

SEM Growth Models

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```
library(lavaan)

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

library(lme4)

## Loading required package: Matrix

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()

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

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 :
```

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

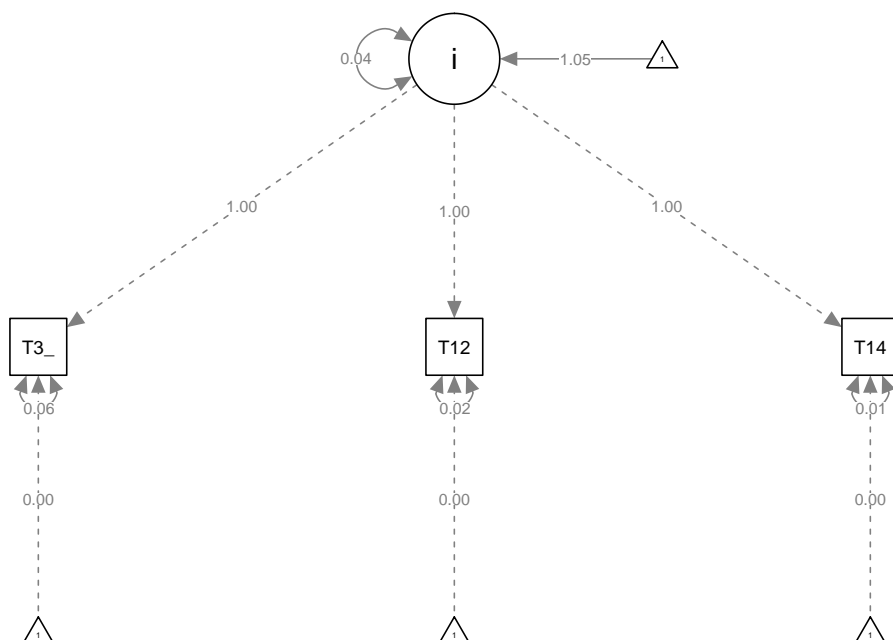
```
## lavaan (0.5-23.1097) converged normally after 59 iterations
##
##
##           Used           Total
## Number of observations      302      348
##
```

```

## 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

```

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



```

# 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.

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

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

summary (fixed.slope.fit)

## lavaan (0.5-23.1097) converged normally after 44 iterations
##
##
## Number of observations      Used      Total
##                            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 =~
## T3gecrs_cmbnd_c      1.000
## T12gecrs_conv      1.000
## T14gecrs_conv      1.000
## s =~
## T3gecrs_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|)

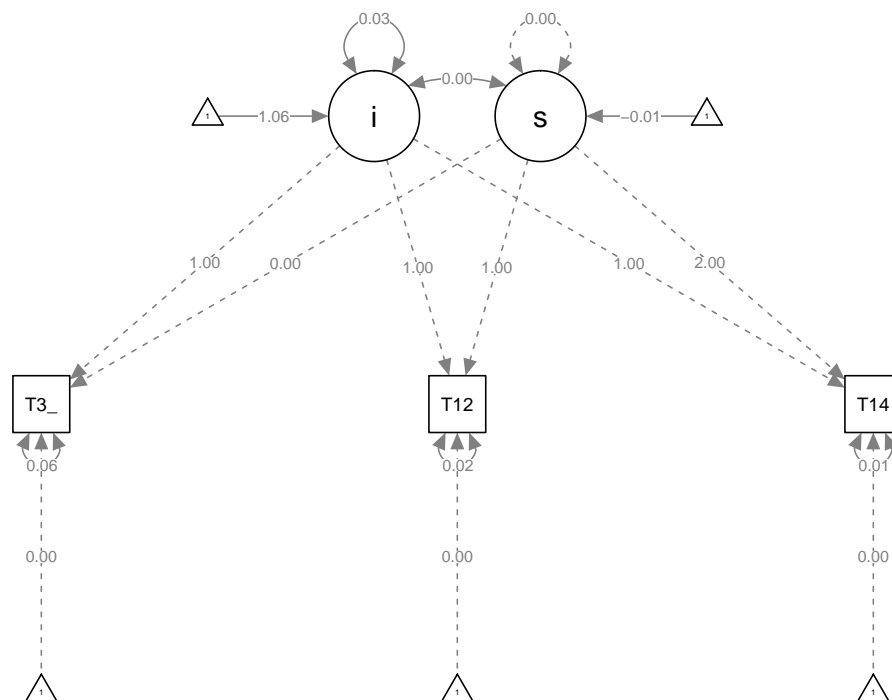
```

```
##      .T3gecrs_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
##      .T3gecrs_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
```

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



```
# 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 :
```

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

```
## lavaan (0.5-23.1097) converged normally after 67 iterations
```

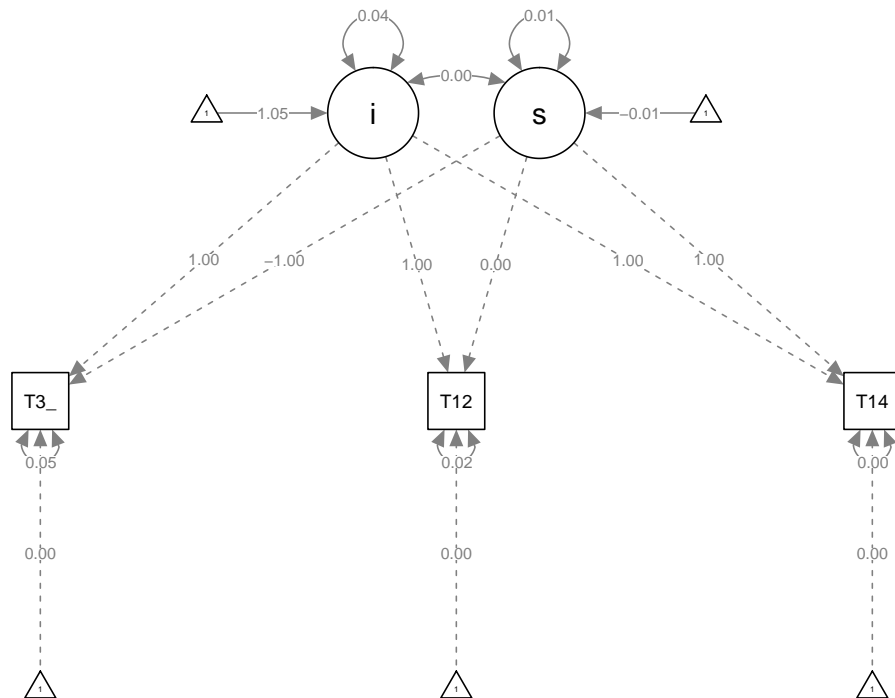
```
##
##              Used      Total
##      Number of observations      302      348
##
##      Number of missing patterns      7
```

```

##
## 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

```

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



```
# 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

```
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|)
##   .T3gecrs_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

```
#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

```

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 factors
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 creates effect #coding: loading
#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 variables

#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 59

## 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
## variables (theta) is not positive definite;
## use inspect(fit,"theta") to investigate.

```

```
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

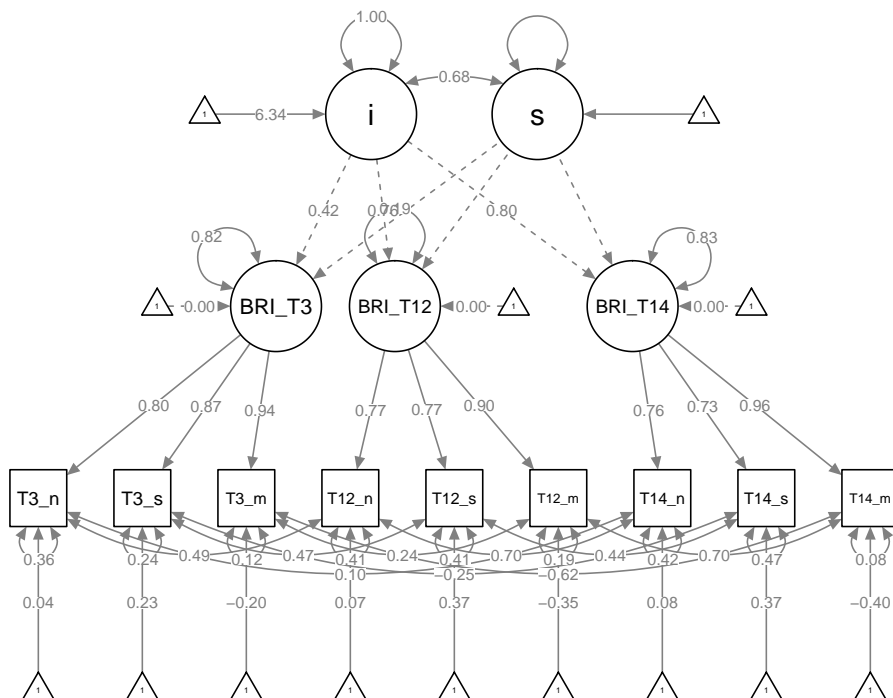
```

```

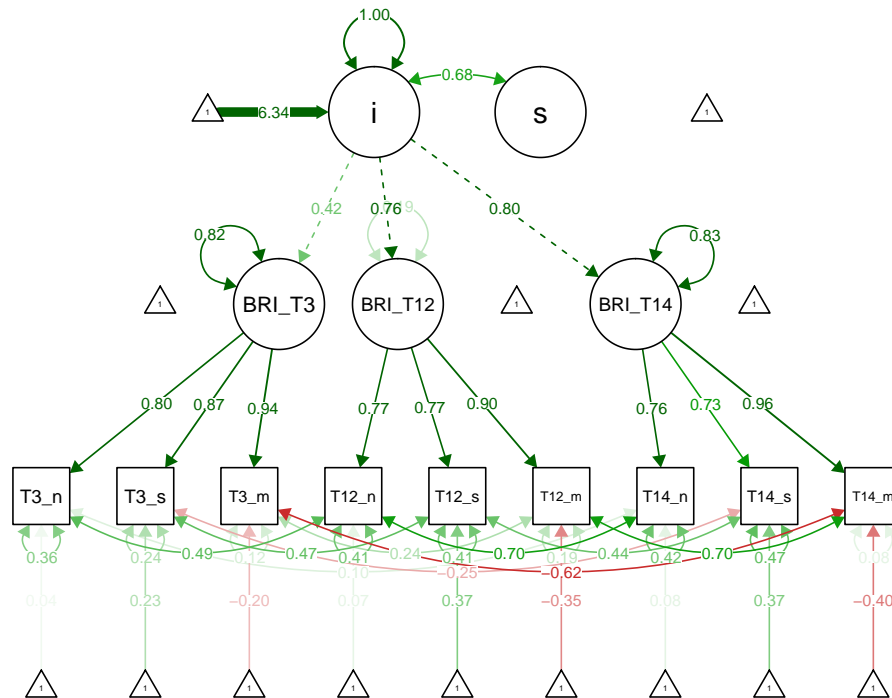
##      s                -1.019    0.214   -4.757    0.000
##
## Variances:
##              Estimate Std.Err  z-value  P(>|z|)
##      .T3_inhibrs    16.007    3.332    4.805    0.000
##      .T3_shftrs     5.298    1.282    4.131    0.000
##      .T3_emcnrs     5.594    2.388    2.342    0.019
##      .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.