

Homework 4 (SEM)

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Chapter 7: SEM

```
library(lme4)
library(ggplot2)
library(lavaan)
library(semPlot)
library(tidyverse)
oysup <- read.csv("~/Desktop/oysup_teacher_self.csv")
```

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?

```
# Marker variable
mod.1 <- 'neuro_t =~ TPER7_08 + TPER7_10 + TPER7_17R + TPER7_12R + TPER7_13R'
fit.1 <- cfa(mod.1, data=oysup)
summary(fit.1, fit.measures=TRUE)
```

```
## lavaan (0.6-1.1141) converged normally after 22 iterations
##
##                               Used      Total
##   Number of observations           523      1074
##
##   Estimator                        ML
##   Model Fit Test Statistic        65.896
##   Degrees of freedom                5
##   P-value (Chi-square)             0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic    983.162
##   Degrees of freedom                 10
##   P-value                           0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)        0.937
##   Tucker-Lewis Index (TLI)          0.875
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)      -3604.684
##   Loglikelihood unrestricted model (H1) -3571.736
##
```

```

## Number of free parameters 10
## Akaike (AIC) 7229.368
## Bayesian (BIC) 7271.964
## Sample-size adjusted Bayesian (BIC) 7240.222
##
## Root Mean Square Error of Approximation:
##
## RMSEA 0.153
## 90 Percent Confidence Interval 0.121 0.186
## P-value RMSEA <= 0.05 0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR 0.046
##
## Parameter Estimates:
##
## Information Expected
## Standard Errors Standard
##
## Latent Variables:
## Estimate Std.Err z-value P(>|z|)
## neuro_t =~
## TPER7_08 1.000
## TPER7_10 0.831 0.071 11.622 0.000
## TPER7_17R 1.176 0.082 14.418 0.000
## TPER7_12R 1.193 0.080 14.935 0.000
## TPER7_13R 0.641 0.061 10.488 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|)
## .TPER7_08 1.031 0.071 14.564 0.000
## .TPER7_10 0.824 0.056 14.793 0.000
## .TPER7_17R 0.514 0.046 11.125 0.000
## .TPER7_12R 0.273 0.037 7.365 0.000
## .TPER7_13R 0.704 0.046 15.226 0.000
## neuro_t 0.675 0.089 7.540 0.000

# Fixed factor
mod.2 <- 'neuro_t =~ TPER7_08 + TPER7_10 + TPER7_17R + TPER7_12R + TPER7_13R'
fit.2 <- cfa(mod.2, std.lv = T, data=oysup)
summary(fit.2, fit.measures=TRUE)

## lavaan (0.6-1.1141) converged normally after 14 iterations
##
## Used Total
## Number of observations 523 1074
##
## Estimator ML
## Model Fit Test Statistic 65.896
## Degrees of freedom 5
## P-value (Chi-square) 0.000
##
## Model test baseline model:
##

```

```

## Minimum Function Test Statistic          983.162
## Degrees of freedom                      10
## P-value                                0.000
##
## User model versus baseline model:
##
## Comparative Fit Index (CFI)              0.937
## Tucker-Lewis Index (TLI)                0.875
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0)            -3604.684
## Loglikelihood unrestricted model (H1)    -3571.736
##
## Number of free parameters                10
## Akaike (AIC)                           7229.368
## Bayesian (BIC)                          7271.964
## Sample-size adjusted Bayesian (BIC)     7240.222
##
## Root Mean Square Error of Approximation:
##
## RMSEA                                  0.153
## 90 Percent Confidence Interval          0.121  0.186
## P-value RMSEA <= 0.05                  0.000
##
## Standardized Root Mean Square Residual:
##
## SRMR                                  0.046
##
## Parameter Estimates:
##
## Information                            Expected
## Standard Errors                       Standard
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)
## neuro_t =~
##   TPER7_08      0.821   0.054   15.080   0.000
##   TPER7_10      0.682   0.048   14.255   0.000
##   TPER7_17R     0.966   0.047   20.715   0.000
##   TPER7_12R     0.980   0.042   23.600   0.000
##   TPER7_13R     0.526   0.043   12.302   0.000
##
## Variances:
##      Estimate  Std.Err  z-value  P(>|z|)
## .TPER7_08      1.031   0.071   14.564   0.000
## .TPER7_10      0.824   0.056   14.793   0.000
## .TPER7_17R     0.514   0.046   11.125   0.000
## .TPER7_12R     0.273   0.037    7.365   0.000
## .TPER7_13R     0.704   0.046   15.226   0.000
## neuro_t        1.000

```

```
# Effects coding
```

```
mod.3 <- 'neuro_t =~ NA*TPER7_08 + L1*TPER7_08 + L2*TPER7_10 + L3*TPER7_17R + L4*TPER7_12R + L5*TPER7_13R'
```

```
L1 == 5 - L2 - L3 - L4 - L5'
fit.3 <- cfa(mod.3, data=oysup)
summary(fit.3, fit.measures=TRUE)
```

```
## lavaan (0.6-1.1141) converged normally after 19 iterations
##
##                               Used      Total
##   Number of observations          523      1074
##
##   Estimator                      ML
##   Model Fit Test Statistic        65.896
##   Degrees of freedom              5
##   P-value (Chi-square)            0.000
##
## Model test baseline model:
##
##   Minimum Function Test Statistic    983.162
##   Degrees of freedom                10
##   P-value                          0.000
##
## User model versus baseline model:
##
##   Comparative Fit Index (CFI)        0.937
##   Tucker-Lewis Index (TLI)         0.875
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)      -3604.684
##   Loglikelihood unrestricted model (H1) -3571.736
##
##   Number of free parameters          10
##   Akaike (AIC)                      7229.368
##   Bayesian (BIC)                    7271.964
##   Sample-size adjusted Bayesian (BIC) 7240.222
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                          0.153
##   90 Percent Confidence Interval    0.121  0.186
##   P-value RMSEA <= 0.05            0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                          0.046
##
## Parameter Estimates:
##
##   Information                      Expected
##   Standard Errors                  Standard
##
## Latent Variables:
##
##           Estimate Std.Err  z-value  P(>|z|)
##   neuro_t =~
##   TPER7_08 (L1)    1.033    0.052   19.929    0.000
```

```

##      TPER7_10 (L2)      0.858    0.048    17.957    0.000
##      TPER7_17R (L3)    1.215    0.043    28.410    0.000
##      TPER7_12R (L4)    1.232    0.040    30.723    0.000
##      TPER7_13R (L5)    0.662    0.045    14.666    0.000
##
## Variances:
##              Estimate Std.Err z-value P(>|z|)
##      .TPER7_08      1.031   0.071   14.564   0.000
##      .TPER7_10      0.824   0.056   14.793   0.000
##      .TPER7_17R     0.514   0.046   11.125   0.000
##      .TPER7_12R     0.273   0.037    7.365   0.000
##      .TPER7_13R     0.704   0.046   15.226   0.000
##      neuro_t        0.632   0.047   13.332   0.000
##
## Constraints:
##                                     |Slack|
##      L1 - (5-L2-L3-L4-L5)          0.000

```

Using the marker variable approach, the loading of the first factor onto the latent variable is fixed to 1, and the other loadings relative to this range from .64 to 1.19. The CFI is .94. Using the fixed factor approach, the item loadings change – they range from .53 to .98. The residual variances of the items stay the same, but of course the variance of the latent neuroticism variable changes to 1. Using effects coding, the item loadings onto the latent variable change once more, ranging from .66 to 1.23, and the variance of the latent variable changes back to being freely estimated (.63).

2) What do the fit statistics say about your latent variable? Good/bad? Is your latent variable just identified/saturated, under-identified, or over-identified?

```
fitMeasures(fit.1)
```

```

##              npar              fmin              chisq
##              10.000              0.063              65.896
##              df              pvalue      baseline.chisq
##              5.000              0.000              983.162
##      baseline.df      baseline.pvalue              cfi
##              10.000              0.000              0.937
##              tli              nnfi              rfi
##              0.875              0.875              0.866
##              nfi              pnfi              ifi
##              0.933              0.466              0.938
##              rni              logl      unrestricted.logl
##              0.937      -3604.684      -3571.736
##              aic              bic              ntotal
##              7229.368      7271.964              523.000
##              bic2              rmsea      rmsea.ci.lower
##              7240.222              0.153              0.121
##      rmsea.ci.upper      rmsea.pvalue              rmr
##              0.186              0.000              0.062
##      rmr_nomean              srmr      srmr_bentler
##              0.062              0.046              0.046
##      srmr_bentler_nomean      srmr_bollen      srmr_bollen_nomean
##              0.046              0.046              0.046
##      srmr_mplus      srmr_mplus_nomean      cn_05

```

##	0.046	0.046	88.863
##	cn_01	gfi	agfi
##	120.735	0.954	0.863
##	pgfi	mfi	ecvi
##	0.318	0.943	0.164

Across all approaches (regardless of scaling), the CFI is .94 (great!), while the RMSEA is .15 (poor). There are 5 degrees of freedom, meaning that the model is over-identified - yay.

3) Fit a longitudinal CFA model where you a) first correlate your latent factors across time and then b) a second model that predicts later times by a previous time (i.e., auto-regressive; $t1 \rightarrow t2 \rightarrow t3$). What are your conclusions? How does one differ from the other?

```
# Residuals correlated over time
mod.4 <- 'neuro_t1 =~ TPER7_08 + TPER7_10 + TPER7_17R + TPER7_12R + TPER7_13R
neuro_t2 =~ TPER8_08 + TPER8_10 + TPER8_17R + TPER8_12R + TPER8_13R
neuro_t3 =~ TPER9_08 + TPER9_10 + TPER9_17R + TPER9_12R + TPER9_13R
neuro_t4 =~ TPER10_08 + TPER10_10 + TPER10_17R + TPER10_12R + TPER10_13R

TPER7_08 ~~ TPER8_08 + TPER9_08 + TPER10_08
TPER8_08 ~~ TPER9_08 + TPER10_08
TPER9_08 ~~ TPER10_08

TPER7_10 ~~ TPER8_10 + TPER9_10 + TPER10_10
TPER8_10 ~~ TPER9_10 + TPER10_10
TPER9_10 ~~ TPER10_10

TPER7_17R ~~ TPER8_17R + TPER9_17R + TPER10_17R
TPER8_17R ~~ TPER9_17R + TPER10_17R
TPER9_17R ~~ TPER10_17R

TPER7_12R ~~ TPER8_12R + TPER9_12R + TPER10_12R
TPER8_12R ~~ TPER9_12R + TPER10_12R
TPER9_12R ~~ TPER10_12R

TPER7_13R ~~ TPER8_13R + TPER9_13R + TPER10_13R
TPER8_13R ~~ TPER9_13R + TPER10_13R
TPER9_13R ~~ TPER10_13R'
fit.4 <- cfa(mod.4, data=oysup)
summary(fit.4, fit.measures=TRUE)
```

```
## lavaan (0.6-1.1141) converged normally after 49 iterations
##
##                               Used      Total
## Number of observations           134      1074
##
## Estimator                        ML
## Model Fit Test Statistic        245.340
## Degrees of freedom              134
## P-value (Chi-square)            0.000
##
## Model test baseline model:
```

```

##
## Minimum Function Test Statistic          1338.250
## Degrees of freedom                      190
## P-value                                0.000
##
## User model versus baseline model:
##
## Comparative Fit Index (CFI)              0.903
## Tucker-Lewis Index (TLI)                0.863
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0)            -3496.104
## Loglikelihood unrestricted model (H1)     -3373.434
##
## Number of free parameters                76
## Akaike (AIC)                            7144.208
## Bayesian (BIC)                          7364.443
## Sample-size adjusted Bayesian (BIC)      7124.037
##
## Root Mean Square Error of Approximation:
##
## RMSEA                                  0.079
## 90 Percent Confidence Interval          0.063  0.094
## P-value RMSEA <= 0.05                  0.002
##
## Standardized Root Mean Square Residual:
##
## SRMR                                  0.071
##
## Parameter Estimates:
##
## Information                            Expected
## Standard Errors                        Standard
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)
## neuro_t1 =~
##   TPER7_08      1.000
##   TPER7_10      0.653    0.106    6.130    0.000
##   TPER7_17R     1.105    0.114    9.697    0.000
##   TPER7_12R     1.086    0.102   10.671    0.000
##   TPER7_13R     0.602    0.089    6.738    0.000
## neuro_t2 =~
##   TPER8_08      1.000
##   TPER8_10      0.949    0.126    7.509    0.000
##   TPER8_17R     1.027    0.124    8.266    0.000
##   TPER8_12R     0.893    0.106    8.431    0.000
##   TPER8_13R     0.654    0.111    5.874    0.000
## neuro_t3 =~
##   TPER9_08      1.000
##   TPER9_10      0.896    0.121    7.430    0.000
##   TPER9_17R     0.844    0.120    7.030    0.000
##   TPER9_12R     0.916    0.117    7.817    0.000

```

```

##      TPER9_13R      0.438    0.097    4.538    0.000
##      neuro_t4 =~
##      TPER10_08      1.000
##      TPER10_10      0.602    0.124    4.849    0.000
##      TPER10_17R     0.963    0.133    7.256    0.000
##      TPER10_12R     1.004    0.134    7.489    0.000
##      TPER10_13R     0.615    0.116    5.307    0.000
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|)
##      .TPER7_08 ~~
##      .TPER8_08      -0.006    0.069   -0.081    0.936
##      .TPER9_08       0.019    0.071    0.275    0.784
##      .TPER10_08      0.243    0.084    2.899    0.004
##      .TPER8_08 ~~
##      .TPER9_08       0.077    0.073    1.059    0.290
##      .TPER10_08      0.031    0.082    0.371    0.711
##      .TPER9_08 ~~
##      .TPER10_08      0.136    0.086    1.579    0.114
##      .TPER7_10 ~~
##      .TPER8_10       0.015    0.069    0.224    0.823
##      .TPER9_10      -0.041    0.077   -0.537    0.591
##      .TPER10_10      0.117    0.079    1.485    0.137
##      .TPER8_10 ~~
##      .TPER9_10      -0.006    0.066   -0.086    0.931
##      .TPER10_10      0.042    0.067    0.635    0.525
##      .TPER9_10 ~~
##      .TPER10_10      0.117    0.075    1.552    0.121
##      .TPER7_17R ~~
##      .TPER8_17R      -0.007    0.051   -0.134    0.893
##      .TPER9_17R       0.023    0.065    0.360    0.719
##      .TPER10_17R     0.021    0.050    0.418    0.676
##      .TPER8_17R ~~
##      .TPER9_17R       0.072    0.062    1.163    0.245
##      .TPER10_17R     0.083    0.046    1.798    0.072
##      .TPER9_17R ~~
##      .TPER10_17R     0.064    0.059    1.075    0.282
##      .TPER7_12R ~~
##      .TPER8_12R      -0.009    0.033   -0.287    0.774
##      .TPER9_12R       0.069    0.048    1.421    0.155
##      .TPER10_12R     -0.013    0.035   -0.377    0.706
##      .TPER8_12R ~~
##      .TPER9_12R       0.156    0.052    3.015    0.003
##      .TPER10_12R     -0.010    0.035   -0.293    0.769
##      .TPER9_12R ~~
##      .TPER10_12R     0.138    0.053    2.581    0.010
##      .TPER7_13R ~~
##      .TPER8_13R       0.068    0.063    1.087    0.277
##      .TPER9_13R       0.193    0.068    2.838    0.005
##      .TPER10_13R     0.160    0.062    2.598    0.009
##      .TPER8_13R ~~
##      .TPER9_13R       0.267    0.076    3.523    0.000
##      .TPER10_13R     0.137    0.067    2.052    0.040
##      .TPER9_13R ~~

```



```
##      .TPER10_13R      0.136    0.070    1.938    0.053
##      neuro_t1 ~~
##      neuro_t2      0.397    0.094    4.206    0.000
##      neuro_t3      0.454    0.106    4.276    0.000
##      neuro_t4      0.368    0.098    3.755    0.000
##      neuro_t2 ~~
##      neuro_t3      0.292    0.091    3.226    0.001
##      neuro_t4      0.244    0.079    3.082    0.002
##      neuro_t3 ~~
##      neuro_t4      0.288    0.092    3.131    0.002
##
## Variances:
##      Estimate Std.Err z-value P(>|z|)
##      .TPER7_08      0.696    0.097    7.161    0.000
##      .TPER7_10      0.905    0.115    7.876    0.000
##      .TPER7_17R     0.507    0.080    6.339    0.000
##      .TPER7_12R     0.174    0.050    3.453    0.001
##      .TPER7_13R     0.635    0.081    7.812    0.000
##      .TPER8_08      0.706    0.101    6.976    0.000
##      .TPER8_10      0.580    0.085    6.844    0.000
##      .TPER8_17R     0.420    0.070    5.989    0.000
##      .TPER8_12R     0.285    0.050    5.651    0.000
##      .TPER8_13R     0.748    0.097    7.711    0.000
##      .TPER9_08      0.653    0.112    5.818    0.000
##      .TPER9_10      0.698    0.109    6.391    0.000
##      .TPER9_17R     0.785    0.116    6.783    0.000
##      .TPER9_12R     0.685    0.108    6.319    0.000
##      .TPER9_13R     0.849    0.108    7.853    0.000
##      .TPER10_08     1.016    0.139    7.287    0.000
##      .TPER10_10     0.842    0.108    7.805    0.000
##      .TPER10_17R    0.390    0.068    5.753    0.000
##      .TPER10_12R    0.248    0.060    4.134    0.000
##      .TPER10_13R    0.693    0.090    7.703    0.000
##      neuro_t1      0.851    0.172    4.940    0.000
##      neuro_t2      0.685    0.155    4.412    0.000
##      neuro_t3      0.865    0.183    4.719    0.000
##      neuro_t4      0.659    0.170    3.873    0.000
```

```
# Auto-regressive model
```

```
mod.5 <- 'neuro_t1 =~ TPER7_08 + TPER7_10 + TPER7_17R + TPER7_12R + TPER7_13R
neuro_t2 =~ TPER8_08 + TPER8_10 + TPER8_17R + TPER8_12R + TPER8_13R
neuro_t3 =~ TPER9_08 + TPER9_10 + TPER9_17R + TPER9_12R + TPER9_13R
neuro_t4 =~ TPER10_08 + TPER10_10 + TPER10_17R + TPER10_12R + TPER10_13R

TPER7_08 ~~ TPER8_08 + TPER9_08 + TPER10_08
TPER8_08 ~~ TPER9_08 + TPER10_08
TPER9_08 ~~ TPER10_08

TPER7_10 ~~ TPER8_10 + TPER9_10 + TPER10_10
TPER8_10 ~~ TPER9_10 + TPER10_10
TPER9_10 ~~ TPER10_10

TPER7_17R ~~ TPER8_17R + TPER9_17R + TPER10_17R
TPER8_17R ~~ TPER9_17R + TPER10_17R
```

```

TPER9_17R ~~ TPER10_17R

TPER7_12R ~~ TPER8_12R + TPER9_12R + TPER10_12R
TPER8_12R ~~ TPER9_12R + TPER10_12R
TPER9_12R ~~ TPER10_12R

TPER7_13R ~~ TPER8_13R + TPER9_13R + TPER10_13R
TPER8_13R ~~ TPER9_13R + TPER10_13R
TPER9_13R ~~ TPER10_13R

neuro_t4 ~ neuro_t3
neuro_t3 ~ neuro_t2
neuro_t2 ~ neuro_t1'
fit.5 <- cfa(mod.5, data=oysup)
summary(fit.5, fit.measures=TRUE)

## lavaan (0.6-1.1141) converged normally after 44 iterations
##
##
##           Used           Total
## Number of observations           134           1074
##
## Estimator                       ML
## Model Fit Test Statistic         277.039
## Degrees of freedom               137
## P-value (Chi-square)             0.000
##
## Model test baseline model:
##
## Minimum Function Test Statistic    1338.250
## Degrees of freedom                 190
## P-value                           0.000
##
## User model versus baseline model:
##
## Comparative Fit Index (CFI)        0.878
## Tucker-Lewis Index (TLI)          0.831
##
## Loglikelihood and Information Criteria:
##
## Loglikelihood user model (H0)      -3511.953
## Loglikelihood unrestricted model (H1) -3373.434
##
## Number of free parameters           73
## Akaike (AIC)                       7169.906
## Bayesian (BIC)                     7381.449
## Sample-size adjusted Bayesian (BIC) 7150.532
##
## Root Mean Square Error of Approximation:
##
## RMSEA                             0.087
## 90 Percent Confidence Interval      0.072 0.102
## P-value RMSEA <= 0.05              0.000
##
## Standardized Root Mean Square Residual:

```

```

##
##      SRMR                                0.117
##
## Parameter Estimates:
##
##      Information                                Expected
##      Standard Errors                            Standard
##
## Latent Variables:
##      Estimate   Std.Err   z-value   P(>|z|)
##      neuro_t1 =~
##      TPER7_08      1.000
##      TPER7_10      0.659    0.109    6.033    0.000
##      TPER7_17R     1.127    0.118    9.573    0.000
##      TPER7_12R     1.112    0.106   10.495    0.000
##      TPER7_13R     0.600    0.090    6.627    0.000
##      neuro_t2 =~
##      TPER8_08      1.000
##      TPER8_10      0.943    0.127    7.421    0.000
##      TPER8_17R     1.028    0.125    8.226    0.000
##      TPER8_12R     0.903    0.108    8.387    0.000
##      TPER8_13R     0.655    0.112    5.853    0.000
##      neuro_t3 =~
##      TPER9_08      1.000
##      TPER9_10      0.905    0.125    7.215    0.000
##      TPER9_17R     0.871    0.125    6.958    0.000
##      TPER9_12R     0.958    0.123    7.788    0.000
##      TPER9_13R     0.436    0.099    4.407    0.000
##      neuro_t4 =~
##      TPER10_08     1.000
##      TPER10_10     0.604    0.131    4.622    0.000
##      TPER10_17R    1.010    0.143    7.061    0.000
##      TPER10_12R    1.085    0.149    7.281    0.000
##      TPER10_13R    0.621    0.122    5.107    0.000
##
## Regressions:
##      Estimate   Std.Err   z-value   P(>|z|)
##      neuro_t4 ~
##      neuro_t3      0.348    0.095    3.647    0.000
##      neuro_t3 ~
##      neuro_t2      0.478    0.118    4.037    0.000
##      neuro_t2 ~
##      neuro_t1      0.490    0.098    4.980    0.000
##
## Covariances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .TPER7_08 ~~
##      .TPER8_08     -0.017    0.069   -0.251    0.801
##      .TPER9_08      0.031    0.072    0.430    0.667
##      .TPER10_08     0.239    0.085    2.812    0.005
##      .TPER8_08 ~~
##      .TPER9_08      0.075    0.074    1.019    0.308
##      .TPER10_08     0.035    0.083    0.415    0.678
##      .TPER9_08 ~~

```

##	.TPER10_08	0.151	0.089	1.710	0.087
##	.TPER7_10 ~~				
##	.TPER8_10	0.008	0.069	0.122	0.903
##	.TPER9_10	-0.038	0.078	-0.489	0.625
##	.TPER10_10	0.114	0.080	1.424	0.155
##	.TPER8_10 ~~				
##	.TPER9_10	-0.005	0.067	-0.077	0.939
##	.TPER10_10	0.049	0.068	0.728	0.466
##	.TPER9_10 ~~				
##	.TPER10_10	0.117	0.077	1.531	0.126
##	.TPER7_17R ~~				
##	.TPER8_17R	-0.003	0.050	-0.062	0.951
##	.TPER9_17R	0.031	0.065	0.471	0.637
##	.TPER10_17R	0.028	0.049	0.563	0.573
##	.TPER8_17R ~~				
##	.TPER9_17R	0.054	0.061	0.875	0.381
##	.TPER10_17R	0.075	0.045	1.654	0.098
##	.TPER9_17R ~~				
##	.TPER10_17R	0.053	0.059	0.898	0.369
##	.TPER7_12R ~~				
##	.TPER8_12R	-0.006	0.033	-0.181	0.856
##	.TPER9_12R	0.089	0.048	1.852	0.064
##	.TPER10_12R	0.007	0.034	0.210	0.834
##	.TPER8_12R ~~				
##	.TPER9_12R	0.146	0.052	2.840	0.005
##	.TPER10_12R	-0.012	0.035	-0.345	0.730
##	.TPER9_12R ~~				
##	.TPER10_12R	0.115	0.052	2.211	0.027
##	.TPER7_13R ~~				
##	.TPER8_13R	0.066	0.063	1.056	0.291
##	.TPER9_13R	0.196	0.069	2.860	0.004
##	.TPER10_13R	0.162	0.062	2.604	0.009
##	.TPER8_13R ~~				
##	.TPER9_13R	0.265	0.076	3.492	0.000
##	.TPER10_13R	0.137	0.067	2.045	0.041
##	.TPER9_13R ~~				
##	.TPER10_13R	0.137	0.071	1.928	0.054

Variances:

##		Estimate	Std.Err	z-value	P(> z)
##	.TPER7_08	0.709	0.098	7.208	0.000
##	.TPER7_10	0.912	0.116	7.883	0.000
##	.TPER7_17R	0.506	0.081	6.266	0.000
##	.TPER7_12R	0.168	0.052	3.230	0.001
##	.TPER7_13R	0.639	0.082	7.829	0.000
##	.TPER8_08	0.709	0.102	6.981	0.000
##	.TPER8_10	0.589	0.086	6.882	0.000
##	.TPER8_17R	0.416	0.070	5.970	0.000
##	.TPER8_12R	0.290	0.051	5.687	0.000
##	.TPER8_13R	0.744	0.096	7.709	0.000
##	.TPER9_08	0.689	0.115	5.969	0.000
##	.TPER9_10	0.712	0.111	6.412	0.000
##	.TPER9_17R	0.771	0.116	6.674	0.000
##	.TPER9_12R	0.646	0.107	6.044	0.000

##	.TPER9_13R	0.859	0.109	7.865	0.000
##	.TPER10_08	1.055	0.142	7.407	0.000
##	.TPER10_10	0.860	0.110	7.851	0.000
##	.TPER10_17R	0.382	0.068	5.592	0.000
##	.TPER10_12R	0.214	0.061	3.476	0.001
##	.TPER10_13R	0.705	0.091	7.754	0.000
##	neuro_t1	0.813	0.167	4.866	0.000
##	.neuro_t2	0.485	0.115	4.226	0.000
##	.neuro_t3	0.677	0.152	4.459	0.000
##	.neuro_t4	0.502	0.136	3.707	0.000

Based on CFI and RSMEA values, the auto-regressive model fits the data a bit poorer than the other.

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

```
# SEM
model.6 <- 'neuro_i =~ 1*neuro_7t + 1*neuro_8t + 1*neuro_9t + 1*neuro_10t
            neuro_s =~ 0*neuro_7t + 1*neuro_8t + 2*neuro_9t + 3*neuro_10t'
fit.6 <- growth(model.6, data = oysup)

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

summary(fit.6)

## lavaan (0.6-1.1141) converged normally after 30 iterations
##
##                                     Used      Total
##   Number of observations                135      1074
##
##   Estimator                             ML
##   Model Fit Test Statistic              3.768
##   Degrees of freedom                     5
##   P-value (Chi-square)                  0.583
##
## Parameter Estimates:
##
##   Information                          Expected
##   Standard Errors                      Standard
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)
##   neuro_i =~
##     neuro_7t        1.000
##     neuro_8t        1.000
##     neuro_9t        1.000
##     neuro_10t       1.000
##   neuro_s =~
##     neuro_7t        0.000
##     neuro_8t        1.000
##     neuro_9t        2.000
##     neuro_10t       3.000
##
```

```
## Covariances:
##           Estimate Std.Err z-value P(>|z|)
##   neuro_i ~~
##   neuro_s      0.054   0.048   1.112   0.266
##
## Intercepts:
##           Estimate Std.Err z-value P(>|z|)
##   .neuro_7t      0.000
##   .neuro_8t      0.000
##   .neuro_9t      0.000
##   .neuro_10t     0.000
##   neuro_i        2.287   0.077  29.776   0.000
##   neuro_s       -0.066   0.030  -2.165   0.030
##
## Variances:
##           Estimate Std.Err z-value P(>|z|)
##   .neuro_7t      0.806   0.147   5.476   0.000
##   .neuro_8t      0.795   0.116   6.834   0.000
##   .neuro_9t      0.897   0.127   7.086   0.000
##   .neuro_10t     0.946   0.161   5.890   0.000
##   neuro_i        0.228   0.125   1.824   0.068
##   neuro_s       -0.050   0.027  -1.826   0.068
```

```
# restructuring for HLM
```

```
oysup_long <- tbl_df(oysup) %>%
  gather(c(neuro_7t:neuro_10t), key = "grade", value = "value") %>%
  separate(grade, into = c("variable", "grade"), sep = "_", convert = T) %>%
  separate(grade, into = c("grade", "delete"), sep = "t") %>%
  mutate(grade = as.numeric(grade)) %>%
  dplyr::select(-delete) %>%
  spread(variable, value)
```

```
# HLM
```

```
model.7 <- lmer(neuro ~ 1 + grade + (1 + grade | FAMID), data=oysup_long)
summary(model.7)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: neuro ~ 1 + grade + (1 + grade | FAMID)
## Data: oysup_long
##
## REML criterion at convergence: 6640.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.99345 -0.74109 -0.09588  0.68525  2.35649
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## FAMID (Intercept) 0.758431 0.87088
##      grade      0.001348 0.03671 -1.00
## Residual      0.755907 0.86943
## Number of obs: 2337, groups: FAMID, 939
##
## Fixed effects:
##           Estimate Std. Error t value
```

```
## (Intercept)  2.82385    0.16432  17.185
## grade       -0.07221    0.01902  -3.796
##
## Correlation of Fixed Effects:
##      (Intr)
## grade -0.987
```

Both models estimate the average slope at about -.07. The intercepts and random effects are estimated differently.

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

```
model.8 <- 'neuro_i =~ 1*neuro_7t + 1*neuro_8t + 1*neuro_9t + 1*neuro_10t
            neuro_s =~ 0*neuro_7t + 1*neuro_8t + 2*neuro_9t + 3*neuro_10t

neuro_7t ~~ u*neuro_7t
neuro_8t ~~ u*neuro_8t
neuro_9t ~~ u*neuro_9t
neuro_10t ~~ u*neuro_10t'
fit.8 <- growth(model.8, data = oysup)
```

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

```
summary(fit.8)
```

```
## lavaan (0.6-1.1141) converged normally after 24 iterations
##
##                                     Used      Total
##   Number of observations                135      1074
##
##   Estimator                             ML
##   Model Fit Test Statistic              4.583
##   Degrees of freedom                     8
##   P-value (Chi-square)                  0.801
##
## Parameter Estimates:
##
##   Information                          Expected
##   Standard Errors                      Standard
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)
##   neuro_i =~
##     neuro_7t         1.000
##     neuro_8t         1.000
##     neuro_9t         1.000
##     neuro_10t        1.000
##   neuro_s =~
##     neuro_7t         0.000
##     neuro_8t         1.000
##     neuro_9t         2.000
##     neuro_10t        3.000
```

```
##
## Covariances:
##           Estimate Std.Err z-value P(>|z|)
##   neuro_i ~~
##   neuro_s      0.061   0.039   1.561   0.119
##
## Intercepts:
##           Estimate Std.Err z-value P(>|z|)
##   .neuro_7t      0.000
##   .neuro_8t      0.000
##   .neuro_9t      0.000
##   .neuro_10t     0.000
##   neuro_i        2.287   0.077  29.745   0.000
##   neuro_s       -0.064   0.030  -2.117   0.034
##
## Variances:
##           Estimate Std.Err z-value P(>|z|)
##   .neuro_7t (u)   0.853   0.073  11.619   0.000
##   .neuro_8t (u)   0.853   0.073  11.619   0.000
##   .neuro_9t (u)   0.853   0.073  11.619   0.000
##   .neuro_10t (u)  0.853   0.073  11.619   0.000
##   neuro_i      0.201   0.110   1.830   0.067
##   neuro_s     -0.045   0.021  -2.150   0.032
```

```
fitMeasures(fit.8)
```

```
##           npar           fmin           chisq
##           6.000           0.017           4.583
##           df           pvalue baseline.chisq
##           8.000           0.801           56.057
## baseline.df baseline.pvalue           cfi
##           6.000           0.000           1.000
##           tli           nnfi           rfi
##           1.051           1.051           0.939
##           nfi           pnfi           ifi
##           0.918           1.224           1.071
##           rni           logl unrestricted.logl
##           1.068          -759.039          -756.747
##           aic           bic           ntotal
##           1530.078          1547.510           135.000
##           bic2           rmsea rmsea.ci.lower
##           1528.530           0.000           0.000
## rmsea.ci.upper rmsea.pvalue           rmr
##           0.065           0.911           0.045
## rmr_nomean srmr srmr_bentler
##           0.045           0.051           0.051
## srmr_bentler_nomean srmr_bollen srmr_bollen_nomean
##           0.043           0.028           0.023
## srmr_mplus srmr_mplus_nomean           cn_05
##           0.040           0.041           457.752
##           cn_01           gfi           agfi
##           592.738           0.997           0.995
##           pgfi           mfi           ecvi
##           0.570           1.013           NA
```


Yep. These constraints are overly restrictive for the nature of this data across four years, and so the model becomes fully saturated and the cfi defaults to 1.

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

```
model.9 <- 'neuro_i =~ 1*neuro_7t + 1*neuro_8t + 1*neuro_9t + 1*neuro_10t
           neuro_s =~ 0*neuro_7t + 1*neuro_8t + 2*neuro_9t + 3*neuro_10t
           neuro_s ~~ 0*neuro_s'
fit.9 <- growth(model.9, data = oysup)
```

```
## 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.
```

```
summary(fit.9)
```

```
## lavaan (0.6-1.1141) converged normally after 24 iterations
```

```
##
##                               Used      Total
##   Number of observations           135      1074
##
##   Estimator                      ML
##   Model Fit Test Statistic        7.073
##   Degrees of freedom              6
##   P-value (Chi-square)            0.314
##
```

```
## Parameter Estimates:
```

```
##
##   Information                      Expected
##   Standard Errors                  Standard
##
```

```
## Latent Variables:
```

```
##           Estimate Std.Err z-value P(>|z|)
##   neuro_i =~
##     neuro_7t      1.000
##     neuro_8t      1.000
##     neuro_9t      1.000
##     neuro_10t     1.000
##   neuro_s =~
##     neuro_7t      0.000
##     neuro_8t      1.000
##     neuro_9t      2.000
##     neuro_10t     3.000
##
```

```
## Covariances:
```

```
##           Estimate Std.Err z-value P(>|z|)
##   neuro_i ~~
##     neuro_s      -0.022    0.028   -0.782    0.434
##
```

```
## Intercepts:
```

```
##           Estimate Std.Err z-value P(>|z|)
##   .neuro_7t      0.000
```

```
##      .neuro_8t          0.000
##      .neuro_9t          0.000
##      .neuro_10t         0.000
##      neuro_i           2.296    0.079    28.890    0.000
##      neuro_s          -0.068    0.033    -2.082    0.037
##
## Variances:
##              Estimate Std.Err  z-value  P(>|z|)
##      neuro_s          0.000
##      .neuro_7t         0.655    0.111    5.919    0.000
##      .neuro_8t         0.796    0.116    6.858    0.000
##      .neuro_9t         0.873    0.124    7.072    0.000
##      .neuro_10t        0.779    0.121    6.456    0.000
##      neuro_i          0.368    0.105    3.512    0.000
```

```
anova(fit.6, fit.9)
```

```
## Chi Square Difference Test
##
##      Df      AIC      BIC  Chisq Chisq diff Df diff Pr(>Chisq)
## fit.6  5 1535.3 1561.4 3.7675
## fit.9  6 1536.6 1559.8 7.0729      3.3053      1    0.06906 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Honestly, not much changed, but there wasn't much variation in the slope to begin with. Now, the slope's variance is constrained to zero, whereas before, it was estimated at -.05 (basically zero). The intercept increased by a teeny tiny bit, and the magnitude of the (negative) fixed slope became a teeny tiny bit larger. However, the intercept variance did increase from .23 to .37, likely because that extra variance has to go somewhere!

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

```
model.10 <- 'neuro_i =~ 1*neuro_7t + 1*neuro_8t + 1*neuro_9t + 1*neuro_10t
             neuro_s =~ 1*neuro_7t + 2*neuro_8t + 3*neuro_9t + 4*neuro_10t'
fit.10 <- growth(model.10, data = oysup)
```

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

```
summary(fit.10)
```

```
## lavaan (0.6-1.1141) converged normally after 36 iterations
##
##              Used      Total
## Number of observations          135      1074
##
## Estimator                      ML
## Model Fit Test Statistic        3.768
## Degrees of freedom              5
## P-value (Chi-square)            0.583
##
## Parameter Estimates:
##
```

```

##      Information                                Expected
##      Standard Errors                            Standard
##
## Latent Variables:
##      Estimate   Std.Err   z-value   P(>|z|)
##      neuro_i =~
##      neuro_7t      1.000
##      neuro_8t      1.000
##      neuro_9t      1.000
##      neuro_10t     1.000
##      neuro_s =~
##      neuro_7t      1.000
##      neuro_8t      2.000
##      neuro_9t      3.000
##      neuro_10t     4.000
##
## Covariances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      neuro_i ~~
##      neuro_s      0.103    0.073    1.422    0.155
##
## Intercepts:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .neuro_7t    0.000
##      .neuro_8t    0.000
##      .neuro_9t    0.000
##      .neuro_10t   0.000
##      neuro_i      2.353    0.099    23.879    0.000
##      neuro_s     -0.066    0.030    -2.165    0.030
##
## Variances:
##      Estimate   Std.Err   z-value   P(>|z|)
##      .neuro_7t    0.806    0.147    5.476    0.000
##      .neuro_8t    0.795    0.116    6.834    0.000
##      .neuro_9t    0.897    0.127    7.086    0.000
##      .neuro_10t   0.946    0.161    5.890    0.000
##      neuro_i      0.071    0.234    0.305    0.760
##      neuro_s     -0.050    0.027    -1.826    0.068

```

```
fitMeasures(fit.10)
```

```

##      npar      fmin      chisq
##      9.000      0.014      3.768
##      df      pvalue      baseline.chisq
##      5.000      0.583      56.057
##      baseline.df      baseline.pvalue      cfi
##      6.000      0.000      1.000
##      tli      nnfi      rfi
##      1.030      1.030      0.919
##      nfi      pnfi      ifi
##      0.933      0.777      1.024
##      rni      logl      unrestricted.logl
##      1.025      -758.631      -756.747
##      aic      bic      ntotal
##      1535.262      1561.410      135.000

```

```
##          bic2          rmsea      rmsea.ci.lower
##      1532.940          0.000          0.000
##      rmsea.ci.upper      rmsea.pvalue          rmr
##          0.103          0.738          0.030
##      rmr_nomean          srmr          srmr_bentler
##          0.030          0.043          0.043
## srmr_bentler_nomean      srmr_bollen srmr_bollen_nomean
##          0.028          0.028          0.019
##      srmr_mplus      srmr_mplus_nomean          cn_05
##          0.031          0.026          397.685
##          cn_01          gfi          agfi
##          541.581          0.998          0.993
##          pgfi          mfi          ecvi
##          0.356          1.005          NA
```

The estimate of the slope did not change; however, the estimate of the intercept and its variance did.

8) Try a different type of estimation (see lavaan tutorial for details). How does that change your model?

```
model.11 <- 'neuro_i =~ 1*neuro_7t + 1*neuro_8t + 1*neuro_9t + 1*neuro_10t
             neuro_s =~ 0*neuro_7t + 1*neuro_8t + 2*neuro_9t + 3*neuro_10t'
fit.11 <- growth(model.11, data = oysup, estimator = "DWLS")
```

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

```
summary(fit.11)
```

```
## lavaan (0.6-1.1141) converged normally after 21 iterations
##
##                                     Used      Total
##      Number of observations          135      1074
##
##      Estimator                      DWLS
##      Model Fit Test Statistic        2.962
##      Degrees of freedom              5
##      P-value (Chi-square)            0.706
##
## Parameter Estimates:
##
##      Information                      Expected
##      Standard Errors                  Standard
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)
##      neuro_i =~
##      neuro_7t      1.000
##      neuro_8t      1.000
##      neuro_9t      1.000
##      neuro_10t     1.000
##      neuro_s =~
##      neuro_7t      0.000
##      neuro_8t      1.000
```

```
##      neuro_9t          2.000
##      neuro_10t         3.000
##
## Covariances:
##              Estimate Std.Err z-value P(>|z|)
##      neuro_i ~~
##      neuro_s          0.055    0.063    0.868    0.385
##
## Intercepts:
##              Estimate Std.Err z-value P(>|z|)
##      .neuro_7t          0.000
##      .neuro_8t          0.000
##      .neuro_9t          0.000
##      .neuro_10t         0.000
##      neuro_i           2.286    0.074   30.903    0.000
##      neuro_s          -0.064    0.040   -1.625    0.104
##
## Variances:
##              Estimate Std.Err z-value P(>|z|)
##      .neuro_7t          0.828    0.169    4.912    0.000
##      .neuro_8t          0.750    0.112    6.705    0.000
##      .neuro_9t          0.927    0.108    8.574    0.000
##      .neuro_10t         0.948    0.183    5.192    0.000
##      neuro_i           0.231    0.136    1.695    0.090
##      neuro_s          -0.051    0.039   -1.315    0.189
```

```
fitMeasures(fit.11, c("cfi", "rmsea"))
```

```
##      cfi rmsea
##      1      0
```

```
fitMeasures(fit.6, c("cfi", "rmsea"))
```

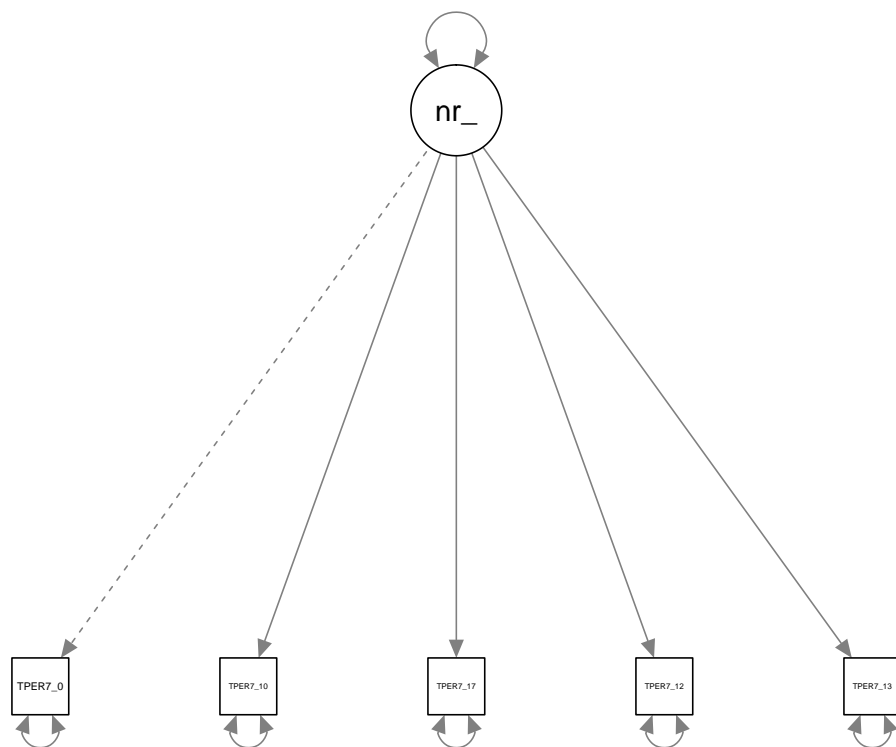
```
##      cfi rmsea
##      1      0
```

Not much of a difference between using diagonal weighted least squares estimation and the default (maximum likelihoods).

9) Provide semplots for each of the models.

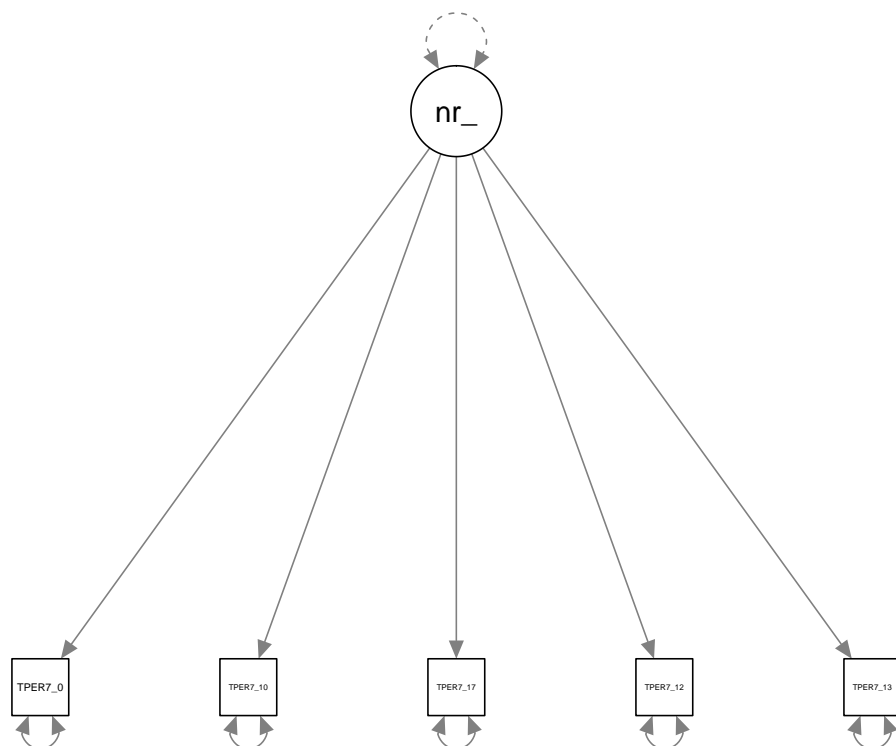
```
semPaths(fit.1)
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed
## = Directed, : The following arguments are not documented and likely not
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;
## residEdge; CircleEdgeEnd
```



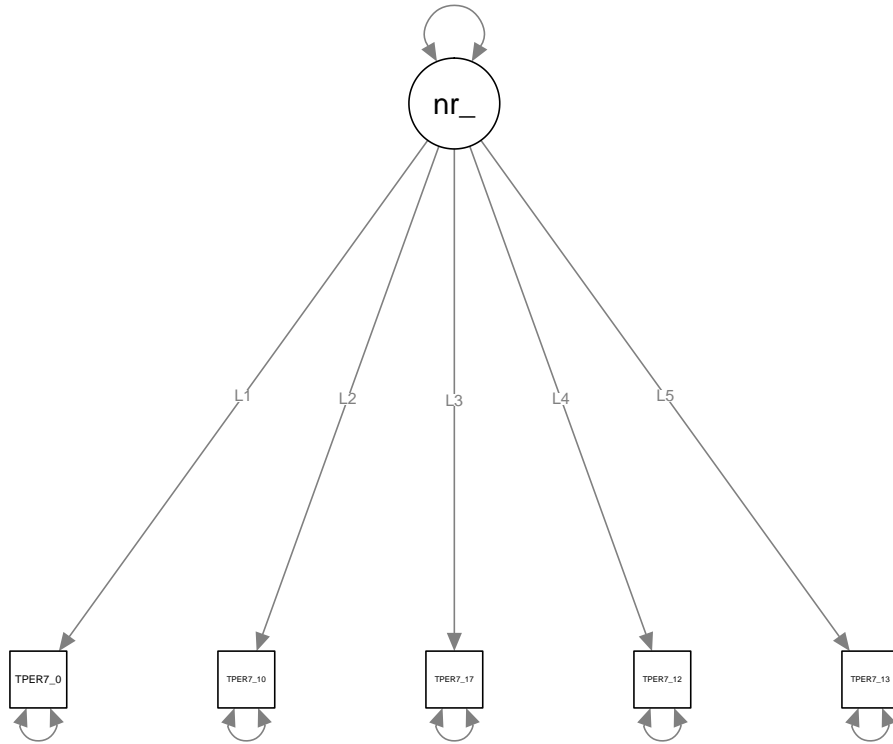
```
semPaths(fit.2)
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed
## = Directed, : The following arguments are not documented and likely not
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;
## residEdge; CircleEdgeEnd
```



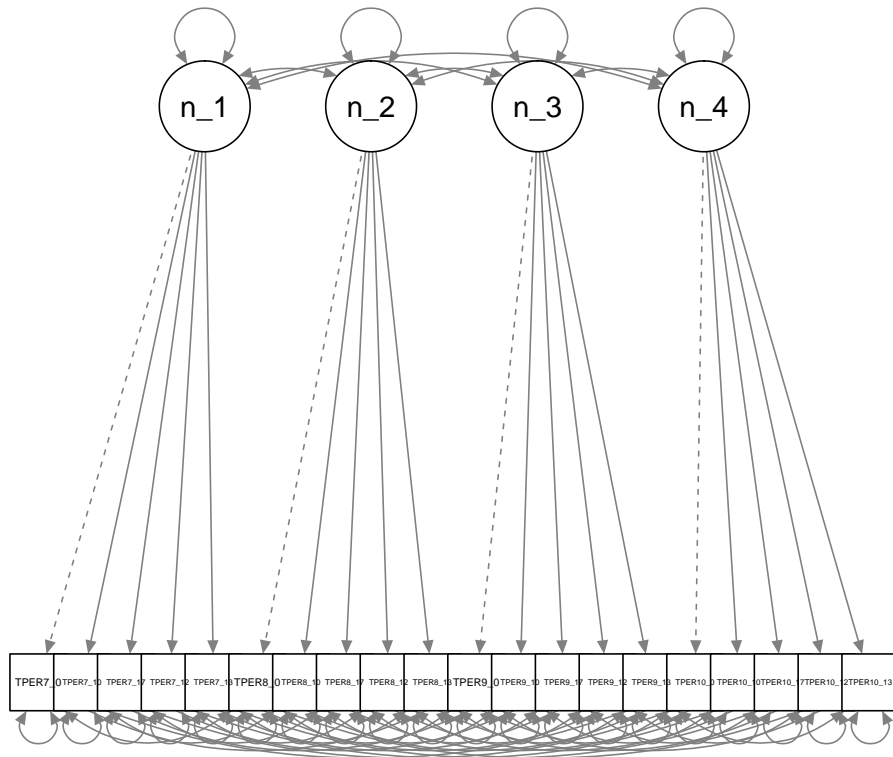
```
semPaths(fit.3)
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed  
## = Directed, : The following arguments are not documented and likely not  
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;  
## residEdge; CircleEdgeEnd
```



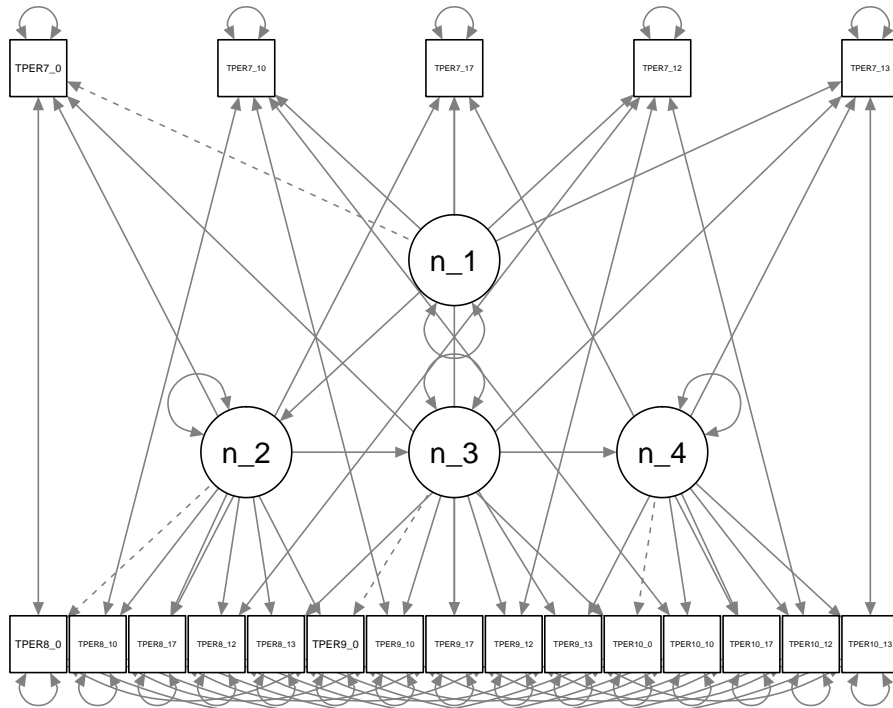
```
semPaths(fit.4)
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed  
## = Directed, : The following arguments are not documented and likely not  
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;  
## residEdge; CircleEdgeEnd
```



```
semPaths(fit.5)
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed
## = Directed, : The following arguments are not documented and likely not
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;
## residEdge; CircleEdgeEnd
```



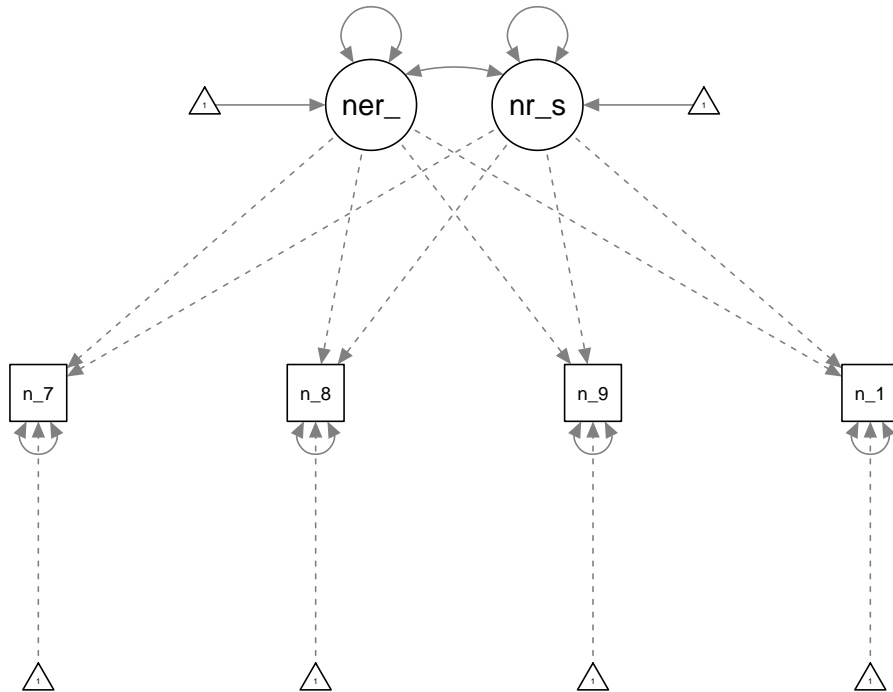

```
semPaths(fit.6)
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed  
## = Directed, : The following arguments are not documented and likely not  
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;  
## residEdge; CircleEdgeEnd
```



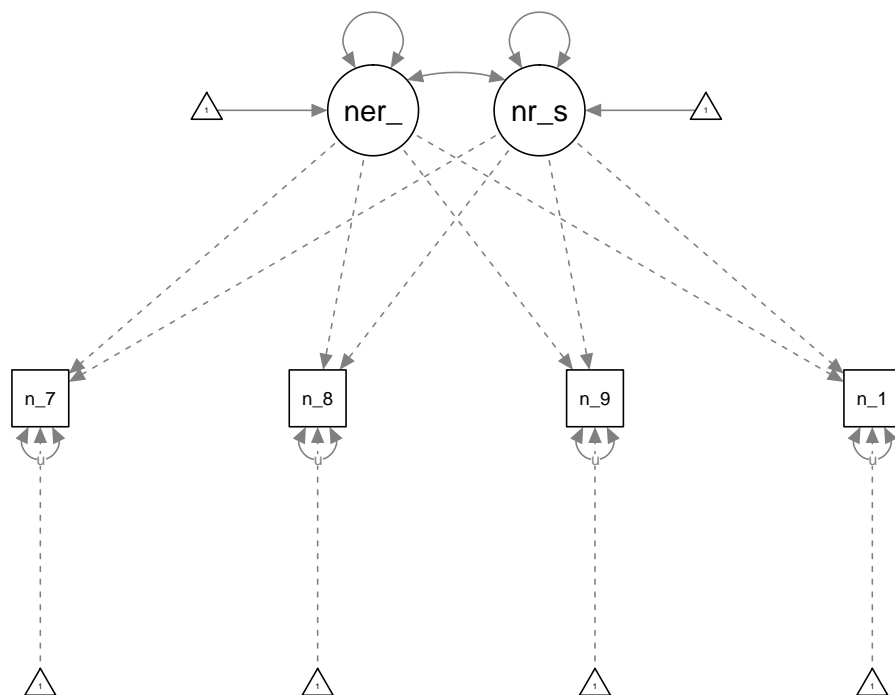
```
semPaths(fit.8)
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in sqrt(ETA2): NaNs produced
```

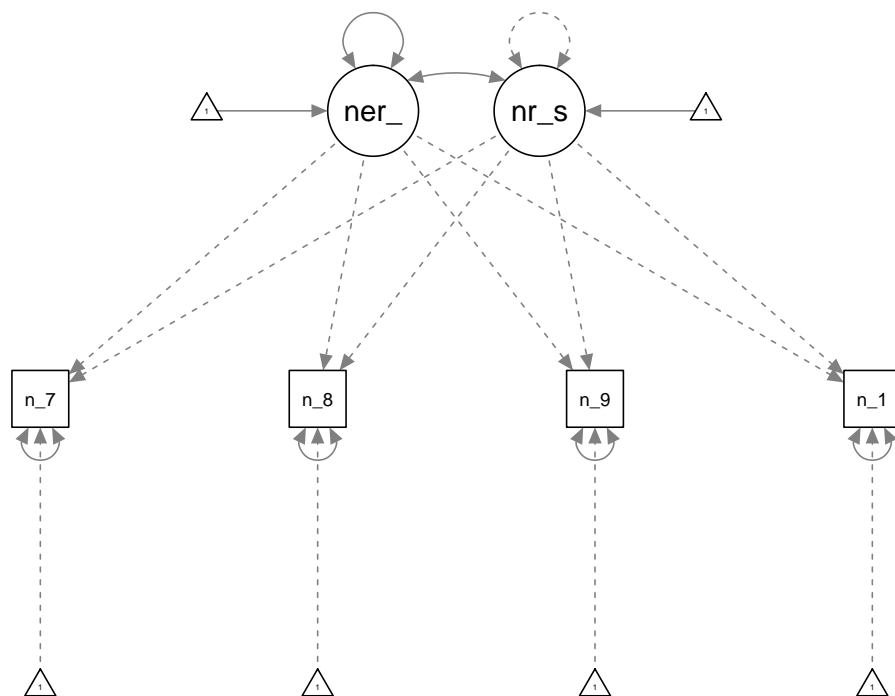
```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed  
## = Directed, : The following arguments are not documented and likely not  
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;  
## residEdge; CircleEdgeEnd
```



```
semPaths(fit.9)
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed
## = Directed, : The following arguments are not documented and likely not
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;
## residEdge; CircleEdgeEnd
```



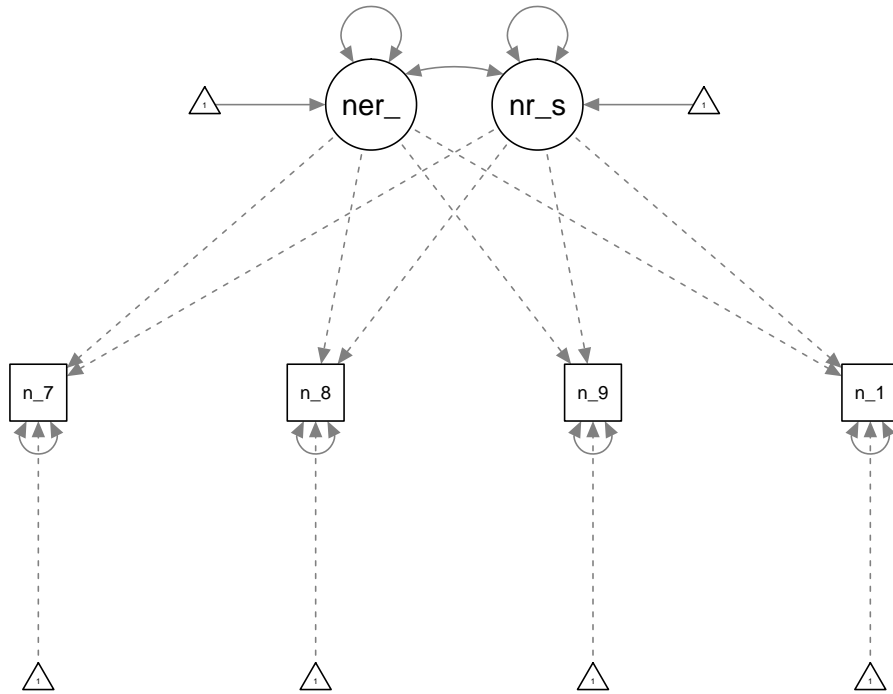
```
semPaths(fit.10)
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in qgraph(Edgelist, labels = nLab, bidirectional = Bidir, directed
## = Directed, : The following arguments are not documented and likely not
## arguments of qgraph and thus ignored: loopRotation; residuals; residScale;
## residEdge; CircleEdgeEnd
```



10) Test measurement invariance across time for your construct. Can you run growth models? If there is evidence of non-invariance, what seems to be the problem?

11) Fit a second order growth model. Compare and contrast the estimates with the normal latent growth model.

12) Fit a series of multiple group models. Constrain some parameters and compare the fit.

```
mod.8 <- 'neuro_t1 =~ TPER7_08 + TPER7_10 + TPER7_17R + TPER7_12R + TPER7_13R neuro_t2
 =~ TPER8_08 + TPER8_10 + TPER8_17R + TPER8_12R + TPER8_13R neuro_t3 =~ TPER9_08 +
 TPER9_10 + TPER9_17R + TPER9_12R + TPER9_13R neuro_t4 =~ TPER10_08 + TPER10_10 +
 TPER10_17R + TPER10_12R + TPER10_13R
```

```
TPER7_08 ~ TPER8_08 + TPER9_08 + TPER10_08 TPER8_08 ~ TPER9_08 + TPER10_08
TPER9_08 ~ TPER10_08
```

```
TPER7_10 ~ TPER8_10 + TPER9_10 + TPER10_10 TPER8_10 ~ TPER9_10 + TPER10_10
TPER9_10 ~ TPER10_10
```

```
TPER7_17R ~ TPER8_17R + TPER9_17R + TPER10_17R TPER8_17R ~ TPER9_17R +
TPER10_17R TPER9_17R ~ TPER10_17R
```

TPER7_12R \sim TPER8_12R + TPER9_12R + TPER10_12R TPER8_12R \sim TPER9_12R +
 TPER10_12R TPER9_12R \sim TPER10_12R

TPER7_13R \sim TPER8_13R + TPER9_13R + TPER10_13R TPER8_13R \sim TPER9_13R +
 TPER10_13R TPER9_13R \sim TPER10_13R

TPER7_08 \sim uTPER7_08 TPER7_10 \sim uTPER7_10 TPER7_17R \sim uTPER7_17R TPER7_12R \sim
 uTPER7_12R TPER7_13R \sim uTPER7_13R TPER8_08 \sim uTPER8_08 TPER8_10 \sim uTPER8_10
 TPER8_17R \sim uTPER8_17R TPER8_12R \sim uTPER8_12R TPER8_13R \sim uTPER8_13R TPER9_08
 \sim uTPER9_08 TPER9_10 \sim uTPER9_10 TPER9_17R \sim uTPER9_17R TPER9_12R \sim uTPER9_12R
 TPER9_13R \sim uTPER9_13R TPER10_08 \sim uTPER10_08 TPER10_10 \sim uTPER10_10 TPER10_17R
 \sim uTPER10_17R TPER10_12R \sim uTPER10_12R TPER10_13R \sim uTPER10_13R'