SEM Growth Models

Elizabeth Hawkey

11/5/2017

```r
library(lavaan)
```

```
## This is lavaan 0.5-23.1097
## lavaan is BETA software! Please report any bugs.
```

```r
library(lme4)
```

```
## Loading required package: Matrix
```

```r
library(tidyverse)
```

```
## -- 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()
```

```r
library(broom)
library(dplyr)
library(psych)
```

```
##
## Attaching package: 'psych'
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
## The following object is masked from 'package:lavaan':
##
##     cor2cov
```

```r
library(tidyr)
library(merTools)
```

```
## 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
##
## Attaching package: 'arm'
## The following objects are masked from 'package:psych':
##
##     logit, rescale, sim
##
## Attaching package: 'merTools'
## The following object is masked from 'package:psych':
##
##     ICC
```

```
library(lavaan)
library(semTools)
```

```
##
## ###############################################################################
## This is semTools 0.4-14
## All users of R (or SEM) are invited to submit functions or ideas for functions.
## ###############################################################################
##
## Attaching package: 'semTools'
## The following object is masked from 'package:psych':
##
##     skew
```

```
library(semPlot)

growth_stats <- read.csv(file =  "~/ejhawkey/STATS_resting_state_BRIEF.csv")

#convert variables
growth_stats$T3gecrs_combined_conv <- as.numeric(growth_stats$T3_gecrscombined/100)
growth_stats$T12gecrs_conv  <- as.numeric(growth_stats$T12_gecrs/100)
growth_stats$T14gecrs_conv=growth_stats$T14_gecrs/100
```

1a. Start with a Univariate Growth Model

```
# Global Executive Composite raw scores
# with intercept only
 Intercept.only= ' i=~ 1*T3gecrs_combined_conv + 1*T12gecrs_conv + 1*T14gecrs_conv'
 Intercept.only.fit= growth(Intercept.only, data = growth_stats, missing= "ML")
```

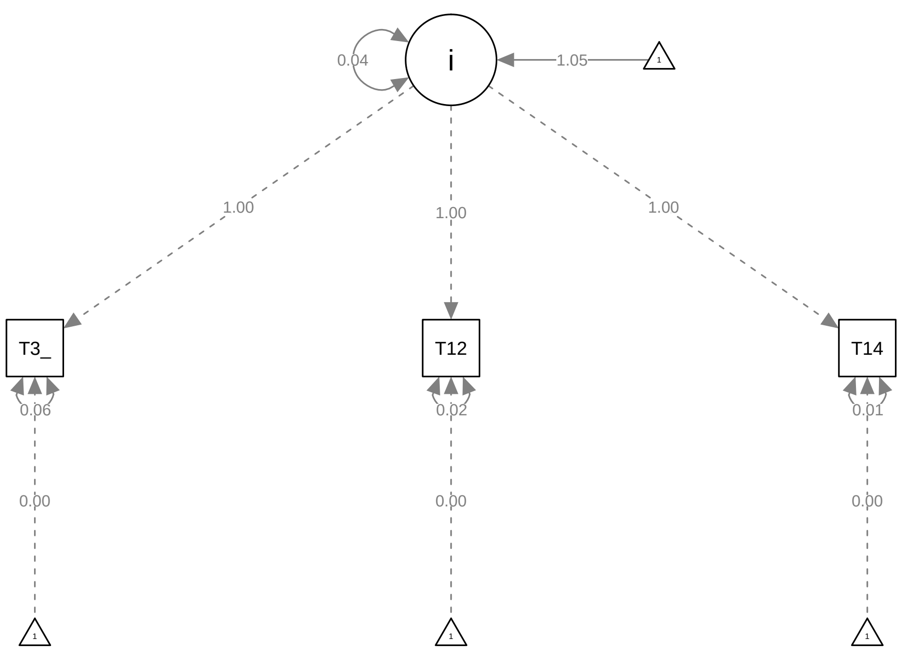
```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
##   6 19 21 28 29 34 36 49 52 64 72 81 83 84 86 91 94 103 113 115 141 169 180 187 194 198 199 205 217 2
```

```
 summary (Intercept.only.fit)
```

```
## lavaan (0.5-23.1097) converged normally after  59 iterations
##
##                                                   Used       Total
##   Number of observations                           302         348
##
```

```
##   Number of missing patterns                         7
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                4.592
##   Degrees of freedom                                 4
##   P-value (Chi-square)                           0.332
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     T3gcrs_cmbnd_c    1.000
##     T12gecrs_conv     1.000
##     T14gecrs_conv     1.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3gcrs_cmbnd_c    0.000
##    .T12gecrs_conv     0.000
##    .T14gecrs_conv     0.000
##     i                 1.048    0.015   69.868    0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3gcrs_cmbnd_c    0.056    0.007    7.891    0.000
##    .T12gecrs_conv     0.018    0.004    4.589    0.000
##    .T14gecrs_conv     0.015    0.004    3.709    0.000
##     i                 0.044    0.005    8.056    0.000
```

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



```r
# with a fixed slope
fixed.slope= ' i=~ 1*T3gecrs_combined_conv + 1*T12gecrs_conv + 1*T14gecrs_conv
s=~ 0*T3gecrs_combined_conv + 1*T12gecrs_conv + 2*T14gecrs_conv
s ~~ 0*s'  #fixes slope
fixed.slope.fit= growth(fixed.slope, data = growth_stats, missing= "ML")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
##   6 19 21 28 29 34 36 49 52 64 72 81 83 84 86 91 94 103 113 115 141 169 180 187 194 198 199 205 217 
```

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

```r
inspect(fixed.slope.fit, "cov.lv")
```

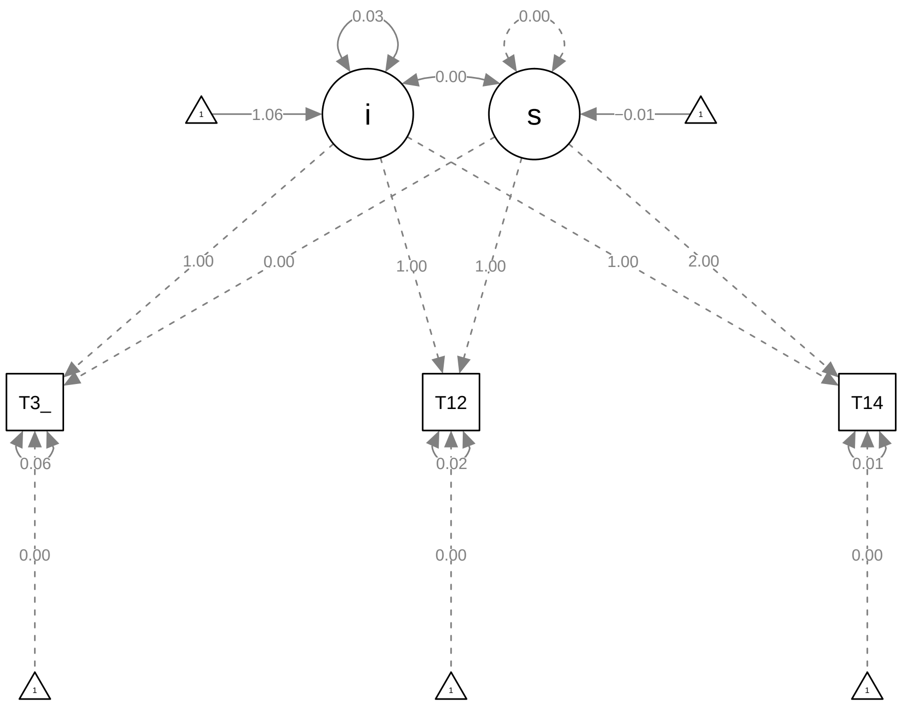
```
##   i     s
## i 0.034
## s 0.005 0.000
```

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

```
## lavaan (0.5-23.1097) converged normally after  44 iterations
##
##                                                   Used       Total
##   Number of observations                           302         348
##
##   Number of missing patterns                         7
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                1.473
##   Degrees of freedom                                 2
##   P-value (Chi-square)                           0.479
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     T3gcrs_cmbnd_c    1.000
##     T12gecrs_conv     1.000
##     T14gecrs_conv     1.000
##   s =~
##     T3gcrs_cmbnd_c    0.000
##     T12gecrs_conv     1.000
##     T14gecrs_conv     2.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i ~~
##     s                 0.005    0.003    1.476    0.140
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
```

```
##    .T3gcrs_cmbnd_c    0.000
##    .T12gecrs_conv     0.000
##    .T14gecrs_conv     0.000
##     i                 1.057    0.017   61.047    0.000
##     s                -0.011    0.012   -0.941    0.347
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##     s                 0.000
##    .T3gcrs_cmbnd_c    0.061    0.008    7.460    0.000
##    .T12gecrs_conv     0.020    0.004    4.632    0.000
##    .T14gecrs_conv     0.011    0.004    2.531    0.011
##     i                 0.034    0.008    4.053    0.000
```

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




```r
# with a random slope

random.intercept= ' i=~ 1*T3gecrs_combined_conv + 1*T12gecrs_conv + 1*T14gecrs_conv
s=~ -1*T3gecrs_combined_conv + 0*T12gecrs_conv + 1*T14gecrs_conv'
random.intercept.fit= growth(random.intercept, data = growth_stats, missing= "ML")
```

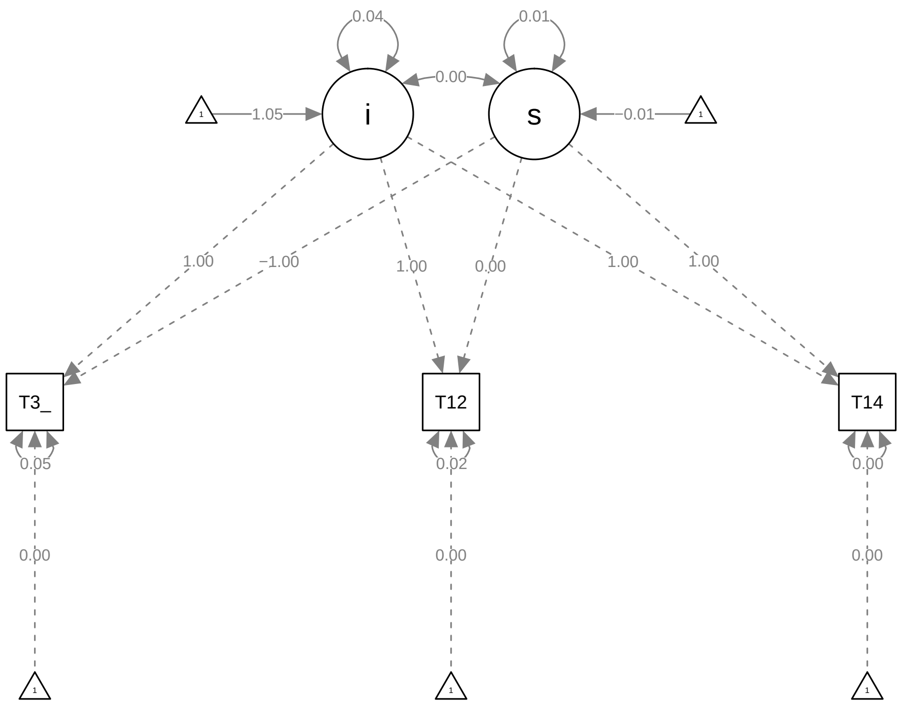
```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
##   6 19 21 28 29 34 36 49 52 64 72 81 83 84 86 91 94 103 113 115 141 169 180 187 194 198 199 205 217 2
```

```r
summary (random.intercept.fit)
```

```
## lavaan (0.5-23.1097) converged normally after  67 iterations
##
##                                                   Used       Total
##   Number of observations                           302         348
##
##   Number of missing patterns                         7
```

```
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                0.477
##   Degrees of freedom                                 1
##   P-value (Chi-square)                           0.490
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i =~
##     T3gcrs_cmbnd_c    1.000
##     T12gecrs_conv     1.000
##     T14gecrs_conv     1.000
##   s =~
##     T3gcrs_cmbnd_c   -1.000
##     T12gecrs_conv     0.000
##     T14gecrs_conv     1.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i ~~
##     s                 0.005    0.003    1.471    0.141
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3gcrs_cmbnd_c    0.000
##    .T12gecrs_conv     0.000
##    .T14gecrs_conv     0.000
##     i                 1.045    0.015   68.656    0.000
##     s                -0.013    0.012   -1.084    0.278
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3gcrs_cmbnd_c    0.053    0.011    4.791    0.000
##    .T12gecrs_conv     0.021    0.005    4.688    0.000
##    .T14gecrs_conv     0.003    0.010    0.264    0.792
##     i                 0.044    0.006    7.739    0.000
##     s                 0.006    0.006    1.000    0.317
```

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




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

```
## Chi Square Test Statistic (unscaled)
##
##           Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## Saturated  0               0.0000
## Model      4 39.036 57.589 4.5922     4.5922       4     0.3318
```

```r
anova(fixed.slope.fit, random.intercept.fit)
```

```
## Chi Square Difference Test
##
##                      Df    AIC    BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## random.intercept.fit  1 40.921 70.604 0.4766
## fixed.slope.fit       2 39.917 65.890 1.4731    0.99658       1     0.3181
```

1b. Multivariate growth curves - start with this first (just using indicators - no latent variables)

As a rule of thumb you need at least three indicators for each latent variable.

```
## lavaan (0.5-23.1097) converged normally after 129 iterations
##
##                                                   Used       Total
##   Number of observations                           310         348
##
##   Number of missing patterns                        44
```

```
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                6.070
##   Degrees of freedom                                 7
##   P-value (Chi-square)                           0.532
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i.behavior =~
##     T3gcrs_cmbnd_c    1.000
##     T12gecrs_conv     1.000
##     T14gecrs_conv     1.000
##   s.behavior =~
##     T3gcrs_cmbnd_c    0.000
##     T12gecrs_conv     1.000
##     T14gecrs_conv     2.000
##   i.network =~
##     S1_FPNGEK1to5     1.000
##     S2_FPNGEK1to5     1.000
##     S3_FPNGEK1to5     1.000
##   s.network =~
##     S1_FPNGEK1to5     0.000
##     S2_FPNGEK1to5     1.000
##     S3_FPNGEK1to5     2.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   i.behavior ~~
##     s.behavior       -0.002    0.007   -0.272    0.786
##     i.network        -0.000    0.003   -0.129    0.897
##     s.network        -0.001    0.002   -0.493    0.622
##   s.behavior ~~
##     i.network         0.000    0.002    0.205    0.838
##     s.network         0.000    0.001    0.013    0.990
##   i.network ~~
##     s.network        -0.000    0.001   -0.096    0.923
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3gcrs_cmbnd_c    0.000
##    .T12gecrs_conv     0.000
##    .T14gecrs_conv     0.000
##    .S1_FPNGEK1to5     0.000
##    .S2_FPNGEK1to5     0.000
##    .S3_FPNGEK1to5     0.000
##     i.behavior        1.058    0.017   60.666    0.000
##     s.behavior       -0.013    0.012   -1.098    0.272
##     i.network         0.225    0.008   28.585    0.000
##     s.network         0.015    0.005    3.014    0.003
```

```
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3gcrs_cmbnd_c    0.052    0.011    4.697    0.000
##    .T12gecrs_conv     0.021    0.005    4.702    0.000
##    .T14gecrs_conv     0.002    0.010    0.158    0.874
##    .S1_FPNGEK1to5     0.006    0.002    2.662    0.008
##    .S2_FPNGEK1to5     0.008    0.001    6.485    0.000
##    .S3_FPNGEK1to5     0.005    0.002    2.641    0.008
##     i.behavior        0.040    0.011    3.824    0.000
##     s.behavior        0.007    0.006    1.081    0.280
##     i.network         0.003    0.002    1.649    0.099
##     s.network         0.000    0.001    0.212    0.832
```

```
##                    name idx nobs    type exo user  mean   var nlev lnam
## 1 T3gecrs_combined_conv 409  247 numeric   0    0 1.057 0.094    0
## 2         T12gecrs_conv 410  162 numeric   0    0 1.052 0.066    0
## 3         T14gecrs_conv 411   97 numeric   0    0 1.024 0.062    0
## 4         S1_FPNGEK1to5 339  124 numeric   0    0 0.231 0.009    0
## 5         S2_FPNGEK1to5 343  142 numeric   0    0 0.236 0.011    0
## 6         S3_FPNGEK1to5 401  132 numeric   0    0 0.258 0.009    0
```

```
## $lambda
##                        i.bhvr s.bhvr i.ntwr s.ntwr
## T3gecrs_combined_conv      0      0      0      0
## T12gecrs_conv              0      0      0      0
## T14gecrs_conv              0      0      0      0
## S1_FPNGEK1to5              0      0      0      0
## S2_FPNGEK1to5              0      0      0      0
## S3_FPNGEK1to5              0      0      0      0
##
## $theta
##                        T3gc__ T12gc_ T14gc_ S1_FPN S2_FPN S3_FPN
## T3gecrs_combined_conv 1
## T12gecrs_conv         0      2
## T14gecrs_conv         0      0      3
## S1_FPNGEK1to5         0      0      0      4
## S2_FPNGEK1to5         0      0      0      0      5
## S3_FPNGEK1to5         0      0      0      0      0      6
##
## $psi
##            i.bhvr s.bhvr i.ntwr s.ntwr
## i.behavior  7
## s.behavior 11      8
## i.network  12     14      9
## s.network  13     15     16     10
##
## $nu
##                        intrcp
## T3gecrs_combined_conv      0
## T12gecrs_conv              0
## T14gecrs_conv              0
## S1_FPNGEK1to5              0
## S2_FPNGEK1to5              0
## S3_FPNGEK1to5              0
```

```
##
## $alpha
##              intrcp
## i.behavior       17
## s.behavior       18
## i.network        19
## s.network        20
```

2a. Second order growth models - on BRIEF (using BRIEF composite scores (GEC = BRI + MI)

Begin with a simple CFA to determine if latent variable is appropriate

```r
#BRIEF: Behavioral Regulation Index
BRI.model <- ' BRI.T3 =~ T3_inhibrs + T3_shftrs + T3_emcnrs '
fit= cfa(BRI.model, data=growth_stats, missing= "ML")
##Options: std.lv = TRUE: standardizes latent var. (but not your results) uses fixed factor method
summary(fit, fit.measures=TRUE)
```

```
## lavaan (0.5-23.1097) converged normally after  42 iterations
##
##                                                   Used       Total
##   Number of observations                            67         348
##
##   Number of missing patterns                         1
##
##   Estimator                                         ML
##   Minimum Function Test Statistic                0.000
##   Degrees of freedom                                 0
##
## Model test baseline model:
##
##   Minimum Function Test Statistic               99.389
##   Degrees of freedom                                 3
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    1.000
##   Tucker-Lewis Index (TLI)                       1.000
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -563.818
##   Loglikelihood unrestricted model (H1)       -563.818
##
##   Number of free parameters                          9
##   Akaike (AIC)                                1145.636
##   Bayesian (BIC)                              1165.479
```

```
##   Sample-size adjusted Bayesian (BIC)        1137.141
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.000
##   90 Percent Confidence Interval          0.000  0.000
##   P-value RMSEA <= 0.05                             NA
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.000
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   BRI.T3 =~
##     T3_inhibrs        1.000
##     T3_shftrs         0.691    0.112    6.167    0.000
##     T3_emcnrs         1.409    0.227    6.210    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3_inhibrs       18.731    0.717   26.128    0.000
##    .T3_shftrs        14.194    0.464   30.590    0.000
##    .T3_emcnrs        19.045    0.736   25.870    0.000
##     BRI.T3            0.000
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3_inhibrs       16.907    3.474    4.867    0.000
##    .T3_shftrs         6.056    1.379    4.392    0.000
##    .T3_emcnrs         1.510    3.743    0.404    0.687
##     BRI.T3           17.529    5.514    3.179    0.001
```

```
#std.fit
```

2b. Build second order growth models

```
sec.order <- '
###define latent variables
#NA This is freeing the default of the marker variable method, and labeling the indicators
BRI_T3 =~ NA*T3_inhibrs + L1*T3_inhibrs + L2*T3_shftrs + L3*T3_emcnrs
BRI_T12 =~ NA*T12_inhibrs + L1*T12_inhibrs + L2*T12_shftrs + L3*T12_emcnrs
BRI_T14 =~ NA*T14_inhibrs + L1*T14_inhibrs + L2*T14_shftrs + L3*T14_emcnrs


### intercepts; setting the mean of each indicator (imposing measurement invariance)
#this is setting the means equal across waves
```

```
#in lavaan code whenever you put *1 here it is referring to the intercept
T3_inhibrs ~ t1*1
T3_shftrs ~ t2*1
T3_emcnrs ~ t3*1

T12_inhibrs ~ t1*1
T12_shftrs ~ t2*1
T12_emcnrs ~ t3*1

T14_inhibrs ~ t1*1
T14_shftrs ~ t2*1
T14_emcnrs ~ t3*1


## correlated residuals across time; occassion specific variance that is not common to the latent facto
T3_inhibrs ~~ T12_inhibrs + T14_inhibrs
T12_inhibrs ~~ T14_inhibrs
T3_shftrs ~~ T12_shftrs + T14_shftrs
T12_shftrs ~~ T14_shftrs
T3_emcnrs ~~ T12_emcnrs + T14_emcnrs
T12_emcnrs ~~ T14_emcnrs

## latent variable intercepts; constrains the means of the latent variable intercepts to 0
#the reason that you do this is so that the means will be pushed up to the second order LVs
BRI_T3 ~ 0*1
BRI_T12 ~ 0*1
BRI_T14 ~ 0*1

#model constraints for effect coding (this part is not necessary); but it creats effect #coding: loadin
#try it with and without this, should make models easier to interpret
L1 == 3 - L2 - L3
## means of indicators must average to 0 (in terms of the indicator means)
t1 == 0 - t2 - t3

#the intercept and slope done with effect coding will give you the actual metric from your indicator va

#final step is defining the normal growth model
i =~ 1*BRI_T3 + 1*BRI_T12 + 1*BRI_T14
s =~ 0*BRI_T3 + 1*BRI_T12 + 2*BRI_T14 '

fit.sec.order <- growth(sec.order, data=growth_stats, missing = "ML")
```

```
## 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 lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: the covariance matrix of the residuals of t
##                 variables (theta) is not positive definite;
##                 use inspect(fit,"theta") to investigate.
```

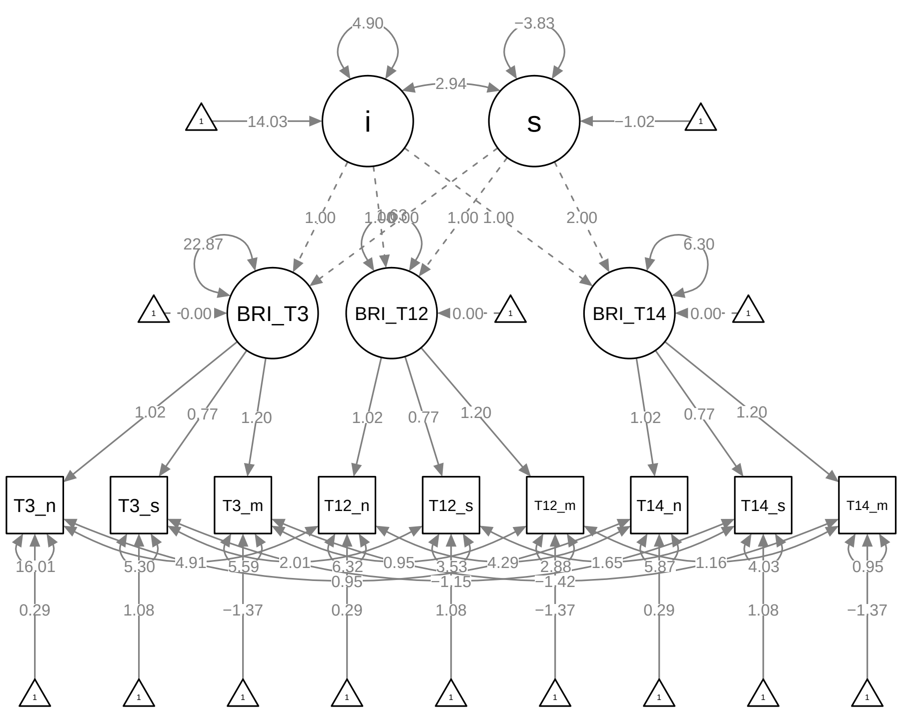
```r
summary(fit.sec.order, fit.measures=TRUE)
```

```
## lavaan (0.5-23.1097) converged normally after 185 iterations
##
##                                                   Used       Total
##   Number of observations                           205         348
##
##   Number of missing patterns                         7
##
##   Estimator                                         ML
##   Minimum Function Test Statistic               77.404
##   Degrees of freedom                                24
##   P-value (Chi-square)                           0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic              680.471
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)                    0.917
##   Tucker-Lewis Index (TLI)                       0.876
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -2380.070
##   Loglikelihood unrestricted model (H1)      -2341.368
##
##   Number of free parameters                         30
##   Akaike (AIC)                                4820.139
##   Bayesian (BIC)                              4919.830
##   Sample-size adjusted Bayesian (BIC)         4824.779
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.104
##   90 Percent Confidence Interval          0.079  0.131
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.189
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Standard Errors                             Standard
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   BRI_T3 =~
##     T3_inhbrs (L1)    1.021    0.038   26.715    0.000
```

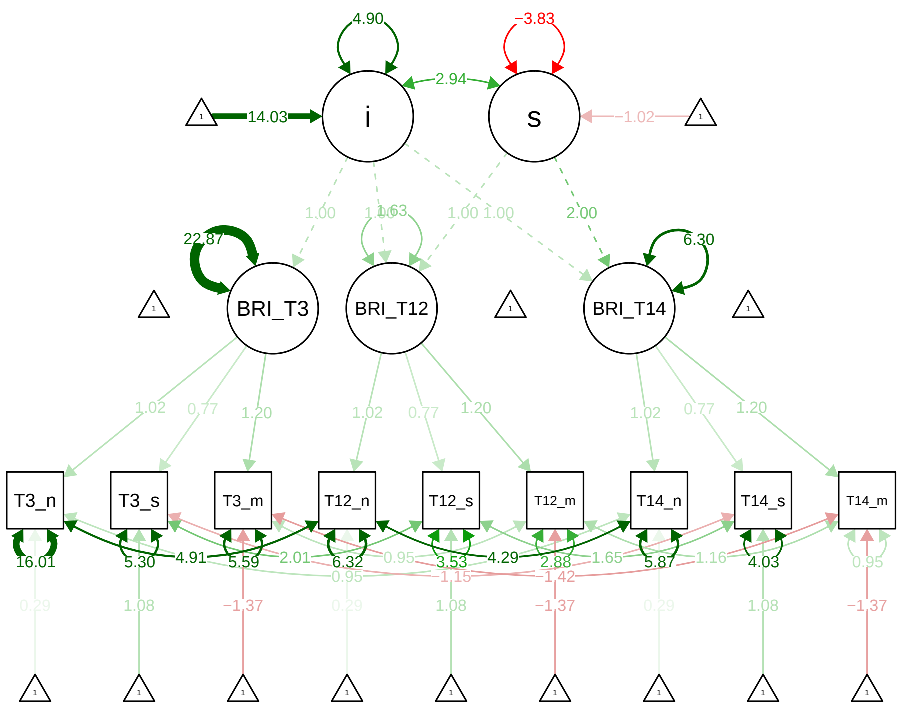
```
##     T3_shftrs (L2)    0.775    0.032   24.400    0.000
##     T3_emcnrs (L3)    1.204    0.036   33.392    0.000
##   BRI_T12 =~
##     T12_nhbrs (L1)    1.021    0.038   26.715    0.000
##     T12_shftr (L2)    0.775    0.032   24.400    0.000
##     T12_mcnrs (L3)    1.204    0.036   33.392    0.000
##   BRI_T14 =~
##     T14_nhbrs (L1)    1.021    0.038   26.715    0.000
##     T14_shftr (L2)    0.775    0.032   24.400    0.000
##     T14_mcnrs (L3)    1.204    0.036   33.392    0.000
##   i =~
##     BRI_T3            1.000
##     BRI_T12           1.000
##     BRI_T14           1.000
##   s =~
##     BRI_T3            0.000
##     BRI_T12           1.000
##     BRI_T14           2.000
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)
##  .T3_inhibrs ~~
##    .T12_inhibrs       4.908    1.571    3.124    0.002
##    .T14_inhibrs       0.953    2.627    0.363    0.717
##  .T12_inhibrs ~~
##    .T14_inhibrs       4.287    0.837    5.124    0.000
##  .T3_shftrs ~~
##    .T12_shftrs        2.014    0.752    2.680    0.007
##    .T14_shftrs       -1.146    0.995   -1.152    0.249
##  .T12_shftrs ~~
##    .T14_shftrs        1.648    0.527    3.124    0.002
##  .T3_emcnrs ~~
##    .T12_emcnrs        0.949    1.346    0.705    0.481
##    .T14_emcnrs       -1.424    1.283   -1.110    0.267
##  .T12_emcnrs ~~
##    .T14_emcnrs        1.162    0.620    1.876    0.061
##   i ~~
##     s                 2.937    2.057    1.428    0.153
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .T3_inhbrs (t1)    0.288    0.507    0.568    0.570
##    .T3_shftrs (t2)    1.082    0.427    2.535    0.011
##    .T3_emcnrs (t3)   -1.370    0.477   -2.873    0.004
##    .T12_nhbrs (t1)    0.288    0.507    0.568    0.570
##    .T12_shftr (t2)    1.082    0.427    2.535    0.011
##    .T12_mcnrs (t3)   -1.370    0.477   -2.873    0.004
##    .T14_nhbrs (t1)    0.288    0.507    0.568    0.570
##    .T14_shftr (t2)    1.082    0.427    2.535    0.011
##    .T14_mcnrs (t3)   -1.370    0.477   -2.873    0.004
##     BRI_T3            0.000
##     BRI_T12           0.000
##     BRI_T14           0.000
##     i                14.025    0.387   36.199    0.000
```

```
##     s                 -1.019    0.214   -4.757    0.000
##
## Variances:
##                     Estimate  Std.Err  z-value  P(>|z|)
##    .T3_inhibrs        16.007    3.332    4.805    0.000
##    .T3_shftrs          5.298    1.282    4.131    0.000
##    .T3_emcnrs          5.594    2.388    2.342    0.019
##    .T12_inhibrs        6.317    0.904    6.989    0.000
##    .T12_shftrs         3.527    0.513    6.876    0.000
##    .T12_emcnrs         2.881    0.791    3.642    0.000
##    .T14_inhibrs        5.870    1.075    5.462    0.000
##    .T14_shftrs         4.034    0.677    5.960    0.000
##    .T14_emcnrs         0.947    0.725    1.306    0.192
##     BRI_T3            22.869    5.556    4.116    0.000
##     BRI_T12            1.630    1.331    1.225    0.221
##     BRI_T14            6.300    2.706    2.328    0.020
##     i                  4.901    3.708    1.322    0.186
##     s                 -3.831    1.922   -1.993    0.046
##
## Constraints:
##                                                |Slack|
##     L1 - (3-L2-L3)                               0.000
##     t1 - (0-t2-t3)                               0.000
```

Semplots



Semplots



For longitudinal models, occasion specific variance can lead to biased estimates. We want to separate the time specific variance from the overall construct variance. Or, we want to make sure that the time specific variance doesn't make it appear that a construct is changing when really it is not.

Second-order growth models add a second level of latent variables representing a latent construct measured by multiple items at each time point

The factor loading ( ) for each item is interpreted as a regression slope relating the observed score to the latent construct. Loadings represent the amount of change in the observed score given a one unit change in the amount of the latent construct. Item intercepts ( ) represent the value of the observed score on an item when the value of the latent construct is zero.