PSC205A Assignment 06: SEM

```
library(lavaan)
library(dplyr)
library(weights)
```

```
dat <- read.table("mhs_latent.dat", na.string='.')
names(dat) <- c("id", "female", "age",
                "pc1", "app1", "gw1", "pw1", "par1", "teach1", "mate1", "fri1", "mot1", "a
                "pc2", "app2", "gw2", "pw2", "par2", "teach2", "mate2", "fri2", "mot2", "a
                "pc3", "app3", "gw3", "pw3", "par3", "teach3", "mate3", "fri3", "mot3", 'a
                "pc4", "app4", "gw4", "pw4", "par4", "teach4", "mate4", "fri4", "mot4", "a
```

1. SEM analysis

Overall all observable variables had high loadings on the factors. This suggest they can be good indicators of their respective latent variables. By observing the structural relations among the factors, we identify that Global self-worth has a stronger relationship with perceived appearance than with any other latent variable. Additionally, Physical self-worth is also strongly related to perceived appearance but also with perceived competence.

```
mod1 <- "
#factor loadings
pc =~ pc1 + pc2 + pc3 + pc4
app =~ app1 + app2 + app3 + app4
gw =~ gw1 + gw2 + gw3 + gw4
pw =~ pw1 + pw2 + pw3
par =~ par1 + par2 + par3 + par4
teach =~ teach1 + teach2 + teach3 + teach4
mate =~ mate1 + mate2 + mate3 + mate4
fri =~ fri1 + fri2 + fri3 + fri4
```

```
mot =~ mot1 + mot2 + mot3 + mot4
aff =~ aff1 + aff2 + aff3 + aff4


# structural relations
gw ~ app + pc + teach + par + mate + fri
pw ~ app +pc + teach + par + mate + fri

aff ~ pw
mot ~ pw + aff

# covariances
app ~~ 0*pc
app ~~ 0*teach
app ~~ 0*par
app ~~ 0*mate
app ~~ 0*fri
app ~~ 0*aff
app ~~ 0*mot

pc ~~ 0*teach
pc ~~ 0*par
pc ~~ 0*mate
pc ~~ 0*fri
pc ~~ 0*aff
pc ~~ 0*mot

gw ~~ 0*pw
gw ~~ 0*aff
gw ~~ 0*mot

teach ~~ 0*par
teach ~~ 0*mate
teach ~~ 0*fri
teach ~~ 0*aff
teach ~~ 0*mot

par ~~ 0*mate
par ~~ 0*fri
par ~~ 0*aff
par ~~ 0*mot
```

```
mate ~~ 0*fri
mate ~~ 0*aff
mate ~~ 0*mot

fri ~~ 0*aff
fri ~~ 0*mot
"
```

```
fit1 <- cfa(mod1, data = dat, missing="fiml")
res1 <- summary(fit1, fit.measures=T, standardized=TRUE)
```

2. Additional models

```
mod_ind_m1 <- modindices(fit1)
head(arrange(mod_ind_m1, desc(mi)))
```

```
   lhs op  rhs      mi   epc sepc.lv sepc.all sepc.nox
1 mate  ~   gw 144.465 1.017   0.941    0.941    0.941
2  app  ~   gw 141.580 3.221   2.109    2.109    2.109
3 mate  ~  fri 121.437 0.758   0.834    0.834    0.834
4 mate ~~  fri 121.437 0.176   0.834    0.834    0.834
5  fri  ~ mate 121.437 0.918   0.834    0.834    0.834
6 mate  ~   pw 114.386 0.702   0.773    0.773    0.773
```

The modification indices tell us that the model might be improved by allowing the variables friend support and classmate support to correlate. We can start by freeing this relation.

2.1. Model 2: mate ~~ fri

```
mod2 <- "
#factor loadings
pc =~ pc1 + pc2 + pc3 + pc4
app =~ app1 + app2 + app3 + app4
gw =~ gw1 + gw2 + gw3 + gw4
pw =~ pw1 + pw2 + pw3
par =~ par1 + par2 + par3 + par4
teach =~ teach1 + teach2 + teach3 + teach4
mate =~ mate1 + mate2 + mate3 + mate4
```

```
fri =~ fri1 + fri2 + fri3 + fri4
mot =~ mot1 + mot2 + mot3 + mot4
aff =~ aff1 + aff2 + aff3 + aff4

# structural relations
gw ~ app + pc + teach + par + mate + fri
pw ~ app +pc + teach + par + mate + fri

aff ~ pw
mot ~ pw + aff

# covariances
app ~~ 0*pc
app ~~ 0*teach
app ~~ 0*par
app ~~ 0*mate
app ~~ 0*fri
app ~~ 0*aff
app ~~ 0*mot

pc ~~ 0*teach
pc ~~ 0*par
pc ~~ 0*mate
pc ~~ 0*fri
pc ~~ 0*aff
pc ~~ 0*mot

gw ~~ 0*pw
gw ~~ 0*aff
gw ~~ 0*mot

teach ~~ 0*par
teach ~~ 0*mate
teach ~~ 0*fri
teach ~~ 0*aff
teach ~~ 0*mot

par ~~ 0*mate
par ~~ 0*fri
par ~~ 0*aff
par ~~ 0*mot
```

```r
mate ~~ fri
mate ~~ 0*aff
mate ~~ 0*mot

fri ~~ 0*aff
fri ~~ 0*mot
"
```

```r
fit2 <- cfa(mod2, data = dat, fixed.x=FALSE, missing="fiml")
```

```
Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: so
  161 163
```

```r
res2 <- summary(fit2, fit.measures=T, standardized=TRUE)

mod_ind_m2 <- modindices(fit2)
head(arrange(mod_ind_m2, desc(mi)),20)
```

```
     lhs op   rhs      mi   epc sepc.lv sepc.all sepc.nox
1    app  ~    gw 114.374 2.604   1.732    1.732    1.732
2  teach  ~    gw 110.085 0.795   0.820    0.820    0.820
3     pc  ~    gw 102.696 1.233   0.760    0.760    0.760
4    app  ~    pw 100.374 1.200   0.935    0.935    0.935
5     pc  ~    pw  91.374 1.383   0.998    0.998    0.998
6  teach  ~  mate  90.777 0.670   0.703    0.703    0.703
7    par ~~ teach  88.940 0.154   0.699    0.699    0.699
8    par  ~ teach  88.940 0.965   0.699    0.699    0.699
9  teach  ~   par  88.940 0.506   0.699    0.699    0.699
10 teach  ~   fri  86.415 0.579   0.694    0.694    0.694
11    pc  ~   aff  85.223 1.038   1.011    1.011    1.011
12  mate  ~    pw  83.765 0.403   0.464    0.464    0.464
13   par  ~    gw  80.739 0.962   0.719    0.719    0.719
14   par  ~  mate  79.626 0.844   0.641    0.641    0.641
15   app  ~    pc  77.795 0.571   0.616    0.616    0.616
16    pc ~~   app  77.795 0.255   0.616    0.616    0.616
17    pc  ~   app  77.795 0.665   0.616    0.616    0.616
18   par  ~   fri  74.667 0.724   0.628    0.628    0.628
19 mate4 ~~  fri4  63.390 0.121   0.121    0.646    0.646
20    pc  ~   mot  63.243 1.459   0.866    0.866    0.866
```

The new modification indices suggest the model can be further improved by allowing parent support and teacher support to correlate.

2.2. Model 3: teach ~~ par

```
mod3 <- "
#factor loadings
pc =~ pc1 + pc2 + pc3 + pc4
app =~ app1 + app2 + app3 + app4
gw =~ gw1 + gw2 + gw3 + gw4
pw =~ pw1 + pw2 + pw3
par =~ par1 + par2 + par3 + par4
teach =~ teach1 + teach2 + teach3 + teach4
mate =~ mate1 + mate2 + mate3 + mate4
fri =~ fri1 + fri2 + fri3 + fri4
mot =~ mot1 + mot2 + mot3 + mot4
aff =~ aff1 + aff2 + aff3 + aff4

# structural relations
gw ~ app + pc + teach + par + mate + fri
pw ~ app +pc + teach + par + mate + fri

aff ~ pw
mot ~ pw + aff

# covariances
app ~~ 0*pc
app ~~ 0*teach
app ~~ 0*par
app ~~ 0*mate
app ~~ 0*fri
app ~~ 0*aff
app ~~ 0*mot

pc ~~ 0*teach
pc ~~ 0*par
pc ~~ 0*mate
pc ~~ 0*fri
pc ~~ 0*aff
pc ~~ 0*mot
```

```
gw ~~ 0*pw
gw ~~ 0*aff
gw ~~ 0*mot

teach ~~ par
teach ~~ 0*mate
teach ~~ 0*fri
teach ~~ 0*aff
teach ~~ 0*mot

par ~~ 0*mate
par ~~ 0*fri
par ~~ 0*aff
par ~~ 0*mot

mate ~~ fri
mate ~~ 0*aff
mate ~~ 0*mot

fri ~~ 0*aff
fri ~~ 0*mot
"
```

```
fit3 <- cfa(mod3, data = dat, fixed.x=FALSE, missing="fiml")
res3 <- summary(fit3, fit.measures=T, standardized=TRUE)

mod_ind_m3 <- modindices(fit3)
head(arrange(mod_ind_m3, desc(mi)), 20)
```

```
     lhs op   rhs      mi   epc sepc.lv sepc.all sepc.nox
1    app  ~    gw 120.431 2.750   1.824    1.824    1.824
2     pc  ~    gw 103.921 1.246   0.765    0.765    0.765
3    app  ~    pw  97.613 1.174   0.919    0.919    0.919
4     pc  ~    pw  88.822 1.340   0.972    0.972    0.972
5     pc  ~   aff  83.331 1.014   0.988    0.988    0.988
6   mate  ~    pw  82.721 0.398   0.461    0.461    0.461
7    app  ~    pc  77.792 0.571   0.617    0.617    0.617
8     pc ~~   app  77.792 0.255   0.617    0.617    0.617
9     pc  ~   app  77.792 0.666   0.617    0.617    0.617
10 mate4 ~~  fri4  63.502 0.122   0.122    0.646    0.646
11    pc  ~   mot  61.934 1.426   0.847    0.847    0.847
```

```
12    mate  ~      gw  60.338 0.451   0.442    0.442    0.442
13    app4 ~~     gw4  55.049 0.116   0.116    0.589    0.589
14     app  ~    mate  48.963 0.739   0.499    0.499    0.499
15    par4 ~~   mate4  48.094 0.091   0.091    0.576    0.576
16  teach4 ~~   mate4  46.481 0.092   0.092    0.554    0.554
17    app1 ~~     gw1  45.494 0.103   0.103    0.515    0.515
18     gw4 ~~   mate4  44.215 0.087   0.087    0.523    0.523
19   mate2 ~~    fri2  41.688 0.075   0.075    0.657    0.657
20    par4 ~~  teach4  40.036 0.092   0.092    0.536    0.536
```

Now the modification indices suggest an improvement in fit by allowing perceived competence to correlate with perceived appearance.

2.3. Model 4: pc ~~ app

```
mod4 <- "
#factor loadings
pc =~ pc1 + pc2 + pc3 + pc4
app =~ app1 + app2 + app3 + app4
gw =~ gw1 + gw2 + gw3 + gw4
pw =~ pw1 + pw2 + pw3
par =~ par1 + par2 + par3 + par4
teach =~ teach1 + teach2 + teach3 + teach4
mate =~ mate1 + mate2 + mate3 + mate4
fri =~ fri1 + fri2 + fri3 + fri4
mot =~ mot1 + mot2 + mot3 + mot4
aff =~ aff1 + aff2 + aff3 + aff4

mate4 ~~ fri4

# structural relations
gw ~ app + pc + teach + par + mate + fri
pw ~ app +pc + teach + par + mate + fri

aff ~ pw
mot ~ pw + aff

# covariances
app ~~ pc
app ~~ 0*teach
app ~~ 0*par
```

```
app ~~ 0*mate
app ~~ 0*fri
app ~~ 0*aff
app ~~ 0*mot

pc ~~ 0*teach
pc ~~ 0*par
pc ~~ 0*mate
pc ~~ 0*fri
pc ~~ 0*aff
pc ~~ 0*mot

gw ~~ 0*pw
gw ~~ 0*aff
gw ~~ 0*mot

teach ~~ par
teach ~~ 0*mate
teach ~~ 0*fri
teach ~~ 0*aff
teach ~~ 0*mot

par ~~ 0*mate
par ~~ 0*fri
par ~~ 0*aff
par ~~ 0*mot

mate ~~ fri
mate ~~ 0*aff
mate ~~ 0*mot

fri ~~ 0*aff
fri ~~ 0*mot
"
```

```
fit4 <- cfa(mod4, data = dat, fixed.x=FALSE, missing="fiml")
res4 <- summary(fit4, fit.measures=T, standardized=TRUE)
```

Model comparison

```r
anova(fit1, fit2, fit3, fit4) |> knitr::kable(caption = "Fit indices comparisons of the fo
```

Table 1: Fit indices comparisons of the four models.

	Df	AIC	BIC	Chisq	Chisq diff	RMSEA	Df diff	Pr(>Chisq)
fit4	683	11414.88	11899.65	2378.562	NA	NA	NA	NA
fit3	685	11577.99	12055.63	2545.670	167.1075	0.5624037	2	0
fit2	686	11694.16	12168.24	2663.842	118.1725	0.6700273	1	0
fit1	687	11862.94	12333.45	2834.621	170.7785	0.8065311	1	0

3. Results summary

```r
items_loadings <- lavInspect(fit4, what = "std")$lambda
items_var <- diag(lavInspect(fit4, what = "std")$theta)
latent_var <- diag(lavInspect(fit4, what = "std")$psi)
latent_loadings <- lavInspect(fit4, what = "std")$beta
```

```r
knitr::kable(items_loadings, caption = "Standardized loadings of the observable variabels.
```

Table 2: Standardized loadings of the observable variabels.

	pc	app	gw	pw	par	teach	mate	fri	mot	aff
pc1	0.866	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pc2	0.855	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pc3	0.911	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pc4	0.855	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
app1	0.000	0.790	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
app2	0.000	0.819	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
app3	0.000	0.897	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
app4	0.000	0.788	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
gw1	0.000	0.000	0.730	0.000	0.000	0.000	0.000	0.000	0.000	0.000
gw2	0.000	0.000	0.805	0.000	0.000	0.000	0.000	0.000	0.000	0.000
gw3	0.000	0.000	0.875	0.000	0.000	0.000	0.000	0.000	0.000	0.000
gw4	0.000	0.000	0.717	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pw1	0.000	0.000	0.000	0.843	0.000	0.000	0.000	0.000	0.000	0.000

	pc	app	gw	pw	par	teach	mate	fri	mot	aff
pw2	0.000	0.000	0.000	0.854	0.000	0.000	0.000	0.000	0.000	0.000
pw3	0.000	0.000	0.000	0.902	0.000	0.000	0.000	0.000	0.000	0.000
par1	0.000	0.000	0.000	0.000	0.761	0.000	0.000	0.000	0.000	0.000
par2	0.000	0.000	0.000	0.000	0.825	0.000	0.000	0.000	0.000	0.000
par3	0.000	0.000	0.000	0.000	0.887	0.000	0.000	0.000	0.000	0.000
par4	0.000	0.000	0.000	0.000	0.807	0.000	0.000	0.000	0.000	0.000
teach1	0.000	0.000	0.000	0.000	0.000	0.655	0.000	0.000	0.000	0.000
teach2	0.000	0.000	0.000	0.000	0.000	0.756	0.000	0.000	0.000	0.000
teach3	0.000	0.000	0.000	0.000	0.000	0.888	0.000	0.000	0.000	0.000
teach4	0.000	0.000	0.000	0.000	0.000	0.737	0.000	0.000	0.000	0.000
mate1	0.000	0.000	0.000	0.000	0.000	0.000	0.744	0.000	0.000	0.000
mate2	0.000	0.000	0.000	0.000	0.000	0.000	0.869	0.000	0.000	0.000
mate3	0.000	0.000	0.000	0.000	0.000	0.000	0.860	0.000	0.000	0.000
mate4	0.000	0.000	0.000	0.000	0.000	0.000	0.738	0.000	0.000	0.000
fri1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.741	0.000	0.000
fri2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.841	0.000	0.000
fri3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.791	0.000	0.000
fri4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.701	0.000	0.000
mot1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.766	0.000
mot2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.778	0.000
mot3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.887	0.000
mot4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.876	0.000
aff1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.760
aff2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.817
aff3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.881
aff4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.829

```
knitr::kable(as.data.frame(items_var), caption = "Item variances.", digits= 3)
```

Table 3: Item variances.

	items_var
pc1	0.249
pc2	0.269
pc3	0.170
pc4	0.269
app1	0.376
app2	0.329
app3	0.196

	items_var
app4	0.380
gw1	0.468
gw2	0.352
gw3	0.235
gw4	0.486
pw1	0.289
pw2	0.270
pw3	0.187
par1	0.420
par2	0.319
par3	0.214
par4	0.349
teach1	0.571
teach2	0.429
teach3	0.212
teach4	0.456
mate1	0.447
mate2	0.244
mate3	0.260
mate4	0.456
fri1	0.450
fri2	0.293
fri3	0.375
fri4	0.509
mot1	0.413
mot2	0.394
mot3	0.213
mot4	0.232
aff1	0.423
aff2	0.333
aff3	0.224
aff4	0.313

```r
knitr::kable(as.data.frame(latent_var), caption = "Latent variances.", digits= 3)
```

Table 4: Latent variances.

	latent_var
pc	1.000

	latent_var
app	1.000
gw	0.099
pw	0.011
par	1.000
teach	1.000
mate	1.000
fri	1.000
mot	0.490
aff	0.634

```
knitr::kable(latent_loadings, caption = "Standardized loadings of the latent variabels.",
```

Table 5: Standardized loadings of the latent variabels.

	pc	app	gw	pw	par	teach	mate	fri	mot	aff
pc	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0.00
app	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0.00
gw	0.046	0.841	0	0.000	0.311	-0.065	0.098	0.184	0	0.00
pw	0.564	0.529	0	0.000	0.081	0.081	-0.040	0.039	0	0.00
par	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0.00
teach	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0.00
mate	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0.00
fri	0.000	0.000	0	0.000	0.000	0.000	0.000	0.000	0	0.00
mot	0.000	0.000	0	0.312	0.000	0.000	0.000	0.000	0	0.48
aff	0.000	0.000	0	0.605	0.000	0.000	0.000	0.000	0	0.00

4. Model summary

The structural model showed below acceptable fit indices, suggesting that it might not be a good representation of the relation between self-worth and motivation: χ^2 (683) = 2378.56, RMSEA = 0.098 90% CI [0.093, 0.102], CFI = 0.764, SRMR = 0.212.

This model has shown that perceived self-worth positively predicts affect (β = 0.605) and motivation (β = 0.312). Motivation was also a strong predictor of affect (β = 0.480). That means that a positive self-worth can improve affect, which also improves motivation.

5. Males vs Females

```
fit.configural = sem(mod4,data=dat, group="female", group.equal=c(""))
fit.loadings   = sem(mod4,data=dat, group="female", group.equal=c("loadings"))
fit.intercepts = sem(mod4,data=dat, group="female", group.equal=c("loadings","intercepts")
fit.varcov     = sem(mod4,data=dat, group="female", group.equal=c("loadings","intercepts",
fit.regress    = sem(mod4,data=dat, group="female", group.equal=c("loadings","intercepts",
fit.invariant  = sem(mod4,data=dat, group="female",
                     group.equal=c("loadings","intercepts", "lv.variances","lv.covariances
```

```
anova(fit.configural, fit.loadings, fit.intercepts, fit.varcov, fit.regress, fit.invariant
  knitr::kable(caption = "Multiple group invariance test.", digits=3)
```

Table 6: Multiple group invariance test.

	Df	AIC	BIC	Chisq	Chisq diff	RMSEA	Df diff	Pr(>Chisq)
fit.configural	1366	7049.978	7861.519	3063.426	NA	NA	NA	NA
fit.loadings	1395	7039.437	7764.454	3110.886	47.459	0.093	29	0.017
fit.intercepts	1424	7049.097	7687.589	3178.546	67.660	0.135	29	0.000
fit.varcov	1437	7056.920	7656.625	3212.368	33.822	0.148	13	0.001
fit.regress	1452	7067.019	7621.970	3252.467	40.099	0.151	15	0.000
fit.invariant	1491	7081.834	7520.424	3345.283	92.815	0.137	39	0.000