

Thesis Script: Motivated Responses to a Masculinity Threat in a German Cultural Context

2025-11-30

```
df <- read.csv(here("data", "fragile_masculinity_motivation_anonymized.csv"))
df <- preprocessData(df, all_items)
```

```
## Number of Observations: 193
## Condition threat: 99 participants
## Condition noThreat: 94 participants
```

1. Study Inclusion Criteria

1.1 Debrief Consent

Participants that withdrew their consent after the debrief are excluded

```
df <- exclude_participants(
  df,
  DEBRIEFCONSENT == "Y",
  vars = "DEBRIEFCONSENT",
  description = "Debrief consent"
)
```

```
## Debrief consent: Excluded 8 participants (8 of 193).
## Remaining: 185
## Excluded responses summary for `DEBRIEFCONSENT`:  DEBRIEFCONSENT n
## 1                N 8
```

1.2 Demographic criteria

Participants have to be older than 18 years, self-identify as male and native level German skills

```
df <- exclude_participants(df, AGE >= 18, vars = "AGE", description = "Age")
```

```
## Age: Excluded 3 participants (3 of 185).
## Remaining: 182
## Excluded responses summary for `AGE`:  AGE n
## 1    0 1
## 2    3 1
## 3   12 1
```

```
df <- exclude_participants(df, SEX == "A001", vars = "SEX", description = "Gender")
```

```
## Gender: Excluded 9 participants (9 of 182).
## Remaining: 173
## Excluded responses summary for `SEX`:  SEX n
## 1 A002 7
## 2 A004 2
```

```
df <- exclude_participants(df, GER %in% c("A004", "A005"), vars = "GER", description = "German skills")
```

```
## German skills: Excluded 1 participants (1 of 173).
## Remaining: 172
## Excluded responses summary for `GER`:  GER n
## 1 A003 1
```

1.3 Suspicion

Participants may not indicate a strong suspicion about the study (coded in column SUSPICIONEXCLUSION, free text are excluded in anonymous data set)

```
df <- exclude_participants(
  df,
  SUSPICIONEXCLUSION == FALSE,
  vars = "SUSPICIONEXCLUSION",
  description = "Suspicion"
)
```

```
## Suspicion: Excluded 9 participants (9 of 172).
## Remaining: 163
## Excluded responses summary for `SUSPICIONEXCLUSION`:  SUSPICIONEXCLUSION n
## 1                TRUE 9
```

1.4 WFCT comprehension

Participants should complete more than 50% of word fragments with existing words

```
df <- exclude_participants(
  df,
  validWordCompletionScore >= 0.5,
  vars = "validWordCompletionScore",
  description = "WFCT comprehension"
)
```

```
## WFCT comprehension: Excluded 10 participants (10 of 163).
## Remaining: 153
## Excluded responses summary for `validWordCompletionScore`:  validWordCompletionScore n
## 1                0.00 6
## 2                0.40 2
## 3                0.05 1
## 4                0.15 1
```

1.5 Responses to Motivation for Masculine Behaviour

Participants should respond to at least one item of each MMB scale

```
df <- exclude_participants(
  df,
  rowSums(!is.na(df[mmb_pressured_items])) >= 1,
  vars = mmb_pressured_items,
  description = "Missing all Pressured items"
)
```

```
## Missing all Pressured items: Excluded 1 participants (1 of 153).
## Remaining: 152
## Excluded responses summary for `MMBi1`: MMBi1 n
## 1      NA 1
##
## Excluded responses summary for `MMBi2`: MMBi2 n
## 1      NA 1
##
## Excluded responses summary for `MMBi3`: MMBi3 n
## 1      NA 1
##
## Excluded responses summary for `MMBi4`: MMBi4 n
## 1      NA 1
##
## Excluded responses summary for `MMBi5`: MMBi5 n
## 1      NA 1
```

```
df <- exclude_participants(
  df,
  rowSums(!is.na(df[mmb_autonomous_items])) >= 1,
  vars = mmb_autonomous_items,
  description = "Missing all Autonomous items"
)
```

```
## Missing all Autonomous items: Excluded 0 participants (0 of 152).
## Remaining: 152
```

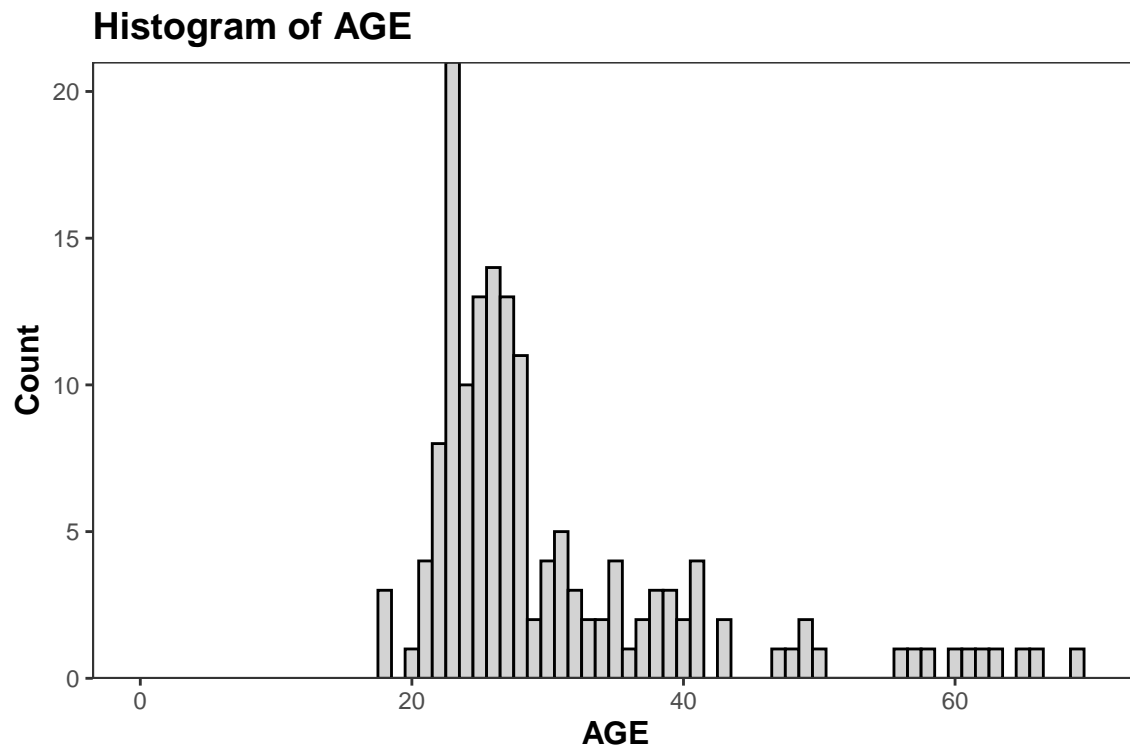
2. Demographics

2.2 Age

```
summary_mean_sd(df, "AGE")
```

```
## # A tibble: 1 x 5
##   variable mean    sd    n missing
##   <chr>    <dbl> <dbl> <dbl>    <dbl>
## 1 AGE      30.5  10.6  152      0
```

```
plotHist("AGE", c(0, 70), condition = NULL, binwidth = 1)
```

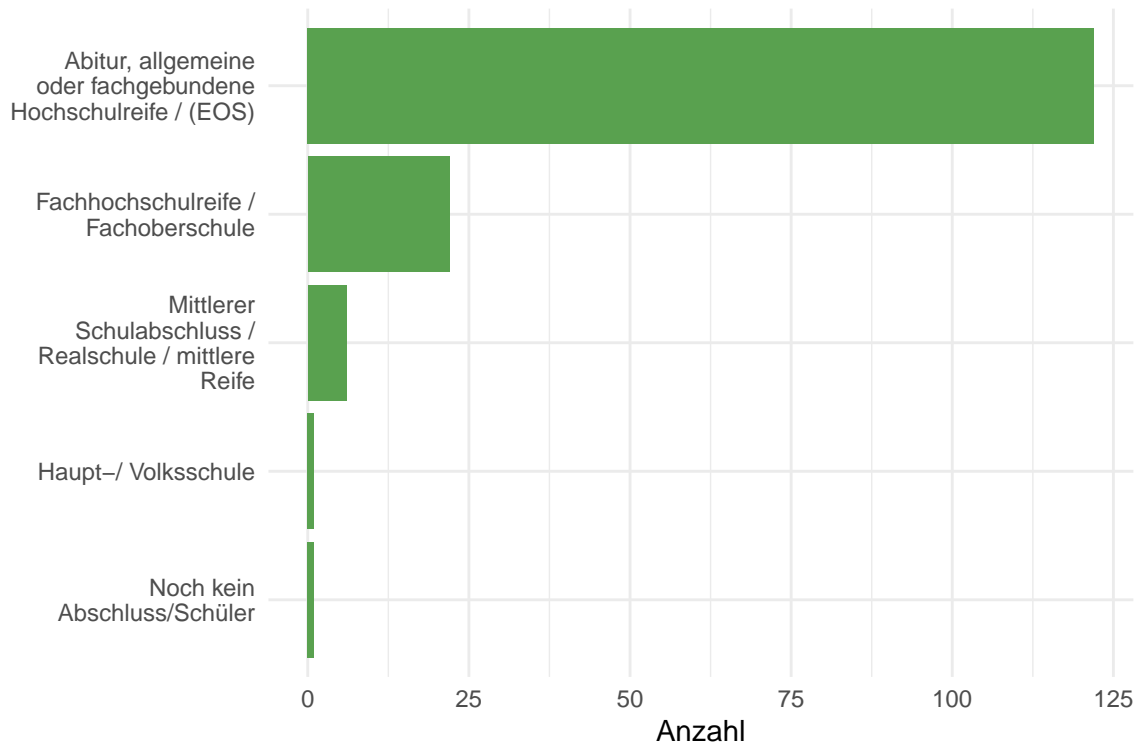


2.3 Educational Degree

```
freq_table(df, EDU_label)
```

```
## # A tibble: 5 x 3
##   EDU_label                                Count Percent
##   <chr>                                <int>     <dbl>
## 1 "Abitur, allgemeine\noder fachgebundene\nHochschulreife / (EOS)"      122      80.3
## 2 "Fachhochschulreife /\nFachoberschule"                22      14.5
## 3 "Mittlerer\nSchulabschluss /\nRealschule / mittlere\nReife"              6       3.9
## 4 "Haupt-/ Volksschule"                  1       0.7
## 5 "Noch kein\nAbschluss/Schüler"              1       0.7
```

```
plotBarHorizontal("EDU_label") +
  labs(
    x = NULL,
    y = "Anzahl"
  )
```



```
freq_table(df, EDUPUPIL_label)
```

```
## # A tibble: 2 x 3
##   EDUPUPIL_label      Count Percent
##   <chr>             <int>   <dbl>
## 1 <NA>              151     99.3
## 2 Haupt-/ Volksschule    1      0.7
```

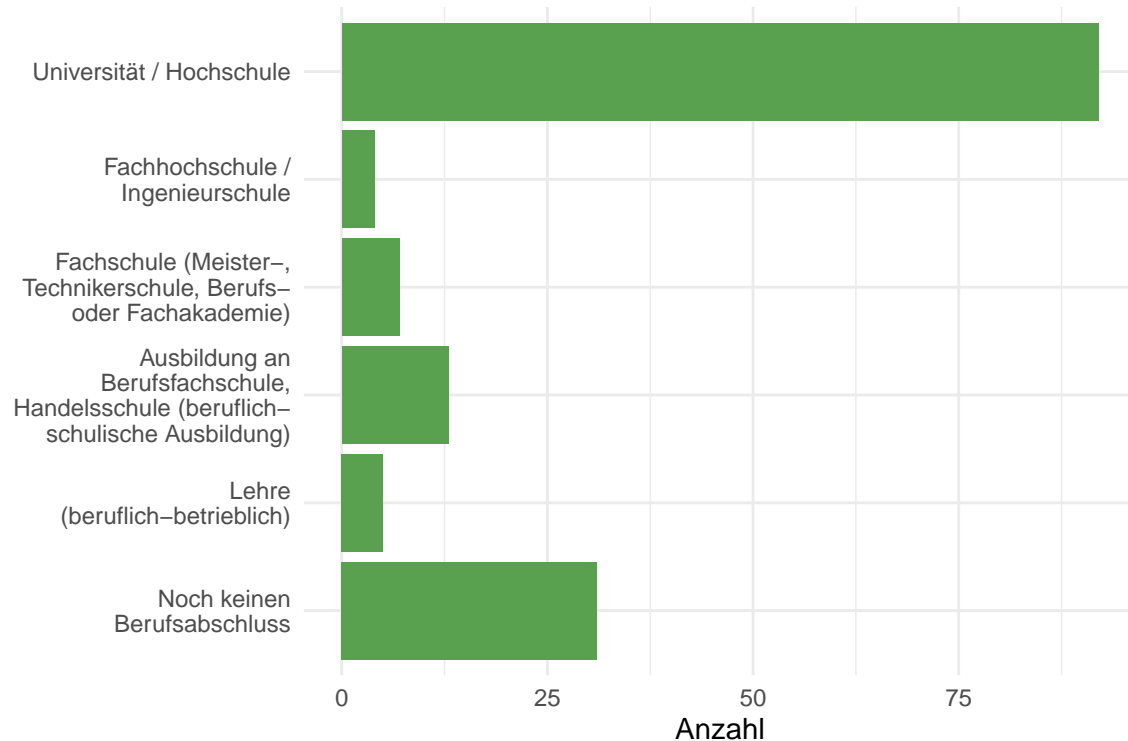
2.4 Occupational Degree

```
freq_table(df, OCC_label)
```

```
## # A tibble: 6 x 3
##   OCC_label                                Count Percent
##   <chr>                                <int>   <dbl>
## 1 "Universität / Hochschule"                92     60.5
## 2 "Noch keinen\nBerufsabschluss"            31     20.4
## 3 "Ausbildung an\nBerufsfachschule,\nHandelsschule (beruflich-\ns~"    13      8.6
## 4 "Fachschule (Meister-\nTechnikerschule, Berufs-\noder Fachakad~"    7      4.6
## 5 "Lehre\n(beruflich-betrieblich)"           5      3.3
## 6 "Fachhochschule /\nIngenieurschule"         4      2.6
```

```
plotBarHorizontal("OCC_label") +
  labs(
    x = NULL,
```

```
y = "Anzahl"
)
```



3. Experimental Manipulation Check

3.1 Conditions

```
printNumberOfParticipants(df, "threatCondition")
```

```
## Number of Observations: 152
## Condition threat: 74 participants
## Condition noThreat: 78 participants
```

3.2 Gender Knowledge Feedback

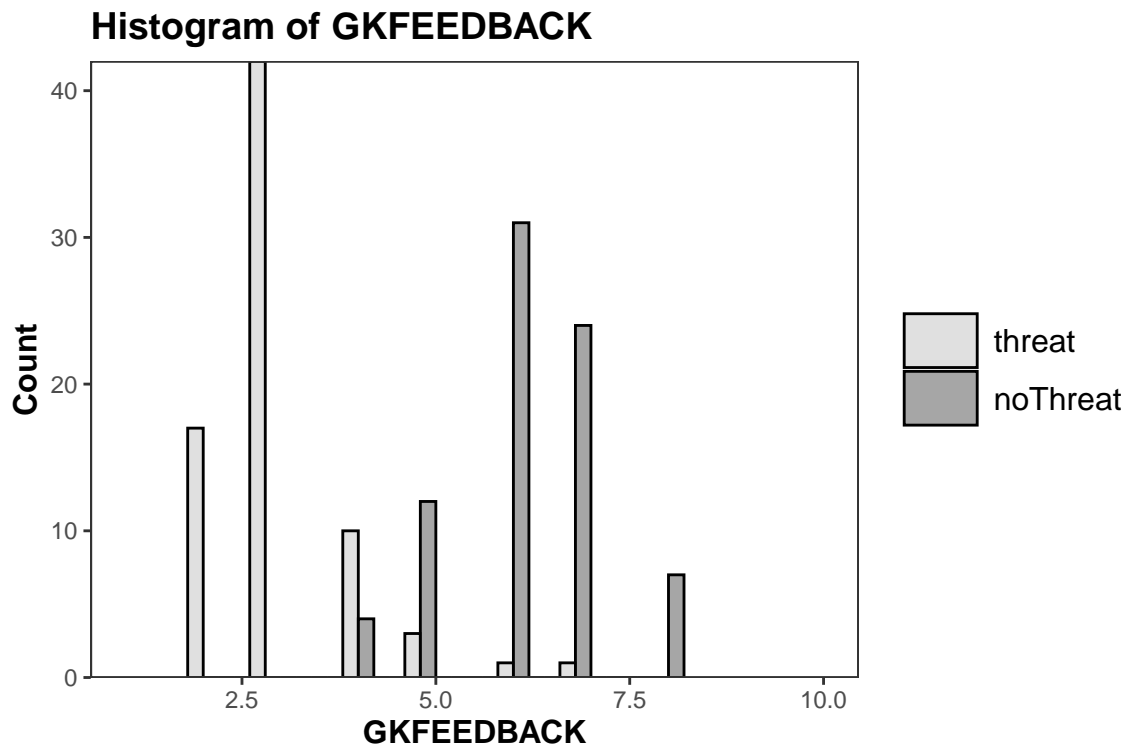
[GKFEEDBACK] Welche Rückmeldung haben Sie im Verlauf der Studie zu Ihrem Wissen in geschlechtsspezifischen Themen erhalten? Scale 1 to 10

```
summary_gkfeedback <- summary_mean_sd(df, "GKFEEDBACK", "threatCondition")
summary_gkfeedback
```

```
## # A tibble: 2 x 6
##   threatCondition variable    mean    sd    n missing
```

```
##   <fct>          <chr>      <dbl> <dbl> <dbl>   <dbl>
## 1 threat        GKFEEDBACK 3.08  0.93   74     0
## 2 noThreat      GKFEEDBACK 6.23  0.99   78     0
```

```
plotHist("GKFEEDBACK", c(1, 10), "threatCondition")
```



Interpretation

- There is a clear split between the two conditions, meaning that participants paid attention to the feedback on the GenderKnowledge task and that the feedback was comprehensible

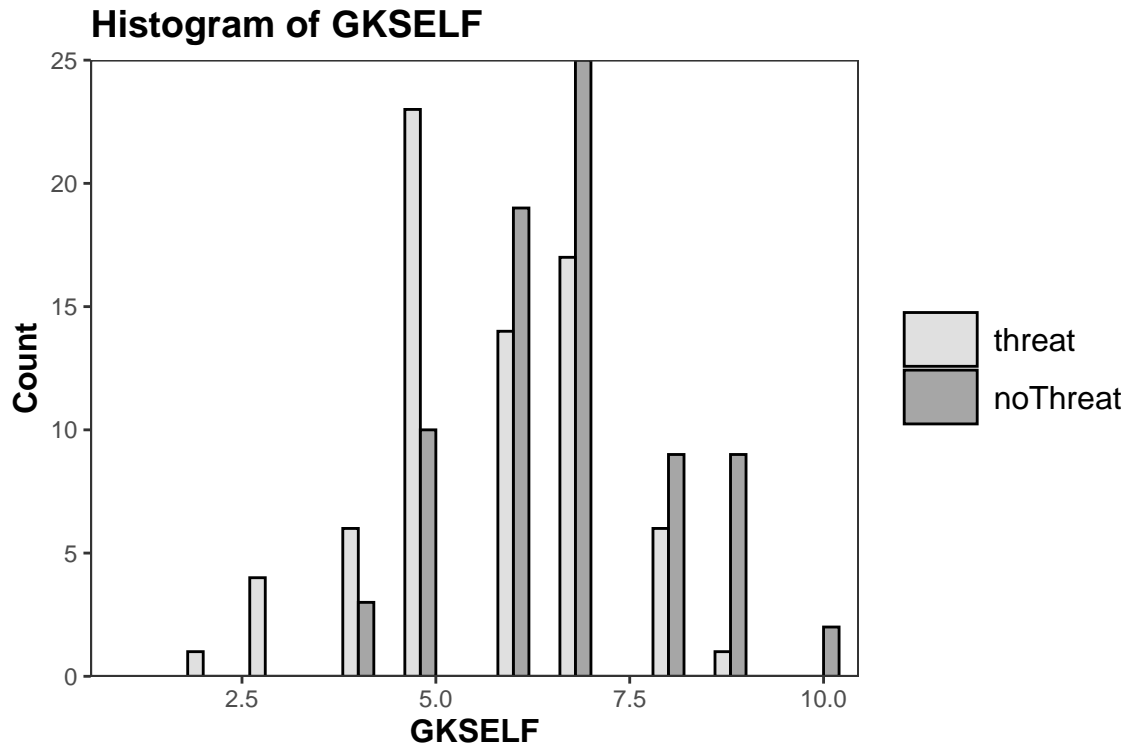
3.3 Self evaluation of Gender Knowledge

[GKSELF] Wie würden Sie Ihr Wissen in geschlechtsspezifischen Themen einschätzen?

```
summary_gkself <- summary_mean_sd(df, "GKSELF", "threatCondition")
summary_gkself
```

```
## # A tibble: 2 x 6
##   threatCondition variable  mean    sd    n missing
##   <fct>          <chr>    <dbl> <dbl> <dbl>   <dbl>
## 1 threat        GKSELF    5.74  1.42   72     2
## 2 noThreat      GKSELF    6.81  1.39   77     1
```

```
plotHist("GKSELF", c(1, 10), "threatCondition")
```



Interpretation

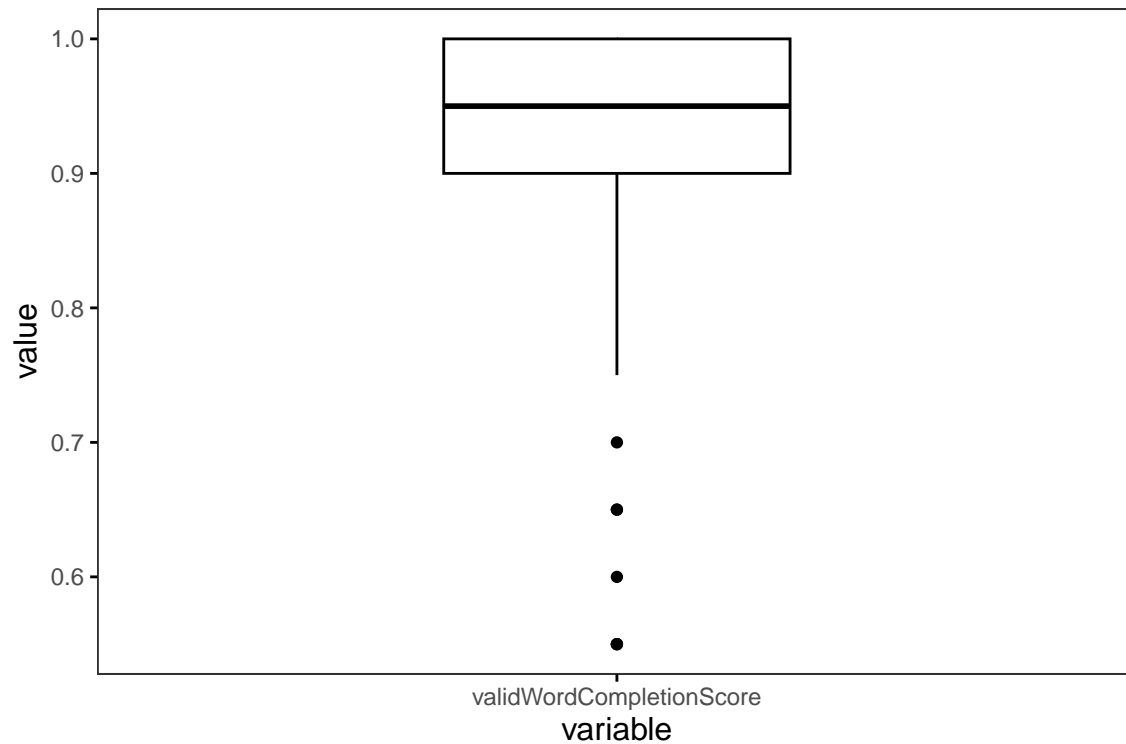
- The mean of self evaluated gender knowledge is lower in the threat condition, than noThreat condition
- This shows that the feedback did have an effect on the self perception of gender knowledge
- The split is not very clear though...

3.4 Valid Word Completions

```
summary_mean_sd(df, "validWordCompletionScore")
```

```
## # A tibble: 1 x 5
##   variable      mean    sd    n missing
##   <chr>      <dbl> <dbl> <dbl>    <dbl>
## 1 validWordCompletionScore 0.92  0.1  152      0
```

```
plotBox("validWordCompletionScore")
```

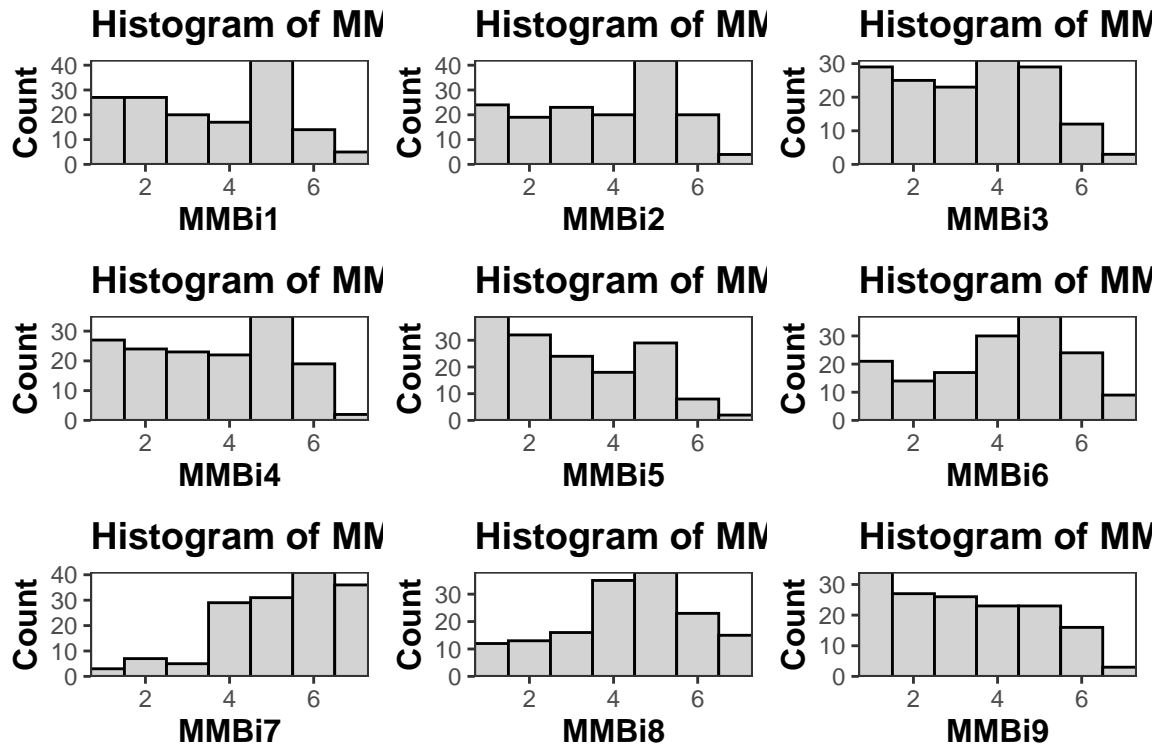
Interpretation

- Participants with a score lower than 50% were excluded
- Generally participants were able to complete the WCFT

3.5 Motivation for Masculine Behaviour

```
plots <- lapply(MMB_item_codes, function(item) {
  plotHist(item, c(1, 7), condition = NULL, binwidth = 1)
})

do.call(grid.arrange, c(plots, ncol = 3))
```



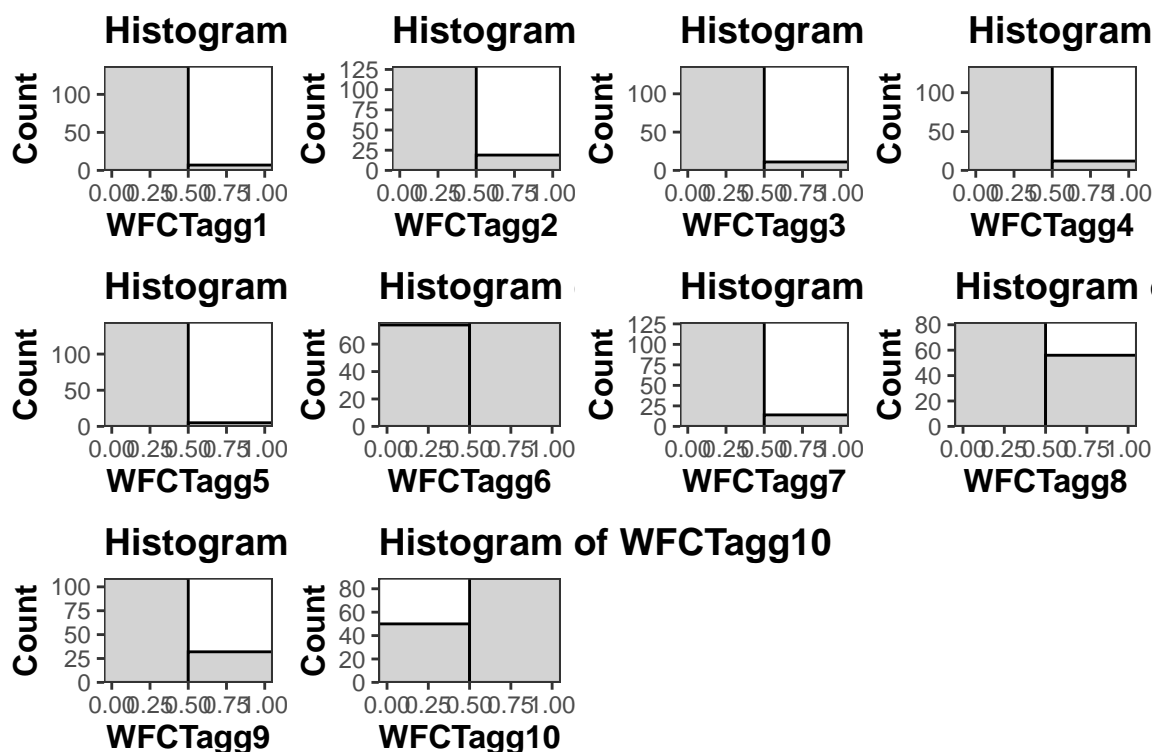
```
summary_mean_sd(df, MMB_item_codes)
```

```
## # A tibble: 9 x 5
##   variable mean    sd    n missing
##   <chr>    <dbl> <dbl> <dbl>    <dbl>
## 1 MMBi1     3.54  1.79  152      0
## 2 MMBi2     3.74  1.75  152      0
## 3 MMBi3     3.36  1.68  152      0
## 4 MMBi4     3.52  1.74  152      0
## 5 MMBi5     2.99  1.68  152      0
## 6 MMBi6     4.03  1.78  152      0
## 7 MMBi7     5.27  1.49  152      0
## 8 MMBi8     4.34  1.68  152      0
## 9 MMBi9     3.22  1.75  152      0
```

3.6 Aggressive Cognition

```
plots <- lapply(WFCT_aggression_items, function(item) {
  plotHist(item, c(0, 1), condition = NULL, binwidth = 1)
})

do.call(grid.arrange, c(plots, ncol = 4))
```



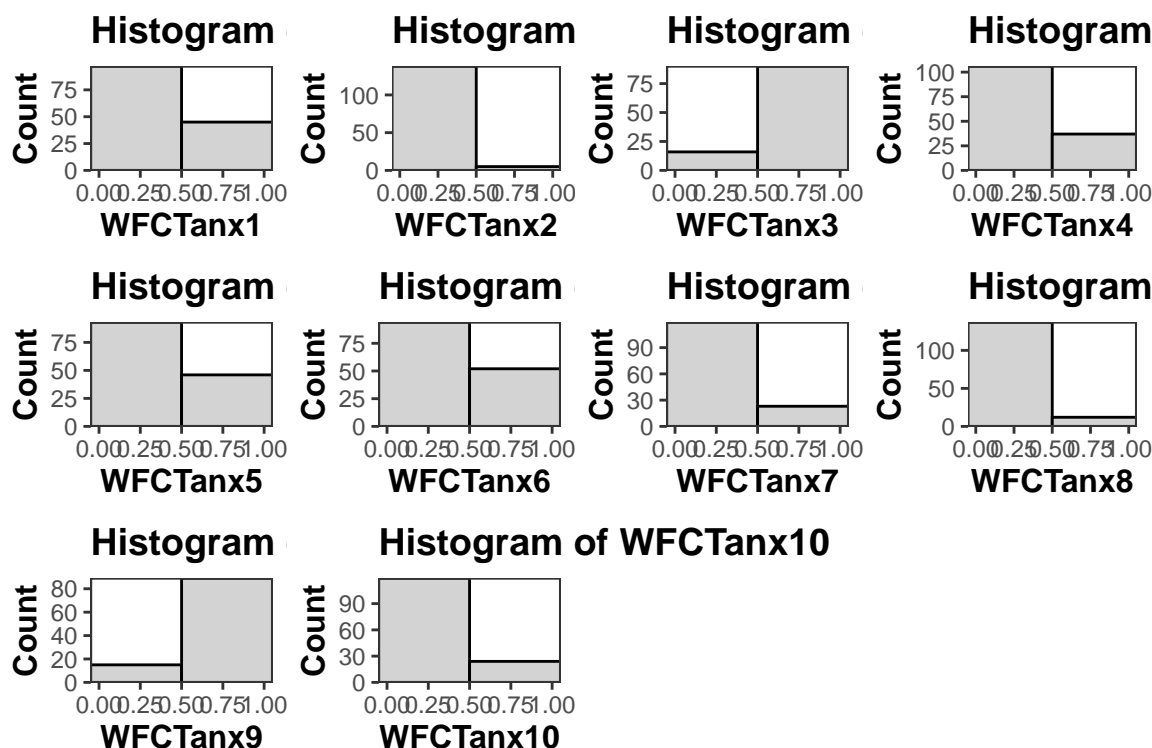
```
summary_mean_sd(df, WFCT_aggression_items)
```

```
## # A tibble: 10 x 5
##   variable   mean    sd    n missing
##   <chr>     <dbl> <dbl> <dbl>   <dbl>
## 1 WFCTagg1  0.05  0.22  144     8
## 2 WFCTagg2  0.13  0.34  148     4
## 3 WFCTagg3  0.07  0.26  147     5
## 4 WFCTagg4  0.08  0.28  146     6
## 5 WFCTagg5  0.03  0.18  149     3
## 6 WFCTagg6  0.51  0.5   150     2
## 7 WFCTagg7  0.1   0.3   141    11
## 8 WFCTagg8  0.41  0.49  138    14
## 9 WFCTagg9  0.23  0.42  141    11
## 10 WFCTagg10 0.64  0.48  139    13
```

3.7 Anxious Cognition

```
plots <- lapply(WFCT_anxiety_items, function(item) {
  plotHist(item, c(0, 1), condition = NULL, binwidth = 1)
})

do.call(grid.arrange, c(plots, ncol = 4))
```



```
summary_mean_sd(df, WFCT_anxiety_items)
```

```
## # A tibble: 10 x 5
##   variable   mean    sd   n missing
##   <chr>     <dbl> <dbl> <dbl>   <dbl>
## 1 WFCTanx1  0.32  0.47  142     10
## 2 WFCTanx2  0.03  0.18  143      9
## 3 WFCTanx3  0.85  0.36  106     46
## 4 WFCTanx4  0.26  0.44  143      9
## 5 WFCTanx5  0.33  0.47  139     13
## 6 WFCTanx6  0.36  0.48  146      6
## 7 WFCTanx7  0.16  0.37  142     10
## 8 WFCTanx8  0.08  0.27  149      3
## 9 WFCTanx9  0.86  0.35  104     48
## 10 WFCTanx10 0.17  0.38  143      9
```

4. Test Quality Criteria: Motivation for Masculine Behaviour

Objectives:

- Assess the *validity* and *reliability* of the scale Motivation for Masculine Behaviour (MMB)
- Compute participant latent trait scores

Methodology:

- Visualization & Descriptives

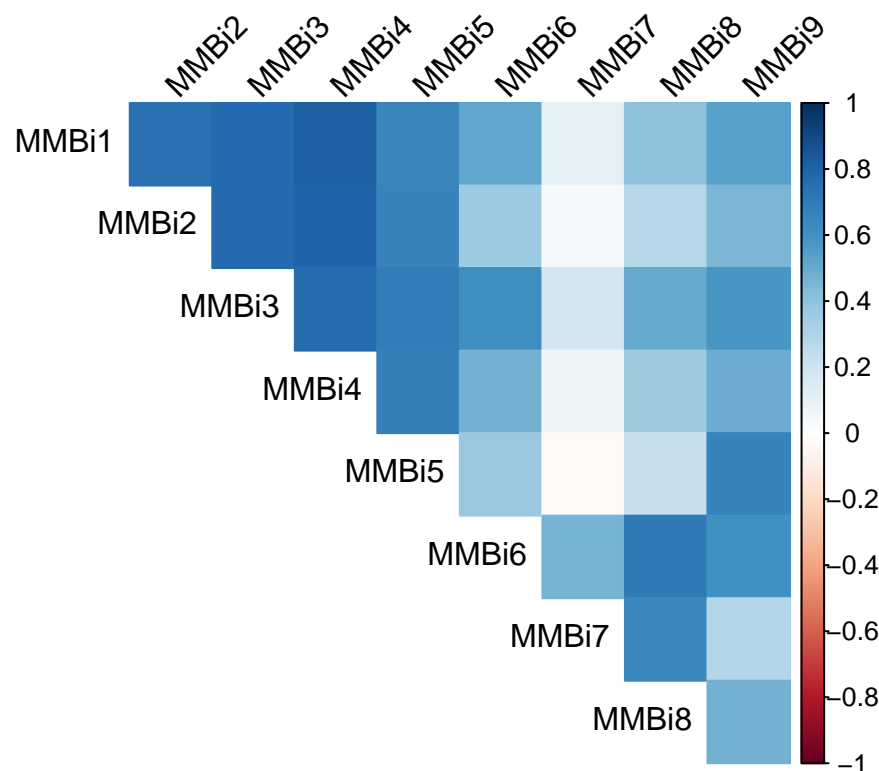
- CFA and EFA to => construct validity
- McDonald's Omega => Reliability
- Regression scoring => latent trait scores

4.1 Construct Validity

4.1.1 Visualization & Descriptives

```
cor_mmb <- psych::polychoric(df[MMB_item_codes])$rho

corrplot(cor_mmb,
  method = "color",
  type = "upper",
  order = "original",
  tl.col = "black",
  tl.srt = 45,
  diag = FALSE
)
```



Interpretation

- The correlation plot shows a very clear block for MMB 1-5 items (pressured scale)
- The block for autonomous items (MMB 6 - 9) is way less clear

```
summary_mean_sd(df, MMB_item_codes)
```

```
## # A tibble: 9 x 5
##   variable mean    sd    n missing
##   <chr>    <dbl> <dbl> <dbl>    <dbl>
## 1 MMBi1     3.54  1.79  152      0
## 2 MMBi2     3.74  1.75  152      0
## 3 MMBi3     3.36  1.68  152      0
## 4 MMBi4     3.52  1.74  152      0
## 5 MMBi5     2.99  1.68  152      0
## 6 MMBi6     4.03  1.78  152      0
## 7 MMBi7     5.27  1.49  152      0
## 8 MMBi8     4.34  1.68  152      0
## 9 MMBi9     3.22  1.75  152      0
```

Interpretation

- The item scores ranged between 1 and 7
- Most items show a mean in the center of the scale
- Item MMBi7 shows a very high mean (5.27). “Ich bin gerne männlich”
- Generally, the items do not show bottom or ceiling effects, and there is some variance to the responses

4.1.2 Check sampling adequacy for Factory Analysis

```
KMO(cor_mmb)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = cor_mmb)
## Overall MSA = 0.86
## MSA for each item =
## MMBi1 MMBi2 MMBi3 MMBi4 MMBi5 MMBi6 MMBi7 MMBi8 MMBi9
## 0.92 0.88 0.90 0.88 0.84 0.85 0.72 0.81 0.83
```

```
cortest.bartlett(cor_mmb, n = nrow(df))
```

```
## $chisq
## [1] 1042.603
##
## $p.value
## [1] 1.800657e-195
##
## $df
## [1] 36
```

KMO (Kaiser-Meyer-Olkin) should be > 0.6 (ideally > 0.8) Bartlett's test should be significant ($p < .05$)

Interpretation

- The overall KMO is 0.86 showing a good sampling adequacy for factor analysis
- Individual scores of items are good as well, except MMBi7, which has a sufficient, yet lower KMO value (0.72) due to its ceiling effect
- The Bartlett test is significant as well, showing a sampling adequacy for factor analysis

4.1.3 Two-Factor Uncorrelated CFA

Testing the proposed 2 factor structure by Stanaland & Gaither (2021)

=> 2 factors => no covariance between factors

```
model_twof <- "  
  # latent variables  
  Pressured =~ MMBi1 + MMBi2 + MMBi3 + MMBi4 + MMBi5  
  Autonomous =~ MMBi6 + MMBi7 + MMBi8 + MMBi9  
  
  # constrain covariance to 0  
  Pressured ~~ 0*Autonomous  
"  
  
results_twof <- run_cfa_model(model_twof, df, model_name = "Two-Factor Uncorrelated", show_mi = TRUE)
```

```
##  
## -----  
## MODEL SUMMARY  
## -----  
## lavaan 0.6.15 ended normally after 22 iterations  
##  
##      Estimator                      ML  
##      Optimization method          NLMINB  
##      Number of model parameters    18  
##  
##      Number of observations        152  
##  
## Model Test User Model:  
##  
##      Test statistic                165.739  
##      Degrees of freedom            27  
##      P-value (Chi-square)          0.000  
##  
## Model Test Baseline Model:  
##  
##      Test statistic                930.059  
##      Degrees of freedom            36  
##      P-value                      0.000  
##  
## User Model versus Baseline Model:  
##  
##      Comparative Fit Index (CFI)    0.845  
##      Tucker-Lewis Index (TLI)      0.793  
##  
## Loglikelihood and Information Criteria:  
##  
##      Loglikelihood user model (H0)  -2280.240  
##      Loglikelihood unrestricted model (H1) -2197.371  
##  
##      Akaike (AIC)                  4596.480  
##      Bayesian (BIC)                 4650.910  
##      Sample-size adjusted Bayesian (SABIC) 4593.940
```

```

##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                0.184
##   90 Percent confidence interval - lower    0.158
##   90 Percent confidence interval - upper    0.211
##   P-value H_0: RMSEA <= 0.050              0.000
##   P-value H_0: RMSEA >= 0.080              1.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                0.255
##
## Parameter Estimates:
##
##   Standard errors                    Standard
##   Information                      Expected
##   Information saturated (h1) model    Structured
##
## Latent Variables:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   Pressured =~
##     MMBi1           1.538    0.117   13.155    0.000    1.538    0.864
##     MMBi2           1.498    0.115   13.027    0.000    1.498    0.858
##     MMBi3           1.432    0.110   12.974    0.000    1.432    0.856
##     MMBi4           1.547    0.111   13.895    0.000    1.547    0.893
##     MMBi5           1.248    0.118   10.541    0.000    1.248    0.746
##   Autonomous =~
##     MMBi6           1.394    0.134   10.434    0.000    1.394    0.788
##     MMBi7           0.924    0.118    7.854    0.000    0.924    0.623
##     MMBi8           1.412    0.124   11.376    0.000    1.412    0.845
##     MMBi9           1.001    0.141    7.107    0.000    1.001    0.574
##
## Covariances:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   Pressured ~~
##     Autonomous      0.000
##
## Variances:
##
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##     .MMBi1          0.805    0.119    6.780    0.000    0.805    0.254
##     .MMBi2          0.801    0.117    6.871    0.000    0.801    0.263
##     .MMBi3          0.745    0.108    6.907    0.000    0.745    0.267
##     .MMBi4          0.607    0.099    6.112    0.000    0.607    0.203
##     .MMBi5          1.245    0.157    7.908    0.000    1.245    0.444
##     .MMBi6          1.187    0.217    5.482    0.000    1.187    0.379
##     .MMBi7          1.344    0.177    7.607    0.000    1.344    0.612
##     .MMBi8          0.796    0.193    4.137    0.000    0.796    0.286
##     .MMBi9          2.041    0.259    7.871    0.000    2.041    0.671
##     Pressured       1.000
##     Autonomous      1.000
##
## -----

```



```

## MODEL FIT INDICES
## -----
##      Index Value Criteria
## cfi      cfi 0.845      0.95
## tli      tli 0.793      0.95
## rmsea    rmsea 0.184      0.06
## srmr     srmr 0.255      0.08
##
## -----
## STANDARDIZED FACTOR LOADINGS
## -----
##      Factor Item Std_Loading
## 1 Pressured MMBi1      0.864
## 2 Pressured MMBi2      0.858
## 3 Pressured MMBi3      0.856
## 4 Pressured MMBi4      0.893
## 5 Pressured MMBi5      0.746
## 6 Autonomous MMBi6      0.788
## 7 Autonomous MMBi7      0.623
## 8 Autonomous MMBi8      0.845
## 9 Autonomous MMBi9      0.574
##
## -----
## TOP MODIFICATION INDICES
## -----
##      lhs op      rhs      mi      epc sepc.lv sepc.all sepc.nox
## 10 Pressured ~~ Autonomous 34.383 0.537 0.537 0.537 0.537
## 60 MMBi5 ~~ MMBi9 33.019 0.809 0.809 0.508 0.508
## 25 Pressured =~ MMBi9 21.961 0.586 0.586 0.336 0.336
## 64 MMBi7 ~~ MMBi8 18.715 0.799 0.799 0.772 0.772
## 63 MMBi6 ~~ MMBi9 18.715 0.855 0.855 0.549 0.549

```

Interpretation

- None of the model fit indices is satisfying
- Mod Indices suggest a correlation between latent pressured and autonomous factors

4.1.4 Exploratory Factor Analysis

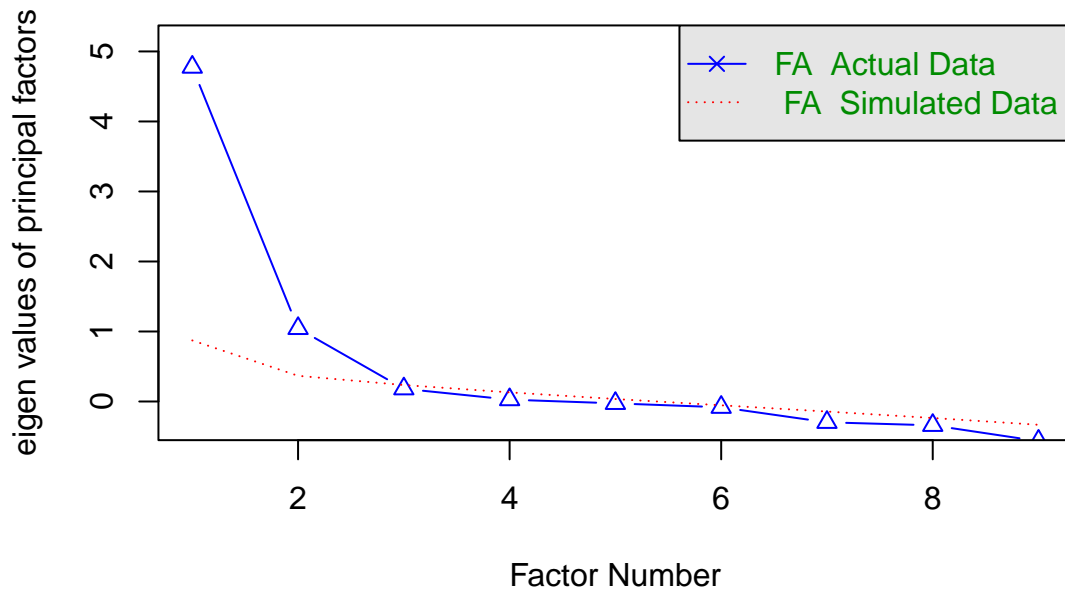
```

fa.parallel(cor_mmb,
  fm = "ml",
  fa = "fa", n.iter = 100, show.legend = TRUE,
  main = "Parallel Analysis Scree Plot"
)

```

Determine the number of latent factors

Parallel Analysis Scree Plot



Parallel analysis suggests that the number of factors = 2 and the number of components = NA

Interpretation:

- The “elbow” of the scree plot suggest a two factor model

```
efa_result_twof <- fa(df[MMB_item_codes], nfactors = 2, rotate = "oblimin", fm = "ml")
print(efa_result_twof, cut = 0.3) # only loadings > .30
```

Compute EFA

```
## Factor Analysis using method = ml
## Call: fa(r = df[MMB_item_codes], nfactors = 2, rotate = "oblimin",
##       fm = "ml")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      ML1    ML2    h2    u2 com
## MMBi1 0.83      0.75 0.25 1.0
## MMBi2 0.90      0.74 0.26 1.0
## MMBi3 0.79      0.78 0.22 1.1
## MMBi4 0.89      0.78 0.22 1.0
## MMBi5 0.79      0.58 0.42 1.0
## MMBi6      0.67 0.64 0.36 1.3
## MMBi7      0.73 0.47 0.53 1.1
## MMBi8      0.85 0.74 0.26 1.0
## MMBi9 0.43 0.36 0.43 0.57 1.9
```

```
##
##               ML1  ML2
## SS loadings      3.92 1.99
## Proportion Var    0.44 0.22
## Cumulative Var    0.44 0.66
## Proportion Explained 0.66 0.34
## Cumulative Proportion 0.66 1.00
##
## With factor correlations of
##      ML1  ML2
## ML1 1.00 0.39
## ML2 0.39 1.00
##
## Mean item complexity = 1.2
## Test of the hypothesis that 2 factors are sufficient.
##
## df null model = 36 with the objective function = 6.12 with Chi Square = 900.48
## df of the model are 19 and the objective function was 0.38
##
## The root mean square of the residuals (RMSR) is 0.04
## The df corrected root mean square of the residuals is 0.06
##
## The harmonic n.obs is 152 with the empirical chi square 20.35 with prob < 0.37
## The total n.obs was 152 with Likelihood Chi Square = 55.95 with prob < 1.7e-05
##
## Tucker Lewis Index of factoring reliability = 0.918
## RMSEA index = 0.113 and the 90 % confidence intervals are 0.08 0.149
## BIC = -39.51
## Fit based upon off diagonal values = 0.99
## Measures of factor score adequacy
##
##               ML1  ML2
## Correlation of (regression) scores with factors 0.97 0.92
## Multiple R square of scores with factors         0.94 0.85
## Minimum correlation of possible factor scores    0.87 0.70
```

```
# Create loadings matrix
loadings_matrix <- as.data.frame(efa_result_twof$loadings[1:length(mmb_labels), ])

# Format table
loading_table <- data.frame(
  Item = MMB_item_codes,
  Label = mmb_labels,
  Factor1 = round(loadings_matrix$ML1, 2),
  Factor2 = round(loadings_matrix$ML2, 2)
)

# Hide loadings < .30
loading_table <- loading_table %>%
  mutate(
    Factor1 = ifelse(abs(Factor1) < 0.30, "", as.character(Factor1)),
    Factor2 = ifelse(abs(Factor2) < 0.30, "", as.character(Factor2))
  )

# Render nice APA-style table
```

```
loading_table %>%
  kbl(
    caption = "EFA Loadings for MMB Items (2-Factor Solution)",
    align = "lccc",
    booktabs = TRUE
  ) %>%
  kable_styling(
    full_width = FALSE,
    position = "center",
    bootstrap_options = c("striped", "hover", "condensed"),
    latex_options = "hold_position"
  ) %>%
  column_spec(2, width = "10cm") %>%
  row_spec(0, bold = TRUE, background = "#f2f2f2") %>%
  row_spec(1:nrow(loading_table), background = "white", color = "black")
```

Table 1: EFA Loadings for MMB Items (2-Factor Solution)

Item	Label	Factor1	Factor2
MMBi1	Allgemein verhalte ich mich männlich, weil ich die Akzeptanz und Anerkennung anderer möchte	0.83	
MMBi2	Allgemein bin ich männlich, weil das von mir erwartet wird	0.9	
MMBi3	Ich verhalte mich männlich, weil ich möchte, dass man mich mag	0.79	
MMBi4	Ich verhalte mich in Gegenwart anderer männlich, um ihre Erwartungen zu erfüllen	0.89	
MMBi5	Ich verhalte mich nicht weiblich, weil ich glaube, dass mich die Leute sonst nicht mögen würden	0.79	
MMBi6	Es ist mir wichtig, männlich zu sein		0.67
MMBi7	Ich bin gerne männlich		0.73
MMBi8	Es macht mich glücklich, mich männlich zu verhalten		0.85
MMBi9	Es ist mir wichtig, mich nicht weiblich zu verhalten	0.43	0.36

Interpretation

- EFA sows a very distinct factor for pressured motivation
- The factor for autonomous motivation is less clear and MMBi9 shows loadings on both factors

4.1.5 Two-Factor Correlated CFA

- 2 latent factors,
- correlation allowed between factors

```
model_twof_cor <- "
# latent variables
Pressured =~ MMBi1 + MMBi2 + MMBi3 + MMBi4 + MMBi5
Autonomous =~ MMBi6 + MMBi7 + MMBi8 + MMBi9

# allow correlation between factors
Pressured ~~ Autonomous
"
```

```
results_twof_cor <- run_cfa_model(model_twof_cor, df, model_name = "Two-Factor Correlated", show_mi = T
```

```
##
## -----
## MODEL SUMMARY
## -----
## lavaan 0.6.15 ended normally after 21 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of model parameters      19
##
##      Number of observations          152
##
## Model Test User Model:
##
##      Test statistic                  121.065
##      Degrees of freedom              26
##      P-value (Chi-square)            0.000
##
## Model Test Baseline Model:
##
##      Test statistic                  930.059
##      Degrees of freedom              36
##      P-value                        0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.894
##      Tucker-Lewis Index (TLI)        0.853
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)    -2257.903
##      Loglikelihood unrestricted model (H1) -2197.371
##
##      Akaike (AIC)                    4553.806
##      Bayesian (BIC)                   4611.259
##      Sample-size adjusted Bayesian (SABIC) 4551.125
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                          0.155
##      90 Percent confidence interval - lower 0.128
##      90 Percent confidence interval - upper 0.184
##      P-value H_0: RMSEA <= 0.050        0.000
##      P-value H_0: RMSEA >= 0.080        1.000
##
## Standardized Root Mean Square Residual:
##
##      SRMR                          0.105
##
## Parameter Estimates:
```

```

##
## Standard errors
## Information
## Information saturated (h1) model
## Standard Expected Structured
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## Pressured =~
## MMBi1 1.545 0.116 13.269 0.000 1.545 0.868
## MMBi2 1.479 0.116 12.777 0.000 1.479 0.848
## MMBi3 1.454 0.109 13.309 0.000 1.454 0.869
## MMBi4 1.536 0.112 13.747 0.000 1.536 0.887
## MMBi5 1.246 0.118 10.526 0.000 1.246 0.744
## Autonomous =~
## MMBi6 1.508 0.127 11.861 0.000 1.508 0.852
## MMBi7 0.798 0.120 6.646 0.000 0.798 0.538
## MMBi8 1.287 0.124 10.386 0.000 1.287 0.771
## MMBi9 1.135 0.136 8.365 0.000 1.135 0.651
##
## Covariances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## Pressured ~~
## Autonomous 0.592 0.064 9.268 0.000 0.592 0.592
##
## Variances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .MMBi1 0.782 0.116 6.764 0.000 0.782 0.247
## .MMBi2 0.857 0.121 7.089 0.000 0.857 0.281
## .MMBi3 0.682 0.101 6.733 0.000 0.682 0.244
## .MMBi4 0.641 0.101 6.356 0.000 0.641 0.214
## .MMBi5 1.250 0.157 7.936 0.000 1.250 0.446
## .MMBi6 0.857 0.193 4.437 0.000 0.857 0.274
## .MMBi7 1.560 0.193 8.081 0.000 1.560 0.710
## .MMBi8 1.131 0.182 6.207 0.000 1.131 0.406
## .MMBi9 1.754 0.233 7.542 0.000 1.754 0.576
## Pressured 1.000 1.000 1.000
## Autonomous 1.000 1.000 1.000
##
##
## -----
## MODEL FIT INDICES
## -----
## Index Value Criteria
## cfi cfi 0.894 0.95
## tli tli 0.853 0.95
## rmsea rmsea 0.155 0.06
## srmr srmr 0.105 0.08
##
## -----
## STANDARDIZED FACTOR LOADINGS
## -----
## Factor Item Std_Loading
## 1 Pressured MMBi1 0.868
## 2 Pressured MMBi2 0.848

```

```
## 3 Pressured MMBi3      0.869
## 4 Pressured MMBi4      0.887
## 5 Pressured MMBi5      0.744
## 6 Autonomous MMBi6     0.852
## 7 Autonomous MMBi7     0.538
## 8 Autonomous MMBi8     0.771
## 9 Autonomous MMBi9     0.651
##
## -----
## TOP MODIFICATION INDICES
## -----
##          lhs op   rhs      mi      epc sepc.lv sepc.all sepc.nox
## 60      MMBi5 ~~ MMBi9 35.038  0.787   0.787   0.531   0.531
## 64      MMBi7 ~~ MMBi8 28.852  0.759   0.759   0.571   0.571
## 28 Autonomous =~ MMBi3 17.444  0.461   0.461   0.276   0.276
## 25 Pressured =~ MMBi9 17.295  0.679   0.679   0.389   0.389
## 23 Pressured =~ MMBi7 14.552 -0.559  -0.559  -0.377  -0.377
```

Interpretation

- Allowing for a correlation between latent factors creates a better fit but still not sufficient
- Mod indices suggest A correlation between Item MMBi5 and MMBi9, This makes conceptually sense, because they both deal with anti femininity.

4.1.6 Two-Factor Correlated + Residuals CFA

- 2 latent factors
- correlation allowed between factors
- allow correlated residuals

```
model_twof_cor_mod <- "
# latent variables
Pressured =~ MMBi1 + MMBi2 + MMBi3 + MMBi4 + MMBi5
Autonomous =~ MMBi6 + MMBi7 + MMBi8 + MMBi9

Pressured ~~ Autonomous

# theory-based correlated residuals
MMBi3 ~~ MMBi4
MMBi5 ~~ MMBi9
MMBi7 ~~ MMBi8
"

results_twof_cor_mod <- run_cfa_model(model_twof_cor_mod, df, model_name = "Two-Factor Correlated Modif

##
## -----
## MODEL SUMMARY
## -----
## lavaan 0.6.15 ended normally after 27 iterations
##
## Estimator ML
```

```

## Optimization method NLMINB
## Number of model parameters 22
##
## Number of observations 152
##
## Model Test User Model:
##
## Test statistic 47.932
## Degrees of freedom 23
## P-value (Chi-square) 0.002
##
## Model Test Baseline Model:
##
## Test statistic 930.059
## Degrees of freedom 36
## P-value 0.000
##
## User Model versus Baseline Model:
##
## Comparative Fit Index (CFI) 0.972
## Tucker-Lewis Index (TLI) 0.956
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0) -2221.337
## Loglikelihood unrestricted model (H1) -2197.371
##
## Akaike (AIC) 4486.674
## Bayesian (BIC) 4553.199
## Sample-size adjusted Bayesian (SABIC) 4483.569
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.084
## 90 Percent confidence interval - lower 0.050
## 90 Percent confidence interval - upper 0.118
## P-value H_0: RMSEA <= 0.050 0.049
## P-value H_0: RMSEA >= 0.080 0.615
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.078
##
## Parameter Estimates:
##
## Standard errors Standard
## Information Expected
## Information saturated (h1) model Structured
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## Pressured =~
## MMBi1 1.509 0.118 12.835 0.000 1.509 0.848
## MMBi2 1.456 0.116 12.521 0.000 1.456 0.834

```



```

##      MMBi3      1.510    0.108    13.979    0.000    1.510    0.903
##      MMBi4      1.586    0.111    14.332    0.000    1.586    0.916
##      MMBi5      1.137    0.111    10.209    0.000    1.137    0.703
##      Autonomous =~
##      MMBi6      1.524    0.128    11.942    0.000    1.524    0.861
##      MMBi7      0.674    0.125     5.391    0.000    0.674    0.455
##      MMBi8      1.221    0.126     9.683    0.000    1.221    0.731
##      MMBi9      1.187    0.130     9.161    0.000    1.187    0.676
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      Pressured ~~
##      Autonomous      0.637    0.059    10.871    0.000    0.637    0.637
##      .MMBi3 ~~
##      .MMBi4      -0.245    0.077     -3.168    0.002   -0.245   -0.491
##      .MMBi5 ~~
##      .MMBi9      0.791    0.147     5.376    0.000    0.791    0.531
##      .MMBi7 ~~
##      .MMBi8      0.646    0.157     4.100    0.000    0.646    0.429
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .MMBi1      0.892    0.121     7.364    0.000    0.892    0.282
##      .MMBi2      0.927    0.123     7.549    0.000    0.927    0.304
##      .MMBi3      0.513    0.103     4.963    0.000    0.513    0.184
##      .MMBi4      0.484    0.105     4.606    0.000    0.484    0.161
##      .MMBi5      1.322    0.159     8.309    0.000    1.322    0.506
##      .MMBi6      0.809    0.199     4.074    0.000    0.809    0.258
##      .MMBi7      1.743    0.212     8.232    0.000    1.743    0.793
##      .MMBi8      1.297    0.192     6.760    0.000    1.297    0.465
##      .MMBi9      1.678    0.231     7.266    0.000    1.678    0.544
##      Pressured      1.000
##      Autonomous      1.000
##
## -----
## MODEL FIT INDICES
## -----
##      Index Value Criteria
## cfi      cfi 0.972    0.95
## tli      tli 0.956    0.95
## rmsea    rmsea 0.084    0.06
## srmr     srmr 0.078    0.08
##
## -----
## STANDARDIZED FACTOR LOADINGS
## -----
##      Factor Item Std_Loading
## 1 Pressured MMBi1      0.848
## 2 Pressured MMBi2      0.834
## 3 Pressured MMBi3      0.903
## 4 Pressured MMBi4      0.916
## 5 Pressured MMBi5      0.703
## 6 Autonomous MMBi6      0.861

```

```
## 7 Autonomous MMBi7      0.455
## 8 Autonomous MMBi8      0.731
## 9 Autonomous MMBi9      0.676
##
## -----
## TOP MODIFICATION INDICES
## -----
##          lhs op   rhs      mi      epc sepc.lv sepc.all sepc.nox
## 31 Autonomous =~ MMBi3 14.256  0.445   0.445   0.266   0.266
## 30 Autonomous =~ MMBi2 12.125 -0.437 -0.437  -0.250  -0.250
## 28 Pressured  =~ MMBi9  7.224  0.457   0.457   0.260   0.260
## 26 Pressured  =~ MMBi7  7.090 -0.369 -0.369  -0.249  -0.249
## 45          MMBi2 ~~ MMBi6 4.875 -0.218 -0.218  -0.252  -0.252
```

Interpretation

- ...

4.2 Reliability

```
fit_twof_cor_mod <- cfa(model_twof_cor_mod, data = df, std.lv = TRUE)
rel <- reliability(fit_twof_cor_mod)
print(rel)
```

```
##          Pressured Autonomous
## alpha  0.9248217  0.7952438
## omega  0.9342117  0.7567546
## omega2 0.9342117  0.7567546
## omega3 0.9100246  0.7671529
## avevar 0.7170080  0.5066354
```

Interpretation

- Pressured scale shows an excellent reliability ($> .9$)
- Autonomous scale shows an acceptable reliability ($> .7$) => reliability is sufficient, so we use the proposed factor structure to compute factor scores for autonomous and pressured motivation

Omega values .70 (acceptable), .80 (good). => Alpha assumes tau-equivalence (all items same loading), which isn't true here, so we trust omega more

4.3 Latent Trait Scores

4.3.1 Compute Scores

Use regression scoring from the chosen model, to compute latent trait scores

```
fs_reg <- lavPredict(fit_twof_cor_mod, method = "regression")
df$regPressured <- scale(fs_reg[, "Pressured"])
df$regAutonomous <- scale(fs_reg[, "Autonomous"])
```

Also compute Row means for visualizations

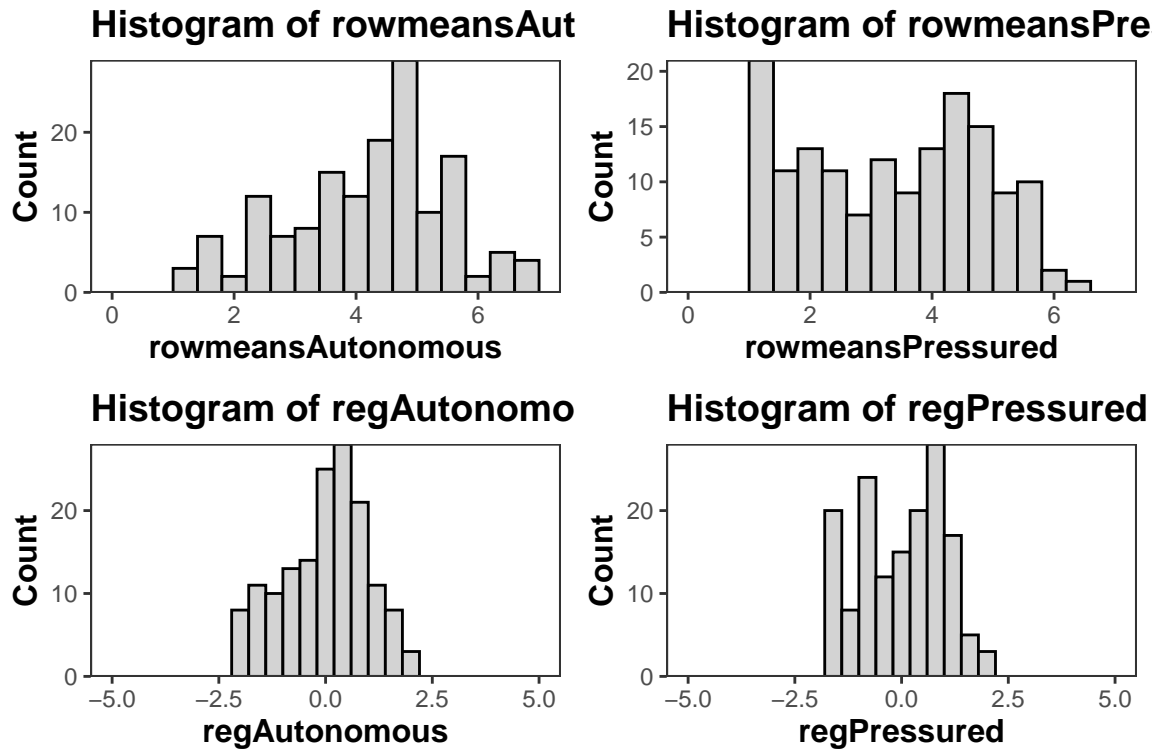
```
df$rowmeansAutonomous <- rowMeans(  
  df[mmb_autonomous_items],  
  na.rm = TRUE  
)  
  
df$rowmeansPressured <- rowMeans(  
  df[mmb_pressured_items],  
  na.rm = TRUE  
)
```

4.3.2 Visualization & Descriptives

```
summary_mean_sd(df, c("rowmeansAutonomous", "rowmeansPressured", "regAutonomous", "regPressured"))
```

```
## # A tibble: 4 x 5  
##   variable      mean    sd    n missing  
##   <chr>      <dbl> <dbl> <dbl>    <dbl>  
## 1 rowmeansAutonomous  4.21  1.32  152      0  
## 2 rowmeansPressured  3.43  1.51  152      0  
## 3 regAutonomous      0     1    152      0  
## 4 regPressured       0     1    152      0
```

```
rm_aut_hist <- plotHist("rowmeansAutonomous", c(0, 7))  
rm_pres_hist <- plotHist("rowmeansPressured", c(0, 7))  
reg_aut_hist <- plotHist("regAutonomous", c(-5, 5))  
reg_pres_hist <- plotHist("regPressured", c(-5, 5))  
  
grid.arrange(rm_aut_hist, rm_pres_hist, reg_aut_hist, reg_pres_hist, ncol = 2)
```

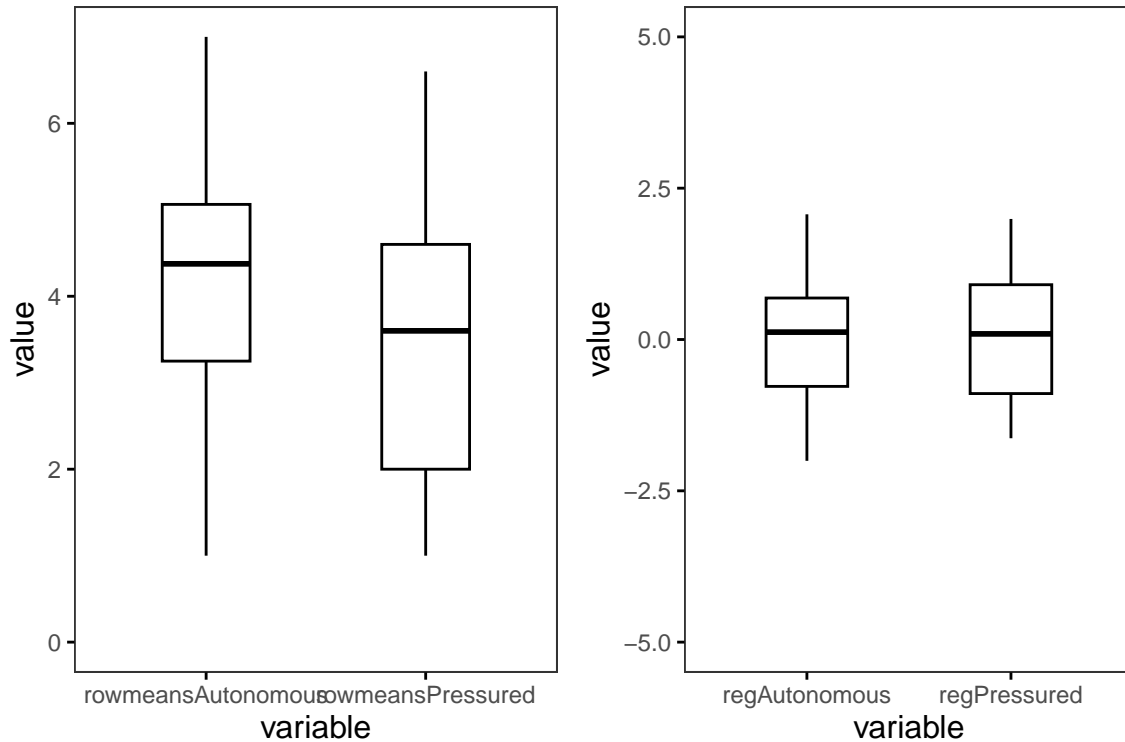


-> regression scoring reduces measurement error at the price of losing variance

```
rm_box <- plotBox(c("rowmeansAutonomous", "rowmeansPressured"))
# ggpar(rm_box, ylim = c(0, 7))

reg_box <- plotBox(c("regAutonomous", "regPressured"))
# ggpar(rm_box, ylim = c(-5, 5))

grid.arrange(ggpar(rm_box, ylim = c(0, 7)), ggpar(reg_box, ylim = c(-5, 5)), ncol = 2)
```



```
cor(df$regAutonomous, df$regPressured)
```

```
##           [,1]
## [1,] 0.6925599
```

```
cor(df$rowmeansAutonomous, df$rowmeansPressured)
```

```
## [1] 0.5017603
```

Interpretation

- moderate to high correlation between pressured and autonomous factor
- the correlation increases with the regression scores (because factors are modeled as correlative)

5. Test Quality Criteria: Aggressive Cognition

Objectives:

- Assess the *validity* and *reliability* of the scale for aggressive cognition
- Compute participant latent trait scores

Methodology:

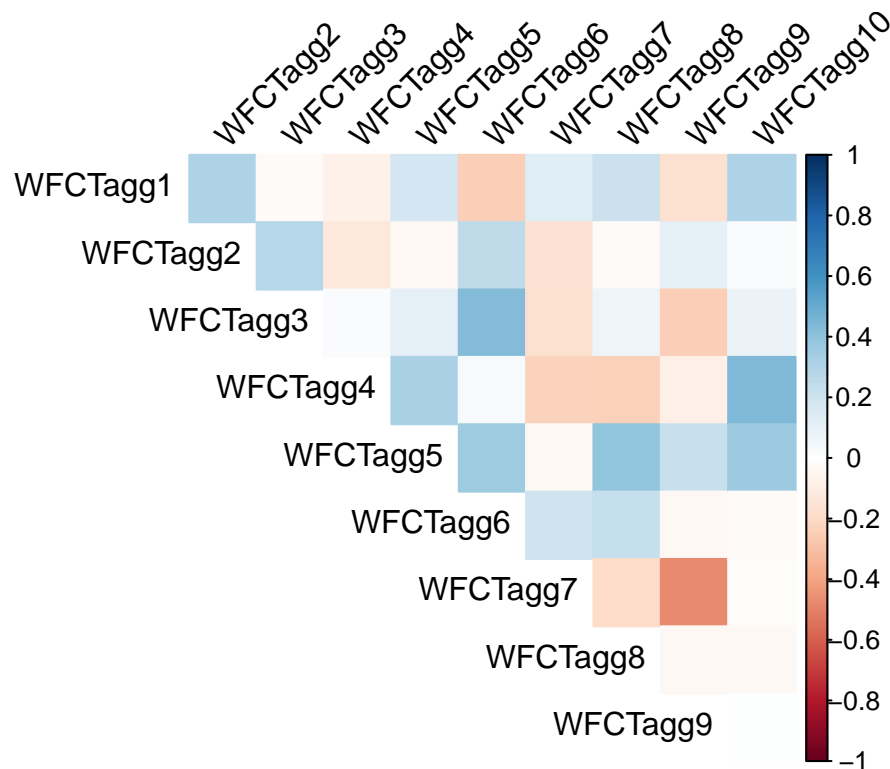
- Visualization & Descriptives

5.1 Construct Validity

5.1.1 Visualization & Descriptives

```
cor_aggr <- psych::tetrachoric( df[, WFCT_aggression_items])$rho
```

```
corrplot::corrplot(cor_aggr,  
  method = "color",  
  type = "upper",  
  order = "original",  
  tl.col = "black",  
  tl.srt = 45,  
  diag = FALSE  
)
```



-> a tetrachoric correlation is used, because responses are always binary (aggressive, vs. non-aggressive response)

Interpretation

- The correlation plot shows no clear pattern between the items
- If all items were to measure the same latent construct (aggressive cognition) we would expect (some-what) positive correlations between all the items

```
summary_mean_sd(df, WFCT_aggression_items)
```

```
## # A tibble: 10 x 5
##   variable    mean    sd    n missing
##   <chr>      <dbl> <dbl> <dbl>   <dbl>
## 1 WFCTagg1  0.05  0.22  144     8
## 2 WFCTagg2  0.13  0.34  148     4
## 3 WFCTagg3  0.07  0.26  147     5
## 4 WFCTagg4  0.08  0.28  146     6
## 5 WFCTagg5  0.03  0.18  149     3
## 6 WFCTagg6  0.51  0.5   150     2
## 7 WFCTagg7  0.1   0.3   141    11
## 8 WFCTagg8  0.41  0.49  138    14
## 9 WFCTagg9  0.23  0.42  141    11
## 10 WFCTagg10 0.64  0.48  139    13
```

Interpretation

- *Low Means:* On items 1, 2, 3, 4, 5, 7
- *Missing Values:* 10% missings on items 7, 8, 9, 10

5.1.2 Check sampling adequacy for Factor Analysis

```
KMO(cor_aggr)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = cor_aggr)
## Overall MSA = 0.17
## MSA for each item =
##   WFCTagg1 WFCTagg2 WFCTagg3 WFCTagg4 WFCTagg5 WFCTagg6 WFCTagg7 WFCTagg8
##       0.25    0.20    0.15    0.14    0.31    0.18    0.11    0.11
##   WFCTagg9 WFCTagg10
##       0.13    0.51
```

```
cortest.bartlett(cor_aggr, n = nrow(df))
```

```
## $chisq
## [1] 605.325
##
## $p.value
## [1] 3.55422e-99
##
## $df
## [1] 45
```

KMO (Kaiser-Meyer-Olkin) should be > 0.6 (ideally > 0.8) Bartlett's test should be significant ($p < .05$)

Interpretation

- The KMO is extremely low, indicating that the items are not suited for a factor analysis
- This is because the items share very little variance (are not correlating)

5.2 Reliability

```
psych::alpha(cor_aggr, check.keys = FALSE)
```

```
## Some items ( WFCTagg7 ) were negatively correlated with the first principal component and
## probably should be reversed.
## To do this, run the function again with the 'check.keys=TRUE' option
```

```
##
## Reliability analysis
## Call: psych::alpha(x = cor_aggr, check.keys = FALSE)
##
##   raw_alpha std.alpha G6(smc) average_r  S/N median_r
##       0.37      0.37   0.78    0.055 0.58    0.022
##
##   95% confidence boundaries
##       lower alpha upper
## Feldt -0.44  0.37  0.82
##
## Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r  S/N var.r   med.r
## WFCTagg1    0.33    0.33   0.73    0.051 0.49 0.047  0.0114
## WFCTagg2    0.33    0.33   0.74    0.051 0.49 0.050  0.0114
## WFCTagg3    0.34    0.34   0.70    0.053 0.50 0.047 -0.0089
## WFCTagg4    0.39    0.39   0.68    0.067 0.64 0.044  0.0513
## WFCTagg5    0.13    0.13   0.66    0.017 0.15 0.043 -0.0229
## WFCTagg6    0.25    0.25   0.63    0.036 0.33 0.044 -0.0089
## WFCTagg7    0.48    0.48   0.68    0.094 0.94 0.040  0.0553
## WFCTagg8    0.36    0.36   0.66    0.058 0.55 0.047  0.0252
## WFCTagg9    0.47    0.47   0.71    0.089 0.88 0.042  0.0553
## WFCTagg10   0.26    0.26   0.76    0.037 0.35 0.047 -0.0026
##
## Item statistics
##      r  r.cor r.drop
## WFCTagg1 0.424 0.363 0.180
## WFCTagg2 0.423 0.341 0.179
## WFCTagg3 0.408 0.359 0.161
## WFCTagg4 0.280 0.244 0.022
## WFCTagg5 0.745 0.747 0.589
## WFCTagg6 0.570 0.576 0.355
## WFCTagg7 0.025 -0.022 -0.228
## WFCTagg8 0.365 0.339 0.113
## WFCTagg9 0.074 0.012 -0.182
## WFCTagg10 0.557 0.453 0.338
```

Interpretation

5.3 Latent Trait Scores

5.3.1 Compute Scores

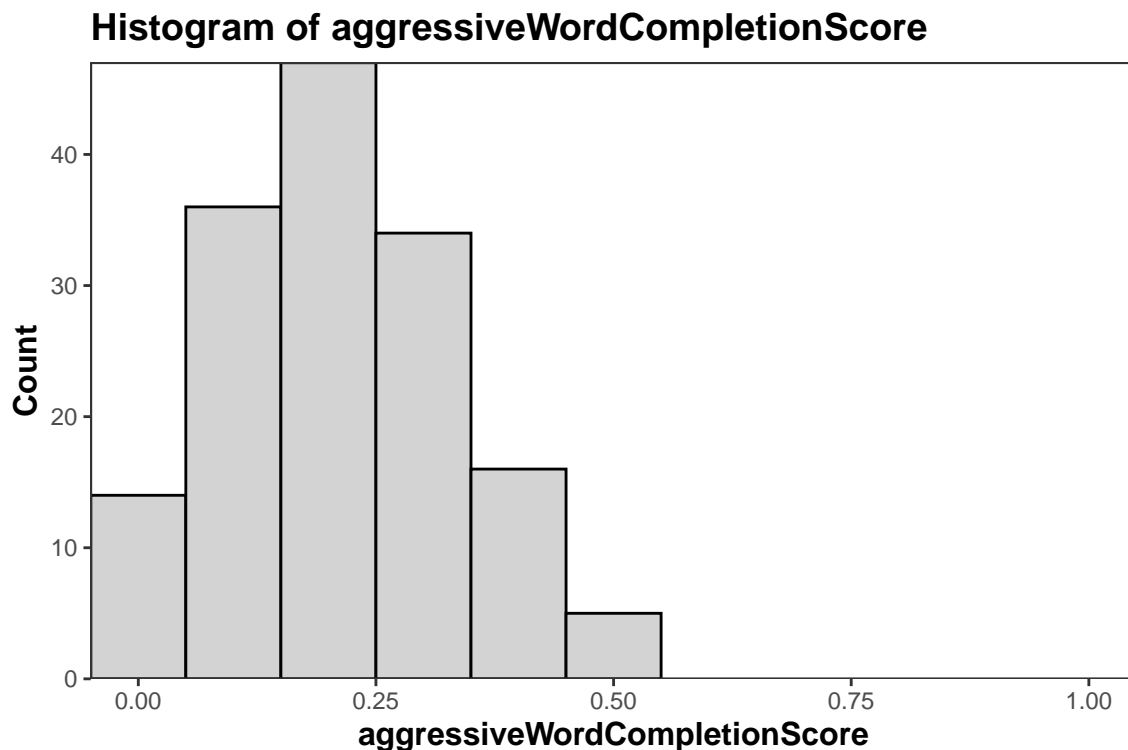
```
df$aggressiveWordCompletionScore <- rowMeans(  
  replace(df[WFCT_aggression_items], is.na(df[WFCT_aggression_items]), 0)  
)  
  
df$aggressiveWordCompletionScoreTransformed <- asin(sqrt(df$aggressiveWordCompletionScore))
```

5.3.2 Visualization & Descriptives

```
summary_mean_sd(df, c("aggressiveWordCompletionScore"))
```

```
## # A tibble: 1 x 5  
##   variable          mean    sd    n missing  
##   <chr>          <dbl> <dbl> <dbl>   <dbl>  
## 1 aggressiveWordCompletionScore 0.21 0.12  152      0
```

```
plotHist("aggressiveWordCompletionScore", c(0, 1), condition = NULL, binwidth = 0.1)
```



Summary

...

6. Test Quality Criteria: Anxious Cognition

Objectives:

- Assess the *validity* and *reliability* of the scale for anxious cognition
- Compute participant latent trait scores

Methodology:

- Descriptives * Visualization

6.1 Construct Validity

6.1.1 Visualization & Descriptives

```
summary_mean_sd(df, WFCT_anxiety_items)
```

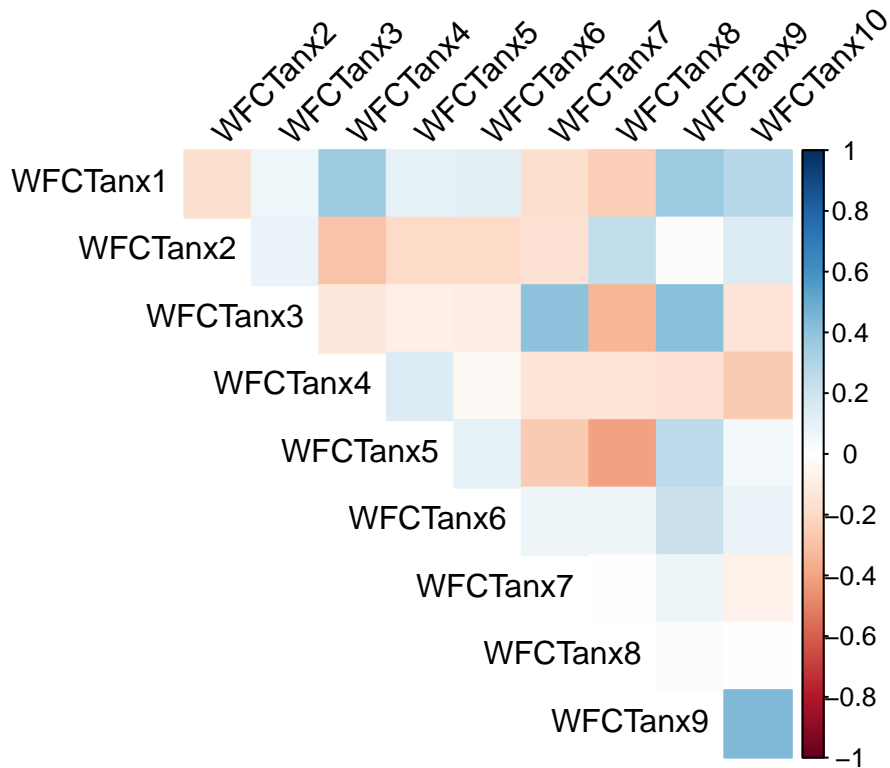
```
## # A tibble: 10 x 5
##   variable    mean    sd      n missing
##   <chr>      <dbl> <dbl> <dbl>   <dbl>
## 1 WFCTanx1   0.32  0.47   142     10
## 2 WFCTanx2   0.03  0.18   143      9
## 3 WFCTanx3   0.85  0.36   106     46
## 4 WFCTanx4   0.26  0.44   143      9
## 5 WFCTanx5   0.33  0.47   139     13
## 6 WFCTanx6   0.36  0.48   146      6
## 7 WFCTanx7   0.16  0.37   142     10
## 8 WFCTanx8   0.08  0.27   149      3
## 9 WFCTanx9   0.86  0.35   104     48
## 10 WFCTanx10 0.17  0.38   143      9
```

Interpretation

- *Low Means:*
- *Missing Values:* ...

```
cor_anx <- psych::tetrachoric(df[, WFCT_anxiety_items])$rho
```

```
corrplot::corrplot(cor_anx,
  method = "color",
  type = "upper",
  order = "original",
  tl.col = "black",
  tl.srt = 45,
  diag = FALSE
)
```



-> a tetrachoric correlation is used, because responses are always binary (aggressive, vs. non-aggressive)

Interpretation

- ...

6.1.2 Check sampling adequacy for Factor Analysis

```
KMO(cor_anx)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = cor_anx)
## Overall MSA = 0.31
## MSA for each item =
##   WFCTanx1 WFCTanx2 WFCTanx3 WFCTanx4 WFCTanx5 WFCTanx6 WFCTanx7 WFCTanx8
##         0.47         0.36         0.22         0.52         0.27         0.52         0.45         0.22
##   WFCTanx9 WFCTanx10
##         0.27         0.27
```

```
cortest.bartlett(cor_anx, n = nrow(df))
```

```
## $chisq
## [1] 432.8331
##
## $p.value
## [1] 7.733013e-65
```

```
##
## $df
## [1] 45
```

KMO (Kaiser-Meyer-Olkin) should be > 0.6 (ideally > 0.8) Bartlett's test should be significant ($p < .05$)

Interpretation

- The KMO is extremely low, indicating that the items are not suited for a factor analysis
- This is because the items share very little variance ...

6.2 Reliability

```
psych::alpha(cor_anx, check.keys = FALSE)
```

```
## Some items ( WFCTanx2 WFCTanx7 WFCTanx8 ) were negatively correlated with the first principal component
## probably should be reversed.
## To do this, run the function again with the 'check.keys=TRUE' option
```

```
##
## Reliability analysis
## Call: psych::alpha(x = cor_anx, check.keys = FALSE)
##
##   raw_alpha std.alpha G6(smc) average_r  S/N median_r
##      0.096      0.096      0.52      0.01 0.11      0.0055
##
##   95% confidence boundaries
##      lower alpha upper
## Feldt -1.06      0.1  0.74
##
## Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r  S/N var.r  med.r
## WFCTanx1    -0.061    -0.061   0.409   -0.0064 -0.057 0.043 -0.0050
## WFCTanx2     0.205     0.205   0.558    0.0279  0.258 0.048  0.0329
## WFCTanx3     0.066     0.066   0.356    0.0078  0.070 0.042  0.0082
## WFCTanx4     0.225     0.225   0.570    0.0312  0.290 0.046  0.0622
## WFCTanx5     0.156     0.156   0.494    0.0201  0.185 0.046  0.0051
## WFCTanx6     0.031     0.031   0.516    0.0035  0.032 0.053 -0.0050
## WFCTanx7     0.157     0.157   0.538    0.0202  0.186 0.048  0.0329
## WFCTanx8     0.244     0.244   0.504    0.0346  0.322 0.044  0.0622
## WFCTanx9    -0.387    -0.387   0.086   -0.0320 -0.279 0.038 -0.0534
## WFCTanx10   -0.019    -0.019   0.398   -0.0021 -0.019 0.046 -0.0046
##
## Item statistics
##      r  r.cor r.drop
## WFCTanx1  0.515  0.486  0.240
## WFCTanx2  0.141 -0.085 -0.160
## WFCTanx3  0.360  0.381  0.062
## WFCTanx4  0.105 -0.125 -0.194
## WFCTanx5  0.226  0.107 -0.078
## WFCTanx6  0.407  0.208  0.114
```

```
## WFCTanx7  0.225  0.043 -0.079
## WFCTanx8  0.068 -0.074 -0.228
## WFCTanx9  0.793  0.986  0.627
## WFCTanx10 0.467  0.456  0.184
```

6.3 Latent Trait Scores

6.3.1 Compute Scores

```
df$anxiousWordCompletionScore <- rowMeans(
  replace(df[WFCT_anxiety_items], is.na(df[WFCT_anxiety_items]), 0)
)

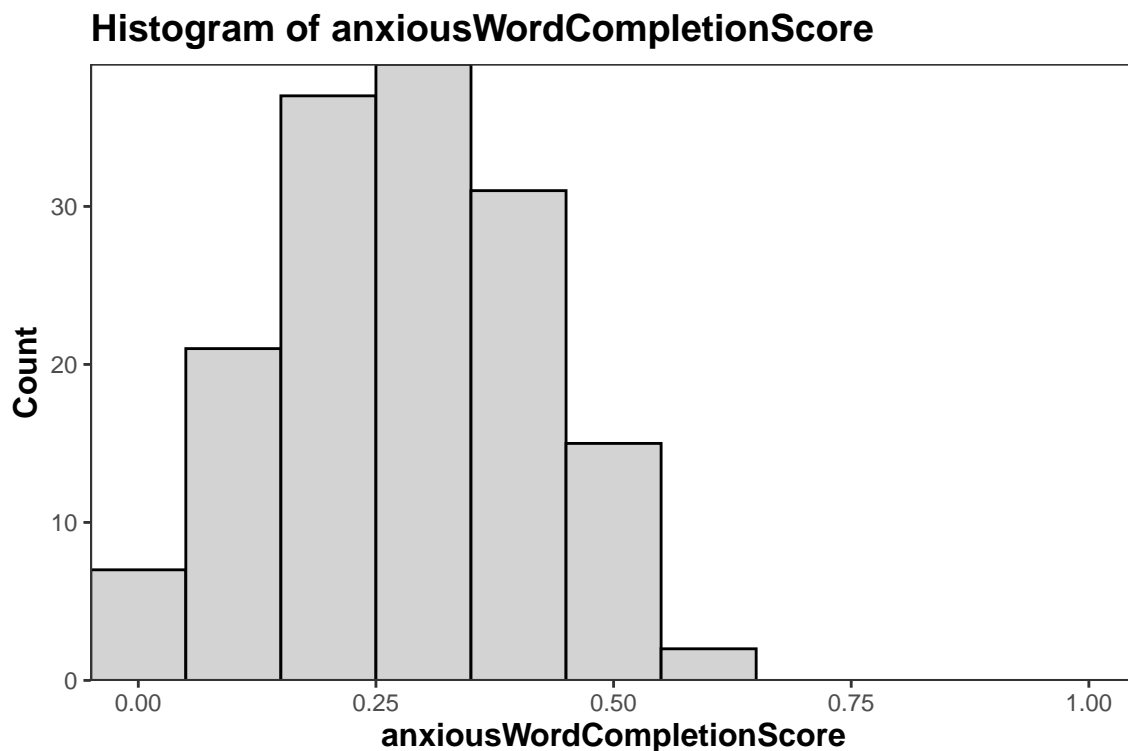
df$anxiousWordCompletionScoreTransformed <- asin(sqrt(df$anxiousWordCompletionScore))
```

6.3.2 Visualization & Descriptives

```
summary_mean_sd(df, c("anxiousWordCompletionScore"))
```

```
## # A tibble: 1 x 5
##   variable          mean    sd    n missing
##   <chr>          <dbl> <dbl> <dbl>   <dbl>
## 1 anxiousWordCompletionScore 0.28  0.14  152      0
```

```
plotHist("anxiousWordCompletionScore", c(0, 1), condition = NULL, binwidth = 0.1)
```



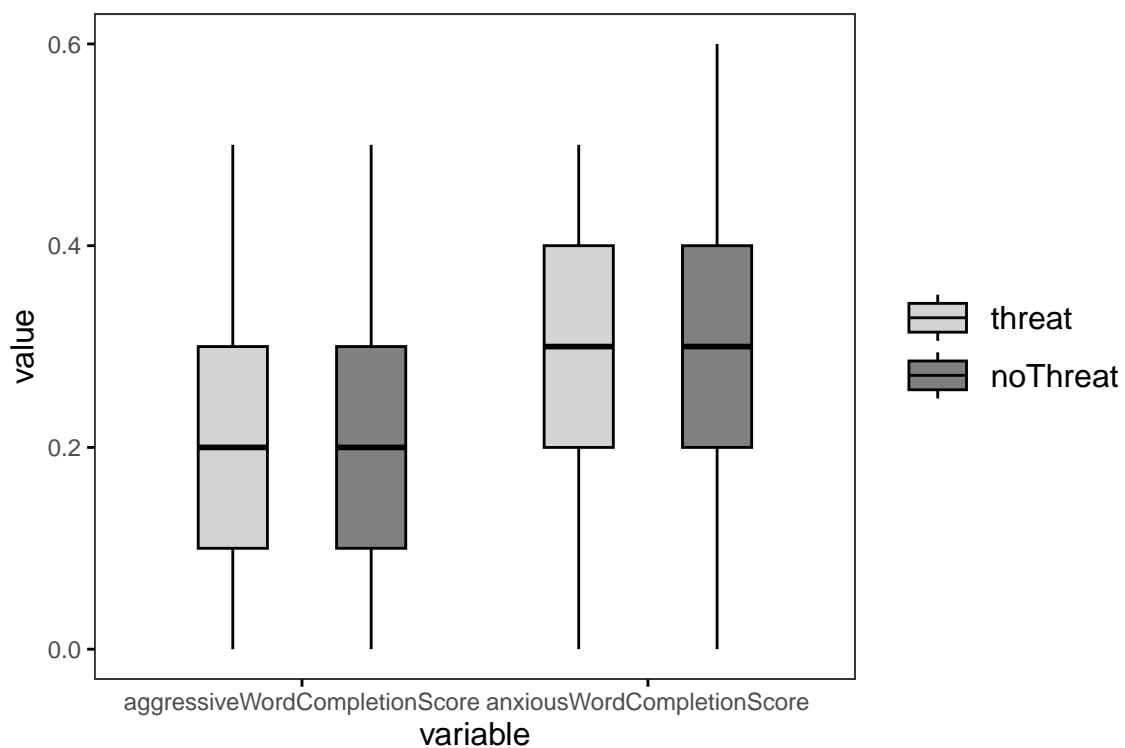
Summary

Hypothesis 1a & 1b

Visualization

Aggressive and anxious word completions by threat condition

```
plotBox(  
  c("aggressiveWordCompletionScore", "anxiousWordCompletionScore"),  
  "threatCondition"  
)
```



```
summary_mean_sd(df, c("aggressiveWordCompletionScore", "anxiousWordCompletionScore"))
```

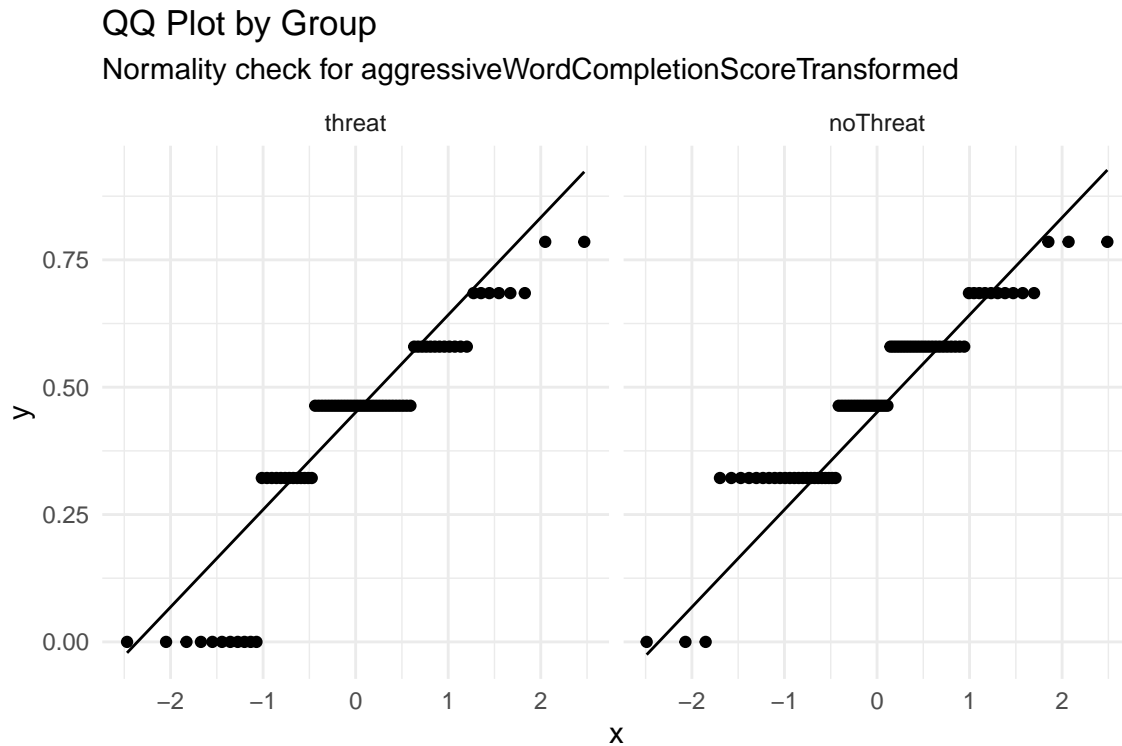
```
## # A tibble: 2 x 5  
##   variable      mean    sd    n missing  
##   <chr>      <dbl> <dbl> <dbl>    <dbl>  
## 1 aggressiveWordCompletionScore 0.21 0.12 152      0  
## 2 anxiousWordCompletionScore    0.28 0.14 152      0
```

Hypothesis 1a t-test

Assumption 1: Normality withing each group

Check Visually

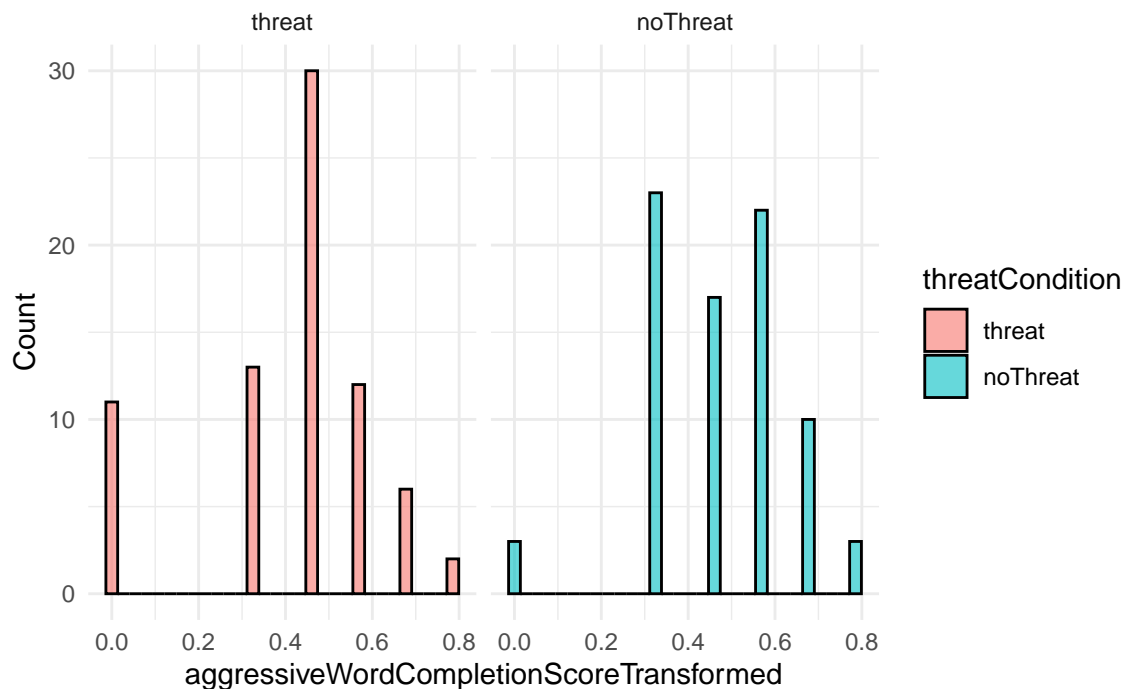
```
check_normality_qq(
  df, aggressiveWordCompletionScoreTransformed,
  threatCondition
)
```



-> data points should be roughly on the line

```
check_normality_hist(
  df, aggressiveWordCompletionScoreTransformed,
  threatCondition
)
```

Distribution of aggressiveWordCompletionScoreTransformed by threa



-> should roughly resemble a normal distribution

Assumption 2: Homogeneity of variance

Levene Test

```
check_homogeneity(
  df, aggressiveWordCompletionScoreTransformed,
  threatCondition
)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 1  0.0811 0.7762
##      150
```

$p > .05 \rightarrow$ equal variances (use Student's t-test: `var.equal = TRUE`)

```
summary_mean_sd(df, "aggressiveWordCompletionScore", group = "threatCondition")
```

```
## # A tibble: 2 x 6
##   threatCondition variable      mean    sd    n missing
##   <fct>          <chr>      <dbl> <dbl> <dbl>   <dbl>
## 1 threat      aggressiveWordCompletionScore 0.19 0.12   74     0
## 2 noThreat    aggressiveWordCompletionScore 0.23 0.12   78     0
```



```
run_ttest(df, aggressiveWordCompletionScoreTransformed, threatCondition,
         alternative = "greater", var_equal = TRUE
)
```

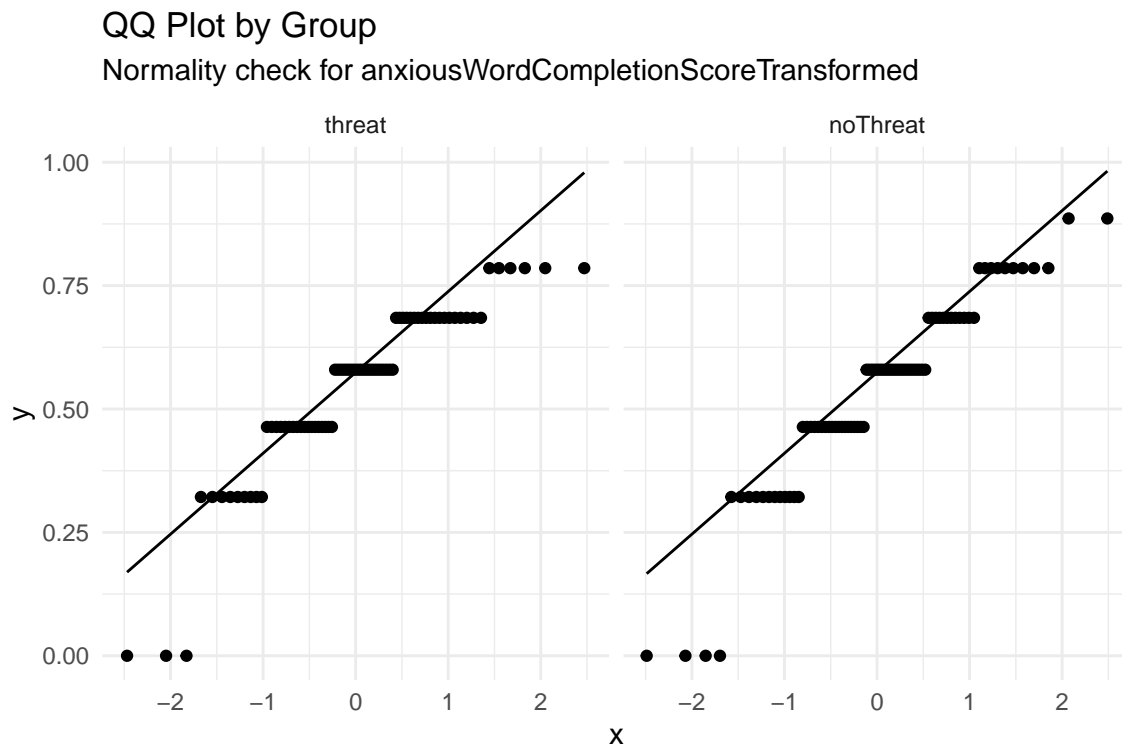
```
##
## Two Sample t-test
##
## data: aggressiveWordCompletionScoreTransformed by threatCondition
## t = -2.0378, df = 150, p-value = 0.9783
## alternative hypothesis: true difference in means between group threat and group noThreat is greater
## 95 percent confidence interval:
##  -0.1126784      Inf
## sample estimates:
##  mean in group threat mean in group noThreat
##           0.4152294           0.4774068
```

Hypothesis 1b t-test

Assumption 1: Normality withing each group

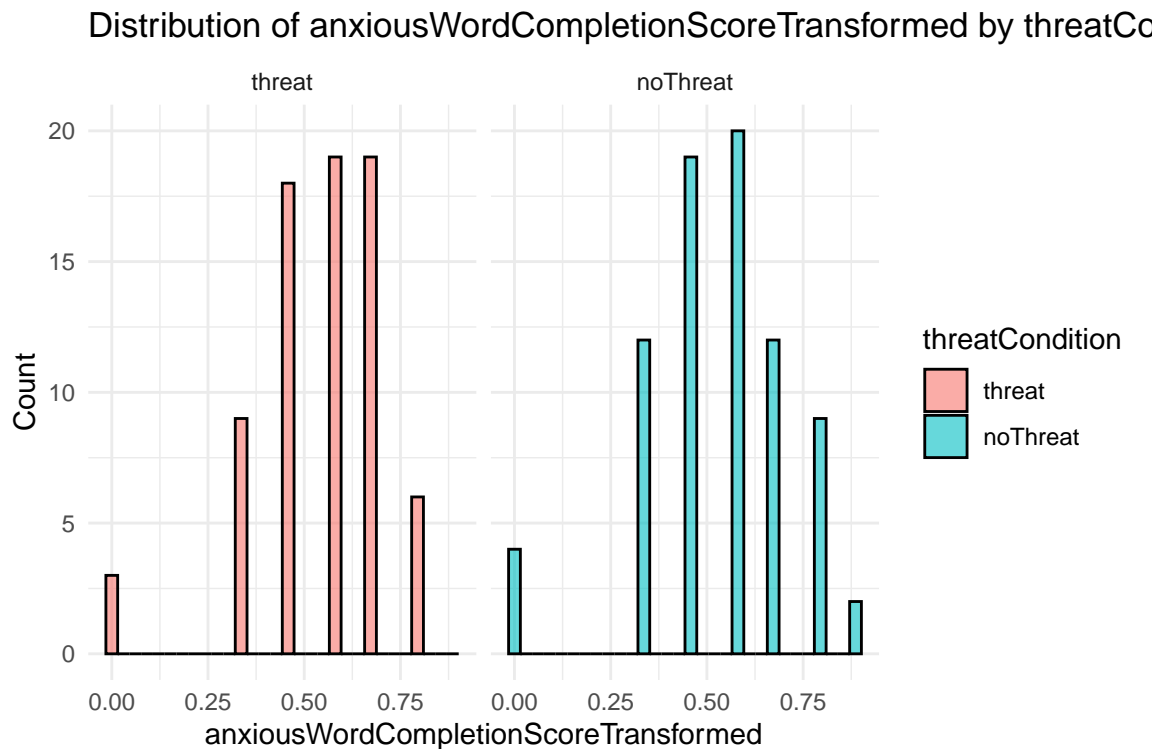
Check Visually

```
check_normality_qq(df, anxiousWordCompletionScoreTransformed, threatCondition)
```



-> data points should be roughly on the line

```
check_normality_hist(
  df, anxiousWordCompletionScoreTransformed,
  threatCondition
)
```



-> should roughly resemble a normal distribution

Assumption 2: Homogeneity of variance

Levene Test

```
check_homogeneity(df, anxiousWordCompletionScoreTransformed, threatCondition)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 1  0.7723 0.3809
##      150
```

$p > .05 \rightarrow$ equal variances (use Student's t-test: `var.equal = TRUE`)

```
summary_mean_sd(df, "anxiousWordCompletionScore", group = "threatCondition")
```

```
## # A tibble: 2 x 6
##   threatCondition variable      mean    sd    n missing
##   <fct>          <chr>      <dbl> <dbl> <dbl>   <dbl>
## 1 threat      anxiousWordCompletionScore 0.28  0.13   74     0
## 2 noThreat    anxiousWordCompletionScore 0.28  0.15   78     0
```

Run inference statistic

```
run_ttest(df, anxiousWordCompletionScoreTransformed, threatCondition,  
  alternative = "greater", var_equal = TRUE  
)
```

```
##
```

```
## Two Sample t-test
```

```
##
```

```
## data: anxiousWordCompletionScoreTransformed by threatCondition
```

```
## t = 0.34999, df = 150, p-value = 0.3634
```

```
## alternative hypothesis: true difference in means between group threat and group noThreat is greater
```

```
## 95 percent confidence interval:
```

```
## -0.03906057      Inf
```

```
## sample estimates:
```

```
## mean in group threat mean in group noThreat
```

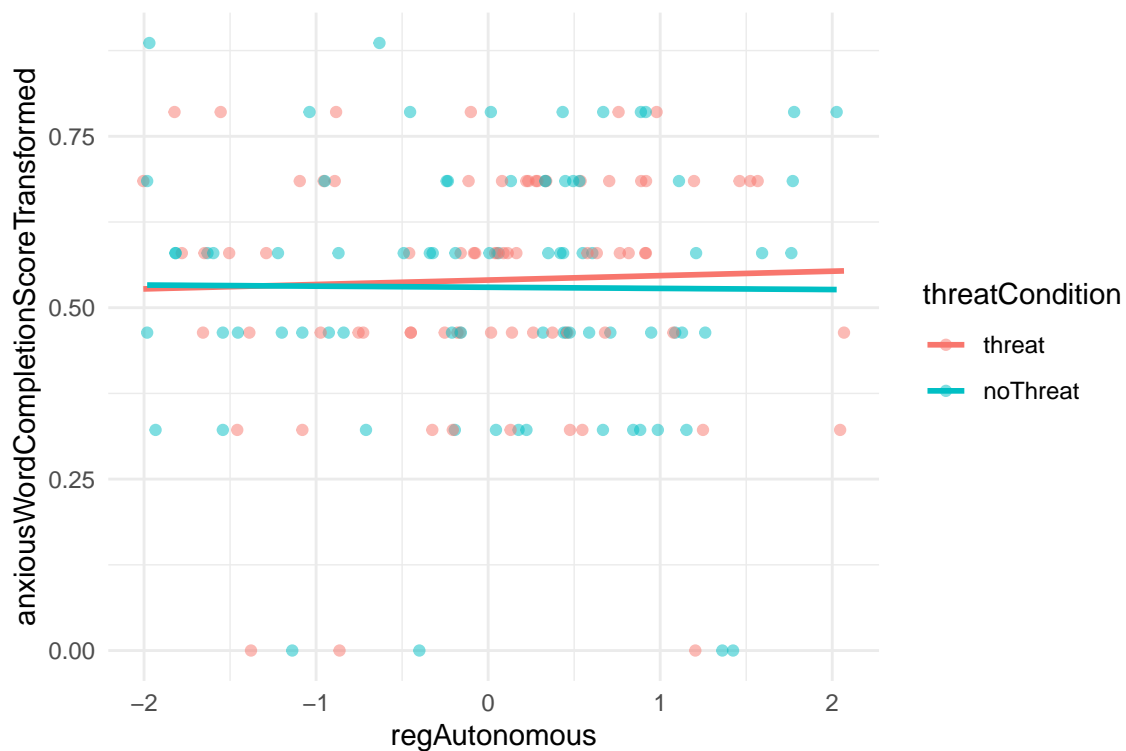
```
## 0.5402246 0.5297497
```

Hypothesis 2a & 2b: Moderation of Threat Response

Visualization

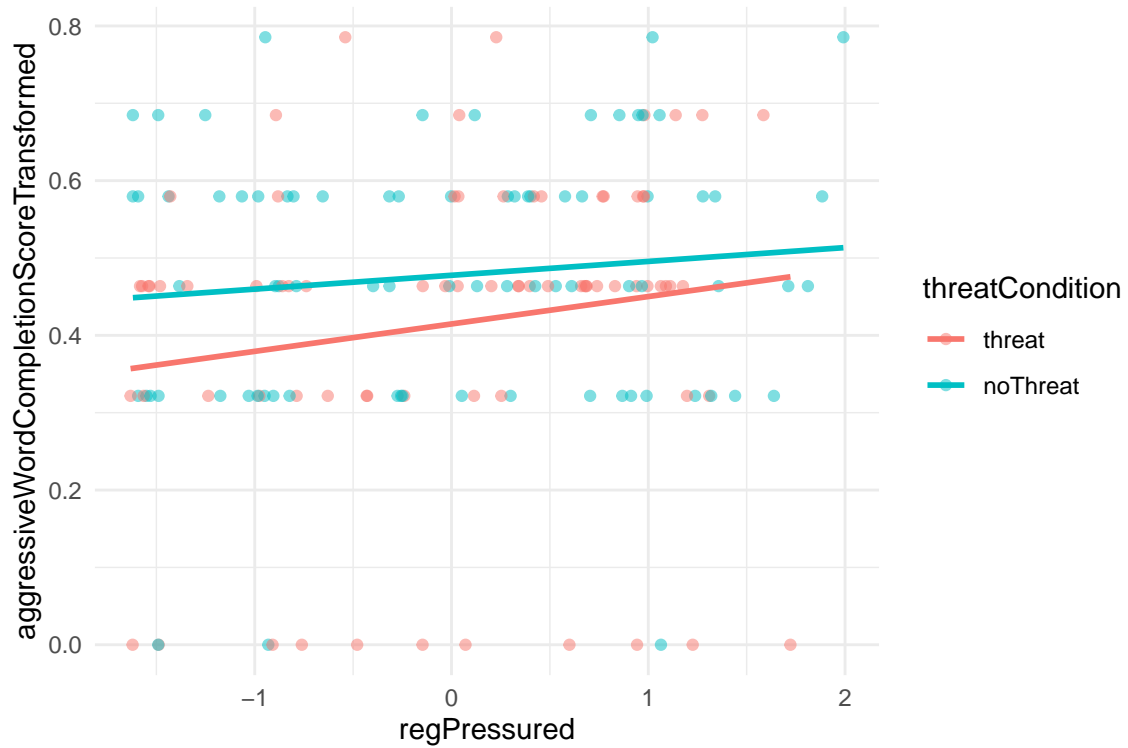
2a: Moderation autonomous motivation for masculine behavior on aggressive word completions

```
plotLine("regAutonomous", "anxiousWordCompletionScoreTransformed",  
  condition = "threatCondition", df = df  
)
```



2b: Moderation pressured motivation for masculine behavior on aggressive word completions

```
plotLine("regPressured", "aggressiveWordCompletionScoreTransformed",  
  condition = "threatCondition", df = df  
)
```



Hypothesis 2a

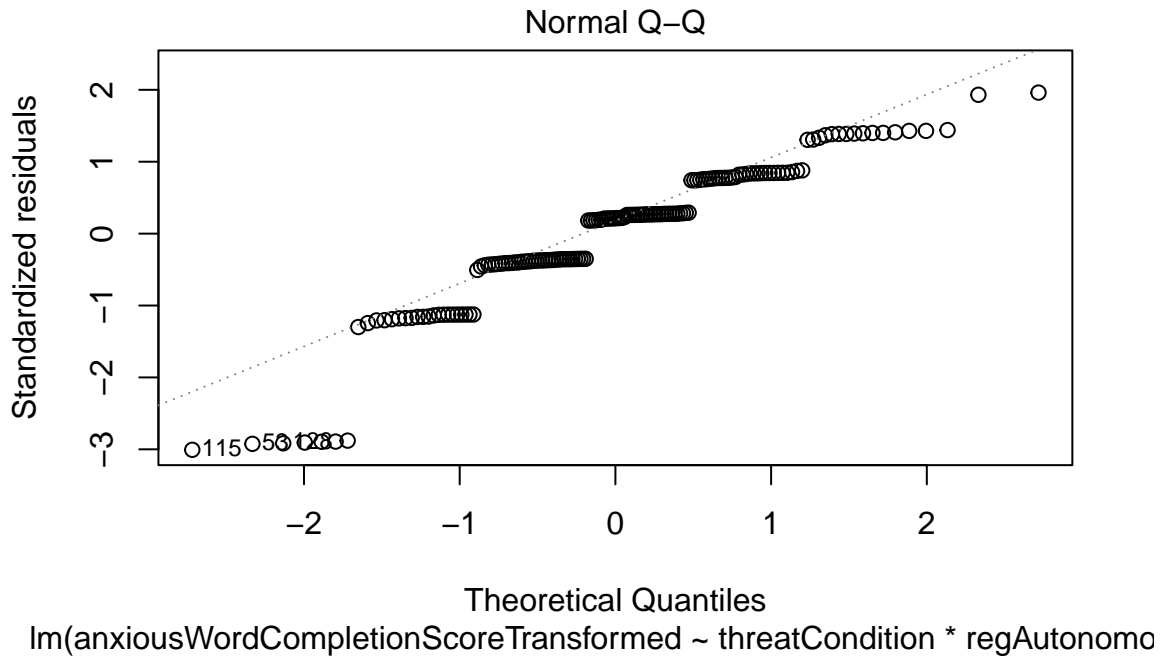
Multiple linear regression

Establish model

```
model_anxious <- lm(anxiousWordCompletionScoreTransformed ~  
  threatCondition * regAutonomous, data = df)
```

```
plot(model_anxious, which = 2)
```

Assumption 1: Normality



-> Q-Q plot points roughly on the line → residuals ~ normal. -> identify possible outliers (highly influential points)

Assumption 2: Outliers Examine outliers via residuals

```
res <- residuals(model_anxious)

# Standardized residuals
res_std <- rstandard(model_anxious)

# Flag extreme residuals
outliers <- which(abs(res_std) > 2)
outliers
```

```
## 35 53 73 96 115 128 141
## 35 53 73 96 115 128 141
```

Examine outliers via cook's distance

```
influential_obs <- df
influential_obs$cooksd <- cooks.distance(model_anxious)

n <- nrow(df)
k <- length(coef(model_anxious)) - 1
threshold <- 4 / (n - k - 1)
```

```
# influential_obs %>%
# filter(cooksD > threshold)
```

Cook's distance $> 4/(n-k-1) \rightarrow$ potentially influential

```
cor(df$regAutonomous, as.numeric(factor(df$threatCondition,
  levels = c("noThreat", "threat")
)) - 1)
```

Assumption 3: No Multikollinearity

```
##           [,1]
## [1,] -0.01239724
```

-> would also make no sense, since I randomly assign threatCondition

Inference statistics

```
summary(model_anxious)
```

```
##
## Call:
## lm(formula = anxiousWordCompletionScoreTransformed ~ threatCondition *
##     regAutonomous, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.54808 -0.07515  0.03944  0.14258  0.35527
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.540307   0.021580  25.038  <2e-16 ***
## threatConditionnoThreat -0.010537   0.030124  -0.350   0.727
## regAutonomous      0.006456   0.022624   0.285   0.776
## threatConditionnoThreat:regAutonomous -0.008095   0.030392  -0.266   0.790
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1856 on 148 degrees of freedom
## Multiple R-squared:  0.001409, Adjusted R-squared:  -0.01883
## F-statistic: 0.06963 on 3 and 148 DF, p-value: 0.9761
```

Post Hoc Analysis

...