

Mplus Short Courses
Day 5A

**Multilevel Modeling With Latent
Variables Using Mplus**

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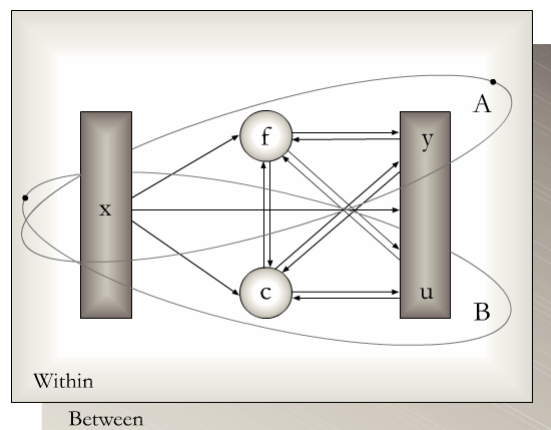
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Mplus Background

- 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
- Mplus versions
 - V1: November 1998
 - V2: February 2001
 - V3: March 2004
 - V4: February 2006
- Mplus team: Linda & Bengt Muthén, Thuy Nguyen, Tihomir Asparouhov, Michelle Conn

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General Latent Variable Modeling Framework



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Mplus

Several programs in one

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

Fully integrated in the general latent variable framework

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Overview

Single-Level Analysis

	Cross-Sectional	Longitudinal
Continuous Observed And Latent Variables	Day 1 Regression Analysis Path Analysis Exploratory Factor Analysis Confirmatory Factor Analysis Structural Equation Modeling	Day 2 Growth Analysis
Adding Categorical Observed And Latent Variables	Day 3 Regression Analysis Path Analysis Exploratory Factor Analysis Confirmatory Factor Analysis Structural Equation Modeling Latent Class Analysis Factor Mixture Analysis Structural Equation Mixture Modeling	Day 4 Latent Transition Analysis Latent Class Growth Analysis Growth Analysis Growth Mixture Modeling Discrete-Time Survival Mixture Analysis Missing Data Analysis

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Overview (Continued)

Multilevel Analysis

	Cross-Sectional	Longitudinal
Continuous Observed And Latent Variables	Day 5 Regression Analysis Path Analysis Exploratory Factor Analysis Confirmatory Factor Analysis Structural Equation Modeling	Day 5 Growth Analysis
Adding Categorical Observed And Latent Variables	Day 5 Latent Class Analysis Factor Mixture Analysis	Day 5 Growth Mixture Modeling

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Analysis With Multilevel Data

Used when data have been obtained by cluster sampling and/or unequal probability sampling to avoid biases in parameter estimates, standard errors, and tests of model fit and to learn about both within- and between-cluster relationships.

Analysis Considerations

- Sampling perspective
 - Aggregated modeling – SUDAAN
 - TYPE = COMPLEX
 - Clustering, sampling weights, stratification (Asparouhov, 2005)

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Analysis With Multilevel Data (Continued)

- Multilevel perspective
 - Disaggregated modeling – multilevel modeling
 - TYPE = TWOLEVEL
 - Clustering, sampling weights, stratification
 - Multivariate modeling
 - TYPE = GENERAL
 - Clustering, sampling weights, stratification
- Combined sampling and multilevel perspective
 - TYPE = COMPLEX TWOLEVEL
 - Clustering, sampling weights, stratification

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Analysis With Multilevel Data (Continued)

Analysis Areas

- Multilevel regression analysis
- Multilevel path analysis
- Multilevel factor analysis
- Multilevel SEM
- Multilevel growth modeling
- Multilevel latent class analysis
- Multilevel latent transition analysis
- Multilevel growth mixture modeling

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Complex Survey Data Analysis

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Intraclass Correlation

Consider nested, random-effects ANOVA for unit i in cluster j ,

$$y_{ij} = \nu + \eta_j + \varepsilon_{ij}; i = 1, 2, \dots, n_j; j = 1, 2, \dots, J. \quad (44)$$

Random sample of J clusters (e.g. schools).

With timepoint as i and individual as j , this is a repeated measures model with random intercepts.

Consider the covariance and variances for cluster members $i = k$ and $i = l$,

$$\text{Cov}(y_{kj}, y_{lj}) = V(\eta), \quad (45)$$

$$V(y_{kj}) = V(y_{lj}) = V(\eta) + V(\varepsilon), \quad (46)$$

resulting in the intraclass correlation

$$\rho(y_{kj}, y_{lj}) = V(\eta) / [V(\eta) + V(\varepsilon)]. \quad (47)$$

Interpretation: Between-cluster variability relative to total variation, intra-cluster homogeneity.

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NLSY Household Clusters

Household Type (# of respondents)	# of Households*	Intraclass Correlations for Siblings	
		Year	Heavy Drinking
Single	5,944	1982	0.19
Two	1,985	1983	0.18
Three	634	1984	0.12
Four	170	1985	0.09
Five	32	1988	0.04
Six	5	1989	0.06

Total number of households: 8,770
 Total number of respondents: 12,686
 Average number of respondents per household: 1.4

*Source: NLS User's Guide, 1994, p.247

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Design Effects

Consider cluster sampling with equal cluster sizes and the sampling variance of the mean.

V_C : correct variance under cluster sampling

V_{SRS} : variance assuming simple random sampling

$V_C \geq V_{SRS}$ but cluster sampling more convenient, less expensive.

$$DEFF = V_C / V_{SRS} = 1 + (s - 1) \rho, \quad (47)$$

where s is the common cluster size and ρ is the intraclass correlation (common range: 0.00 – 0.50).

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Random Effects ANOVA Example

200 clusters of size 10 with intraclass correlation 0.2 analyzed as:

- TYPE = TWOLEVEL
- TYPE = COMPLEX
- Regular analysis, ignoring clustering

$$DEFF = 1 + 9 * 0.2 = 2.8$$

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Input For Two-Level Random Effects ANOVA Analysis

```
TITLE:      Random effects ANOVA data
            Two-level analysis with balanced data

DATA:      FILE = anova.dat;

VARIABLE:  NAMES = y cluster;
            USEV = y;
            CLUSTER = cluster;

ANALYSIS:  TYPE = TWOLEVEL;

MODEL:
            %WITHIN%
            y;
            %BETWEEN%
            y;
```

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Output Excerpts Two-Level Random Effects ANOVA Analysis

Model Results

	Estimates	S.E.	Est./S.E.
Within Level			
Variances			
Y	0.779	0.025	31.293
Between Level			
Means			
Y	0.003	0.038	0.076
Variances			
Y	0.212	0.028	7.496

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Input For Complex Random Effects ANOVA Analysis

```
TITLE:      Random effects ANOVA data
           Complex analysis with balanced data

DATA:      FILE = anova.dat;

VARIABLE:  NAMES = y cluster;
           USEV = y;
           CLUSTER = cluster;

ANALYSIS:  TYPE = COMPLEX;
```

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Output Excerpts Complex Random Effects ANOVA Analysis

Model Results

	Estimates	S.E.	Est./S.E.
Means			
Y	0.003	0.038	0.076
Variances			
Y	0.990	0.036	27.538

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Input For Random Effects ANOVA Analysis Ignoring Clustering

```
TITLE:      Random effects ANOVA data
            Ignoring clustering

DATA:      FILE = anova.dat;

VARIABLE:  NAMES = y cluster;
            USEV = y;
            CLUSTER = cluster;

!

ANALYSIS:  TYPE = MEANSTRUCTURE;
```

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Output Excerpts Random Effects ANOVA Analysis Ignoring Clustering

Model Results

	Estimates	S.E.	Est./S.E.
Means			
Y	0.003	0.022	0.131
Variiances			
Y	0.990	0.031	31.623

Note: The estimated mean has SE = 0.022 instead of the correct 0.038

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Further Readings On Complex Survey Data

- Asparouhov, T. (2005). Sampling weights in latent variable modeling. Structural Equation Modeling, 12, 411-434.
- Chambers, R.L. & Skinner, C.J. (2003). Analysis of survey data. Chichester: John Wiley & Sons.
- Kaplan, D. & Ferguson, A.J (1999). On the utilization of sample weights in latent variable models. Structural Equation Modeling, 6, 305-321.
- Korn, E.L. & Graubard, B.I (1999). Analysis of health surveys. New York: John Wiley & Sons.
- Patterson, B.H., Dayton, C.M. & Graubard, B.I. (2002). Latent class analysis of complex sample survey data: application to dietary data. Journal of the American Statistical Association, 97, 721-741.
- Skinner, C.J., Holt, D. & Smith, T.M.F. (1989). Analysis of complex surveys. West Sussex, England: Wiley.
- Stapleton, L. (2002). The incorporation of sample weights into multilevel structural equation models. Structural Equation Modeling, 9, 475-502.

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Two-Level Regression Analysis

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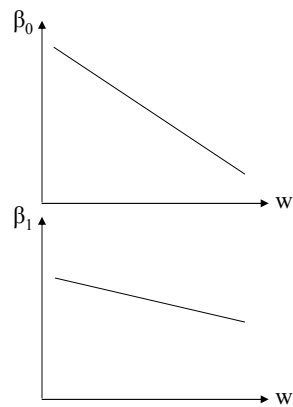
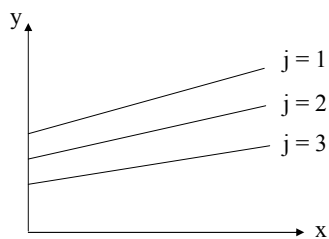
Cluster-Specific Regressions

Individual i in cluster j

$$(1) y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + r_{ij}$$

$$(2a) \beta_{0j} = \gamma_{00} + \gamma_{01} w_j + u_{0j}$$

$$(2b) \beta_{1j} = \gamma_{10} + \gamma_{11} w_j + u_{1j}$$



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Two-Level Regression Analysis With Random Intercepts And Random Slopes In Multilevel Terms

Two-level analysis (individual i in cluster j):

y_{ij} : individual-level outcome variable

x_{ij} : individual-level covariate

w_j : cluster-level covariate

Random intercepts, random slopes:

$$\text{Level 1 (Within)} : y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + r_{ij}, \quad (1)$$

$$\text{Level 2 (Between)} : \beta_{0j} = \gamma_{00} + \gamma_{01} w_j + u_{0j}, \quad (2a)$$

$$\text{Level 2 (Between)} : \beta_{1j} = \gamma_{10} + \gamma_{11} w_j + u_{1j}. \quad (2b)$$

- Mplus gives the same estimates as HLM/MLwiN ML (not REML):
 - $V(r)$ (residual variance for level 1)
 - $\gamma_{00}, \gamma_{01}, \gamma_{10}, \gamma_{11}, V(u_0), V(u_1), Cov(u_0, u_1)$
- Centering of x : subtracting grand mean or group (cluster) mean

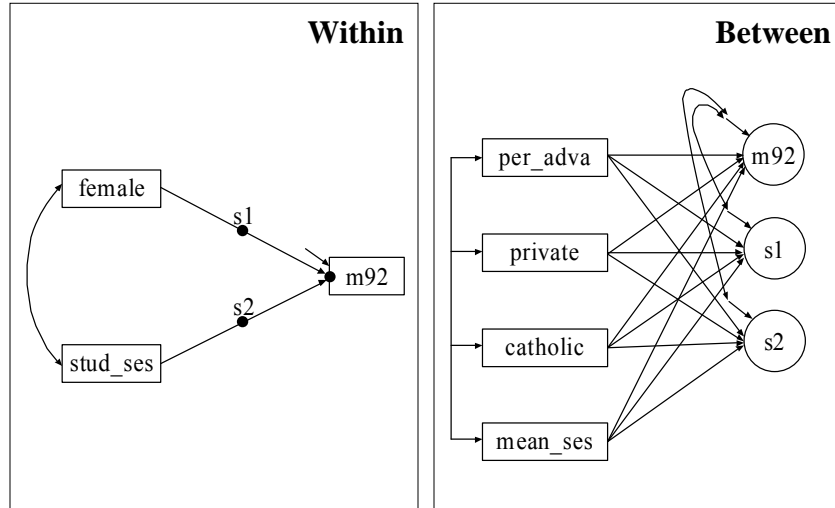
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NELS Data

- The data—National Education Longitudinal Study (NELS:88)
 - Base year Grade 8—followed up in Grades 10 and 12
 - Students sampled within 1,035 schools—approximately 26 students per school, $n = 14,217$
 - Variables—reading, math, science, history-citizenship-geography, and background variables

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NELS Math Achievement Regression



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Input For NELS Math Achievement Regression

```

TITLE:      NELS math achievement regression

DATA:      FILE IS completev2.dat;
           ! National Education Longitudinal Study (NELS)
           FORMAT IS f8.0 12f5.2 f6.3 f11.4 23f8.2
           f18.2 f8.0 4f8.2;

VARIABLE:  NAMES ARE school r88 m88 s88 h88 r90 m90 s90 h90 r92
           m92 s92 h92 stud_ses f2pnlwt transfer minor coll_asp
           algebra retain aca_back female per_mino hw_time
           salary dis_fair clas_dis mean_col per_high unsafe
           num_frie teaqual par_invo ac_track urban size rural
           private mean_ses catholic stu_teach per_adva tea_exce
           tea_res;

           USEV = m92 female stud_ses per_adva private catholic
           mean_ses;

           !per_adva = percent teachers with an MA or higher

           WITHIN = female stud_ses;
           BETWEEN = per_adva private catholic mean_ses;
           MISSING = blank;
           CLUSTER = school;
           CENTERING = GRANDMEAN (stud_ses per_adva mean_ses);
    
```

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Input For NELS Math Achievement Regression (Continued)

```

ANALYSIS: TYPE = TWOLEVEL RANDOM MISSING;

MODEL:
    %WITHIN%
    s1 | m92 ON female;
    s2 | m92 ON stud_ses;

    %BETWEEN%
    m92 s1 s2 ON per_adva private catholic mean_ses;
    m92 WITH s1 s2;

OUTPUT: TECH8 SAMPSTAT;

```

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Output Excerpts NELS Math Achievement Regression

N = 10,933

Summary of Data

Number of clusters 902

Size (s) Cluster ID with Size s

1	89863	75862	52654	1995	32661	89239	56214	
2	41743	81263	45025	26790	60281	82860	56241	21474
	4570	27159	11662	87842	38454			
3	65407	61407	83048	42640	41412	67708	83085	39685
	40402	93469	98582	68595	11517	17543	75498	81069
	66512							
4	31646	68153	85508	26234	83390	60835	74400	20770
	5095	10904	93569	38063	86733	66125	51670	10910
	98461	44395	95317	64112	50880	77381	12835	47555
	9208	93859	35719	67574	20048	34139	25784	80675
5	14464	74791	18219	10468	72193	97616	15773	877
	9471	83234	68254	68028	70718	3496	6842	45854

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Output Excerpts NELS Math Achievement Regression (Continued)

22	79570	15426	97947	93599	85125	10926	4603
23	6411	60328	70024	67835			
24	36988	22874	50626	19091			
25	56619	59710	34292	18826	62209		
26	44586	67832	16515				
27	82887						
28	847	76909					
30	36177						
31	12786	53660	47120	94802			
32	80553						
34	53272						
36	89842	31572					
42	99516						
43	75115						

Average cluster size 12.187
 Estimated Intraclass Correlations for the Y Variables

	Intraclass	
Variable	Correlation	
M92	0.107	

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Output Excerpts NELS Math Achievement Regression (Continued)

Tests of Model Fit

Loglikelihood		
H0 Value		-39390.404
Information Criteria		
Number of Free parameters		21
Akaike (AIC)		78822.808
Bayesian (BIC)		78976.213
Sample-Size Adjusted BIC		78909.478
	(n* = (n + 2) / 24)	

Model Results

	Estimates	S.E.	Est./S.E.
Within Level			
Residual			
Variances			
M92	70.577	1.149	61.442
Between Level			
S1	ON		
PER_ADVA	0.084	0.841	0.100
PRIVATE	-0.134	0.844	-0.159
CATHOLIC	-0.736	0.780	-0.944
MEAN_SES	-0.232	0.428	-0.542

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Output Excerpts NELS Math Achievement Regression (Continued)

		Estimates	S.E.	Est./S.E.
S2	ON			
	PER_ADVA	1.348	0.521	2.587
	PRIVATE	-1.890	0.706	-2.677
	CATHOLIC	-1.467	0.562	-2.612
	MEAN_SES	1.031	0.283	3.640
M92	ON			
	PER_ADVA	0.195	0.727	0.268
	PRIVATE	1.505	1.108	1.358
	CATHOLIC	0.765	0.650	1.178
	MEAN_SES	3.912	0.399	9.814
S1	WITH			
	M92	-4.456	1.007	-4.427
S2	WITH			
	M92	0.128	0.399	0.322
Intercepts				
	M92	55.136	0.185	297.248
	S1	-0.819	0.211	-3.876
	S2	4.841	0.152	31.900
Residual Variances				
	M92	8.679	1.003	8.649
	S1	5.740	1.411	4.066
	S2	0.307	0.527	0.583

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Cross-Level Influence

Between-level (level 2) variable w influencing within-level (level 1) y variable:

Random intercept

$$y_{ij} = \beta_{0j} + \beta_1 x_{ij} + r_{ij}$$

$$\beta_{0j} = \underbrace{\gamma_{00} + \gamma_{01} w_j + u_{0j}}$$

Mplus:

```
MODEL:
  %WITHIN%;
  y ON x; ! estimates beta1
  %BETWEEN%;
  y ON w; ! y is the same as beta0
           ! estimates gamma01
```

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Cross-Level Influence (Continued)

Cross-level interaction, or between-level (level 2) variable moderating a within level (level 1) relationship:

Random slope

$$y_{ij} = \beta_0 + \beta_{1j} x_{ij} + r_{ij}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} w_j + u_{1j}$$

Mplus:

MODEL:

```
%WITHIN%;
beta1 | y ON x;
%BETWEEN%;
beta1 ON w;           ! estimates gammall
```

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Random Slopes

- In single-level modeling random slopes β_i describe variation across individuals i ,

$$y_i = \alpha_i + \beta_i x_i + \varepsilon_i, \quad (100)$$

$$\alpha_i = \alpha + \zeta_{0i}, \quad (101)$$

$$\beta_i = \beta + \zeta_{1i}, \quad (102)$$

resulting in heteroscedastic residual variances

$$V(y_i | x_i) = V(\beta_i) x_i^2 + \theta. \quad (103)$$

- In two-level modeling random slopes β_j describe variation across clusters j

$$y_{ij} = a_j + \beta_j x_{ij} + \varepsilon_{ij}, \quad (104)$$

$$a_j = a + \zeta_{0j}, \quad (105)$$

$$\beta_j = \beta + \zeta_{1j}, \quad (106)$$

A small variance for a random slope typically leads to slow convergence of the ML-EM iterations. This suggests respecifying the slope as fixed.

Mplus allows random slopes for predictors that are

- Observed covariates
- Observed dependent variables
- Continuous latent variables

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Further Readings On Multilevel Regression Analysis

- Ludtke Marsh, Robitzsch, Trautwein, Asparouhov, Muthen (2007). Analysis of group level effects using multilevel modeling: Probing a latent covariate approach. Submitted for publication.
- 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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Logistic And Probit Regression

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