Structural Equation Models 2019 / WEEK 6

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Exercise 6

First let us import the data file in R and prepare it for the excercises.

```
library(lavaan); library(semPlot); library(dplyr); library(knitr)
```

```
## This is lavaan 0.6-3

## lavaan is BETA software! Please report any bugs.

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
E1 <- read.table("ELEMIND1.txt") # calibration group
E2 <- read.table("ELEMIND2.txt") # validation group

# name the variables
variables <- c("ROLEA1", "ROLEA2", "ROLEC1", "ROLEC2", "WORK1", "WORK2",
               "CCLIM1", "CCLIM2", "CCLIM3", "CCLIM4", "DEC1", "DEC2",
               "SSUP1", "SSUP2", "PSUP1", "PSUP2", "SELF1", "SELF2",
               "SELF3", "ELC1", "ELC2", "ELC3", "ELC4", "ELC5",
               "EE1", "EE2", "EE3", "DP1", "DP2", "PA1", "PA2", "PA3")

names(E2) <- names(E1) <- variables
```

Exercise 6.1

Let us specify and establish a well-fitting and parsimonious baseline model for the calibration group. We begin with the hypothesized model:

Hypothesized model:

```
model <- '
RA  =~ ROLEA1 + ROLEA2
RC  =~ ROLEC1 + ROLEC2
WO  =~ WORK1 + WORK2
CC  =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM  =~ DEC1 + DEC2
SS  =~ SSUP1 + SSUP2
PS  =~ PSUP1 + PSUP2
```

```
SE  =~ SELF1 + SELF2 + SELF3
ELC  =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE  =~ EE1 + EE2 + EE3
DP  =~ DP1 + DP2
PA  =~ PA1 + PA2 + PA3

SE ~ DM + SS + PS
ELC ~ DM
EE ~ RC + WO + CC
DP ~ RC + EE
PA ~ RA + SE + ELC + EE + DP
'

fit <- sem(model, data = E1, estimator="MLM")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##                 is not positive definite;
##                 use lavInspect(fit, "cov.lv") to investigate.
```

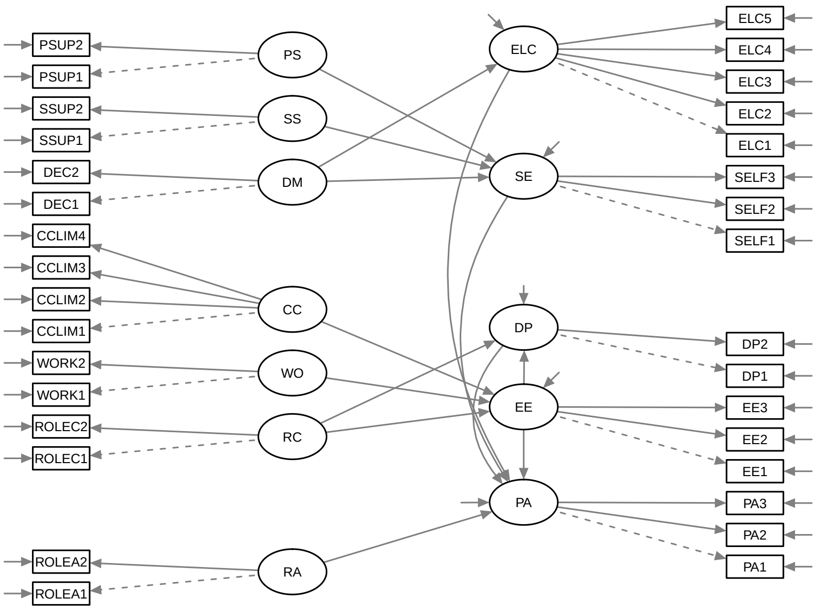
First we draw the hypothesized model in Figure 1.

The factor names are as follows:

- RA = Role ambiguity
- RC = Role conflict
- WO = Work overload
- CC = Classroom climate
- DM = Decision-making
- SS = Superior support
- PS = Peer support
- SE = Self-esteem
- ELC = External locus of control
- EE = Emotional exhaustion
- DP = Depersonalization
- PA = Personal accomplishment

```
semPaths(fit, what = "path", whatLabels = "hide", style = "lisrel", label.scale = F,
         layout = "tree2", residuals = TRUE, nCharNodes = 0, rotation = 2,
         sizeMan = 5, sizeMan2= 2, sizeLat = 6, sizeLat2 = 4, esize = 1, label.cex = 0.4,
         optimizeLatRes = TRUE, edge.label.cex=0.4, reorder=T, exoCov = FALSE)
title("Figure 1: Hypothesized model")
```

Figure 1: Hypothesized model



Let us view the standardized covariance estimates exceeding the value of 1:

```r
parameterestimates(fit, standardized = TRUE) %>%
  filter(op == "~~", std.all > 1) %>%
  select("Item/Factor"=lhs, op, "Item/Factor"=rhs, "Est.covariance"=est,
         "Std.covariance"=std.all, pvalue) %>%
  kable(digits=3, caption="Covariance estimates of the initial model that exceed 1")
```

Table 1: Covariance estimates of the initial model that exceed 1

Item/Factor	op	Item/Factor	Est.covariance	Std.covariance	pvalue
EE	~~	EE	3.457	2.371	0.533
RC	~~	WO	0.674	1.005	0.000

Table 1 shows that the standardized covariance of factors RC and WO is 1.005, which means the factors are representing the same construct. Therefore we can combine them. Let us specify a new model and view a graph of the model:

Modified model:

```r
# Modified model (combined factors RC and WO)
model_modif <-'
RA   =~ ROLEA1 + ROLEA2
RCWO   =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC   =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM   =~ DEC1 + DEC2
SS   =~ SSUP1 + SSUP2
PS   =~ PSUP1 + PSUP2
SE   =~ SELF1 + SELF2 + SELF3
ELC   =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
```

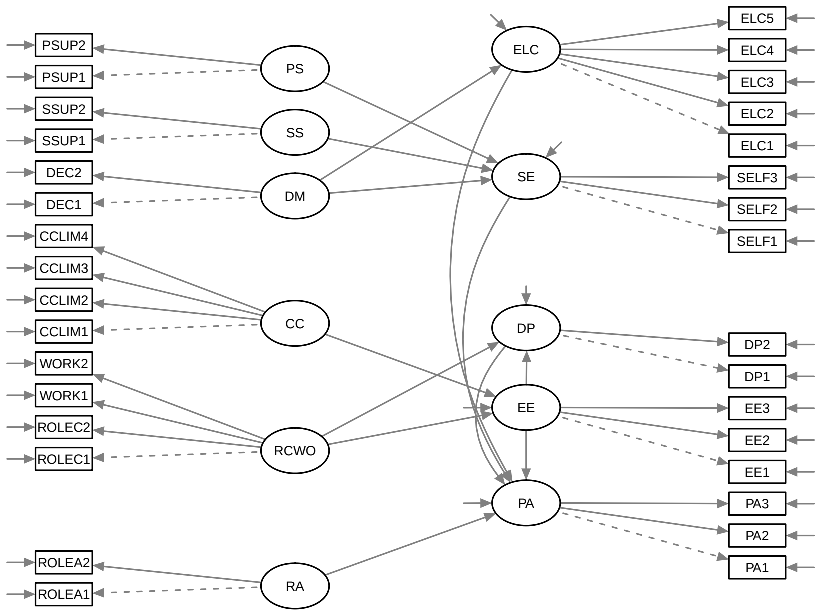
```
EE  =~ EE1 + EE2 + EE3
DP  =~ DP1 + DP2
PA  =~ PA1 + PA2 + PA3

SE ~ DM + SS + PS
ELC ~ DM
EE ~ RCWO + CC
DP ~ RCWO + EE
PA ~ RA + SE + ELC + EE + DP
'

fit.mod <- sem(model_modif, data = E1, estimator="MLM")

semPaths(fit.mod, what = "path", whatLabels = "hide", style = "lisrel", label.scale = F,
         layout = "tree2", residuals = TRUE, nCharNodes = 0, rotation = 2,
         sizeMan = 5, sizeMan2= 2, sizeLat = 6, sizeLat2 = 4, esize = 1, label.cex = 0.4,
         optimizeLatRes = TRUE, edge.label.cex=0.4, reorder=T, exoCov = FALSE)
title("Figure 2: Modified model")
```

Figure 2: Modified model



Let us view the fit measures of the modified model:

```
model <- c("Modified")

chisq = fitMeasures(fit.mod, "chisq.scaled")
df = fitMeasures(fit.mod, "df.scaled")
pvalue = fitMeasures(fit.mod, "pvalue.scaled")
cfi = fitMeasures(fit.mod, "cfi.robust") %>% round(3)
tli = fitMeasures(fit.mod, "tli.robust") %>% round(3)
rmsea = fitMeasures(fit.mod, "rmsea.robust") %>% round(3)
srmr = fitMeasures(fit.mod, "srmr") %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
```

```r
kable(tabledata, row.names = F, caption = "Fit indices (Modified model)")
```

Table 2: Fit indices (Modified model)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062

The fit indices indicate that the fit is not good - let us view modification indices:

```r
mi <- modindices(fit.mod, standardized = T, minimum.value = 35, sort. = T)
mi
```

```
##      lhs op  rhs     mi    epc sepc.lv sepc.all sepc.nox
## 973  ELC  ~ RCWO 51.043  0.281   0.503    0.503    0.503
## 892  EE1 ~~  EE2 46.273  0.297   0.297    0.876    0.876
## 141 RCWO =~ DEC2 44.663  0.668   0.504    0.405    0.405
## 231   SS =~ DEC2 40.963  1.043   1.139    0.917    0.917
## 971  ELC  ~   SS 39.419  0.384   0.994    0.994    0.994
## 421   PA =~  EE3 38.198 -0.356  -0.249   -0.184   -0.184
```

According to MI's we should refine the model by adding ELC ~ RCWO. Let us do that:

Modified model 2:

```r
# Modified model 2 (add ELC ~ RCWO)
model_modif2 <-'
RA  =~ ROLEA1 + ROLEA2
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC  =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM  =~ DEC1 + DEC2
SS  =~ SSUP1 + SSUP2
PS  =~ PSUP1 + PSUP2
SE  =~ SELF1 + SELF2 + SELF3
ELC  =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE  =~ EE1 + EE2 + EE3
DP  =~ DP1 + DP2
PA  =~ PA1 + PA2 + PA3

SE ~ DM + SS + PS
ELC ~ DM + RCWO
EE ~ RCWO + CC
DP ~ RCWO + EE
PA ~ RA + SE + ELC + EE + DP
'

fit.mod2 <- sem(model_modif2, data = E1, estimator="MLM")

# Fit indices
model <- c("Modified", "Modified 2")
chisq = c(fitMeasures(fit.mod, "chisq.scaled"),
          fitMeasures(fit.mod2, "chisq.scaled"))
df = c(fitMeasures(fit.mod, "df.scaled"),
```

```r
       fitMeasures(fit.mod2, "df.scaled"))
pvalue = c(fitMeasures(fit.mod, "pvalue.scaled"),
           fitMeasures(fit.mod2, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod, "cfi.robust"),
        fitMeasures(fit.mod2, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod, "tli.robust"),
        fitMeasures(fit.mod2, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod, "rmsea.robust"),
          fitMeasures(fit.mod2, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod, "srmr"),
         fitMeasures(fit.mod2, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices (Modified models)")
```

Table 3: Fit indices (Modified models)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062
Modified 2	894.6600	435	0	0.949	0.942	0.044	0.052

The fit improved a lot, but we can still refine the model. Let us print the modification indices:

```r
mi2 <- modindices(fit.mod2, standardized = T, minimum.value = 35, sort. = T)
mi2
```

```
##     lhs op rhs     mi    epc sepc.lv sepc.all sepc.nox
## 893 EE1 ~~ EE2 48.193  0.304   0.304    0.894    0.894
## 422  PA =~ EE3 37.738 -0.354  -0.249   -0.183   -0.183
```

The highest MI value suggests that in the next step we should allow the residual covariance between EE1 and EE2:

Modified model 3:

```r
# Modified model 3 (add EE1 ~~ EE2)
model_modif3 <-'
RA   =~ ROLEA1 + ROLEA2
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC   =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM   =~ DEC1 + DEC2
SS   =~ SSUP1 + SSUP2
PS   =~ PSUP1 + PSUP2
SE   =~ SELF1 + SELF2 + SELF3
ELC   =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE   =~ EE1 + EE2 + EE3
DP   =~ DP1 + DP2
PA   =~ PA1 + PA2 + PA3

SE ~ DM + SS + PS
ELC ~ DM + RCWO
EE ~ RCWO + CC
```

```r
DP ~ RCWO + EE
PA ~ RA + SE + ELC + EE + DP

EE1 ~~ EE2
'

fit.mod3 <- sem(model_modif3, data = E1, estimator="MLM")

# Fit indices
model <- c("Modified", "Modified 2", "Modified 3")
chisq = c(fitMeasures(fit.mod, "chisq.scaled"),
          fitMeasures(fit.mod2, "chisq.scaled"),
          fitMeasures(fit.mod3, "chisq.scaled"))
df = c(fitMeasures(fit.mod, "df.scaled"),
       fitMeasures(fit.mod2, "df.scaled"),
       fitMeasures(fit.mod3, "df.scaled"))
pvalue = c(fitMeasures(fit.mod, "pvalue.scaled"),
           fitMeasures(fit.mod2, "pvalue.scaled"),
           fitMeasures(fit.mod3, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod, "cfi.robust"),
        fitMeasures(fit.mod2, "cfi.robust"),
        fitMeasures(fit.mod3, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod, "tli.robust"),
        fitMeasures(fit.mod2, "tli.robust"),
        fitMeasures(fit.mod3, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod, "rmsea.robust"),
          fitMeasures(fit.mod2, "rmsea.robust"),
          fitMeasures(fit.mod3, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod, "srmr"),
         fitMeasures(fit.mod2, "srmr"),
         fitMeasures(fit.mod3, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices (Modified models)")
```

Table 4: Fit indices (Modified models)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062
Modified 2	894.6600	435	0	0.949	0.942	0.044	0.052
Modified 3	856.4721	434	0	0.954	0.947	0.042	0.049

The model fit seems quite good at this round. Let us view the MI´s:

```r
mi3 <- modindices(fit.mod3, standardized = T, minimum.value = 30, sort. = T)
mi3
```

```
## [1] lhs      op       rhs      mi       epc      sepc.lv  sepc.all sepc.nox
## <0 rows> (or 0-length row.names)
```

There are no MI values larger than 30.

```r
parameterEstimates(fit.mod3, standardized = T) %>%
  filter(op == "~") %>%
```

```r
select("Factor"=lhs, op, "Factor"=rhs, "Beta"=std.all, "p-value"=pvalue) %>%
kable(digits = 3, format = "pandoc", caption = "Standardized estimates")
```

Table 5: Standardized estimates

Factor	op	Factor	Beta	p-value
SE	~	DM	2.256	0.003
SE	~	SS	-1.772	0.007
SE	~	PS	-0.226	0.239
ELC	~	DM	-0.086	0.167
ELC	~	RCWO	0.498	0.000
EE	~	RCWO	0.577	0.000
EE	~	CC	-0.213	0.000
DP	~	RCWO	0.066	0.345
DP	~	EE	0.620	0.000
PA	~	RA	-0.104	0.166
PA	~	SE	0.154	0.006
PA	~	ELC	-0.034	0.535
PA	~	EE	-0.180	0.016
PA	~	DP	-0.293	0.001

There are five statistically non-significant parameters that can be deleted from the model. They are SE ~ PS, ELC ~ DM, DP ~ RCWO, PA ~ RA and PA ~ ELC.

Modified model 4:

```r
# Modified model 4
# (remove SE ~ PS, ELC ~ DM, DP ~ RCWO, PA ~ RA and PA ~ ELC)
model_modif4 <-'
RA   =~ ROLEA1 + ROLEA2
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC   =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM   =~ DEC1 + DEC2
SS   =~ SSUP1 + SSUP2
PS   =~ PSUP1 + PSUP2
SE   =~ SELF1 + SELF2 + SELF3
ELC   =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE   =~ EE1 + EE2 + EE3
DP   =~ DP1 + DP2
PA   =~ PA1 + PA2 + PA3

SE ~ DM + SS
ELC ~ RCWO
EE ~ RCWO + CC
DP ~ EE
PA ~ SE + EE + DP

EE1 ~~ EE2
'

fit.mod4 <- sem(model_modif4, data = E1, estimator="MLM")
```

```r
# Fit indices
model <- c("Modified", "Modified 2", "Modified 3", "Modified 4")
chisq = c(fitMeasures(fit.mod, "chisq.scaled"),
          fitMeasures(fit.mod2, "chisq.scaled"),
          fitMeasures(fit.mod3, "chisq.scaled"),
          fitMeasures(fit.mod4, "chisq.scaled"))
df = c(fitMeasures(fit.mod, "df.scaled"),
       fitMeasures(fit.mod2, "df.scaled"),
       fitMeasures(fit.mod3, "df.scaled"),
       fitMeasures(fit.mod4, "df.scaled"))
pvalue = c(fitMeasures(fit.mod, "pvalue.scaled"),
           fitMeasures(fit.mod2, "pvalue.scaled"),
           fitMeasures(fit.mod3, "pvalue.scaled"),
           fitMeasures(fit.mod4, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod, "cfi.robust"),
        fitMeasures(fit.mod2, "cfi.robust"),
        fitMeasures(fit.mod3, "cfi.robust"),
        fitMeasures(fit.mod4, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod, "tli.robust"),
        fitMeasures(fit.mod2, "tli.robust"),
        fitMeasures(fit.mod3, "tli.robust"),
        fitMeasures(fit.mod4, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod, "rmsea.robust"),
          fitMeasures(fit.mod2, "rmsea.robust"),
          fitMeasures(fit.mod3, "rmsea.robust"),
          fitMeasures(fit.mod4, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod, "srmr"),
         fitMeasures(fit.mod2, "srmr"),
         fitMeasures(fit.mod3, "srmr"),
         fitMeasures(fit.mod4, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices (Modified models)")
```

Table 6: Fit indices (Modified models)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062
Modified 2	894.6600	435	0	0.949	0.942	0.044	0.052
Modified 3	856.4721	434	0	0.954	0.947	0.042	0.049
Modified 4	863.2885	438	0	0.953	0.947	0.042	0.052

The model fit did not improve, but we got rid of unnecessary non-significant factors. Now there are factors RA (Role ambiguity) and PS (Peer support) that are not related to other factors, so they can be removed from the model in the next step.

Modified model 5:

```r
# Modified model 5 (remove RA and PS)
model_modif5 <-'
```

```
# RA  =~ ROLEA1 + ROLEA2
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC  =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM  =~ DEC1 + DEC2
SS  =~ SSUP1 + SSUP2
# PS  =~ PSUP1 + PSUP2
SE  =~ SELF1 + SELF2 + SELF3
ELC  =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE  =~ EE1 + EE2 + EE3
DP  =~ DP1 + DP2
PA  =~ PA1 + PA2 + PA3

SE ~ DM + SS
ELC ~ RCWO
EE ~ RCWO + CC
DP ~ EE
PA ~ SE + EE + DP

EE1 ~~ EE2
'

fit.mod5 <- sem(model_modif5, data = E1, estimator="MLM")

# Fit indices
model <- c("Modified", "Modified 2", "Modified 3", "Modified 4", "Modified 5")
chisq = c(fitMeasures(fit.mod, "chisq.scaled"),
          fitMeasures(fit.mod2, "chisq.scaled"),
          fitMeasures(fit.mod3, "chisq.scaled"),
          fitMeasures(fit.mod4, "chisq.scaled"),
          fitMeasures(fit.mod5, "chisq.scaled"))
df = c(fitMeasures(fit.mod, "df.scaled"),
       fitMeasures(fit.mod2, "df.scaled"),
       fitMeasures(fit.mod3, "df.scaled"),
       fitMeasures(fit.mod4, "df.scaled"),
       fitMeasures(fit.mod5, "df.scaled"))
pvalue = c(fitMeasures(fit.mod, "pvalue.scaled"),
           fitMeasures(fit.mod2, "pvalue.scaled"),
           fitMeasures(fit.mod3, "pvalue.scaled"),
           fitMeasures(fit.mod4, "pvalue.scaled"),
           fitMeasures(fit.mod5, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod, "cfi.robust"),
        fitMeasures(fit.mod2, "cfi.robust"),
        fitMeasures(fit.mod3, "cfi.robust"),
        fitMeasures(fit.mod4, "cfi.robust"),
        fitMeasures(fit.mod5, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod, "tli.robust"),
        fitMeasures(fit.mod2, "tli.robust"),
        fitMeasures(fit.mod3, "tli.robust"),
        fitMeasures(fit.mod4, "tli.robust"),
        fitMeasures(fit.mod5, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod, "rmsea.robust"),
          fitMeasures(fit.mod2, "rmsea.robust"),
          fitMeasures(fit.mod3, "rmsea.robust"),
```

```r
          fitMeasures(fit.mod4, "rmsea.robust"),
          fitMeasures(fit.mod5, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod, "srmr"),
         fitMeasures(fit.mod2, "srmr"),
         fitMeasures(fit.mod3, "srmr"),
         fitMeasures(fit.mod4, "srmr"),
         fitMeasures(fit.mod5, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices (Modified models)")
```

Table 7: Fit indices (Modified models)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062
Modified 2	894.6600	435	0	0.949	0.942	0.044	0.052
Modified 3	856.4721	434	0	0.954	0.947	0.042	0.049
Modified 4	863.2885	438	0	0.953	0.947	0.042	0.052
Modified 5	720.0179	333	0	0.951	0.944	0.046	0.053

The fit indices from table 7 indicate that the fit did not improve with this model. Let us view the standardized estimates:

```r
parameterEstimates(fit.mod5, standardized = T) %>%
  select("Item"=lhs, op, "Item"=rhs, "B"=est, "SE"=se,
         "Z"=z, "p-value"=pvalue, "Beta"=std.all) %>%
  kable(digits = 3, format = "pandoc", caption = "Standardized estimates")
```

Table 8: Standardized estimates

Item	op	Item	B	SE	Z	p-value	Beta
RCWO	=~	ROLEC1	1.000	0.000	NA	NA	0.673
RCWO	=~	ROLEC2	1.331	0.084	15.895	0.000	0.772
RCWO	=~	WORK1	1.161	0.068	16.982	0.000	0.762
RCWO	=~	WORK2	1.008	0.086	11.753	0.000	0.625
CC	=~	CCLIM1	1.000	0.000	NA	NA	0.620
CC	=~	CCLIM2	1.344	0.105	12.786	0.000	0.770
CC	=~	CCLIM3	1.001	0.091	10.967	0.000	0.654
CC	=~	CCLIM4	1.425	0.109	13.084	0.000	0.698
DM	=~	DEC1	1.000	0.000	NA	NA	0.696
DM	=~	DEC2	1.326	0.072	18.468	0.000	0.799
SS	=~	SSUP1	1.000	0.000	NA	NA	0.888
SS	=~	SSUP2	1.068	0.030	35.443	0.000	0.947
SE	=~	SELF1	1.000	0.000	NA	NA	0.771
SE	=~	SELF2	1.230	0.077	16.008	0.000	0.822
SE	=~	SELF3	1.382	0.080	17.213	0.000	0.890
ELC	=~	ELC1	1.000	0.000	NA	NA	0.701
ELC	=~	ELC2	0.845	0.061	13.786	0.000	0.585
ELC	=~	ELC3	1.025	0.068	15.095	0.000	0.735
ELC	=~	ELC4	1.032	0.068	15.255	0.000	0.666
ELC	=~	ELC5	1.284	0.080	16.095	0.000	0.792
EE	=~	EE1	1.000	0.000	NA	NA	0.815

Item	op	Item	B	SE	Z	p-value	Beta
EE	=~	EE2	1.032	0.028	37.189	0.000	0.842
EE	=~	EE3	1.135	0.048	23.883	0.000	0.925
DP	=~	DP1	1.000	0.000	NA	NA	0.831
DP	=~	DP2	0.902	0.068	13.353	0.000	0.770
PA	=~	PA1	1.000	0.000	NA	NA	0.862
PA	=~	PA2	0.885	0.063	14.118	0.000	0.713
PA	=~	PA3	0.856	0.075	11.342	0.000	0.697
SE	~	DM	1.002	0.274	3.661	0.000	2.079
SE	~	SS	-0.572	0.186	-3.073	0.002	-1.728
ELC	~	RCWO	0.315	0.031	10.022	0.000	0.562
EE	~	RCWO	0.869	0.080	10.833	0.000	0.591
EE	~	CC	-0.679	0.146	-4.643	0.000	-0.211
DP	~	EE	0.563	0.044	12.860	0.000	0.668
PA	~	SE	0.340	0.094	3.617	0.000	0.175
PA	~	EE	-0.154	0.044	-3.469	0.001	-0.243
PA	~	DP	-0.225	0.067	-3.367	0.001	-0.298
EE1	~~	EE2	0.263	0.049	5.314	0.000	0.459
ROLEC1	~~	ROLEC1	0.682	0.045	15.249	0.000	0.547
ROLEC2	~~	ROLEC2	0.679	0.057	11.824	0.000	0.405
WORK1	~~	WORK1	0.551	0.046	12.005	0.000	0.420
WORK2	~~	WORK2	0.892	0.076	11.723	0.000	0.609
CCLIM1	~~	CCLIM1	0.189	0.012	15.632	0.000	0.616
CCLIM2	~~	CCLIM2	0.147	0.013	10.961	0.000	0.408
CCLIM3	~~	CCLIM3	0.158	0.012	13.406	0.000	0.572
CCLIM4	~~	CCLIM4	0.253	0.021	11.954	0.000	0.513
DEC1	~~	DEC1	0.598	0.038	15.627	0.000	0.516
DEC2	~~	DEC2	0.557	0.049	11.282	0.000	0.361
SSUP1	~~	SSUP1	0.321	0.038	8.444	0.000	0.212
SSUP2	~~	SSUP2	0.156	0.031	5.090	0.000	0.103
SELF1	~~	SELF1	0.089	0.009	9.450	0.000	0.406
SELF2	~~	SELF2	0.095	0.013	7.534	0.000	0.325
SELF3	~~	SELF3	0.066	0.008	7.924	0.000	0.209
ELC1	~~	ELC1	0.184	0.013	14.007	0.000	0.509
ELC2	~~	ELC2	0.245	0.017	14.578	0.000	0.658
ELC3	~~	ELC3	0.159	0.012	13.742	0.000	0.460
ELC4	~~	ELC4	0.238	0.017	13.946	0.000	0.557
ELC5	~~	ELC5	0.174	0.017	10.508	0.000	0.373
EE1	~~	EE1	0.616	0.055	11.285	0.000	0.335
EE2	~~	EE2	0.533	0.058	9.142	0.000	0.290
EE3	~~	EE3	0.266	0.044	6.108	0.000	0.144
DP1	~~	DP1	0.389	0.060	6.460	0.000	0.310
DP2	~~	DP2	0.485	0.068	7.149	0.000	0.407
PA1	~~	PA1	0.170	0.026	6.651	0.000	0.257
PA2	~~	PA2	0.372	0.041	9.102	0.000	0.492
PA3	~~	PA3	0.381	0.043	8.827	0.000	0.515
RCWO	~~	RCWO	0.565	0.064	8.871	0.000	1.000
CC	~~	CC	0.118	0.018	6.682	0.000	1.000
DM	~~	DM	0.561	0.059	9.520	0.000	1.000
SS	~~	SS	1.190	0.097	12.318	0.000	1.000
SE	~~	SE	0.090	0.014	6.272	0.000	0.690
ELC	~~	ELC	0.122	0.014	8.413	0.000	0.684
EE	~~	EE	0.617	0.060	10.295	0.000	0.504

Item	op	Item	B	SE	Z	p-value	Beta
DP	~~	DP	0.479	0.066	7.309	0.000	0.553
PA	~~	PA	0.331	0.040	8.245	0.000	0.675
RCWO	~~	CC	-0.106	0.017	-6.296	0.000	-0.411
RCWO	~~	DM	-0.390	0.042	-9.231	0.000	-0.693
RCWO	~~	SS	-0.473	0.052	-9.029	0.000	-0.577
CC	~~	DM	0.095	0.017	5.453	0.000	0.368
CC	~~	SS	0.108	0.023	4.697	0.000	0.287
DM	~~	SS	0.796	0.063	12.722	0.000	0.974
ELC	~~	PA	-0.016	0.012	-1.262	0.207	-0.078

The output reveals an estimated residual covariance between ELC and PA, which was not specified in the model. We fix it to zero in the next model:

Modified model 6:

```
# Modified model 6 (fix ELC ~~ PA to zero)
model_modif6 <-'
# RA  =~ ROLEA1 + ROLEA2
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC  =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM  =~ DEC1 + DEC2
SS  =~ SSUP1 + SSUP2
# PS  =~ PSUP1 + PSUP2
SE  =~ SELF1 + SELF2 + SELF3
ELC  =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE  =~ EE1 + EE2 + EE3
DP  =~ DP1 + DP2
PA  =~ PA1 + PA2 + PA3

SE ~ DM + SS
ELC ~ RCWO
EE ~ RCWO + CC
DP ~ EE
PA ~ SE + EE + DP

EE1 ~~ EE2
ELC~~0*PA
'

fit.mod6 <- sem(model_modif6, data = E1, estimator="MLM")

# Fit indices
model <- c("Modified", "Modified 2", "Modified 3",
           "Modified 4", "Modified 5", "Modified 6")
chisq = c(fitMeasures(fit.mod, "chisq.scaled"),
          fitMeasures(fit.mod2, "chisq.scaled"),
          fitMeasures(fit.mod3, "chisq.scaled"),
          fitMeasures(fit.mod4, "chisq.scaled"),
          fitMeasures(fit.mod5, "chisq.scaled"),
          fitMeasures(fit.mod6, "chisq.scaled"))
```

```r
df = c(fitMeasures(fit.mod, "df.scaled"),
       fitMeasures(fit.mod2, "df.scaled"),
       fitMeasures(fit.mod3, "df.scaled"),
       fitMeasures(fit.mod4, "df.scaled"),
       fitMeasures(fit.mod5, "df.scaled"),
       fitMeasures(fit.mod6, "df.scaled"))
pvalue = c(fitMeasures(fit.mod, "pvalue.scaled"),
           fitMeasures(fit.mod2, "pvalue.scaled"),
           fitMeasures(fit.mod3, "pvalue.scaled"),
           fitMeasures(fit.mod4, "pvalue.scaled"),
           fitMeasures(fit.mod5, "pvalue.scaled"),
           fitMeasures(fit.mod6, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod, "cfi.robust"),
        fitMeasures(fit.mod2, "cfi.robust"),
        fitMeasures(fit.mod3, "cfi.robust"),
        fitMeasures(fit.mod4, "cfi.robust"),
        fitMeasures(fit.mod5, "cfi.robust"),
        fitMeasures(fit.mod6, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod, "tli.robust"),
        fitMeasures(fit.mod2, "tli.robust"),
        fitMeasures(fit.mod3, "tli.robust"),
        fitMeasures(fit.mod4, "tli.robust"),
        fitMeasures(fit.mod5, "tli.robust"),
        fitMeasures(fit.mod6, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod, "rmsea.robust"),
          fitMeasures(fit.mod2, "rmsea.robust"),
          fitMeasures(fit.mod3, "rmsea.robust"),
          fitMeasures(fit.mod4, "rmsea.robust"),
          fitMeasures(fit.mod5, "rmsea.robust"),
          fitMeasures(fit.mod6, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod, "srmr"),
         fitMeasures(fit.mod2, "srmr"),
         fitMeasures(fit.mod3, "srmr"),
         fitMeasures(fit.mod4, "srmr"),
         fitMeasures(fit.mod5, "srmr"),
         fitMeasures(fit.mod6, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices (Modified models)")
```

Table 9: Fit indices (Modified models)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062
Modified 2	894.6600	435	0	0.949	0.942	0.044	0.052
Modified 3	856.4721	434	0	0.954	0.947	0.042	0.049
Modified 4	863.2885	438	0	0.953	0.947	0.042	0.052
Modified 5	720.0179	333	0	0.951	0.944	0.046	0.053
Modified 6	721.5229	334	0	0.951	0.944	0.046	0.053

The model did not improve at all with this model. Let us cancel the previous step and specify the model so that the factor ELC and all the related observed variables are removed.

Modified model 7:

```
# Modified model 7 (remove ELC and related observed variables)
model_modif7 <-'
# RA  =~ ROLEA1 + ROLEA2
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC  =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM  =~ DEC1 + DEC2
SS  =~ SSUP1 + SSUP2
# PS  =~ PSUP1 + PSUP2
SE  =~ SELF1 + SELF2 + SELF3
# ELC  =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE  =~ EE1 + EE2 + EE3
DP  =~ DP1 + DP2
PA  =~ PA1 + PA2 + PA3

SE ~ DM + SS
# ELC ~ RCWO
EE ~ RCWO + CC
DP ~ EE
PA ~ SE + EE + DP

EE1 ~~ EE2
# ELC~~0*PA
'

fit.mod7 <- sem(model_modif7, data = E1, estimator="MLM")

# Fit indices
model <- c("Modified", "Modified 2", "Modified 3",
           "Modified 4", "Modified 5", "Modified 6", "Modified 7")
chisq = c(fitMeasures(fit.mod, "chisq.scaled"),
          fitMeasures(fit.mod2, "chisq.scaled"),
          fitMeasures(fit.mod3, "chisq.scaled"),
          fitMeasures(fit.mod4, "chisq.scaled"),
          fitMeasures(fit.mod5, "chisq.scaled"),
          fitMeasures(fit.mod6, "chisq.scaled"),
          fitMeasures(fit.mod7, "chisq.scaled"))
df = c(fitMeasures(fit.mod, "df.scaled"),
       fitMeasures(fit.mod2, "df.scaled"),
       fitMeasures(fit.mod3, "df.scaled"),
       fitMeasures(fit.mod4, "df.scaled"),
       fitMeasures(fit.mod5, "df.scaled"),
       fitMeasures(fit.mod6, "df.scaled"),
       fitMeasures(fit.mod7, "df.scaled"))
pvalue = c(fitMeasures(fit.mod, "pvalue.scaled"),
           fitMeasures(fit.mod2, "pvalue.scaled"),
           fitMeasures(fit.mod3, "pvalue.scaled"),
           fitMeasures(fit.mod4, "pvalue.scaled"),
           fitMeasures(fit.mod5, "pvalue.scaled"),
           fitMeasures(fit.mod6, "pvalue.scaled"),
           fitMeasures(fit.mod7, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod, "cfi.robust"),
```

```r
        fitMeasures(fit.mod2, "cfi.robust"),
        fitMeasures(fit.mod3, "cfi.robust"),
        fitMeasures(fit.mod4, "cfi.robust"),
        fitMeasures(fit.mod5, "cfi.robust"),
        fitMeasures(fit.mod6, "cfi.robust"),
        fitMeasures(fit.mod7, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod, "tli.robust"),
        fitMeasures(fit.mod2, "tli.robust"),
        fitMeasures(fit.mod3, "tli.robust"),
        fitMeasures(fit.mod4, "tli.robust"),
        fitMeasures(fit.mod5, "tli.robust"),
        fitMeasures(fit.mod6, "tli.robust"),
        fitMeasures(fit.mod7, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod, "rmsea.robust"),
          fitMeasures(fit.mod2, "rmsea.robust"),
          fitMeasures(fit.mod3, "rmsea.robust"),
          fitMeasures(fit.mod4, "rmsea.robust"),
          fitMeasures(fit.mod5, "rmsea.robust"),
          fitMeasures(fit.mod6, "rmsea.robust"),
          fitMeasures(fit.mod7, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod, "srmr"),
         fitMeasures(fit.mod2, "srmr"),
         fitMeasures(fit.mod3, "srmr"),
         fitMeasures(fit.mod4, "srmr"),
         fitMeasures(fit.mod5, "srmr"),
         fitMeasures(fit.mod6, "srmr"),
         fitMeasures(fit.mod7, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices (Modified models)")
```

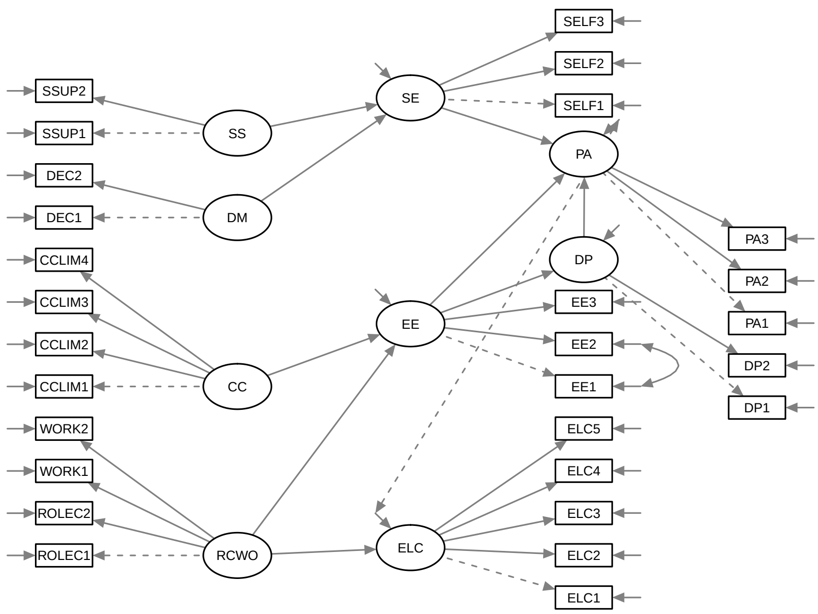
Table 10: Fit indices (Modified models)

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Modified	942.1924	436	0	0.944	0.936	0.046	0.062
Modified 2	894.6600	435	0	0.949	0.942	0.044	0.052
Modified 3	856.4721	434	0	0.954	0.947	0.042	0.049
Modified 4	863.2885	438	0	0.953	0.947	0.042	0.052
Modified 5	720.0179	333	0	0.951	0.944	0.046	0.053
Modified 6	721.5229	334	0	0.951	0.944	0.046	0.053
Modified 7	499.7665	215	0	0.958	0.950	0.049	0.054

With this model the model fit indices show relatively good fit: the Chi Squared -value (499.77), CFI (0.958) and TLI (0.95). On the other hand the RMSEA and SRMR values are not the best of all the models, but they are acceptable. We will use the previous model ("Modified 6") as our restructured baseline model since it has better values in RMSEA and SRMR. Here is a graph of it:

```r
semPaths(fit.mod6, what = "path", whatLabels = "hide", style = "lisrel", label.scale = F,
         layout = "tree2", residuals = TRUE, nCharNodes = 0, rotation = 2,
         sizeMan = 5, sizeMan2= 2, sizeLat = 6, sizeLat2 = 4, esize = 1, label.cex = 0.4,
         optimizeLatRes = TRUE, edge.label.cex=0.4, reorder=T, exoCov = FALSE)
title("Figure 3: Restructured baseline model")
```

Figure 3: Restructured baseline model



Exercise 6.2

Let us combine the groups and specify the common baseline (configural) model and draw the graphs.

```
# Combine (merge) the data sets into one:

combined <- merge(data.frame(E1, group = "calibration"),
                  data.frame(E2, group = "validation"),
                  all = TRUE, sort = FALSE)
```

```
fit.conf <- sem(model_modif6, data = combined, group = "group", estimator="MLM")
fit.conf
```

```
## lavaan 0.6-3 ended normally after 116 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                        200
##
##   Number of observations per group
##   calibration                                      602
##   validation                                       601
##
##   Estimator                                         ML      Robust
##   Model Fit Test Statistic                    1622.707    1484.062
##   Degrees of freedom                               668         668
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  1.093
##     for the Satorra-Bentler correction
##
## Chi-square for each group:
##
##   calibration                                  789.858     722.373
```

```
##   validation                                         832.848     761.689
```

```
model <- c("Baseline model", "Configural model")
chisq = c(fitMeasures(fit.mod6, "chisq.scaled"),
          fitMeasures(fit.conf, "chisq.scaled"))
df = c(fitMeasures(fit.mod6, "df.scaled"),
       fitMeasures(fit.conf, "df.scaled"))
pvalue = c(fitMeasures(fit.mod6, "pvalue.scaled"),
           fitMeasures(fit.conf, "pvalue.scaled"))
cfi = c(fitMeasures(fit.mod6, "cfi.robust"),
        fitMeasures(fit.conf, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.mod6, "tli.robust"),
        fitMeasures(fit.conf, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.mod6, "rmsea.robust"),
          fitMeasures(fit.conf, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.mod6, "srmr"),
         fitMeasures(fit.conf, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices")
```

Table 11: Fit indices

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Baseline model	721.5229	334	0	0.951	0.944	0.046	0.053
Configural model	1484.0618	668	0	0.949	0.942	0.047	0.056

The model fit indices in this multigroup configural model are almost as good (but not exactly) as in the calibration group's baseline model.

Exercise 6.3

In the invariant model we fix factor means to zero.

```
model_inv <-'
RCWO  =~ ROLEC1 + ROLEC2 + WORK1 + WORK2
CC   =~ CCLIM1 + CCLIM2 + CCLIM3 + CCLIM4
DM   =~ DEC1 + DEC2
SS   =~ SSUP1 + SSUP2
SE   =~ SELF1 + SELF2 + SELF3
ELC   =~ ELC1 + ELC2 + ELC3 + ELC4 + ELC5
EE   =~ EE1 + EE2 + EE3
DP   =~ DP1 + DP2
PA   =~ PA1 + PA2 + PA3

SE ~ DM + SS
ELC ~ RCWO
EE ~ RCWO + CC
DP ~ EE
PA ~ SE + EE + DP

EE1 ~~ EE2
ELC~~0*PA
```

```
RCWO + CC + DM + SS + SE + ELC + EE + DP + PA ~ 0
'

fit.inv <- sem(model_inv, data = combined, group = "group",
               group.equal = c("loadings", "intercepts", "regressions") , estimator="MLM")
fit.inv
```

```
## lavaan 0.6-3 ended normally after 178 iterations
##
##   Optimization method                           NLMINB
##   Number of free parameters                        200
##   Number of equality constraints                    56
##
##   Number of observations per group
##   calibration                                      602
##   validation                                       601
##
##   Estimator                                         ML      Robust
##   Model Fit Test Statistic                    1682.811    1544.170
##   Degrees of freedom                               724         724
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  1.090
##     for the Satorra-Bentler correction
##
## Chi-square for each group:
##
##   calibration                                  820.825     753.200
##   validation                                   861.986     790.970
```

```
model <- c("Configural model", "Invariant model")
chisq = c(fitMeasures(fit.conf, "chisq.scaled"),
          fitMeasures(fit.inv, "chisq.scaled"))
df = c(fitMeasures(fit.conf, "df.scaled"),
       fitMeasures(fit.inv, "df.scaled"))
pvalue = c(fitMeasures(fit.conf, "pvalue.scaled"),
           fitMeasures(fit.inv, "pvalue.scaled"))
cfi = c(fitMeasures(fit.conf, "cfi.robust"),
        fitMeasures(fit.inv, "cfi.robust")) %>% round(3)
tli = c(fitMeasures(fit.conf, "tli.robust"),
        fitMeasures(fit.inv, "tli.robust")) %>% round(3)
rmsea = c(fitMeasures(fit.conf, "rmsea.robust"),
          fitMeasures(fit.inv, "rmsea.robust")) %>% round(3)
srmr = c(fitMeasures(fit.conf, "srmr"),
         fitMeasures(fit.inv, "srmr")) %>% round(3)
tabledata <- data.frame("Model"=model, "Chi.square"=chisq, "Df"=df, "p-value"=pvalue,
                        "CFI"=cfi, "TLI"=tli, "RMSEA"=rmsea, "SRMR"=srmr)
kable(tabledata, row.names = F, caption = "Fit indices")
```

Table 12: Fit indices

Model	Chi.square	Df	p.value	CFI	TLI	RMSEA	SRMR
Configural model	1484.062	668	0	0.949	0.942	0.047	0.056
Invariant model	1544.170	724	0	0.949	0.946	0.045	0.058

The model fit indices are quite similar.

```r
anova(fit.conf, fit.inv)
```

```
## Scaled Chi Square Difference Test (method = "satorra.bentler.2001")
##
##           Df   AIC   BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit.conf 668 68153 69172 1622.7
## fit.inv  724 68101 68835 1682.8      57.44      56     0.4216
```

The model that was specified step by step with the calibration group seems to have a good fit with the validation group also. It seems that the model is rather well built since the performed changes are not significant.