On the Importance of Integrated Psychometrics and Multilevel Impact Estimation in Multi-Site RCTs: Lessons Learned from CATS

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CRESST

CATS Conference
Redondo Beach, CA
April 2014

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Statistical Routines in Multi-Site RCTs

- Random assignment, measurement at pretest and posttest.
- Standard off-the-shelf outcomes (e.g., commercially developed instruments, end-of-grade assessments).
- Or, researcher developed outcome measures.
- Classical or more modern psychometric analyses to gather technical quality information.
- Outcome scores are computed and hierarchical linear models fitted for estimating the impact of the intervention on the outcome.

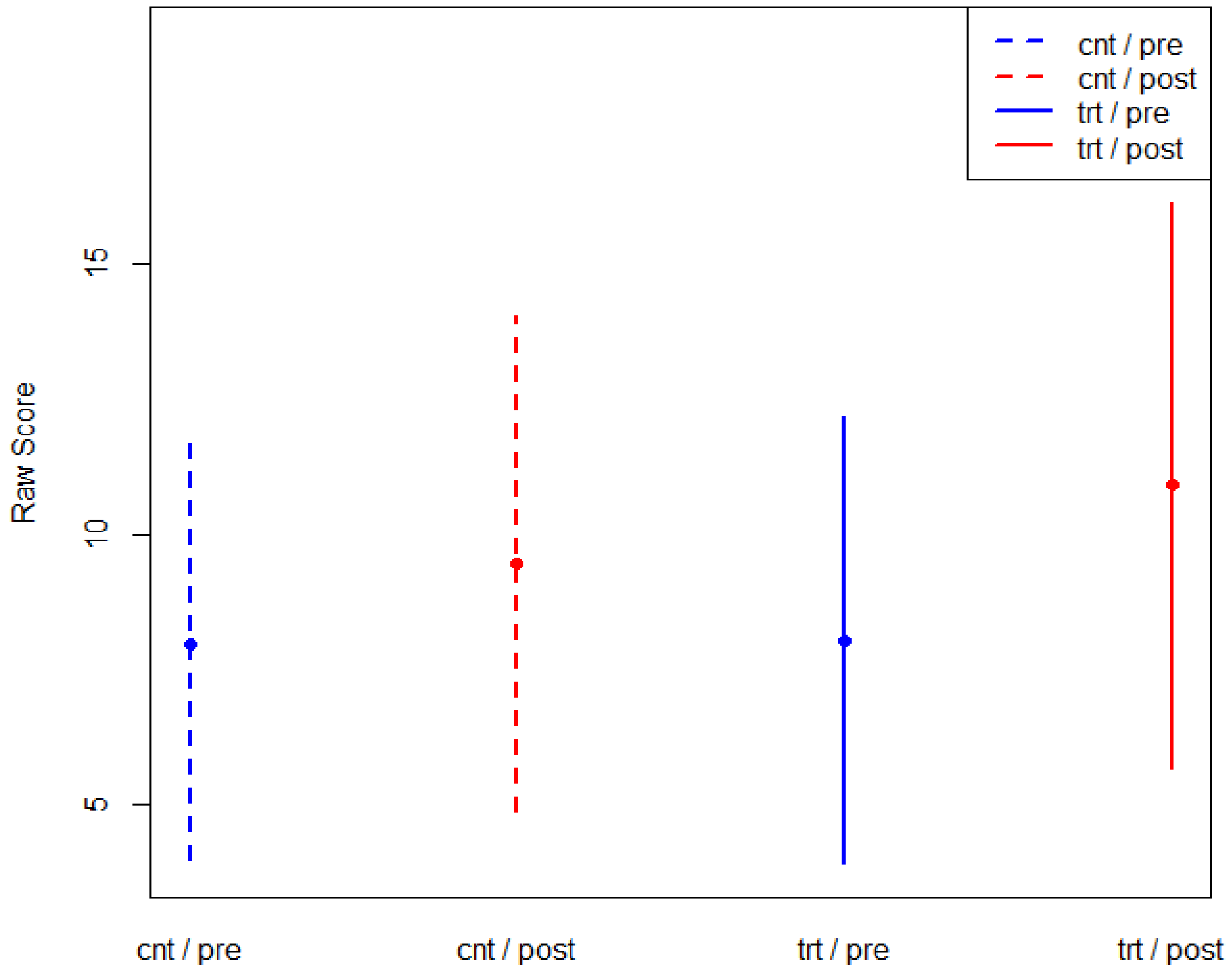
What the Routine Ignores

- The dependence between the outcome constructs at each occasion due to a longitudinal design.
- The item-level residual dependence due to repeated (pre-post) exposure to the same set of measures.
- The practical implausibility of assuming full exchangeability of subjects across treatment and control conditions.
- The obvious dependence of individuals due to their nesting in sites.

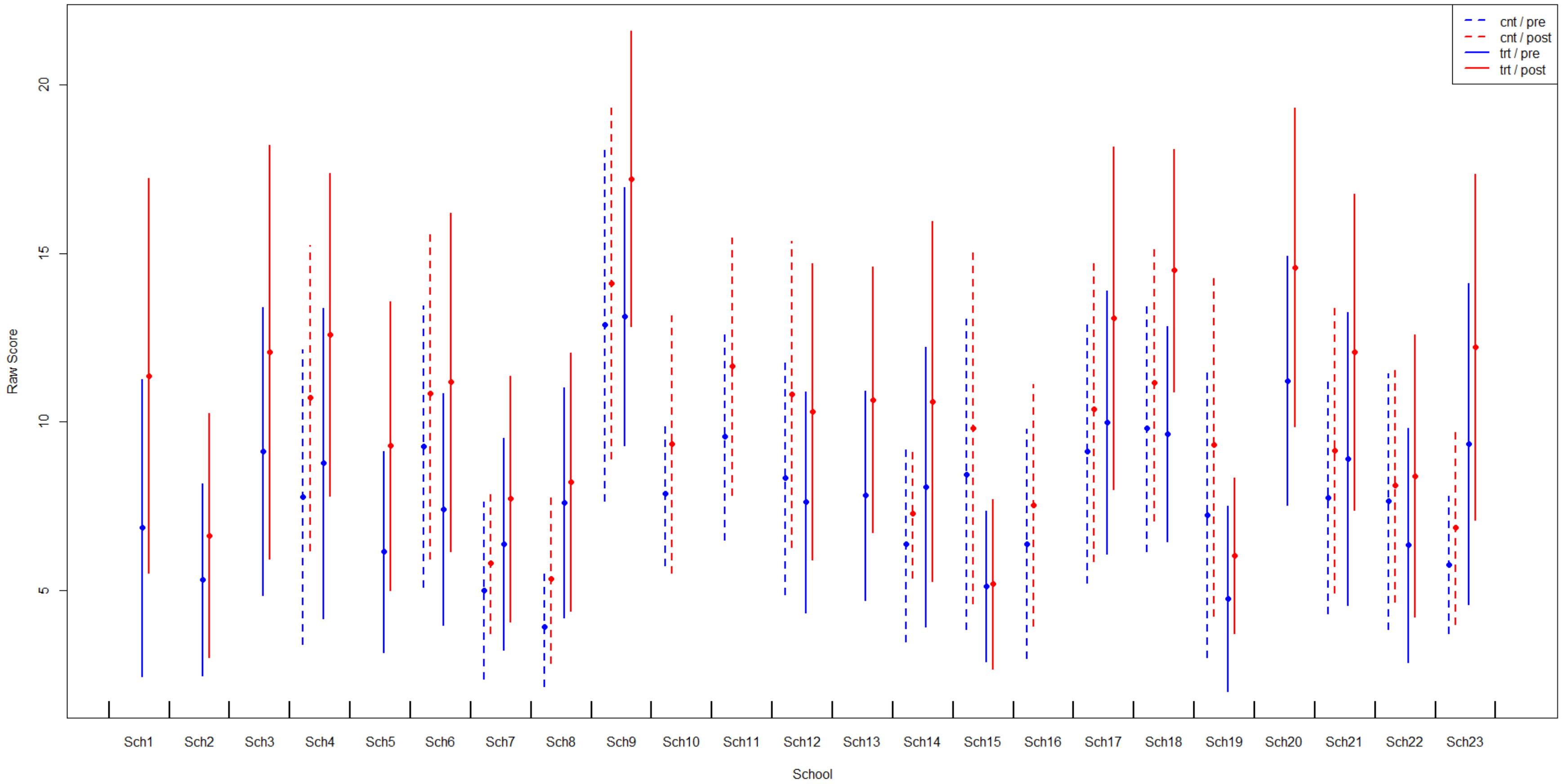
CATS

- Detailed knowledge specifications for assessment development, game development, and PD.
- Intervention classrooms played games focusing on rational number and fraction concepts.
- Comparison classrooms played games focusing on solving equations.
- The main outcome is developed to principally measure rational number and fraction knowledge.
- Within site randomization led to 30 intervention classrooms, and 29 comparison classrooms.
- Total efficacy sample: ~1500 students, 9 districts, 24 schools.

Raw Scores


cnt / pre
cnt / post
trt / pre
trt / post
Raw Score
5
10
15
cnt / pre
cnt / post
trt / pre
trt / post

Raw Scores (by Site)



Multilevel Impact Models

M1:

$$Y_{ij} = \beta_{0j} + \beta_{1j} * Trt_{ij} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma^2)$$
$$\beta_{0j} = \gamma_{00} + u_{0j} \quad u_{0j} \sim N(0, \tau_{00})$$
$$\beta_{1j} = \gamma_{10} + u_{1j} \quad u_{1j} \sim N(0, \tau_{11})$$

M2:

$$Y_{ij} = \beta_{0j} + \beta_{1j} * Trt_{ij} + \beta_{2j} * Pre_{ij} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma^2)$$
$$\beta_{0j} = \gamma_{00} + u_{0j}, \quad u_{0j} \sim N(0, \tau_{00})$$
$$\beta_{1j} = \gamma_{10} + u_{1j}, \quad u_{1j} \sim N(0, \tau_{11})$$
$$\beta_{2j} = \gamma_{20} + u_{2j}, \quad u_{2j} \sim N(0, \tau_{22})$$

Impact Estimates with Raw Scores

	Model 1: Unconditional			Model 2: Pretest as covariate		
Fixed Effects	Estimate	*SE*	*p*-value	Estimate	*SE*	*p*-value
Intercept (γ_{00})	10.062	0.489	< .0001	10.334	0.486	< .0001
Trt (γ_{10})	1.388	0.636	.029	1.119	0.332	.001
Pretest(γ_{20})				0.9304	0.026	< .0001
Variance Components	Estimate	*SE*	*p*-value	Estimate	*SE*	*p*-value
Level-1 (σ^2)	19.914	0.728	< .0001	7.919	0.298	< .0001
Intercept (τ_{00})	4.723	1.634	.002	5.178	1.646	.001
Trt (τ_{11})	5.669	2.436	.010	1.307	0.686	.029
Pretest (τ_{22})				0.005	0.298	< .0001

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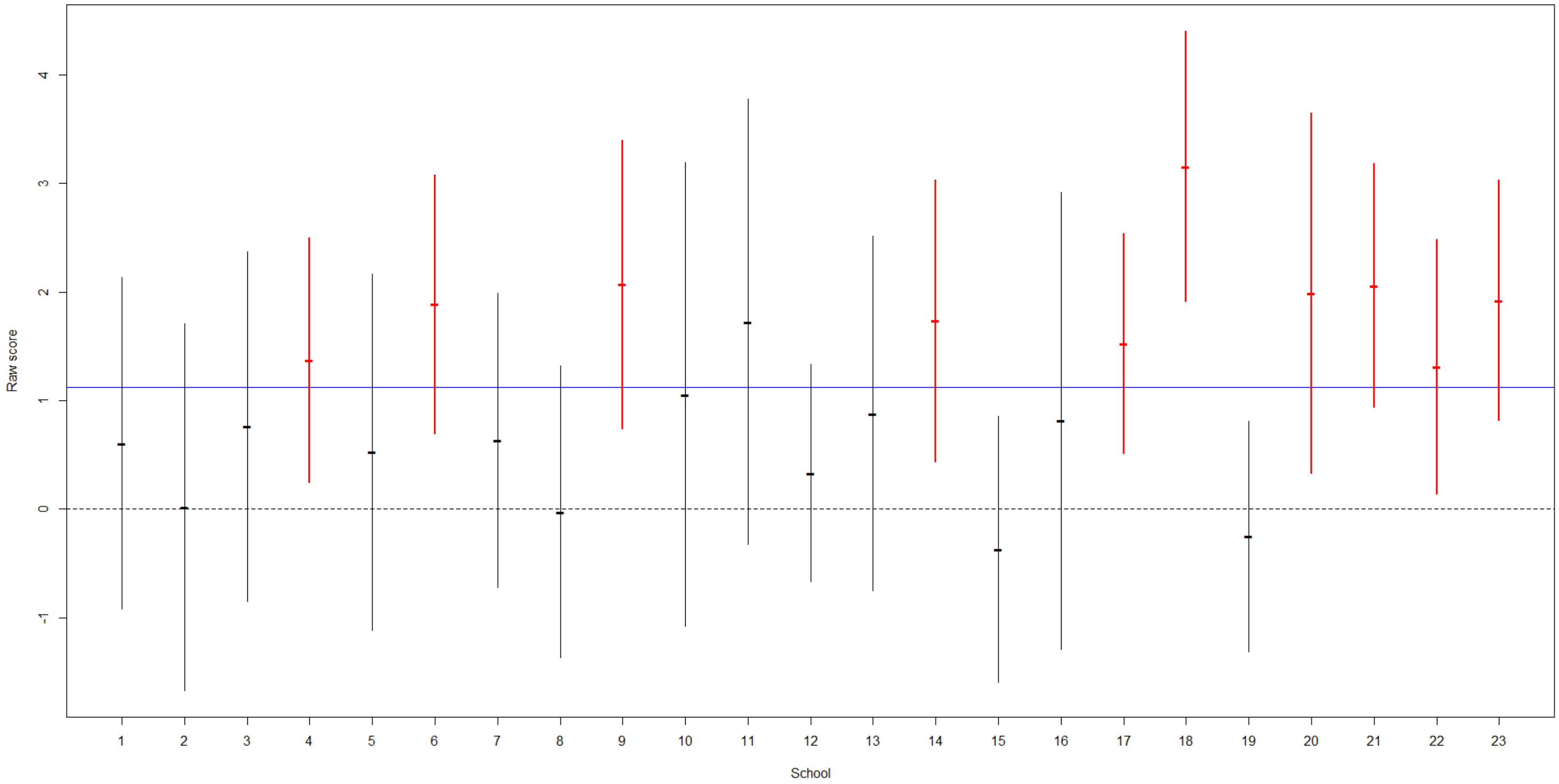
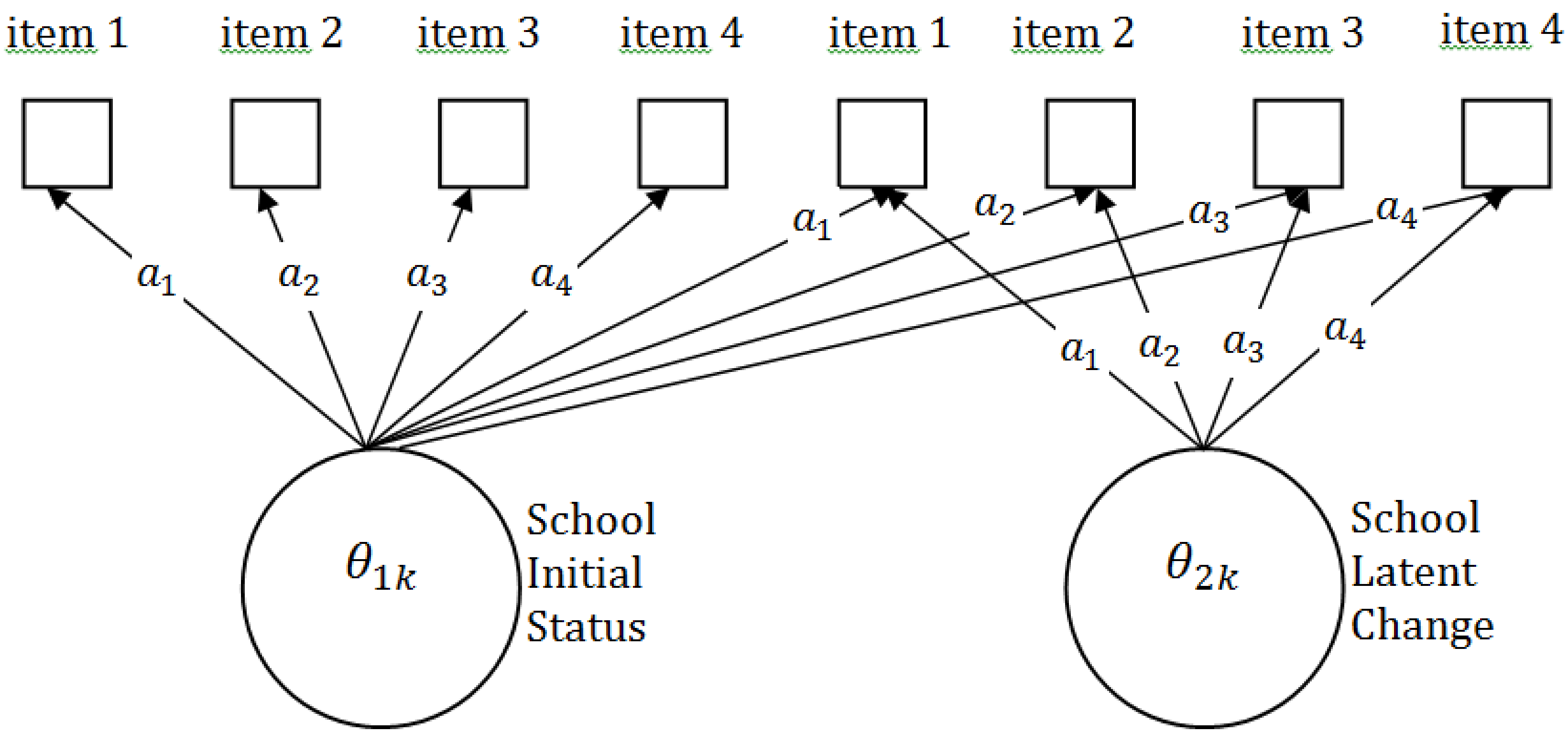
Empirical Bayes Impact Estimates

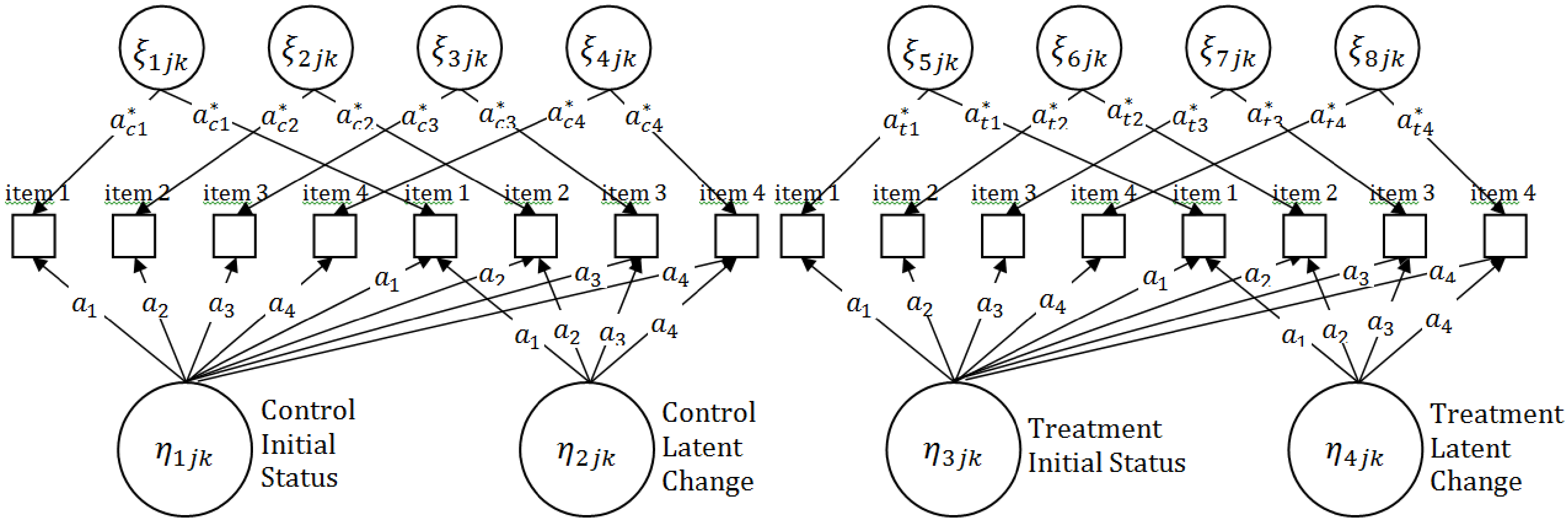


Multilevel Two-Tier (MTT) Model Example



Between-School (Site-Level) Model

Multilevel Two-Tier (MTT) Model Example



Within-School (Student-Level) Model

Item Level Formulation

Pretest Control:

$$a_i(\theta_{1k}+\eta_{1jk}) + a_{ci}^{*}\xi_{ijk}$$

Posttest Control:

$$a_i[(\theta_{1k}+\eta_{1jk}) + (\theta_{2k} + \eta_{2jk})] + a_{ci}^{*}\xi_{ijk}$$

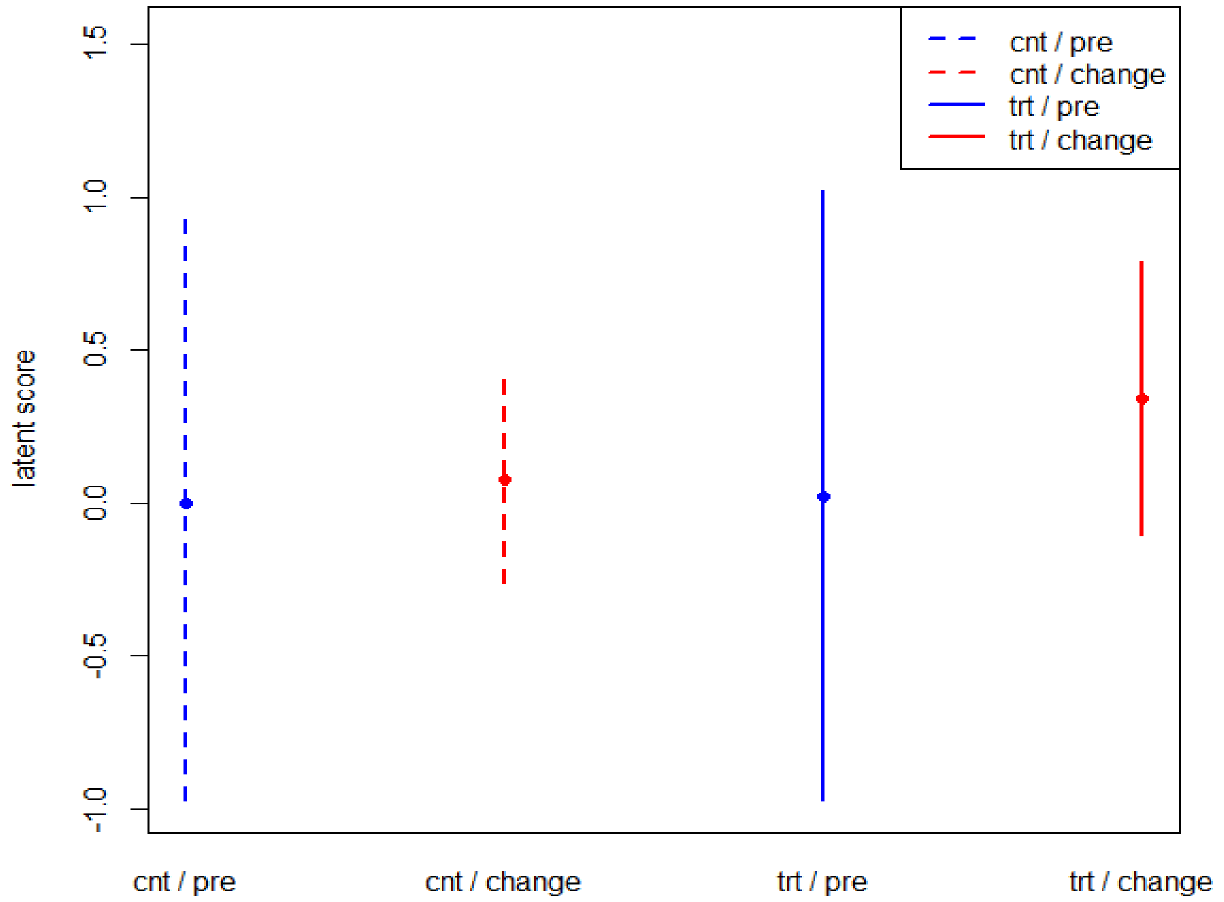
Pretest Treatment:

$$a_i(\theta_{1k}+\eta_{3jk}) + a_{ti}^{*}\xi_{ijk}$$

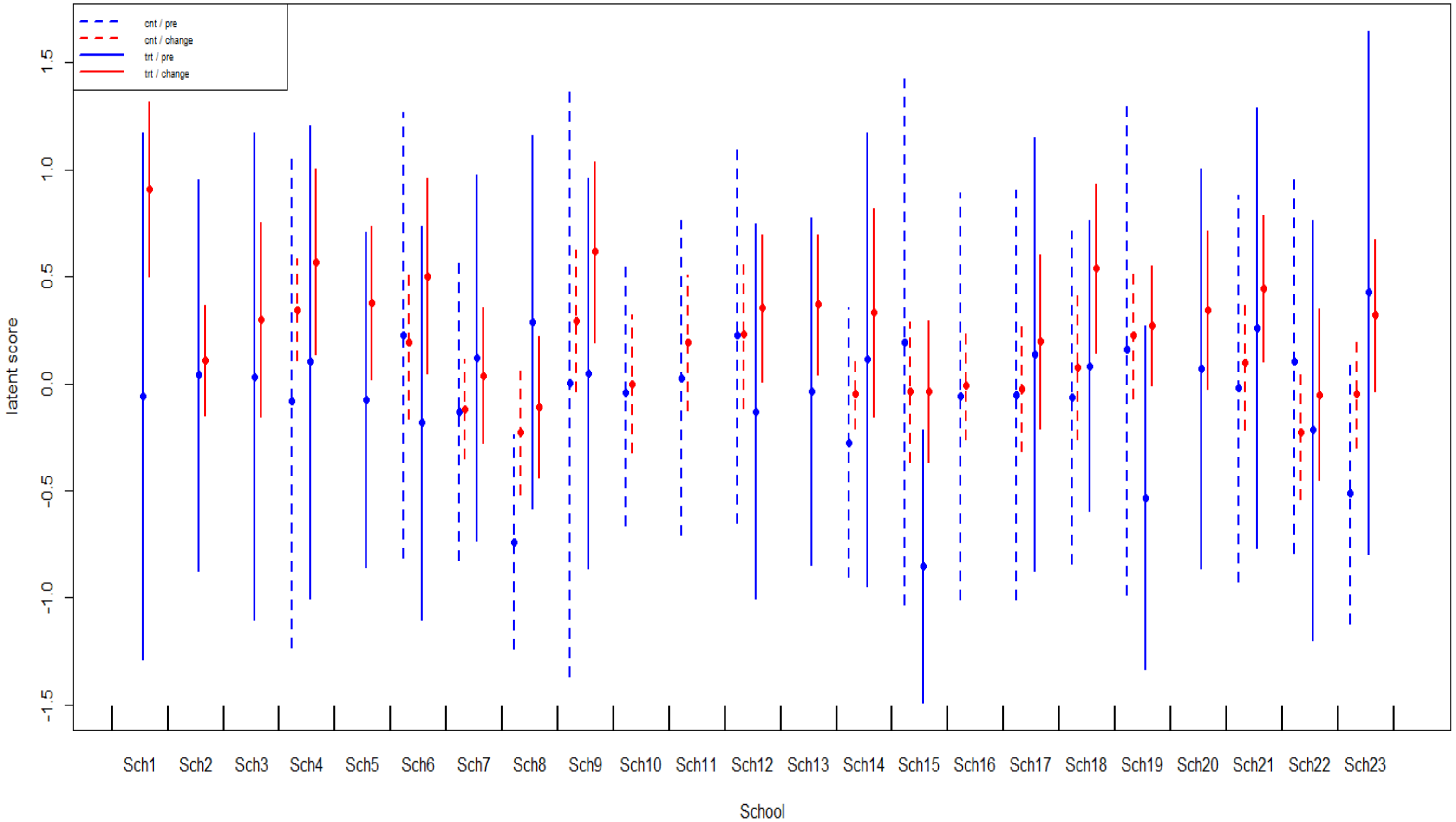
Posttest Treatment:

$$a_i[(\theta_{1k}+\eta_{3jk}) + (\theta_{2k} + \eta_{4jk})] + a_{ti}^{*}\xi_{ijk}$$

Latent Variable Pre and Change Scores



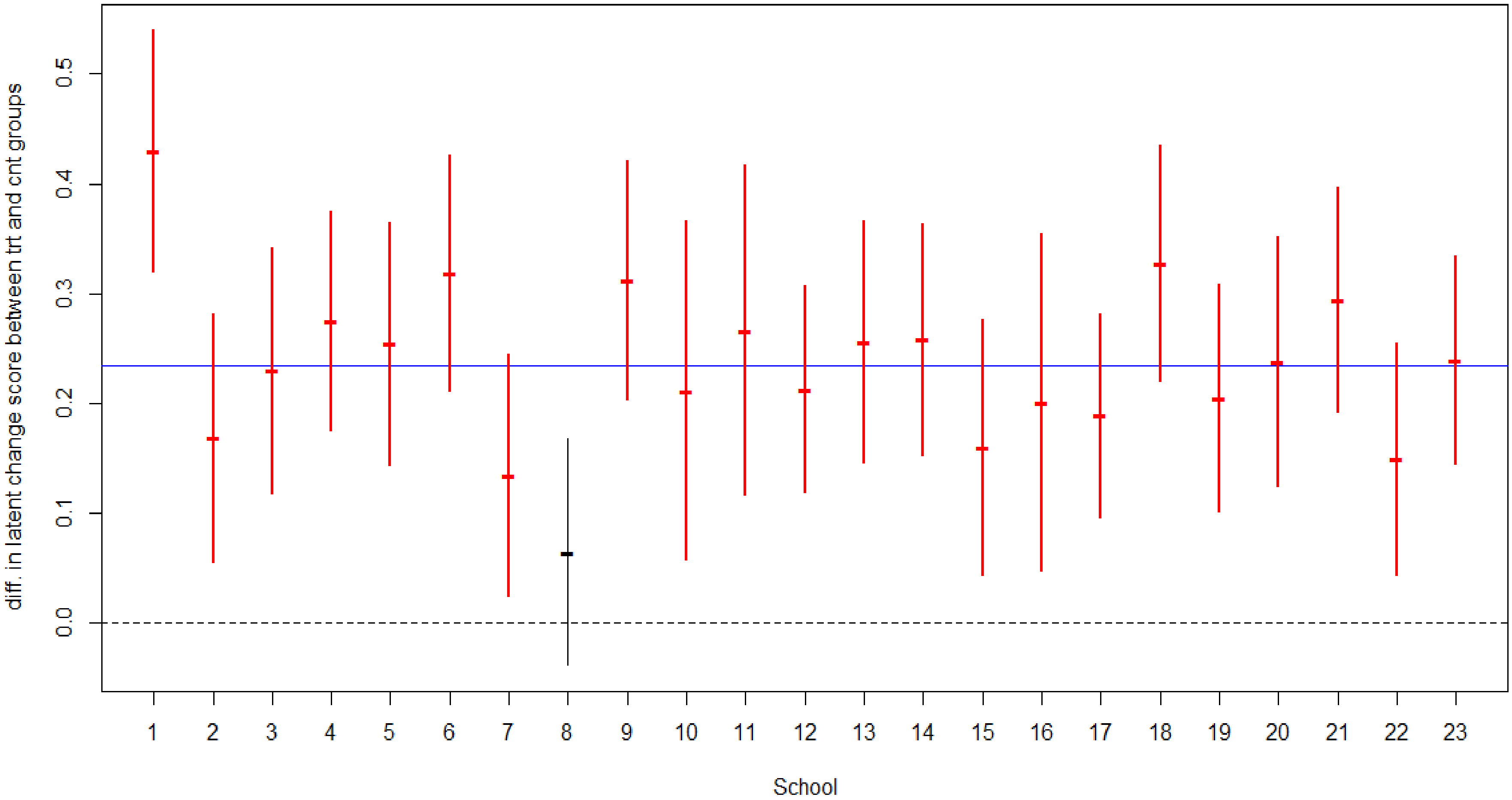
Latent Variable Pre and Change Scores (by Site)



Impact Estimates with Latent Change Scores

	Model 1: Unconditional			Model 2: Pretest as covariate		
Fixed Effects	Estimate	*SE*	*p*-value	Estimate	*SE*	*p*-value
Intercept (γ_{00})	0.199	0.042	.0001	0.207	0.042	< .0001
Trt (γ_{10})	0.243	0.035	< .0001	0.236	0.029	< .0001
Pretest(γ_{20})				0.107	0.009	< .0001
Variance Components	Estimate	*SE*	*p*-value	Estimate	*SE*	*p*-value
Level-1 (σ^2)	0.119	0.012	< .0001	0.110	0.004	< .0001
Intercept (τ_{00})	0.038	0.008	.001	0.037	0.012	.001
Trt (τ_{11})	0.013	0.004	.049	0.008	0.006	.094
Pretest (τ_{22})				0.000	0.298	.423

Empirical Bayes Impact Estimates



Effect Size Estimates

Cohen's δ = γ_{10}/ SD of outcome

Hedges' ES = γ_{10}/ sqrt $(\sigma^2 + \tau_{00} + \tau_{11})$

Conditional ES = γ_{10}/ sqrt (σ^2)

Outcome scores	Est. (γ_{10})	Posttest SD	Lev-1 var(σ^2)	Lev-2 Int var(τ_{00})	Lev-2 Trt var(τ_{11})	Hedges' ES	Cond. ES	Cohen's δ
Raw Score	1.139	4.986	19.914	4.723	5.669	0.207	0.405	0.228
Latent Change	0.236	0.419	0.110	0.037	0.009	0.615	0.705	0.579

Summary

- Integration of domain understanding, design of intervention, design of assessment, psychometric analysis, and impact modeling.
- Full exchangeability vs. conditional exchangeability.
- Psychometric models should reflect design constraints.
- Improved measurement => increased sensitivity.

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