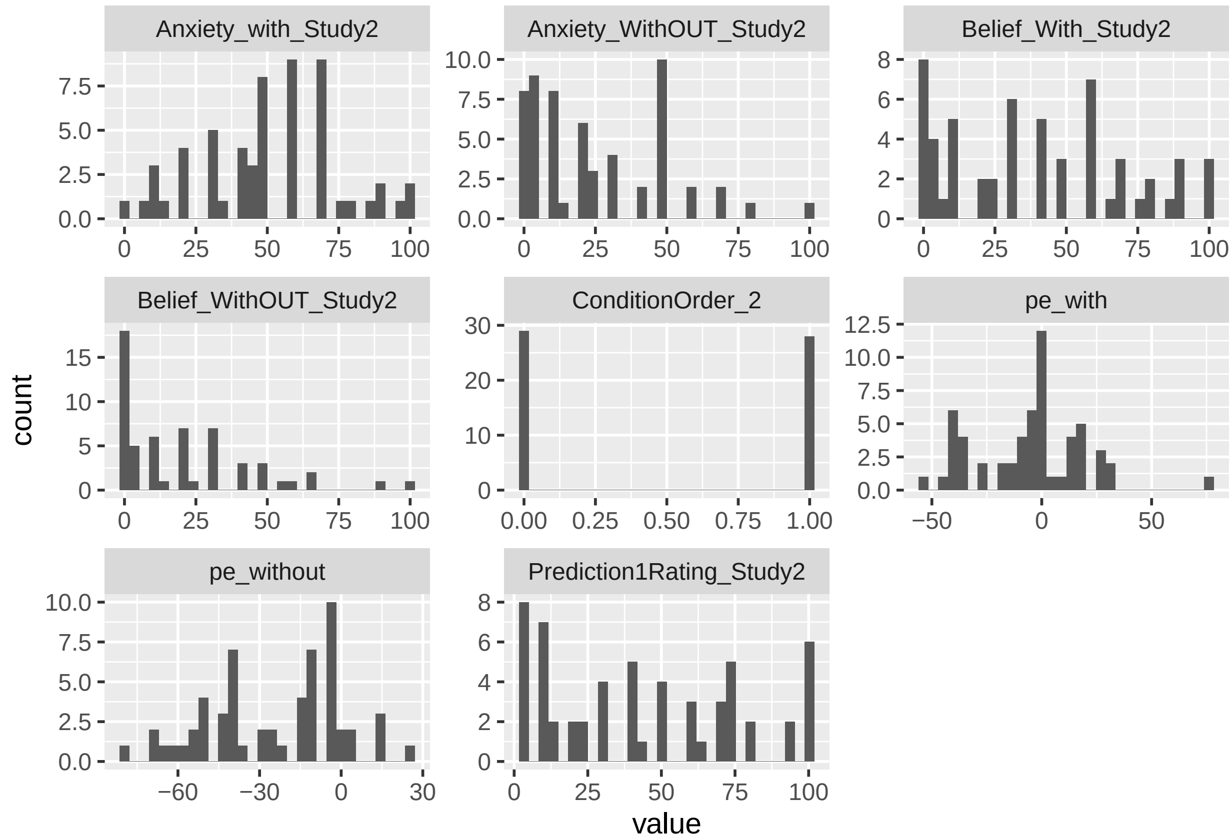
Create a long dataset too in order to do some plotting

```r
el_soph_exp_pe_long <- el_soph_exp_pe %>%
dplyr:: select(Prediction1Rating_Study2, ConditionOrder_2, Anxiety_with_Study2, Belief_With_Study2, Anx

el_soph_exp_pe_long  <- el_soph_exp_pe_long  %>%
  pivot_longer(colnames(el_soph_exp_pe_long)) %>%
  as.data.frame()
head(el_soph_exp_pe_long)
```

```
##                        name value
## 1 Prediction1Rating_Study2    15
## 2         ConditionOrder_2     0
## 3      Anxiety_with_Study2    30
## 4       Belief_With_Study2    30
## 5   Anxiety_WithOUT_Study2    20
## 6    Belief_WithOUT_Study2    30
```

Now plot the distributions of the main variables

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



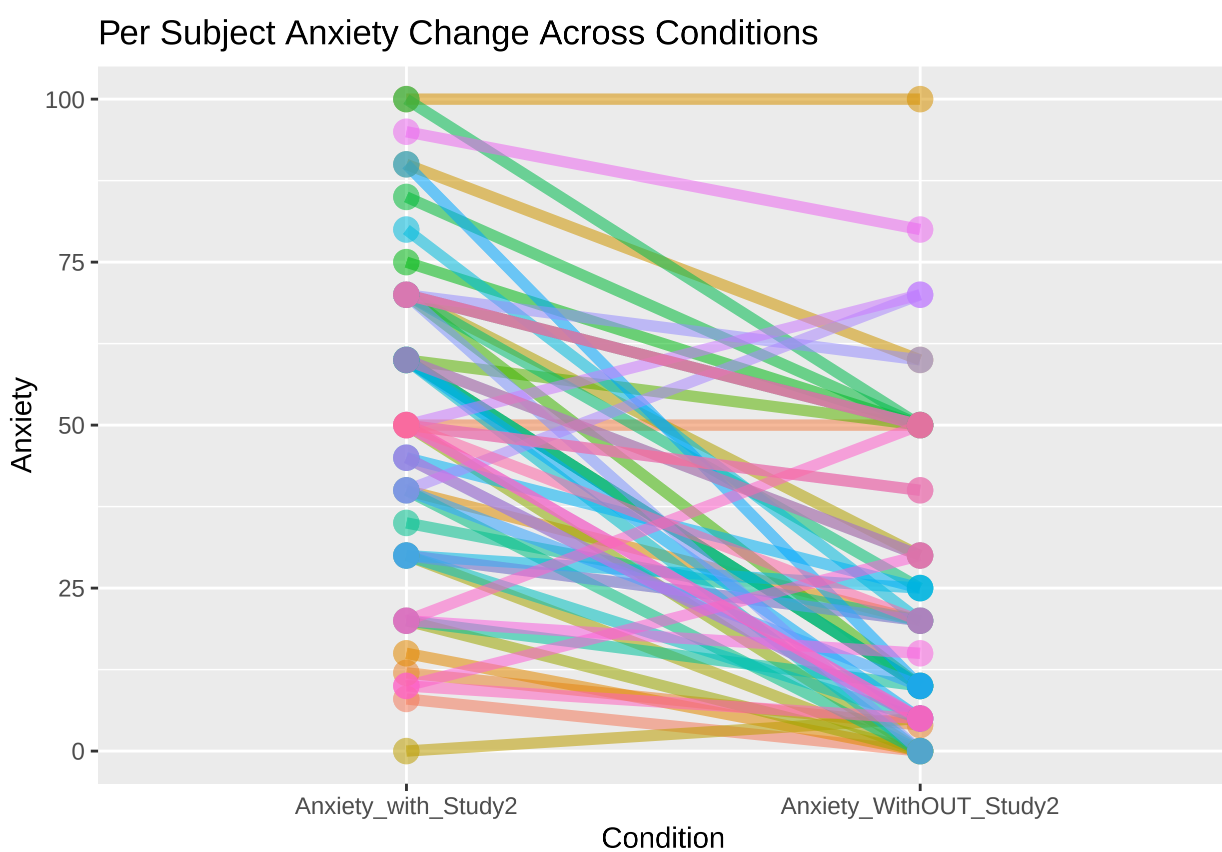
There is a clear shift through the experimental manipulation in both anxiety and belief, as well as PE. Interestingly, predictions follow a nearly bimodal distribution, possibly influenced by the group distributions (high vs low SoPh)

I am creating a more principled long dataset to test our hypotheses in regression

```
anxiety <- el_soph_exp_pe  %>%
 dplyr:: select(ID,MFQ_St2_T, LSAS_St2_T,  Anxiety_with_Study2,Prediction1Rating_Study2, Anxiety_WithOU
anxiety <- anxiety %>%
  pivot_longer(
    cols = starts_with("Anx"),
    names_to = "condition",
    names_prefix = "anx",
    values_to = "anx_value",
    values_drop_na = TRUE
  )

pe <- el_soph_exp_pe  %>%
 dplyr:: select(ID, pe_with, pe_without)
pe <- pe %>%
  pivot_longer(
    cols = starts_with("pe"),
    names_to = "condition",
    names_prefix = "pe",
    values_to = "pe_value",
    values_drop_na = TRUE
  )
```

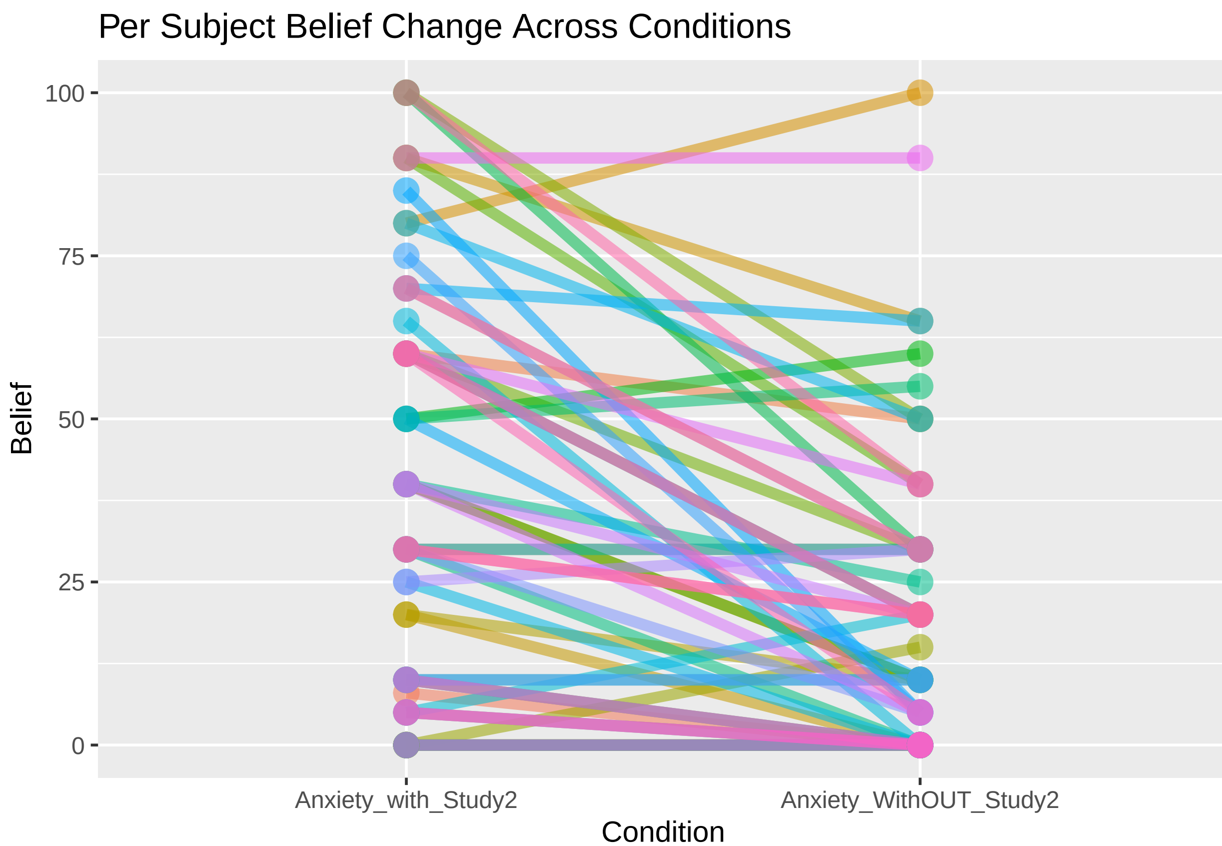
```r
pe_anx_merged <- cbind(anxiety, pe)

belief <- el_soph_exp_pe  %>%
 dplyr:: select(ID, Belief_With_Study2, Belief_WithOUT_Study2 )
belief <- belief %>%
  pivot_longer(
    cols = starts_with("Belief"),
    names_to = "condition",
    names_prefix = "belief",
    values_to = "belief_value",
    values_drop_na = TRUE
  )

pe_anx_merged <- cbind(pe_anx_merged, belief)
pe_anx_merged <- pe_anx_merged[!duplicated(colnames(pe_anx_merged))]
# pe_anx_merged <-pe_anx_merged %>%
#   dplyr:: select(- (ends_with(".1"))) %>%
#   dplyr:: select(- (ends_with(".2")))

 pe_anx_merged <- pe_anx_merged %>%
 dplyr::rename(exp_value = Prediction1Rating_Study2)
```

Let's plot anxiety change



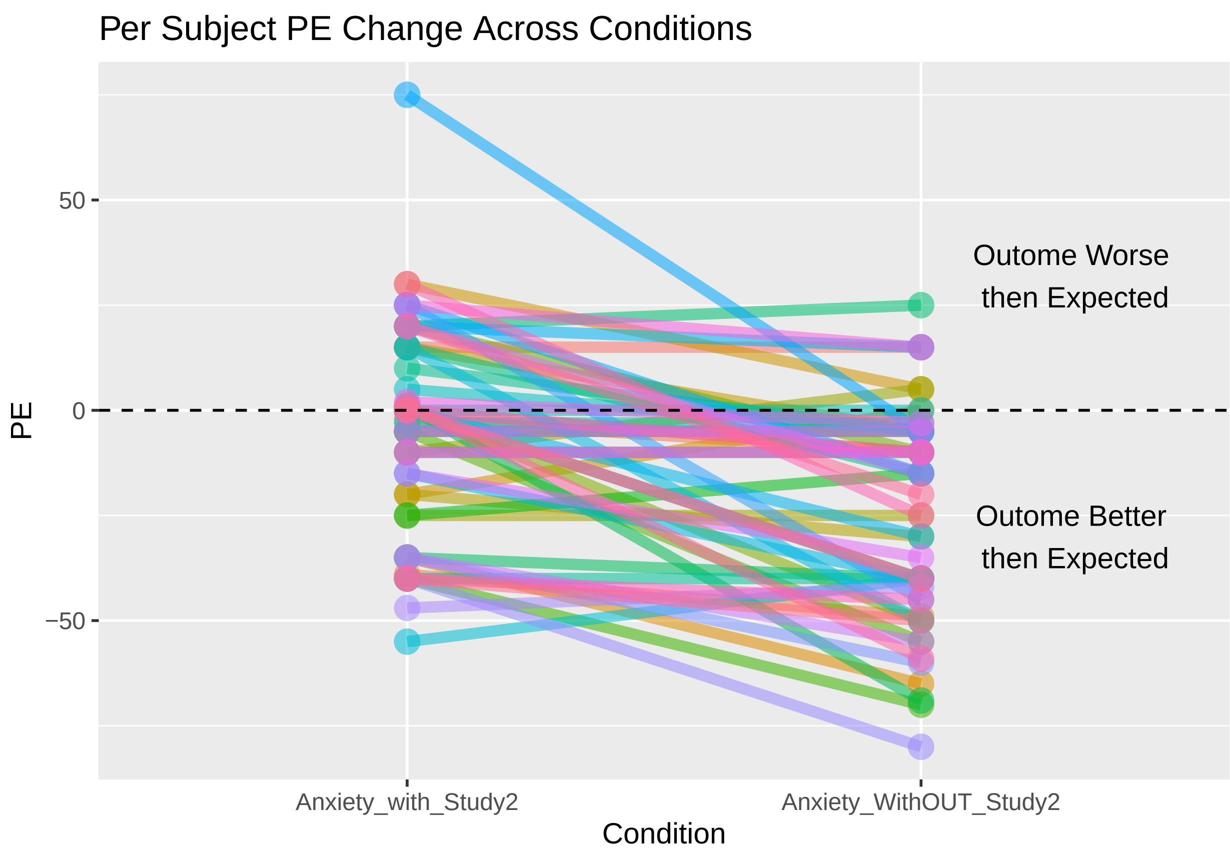
There is a clear change in anxiety across experimental conditions: it drops when safetey behaviours are dropped.

Let's plot belief change



There is a clear change in belief across experimental conditions: it drops when safetey behaviours are dropped.

Let's plot pe change



There is a clear change in pe across experimental conditions: it drops when safetey behaviours are dropped.

**create an even "longer" dataset, or two of them, so that you can plot expectations and outcomes

```
without_ratings_pred_belief <- pe_anx_merged %>%
   filter(condition == "_without") %>%
  dplyr:: select(ID, exp_value, belief_value) %>%
  pivot_longer(
    cols = !ID,
    names_to = c("time_point", "measure"),
    names_sep = "_",
    values_to = "score"
  )

without_ratings_pred_belief$time_point <-  recode_factor(without_ratings_pred_belief$time_point, exp =
without_ratings_pred_belief $measure <-  recode_factor(without_ratings_pred_belief$measure, value = "ce

head(without_ratings_pred_belief )
```

```
## # A tibble: 0 x 4
## # ... with 4 variables: ID <int>, time_point <fct>, measure <fct>, score <int>
```

```
with_ratings_pred_belief <- pe_anx_merged %>%
   filter(condition == "_with") %>%
  dplyr:: select(ID, exp_value, belief_value) %>%
  pivot_longer(
```

```r
    cols = !ID,
    names_to = c("time_point", "measure"),
    names_sep = "_",
    values_to = "score"
  )

with_ratings_pred_belief$time_point <-  recode_factor(with_ratings_pred_belief$time_point, exp = "expect
with_ratings_pred_belief$measure <-  recode_factor(with_ratings_pred_belief$measure, value = "certainty

head(with_ratings_pred_belief )
```

```
## # A tibble: 0 x 4
## # ... with 4 variables: ID <int>, time_point <fct>, measure <fct>, score <int>
```

```r
sum_stats_pe_by_condition <- pe_anx_merged %>%
  group_by(condition) %>%
  summarise(avg_pe = mean(pe_value), std_pe = sd(pe_value))

cohen_d_with <- (mean(pe_anx_merged$exp) - mean(pe_anx_merged$belief_value))/
  sqrt(((sd(pe_anx_merged$exp))^2 + (sd(pe_anx_merged$belief_value))^2)/2)

cohen_d_without <- pe_anx_merged %>%
  filter(condition == "_without" ) %>%
 mutate(cohen_d_without = (mean(exp_value) - mean(belief_value))/
  sqrt(((sd(exp_value))^2 + (sd(belief_value))^2)/2))
cohen_d_without$cohen_d_without[1]
```

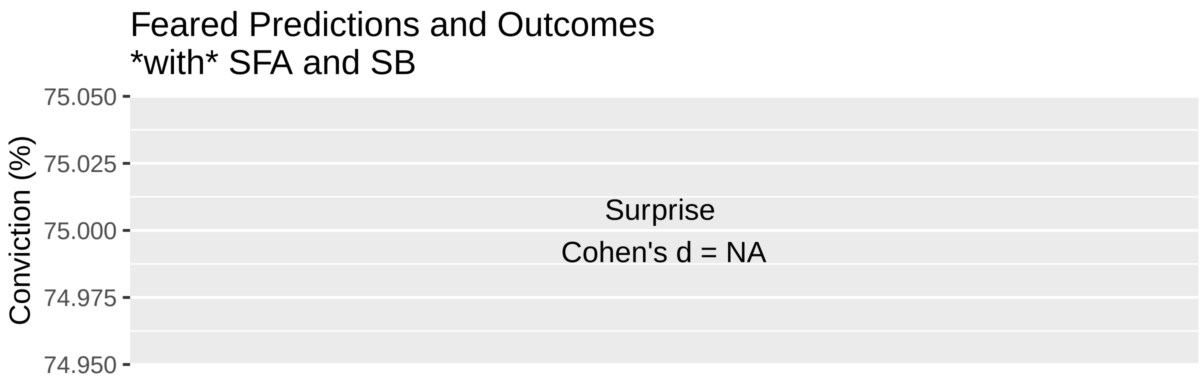
```
## [1] NA
```

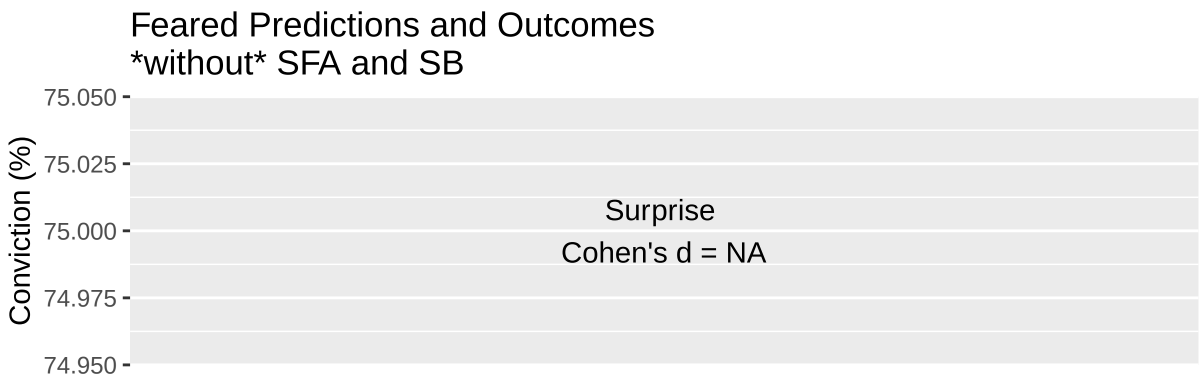
```r
cohen_d_with <- pe_anx_merged %>%
  filter(condition == "_with" ) %>%
 mutate(cohen_d_with = (mean(exp_value) - mean(belief_value))/
  sqrt(((sd(exp_value))^2 + (sd(belief_value))^2)/2))
cohen_d_with$cohen_d_with[1]
```

```
## [1] NA
```

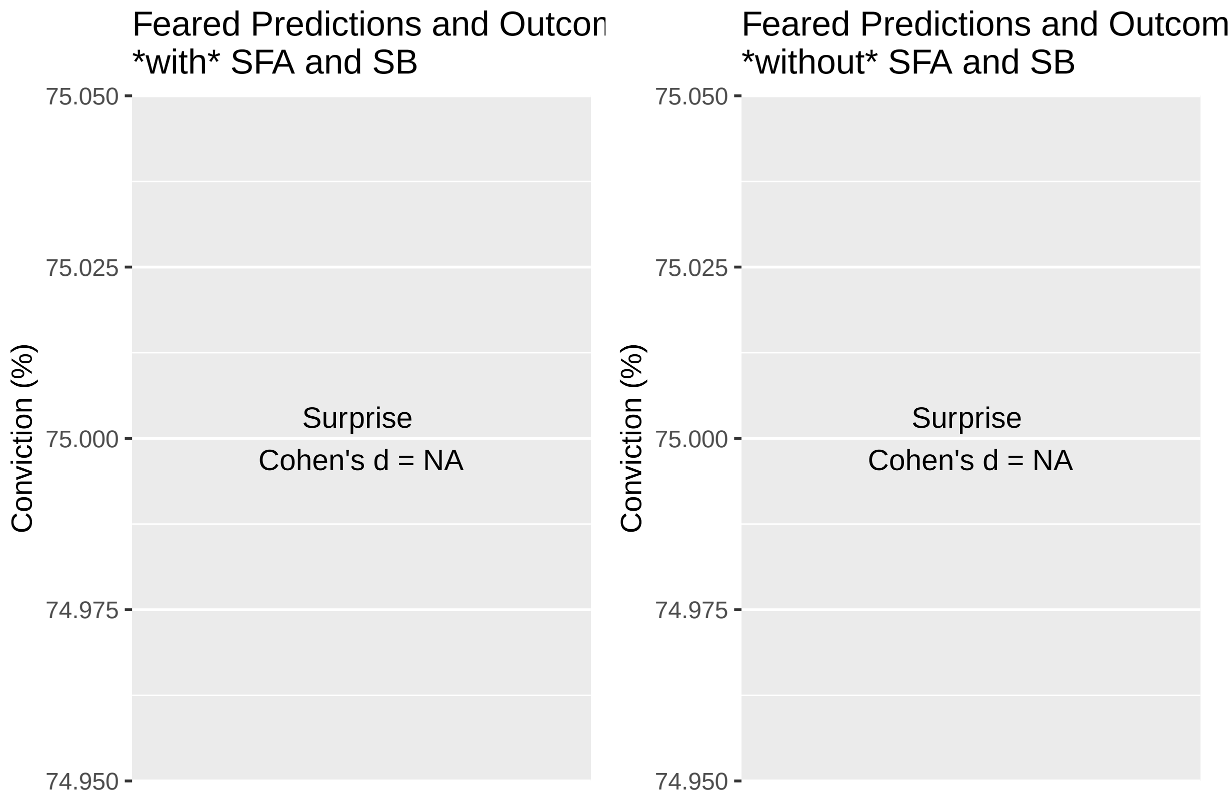
```r
plot_without <- without_ratings_pred_belief %>%
  ggplot(aes(x= time_point, y = score, fill = time_point))+
  geom_boxplot(width=0.1, color="grey") +
   geom_jitter(shape=16, position=position_jitter(0.2), alpha = 0.2)+
  theme(legend.position = "none")
plot_without <-plot_without +
  ggtitle("Feared Predictions and Outcomes \n*without* SFA and SB" ) +
   labs(x= "", y="Conviction (%)")
plot_without  <- plot_without + annotate("text",x= 1.5,y=75,label=paste0("Surprise \nCohen's d = ", rou

plot_without <- plot_without + scale_x_discrete(breaks=c("pre","post"),
        labels=c("Prediction", "Outcome"))

plot_with <- with_ratings_pred_belief %>%
```

```
  ggplot(aes(x= time_point, y = score, fill = time_point))+
  geom_boxplot(width=0.1, color="grey")  +
  geom_jitter(shape=16, position=position_jitter(0.2), alpha = 0.2)+
  theme(legend.position = "none")
plot_with <-plot_with +
  ggtitle("Feared Predictions and Outcomes \n*with* SFA and SB" )+
   labs(x= "", y="Conviction (%)")
plot_with  <- plot_with + annotate("text",x= 1.5,y=75,label=paste0("Surprise \nCohen's d = ", round(coh
plot_with <- plot_with +  scale_x_discrete(breaks=c("pre","post"),
        labels=c("Prediction", "Outcome"))

plot_with / plot_without
```






```
plot_with + plot_without
```

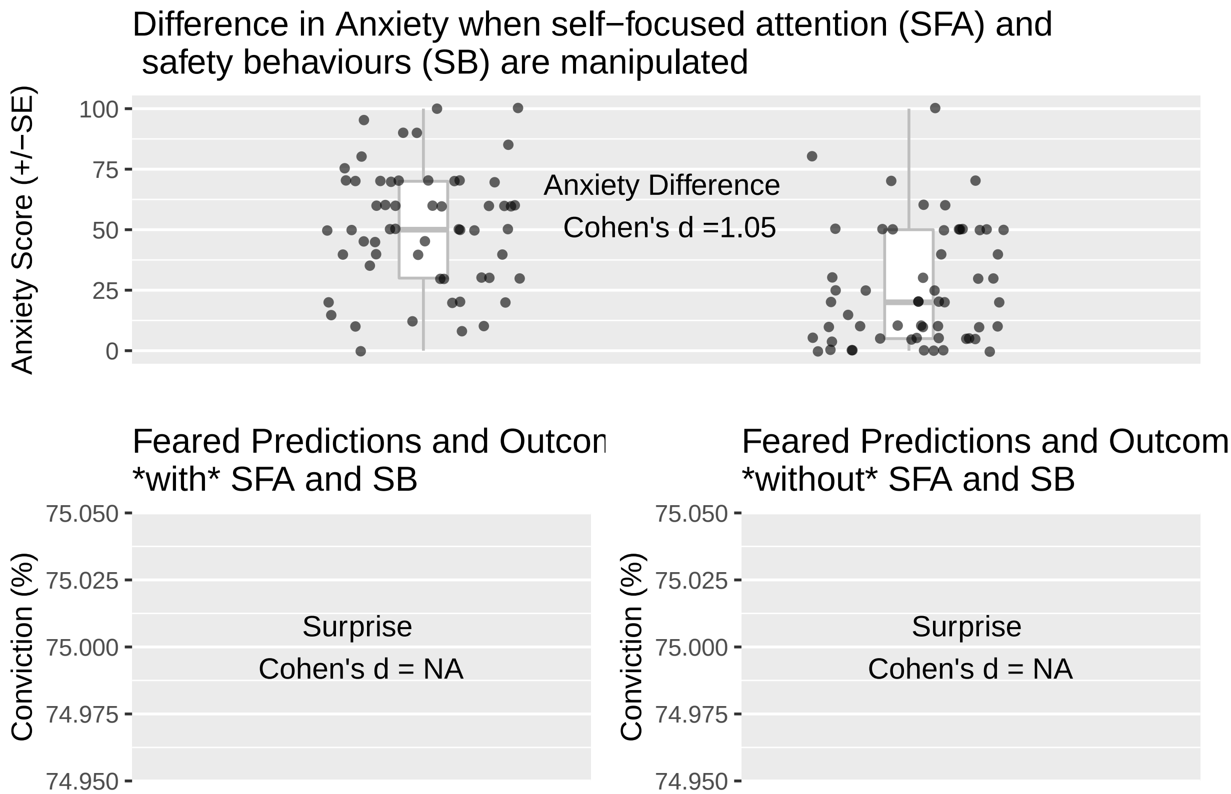


**anxiety change

```
##
##  Paired t-test
##
## data:  el_soph_exp_pe$Anxiety_with_Study2 and el_soph_exp_pe$Anxiety_WithOUT_Study2
## t = 7.9258, df = 56, p-value = 1.024e-10
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  18.69436 31.34072
## sample estimates:
## mean of the differences
##                25.01754
```

```
## [1] 1.049796
```

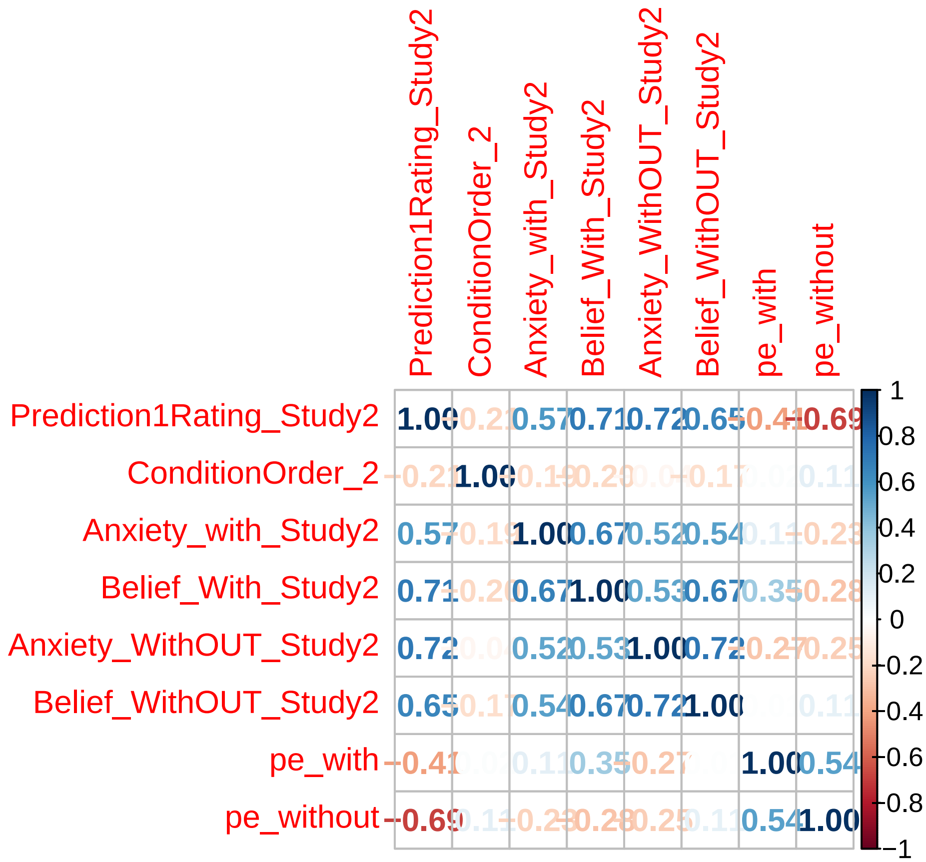
```
mean_plot_anx /(plot_with + plot_without)
```



does depression moderate anxiety or belief outcomes

```
# create MFQ dichotomous
pe_anx_merged <- pe_anx_merged %>%
  mutate(mfq_dichot = cut(MFQ_St2_T, breaks = c(-Inf, 9, Inf), labels = c("low","high")) )

anx_outcome  <- lm(anx_value ~ condition*mfq_dichot, data = pe_anx_merged)

belief_outcome  <- lm(belief_value ~ condition*mfq_dichot, data = pe_anx_merged)
```

Now let's look at a correlation matrix of all the variables



Belief and Anxiety are strongly correlated, perhaps unsurprisingly, but PE is not much. *Eleanor, what column are the stooges' anxiety ratings? Do we have an end of session LSAS? I see lots of LSASs and MFQs there–are they related to St2?

Now let's test formally that pe differs by condition to which subjects were randomised to

```
t_test_for_pe <- t.test(el_soph_exp_pe$pe_with , el_soph_exp_pe$pe_without, paired = TRUE, alternative =
t_test_for_pe
```

```
##
##  Paired t-test
##
## data:  el_soph_exp_pe$pe_with and el_soph_exp_pe$pe_without
## t = 6.19, df = 56, p-value = 7.448e-08
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  13.08843 25.61332
## sample estimates:
## mean of the differences
##                19.35088
```

It clearly does

The effect size can then be derived as follows, according to Lakens

```r
d_pe <- t_test_for_pe$statistic/sqrt(57)
print(as.numeric(d_pe))
```

```
## [1] 0.8198838
```

Which is a pretty decent effect size.

Similarly, we can show that anxiety differs by the the condition to which participants were randomised to

```r
t_test_for_anx <- t.test(el_soph_exp_pe$Anxiety_with_Study2 , el_soph_exp_pe$Anxiety_WithOUT_Study2, pa
t_test_for_anx
```

```
##
##  Paired t-test
##
## data:  el_soph_exp_pe$Anxiety_with_Study2 and el_soph_exp_pe$Anxiety_WithOUT_Study2
## t = 7.9258, df = 56, p-value = 1.024e-10
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  18.69436 31.34072
## sample estimates:
## mean of the differences
##                25.01754
```

For which the effect size can be estimated as above

```r
d_anx <- t_test_for_anx$statistic/sqrt(57)
print(as.numeric(d_anx))
```

```
## [1] 1.049796
```

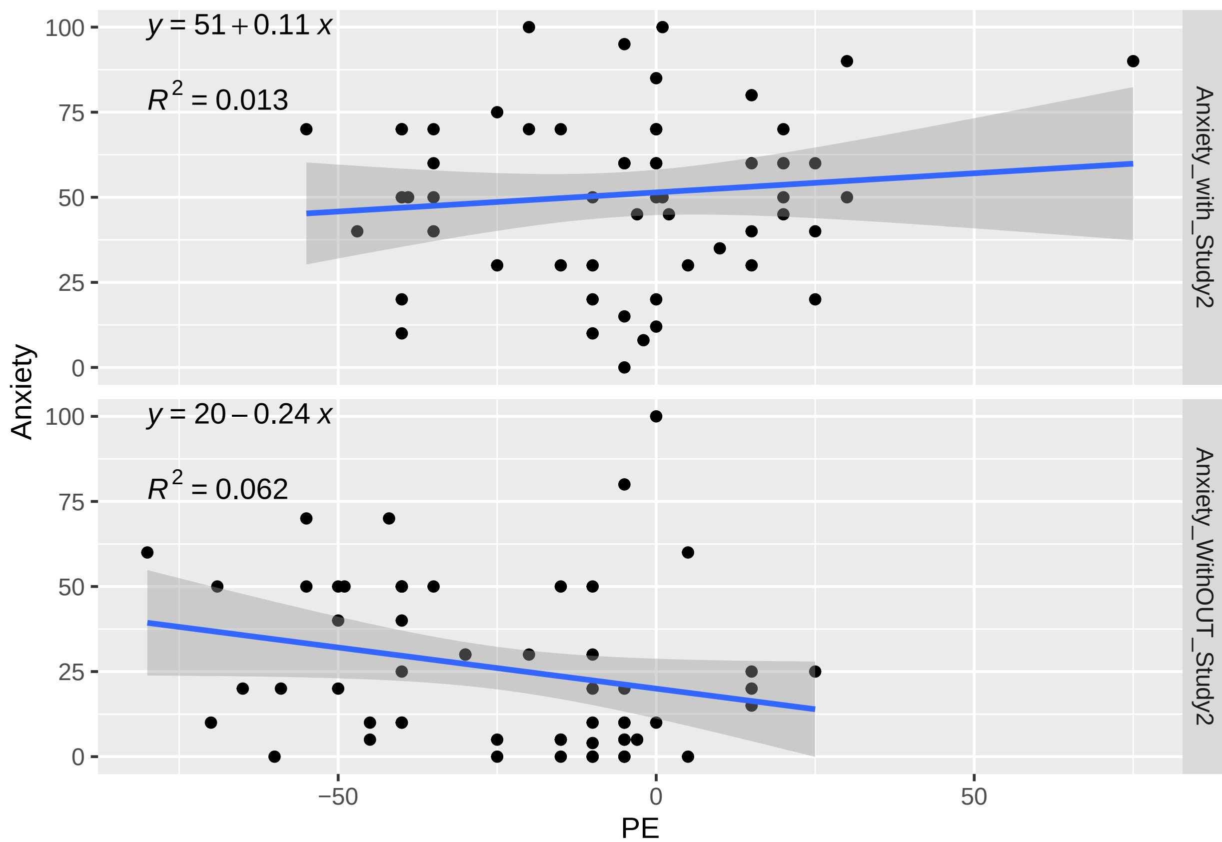
Which is also very big

And finally, let's show the direct relationship between PE and anxiety in the two different conditions

Let's now plot the relationship between PE and anxiety outcome across conditions

```r
library(ggpubr)

pe_anx_merged %>%
  ggplot(aes(x = pe_value, y = anx_value)) +
  geom_point()+
  labs(x= "PE", y="Anxiety")+
  geom_smooth(method = lm) +
  facet_grid(rows = vars(condition)) +
    stat_regline_equation(label.y = 100, aes(label = ..eq.label..)) +
  stat_regline_equation(label.y = 80, aes(label = ..rr.label..))
```

```
## `geom_smooth()` using formula 'y ~ x'
```



This clearly shows that there is no relationship between PE and anxiety.

Let's look at how PE relates to anxiety broken down by conditions

```
pe_anx_merged %>%
  group_by(condition) %>%
summarize(cor_coef= stats:: cor.test(anx_value, pe_value)$estimate,
          p_value = stats:: cor.test(anx_value, pe_value)$p.value)
```

```
## # A tibble: 2 x 3
##   condition              cor_coef p_value
##   <chr>                     <dbl>   <dbl>
## 1 Anxiety_with_Study2       0.112  0.407
## 2 Anxiety_WithOUT_Study2   -0.249  0.0619
```

Which is confirmed here

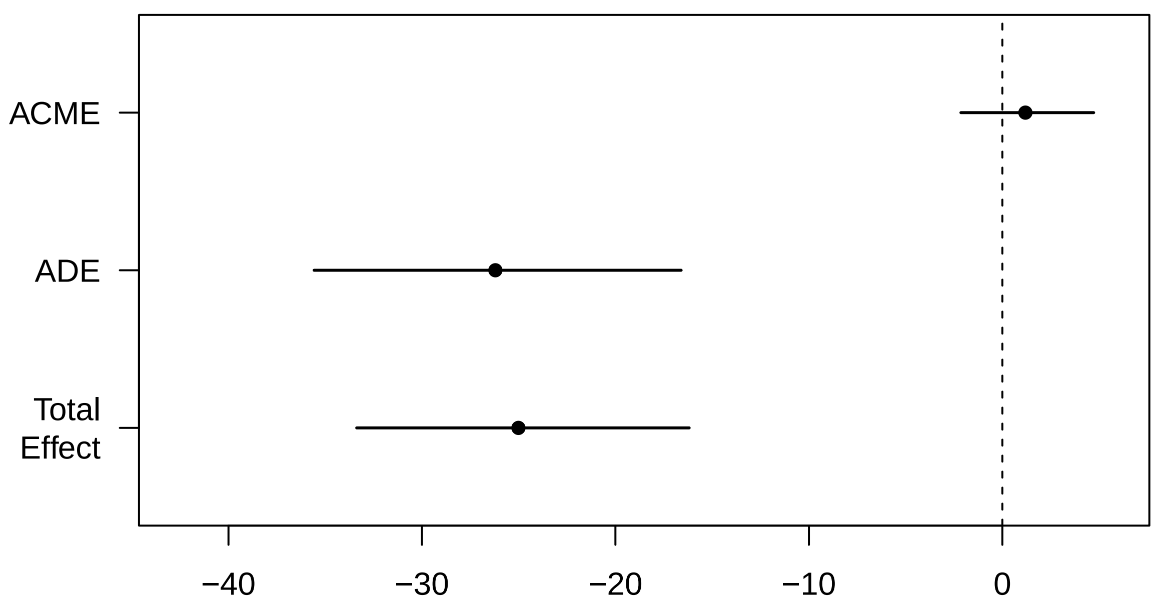
The findings from the last two regression models and the correlation matrix further up suggest to me that PE is not associated with anxiety ratings during the conversation. The pedestrian analyses above suggest not

I am going to try it with mediation–these models do not take dependence into account, but this should if anything inflate the p-values because it underestimates the SEs

Trying it with a standard mediation package in R

```
## Warning in mediate(model_mediator, model_outcome, sims = 500, treat =
```

```
## "condition", : treatment and control values do not match factor levels; using
## Anxiety_with_Study2 and Anxiety_WithOUT_Study2 as control and treatment,
## respectively

##
## Causal Mediation Analysis
##
## Quasi-Bayesian Confidence Intervals
##
##                 Estimate 95% CI Lower 95% CI Upper p-value
## ACME               1.192       -2.142         4.72     0.5
## ADE              -26.204      -35.576       -16.60  <2e-16 ***
## Total Effect     -25.012      -33.372       -16.19  <2e-16 ***
## Prop. Mediated    -0.044       -0.201         0.09     0.5
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 114
##
##
## Simulations: 500
```



This result suggests no mediation

Trying it also with SEM

```r
sem_model = '
  pe_value ~ a*condition
  anx_value ~ c*condition +  b*pe_value

  # direct effect
  direct := c

  # indirect effect
  indirect := a*b

  # total effect
  total := c + (a*b)
'

model_sem = sem(sem_model, data=pe_anx_merged, se='boot', bootstrap=500)
summary(model_sem, rsq=T)
```

```
## lavaan 0.6-12 ended normally after 1 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                         5
##
##   Number of observations                           114
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##
## Parameter Estimates:
##
##   Standard errors                            Bootstrap
##   Number of requested bootstrap draws              500
##   Number of successful bootstrap draws             500
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   pe_value ~
##     condition  (a)  -19.351    4.786   -4.043    0.000
##   anx_value ~
##     condition  (c)  -26.315    4.952   -5.314    0.000
##     pe_value   (b)   -0.067    0.097   -0.693    0.488
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .pe_value        597.814   72.802    8.212    0.000
##    .anx_value       580.323   71.283    8.141    0.000
##
## R-Square:
##                    Estimate
##     pe_value          0.135
##     anx_value         0.215
```

```
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     direct          -26.315    4.957   -5.309    0.000
##     indirect          1.297    1.880    0.690    0.490
##     total           -25.018    4.534   -5.518    0.000
```

This result confirms that there is no mediation.

More generally, it seems that the correlation between anxiety and pe is minimal across conditions

```
cor.test(pe_anx_merged$anx_value, pe_anx_merged$pe_value )
```

```
##
##  Pearson's product-moment correlation
##
## data:  pe_anx_merged$anx_value and pe_anx_merged$pe_value
## t = 1.206, df = 112, p-value = 0.2304
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.07219872  0.29107331
## sample estimates:
##       cor
## 0.1132195
```

**Check: just in case I have mis-construed the pe variable, I have also used the variable foundin Eleanor's database and correlated with mine

```
el_soph_exp_pe_cor <- el_soph_exp_pe %>%
 dplyr:: select(c(PredErrorWITH ,PredErrorWITHOUT, pe_with, pe_without))%>%
  correlate()
```

```
##
## Correlation method: 'pearson'
## Missing treated using: 'pairwise.complete.obs'
```

```
el_soph_exp_pe_cor
```

```
## # A tibble: 4 x 5
##   term             PredErrorWITH PredErrorWITHOUT pe_with pe_without
##   <chr>                    <dbl>            <dbl>   <dbl>      <dbl>
## 1 PredErrorWITH           NA                0.542   1          0.542
## 2 PredErrorWITHOUT         0.542           NA       0.542      1
## 3 pe_with                  1                0.542  NA          0.542
## 4 pe_without               0.542            1       0.542     NA
```

As can be seen Eleanor's and my pe variables are perfectly correlated.

Now let's try the mediation steps above to see whether we get anything with belief

starting again using beliefs this time

**Here is the relatinoship between anxiety and belief broken down by condition

```r
pe_anx_merged %>%
  group_by(condition) %>%
summarize(cor_coef= stats:: cor.test(anx_value, belief_value)$estimate,
          p_value = stats:: cor.test(anx_value, belief_value)$p.value)
```

```
## # A tibble: 2 x 3
##   condition              cor_coef  p_value
##   <chr>                     <dbl>    <dbl>
## 1 Anxiety_with_Study2       0.674 9.25e- 9
## 2 Anxiety_WithOUT_Study2    0.724 1.95e-10
```

Here is the relatinoship between anxiety and belief in the "without"

```r
lm_anx_pe_with <- lm(Anxiety_with_Study2 ~ Belief_With_Study2 , data = el_soph_exp_pe)
summary(lm_anx_pe_with)
```

```
##
## Call:
## lm(formula = Anxiety_with_Study2 ~ Belief_With_Study2, data = el_soph_exp_pe)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -32.217 -15.166  -1.305  15.625  37.448
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        29.93805    3.93528   7.608 3.81e-10 ***
## Belief_With_Study2  0.52279    0.07731   6.762 9.25e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.34 on 55 degrees of freedom
## Multiple R-squared:  0.454,  Adjusted R-squared:  0.444
## F-statistic: 45.73 on 1 and 55 DF,  p-value: 9.246e-09
```

This clearly suggests a relationship

Now let's check the standard mediation model for beliefs, instead of PE

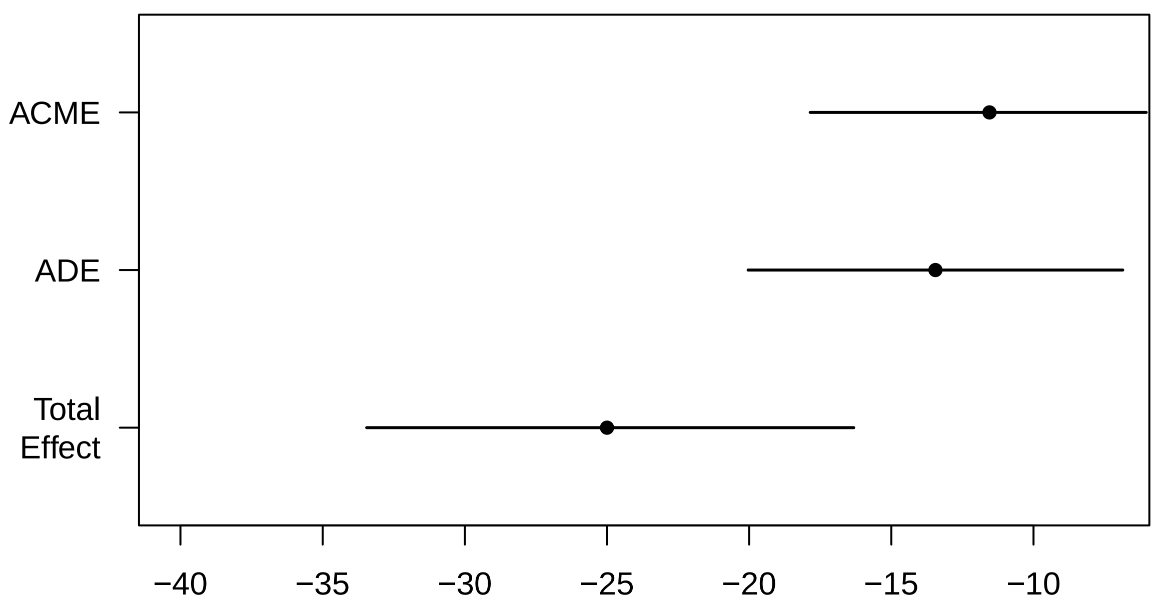
```r
model_mediator <- lm(belief_value ~ condition , data = pe_anx_merged)
model_outcome  <- lm(anx_value ~ condition + belief_value, data = pe_anx_merged)

mediation_result <- mediate(
  model_mediator,
  model_outcome,
  sims = 500,
  treat = "condition",
  mediator = "belief_value"
)
```

```
## Warning in mediate(model_mediator, model_outcome, sims = 500, treat =
## "condition", : treatment and control values do not match factor levels; using
## Anxiety_with_Study2 and Anxiety_WithOUT_Study2 as control and treatment,
## respectively
```

```r
summary(mediation_result)
```

```
##
## Causal Mediation Analysis
##
## Quasi-Bayesian Confidence Intervals
##
##                 Estimate 95% CI Lower 95% CI Upper p-value
## ACME             -11.549      -17.856        -6.04  <2e-16 ***
## ADE              -13.450      -20.038        -6.86  <2e-16 ***
## Total Effect     -24.999      -33.451       -16.32  <2e-16 ***
## Prop. Mediated     0.469        0.283         0.65  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Sample Size Used: 114
##
##
## Simulations: 500
```

```r
plot(mediation_result)
```



and there is a clear mediation here

And for confirmation, here is also the SEM mediation model for beliefs, instead of PE

```r
sem_model = '
  belief_value ~ a*condition
  anx_value ~ c*condition +  b*belief_value

  # direct effect
  direct := c

  # indirect effect
  indirect := a*b

  # total effect
  total := c + (a*b)
'

model_sem = sem(sem_model, data=pe_anx_merged, se='boot', bootstrap=500)
summary(model_sem, rsq=T)
```

```
## lavaan 0.6-12 ended normally after 1 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                         5
##
##   Number of observations                           114
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##
## Parameter Estimates:
##
##   Standard errors                            Bootstrap
##   Number of requested bootstrap draws              500
##   Number of successful bootstrap draws             500
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   belief_value ~
##     condition  (a)  -19.351    5.590   -3.461    0.001
##   anx_value ~
##     condition  (c)  -13.427    3.563   -3.769    0.000
##     belief_val (b)    0.599    0.065    9.273    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .belief_value    771.673   90.388    8.537    0.000
##    .anx_value       306.158   34.837    8.788    0.000
##
## R-Square:
##                    Estimate
##     belief_value      0.108
##     anx_value         0.586
```

```
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     direct          -13.427    3.566   -3.765    0.000
##     indirect        -11.591    3.509   -3.303    0.001
##     total           -25.018    4.792   -5.221    0.000
```

This too confirms it, but remember that the p-value estimates will be biased because of the clustering.

Now let's examine the properties of prediction, i.e. the *expectation as such as opposed to the PE*. First some correlations First, between anxiety and expectation

```
pe_anx_merged %>%
  group_by(condition) %>%
summarize(cor_coef= stats:: cor.test(anx_value, exp_value)$estimate,
          p_value = stats:: cor.test(anx_value, exp_value)$p.value)
```

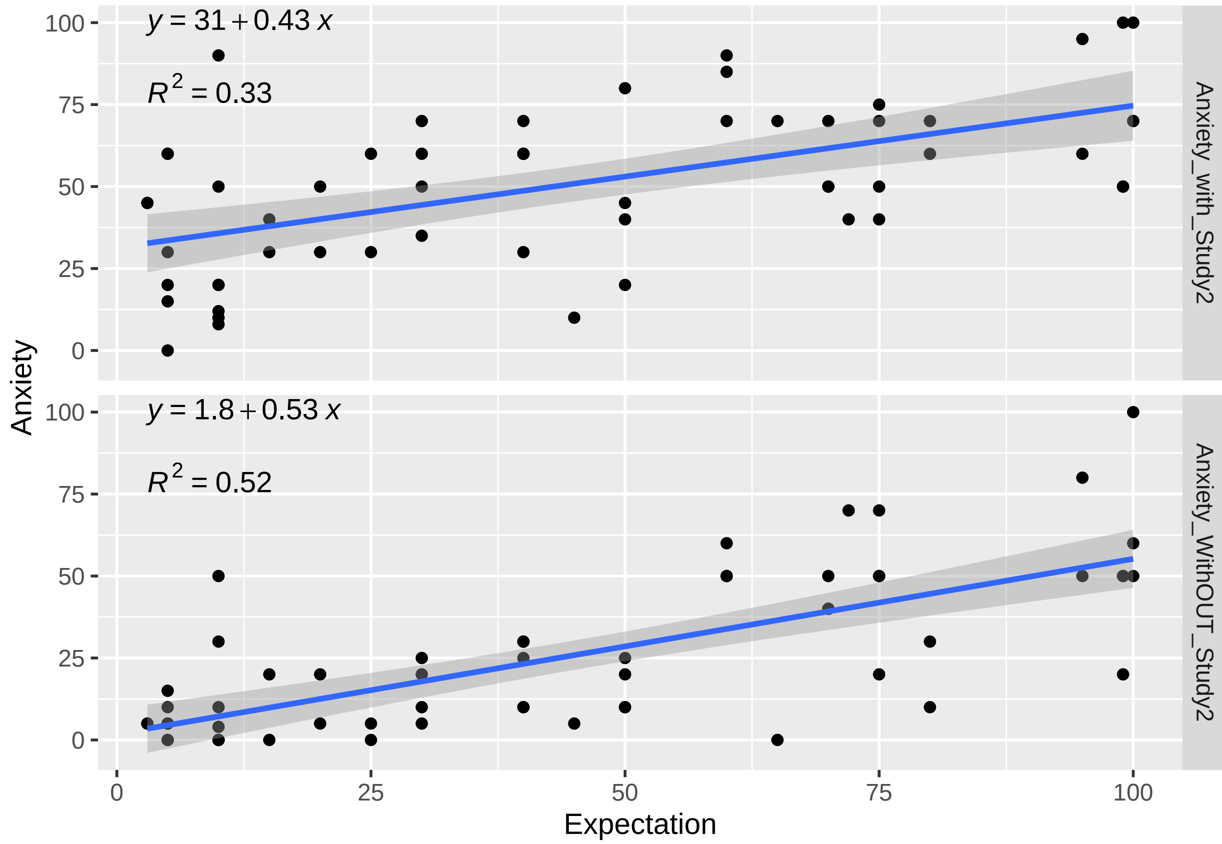
```
## # A tibble: 2 x 3
##   condition              cor_coef  p_value
##   <chr>                     <dbl>    <dbl>
## 1 Anxiety_with_Study2       0.572 3.32e- 6
## 2 Anxiety_WithOUT_Study2    0.720 2.77e-10
```

There is a fairly strong correlation with anxiety across both conditions

Let's now plot the relationship between expectation and anxiety outcome across conditions

```
library(ggpubr)

pe_anx_merged %>%
  ggplot(aes(x = exp_value, y = anx_value)) +
  geom_point()+
  labs(x= "Expectation", y="Anxiety")+
  geom_smooth(method = lm) +
  facet_grid(rows = vars(condition)) +
    stat_regline_equation(label.y = 100, aes(label = ..eq.label..)) +
  stat_regline_equation(label.y = 80, aes(label = ..rr.label..))
```

```
## `geom_smooth()` using formula 'y ~ x'
```



This indicates a consistent relationship across conditions, perhaps with a stronger one for the without.

Now let's examine whether expectation moderates outcomes in lme for anxiety (no strong indication from the plots)

```
mod_interaction_anxiety <- lmer(anx_value ~ exp_value*condition + (1|ID), data = pe_anx_merged)
summary(mod_interaction_anxiety )
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: anx_value ~ exp_value * condition + (1 | ID)
##    Data: pe_anx_merged
##
## REML criterion at convergence: 984.5
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.92347 -0.63485 -0.02375  0.57839  2.68257
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept)  66.25    8.139
##  Residual             283.57   16.840
## Number of obs: 114, groups:  ID, 57
##
## Fixed effects:
##                                             Estimate Std. Error        df
```

```
## (Intercept)                               31.40860    4.25408 106.19169
## exp_value                                  0.43264    0.07685 106.19169
## conditionAnxiety_WithOUT_Study2          -29.58364    5.41665  55.00000
## exp_value:conditionAnxiety_WithOUT_Study2   0.10147    0.09785  55.00000
##                                          t value Pr(>|t|)
## (Intercept)                                7.383 3.64e-11 ***
## exp_value                                  5.630 1.49e-07 ***
## conditionAnxiety_WithOUT_Study2           -5.462 1.17e-06 ***
## exp_value:conditionAnxiety_WithOUT_Study2   1.037    0.304
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) exp_vl cA_WOU
## exp_value   -0.813
## cnA_WOUT_S2 -0.637  0.518
## e_:A_WOUT_S  0.518 -0.637 -0.813
```

The interaction seems very weak.

Perhaps a simple additive model will be just fine, where expectation simply predicts

```r
mod_additive_anxiety <- lmer(anx_value ~ exp_value + condition + (1|ID), data = pe_anx_merged)
anova(mod_additive_anxiety ,mod_interaction_anxiety )
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: pe_anx_merged
## Models:
## mod_additive_anxiety: anx_value ~ exp_value + condition + (1 | ID)
## mod_interaction_anxiety: anx_value ~ exp_value * condition + (1 | ID)
##                         npar    AIC    BIC  logLik deviance  Chisq Df
## mod_additive_anxiety       5 996.21 1009.9 -493.11   986.21
## mod_interaction_anxiety    6 997.11 1013.5 -492.56   985.11 1.1036  1
##                         Pr(>Chisq)
## mod_additive_anxiety
## mod_interaction_anxiety     0.2935
```

The evidence of moderation seems extremely weak to me.

Now compare to a simple model with just condition

```r
mod_simple_anxiety <- lmer(anx_value ~ condition + (1|ID), data = pe_anx_merged)
anova(mod_simple_anxiety, mod_additive_anxiety)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: pe_anx_merged
## Models:
## mod_simple_anxiety: anx_value ~ condition + (1 | ID)
## mod_additive_anxiety: anx_value ~ exp_value + condition + (1 | ID)
##                      npar     AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod_simple_anxiety      4 1039.40 1050.3 -515.70  1031.40
```

```
## mod_additive_anxiety    5  996.21 1009.9 -493.11   986.21 45.188  1   1.79e-11
##
## mod_simple_anxiety
## mod_additive_anxiety ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The additive model seems clearly superior. People's expectation seems to play an important role in anxiety outcome.

But is it just severity

```
mod_additive_anxiety <- lmer(anx_value ~ exp_value + condition +  (1|ID), data = pe_anx_merged)
summary(mod_additive_anxiety)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: anx_value ~ exp_value + condition + (1 | ID)
##    Data: pe_anx_merged
##
## REML criterion at convergence: 982.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.86267 -0.65619 -0.06211  0.57638  2.78770
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept)  66.06    8.128
##  Residual             283.96   16.851
## Number of obs: 114, groups:  ID, 57
##
## Fixed effects:
##                                Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                    29.12555    3.64047  79.23637   8.001 8.54e-12
## exp_value                       0.48337    0.05926  55.00000   8.156 4.86e-11
## conditionAnxiety_WithOUT_Study2 -25.01754    3.15648  56.00000  -7.926 1.02e-10
##
## (Intercept)                    ***
## exp_value                      ***
## conditionAnxiety_WithOUT_Study2 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) exp_vl
## exp_value   -0.733
## cnA_WOUT_S2 -0.434  0.000
```

```
mod_additive_anxiety_lsas <- lmer(anx_value ~ exp_value + condition + LSAS_St2_T + (1|ID), data = pe_an
summary(mod_additive_anxiety_lsas)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
```

```
## lmerModLmerTest]
## Formula: anx_value ~ exp_value + condition + LSAS_St2_T + (1 | ID)
##    Data: pe_anx_merged
##
## REML criterion at convergence: 956.6
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.94428 -0.57827 -0.06127  0.65793  3.05042
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept)  23.73    4.871
##  Residual             287.03   16.942
## Number of obs: 112, groups:  ID, 56
##
## Fixed effects:
##                                 Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)                     29.61100    3.38383  81.44670   8.751 2.37e-13
## exp_value                        0.20694    0.08829  53.00000   2.344 0.022863
## conditionAnxiety_WithOUT_Study2 -25.28571    3.20174  54.99999  -7.898 1.28e-10
## LSAS_St2_T                       0.29092    0.07412  53.00000   3.925 0.000252
##
## (Intercept)                     ***
## exp_value                       *
## conditionAnxiety_WithOUT_Study2 ***
## LSAS_St2_T                      ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) exp_vl cA_WOU
## exp_value   -0.452
## cnA_WOUT_S2 -0.473  0.000
## LSAS_St2_T   0.023 -0.796  0.000
```

Now let's examine the relationship between *belief and prediction*

```
pe_anx_merged %>%
  group_by(condition) %>%
summarize(cor_coef= stats:: cor.test(belief_value, exp_value)$estimate,
          p_value = stats:: cor.test(belief_value, exp_value)$p.value)
```

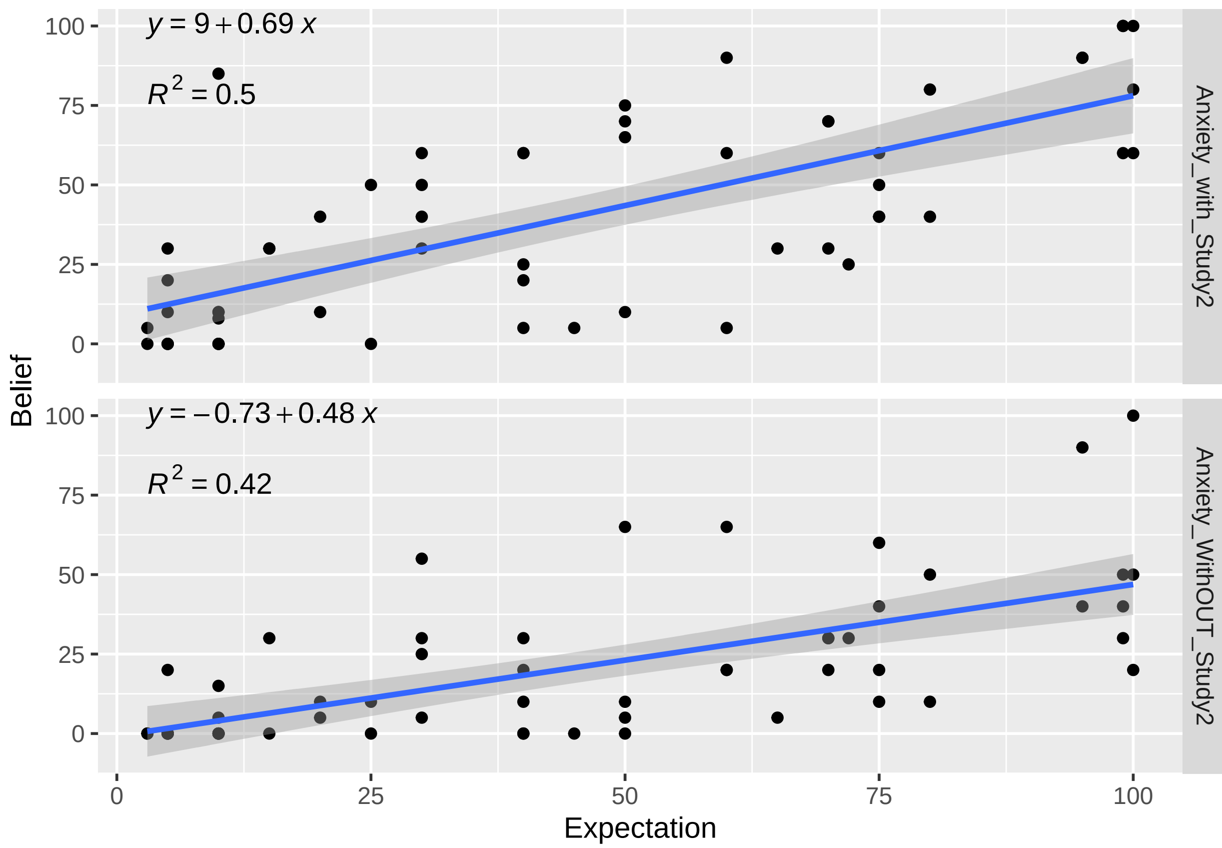
```
## # A tibble: 2 x 3
##   condition              cor_coef  p_value
##   <chr>                     <dbl>    <dbl>
## 1 Anxiety_with_Study2       0.709 6.74e-10
## 2 Anxiety_WithOUT_Study2    0.651 4.21e- 8
```

There is a strong correlation with belief across both conditions

Let's now plot the relationship between expectation and anxiety outcome across conditions

```
library(ggpubr)

pe_anx_merged %>%
  ggplot(aes(x = exp_value, y = belief_value)) +
  geom_point()+
  labs(x= "Expectation", y="Belief")+
  geom_smooth(method = lm) +
  facet_grid(rows = vars(condition)) +
    stat_regline_equation(label.y = 100, aes(label = ..eq.label..)) +
  stat_regline_equation(label.y = 80, aes(label = ..rr.label..))
```

```
## `geom_smooth()` using formula 'y ~ x'
```



This indicates a consistent relationship across conditions, perhaps with a stronger one for the without.

Now let's examine whether expectation moderates outcomes in lme for beliefs

```
mod_interaction_belief <- lmer(belief_value ~ exp_value*condition + (1|ID), data = pe_anx_merged)
summary(mod_interaction_belief )
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: belief_value ~ exp_value * condition + (1 | ID)
##    Data: pe_anx_merged
##
```

```
## REML criterion at convergence: 998
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.90362 -0.57817 -0.09038  0.47097  3.08702
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  ID       (Intercept) 161.7    12.72
##  Residual             258.8    16.09
## Number of obs: 114, groups:  ID, 57
##
## Fixed effects:
##                                           Estimate Std. Error       df t value
## (Intercept)                                8.95986    4.66397 95.83054   1.921
## exp_value                                  0.69095    0.08426 95.83054   8.201
## conditionAnxiety_WithOUT_Study2           -9.69445    5.17459 55.00000  -1.873
## exp_value:conditionAnxiety_WithOUT_Study2 -0.21459    0.09348 55.00000  -2.296
##                                           Pr(>|t|)
## (Intercept)                                 0.0577 .
## exp_value                                 1.08e-12 ***
## conditionAnxiety_WithOUT_Study2             0.0663 .
## exp_value:conditionAnxiety_WithOUT_Study2   0.0255 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) exp_vl cA_WOU
## exp_value   -0.813
## cnA_WOUT_S2 -0.555  0.451
## e_:A_WOUT_S  0.451 -0.555 -0.813
```

The interaction seems very weak.

Perhaps a simple additive model will be just fine, where expectation simply predicts

```
mod_additive_belief <- lmer(belief_value ~ exp_value + condition + (1|ID), data = pe_anx_merged)
anova(mod_additive_belief ,mod_interaction_belief )
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: pe_anx_merged
## Models:
## mod_additive_belief: belief_value ~ exp_value + condition + (1 | ID)
## mod_interaction_belief: belief_value ~ exp_value * condition + (1 | ID)
##                        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod_additive_belief       5 1014.3 1027.9 -502.13  1004.26
## mod_interaction_belief    6 1011.0 1027.5 -499.52   999.05 5.215  1    0.02239
##
## mod_additive_belief
## mod_interaction_belief *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The evidence of moderation seems pretty weak to me.

Now compare to a simple model with just condition

```
mod_simple_belief <- lmer(belief_value ~ condition + (1|ID), data = pe_anx_merged)
anova(mod_simple_belief, mod_additive_belief)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: pe_anx_merged
## Models:
## mod_simple_belief: belief_value ~ condition + (1 | ID)
## mod_additive_belief: belief_value ~ exp_value + condition + (1 | ID)
##                     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod_simple_belief      4 1058.7 1069.7 -525.37   1050.7
## mod_additive_belief    5 1014.3 1027.9 -502.13   1004.3 46.483  1  9.239e-12
##
## mod_simple_belief
## mod_additive_belief ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The additive model seems clearly superior. People's expectation seems to play an important role in anxiety outcome.

Conclusions

1. The experimental manipulation **impact all three of the following variables**:

- anxiety
- beliefs
- prediction error
- prediction, which I have termed *expectation* here to differentiate from PE.

2. The prediction error is minimally related to anxiety. **This makes it very unlikely that pe is a mediator of the relationship between experimental condition and anxiety as an outcome.**
3. Belief is fairly strongly related to anxiety in both experimental conditions. **This makes belief change a possible mediator of the relationship between experimental condition and anxiety** Although, because belief and anxiety are measured at the same time (and may be hard to measure separately from each other), it may be hard to exclude the possibility of reverse causality, or of a common third factor(s).
4. Expectation, that is, how people think at the beginning of the experiment seems to play an important for the outcomes of both anxiety and belief. The higher the expectation of outcome, the higher the change in both the outcomes across both conditions.

##Thoughts about the grant

I think that the manipulation in Eleanor's experiments are really powerful and I believe that we could make the most of them to be impactful with our grant application. Here are the main thoughts

1. Social Anxiety works really well as a treatment. This satisfies Wellcome's condition of having something that is efficacious and therefore worth understanding its mechanism of action.

2. Eleanor's experimental manipulation (and similar ones in adults I presume) are a powerful demonstration of the active ingredient that is self-focused attention, which is extremely important. It does not tell us what the responsible mechanism is for that active ingredient, which is part of what the point of this grant would be.

3. The above allow us to use and expand the experiment to test what the mechanisms are that underlie the effects of diverting self-focused attention. Because we have a good experimental set up (that we can further tweak), we shouldn't need to run new case series. We could establish this using the experimental set up, to which we bring interoception, MEG etc to bear upon.

4. I think that it would be great if we tried to create a similar experimental set up as above for depression and also test mechanisms in a similar way. It would follow on nicely for two reasons: first, because depression and anxiety are cross-sectionally and longitudinally comorbid; second, because there is prior evidence suggesting that self-focused attention is a potential mechanism in depression. Ideally, we should build something that involves mood or hedonic response and demonstrate the influence of self-focused attention (and any mechanisms we find) on it. One idea is that the mechanism that makes you socially anxious is the same as the one that makes you not appreciate/dislike something enjoyable.

5. By doing so, we will have a) isolated an active ingredient; b) shown its mechanisms; c) used it to make progress in another illness, depression, which is arguably more difficult. We could do all this without the need to do patient series, involve IAPT etc.

6. You may ask where all this leaves prediction errors. We could and should still include this as a mechanism but it won't be the sole candidate, but rather one of many. This would involve changing the title of the application too.

Some of Eleanor's OSCA data to see effects on depression and anxiety side by side

Load depression data

```
osca_dep_anx <- read.csv("~/argyris_code/Wellcom_Application_Active_Ingredients/OSCApremidpostscores.cs

View(osca_dep_anx )
```

```
efs <- osca_dep_anx %>%
  group_by(condition) %>%
  summarise(avg_lsas_post = mean(LSAS_post_total, na.rm = T), std_lsas_post = sd(LSAS_post_total, na.rm
sq_sd1 <- (efs$std_lsas_post[1])^2
sq_sd2 <- (efs$std_lsas_post[1])^2
effect_size_lsas = (efs$avg_lsas_post[1] - efs$avg_lsas_post[2])/sqrt((sq_sd1 +sq_sd2)/2)



effect_size_lsas
```

```
## [1] 2.018941
```

```
efs_mfq <- osca_dep_anx %>%
  group_by(condition) %>%
  summarise(avg_mfq_post = mean(SMFQ_post, na.rm = T), std_mfq_post = sd(SMFQ_post, na.rm = T))
```

```r
sq_sd1_mfq <- (efs_mfq$std_mfq_post[1])^2
sq_sd2_mfq <- (efs_mfq$std_mfq_post[1])^2
effect_size_mfq = (efs_mfq$avg_mfq_post[1] - efs_mfq$avg_mfq_post[2])/sqrt((sq_sd1_mfq +sq_sd2_mfq)/2)


effect_size_mfq
```

```
## [1] 1.227604
```

Create a long dataset too in order to do some plotting

```r
osca_dep_anx_long_anx <- osca_dep_anx %>%
  dplyr:: select(id, LSAS_B_Total, LSAS_M_Total, LSAS_post_total)

osca_dep_anx_long_anx <-osca_dep_anx_long_anx    %>%
  pivot_longer(cols = c("LSAS_B_Total", "LSAS_M_Total", "LSAS_post_total"),
               names_to = c("time_point"), values_to = c("lsas_values")) %>%
  as.data.frame()
head(osca_dep_anx_long_anx )
```

```
##       id      time_point lsas_values
## 1 110002    LSAS_B_Total         104
## 2 110002    LSAS_M_Total          84
## 3 110002 LSAS_post_total          77
## 4 110004    LSAS_B_Total         116
## 5 110004    LSAS_M_Total         102
## 6 110004 LSAS_post_total         104
```

```r
osca_dep_anx_long_dep <- osca_dep_anx %>%
  dplyr:: select(id, SMFQ_B, SMFQ_M, SMFQ_post,  response, condition)

osca_dep_anx_long_dep <-osca_dep_anx_long_dep    %>%
  pivot_longer(cols = c("SMFQ_B", "SMFQ_M", "SMFQ_post"),
               names_to = c("time_point"), values_to = c("mfq_values")) %>%
  as.data.frame()
head(osca_dep_anx_long_dep )
```

```
##       id response condition time_point mfq_values
## 1 110002        0         0     SMFQ_B         22
## 2 110002        0         0     SMFQ_M         21
## 3 110002        0         0  SMFQ_post         16
## 4 110004        0         0     SMFQ_B          8
## 5 110004        0         0     SMFQ_M          2
## 6 110004        0         0  SMFQ_post          5
```

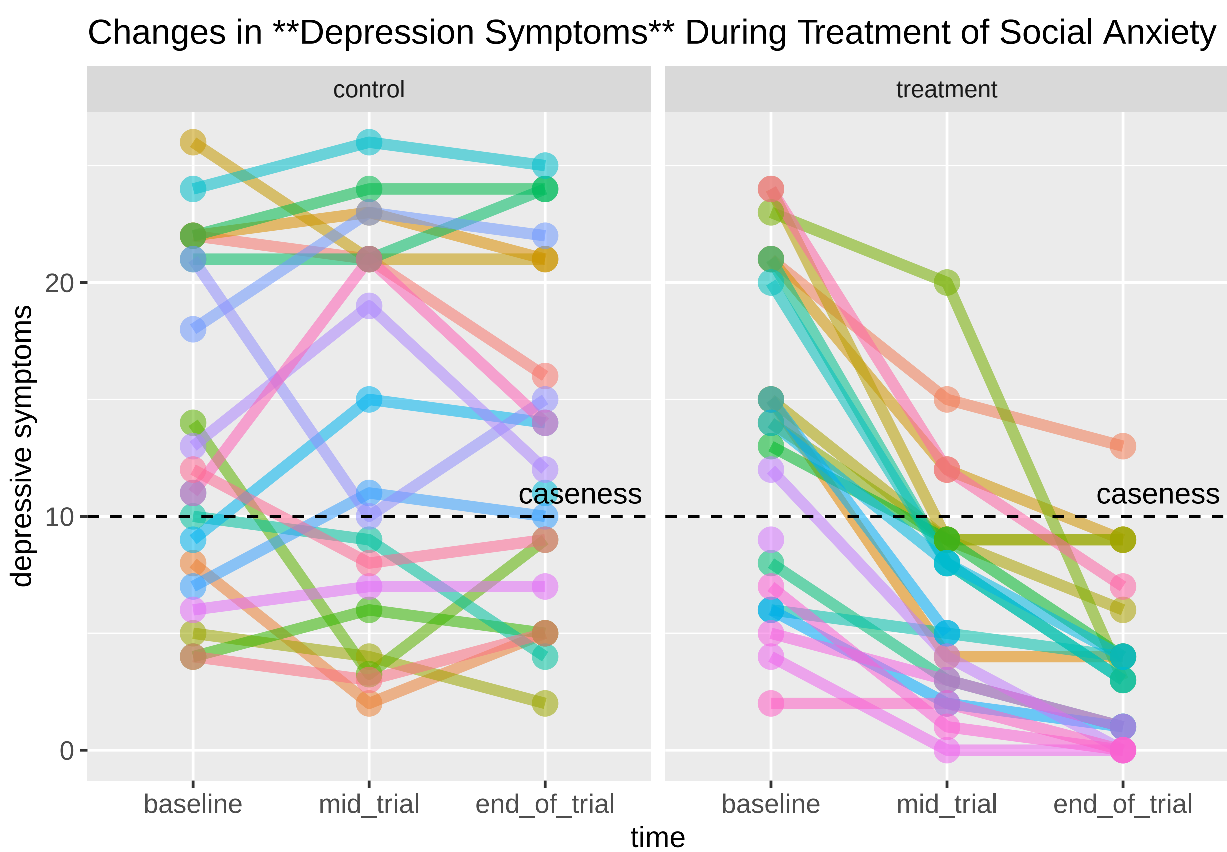
```r
osca_dep_anx_long <- cbind (osca_dep_anx_long_anx, osca_dep_anx_long_dep)
osca_dep_anx_long <- osca_dep_anx_long[-c(4, 7)]

osca_dep_anx_long$time_point <- factor(osca_dep_anx_long$time_point)
osca_dep_anx_long$condition <- factor(osca_dep_anx_long$condition)
```

```r
levels(osca_dep_anx_long$time_point) <- c('baseline', 'mid_trial', 'end_of_trial')
levels(osca_dep_anx_long$condition) <- c('control', 'treatment')

head(osca_dep_anx_long)
```

```
##       id   time_point lsas_values response condition mfq_values
## 1 110002     baseline         104        0   control         22
## 2 110002    mid_trial          84        0   control         21
## 3 110002 end_of_trial          77        0   control         16
## 4 110004     baseline         116        0   control          8
## 5 110004    mid_trial         102        0   control          2
## 6 110004 end_of_trial         104        0   control          5
```

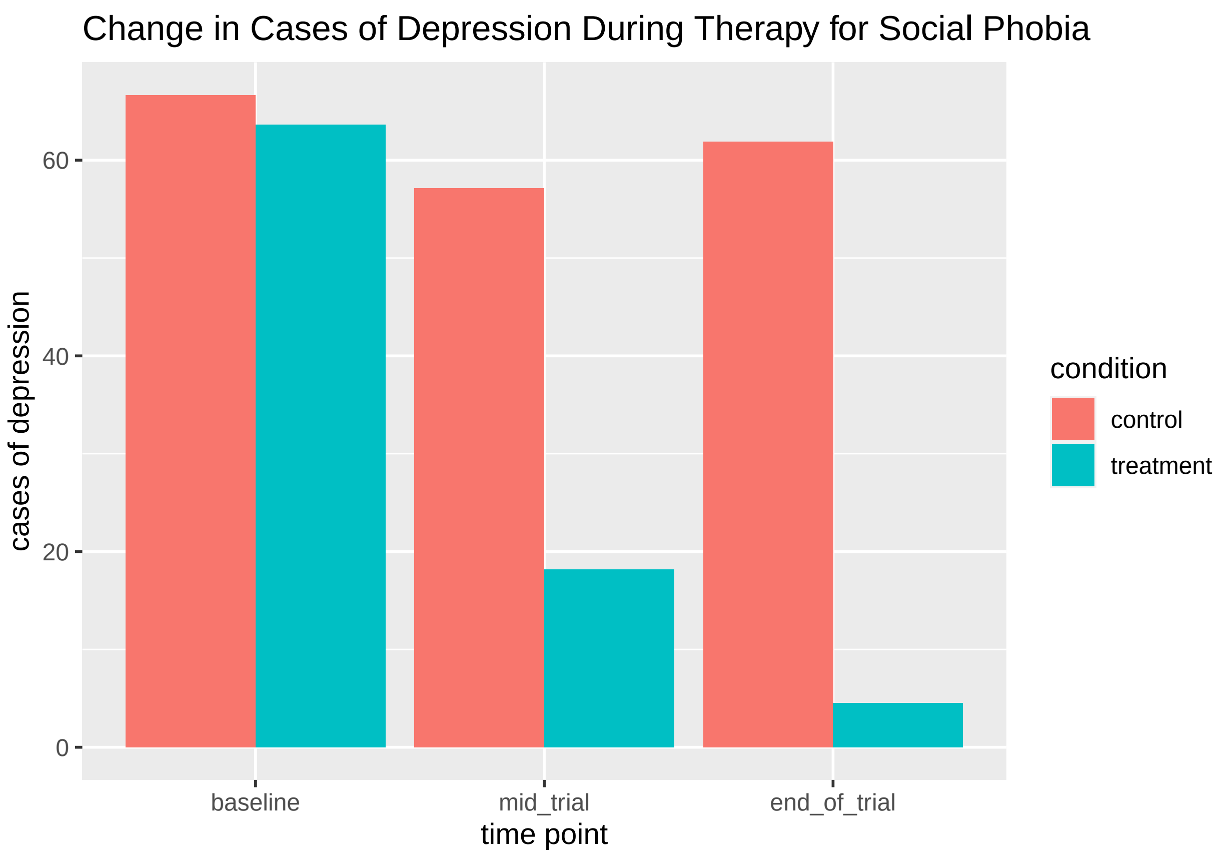
```
## Warning: Removed 3 row(s) containing missing values (geom_path).
```

```
## Warning: Removed 4 rows containing missing values (geom_point).
```




```r
osca_dep_anx_long <- osca_dep_anx_long %>%
  mutate(depression_case = ifelse(mfq_values >= 10, 1, 0))

percentages_depression <- osca_dep_anx_long %>%
  group_by(condition, time_point) %>%
  count(depression_case)
```

```r
percentages_depression <- percentages_depression %>%
  group_by(condition, time_point) %>%
mutate(perc = (n / sum(n, na.rm = TRUE)*100))  %>%
  as.data.frame()

percentages_depression %>%
  filter(depression_case == 1) %>%
ggplot(aes(x=time_point, y=perc, fill=condition)) +
  xlab("time point") + ylab("cases of depression") +
  ggtitle("Change in Cases of Depression During Therapy for Social Phobia")+
geom_bar(stat="identity",  position=position_dodge())#+
```

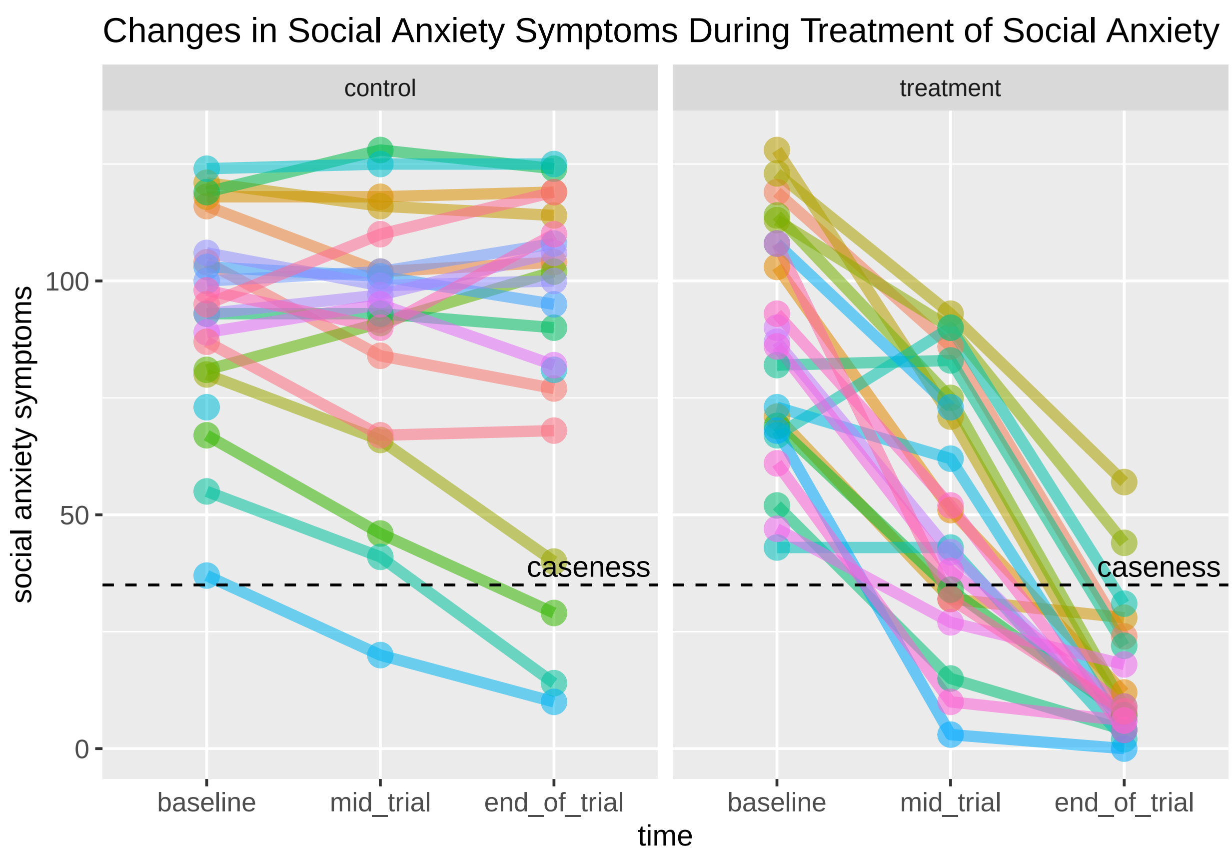



```r
  #theme_minimal()
```

```r
anx_change_plot <- ggplot(data = osca_dep_anx_long , aes(x = time_point , y = lsas_values, group = id, c
  geom_line( size = 2) +
  geom_point( size = 4) +
  xlab("time") + ylab("social anxiety symptoms") +
  ggtitle("Changes in Social Anxiety Symptoms During Treatment of Social Anxiety")
legend.position = "none"
anx_change_plot <- anx_change_plot+
  theme(legend.position = "none")
anx_change_plot <- anx_change_plot +
  facet_wrap(~ condition, ncol =2 )
anx_change_plot <- anx_change_plot + geom_hline(yintercept = 35, linetype = "dashed") +
```

```r
  annotate("text",x= 3.2,y=39,label="caseness") + coord_cartesian(ylim=c(0,130),clip="off")
anx_change_plot + theme(axis.text = element_text(size = 10))
```

```
## Warning: Removed 3 row(s) containing missing values (geom_path).

## Warning: Removed 4 rows containing missing values (geom_point).
```



Some analyses of individual studies from the review that Eleanor did from which Katie Cunningham-Rowe pulled out means and sds.

```r
soc_phobia_review <- read.csv("~/Downloads/soc_phobia_review.csv")

View(soc_phobia_review)
```

```r
### effect sizes between CT and Waitlist
soc_phobia_review_for_table_between <- soc_phobia_review %>%
  filter(time_point == "post") %>%
  mutate(es_between_dep_CT_WL =
           (dep_mean_CT - dep_mean_WL)
         /sqrt((dep_sd_CT^2 + dep_sd_WL^2))/2, es_between_sp_CT_WL =
           (sp_mean_CT - sp_mean_WL)
         /sqrt((sp_sd_CT^2 + sp_sd_WL^2))/2)
```

```
soc_phobia_review_for_table_between %>%
  dplyr:: select("name_study", "es_between_dep_CT_WL", "es_between_sp_CT_WL") %>%
  knitr::kable()
```

name_study	es_between_dep_CT_WL	es_between_sp_CT_WL
Clark2006	-0.5225143	-0.8867639
Clark2003	NA	NA
Stangier2003	-0.0777749	-0.1569708
Mortberg2006	NA	NA
Stangier2011	-0.1548009	-0.2842750
Leichsenring2013	-0.1545931	-0.3509754
Yoshinaga2016	NA	NA
Nordahl2016	NA	NA
Thew2022	NA	NA
Clark2022	NA	-0.4577928
Leigh2022	NA	NA
Ingul2014	NA	NA
Melfsen2011	-0.0666490	-0.2445035

do for young people

```
### effect sizes between CT and Waitlist
soc_phobia_review_Eleanor_between <- soc_phobia_review %>%
 filter(time_point == "post", name_study == "Leigh2022") %>%
  mutate(es_between_dep_CT_WL_Eleanor =
           (dep_mean_internet_CT - dep_mean_WL)
         /sqrt((dep_sd_internet_CT^2 + dep_sd_WL^2))/2,
         es_between_sp_CT_WL_Eleanor =
           (sp_mean_internet_CT - sp_mean_WL)
         /sqrt((sp_sd_internet_CT^2 + sp_sd_WL^2))/2)

soc_phobia_review_Eleanor_between %>%
  dplyr:: select("name_study", "es_between_dep_CT_WL_Eleanor", "es_between_sp_CT_WL_Eleanor") %>%
  knitr::kable()
```

name_study	es_between_dep_CT_WL_Eleanor	es_between_sp_CT_WL_Eleanor
Leigh2022	-0.6910453	-0.9279319

do for all internet thereapy

```
### effect sizes between CT and Waitlist
soc_phobia_review_internet_between <- soc_phobia_review %>%
 filter(time_point == "post") %>%
  mutate(es_between_dep_CT_WL_internet =
```

```
            (dep_mean_internet_CT - dep_mean_WL)
          /sqrt((dep_sd_internet_CT^2 + dep_sd_WL^2))/2,
          es_between_sp_CT_WL_internet =
            (sp_mean_internet_CT - sp_mean_WL)
          /sqrt((sp_sd_internet_CT^2 + sp_sd_WL^2))/2)

soc_phobia_review_internet_between %>%
  dplyr:: select("name_study", "es_between_dep_CT_WL_internet", "es_between_sp_CT_WL_internet") %>%
  knitr::kable()
```

name_study	es_between_dep_CT_WL_internet	es_between_sp_CT_WL_internet
Clark2006	NA	NA
Clark2003	NA	NA
Stangier2003	NA	NA
Mortberg2006	NA	NA
Stangier2011	NA	NA
Leichsenring2013	NA	NA
Yoshinaga2016	NA	NA
Nordahl2016	NA	NA
Thew2022	-0.3453342	-0.8469335
Clark2022	NA	-0.3909289
Leigh2022	-0.6910453	-0.9279319
Ingul2014	NA	NA
Melfsen2011	NA	NA

```
### effect sizes within CT for dep and SP
pre_df <- soc_phobia_review %>%
  filter(time_point == "pre")

post_df <- soc_phobia_review %>%
  filter(time_point == "post")

joined_pre_post_df <- data.frame(cbind(pre_df, post_df))
head(joined_pre_post_df)
```

```
##    X       name_study time_point age_range age_mean dep_measure dep_mean_CT
## 1 NA        Clark2006        pre               31.95         BDI       12.40
## 2 NA        Clark2003        pre               33.20         BDI       13.25
## 3 NA     Stangier2003        pre               38.80         BDI       15.50
## 4 NA     Mortberg2006        pre               34.60         BDI       11.80
## 5 NA     Stangier2011        pre               35.60        HRSD        8.11
## 6 NA Leichsenring2013        pre               35.23         BDI       14.78
##   dep_sd_CT dep_n_CT dep_mean_WL dep_sd_WL dep_n_WL dep_mean_TAU dep_sd_TAU
## 1      8.65       21       13.20      6.00       20           NA         NA
## 2      7.48       20          NA        NA       NA           NA         NA
## 3      9.10       NA       13.40      8.60       NA           NA         NA
## 4      8.00       32          NA        NA       NA         14.4         10
## 5      5.43       38        7.81      6.06       41           NA         NA
## 6      8.94      209       15.14      9.16       79           NA         NA
##   dep_n_TAU dep_mean_control_active dep_sd_control_active dep_n_control_active
## 1        NA                   16.85                 10.30                   21
```

```
## 2        NA                   12.75                  6.98                   20
## 3        NA                      NA                    NA                   NA
## 4        33                      NA                    NA                   NA
## 5        NA                    8.24                  5.93                   38
## 6        NA                   14.18                  9.93                  207
##   dep_mean_internet_CT dep_sd_internet_CT dep_n_internet_CT dep_mean_group_CT
## 1                   NA                 NA                NA                NA
## 2                   NA                 NA                NA                NA
## 3                   NA                 NA                NA              17.8
## 4                   NA                 NA                NA              11.8
## 5                   NA                 NA                NA                NA
## 6                   NA                 NA                NA                NA
##   dep_sd_group_CT dep_n_group_CT SP_measure sp_mean_CT sp_sd_CT sp_n_CT
## 1              NA             NA       LSAS      74.83    24.10      21
## 2              NA             NA       LSAS      78.65    25.56      20
## 3             9.3             NA       SPAI      80.90    12.00      NA
## 4             7.7             35       LSAS      81.80    21.10      32
## 5              NA             NA       LSAS      69.17    23.36      38
## 6              NA             NA       LSAS      72.06    22.39     209
##   sp_mean_WL sp_sd_WL sp_n_WL sp_mean_TAU sp_sd_TAU sp_n_TAU
## 1      77.91    22.48      20          NA        NA       NA
## 2         NA       NA      NA          NA        NA       NA
## 3      64.40    14.80      NA          NA        NA       NA
## 4         NA       NA      NA        71.8      23.5       33
## 5      62.75    26.76      41          NA        NA       NA
## 6      73.32    20.93      79          NA        NA       NA
##   sp_mean_active_control sp_sd_active_control sp_n_active_control
## 1                  78.70                23.70                  21
## 2                  75.34                17.63                  20
## 3                     NA                   NA                  NA
## 4                     NA                   NA                  NA
## 5                  68.35                22.60                  38
## 6                  73.26                22.13                 207
##   sp_mean_internet_CT sp_sd_internet_CT sp_n_internet_CT sp_mean_group_CT
## 1                  NA                NA               NA               NA
## 2                  NA                NA               NA               NA
## 3                  NA                NA               NA             77.6
## 4                  NA                NA               NA             68.1
## 5                  NA                NA               NA               NA
## 6                  NA                NA               NA               NA
##   sp_sd_group_CT sp_n_group_CT X.1 X.2         active_control_type X.3
## 1             NA            NA  NA  NA     Self exposure, waitlist  NA
## 2             NA            NA  NA  NA    Self exposure+Fluoxetine  NA
## 3           16.9            NA  NA  NA                              NA
## 4           20.9            35  NA  NA                              NA
## 5             NA            NA  NA  NA Interpersonal psychotherapy  NA
## 6             NA            NA  NA  NA       Psychodynamic therapy  NA
##       name_study.1 time_point.1 age_range.1 age_mean.1 dep_measure.1
## 1        Clark2006         post                  31.95           BDI
## 2        Clark2003         post                  33.20           BDI
## 3     Stangier2003         post                  38.80           BDI
## 4     Mortberg2006         post                  34.60           BDI
## 5     Stangier2011         post                  35.60          HRSD
## 6 Leichsenring2013         post                  35.23           BDI
```

```
##   dep_mean_CT.1 dep_sd_CT.1 dep_n_CT.1 dep_mean_WL.1 dep_sd_WL.1 dep_n_WL.1
## 1          2.57        3.93         21         10.25        6.21         20
## 2          4.70        5.60         20            NA          NA         NA
## 3         11.40        9.40         NA         13.30        7.80         NA
## 4          6.20        9.50         32            NA          NA         NA
## 5          5.43        5.74         38          8.03        6.13         41
## 6         10.40       10.98        209         15.37       11.74         79
##   dep_mean_TAU.1 dep_sd_TAU.1 dep_n_TAU.1 dep_mean_control_active.1
## 1             NA           NA          NA                      7.91
## 2             NA           NA          NA                      7.70
## 3             NA           NA          NA                     13.40
## 4             13         10.1          33                        NA
## 5             NA           NA          NA                      4.50
## 6             NA           NA          NA                     12.58
##   dep_sd_control_active.1 dep_n_control_active.1 dep_mean_internet_CT.1
## 1                   10.80                     21                     NA
## 2                    7.64                     20                     NA
## 3                    9.40                     NA                     NA
## 4                      NA                     NA                     NA
## 5                    4.00                     38                     NA
## 6                   12.40                    207                     NA
##   dep_sd_internet_CT.1 dep_n_internet_CT.1 dep_mean_group_CT.1
## 1                   NA                  NA                  NA
## 2                   NA                  NA                  NA
## 3                   NA                  NA                13.4
## 4                   NA                  NA                11.8
## 5                   NA                  NA                  NA
## 6                   NA                  NA                  NA
##   dep_sd_group_CT.1 dep_n_group_CT.1 SP_measure.1 sp_mean_CT.1 sp_sd_CT.1
## 1                NA               NA         LSAS        28.00      17.71
## 2                NA               NA         LSAS        35.41      22.90
## 3               9.4               NA         SPAI        59.90      20.00
## 4               7.7               35         LSAS        51.30      27.90
## 5                NA               NA         LSAS        39.49      21.09
## 6                NA               NA         LSAS        42.94      25.41
##   sp_n_CT.1 sp_mean_WL.1 sp_sd_WL.1 sp_n_WL.1 sp_mean_TAU.1 sp_sd_TAU.1
## 1        21        77.21      21.36        20            NA          NA
## 2        20           NA         NA        NA            NA          NA
## 3        NA        68.00      16.30        NA            NA          NA
## 4        32           NA         NA        NA          65.5        25.7
## 5        38        59.90      29.05        41            NA          NA
## 6       209        68.13      25.34        79            NA          NA
##   sp_n_TAU.1 sp_mean_active_control.1 sp_sd_active_control.1
## 1         NA                    52.32                  33.89
## 2         NA                    56.16                  30.61
## 3         NA                       NA                     NA
## 4         33                       NA                     NA
## 5         NA                    48.16                  22.36
## 6         NA                    50.70                  27.49
##   sp_n_active_control.1 sp_mean_internet_CT.1 sp_sd_internet_CT.1
## 1                    21                    NA                  NA
## 2                    19                    NA                  NA
## 3                    NA                    NA                  NA
## 4                    NA                    NA                  NA
```

```
## 5                    38                     NA                   NA
## 6                   207                     NA                   NA
##   sp_n_internet_CT.1 sp_mean_group_CT.1 sp_sd_group_CT.1 sp_n_group_CT.1 X.1.1
## 1                 NA                 NA               NA              NA    NA
## 2                 NA                 NA               NA              NA    NA
## 3                 NA               67.5             16.8              NA    NA
## 4                 NA               52.5             19.4              35    NA
## 5                 NA                 NA               NA              NA    NA
## 6                 NA                 NA               NA              NA    NA
##   X.2.1       active_control_type.1
## 1    NA      Self exposure, waitlist
## 2    NA    Self exposure+Fluoxetine
## 3    NA
## 4    NA
## 5    NA Interpersonal psychotherapy
## 6    NA        Psychodynamic therapy
```

```
joined_pre_post_df <- joined_pre_post_df %>%

  mutate(es_within_mean_dep_CT = (dep_mean_CT - dep_mean_CT.1)/((dep_sd_CT + dep_sd_CT.1)/2),

         es_within_mean_sp_CT = (sp_mean_CT - sp_mean_CT.1)/((sp_sd_CT + sp_sd_CT.1)/2))



joined_pre_post_df %>%
  dplyr:: select("name_study", "es_within_mean_dep_CT", "es_within_mean_sp_CT") %>%
  knitr::kable()
```

name_study	es_within_mean_dep_CT	es_within_mean_sp_CT
Clark2006	1.5627981	2.240134
Clark2003	1.3073394	1.784565
Stangier2003	0.4432432	1.312500
Mortberg2006	0.6400000	1.244898
Stangier2011	0.4798568	1.335433
Leichsenring2013	0.4397590	1.218410
Yoshinaga2016	1.0363636	1.003559
Nordahl2016	NA	1.466381
Thew2022	NA	NA
Clark2022	2.7950000	1.418367
Leigh2022	NA	NA
Ingul2014	1.6679189	3.024741
Melfsen2011	0.2272442	1.487775

```
### effect sizes within CT for dep and SP YOUNG PEOPLE
pre_df <- soc_phobia_review %>%
  filter(time_point == "pre")

post_df <- soc_phobia_review %>%
  filter(time_point == "post")
```

```r
joined_pre_post_df <- data.frame(cbind(pre_df, post_df))
head(joined_pre_post_df)
```

```
##    X       name_study time_point age_range age_mean dep_measure dep_mean_CT
## 1 NA        Clark2006        pre               31.95         BDI       12.40
## 2 NA        Clark2003        pre               33.20         BDI       13.25
## 3 NA     Stangier2003        pre               38.80         BDI       15.50
## 4 NA     Mortberg2006        pre               34.60         BDI       11.80
## 5 NA     Stangier2011        pre               35.60        HRSD        8.11
## 6 NA Leichsenring2013        pre               35.23         BDI       14.78
##   dep_sd_CT dep_n_CT dep_mean_WL dep_sd_WL dep_n_WL dep_mean_TAU dep_sd_TAU
## 1      8.65       21       13.20      6.00       20           NA         NA
## 2      7.48       20          NA        NA       NA           NA         NA
## 3      9.10       NA       13.40      8.60       NA           NA         NA
## 4      8.00       32          NA        NA       NA         14.4         10
## 5      5.43       38        7.81      6.06       41           NA         NA
## 6      8.94      209       15.14      9.16       79           NA         NA
##   dep_n_TAU dep_mean_control_active dep_sd_control_active dep_n_control_active
## 1        NA                   16.85                 10.30                   21
## 2        NA                   12.75                  6.98                   20
## 3        NA                      NA                    NA                   NA
## 4        33                      NA                    NA                   NA
## 5        NA                    8.24                  5.93                   38
## 6        NA                   14.18                  9.93                  207
##   dep_mean_internet_CT dep_sd_internet_CT dep_n_internet_CT dep_mean_group_CT
## 1                   NA                 NA                NA                NA
## 2                   NA                 NA                NA                NA
## 3                   NA                 NA                NA              17.8
## 4                   NA                 NA                NA              11.8
## 5                   NA                 NA                NA                NA
## 6                   NA                 NA                NA                NA
##   dep_sd_group_CT dep_n_group_CT SP_measure sp_mean_CT sp_sd_CT sp_n_CT
## 1              NA             NA       LSAS      74.83    24.10      21
## 2              NA             NA       LSAS      78.65    25.56      20
## 3             9.3             NA       SPAI      80.90    12.00      NA
## 4             7.7             35       LSAS      81.80    21.10      32
## 5              NA             NA       LSAS      69.17    23.36      38
## 6              NA             NA       LSAS      72.06    22.39     209
##   sp_mean_WL sp_sd_WL sp_n_WL sp_mean_TAU sp_sd_TAU sp_n_TAU
## 1      77.91    22.48      20          NA        NA       NA
## 2         NA       NA      NA          NA        NA       NA
## 3      64.40    14.80      NA          NA        NA       NA
## 4         NA       NA      NA        71.8      23.5       33
## 5      62.75    26.76      41          NA        NA       NA
## 6      73.32    20.93      79          NA        NA       NA
##   sp_mean_active_control sp_sd_active_control sp_n_active_control
## 1                  78.70                23.70                  21
## 2                  75.34                17.63                  20
## 3                     NA                   NA                  NA
## 4                     NA                   NA                  NA
## 5                  68.35                22.60                  38
## 6                  73.26                22.13                 207
##   sp_mean_internet_CT sp_sd_internet_CT sp_n_internet_CT sp_mean_group_CT
```

```
## 1                  NA                 NA                NA                NA
## 2                  NA                 NA                NA                NA
## 3                  NA                 NA                NA              77.6
## 4                  NA                 NA                NA              68.1
## 5                  NA                 NA                NA                NA
## 6                  NA                 NA                NA                NA
##   sp_sd_group_CT sp_n_group_CT X.1 X.2         active_control_type X.3
## 1             NA            NA  NA  NA     Self exposure, waitlist  NA
## 2             NA            NA  NA  NA    Self exposure+Fluoxetine  NA
## 3           16.9            NA  NA  NA                              NA
## 4           20.9            35  NA  NA                              NA
## 5             NA            NA  NA  NA Interpersonal psychotherapy  NA
## 6             NA            NA  NA  NA       Psychodynamic therapy  NA
##       name_study.1 time_point.1 age_range.1 age_mean.1 dep_measure.1
## 1        Clark2006         post                  31.95           BDI
## 2        Clark2003         post                  33.20           BDI
## 3     Stangier2003         post                  38.80           BDI
## 4     Mortberg2006         post                  34.60           BDI
## 5     Stangier2011         post                  35.60          HRSD
## 6 Leichsenring2013         post                  35.23           BDI
##   dep_mean_CT.1 dep_sd_CT.1 dep_n_CT.1 dep_mean_WL.1 dep_sd_WL.1 dep_n_WL.1
## 1          2.57        3.93         21         10.25        6.21         20
## 2          4.70        5.60         20            NA          NA         NA
## 3         11.40        9.40         NA         13.30        7.80         NA
## 4          6.20        9.50         32            NA          NA         NA
## 5          5.43        5.74         38          8.03        6.13         41
## 6         10.40       10.98        209         15.37       11.74         79
##   dep_mean_TAU.1 dep_sd_TAU.1 dep_n_TAU.1 dep_mean_control_active.1
## 1             NA           NA          NA                      7.91
## 2             NA           NA          NA                      7.70
## 3             NA           NA          NA                     13.40
## 4             13         10.1          33                        NA
## 5             NA           NA          NA                      4.50
## 6             NA           NA          NA                     12.58
##   dep_sd_control_active.1 dep_n_control_active.1 dep_mean_internet_CT.1
## 1                   10.80                     21                     NA
## 2                    7.64                     20                     NA
## 3                    9.40                     NA                     NA
## 4                      NA                     NA                     NA
## 5                    4.00                     38                     NA
## 6                   12.40                    207                     NA
##   dep_sd_internet_CT.1 dep_n_internet_CT.1 dep_mean_group_CT.1
## 1                   NA                  NA                  NA
## 2                   NA                  NA                  NA
## 3                   NA                  NA                13.4
## 4                   NA                  NA                11.8
## 5                   NA                  NA                  NA
## 6                   NA                  NA                  NA
##   dep_sd_group_CT.1 dep_n_group_CT.1 SP_measure.1 sp_mean_CT.1 sp_sd_CT.1
## 1                NA               NA         LSAS        28.00      17.71
## 2                NA               NA         LSAS        35.41      22.90
## 3               9.4               NA         SPAI        59.90      20.00
## 4               7.7               35         LSAS        51.30      27.90
## 5                NA               NA         LSAS        39.49      21.09
```

```
## 6               NA               NA         LSAS        42.94      25.41
##   sp_n_CT.1 sp_mean_WL.1 sp_sd_WL.1 sp_n_WL.1 sp_mean_TAU.1 sp_sd_TAU.1
## 1        21        77.21      21.36        20            NA          NA
## 2        20           NA         NA        NA            NA          NA
## 3        NA        68.00      16.30        NA            NA          NA
## 4        32           NA         NA        NA          65.5        25.7
## 5        38        59.90      29.05        41            NA          NA
## 6       209        68.13      25.34        79            NA          NA
##   sp_n_TAU.1 sp_mean_active_control.1 sp_sd_active_control.1
## 1         NA                    52.32                  33.89
## 2         NA                    56.16                  30.61
## 3         NA                       NA                     NA
## 4         33                       NA                     NA
## 5         NA                    48.16                  22.36
## 6         NA                    50.70                  27.49
##   sp_n_active_control.1 sp_mean_internet_CT.1 sp_sd_internet_CT.1
## 1                    21                    NA                  NA
## 2                    19                    NA                  NA
## 3                    NA                    NA                  NA
## 4                    NA                    NA                  NA
## 5                    38                    NA                  NA
## 6                   207                    NA                  NA
##   sp_n_internet_CT.1 sp_mean_group_CT.1 sp_sd_group_CT.1 sp_n_group_CT.1 X.1.1
## 1                 NA                 NA               NA              NA    NA
## 2                 NA                 NA               NA              NA    NA
## 3                 NA               67.5             16.8              NA    NA
## 4                 NA               52.5             19.4              35    NA
## 5                 NA                 NA               NA              NA    NA
## 6                 NA                 NA               NA              NA    NA
##   X.2.1       active_control_type.1
## 1    NA     Self exposure, waitlist
## 2    NA    Self exposure+Fluoxetine
## 3    NA
## 4    NA
## 5    NA Interpersonal psychotherapy
## 6    NA       Psychodynamic therapy
```

```
joined_pre_post_df_Eleanor <- joined_pre_post_df %>%
  mutate(es_within_mean_dep_CT = (dep_mean_internet_CT - dep_mean_internet_CT.1)/((dep_sd_internet_CT + 

         es_within_mean_sp_CT = (sp_mean_internet_CT - sp_mean_internet_CT.1)/((sp_sd_internet_CT + sp_


joined_pre_post_df_Eleanor %>%
  dplyr:: select("name_study", "es_within_mean_dep_CT", "es_within_mean_sp_CT") %>%
  filter(name_study == "Leigh2022") %>%
  knitr::kable()
```

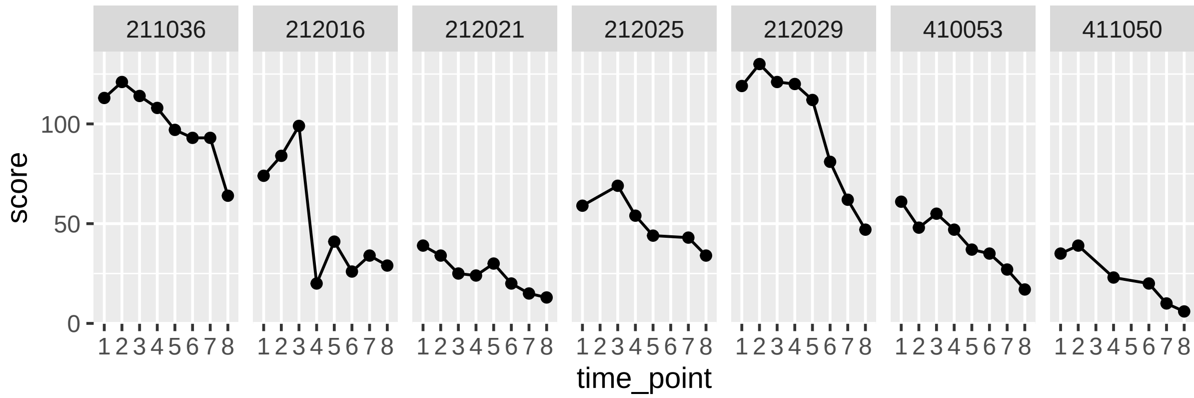
name_study	es_within_mean_dep_CT	es_within_mean_sp_CT
Leigh2022	2.42756	3.522918

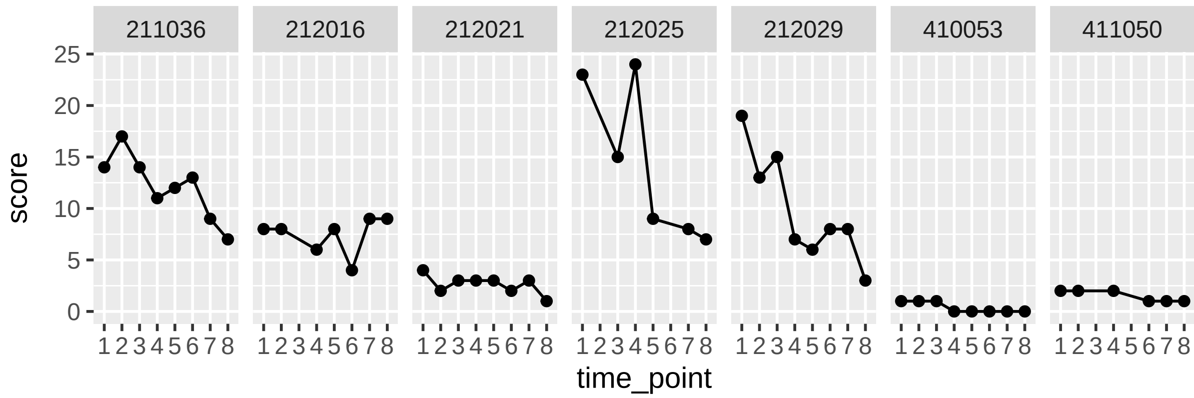
look at the per session data for social phobia

```
mfqlsas_sessional_osca <- read.csv("~/argyris_code/Wellcom_Application_Active_Ingredients/mfqlsas_sessio
   View(mfqlsas_sessional_osca)
```

Random Invididual Cases

```
mfqlsas_sessional_osca_long <- mfqlsas_sessional_osca


mfqlsas_sessional_osca_long <-mfqlsas_sessional_osca_long   %>%
  pivot_longer(
    cols = !ID,
    names_to = c("measure", "time_point"),
    names_sep = "_",
    values_to = "score"
  )



treated_ids <- osca_dep_anx$id[osca_dep_anx$condition==1]

for_plotting <- mfqlsas_sessional_osca_long %>%
  drop_na() %>%
  filter(ID %in% treated_ids)



for_plotting_ids <- sample(for_plotting$ID, 8)

plot_three_sub_lsas <- for_plotting %>%
  filter(ID %in% for_plotting_ids, time_point %in% seq(1:8), measure == "lsas") %>%
  ggplot(aes(x = time_point, y = score, group = ID)) +
  geom_point()+
  geom_line ()+
  facet_grid(~ID)

plot_three_sub_mfq <- for_plotting %>%
  filter(ID %in% for_plotting_ids, time_point %in% seq(1:8), measure == "mfq") %>%
  ggplot(aes(x = time_point, y = score, group = ID)) +
  geom_point()+
  geom_line ()+
  facet_grid(~ID)

plot_three_sub_lsas / plot_three_sub_mfq
```





Average over time

```
sum_stats_by_session_lsas <- mfqlsas_sessional_osca_long %>%
  filter(measure == "lsas", time_point %in% 0:14) %>%
  group_by(time_point) %>%
  summarise(avg_lsas = mean(score, na.rm = TRUE), std_lsas = sd(score, na.rm = TRUE),
            n = n(),
            se = std_lsas/sqrt(n))

sum_stats_by_session_lsas  <-sum_stats_by_session_lsas [order(as.numeric(as.character(sum_stats_by_sess

sum_stats_by_session_lsas
```

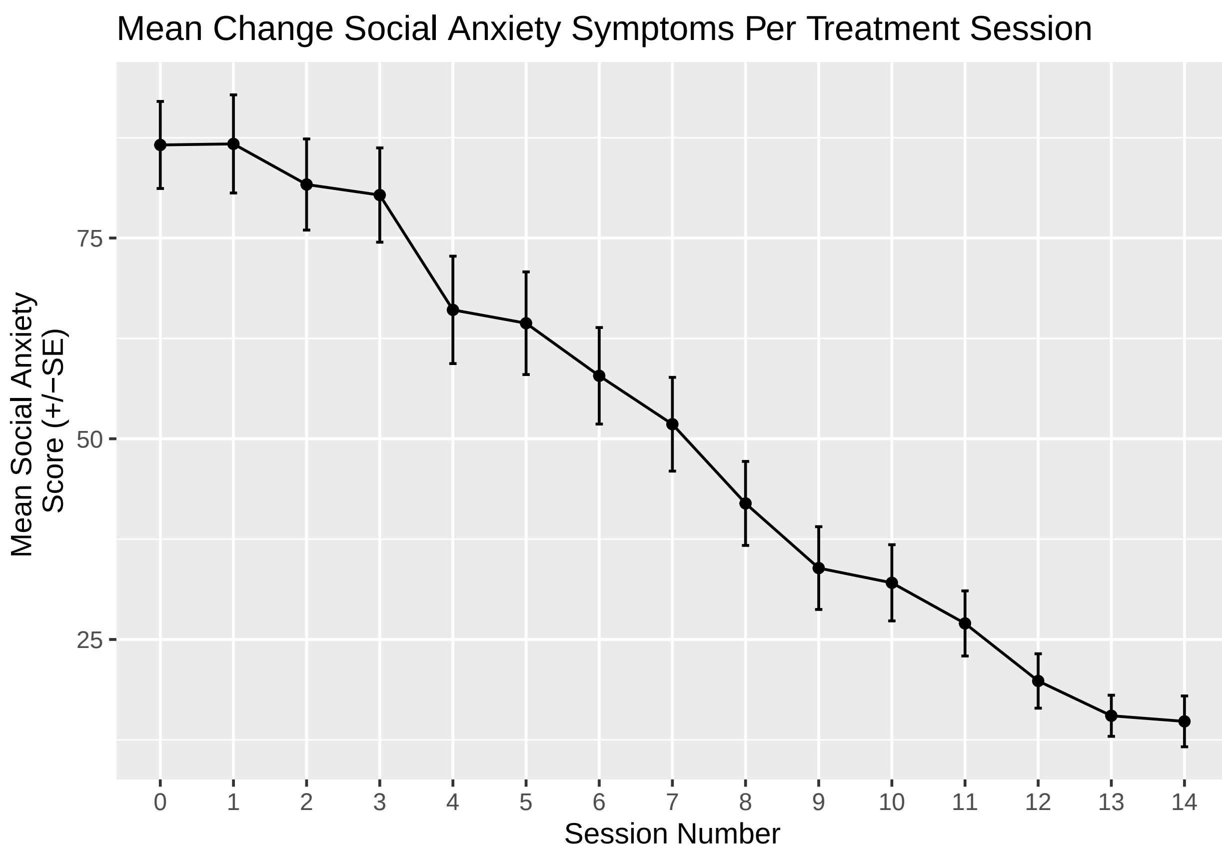
```
## # A tibble: 15 x 5
##    time_point avg_lsas std_lsas     n    se
##    <chr>         <dbl>    <dbl> <int> <dbl>
##  1 0              86.6     25.4    22  5.42
##  2 1              86.7     28.7    22  6.11
##  3 2              81.7     26.6    22  5.67
##  4 3              80.4     27.5    22  5.87
##  5 4              66.0     31.4    22  6.69
##  6 5              64.4     30.0    22  6.39
##  7 6              57.8     28.2    22  6.01
##  8 7              51.8     27.4    22  5.84
##  9 8              41.9     24.5    22  5.23
## 10 9              33.9     24.2    22  5.15
```

```
## 11 10             32.1     22.3    22  4.74
## 12 11             27       19.0    22  4.06
## 13 12             19.8     15.9    22  3.39
## 14 13             15.5     12.0    22  2.56
## 15 14             14.8     14.8    22  3.17
```

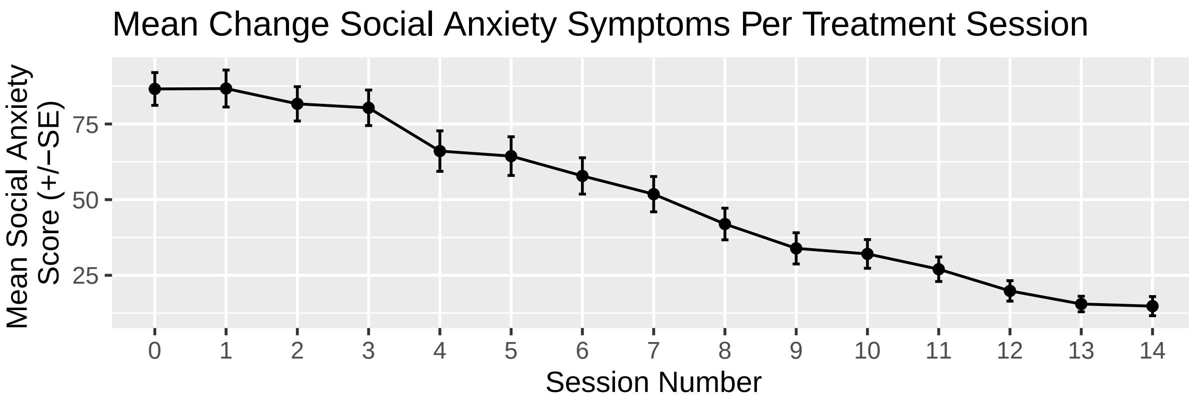
```
sum_stats_by_session_mfq <- mfqlsas_sessional_osca_long %>%
  filter(measure == "mfq", time_point %in% 0:14) %>%
  group_by(time_point) %>%
  summarise(avg_mfq = mean(score, na.rm = TRUE), std_mfq = sd(score, na.rm = TRUE),
            n = n(),
            se = std_mfq/sqrt(n))

sum_stats_by_session_mfq  <-sum_stats_by_session_mfq [order(as.numeric(as.character(sum_stats_by_sessio

sum_stats_by_session_mfq
```

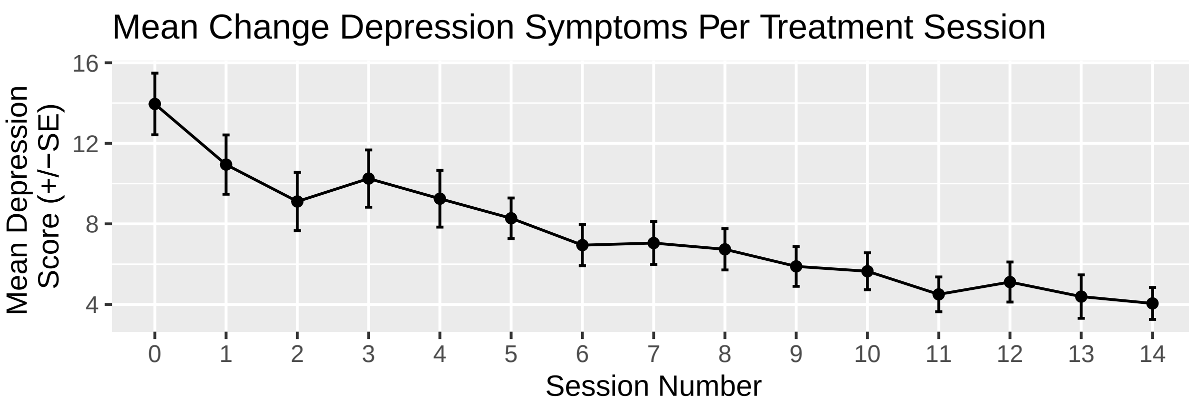
```
## # A tibble: 15 x 5
##    time_point avg_mfq std_mfq     n    se
##    <chr>        <dbl>   <dbl> <int> <dbl>
##  1 0            14.0     7.18    22 1.53
##  2 1            10.9     6.91    22 1.47
##  3 2             9.11    6.81    22 1.45
##  4 3            10.2     6.67    22 1.42
##  5 4             9.25    6.62    22 1.41
##  6 5             8.28    4.73    22 1.01
##  7 6             6.94    4.80    22 1.02
##  8 7             7.05    4.97    22 1.06
##  9 8             6.74    4.81    22 1.02
## 10 9             5.89    4.64    22 0.989
## 11 10            5.65    4.30    22 0.917
## 12 11            4.5     4.05    22 0.863
## 13 12            5.11    4.66    22 0.994
## 14 13            4.39    5.05    22 1.08
## 15 14            4.05    3.72    22 0.793
```

```
mean_plot_lsas <- ggplot(sum_stats_by_session_lsas, aes(x=reorder(time_point, 0:14), y=avg_lsas, group
    geom_errorbar(aes(ymin=avg_lsas-se, ymax=avg_lsas+se), width=.1) +
    geom_line() +
    geom_point() +
    ggtitle("Mean Change Social Anxiety Symptoms Per Treatment Session")+
  ylab("Mean Social Anxiety \nScore (+/-SE)") +
  xlab("Session Number")


mean_plot_lsas
```




```
mean_plot_mfq <- ggplot(sum_stats_by_session_mfq, aes(x=reorder(time_point, 0:14), y=avg_mfq, group = "
    geom_errorbar(aes(ymin=avg_mfq-se, ymax=avg_mfq+se), width=.1) +
    geom_line() +
    geom_point() +
  ggtitle("Mean Change Depression Symptoms Per Treatment Session")+
  ylab("Mean Depression \nScore (+/-SE)") +
  xlab("Session Number")

mean_plot_lsas /
  mean_plot_mfq
```






```
mean_plot_lsas <- ggplot(sum_stats_by_session_mfq, aes(x=reorder(time_point, seq(1:12)), y=avg_lsas, gr
    geom_errorbar(aes(ymin=avg_lsas-se, ymax=avg_lsas+se), width=.1) +
    geom_line() +
    geom_point()
```

draw overlappin distributions

```
df <- data.frame(soc_anx=rnorm(10000, mean=1, sd=1),
                 dep=rnorm(10000, mean=2, sd=1))

head(df)
```

```
##      soc_anx       dep
## 1  1.3608784 0.5269567
## 2 -0.2127724 0.1141096
## 3  2.6521084 1.9940512
## 4  1.1648030 0.9561695
## 5  0.1292033 2.9363719
## 6  0.1146017 1.8852735
```

```
library(reshape)
```

```
##
## Attaching package: 'reshape'
```

```
## The following object is masked from 'package:Matrix':
##
##     expand

## The following object is masked from 'package:dplyr':
##
##     rename

## The following objects are masked from 'package:tidyr':
##
##     expand, smiths
```

```r
#convert from wide format to long format
data <- melt(df)
```

```
## Using  as id variables
```

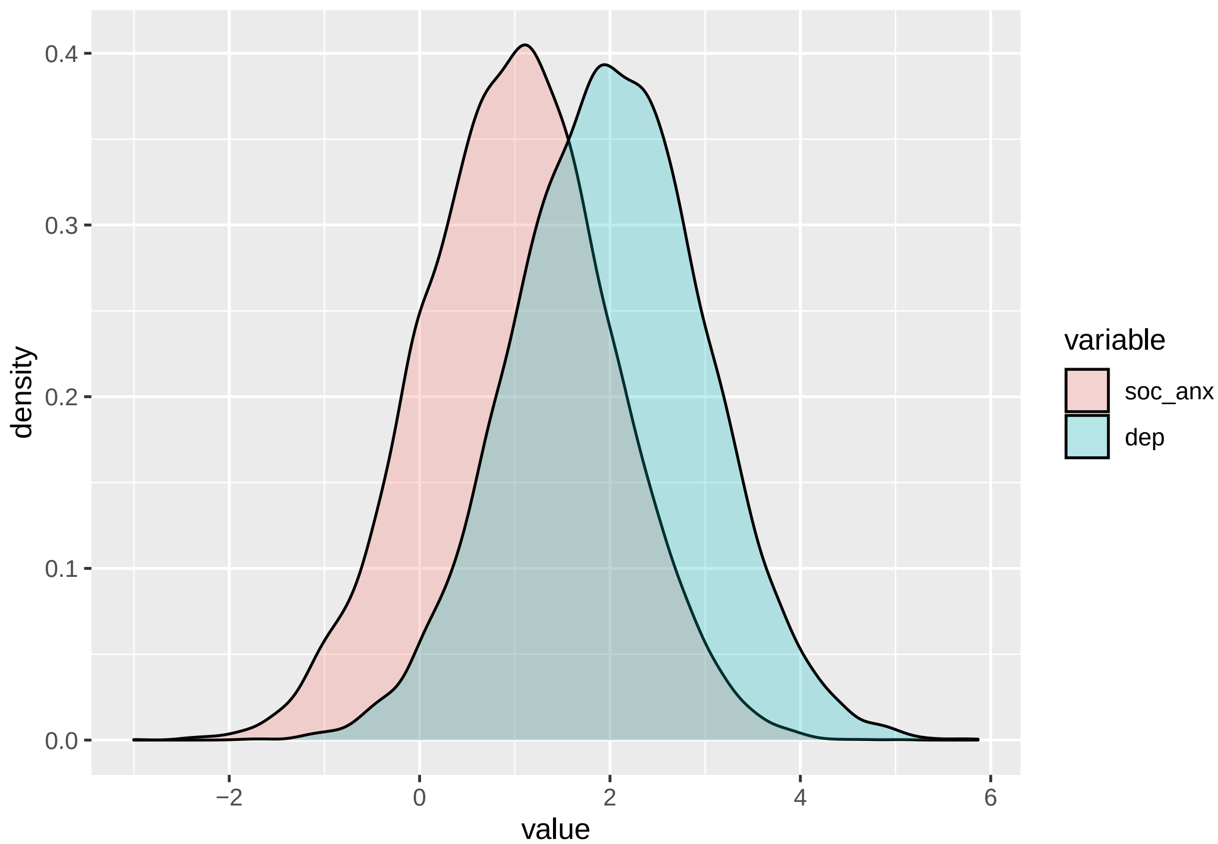
```r
head(data)
```

```
##   variable      value
## 1  soc_anx  1.3608784
## 2  soc_anx -0.2127724
## 3  soc_anx  2.6521084
## 4  soc_anx  1.1648030
## 5  soc_anx  0.1292033
## 6  soc_anx  0.1146017
```

```r
tail(data)
```

```
##       variable    value
## 19995      dep 1.273461
## 19996      dep 1.748631
## 19997      dep 2.800592
## 19998      dep 1.018225
## 19999      dep 1.915212
## 20000      dep 1.097792
```

```r
ggplot(data, aes(x=value, fill=variable)) +
  geom_density(alpha=.25)
```




```r
# pred_err_metanalysis <- read.csv("~/Downloads/All_Included_Contrasts (1).csv")
# pred_err_metanalysis$OutcomeType
#
# pred_err_metanalysis %>%
#   count(OutcomeType)
#
#
# pred_err_metanalysis %>%
#   count(OutcomeType) %>%
#
#
# study_freq_by_outcome <- pred_err_metanalysis %>%
#   group_by(OutcomeType) %>%
#   summarise(cnt = n()) %>%
#   mutate(freq = round(cnt / sum(cnt), 3)) %>%
#   arrange(desc(freq))
#
# study_freq_by_outcome
```