Mplus Short Courses
Topic 8

Multilevel Modeling With Latent Variables Using Mplus: Longitudinal Analysis

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Table Of Contents

Mplus Background

- Inefficient dissemination of statistical methods:
  - Many good methods contributions from biostatistics, psychometrics, etc are underutilized in practice
- Fragmented presentation of methods:
  - Technical descriptions in many different journals
  - Many different pieces of limited software
- Mplus: Integration of methods in one framework
  - Easy to use: Simple, non-technical language, graphics
  - Powerful: General modeling capabilities

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Mplus Background

- Mplus versions
  - V1: November 1998
  - V2: February 2001
  - V3: March 2004
  - V4: February 2006
  - V5: November 2007
  - V5.21: May 2009
  - V6: April, 2010
- Mplus team: Linda & Bengt Muthén, Thuy Nguyen, Tihomir Asparouhov, Michelle Conn, Jean Maninger

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Statistical Analysis With Latent Variables
A General Modeling Framework

Statistical Concepts Captured By Latent Variables

Continuous Latent Variables

- Measurement errors
- Factors
- Random effects
- Frailties, liabilities
- Variance components
- Missing data

Categorical Latent Variables

- Latent classes
- Clusters
- Finite mixtures
- Missing data

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Statistical Analysis With Latent Variables
A General Modeling Framework (Continued)

Models That Use Latent Variables

Continuous Latent Variables

- Factor analysis models
- Structural equation models
- Growth curve models
- Multilevel models

Categorical Latent Variables

- Latent class models
- Mixture models
- Discrete-time survival models
- Missing data models

Mplus integrates the statistical concepts captured by latent variables into a general modeling framework that includes not only all of the models listed above but also combinations and extensions of these models.

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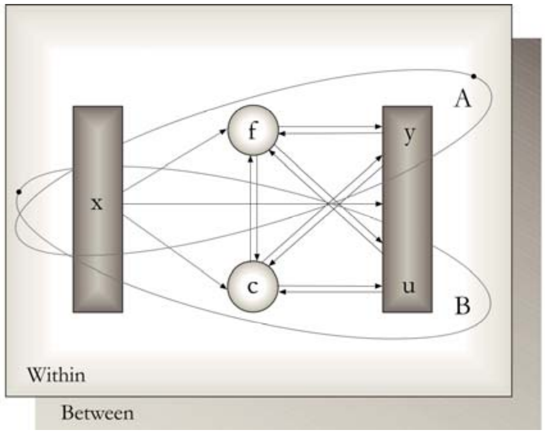
General Latent Variable Modeling Framework



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Mplus

Several programs in one

- Exploratory factor analysis
- Structural equation modeling
- Item response theory analysis
- Latent class analysis
- Latent transition analysis
- Survival analysis
- Growth modeling
- Multilevel analysis
- Complex survey data analysis
- Monte Carlo simulation

Fully integrated in the general latent variable framework

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Overview Of Mplus Courses

- **Topic 9.** Bayesian analysis using Mplus. University of Connecticut, May 24, 2011
- Courses taught by other groups in the US and abroad (see the Mplus web site)

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Multilevel Growth Models

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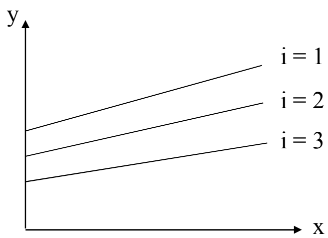
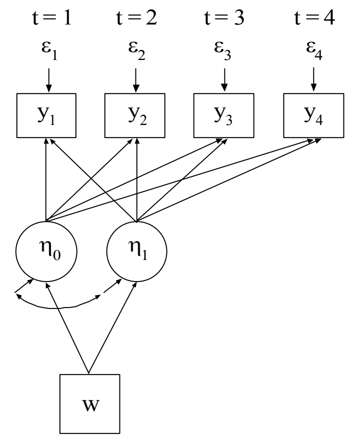
Individual Development Over Time





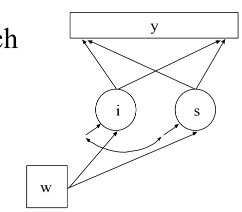
(1) $y_{ti} = \eta_{0i} + \eta_{1i}\, x_t + \varepsilon_{ti}$

(2a) $\eta_{0i} = \alpha_0 + \gamma_0\, w_i + \zeta_{0i}$

(2b) $\eta_{1i} = \alpha_1 + \gamma_1\, w_i + \zeta_{1i}$

Growth Modeling Approached In Two Ways: Data Arranged As Wide Versus Long

- Wide: Multivariate, Single-Level Approach

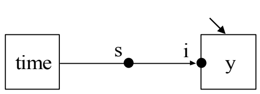


$y_{ti} = i_i + s_i \times \text{time}_{ti} + \varepsilon_{ti}$

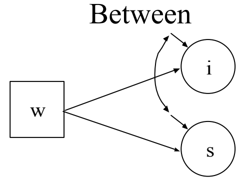
i_i regressed on w_i
s_i regressed on w_i

- Long: Univariate, 2-Level Approach (CLUSTER = id)

Within



Between



The intercept *i* is called *y* in Mplus

Growth Modeling Approached In Two Ways: Data Arranged As Wide Versus Long (Continued)

- Wide (one person):

		t1	t2	t3	t1	t2	t3	
Person i:	id	y1	y2	y3	x1	x2	x3	w

- Long (one cluster):

Person i:	t1	id	y1	x1	w
	t2	id	y2	x2	w
	t3	id	y3	x3	w

Mplus command: DATA LONGTOWIDE (UG ex 9.16)
DATA WIDETOLONG

Pros And Cons Of Wide Versus Long

- Advantages of the wide approach:
  - Modeling flexibility
    - Unequal residual variances and covariances
    - Testing of measurement invariance with multiple indicator growth
    - Allowing partial measurement non-invariance
  - Missing data modeling
  - Reduction of the number of levels by one (or more)
- Advantages of the long approach
  - Many time points
  - Individually-varying times of observation with missingness

Advantages Of Growth Modeling In A Latent Variable Framework

- Flexible curve shape
- Individually-varying times of observation
- Regressions among random effects
- Multiple processes
- Modeling of zeroes
- Multiple populations
- Multiple indicators
- Embedded growth models
- Categorical latent variables: growth mixtures

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Growth Models With Categorical Outcomes

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Growth Model With Categorical Outcomes

- Individual differences in development of probabilities over time
- Logistic model considers growth in terms of log odds (logits), e.g.

$$(1) \quad \log\left[\frac{P(u_{ti}=1 \mid \eta_{0i}, \eta_{1i}, \eta_{2i}, x_{ti})}{P(u_{ti}=0 \mid \eta_{0i}, \eta_{1i}, \eta_{2i}, x_{ti})}\right] = \eta_{0i} + \eta_{1i} \cdot (x_{ti} - c) + \eta_{2i} \cdot (x_{ti} - c)^2$$

Level 1

for a binary outcome using a quadratic model with centering at time c. The growth factors η_{0i}, η_{1i}, and η_{2i} are assumed multivariate normal given covariates,

$$(2a) \quad \eta_{0i} = \alpha_0 + \gamma_0 \, w_i + \zeta_{0i}$$

$$(2b) \quad \eta_{1i} = \alpha_1 + \gamma_1 \, w_i + \zeta_{1i}$$

$$(2c) \quad \eta_{2i} = \alpha_2 + \gamma_2 \, w_i + \zeta_{2i}$$

Level 2

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Aggression Growth Analysis

- Baltimore cohort 1: 1174 students in 41 classrooms (clustering due to classroom initially ignored)
- 8 time points over grades 1-7
- Quadratic growth
- Dichotomized items from the aggression instrument
- 4 analyses
  - Single item ("Breaks Things"), ignoring classroom clustering (ML uses 3 dimensions of numerical integration)
  - Multiple indicators (Property aggression factor), ignoring classroom clustering (ML: 8 dimensions; WLSM)
  - Single item with clustering (ML: 6 dimensions; WLSM)
  - Multiple indicators with clustering(ML: 16 dimensions; WLSM)

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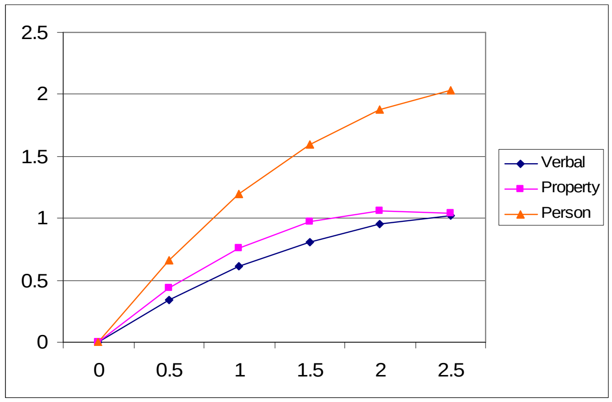
Different Growth Curves For Different Aspects Of Aggression



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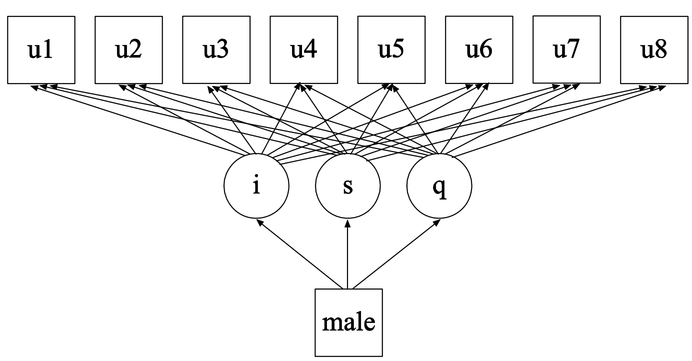
Binary Growth Modeling Of Aggression Item (No Clustering)



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Input Binary Growth Modeling

```
TITLE:     Hopkins Cohort 1 All time points with Classroom
           Information
DATA:      FILE = Cohort1_classroom_ALL.DAT;
VARIABLE:  NAMES ARE PRCID

           stub1F bkRule1F harmO1F bkThin1F yell1F takeP1F fight1F
           lies1F tease1F

           stub1S bkRule1S harmO1S bkThin1S yell1S takeP1S fight1S
           lies1S tease1S

           stub2S bkRule2S harmO2S bkThin2S yell2S takeP2S fight2S
           lies2S tease2S

           stub3S bkRule3S harmO3S bkThin3S yell3S takeP3S fight3S
           lies3S tease3S
```

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Input Binary Growth Modeling (Continued)

```
           stub4S bkRule4S harmO4S bkThin4S yell4S takeP4S
           fight4S lies4S tease4S

           stub5S bkRule5S harmO5S bkThin5S yell5S takeP5S
           fight5S lies5S tease5S

           stub6S bkRule6S harmO6S bkThin6S yell6S takeP6S
           fight6S lies6S tease6S

           stub7S bkRule7S harmO7S bkThin7S yell7S takeP7S
           fight7S lies7S tease7S

           gender race des011 sch011 sec011 juv99 violchld
           antisocr conductr

           athort1F harmP1S athort1S harmP2S athort2S harmP3S
           athort3S harmP4S athort4S harmP5S athort5S harmP6S
           harmP7S athort7S
```

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Input Binary Growth Modeling (Continued)

```
             stub2F bkRule2F harmO2F bkThin2F yell2F takeP2F
             fight2F harmP2F lies2F athort2F tease2F
             classrm;
!            CLUSTER = classrm;
             USEVAR = bkthin1f bkthin1s bkthin2s bkthin3s bkthin4s
             bkthin5s bkthin6s bkthin7s male;
             CATEGORICAL = bkthin1f - bkthin7s;
             MISSING = ALL (999);
DEFINE:      CUT bkThin1f(1.5);
             CUT bkThin1s(1.5);
             CUT bkThin2s(1.5);
             CUT bkThin3s(1.5);
             CUT bkThin4s(1.5);
             CUT bkThin5s(1.5);
             CUT bkThin6s(1.5);
             CUT bkThin7s(1.5);
             male = 2 - gender;
```

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Input Binary Growth Modeling (Continued)

```
ANALYSIS:    ESTIMATOR = MLR;
             INTEGRATION = 10;
             PROCESS = 4;
MODEL:       i s q | bkthin1f@0 bkthin1s@.5 bkthin2s@1.5
             bkthin3s@2.5 bkthin4s@3.5 bkthin5s@4.5 bkthin6s@5.5
             bkthin7s@6.5;
             i-q ON male;
OUTPUT:      TECH1 TECH8 STANDARDIZED;
```

10 integration points per dimension: 1000 points, 5 seconds
15 integration points per dimension: 3375 points, 1 minute 50 seconds

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Output Excerpts Binary Growth (No Clustering)

```
Tests of Model Fit

Loglikelihood
      H0 Value                                  -3546.377
      H0 Scaling Correction Factor for MLR         1.0005
Information Criteria
      Number of Free Parameters                        12
      Akaike (AIC)                               7116.754
      Bayesian (BIC)                             7177.572
      Sample-Size Adjusted BIC                   7139.455
         (n* = (n + 2) / 24)
```

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Output Excerpts Binary Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
i |				
bkthin1f	1.000	0.000	999.000	999.000
bkthin1s	1.000	0.000	999.000	999.000
bkthin2s	1.000	0.000	999.000	999.000
bkthin3s	1.000	0.000	999.000	999.000
bkthin4s	1.000	0.000	999.000	999.000
bkthin5s	1.000	0.000	999.000	999.000
bkthin6s	1.000	0.000	999.000	999.000
bkthin7s	1.000	0.000	999.000	999.000

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Output Excerpts Binary Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
s |				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.500	0.000	999.000	999.000
bkthin2s	1.500	0.000	999.000	999.000
bkthin3s	2.500	0.000	999.000	999.000
bkthin4s	3.500	0.000	999.000	999.000
bkthin5s	4.500	0.000	999.000	999.000
bkthin6s	5.500	0.000	999.000	999.000
bkthin7s	6.500	0.000	999.000	999.000

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Output Excerpts Binary Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
q |				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.250	0.000	999.000	999.000
bkthin2s	2.250	0.000	999.000	999.000
bkthin3s	6.250	0.000	999.000	999.000
bkthin4s	12.250	0.000	999.000	999.000
bkthin5s	20.250	0.000	999.000	999.000
bkthin6s	30.250	0.000	999.000	999.000
bkthin7s	42.250	0.000	999.000	999.000

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Output Excerpts Binary Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
i ON				
male	1.109	0.186	5.960	0.000
s ON				
male	-0.137	0.121	-1.132	0.258
q ON				
male	0.028	0.019	1.494	0.135
s WITH				
i	-1.298	0.314	-4.137	0.000
q WITH				
i	0.138	0.040	3.435	0.001
s	-0.059	0.026	-2.260	0.024

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Output Excerpts Binary Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Intercepts				
I	0.000	0.000	999.000	999.000
S	0.204	0.102	1.998	0.046
Q	-0.045	0.017	-2.689	0.007
Thresholds				
bkthin1f$1	1.839	0.149	12.324	0.000
bkthin1s$1	1.839	0.149	12.324	0.000
bkthin2s$1	1.839	0.149	12.324	0.000
bkthin3s$1	1.839	0.149	12.324	0.000
bkthin4s$1	1.839	0.149	12.324	0.000

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Output Excerpts Binary Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
bkthin5s$1	1.839	0.149	12.324	0.000
bkthin6s$1	1.839	0.149	12.324	0.000
bkthin7s$1	1.839	0.149	12.324	0.000
Residual Variances				
i	3.803	0.625	6.083	0.000
s	0.545	0.190	2.868	0.004
q	0.007	0.004	1.781	0.075

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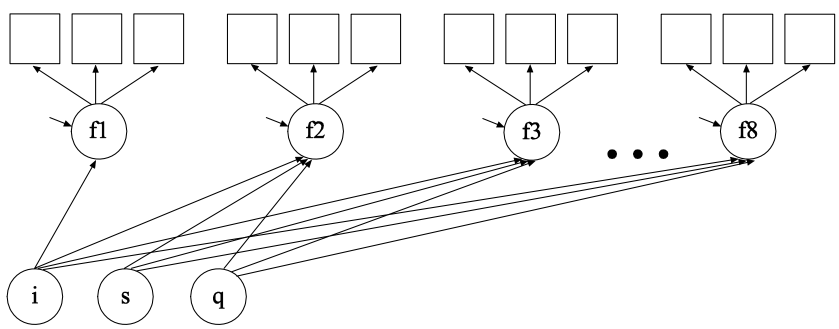
Multiple Indicator Growth (No Clustering)



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Input Excerpts Multiple Indicator Growth (No Clustering)

```
         USEVAR = bkThin1f bkThin1s bkThin2s bkThin3s bkThin4s
         bkThin5s bkThin6s bkThin7s harmO1f harmO1s harmO2s
         harmO3s harmO4s harmO5s harmO6s harmO7s takeP1f takeP1s
         takeP2s takeP3s takeP4s takeP5s takeP6s takeP7s male;
         CATEGORICAL = bkThin1f - takeP7s;
         MISSING = ALL (999);
DEFINE:  CUT bkThin1f(1.5);
         CUT bkThin1s(1.5);
         CUT bkThin2s(1.5);
         CUT bkThin3s(1.5);
         CUT bkThin4s(1.5);
         CUT bkThin5s(1.5);
         CUT bkThin6s(1.5);
         CUT bkThin7s(1.5);

         CUT harmO1f (1.5);
         CUT harmO1s (1.5);
         CUT harmO2s (1.5);
         CUT harmO3s (1.5);
```

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Input Excerpts Multiple Indicator Growth (No Clustering) (Continued)

```
         CUT harmO4s (1.5);
         CUT harmO5s (1.5);
         CUT harmO6s (1.5);
         CUT harmO7s (1.5);

         CUT takeP1f(1.5);
         CUT takeP1s(1.5);
         CUT takeP2s(1.5);
         CUT takeP3s(1.5);
         CUT takeP4s(1.5);
         CUT takeP5s(1.5);
         CUT takeP6s(1.5);
         CUT takeP7s(1.5);

         male = 2 - gender;
```

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Input Excerpts Multiple Indicator Growth (No Clustering)

```
ANALYSIS:     PROCESS = 4;
              ESTIMATOR = WLSM;
              PARAMETERIZATION = THETA;
MODEL:        f1 BY bkthin1f
              harmo1f (1)
              takep1f (2);
              f2 BY bkthin1s
              harmo1s (1)
              takep1s (2);
              f3 BY bkthin2s
              harmo2s (1)
              takep2s (2);
```


Input Excerpts Multiple Indicator Growth (No Clustering) (Continued)

```
              f4 BY bkthin3s
              harmo3s (1)
              takep3s (2);
              f5 BY bkthin4s
              harmo4s (1)
              takep4s (2);
              f6 BY bkthin5s
              harmo5s (1)
              takep5s (2);
              f7 BY bkthin6s
              harmo6s (1)
              takep6s (2);
```

Input Excerpts Multiple Indicator Growth (No Clustering) (Continued)

```
                f8 BY bkthin7s
                harmo7s (1)
                takep7s (2);

                [bkthin1f$1-bkthin7s$1] (11);
                [harmo1f$1-harmo7s$1] (12);
                [takep1f$1-takep7s$1] (13);

                i s q | f1@0 f2@.5 f3@1.5 f4@2.5 f5@3.5 f6@4.5
                f7@5.5 f8@6.5;
                i-q ON male;

OUTPUT:         TECH1 TECH8 STANDARDIZED;
```


Output Excerpts Multiple Indicator Growth (No Clustering)

```
Test of Model Fit

Chi-Square Test of Model Fit
         Value                                      524.261
         Degrees of Freedom                             300
         P-Value                                     0.0000
         Scaling Correction Factor for WLSM           0.757

*        The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and
         WLSMV cannot be used for chi-square difference tests.
         MLM, MLR and WLSM chi-square difference testing is
         described in the Mplus Technical Appendices at
         www.statmodel.com. See chi-square difference testing in
         the index of the Mplus Users' Guide.
```

Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

```
Chi-Square Test of Model Fit for the Baseline Model
        Value                                  37306.671
        Degrees of Freedom                           300
        P-Value                                   0.0000

CFI/TLI
        CFI                                        0.994
        TLI                                        0.994

Number of Free Parameters                             24
RMSEA (Root Mean Square Error of Approximation)
        Estimate                                   0.025
```


Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
i |				
f1	1.000	0.000	999.000	999.000
f2	1.000	0.000	999.000	999.000
f3	1.000	0.000	999.000	999.000
f4	1.000	0.000	999.000	999.000
f5	1.000	0.000	999.000	999.000
f6	1.000	0.000	999.000	999.000
f7	1.000	0.000	999.000	999.000
f8	1.000	0.000	999.000	999.000

Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
s |				
f1	0.000	0.000	999.000	999.000
f2	0.500	0.000	999.000	999.000
f3	1.500	0.000	999.000	999.000
f4	2.500	0.000	999.000	999.000
f5	3.500	0.000	999.000	999.000
f6	4.500	0.000	999.000	999.000
f7	5.500	0.000	999.000	999.000
f8	6.500	0.000	999.000	999.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
q |				
f1	0.000	0.000	999.000	999.000
f2	0.250	0.000	999.000	999.000
f3	2.250	0.000	999.000	999.000
f4	6.250	0.000	999.000	999.000
f5	12.250	0.000	999.000	999.000
f6	20.250	0.000	999.000	999.000
f7	30.250	0.000	999.000	999.000
f8	42.250	0.000	999.000	999.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f1 BY				
bkthin1f	1.000	0.000	999.000	999.000
harmo1f	1.239	0.112	11.089	0.000
takep1f	1.045	0.078	13.432	0.000
f2 BY				
bkthin1s	1.000	0.000	999.000	999.000
harmo1s	1.239	0.112	11.089	0.000
takep1s	1.045	0.078	13.432	0.000
f3 BY				
bkthin2s	1.000	0.000	999.000	999.000
harmo2s	1.239	0.112	11.089	0.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
takep2s	1.045	0.078	13.432	0.000
f4 BY				
bkthin3s	1.000	0.000	999.000	999.000
harmo3s	1.239	0.112	11.089	0.000
takep3s	1.045	0.078	13.432	0.000
f5 BY				
bkthin4s	1.000	0.000	999.000	999.000
harmo4s	1.239	0.112	11.089	0.000
takep4s	1.045	0.078	13.432	0.000
f6 BY				
bkthin5s	1.000	0.000	999.000	999.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
harmo5s	1.239	0.112	11.089	0.000
takep5s	1.045	0.078	13.432	0.000
f7 BY				
bkthin6s	1.000	0.000	999.000	999.000
harmo6s	1.239	0.112	11.089	0.000
takep6s	1.045	0.078	13.432	0.000
f8 BY				
bkthin7s	1.000	0.000	999.000	999.000
harmo7s	1.239	0.112	11.089	0.000
takep7s	1.045	0.078	13.432	0.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
i ON				
male	1.122	0.169	6.634	0.000
s ON				
male	0.046	0.108	0.424	0.671
q ON				
male	-0.006	0.016	-0.350	0.727
s WITH				
i	-1.225	0.227	-5.405	0.000
q WITH				
i	0.113	0.028	4.098	0.000
s	-0.086	0.019	-4.493	0.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Intercepts				
f1	0.000	0.000	999.000	999.000
f2	0.000	0.000	999.000	999.000
f3	0.000	0.000	999.000	999.000
f4	0.000	0.000	999.000	999.000
f5	0.000	0.000	999.000	999.000
f6	0.000	0.000	999.000	999.000
f7	0.000	0.000	999.000	999.000
f8	0.000	0.000	999.000	999.000
i	0.000	0.000	999.000	999.000
s	-0.071	0.090	-0.789	0.430
q	0.005	0.014	0.362	0.717

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Thresholds				
bthin1f$1	1.944	0.150	12.995	0.000
bthin1s$1	1.944	0.150	12.995	0.000
bthin2s$1	1.944	0.150	12.995	0.000
bthin3s$1	1.944	0.150	12.995	0.000
bthin4s$1	1.944	0.150	12.995	0.000
bthin5s$1	1.944	0.150	12.995	0.000
bthin6s$1	1.944	0.150	12.995	0.000
bthin7s$1	1.944	0.150	12.995	0.000
harmo1f$1	1.477	0.175	8.437	0.000
harmo1s$1	1.477	0.175	8.437	0.000
harmo2s$1	1.477	0.175	8.437	0.000

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Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
harmo3s$1	1.477	0.175	8.437	0.000
harmo4s$1	1.477	0.175	8.437	0.000
harmo5s$1	1.477	0.175	8.437	0.000
harmo6f$1	1.477	0.175	8.437	0.000
harmo7s$1	1.477	0.175	8.437	0.000
takep1f$1	1.288	0.142	9.075	0.000
takep1s$1	1.288	0.142	9.075	0.000
takep2s$1	1.288	0.142	9.075	0.000
takep3s$1	1.288	0.142	9.075	0.000
takep4s$1	1.288	0.142	9.075	0.000
takep5s$1	1.288	0.142	9.075	0.000

Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
takep6s$1	1.288	0.142	9.075	0.000
takep7s$1	1.288	0.142	9.075	0.000
Residual variances				
f1	0.564	0.329	1.714	0.087
f2	1.648	0.396	4.161	0.000
f3	7.274	1.488	4.888	0.000
f4	2.278	0.510	4.462	0.000
f5	1.911	0.414	4.615	0.000

Output Excerpts Multiple Indicator Growth (No Clustering) (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f6	2.281	0.463	4.926	0.000
f7	2.462	0.526	4.682	0.000
f8	1.536	0.447	3.437	0.001
i	4.234	0.556	7.621	0.000
s	0.749	0.142	5.291	0.000
q	0.011	0.003	3.854	0.000

Multivariate Approach To Multilevel Modeling

Multivariate Modeling Of Family Members

- Multilevel modeling: clusters independent, model for between- and within-cluster variation, members of a cluster statistically equivalent
- Multivariate approach: clusters independent, model for all variables for each cluster member, different parameters for different cluster members.
  - Used in latent variable growth modeling where the cluster members are the repeated measures over time
  - Allows for different cluster sizes by missing data techniques
  - More flexible than the multilevel approach, but computationally convenient only for applications with small cluster sizes (e.g. twins, spouses)

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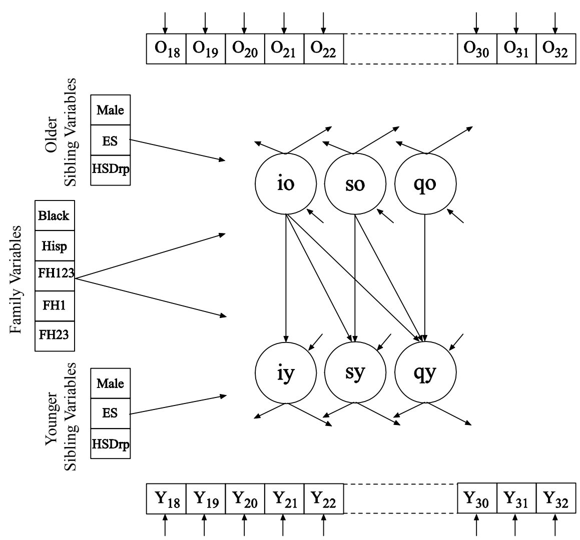
Figure 1. A Longitudinal Growth Model of Heavy Drinking for Two-Sibling Families



Source: Khoo, S.T. & Muthen, B. (2000). Longitudinal data on families: Growth modeling alternatives. Multivariate Applications in Substance Use Research, J. Rose, L. Chassin, C. Presson & J. Sherman (eds.), Hillsdale, N.J.: Erlbaum, pp. 43-78.

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Three-Level Modeling As Single-Level Analysis

- The sibling growth model has 3 levels:
  - Time
  - Individual
  - Family
- Analyzed as doubly multivariate:
  - Repeated measures in wide, multivariate form
  - Siblings in wide, multivariate form

It is possible to do four-level by TYPE = TWOLEVEL, for instance families within geographical segments

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Input For Multivariate Modeling Of Family Data

```
TITLE:      Multivariate modeling of family data
            one observation per family
DATA:       FILE IS multi.dat;
VARIABLE:   NAMES ARE o18-o32 y18-y32 omale oes ohsdrop ymale yes
            yhsdrop black hisp fh123 fh1 fh23;
MODEL:      io so qo | o18@0 o19@1 o20@2 o21@3 o22@4
            o23@5 o24@6 o25@7 o26@8 o27@9 o28@10 o29@11 o30@12
            o31@13 o32@14;
            iy sy qy | y18@0 y19@1 y20@2 y21@3 y22@4 y23@5 y24@6
            y25@7 y26@8 y27@9 y28@10 y29@11 y30@12
            y31@13 y32@14;
            io ON omale oes ohsdrop black hisp fh123 fh1 fh23;
            iy ON ymale yes yhsdrop black hisp fh123 fh1 fh23;
            iy ON io;
            sy ON io so;
            qy ON io so qo;
```

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Multilevel Growth Modeling (3-Level Analysis)

Three-Level Analysis In Multilevel Terms

Time point t, individual i, cluster j.

y_{tij} : individual-level, outcome variable
a_{1tij} : individual-level, time-related variable (age, grade)
a_{2tij} : individual-level, time-varying covariate
x_{ij} : individual-level, time-invariant covariate
w_j : cluster-level covariate

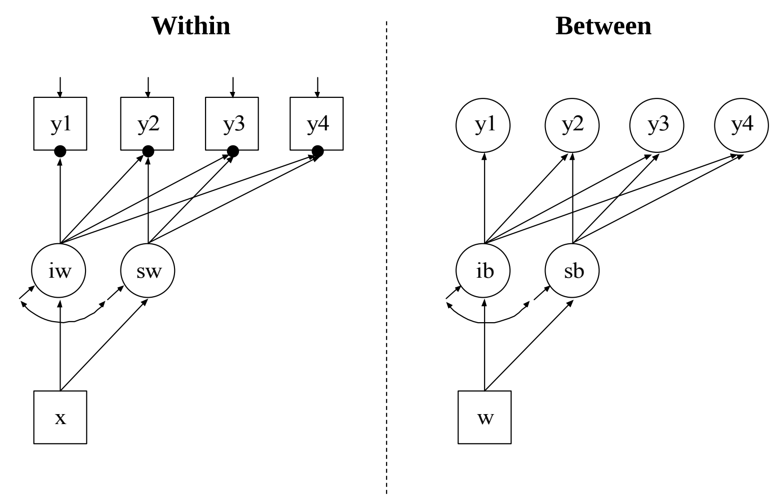
Three-level analysis (Mplus considers Within and Between)

$$Level\ 1\ (Within):\ y_{tij} = \pi_{0ij} + \pi_{1ij}\, a_{1tij} + \pi_{2tij}\, a_{2tij} + e_{tij}, \quad (1)$$

$$Level\ 2\ (Within): \begin{cases} \pi_{0ij} = \beta_{00j} + \beta_{01j}\, x_{ij} + r_{0ij}, & \rightarrow iw \\ \pi_{1ij} = \beta_{10j} + \beta_{11j}\, x_{ij} + r_{1ij}, & \rightarrow sw \\ \pi_{2tij} = \beta_{20tj} + \beta_{21tj}\, x_{ij} + r_{2tij}. \end{cases} \quad (2)$$

$$Level\ 3\ (Between): \begin{cases} \beta_{00j} = \gamma_{000} + \gamma_{001}\, w_j + u_{00j}, & \rightarrow ib \\ \beta_{10j} = \gamma_{100} + \gamma_{101}\, w_j + u_{10j}, & \rightarrow sb \\ \beta_{20tj} = \gamma_{200t} + \gamma_{201t}\, w_j + u_{20tj}, \\ \beta_{01j} = \gamma_{010} + \gamma_{011}\, w_j + u_{01j}, \\ \beta_{11j} = \gamma_{110} + \gamma_{111}\, w_j + u_{11j}, \\ \beta_{21tj} = \gamma_{2t0} + \gamma_{2t1}\, w_j + u_{2tj}. \end{cases} \quad (3)$$

Two-Level Growth Modeling (Three-Level Analysis)



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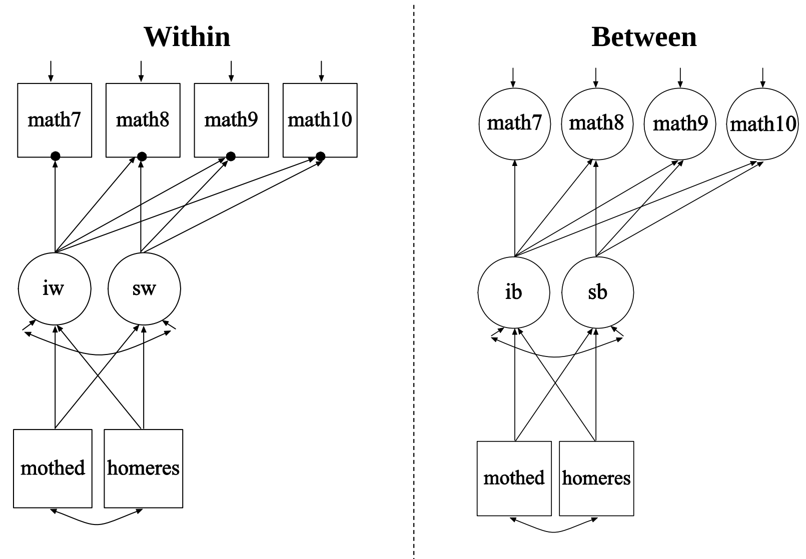
LSAY Two-Level Growth Model



60

Input For LSAY Two-Level Growth Model With Free Time Scores And Covariates

```
TITLE:     LSAY two-level growth model with free time scores
           and covariates
DATA:      FILE IS lsay98.dat;
           FORMAT IS 3f8 f8.4 8f8.2 3f8 2f8.2;
VARIABLE:  NAMES ARE cohort id school weight math7 math8 math9
           math10 att7 att8 att9 att10 gender mothed homeres;
           USEOBS = (gender EQ 1 AND cohort EQ 2);
           MISSING = ALL (999);
           USEVAR = math7-math10 mothed homeres;
           CLUSTER = school;
ANALYSIS:  TYPE = TWOLEVEL;
           ESTIMATOR = MUML;
```

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Input For LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

```
MODEL:     %WITHIN%
           iw sw | math7@0 math8@1
           math9*2  (1)
           math10*3 (2);
           iw sw ON mothed homeres;
           %BETWEEN%
           ib sb | math7@0 math8@1
           math9*2  (1)
           math10*3 (2);
           ib sb ON mothed homeres;

OUTPUT     SAMPSTAT STANDARDIZED RESIDUAL;
```

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates

Summary of Data

```
Number of clusters       50

  Size (s)  Cluster ID with Size s
    1         114
    2         136
    6         132     304

   34         104
   39         309
   40         302

Average cluster size 18.627

Estimated Intraclass Correlations for the Y Variables
```

Variable	Intraclass Correlation	Variable	Intraclass Correlation	Variable	Intraclass Correlation
MATH7	0.199	MATH8	0.149	MATH9	0.168
MATH10	0.165				

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

Tests Of Model Fit

```
Chi-square Test of Model Fit
            Value                          24.058*
            Degrees of Freedom                 14
            P-Value                         0.0451
CFI / TLI
            CFI                              0.997
            TLI                              0.995
RMSEA (Root Mean Square Error Of Approximation)
            Estimate                         0.028
SRMR (Standardized Root Mean Square Residual)
            Value for Between                0.048
            Value for Within                 0.007
```

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

Model Results

Within Level

	Estimates	S.E.	Est./S.E.	Std	StdYX
SW |					
MATH8	1.000	0.000	0.000	1.073	0.128
MATH9	2.487	0.163	15.220	2.670	0.288
MATH10	3.589	0.223	16.076	3.853	0.368
IW ON					
MOTHED	**1.780**	**0.232**	**7.665**	**0.246**	**0.226**
HOMERES	**0.892**	**0.221**	**4.031**	**0.124**	**0.173**
SW ON					
MOTHED	**0.053**	**0.063**	**0.836**	**0.049**	**0.045**
HOMERES	**0.135**	**0.044**	**3.047**	**0.125**	**0.176**

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

	Estimates	S.E.	Est./S.E.	Std	StdYX
SW WITH					
IW	2.112	0.522	4.044	0.273	0.273
HOMERES WITH					
MOTHED	0.261	0.039	6.709	0.261	0.203
Residual Variances					
MATH7	12.748	1.434	8.888	12.748	0.197
MATH8	12.298	0.893	13.771	12.298	0.174
MATH9	14.237	1.132	12.578	14.237	0.166
MATH10	24.829	2.230	11.133	24.829	0.226
IW	47.060	3.069	15.333	0.903	0.903
SW	1.110	0.286	3.879	0.964	0.964
Variances					
MOTHED	0.841	0.049	17.217	0.841	1.000
HOMERES	1.970	0.069	28.643	1.970	1.000

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

Between Level

	Estimates	S.E.	Est./S.E.	Std	StdYX
SB |					
MATH8	1.000	0.000	0.000	0.196	0.052
MATH9	2.487	0.163	15.220	0.488	0.119
MATH10	3.589	0.223	16.076	0.704	0.115
IB ON					
MOTHED	**-1.225**	**2.587**	**-0.474**	**-0.362**	**-0.107**
HOMERES	**7.160**	**1.847**	**3.876**	**2.117**	**1.011**
SB ON					
MOTHED	**0.995**	**0.647**	**1.538**	**5.073**	**1.493**
HOMERES	**0.017**	**0.373**	**0.045**	**0.086**	**0.041**
SB WITH					
IB	0.382	0.248	1.538	0.575	0.575

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

HOMERES WITH					
MOTHED	0.103	0.019	5.488	0.103	0.733
Residual Variances					
MATH7	2.059	0.552	3.732	2.059	0.153
MATH8	0.544	0.268	2.033	0.544	0.039
MATH9	0.105	0.213	0.493	0.105	0.006
MATH10	1.395	0.504	2.767	1.395	0.067
IB	1.428	1.690	0.845	0.125	0.125
SB	-0.051	0.071	-0.713	-1.321	-1.321
Variances					
MOTHED	0.087	0.023	3.801	0.087	1.000
HOMERES	0.228	0.056	4.066	0.228	1.000
Means					
MOTHED	2.307	0.043	53.277	2.307	7.838
HOMERES	3.108	0.062	50.375	3.108	6.509
Intercepts					
IB	33.510	2.678	12.512	9.909	9.909
SB	0.163	0.776	0.210	0.830	0.830

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Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

R-Square

Within Level

Observed Variable	R-Square
MATH7	0.803
MATH8	0.826
MATH9	0.834
MATH10	0.774

Latent Variable	R-Square
IW	0.097
SW	0.036

Output Excerpts LSAY Two-Level Growth Model With Free Time Scores And Covariates (Continued)

R-Square

Between Level

Observed Variable	R-Square
MATH7	0.847
MATH8	0.961
MATH9	0.994
MATH10	0.933

Latent Variable	R-Square	
IB	0.875	
SB	Undefined	0.23207E+01

Further Readings On Three-Level Growth Analysis

Muthén, B. (1997). Latent variable modeling with longitudinal and multilevel data. In A. Raftery (ed), Sociological Methodology (pp. 453-480). Boston: Blackwell Publishers. (#73)

Muthén, B. & Asparouhov, T. (2011). Beyond multilevel regression modeling: Multilevel analysis in a general latent variable framework. In J. Hox & J.K. Roberts (eds), The Handbook of Advanced Multilevel Analysis, pp 15-40. New York: Taylor and Francis.

Raudenbush, S.W. & Bryk, A.S. (2002). Hierarchical linear models: Applications and data analysis methods. Second edition. Newbury Park, CA: Sage Publications.

Snijders, T. & Bosker, R. (1999). Multilevel analysis. An introduction to basic and advanced multilevel modeling. Thousand Oakes, CA: Sage Publications.

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Multilevel Growth Modeling Of Binary Outcomes (3-Level Analysis)

72

Multilevel Growth Model With Binary Outcomes

Time point t, individual i, cluster j.
Logit-linear growth.

Level 1 (*Within Cluster*):

$$\log\left[\frac{P(u_{ti}=1 \mid \eta_{0ij}, \eta_{1ij}, a_{ti})}{P(u_{ti}=0 \mid \eta_{0ij}, \eta_{1ij}, a_{ti})}\right] = \eta_{0ij} + \eta_{1ij} \cdot (a_{ti} - c) \quad (1)$$

Level 2 (*Within Cluster*):

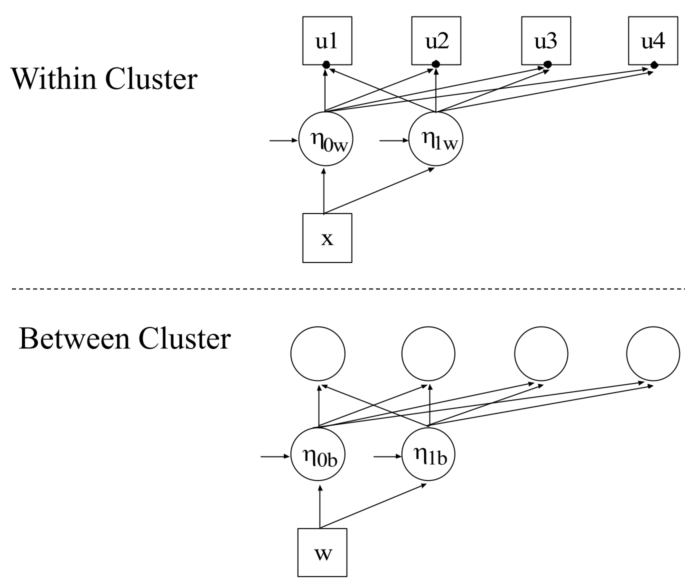
$$\begin{cases} \eta_{0ij} = \beta_{00j} + \beta_{01}\, x_{ij} + r_{0ij}, & \rightarrow \eta_{0w} \\ \eta_{1ij} = \beta_{10j} + \beta_{11}\, x_{ij} + r_{1ij}, & \rightarrow \eta_{1w} \end{cases} \quad (2)$$

Level 3 (*Between Cluster*):

$$\begin{cases} \beta_{00j} = \gamma_{000} + \gamma_{001}\, w_j + r_{00j}, & \rightarrow \eta_{0b} \\ \beta_{10j} = \gamma_{100} + \gamma_{101}\, w_j + r_{10j}, & \rightarrow \eta_{1b} \end{cases} \quad (3)$$

Fitzmaurice, Laird, & Ware (2004). Applied longitudinal analysis. Wiley & Sons.
Fitzmaurice, Davidian, Verbeke, & Molenberghs (2009). Longitudinal Data Analysis. Chapman & Hall/CRC Press.

Growth Model With Binary Outcomes



Observed Data Likelihood

Individual *i* in cluster j

$$\prod_j \int \phi_j(\eta_{bj}) \prod_i \left(\int f_{ij}(u_{ij} \mid \eta_{bj}, \eta_{wij}) \phi_{ij}(\eta_{wij}) \, d\eta_{wij} \right) d\eta_{bj}$$

- Maximum likelihood estimation
- Numerical integration
- The logit-linear binary growth model results in 4 dimensions of integration

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Input Excerpts Two-Level Binary Growth

```
           USEVAR = bkthin1f bkthin1s bkthin2s bkthin3s bkthin4s
           bkthin5s bkthin6s bkthin7s male;
           CATEGORICAL = bkthin1f - bkthin7s;
           MISSING = ALL (999);
           CLUSTER = classrm;
           WITHIN = male;
DEFINE:    CUT bkThin1f(1.5);
           CUT bkThin1s(1.5);
           CUT bkThin2s(1.5);
           CUT bkThin3s(1.5);
           CUT bkThin4s(1.5);
           CUT bkThin5s(1.5);
           CUT bkThin6s(1.5);
           CUT bkThin7s(1.5);
           male = 2 - gender;
ANALYSIS:  TYPE = TWOLEVEL;
           PROCESS = 4;
           ESTIMATOR = WLSM;
```

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Input Excerpts Two-Level Binary Growth

```
MODEL:      %WITHIN%

            iw sw qw | bkthin1f@0 bkthin1s@.5 bkthin2s@1.5
            bkthin3s@2.5 bkthin4s@3.5 bkthin5s@4.5 bkthin6s@5.5
            bkthin7s@6.5;

            iw-qw on male;

            %BETWEEN%

            ib sb qb |bkthin1f@0 bkthin1s@.5 bkthin2s@1.5
            bkthin3s@2.5 bkthin4s@3.5 bkthin5s@4.5 bkthin6s@5.5
            bkthin7s@6.5;

            bkthin1f-bkthin7s@0;


OUTPUT:     TECH1 TECH8 STANDARDIZED;
```

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Output Excerpts Two-Level Binary Growth

```
Number of clusters                      41
Average cluster size                28.634
```

Estimated Intraclass Correlations for the Y Variables

Variable	Intraclass Correlation	Variable	Intraclass Correlation	Variable	Intraclass Correlation
bkthin1f	0.470	bkthin1s	0.484	bkthin2s	0.385
bkthin3s	0.089	bkthin4s	0.052	bkthin5s	0.094
bkthin6s	0.137	bkthin7s	0.104		

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Output Excerpts Two-Level Binary Growth (Continued)

```
Tests of Model Fit

Chi-Square Test of Model Fit
     Value                                      101.742*
     Degrees of Freedom                              62
     P-Value                                     0.0011

*    The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM
     and WLSMV cannot be used for chi-square difference
     tests. MLM, MLR and WLSM chi-square difference testing
     is described in the Mplus Technical Appendices at
     www.statmodel.com. See chi-square difference testing in
     the index of the Mplus Users' Guide.
```

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Output Excerpts Two-Level Binary Growth (Continued)

```
Chi-Square Test of Model Fit for the Baseline Model
     Value                                      924.374
     Degrees of Freedom                              64
     P-Value                                     0.0000
CFI/TLI
     CFI                                          0.954
     TLI                                          0.952
Number of Free Parameters                            18
RMSEA (Root Mean Square Error Of Approximation)
     Estimate                                     0.023
SRMR (Standardized Root Mean Square Residual)
     Value for Within                             0.056
     Value for Between                            0.513
```

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Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
iw |				
bkthin1f	1.000	0.000	999.000	999.000
bkthin1s	1.000	0.000	999.000	999.000
bkthin2s	1.000	0.000	999.000	999.000
bkthin3s	1.000	0.000	999.000	999.000
bkthin4s	1.000	0.000	999.000	999.000
bkthin5s	1.000	0.000	999.000	999.000
bkthin6s	1.000	0.000	999.000	999.000
bkthin7s	1.000	0.000	999.000	999.000

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Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
sw |				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.500	0.000	999.000	999.000
bkthin2s	1.500	0.000	999.000	999.000
bkthin3s	2.500	0.000	999.000	999.000
bkthin4s	3.500	0.000	999.000	999.000
bkthin5s	4.500	0.000	999.000	999.000
bkthin6s	5.500	0.000	999.000	999.000
bkthin7s	6.500	0.000	999.000	999.000

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Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
qw |				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.250	0.000	999.000	999.000
bkthin2s	2.250	0.000	999.000	999.000
bkthin3s	6.250	0.000	999.000	999.000
bkthin4s	12.250	0.000	999.000	999.000
bkthin5s	20.250	0.000	999.000	999.000
bkthin6s	30.250	0.000	999.000	999.000
bkthin7s	42.250	0.000	999.000	999.000

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Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
iw ON				
male	0.980	0.131	7.496	0.000
sw ON				
male	-0.177	0.087	-2.032	0.042
qw ON				
male	0.023	0.013	1.707	0.088
sw WITH				
iw	-0.290	0.121	-2.388	0.017
qw WITH				
iw	0.022	0.016	1.434	0.151
sw	-0.010	0.010	-0.987	0.324

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Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Residual Variances				
iw	1.315	0.284	4.637	0.000
sw	0.102	0.071	1.430	0.153
qw	0.001	0.001	0.683	0.495
Between Level				
ib |				
bkthin1f	1.000	0.000	999.000	999.000
bkthin1s	1.000	0.000	999.000	999.000
bkthin2s	1.000	0.000	999.000	999.000
bkthin3s	1.000	0.000	999.000	999.000

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Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
bkthin4s	1.000	0.000	999.000	999.000
bkthin5s	1.000	0.000	999.000	999.000
bkthin6s	1.000	0.000	999.000	999.000
bkthin7s	1.000	0.000	999.000	999.000
sb |				
bkthin1f	1.000	0.000	999.000	999.000
bkthin1s	0.500	0.000	999.000	999.000
bkthin2s	1.500	0.000	999.000	999.000
bkthin3s	2.500	0.000	999.000	999.000
bkthin4s	3.500	0.000	999.000	999.000
bkthin5s	4.500	0.000	999.000	999.000

86

Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
bkthin6s	5.500	0.000	999.000	999.000
bkthin7s	6.500	0.000	999.000	999.000
qb |				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.250	0.000	999.000	999.000
bkthin2s	2.250	0.000	999.000	999.000
bkthin3s	6.250	0.000	999.000	999.000
bkthin4s	12.250	0.000	999.000	999.000
bkthin5s	20.250	0.000	999.000	999.000
bkthin6s	30.250	0.000	999.000	999.000
bkthin7s	42.250	0.000	999.000	999.000

87

Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
sw WITH				
ib	-0.395	0.122	-3.246	0.001
qb WITH				
ib	0.043	0.014	3.069	0.002
sb	-0.018	0.007	-2.451	0.014
Means				
ib	0.000	0.000	999.000	999.000
sb	0.219	0.133	1.648	0.099
qb	-0.028	0.018	-1.614	0.107

88

Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Thresholds				
bkthin1f$1	1.592	0.253	6.304	0.000
bkthin1s$1	1.592	0.253	6.304	0.000
bkthin2s$1	1.592	0.253	6.304	0.000
bkthin3s$1	1.592	0.253	6.304	0.000
bkthin4s$1	1.592	0.253	6.304	0.000
bkthin5s$1	1.592	0.253	6.304	0.000
bkthin6s$1	1.592	0.253	6.304	0.000
bkthin7s$1	1.592	0.253	6.304	0.000

89

Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Variances				
ib	0.935	0.285	3.278	0.001
sb	0.165	0.058	2.842	0.004
qb	0.002	0.001	2.071	0.038
Residual Variances				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.000	0.000	999.000	999.000
bkthin2s	0.000	0.000	999.000	999.000

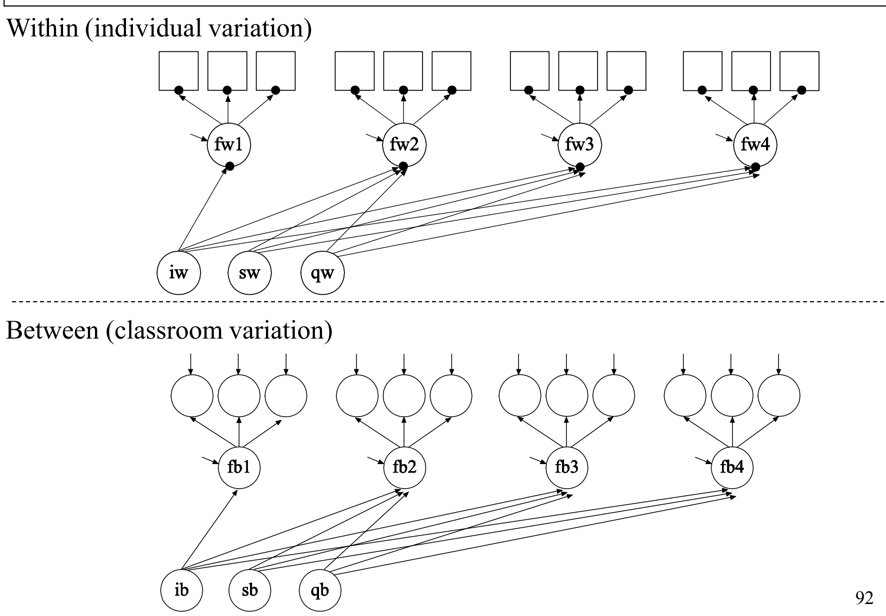
90

Output Excerpts Two-Level Binary Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
bkthin3s	0.000	0.000	999.000	999.000
bkthin4s	0.000	0.000	999.000	999.000
bkthin5s	0.000	0.000	999.000	999.000
bkthin6s	0.000	0.000	999.000	999.000
bkthin7s	0.000	0.000	999.000	999.000

91

Two-Level Multiple Indicator Growth



92

Multilevel Multiple Indicator Growth In Other Software

Treated as 4-level analysis:

- Level 1: Indicators
- Level 2: Time points
- Level 3: Individuals
- Level 4: Clusters

This approach is

- Cumbersome requiring dummy variables to indicate indicators
- Limiting in that only intercepts/thresholds and not loadings are allowed to vary across indicators (Rasch model for categorical outcomes).

93

Multilevel Multiple Indicator Growth In Other Software (Continued)

In contrast, Mplus treats such analysis as two-level modeling with

- Within: Indicators, time points, individuals (doubly wide format: indicators x time points)
- Between: Clusters

  and allowing intercepts/thresholds and loadings to vary across indicators and, if needed, across time.

94

Input Excerpts
Two-Level Multiple Indicator Growth

```
ANALYSIS:   TYPE = TWOLEVEL;
            PROCESS = 4;
            ESTIMATOR = WLSM;
MODEL:      %WITHIN%
            f1 BY bkthin1f
            harmo1f (1)
            takep1f (2);
            f2 BY bkthin1s
            harmo1s (1)
            takep1s (2);
            f3 BY bkthin2s
            harmo2s (1)
            takep2s (2);
```

95

Input Excerpts Two-Level
Multiple Indicator Growth (Continued)

```
            f4 BY bkthin3s
            harmo3s (1)
            takep3s (2);
            f5 BY bkthin4s
            harmo4s (1)
            takep4s (2);
            f6 BY bkthin5s
            harmo5s (1)
            takep5s (2);
            f7 BY bkthin6s
            harmo6s (1)
            takep6s (2);
```

96

Input Excerpts Two-Level Multiple Indicator Growth (Continued)

```
f8 BY bkthin7s
harmo7s (1)
takep7s (2);
iw sw qw | f1@0 f2@.5 f3@1.5 f4@2.5 f5@3.5 f6@4.5
f7@5.5 f8@6.5;
iw-qw ON male;
%BETWEEN%
f1b BY bkthin1f
harmo1f (3)
takep1f (4);
f2b BY bkthin1s
harmo1s (3)
takep1s (4);
```

97

Input Excerpts Two-Level Multiple Indicator Growth (Continued)

```
f3b BY bkthin2s
harmo2s (3)
takep2s (4);
f4b BY bkthin3s
harmo3s (3)
takep3s (4);
f5b BY bkthin4s
harmo4s (3)
takep4s (4);
f6b BY bkthin5s
harmo5s (3)
takep5s (4);
```

98

Input Excerpts Two-Level Multiple Indicator Growth (Continued)

```
            f7b BY bkthin6s
            harmo6s (3)
            takep6s (4);
            f8b BY bkthin7s
            harmo7s (3)
            takep7s (4);
            [bkthin1f$1-bkthin7s$1] (11);
            [harmo1f$1-harmo7s$1] (12);
            [takep1f$1-takep7s$1] (13);
            ib sb qb |f1b@0 f2b@.5 f3b@1.5 f4b@2.5 f5b@3.5 f6b@4.5
            f7b@5.5 f8b@6.5;
            bkthin1f-takep7s@0;
OUTPUT:     TECH1 TECH8 STANDARDIZED;
```

99

Output Excerpts Two-Level Multiple Indicator Growth

```
Tests of Model Fit


Chi-Square Test of Model Fit
    Value                                          767.730*
    Degrees of Freedom                                  584
    P-Value                                          0.0000


*   The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and
    WLSMV cannot be used for chi-square difference tests. MLM,
    MLR and WLSM chi-square difference testing is described in
    the Mplus Technical Appendices at www.statmodel.com. See chi-
    square difference testing in the index of the Mplus Users'
    Guide.
```

100

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

```
Chi-Square Test of Model Fit for the Baseline Model
    Value                                        28765.253
    Degrees of Freedom                                 576
    P-Value                                         0.0000
CFI/TLI
    CFI                                              0.993
    TLI                                              0.994
Number of Free Parameters                               40
RMSEA (Root Mean Square Error of Approximation)
    Estimate                                         0.016
SRMR (Standardized Root Mean Square Residual)
    Value for Within                                 0.065
    Value for Between                                0.232
```

101

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
iw |				
f1	1.000	0.000	999.000	999.000
f2	1.000	0.000	999.000	999.000
f3	1.000	0.000	999.000	999.000
f4	1.000	0.000	999.000	999.000
f5	1.000	0.000	999.000	999.000
f6	1.000	0.000	999.000	999.000
f7	1.000	0.000	999.000	999.000
f8	1.000	0.000	999.000	999.000

102

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
sw |				
f1	0.000	0.000	999.000	999.000
f2	0.500	0.000	999.000	999.000
f3	1.500	0.000	999.000	999.000
f4	2.500	0.000	999.000	999.000
f5	3.500	0.000	999.000	999.000
f6	4.500	0.000	999.000	999.000
f7	5.500	0.000	999.000	999.000
f8	6.500	0.000	999.000	999.000
qw |				
f1	0.000	0.000	999.000	999.000

103

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f2	0.250	0.000	999.000	999.000
f3	2.250	0.000	999.000	999.000
f4	6.250	0.000	999.000	999.000
f5	12.250	0.000	999.000	999.000
f6	20.250	0.000	999.000	999.000
f7	30.250	0.000	999.000	999.000
f8	42.250	0.000	999.000	999.000
f1 BY				
bkthin1f	1.000	0.000	999.000	999.000
harmo1f	1.143	0.088	12.932	0.000

104

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
harmo3s	1.143	0.088	12.932	0.000
takep3s	0.993	0.067	14.782	0.000
f5 BY				
bkthin4s	1.000	0.000	999.000	999.000
harmo4s	1.143	0.088	12.932	0.000
takep4s	0.993	0.067	14.782	0.000
f6 BY				
bkthin5s	1.000	0.000	999.000	999.000
harmo5s	1.143	0.088	12.932	0.000
takep5s	0.993	0.067	14.782	0.000

105

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f7 BY				
bkthin6s	1.000	0.000	999.000	999.000
harmo6s	1.143	0.088	12.932	0.000
takep6s	0.993	0.067	14.782	0.000
f8 BY				
bkthin7s	1.000	0.000	999.000	999.000
harmo7s	1.143	0.088	12.932	0.000
takep7s	0.993	0.067	14.782	0.000
iw ON				
male	1.449	0.175	8.258	0.000

106

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
sw ON				
male	-0.091	0.129	-0.705	0.481
qw ON				
male	0.011	0.021	0.553	0.580
sw WITH				
iw	-0.394	0.141	-2.793	0.005
qw WITH				
iw	0.017	0.020	0.835	0.404
sw	-0.031	0.016	-1.973	0.049
Residual Variances				
f1	1.093	0.259	4.221	0.000

107

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f2	0.739	0.236	3.131	0.002
f3	2.850	0.497	5.731	0.000
f4	1.985	0.561	3.541	0.000
f5	2.255	0.487	4.630	0.000
f6	2.581	0.317	8.150	0.000
f7	2.171	0.383	5.667	0.000
f8	2.332	0.557	4.188	0.000
iw	2.812	0.366	7.679	0.000
sw	0.277	0.110	2.510	0.012
qw	0.004	0.002	1.797	0.072

108

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Between Level				
ib |				
f1b	1.000	0.000	999.000	999.000
f2b	1.000	0.000	999.000	999.000
f3b	1.000	0.000	999.000	999.000
f4b	1.000	0.000	999.000	999.000
f5b	1.000	0.000	999.000	999.000
f6b	1.000	0.000	999.000	999.000
f7b	1.000	0.000	999.000	999.000
f8b	1.000	0.000	999.000	999.000

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
sb |				
f1b	0.000	0.000	999.000	999.000
f2b	0.500	0.000	999.000	999.000
f3b	1.500	0.000	999.000	999.000
f4b	2.500	0.000	999.000	999.000
f5b	3.500	0.000	999.000	999.000
f6b	4.500	0.000	999.000	999.000
f7b	5.500	0.000	999.000	999.000
f8b	6.500	0.000	999.000	999.000
qb |				
f1b	0.000	0.000	999.000	999.000

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f2b	0.250	0.000	999.000	999.000
f3b	2.250	0.000	999.000	999.000
f4b	6.250	0.000	999.000	999.000
f5b	12.250	0.000	999.000	999.000
f6b	20.250	0.000	999.000	999.000
f7b	30.250	0.000	999.000	999.000
f8b	42.250	0.000	999.000	999.000
f1b BY				
bkthin1f	1.000	0.000	999.000	999.000
harmo1f	1.099	0.145	7.603	0.000
takep1f	0.979	0.126	7.798	0.000

111

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f2b BY				
bkthin1s	1.000	0.000	999.000	999.000
harmo1s	1.099	0.145	7.603	0.000
takep1s	0.979	0.126	7.798	0.000
f3b BY				
bkthin2s	1.000	0.000	999.000	999.000
harmo2s	1.099	0.145	7.603	0.000
takep2s	0.979	0.126	7.798	0.000
f4b BY				
bkthin3s	1.000	0.000	999.000	999.000
harmo3s	1.099	0.145	7.603	0.000

112

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
takep3s	0.979	0.126	7.798	0.000
f5b BY				
bkthin4s	1.000	0.000	999.000	999.000
harmo4s	1.099	0.145	7.603	0.000
takep4s	0.979	0.126	7.798	0.000
f6b BY				
bkthin5s	1.000	0.000	999.000	999.000
harmo5s	1.099	0.145	7.603	0.000
takep5s	0.979	0.126	7.798	0.000
f7b BY				
bkthin6s	1.000	0.000	999.000	999.000

113

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
harmo6s	1.099	0.145	7.603	0.000
takep6s	0.979	0.126	7.798	0.000
f8b BY				
bkthin7s	1.000	0.000	999.000	999.000
harmo7s	1.099	0.145	7.603	0.000
takep7s	0.979	0.126	7.798	0.000
sb WITH				
ib	-0.563	0.200	-2.813	0.005
qb WITH				
ib	0.066	0.023	2.927	0.003
sb	-0.031	0.012	-2.530	0.011

114

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Means				
f1	0.000	0.000	999.000	999.000
f2	0.000	0.000	999.000	999.000
f3	0.000	0.000	999.000	999.000
f4	0.000	0.000	999.000	999.000
f5	0.000	0.000	999.000	999.000
f6	0.000	0.000	999.000	999.000
f7	0.000	0.000	999.000	999.000
f8	0.000	0.000	999.000	999.000
ib	0.000	0.000	999.000	999.000
sb	0.063	0.170	0.371	0.711

115

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
qb	-0.014	0.023	-0.615	0.538
Intercepts				
f1b	0.000	0.000	999.000	999.000
f2b	0.000	0.000	999.000	999.000
f3b	0.000	0.000	999.000	999.000
f4b	0.000	0.000	999.000	999.000
f5b	0.000	0.000	999.000	999.000
f6b	0.000	0.000	999.000	999.000
f7b	0.000	0.000	999.000	999.000
f8b	0.000	0.000	999.000	999.000

116

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Thresholds				
bkthin1f$1	2.364	0.357	6.625	0.000
bkthin1s$1	2.364	0.357	6.625	0.000
bkthin2s$1	2.364	0.357	6.625	0.000
bkthin3s$1	2.364	0.357	6.625	0.000
bkthin4s$1	2.364	0.357	6.625	0.000
bkthin5s$1	2.364	0.357	6.625	0.000
bkthin6s$1	2.364	0.357	6.625	0.000
bkthin7s$1	2.364	0.357	6.625	0.000
harmo1f$1	1.676	0.353	4.746	0.000
harmo1s$1	1.676	0.353	4.746	0.000

117

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
harmo2s$1	1.676	0.353	4.746	0.000
harmo3s$1	1.676	0.353	4.746	0.000
harmo4s$1	1.676	0.353	4.746	0.000
harmo5s$1	1.676	0.353	4.746	0.000
harmo6s$1	1.676	0.353	4.746	0.000
harmo7s$1	1.676	0.353	4.746	0.000
takep1f$1	1.612	0.288	5.595	0.000
takep1s$1	1.612	0.288	5.595	0.000
takep2s$1	1.612	0.288	5.595	0.000
takep3s$1	1.612	0.288	5.595	0.000
takep4s$1	1.612	0.288	5.595	0.000

118

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
takep5s$1	1.612	0.288	5.595	0.000
takep6s$1	1.612	0.288	5.595	0.000
takep7s$1	1.612	0.288	5.595	0.000
Variances				
ib	1.328	0.515	2.580	0.010
sb	0.258	0.097	2.669	0.008
qb	0.004	0.002	2.298	0.022
Residual Variances				
bkthin1f	0.000	0.000	999.000	999.000
bkthin1s	0.000	0.000	999.000	999.000
bkthin2s	0.000	0.000	999.000	999.000

119

Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
bkthin3s	0.000	0.000	999.000	999.000
bkthin4s	0.000	0.000	999.000	999.000
bkthin5s	0.000	0.000	999.000	999.000
bkthin6s	0.000	0.000	999.000	999.000
bkthin7s	0.000	0.000	999.000	999.000
harmo1f	0.000	0.000	999.000	999.000
harmo1s	0.000	0.000	999.000	999.000
harmo2s	0.000	0.000	999.000	999.000
harmo3s	0.000	0.000	999.000	999.000
harmo4s	0.000	0.000	999.000	999.000
harmo5s	0.000	0.000	999.000	999.000

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Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
harmo6s	0.000	0.000	999.000	999.000
harmo7s	0.000	0.000	999.000	999.000
takep1f	0.000	0.000	999.000	999.000
takep1s	0.000	0.000	999.000	999.000
takep2s	0.000	0.000	999.000	999.000
takep3s	0.000	0.000	999.000	999.000
takep4s	0.000	0.000	999.000	999.000
takep5s	0.000	0.000	999.000	999.000
takep6s	0.000	0.000	999.000	999.000
takep7s	0.000	0.000	999.000	999.000
f1b	2.258	0.786	2.871	0.004

121

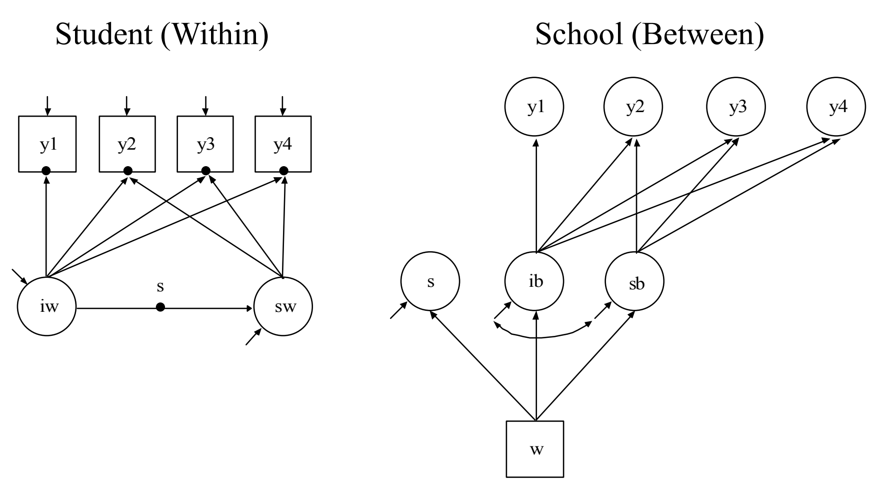
Output Excerpts Two-Level Multiple Indicator Growth (Continued)

Parameter	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
f2b	2.206	0.821	2.685	0.007
f3b	3.002	1.062	2.827	0.005
f4b	0.377	0.237	1.594	0.111
f5b	0.051	0.117	0.440	0.660
f6b	0.251	0.214	1.176	0.239
f7b	0.543	0.303	1.790	0.073
f8b	-0.468	0.298	-1.567	0.117

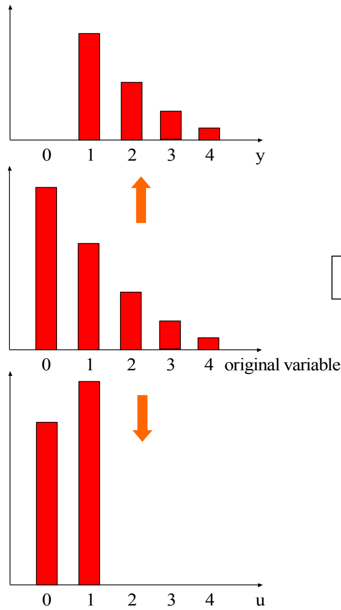
122

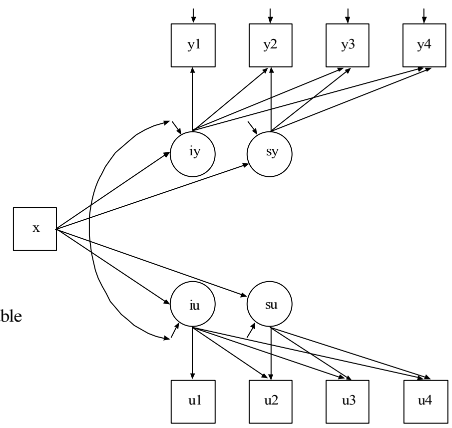
Special Multilevel Growth Models

Multilevel Modeling With A Random Slope For Latent Variables



Two-Part (Semicontinuous) Growth Modeling

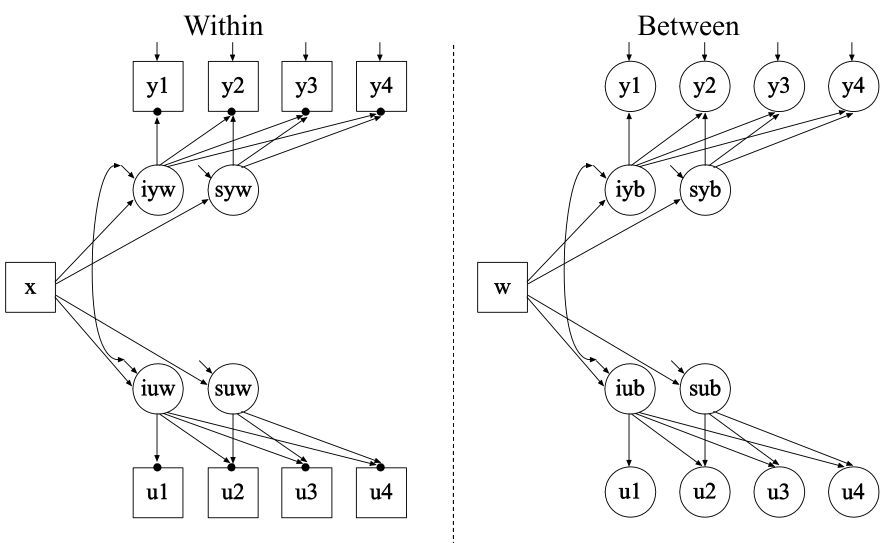




Olsen & Schafer (2001)

125

Two-Level, Two-Part Growth Modeling

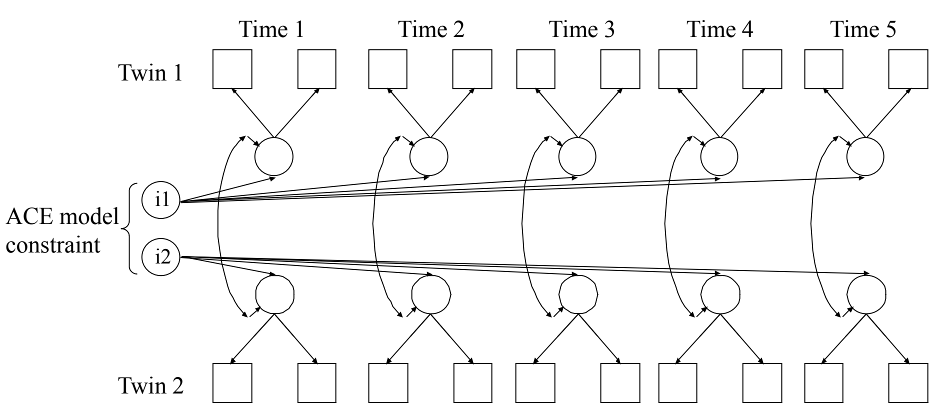


126

Multiple Indicator Growth Modeling As Two-Level Analysis

127

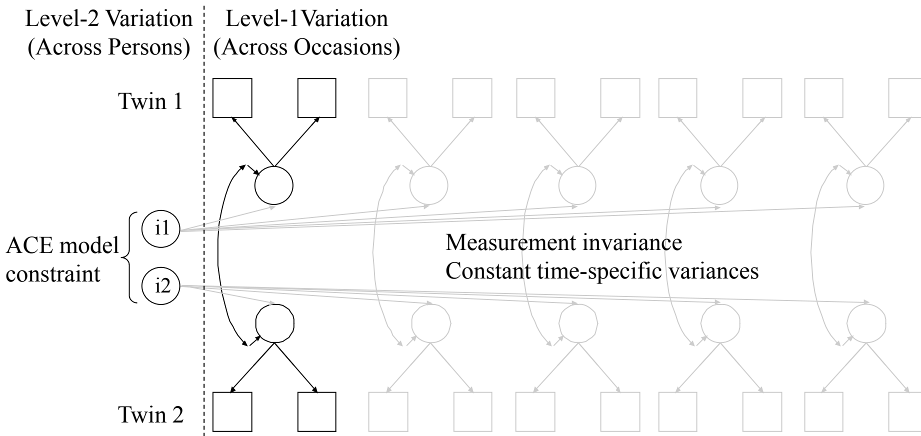
Wide Data Format, Single-Level Approach



20 variables, 12 factors, 10 dimensions of integration for ML with categorical items
ML very hard, WLS easy

128

Long Format, Two-Level Approach



4 variables, 2 Level-2 and 2 Level-1 factors, 4 dimensions of integration for ML with categorical items

ML feasible, WLS available in Version 5

129

Multilevel Discrete-Time Survival Analysis

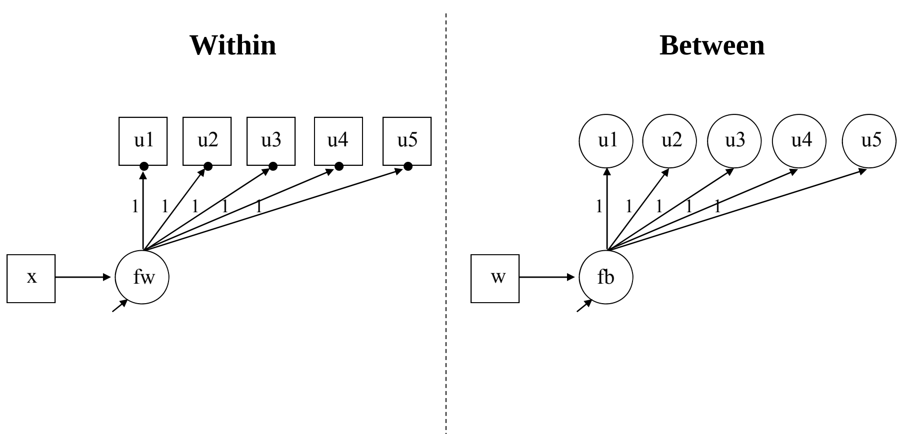
130

Multilevel Discrete-Time Survival Analysis

- Muthén and Masyn (2005) in Journal of Educational and Behavioral Statistics
- Masyn dissertation
- Continuous-time survival:
  - Asparouhov, Masyn and Muthén (2006)
  - Muthén, B., Asparouhov, T., Boye, M., Hackshaw, M. & Naegeli, A. (2009). Applications of continuous-time survival in latent variable models for the analysis of oncology randomized clinical trial data using Mplus. Technical Report.

131

Multilevel Discrete-Time Survival Frailty Modeling



Vermunt (2003)

132

Two-Level Latent Transition Analysis

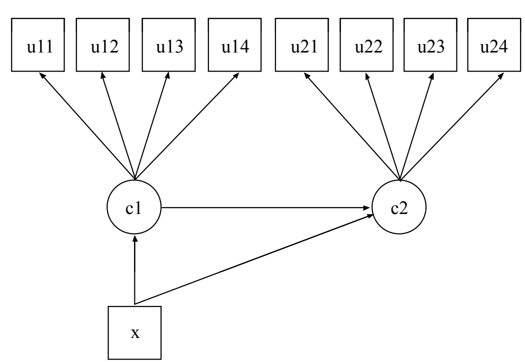
133

Latent Transition Analysis

Transition Probabilities

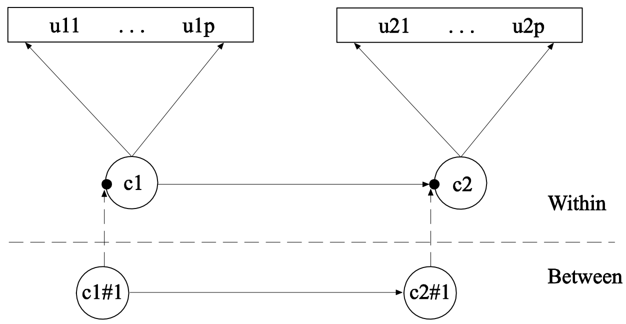
c1 \ c2	1	2
1	0.8	0.2
2	0.4	0.6

Time Point 1 Time Point 2



134

Two-Level Latent Transition Analysis



Asparouhov, T. & Muthen, B. (2008). Multilevel mixture models. In Hancock, G. R., & Samuelsen, K. M. (Eds.). Advances in latent variable mixture models, pp 27 - 51. Charlotte, NC: Information Age Publishing, Inc.

135

Input For Two-Level LTA

```
        CLUSTER = classrm;
        USEVAR = stub1f bkrule1f bkthin1f-tease1f athort1f
                 stub1s bkrule1s bkthin1s-tease1s athort1s;
        CATEGORICAL =  stub1f-athort1s;
        MISSING = all (999);
        CLASSES = cf(2) cs(2);
DEFINE:
        CUT stub1f-athort1s(1.5);
ANALYSIS:
        TYPE = TWOLEVEL MIXTURE;
        PROCESS = 2;
MODEL:
        %WITHIN%
        %OVERALL%
        cs#1 ON cf#1;
        %BETWEEN%
        OVERALL%
        cs#1 ON cf#1;
        cs#1*1 cf#1*1;
```

136

Input For Two-Level LTA (Continued)

```
MODEL cf:
   %BETWEEN%
        %cf#1%
        [stub1f$1-athort1f$1] (1-9);
        %cf#2%
        [stub1f$1-athort1f$1] (11-19);
MODEL cs:
   %BETWEEN%
        %cs#1%
        [stub1s$1-athort1s$1] (1-9);
        %cs#2%
        [stub1s$1-athort1s$1] (11-19);
OUTPUT:
        TECH1 TECH8;
PLOT:
        TYPE = PLOT3;
        SERIES = stub1f-athort1f(*);
```

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Output Excerpts Two-Level LTA

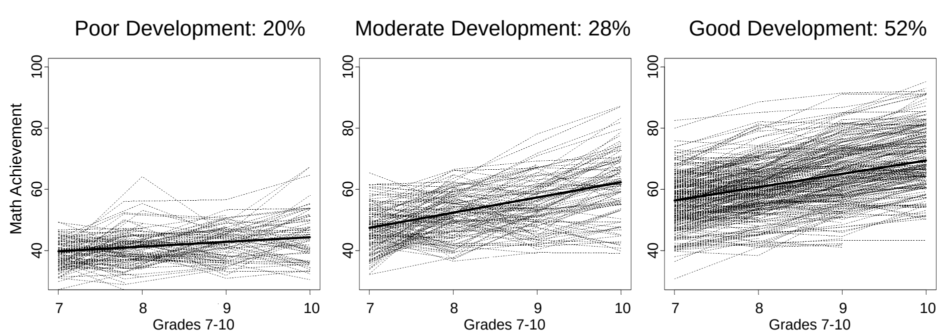
Categorical Latent Variables

Within Level	Estimates	S.E.	Est./S.E.
CS#1 ON			
CF#1	3.938	0.407	9.669
Means			
CF#1	-0.126	0.189	-0.664
CS#1	-1.514	0.221	-6.838
Between Level			
CS#1 ON			
CF#1	0.411	0.15	2.735
Variances			
CF#1	2.062	0.672	3.067
Residual Variances			
CS#1	0.469	0.237	1.984

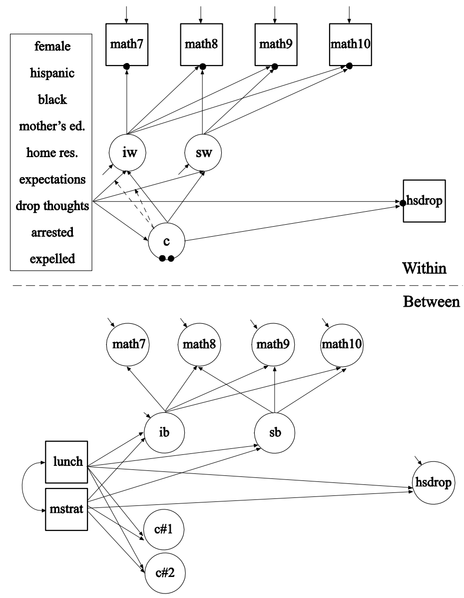
138

Multilevel Growth Mixture Modeling

Growth Mixture Modeling:
LSAY Math Achievement Trajectory Classes
And The Prediction Of High School Dropout



Dropout:	69%	8%	1%



141

Input For A Multilevel Growth Mixture Model For LSAY Math Achievement

```
TITLE:      multilevel growth mixture model for LSAY math
            achievement

DATA:       FILE = lsayfull_Dropout.dat;

VARIABLE:   NAMES = female mothed homeres math7 math8 math9 math10
            expel arrest hisp black hsdrop expect lunch mstrat
            droptht7 schcode;
            !lunch = % of students eligible for full lunch
            !assistance (9th)
            !mstrat = ratio of students to full time math
            !teachers (9th)
            MISSING = ALL (9999);
            CATEGORICAL = hsdrop;
            CLASSES = c (3);
            CLUSTER = schcode;
            WITHIN = female mothed homeres expect droptht7 expel
            arrest hisp black;
            BETWEEN = lunch mstrat;
```

142

Input For A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

```
DEFINE:     lunch = lunch/100;
            mstrat = mstrat/1000;

ANALYSIS:   TYPE = MIXTURE TWOLEVEL;
            ALGORITHM = INTEGRATION;

OUTPUT:     SAMPSTAT STANDARDIZED TECH1 TECH8;

PLOT:       TYPE = PLOT3;
            SERIES = math7-math10 (s);
```

143

Input For A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

```
MODEL:      %WITHIN%
            %OVERALL%
            iw sw | math7@0 math8@1 math9@2 math10@3;
            iw sw c hsdrop ON female hisp black mothed homeres
            expect droptht7 expel arrest;

            %c#1%
            math7-math10*20;
            iw*13 sw*3;

            %c#2%
            math7-math10*30;
            iw*8 sw*3;
            iw sw ON female hisp black mothed homeres expect
            droptht7 expel arrest;
```

144

Input For A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

```
%c#3%
math7-math10*10;
iw*34 sw*2;
iw sw ON female hisp black mothed homeres expect
droptht7 expel arrest;

%BETWEEN%
%OVERALL%
ib sb | math7@0 math8@1 math9@2 math10@3;
sb@0;
ib*1; hsdrop*1; ib WITH hsdrop;
math7-math10@0;
ib sb c hsdrop ON lunch mstrat;
```

145

Input For A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

```
%c#1%
[ib*40 sb*1];
[hsdrop$1*-.3];

%c#2%
[ib*40 sb*5];
[hsdrop$1*.9];

%c#3%
[ib*45 sb*3];
[hsdrop$1*1.2];
```

146

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement

Summary of Data

```
          Number of patterns          13
          Number of y patterns        13
          Number of u patterns         1
          Number of clusters          44

      Size (s)     Cluster ID with Size s

         12            304
         13            305
         38            112
         39            109
         40            138
         42            120
         43            307
         44            303
         45            143       146
```

147

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

```
         46            101
         48            144       106
         51            102       308
         52            136       118     133     111
         53            140       142     108     131     122     124
         54            301       117     127     137     126
         55            103       141     123
         56            110
         57            147
         58            121       105     145     135
         59            119
         73            104
         89            302
         94            309
        118            115
```

148

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

```
THE STANDARD ERRORS OF THE MODEL PARAMETER ESTIMATES MAY NOT BE
TRUSTWORTHY FOR SOME PARAMETERS DUE TO A NON-POSITIVE DEFINITE
FIRST-ORDER DERIVATIVE PRODUCT MATRIX. THIS MAY BE DUE TO THE
STARTING VALUES BUT MAY ALSO BE AN INDICATION OF MODEL
NONIDENTIFICATION. THE CONDITION NUMBER IS -0.333D-16. PROBLEM
INVOLVING PARAMETER 54.

THE NONIDENTIFICATION IS MOST LIKELY DUE TO HAVING MORE
PARAMETERS THAN THE NUMBER OF CLUSTERS. REDUCE THE NUMBER OF
PARAMETERS.

THE MODEL ESTIMATION TERMINATED NORMALLY
```


Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Tests Of Model Fit

```
Loglikelihood
             H0 Value                          -26245.590
             H0 Scaling Correction                  1.210
             Factor for MLR
Information Criteria
             Number of Free Parameters                124
             Akaike (AIC)                       52739.179
             Bayesian (BIC)                     53453.372
             Sample-Size Adjusted BIC           53059.399
                (n* = (n + 2) / 24)
FINAL  CLASS COUNTS AND PROPORTIONS OF TOTAL SAMPLE SIZE BASED
ON ESTIMATED POSTERIOR PROBABILITIES
 Latent Classes
    1          664.86988          0.28365
    2          452.46710          0.19303
    3         1226.66302          0.52332
 CLASSIFICATION QUALITY
 Entropy                            0.625
```

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Parameter	Estimates	S.E.	Est./S.E.	Two-Tailed P-Value
Between Level				
Latent Class 1				
ib |				
math7	1.000	0.000	999.000	999.000
math8	1.000	0.000	999.000	999.000
math9	1.000	0.000	999.000	999.000
math10	1.000	0.000	999.000	999.000
sb |				
math7	0.000	0.000	999.000	999.000
math8	1.000	0.000	999.000	999.000
math9	2.000	0.000	999.000	999.000
math10	3.000	0.000	999.000	999.000
ib ON				
lunch	-2.154	1.298	-1.659	0.097
mstrat	-14.197	2.928	-4.849	0.000

151

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Parameter	Estimates	S.E.	Est./S.E.	Two-Tailed P-Value
sb ON				
lunch	-0.610	0.624	-0.978	0.328
mstrat	0.716	1.065	0.673	0.501
hsdrop ON				
lunch	1.226	0.543	2.256	0.024
mstrat	-0.269	1.455	-0.185	0.854
ib WITH				
hsdrop	-0. 413	0.329	-1.256	0.209
Intercepts				
math7	0.000	0.000	999.000	999.000
math8	0.000	0.000	999.000	999.000
math9	0.000	0.000	999.000	999.000
math10	0.000	0.000	999.000	999.000
ib	40.636	1.672	24.310	0.000
sb	0.951	0.906	1.050	0.294

152

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Parameter	Estimates	S.E.	Est./S.E.	Two-Tailed P-Value
Thresholds				
hsdrop$1	-0.350	0.490	-0.716	0.474
Residual Variances				
hsdrop	0.548	0.217	2.521	0.012
math7	0.000	0.000	999.000	999.000
math8	0.000	0.000	999.000	999.000
math9	0.000	0.000	999.000	999.000
math10	0.000	0.000	999.000	999.000
ib	3.469	1.012	3.429	0.001
sb	0.000	0.000	999.000	999.000

153

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Parameter	Estimates	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
Categorical Latent Variables				
c#1 ON				
female	-0.801	0.261	-3.067	0.002
hisp	-0.066	0.616	-0.107	0.914
black	0.927	0.386	2.400	0.016
mothed	-0.015	0.107	-0.144	0.886
homeres	-0.058	0.080	-0.720	0.472
expect	-0.251	0.073	-3.425	0.001
droptht7	1.715	0.413	4.151	0.000
expel	0.606	0.389	1.559	0.119
arrest	1.076	0.378	2.845	0.004

154

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Parameter	Estimates	S.E.	Est./S.E.	Two-Tailed P-Value
c#2 ON				
female	-1.507	0.639	-2.359	0.018
hisp	1.093	0.549	1.990	0.047
black	-1.078	0.715	-1.509	0.131
mothed	-0.229	0.138	-1.660	0.097
homeres	0.121	0.102	1.188	0.235
expect	-0.801	0.261	-3.067	0.002
droptht7	-0.066	0.616	-0.107	0.914
expel	0.927	0.386	2.400	0.016
arrest	-0.015	0.107	-0.144	0.886
Intercepts				
c#1	0.526	0.552	0.953	0.341
c#2	-0.518	0.659	-0.786	0.432

155

Output Excerpts A Multilevel Growth Mixture Model For LSAY Math Achievement (Continued)

Parameter	Estimates	S.E.	Est./S.E.	Two-Tailed P-Value
Between Level				
c#1 ON				
lunch	1.946	0.851	2.285	0.022
mstrat	-2.408	2.634	-0.914	0.361
c#2 ON				
lunch	0.248	1.450	0.171	0.864
mstrat	-0.810	2.382	-0.340	0.734

156

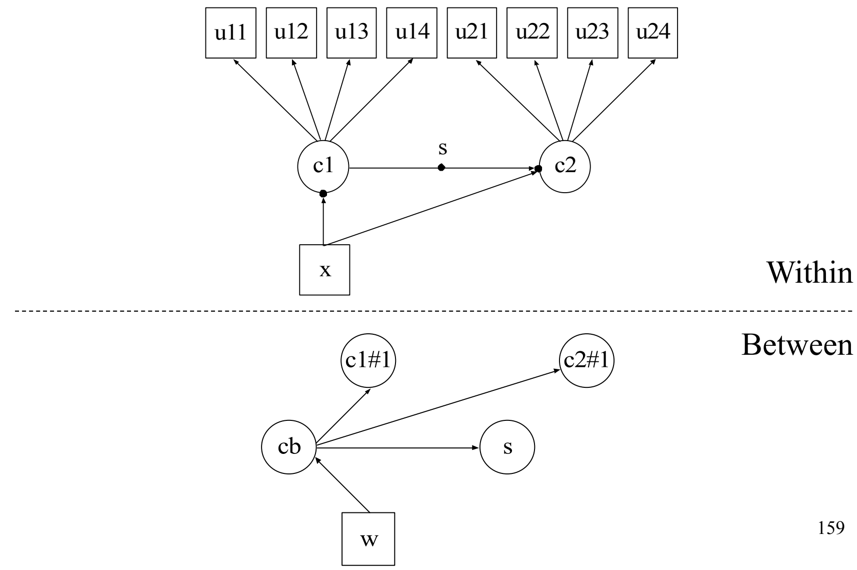
Between-Level Latent Classes

157

Latent Transition Analysis

158

UG Ex. 10.3 : Two-Level LTA With A Covariate And A Between-Level Categorical Latent Variable



159

Input For Two-Level LTA

```
TITLE:     this is an example of a two-level LTA with a covariate
           and a between-level categorical latent variable
DATA:      FILE = ex8.dat;
VARIABLE:  NAMES ARE u11-u14 u21-u24 x w dumb dum1 dum2 clus;
           USEVARIABLES = u11-w;
           CATEGORICAL = u11-u14 u21-u24;
           CLASSES = cb(2) c1(2) c2(2);
           WITHIN = x;
           BETWEEN = cb w;
           CLUSTER = clus;
ANALYSIS:  TYPE = TWOLEVEL MIXTURE;
           PROCESSORS = 2;
MODEL:
           %WITHIN%
           %OVERALL%
           c2#1 ON c1#1 x;
           c1#1 ON x;
           %BETWEEN%
           %OVERALL%
           c1#1 ON cb#1;
```

160

Input For Two-Level LTA (Continued)

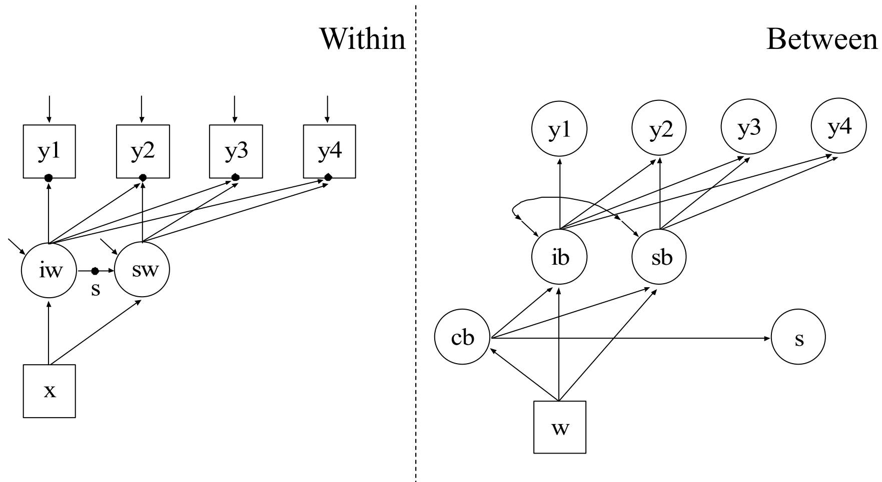
```
                c2#1 ON cb#1;
                cb#1 ON w;
MODEL cb:
                %WITHIN%
                %cb#1%
                c2#1 ON c1#1;
MODEL c1:
                %BETWEEN%
                %c1#1%
                [u11$1-u14$1] (1-4);
                %c1#2%
                [u11$1-u14$1] (5-8);
MODEL c2:
                %BETWEEN%
                %c2#1%
                [u21$1-u24$1] (1-4);
                %c2#2%
                [u21$1-u24$1] (5-8);
OUTPUT:         TECH1 TECH8;
```

161

Growth Modeling

162

UG Ex. 10.8: Two-Level Growth Model For A Continuous Outcome (Three-Level Analysis) With A Between-Level Categorical Latent Variable



163

Input For Two-Level Growth Model

```
TITLE:      this is an example of a two-level growth model for a
            continuous outcome (three-level analysis) with a
            between-level  categorical latent variable
DATA:       FILE = ex5.dat;
VARIABLE:   NAMES ARE y1-y4 x w dummy clus;
            USEVARIABLES = y1-w;
            CLASSES = cb(2);
            WITHIN = x;
            BETWEEN = cb w;
            CLUSTER = clus;
ANALYSIS:   TYPE = TWOLEVEL MIXTURE RANDOM;
            PROCESSORS = 2;
MODEL:
            %WITHIN%
            %OVERALL%
            iw sw | y1@0 y2@1 y3@2 y4@3;
            y1-y4 (1);
            iw sw ON x;
            s | sw ON iw;
```

164

Input For Two-Level Growth Model (Continued)

```
            %BETWEEN%
            %OVERALL%
            ib sb | y1@0 y2@1 y3@2 y4@3;
            y1-y4@0;
            ib sb ON w;
            cb#1 ON w;
            s@0;
            %cb#1%
            [ib sb s];
            %cb#2%
            [ib sb s];
OUTPUT:     TECH1 TECH8;
```

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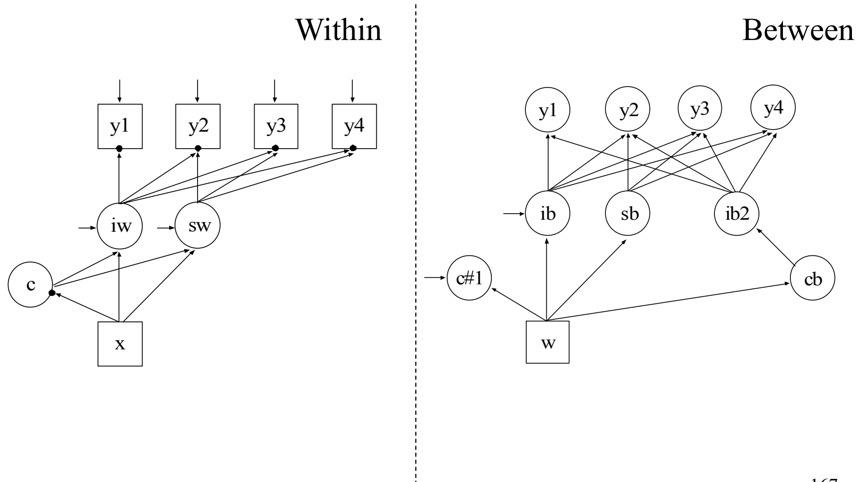
Growth Mixture Modeling

166

UG Ex.10.10: Two-Level GMM (Three-Level Analysis) For A Continuous Outcome With A Between-Level Categorical Latent Variable



Input For Two-Level GMM (Three-Level Analysis)

```
TITLE:      this is an example of a two-level GMM (three-level
            analysis) for a continuous outcome with a between-
            level categorical latent variable
DATA:       FILE = ex6.dat;
VARIABLE:   NAMES ARE y1-y4 x w dummyb dummy clus;
            USEVARIABLES = y1-w;
            CLASSES = cb(2) c(2);
            WITHIN = x;
            BETWEEN = cb w;
            CLUSTER = clus;
ANALYSIS:   TYPE = TWOLEVEL MIXTURE;
            PROCESSORS = 2;
MODEL:
            %WITHIN%
            %OVERALL%
            iw sw | y1@0 y2@1 y3@2 y4@3;
            iw sw ON x;
            c#1 ON x;
            %BETWEEN%
            %OVERALL%
```

Input For Two-Level GMM (Continued)

```
   ib sb | y1@0 y2@1 y3@2 y4@3;
   ib2 | y1-y4@1;
   y1-y4@0;
   ib sb ON w;
   c#1 ON w;
   sb@0; c#1;
   ib2@0;
   cb#1 ON w;
MODEL c:
   %BETWEEN%
   %c#1%
   [ib sb];
   %c#2%
   [ib sb];
MODEL cb:
   %BETWEEN%
   %cb#1%
   [ib2@0];
   %cb#2%
   [ib2];
OUTPUT: TECH1 TECH8;
```

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Multilevel Growth Mixture Modeling Example

Baltimore randomized field trial (Muthén, B. & Asparouhov, 2008, pp. 155-157):

- 362 boys in Baltimore public schools observed four times in grades 1-3 in 27 classrooms
- Outcome is aggressive-disruptive behavior
- Classroom-based good behavior intervention in Fall of 1st grade
- Student-level trajectory classes and classroom-level classes

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Multilevel Growth Mixture Modeling Example (Continued)

Findings:

- 3 student-level trajectory classes, 2 classroom-level classes
- In classrooms with a low level of aggressive behavior, students who are in the two highest trajectory classes benefit from the intervention
- In classrooms with a high level of aggression, only students who are in the lowest trajectory class benefit from the intervention

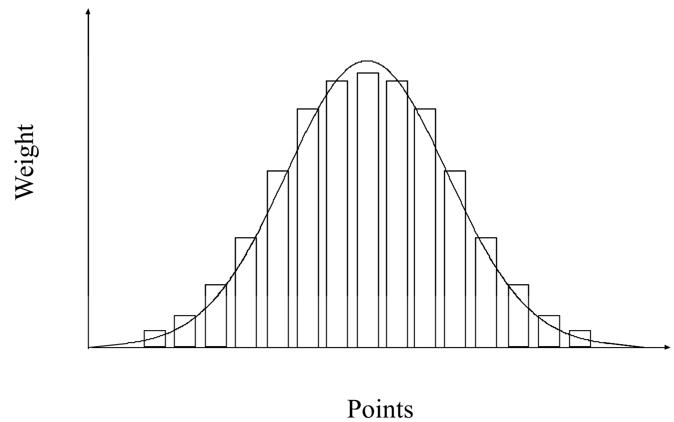
Source: Muthén, B. & Asparouhov, T. (2009). Growth mixture modeling: Analysis with non-Gaussian random effects. In Fitzmaurice, G., Davidian, M., Verbeke, G. & Molenberghs, G. (eds.), Longitudinal Data Analysis, pp. 143-165. Boca Raton: Chapman & Hall/CRC Press.

171

Technical Aspects Of Multilevel Modeling

172

Numerical Integration With A Normal Latent Variable Distribution



Fixed weights and points

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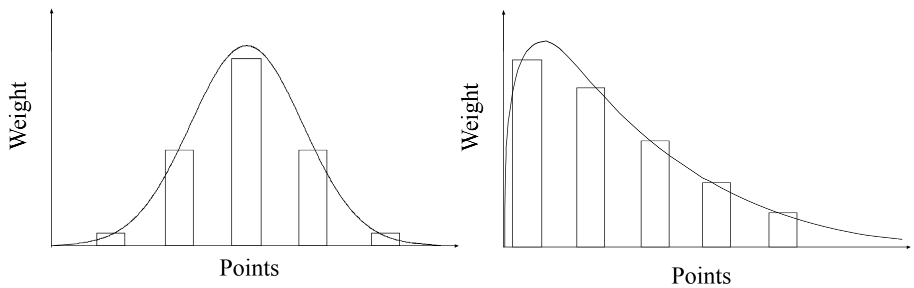
Non-Parametric Estimation Of The Random Effect Distribution



Estimated weights and points
(class probabilities and class means)

174

Numerical Integration

Numerical integration is needed with maximum likelihood estimation when the posterior distribution for the latent variables does not have a closed form expression. This occurs for models with categorical outcomes that are influenced by continuous latent variables, for models with interactions involving continuous latent variables, and for certain models with random slopes such as multilevel mixture models.

When the posterior distribution does not have a closed form, it is necessary to integrate over the density of the latent variables multiplied by the conditional distribution of the outcomes given the latent variables. Numerical integration approximates this integration by using a weighted sum over a set of integration points (quadrature nodes) representing values of the latent variable.

Numerical Integration (Continued)

Numerical integration is computationally heavy and thereby time-consuming because the integration must be done at each iteration, both when computing the function value and when computing the derivative values. The computational burden increases as a function of the number of integration points, increases linearly as a function of the number of observations, and increases exponentially as a function of the dimension of integration, that is, the number of latent variables for which numerical integration is needed.

Practical Aspects Of Numerical Integration

- Types of numerical integration available in Mplus with or without adaptive quadrature
  - Standard (rectangular, trapezoid) – default with 15 integration points per dimension
  - Gauss-Hermite
  - Monte Carlo
- Computational burden for latent variables that need numerical integration
  - One or two latent variables Light
  - Three to five latent variables Heavy
  - Over five latent variables Very heavy

Practical Aspects Of Numerical Integration (Continued)

- Suggestions for using numerical integration
  - Start with a model with a small number of random effects and add more one at a time
  - Start with an analysis with TECH8 and MITERATIONS=1 to obtain information from the screen printing on the dimensions of integration and the time required for one iteration and with TECH1 to check model specifications
  - With more than 3 dimensions, reduce the number of integration points to 5 or 10 or use Monte Carlo integration with the default of 500 integration points
  - If the TECH8 output shows large negative values in the column labeled ABS CHANGE, increase the number of integration points to improve the precision of the numerical integration and resolve convergence problems
  - Explore using a random subsample

Technical Aspects Of Numerical Integration

Maximum likelihood estimation using the EM algorithm computes in each iteration the posterior distribution for normally distributed latent variables *f*,

$$[f \mid y] = [f]\,[y \mid f] \,/\, [y], \qquad (97)$$

where the marginal density for [*y*] is expressed by integration

$$[y] = \int [f]\,[y \mid f]\, df. \qquad (98)$$

- Numerical integration is not needed for normally distributed *y* - the posterior distribution is normal

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Technical Aspects Of Numerical Integration (Continued)

- Numerical integration needed for:
  - Categorical outcomes *u* influenced by continuous latent variables *f*, because [*u*] has no closed form
  - Latent variable interactions f x x, f x y, f_1 x f_2, where [*y*] has no closed form, for example

$$[y] = \int [f_1, f_2]\,[y \mid f_1, f_2, f_1 f_2]\, df_1\, df_2 \qquad (99)$$

  - Random slopes, e.g. with two-level mixture modeling

Numerical integration approximates the integral by a sum

$$[y] = \int [f]\,[y \mid f]\, df = \sum_{k=1}^{K} w_k\,[y \mid f_k] \qquad (100)$$

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