Emotion as a Predictor of Cognitive Function

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```
knitr::opts_chunk$set(echo = TRUE)
```

Introduction

For this project, we looked at the MIDUS 2 dataset available here and attempted to find out if emotional status can be used as a way to predict one's cognitive function. The MIDUS 2 project measured subjects' emotional states, traits, and general regulation using two different methods: the Positive & Negative Affect Schedule and the Spielberg Trait and State Anxiety Scale. These were recorded via questionnaire while the subjects were sat down in a quiet room and shown emotionally distressing images along with a quickly flashed color bordering each image. They were then asked to recall the color of the border, and their accuracy and response times were recorded. Our project aims to look for correlations and dependencies within these measured values.

Research Question

Does emotion play a factor in cognitive ability during a testing state?

In order to answer this question, we first had to prepare the dataset:

```
library(dplyr)
library(tidyr)
library(readr)
library(stringr)
library(tibble)
library(ggplot2)
library(psych)
library(yarrr)
library(truncnorm)
library(Rcpp)
library(dplyr)
library(readr)
library(tidyr)
library(stringr)
library(tibble)
library(ggplot2)
library(psych)
library(yarrr)
library(lavaan)
library(GPArotation)
library(lm.beta)

grossTXT <- read.delim('/media/data/shared_data/johnsondr/CBSC_240_01_F22/MA project datasets/ICPSR_2868
df <- separate(grossTXT,
```

```
V1,
c(
  'M2ID','SAMPLMAJ','B1PAGE_M2','B1PRSEX','B5PEEGDATE_MO','B5PEEGDATE_YR','B5MRIDATE_
  'ASYMMETRY_USELESS','ALPHA_FREQ_USELESS',
  'B5E3EMG',
  'B5BNEM','B5BNMM','B5BNLM','B5BOEM','B5BOMM','B5BOLM','B5BPEM','B5BPMM','B5BPLM','
  'B5BNMA','B5BNLA','B5BOEA','B5BOMA','B5BOLA','B5BPEA','B5BPMA','B5BPLA',
  'B5CNE','B5CNM','B5CNL','B5COE','B5COM','B5COL','B5CPE','B5CPM','B5CPL',
  'B5SDPC01','B5SDPJ01','B5SDPH01','B5SDPL01','B5SDPD01','B5SDPO01','B5SDPP01','B5SD
  'B5SDPC02','B5SDPJ02','B5SDPH02','B5SDPL02','B5SDPD02','B5SDPO02','B5SDPP02','B5SD
  'B5SDPC03','B5SDPJ03','B5SDPH03','B5SDPL03','B5SDPD03','B5SDPO03','B5SDPP03','B5SD
  'B5SDPC04','B5SDPJ04','B5SDPH04','B5SDPL04','B5SDPD04','B5SDPO04','B5SDPP04','B5SD
  'B5SDPC05','B5SDPJ05','B5SDPH05','B5SDPL05','B5SDPD05','B5SDPO05','B5SDPP05','B5SD
  'B5SDPC06','B5SDPJ06','B5SDPH06','B5SDPL06','B5SDPD06','B5SDPO06','B5SDPP06','B5SD
  'B5SDPC07','B5SDPJ07','B5SDPH07','B5SDPL07','B5SDPD07','B5SDPO07','B5SDPP07','B5SD
  'B5SPGP01','B5SPGN01','B5SPGP02','B5SPGN02','B5SPGP03','B5SPGN03','B5SPGN04','B5SP
  'B5SPGN06','B5SPGP06','B5SPGN07','B5SPGP07','B5SPGN08','B5SPGP08','B5SPGP09','B5SP
  'B5SP1P01','B5SP1N01','B5SP1P02','B5SP1N02','B5SP1P03','B5SP1N03','B5SP1N04','B5SP
  'B5SP1N06','B5SP1P06','B5SP1N07','B5SP1P07','B5SP1N08','B5SP1P08','B5SP1P09','B5SP
  'B5SP2P01','B5SP2N01','B5SP2P02','B5SP2N02','B5SP2P03','B5SP2N03','B5SP2N04','B5SP
  'B5SP2N06','B5SP2P06','B5SP2N07','B5SP2P07','B5SP2N08','B5SP2P08','B5SP2P09','B5SP
  'B5SRQE01','B5SRQV01','B5SRQB01','B5SRQB02','B5SRQB03','B5SRQV02','B5SRQV03','B5SR
  'B5SS101','B5SS102','B5SS103','B5SS104','B5SS105','B5SS106','B5SS107','B5SS108','B
  'B5SS111','B5SS112','B5SS113','B5SS114','B5SS115','B5SS116','B5SS117','B5SS118','B
  'B5SS201','B5SS202','B5SS203','B5SS204','B5SS205','B5SS206','B5SS207','B5SS208','B
  'B5SS211','B5SS212','B5SS213','B5SS214','B5SS215','B5SS216','B5SS217','B5SS218','B
  'B5SST01','B5SST02','B5SST03','B5SST04','B5SST05','B5SST06','B5SST07','B5SST08','B
  'B5SST11','B5SST12','B5SST13','B5SST14','B5SST15','B5SST16','B5SST17','B5SST18','B
  'B5SER01','B5SES02','B5SER03','B5SES04','B5SER05','B5SES06','B5SER07','B5SER08','B
  'B5SDPC',  'B5SDPJ',  'B5SDPH',  'B5SDPL',  'B5SDPD',  'B5SDPO',  'B5SDPP',  'B5SD
  # content  # joy      # hope     # love     # desire  #compassion # pride    #grat

  'B5SDPT',     'B5SPGP',         'B5SPGN',         'B5SP1P',          'B5SP1N',
  #ALL pos aff  #posANDneg genPOS #posANDneg genNEG #posANDneg nowPOS1 #posANDneg no

  'B5SRQB', 'B5SRQV',  'B5SRQE',
  #rasq BEV # rasq VR  # rasq Exp

  'B5SS1',   'B5SS2',   'B5SST',
  #staixNOW1 #staixNOW2 #staixGEN

  'B5SES',   'B5SER',
  #ERQ suppr #ERQ reapp

  'B5RN','B5RO','B5RP',
   #NEG   #NEU   #POS

  'B5AN','B5AO','B5AP',
   #NEG   #NEU   #POS

  'B5C',
  'B5B'
  ),
```

```
                   sep = c(5,7,9,10,12,16,18,22,24,25,26, # identifying info
                           288,478, # useless stuff
                           487,                                           # corrugator info
                           502,517,532,547,562,577,592,607,622,637,       # ebr info
                           652,667,682,697,712,727,742,757,               # more ebr info
                           772,787,802,817,832,847,862,877,892,           # more corrugator
                           893,894,895,896,897,898,899,900,901,902,903,   # beliefs and feelings questio
                           904,905,906,907,908,909,910,911,912,913,914,   # beliefs and feelings questio
                           915,916,917,918,919,920,921,922,923,924,925,   # beliefs and feelings questio
                           926,927,928,929,930,931,932,933,934,935,936,   # beliefs and feelings questio
                           937,938,939,940,941,942,943,944,945,946,947,   # beliefs and feelings questio
                           948,949,950,951,952,953,954,955,956,957,958,   # beliefs and feelings questio
                           959,960,961,962,963,964,965,966,967,           # beliefs and feelings questio
                           968,969,970,971,972,973,974,975,976,977,         # feelings and emotions pnag
                           978,979,980,981,982,983,984,985,986,987,           # feelings and emotions pn
                           988,989,990,991,992,993,994,995,996,997,             # f and e RIGHT NOW pnan
                           998,999,1000,1001,1002,1003,1004,1005,1006,1007,       # f and e RIGHT NOW pn
                           1008,1009,1010,1011,1012,1013,1014,1015,1016,1017,       # f and e RIGHT NOW f
                           1018,1019,1020,1021,1022,1023,1024,1025,1026,1027,         # f and e RIGHT NO
                           1028,1029,1030,1031,1032,1033,1034,1035,1036,1037,1038,      # gen desc self
                           1039,1040,1041,1042,1043,1044,1045,1046,1047,1048,           # feel right now
                           1049,1050,1051,1052,1053,1054,1055,1056,1057,1058,           # feel right now
                           1059,1060,1061,1062,1063,1064,1065,1066,1067,1068,           # feel right now
                           1069,1070,1071,1072,1073,1074,1075,1076,1077,1078,           # feel right now
                           1079,1080,1081,1082,1083,1084,1085,1086,1087,1088,           # gen feel stmt
                           1089,1090,1091,1092,1093,1094,1095,1096,1097,1098,           # gen feel stmt
                           1099,1100,1101,1102,1103,1104,1105,1106,1107,1108,           # emotional regu
                           1123,1138,1153,1168,1183,1198,1213,1228,1243,1258,1273,      # mean values of

                           1288,1303,1318,1333,1336,1351,1366,                          # pos and neg af

                           1381,1396,1411,                                           # reactivity to aff

                           1426,1441,1456,                                         # spielberger state-t

                           1471,1486,                                            # ERQ suppression and r

                           1492,1498,1504,                                     # median reaction time

                           1519,1534,1549,                                   # accuracy (proportion of t

                           1550,                                           # filter for good corrugator
                           1552                                          # num valid eyeblink responses


                            ),

                   remove = TRUE,
                   convert = TRUE
                   )

df_milwaukee <- df %>%
  filter(SAMPLMAJ == 13)
```

```r
df_madison <- df %>%
  filter(SAMPLMAJ %in% c(1,2,3))
```

We chose to look at certain variables from the dataset in order to answer this question. The variables, and the abbreviations used to represent each one, are as follows:

Variable Information	Variable Name
General Form of the Positive and Negative Affect Schedule: Positive Results	PG_P_mean
General Form of the Positive and Negative Affect Schedule: Negative Results	PG_N_mean
Now Form of the Positive and Negative Affect Schedule: Positive Results from early in session	P1_P_mean
Now Form of the Positive and Negative Affect Schedule: Negative Results from early in session	P1_N_mean
Now Form of the Positive and Negative Affect Schedule: Positive Results from late in session	P1_P_mean
Now Form of the Positive and Negative Affect Schedule: Negative Results from late in session	P1_N_mean
Spielberger State Anxiety Scale: Time 1 from early in session	SS1_mean
Spielberger State Anxiety Scale: Time 2 from early in session	SS2_mean
Spielberger Trait Anxiety Scale	ST_mean

Using these variables, we first decided to build a 2 factor model to determine the relationships between the Positive and Negative Affect Schedule (PANAS), the Spielberger Trait Anxiety Scale (ST), and the Spielberger State Anxiety Scale (SS). We originally believed that there would be only two factors: the positive results and the negative results.

Data Selection and Analysis

First, we selected our data from the dataset and dropped missing values.

```r
# selecting data
df_PANAS_STT <- df %>%
  select(B5SP1N01, B5SP1N02, B5SP1N03, B5SP1N04, B5SP1N05, B5SP1N06, B5SP1N07, B5SP1N08,
         B5SP1N09, B5SP1N10, B5SP1P01, B5SP1P02, B5SP1P03, B5SP1P04, B5SP1P05, B5SP1P06,
         B5SP1P07, B5SP1P08, B5SP1P09, B5SP1P10, B5SP2P01, B5SP2P02, B5SP2P03, B5SP2P04,
         B5SP2P05, B5SP2P06, B5SP2P07, B5SP2P08, B5SP2P09, B5SP2P10, B5SP2N01, B5SP2N02,
         B5SP2N03, B5SP2N04, B5SP2N05, B5SP2N06, B5SP2N07, B5SP2N08, B5SP2N09, B5SP2N10,
         B5SS101, B5SS102, B5SS103, B5SS104, B5SS105, B5SS106, B5SS107, B5SS108, B5SS109,
         B5SS110, B5SS111, B5SS112, B5SS113, B5SS114, B5SS115, B5SS116, B5SS117, B5SS118,
         B5SS119, B5SS120, B5SS201, B5SS202, B5SS203, B5SS204, B5SS205, B5SS206, B5SS207,
         B5SS208, B5SS209, B5SS210, B5SS211, B5SS212, B5SS213, B5SS214, B5SS215, B5SS216,
         B5SS217, B5SS218, B5SS218, B5SS219, B5SS220, B5SST01, B5SST02, B5SST03, B5SST04,
         B5SST05, B5SST06, B5SST07, B5SST08, B5SST09, B5SST10, B5SST11, B5SST12, B5SST13,
         B5SST14, B5SST15, B5SST16, B5SST17, B5SST18, B5SST19, B5SST20, B5SPGP01, B5SPGP02,
         B5SPGP03, B5SPGP04, B5SPGP05, B5SPGP06, B5SPGP07, B5SPGP08, B5SPGP09, B5SPGP10,
         B5SPGN01, B5SPGN02, B5SPGN03, B5SPGN04, B5SPGN05, B5SPGN06, B5SPGN07, B5SPGN08,
         B5SPGN09, B5SPGN10, B5SPGP, B5SPGN, B5SP1P, B5SP1N, B5SP2N, B5SP2P, B5SST, B5SS1,
         B5SS2, B1PRSEX, B5RN, B5RP, B5RO, B5AN, B5AO, B5AP ) %>%
  # renaming columns
  rename( sex = B1PRSEX,
```

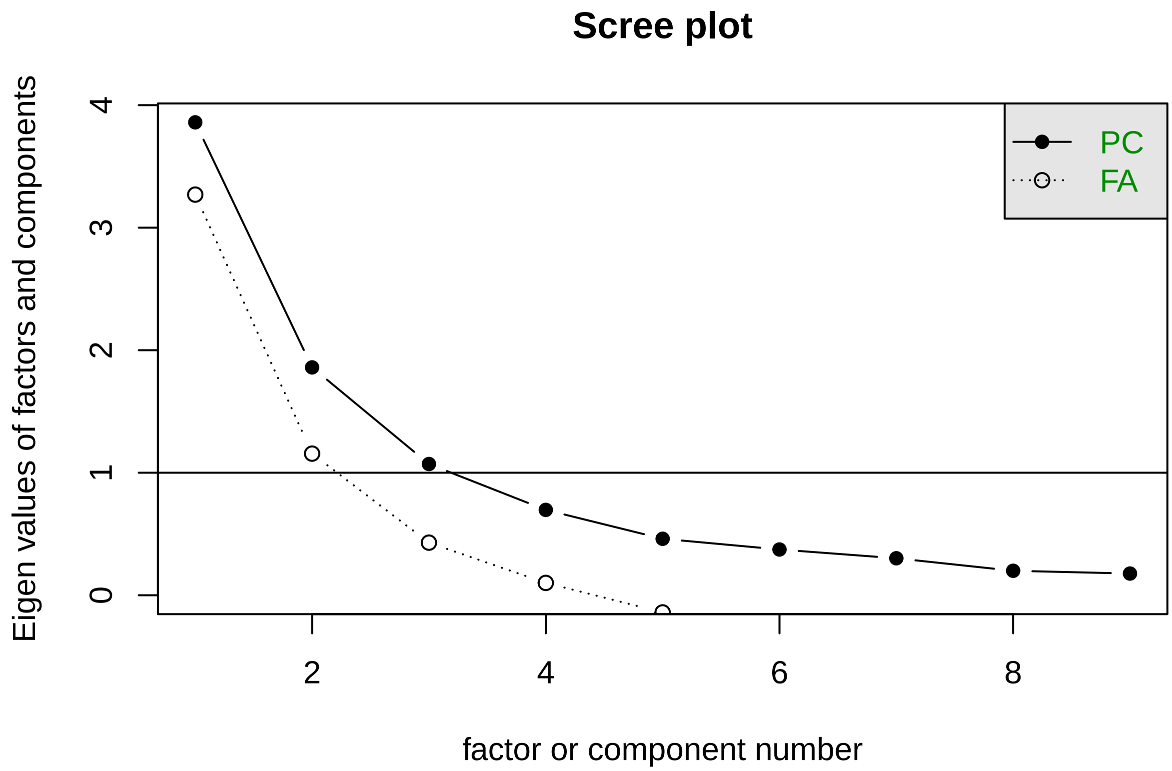
```r
          PG_P_mean = B5SPGP,
          PG_N_mean = B5SPGN,
          P1_P_mean= B5SP1P,
          P1_N_mean = B5SP1N,
          P2_N_mean = B5SP2N,
          P2_P_mean = B5SP2P,
          ST_mean = B5SST,
          SS1_mean = B5SS1,
          SS2_mean = B5SS2,
          Response_neg = B5RN,
          Response_pos = B5RP,
          Response_neut = B5RO,
          Acc_neg = B5AN,
          Acc_neut = B5AO,
          Acc_pos = B5AP
          ) %>%
  # sets values of 8 and 9998 to missing
  na_if(8) %>%
  na_if(9998)


# removes missing data
PANAS_STT <- df_PANAS_STT %>%
  drop_na()

#This dataframe will be used to test predictive ability strength when running a
#multiple regression
PANAS_means <- PANAS_STT %>%
  select(PG_P_mean,PG_N_mean, P1_P_mean, P1_N_mean, P2_N_mean, P2_P_mean, ST_mean,SS1_mean, SS2_mean,Res
       mutate(
         PG_P_mean = 6-PG_P_mean,
         P1_P_mean = 6-P1_P_mean,
         P2_P_mean = 6-P2_P_mean,
         PG_N_mean = 6-PG_N_mean,
         P1_N_mean = 6-P1_N_mean,
         Acc_neg = 1-Acc_neg,
         Acc_neut = 1-Acc_neut,
         Acc_pos = 1-Acc_pos)

#Dataframe used to test correlation between our factors
PANAS_means_model <- PANAS_STT %>%
  select(PG_P_mean,PG_N_mean, P1_P_mean, P1_N_mean, P2_N_mean, P2_P_mean, ST_mean,SS1_mean, SS2_mean) %
       mutate(
         PG_P_mean = 6-PG_P_mean,
         P1_P_mean = 6-P1_P_mean,
         P2_P_mean = 6-P2_P_mean)

#Reliability computed for the variables in this factor model, and which factors
#should be reversed
alpha(PANAS_means_model)
```

```
##
## Reliability analysis
## Call: alpha(x = PANAS_means_model)
```

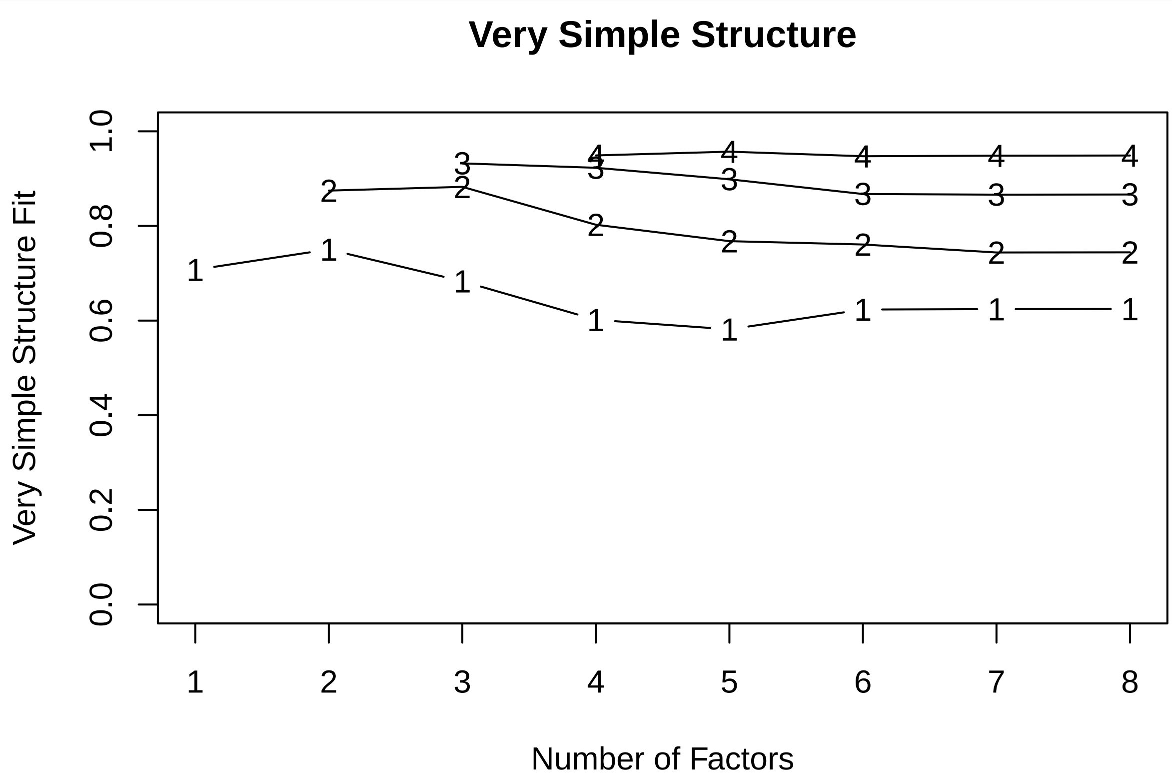
```
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
##        0.8      0.83    0.89      0.35 4.8 0.019  1.9 0.32     0.36
##
##  lower alpha upper     95% confidence boundaries
## 0.76 0.8 0.83
##
##  Reliability if an item is dropped:
##           raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## PG_P_mean      0.75      0.81    0.87      0.34 4.2    0.024 0.037  0.35
## PG_N_mean      0.80      0.82    0.88      0.37 4.7    0.018 0.039  0.37
## P1_P_mean      0.76      0.82    0.87      0.36 4.4    0.023 0.032  0.37
## P1_N_mean      0.79      0.81    0.87      0.35 4.3    0.019 0.041  0.34
## P2_N_mean      0.80      0.82    0.87      0.37 4.7    0.019 0.038  0.38
## P2_P_mean      0.79      0.82    0.88      0.36 4.6    0.021 0.035  0.37
## ST_mean        0.78      0.81    0.87      0.34 4.2    0.020 0.043  0.34
## SS1_mean       0.77      0.79    0.86      0.32 3.8    0.021 0.042  0.32
## SS2_mean       0.77      0.79    0.85      0.33 3.9    0.021 0.044  0.30
##
##  Item statistics
##             n raw.r std.r r.cor r.drop mean   sd
## PG_P_mean 229  0.77  0.67  0.64   0.66  2.4 0.61
## PG_N_mean 229  0.46  0.56  0.49   0.32  1.4 0.44
## P1_P_mean 229  0.75  0.61  0.59   0.61  2.6 0.69
## P1_N_mean 229  0.51  0.64  0.59   0.42  1.2 0.29
## P2_N_mean 229  0.42  0.55  0.50   0.34  1.2 0.26
## P2_P_mean 229  0.73  0.58  0.53   0.54  3.0 0.85
## ST_mean   229  0.61  0.69  0.65   0.51  1.7 0.39
## SS1_mean  229  0.72  0.79  0.78   0.64  1.6 0.38
## SS2_mean  229  0.69  0.76  0.74   0.61  1.6 0.38
```

After doing this, we decided to analyze the scree and vss plots for the data to determine if using a two factor model was a good idea or not.

```
scree(PANAS_means_model)
```




```
vss(PANAS_means_model)
```




```
##
## Very Simple Structure
## Call: vss(x = PANAS_means_model)
```

```
## VSS complexity 1 achieves a maximimum of 0.75  with  2  factors
## VSS complexity 2 achieves a maximimum of 0.88  with  3  factors
##
## The Velicer MAP achieves a minimum of 0.07  with  2  factors
## BIC achieves a minimum of  -8.73  with  4  factors
## Sample Size adjusted BIC achieves a minimum of  8.68  with  5  factors
##
## Statistics by number of factors
##   vss1 vss2   map dof   chisq    prob sqresid  fit RMSEA   BIC SABIC complex
## 1 0.71 0.00 0.101  27 5.0e+02 3.1e-89    6.00 0.71  0.28 356.7 442.3     1.0
## 2 0.75 0.87 0.075  19 2.1e+02 3.7e-35    2.57 0.87  0.21 111.6 171.9     1.1
## 3 0.68 0.88 0.089  12 9.7e+01 2.2e-15    1.39 0.93  0.18  31.8  69.8     1.3
## 4 0.60 0.80 0.129   6 2.4e+01 5.5e-04    1.05 0.95  0.11  -8.7  10.3     1.5
## 5 0.58 0.77 0.191   1 1.1e+01 9.4e-04    0.68 0.97  0.21   5.5   8.7     1.6
## 6 0.62 0.76 0.277  -3 9.0e-06      NA    0.56 0.97    NA    NA    NA     1.6
## 7 0.62 0.74 0.447  -6 1.5e-09      NA    0.52 0.97    NA    NA    NA     1.6
## 8 0.62 0.74 1.000  -8 1.7e-09      NA    0.51 0.98    NA    NA    NA     1.6
##    eChisq    SRMR eCRMS  eBIC
## 1 5.0e+02 1.7e-01 0.201 351.1
## 2 1.1e+02 8.2e-02 0.113   8.2
## 3 2.9e+01 4.2e-02 0.072 -36.5
## 4 4.7e+00 1.7e-02 0.042 -27.9
## 5 1.5e+00 9.5e-03 0.057  -3.9
## 6 1.2e-06 8.4e-06    NA    NA
## 7 1.9e-10 1.1e-07    NA    NA
## 8 1.5e-10 9.4e-08    NA    NA
```

```r
#the flip of map values around 2-3 factors shows either 2 or 3 factors will
#best fit our model
```

EFA Models

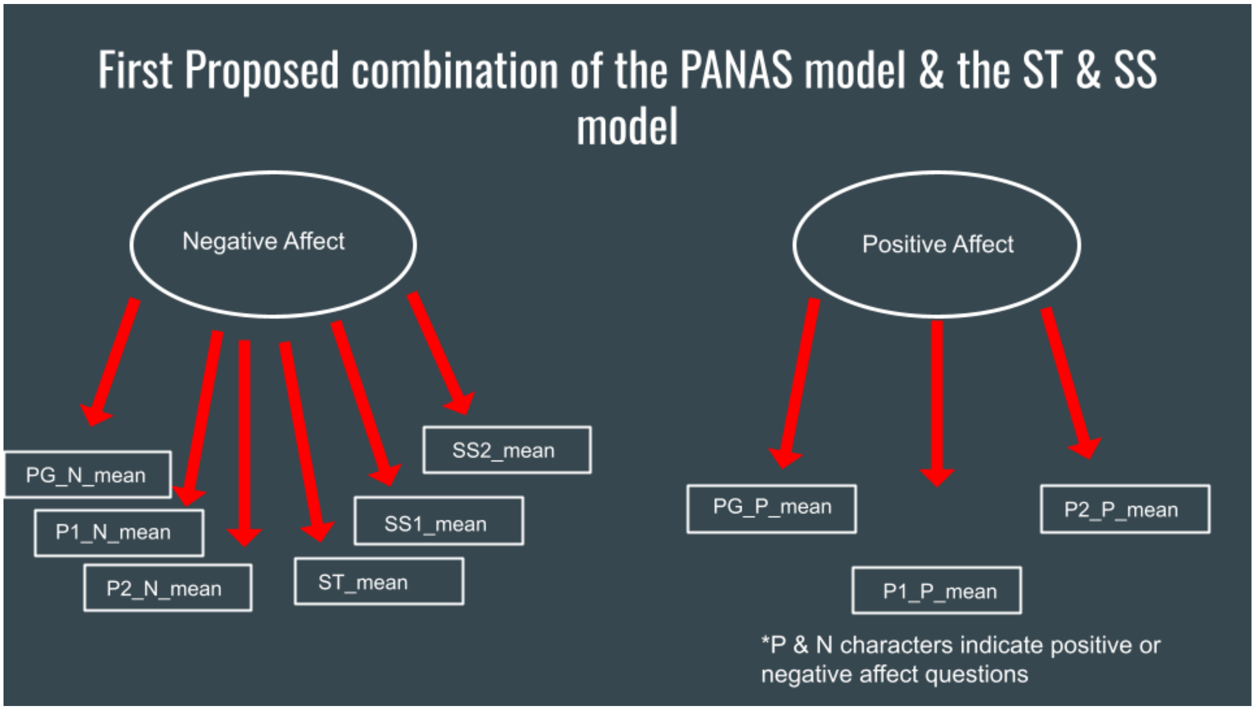
Given the VSS and Scree plots shown, we decided that either a 2 or 3 factor model would be best for our data. So, we performed an EFA for both to determine where the variables correlate. we also create the model for CFA based on this EFA.

```r
#Assign categories for two factor model using EFA
PANAS_obliq_2 <- fa(PANAS_means_model,
                    nfactors = 2,
                    fm = "minres",
                    rotate = "oblimin")
PANAS_obliq_2
```

```
## Factor Analysis using method =  minres
## Call: fa(r = PANAS_means_model, nfactors = 2, rotate = "oblimin", fm = "minres")
## Standardized loadings (pattern matrix) based upon correlation matrix
##             MR1   MR2   h2   u2 com
## PG_P_mean  0.12  0.76 0.66 0.34 1.0
## PG_N_mean  0.67 -0.17 0.40 0.60 1.1
## P1_P_mean -0.05  0.93 0.83 0.17 1.0
## P1_N_mean  0.73 -0.10 0.50 0.50 1.0
## P2_N_mean  0.56 -0.07 0.29 0.71 1.0
## P2_P_mean  0.00  0.74 0.56 0.44 1.0
## ST_mean    0.67  0.04 0.47 0.53 1.0
```

```
## SS1_mean   0.74  0.17 0.66 0.34 1.1
## SS2_mean   0.62  0.20 0.51 0.49 1.2
##
##                        MR1  MR2
## SS loadings           2.75 2.14
## Proportion Var        0.31 0.24
## Cumulative Var        0.31 0.54
## Proportion Explained  0.56 0.44
## Cumulative Proportion 0.56 1.00
##
##  With factor correlations of
##      MR1  MR2
## MR1 1.00 0.35
## MR2 0.35 1.00
##
## Mean item complexity =  1.1
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are  36  and the objective function was  4.62 with Chi Squa
## The degrees of freedom for the model are 19  and the objective function was  0.96
##
## The root mean square of the residuals (RMSR) is  0.08
## The df corrected root mean square of the residuals is  0.11
##
## The harmonic number of observations is  229 with the empirical chi square  111.42  with prob <  4.4e-
## The total number of observations was  229  with Likelihood Chi Square =  214.88  with prob <  3.7e-35
##
## Tucker Lewis Index of factoring reliability =  0.626
## RMSEA index =  0.212  and the 90 % confidence intervals are  0.188 0.239
## BIC =  111.64
## Fit based upon off diagonal values = 0.96
## Measures of factor score adequacy
##                                                    MR1  MR2
## Correlation of (regression) scores with factors   0.92 0.95
## Multiple R square of scores with factors          0.85 0.90
## Minimum correlation of possible factor scores     0.70 0.79
```

```
#Model for 2 Factors
PANAS_means_Model2 <-
'
Neg =~ PG_N_mean + P1_N_mean + P2_N_mean + ST_mean + SS1_mean + SS2_mean
Pos =~ PG_P_mean + P1_P_mean + P2_P_mean
'
```



Picture above: illustration depicting 2 factor model.

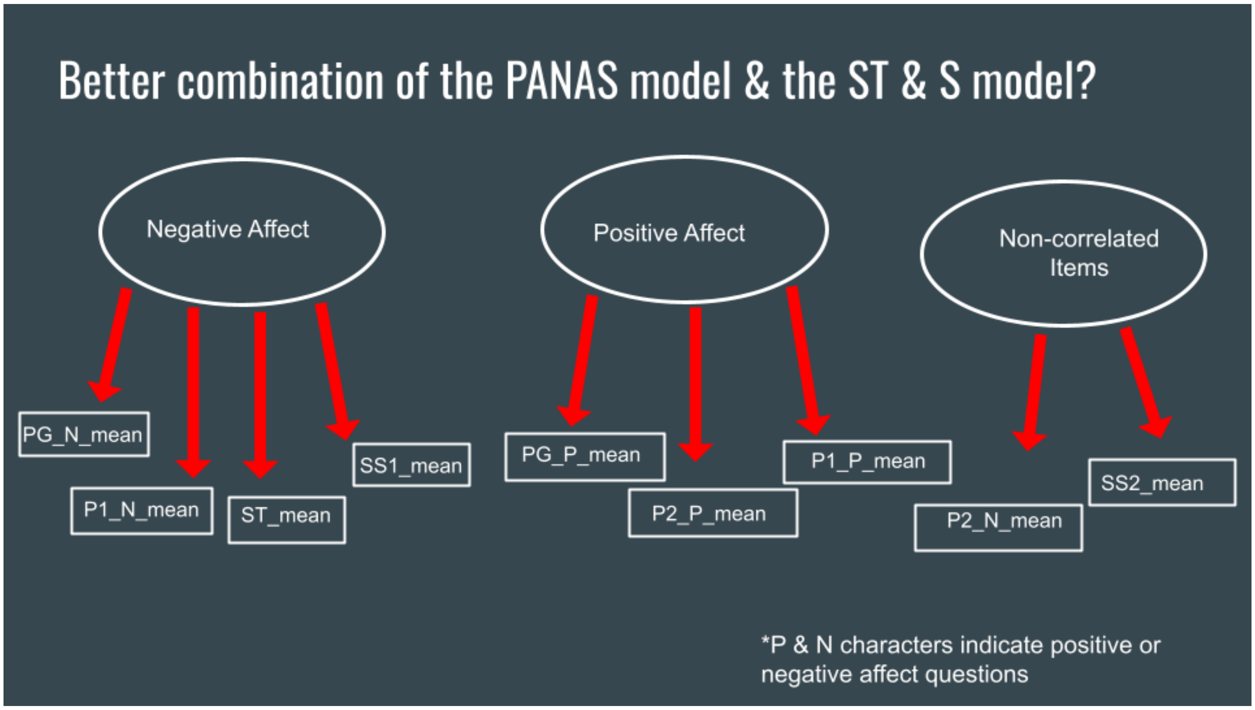
EFA and model for 3 factor.

```r
#Assign categories for 3 Factor model using EFA
PANAS_obliq_3 <- fa(PANAS_means_model,
                    nfactors = 3,
                    fm = "minres",
                    rotate = "oblimin")
PANAS_obliq_3
```

```
## Factor Analysis using method =  minres
## Call: fa(r = PANAS_means_model, nfactors = 3, rotate = "oblimin", fm = "minres")
## Standardized loadings (pattern matrix) based upon correlation matrix
##             MR2   MR1   MR3   h2   u2 com
## PG_P_mean  0.78  0.17 -0.06 0.69 0.31 1.1
## PG_N_mean -0.16  0.70  0.02 0.46 0.54 1.1
## P1_P_mean  0.92 -0.03 -0.02 0.82 0.18 1.0
## P1_N_mean -0.07  0.62  0.16 0.48 0.52 1.2
## P2_N_mean -0.10 -0.01  0.90 0.77 0.23 1.0
## P2_P_mean  0.75 -0.10  0.13 0.57 0.43 1.1
## ST_mean    0.05  0.80 -0.08 0.62 0.38 1.0
## SS1_mean   0.20  0.65  0.13 0.66 0.34 1.3
## SS2_mean   0.23  0.14  0.70 0.74 0.26 1.3
##
##                        MR2  MR1  MR3
## SS loadings           2.19 2.13 1.48
## Proportion Var        0.24 0.24 0.16
## Cumulative Var        0.24 0.48 0.64
## Proportion Explained  0.38 0.37 0.26
## Cumulative Proportion 0.38 0.74 1.00
##
##  With factor correlations of
```

```
##      MR2  MR1  MR3
## MR2 1.00 0.32 0.21
## MR1 0.32 1.00 0.46
## MR3 0.21 0.46 1.00
##
## Mean item complexity =  1.1
## Test of the hypothesis that 3 factors are sufficient.
##
## The degrees of freedom for the null model are  36  and the objective function was  4.62 with Chi Squa
## The degrees of freedom for the model are 12  and the objective function was  0.44
##
## The root mean square of the residuals (RMSR) is  0.04
## The df corrected root mean square of the residuals is  0.07
##
## The harmonic number of observations is  229 with the empirical chi square  28.67  with prob <  0.004
## The total number of observations was  229  with Likelihood Chi Square =  96.98  with prob <  2.2e-15
##
## Tucker Lewis Index of factoring reliability =  0.743
## RMSEA index =  0.176  and the 90 % confidence intervals are  0.145 0.21
## BIC =  31.77
## Fit based upon off diagonal values = 0.99
## Measures of factor score adequacy
##                                                    MR2  MR1  MR3
## Correlation of (regression) scores with factors   0.95 0.92 0.92
## Multiple R square of scores with factors          0.89 0.84 0.85
## Minimum correlation of possible factor scores     0.79 0.67 0.70
```

```
#Model for 3 Factors
PANAS_means_Model3 <-
'
Neg =~ PG_N_mean + P1_N_mean + ST_mean + SS1_mean
Pos =~ PG_P_mean + P1_P_mean + P2_P_mean
New Variable =~ P2_N_mean + SS2_mean
'
```



Picture above: illustration depicting 3 factor model. # CFA Models

After using EFAs to create each model, we directly compare the two CFA models.

```
#Look at fit using CFA, CFI, RMSEA, and SRMR
# 2 factor model
fit_means2 <- cfa(PANAS_means_Model2,
                  data = PANAS_means_model)
summary(fit_means2, fit.measures=TRUE)
```

```
## lavaan 0.6-9 ended normally after 47 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        19
##
##   Number of observations                           229
##
## Model Test User Model:
##
##   Test statistic                               263.190
##   Degrees of freedom                                26
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                              1058.179
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.768
```

```
##   Tucker-Lewis Index (TLI)                       0.679
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -851.752
##   Loglikelihood unrestricted model (H1)       -720.157
##
##   Akaike (AIC)                                1741.504
##   Bayesian (BIC)                              1806.745
##   Sample-size adjusted Bayesian (BIC)         1746.527
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.200
##   90 Percent confidence interval - lower         0.178
##   90 Percent confidence interval - upper         0.222
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.098
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mean         1.000
##     P1_N_mean         0.821    0.107    7.677    0.000
##     P2_N_mean         0.536    0.088    6.125    0.000
##     ST_mean           1.062    0.142    7.483    0.000
##     SS1_mean          1.312    0.156    8.407    0.000
##     SS2_mean          1.067    0.141    7.581    0.000
##   Pos =~
##     PG_P_mean         1.000
##     P1_P_mean         1.224    0.090   13.663    0.000
##     P2_P_mean         1.250    0.104   12.021    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos               0.053    0.012    4.555    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.132    0.013    9.892    0.000
##    .P1_N_mean         0.042    0.005    8.946    0.000
##    .P2_N_mean         0.051    0.005   10.105    0.000
##    .ST_mean           0.083    0.009    9.215    0.000
##    .SS1_mean          0.042    0.007    6.253    0.000
```

```
##    .SS2_mean          0.077    0.008    9.088    0.000
##    .PG_P_mean         0.121    0.017    6.966    0.000
##    .P1_P_mean         0.093    0.021    4.363    0.000
##    .P2_P_mean         0.318    0.036    8.712    0.000
##     Neg               0.060    0.014    4.299    0.000
##     Pos               0.252    0.036    7.102    0.000
```

```
#Look at fit using CFA, CFI, RMSEA, and SRMR
# 3 factor model
fit_means3 <- cfa(PANAS_means_Model3,
                  data = PANAS_means_model)
summary(fit_means3, fit.measures=TRUE)
```

```
## lavaan 0.6-9 ended normally after 76 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        21
##
##   Number of observations                           229
##
## Model Test User Model:
##
##   Test statistic                               158.458
##   Degrees of freedom                                24
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                              1058.179
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.868
##   Tucker-Lewis Index (TLI)                       0.803
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -799.386
##   Loglikelihood unrestricted model (H1)       -720.157
##
##   Akaike (AIC)                                1640.773
##   Bayesian (BIC)                              1712.881
##   Sample-size adjusted Bayesian (BIC)         1646.324
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.156
##   90 Percent confidence interval - lower         0.134
##   90 Percent confidence interval - upper         0.180
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
```

```
##
##   SRMR                                           0.080
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mean         1.000
##     P1_N_mean         0.850    0.113    7.497    0.000
##     ST_mean           1.103    0.150    7.335    0.000
##     SS1_mean          1.431    0.175    8.187    0.000
##   Pos =~
##     PG_P_mean         1.000
##     P1_P_mean         1.225    0.089   13.827    0.000
##     P2_P_mean         1.266    0.104   12.130    0.000
##   NewVariable =~
##     P2_N_mean         1.000
##     SS2_mean          2.705    0.410    6.595    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos               0.051    0.011    4.451    0.000
##     NewVariable       0.020    0.005    4.091    0.000
##   Pos ~~
##     NewVariable       0.032    0.008    4.073    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.136    0.014    9.999    0.000
##    .P1_N_mean         0.042    0.005    8.918    0.000
##    .ST_mean           0.082    0.009    9.191    0.000
##    .SS1_mean          0.030    0.007    4.346    0.000
##    .PG_P_mean         0.122    0.017    7.169    0.000
##    .P1_P_mean         0.095    0.021    4.596    0.000
##    .P2_P_mean         0.311    0.036    8.659    0.000
##    .P2_N_mean         0.043    0.005    8.531    0.000
##    .SS2_mean         -0.039    0.023   -1.705    0.088
##     Neg               0.056    0.014    4.143    0.000
##     Pos               0.251    0.035    7.101    0.000
##     NewVariable       0.025    0.006    4.319    0.000
```

```
#lambda values tells us standardized loadings of each variable
lavInspect(fit_means3, what = "std")
```

```
## $lambda
##             Neg   Pos NwVrbl
## PG_N_mean 0.541 0.000  0.000
## P1_N_mean 0.701 0.000  0.000
## ST_mean   0.675 0.000  0.000
```

```
## SS1_mean  0.890 0.000  0.000
## PG_P_mean 0.000 0.820  0.000
## P1_P_mean 0.000 0.893  0.000
## P2_P_mean 0.000 0.751  0.000
## P2_N_mean 0.000 0.000  0.606
## SS2_mean  0.000 0.000  1.125
##
## $theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.707
## P1_N_mean  0.000  0.508
## ST_mean    0.000  0.000  0.544
## SS1_mean   0.000  0.000  0.000  0.208
## PG_P_mean  0.000  0.000  0.000  0.000  0.328
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.202
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.436
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.632
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.266
##
## $psi
##             Neg   Pos   NwVrbl
## Neg         1.000
## Pos         0.426 1.000
## NewVariable 0.534 0.398 1.000
```

We saw that the 3 factor model performed better than the 2 Factor model given the CFI, RMSEA, and SRMR values. In our 2 factor model, we observed a CFI value of 0.768, a RMSEA value of 0.2, and a SRMR value of 0.098. Looking at this model alone, we can infer that the two factor model could fit our data but may not be the best fit. In our 3 Factor model, we observed a CFI value of 0.868, a RMSEA value of 0.156, and a SRMR value of 0.08. While the RMSEA value seems to be higher regardless of our model fit, we ran lavInspect to look further into the correlation in our loadings. The lambda value shows that our variables still have high significance in their factors. This tells us that even though our RMSEA values do not meet the required range and cause doubt for a good fit model, our proposed 3 Factor model still shows a good fit in our standardized loadings.

Regression Models

We then applied regression to the 3 Factor model to determine how strong its' predictive ability is for response time and accuracy given emotions experienced during the emotion inducing test. However, when applying the regression, we chose to drop the P2_N_mean and SS2_mean variables because they damaged correlations.

```
#Create new data frame of means of the factors for regression analysis
PANAS_reg <- mutate(PANAS_means, Response = rowMeans(select(PANAS_means,
                                              c(Response_neut, Response_pos, Response_neg))),
                    Neg = rowMeans(select(PANAS_means,
                                              c(PG_N_mean, P1_N_mean, ST_mean ))),
                    Pos = rowMeans(select(PANAS_means,
                                              c(PG_P_mean, P1_P_mean, P2_P_mean))),
                    Accuracy = rowMeans(select(PANAS_means,
                                              c(Acc_pos, Acc_neut, Acc_neg))),
                    Late_NEG = rowMeans(select(PANAS_means,
                                              c(P2_N_mean, SS2_mean)))) %>%
  select(Response, Neg, Pos, Accuracy, Late_NEG)
```

```r
#multi regression Response
reg_response <- lm.beta(lm(Response ~ Neg + Pos, data = PANAS_reg))
summary(reg_response)
```

```
##
## Call:
## lm(formula = Response ~ Neg + Pos, data = PANAS_reg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -409.28 -165.18  -58.42  108.49 1071.53
##
## Coefficients:
##              Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept) -152.9523           NA   357.2254  -0.428   0.6689
## Neg          233.8424       0.1591    95.9481   2.437   0.0156 *
## Pos           43.0825       0.1141    24.6390   1.749   0.0817 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 234.5 on 226 degrees of freedom
## Multiple R-squared:  0.04034,    Adjusted R-squared:  0.03185
## F-statistic:  4.75 on 2 and 226 DF,  p-value: 0.009534
```

```r
#Bivariate regressions Response
reg_bi_response1 <- lm.beta(lm(Response ~ Neg, data = PANAS_reg))
summary(reg_bi_response1)
```

```
##
## Call:
## lm(formula = Response ~ Neg, data = PANAS_reg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -365.34 -162.25  -57.05  115.22 1084.94
##
## Coefficients:
##             Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept) -71.3612           NA   355.7660  -0.201   0.8412
## Neg         243.1612       0.1654    96.2331   2.527   0.0122 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 235.6 on 227 degrees of freedom
## Multiple R-squared:  0.02736,    Adjusted R-squared:  0.02307
## F-statistic: 6.385 on 1 and 227 DF,  p-value: 0.01219
```

```r
reg_bi_response2 <- lm.beta(lm(Response ~ Pos, data = PANAS_reg))
summary(reg_bi_response2)
```

```
##
## Call:
## lm(formula = Response ~ Pos, data = PANAS_reg)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -362.84 -167.62  -55.63  103.79 1138.08
##
## Coefficients:
##             Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept)  701.734           NA     68.768  10.204   <2e-16 ***
## Pos           46.418        0.123     24.867   1.867   0.0632 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 237.1 on 227 degrees of freedom
## Multiple R-squared:  0.01512,    Adjusted R-squared:  0.01078
## F-statistic: 3.484 on 1 and 227 DF,  p-value: 0.06324
```

```
#Multiregression accuracy
reg_accuracy <- lm.beta(lm(Accuracy ~ Neg + Pos, data = PANAS_reg))
summary(reg_accuracy)
```

```
##
## Call:
## lm(formula = Accuracy ~ Neg + Pos, data = PANAS_reg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.06492 -0.02795 -0.01304  0.00718  0.56511
##
## Coefficients:
##             Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept) -0.16765           NA    0.11048  -1.518   0.1305
## Neg          0.06076      0.13506    0.02967   2.048   0.0418 *
## Pos         -0.00539     -0.04666    0.00762  -0.707   0.4801
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07253 on 226 degrees of freedom
## Multiple R-squared:  0.01972,    Adjusted R-squared:  0.01104
## F-statistic: 2.273 on 2 and 226 DF,  p-value: 0.1054
```

```
#Bivariate regressions Accuracy
reg_bi_accuracy1 <- lm.beta(lm(Accuracy ~ Neg, data = PANAS_reg))
summary(reg_bi_accuracy1)
```

```
##
## Call:
## lm(formula = Accuracy ~ Neg, data = PANAS_reg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.05951 -0.02953 -0.01327  0.00598  0.56749
##
## Coefficients:
##             Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept) -0.17786           NA    0.10941  -1.626   0.1054
## Neg          0.05959      0.13247    0.02959   2.014   0.0452 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.07245 on 227 degrees of freedom
## Multiple R-squared:  0.01755,    Adjusted R-squared:  0.01322
## F-statistic: 4.055 on 1 and 227 DF,  p-value: 0.04523
```

```
reg_bi_accuracy2 <- lm.beta(lm(Accuracy ~ Pos, data = PANAS_reg))
summary(reg_bi_accuracy2)
```

```
##
## Call:
## lm(formula = Accuracy ~ Pos, data = PANAS_reg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.04989 -0.02973 -0.01399  0.00300  0.58228
##
## Coefficients:
##              Estimate Standardized Std. Error t value Pr(>|t|)
## (Intercept)  0.054413           NA   0.021187   2.568   0.0109 *
## Pos         -0.004523    -0.039156   0.007661  -0.590   0.5555
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07303 on 227 degrees of freedom
## Multiple R-squared:  0.001533,   Adjusted R-squared:  -0.002865
## F-statistic: 0.3486 on 1 and 227 DF,  p-value: 0.5555
```

Measurement of Invariance

Here we ran a measurement invariance test to observe any bias between the two gender groups in our dataset. Since our dataset didn't provide many demographics about the subject, in order to maintain anonymity, gender will be our only grouping.

Configural Model test

Our configural model shows our original fit of our model with a CFI of 0.861, RMSEA of 0.162, and SRMR of 0.082. Previously we discussed that our model does not meet the requirments for the RMSEA values, however the loadings are still correlated so we will proceeed with caution.

```
fit_config <- cfa(PANAS_means_Model3,
                  data = PANAS_means,
                  group = "sex")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated ov
## variances are negative
```

```
summary(fit_config, fit.measures=TRUE)
```

```
## lavaan 0.6-9 ended normally after 144 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        60
##
##   Number of observations per group:
##     1                                              110
```

```
##     2                                             119
##
## Model Test User Model:
##
##   Test statistic                               193.125
##   Degrees of freedom                                48
##   P-value (Chi-square)                           0.000
##   Test statistic for each group:
##     1                                           92.537
##     2                                          100.589
##
## Model Test Baseline Model:
##
##   Test statistic                              1117.895
##   Degrees of freedom                                72
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.861
##   Tucker-Lewis Index (TLI)                       0.792
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -765.530
##   Loglikelihood unrestricted model (H1)       -668.968
##
##   Akaike (AIC)                                1651.061
##   Bayesian (BIC)                              1857.084
##   Sample-size adjusted Bayesian (BIC)         1666.923
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.162
##   90 Percent confidence interval - lower         0.139
##   90 Percent confidence interval - upper         0.187
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.082
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [1]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
```

```
##     PG_N_mean         1.000
##     P1_N_mean         0.789    0.123    6.413    0.000
##     ST_mean          -1.114    0.161   -6.900    0.000
##     SS1_mean         -1.200    0.156   -7.716    0.000
##   Pos =~
##     PG_P_mean         1.000
##     P1_P_mean         1.145    0.085   13.413    0.000
##     P2_P_mean         1.154    0.113   10.253    0.000
##   NewVariable =~
##     P2_N_mean         1.000
##     SS2_mean          3.974    1.375    2.891    0.004
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.078    0.022   -3.524    0.000
##     NewVariable      -0.017    0.008   -2.151    0.032
##   Pos ~~
##     NewVariable       0.030    0.014    2.169    0.030
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         4.574    0.043  107.034    0.000
##    .P1_N_mean         4.791    0.032  149.232    0.000
##    .ST_mean           1.717    0.042   41.322    0.000
##    .SS1_mean          1.586    0.037   42.999    0.000
##    .PG_P_mean         2.417    0.064   37.848    0.000
##    .P1_P_mean         2.657    0.070   38.174    0.000
##    .P2_P_mean         2.985    0.085   35.282    0.000
##    .P2_N_mean         1.185    0.026   45.217    0.000
##    .SS2_mean          1.662    0.039   42.925    0.000
##     Neg               0.000
##     Pos               0.000
##     NewVariable       0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.113    0.017    6.715    0.000
##    .P1_N_mean         0.059    0.009    6.558    0.000
##    .ST_mean           0.081    0.013    6.098    0.000
##    .SS1_mean          0.023    0.008    2.781    0.005
##    .PG_P_mean         0.093    0.021    4.437    0.000
##    .P1_P_mean         0.066    0.024    2.815    0.005
##    .P2_P_mean         0.314    0.049    6.449    0.000
##    .P2_N_mean         0.057    0.009    6.019    0.000
##    .SS2_mean         -0.134    0.089   -1.512    0.130
##     Neg               0.088    0.024    3.740    0.000
##     Pos               0.356    0.062    5.779    0.000
##     NewVariable       0.019    0.009    2.175    0.030
##
##
## Group 2 [2]:
##
## Latent Variables:
```

```
##                     Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mean          1.000
##     P1_N_mean          0.963    0.239    4.023    0.000
##     ST_mean           -1.080    0.295   -3.659    0.000
##     SS1_mean          -1.892    0.456   -4.152    0.000
##   Pos =~
##     PG_P_mean          1.000
##     P1_P_mean          1.368    0.189    7.236    0.000
##     P2_P_mean          1.466    0.211    6.944    0.000
##   NewVariable =~
##     P2_N_mean          1.000
##     SS2_mean           2.007    0.308    6.522    0.000
##
## Covariances:
##                     Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos               -0.029    0.011   -2.718    0.007
##     NewVariable       -0.020    0.006   -3.087    0.002
##   Pos ~~
##     NewVariable        0.027    0.009    3.007    0.003
##
## Intercepts:
##                     Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean          4.566    0.039  115.734    0.000
##    .P1_N_mean          4.838    0.021  227.568    0.000
##    .ST_mean            1.675    0.031   54.104    0.000
##    .SS1_mean           1.553    0.035   44.974    0.000
##    .PG_P_mean          2.379    0.050   47.172    0.000
##    .P1_P_mean          2.612    0.059   44.326    0.000
##    .P2_P_mean          3.104    0.073   42.466    0.000
##    .P2_N_mean          1.131    0.023   49.972    0.000
##    .SS2_mean           1.597    0.033   49.011    0.000
##     Neg                0.000
##     Pos                0.000
##     NewVariable        0.000
##
## Variances:
##                     Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean          0.155    0.021    7.443    0.000
##    .P1_N_mean          0.026    0.004    5.981    0.000
##    .ST_mean            0.079    0.011    7.070    0.000
##    .SS1_mean           0.034    0.011    3.219    0.001
##    .PG_P_mean          0.145    0.025    5.770    0.000
##    .P1_P_mean          0.119    0.034    3.503    0.000
##    .P2_P_mean          0.298    0.053    5.655    0.000
##    .P2_N_mean          0.031    0.005    5.700    0.000
##    .SS2_mean           0.006    0.015    0.373    0.709
##     Neg                0.030    0.014    2.113    0.035
##     Pos                0.157    0.038    4.112    0.000
##     NewVariable        0.030    0.008    3.883    0.000
```

```
lavInspect(fit_config, what = "std")
```

```
## $`1`
```

```
## $`1`$lambda
##              Neg   Pos NwVrbl
## PG_N_mean  0.662 0.000  0.000
## P1_N_mean  0.695 0.000  0.000
## ST_mean   -0.758 0.000  0.000
## SS1_mean  -0.920 0.000  0.000
## PG_P_mean  0.000 0.890  0.000
## P1_P_mean  0.000 0.936  0.000
## P2_P_mean  0.000 0.775  0.000
## P2_N_mean  0.000 0.000  0.500
## SS2_mean   0.000 0.000  1.347
##
## $`1`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.562
## P1_N_mean  0.000  0.518
## ST_mean    0.000  0.000  0.426
## SS1_mean   0.000  0.000  0.000  0.154
## PG_P_mean  0.000  0.000  0.000  0.000  0.208
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.125
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.399
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.750
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.813
##
## $`1`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.441  1.000
## NewVariable -0.408  0.362  1.000
##
## $`1`$nu
##           intrcp
## PG_N_mean 10.205
## P1_N_mean 14.229
## ST_mean    3.940
## SS1_mean   4.100
## PG_P_mean  3.609
## P1_P_mean  3.640
## P2_P_mean  3.364
## P2_N_mean  4.311
## SS2_mean   4.093
##
## $`1`$alpha
##             intrcp
## Neg              0
## Pos              0
## NewVariable      0
##
##
## $`2`
## $`2`$lambda
##              Neg   Pos NwVrbl
## PG_N_mean  0.403 0.000  0.000
## P1_N_mean  0.720 0.000  0.000
```

```
## ST_mean   -0.554 0.000  0.000
## SS1_mean  -0.870 0.000  0.000
## PG_P_mean  0.000 0.721  0.000
## P1_P_mean  0.000 0.844  0.000
## P2_P_mean  0.000 0.729  0.000
## P2_N_mean  0.000 0.000  0.702
## SS2_mean   0.000 0.000  0.978
##
## $`2`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean 0.838
## P1_N_mean 0.000  0.482
## ST_mean   0.000  0.000  0.693
## SS1_mean  0.000  0.000  0.000  0.243
## PG_P_mean 0.000  0.000  0.000  0.000  0.480
## P1_P_mean 0.000  0.000  0.000  0.000  0.000  0.287
## P2_P_mean 0.000  0.000  0.000  0.000  0.000  0.000  0.468
## P2_N_mean 0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.508
## SS2_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.044
##
## $`2`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.429  1.000
## NewVariable -0.662  0.386  1.000
##
## $`2`$nu
##           intrcp
## PG_N_mean 10.609
## P1_N_mean 20.861
## ST_mean    4.960
## SS1_mean   4.123
## PG_P_mean  4.324
## P1_P_mean  4.063
## P2_P_mean  3.893
## P2_N_mean  4.581
## SS2_mean   4.493
##
## $`2`$alpha
##             intrcp
## Neg              0
## Pos              0
## NewVariable      0
```

Weak Invariance test

Our test of a weak invariance model shows our CFI dropped slightly to 0.854, our RMSEA surprisingly decreased slightly to 0.157, and our SRMR raised slightly to 0.091. Since these changes are not significant enough, we can assume we have a weak invariance model and will proceed.

```
fit_weak <- cfa(PANAS_means_Model3,
                  data = PANAS_means,
                  group = "sex",
                group.equal = c("loadings")
```

```
                )
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated ov
## variances are negative
```

```
summary(fit_weak, fit.measures=TRUE)
```

```
## lavaan 0.6-9 ended normally after 111 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        60
##   Number of equality constraints                     6
##
##   Number of observations per group:
##     1                                              110
##     2                                              119
##
## Model Test User Model:
##
##   Test statistic                               206.499
##   Degrees of freedom                                54
##   P-value (Chi-square)                           0.000
##   Test statistic for each group:
##     1                                           97.809
##     2                                          108.690
##
## Model Test Baseline Model:
##
##   Test statistic                              1117.895
##   Degrees of freedom                                72
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.854
##   Tucker-Lewis Index (TLI)                       0.806
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -772.217
##   Loglikelihood unrestricted model (H1)       -668.968
##
##   Akaike (AIC)                                1652.434
##   Bayesian (BIC)                              1837.855
##   Sample-size adjusted Bayesian (BIC)         1666.710
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.157
##   90 Percent confidence interval - lower         0.135
##   90 Percent confidence interval - upper         0.180
##   P-value RMSEA <= 0.05                          0.000
##
```

```
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.091
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [1]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mn           1.000
##     P1_N_mn (.p2.)    0.828    0.108    7.670    0.000
##     ST_mean (.p3.)   -1.079    0.144   -7.517    0.000
##     SS1_men (.p4.)   -1.385    0.163   -8.520    0.000
##   Pos =~
##     PG_P_mn           1.000
##     P1_P_mn (.p6.)    1.192    0.079   15.122    0.000
##     P2_P_mn (.p7.)    1.236    0.099   12.476    0.000
##   NewVariable =~
##     P2_N_mn           1.000
##     SS2_men (.p9.)    2.619    0.380    6.892    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.070    0.019   -3.651    0.000
##     NewVariable      -0.025    0.007   -3.593    0.000
##   Pos ~~
##     NewVariable       0.045    0.013    3.546    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         4.574    0.042  108.393    0.000
##    .P1_N_mean         4.791    0.031  152.270    0.000
##    .ST_mean           1.717    0.040   42.908    0.000
##    .SS1_mean          1.586    0.037   42.476    0.000
##    .PG_P_mean         2.417    0.063   38.595    0.000
##    .P1_P_mean         2.657    0.070   38.027    0.000
##    .P2_P_mean         2.985    0.086   34.534    0.000
##    .P2_N_mean         1.185    0.027   43.245    0.000
##    .SS2_mean          1.662    0.040   41.988    0.000
##     Neg               0.000
##     Pos               0.000
##     NewVariable       0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.123    0.018    7.003    0.000
```

```
##    .P1_N_mean         0.059    0.009    6.784    0.000
##    .ST_mean           0.091    0.014    6.695    0.000
##    .SS1_mean          0.014    0.008    1.660    0.097
##    .PG_P_mean         0.098    0.020    4.838    0.000
##    .P1_P_mean         0.063    0.023    2.741    0.006
##    .P2_P_mean         0.312    0.049    6.377    0.000
##    .P2_N_mean         0.050    0.008    6.337    0.000
##    .SS2_mean         -0.053    0.029   -1.819    0.069
##     Neg               0.073    0.019    3.902    0.000
##     Pos               0.334    0.057    5.907    0.000
##     NewVariable       0.033    0.008    4.030    0.000
##
##
## Group 2 [2]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mn           1.000
##     P1_N_mn (.p2.)    0.828    0.108    7.670    0.000
##     ST_mean (.p3.)   -1.079    0.144   -7.517    0.000
##     SS1_men (.p4.)   -1.385    0.163   -8.520    0.000
##   Pos =~
##     PG_P_mn           1.000
##     P1_P_mn (.p6.)    1.192    0.079   15.122    0.000
##     P2_P_mn (.p7.)    1.236    0.099   12.476    0.000
##   NewVariable =~
##     P2_N_mn           1.000
##     SS2_men (.p9.)    2.619    0.380    6.892    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.039    0.012   -3.302    0.001
##     NewVariable      -0.018    0.005   -3.775    0.000
##   Pos ~~
##     NewVariable       0.024    0.007    3.226    0.001
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         4.566    0.040  114.045    0.000
##    .P1_N_mean         4.838    0.022  223.863    0.000
##    .ST_mean           1.675    0.032   51.832    0.000
##    .SS1_mean          1.553    0.033   46.915    0.000
##    .PG_P_mean         2.379    0.052   45.568    0.000
##    .P1_P_mean         2.612    0.058   44.766    0.000
##    .P2_P_mean         3.104    0.071   43.572    0.000
##    .P2_N_mean         1.131    0.022   52.007    0.000
##    .SS2_mean          1.597    0.032   49.432    0.000
##     Neg               0.000
##     Pos               0.000
##     NewVariable       0.000
##
## Variances:
```

```
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.147    0.020    7.277    0.000
##    .P1_N_mean         0.026    0.004    5.854    0.000
##    .ST_mean           0.073    0.011    6.656    0.000
##    .SS1_mean          0.047    0.009    4.906    0.000
##    .PG_P_mean         0.133    0.024    5.455    0.000
##    .P1_P_mean         0.133    0.029    4.555    0.000
##    .P2_P_mean         0.312    0.050    6.272    0.000
##    .P2_N_mean         0.036    0.005    6.637    0.000
##    .SS2_mean         -0.016    0.019   -0.864    0.388
##     Neg               0.044    0.012    3.784    0.000
##     Pos               0.191    0.034    5.556    0.000
##     NewVariable       0.021    0.005    4.027    0.000
```

```r
lavInspect(fit_weak, what = "std")
```

```
## $`1`
## $`1`$lambda
##               Neg   Pos NwVrbl
## PG_N_mean  0.610 0.000  0.000
## P1_N_mean  0.677 0.000  0.000
## ST_mean   -0.694 0.000  0.000
## SS1_mean  -0.954 0.000  0.000
## PG_P_mean  0.000 0.880  0.000
## P1_P_mean  0.000 0.940  0.000
## P2_P_mean  0.000 0.788  0.000
## P2_N_mean  0.000 0.000  0.630
## SS2_mean   0.000 0.000  1.142
##
## $`1`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.628
## P1_N_mean  0.000  0.542
## ST_mean    0.000  0.000  0.519
## SS1_mean   0.000  0.000  0.000  0.090
## PG_P_mean  0.000  0.000  0.000  0.000  0.226
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.117
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.379
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.603
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.305
##
## $`1`$psi
##              Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.452  1.000
## NewVariable -0.513  0.427  1.000
##
## $`1`$nu
##           intrcp
## PG_N_mean 10.335
## P1_N_mean 14.518
## ST_mean    4.091
## SS1_mean   4.050
## PG_P_mean  3.680
## P1_P_mean  3.626
```

```
## P2_P_mean  3.293
## P2_N_mean  4.123
## SS2_mean   4.003
##
## $`1`$alpha
##             intrcp
## Neg              0
## Pos              0
## NewVariable      0
##
##
## $`2`
## $`2`$lambda
##              Neg   Pos NwVrbl
## PG_N_mean  0.479 0.000  0.000
## P1_N_mean  0.735 0.000  0.000
## ST_mean   -0.641 0.000  0.000
## SS1_mean  -0.802 0.000  0.000
## PG_P_mean  0.000 0.768  0.000
## P1_P_mean  0.000 0.819  0.000
## P2_P_mean  0.000 0.696  0.000
## P2_N_mean  0.000 0.000  0.604
## SS2_mean   0.000 0.000  1.064
##
## $`2`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.771
## P1_N_mean  0.000  0.460
## ST_mean    0.000  0.000  0.590
## SS1_mean   0.000  0.000  0.000  0.357
## PG_P_mean  0.000  0.000  0.000  0.000  0.411
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.330
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.516
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.636
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.132
##
## $`2`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.427  1.000
## NewVariable -0.587  0.382  1.000
##
## $`2`$nu
##           intrcp
## PG_N_mean 10.455
## P1_N_mean 20.521
## ST_mean    4.751
## SS1_mean   4.301
## PG_P_mean  4.177
## P1_P_mean  4.104
## P2_P_mean  3.994
## P2_N_mean  4.768
## SS2_mean   4.531
##
```

```
## $`2`$alpha
##             intrcp
## Neg              0
## Pos              0
## NewVariable      0
```

Strong Invariance test

Our test of a strong invariance model shows our CFI dropped slightly to 0.853, our RMSEA surprisingly decreased more to 0.149, and our SRMR raised slightly to 0.093. Since these differences in values are substantially different, we can assume we have a strong invariance model and will proceed.

```
fit_strong <- cfa(PANAS_means_Model3,
                  data = PANAS_means,
                  group = "sex",
                group.equal = c("loadings", "intercepts")
                )
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated ov
## variances are negative
```

```
summary(fit_strong, fit.measures=TRUE)
```

```
## lavaan 0.6-9 ended normally after 142 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        63
##   Number of equality constraints                    15
##
##   Number of observations per group:
##     1                                              110
##     2                                              119
##
## Model Test User Model:
##
##   Test statistic                               213.354
##   Degrees of freedom                                60
##   P-value (Chi-square)                           0.000
##   Test statistic for each group:
##     1                                          101.650
##     2                                          111.704
##
## Model Test Baseline Model:
##
##   Test statistic                              1117.895
##   Degrees of freedom                                72
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.853
##   Tucker-Lewis Index (TLI)                       0.824
##
## Loglikelihood and Information Criteria:
##
```

```
##   Loglikelihood user model (H0)               -775.645
##   Loglikelihood unrestricted model (H1)       -668.968
##
##   Akaike (AIC)                                1647.289
##   Bayesian (BIC)                              1812.108
##   Sample-size adjusted Bayesian (BIC)         1659.979
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.149
##   90 Percent confidence interval - lower         0.128
##   90 Percent confidence interval - upper         0.171
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.093
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [1]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mn           1.000
##     P1_N_mn (.p2.)    0.835    0.109    7.661    0.000
##     ST_mean (.p3.)   -1.086    0.145   -7.509    0.000
##     SS1_men (.p4.)   -1.389    0.163   -8.499    0.000
##   Pos =~
##     PG_P_mn           1.000
##     P1_P_mn (.p6.)    1.191    0.079   15.070    0.000
##     P2_P_mn (.p7.)    1.229    0.099   12.356    0.000
##   NewVariable =~
##     P2_N_mn           1.000
##     SS2_men (.p9.)    2.559    0.360    7.117    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.070    0.019   -3.649    0.000
##     NewVariable      -0.026    0.007   -3.638    0.000
##   Pos ~~
##     NewVariable       0.046    0.013    3.582    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mn (.25.)    4.557    0.036  127.083    0.000
##    .P1_N_mn (.26.)    4.807    0.026  185.253    0.000
```

```
##    .ST_mean (.27.)    1.711    0.035   49.467    0.000
##    .SS1_men (.28.)    1.588    0.037   42.703    0.000
##    .PG_P_mn (.29.)    2.407    0.060   39.789    0.000
##    .P1_P_mn (.30.)    2.648    0.069   38.251    0.000
##    .P2_P_mn (.31.)    3.057    0.079   38.682    0.000
##    .P2_N_mn (.32.)    1.166    0.021   54.555    0.000
##    .SS2_men (.33.)    1.655    0.039   42.387    0.000
##     Neg               0.000
##     Pos               0.000
##     NewVrbl           0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.123    0.018    7.007    0.000
##    .P1_N_mean         0.059    0.009    6.779    0.000
##    .ST_mean           0.091    0.014    6.690    0.000
##    .SS1_mean          0.014    0.008    1.672    0.094
##    .PG_P_mean         0.098    0.020    4.805    0.000
##    .P1_P_mean         0.063    0.023    2.712    0.007
##    .P2_P_mean         0.319    0.050    6.408    0.000
##    .P2_N_mean         0.050    0.008    6.326    0.000
##    .SS2_mean         -0.049    0.028   -1.780    0.075
##     Neg               0.072    0.019    3.893    0.000
##     Pos               0.335    0.057    5.905    0.000
##     NewVariable       0.034    0.008    4.107    0.000
##
##
## Group 2 [2]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mn           1.000
##     P1_N_mn (.p2.)    0.835    0.109    7.661    0.000
##     ST_mean (.p3.)   -1.086    0.145   -7.509    0.000
##     SS1_men (.p4.)   -1.389    0.163   -8.499    0.000
##   Pos =~
##     PG_P_mn           1.000
##     P1_P_mn (.p6.)    1.191    0.079   15.070    0.000
##     P2_P_mn (.p7.)    1.229    0.099   12.356    0.000
##   NewVariable =~
##     P2_N_mn           1.000
##     SS2_men (.p9.)    2.559    0.360    7.117    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.039    0.012   -3.308    0.001
##     NewVariable      -0.018    0.005   -3.827    0.000
##   Pos ~~
##     NewVariable       0.024    0.008    3.248    0.001
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
```

```
##    .PG_N_mn (.25.)    4.557    0.036  127.083    0.000
##    .P1_N_mn (.26.)    4.807    0.026  185.253    0.000
##    .ST_mean (.27.)    1.711    0.035   49.467    0.000
##    .SS1_men (.28.)    1.588    0.037   42.703    0.000
##    .PG_P_mn (.29.)    2.407    0.060   39.789    0.000
##    .P1_P_mn (.30.)    2.648    0.069   38.251    0.000
##    .P2_P_mn (.31.)    3.057    0.079   38.682    0.000
##    .P2_N_mn (.32.)    1.166    0.021   54.555    0.000
##    .SS2_men (.33.)    1.655    0.039   42.387    0.000
##     Neg               0.029    0.035    0.829    0.407
##     Pos              -0.015    0.073   -0.213    0.831
##     NewVrbl          -0.022    0.020   -1.077    0.282
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mean         0.147    0.020    7.283    0.000
##    .P1_N_mean         0.026    0.004    5.844    0.000
##    .ST_mean           0.073    0.011    6.656    0.000
##    .SS1_mean          0.047    0.009    4.929    0.000
##    .PG_P_mean         0.133    0.024    5.421    0.000
##    .P1_P_mean         0.135    0.030    4.555    0.000
##    .P2_P_mean         0.319    0.051    6.312    0.000
##    .P2_N_mean         0.035    0.005    6.613    0.000
##    .SS2_mean         -0.014    0.018   -0.770    0.441
##     Neg               0.043    0.011    3.774    0.000
##     Pos               0.191    0.034    5.551    0.000
##     NewVariable       0.021    0.005    4.101    0.000
```

```
lavInspect(fit_strong, what = "std")
```

```
## $`1`
## $`1`$lambda
##               Neg   Pos NwVrbl
## PG_N_mean  0.608 0.000  0.000
## P1_N_mean  0.678 0.000  0.000
## ST_mean   -0.695 0.000  0.000
## SS1_mean  -0.953 0.000  0.000
## PG_P_mean  0.000 0.880  0.000
## P1_P_mean  0.000 0.940  0.000
## P2_P_mean  0.000 0.783  0.000
## P2_N_mean  0.000 0.000  0.636
## SS2_mean   0.000 0.000  1.134
##
## $`1`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.631
## P1_N_mean  0.000  0.541
## ST_mean    0.000  0.000  0.517
## SS1_mean   0.000  0.000  0.000  0.091
## PG_P_mean  0.000  0.000  0.000  0.000  0.226
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.117
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.387
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.595
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.286
##
```

```
## $`1`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.452  1.000
## NewVariable -0.518  0.429  1.000
##
## $`1`$nu
##           intrcp
## PG_N_mean 10.303
## P1_N_mean 14.523
## ST_mean    4.072
## SS1_mean   4.055
## PG_P_mean  3.661
## P1_P_mean  3.613
## P2_P_mean  3.367
## P2_N_mean  4.030
## SS2_mean   3.982
##
## $`1`$alpha
##             intrcp
## Neg              0
## Pos              0
## NewVariable      0
##
##
## $`2`
## $`2`$lambda
##              Neg   Pos NwVrbl
## PG_N_mean  0.476 0.000  0.000
## P1_N_mean  0.735 0.000  0.000
## ST_mean   -0.641 0.000  0.000
## SS1_mean  -0.801 0.000  0.000
## PG_P_mean  0.000 0.769  0.000
## P1_P_mean  0.000 0.818  0.000
## P2_P_mean  0.000 0.689  0.000
## P2_N_mean  0.000 0.000  0.611
## SS2_mean   0.000 0.000  1.055
##
## $`2`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.773
## P1_N_mean  0.000  0.459
## ST_mean    0.000  0.000  0.590
## SS1_mean   0.000  0.000  0.000  0.359
## PG_P_mean  0.000  0.000  0.000  0.000  0.409
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.332
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.525
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.626
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.112
##
## $`2`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.429  1.000
```

```
## NewVariable -0.595  0.385  1.000
##
## $`2`$nu
##           intrcp
## PG_N_mean 10.435
## P1_N_mean 20.358
## ST_mean    4.851
## SS1_mean   4.400
## PG_P_mean  4.230
## P1_P_mean  4.158
## P2_P_mean  3.920
## P2_N_mean  4.898
## SS2_mean   4.686
##
## $`2`$alpha
##             intrcp
## Neg          0.138
## Pos         -0.035
## NewVariable -0.148
```

Strict Invariance test

Our test of a strict invariance model shows our CFI dropped slightly to 0.829, our RMSEA increased slightly to 0.141, and our SRMR raised slightly to 0.102. Our values of fit changed by, at most, 0.02 during our testing of invariance. Since these differences in values are not substantially different, we can conclude that we have a strict invariance model. While our original configuration model barely fit the requirements of a good fit, we will cautiously conclude that the three correlated factors fit both genders equally.

```
fit_strict <- cfa(PANAS_means_Model3,
                  data = PANAS_means,
                  group = "sex",
                group.equal = c("loadings", "intercepts", "residuals")
                )
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated ov
## variances are negative
```

```
summary(fit_strict, fit.measures=TRUE)
```

```
## lavaan 0.6-9 ended normally after 115 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        63
##   Number of equality constraints                    24
##
##   Number of observations per group:
##     1                                              110
##     2                                              119
##
## Model Test User Model:
##
##   Test statistic                               248.000
##   Degrees of freedom                                69
##   P-value (Chi-square)                           0.000
##   Test statistic for each group:
```

```
##     1                                           119.678
##     2                                           128.322
##
## Model Test Baseline Model:
##
##   Test statistic                              1117.895
##   Degrees of freedom                                72
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.829
##   Tucker-Lewis Index (TLI)                       0.821
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -792.968
##   Loglikelihood unrestricted model (H1)       -668.968
##
##   Akaike (AIC)                                1663.936
##   Bayesian (BIC)                              1797.851
##   Sample-size adjusted Bayesian (BIC)         1674.246
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.151
##   90 Percent confidence interval - lower         0.131
##   90 Percent confidence interval - upper         0.171
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.102
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
##
## Group 1 [1]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mn           1.000
##     P1_N_mn (.p2.)    0.832    0.107    7.752    0.000
##     ST_mean (.p3.)   -1.091    0.143   -7.623    0.000
##     SS1_men (.p4.)   -1.349    0.160   -8.447    0.000
##   Pos =~
##     PG_P_mn           1.000
##     P1_P_mn (.p6.)    1.208    0.087   13.924    0.000
##     P2_P_mn (.p7.)    1.257    0.103   12.180    0.000
```

```
##   NewVariable =~
##     P2_N_mn           1.000
##     SS2_men (.p9.)    2.552    0.355    7.178    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.065    0.019   -3.375    0.001
##     NewVariable      -0.026    0.007   -3.685    0.000
##   Pos ~~
##     NewVariable       0.044    0.012    3.602    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mn (.25.)    4.554    0.036  125.532    0.000
##    .P1_N_mn (.26.)    4.802    0.026  182.847    0.000
##    .ST_mean (.27.)    1.712    0.035   48.972    0.000
##    .SS1_men (.28.)    1.590    0.039   41.111    0.000
##    .PG_P_mn (.29.)    2.405    0.060   40.204    0.000
##    .P1_P_mn (.30.)    2.642    0.070   37.742    0.000
##    .P2_P_mn (.31.)    3.056    0.079   38.851    0.000
##    .P2_N_mn (.32.)    1.169    0.021   56.077    0.000
##    .SS2_men (.33.)    1.658    0.039   42.940    0.000
##     Neg               0.000
##     Pos               0.000
##     NewVrbl           0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mn (.10.)    0.132    0.013    9.886    0.000
##    .P1_N_mn (.11.)    0.041    0.005    8.786    0.000
##    .ST_mean (.12.)    0.079    0.009    9.005    0.000
##    .SS1_men (.13.)    0.036    0.007    5.200    0.000
##    .PG_P_mn (.14.)    0.119    0.017    7.037    0.000
##    .P1_P_mn (.15.)    0.100    0.021    4.875    0.000
##    .P2_P_mn (.16.)    0.311    0.036    8.665    0.000
##    .P2_N_mn (.17.)    0.042    0.005    8.546    0.000
##    .SS2_men (.18.)   -0.028    0.019   -1.463    0.143
##     Neg               0.075    0.019    3.895    0.000
##     Pos               0.318    0.056    5.715    0.000
##     NewVrbl           0.030    0.007    4.119    0.000
##
##
## Group 2 [2]:
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg =~
##     PG_N_mn           1.000
##     P1_N_mn (.p2.)    0.832    0.107    7.752    0.000
##     ST_mean (.p3.)   -1.091    0.143   -7.623    0.000
##     SS1_men (.p4.)   -1.349    0.160   -8.447    0.000
##   Pos =~
##     PG_P_mn           1.000
```

```
##     P1_P_mn (.p6.)    1.208    0.087   13.924    0.000
##     P2_P_mn (.p7.)    1.257    0.103   12.180    0.000
##   NewVariable =~
##     P2_N_mn           1.000
##     SS2_men (.p9.)    2.552    0.355    7.178    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   Neg ~~
##     Pos              -0.040    0.012   -3.322    0.001
##     NewVariable      -0.019    0.005   -3.811    0.000
##   Pos ~~
##     NewVariable       0.024    0.008    3.201    0.001
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mn (.25.)    4.554    0.036  125.532    0.000
##    .P1_N_mn (.26.)    4.802    0.026  182.847    0.000
##    .ST_mean (.27.)    1.712    0.035   48.972    0.000
##    .SS1_men (.28.)    1.590    0.039   41.111    0.000
##    .PG_P_mn (.29.)    2.405    0.060   40.204    0.000
##    .P1_P_mn (.30.)    2.642    0.070   37.742    0.000
##    .P2_P_mn (.31.)    3.056    0.079   38.851    0.000
##    .P2_N_mn (.32.)    1.169    0.021   56.077    0.000
##    .SS2_men (.33.)    1.658    0.039   42.940    0.000
##     Neg               0.030    0.036    0.843    0.399
##     Pos              -0.014    0.072   -0.194    0.846
##     NewVrbl          -0.022    0.020   -1.105    0.269
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .PG_N_mn (.10.)    0.132    0.013    9.886    0.000
##    .P1_N_mn (.11.)    0.041    0.005    8.786    0.000
##    .ST_mean (.12.)    0.079    0.009    9.005    0.000
##    .SS1_men (.13.)    0.036    0.007    5.200    0.000
##    .PG_P_mn (.14.)    0.119    0.017    7.037    0.000
##    .P1_P_mn (.15.)    0.100    0.021    4.875    0.000
##    .P2_P_mn (.16.)    0.311    0.036    8.665    0.000
##    .P2_N_mn (.17.)    0.042    0.005    8.546    0.000
##    .SS2_men (.18.)   -0.028    0.019   -1.463    0.143
##     Neg               0.046    0.012    3.849    0.000
##     Pos               0.195    0.035    5.636    0.000
##     NewVrbl           0.024    0.005    4.526    0.000
```

```
lavInspect(fit_strict, what = "std")
```

```
## $`1`
## $`1`$lambda
##               Neg   Pos NwVrbl
## PG_N_mean  0.602 0.000  0.000
## P1_N_mean  0.748 0.000  0.000
## ST_mean   -0.729 0.000  0.000
## SS1_mean  -0.890 0.000  0.000
## PG_P_mean  0.000 0.853  0.000
## P1_P_mean  0.000 0.907  0.000
```

```
## P2_P_mean  0.000 0.786  0.000
## P2_N_mean  0.000 0.000  0.644
## SS2_mean   0.000 0.000  1.082
##
## $`1`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.638
## P1_N_mean  0.000  0.441
## ST_mean    0.000  0.000  0.468
## SS1_mean   0.000  0.000  0.000  0.208
## PG_P_mean  0.000  0.000  0.000  0.000  0.272
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.177
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.382
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.585
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.171
##
## $`1`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.420  1.000
## NewVariable -0.542  0.450  1.000
##
## $`1`$nu
##           intrcp
## PG_N_mean  9.999
## P1_N_mean 15.736
## ST_mean    4.172
## SS1_mean   3.827
## PG_P_mean  3.638
## P1_P_mean  3.518
## P2_P_mean  3.390
## P2_N_mean  4.363
## SS2_mean   4.073
##
## $`1`$alpha
##             intrcp
## Neg              0
## Pos              0
## NewVariable      0
##
##
## $`2`
## $`2`$lambda
##              Neg   Pos NwVrbl
## PG_N_mean  0.510 0.000  0.000
## P1_N_mean  0.663 0.000  0.000
## ST_mean   -0.642 0.000  0.000
## SS1_mean  -0.838 0.000  0.000
## PG_P_mean  0.000 0.788  0.000
## P1_P_mean  0.000 0.860  0.000
## P2_P_mean  0.000 0.706  0.000
## P2_N_mean  0.000 0.000  0.601
## SS2_mean   0.000 0.000  1.107
##
```

```
## $`2`$theta
##           PG_N_m P1_N_m ST_men SS1_mn PG_P_m P1_P_m P2_P_m P2_N_m SS2_mn
## PG_N_mean  0.740
## P1_N_mean  0.000  0.561
## ST_mean    0.000  0.000  0.588
## SS1_mean   0.000  0.000  0.000  0.298
## PG_P_mean  0.000  0.000  0.000  0.000  0.379
## P1_P_mean  0.000  0.000  0.000  0.000  0.000  0.260
## P2_P_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.502
## P2_N_mean  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.638
## SS2_mean   0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.225
##
## $`2`$psi
##             Neg    Pos    NwVrbl
## Neg          1.000
## Pos         -0.421  1.000
## NewVariable -0.568  0.354  1.000
##
## $`2`$nu
##           intrcp
## PG_N_mean 10.772
## P1_N_mean 17.745
## ST_mean    4.673
## SS1_mean   4.583
## PG_P_mean  4.289
## P1_P_mean  4.257
## P2_P_mean  3.884
## P2_N_mean  4.559
## SS2_mean   4.665
##
## $`2`$alpha
##             intrcp
## Neg          0.140
## Pos         -0.031
## NewVariable -0.143
```

Ethical Considerations

How can this technology be attacked or abused?

This information can be used to potentially attack those with poor results with advertisements for medicine that might help with cognitive ability or emotional regulation. Specific ad targeting is never ideal, especially for those that are older or don't know how to avoid phishing scams. Can also indirectly and unintentionally bias towards one gender group or locale or age range. Could also misinform MDs if they only rely on this model.

Test to ensure it is fair and representative?

Our measurement of invariance showed our model achieved a strict invariance model and proved that the data is fair across our gender demographic. It is difficult to test for representation since our only demographic provided was gender.

Understand possible biases?

The dataset could possibly bias towards one recorded gender, or a specific age group.

Diversity of opinions, backgrounds, and kinds of thought?

Dataset only includes data from two areas, Milwaukee and Madison, Wisconsin. However, the age range varies from 25 to 74, so different kinds of thought are represented that way. No demographics other than age and gender are provided, so we have no way of confirming different ethnic groups are represented.

User consent to collect data?

Midlife Development of the U.S. collected data and ensured consent from each participant on conducting the test, but does not mention any specifics about the data.

Mechanism for gathering consent?

Asked for consent upon beginning the test, prior to the administering of the written test.

Explained clearly what users are consenting to?

Was not clearly stated in the available literature, however we can assume the data collectors informed the participants the purpose of their study.

Redress if people are harmed by results?

Take down our software / model and kill it. Put mechanisms in place to reach out to MIDUS group in case of severe fallout or harm.

Shut down software in production if behaving badly?

Our software / model is just a simple model showing correlations between emotional regulation and cognitive ability. "Behaving badly" doesn't seem to be a real concern for us, other than showing no correlation. Also, not pushing this to production. This is for a class project.

Fairness with respect to different user groups?

The tests were administered the same to each group of people, Milwaukee and Madison participants.

Tested for disparate error rates among different user groups?

Our dataset did not include many demographics beside gender and age, therefore it would be difficult to test if specific user groups had error rates. Neverless, a test of invariance was conducted and concluded that our model met a strict invariance model.

Test and monitor for model drift to ensure software remains fair over time?

Model will not change unless the data changes, and the data is not changing. Revisit ethical questions to check if this model is still fair overtime.

Plan to protect and secure user data?

The MIDUS 2 dataset is available online for download, however the data collectors have maintained anonymity to ensure subjects protection.