NTNU

**Quantitative Methods
Seminar Series in Psychology**

Longitudinal Data Analysis using Mplus and R

Frederick Anyan, Ph.D.

frederick.anyan@ntnu.no

Personal website

Håvard R. Karlsen, Ph.D.

h.karlsen@ntnu.no

Personal website

Plan for today

- Objectives of longitudinal research
- Role of time scores/factor loadings in LGCM

- Growth Curve Models
  - No growth, linear and quadratic LGCM
  - Spline/Piecewise/Multiphase LGCM
  - Adding time-invariant and time-varying (dynamical) predictors, and (distal) outcomes
  - Multi-group LGCM and invariance testing
  - Multi (Parallel) process LGCM

Objectives of longitudinal research

1.   Identification of intraindividual (within-person) changes (and stability)
   - Is there change over time on average?
      - ✓ Growth models can address various linear and nonlinear patterns of intraindividual change

2.   Analysis of causes (determinants) of intraindividual change
   - What factors/mechanisms – time-varying/dynamical predictors – drive change?
      - ✓ Inclusion of time-varying (dynamical) predictors in growth models

3.   Identification of interindividual differences (or similarity) in intraindividual change
   - Do different individuals change in different ways?
      - ✓ Growth models are structured to address interindividual differences in the growth factors

4.   Analysis of causes (determinants) of interindividual differences in intraindividual change
   - What factors explain between-person differences in change?
      - ✓ Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5.   Interrelationships in change
   - Does change in one variable related (*precede, covary and/or follow*) to change in another variable?
   - Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
   - ✓ Multi (parallel & sequentially contingent) process LGCM

Objectives of longitudinal research

1.   Identification of intraindividual (within-person) changes (and stability)
   •   Is there change over time on average?
      ✓   Growth models can address various linear and nonlinear patterns of intraindividual change

2.   Analysis of causes (determinants) of intraindividual change
   •   What factors/mechanisms – time-varying/dynamical predictors – drive change?
      ✓   Inclusion of time-varying (dynamical) predictors in growth models

3.   Identification of interindividual differences (or similarity) in intraindividual change
   •   Do different individuals change in different ways?
      ✓   Differences between groups of persons in the way people change

4.   Analysis of causes (determinants) of interindividual differences in intraindividual change
   •   What factors explain between-person differences in change?
      ✓   Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5.   Interrelationships in change
   •   Does change in one variable related (*precede, covary and/or follow*) to change in another variable?
   •   Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
      ✓   Multi (parallel & sequentially contingent) process LGCM

Objectives of longitudinal research

1. Identification of intraindividual (within-person) changes (and stability)
   - Is there change over time on average?
     - ✓ Growth models can address various linear and nonlinear patterns of intraindividual change

2. Analysis of causes (determinants) of intraindividual change
   - What factors/mechanisms – time-varying/dynamical predictors – drive change?
     - ✓ Inclusion of time-varying (dynamical) predictors in growth models

3. Identification of interindividual differences (or similarity) in intraindividual change
   - Do different individuals change in different ways?
     - ✓ Differences between groups of persons in the way people change

4. Analysis of causes (determinants) of interindividual differences in intraindividual change
   - What factors explain between-person differences change?
     - ✓ Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5. Interrelationships in change
   - Does change in one variable relate (*precede, covary and/or follow*) to change in another variable?
   - Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
     - ✓ Multi (parallel & sequentially contingent) process LGCM

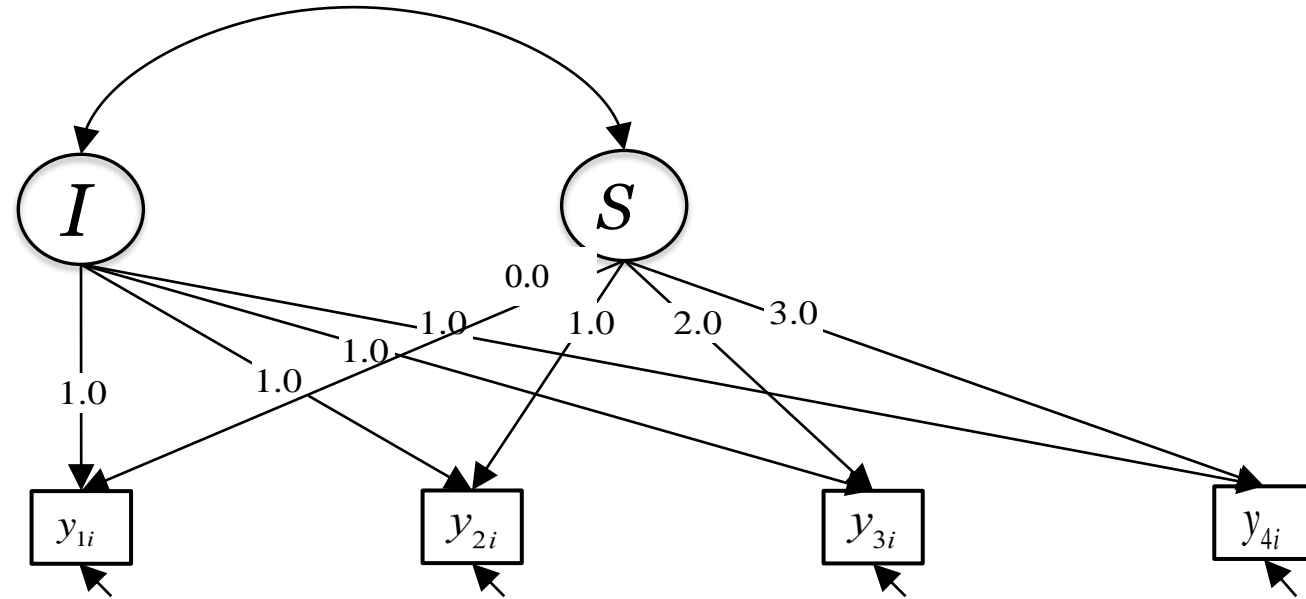# Modelling change over time
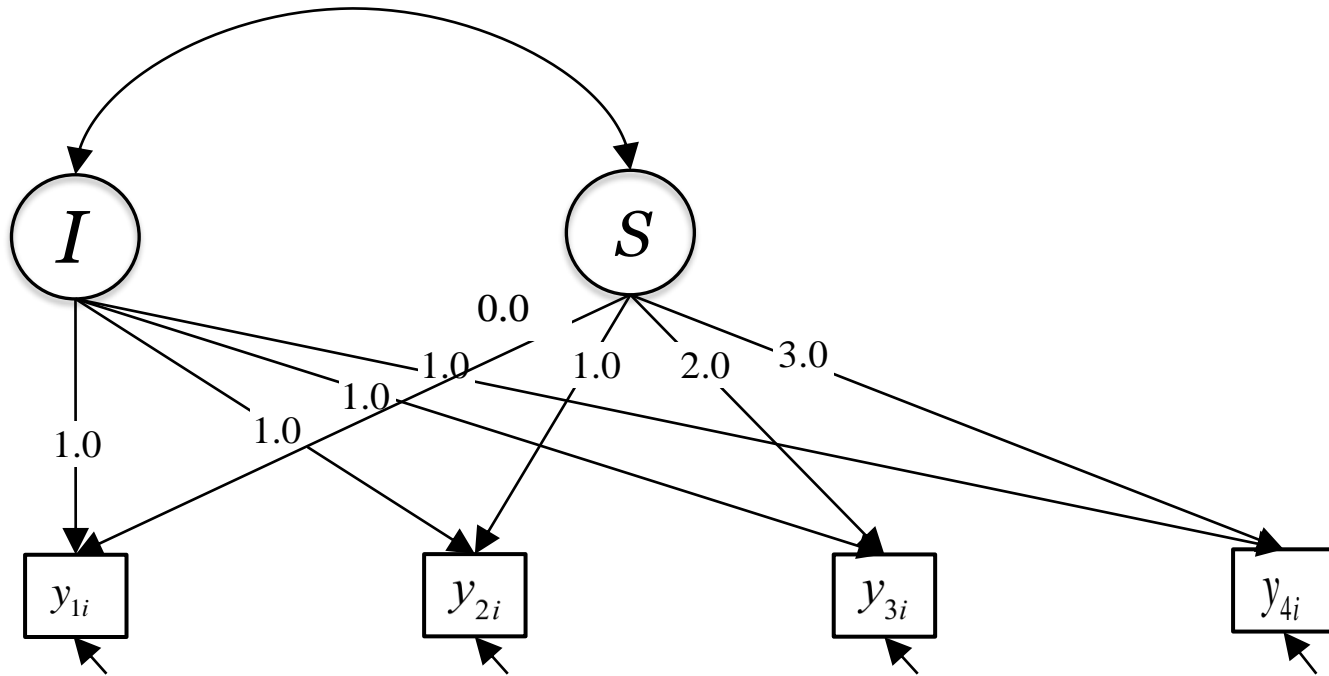
Modelling change over time

- Role of time scores
  - Time of observation as factor loading
  - Time scores determine
    1. Form/shape of growth process
    2. Centering point of growth process
    3. Scaling of growth factors

Frederick Anyan, PhD - NTNU

Modelling change over time

- ## Role of time scores
  - Time of observation as factor loading
  - Time scores determine
    1. Form/shape of growth process
    2. Centering point of growth process
    3. Scaling of growth factors

Modelling change over time

- ## Role of time scores
  - Time of observation as factor loading
  - Time scores determine
    1. Form/shape of growth process
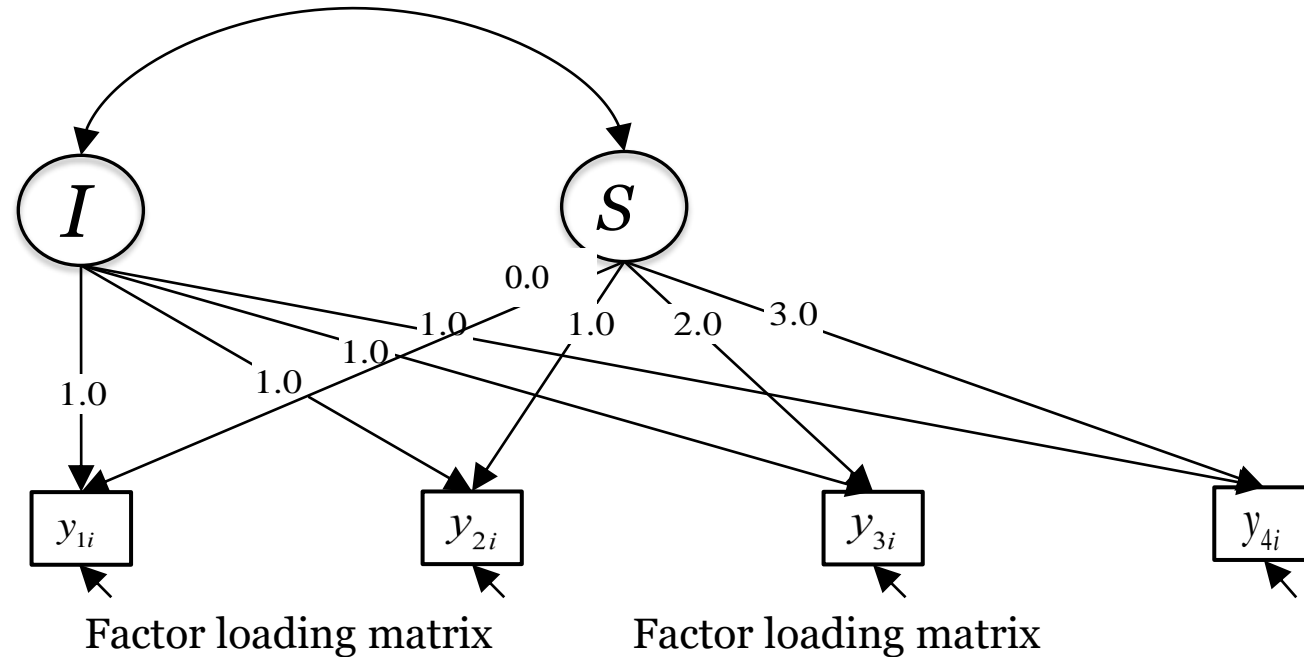   2. Centering point of growth process
    3. Scaling of growth factors

Factor loading matrix

1	0	Time 1
1	1	Time 2
1	2	Time 3
1	3	Time 4

I S | y1@0 y2@1 y3@2 y4@3

Factor loading matrix

1	-3	Time 1
1	-2	Time 2
1	-1	Time 3
1	0	Time 4

I S | y1@-3 y2@-2 y3@-1 y4@0

I S | y1@-1 y2@0 y3@1 y4@2; centering at Time 2

Factor loadings should be proportionate to time intervals/spacing

Factor loading matrix

1	0	Time 1
1	1	Time 2
1	2	Time 3
1	3	Time 4

Factor loading matrix

1	0	Month 1
1	1	Month 6
1	2	Month 12
1	3	Month 18
1	4	Month 24

Factor loading matrix
(unequal time interval)

1	0	Month 1
1	1	Month 2
1	2	Month 3
1	3	Month 4
1	4	Month 5
1	5	Month 6
1	6	Month 7

Factor loading matrix

1	-5	Month 1
1	-4	Month 2
1	-3	Month 3
1	-2	Month 4
1	-1	Month 5
1	0	Month 6

I S | y1@0 y2@1 y3@2 y4@3)

I S | y1@0 y2@1 y3@2 y4@3 y5@4
I S | y1@0 y2@6 y3@12 y4@18 y5@24

Either one is correct, same model fit indices

I S | y1@0 y2@1 y3@3 y4@4 y5@6 [No observations on Months 3 & 6, time scores specified to match observed time points]

I S | y1@-5 y2@-4 y3@-3 y4@-2 y5@-1 y6@0 [End of observation defined as centering point; intercept status; predicted level of y at end of obs.]

Free time score/Unspecified LGCM/Model estimated time score = empirically determines shape of outcome growth
I S | y1@0 y2@1 y3* y4* y5*

Latent basis model/Unstructured growth model
I S | y1@0 y2* y3* y4@1
• Freely estimated parameters represent the proportion of predicted overall change that occurred up to a specific point in time eg Time 2, for y2*
• The Slope growth factor represents the total amount of change from the first to the last timepoints

Frederick Anyan, PhD - NTNU

Factor loadings should be proportionate to time intervals/spacing

Factor loading matrix

1	0	Time 1
1	1	Time 2
1	2	Time 3
1	3	Time 4

Factor loading matrix

1	0	Month 1
1	1	Month 6
1	2	Month 12
1	3	Month 18
1	4	Month 24

Factor loading matrix
(unequal time interval)

1	0	Month 1
1	1	Month 2
1	2	Month 3
1	3	Month 4
1	4	Month 5
1	5	Month 6
1	6	Month 7

Factor loading matrix

1	-5	Month 1
1	-4	Month 2
1	-3	Month 3
1	-2	Month 4
1	-1	Month 5
1	0	Month 6

I S | y1@0 y2@1 y3@2 y4@3)

I S | y1@0 y2@1 y3@2 y4@3 y5@4
I S | y1@0 y2@6 y3@12 y4@18 y5@24

Either one is correct, same model fit indices

I S | y1@0 y2@1 y3@3 y4@4 y5@6 [No observations on Months 3 & 6, time scores specified to match observed time points]

I S | y1@-5 y2@-4 y3@-3 y4@-2 y5@-1 y6@0 [End of observation defined as centering point; intercept status; predicted level of y at end of obs.]

Free time score/Unspecified LGCM/Model estimated time score = empirically determines shape of outcome growth
I S | y1@0 y2@1 y3* y4* y5*

Latent basis model/Unstructured growth model
I S | y1@0 y2* y3* y4@1
• Freely estimated parameters represent the proportion of predicted overall change that occurred up to a specific point in time eg Time 2, for y2*
• The Slope growth factor represents the total amount of change from the first to the last timepoints

11

Factor loadings should be proportionate to time intervals/spacing

Factor loading matrix

1	0	Time 1
1	1	Time 2
1	2	Time 3
1	3	Time 4

Factor loading matrix

1	0	Month 1
1	1	Month 6
1	2	Month 12
1	3	Month 18
1	4	Month 24

Factor loading matrix
(unequal time interval)

1	0	Month 1
1	1	Month 2
1	2	Month 3
1	3	Month 4
1	4	Month 5
1	5	Month 6
1	6	Month 7

Factor loading matrix

1	-5	Month 1
1	-4	Month 2
1	-3	Month 3
1	-2	Month 4
1	-1	Month 5
1	0	Month 6

I S | y1@0 y2@1 y3@2 y4@3)

I S | y1@0 y2@1 y3@2 y4@3 y5@4
I S | y1@0 y2@6 y3@12 y4@18 y5@24

Either one is correct, same model fit indices

I S | y1@0 y2@1 y3@3 y4@4 y5@6 [No observations on Months 3 & 6, time scores specified to match observed time points]

I S | y1@-5 y2@-4 y3@-3 y4@-2 y5@-1 y6@0 [End of observation defined as centering point; intercept status; predicted level of y at end of obs.]

Free time score/Unspecified LGCM/Model estimated time score = empirically determines shape of outcome growth
I S | y1@0 y2@1 y3* y4* y5*

Latent basis model/Unstructured growth model
I S | y1@0 y2* y3* y4@1
•   Freely estimated parameters represent the proportion of predicted overall change that occurred up to a specific point in time eg Time 2, for y2*
•   The Slope growth factor represents the total amount of change from the first to the last timepoints

12

Frederick Anyan, PhD - NTNUFrederick Anyan, PhD - NTNU

Factor loadings should be proportionate to time intervals/spacing

Factor loading matrix

1	0	Time 1
1	1	Time 2
1	2	Time 3
1	3	Time 4

I S | y1@0 y2@1 y3@2 y4@3)

Factor loading matrix

1	0	Month 1
1	1	Month 6
1	2	Month 12
1	3	Month 18
1	4	Month 24

Factor loading matrix
(unequal time interval)

1	0	Month 1
1	1	Month 2
1	2	Month 3
1	3	Month 4
1	4	Month 5
1	5	Month 6
1	6	Month 7

Factor loading matrix

1	-5	Month 1
1	-4	Month 2
1	-3	Month 3
1	-2	Month 4
1	-1	Month 5
1	0	Month 6

I S | y1@0 y2@1 y3@2 y4@3 y5@4
I S | y1@0 y2@6 y3@12 y4@18 y5@24
Either one is correct, same model fit indices

I S | y1@0 y2@1 y3@3 y4@4 y5@6 [No observations on Months 3 & 6, time scores specified to match observed time points]

I S | y1@-5 y2@-4 y3@-3 y4@-2 y5@-1 y6@0 [End of observation defined as centering point; intercept status; predicted level of y at end of obs.]

Free time score/Unspecified LGCM/Model estimated time score = empirically determines shape of outcome growth
I S | y1@0 y2@1 y3* y4* y5*

Latent basis model/Unstructured growth model
I S | y1@0 y2* y3* y4@1
• Freely estimated parameters represent the proportion of predicted overall change that occurred up to a specific point in time eg Time 2, for y2*
• The Slope growth factor represents the total amount of change from the first to the last timepoints

Frederick Anyan, PhD - NTNU

Factor loadings should be proportionate to time intervals/spacing

Factor loading matrix

1	0	Time 1
1	1	Time 2
1	2	Time 3
1	3	Time 4

Factor loading matrix

1	0	Month 1
1	1	Month 6
1	2	Month 12
1	3	Month 18
1	4	Month 24

Factor loading matrix
(unequal time interval)

1	0	Month 1
1	1	Month 2
1	2	Month 3
1	3	Month 4
1	4	Month 5
1	5	Month 6
1	6	Month 7

Factor loading matrix

1	-5	Month 1
1	-4	Month 2
1	-3	Month 3
1	-2	Month 4
1	-1	Month 5
1	0	Month 6

I S | y1@0 y2@1 y3@2 y4@3)

I S | y1@0 y2@1 y3@2 y4@3 y5@4
I S | y1@0 y2@6 y3@12 y4@18 y5@24

Either one is correct, same model fit indices

I S | y1@0 y2@1 y3@3 y4@4 y5@6 [No observations on Months 3 & 6, time scores specified to match observed time points]

I S | y1@-5 y2@-4 y3@-3 y4@-2 y5@-1 y6@0 [End of observation defined as centering point; intercept status; predicted level of y at end of obs.]

Free time score/Unspecified LGCM/Model estimated time score = empirically determines shape of outcome growth
I S | y1@0 y2@1 y3* y4* y5*

Latent basis model/Unstructured growth model
I S | y1@0 y2* y3* y4@1
- Freely estimated parameters represent the proportion of predicted overall change that occurred up to a specific point in time eg Time 2, for y2*
- The Slope growth factor represents the total amount of change from the first to the last timepoints

Frederick Anyan, PhD - NTNU

Non-linear change (e.g., quadratic)
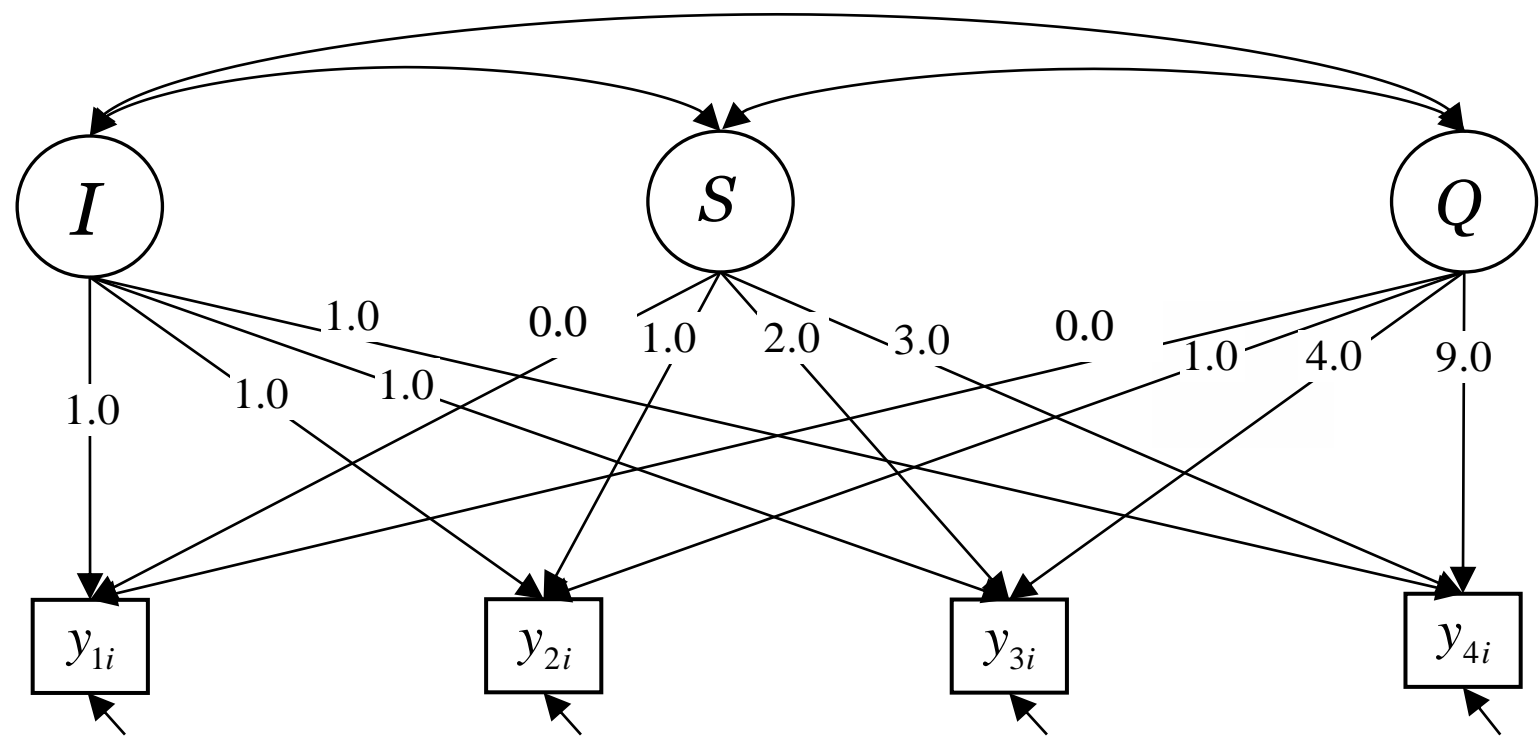
Factor loading matrix

1	0	0	Time 1
1	1	1	Time 2
1	2	4	Time 3
1	3	9	Time 4

(I S Q| y1@0 y2@1 y3@2 y4@3)

Dataset

Variable Names	Time 1 (2015)	Time 2 (2016)	Time 3 (2018)	Time 4 (2019)	Time 5 (2021)
Id	personid				
Female	female				
Parental drug use	pdu1				
Adverse childhood environment	ace1				
Worry	worry1				
Loneliness	lone1	lone2	lone3	lone4	lone5
Anxiety symptoms	anx1	anx2	anx3	anx4	anx5
Depression symptoms	dep1	dep2	dep3	dep4	dep5
Hostility	host1	host2	host3	host4	host5
Peer conflict					percon5
Peer conflict					percon5b
Substance use					subs5
Substance use					subs5b
Difficulty sleeping					sleep5
Difficulty sleeping					sleep5b

1. Examine univariate and bivariat

▶ Code

	vars	n	mean	sd	median	trimmed	mad	min	max	range	sl
lone1	1	398	1.46	0.46	1.32	1.38	0.34	1	3.75	2.75	1.
lone2	2	395	1.47	0.52	1.31	1.38	0.31	1	5.00	4.00	2.
lone3	3	390	1.53	0.52	1.36	1.44	0.37	1	3.78	2.78	1.
lone4	4	413	1.35	0.47	1.22	1.25	0.25	1	4.92	3.92	3.
lone5	5	409	1.32	0.39	1.20	1.24	0.25	1	3.43	2.43	2.

The means and standard deviations show a simple pattern with increases in the feeling of loneliness from T1 through to T3 and begins to decline afterwards though to T5 coupled with increases in variation and then a decline after T3.

5. Examine separate individual longitudinal plots

▶ Code

Warning: Removed 5 rows containing missing values (`geom_line()`).

Warning: Removed 5 rows containing missing values (`geom_point()`).

N = 11 (2.5% of the sample)

Objectives of longitudinal research

1.   Identification of intraindividual (within-person) changes (and stability)
     - Is there change over time on average?
       - ✓ Growth models can address various linear and nonlinear patterns of intraindividual change

2.   Analysis of causes (determinants) of intraindividual change
     - What factors/mechanisms – time-varying/dynamical predictors – drive change?
       - ✓ Inclusion of time-varying (dynamical) predictors in growth models

3.   Identification of interindividual differences (or similarity) in intraindividual change
     - Do different individuals change in different ways?
       - ✓ Differences between groups of persons in the way people change

4.   Analysis of causes (determinants) of interindividual differences in intraindividual change
     - What factors explain between-person differences in change?
       - ✓ Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5.   Interrelationships in change
     - Does change in one variable relate (*precede, covary and/or follow*) to change in another variable?
     - Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
       - ✓ Multi (parallel & sequentially contingent) process LGCM

- What does the overall trajectory of loneliness look like?

  - Is there change over time on average?
    - What growth function characterizes change over time/shape of growth?

No growth/Intercept only model

No growth/Intercept only model

y_{1i} y_{2i} y_{2i} y_{4i} y_{5i}

1.0   1.0   1.0   1.0   1.0

I

```
001_No_change_No_growth_Intercept_only_model
TITLE:   001_No_change_No_growth_Intercept_only_model

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I|lone1@1 lone2@1 lone3@1 lone4@1 lone5@1;
    !I|lone1-lone5@1;

OUTPUT:
    SAMPSTAT;
```

```
26  # 001_No growth model
27  nogrowth <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5'
28  fit_nogrowth <- growth(nogrowth, data = data)
29  summary(fit_nogrowth, fit.measures = TRUE)
30
```

Frederick Anyan, PhD - NTNU

No growth/Intercept only model
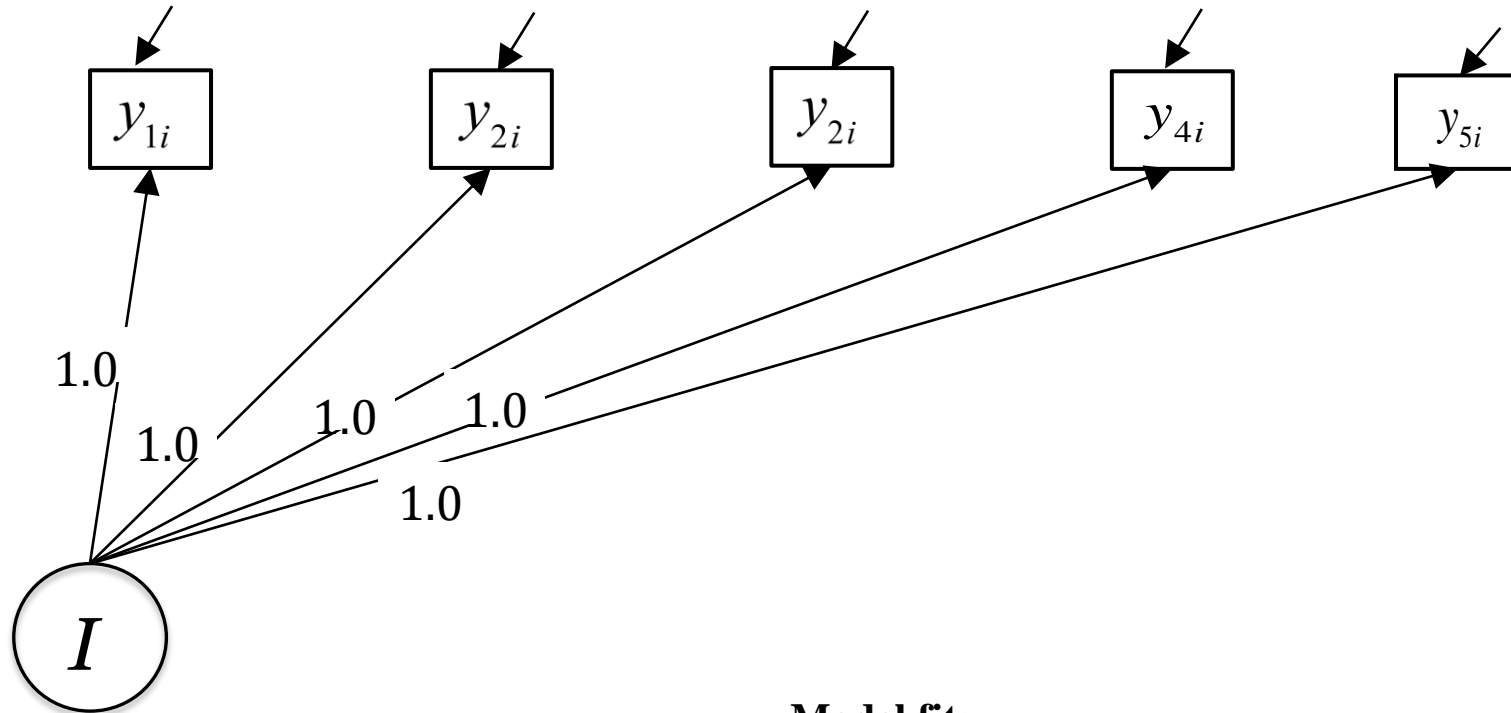
RESULTS

Model fit:
(χ^2 = 186.433, df = 13; p < .001; *RMSEA* = .204, [90% CI = 0.179, 0.230]; *CFI* = .607; *TLI* = .698)

Parameter estimates:

Intercept:	1.398***
Intercept variance:	0.075***
Residual variance:	0.092 – 1.167, all***

Frederick Anyan, PhD - NTNU
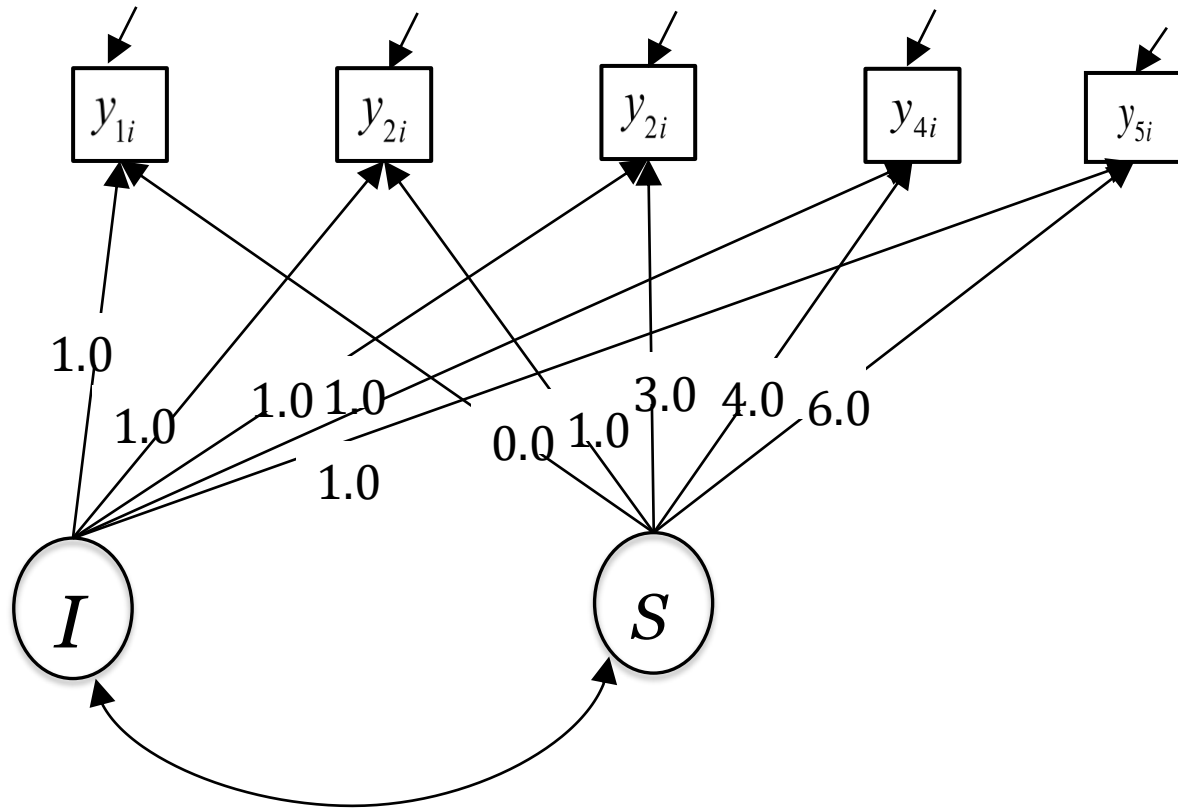
Linear growth

Unconditional Linear LGCM

Linear growth
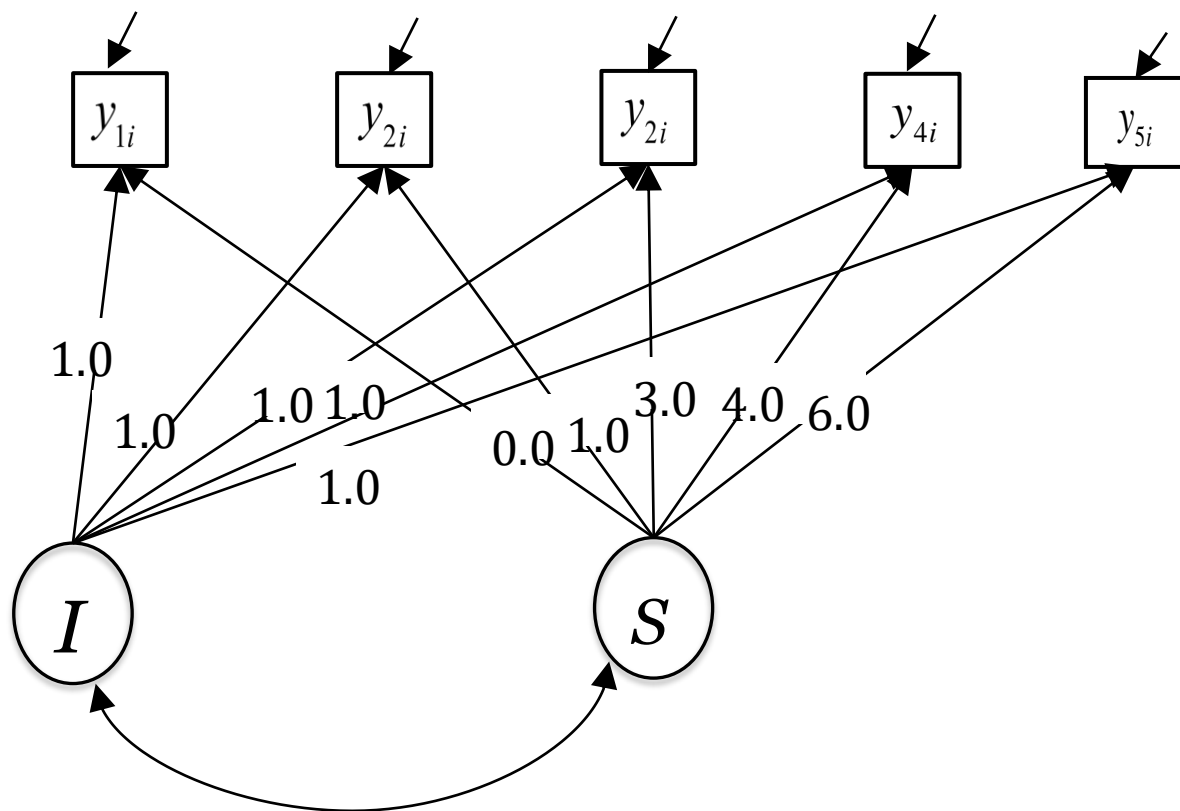

```
32  # 002_Linear growth model
33  linear <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
34            s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5'
35  fit_linear <- growth(linear, data = data)
36  summary(fit_linear, fit.measures = TRUE)
```

```
002_Linear_growht_curve_model

TITLE:   002_Linear_growht_curve_model

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

OUTPUT:
    SAMPSTAT;

PLOT:
    TYPE = PLOT3;
    SERIES = lone1 - lone5(S);
```

Frederick Anyan, PhD - NTNU

Linear growth
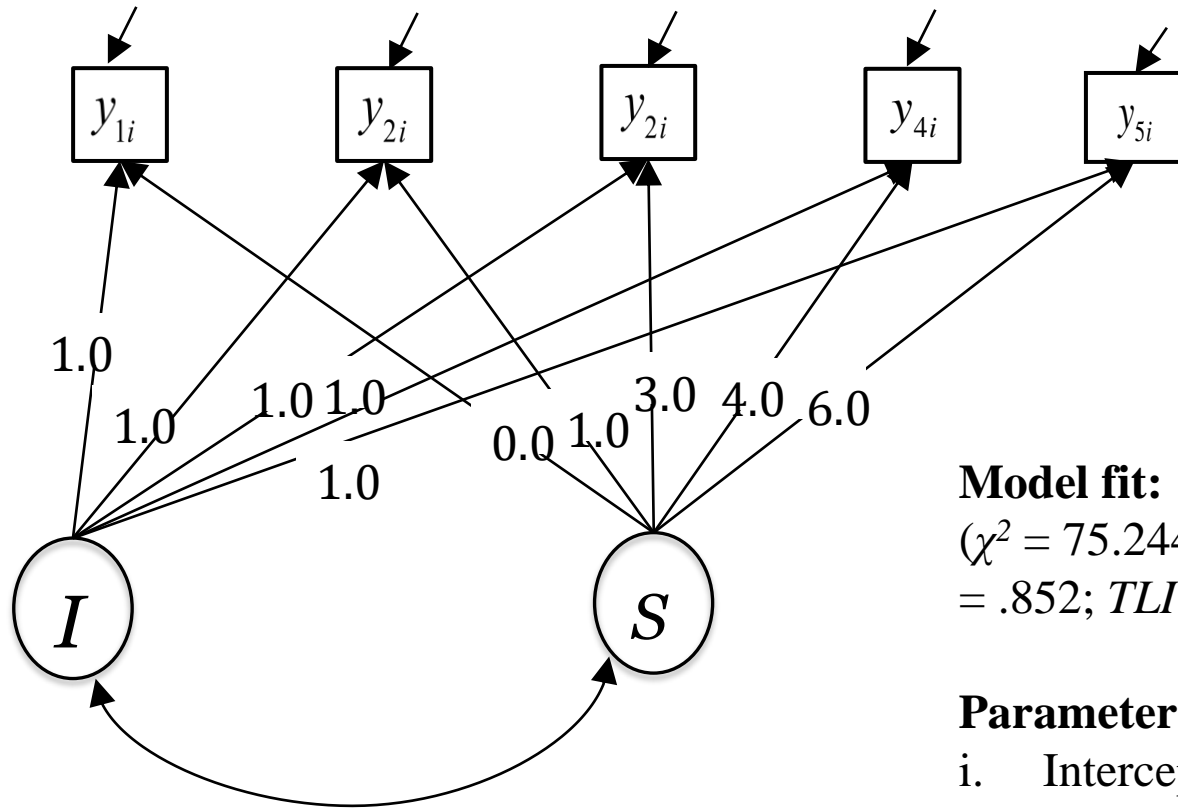
RESULTS

Model fit:
($\chi^2 = 75.244$, $df = 10$; $p < .001$; *RMSEA* $= .143$, [90% CI $= 0.113, 0.174$]; *CFI* $= .852$; *TLI* $= .852$)

Parameter estimates:

i.	Intercept:	1.466***
ii.	Slope:	-0.025***

(Co)Variances:

i.	Intercept:	0.139***
ii.	Slope:	0.003***
iii.	Intercept WITH Slope:	-0.015***

Unconditional Linear LGCM

Frederick Anyan, PhD - NTNU
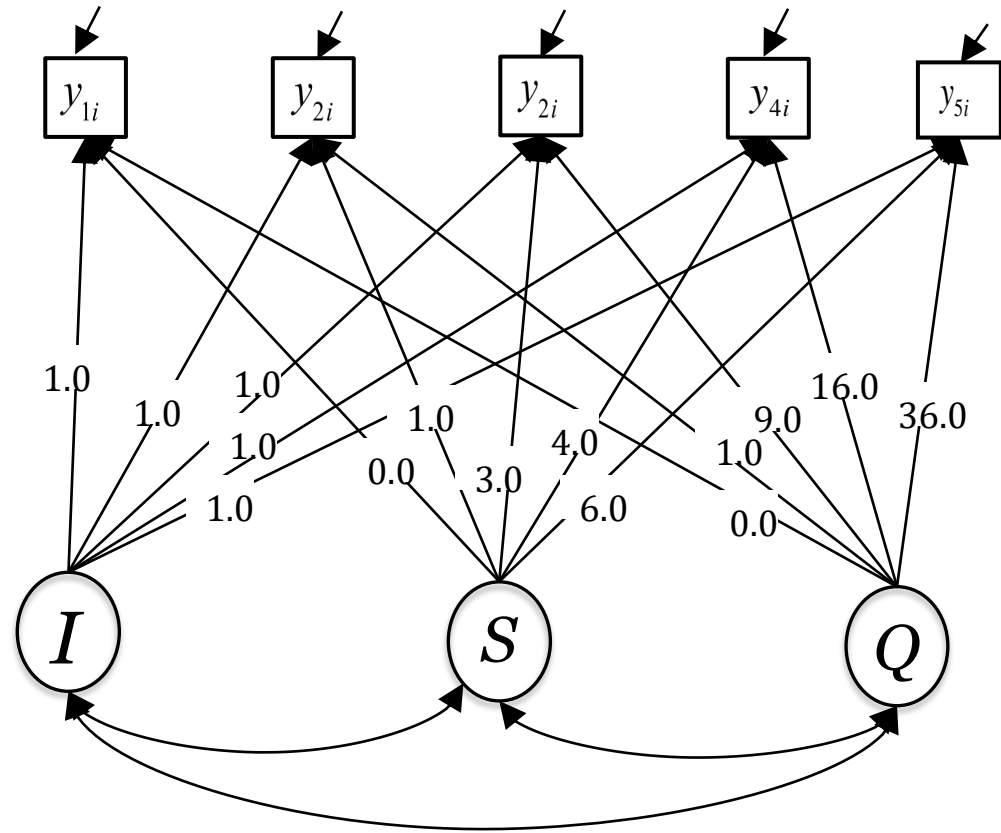
Quadratic growth

Unconditional Quadratic LGCM

Quadratic growth
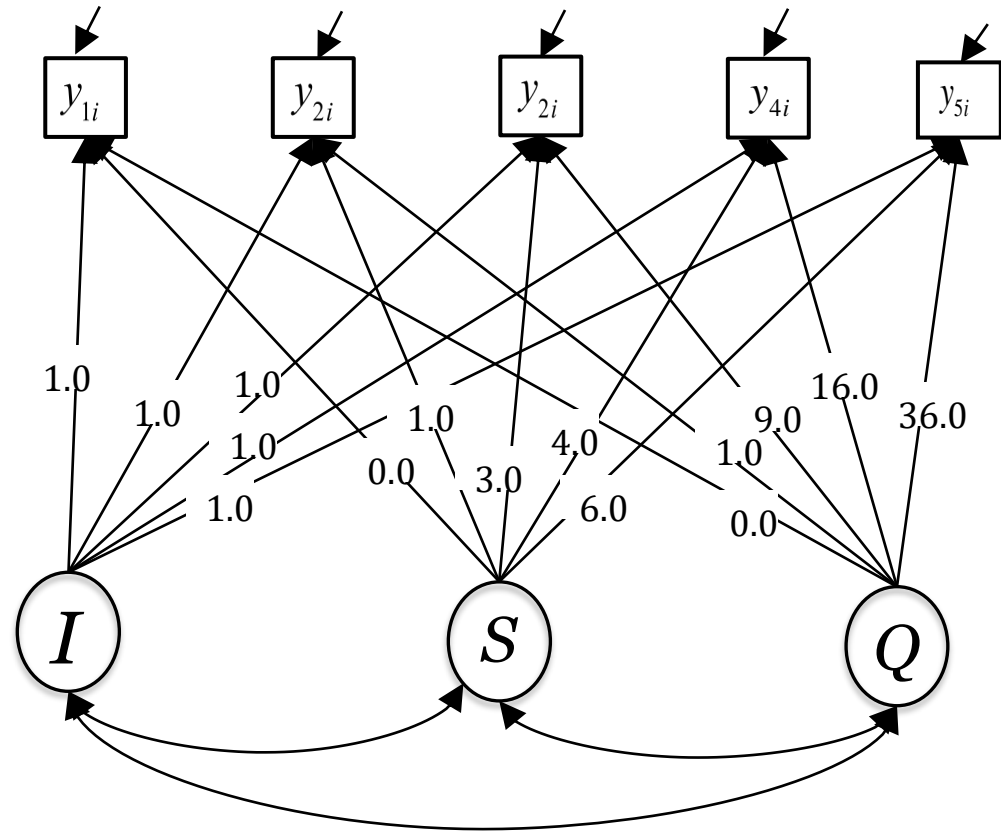

```
40   # 003_Quadratic growth model
41   quadratic <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
42              s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
43              q =~ 0*lone1 + 1*lone2 + 9*lone3 + 16*lone4 + 36*lone5'
44   fit_quadratic <- growth(quadratic, data = data)
45   summary(fit_quadratic, fit.measures = TRUE)
```

003_Quadratic_growht_curve_model

```
TITLE:  003_Quadratic_growht_curve_model

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S Q|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

OUTPUT:
    SAMPSTAT;

PLOT:
    TYPE = PLOT3;
    SERIES = lone1 - lone5(S);
```

Quadratic growth
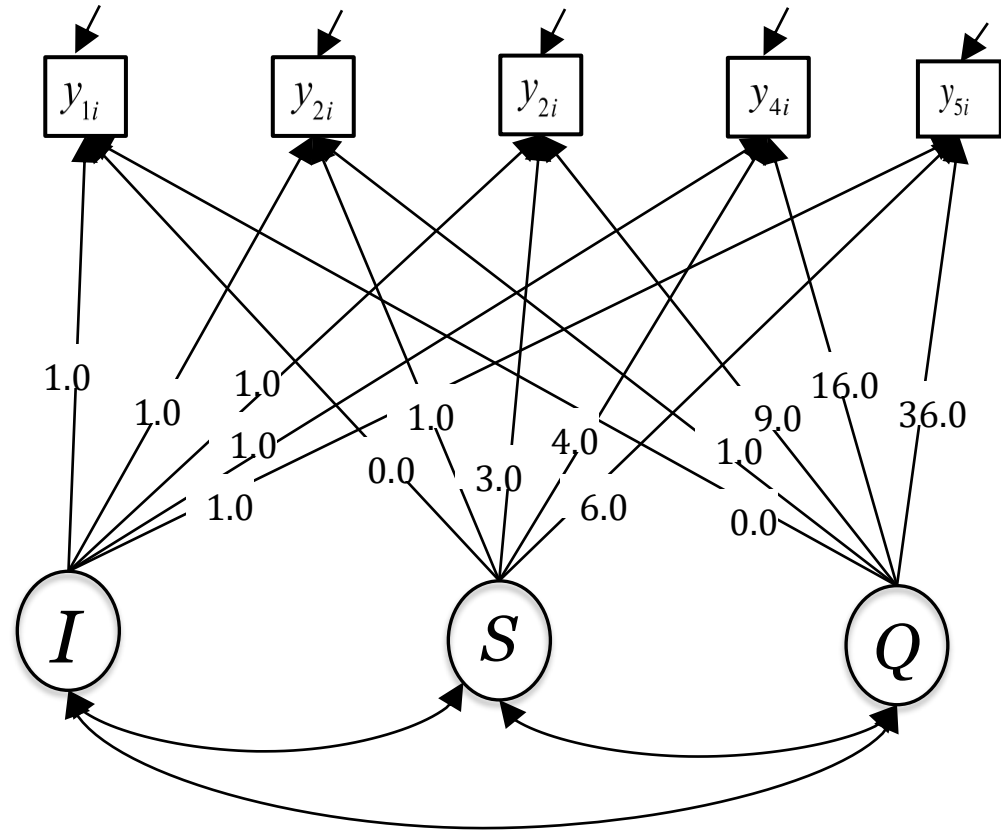
Unconditional Quadratic LGCM

RESULTS

Model fit:
(χ^2 = 46.671, df = 6; p < .001; $RMSEA$ = .145, [90% CI = 0.108, 0.185]; CFI = .908; TLI = .846)

Parameter estimates:

i.   Intercept: 1.466***
ii. Slope: 0.017
iii. Quadratic: -0.007**

(Co)Variances:

i.   Intercept: 0.148***
ii. Slope: 0.003**
iii. Quadratic: 0.000
iv. Intercept WITH Slope: -0.020*
v.   Intercept WITH Quadratic   0.000
vi. Slope WITH Quadratic   -0.002

Frederick Anyan, PhD - NTNU

Spline/Piecewise/Multiphase/Slope-segmented LGCM

- When theoretical reasons suggest to separate time/development into discrete phases
  - Trajectory of loneliness before divorce and after divorce
  - Trajectory of depression before and after intervention
  - Pre-crawling and post-crawling in children
  - Childhood and adolescence

- Different phases of development are captured by more than one slope growth factor
  - Knots or transition points show where one phase is ending, and another phase is beginning

Bilinear Spline/Piecewise/Multiphase LGCM - 1
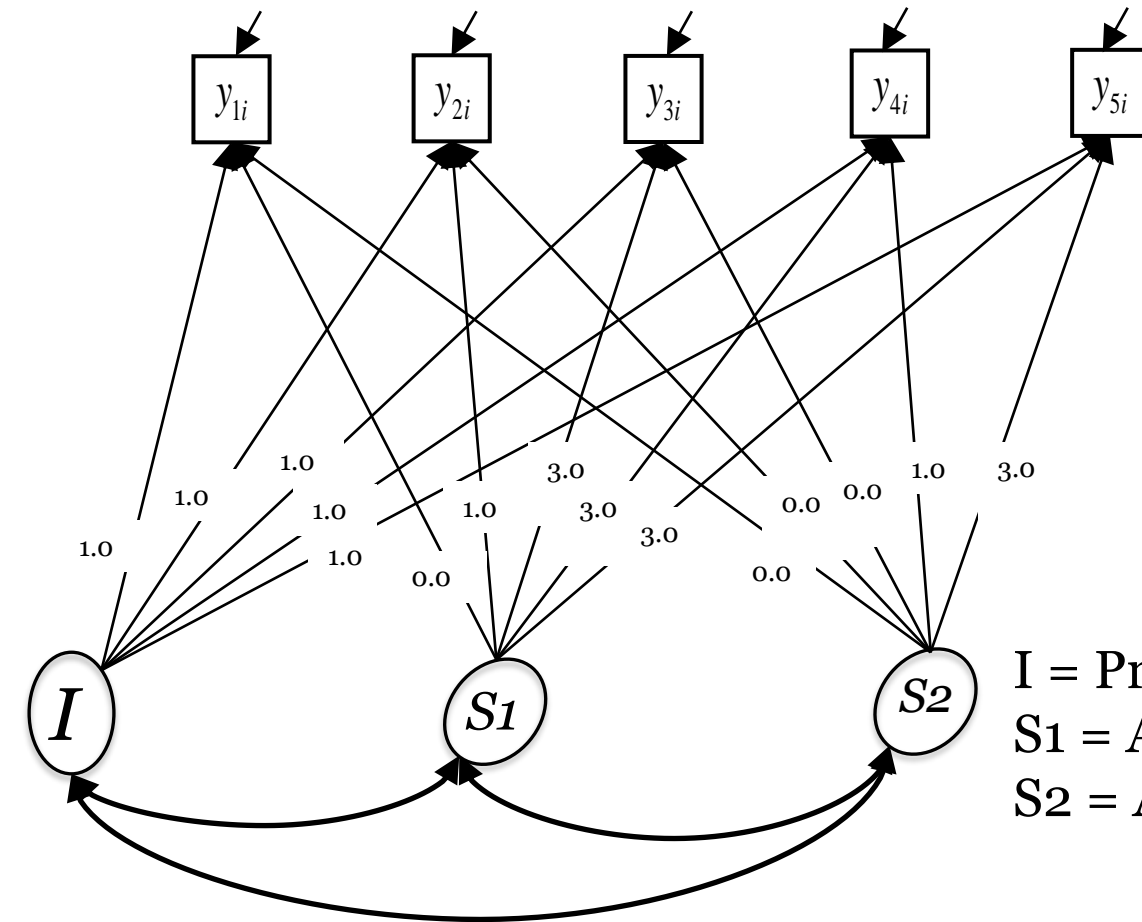
Intercept at Time 1, knot at Time 3

1	0	0	Time 1, 2015
1	1	0	Time 2, 2016
1	3	0	Time 3, 2018
1	3	1	Time 4, 2019
1	3	3	Time 5, 2021

I = Predicted average value of outcome in 2015
S1 = Average rate of change in outcome from 2015 through 2018
S2 = Average rate of change in outcome from 2018 through 2021

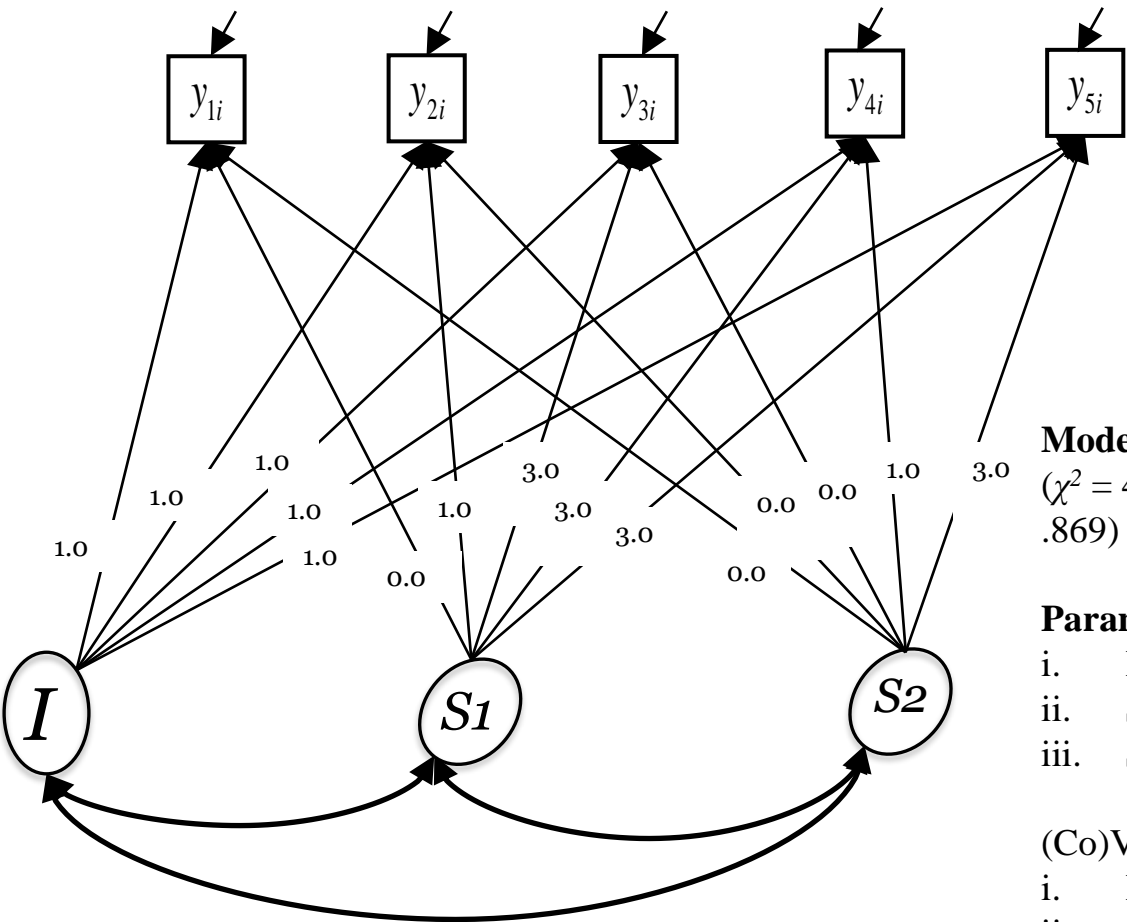# Bilinear Spline/Piecewise/Multiphase LGCM - 1
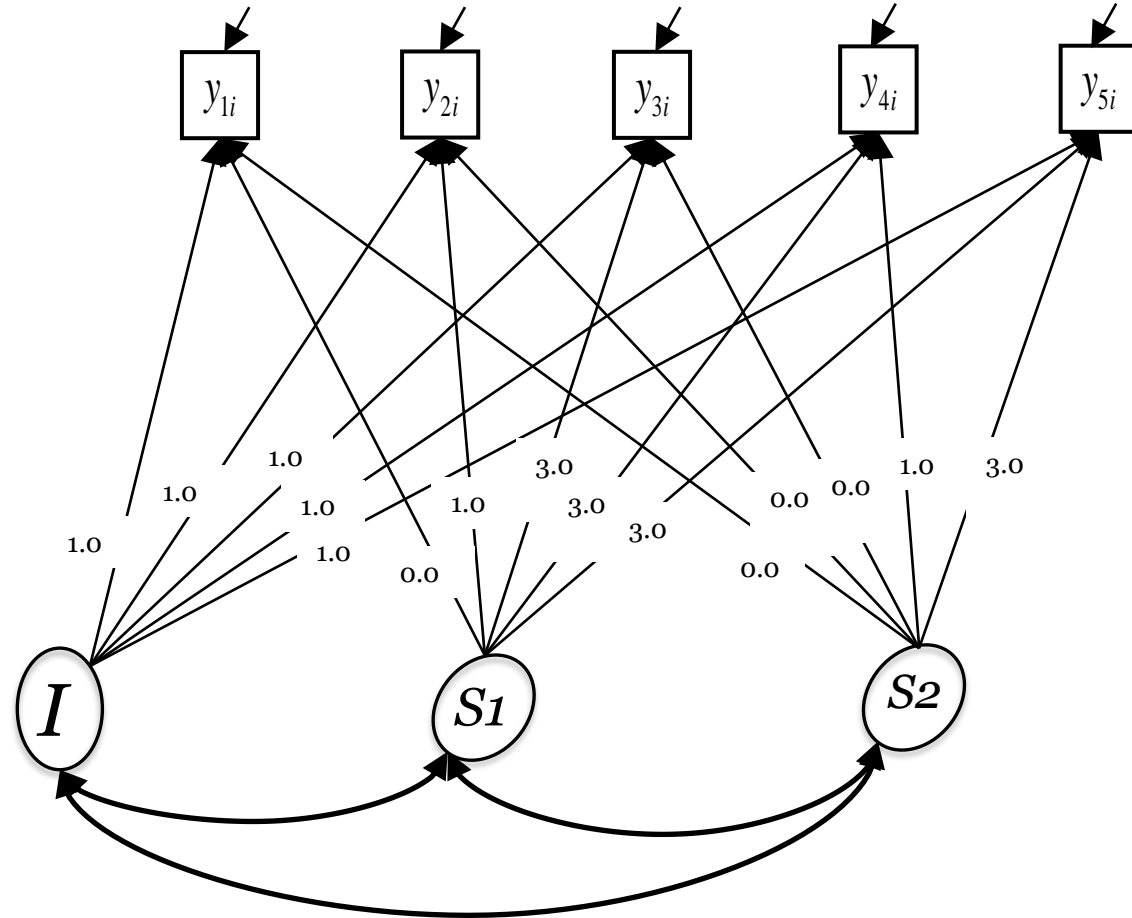
Intercept at Time 1, knot at Time 3

I = Predicted average value of outcome in 2015
S1 = Average rate of change in outcome from 2015 through 2018
S2 = Average rate of change in outcome from 2018 through 2021

004_1_Bilinear_spline_growht_curve_model

```
TITLE:   004_Bilinear_spline_growht_curve_model

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S1|lone1@0 lone2@1 lone3@3 lone4@3 lone5@3;!Slope 1
    I S2|lone1@0 lone2@0 lone3@0 lone4@1 lone5@3;!Slope 2

OUTPUT:
    SAMPSTAT;
```

```
51  # 004_1_Bilinear/Spline growth curve model
52
53  bilinear <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
54          s1 =~ 0*lone1 + 1*lone2 + 3*lone3 + 3*lone4 + 3*lone5
55          s2 =~ 0*lone1 + 0*lone2 + 0*lone3 + 1*lone4 + 3*lone5'
56  fit_bilinear <- growth(bilinear, data = data)
57  summary(fit_bilinear, fit.measures = TRUE)
```

Frederick Anyan, PhD - NTNU

Bilinear Spline/Piecewise/Multiphase LGCM - 1

Intercept at Time 1, knot at Time 3

1	0	0	Time 1, 2015
1	1	0	Time 2, 2016
1	3	0	Time 3, 2018
1	3	1	Time 4, 2019
1	3	3	Time 5, 2021

I = Predicted average value of outcome in 2015
S1 = Average rate of change in outcome from 2015 through 2018
S2 = Average rate of change in outcome from 2018 through 2021

RESULTS

Model fit:
($\chi^2 = 40.781$, $df = 6$; $p < .001$; $RMSEA = .134$, [90% CI = 0.097, 0.175]; $CFI = .921$; $TLI = .869$)

Parameter estimates:

i.	Intercept:	1.444***
ii.	Slope 1:	0.007
iii.	Slope 2:	-0.059***

(Co)Variances:

i.	Intercept:	0.140***
ii.	Slope 1:	0.001**
iii.	Slope 2:	0.002
iv.	Intercept WITH Slope 1:	-0.015**
v.	Intercept WITH Slope 2	-0.019***
vi.	Slope 1 WITH Slope 2	0.000
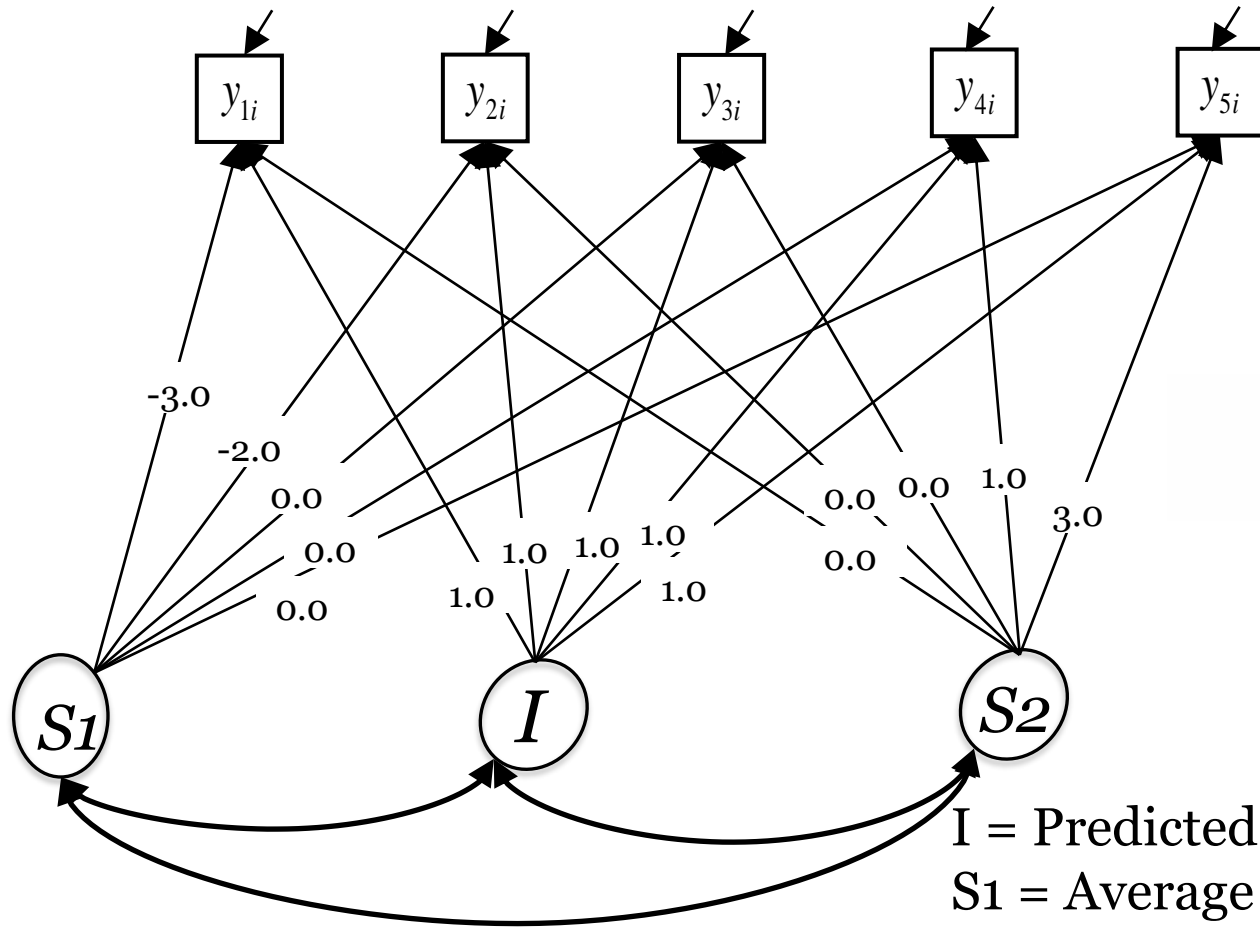
Spline/Piecewise/Multiphase LGCM - 2

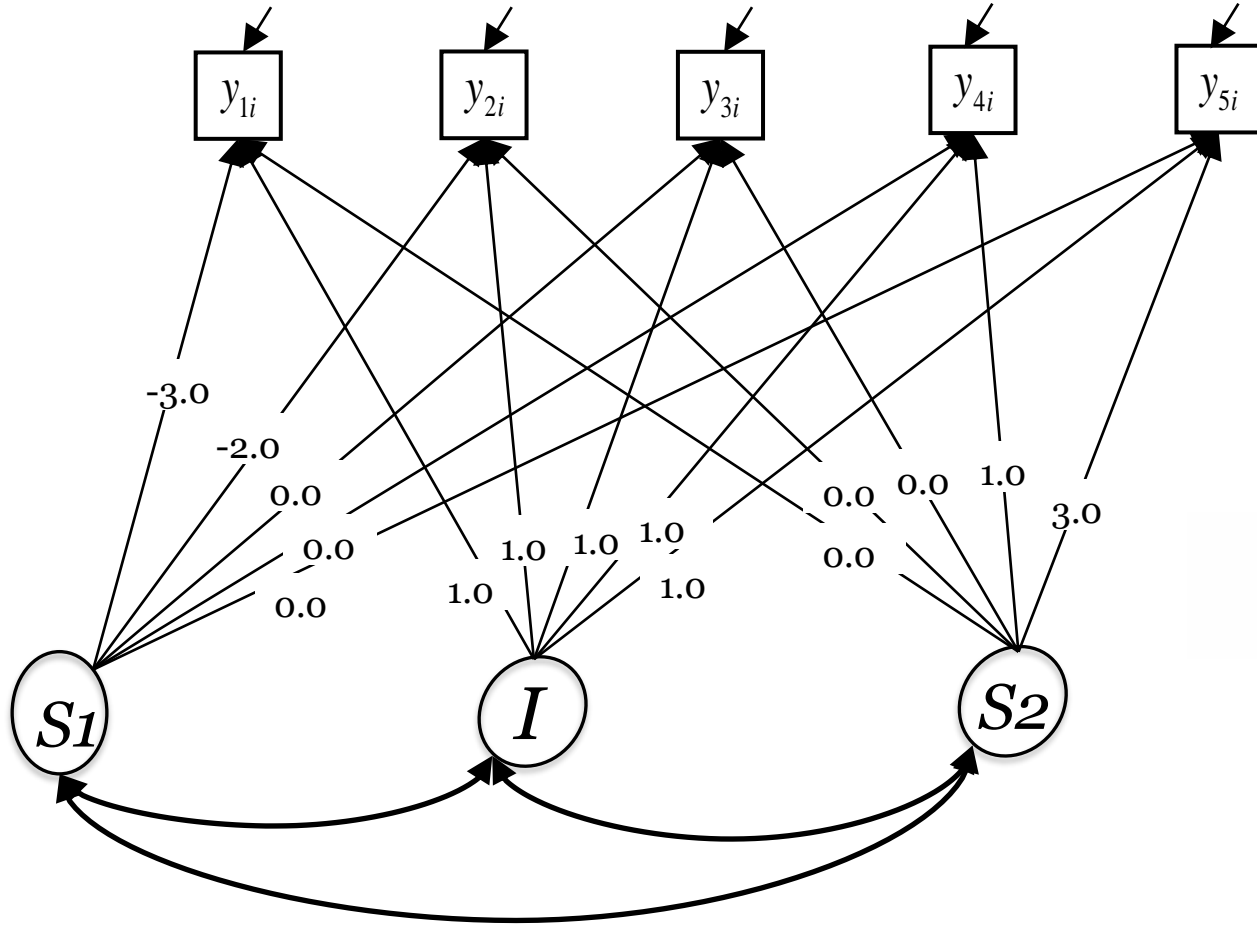Intercept at Time 3, knot at Time 3

-3	1	0	Time 1, 2015
-2	1	0	Time 2, 2016
0	1	0	Time 3, 2018
0	1	1	Time 4, 2019
0	1	3	Time 5, 2021

I = Predicted average value of outcome in 2018
S1 = Average rate of change in outcome prior to 2018
S2 = Average rate of change in outcome from 2018 through 2021

Spline/Piecewise/Multiphase LGCM - 2

Intercept at Time 3, knot at Time 3
I = Predicted average value of outcome in 2018
S1 = Average rate of change in outcome prior to 2018
S2 = Average rate of change in outcome from 2018 through 2021

```
004_2_Bilinear_spline_growht_curve_model_2

TITLE:   002_Bilinear_spline_growht_curve_model

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S1|lone1@-3 lone2@-2 lone3@0 lone4@0 lone5@0;!Slope 1
    I S2|lone1@0 lone2@0 lone3@0 lone4@1 lone5@3;!Slope 2

OUTPUT:
    SAMPSTAT;
```
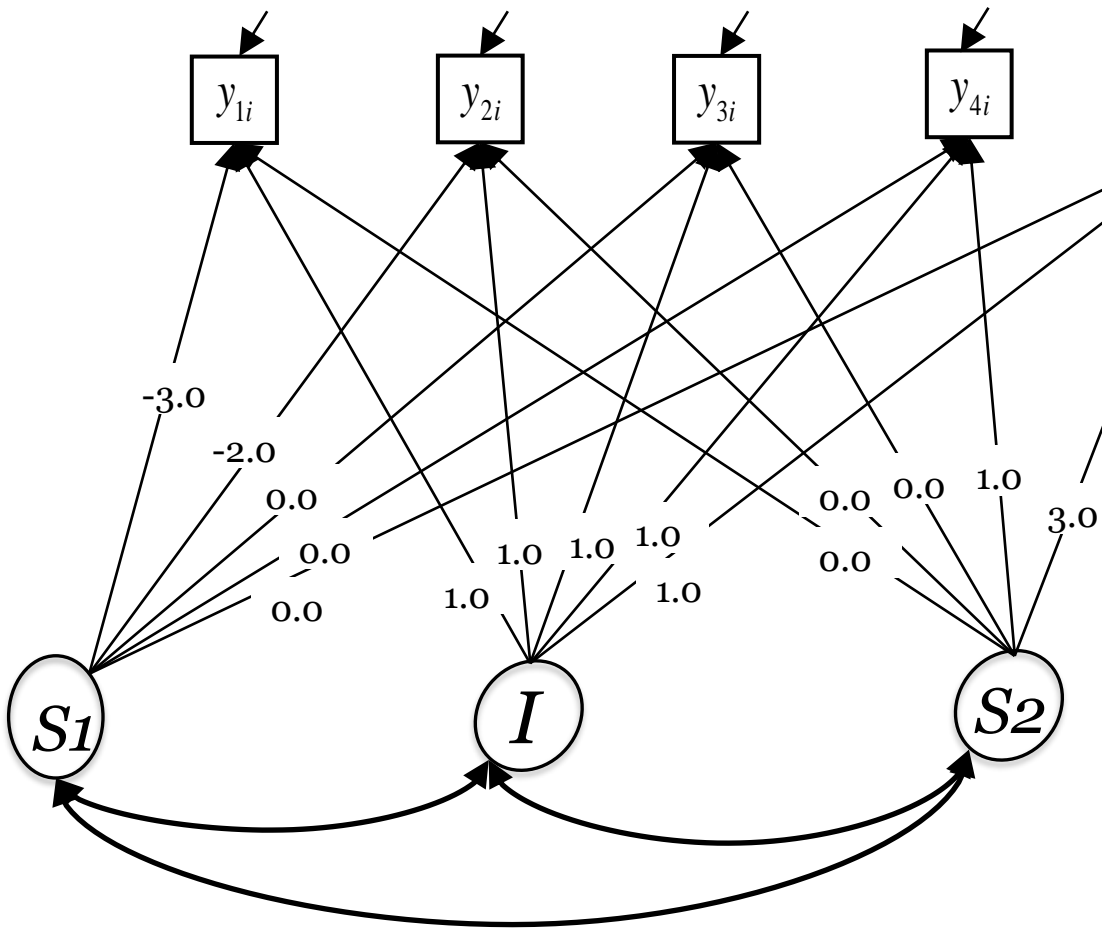
```
60  # 004_2_Bilinear/Spline growth curve model - 2
61  bilinear_2 <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
62              s1 =~ -3*lone1 + -2*lone2 + 0*lone3 + 0*lone4 + 0*lone5
63              s2 =~ 0*lone1 + 0*lone2 + 0*lone3 + 1*lone4 + 3*lone5'
64  fit_bilinear_2 <- growth(bilinear_2, data = data)
65  summary(fit_bilinear_2, fit.measures = TRUE)
```

Frederick Anyan, PhD - NTNU

Spline/Piecewise/Multiphase LGCM - 2

Intercept at Time 3, knot at Time 3

-3	1	0	Time 1, 2015
-2	1	0	Time 2, 2016
0	1	0	Time 3, 2018
0	1	1	Time 4, 2019
0	1	3	Time 5, 2021

I = Predicted average value of outcome in 2018
S1 = Average rate of change in outcome prior to 2018
S2 = Average rate of change in outcome from 2018 through 2021

RESULTS

Model fit:
($\chi^2 = 40.781$, $df = 6$; $p < .001$; $RMSEA = .134$, [90% CI = 0.097, 0.175]; $CFI = .921$; $TLI = .869$)

Parameter estimates:

i.	Intercept:	1.465***
ii.	Slope 1:	0.007
iii.	Slope 2:	-0.059***

(Co)Variances:

i.	Intercept:	0.126***
ii.	Slope 1:	0.008**
iii.	Slope 2:	0.002
iv.	Intercept WITH Slope 1:	0.010*
v.	Intercept WITH Slope 2	-0.018**
vi.	Slope 1 WITH Slope 2	0.000
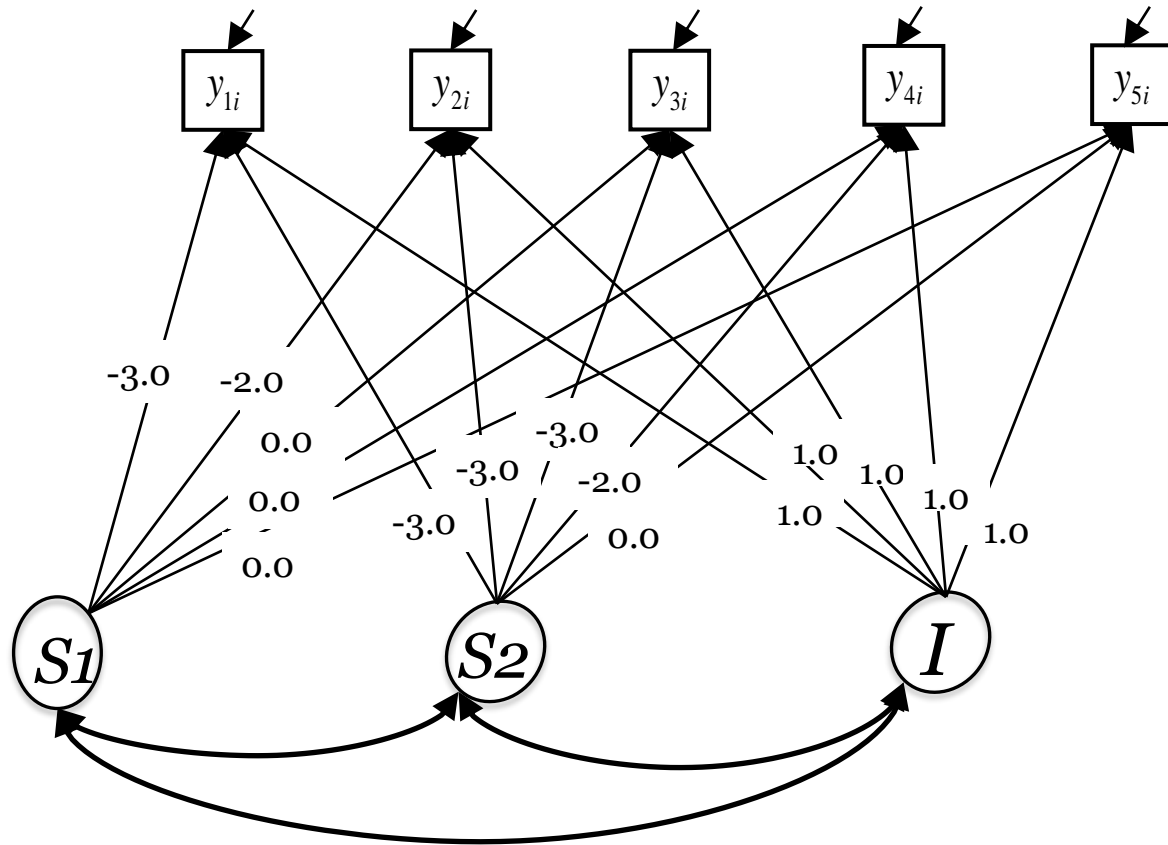
Spline/Piecewise/Multiphase LGCM - 3

Intercept at Time 5, knot at Time 3

-3	-3	1	Time 1, 2015
-2	-3	1	Time 2, 2016
0	-3	1	Time 3, 2018
0	-2	1	Time 4, 2019
0	0	1	Time 5, 2021

I = Predicted average value of outcome at end of observation in 2021
S1 = Average rate of change in outcome prior to 2018
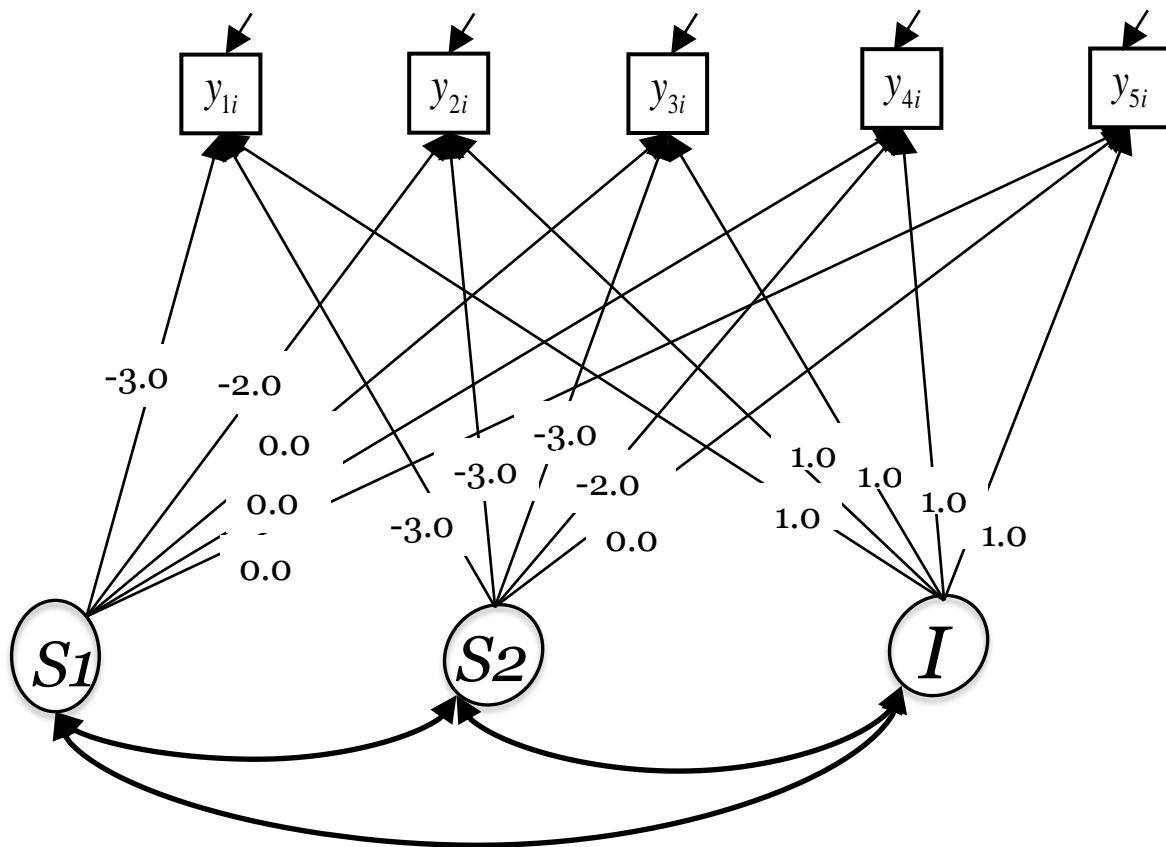S2 = Average rate of change in between 2018 to 2021

Spline/Piecewise/Multiphase LGCM - 3

Intercept at Time 5, knot at Time 3

I = Predicted average value of outcome at end of observation in 2021
S1 = Average rate of change in outcome prior to 2018
S2 = Average rate of change in outcome from 2018 through 2021

```
004_3_Bilinear_spline_growht_curve_model_3

TITLE:  002_Bilinear_spline_growht_curve_model

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S1|lone1@-3 lone2@-3 lone3@-3 lone4@-2 lone5@0;!Slope 1
    I S2|lone1@-3 lone2@-2 lone3@0 lone4@0 lone5@0;!Slope 2

OUTPUT:
    SAMPSTAT;
```

```
68  # 004_3_Bilinear/Spline growth curve model - 3
69  bilinear_3 <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
70          s1 =~ -3*lone1 + -3*lone2 + -3*lone3 + -2*lone4 + 0*lone5
71          s2 =~ -3*lone1 + -2*lone2 + 0*lone3 + 0*lone4 + 0*lone5'
72  fit_bilinear_3 <- growth(bilinear_3, data = data)
73  summary(fit_bilinear_3, fit.measures = TRUE)
74
```

Frederick Anyan, PhD - NTNU

Spline/Piecewise/Multiphase LGCM - 3

Intercept at Time 5, knot at Time 3

-3	-3	1	Time 1, 2015
-2	-3	1	Time 2, 2016
0	-3	1	Time 3, 2018
0	-2	1	Time 4, 2019
0	0	1	Time 5, 2021

I = Predicted average value of outcome at end of observation in 2021
S1 = Average rate of change in outcome prior to 2018
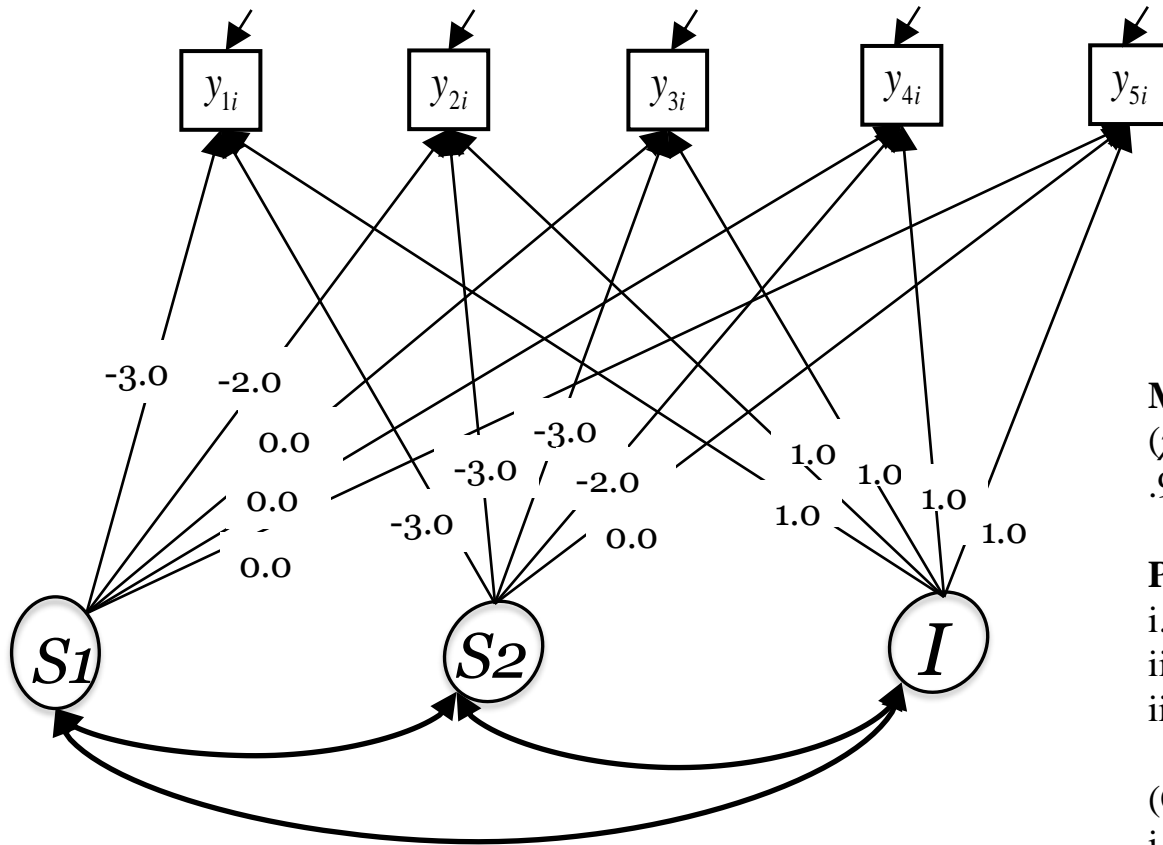S2 = Average rate of change in outcome from 2018 through 2021

RESULTS

Model fit:
($\chi^2 = 40.781$, $df = 6$; $p < .001$; $RMSEA = .134$, [90% CI = 0.097, 0.175]; $CFI = .921$; $TLI = .869$)

Parameter estimates:

i.	Intercept:	1.288***
ii.	Slope 1:	-0.059***
iii.	Slope 2:	0.007

(Co)Variances:

i.	Intercept:	0.036
ii.	Slope 1:	0.002
iii.	Slope 2:	0.008**
iv.	Intercept WITH Slope 1:	-0.012
v.	Intercept WITH Slope 2	0.011**
vi.	Slope 1 WITH Slope 2	0.000

Model comparisons and selection

Model		Compared with	χ^2	df	RMSEA	CFI	TLI
M1	No growth		186.443	13	.204[0.179, 0.230]	.607	.698
M2	Linear growth	M1	75.244	10	.143[0.113, 0.174]	.852	.852
M3	Quadratic growth	M2	46.671	6	.145[0.108, 0.185]	.908	.846
M4	Bilinear spline growth	NON-NESTED!	40.781	6	.134[0.097, 0.175]	.921	.869

Model Comparison

	Model M1 No growth	Model M2 Linear growth	Model M3 Quadratic growth	Model M4 Bilinear spline
Parameters	7	10	14	
-2LL	1629.268	1518.080	1489.508	
AIC	1643.269	1538.080	1517.507	1511.809
BIC	1669.669	1575.796	1570.308	1564.418
Δ parameters	-	3	4	
Δ -2LL	-	111.19***	28.573***	

- Do not compare nested models whose fit indices do not reach acceptable, e.g. M1 and M2

- Bilinear is a non-nested model with M1-M3
 - So use AIC and BIC

Objectives of longitudinal research

1. Identification of intraindividual (within-person) changes (and stability)
   - Is there change over time on average?
     - ✓ Growth models can address various linear and nonlinear patterns of intraindividual change

2. Analysis of causes (determinants) of intraindividual change
   - What factors/mechanisms – time-varying/dynamical predictors – drive change?
     - ✓ Inclusion of time-varying (dynamical) predictors in growth models

3. Identification of interindividual differences (or similarity) in intraindividual change
   - Do different individuals change in different ways?
     - ✓ Differences between groups of persons in the way people change

4. Analysis of causes (determinants) of interindividual differences in intraindividual change
   - What factors explain between-person differences in change?
     - ✓ Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5. Interrelationships in change
   - Does change in one variable relate (*precede, covary and/or follow*) to change in another variable?
   - Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
   - ✓ Multi (parallel & sequentially contingent) process LGCM

- What dynamics or factors drive within-person changes?
  - Does hostility affect the trajectory of loneliness?
    - Loneliness is more elevated than usual when someone is more hostile than usual?

Conditional Linear LGCM, LGCM with Time-varying covariates
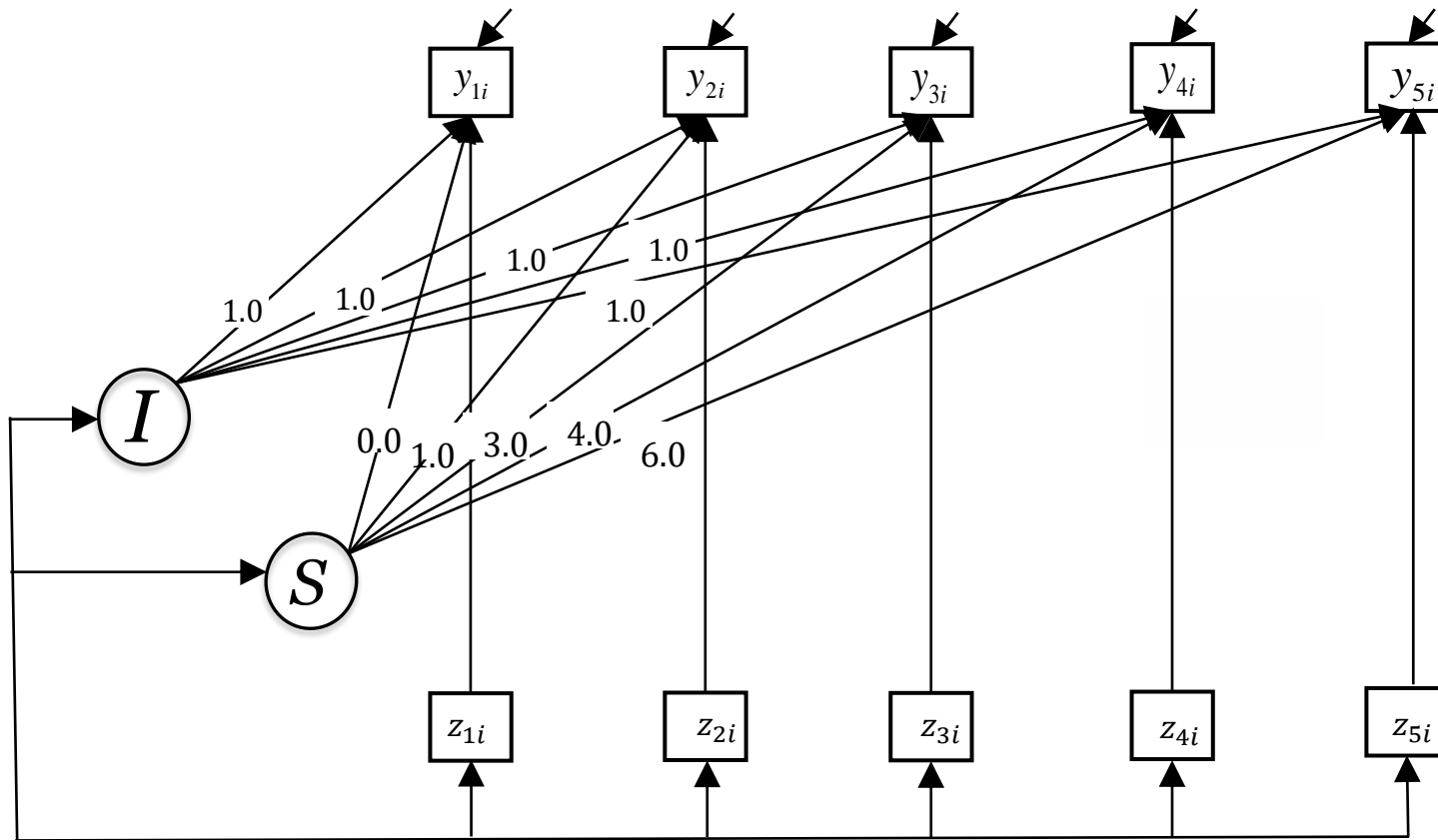
- TVC is exogenous to the developmental process

- The effect of TVC is a within-person effect which influences an individual's change trajectory

- Flexibility in SEM allows correlating TVC with I and S – growth factors.
  - Convergence problems
    - *Fix covariance between TVC with I and S to zero*

Conditional Linear LGCM, LGCM with Time-varying covariates
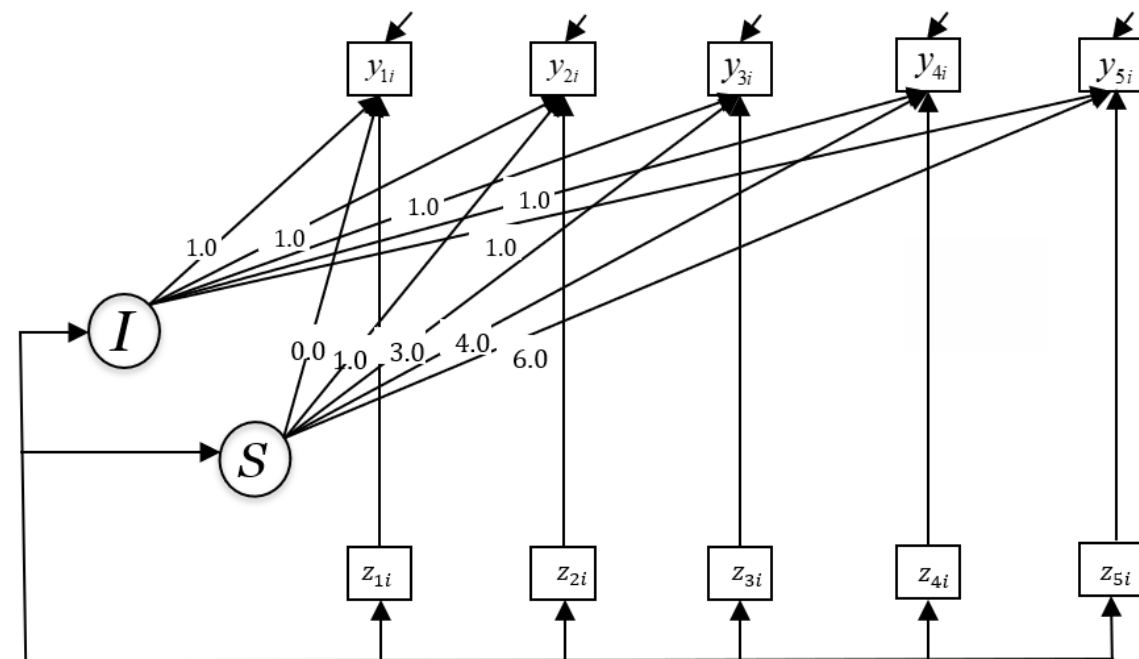

```
005_Linear_growht_curve_model_with_time_varying_covariate

TITLE:   005_Linear_growht_curve_model_with_time_varying_covariate

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5
        host1 host2 host3 host4 host5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;!Growth for loneliness

    !Regress loneliness on time-varying covariate
    lone1 ON host1;!By adding labels to the parameter estimates
    lone2 ON host2;!you can test whether TVC effects are constant over time
    lone3 ON host3;
    lone4 ON host4;
    lone5 ON host5;

    !However, if you already assume constant effect of TVC over time
    !and do not want to test, you can use this model specification
    !lone1 ON host1(a);!By adding the same label (a) to the parameter estimates
    !lone2 ON host2(a);!you constrain the effects to be constant across time
    !lone3 ON host3(a);
    !lone4 ON host4(a);
    !lone5 ON host5(a);

    !Fix TVC covariance with intercept and slope to zero
    I S WITH host1-host5@0;

OUTPUT:
    SAMPSTAT;
```

Conditional Linear LGCM, LGCM with Time-varying covariates
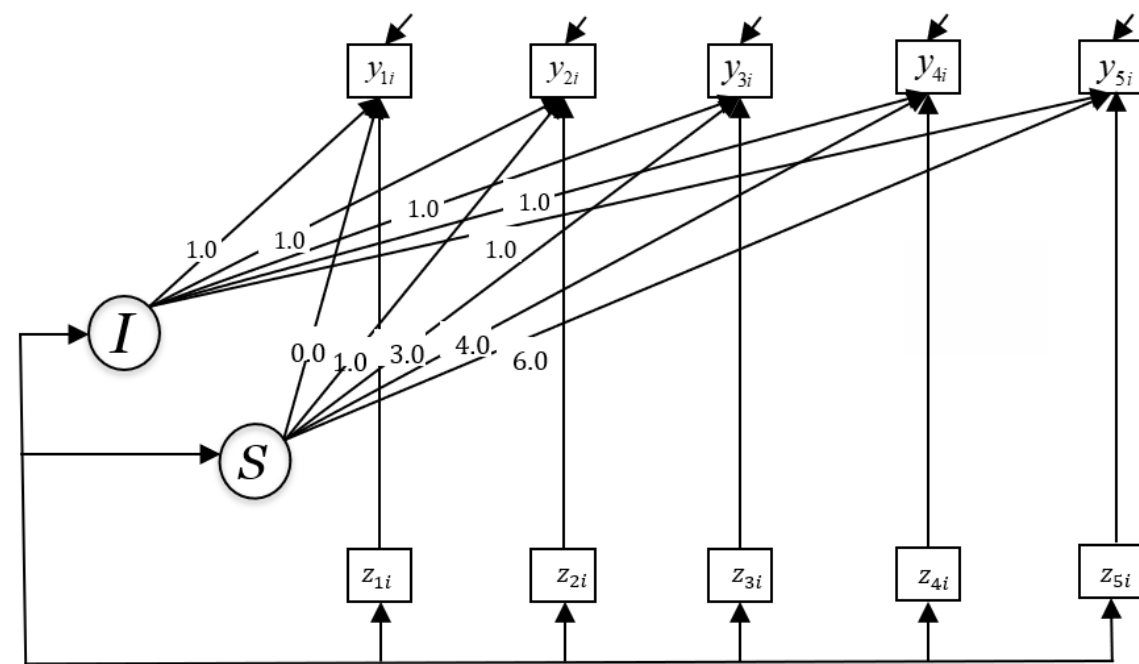


```
87   # 005_Linear growth curve model with time-varying covariates
88   timevaryingcov <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
89                       s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
90   # Time-varying covariates
91   lone1 ~ host1                #lone1 ~ eq*host1
92   lone2 ~ host2                #lone2 ~ eq*host2
93   lone3 ~ host3                #lone3 ~ eq*host3
94   lone4 ~ host4                #lone4 ~ eq*host4
95   lone5 ~ host5                #lone5 ~ eq*host5
96
97   #Estimate the means of the TVC
98   host1 ~ 1
99   host2 ~ 1
100  host3 ~ 1
101  host4 ~ 1
102  host5 ~ 1
103
104  #Estimate covariance between TVC
105  host1 ~~ host2 + host3 + host4 + host5
106  host2 ~~ host3 + host4 + host5
107  host3 ~~ host4 + host5
108  host4 ~~ host5'
109
110  fit_timevaryingcov <- growth(timevaryingcov, data = data)
111  summary(fit_timevaryingcov, fit.measures = TRUE)
```

Conditional Linear LGCM, LGCM with Time-varying covariates
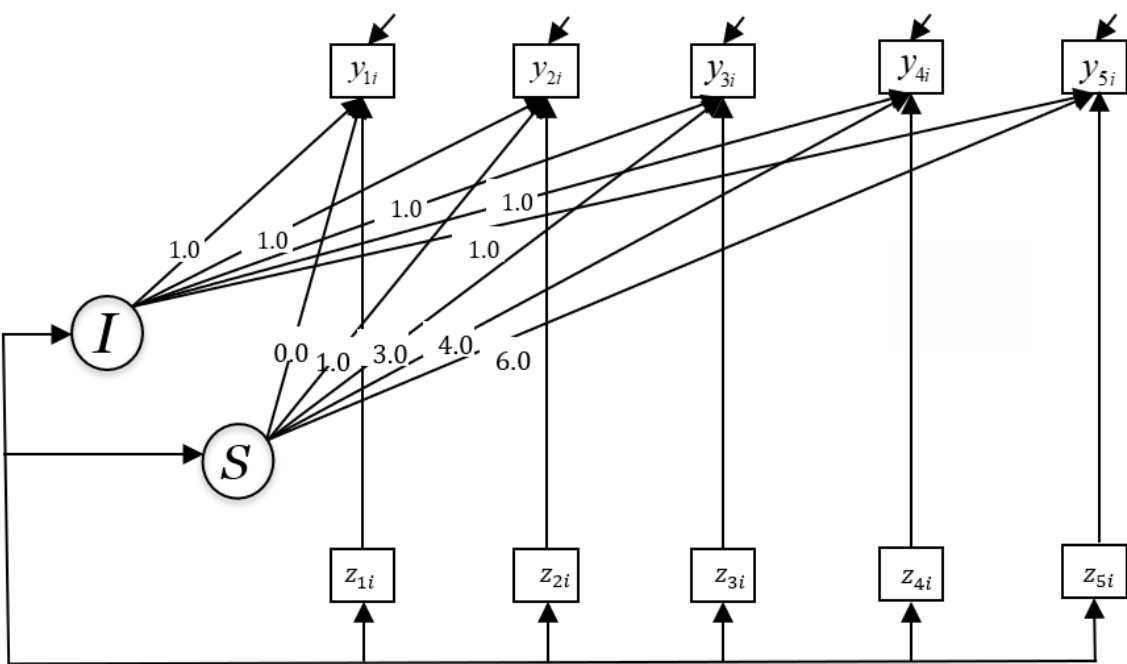
RESULTS

Model fit:
($\chi^2 = 103.191$, $df = 30$; $p < .001$; $RMSEA = .087$, [90% CI = 0.069, 0.106]; $CFI = .972$; $TLI = .967$)

Parameter estimates:

i.	Intercept:	0.414***
ii.	Slope 1:	-0.010

TVC

i.	Hostility:	$0.719 - 0.737$

(Co)Variances:

|		
i.	Intercept:	0.028***
ii.	Slope 1:	0.001***
iii.	Intercept WITH Slope:	-0.003***
iv.	TVC WITH TVC:	$0.036 - 0.161$***

Objectives of longitudinal research

1. Identification of intraindividual (within-person) changes (and stability)
   - Is there change over time on average?
     - ✓ Growth models can address various linear and nonlinear patterns of intraindividual change

2. Analysis of causes (determinants) of intraindividual change
   - What factors/mechanisms – time-varying/dynamical predictors – drive change?
     - ✓ Inclusion of time-varying (dynamical) predictors in growth models

3. Identification of interindividual differences (or similarity) in intraindividual change
   - Do different individuals change in different ways?
     - ✓ Differences between groups of persons in the way people change

4. Analysis of causes (determinants) of interindividual differences in intraindividual change
   - What factors explain between-person differences in change?
     - ✓ Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5. Interrelationships in change
   - Does change in one variable relate (*precede, covary and/or follow*) to change in another variable?
   - Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
     - ✓ Multi (parallel & sequentially contingent) process LGCM

- Do girls have different intercept and slope of the feeling of loneliness from boys ?
  - Does gender influence between-person differences in the trajectory of loneliness?
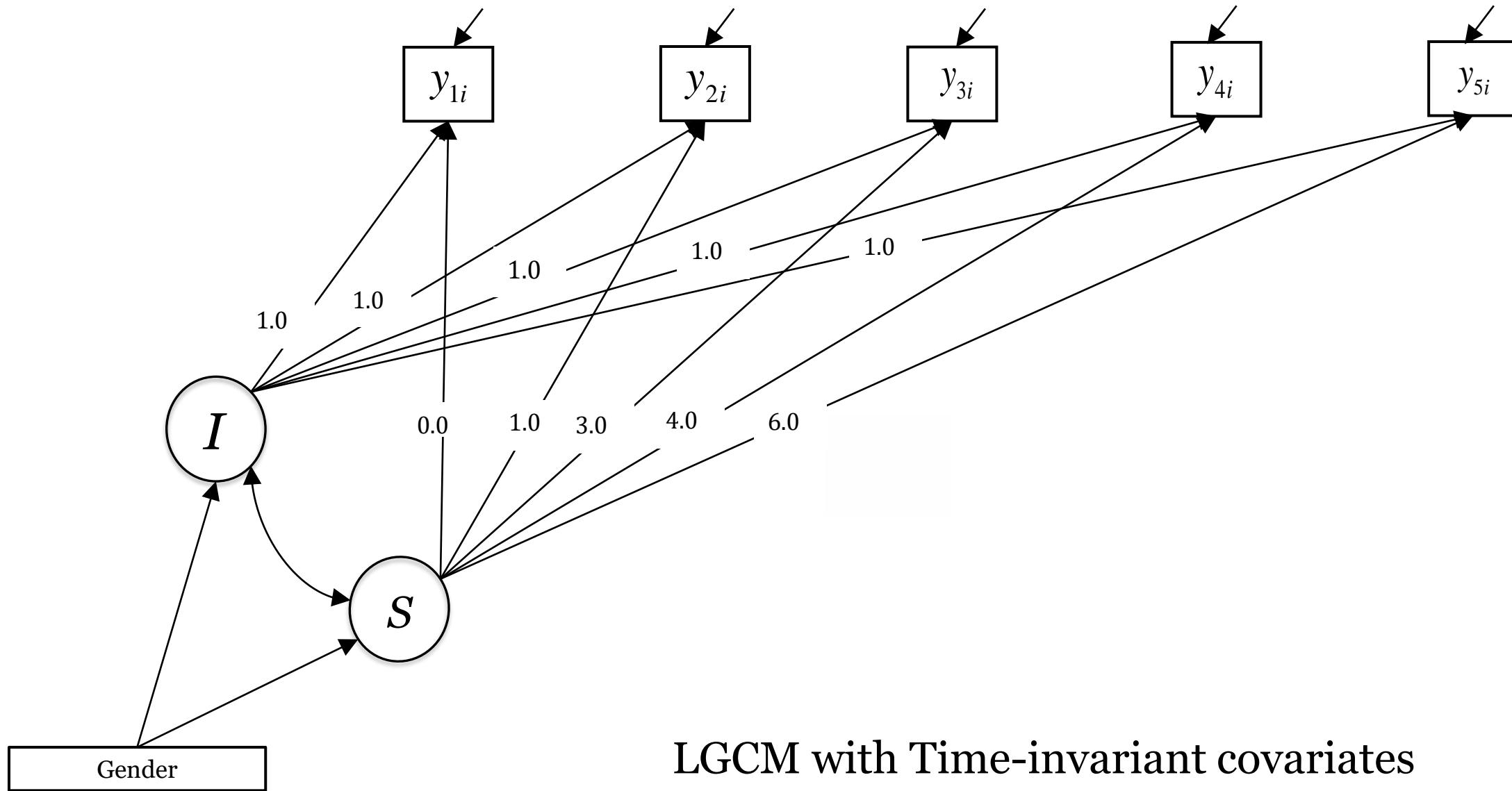
LGCM with Time-invariant covariates
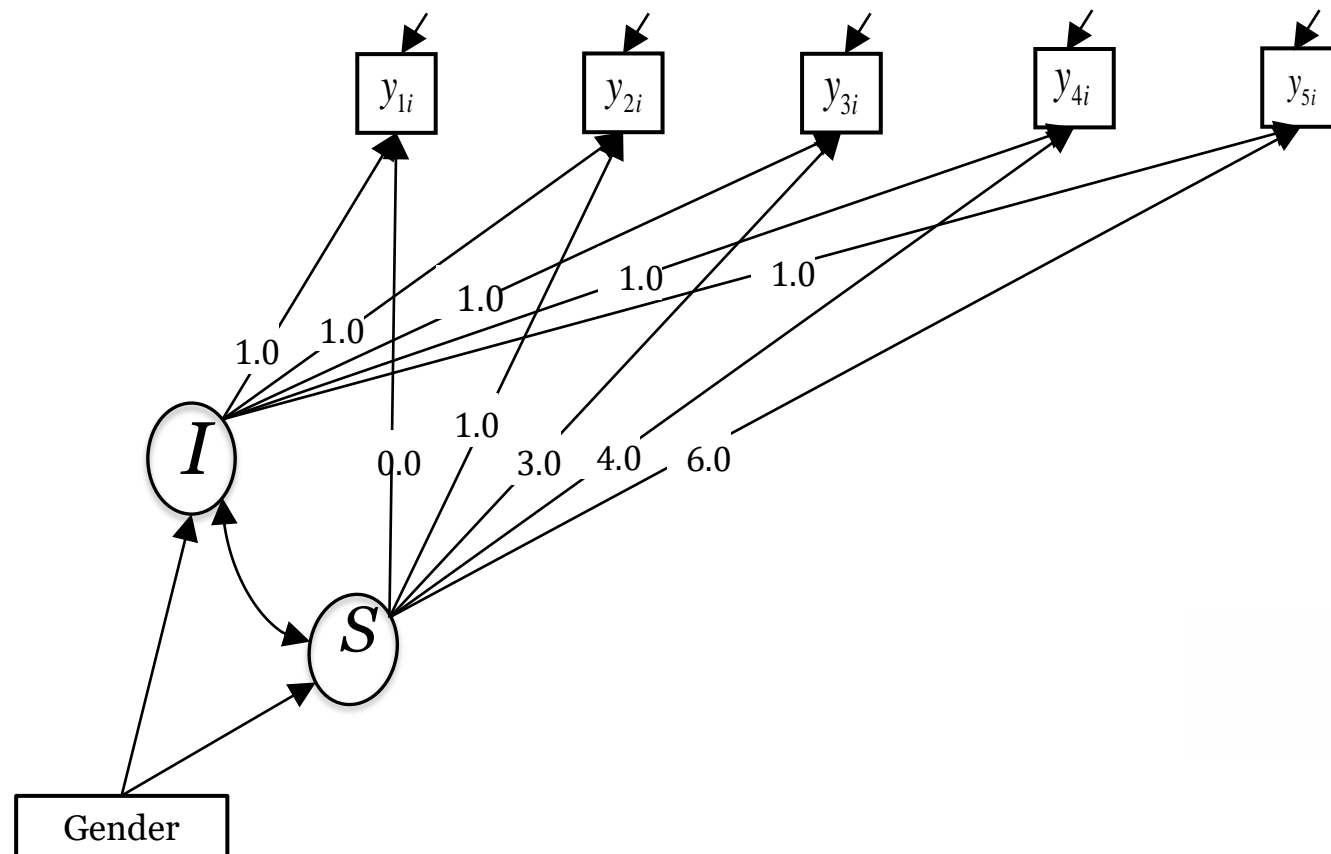
LGCM with Time-invariant covariates

```
TITLE:   006_Linear_growht_curve_model_with_time_invariant_covariate

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
      lone1 lone2 lone3 lone4 lone5 female;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    !Regress growth factors on the time-invariant covariate
    I S ON female;

OUTPUT:
    SAMPSTAT;
```
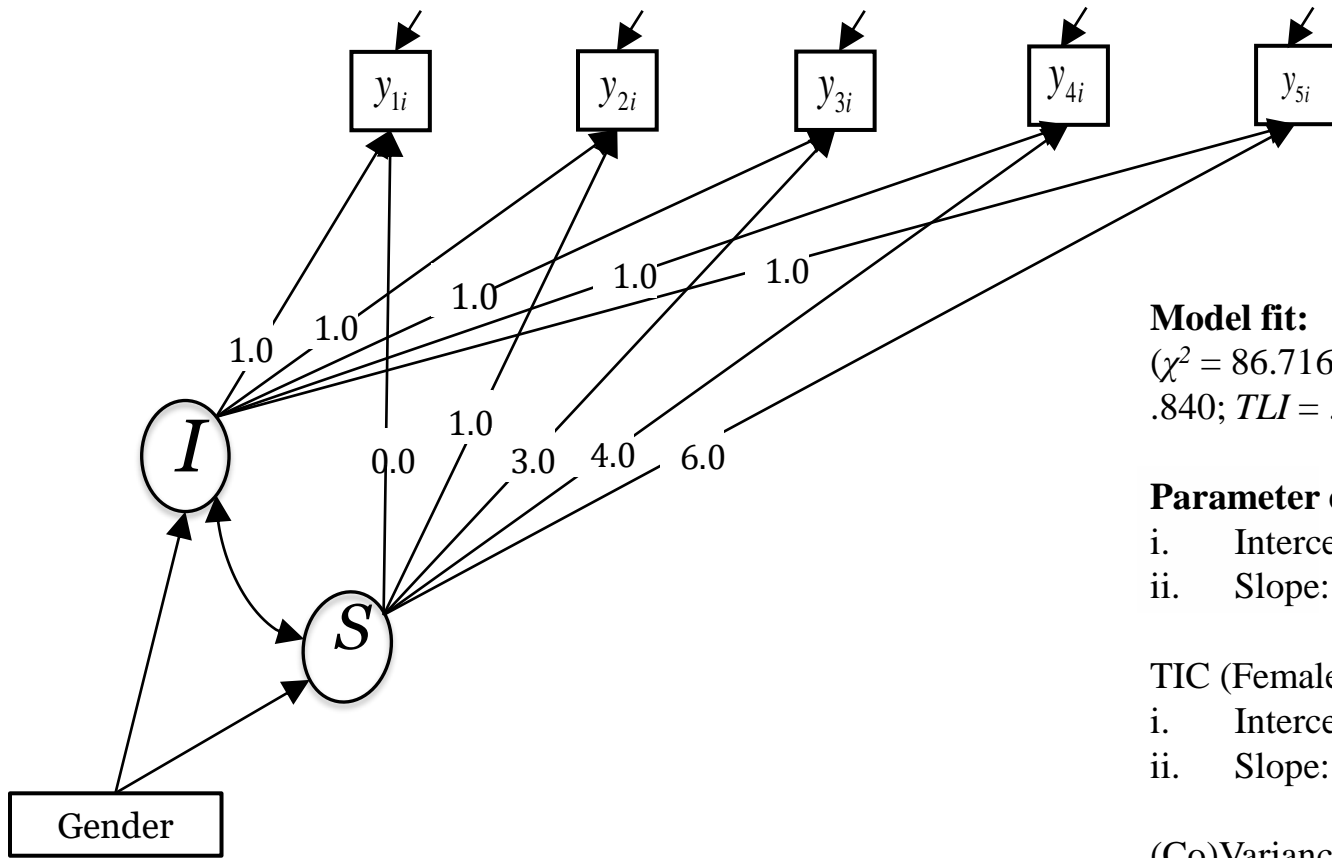
```
114   # 006_Linear growth curve model with time invariant covariates
115   timeinvar <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
116                 s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
117
118   # Time invariant covariates
119   i ~ female
120   s ~ female'
121   fit_timeinvar <- growth(timeinvar, data = data)
122   summary(fit_timeinvar, fit.measures = TRUE)
```
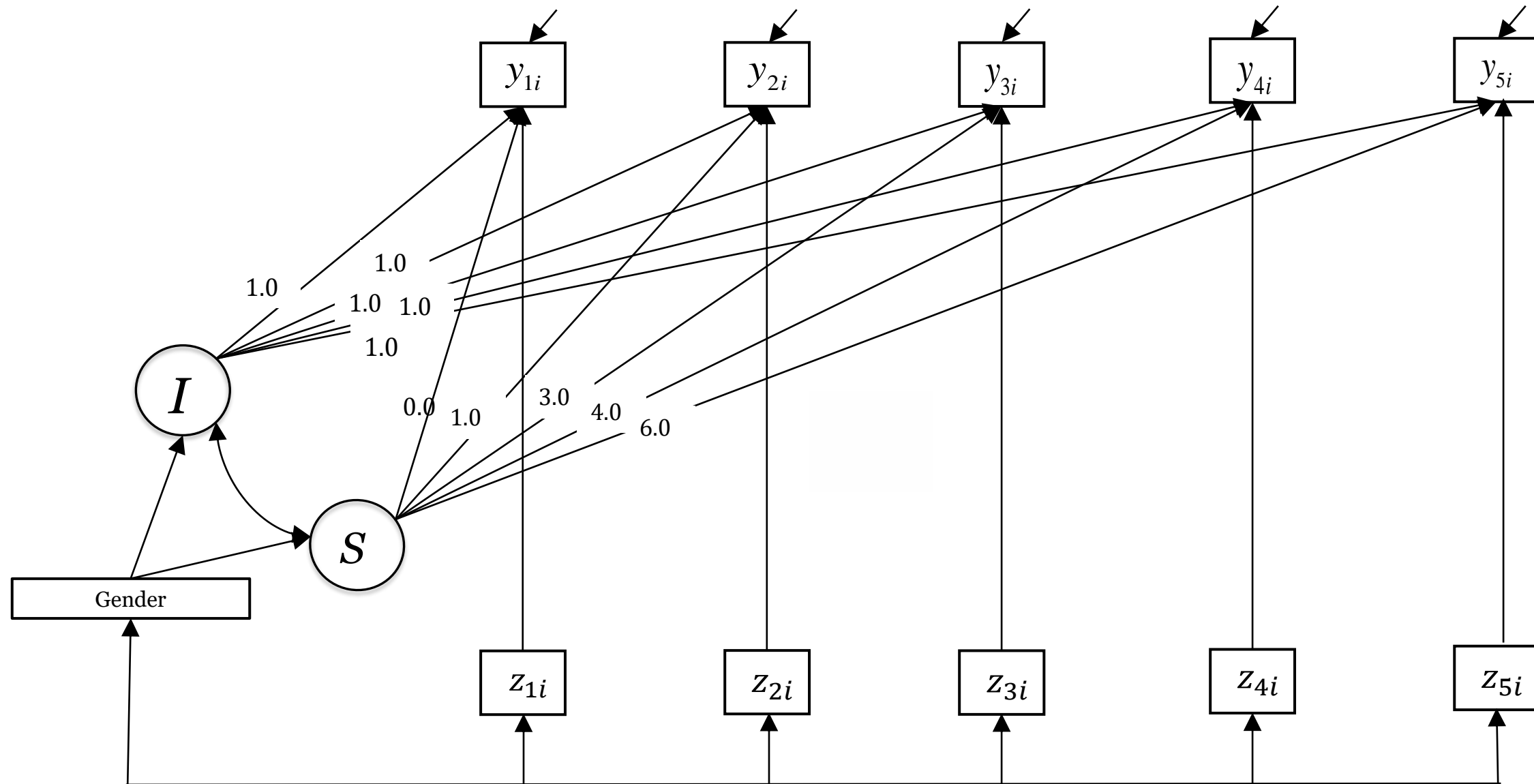
LGCM with Time-invariant covariates

RESULTS

Model fit:
($\chi^2 = 86.716$, $df = 13$; $p < .001$; $RMSEA = .133$, [90% CI = 0.107, 0.160]; $CFI = .840$; $TLI = .815$)

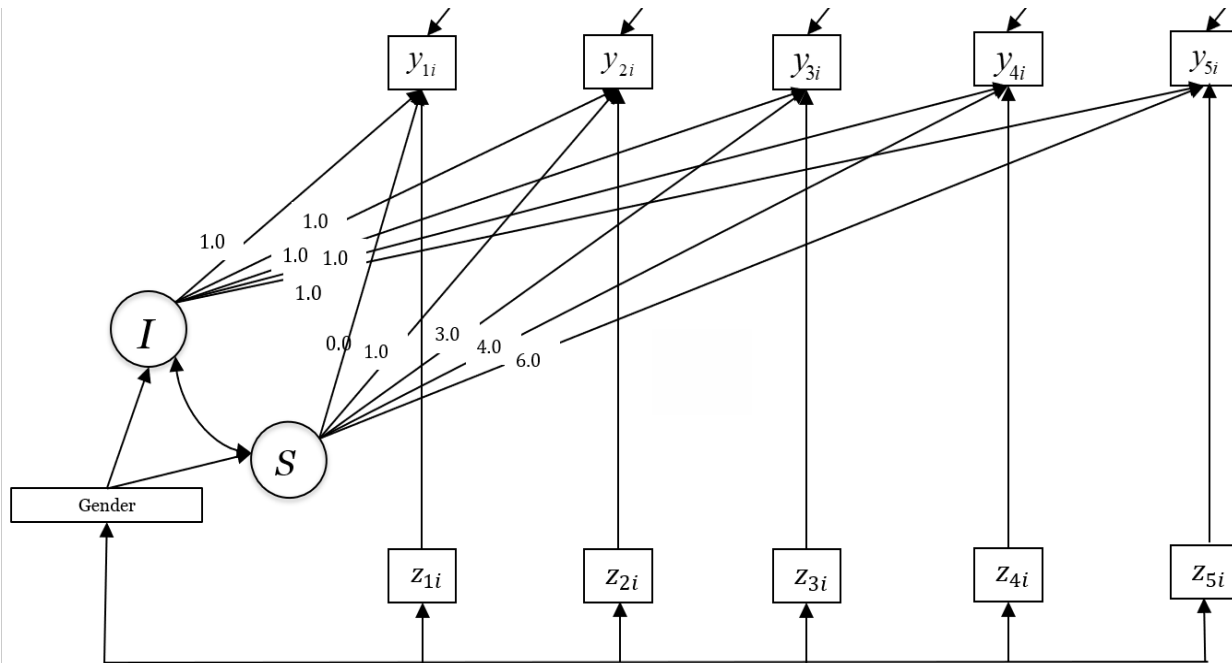**Parameter estimates:**
i.   Intercept: 1.526***
ii. Slope: -0.029***

TIC (Female)
i.   Intercept: -0.132**
ii. Slope: 0.007

(Co)Variances:
i.   Intercept: 0.134***
ii.   Slope: 0.003***
iii. Intercept WITH Slope: -0.015***

LGCM with Time-invariant and time-varying covariates

LGCM with Time-invariant and time-varying covariates

```
TITLE:    007_Linear_growht_curve_model_with_time-invariant and time-v

DATA:
FILE IS data.dat;
LISTWISE = ON;

VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
        lone1 lone2 lone3 lone4 lone5
        host1 host2 host3 host4 host5
        female;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    !Regress growth factors on time-invariant covariates
    I S ON female;

    !Regress loneliness on TVC
    lone1 ON host1(a);!Constrain TVC effect to be equal across time
    lone2 ON host2(a);
    lone3 ON host3(a);
    lone4 ON host4(a);
    lone5 ON host5(a);

    !Fix TVC covariance with intercept and slope to zero
    I S WITH host1-host5@0;

    !Estimate the covaraince between covariates
    female WITH host1-host5;

OUTPUT:
    SAMPSTAT;
```
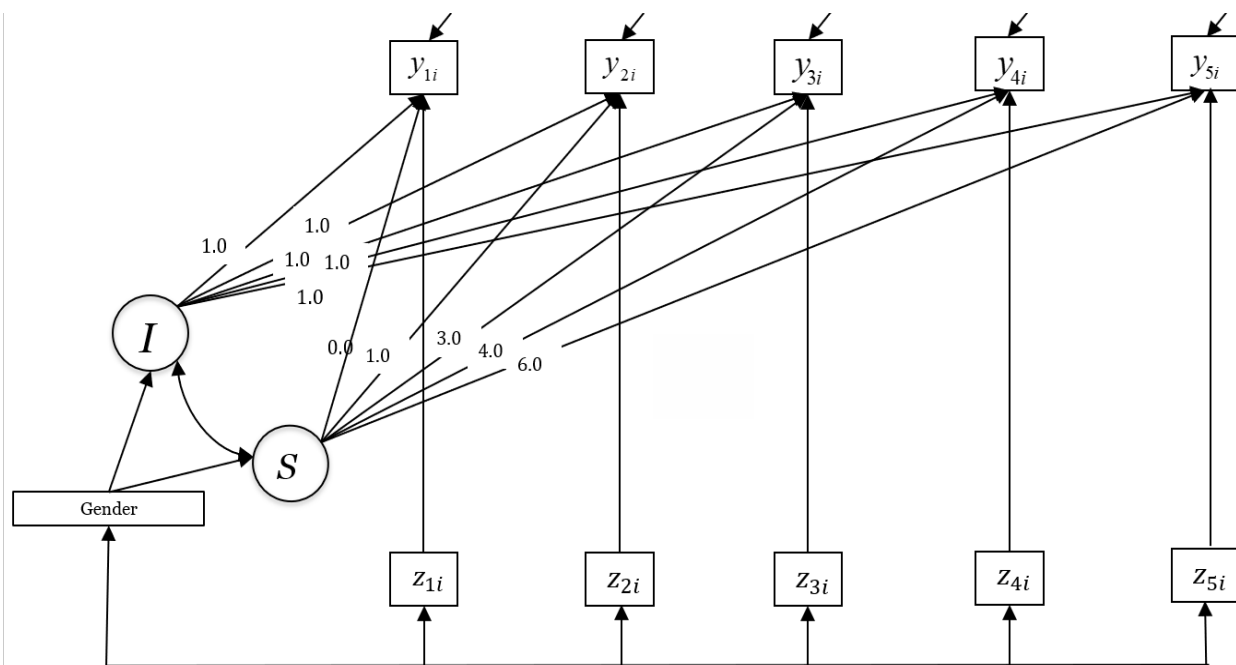
Frederick Anyan, PhD - NTNU

LGCM with Time-invariant and time-varying covariates


```
125  # 007_Linear growth curve model with time invariant and time-varying covariates
126  timeinvartimevar <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
127                       s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
128  # Time-varying covariates held equal
129  lone1 ~ eq*host1
130  lone2 ~ eq*host2
131  lone3 ~ eq*host3
132  lone4 ~ eq*host4
133  lone5 ~ eq*host5
134
135  # Time invariant covariates
136  i ~ female
137  s ~ female
138
139  #Estimate the means of TVC and TIC
140  host1 ~ 1
141  host2 ~ 1
142  host3 ~ 1
143  host4 ~ 1
144  host5 ~ 1
145  female ~ 1
146
147
148  #Estimate covariances between TIC with TVC
149  female ~~ host1 + host2 + host3 + host4 + host5
150  host1 ~~ host2 + host3 + host4 + host5
151  host2 ~~ host3 + host4 + host5
152  host3 ~~ host4 + host5
153  host4 ~~ host5
154
155  #Fix covariances between TVC and growth factors to zero
156  i ~~ 0*host1
157  i ~~ 0*host2
158  i ~~ 0*host3
159  i ~~ 0*host4
160  i ~~ 0*host5
161
162  s ~~ 0*host1
163  s ~~ 0*host2
164  s ~~ 0*host3
165  s ~~ 0*host4
166  s ~~ 0*host5
167  '
168  fit_timeinvar_timevar <- growth(timeinvartimevar, data = data)
169  summary(fit_timeinvar_timevar, fit.measures = TRUE)
```

Model fit:
($\chi^2 = 106.720$, $df = 37$; $p < .001$; $RMSEA = .077$, [90% CI = 0.060, 0.094]; $CFI = .973$; $TLI = .971$)

Parameter estimates:

i.	Intercept:	0.456***
ii.	Slope:	-0.009**

TIC (Female)

i.	Intercept:	-0.131**
ii.	Slope:	0.008

TVC

Host	.731***

(Co)Variances:

i.	Intercept:	0.023***
ii.	Slope:	0.001***
iii.	Intercept WITH Slope:	-0.002***
iv.	TVC WITH TVC:	0.037 – 0.161***
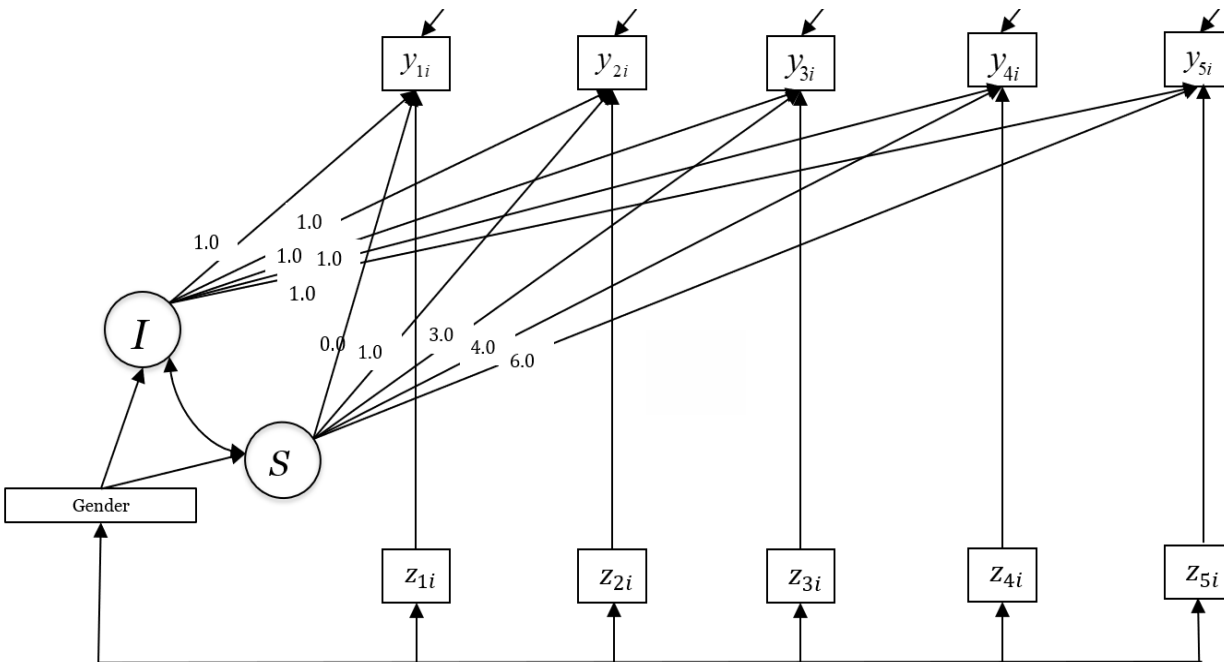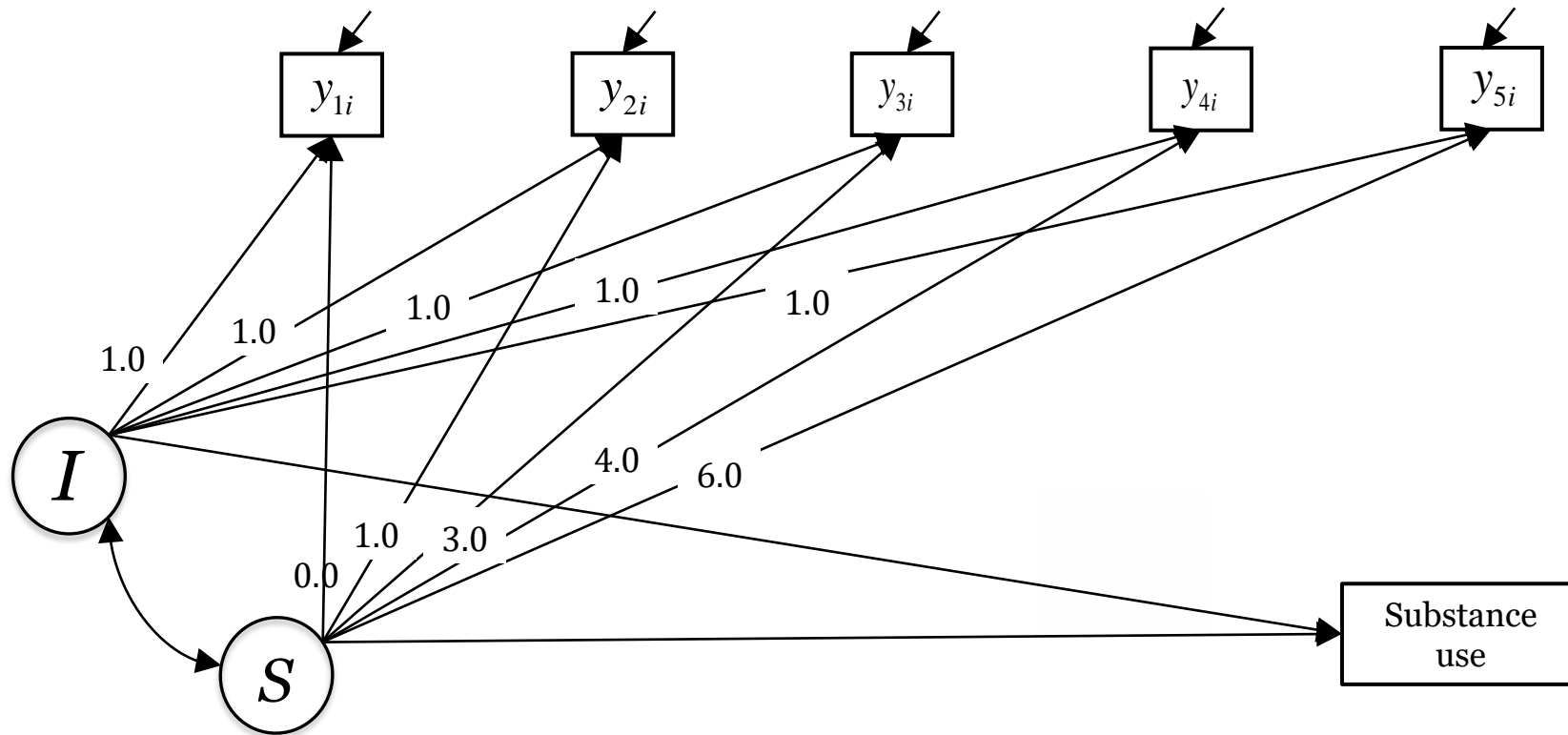
LGCM growth factors predicting distal outcome
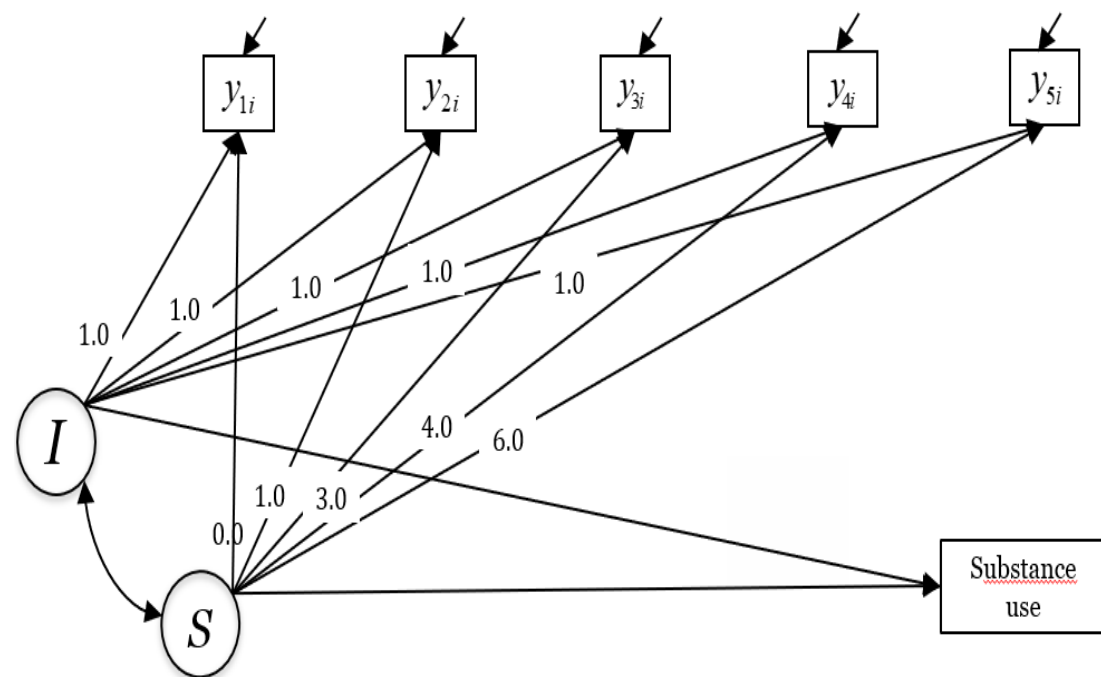
LGCM growth factors predicting distal outcome

```
172  # 008_Linear growth curve model with growth factors predicting distal outcome
173  distal <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
174            s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
175
176  # Time invariant covariates
177  subs5 ~ i + s
178
179  #Estimate the intercept of subs
180  subs5 ~ 1'
181  fit_distal <- growth(distal, data = data)
182  summary(fit_distal, fit.measures = TRUE)
```

008_Linear_growht_curve_model_with_growth_factors_predicting_distal_outcome

```
TITLE:  008_Linear_growht_curve_model_with_growth_factors_predicting_distal_out

DATA:
FILE IS data.dat;
LISTWISE = ON;


VARIABLE:
NAMES ARE
id female pdu1 ace1 worry1
lone1 lone2 lone3 lone4 lone5
anx1 anx2 anx3 anx4 anx5
dep1 dep2 dep3 dep4 dep5
host1 host2 host3 host4 host5
percon5 percon5b subs5 subs5b sleep5 sleep5b;

USEVARIABLES ARE
    lone1 lone2 lone3 lone4 lone5 subs5;
    |

MISSING ARE ALL (-999);


ANALYSIS:
    ESTIMATOR = ML;


MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    !Regress distal outcome on growth factors and time-invariant predictors
    subs5 ON I S;


OUTPUT:
    SAMPSTAT;
```
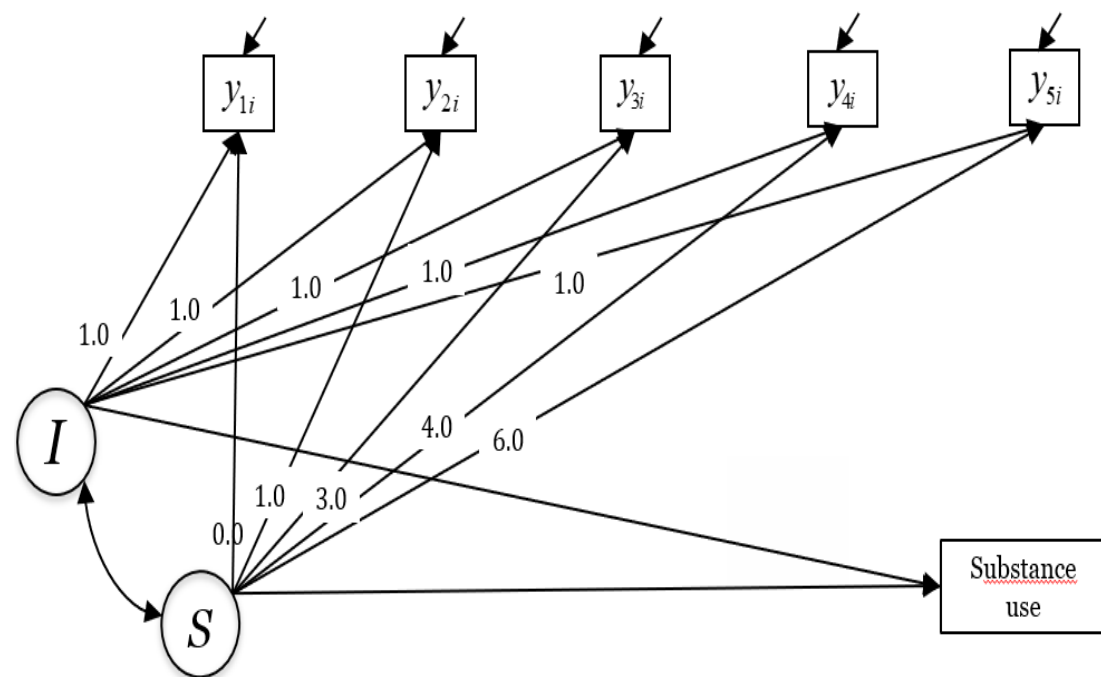
LGCM growth factors predicting distal outcome

RESULTS

Model fit:
(χ^2 = 74.672, df = 13; p < .001; *RMSEA* = .128, [90% CI = 0.101, 0.157]; *CFI* = .854; *TLI* = .832)

Parameter estimates:

i.	Intercept:	1.466***
ii.	Slope:	-0.023***

Distal outcome (substance use)

i.	Intercept:	0.896*
ii.	Slope:	5.889

(Co)Variances:

i.	Intercept:	0.142***
ii.	Slope:	0.003***
iii.	Intercept WITH Slope:	-0.015***
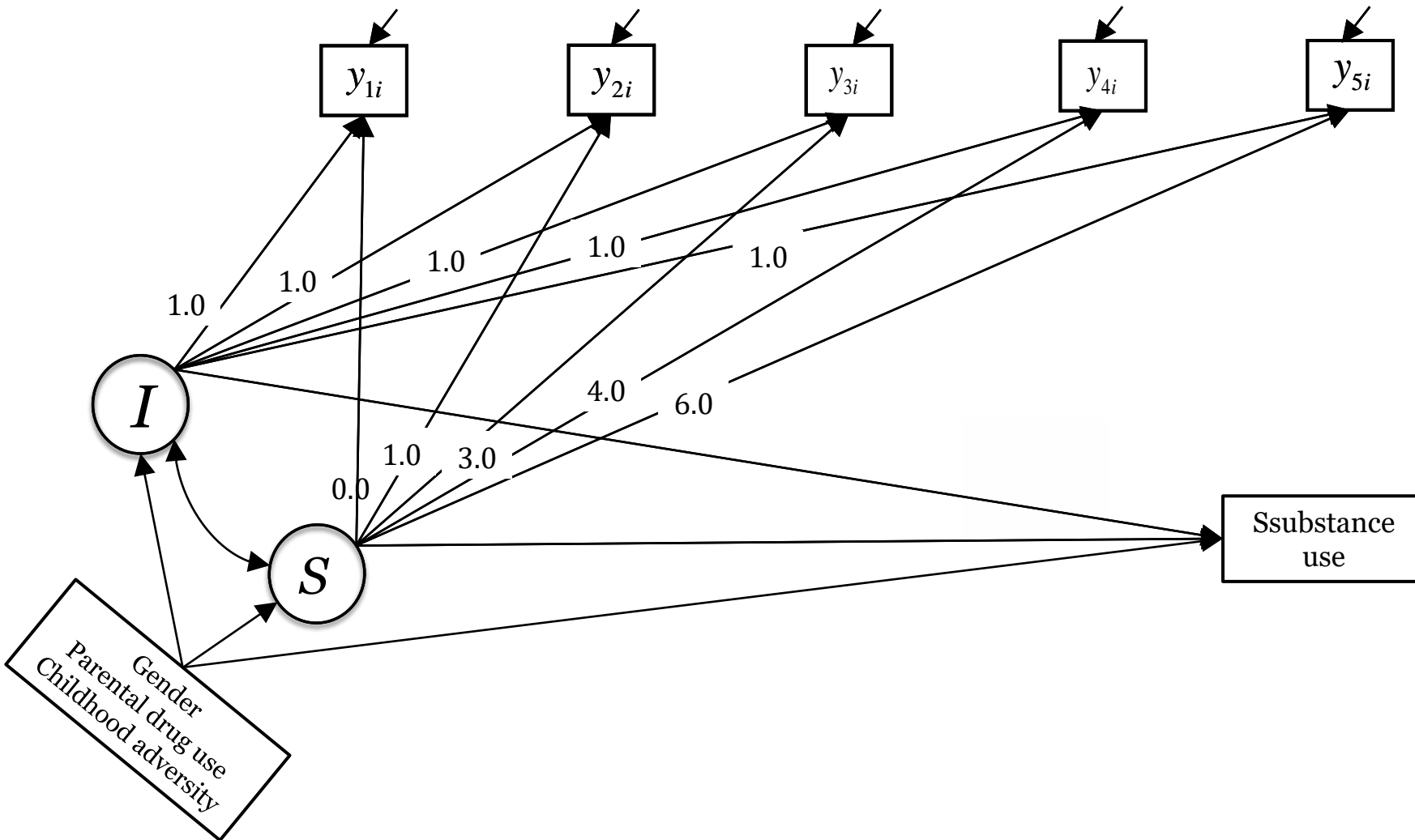
LGCM with Time-invariant covariates and distal outcome

Multigroup LGCM

- How is it different from using time-invariant covariate model?
  - Time-invariant covariate (TIC) models examine the difference in the average growth trajectory
  - TIC models do not examine aspects of the growth model related to
    - Group differences in the
      - i. Average trajectory and invariance testing
      - ii. Variability and covariability of growth trajectories
      - iii. Unexplained within-person variability

- Multigroup LGCM models can examine differences in any aspect of growth trajectory for known, measured or predefined groups
  - Growth mixture models are used for unknown or unmeasured groups that may exist as subpopulations in the data

Multigroup LGCM

- What factors account for between-person differences in the trajectory of loneliness between boys and girls?

  i. Do boys and girls _significantly_ differ in their trajectories of loneliness?
     - What is the extent of differences in the average trajectory of boys and girls?
     - What is the extent of variability around the individual trajectories of boys and girls?

Model comparisons

Model Comparison for the Multiple-Group LGCM

	Model M1 Invariance model	Model M2 Means model	Model M3 Means and covariances model	Model M4 Means, covariances and residual variances model
Parameters				
-2LL				
Δ parameters				
Δ -2LL				

Sequence of testing
- M1: Constrain all parameters (growth factor means, growth factor variances and covariances, and residual variances) to be identical across groups
- M2: Freely estimate growth factor means across groups, while keeping constraints on the growth factor variances and covariance, and residual variances
- M3: Freely estimate growth factor means, growth factor variances and covariances, while keeping the constraints on the residual variances
- M4: Freely estimate growth factor means, growth factor variances and covariances, and residual variances across the groups

Questions to answer
- M1 vs. M2: Tests whether the groups differ in their average trajectory
- M2 vs. M3: Tests the extent of between-person differences in the trajectories of groups
- M3 vs. M4: Tests the extent of within-person variability around individual trajectories
  - If all models fit equally well (i.e., no significant results from the LRT) then choose the model with the smallest number of parameters, M1 – most parsimonious model as it is the most constrained/reduced form

Sequence of testing

- M1: Constrain all parameters (growth factor means, growth factor variances and covariances, and residual variances) to be identical across groups

```
009_1_Multigroup_LGCM_M1_Invariance_model
MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    !Estimate means of growth factors and label them
    [I](INT);
    [S](SLP);

    !Estimate variances of growth factors
    I(INT_V);
    S(SLP_V);

    !Estimate covariance of growth factors
    I WITH S(IS_COV);

    !Estimate residual variance and constrain them equal
    lone1-lone5(RES);

!Sequentially testing models means specific parameters are o
!For those parameters, we will begin by constraining them to
!Those parameters are (MEANS OF GROWTH FACTORS, CO/VARIANCES
!In subsequent models, we will freely estimate those paramet

MODEL MALES:
    !Growth factor means for males
    [I](INT);!The INT label will make the males' intercept g
    [S](SLP);!The labelling for all the parameters will make

    !Growth factor variances for males
    I(INT_V);
    S(SLP_V);

    !Growth factor covariance for males
    I WITH S(IS_COV);

    !Residual variances for males
    lone1-lone5(RES);

MODEL FEMALES:
    !Gorwth factor means for females
    [I](INT);!The INT label will make the females' intercept
    [S](SLP);

    !Growth factor variances for females
    I(INT_V);
    S(SLP_V);

    !Growth factor covariance for females
    I WITH S(IS_COV);

    !Residual variances for females
    lone1-lone5(RES);

OUTPUT:
    SAMPSTAT;
```

```
189  # 009_1_Multigroup LGCM M1 Invariance model
190  multigroupM1 <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
191                   s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
192  #Growth factor means constrained equal
193  i ~ c(int, int)*1
194  s ~ c(slp, slp)*1
195
196  #Growth factor variances held equal
197  i ~~ c(vint, vint)*i
198  s ~~ c(vslp, vslp)*s
199
200  #Growth factor covariances held equal
201  i ~~ c(cvf, cvf)*s
202
203  #Residual variances of observed items held equal
204  lone1 ~~ c(res, res)*lone1
205  lone2 ~~ c(res, res)*lone2
206  lone3 ~~ c(res, res)*lone3
207  lone4 ~~ c(res, res)*lone4
208  lone5 ~~ c(res, res)*lone5
209  '
210  fit_multigroupM1 <- growth(multigroupM1, data = data, group = "female")
211  summary(fit_multigroupM1, fit.measures = TRUE)
212
```

Sequence of testing

- M2: Freely estimate growth factor means across groups, while keeping constraints on the growth factor variances and covariance, and residual

```
009_2_Multigroup_LGCM_M2_Growth_factor_means
        lone1 lone2 lone3 lone4 lone5;

GROUPING = FEMALE (0 = MALES 1 = FEMALES);

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    [I](INT);
    [S](SLP);

    I(INT_V);
    S(SLP_V);

    I WITH S(IS_COV);

    lone1-lone5(RES);

MODEL MALES:
    [I](INT_M);  !Free growth factor means by using
    [S](SLP_M);

    I(INT_V);
    S(SLP_V);

    I WITH S(IS_COV);

    lone1-lone5(RES);

MODEL FEMALES:
    [I](INT_F);!Different labels are used to freel
    [S](SLP_F);

    I(INT_V);
    S(SLP_V);

    I WITH S(IS_COV);

    lone1-lone5(RES);
```

```
214  # 009_2_Multigroup LGCM M2 Free factor means
215  multigroupM2 <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
216                    s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
217  #Growth factor means freely estimated
218  i ~ c(intm, intf)*1
219  s ~ c(slpm, slpf)*1
220
221  #Growth factor variances held equal
222  i ~~ c(vint, vint)*i
223  s ~~ c(vslp, vslp)*s
224
225  #Growth factor covariances held equal
226  i ~~ c(cvf, cvf)*s
227
228  #Residual variances of observed items held equal
229  lone1 ~~ c(res, res)*lone1
230  lone2 ~~ c(res, res)*lone2
231  lone3 ~~ c(res, res)*lone3
232  lone4 ~~ c(res, res)*lone4
233  lone5 ~~ c(res, res)*lone5
234  '
235  fit_multigroupM2 <- growth(multigroupM2, data = data, group = "female")
236  summary(fit_multigroupM2, fit.measures = TRUE)
```

Sequence of testing

- M3: Freely estimate growth factor means, growth factor variances and covariances, while keeping the constraints on the residual variances

```
GROUPING = FEMALE (0 = MALES 1 = FEMALES);

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    [I](INT);
    [S](SLP);

    I(INT_V);
    S(SLP_V);

    I WITH S(IS_COV);

    lone1-lone5(RES);

MODEL MALES:
    [I S];!First: Growth factor means are freely estimated
    I S;!Second: Growth factor variances are freely estimated

    I WITH S;!Second: Growth factor covariances are freely estimated

    lone1-lone5(RES);

MODEL FEMALES:
    [I S];!First: Growth factor means are freely estimated
    I S;!Second: Growth factor variances are freely estimated

    I WITH S;!Second: Growth factor covariances are freely estimated

    lone1-lone5(RES);

OUTPUT:
    SAMPSTAT;
```

```
239  # 009_3_Multigroup LGCM M3 Free factor means and co/variances
240  multigroupM3 <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
241                    s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
242  #Growth factor means freely estimated
243  i ~ c(intm, intf)*1
244  s ~ c(slpm, slpf)*1
245
246  #Growth factor variances freely estimated
247  i ~~ c(vinm, vinf)*i
248  s ~~ c(vslm, vslf)*s
249
250  #Growth factor covariances freely estimated
251  i ~~ c(covm, covf)*s
252
253  #Residual variances of observed items held equal
254  lone1 ~~ c(res, res)*lone1
255  lone2 ~~ c(res, res)*lone2
256  lone3 ~~ c(res, res)*lone3
257  lone4 ~~ c(res, res)*lone4
258  lone5 ~~ c(res, res)*lone5
259  '
260  fit_multigroupM3 <- growth(multigroupM3, data = data, group = "female")
261  summary(fit_multigroupM3, fit.measures = TRUE)
```

64

Sequence of testing

- M4: Freely estimate growth factor means, growth factor variances and covariances, and residual variances across the groups

```
GROUPING = FEMALE (0 = MALES 1 = FEMALES);

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;

MODEL:
    I S|lone1@0 lone2@1 lone3@3 lone4@4 lone5@6;

    [I](INT);
    [S](SLP);

    I(INT_V);
    S(SLP_V);

    I WITH S(IS_COV);

    lone1-lone5(RES);

MODEL MALES:
    [I S](INT_M SLP_M);!First: Growth factor means are freely estimated
    I S;!Second: Growth factor variances are freely estimated

    I WITH S;!Second: Growth factor covariances are freely estimated

    lone1-lone5;!Third, residual variances freely estimated

MODEL FEMALES:
    [I S](INT_F SLP_F);!First: Growth factor means are freely estimated
    I S;!Second: Growth factor variances are freely estimated

    I WITH S;!Second: Growth factor covariances are freely estimated

    lone1-lone5;!Third: residual variances freely estimated

!MODEL TEST:
!    0 = INT_M - INT_F;


OUTPUT:
    SAMPSTAT;
```

```
264  # 009_4_Multigroup LGCM M4 Free factor means and co/variances
265  multigroupM4 <- ' i =~ 1*lone1 + 1*lone2 + 1*lone3 + 1*lone4 + 1*lone5
266                   s =~ 0*lone1 + 1*lone2 + 3*lone3 + 4*lone4 + 6*lone5
267  #Growth factor means freely estimated
268  i ~ c(intm, intf)*1
269  s ~ c(slpm, slpf)*1
270
271  #Growth factor variances freely estimated
272  i ~~ c(vinm, vinf)*i
273  s ~~ c(vslm, vslf)*s
274
275  #Growth factor covariances freely estimated
276  i ~~ c(covm, covf)*s
277
278  #Residual variances of observed items freely estimated
279  lone1 ~~ c(rsm1, rsf1)*lone1
280  lone2 ~~ c(rsm2, rsf2)*lone2
281  lone3 ~~ c(rsm3, rsf3)*lone3
282  lone4 ~~ c(rsm4, rsf4)*lone4
283  lone5 ~~ c(rsm5, rsf5)*lone5
284  '
285  fit_multigroupM4 <- growth(multigroupM4, data = data, group = "female")
286  summary(fit_multigroupM4, fit.measures = TRUE)
```

Sequence of testing
- M1: Constrain all parameters (growth factor means, growth factor variances and covariances, and residual variances) to be identical across groups
- M2: Freely estimate growth factor means across groups, while keeping constraints on the growth factor variances and covariance, and residual variances
- M3: Freely estimate growth factor means, growth factor variances and covariances, while keeping the constraints on the residual variances
- M4: Freely estimate growth factor means, growth factor variances and covariances, and residual variances across the groups

Questions to answer
- M1 vs. M2: Tests whether the groups differ in their average trajectory
- M2 vs. M3: Tests the extent of between-person differences in the trajectories of groups
- M3 vs. M4: Tests the extent of within-person variability around individual trajectories
    - If all models fit equally well (i.e., no significant results from the LRT) then choose the model with the smallest number of parameters, M1 – most parsimonious model as it is the most constrained/reduced form

```
292  #The `anova` function in `lavaan` computes the LRT for nested models.
293  compare_groups <- anova(fit_multigroupM1, fit_multigroupM2, fit_multigroupM3, fit_multigroupM4)
294  compare_groups
```

```
298  # Test of parameter constraints
299  constint = 'intm - intf == 0'
300  lavTestWald(fit_multigroupM4, constraints = constint)
301
302  constslp = 'slpm - slpf ==0'
303  lavTestWald(fit_multigroupM4, constraints = constslp)
```

Multigroup LGCM

Models	Invariance Model		Means model		Means and Co/variances		Means, Co/variances and residual variances	
	GROUP 1	GROUP 2	GROUP 1	GROUP 2	GROUP 1	GROUP 2	GROUP 1	GROUP 2
Model fit								
χ^2(df)	2017.477(34)***		196.543(32)***		186.447(29)***		178.403(28)***	
RMSEA	.179 [0.156, 0.202]		.179 [0.156, 0.204]		.184 [0.159, 0.210]		.183 [0.158, 0.209]	
CFI	.609		.629		.645		.661	
TLI	.770		.768		.755		.758	
Parameter estimates								
Intercept	1.484***	1.484***	**1.550*****	**1.401*****	**1.550*****	**1.401*****	**1.550*****	**1.401*****
Slope	-0.026***	-0.026***	**-0.031*****	**-0.020****	**-0.031*****	**-0.020****	**-0.031*****	**-0.020****
(Co)Variances								
Intercept	0.135***	0.135***	0.130***	0.130***	**0.170*****	**0.079*****	**0.163*****	**0.087*****
Slope	0.001*	0.001*	0.001*	0.001*	**0.002****	**0.000**	**0.001**	**0.003**
Intercept WITH Slope	-0.011***	-0.011	-0.010***	-0.010***	**-0.015*****	**-0.004**	**-0.014*****	**-0.006***
Residual variance	0.109***	0.109***	0.109***	0.109***	0.109***	0.109***	**0.121*****	**0.093*****

Model comparisons

Model Comparison for the Multiple-Group LGCM

	Model M1 Invariance model	Model M2 Means model	Model M3 Means and covariances model	Model M4 Means, covariances and residual variances model
Parameters	6	8	11	12
-2LL	1553.446	1542.510	1532.416	1448.148
Δ parameters	-	2	3	1
Δ -2LL	-	10.936**	10.094*	8.046**

Questions to answer

- M1 vs. M2: Tests whether the groups differ in their average trajectory
- M2 vs. M3: Tests the extent of between-person differences in the trajectories of groups
- M3 vs. M4: Tests the extent of within-person variability around individual trajectories

> Males and females differ in their average growth trajectories of loneliness, the extent of between-person differences in those trajectories and the extent of variability around their individual trajectories

Objectives of longitudinal research

1.   Identification of intraindividual (within-person) changes (and stability)
    •   Is there change over time on average?
        ✓   Growth models can address various linear and nonlinear patterns of intraindividual change

2.   Analysis of causes (determinants) of intraindividual change
    •   What factors/mechanisms – time-varying/dynamical predictors – drive change?
        ✓   Inclusion of time-varying (dynamical) predictors in growth models

3.   Identification of interindividual differences (or similarity) in intraindividual change
    •   Do different individuals change in different ways?
        ✓   Differences between groups of persons in the way people change

4.   Analysis of causes (determinants) of interindividual differences in intraindividual change
    •   What factors explain between-person differences in change?
        ✓   Inclusion of time-invariant covariates in growth models, multigroup LGCM, Growth mixture models

5.   Interrelationships in change
    •   Does change in one variable relate (*precede, covary and/or follow*) to change in another variable?
    •   Correlating slopes of X and Y could provide evidence that one variable is changing in the same people as another variable – correlated changes! Or common changes!
        ✓ Multi (parallel & sequentially contingent) process LGCM

Multi Process LGCM

- Simultaneously model multiple outcomes
    1. Parallel LGCM
        - Covariance between two intercepts
            - Information about association between the two outcomes at the beginning of observation period
        - Covariance between two slopes
            - How rate of change in the two outcomes are associated with each other

    2. Sequential LGCM
        - Change in one subdomain, e.g. Anxiety symptoms (T1-T5) is correlated with change in another subdomain, e.g. depressive symptoms (T6-T10)

Growth model for anxiety symptoms

Growth model for depressive symptoms
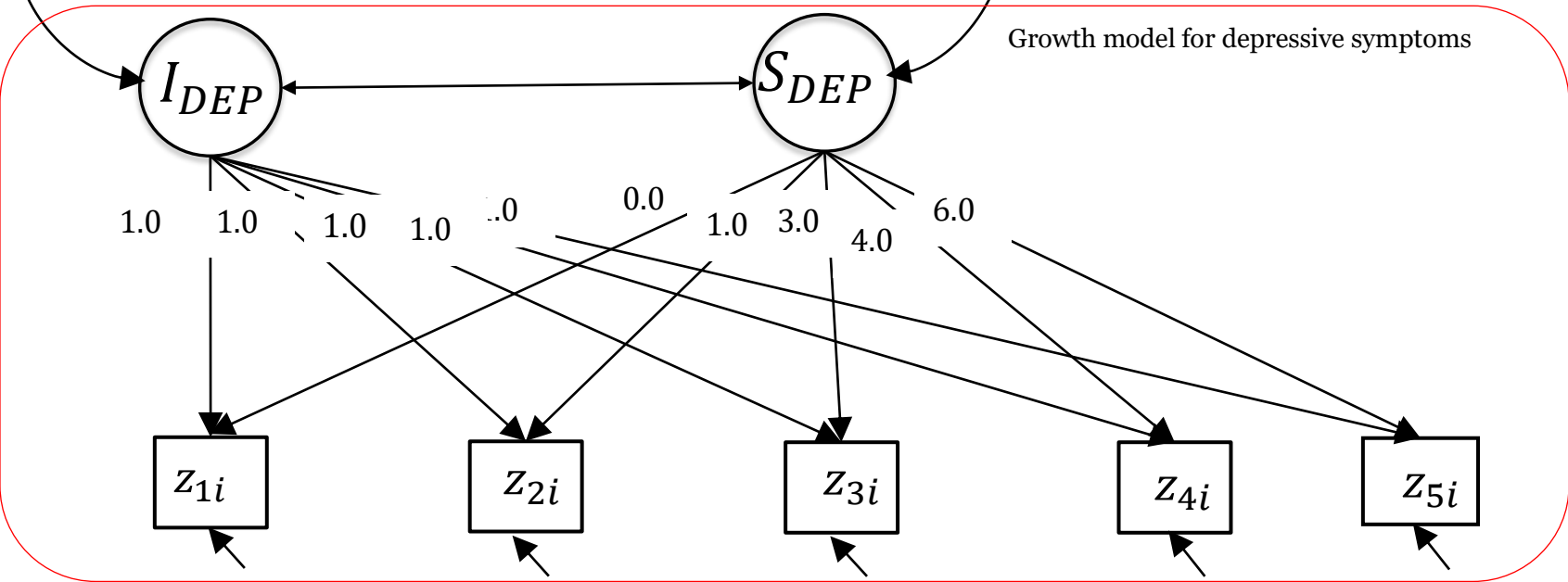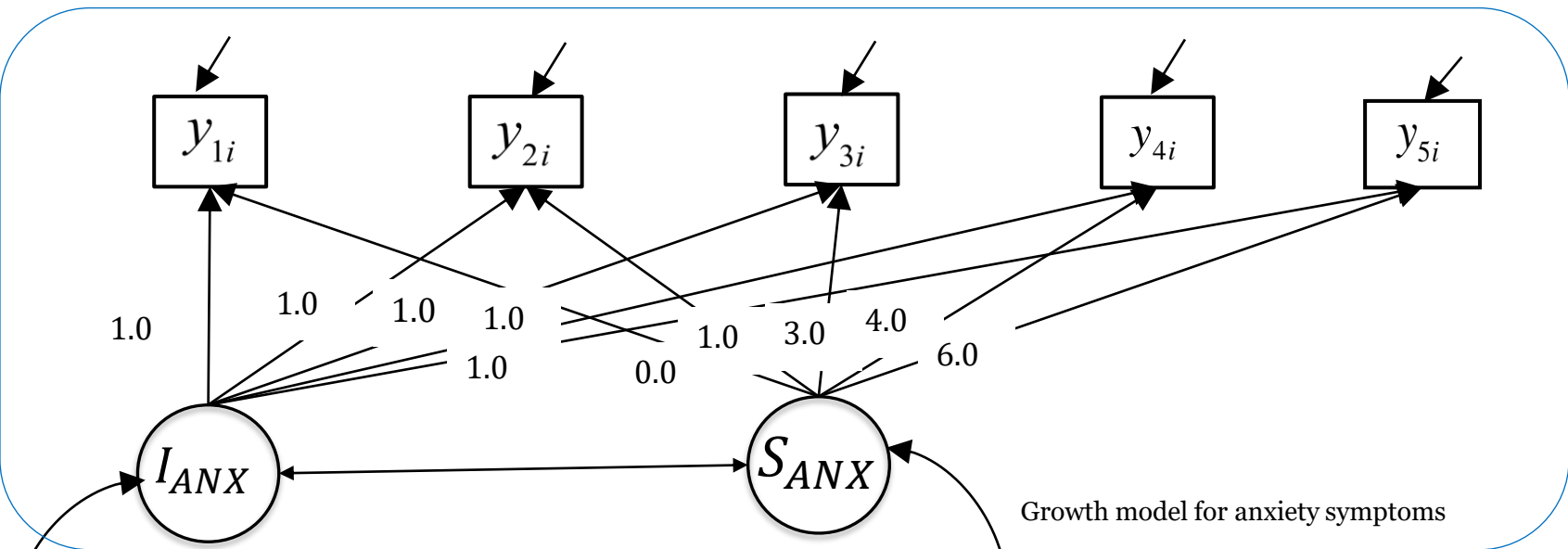
- Study distinct but related subdomains

- Developmental associations (co-development) between anxiety and depressive symptoms

- Non-directional associations represent co-development/occurrence
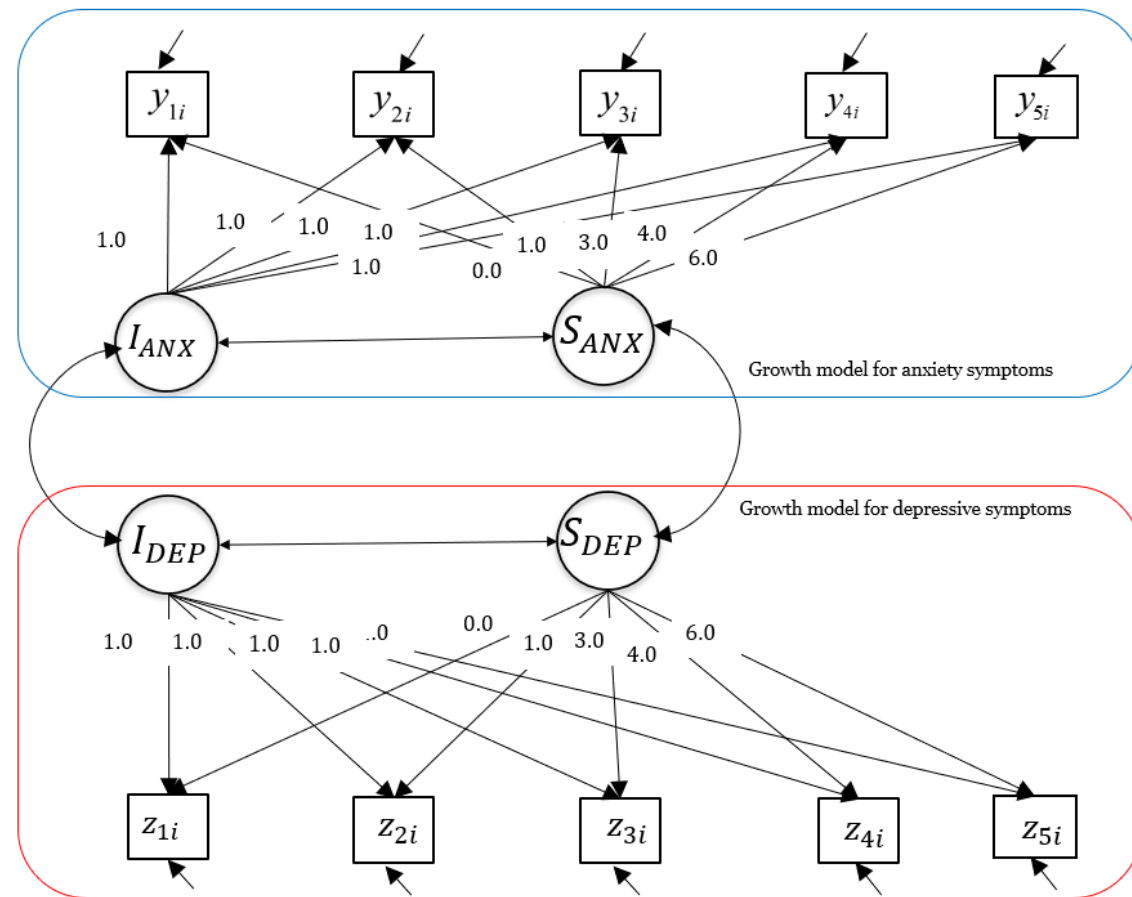
Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms

```
USEVARIABLES ARE
        anx1 anx2 anx3 anx4 anx5
        dep1 dep2 dep3 dep4 dep5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;
    MODEL = NOCOV;!Suppress Mplus default correlations between the growth factor
                   !That way, you have control over what variables you want to co
MODEL:
    I_ANX S_ANX|anx1@0 anx2@1 anx3@3 anx4@4 anx5@6;!anxiety symptoms growth
    I_DEP S_DEP|dep1@0 dep2@1 dep3@3 dep4@4 dep5@6;!depressive symptoms

    !Correlate the growth factors
    I_ANX WITH S_ANX;
    I_DEP WITH S_DEP;

    I_ANX WITH I_DEP;
    S_ANX WITH S_DEP;

OUTPUT:
    SAMPSTAT;
```

```
309  # 010_1_Parallel growth curve models - anxiety and depression symptoms
310  parallel <- ' ia =~ 1*anx1 + 1*anx2 + 1*anx3 + 1*anx4 + 1*anx5
311                sa =~ 0*anx1 + 1*anx2 + 3*anx3 + 4*anx4 + 6*anx5
312                id =~ 1*dep1 + 1*dep2 + 1*dep3 + 1*dep4 + 1*dep5
313                sd =~ 0*dep1 + 1*dep2 + 3*dep3 + 4*dep4 + 6*dep5
314  #Growth factor corelations
315  ia ~~ id + sa
316  sd ~~ id + sa
317  ia ~~ 0*sd
318  id ~~ 0*sa
319  '
320  fit_parallel <- growth(parallel, data = data)
321  summary(fit_parallel, fit.measures = TRUE)
```

Frederick Anyan, PhD - NTNU

RESULTS

Model fit:
($\chi^2 = 820.887$, $df = 43$; $p < .001$; $RMSEA = .237$ [90% CI = 0.223, 0.252]; $CFI = .584$; $TLI = .564$)

Parameter estimates:

Anxiety symptoms

i.	Intercept:	1.397***
ii.	Slope:	-0.032***

Depression symptoms

i.	Intercept:	1.545***
ii.	Slope:	-0.014**

(Co)Variances:

Anxiety symptoms

i.	Intercept:	0.097***
ii.	Slope:	0.002***

Depression symptoms

i.	Intercept:	0.171***
ii.	Slope:	0.002**

iii.	I_ANX WITH S_ANX	0.000
iv.	I_ANX WITH I_DEP	0.125***

v.	I_DEP WITH S_DEP	0.005
vi.	S_ANX WITH S_DEP	0.004***
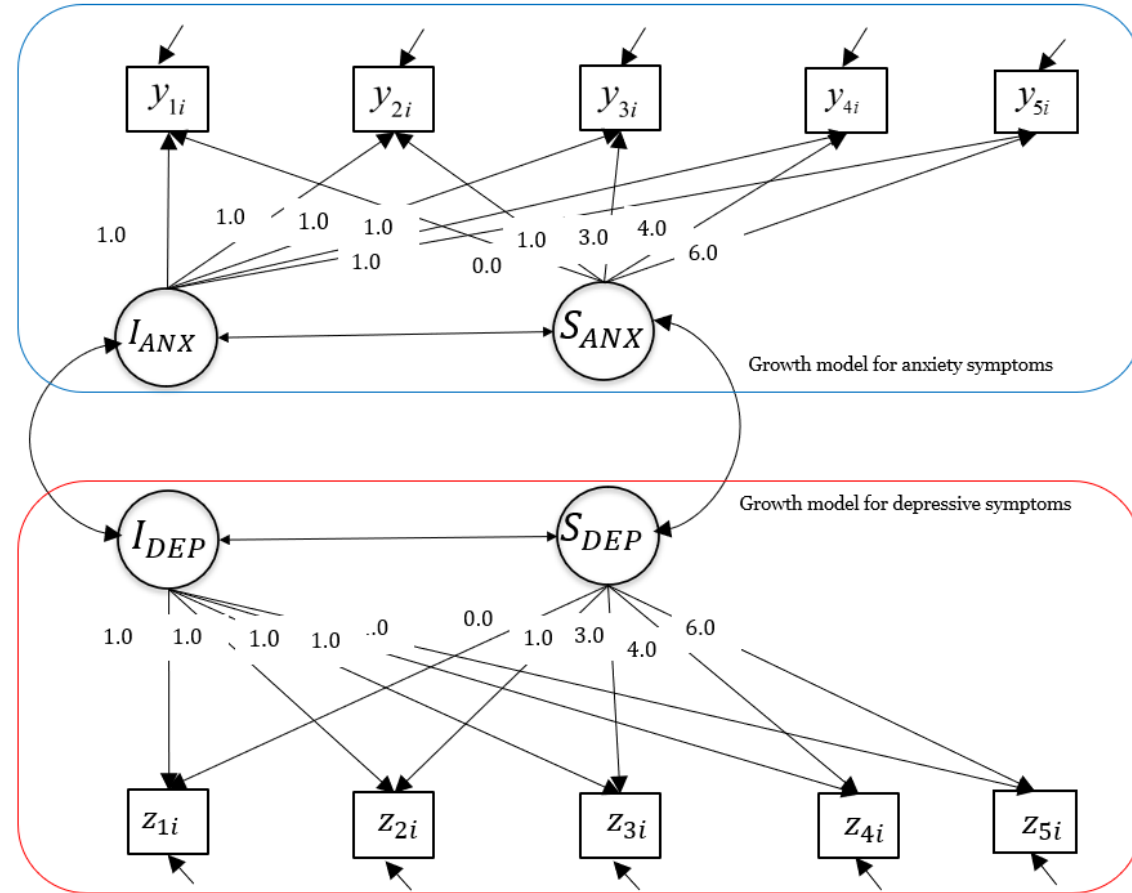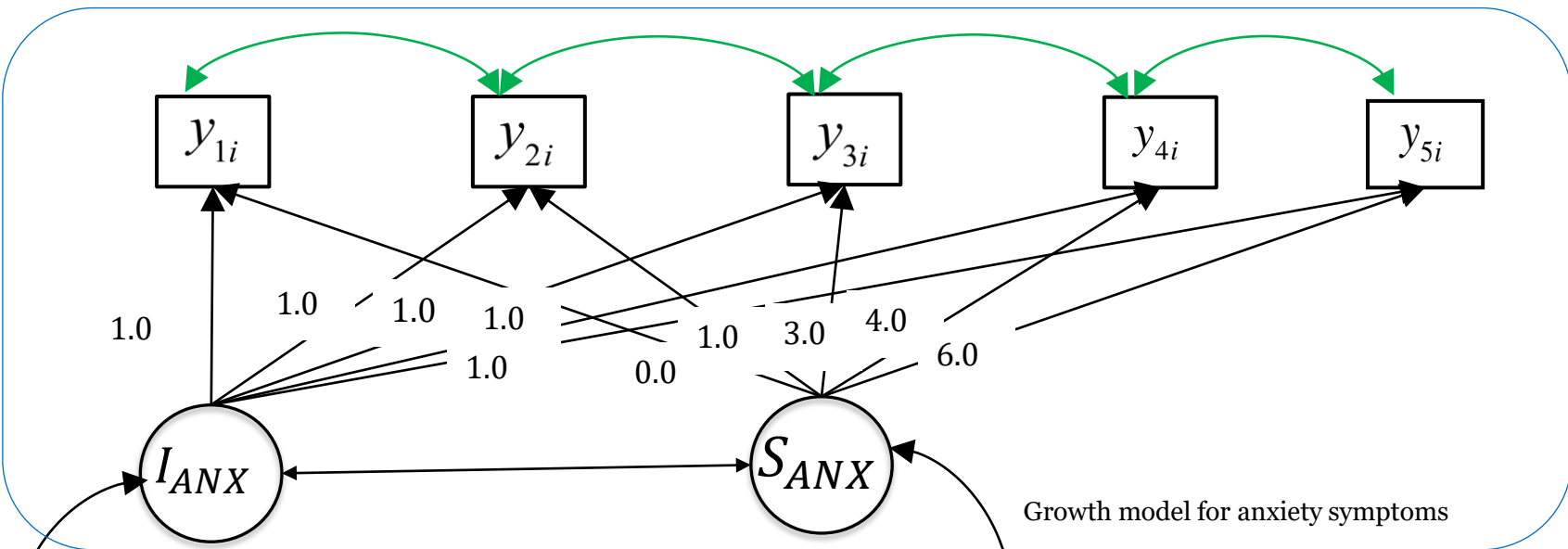
Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms

- Each measure consist of

  i. Item-specific variance component
  ii. Time-specific variance component
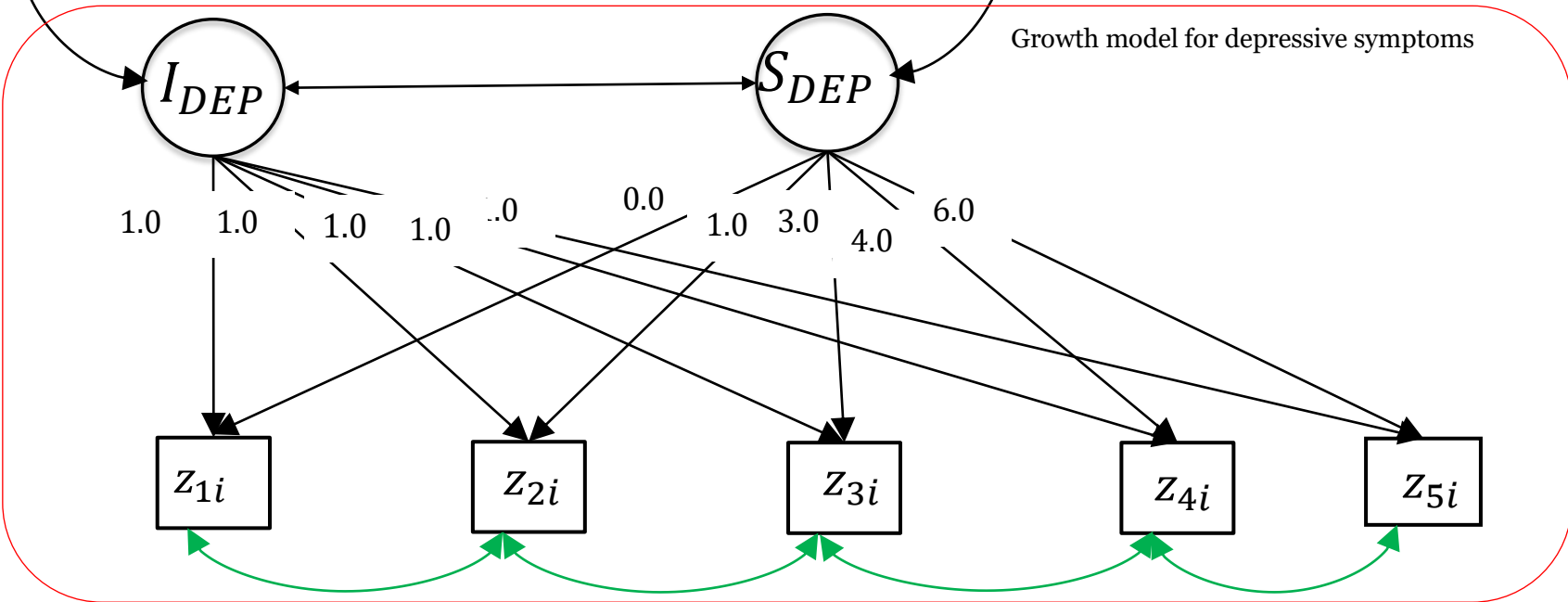
  i. Item-specific variance component = measurement error (within subdomain error correlations – autocorrelated errors)

  - Autocorrelated error capture unique and methodological biases within a measure (e.g., due to repeated administration, reporting biases)
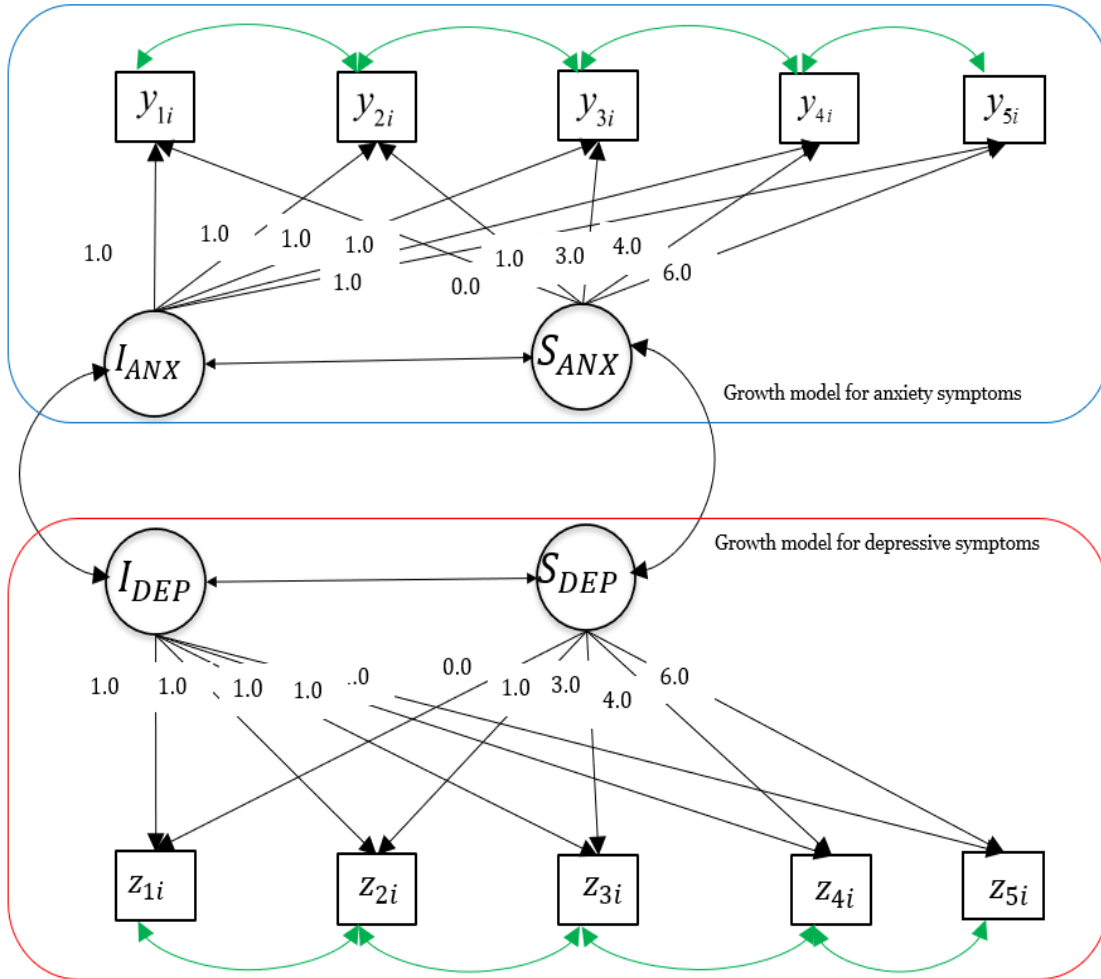
Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms

```
USEVARIABLES ARE
        anx1 anx2 anx3 anx4 anx5
        dep1 dep2 dep3 dep4 dep5;

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;
    MODEL = NOCOV;!Suppress Mplus default correlations between the growth fa
                  !That way, you have control over what variables you want
MODEL:
    I_ANX S_ANX|anx1@0 anx2@1 anx3@3 anx4@4 anx5@6;!anxiety symptoms growth
    I_DEP S_DEP|dep1@0 dep2@1 dep3@3 dep4@4 dep5@6;!depressive symptoms

    !Correlate the growth factors
    I_ANX WITH S_ANX;
    I_DEP WITH S_DEP;

    I_ANX WITH I_DEP;
    S_ANX WITH S_DEP;

    !Within subdomain autocorrelations
    anx1 anx2 anx3 anx4 PWITH anx2 anx3 anx4 anx5 (an); !PWITH means pair w
    dep1 dep2 dep3 dep4 PWITH dep2 dep3 dep4 dep5 (dp);


OUTPUT:
    SAMPSTAT;
```

Frederick Anyan, PhD - NTNU
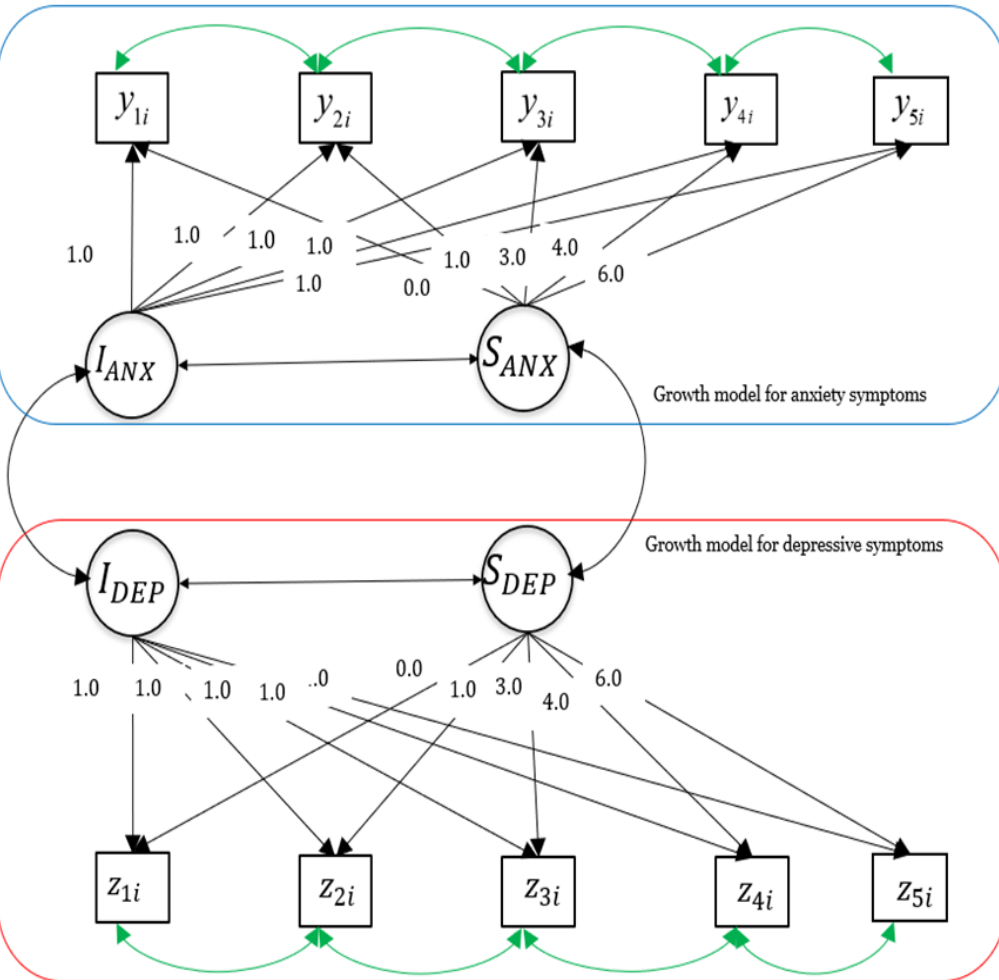
```
324  # 010_2_Parallel growth curve models - anxiety and depression symptoms with autocorrelations
325  parallelautocor <- ' ia =~ 1*anx1 + 1*anx2 + 1*anx3 + 1*anx4 + 1*anx5
326                       sa =~ 0*anx1 + 1*anx2 + 3*anx3 + 4*anx4 + 6*anx5
327                       id =~ 1*dep1 + 1*dep2 + 1*dep3 + 1*dep4 + 1*dep5
328                       sd =~ 0*dep1 + 1*dep2 + 3*dep3 + 4*dep4 + 6*dep5
329  #Growth factor corelations
330  ia ~~ id + sa
331  sd ~~ id + sa
332  ia ~~ 0*sd
333  id ~~ 0*sa
334
335  #Autocorrelations
336  anx1 ~~ eqa*anx2
337  anx2 ~~ eqa*anx3
338  anx3 ~~ eqa*anx4
339  anx4 ~~ eqa*anx5
340
341  dep1 ~~ eqd*dep2
342  dep2 ~~ eqd*dep3
343  dep3 ~~ eqd*dep4
344  dep4 ~~ eqd*dep5
345  '
346  fit_parallelautocor <- growth(parallelautocor, data = data)
347  summary(fit_parallelautocor, fit.measures = TRUE)
```

Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms

RESULTS

Model fit:
(χ^2 = 813.952, df = 41; p < .001; $RMSEA$ = .242 [90% CI = 0.228, 0.257]; CFI = .586; TLI = .546)

Parameter estimates:

Anxiety symptoms
i.	Intercept:	1.395***
ii.	Slope:	-0.031***

Depression symptoms
i.	Intercept:	1.544***
ii.	Slope:	-0.014**

(Co)Variances:

Anxiety symptoms
i.	Intercept:	0.084***
ii.	Slope:	0.001

Depression symptoms
i.	Intercept:	0.156***
ii.	Slope:	0.001

iii.	I_ANX WITH S_ANX	0.003
iv.	I_ANX WITH I_DEP	0.124***
v.	I_DEP WITH S_DEP	0.007*
vi.	S_ANX WITH S_DEP	0.004***

Autocorrelations
i.	Anxiety	0.012*
ii.	Depression	0.013
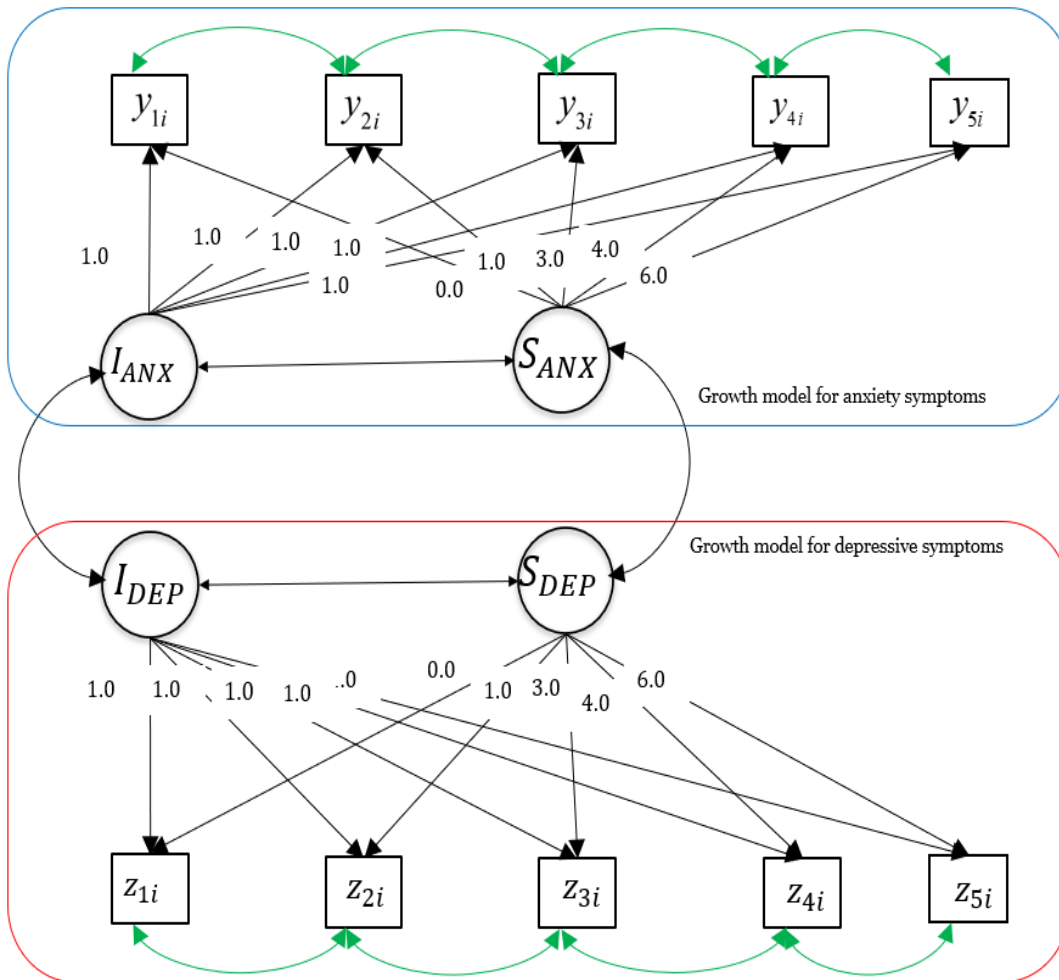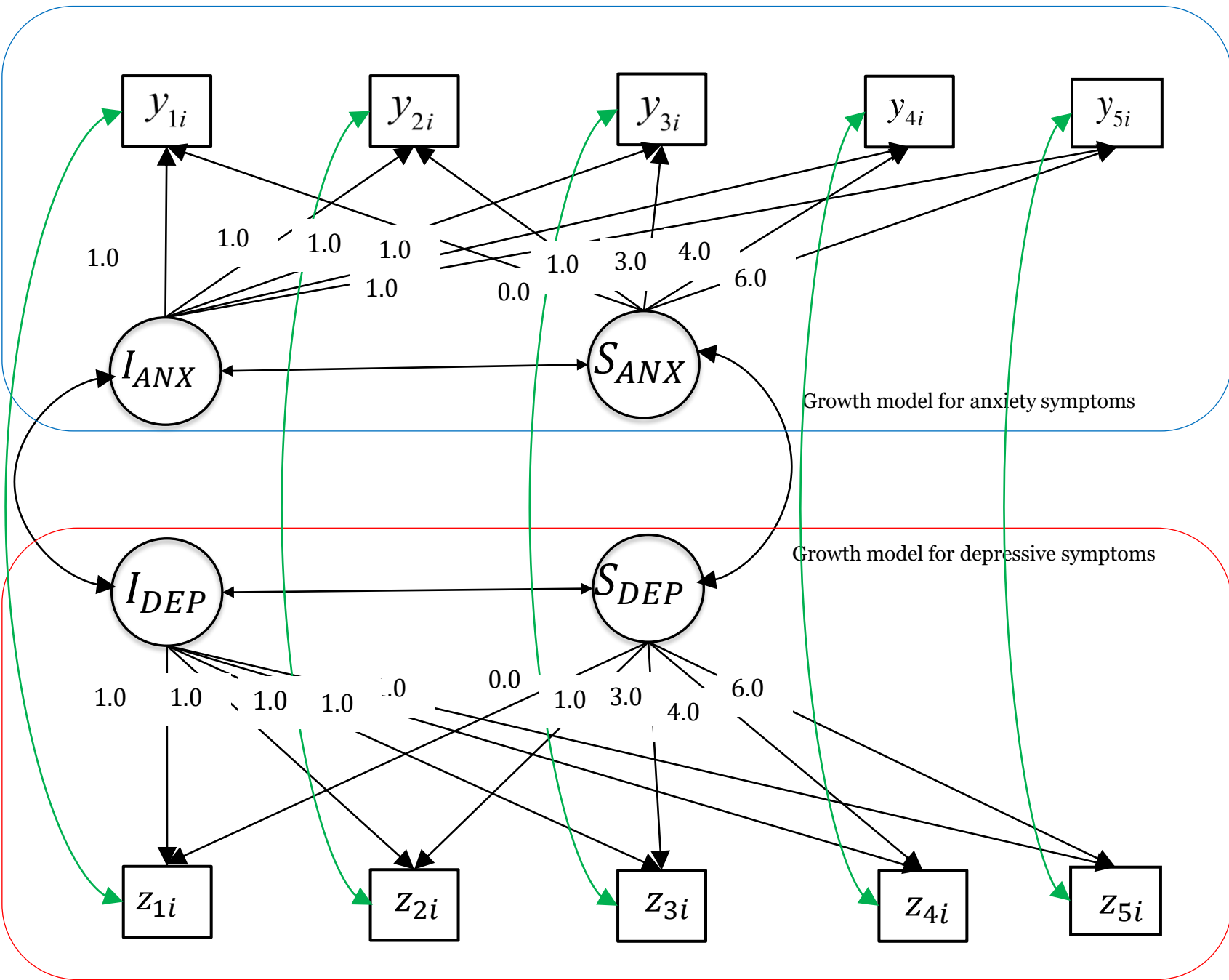
Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms

- Each measure consist of
  - i. Item-specific variance component
  - ii. Time-specific variance component

- ii. Time-specific variance component = between subdomains
  - Attributed to time-specific trends/patterns reporting biases (e.g., reporting lower level of symptoms at first timepoint)

Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms
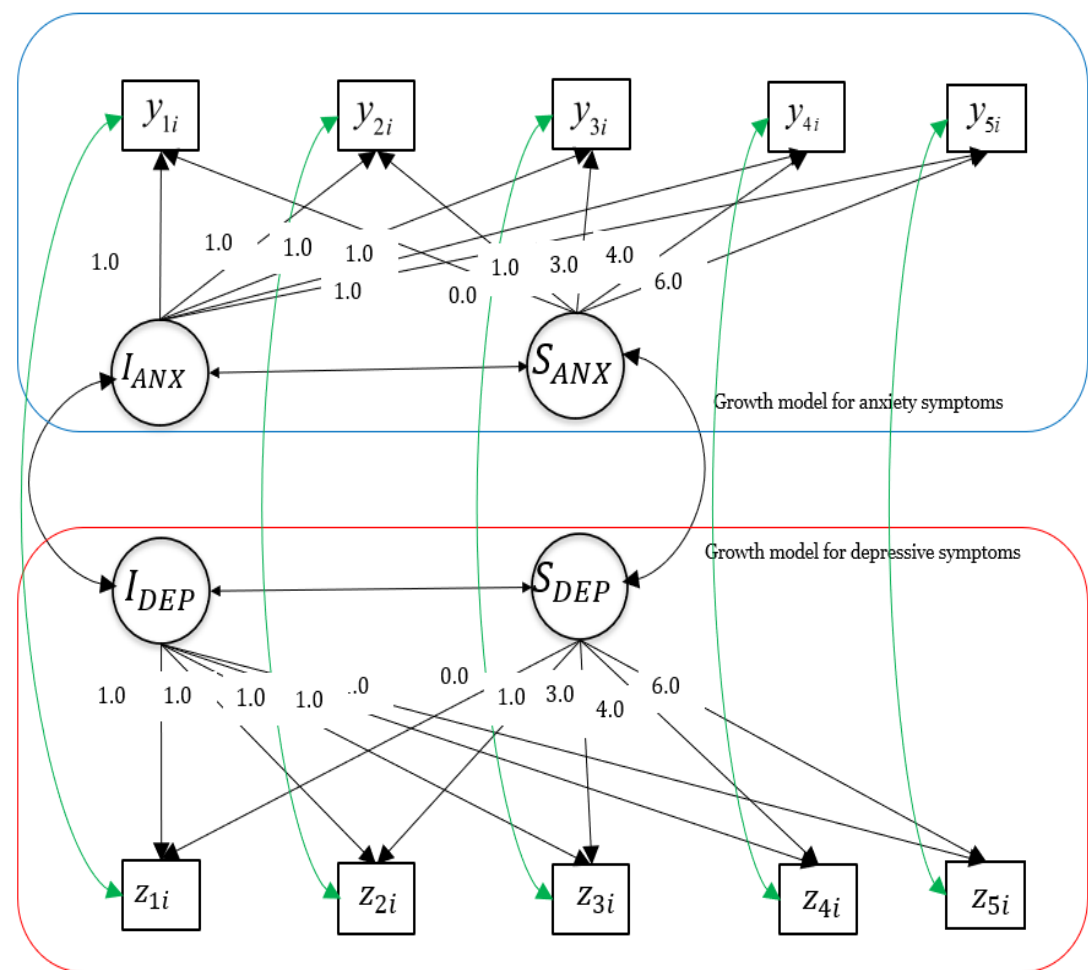
```
350  # 010_3_Parallel growth curve models - anxiety and depression symptoms with cros
351  parallelcross <- ' ia =~ 1*anx1 + 1*anx2 + 1*anx3 + 1*anx4 + 1*anx5
352                     sa =~ 0*anx1 + 1*anx2 + 3*anx3 + 4*anx4 + 6*anx5
353                     id =~ 1*dep1 + 1*dep2 + 1*dep3 + 1*dep4 + 1*dep5
354                     sd =~ 0*dep1 + 1*dep2 + 3*dep3 + 4*dep4 + 6*dep5
355  #Growth factor corelations
356  ia ~~ id + sa
357  sd ~~ id + sa
358  ia ~~ 0*sd
359  id ~~ 0*sa
360
361  #Cross domain correlations
362  anx1 ~~ eq*dep1
363  anx2 ~~ eq*dep2
364  anx3 ~~ eq*dep3
365  anx4 ~~ eq*dep4
366  anx5 ~~ eq*dep5
367  '
368  fit_parallelcross <- growth(parallelcross, data = data)
369  summary(fit_parallelcross, fit.measures = TRUE)
```

RESULTS

Model fit:
($\chi^2 = 178.746$, $df = 42$; $p < .001$; $RMSEA = .101$[90% CI = 0.086, 0.116]; $CFI = .927$; $TLI = .922$)

Parameter estimates:
Anxiety symptoms
    Intercept: 1.399***
    Slope: -0.030***
Depression symptoms
    Intercept: 1.552***
    Slope: -0.013*

(Co)Variances:
Anxiety symptoms
    Intercept: 0.085***
    Slope: 0.001*
Depression symptoms
    Intercept: 0.144***
    Slope: 0.000

i.   I_ANX WITH S_ANX   -0.004**
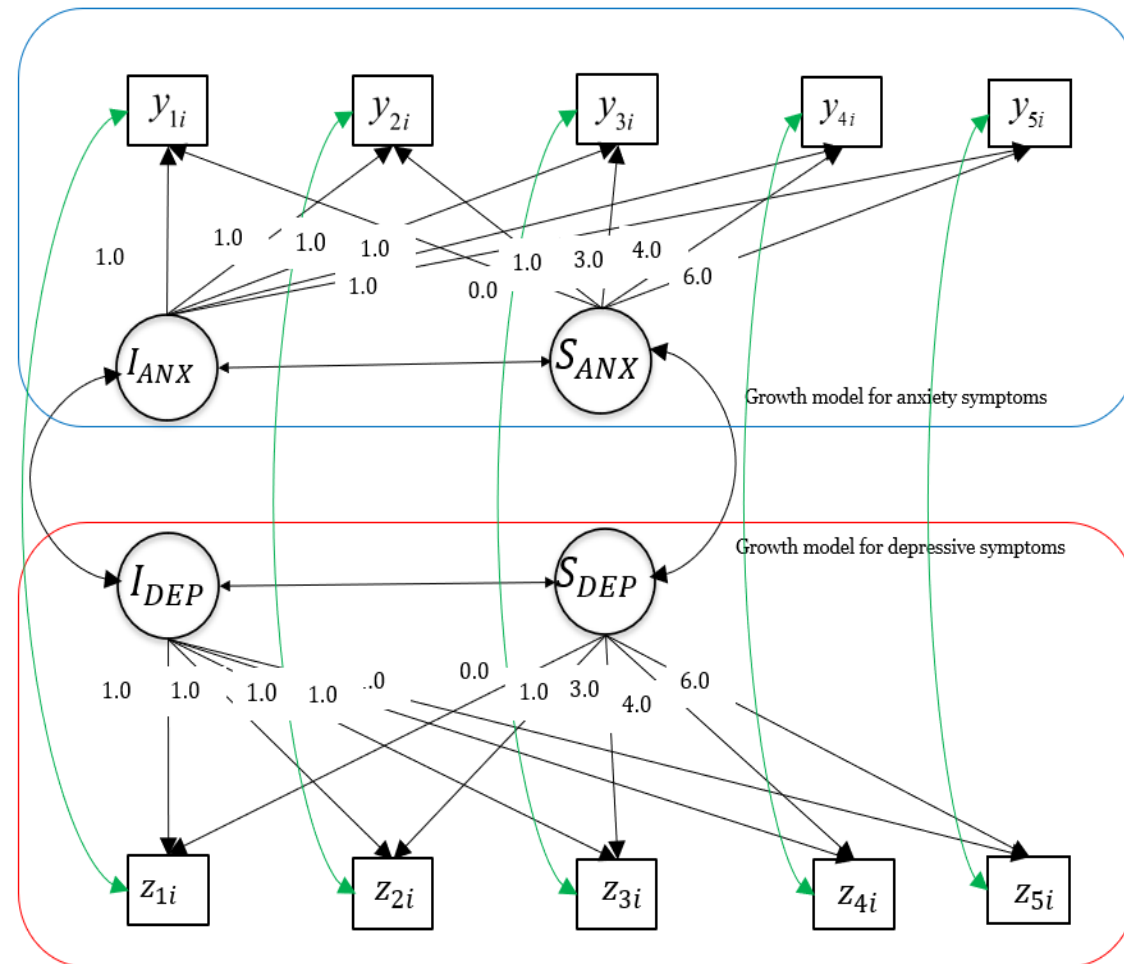ii.   I_ANX WITH I_DEP   0.082***

    I_DEP WITH S_DEP   -0.002
vi.   S_ANX WITH S_DEP   0.000
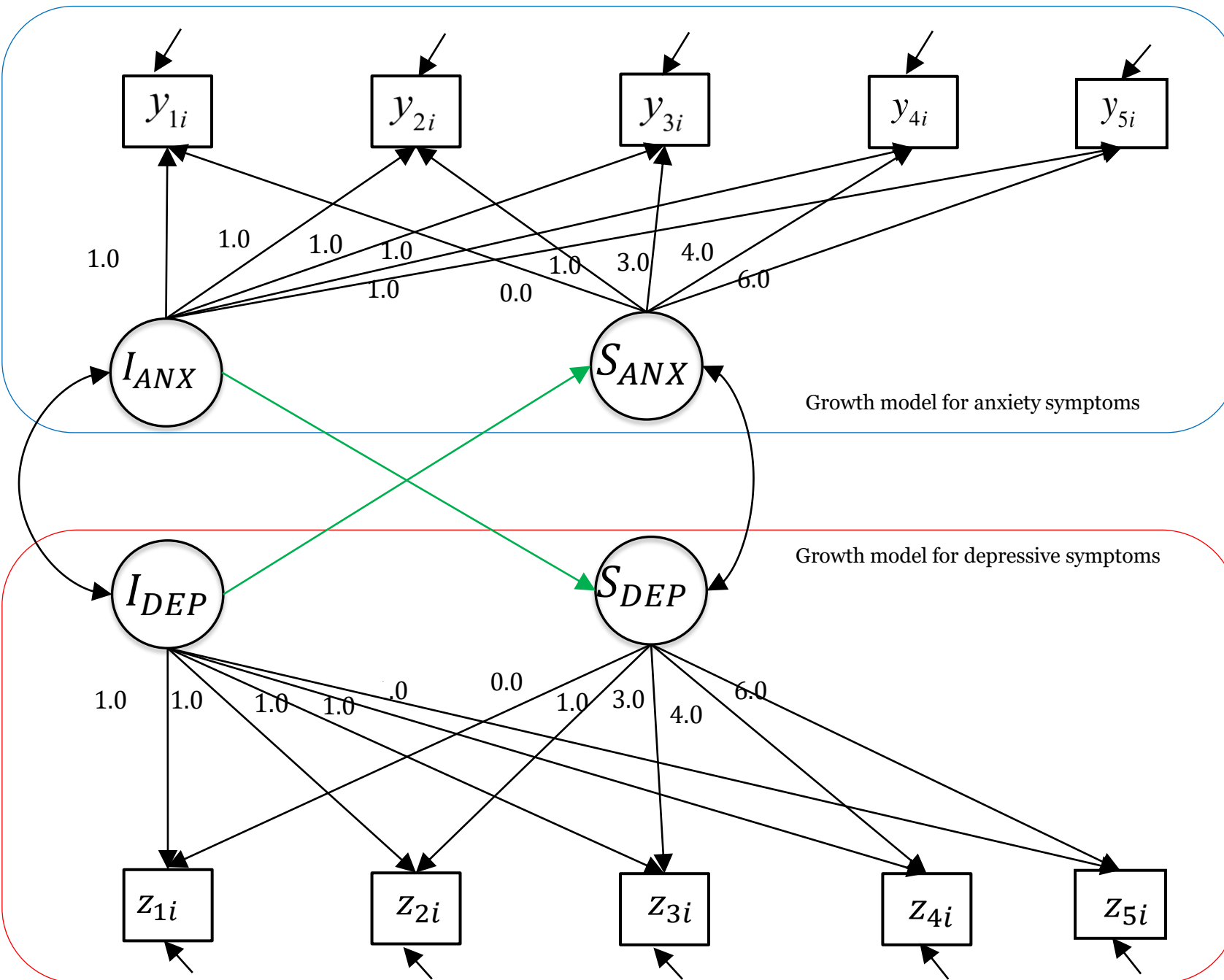
Cross-domain correlations
i.   Anxiety - Depression   0.098***
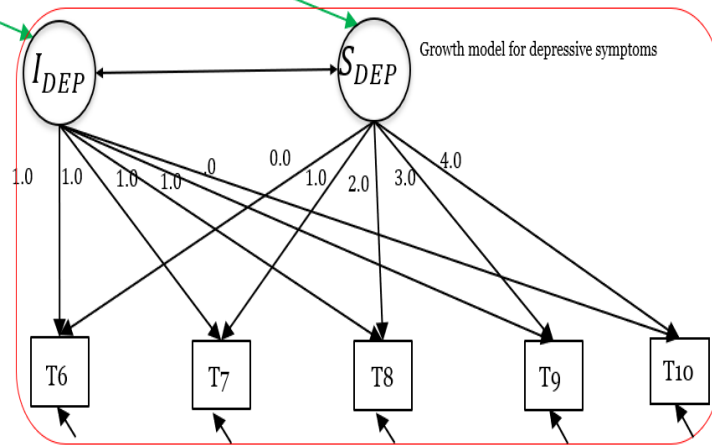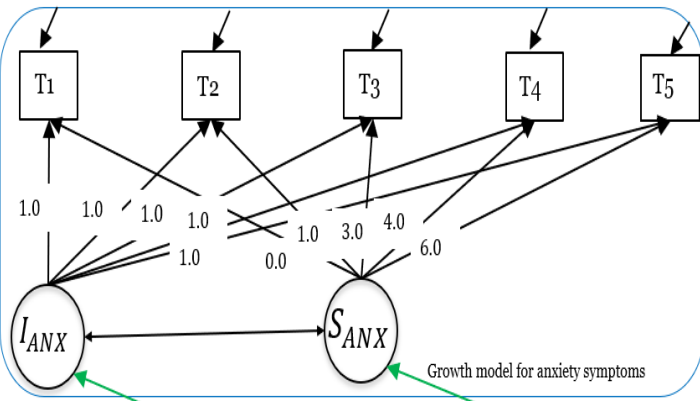
Frederick Anyan, PhD - NTNU

- Parallel growth process with regressions of the slope growth factor
  - Higher initial levels of anxiety symptoms influence the growth rate of depressive symptoms?
  - Higher initial levels of depression symptoms influence the growth rate of anxiety symptoms

Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms
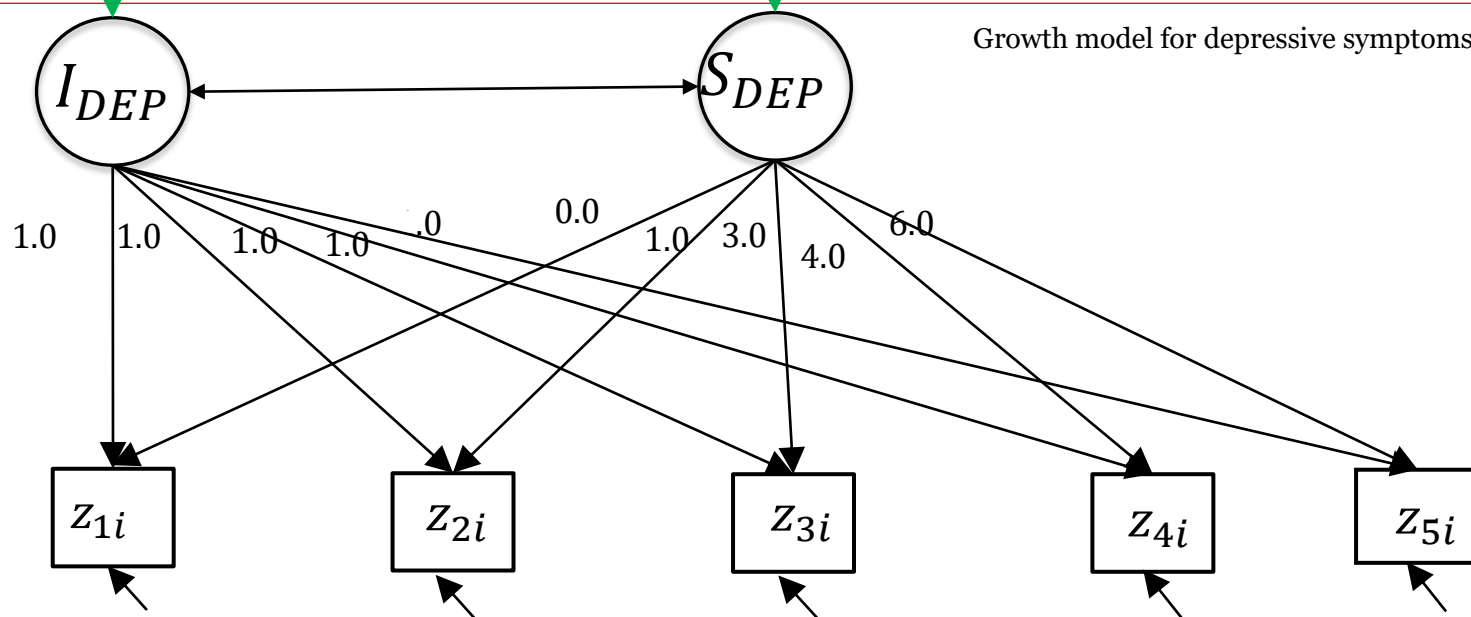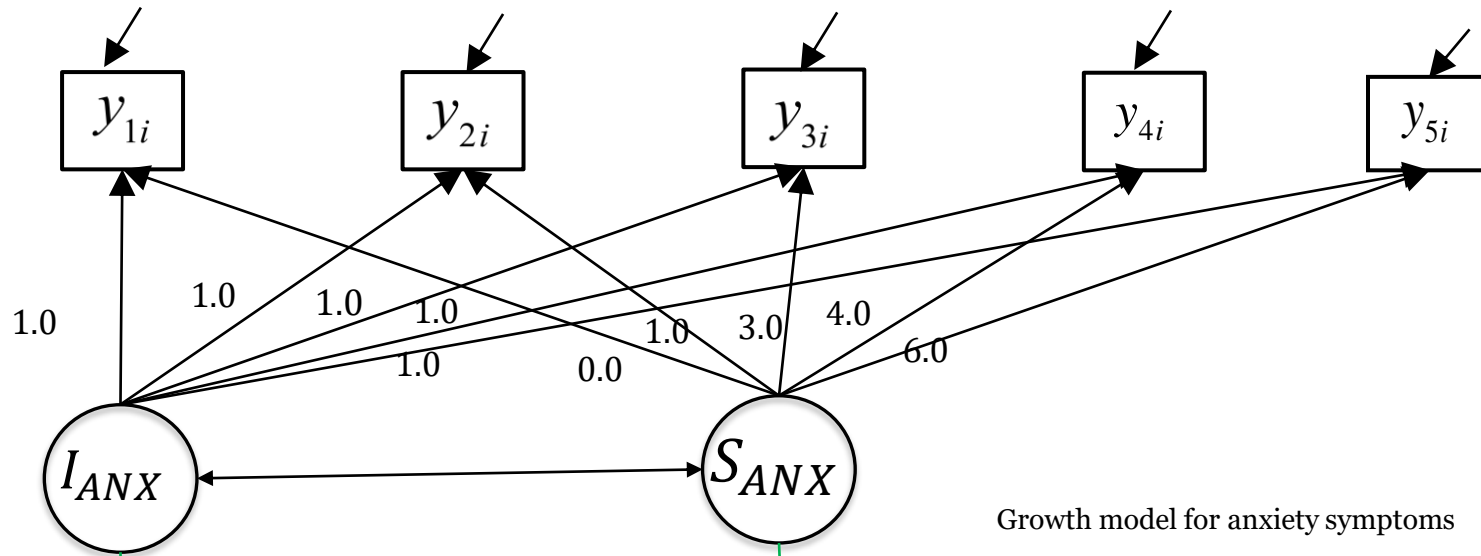
- Parallel growth process with uni-directional effects

  - Evidence of co-development
  - Influence of growth factors of one subdomain on the growth factors of another subdomain

Frederick Anyan, PhD - NTNU

Time scores/factor loading matrix

1	0	Time 1, 2010
1	1	Time 2, 2011
1	3	Time 3, 2013
1	4	Time 4, 2014
1	6	Time 5, 2016

Growth model for anxiety symptoms

Time scores/factor loading matrix

1	0	Time 1, 2017
1	1	Time 2, 2018
1	2	Time 3, 2019
1	3	Time 4, 2020
1	4	Time 5, 2021

Growth model for depressive symptoms

- Sequentially contingent process over time

  - One growth trajectory influencing a later growth trajectory
  - Change in one subdomain (T1-T5) predicting change in another subdomain(T6-T10)
  - Life-course studies

Frederick Anyan, PhD - NTNU

Growth model for anxiety symptoms

Growth model for depressive symptoms

Frederick Anyan, PhD - NTNU

```
USEVARIABLES ARE
        anx1 anx2 anx3 anx4 anx5
        dep6 dep7 dep8 dep9 dep10;!Time of observations modified for ped

MISSING ARE ALL (-999);

ANALYSIS:
    ESTIMATOR = ML;
    MODEL = NOCOV;!Suppress Mplus default correlations between the grow
                  !That way, you have control over what variables you w
MODEL:
    I_ANX S_ANX|anx1@0 anx2@1 anx3@3 anx4@4 anx5@6;!anxiety symptoms gr
    I_DEP S_DEP|dep6@0 dep7@1 dep8@2 dep9@3 dep10@4;!Equidistant time s

    !Correlate the growth factors
    I_ANX WITH S_ANX;
    I_DEP WITH S_DEP;

    !Add sequqntially contingent growth factors
    I_ANX WITH I_DEP;
    S_ANX WITH S_DEP;

OUTPUT:
    SAMPSTAT;
```
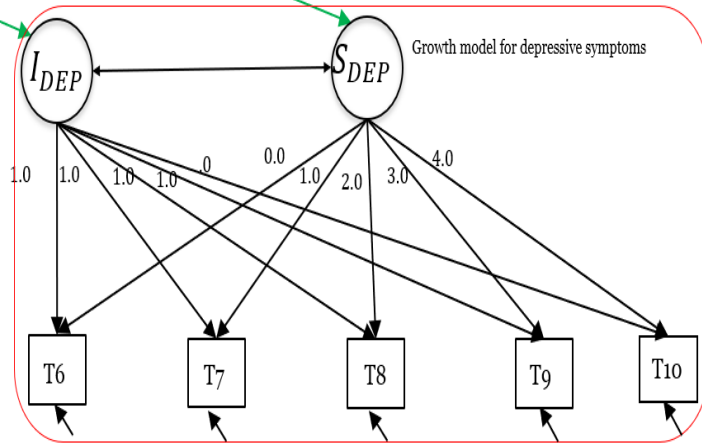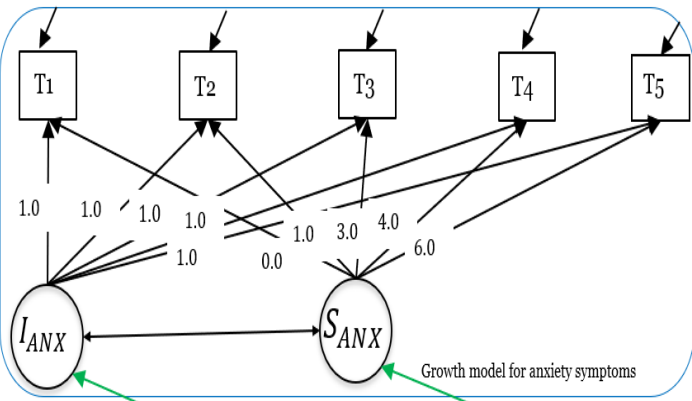
Growth model for anxiety symptoms

Growth model for depressive symptoms

Frederick Anyan, PhD - NTNU

```
375   # 011_Sequentially contigent growth curve model anxiety t1-t5 predicting depress
376   sequential <- ' ia =~ 1*anx1 + 1*anx2 + 1*anx3 + 1*anx4 + 1*anx5
377                   sa =~ 0*anx1 + 1*anx2 + 3*anx3 + 4*anx4 + 6*anx5
378                   id =~ 1*dep6 + 1*dep7 + 1*dep8 + 1*dep9 + 1*dep10
379                   sd =~ 0*dep6 + 1*dep7 + 2*dep8 + 3*dep9 + 4*dep10
380
381   #Growth factor corelations
382   ia ~~ sa
383   id ~~ sd
384   ia ~~ 0*sd
385   id ~~ 0*sa
386
387   #Correlate growth factors across domain (may use regressions depending on theory
388   ia ~~ id
389   sa ~~ sd
390   '
391   #Rename multiple columns using rename()
392   # We rename them to pretend that these variables are actually measured
393   # at a later date.
394   library(dplyr)
395   data <- data %>%
396       rename("dep6" = "dep1",
397              "dep7" = "dep2",
398              "dep8" = "dep3",
399              "dep9" = "dep4",
400              "dep10" = "dep5")
401
402   fit_sequential <- growth(sequential, data = data)
403   summary(fit_sequential, fit.measures = TRUE)
```

Frederick Anyan, PhD - NTNU

RESULTS

Model fit:
($\chi^2 = 825.260$, $df = 43$; $p < .001$; $RMSEA = .238$[90% CI = 0.224, 0.252]; $CFI = .581$; $TLI = .562$)

Parameter estimates:

Anxiety symptoms

i.	Intercept:	1.397***
ii.	Slope:	-0.032***

Depression symptoms

i.	Intercept:	1.546***
ii.	Slope:	-0.021**

(Co)Variances:

Anxiety symptoms

i.	Intercept:	0.097***
ii.	Slope:	0.002***

Depression symptoms

i.	Intercept:	0.171***
ii.	Slope:	0.005**

iii.	I_ANX WITH S_ANX	0.000
iv.	I_ANX WITH I_DEP	0.124***

v.	I_DEP WITH S_DEP	0.007
vi.	S_ANX WITH S_DEP	0.005***
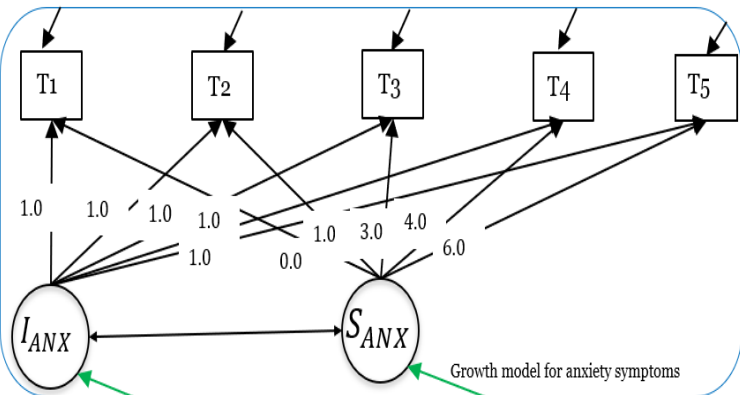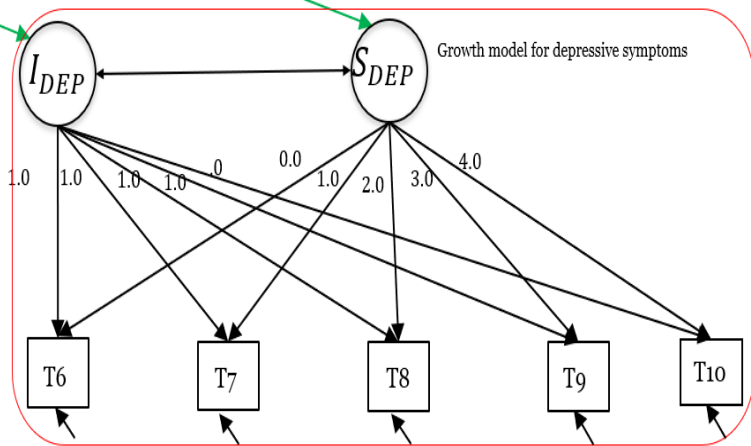
Course/workshop evaluations

Click here