ALDA_HW4_EH

Elizabeth Hawkey

10/30/2017

data management

```
## Loading required package: Matrix

## -- Attaching packages --------------------------------------------------------------- tidyverse 1.2.0 -

## √ ggplot2 2.2.1     √ purrr   0.2.3
## √ tibble  1.3.4     √ dplyr   0.7.4
## √ tidyr   0.7.2     √ stringr 1.2.0
## √ readr   1.1.1     √ forcats 0.2.0

## -- Conflicts ------------------------------------------------------------------ tidyverse_conflicts() -
## x tidyr::expand() masks Matrix::expand()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

## Loading required package: arm

## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

##
## arm (Version 1.9-3, built: 2016-11-21)

## Working directory is /Users/elizabethhawkey/ejhawkey

## Loading required package: lavaan

## This is lavaan 0.5-23.1097

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

##

## ###############################################################################

## This is semTools 0.4-14

## All users of R (or SEM) are invited to submit functions or ideas for functions.

## ###############################################################################

##
## Attaching package: 'psych'

## The following object is masked from 'package:semTools':
##
##     skew
```

```
## The following object is masked from 'package:lavaan':
##
##     cor2cov
## The following object is masked from 'package:merTools':
##
##     ICC
## The following objects are masked from 'package:arm':
##
##     logit, rescale, sim
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

1. 1. Fit a measurement model to your constructs at one time point. Try out the different types of scaling discussed in class. What changes what stays the same?

The fit statistics are the same across the two models but the covariances change.

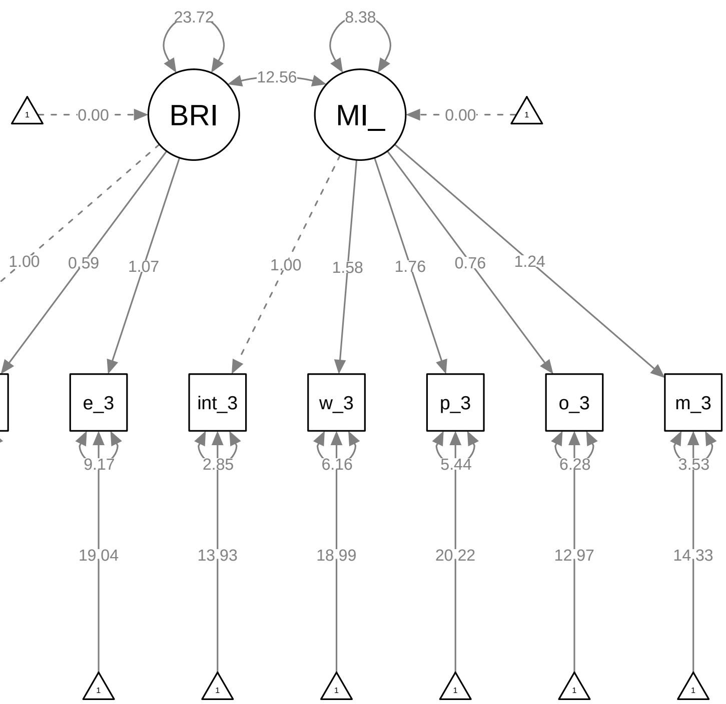
```
#Global executive comppposit at T3
GEC.model <- 'BRI_T3 =~ inhibrs_3 + shftrs_3 + emcnrs_3
              MI_T3 =~ initirs_3 + wrkmrs_3 + plorgrs_3 + orgmars_3 + monirs_3'


#Options for scaling (Largely irrelevant as to what scale is chosen. Serves to establish a point of ref
#Marker variable (R default) Here you fix one factor loading to 1. All other loadings are relative to t
fit.GEC.marker <- cfa(GEC.model, data = PDS_stats, missing = "ML")
summary(fit.GEC.marker, fit.measures = TRUE)
```

```
## lavaan (0.5-23.1097) converged normally after  54 iterations
##
##                                                   Used       Total
##   Number of observations                            67         348
##
##   Number of missing patterns                         1
##
##   Estimator                                         ML
##   Minimum Function Test Statistic               45.573
##   Degrees of freedom                                19
##   P-value (Chi-square)                           0.001
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              468.505
##   Degrees of freedom                                28
##   P-value                                        0.000
##
## User model versus baseline model:
##
```

```
##   Comparative Fit Index (CFI)                    0.940
##   Tucker-Lewis Index (TLI)                       0.911
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -1358.619
##   Loglikelihood unrestricted model (H1)      -1335.832
##
##   Number of free parameters                         25
##   Akaike (AIC)                                2767.238
##   Bayesian (BIC)                              2822.355
##   Sample-size adjusted Bayesian (BIC)         2743.639
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.144
##   90 Percent Confidence Interval          0.091  0.199
##   P-value RMSEA <= 0.05                          0.004
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.043
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   BRI_T3 =~
##     inhibrs_3         1.000
##     shftrs_3          0.588    0.094    6.234    0.000
##     emcnrs_3          1.070    0.143    7.472    0.000
##   MI_T3 =~
##     initirs_3         1.000
##     wrkmrs_3          1.577    0.159    9.885    0.000
##     plorgrs_3         1.760    0.170   10.325    0.000
##     orgmars_3         0.761    0.122    6.218    0.000
##     monirs_3          1.236    0.126    9.779    0.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   BRI_T3 ~~
##     MI_T3            12.555    2.850    4.406    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .inhibrs_3        18.731    0.717   26.128    0.000
##    .shftrs_3         14.194    0.464   30.590    0.000
##    .emcnrs_3         19.045    0.736   25.870    0.000
##    .initirs_3        13.925    0.409   34.009    0.000
##    .wrkmrs_3         18.985    0.635   29.907    0.000
##    .plorgrs_3        20.224    0.685   29.543    0.000
```

```
##    .orgmars_3        12.970    0.408   31.818    0.000
##    .monirs_3         14.328    0.494   29.014    0.000
##     BRI_T3            0.000
##     MI_T3             0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .inhibrs_3        10.717    2.737    3.916    0.000
##    .shftrs_3          6.213    1.379    4.504    0.000
##    .emcnrs_3          9.174    2.866    3.200    0.001
##    .initirs_3         2.850    0.613    4.648    0.000
##    .wrkmrs_3          6.161    1.334    4.617    0.000
##    .plorgrs_3         5.439    1.347    4.040    0.000
##    .orgmars_3         6.278    1.138    5.516    0.000
##    .monirs_3          3.529    0.794    4.447    0.000
##     BRI_T3           23.718    6.002    3.951    0.000
##     MI_T3             8.383    1.913    4.383    0.000
```

```
semPaths(fit.GEC.marker, whatLabels = "est")
```



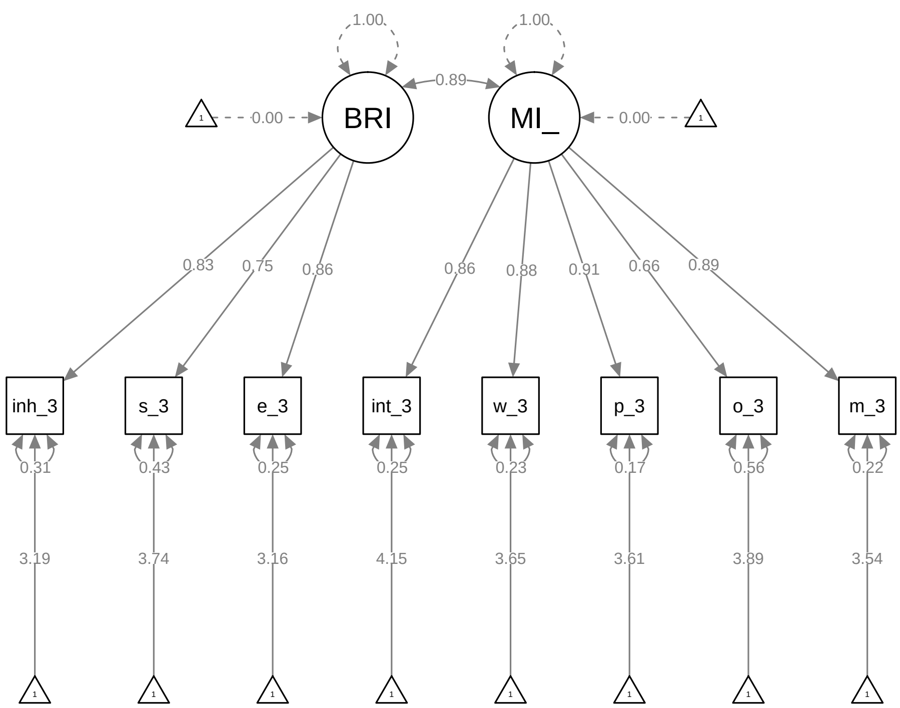

```
#Fixed variable: Here you fix the variance of the latent variable to 1 (standardized)
fit.GEC.fixed <- cfa(GEC.model, data = PDS_stats, std.lv = T, missing = "ML")
summary(fit.GEC.fixed, fit.measures = TRUE, standardized=TRUE)
```

```
## lavaan (0.5-23.1097) converged normally after  41 iterations
##
##                                                  Used       Total
##   Number of observations                           67         348
##
##   Number of missing patterns                        1
##
##   Estimator                                        ML
##   Minimum Function Test Statistic              45.573
```

```
##   Degrees of freedom                                19
##   P-value (Chi-square)                           0.001
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              468.505
##   Degrees of freedom                                28
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.940
##   Tucker-Lewis Index (TLI)                       0.911
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -1358.619
##   Loglikelihood unrestricted model (H1)      -1335.832
##
##   Number of free parameters                         25
##   Akaike (AIC)                                2767.238
##   Bayesian (BIC)                              2822.355
##   Sample-size adjusted Bayesian (BIC)         2743.639
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.144
##   90 Percent Confidence Interval          0.091  0.199
##   P-value RMSEA <= 0.05                          0.004
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.043
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BRI_T3 =~
##     inhibrs_3         4.870    0.616    7.903    0.000    4.870    0.830
##     shftrs_3          2.866    0.421    6.814    0.000    2.866    0.755
##     emcnrs_3          5.209    0.626    8.320    0.000    5.209    0.865
##   MI_T3 =~
##     initirs_3         2.895    0.330    8.766    0.000    2.895    0.864
##     wrkmrs_3          4.565    0.505    9.036    0.000    4.565    0.879
##     plorgrs_3         5.095    0.533    9.563    0.000    5.095    0.909
##     orgmars_3         2.204    0.369    5.974    0.000    2.204    0.660
##     monirs_3          3.579    0.392    9.141    0.000    3.579    0.885
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
```

```
##   BRI_T3 ~~
##     MI_T3             0.890    0.048   18.526    0.000    0.890    0.890
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .inhibrs_3        18.731    0.717   26.128    0.000   18.731    3.192
##    .shftrs_3         14.194    0.464   30.590    0.000   14.194    3.737
##    .emcnrs_3         19.045    0.736   25.870    0.000   19.045    3.160
##    .initirs_3        13.925    0.409   34.009    0.000   13.925    4.155
##    .wrkmrs_3         18.985    0.635   29.907    0.000   18.985    3.654
##    .plorgrs_3        20.224    0.685   29.543    0.000   20.224    3.609
##    .orgmars_3        12.970    0.408   31.818    0.000   12.970    3.887
##    .monirs_3         14.328    0.494   29.014    0.000   14.328    3.545
##     BRI_T3            0.000                               0.000    0.000
##     MI_T3             0.000                               0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .inhibrs_3        10.717    2.737    3.916    0.000   10.717    0.311
##    .shftrs_3          6.213    1.379    4.504    0.000    6.213    0.431
##    .emcnrs_3          9.174    2.866    3.200    0.001    9.174    0.253
##    .initirs_3         2.850    0.613    4.648    0.000    2.850    0.254
##    .wrkmrs_3          6.161    1.334    4.617    0.000    6.161    0.228
##    .plorgrs_3         5.439    1.347    4.040    0.000    5.439    0.173
##    .orgmars_3         6.278    1.138    5.516    0.000    6.278    0.564
##    .monirs_3          3.529    0.794    4.447    0.000    3.529    0.216
##     BRI_T3            1.000                               1.000    1.000
##     MI_T3             1.000                               1.000    1.000
```

```r
semPaths(fit.GEC.fixed, whatLabels = "std")
```



```
#Other option for scaling
#3. Effect coding. Here you constrain loading to average to 1.
#This will be helpful for us as we can then put the scale of measurement into our original metric. #For
```

2. What do the fit statistics say about your latent variable? Good/bad? Is your latent variable Just identified/saturdated, under identified or over identified?

RMSEA = 0.144, SRMR = 0.043; Is this contradictory since one is >.10 and one is <0.08?

CFI and TLI >.90, so this suggests that it is a good fit.

NO negative variances

df = 19 In this model the knowns are greater than the unknowns (over identified)

3. Fit a longitudinal CFA model where you:

a) first correlate your latent factors across time and then a second model that predicts later times by a prevous time (ie auto regressive; t1 -> t2 -> t3). What are your conclusions? How does one differ from the other?

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
##   1 4 6 8 9 11 13 15 19 21 22 25 27 28 29 31 33 34 36 37 38 39 40 41 45 48 49 51 52 53 54 55 56 57 5
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, :
## lavaan WARNING: due to missing values, some pairwise combinations have less
## than 10% coverage
```

```
## Warning in lavaan::lavaan(model = Long.GEC.model, data = PDS_stats, std.lv
## = TRUE, : lavaan WARNING: model has NOT converged!
```

```
## ** WARNING ** lavaan (0.5-23.1097) did NOT converge after 408 iterations
## ** WARNING ** Estimates below are most likely unreliable
##
##                                                   Used       Total
##   Number of observations                           205         348
##
##   Number of missing patterns                         7
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                   NA
##   Degrees of freedom                                NA
##   P-value                                           NA
```

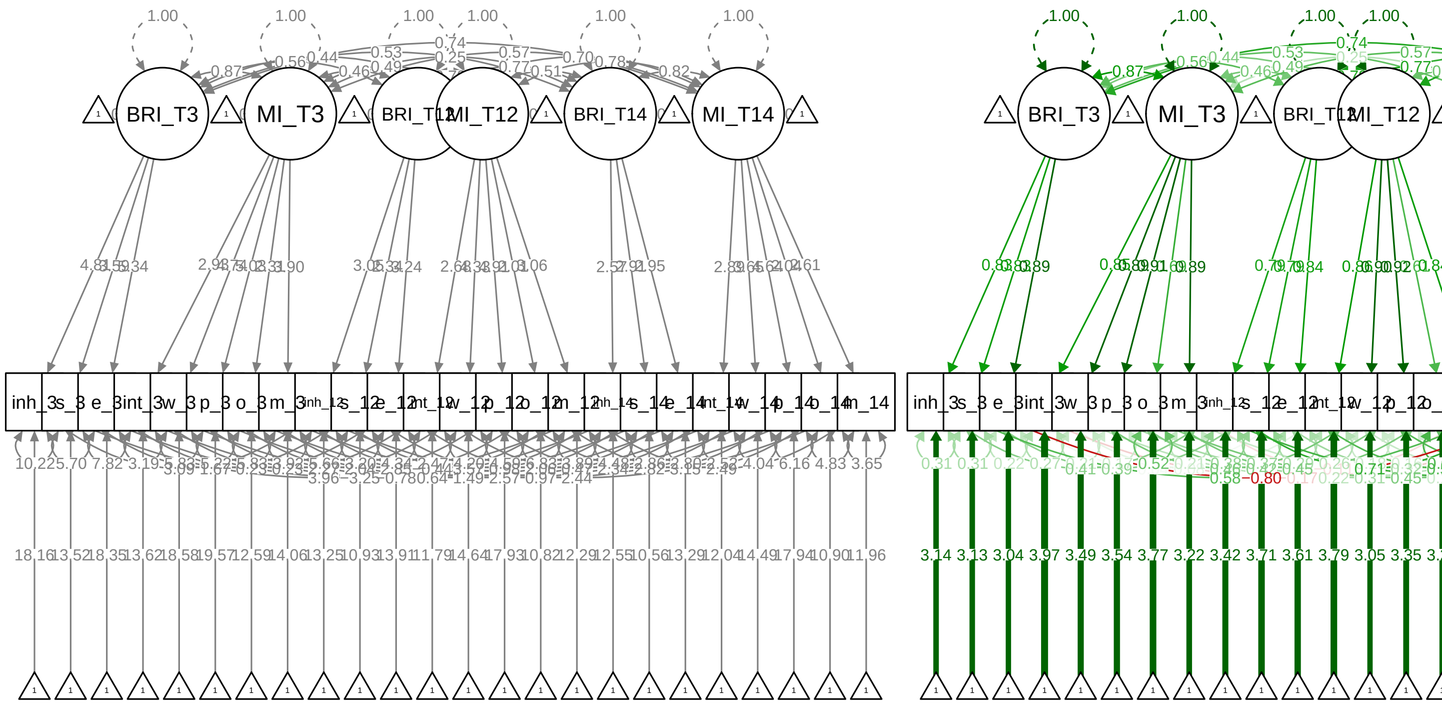
```
## Warning in .local(object, ...): lavaan WARNING: fit measures not available if model did not converge
```

```
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##   BRI_T3 =~
##     inhibrs_3         4.809       NA                      4.809    0.833
##     shftrs_3          3.592       NA                      3.592    0.833
##     emcnrs_3          5.341       NA                      5.341    0.886
##   MI_T3 =~
##     initirs_3         2.933       NA                      2.933    0.854
##     wrkmrs_3          4.743       NA                      4.743    0.891
##     plorgrs_3         5.033       NA                      5.033    0.911
##     orgmars_3         2.310       NA                      2.310    0.691
##     monirs_3          3.899       NA                      3.899    0.892
##   BRI_T12 =~
##     inhibrs_12        3.052       NA                      3.052    0.789
##     shftrs_12         2.338       NA                      2.338    0.794
##     emcnrs_12         3.235       NA                      3.235    0.841
##   MI_T12 =~
##     initirs_12        2.680       NA                      2.680    0.863
##     wrkmrs_12         4.333       NA                      4.333    0.904
##     plorgrs_12        4.911       NA                      4.911    0.917
##     orgmars_12        2.011       NA                      2.011    0.610
##     monirs_12         3.061       NA                      3.061    0.841
##   BRI_T14 =~
##     inhibrs_14        2.569       NA                      2.569    0.772
##     shftrs_14         2.911       NA                      2.911    0.865
##     emcnrs_14         2.946       NA                      2.946    0.869
##   MI_T14 =~
##     initirs_14        2.893       NA                      2.893    0.877
##     wrkmrs_14         3.647       NA                      3.647    0.876
##     plorgrs_14        4.636       NA                      4.636    0.882
##     orgmars_14        2.045       NA                      2.045    0.681
##     monirs_14         2.605       NA                      2.605    0.806
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##  .inhibrs_3 ~~
##    .inhibrs_12        3.086       NA                      3.086    0.406
##    .inhibrs_14        3.957       NA                      3.957    0.585
##  .inhibrs_12 ~~
##    .inhibrs_14        3.571       NA                      3.571    0.709
##  .shftrs_3 ~~
##    .shftrs_12         1.667       NA                      1.667    0.390
##    .shftrs_14        -3.249       NA                     -3.249   -0.804
##  .shftrs_12 ~~
##    .shftrs_14         0.977       NA                      0.977    0.322
##  .emcnrs_3 ~~
##    .emcnrs_12         0.228       NA                      0.228    0.039
##    .emcnrs_14        -0.778       NA                     -0.778   -0.166
```

```
##  .emcnrs_12 ~~
##    .emcnrs_14        2.058       NA                             2.058    0.590
##  .initirs_3 ~~
##    .initirs_12       0.232       NA                             0.232    0.083
##    .initirs_14       0.635       NA                             0.635    0.224
##  .initirs_12 ~~
##    .initirs_14       0.468       NA                             0.468    0.188
##  .wrkmrs_3 ~~
##    .wrkmrs_12        2.274       NA                             2.274    0.460
##    .wrkmrs_14        1.489       NA                             1.489    0.307
##  .wrkmrs_12 ~~
##    .wrkmrs_14        2.341       NA                             2.341    0.569
##  .plorgrs_3 ~~
##    .plorgrs_12       2.039       NA                             2.039    0.416
##    .plorgrs_14       2.573       NA                             2.573    0.454
##  .plorgrs_12 ~~
##    .plorgrs_14       2.817       NA                             2.817    0.530
##  .orgmars_3 ~~
##    .orgmars_12       2.851       NA                             2.851    0.452
##    .orgmars_14       0.967       NA                             0.967    0.182
##  .orgmars_12 ~~
##    .orgmars_14       3.148       NA                             3.148    0.548
##  .monirs_3 ~~
##    .monirs_12       -0.442       NA                            -0.442   -0.113
##    .monirs_14        2.444       NA                             2.444    0.646
##  .monirs_12 ~~
##    .monirs_14        2.492       NA                             2.492    0.662
##   BRI_T3 ~~
##     MI_T3            0.867       NA                             0.867    0.867
##     BRI_T12          0.559       NA                             0.559    0.559
##     MI_T12           0.443       NA                             0.443    0.443
##     BRI_T14          0.532       NA                             0.532    0.532
##     MI_T14           0.743       NA                             0.743    0.743
##   MI_T3 ~~
##     BRI_T12          0.463       NA                             0.463    0.463
##     MI_T12           0.492       NA                             0.492    0.492
##     BRI_T14          0.248       NA                             0.248    0.248
##     MI_T14           0.566       NA                             0.566    0.566
##   BRI_T12 ~~
##     MI_T12           0.786       NA                             0.786    0.786
##     BRI_T14          0.774       NA                             0.774    0.774
##     MI_T14           0.696       NA                             0.696    0.696
##   MI_T12 ~~
##     BRI_T14          0.509       NA                             0.509    0.509
##     MI_T14           0.779       NA                             0.779    0.779
##   BRI_T14 ~~
##     MI_T14           0.823       NA                             0.823    0.823
##
## Intercepts:
##                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .inhibrs_3       18.156       NA                            18.156    3.144
##    .shftrs_3        13.521       NA                            13.521    3.135
##    .emcnrs_3        18.345       NA                            18.345    3.043
##    .initirs_3       13.618       NA                            13.618    3.965
```

```
##    .wrkmrs_3         18.584       NA                          18.584    3.492
##    .plorgrs_3        19.567       NA                          19.567    3.540
##    .orgmars_3        12.587       NA                          12.587    3.766
##    .monirs_3         14.061       NA                          14.061    3.215
##    .inhibrs_12       13.248       NA                          13.248    3.423
##    .shftrs_12        10.935       NA                          10.935    3.714
##    .emcnrs_12        13.911       NA                          13.911    3.615
##    .initirs_12       11.789       NA                          11.789    3.794
##    .wrkmrs_12        14.637       NA                          14.637    3.054
##    .plorgrs_12       17.928       NA                          17.928    3.346
##    .orgmars_12       10.820       NA                          10.820    3.280
##    .monirs_12        12.294       NA                          12.294    3.377
##    .inhibrs_14       12.554       NA                          12.554    3.771
##    .shftrs_14        10.563       NA                          10.563    3.137
##    .emcnrs_14        13.289       NA                          13.289    3.922
##    .initirs_14       12.039       NA                          12.039    3.649
##    .wrkmrs_14        14.487       NA                          14.487    3.480
##    .plorgrs_14       17.936       NA                          17.936    3.411
##    .orgmars_14       10.902       NA                          10.902    3.631
##    .monirs_14        11.958       NA                          11.958    3.701
##     BRI_T3            0.000                                    0.000    0.000
##     MI_T3             0.000                                    0.000    0.000
##     BRI_T12           0.000                                    0.000    0.000
##     MI_T12            0.000                                    0.000    0.000
##     BRI_T14           0.000                                    0.000    0.000
##     MI_T14            0.000                                    0.000    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
##    .inhibrs_3        10.217       NA                          10.217    0.306
##    .shftrs_3          5.701       NA                           5.701    0.306
##    .emcnrs_3          7.824       NA                           7.824    0.215
##    .initirs_3         3.189       NA                           3.189    0.270
##    .wrkmrs_3          5.825       NA                           5.825    0.206
##    .plorgrs_3         5.224       NA                           5.224    0.171
##    .orgmars_3         5.833       NA                           5.833    0.522
##    .monirs_3          3.921       NA                           3.921    0.205
##    .inhibrs_12        5.662       NA                           5.662    0.378
##    .shftrs_12         3.203       NA                           3.203    0.370
##    .emcnrs_12         4.342       NA                           4.342    0.293
##    .initirs_12        2.469       NA                           2.469    0.256
##    .wrkmrs_12         4.195       NA                           4.195    0.183
##    .plorgrs_12        4.594       NA                           4.594    0.160
##    .orgmars_12        6.835       NA                           6.835    0.628
##    .monirs_12         3.887       NA                           3.887    0.293
##    .inhibrs_14        4.483       NA                           4.483    0.404
##    .shftrs_14         2.863       NA                           2.863    0.252
##    .emcnrs_14         2.804       NA                           2.804    0.244
##    .initirs_14        2.516       NA                           2.516    0.231
##    .wrkmrs_14         4.035       NA                           4.035    0.233
##    .plorgrs_14        6.160       NA                           6.160    0.223
##    .orgmars_14        4.832       NA                           4.832    0.536
##    .monirs_14         3.650       NA                           3.650    0.350
##     BRI_T3            1.000                                    1.000    1.000
```

```
##     MI_T3            1.000                                  1.000    1.000
##     BRI_T12          1.000                                  1.000    1.000
##     MI_T12           1.000                                  1.000    1.000
##     BRI_T14          1.000                                  1.000    1.000
##     MI_T14           1.000                                  1.000    1.000
```




```r
#look at correlations between variables
#correlations <- select(PDS_stats, gecrscombined_3, gecrs_12, gecrs_14)
#correlations <- select(PDS_stats, CONTEF_1, CONTEF_2, CONTEF_3, CONPEF_1, CONPEF_2, CONPEF_3)
#correlations
#cor(correlations, use = "pairwise.complete.obs")
```

4. Fit a longitdinal growth model in SEM and in HLM. Compare and contrast the differences.

```r
##Univariate growth model: SEM
#SEM with a fixed slope
 fixed.slope= ' i=~ 1*CONPEF_1 + 1*CONPEF_2 + 1*CONPEF_3
                s=~ 0*CONPEF_1 + 1*CONPEF_2 + 2*CONPEF_3
                s ~~ 0*s'  #fixes slope
 fixed.slope.fit= growth(fixed.slope, data = PDS_stats, missing= "ML")
 inspect(fixed.slope.fit, "cov.lv")
```

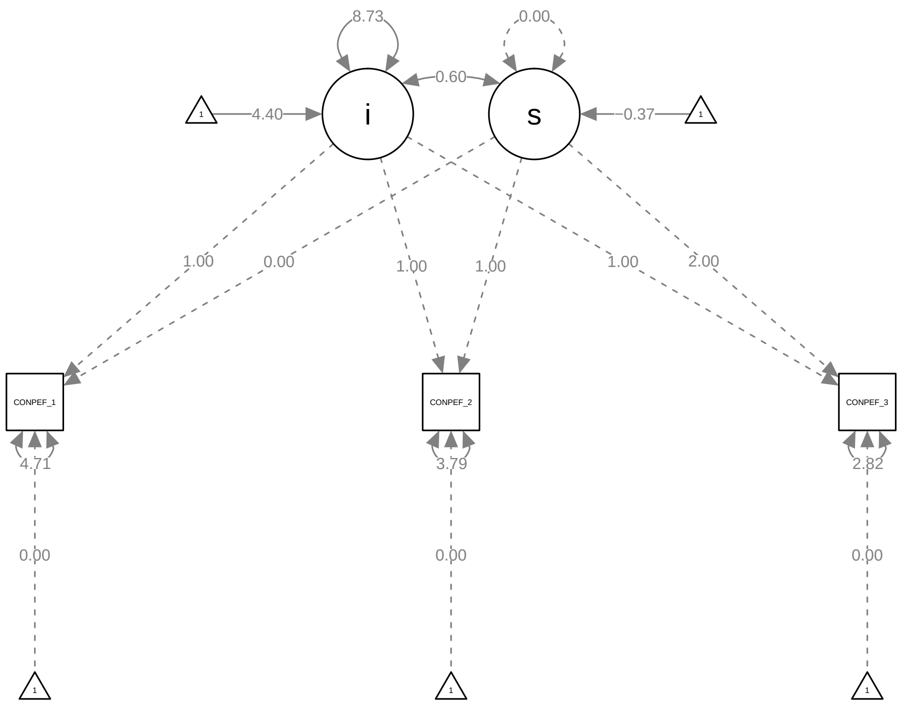
```
##   i     s
## i 8.729
## s 0.601 0.000
```

```r
 summary (fixed.slope.fit)
```

```
## lavaan (0.5-23.1097) converged normally after  36 iterations
```

```
##
##                                                   Used       Total
##   Number of observations                           209         348
##
##   Number of missing patterns                         6
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                3.314
##   Degrees of freedom                                 2
##   P-value (Chi-square)                           0.191
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     CONPEF_1          1.000
##     CONPEF_2          1.000
##     CONPEF_3          1.000
##   s =~
##     CONPEF_1          0.000
##     CONPEF_2          1.000
##     CONPEF_3          2.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i ~~
##     s                 0.601    0.371    1.620    0.105
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          0.000
##    .CONPEF_2          0.000
##    .CONPEF_3          0.000
##     i                 4.398    0.247   17.807    0.000
##     s                -0.368    0.106   -3.478    0.001
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     s                 0.000
##    .CONPEF_1          4.707    0.667    7.054    0.000
##    .CONPEF_2          3.788    0.585    6.480    0.000
##    .CONPEF_3          2.821    0.593    4.754    0.000
##     i                 8.729    1.279    6.827    0.000
```

```
semPaths(fixed.slope.fit, what = "paths", whatLabels= "est", layout = "tree")
```

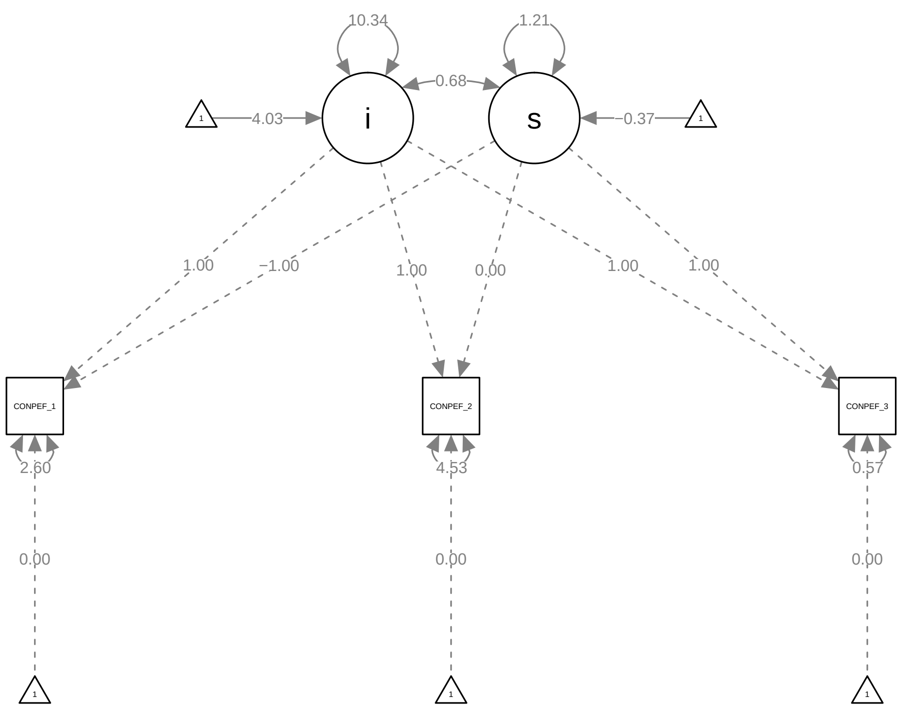



```r
#SEM with a random slope
random.fit= ' i=~ 1*CONPEF_1 + 1*CONPEF_2 + 1*CONPEF_3
              s=~ -1*CONPEF_1 + 0*CONPEF_2 + 1*CONPEF_3'
random.fit= growth(random.fit, data = PDS_stats, missing= "ML")
summary (random.fit)
```

```
## lavaan (0.5-23.1097) converged normally after  45 iterations
##
##                                                   Used       Total
##   Number of observations                           209         348
##
##   Number of missing patterns                         6
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                0.001
##   Degrees of freedom                                 1
##   P-value (Chi-square)                           0.976
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     CONPEF_1          1.000
##     CONPEF_2          1.000
##     CONPEF_3          1.000
##   s =~
##     CONPEF_1         -1.000
##     CONPEF_2          0.000
```

```
##     CONPEF_3          1.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i ~~
##     s                 0.676    0.422    1.602    0.109
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          0.000
##    .CONPEF_2          0.000
##    .CONPEF_3          0.000
##     i                 4.030    0.234   17.257    0.000
##     s                -0.372    0.109   -3.430    0.001
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          2.603    1.270    2.050    0.040
##    .CONPEF_2          4.533    0.753    6.022    0.000
##    .CONPEF_3          0.571    1.320    0.433    0.665
##     i                10.341    1.175    8.804    0.000
##     s                 1.208    0.641    1.885    0.059
```

```r
semPaths(random.fit, what = "paths", whatLabels= "est", layout = "tree")
```




```r
# compare models
anova(fixed.slope.fit, random.fit)
```

```
## Chi Square Difference Test
##
##                 Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## random.fit       1 2720.1 2746.8 0.0009
## fixed.slope.fit  2 2721.4 2744.8 3.3136     3.3127       1    0.06875 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##Growth model in MLM
#Move data into a long format
wide_to_long <- PDS_stats %>%
  gather(sex_1:W3DMNGEK6to10_3, key = "time", value = "value")
#View(wide_to_long)

wide_to_long_1 <- wide_to_long %>%
  separate(time, into = c("var", "timepoint"), sep = "_", convert = TRUE) %>%
  spread(key = var, value = value) %>%
  arrange(Subid)
#View(wide_to_long_1)

##Center predictor variables
timepoint_c <- scale(wide_to_long_1$timepoint, center = T, scale = F)
#add the centered variables into the data frame
wide_to_long_1$timepoint_c <- as.numeric(timepoint_c)

##CATEGORICAL TIME VARIABLE
#a) only predicts the intercept
mod.1 <- lmer(CONPEF ~ timepoint + (1|Subid), data = wide_to_long_1)
summary(mod.1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: CONPEF ~ timepoint + (1 | Subid)
##    Data: wide_to_long_1
##
## REML criterion at convergence: 2715.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2068 -0.5095 -0.0939  0.4204  3.0845
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subid    (Intercept) 9.889    3.145
##  Residual             3.831    1.957
## Number of obs: 548, groups:  Subid, 209
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   4.7646     0.3092   15.41
## timepoint    -0.3693     0.1073   -3.44
##
## Correlation of Fixed Effects:
##           (Intr)
## timepoint -0.653
```

```
#b) predicts both intercept and slope
mod.2 <- lmer(CONPEF ~ timepoint + (timepoint|Subid), data = wide_to_long_1)
summary(mod.2)
```

```
## Linear mixed model fit by REML ['lmerMod']
```

```
## Formula: CONPEF ~ timepoint + (timepoint | Subid)
##    Data: wide_to_long_1
##
## REML criterion at convergence: 2714
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9773 -0.4823 -0.1077  0.4124  2.9958
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  Subid    (Intercept) 9.4586   3.0755
##           timepoint   0.2271   0.4766   -0.06
##  Residual             3.6133   1.9009
## Number of obs: 548, groups:  Subid, 209
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   4.7659     0.3021  15.775
## timepoint    -0.3694     0.1105  -3.342
##
## Correlation of Fixed Effects:
##           (Intr)
## timepoint -0.634
```

```r
anova(mod.1, mod.2)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: wide_to_long_1
## Models:
## mod.1: CONPEF ~ timepoint + (1 | Subid)
## mod.2: CONPEF ~ timepoint + (timepoint | Subid)
##       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## mod.1  4 2719.8 2737.1 -1355.9   2711.8
## mod.2  6 2722.3 2748.2 -1355.2   2710.3 1.5054      2     0.4711
```

```r
#model comparison fit statistics show that the fixed slope is a better fit, indicating that individuals
```

The estimates for the fixed models are very similar, however the variance is larger in the MLM model since the SEM model does a better job estimating variance at each timepoint. In the random effect model, the estimates are also similar, although slightly smaller in the SEM model, and the variance is slightly higher in the SEM model.

5. Constrain the residual variances to be equal. Does this change the fit of your model?

The unconstrained model is a better fit, but only slightly and the p-value is non-significant.

```
constrain.residuals = ' i=~ 1*CONPEF_1 + 1*CONPEF_2 + 1*CONPEF_3
                        s=~ 0*CONPEF_1 + 1*CONPEF_2 + 2*CONPEF_3
                        CONPEF_1 ~~ a*CONPEF_1
                        CONPEF_2 ~~ a*CONPEF_2
                        CONPEF_3 ~~ a*CONPEF_3'
constrain.residuals.fit= growth(constrain.residuals, data = PDS_stats, missing= "ML")
 summary (constrain.residuals.fit)
```

```
## lavaan (0.5-23.1097) converged normally after  35 iterations
##
##                                                   Used       Total
##   Number of observations                           209         348
##
##   Number of missing patterns                         6
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                6.229
##   Degrees of freedom                                 3
##   P-value (Chi-square)                           0.101
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     CONPEF_1          1.000
##     CONPEF_2          1.000
##     CONPEF_3          1.000
##   s =~
##     CONPEF_1          0.000
##     CONPEF_2          1.000
##     CONPEF_3          2.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i ~~
```

```
##     s                 0.154    0.449    0.343    0.732
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          0.000
##    .CONPEF_2          0.000
##    .CONPEF_3          0.000
##     i                 4.396    0.247   17.821    0.000
##     s                -0.369    0.110   -3.351    0.001
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1   (a)    3.613    0.391    9.239    0.000
##    .CONPEF_2   (a)    3.613    0.391    9.239    0.000
##    .CONPEF_3   (a)    3.613    0.391    9.239    0.000
##     i                 9.462    1.288    7.349    0.000
##     s                 0.215    0.300    0.718    0.473
```

```
anova(fixed.slope.fit, constrain.residuals.fit)
```

```
## Chi Square Difference Test
##
##                         Df    AIC    BIC  Chisq Chisq diff Df diff
## fixed.slope.fit          2 2721.4 2744.8 3.3136
## constrain.residuals.fit  3 2722.3 2742.4 6.2287     2.9151       1
##                         Pr(>Chisq)
## fixed.slope.fit
## constrain.residuals.fit    0.08776 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

6. Contrain your slope to be fixed, not random. How does this change your model?

The change is non-significant.

```
constrain.slope = ' i=~ 1*CONPEF_1 + 1*CONPEF_2 + 1*CONPEF_3
                    s=~ 0*CONPEF_1 + 1*CONPEF_2 + 2*CONPEF_3
                        s ~ 0*s'
constrain.slope= growth(constrain.slope, data = PDS_stats, missing= "ML")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
##   1 2 4 6 8 9 11 13 15 19 21 27 28 29 31 32 33 34 36 37 38 39 40 41 42 45 47 48 49 50 52 54 55 56 59
```

```
summary(constrain.slope)
```

```
## lavaan (0.5-23.1097) converged normally after  36 iterations
##
##                                                   Used       Total
##   Number of observations                           209         348
##
##   Number of missing patterns                         6
##
```

```
##   Estimator                                         ML
##   Minimum Function Test Statistic                0.553
##   Degrees of freedom                                 2
##   P-value (Chi-square)                           0.759
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     CONPEF_1          1.000
##     CONPEF_2          1.000
##     CONPEF_3          1.000
##   s =~
##     CONPEF_1          0.000
##     CONPEF_2          1.000
##     CONPEF_3          2.000
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   s ~
##     s                 0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          0.000
##    .CONPEF_2          0.000
##    .CONPEF_3          0.000
##     i                 4.401    0.245   17.986    0.000
##    .s                -0.371    0.108   -3.442    0.001
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          3.399    0.716    4.749    0.000
##    .CONPEF_2          4.272    0.647    6.600    0.000
##    .CONPEF_3          1.231    1.014    1.213    0.225
##     i                 9.399    1.115    8.432    0.000
##    .s                 0.811    0.374    2.166    0.030
```

```
anova(random.fit, constrain.slope)
```

```
## Chi Square Difference Test
##
##                 Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## random.fit       1 2720.1 2746.8 0.0009
## constrain.slope  2 2718.7 2742.1 0.5525     0.5516       1     0.4577
```

7 Change the time metric in your SEM growth model. How does that change your estimates? Does it change your fit statistics?

The estimates are slightly smaller, and the fit statistics indicate that the first model is a significantly better fit.

```
## lavaan (0.5-23.1097) converged normally after  37 iterations
##
##                                                   Used       Total
##   Number of observations                           209         348
##
##   Number of missing patterns                         6
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                5.594
##   Degrees of freedom                                 2
##   P-value (Chi-square)                           0.061
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     CONPEF_1          1.000
##     CONPEF_2          1.000
##     CONPEF_3          1.000
##   s =~
##     CONPEF_1         -2.000
##     CONPEF_2         -1.000
##     CONPEF_3          0.000
##
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   s ~
##     s                 0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          0.000
##    .CONPEF_2          0.000
##    .CONPEF_3          0.000
##     i                 3.660    0.261   13.998    0.000
##    .s                -0.368    0.105   -3.490    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          4.875    1.004    4.856    0.000
##    .CONPEF_2          3.662    0.603    6.071    0.000
##    .CONPEF_3          3.390    0.720    4.711    0.000
##     i                10.071    1.161    8.673    0.000
```

```
##    .s                -0.206    0.334   -0.617    0.537
```

```
## Chi Square Difference Test
##
##                      Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## random.fit            1 2720.1 2746.8 0.0009
## constrain.slope.time  2 2723.7 2747.1 5.5935     5.5926       1    0.01804
##
## random.fit
## constrain.slope.time *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

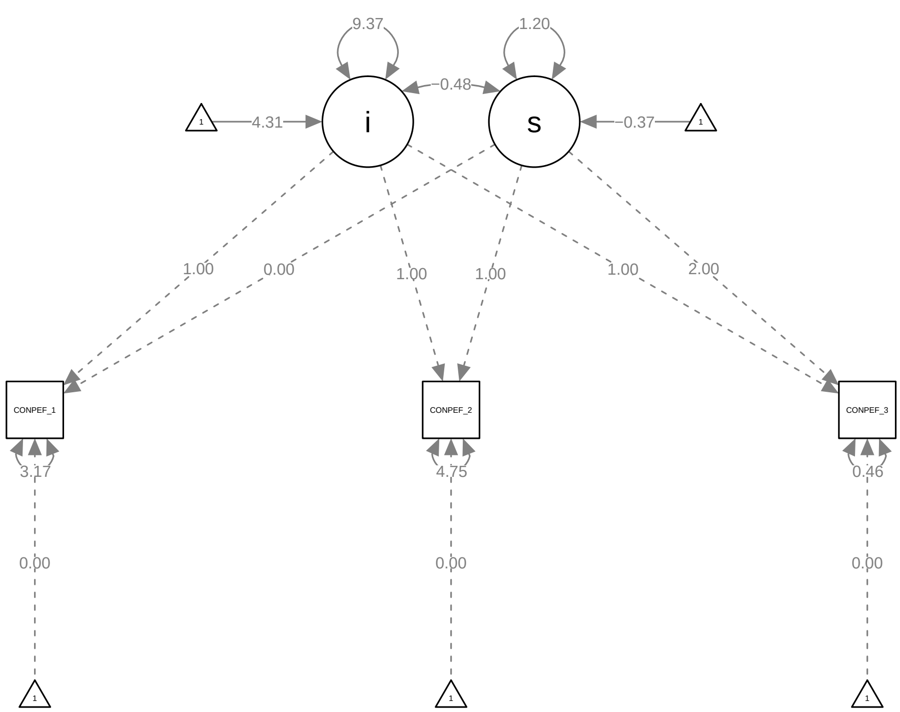
8. Try a different type of estimation (see lavaan tutorial for details). How does that change your model? #Default in lavaan is the ML estimator,There are a number of "robust" estimates that are uniformly better. MLR is Josh's choice if you go this route, but others are just as good and maybe better if you have complete data. "MLR": maximum likelihood estimation with robust (Huber-White) standard errors and a scaled test statistic that is (asymptotically) equal to the Yuan-Bentler test statistic. For both complete and incomplete data.

The fit is significantly better using MLR

```
## lavaan (0.5-23.1097) converged normally after  46 iterations
##
##                                                   Used       Total
##   Number of observations                           145         348
##
##   Estimator                                         ML      Robust
##   Minimum Function Test Statistic                0.011       0.011
##   Degrees of freedom                                 1           1
##   P-value (Chi-square)                           0.917       0.917
##   Scaling correction factor                                  1.001
##     for the Yuan-Bentler correction
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                   Robust.huber.white
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     CONPEF_1          1.000
##     CONPEF_2          1.000
##     CONPEF_3          1.000
##   s =~
```

```
##     CONPEF_1          0.000
##     CONPEF_2          1.000
##     CONPEF_3          2.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i ~~
##     s                -0.481    0.842   -0.571    0.568
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          0.000
##    .CONPEF_2          0.000
##    .CONPEF_3          0.000
##     i                 4.309    0.289   14.923    0.000
##     s                -0.375    0.118   -3.165    0.002
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .CONPEF_1          3.171    1.751    1.811    0.070
##    .CONPEF_2          4.750    0.962    4.935    0.000
##    .CONPEF_3          0.465    1.605    0.289    0.772
##     i                 9.371    2.007    4.669    0.000
##     s                 1.204    0.844    1.426    0.154
```

```
## Chi Square Difference Test
##
##               Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## random.fit     1 2720.1 2746.8 0.0009
## constrain.est  1 2144.7 2168.5 0.0110   0.010028       0  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



9. Provide semplots for each of the models (embedded throughout the code)