# INFLUENCES OF HIERARCHICAL LINEAR MODELING IN EVALUATION

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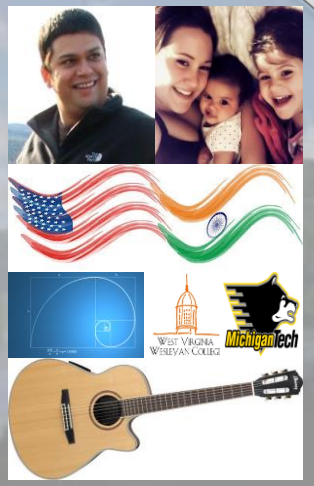
# Interdisciplinary Ph.D. in Evaluation






# Agenda

- What is Hierarchical Data
- What is hierarchical linear modeling (HLM)?
- Rationale for HLM
- Advantages of HLM
- Limitations of HLM
- HLM as a Framework for Evaluating Programmes

# What is Hierarchical Data?

- Primary School Example
  - Students in classrooms (2-levels)
  - Students in classrooms in schools (3-levels)
  - Students in classrooms in schools in regions (4-levels)

- International Development Example
  - Families in villages (2-levels)
  - Families in villages in countries (3-levels)
  - Families in villages in countries in continents (4-levels)

# What is Hierarchical Data?

- Repeated measures in level-1
- Repeated measures in level-1 and in level-2
- Repeated measures in level-1, in level-2, and in level-3

# How to Account for Hierarchical Data?

Example: Students in Classrooms

- Option A: Treat data as level-1
  - Problem: Violate assumptions of GLM
- Option B: Treat data as level-2
  - Problem: Lose data
- Option C: Model the hierarchical structure of the data
  - Hierarchical Linear Modeling (HLM): Education and Psychology
  - Multilevel models: Statistics
  - Mixed effects models: Biostatistics
  - Random effects models: Biostatistics
  - Random coefficient models: Econometrics

Raudenbush, S. W., & Bryk, A. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods. (2nd Ed.)*. Thousand Oaks, CA: Sage.

# Benefits of HLM

- Improved estimation of individual effects
- Formulate and test hypotheses of cross-level effects
- Partition variance and covariance across levels

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# Improved Estimation of Individual Effects

- Braun, Jones, Rubin, & Thayer (1983)
  - Use of standardized test scores for selecting minority applicants for admission to graduate business schools
- Newton & Llosa (2010)
  - Comparison of student outcomes between and within classrooms, and between schools
  - Determination of programme factors that affect outcomes of students by characteristics

Newton, X. A., & Llosa, L. (2010). Toward a more nuanced approach to program effectiveness assessment: Hierarchical linear models in K–12 program evaluation. *American Journal of Evaluation, 31*(2) 162-179.

Raudenbush, S. W., & Bryk, A. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods. (2nd Ed.)*. Thousand Oaks, CA: Sage.

# Formulate and Test Hypotheses of Cross-Level Effects

## Example: Students Nested in Schools

- Dependent variable: Student achievement
- Level-1 covariate: Racial and ethnic status
- Level-2 covariate: School type (public, public-private, private)

Raudenbush, S. W., & Bryk, A. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods. (2nd Ed.)*. Thousand Oaks, CA: Sage.

# Partition Variance and Covariance Across Levels

Example: Students nested in Schools

- Dependent variable: Achievement
- Level-1 Variance: Between students within schools on achievement
- Level-2 Variance: Between schools on achievement

Raudenbush, S. W., & Bryk, A. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods. (2nd Ed.)*. Thousand Oaks, CA: Sage.

# Limitations of HLM

- Sufficient data at each level required
- One dependent variable only
- Estimation of error

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# Example:
# International Development Programme

# Sample Evaluation Questions

1. What was the change in nutritional status for Heifer International project families?
2. Did the change in nutritional status differ by villages within Albania, Nepal, and Uganda?
3. How much of the variability in nutritional status is within villages? Between villages?

# Sample

Table 1

Sample Sizes by Village and Country with Listwise Deletion

| Site | Albania | Nepal | Uganda |
|---|---|---|---|
| 1 | 10 | 9 | 12 |
| 2 | 16 | 7 | 12 |
| 3 | 12 | 11 | 12 |
| 4 | 14 | 6 | 12 |
| 5 | 15 | 9 | 12 |
| 6 | 16 | 11 | 11 |
| 7 | 14 | 7 | 12 |
| 8 | 15 | 8 | 12 |
| Total | 112 | 68 | 95 |

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# Indicators

- Nutritional change
  - Determined by subtracting the reconstructed baseline nutritional status (range: 0 – 20 units) from the nutritional status at the time of the interview for each family (range: 0 – 20 units)
- Nutritional status
  - Measured through four criteria: (a) staples, (b) supplements, (c) protein, and (d) adequate storage procedures
  - Each criterion ranged from 0 to 5 units

# Establishing Models

- First establish and run the unconditional model (excludes covariates)
- Second include covariates, making the unconditional a conditional model

# HLM Unconditional Model

- Level-1 Model: $Y_{ij} = \beta_{0j} + r_{ij}, \qquad r_{ij} \sim N(0,\sigma^2)$
- Level-2 Model: $\beta_{0j} = \gamma_{00} + u_{0j}, \qquad u_{0j} \sim N(0,\tau_{00})$
- Mixed Model: $Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}$

# HLM Conditional Model

- Level-1 Model: $Y_{ij} = \beta_{0j} + r_{ij}$, $r_{ij} \sim N(0,\sigma 2)$
- Level-2 Model: $\beta_{0j} = \gamma_{00} + \gamma_{01}*NEPAL_j +$
  $\gamma_{02}*UGANDA_j + u_{0j}$,
  $u_{0j} \sim N(0,\tau_{00})$
- Mixed Model: $Y_{ij} = \gamma_{00} + \gamma_{01}*NEPAL_j +$
  $\gamma_{02}*UGANDA_j + u_{0j} + r_{ij}$

# Results: Unconditional Model

Table 2

Unconditional Model Fixed Effects

| Fixed Effect | Coefficient | *SE* | *t*-ratio | *df* | *p*-value |
|---|---|---|---|---|---|
| $\gamma_{00}$ | 5.56 | 0.47 | 11.91 | 23 | < 0.001 |

Table 3

Unconditional Model Variance Components

| Variance | *SD* | Variance Component | *df* | $\chi^2$ | *p*-value |
|---|---|---|---|---|---|
| $t_{00}$ | 2.13 | 4.53 | 23 | 147.08 | <0.001 |
| $s^2$ | 3.17 | 10.08 | | | |

# Results: Unconditional Model

- On average, the villages mean change in nutritional status was 5.56 units ($p < 0.001$)
- 31% of the total variance in nutritional change statuses lies between villages
- 69% of the total variance in nutritional change statuses lies within villages

# Results: Conditional Model

Table 4

Conditional Model Variance Components

| Variance | *SD* | Variance Component | *df* | $\chi^2$ | *p*-value |
|---|---|---|---|---|---|
| $\tau_{00}$ | 1.75 | 3.06 | 21 | 91.28 | <0.001 |
| $\sigma^2$ | 3.18 | 10.10 | | | |

Table 5

Conditional Model Fixed Effects

| Fixed Effect | Coefficient | *SE* | *t*-ratio | *df* | *p*-value |
|---|---|---|---|---|---|
| $\gamma_{00}$ | 3.88 | 0.62 | 6.22 | 21 | <0.001 |
| $\gamma_{01}$ | 2.04 | 0.93 | 2.18 | 21 | 0.041 |
| $\gamma_{02}$ | 3.05 | 0.91 | 3.34 | 21 | 0.003 |

# Results: Conditional Model

- 23% of the original between village variance was explained ($p < 0.001$)
- Average village mean nutritional change status in Albania was 3.88 units ($p < 0.001$)
- Average village mean nutritional change status in Nepal was 5.92 units ($p = 0.04$)
- Average village mean nutritional change status in Uganda was 6.93 units ($p = 0.003$)

# Results

- Families in the villages statistically increased their nutritional statuses
- Families' nutritional change statuses statistically differed by villages
- 23% of the remaining between village variance was significant ($p < 0.001$)
  - Existence of village-level variables that were responsible for differences in family nutritional change statuses, for which the conditional level two model did not account

# Applications of HLM in Evaluation

- Appropriately model evaluative data
- Accurately estimate programme effect
- Estimate cross-level interactions (i.e., how level-2 variables affect level-1 relationships)
- Determine variability across and between cases
- Determine which covariates influence programme effect

# References


Braun, H. I., Jones, D. H, Rubin, D. H., & Thayer, D. T. (1983). Empirical Bayes estimation of coefficients in the general linear model from data to deficient rank. *Psychometrika, 489*(2), 171-181.

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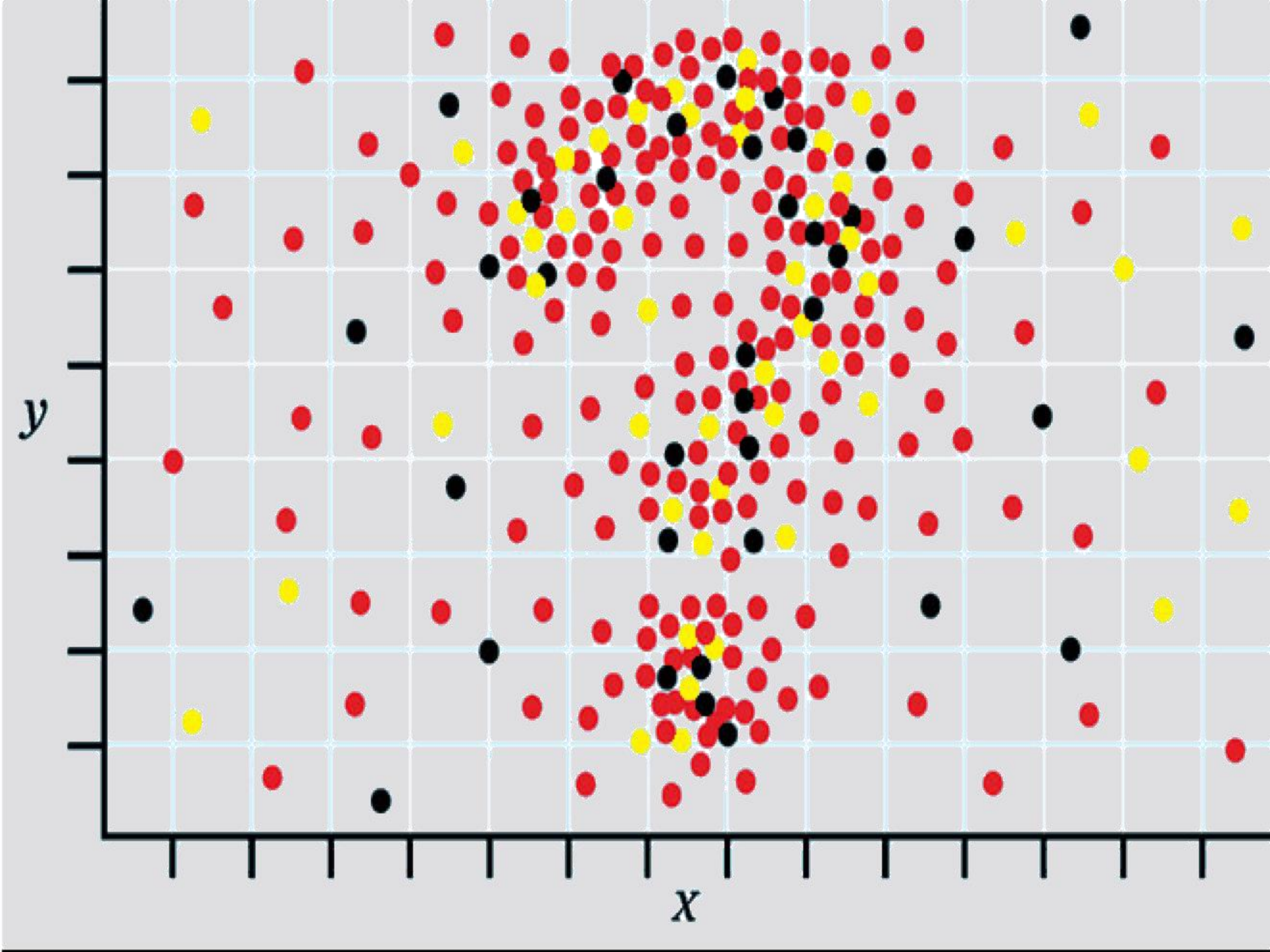
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# Thank You!


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