

## Additional file 2

### R Code

```
#install.packages("psych")
#install.packages("lavaan")
#install.packages("semTools")

library(psych)
library(lavaan)
library(semTools)

# read data
#https://ipip.ori.org/30FacetNEO-PI-RItems.htm
#https://osf.io/tbmh5/

full.data <- read.csv("data/IPIP300_N.csv")

#examine data
names(full.data)

# compute mean scores

full.data$NAng.full =
rowMeans(full.data[c("NAng1", "NAng2", "NAng3", "NAng4", "NAng5", "NAng6", "NAng7", "
NAng8", "NAng9", "NAng10")], na.rm = T)

full.data$NAnx.full =
rowMeans(full.data[c("NAnx1", "NAnx2", "NAnx3", "NAnx4", "NAnx5", "NAnx6", "NAnx7", "
NAnx8", "NAnx9", "NAnx10")], na.rm = T)

full.data$NDep.full =
rowMeans(full.data[c("NDep1", "NDep2", "NDep3", "NDep4", "NDep5", "NDep6", "NDep7", "N
Dep8", "NDep9", "NDep10")], na.rm = T)

full.data$NImm.full =
rowMeans(full.data[c("NImm1", "NImm2", "NImm3", "NImm4", "NImm5", "NImm6", "NImm7
", "NImm8", "NImm9", "NImm10")], na.rm = T)
```

```

full.data$NSel.full =
rowMeans(full.data[c("NSel1","NSel2","NSel3","NSel4","NSel5","NSel6","NSel7","NSel8",
"NSel9","NSel10")], na.rm = T)

full.data$NVul.full =
rowMeans(full.data[c("NVul1","NVul2","NVul3","NVul4","NVul5","NVul6","NVul7","NV
ul8","NVul9","NVul10")], na.rm = T)

full.data$N.full =
rowMeans(full.data[c("NAng.full","NAnx.full","NDep.full","NImm.full","NSel.full","NVul.f
ull")], na.rm = T)

# some basic descriptives

describe(full.data)

table(full.data$SEX)

table(full.data$AGE)

### EFA

fa.sort(fa(full.data[,1:60],6))

#CFA models full

#One factor model

N.one.model <- "
Neuro =~ NAng1 + NAng2 + NAng3 + NAng4 + NAng5 + NAng6 + NAng7 + NAng8 +
NAng9 + NAng10
      + NAnx1 + NAnx2 + NAnx3 + NAnx4 + NAnx5 + NAnx6 + NAnx7 + NAnx8 + NAnx9
+ NAnx10
      + NDep1 + NDep2 + NDep3 + NDep4 + NDep5 + NDep6 + NDep7 + NDep8 + NDep9
+ NDep10
      + NImm1 + NImm2 + NImm3 + NImm4 + NImm5 + NImm6 + NImm7 + NImm8 +
NImm9 + NImm10
      + NSel1 + NSel2 + NSel3 + NSel4 + NSel5 + NSel6 + NSel7 + NSel8 + NSel9 + NSel10
      + NVul1 + NVul2 + NVul3 + NVul4 + NVul5 + NVul6 + NVul7 + NVul8 + NVul9 +
NVul10
"

#correlated factor model

```

```

N.cor.model <- "
NAng =~ NAng1 + NAng2 + NAng3 + NAng4 + NAng5 + NAng6 + NAng7 + NAng8 +
NAng9 + NAng10
NAnx =~ NAnx1 + NAnx2 + NAnx3 + NAnx4 + NAnx5 + NAnx6 + NAnx7 + NAnx8 +
NAnx9 + NAnx10
NDep =~ NDep1 + NDep2 + NDep3 + NDep4 + NDep5 + NDep6 + NDep7 + NDep8 +
NDep9 + NDep10
NImm =~ NImm1 + NImm2 + NImm3 + NImm4 + NImm5 + NImm6 + NImm7 + NImm8 +
NImm9 + NImm10
NSel =~ NSel1 + NSel2 + NSel3 + NSel4 + NSel5 + NSel6 + NSel7 + NSel8 + NSel9 +
NSel10
NVul =~ NVul1 + NVul2 + NVul3 + NVul4 + NVul5 + NVul6 + NVul7 + NVul8 + NVul9 +
NVul10
"

```

#higher-order model

```

N.hio.model <- "
NAng =~ NAng1 + NAng2 + NAng3 + NAng4 + NAng5 + NAng6 + NAng7 + NAng8 +
NAng9 + NAng10
NAnx =~ NAnx1 + NAnx2 + NAnx3 + NAnx4 + NAnx5 + NAnx6 + NAnx7 + NAnx8 +
NAnx9 + NAnx10
NDep =~ NDep1 + NDep2 + NDep3 + NDep4 + NDep5 + NDep6 + NDep7 + NDep8 +
NDep9 + NDep10
NImm =~ NImm1 + NImm2 + NImm3 + NImm4 + NImm5 + NImm6 + NImm7 + NImm8 +
NImm9 + NImm10
NSel =~ NSel1 + NSel2 + NSel3 + NSel4 + NSel5 + NSel6 + NSel7 + NSel8 + NSel9 +
NSel10
NVul =~ NVul1 + NVul2 + NVul3 + NVul4 + NVul5 + NVul6 + NVul7 + NVul8 + NVul9 +
NVul10

Neuro =~ NAng + NAnx + NDep + NImm + NSel + NVul
"

```

#bi-factor model

```

N.bif.model <- "

```

$N\text{Ang} = \sim N\text{Ang}1 + N\text{Ang}2 + N\text{Ang}3 + N\text{Ang}4 + N\text{Ang}5 + N\text{Ang}6 + N\text{Ang}7 + N\text{Ang}8 + N\text{Ang}9 + N\text{Ang}10$

$N\text{Anx} = \sim N\text{Anx}1 + N\text{Anx}2 + N\text{Anx}3 + N\text{Anx}4 + N\text{Anx}5 + N\text{Anx}6 + N\text{Anx}7 + N\text{Anx}8 + N\text{Anx}9 + N\text{Anx}10$

$N\text{Dep} = \sim N\text{Dep}1 + N\text{Dep}2 + N\text{Dep}3 + N\text{Dep}4 + N\text{Dep}5 + N\text{Dep}6 + N\text{Dep}7 + N\text{Dep}8 + N\text{Dep}9 + N\text{Dep}10$

$N\text{Imm} = \sim N\text{Imm}1 + N\text{Imm}2 + N\text{Imm}3 + N\text{Imm}4 + N\text{Imm}5 + N\text{Imm}6 + N\text{Imm}7 + N\text{Imm}8 + N\text{Imm}9 + N\text{Imm}10$

$N\text{Sel} = \sim N\text{Sel}1 + N\text{Sel}2 + N\text{Sel}3 + N\text{Sel}4 + N\text{Sel}5 + N\text{Sel}6 + N\text{Sel}7 + N\text{Sel}8 + N\text{Sel}9 + N\text{Sel}10$

$N\text{Vul} = \sim N\text{Vul}1 + N\text{Vul}2 + N\text{Vul}3 + N\text{Vul}4 + N\text{Vul}5 + N\text{Vul}6 + N\text{Vul}7 + N\text{Vul}8 + N\text{Vul}9 + N\text{Vul}10$

$\text{Neuro} = \sim N\text{Ang}1 + N\text{Ang}2 + N\text{Ang}3 + N\text{Ang}4 + N\text{Ang}5 + N\text{Ang}6 + N\text{Ang}7 + N\text{Ang}8 + N\text{Ang}9 + N\text{Ang}10$

$+ N\text{Anx}1 + N\text{Anx}2 + N\text{Anx}3 + N\text{Anx}4 + N\text{Anx}5 + N\text{Anx}6 + N\text{Anx}7 + N\text{Anx}8 + N\text{Anx}9 + N\text{Anx}10$

$+ N\text{Dep}1 + N\text{Dep}2 + N\text{Dep}3 + N\text{Dep}4 + N\text{Dep}5 + N\text{Dep}6 + N\text{Dep}7 + N\text{Dep}8 + N\text{Dep}9 + N\text{Dep}10$

$+ N\text{Imm}1 + N\text{Imm}2 + N\text{Imm}3 + N\text{Imm}4 + N\text{Imm}5 + N\text{Imm}6 + N\text{Imm}7 + N\text{Imm}8 + N\text{Imm}9 + N\text{Imm}10$

$+ N\text{Sel}1 + N\text{Sel}2 + N\text{Sel}3 + N\text{Sel}4 + N\text{Sel}5 + N\text{Sel}6 + N\text{Sel}7 + N\text{Sel}8 + N\text{Sel}9 + N\text{Sel}10$

$+ N\text{Vul}1 + N\text{Vul}2 + N\text{Vul}3 + N\text{Vul}4 + N\text{Vul}5 + N\text{Vul}6 + N\text{Vul}7 + N\text{Vul}8 + N\text{Vul}9 + N\text{Vul}10$

$\text{Neuro} \sim 0 * N\text{Ang} + 0 * N\text{Anx} + 0 * N\text{Dep} + 0 * N\text{Imm} + 0 * N\text{Sel} + 0 * N\text{Vul}$

"

#estimate models

`fit.one <- cfa(N.one.model , full.data , missing = "FIML")`

`fit.hio <- cfa(N.hio.model , full.data , missing = "FIML")`

`fit.cor <- cfa(N.cor.model , full.data , missing = "FIML")`

`fit.bif <- cfa(N.bif.model , full.data , missing = "FIML", std.lv = T) #std.lv = T for convergence reasons: frees first loading and constrains factor variance to 1`

```

#optional: plot models
#install.packages("semPlot")
#semPlot::semPaths(fit.cor)
#semPlot::semPaths(fit.hio)
#semPlot::semPaths(fit.bif)

#model fit comparison
round(rbind(
fitMeasures(fit.one, c("df","chisq","cfi","rmsea","srmr")),
fitMeasures(fit.hio, c("df","chisq","cfi","rmsea","srmr")),
fitMeasures(fit.cor, c("df","chisq","cfi","rmsea","srmr")),
fitMeasures(fit.bif, c("df","chisq","cfi","rmsea","srmr"))),3)

anova(fit.one,fit.hio,fit.cor,fit.bif)

#model parameters
summary(fit.one, standardized = T)
summary(fit.hio, standardized = T)
summary(fit.cor, standardized = T)
summary(fit.bif, standardized = T)

#reliability
round(reliability(fit.one) , 2)
round(reliability(fit.hio) , 2)
round(reliability(fit.cor) , 2)
round(reliability(fit.bif) , 2)

#measurement invariance example
fit.cor.config <- cfa(N.cor.model , full.data , group = "SEX")
fit.cor.metric <- cfa(N.cor.model , full.data , group = "SEX", group.equal = c("loadings"))

```

```
fit.cor.scalar <- cfa(N.cor.model , full.data , group = "SEX", group.equal = c("loadings",
"intercepts"))
```

```
fit.cor.strict <- cfa(N.cor.model , full.data , group = "SEX", group.equal = c("loadings",
"intercepts", "residuals"))
```

```
round(rbind(
fitMeasures(fit.cor.config,c("df","chisq","CFI","SRMR","RMSEA")),
fitMeasures(fit.cor.metric,c("df","chisq","CFI","SRMR","RMSEA")),
fitMeasures(fit.cor.scalar,c("df","chisq","CFI","SRMR","RMSEA")),
fitMeasures(fit.cor.strict,c("df","chisq","CFI","SRMR","RMSEA"))),3)
```

```
#number of positive / negative items
```

```
pos.items <- c("NAnx1", "NAnx2", "NAnx3", "NAnx4", "NAnx5", "NAng1", "NAng2",
"NAng3", "NAng5", "NAng6", "NDep1", "NDep2", "NDep3", "NDep5", "NDep6", "NDep7",
"NDep8", "NSel1", "NSel2", "NSel3", "NSel5", "NSel6", "NSel7", "NImm1", "NImm5",
"NImm6", "NImm7", "NImm8", "NVul1", "NVul2", "NVul3", "NVul5", "NVul6")
```

```
neg.items <- c("NAnx6", "NAnx7", "NAnx8", "NAnx9", "NAnx10", "NAng4", "NAng7",
"NAng8", "NAng9", "NAng10", "NDep4", "NDep9", "NDep10", "NSel4", "NSel8", "NSel9",
"NSel10", "NImm2", "NImm3", "NImm4", "NImm9", "NImm10", "NVul4", "NVul7",
"NVul8", "NVul9", "NVul10")
```

```
length(pos.items) #how many positively coded items in full form
```

```
length(neg.items) #how many negatively coded items in full form
```

```
# correlation with covariates (higher order model in this case because of multicollinearity)
```

```
N.ho.age.model <- "
```

```
NAng =~ NAng1 + NAng2 + NAng3 + NAng4 + NAng5 + NAng6 + NAng7 + NAng8 +
NAng9 + NAng10
```

```
NAnx =~ NAnx1 + NAnx2 + NAnx3 + NAnx4 + NAnx5 + NAnx6 + NAnx7 + NAnx8 +
NAnx9 + NAnx10
```

```
NDep =~ NDep1 + NDep2 + NDep3 + NDep4 + NDep5 + NDep6 + NDep7 + NDep8 +
NDep9 + NDep10
```

```
NImm =~ NImm1 + NImm2 + NImm3 + NImm4 + NImm5 + NImm6 + NImm7 + NImm8 +
NImm9 + NImm10
```

```
NSel =~ NSel1 + NSel2 + NSel3 + NSel4 + NSel5 + NSel6 + NSel7 + NSel8 + NSel9 +
NSel10
```

```
NVul =~ NVul1 + NVul2 + NVul3 + NVul4 + NVul5 + NVul6 + NVul7 + NVul8 + NVul9 +
NVul10
```

```
Neuro =~ NAng + NAnx + NDep + NImm + NSel + NVul
```

```
AGE ~ Neuro
```

```
"
```

```
fit.ho.age <- cfa(N.ho.age.model , full.data )
```

```
summary(fit.ho.age, standardized = T)
```

```
#####  
#####
```

```
##### Creating an optimization function #####
```

```
#####  
#####
```

```
### Full model items
```

```
# full item list with items per factor
```

```
list.items <- list(
```

```
  NAng =  
  c("NAng1","NAng2","NAng3","NAng4","NAng5","NAng6","NAng7","NAng8","NAng9","  
  NAng10"),
```

```
  NAnx =  
  c("NAnx1","NAnx2","NAnx3","NAnx4","NAnx5","NAnx6","NAnx7","NAnx8","NAnx9","  
  NAnx10"),
```

```
  NDep =  
  c("NDep1","NDep2","NDep3","NDep4","NDep5","NDep6","NDep7","NDep8","NDep9","N  
  Dep10"),
```

```
  NImm =  
  c("NImm1","NImm2","NImm3","NImm4","NImm5","NImm6","NImm7","NImm8","NImm9  
  ","NImm10"),
```

```
  NSel =  
  c("NSel1","NSel2","NSel3","NSel4","NSel5","NSel6","NSel7","NSel8","NSel9","NSel10"),
```

```
NVul =  
c("NVul1","NVul2","NVul3","NVul4","NVul5","NVul6","NVul7","NVul8","NVul9","NVul  
10"))
```

```
#vector with all items (needed for pheromones)
```

```
item.vector <- unlist(list.items, use.names = F)
```

```
### Short model items
```

```
#3 example item selection of 4 items per factor (as would be selected by ACO)
```

```
selected.items.1 <- list(  
  NAng = c("NAng1","NAng2","NAng3","NAng4"),  
  NAnx = c("NAnx1","NAnx2","NAnx3","NAnx4"),  
  NDep = c("NDep1","NDep2","NDep3","NDep4"),  
  NImm = c("NImm1","NImm2","NImm3","NImm4"),  
  NSel = c("NSel1","NSel2","NSel3","NSel4"),  
  NVul = c("NVul1","NVul2","NVul3","NVul4"))
```

```
selected.items.2 <- list(  
  NAng = c("NAng5","NAng6","NAng7","NAng8"),  
  NAnx = c("NAnx5","NAnx6","NAnx7","NAnx8"),  
  NDep = c("NDep5","NDep6","NDep7","NDep8"),  
  NImm = c("NImm5","NImm6","NImm7","NImm8"),  
  NSel = c("NSel5","NSel6","NSel7","NSel8"),  
  NVul = c("NVul5","NVul6","NVul7","NVul8"))
```

```
selected.items.3 <- list(  
  NAng = c("NAng3","NAng6","NAng9","NAng10"),  
  NAnx = c("NAnx3","NAnx6","NAnx9","NAnx10"),  
  NDep = c("NDep3","NDep6","NDep9","NDep10"),  
  NImm = c("NImm3","NImm6","NImm9","NImm10"),  
  NSel = c("NSel3","NSel6","NSel9","NSel10"),  
  NVul = c("NVul3","NVul6","NVul9","NVul10"))
```

## ##### 1. Optimization function

#positive and negative items (used for optimization)

```
pos.items <- c("NAx1", "NAx2", "NAx3", "NAx4", "NAx5", "NAng1", "NAng2",  
"NAng3", "NAng5", "NAng6", "NDep1", "NDep2", "NDep3", "NDep5", "NDep6", "NDep7",  
"NDep8", "NSel1", "NSel2", "NSel3", "NSel5", "NSel6", "NSel7", "NImm1", "NImm5",  
"NImm6", "NImm7", "NImm8", "NVul1", "NVul2", "NVul3", "NVul5", "NVul6")
```

```
neg.items <- c("NAx6", "NAx7", "NAx8", "NAx9", "NAx10", "NAng4", "NAng7",  
"NAng8", "NAng9", "NAng10", "NDep4", "NDep9", "NDep10", "NSel4", "NSel8", "NSel9",  
"NSel10", "NImm2", "NImm3", "NImm4", "NImm9", "NImm10", "NVul4", "NVul7",  
"NVul8", "NVul9", "NVul10")
```

#names of factors (used to write model syntax)

```
factors <- c("NAx", "NAng", "NDep", "NSel", "NImm", "NVul") #factor names for lavaan  
model
```

#pick one item set

```
selected.items = selected.items.1
```

#if you want to go through the fit.function manually (i.e., execute each line)

```
data = full.data
```

### fit function start

```
fit.function = function(selected.items, data){
```

```
  tryCatch({ # used to ignore estimation errors, which would otherwise stop the entire ACO  
run
```

```
    ### write model syntax based on items
```

```
    model <- NULL
```

```
    # loop to specify each factor in the model
```

```
    for (fac in 1:length(factors)) {
```

```
      model <- paste(model, paste0(factors[fac], "=~ ", paste(selected.items[[fac]], collapse=""  
+ ")), "\n") # write factor =~ items (separated by +); "\n" = new line
```

```

}

# possible model modifications:

#model <- paste0(model, paste0("G =~ ", paste(factors, collapse=" + "))) #higher-order
model

#model <- paste0(model, paste0("G =~ ", paste(unlist(selected.items), collapse=" + ")))
#bifactor model

# this is what the model looks like:

model

# estimate model

fit <- cfa(model = model, data = data, missing = "FIML") #,orthogonal = TRUE, std.lv =
TRUE) #required for bi-factor model (std.lv for convergence reasons)

### optimization #1: model fit

# note: I've added ( ) around most commands so you can see the output directly
(mod.fit <- fitMeasures(fit, c("cfi", "rmsea", "srmr")))

(phi.CFI <- 1/(1+exp(50*(.90-mod.fit[1]))) #logistic transformation of CFI with
cutoff at .90 and "slope" of 50

(phi.RMSEA <- 1-(1/(1+exp(100*(.06-mod.fit[2]))))) #logistic transformation of RMSEA
with cutoff at .06 and "slope" of 100

(phi.SRMR <- 1-(1/(1+exp(100*(.06-mod.fit[3]))))) #logistic transformation of SRMR
with cutoff at .06 and "slope" of 100

(phi.fit <- (phi.CFI + phi.RMSEA + phi.SRMR)/3) #mean value of transformed values

### optimization #2: reliability

(omega.all <- semTools::reliability(fit)[4,]) #extract hierarchical omega using reliability
(semTools) function

(omega.mean <- mean(omega.all)) #compute average omega across all factors

```

```
(phi.rel <- 1/(1+exp(100*(.7-omega.mean)))) #logistic transformation of omega with cutoff at .70 and "slope" of 100
```

```
### optimization #3: correlation with full scale
```

```
(cor.full.all <- c(  
cor(data$NAng.full , rowMeans(data[selected.items[[1]]], na.rm = T), use = "p"),  
cor(data$NAnx.full , rowMeans(data[selected.items[[2]]], na.rm = T), use = "p"),  
cor(data$NDep.full , rowMeans(data[selected.items[[3]]], na.rm = T), use = "p"),  
cor(data$NImm.full , rowMeans(data[selected.items[[4]]], na.rm = T), use = "p"),  
cor(data$NSel.full , rowMeans(data[selected.items[[5]]], na.rm = T), use = "p"),  
cor(data$NVul.full , rowMeans(data[selected.items[[6]]], na.rm = T), use = "p"))
```

```
(cor.full.mean <- mean(cor.full.all))
```

```
(phi.cor <- 1/(1+exp(100*(.90-cor.full.mean)))) #logistic transformation of correlation with cutoff at .90 and "slope" of 100
```

```
### optimization #4: item key balance
```

```
(selected.vector <- unlist(selected.items, use.names = F)) # transform list into vector for comparison
```

```
(n.neg.items <- sum(is.element(selected.vector,neg.items))) #how items are negatively coded
```

```
(phi.bal <- 5*(1/sqrt(8*pi)*exp(-((n.neg.items-12)^2/8)))) # transformation into gaussian function with maximum (1) at 12 items
```

```
### end of function
```

```
# save detailed fit information;
```

```
(fit.detail <- round(c(mod.fit, omega.all, cor.full.all,n.neg.items),3))
```

```
#optional: give it nicer names for live feedback
```

```
names(fit.detail) <- c("cfi", "rmsea", "srmr", paste0(factors, ".rel"), paste0(factors, ".r"), "Nneg")
```

```

# compute overall optimization criterion ranging from 0 to 1
(phi.overall <- (phi.fit + phi.rel + phi.cor + phi.bal)/4)

# return information to ACO
return(list(as.numeric(phi.overall),
           fit.detail,
           model))

}, # end of tryCatch
warning = function(w) return(0), #optional, punishes negative residual variances etc.
error = function(e) return(0)) #essential, deals with non-convergence

} #end fit function

##### 2. Evaluate some solutions

# compare the 3 item sets:
fit.function(selected.items.1, full.data)
fit.function(selected.items.2, full.data)
fit.function(selected.items.3, full.data)

# with random selection of items
selected.items.n <- list(
  NAng = sample(list.items[[1]], 4),
  NAnx = sample(list.items[[2]], 4),
  NDep = sample(list.items[[3]], 4),
  NImm = sample(list.items[[4]], 4),
  NSel = sample(list.items[[5]], 4),
  NVul = sample(list.items[[6]], 4))

fit.function(selected.items.n, full.data)

```

### ##### 3. Illustration of the logistic transformation

```
cfi <- seq(.7,1,.001)
```

```
rmsea <- seq(.15,0,-.001)
```

```
neg.item <- seq(0,24,1)
```

#### # Example CFI

```
#1/(1+exp(50*(.90-cfi))) is the same as logistic(cfi, d=.90, a=50, c=0, z=1)
```

```
phi.cfi.90.50 <- logistic(cfi, d=.90, a=50, c=0, z=1) #logistic transformation of CFI with  
cutoff at .90 and "slope" of 50; transformed score from 0 to 1
```

```
phi.cfi.90.100 <- logistic(cfi, d=.90, a=100, c=0, z=1) #logistic transformation of CFI with  
cutoff at .90 and "slope" of 100; transformed score from 0 to 1
```

```
phi.cfi.95.50 <- logistic(cfi, d=.95, a=50, c=0, z=1) #logistic transformation of CFI with  
cutoff at .95 and "slope" of 100; transformed score from 0 to 1
```

```
phi.cfi.95.100 <- logistic(cfi, d=.95, a=100, c=0, z=1) #logistic transformation of CFI with  
cutoff at .95 and "slope" of 100; transformed score from 0 to 1
```

```
plot(cfi,phi.cfi.90.50, type = "l", ylim = c(0,1))
```

```
lines(cfi,phi.cfi.90.100, lty = 2)
```

```
lines(cfi,phi.cfi.95.50, col = "red")
```

```
lines(cfi,phi.cfi.95.100, col = "red", lty = 2)
```

#### ### Example RMSEA (1 - so that lower values are better)

```
phi.rmsea.06.50 <- 1 - logistic(rmseaa, d=.06, a=50, c=0, z=1)
```

```
phi.rmsea.06.100 <- 1 - logistic(rmseaa, d=.06, a=100, c=0, z=1)
```

```
phi.rmsea.08.50 <- 1 - logistic(rmseaa, d=.08, a=50, c=0, z=1)
```

```
phi.rmsea.08.100 <- 1 - logistic(rmseaa, d=.08, a=100, c=0, z=1)
```

```
plot(rmseaa,phi.rmsea.06.50 , type = "l", ylim = c(0,1))
```

```
lines(rmseaa,phi.rmsea.06.100, lty = 2)
```

```
lines(rmseaa,phi.rmsea.08.50 , col = "red")
```

```
lines(rmseaa,phi.rmsea.08.100, col = "red", lty = 2)
```

```
### Example of item key balance transformation into gaussian function
```

```
phi.bal <- 5*(1/sqrt(8*pi)*exp(-((neg.item-12)^2/10)))
```

```
plot(neg.item, phi.bal , type = "l", ylim = c(0,1))
```

```
#alternatively you can "mirror" the logistic transformation by optimizing the absolute difference to a target number of items:
```

```
phi.bal.log <- 1 - logistic(abs(neg.item-12), d=2, a=2, c=0, z=1)
```

```
lines(neg.item, phi.bal.log , col = "green")
```

```
phi.bal.log <- 1 - logistic(abs(neg.item-12), d=4, a=1, c=0, z=1)
```

```
lines(neg.item, phi.bal.log , col = "red")
```

```
library(psych)
```

```
library(lavaan)
```

```
library(semTools)
```

```
#####  
##### Basic ACO #####  
#####
```

```
### 1. create fit function (in this case CFI and RMSEA)
```

```
fit.function = function(selected.items, data){
```

```
  tryCatch({ # used to ignore estimation errors, which would otherwise stop the entire ACO  
    run
```

```
    model <- NULL #create lavan model
```

```
    for(fac in 1:length(factors)){ #for each factor write factor =~ items
```

```
      model <- paste(model, factors[fac], " =~ ", paste(selected.items[[fac]], collapse = " + "),  
"\n")
```

```

}

print(model) # print model while running

fit <- cfa(model, data, missing = "FIML") #estimate model

CFI <- fitMeasures(fit, "cfi") #extract CFI
RMSEA <- fitMeasures(fit, "rmsea") #extract RMSEA

phi.CFI <- 1/(1+exp(100*(.90-CFI))) #logistic transformation of CFI with turning point at
.90 and "slope" of 100

phi.RMSEA <- 1-(1/(1+exp(100*(.06-RMSEA)))) #logistic transformation of RMSEA with
turning point at .06 and "slope" of 100

phi.overall <- (phi.CFI + phi.RMSEA)/2 #mean value of both transformed values
fit.detail <- c(CFI,RMSEA) #also save detailed information

}, # end of tryCatch

#warning = function(w) return(0), #optional, punishes negative residual variances etc.
error = function(e) return(0) #essential, deals with non-convergence

return(list(phi.overall,
            fit.detail,
            model))
}

### 2. required arguments for ACO: names of factors, items, number of items desired,
number of ants and iterations, evaporation rate, names for output files

#item names organized by factor
list.items <- list(

```

```

NAng =
c("NAng1","NAng2","NAng3","NAng4","NAng5","NAng6","NAng7","NAng8","NAng9","
NAng10"),

NAnx =
c("NAnx1","NAnx2","NAnx3","NAnx4","NAnx5","NAnx6","NAnx7","NAnx8","NAnx9","
NAnx10"),

NDep =
c("NDep1","NDep2","NDep3","NDep4","NDep5","NDep6","NDep7","NDep8","NDep9","N
Dep10"),

NImm =
c("NImm1","NImm2","NImm3","NImm4","NImm5","NImm6","NImm7","NImm8","NImm9
","NImm10"),

NSel =
c("NSel1","NSel2","NSel3","NSel4","NSel5","NSel6","NSel7","NSel8","NSel9","NSel10"),

NVul =
c("NVul1","NVul2","NVul3","NVul4","NVul5","NVul6","NVul7","NVul8","NVul9","NVul
10"))

```

```
#factor names (for lavaan)
```

```
factors <- c("NAng","NAnx","NDep","NImm","NSel","NVul")
```

```
#desired number of items per factor
```

```
i.per.f <- c(4,4,4,4,4,4)
```

```
#desired number of ants per iterations and iterations (after a new best solution has been found)
```

```
ants <- 10
```

```
max.iter <- 10
```

```
#evaporation of pheromones after each iteration (multiplied with pheromones each iteration)
```

```
evaporation <- .95 #Empfehlung: .95 bis .99
```

```
#summaryfiles to save the search results
```

```
summaryfile.all <- "ACO_S4_4_all.csv" #for all models
```

```
summaryfile.fin <- "ACO_S4_4_best.csv" #for best model
```

```
#add titles to summary files
```

```
item.vector <- unlist(list.items, use.names = F)
```

```
#for all models (optional, but useful to see pheromones)
```

```
title.all <- matrix(c(item.vector, "Run", "Iteration", "Ant", "Phi.overall", "CFI", "RMSEA",  
paste0(item.vector, ".PH")), 1)
```

```
write.table(title.all, file = summaryfile.all, append = T, quote = F, sep = ";", row.names = F,  
col.names = F)
```

```
#for best model
```

```
title.fin <- matrix(c(item.vector, "Phi.overall", "CFI", "RMSEA"), 1) #change title if you add  
more criteria (names need to match fit.detail)
```

```
write.table(title.fin, file = summaryfile.fin, append = T, quote = F, sep = ";", row.names = F,  
col.names = F)
```

```
### 3. ACO funtion
```

```
#needed if you want to go through the function manually (i.e., execute one line at a time)
```

```
#data = full.data
```

```
#ant = 1
```

```
#fac = 1
```

```
#ACO function start
```

```
ACO <- function(data, list.items, factors, i.per.f, ants, max.iter, evaporation, summaryfile.all,  
summaryfile.fin) {
```

```
  best.phi.overall <- 0 #starting value for best fit within iteration
```

```
  best.so.far.phi.overall <- 0 #starting value for best fit across all iterations
```

```
  #note: I pus some commands in ( ) so you can see the output/values directly
```

```
  (item.vector <- unlist(list.items, use.names = F)) #used for output and number of items in  
total
```

```
  (full <- length(item.vector)) #number of items in total (for pheromones)
```

```

#creates the initial pheromone levels = 1
(pheromones <- rep(1, full))

#creates a list to store items per factor
selected.items <- list.items

#starts counting the iterations (resetable iteration counter)
iter <- 1

#starts counting continuous runs regardless of result.
run <- 1

#starts loop through iterations.
while (iter <= max.iter) { #do not run this line if you go through the function manually

#sends a number of ants per time.
for(ant in 1:ants){ #do not run this line if you go through the function manually

#selects items for all factors.
for (fac in 1:length(factors)) { #run this loop to select items though

#selects the items for a short form for the factor
(positions <- is.element(item.vector, list.items[[fac]])) #identify pheromone levels of
items
(prob <- pheromones[positions] / sum(pheromones[positions])) #determine probability
of items to be selected based on pheromones
(items <- sample(list.items[[fac]], size = i.per.f[fac], prob = prob))

#stores selected items for factor in list
selected.items[[fac]] <- items

```

```

} #finishes factor loop

#creates a vector of selected items.
(selected.vector <- unlist(selected.items, use.names = F))

#creates a 0/1 vector of the same length of the full form indicating
#whether an item was selected or not for the short form.
(solution <- is.element(item.vector,selected.vector))

#evaluate item selection
(item.eval <- fit.function(selected.items,data))

#extract overall fit
phi.overall <- item.eval[[1]]

#in case of non-convergence, this part is skipped
if(phi.overall != 0){

#extract detailed fit statistics
fit.detail <- item.eval[[2]]

#print fit statistics
print(round(fit.detail,3))

#save information in summary file
(fit.save <- matrix(c(solution, run, iter, ant, phi.overall, fit.detail, round(pheromones,2)),
1))
write.table(fit.save, file = summaryfile.all, append = T, quote = F, sep = ";", row.names =
F, col.names = F)
}

#if the new solution is the best solution WITHIN the iteration, update best solution

```

```

if (phi.overall > best.phi.overall) {

  # updates solution.
  best.phi.overall <- phi.overall #best evaluation score
  best.solution <- solution #which items have been selected as 0/1 vector
  best.items <- selected.items #items as list
  best.fit.detail <- fit.detail #detailed psychometrics

}

}#ends loop through ants (= one iteration)

# reduce pheromones by evaporation value
pheromones <- pheromones*evaporation

#updates pheromone for best solution after each iteration by overall evaluation score
(ranging from 0 to 1)
(pheromones <- pheromones + best.phi.overall*best.solution)

#if the new solution is the best solution ACROSS ALL iterations, update best overall
solution
if (best.phi.overall > best.so.far.phi.overall) {

  #updates best so far solution and fit information
  best.so.far.solution <- best.solution
  best.so.far.items <- best.items
  best.so.far.phi.overall <- best.phi.overall
  best.so.far.fit.detail <- best.fit.detail

  #re-starts count.
  iter <- 1

```

```

#end if clause for pheromone adjustment.
} else {

#advances count.
iter <- iter + 1

}

#ends loop.
run <- run + 1
} #end of all iterations

# Compile a matrix with the final solution.
final.solution <- matrix(c(best.so.far.solution, best.so.far.phi.overall, best.so.far.fit.detail),1)
write.table(final.solution, file = summaryfile.fin, append = T,quote = F, sep = ";", row.names
= F, col.names = F)

print(paste0("The best solution achieved a score of: ", round(best.so.far.phi.overall,2)))
print(round(best.so.far.fit.detail,3))

#return best model (for items and optimization values see summaryfile)
return(best.so.far.items)
}

##### 4. Run ACO

set.seed(1) #ensures that run replicates
short.model <- ACO(full.data, list.items, factors, i.per.f, ants, max.iter, evaporation,
summaryfile.all, summaryfile.fin)

short.model

```

```

# you can use the item list in short.model to run the fit function again:
(final.solution <- fit.function(selected.items = short.model, data = full.data))

# and use the model provided by the fit.function to examine the final solution in more detail
final.model <- final.solution[[3]]
fit.final <- cfa(final.model, full.data, missing = "FIML")
summary(fit.final, standardized = T, fit.measures = T)

library(foreign)
library(stuart)
library(semTools)

df <- read.spss(file="R19_SCHMALB_nomiss_nounderage.SAV", to.data.frame = T,
max.value.labels = 0)

#Randomly split df
n <- 2429
data <- data.frame(x=runif(n), y=rnorm(n))
ind <- sample(c(TRUE, FALSE), n, replace=TRUE, prob=c(0.5, 0.5))
df_efa <- df[ind, ]
df_cfa <- df[!ind, ]

cor(df[,132:134], df[,132:134])

#stuart scale shortening
fs <- list(BODY = c("qh101", "qh102", "qh103", "qh104", "qh105", "qh106", "qh107",
"qh108", "qh109", "qh110"),
          COG = c("qh111", "qh112", "qh113", "qh114", "qh115", "qh116", "qh117", "qh118",
"qh119", "qh120"),
          EMO = c("qh121", "qh122", "qh123", "qh124", "qh125", "qh126", "qh127", "qh128",
"qh129", "qh130"))

```

```

ni <- list(5, 5, 5)
combinations(df_efa, fs, ni)
sel <- mmas(df_efa, fs, ni, grouping = "s2", group.invariance = "strong")
summary(sel)
summary(sel$final, fit.measures=T)

#CFA

BOSS_Model <- "BODY =~ qh101 + qh102 + qh103 + qh104 + qh105 + qh106 + qh107 +
qh108 + qh109 + qh110
          COG =~ qh111 + qh112 + qh113 + qh114 + qh115 + qh116 + qh117 + qh118 +
qh119 + qh120
          EMO =~ qh121 + qh122 + qh123 + qh124 + qh125 + qh126 + qh127 + qh128 +
qh129 + qh130"

BOSS_Model <- "BODY =~ qh105 + qh106 + qh108 + qh109 + qh110
          COG =~ qh113 + qh115 + qh116 + qh118 + qh119
          EMO =~ qh121 + qh123 + qh124 + qh125 + qh126"

fit <- cfa(BOSS_Model, data=df_cfa, estimator="MLM")

summary(fit, fit.measures=T)
inspect(fit, what="std")
reliability(fit)

#measurement invariance-----
a <- measurementInvariance(model=BOSS_Model, data=df, estimator="MLM", strict=T,
group="age_group", fit.measures = c("chisq.scaled", "cfi.robust"))
b <- partialInvariance(a, type="strict")

fit <- cfa(BOSS_Model, data=df[df_cfa$age_group==7,], estimator="MLM")
summary(fit, fit.measures=T)

```

```
moreFitIndices(fit)[4]
```

```
fit <- cfa(BOSS_Model, data=df, estimator="MLM", group = "age_group")
```

```
fit <- cfa(BOSS_Model, data=df, estimator="MLM", group = "age_group",  
group.equal="loadings")
```

```
fit <- cfa(BOSS_Model, data=df, estimator="MLM", group = "age_group",  
group.equal=c("loadings","intercepts"))
```

```
fit <- cfa(BOSS_Model, data=df, estimator="MLM", group = "age_group",  
group.equal=c("loadings","intercepts"),
```

```
    group.partial = c("qh106~1", "qh110~1"))
```

```
fit <- cfa(BOSS_Model, data=df, estimator="MLM", group = "age_group",  
group.equal=c("loadings","intercepts","residuals"),
```

```
    group.partial = c("qh106~1", "qh110~1", "qh105~~qh105", "qh106~~qh106",  
"qh110~~qh110", "qh113~~qh113",
```

```
    "qh116~~qh116", "qh118~~qh118", "qh119~~qh119"))
```

```
#correlations----
```

```
cor(df[c("BOSS_Physical", "BOSS_Cognitive", "BOSS_Emotional", "BOSS30_Physical",  
"BOSS30_Cognitive", "BOSS30_Emotional",
```

```
    "euro_qol", "phq_9", "gad_7"]])
```

```
#sociodemographic table
```

```
table(df$s2)
```

```
table(df$age_group)
```

```
table(df$education)
```

```
table(df$family)
```

```
table(df$work)
```

```
table(df$income)
```

```
mean(df$Alter)
```

```
sd(df$Alter)
```

```
aggregate(BOSS_Physical ~ s2, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Cognitive ~ s2, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Emotional ~ s2, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Physical ~ age_group, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Cognitive ~ age_group, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Emotional ~ age_group, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Physical ~ education, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Cognitive ~ education, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Emotional ~ education, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Physical ~ family, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Cognitive ~ family, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Emotional ~ family, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Physical ~ work, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Cognitive ~ work, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Emotional ~ work, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Physical ~ income, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Cognitive ~ income, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
aggregate(BOSS_Emotional ~ income, df, function(x) c(mean = mean(x), sd = sd(x)))
```

```
#norm values----
```

```
#go through s2[sex] and age groups
```

```
cumsum(table(df$BOSS_Physical[df$s2==1 &  
df$age_group==2])/sum(table(df$BOSS_Physical[df$s2==1 & df$age_group==2])))
```

```
cumsum(table(df$BOSS_Cognitive[df$s2==1 &  
df$age_group==2])/sum(table(df$BOSS_Cognitive[df$s2==1 & df$age_group==2])))
```

```
cumsum(table(df$BOSS_Emotional[df$s2==1 &  
df$age_group==2])/sum(table(df$BOSS_Emotional[df$s2==1 & df$age_group==2])))
```