Exploring the Aptitude-by-Treatment Interaction for Latent Subgroups

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Purpose

Aptitude-by-Treatment Interaction

Treatment Effect Heterogeneity

"At risk students are heterogeneous. Often, students respond differently to the treatment."

Key Motivation

Prior studies: Focus on **a single** moderator [L. Fuchs et al., 2014]

Intervention Conceptual & fluency activities → ***Outcome*** At-risk 4th graders' fraction knowledge

Moderator Working memory

- But many learning disabilities are characterized by **multiple** potential predictors, most of which might have small moderation effects individually.
- It is crucial to consider **the joint effect modification** of multiple observed student characteristics.

1 The identification of latent subgroups

Examine the latent profiles that best characterize the cognitive skills of at-risk learners across 11 pre-treatment measures

✓ Latent Profile Analysis

2 Bayesian analysis of heterogeneous treatment effects across latent subgroups

Examine whether the 4th and 5th grades reading intervention affected at-risk learners uniformly or differently such that one latent subgroup of the sample benefited more than another

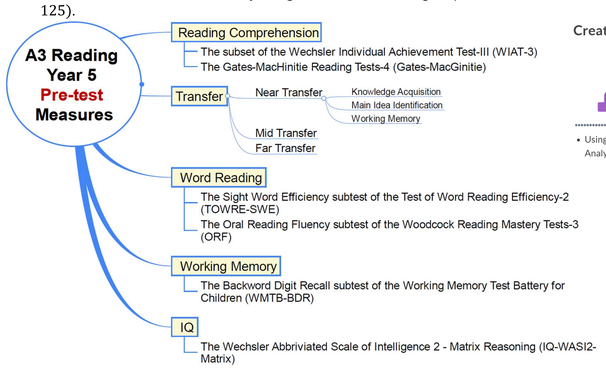
✓ Bayesian Regression & Shrinkage model

Data & Measures

Data - A3 Initiative

Accelerating the Academic Achievement of Students with Learning Disabilities
Research Initiative Year 5 (2017-2018) data

- The purpose of the A3 Initiative is to develop and evaluate the efficacy of math and reading interventions for students with learning disabilities in grades 3-5.
- In the A3 reading project, Tier 2 reading intervention is conducted by tutors for 15 weeks, three times per week, 45 minutes per session with students in grades 3-5 who have reading difficulties.
- The final analytic sample contains 67 teachers of the 189 children (87 4th graders and 102 5th graders). The 189 children were randomly assigned to the control group (n = 64) and two treatment groups (n = 125).



Created 11 factor scores

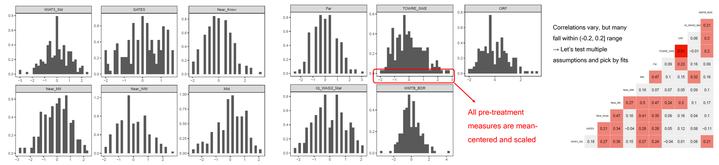
- Using Confirmatory Factor Analysis model

Latent Profile Analysis

3 Three modeling questions for LPA

1. Which is the suitable probability distribution?

- Multivariate normal distribution (MVN). We consider a Gaussian finite mixture model.



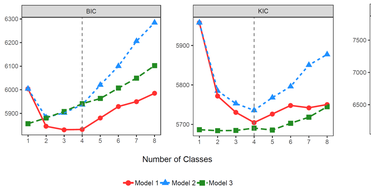
2. Which are the parameters and their estimations?

- The means and the variance-covariance matrix for MVN.
- The proportions of subgroups in the population

- Model 1: Equal variances & covariances fixed to zero
- Model 2: Varying variances & covariances fixed to zero
- Model 3: Equal variances & equal covariances

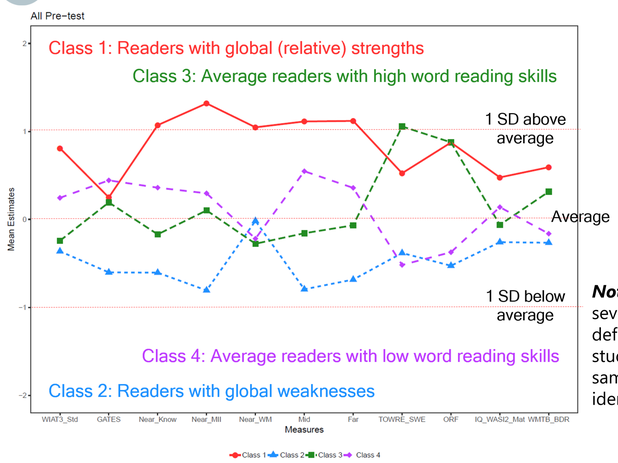
3. How many subgroups should we consider?

- We tried from 1 to 8 clusters and picked by goodness of fit indices



An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests the best solution is **Model 1 with 4 classes** (Equal variances & zero covariances)

4 Four identified latent profiles



Note : The order of severity is relatively defined since the students in the sample were all identified as at risk.

2 Two competing hypotheses

Synergistic interaction vs. compensatory interaction? [Preacher & Sterba, 2019]

- Do readers with global weaknesses (Class 2) benefit more from the intervention than those with global strengths (Class 1)?

Compensatory interaction between pre-treatment word reading and the intervention? [D. Fuchs et al., 2019]

- Do average readers with low word reading skills (Class 4) benefit more from the intervention than those with low word reading skills (Class 3)?

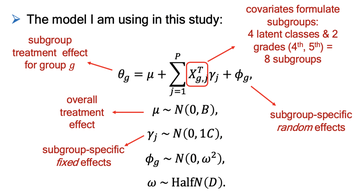
Bayesian Analysis of ATI

Why consider Bayesian analysis for ATI?

- A Bayesian approach can **facilitate interpretation** because it supports probability statements about the subgroup effects given the observed data
  ⇢ *"The probability that Class 2's treatment effect is larger than Class 1's effect is 95.7%"*
- A Bayesian approach allows **precision of estimation with the small sample size** by sharing information across subgroups and exploiting prior information
  ⇢ The sample sizes in subgroups defined by moderators tend to be small

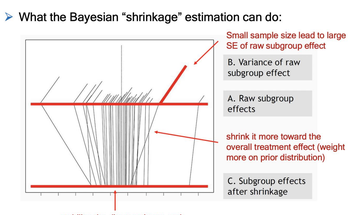
Bayesian regression & shrinkage model

➢ The model I am using in this study:



The B, C, and D are large constants so that the prior distribution for each is non-informative (Wang et al., 2019).

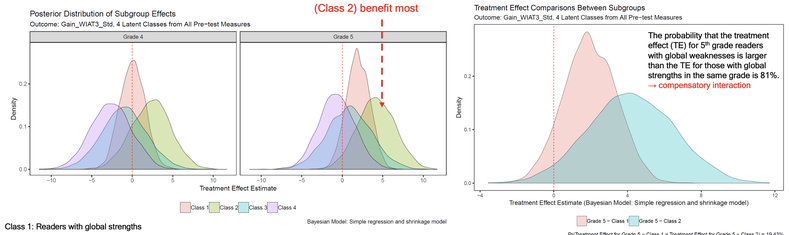
➢ What the Bayesian "shrinkage" estimation can do:



Findings & Conclusions

- Readers with global weaknesses (Class 2) benefit more from the intervention than those with global strength (Class 1), particularly for the gains in reading comprehension measures (WIAT3, GATES, and Mid transfer)

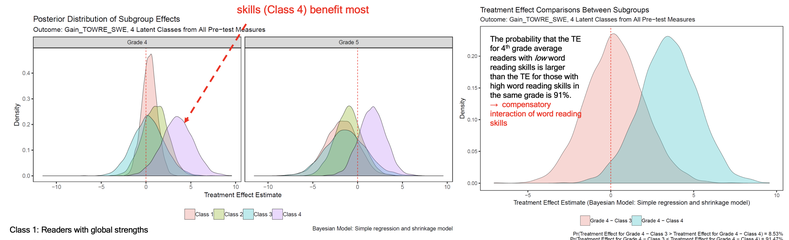
Readers with gobal weaknesses (Class 2) benefit most



Class 1: Readers with global strengths
Class 2: Readers with global weaknesses
Class 3: Average readers with *high* word reading skills
Class 4: Average readers with *low* word reading skills

- Average readers with low word reading skills. (Class 4) benefit more from the intervention than those with high work reading skills (Class 3), only for gains in word reading measure, TOWRE Sight Word Efficiency.

Average readers with low word reading skills (Class 4) benefit most



Class 1: Readers with global strengths
Class 2: Readers with global weaknesses
Class 3: Average readers with *high* word reading skills
Class 4: Average readers with *low* word reading skills

- These results indicate that the reading intervention particularly benefited the youngsters with relatively low pre-treatment cognitive skills, compensating learning more for low-aptitude learners (**compensatory interaction**, Preacher & Sterba, 2019). The results are also consistent with the previous finding (D. Fuchs et al., 2019) supporting compensatory moderation of pre-treatment word reading.
- But these subgroup analyses are mainly explanatory, unless they were pre-specified in the study protocol at the design stage. Finding that *x* moderated *y* requires corroboration through formal experimentation (p. 244 in D. Fuchs et al., 2019).

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