

**PLANNING, EXECUTING, AND
ANALYSING LONGITUDINAL
STUDIES ON CHILDREN'S
DEVELOPMENT**

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PECERA-HK 2024-2025 Annual Meeting cum Young Scholars Conference

CONTENT

Problems with using cross-sectional designs to study child development

Varieties of longitudinal designs

Statistical models for analysing longitudinal data

Practical considerations




STUDYING CHILD DEVELOPMENT

Identifying variables that underpin development

- Are children's math achievement associated with their executive functioning?
- Are motor skills related to children's math performance?
- Is socioeconomic status related to children's executive functioning?
- Questions are correlational in nature and can theoretically be answered by data collected at the same time point

Relations between socioeconomic status, parental stress, parenting practices, and working memory in Hong Kong kindergarten children

Kerry Lee 

The Education University of Hong Kong, Hong Kong

Question

Are individual differences in children's working memory explained by family socioeconomic status and parents-related variables?

Working memory

- Corsi, backward digits, animal updating

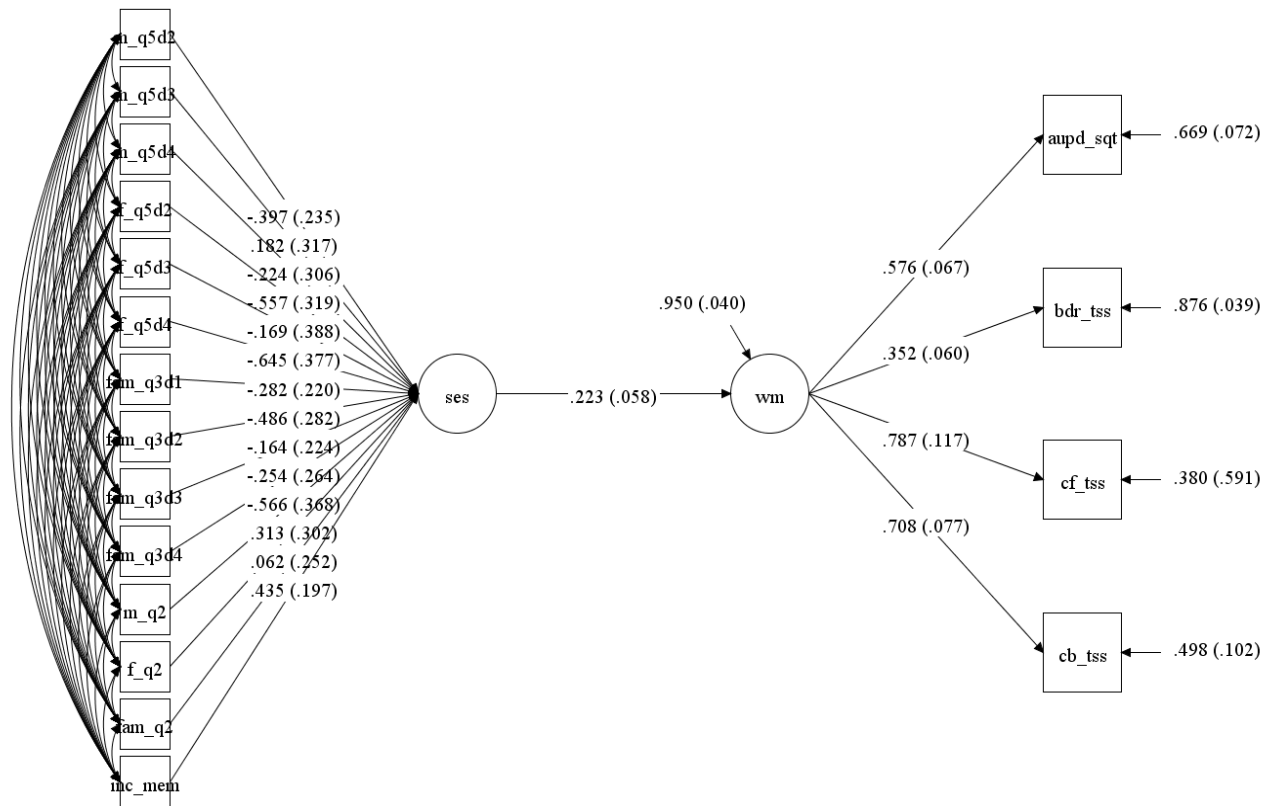
SES

- Education, income, household size & type, financial sufficiency

Parents

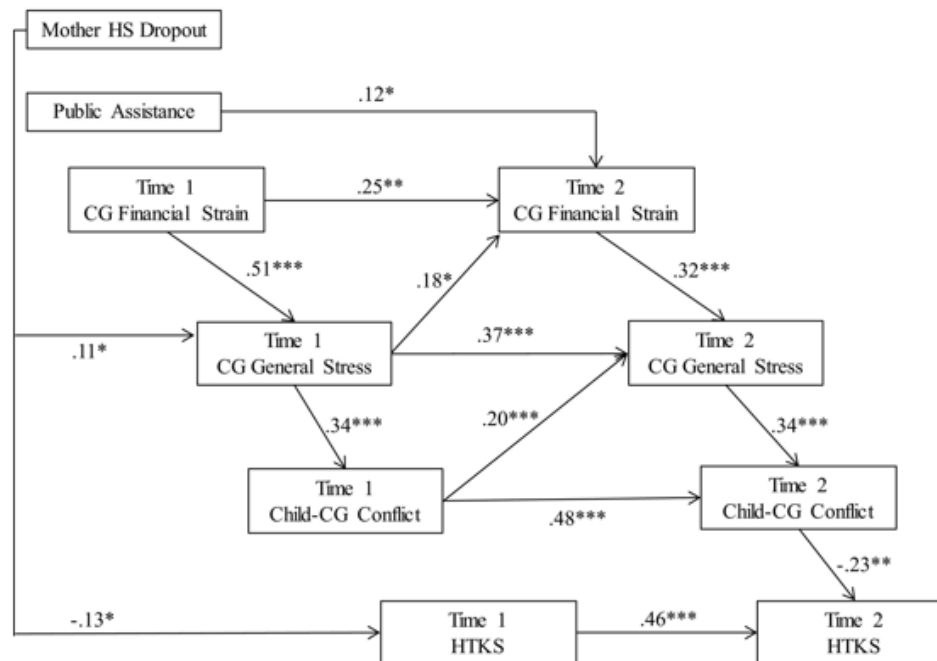
- Psychological distress, parenting style, home learning environment

WM REGRESSED ON THE EXPLANATORY VARIABLES



STRESS, ENVIRONMENT, PARENTING STYLES

Family Stress Processes and Children's Self-Regulation



Duran et al. (2020)



STUDYING CHILD DEVELOPMENT

- Are children's math achievement associated with their executive functioning?
- Are motor skills related to children's math performance?
- Is socioeconomic status related to children's executive functioning?

Implicit in these questions is a more fundamental question: What causes development?

- Is children's math performance causally related to their executive functioning or motor skills?
- Does variation in socioeconomic status cause changes in children's executive functioning?



DETERMINING CAUSATION

At least three conditions need to be satisfied

- Covariation
- Temporal precedence
- Ruling out alternative explanations



LOGICAL DIFFICULTIES

Causation

At least three conditions need to be satisfied

- Covariation
- Temporal precedence
- Ruling out alternative explanations

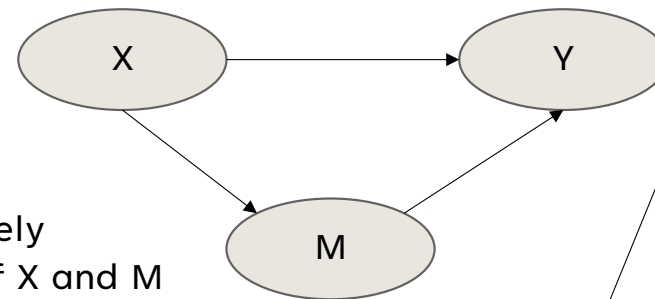
Cross-sectional designs

- Covariation is established by examining the strength and direction of the association
- Establishing that X is associated with Y, in itself, does not provide any empirical evidence of temporal relations; $X \leftrightarrow Y \neq X \rightarrow Y$ or $X \leftarrow Y$
- Covariation does it rule out the possibility that the association is caused by unmeasured variables (e.g., weight & height)

EMPIRICAL DIFFICULTIES

Strength of associations from cross-sectional data are often misleading when they are used to depict longitudinal relations

- Maxwell & Cole (2007) Considered optimal scenarios where there are complete mediation (i.e., addition of M in explanatory results in $X \rightarrow Y \sim 0$)
- All three parameters are negatively or positively biased depending on the relative stabilities of X and M
- Main problem is that cross-sectional models fail to take account of correlations between variables across time points



An abstract graphic design consisting of several overlapping, irregular white lines on a black background. The lines form a complex, layered structure that resembles a series of overlapping rectangles or polygons, creating a sense of depth and movement. The lines are thin and white, contrasting sharply with the solid black background.

EXAMPLES OF
LONGITUDINAL
DESIGNS



TWO TIMEPOINTS

- Intervention
- Testing for underpinning processes
- Testing for reciprocity of effects

TESTING THE EFFICACY OF UPDATING/WM INTERVENTION

Chapter 11 Helping Children with Mathematical Difficulties Level Up: Evaluating the Efficacy of a Novel Updating Training Programme



Su Yin Ang, Kerry Lee, Kenneth K. Poon, and Imelda Suryadarma

Ang et al., 2019

- 6 to 7-year-olds (N = 70) with learning difficulties in math assigned to treatment and control
- Pretest & posttest
 - Working Memory Test Battery for Children ; Updating; WISC; WIAT; Schonell; BLAB
- Training
 - Four adaptive games based on the running span and keep track paradigms
 - 30 min/day; twice/week ~ 10 weeks
- Control
 - Passive
 - Active; same dosage as training but no mnemonic component

Table 11.1 Means and standard deviations (in parentheses) of the outcome measures

Task	Intervention		Active control		Passive control	
	Pre-test	Post-test	Pre-test	Post-test	Pre-test	Post-test
Pictorial Updating	47.12 (12.71)	55.64 (10.20)	47.92 (15.34)	49.25 (16.99)	51.05 (19.50)	54.81 (14.06)
Listening Recall	6.28 (2.61)	7.52 (2.567)	4.54 (3.41)	6.67 (2.57)	5.81 (3.93)	8.62 (3.04)
Backward Digit Recall	8.38 (2.34)	9.36 (3.01)	8.08 (4.20)	10.25 (3.45)	8.95 (4.20)	11.00 (3.87)
Block Recall	22.24 (5.00)	22.08 (4.723)	21.38 (3.90)	20.96 (4.52)	21.86 (3.68)	22.52 (3.37)
Digit Recall	26.60 (4.31)	28.85 (6.65)	25.38 (4.54)	27.75 (4.87)	25.95 (4.96)	27.95 (5.59)
Numerical Operations	13.52 (2.87)	17.58 (2.80)	12.71 (4.39)	16.89 (4.12)	14.38 (3.37)	18.52 (4.46)
Math Problem Solving	27.72 (3.84)	30.92 (3.81)	26.13 (4.45)	30.78 (4.84)	29.00 (4.52)	31.38 (5.11)
Fluency – Addition	8.84 (5.81)	13.00 (5.32)	7.75 (6.60)	13.35 (6.58)	7.81 (6.03)	13.38 (6.45)
Fluency – Subtraction	4.16 (3.02)	8.25 (4.50)	4.42 (5.69)	8.61 (4.58)	3.76 (4.39)	8.48 (4.09)
Block Design	12.60 (8.49)	19.76 (9.58)	16.42 (10.07)	21.39 (11.88)	18.00 (11.64)	24.10 (10.43)
Vocabulary	6.72 (4.112)	7.80 (4.35)	5.42 (4.28)	7.13 (4.96)	7.52 (4.86)	7.57 (3.97)

Scores in the table are raw scores

TESTING FOR UNDERPINNING PROCESSES

Journal of Educational Psychology
2011, Vol. 103, No. 2, 269–281

© 2011 American Psychological Association
0022-0663/11/\$12.00 DOI: 10.1037/a0023068

Are Patterns Important? An Investigation of the Relationships Between Proficiencies in Patterns, Computation, Executive Functioning, and Algebraic Word Problems

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Nanyang Technological University

Rebecca Bull
University of Aberdeen

Madeline Lee Pe
National Institute of Education,
Nanyang Technological University

Ringo Ho Moon Ho
Nanyang Technological University

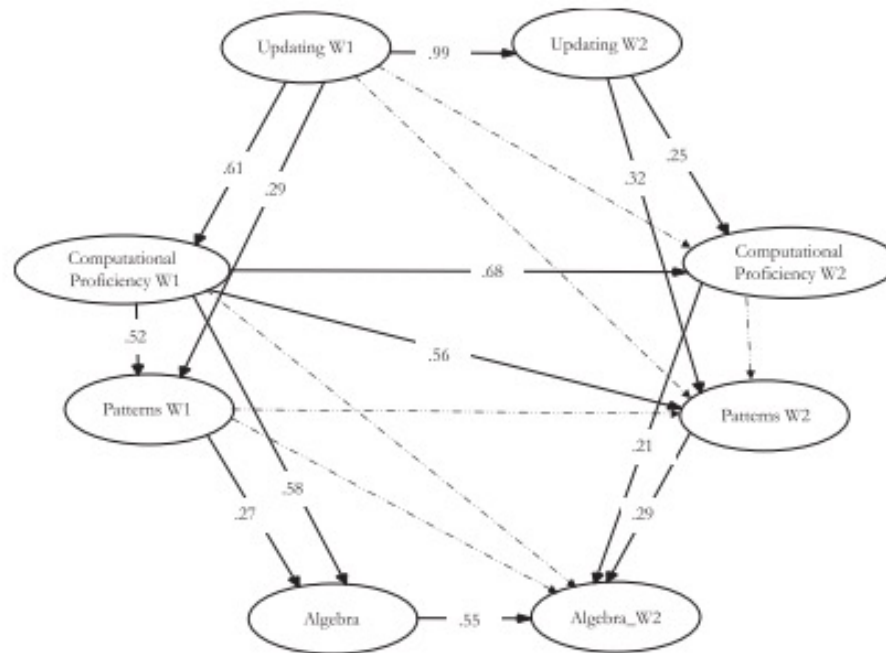


Figure 3. Structural longitudinal model of the relationships between updating, computational, and patterns proficiencies on algebraic performance. Dash-and-dot lines represent relationships that were not significant. Values are standardized path coefficients of the final model (Model 5). W1 = Wave 1; W2 = Wave 2.

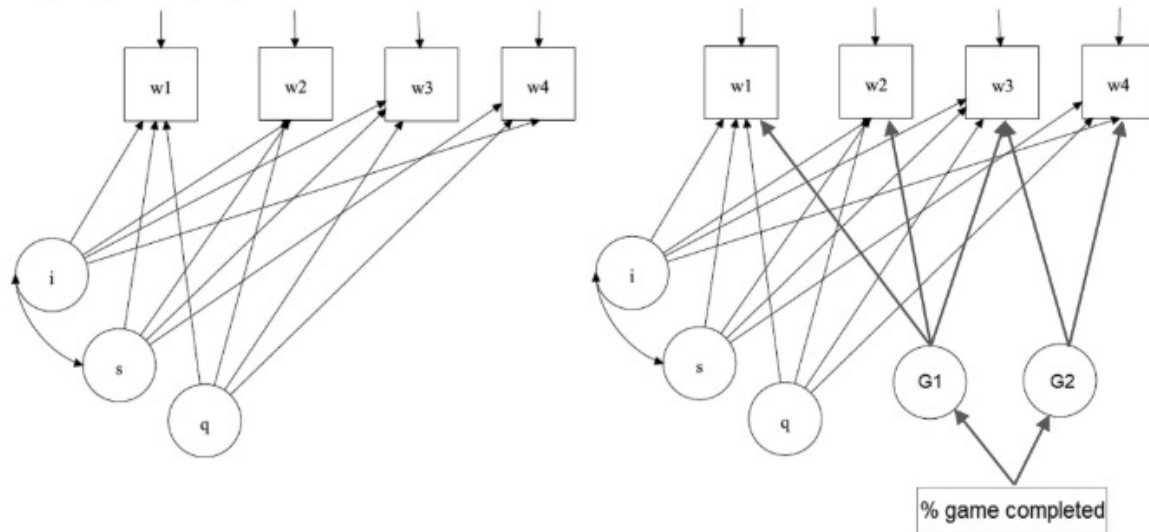


THREE TIMEPOINTS

- Intervention with tests for long-term effects
- Testing for mediation
- Testing for the shape of growth

INTERVENTION WITH TESTS FOR LONG-TERM EFFECTS

Figure 1
Diagram of the Multigroup LGCM



Note. Left (Control group; i = intercept; s = linear slope; q = quadratic slope); Right (Training group; G1 and G2 correspond to immediate and long-term treatment effects, respectively). LGCM = latent growth curve model.

TESTING FOR MEDIATION

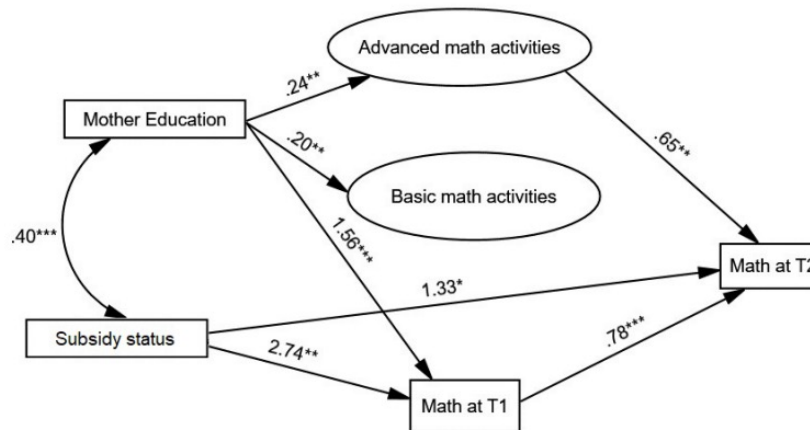
Developmental Science

PAPER

Socioeconomic status, home mathematics environment and math achievement in kindergarten: A mediation analysis

David Muñoz ✉ Rebecca Bull, Kerry Lee

Figure 2: Parameter estimates of the mediation model



Note: For clarity, indicators of the HME factors and control variables are omitted and only significant paths of the variables of interest are included in the diagram. Estimates on single-headed arrows are unstandardized regression coefficients. The estimate on the double-headed arrow relates to the covariance between variables ($*** p < .001$; $** p < .01$; $* p < .05$). T1 and T2 correspond to the first and second time points, respectively.

Incomplete temporal separation

TESTING FOR THE SHAPE OF GROWTH

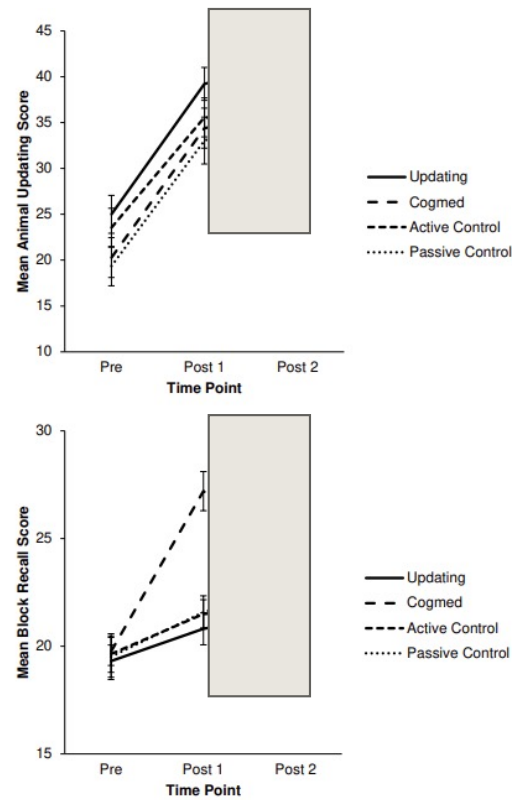


Figure 2. Mean Animal Updating and Block Recall scores by condition and time of test. The error bars depict standard errors.

TESTING FOR THE SHAPE OF GROWTH

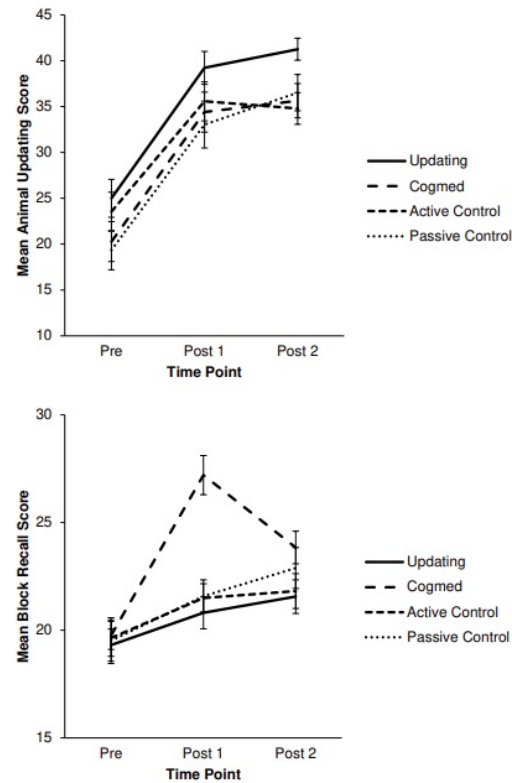


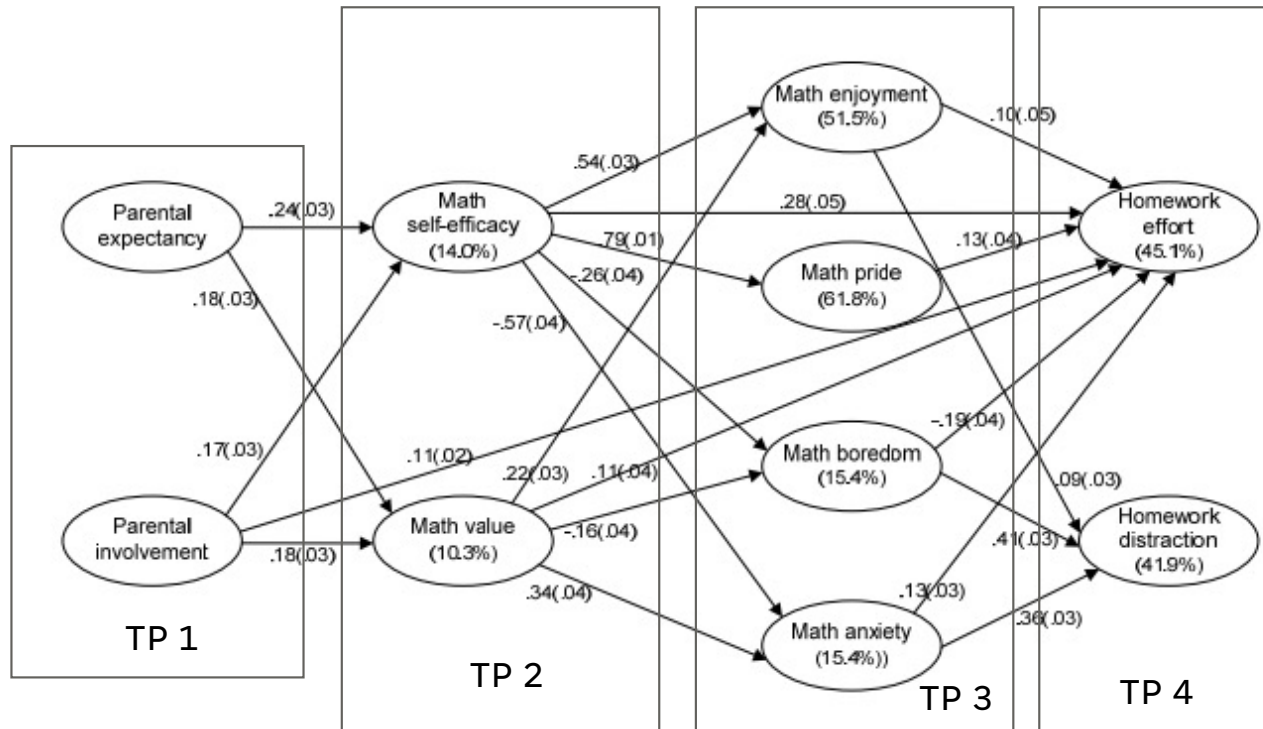
Figure 2. Mean Animal Updating and Block Recall scores by condition and time of test. The error bars depict standard errors.



MORE THAN THREE TIMEPOINTS

- Testing for multi-layered mediation
- Testing for more complex patterns of growth

TESTING FOR MULTI-LAYERED MEDIATION



TP 2, 3, 4 → TP 2

TESTING FOR MORE COMPLEX PATTERNS OF GROWTH

Developmental Changes in Working Memory, Updating, and Math Achievement

Kerry Lee and Rebecca Bull
Nanyang Technological University

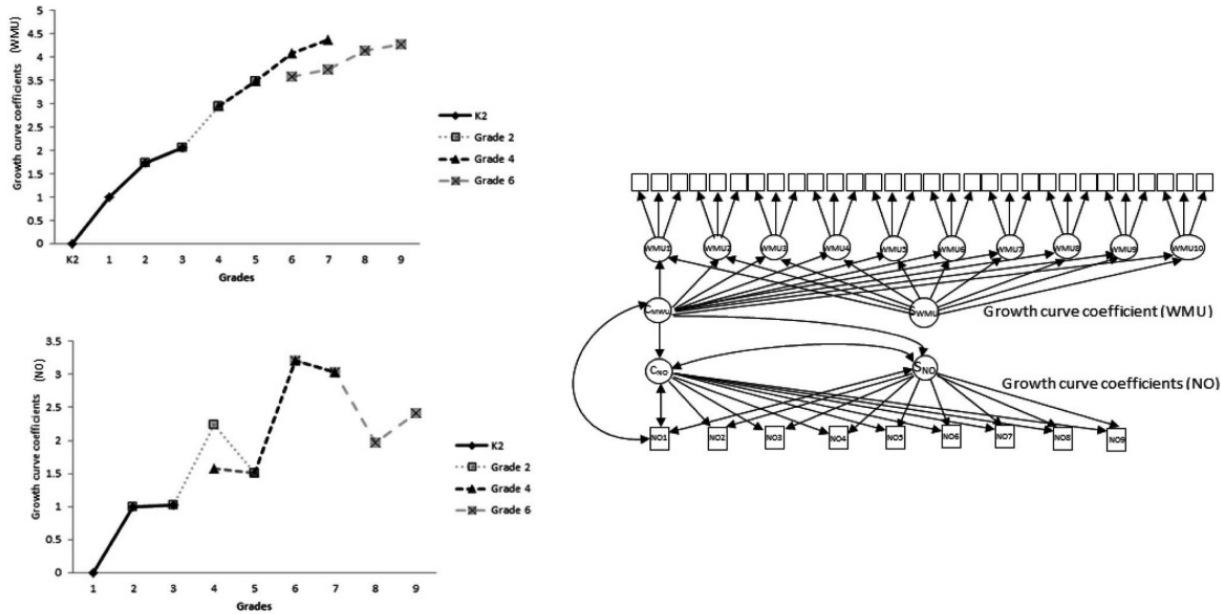


Figure 2. Estimated slope coefficients for the Numerical Operations task (lower left panel) for working memory and updating (WMU; upper left panel), and a schematic for the growth model used to estimate the coefficients (right). Residuals from the same measure were allowed to covary across time-points within each cohort, but are not depicted here. Regression paths to school clusters are not shown.

An abstract graphic consisting of several overlapping, irregular white polygons and lines on a black background. The shapes are interconnected, creating a complex, layered geometric pattern. The lines vary in length and orientation, some forming closed shapes while others are open or overlapping.

STATISTICAL MODELS

SIMPLE REGRESSION

TITLE:

this is an example of a linear regression for a continuous observed dependent variable with two covariates

DATA:

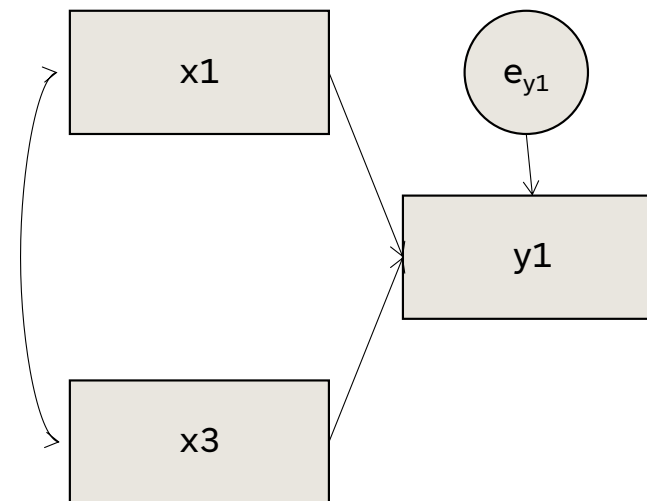
FILE IS ex3.1.dat;

VARIABLE:

NAMES ARE y1-y6 x1-x4;
USEVARIABLES ARE y1 x1 x3;

MODEL:

y1 ON x1 x3;



Input examples from Muthen & Muthen (2013) Mplus User's Guide.

LOGISTIC REGRESSION

TITLE:

this is an example of a logistic regression for a categorical observed dependent variable with two covariates

DATA:

FILE IS ex3.5.dat;

VARIABLE:

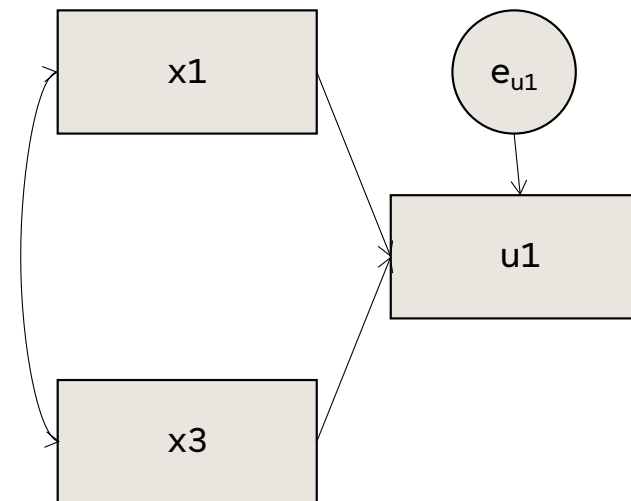
NAMES ARE u1-u6 x1-x4;
USEVARIABLES ARE u1 x1 x3;
CATEGORICAL IS u1;

ANALYSIS:

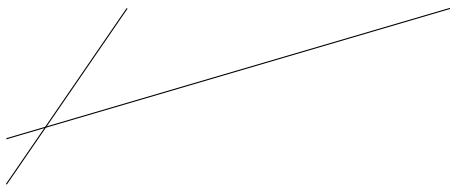
ESTIMATOR = ML;

MODEL:

u1 ON x1 x3;



Input examples from Muthen & Muthen (2013) Mplus User's Guide.



MEDIATION ANALYSIS

TITLE:

this is an example of a path analysis with continuous dependent variables

DATA:

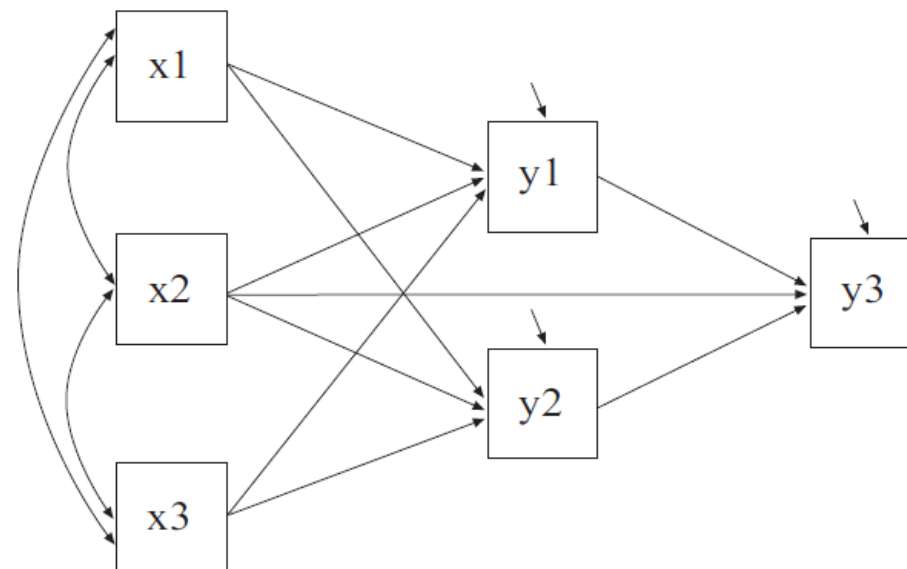
FILE IS ex3.11.dat;

VARIABLE:

NAMES ARE y1-y6 x1-x4;
USEVARIABLES ARE y1-y3 x1-x3;

MODEL:

y1 y2 ON x1 x2 x3;
y3 ON y1 y2 x2;



Input examples from Muthen & Muthen (2013) Mplus User's Guide.

AUTOREGRESSIVE MODEL

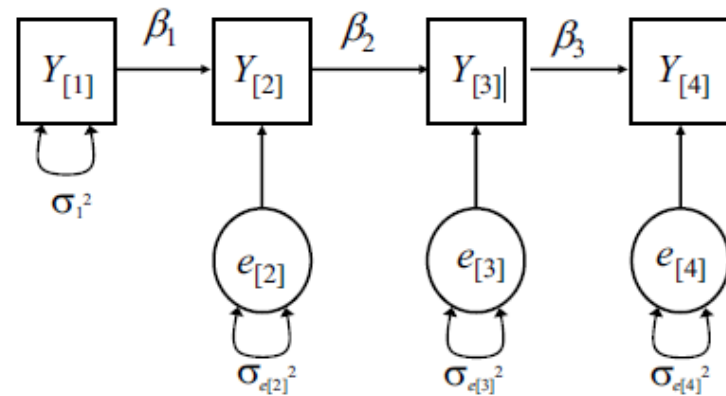
*“First-Order” Markov Simplex Model
with Time-Based Effects*

MODEL:

norw4 ON norw3;

norw3 ON norw2;

norw2 ON norw1;

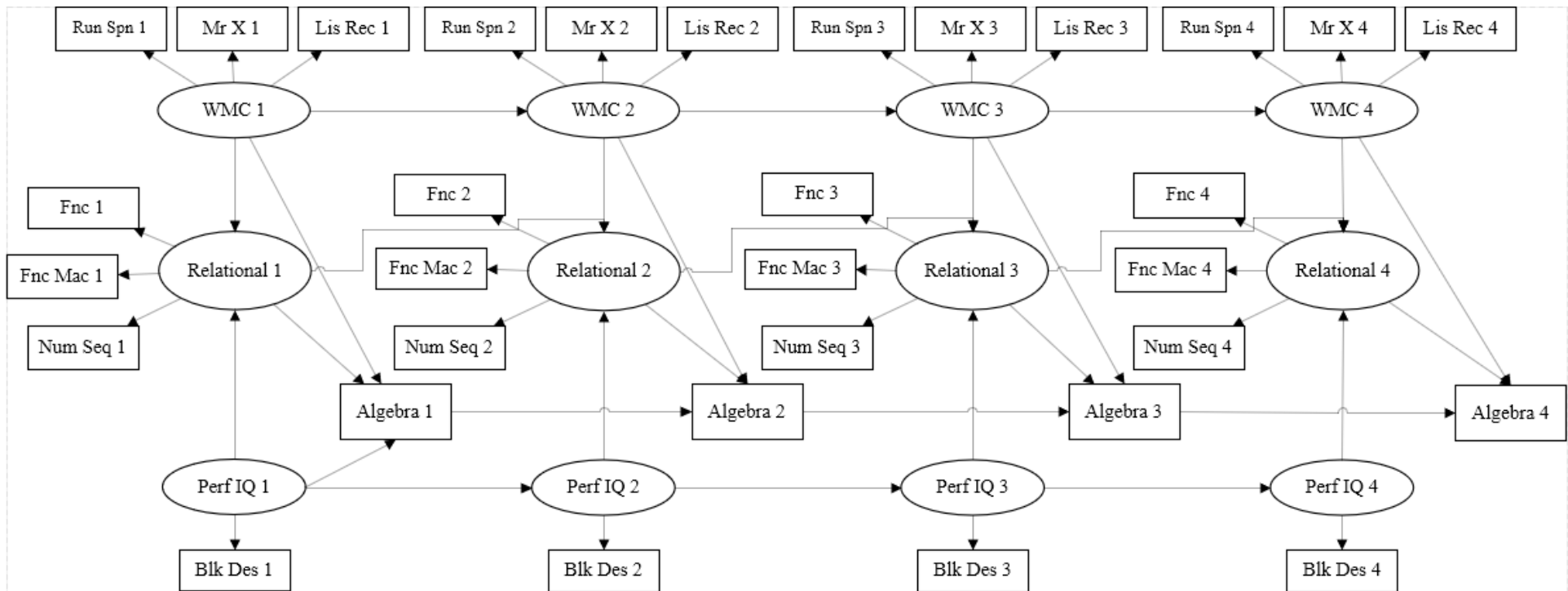


Figures from APA ATI 2010



MORE COMPLEX
MODELS

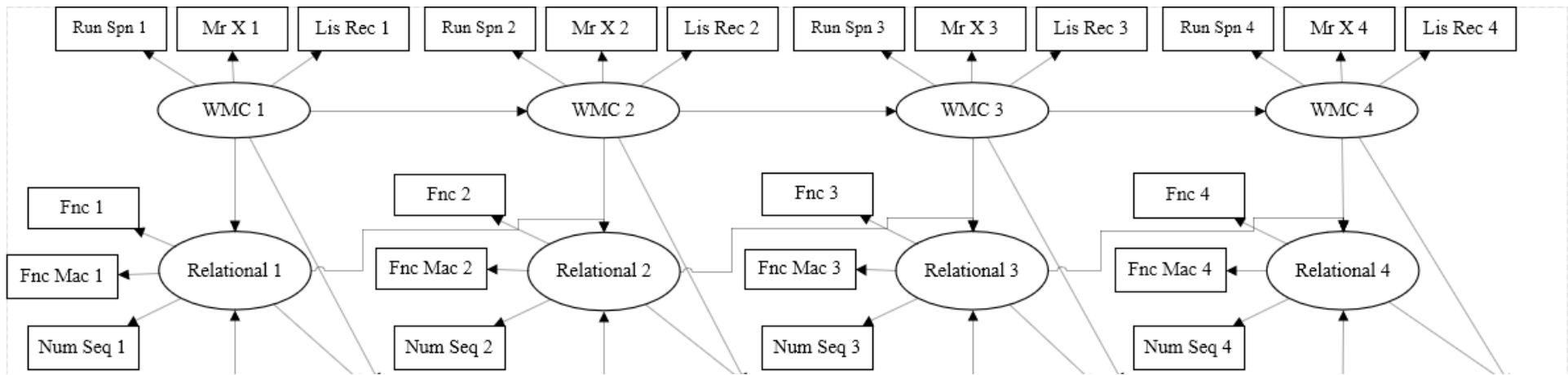
PARALLEL GROWTH PROCESSES



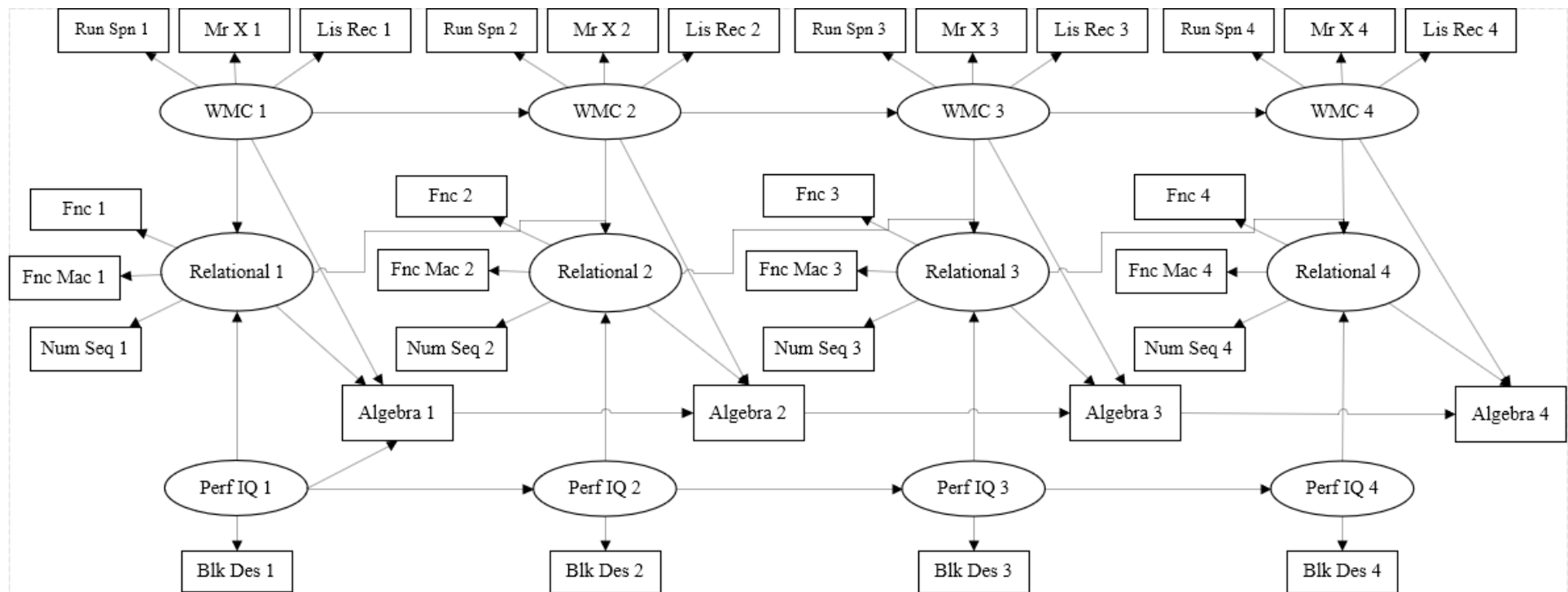
AUTOREGRESSIVE MODEL WITH LATENT MEASURES



TWO AUTOREGRESSIVE CHAINS



FOUR AUTOGRESSIVE CHAINS WITH LATENT AND MANIFEST MEASURES



WE ARE MISSING SOMETHING!



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0003-066X/18/\$12.00

American Psychologist

2018, Vol. 73, No. 1, 81–94
<http://dx.doi.org/10.1037/amp000146>

Risky Business: Correlation and Causation in Longitudinal Studies of Skill Development

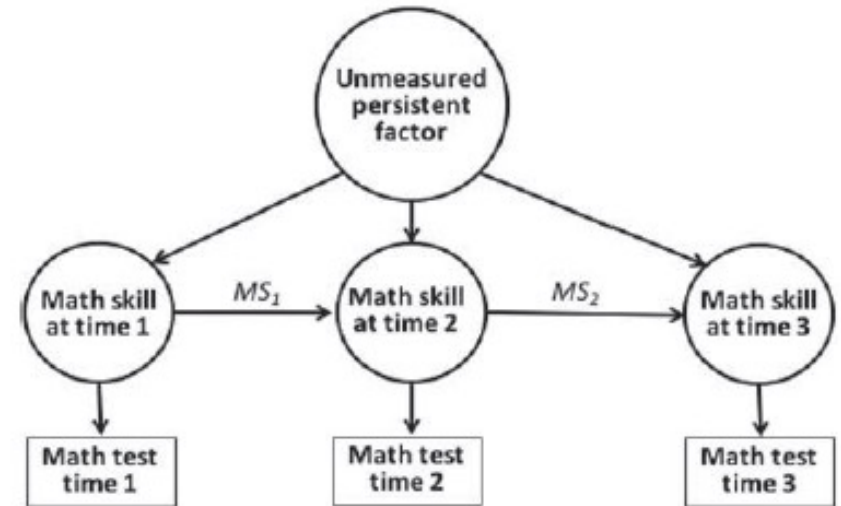
Drew H. Bailey, Greg J. Duncan, and Tyler Watts
University of California, Irvine

Doug H. Clements and Julie Sarama
University of Denver

Developmental theories often posit that changes in children's early psychological characteristics will affect much later psychological, social, and economic outcomes. However, tests of these theories frequently yield results that are consistent with plausible alternative theories that posit a much smaller causal role for earlier levels of these psychological characteristics. Our article explores this issue with empirical tests of skill-building theories, which predict that early boosts to simpler skills (e.g., numeracy or literacy) or behaviors (e.g., antisocial behavior or executive functions) support the long-term development of more sophisticated skills or behaviors. Substantial longitudinal associations between academic or socioemotional skills measured early and then later in childhood or adolescence are often taken as support of these skill-building processes. Using the example of skill-building in mathematics, we argue that longitudinal correlations, even if adjusted for an extensive set of baseline covariates, constitute an insufficiently risky test of skill-building theories. We first show that experimental manipulation of early math skills generates much smaller effects on later math achievement than the nonexperimental literature has suggested. We then conduct falsification tests that show puzzlingly high cross-domain associations between early math and later literacy achievement. Finally, we show that a skill-building model positing a combination of unmeasured stable factors and skill-building processes can reproduce the pattern of experimental impacts on children's mathematics achievement. Implications for developmental theories, methods, and practice are discussed.

Keywords: early childhood, interventions, skill-building, cognitive development, education

Supplemental materials: <http://dx.doi.org/10.1037/amp000146.supp>



Predicted standardized treatment effects on math skill following 1 SD boost in Math skill at time 1:

- Math skill at time 1: 1
- Math skill at time 2: MS_1
- Math skill at time 3: $MS_1 * MS_2$

MODELLING STRUCTURED RESIDUALS

Journal of Consulting and Clinical Psychology
2014, Vol. 82, No. 5, 879–894

© 2013 American Psychological Association
0022-006X/14/\$12.00 DOI: 10.1037/a0035297

The Separation of Between-Person and Within-Person Components of Individual Change Over Time: A Latent Curve Model With Structured Residuals

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University of North Carolina at Chapel Hill

Andrea L. Howard
Carleton University

Sierra A. Bainter, Stephanie T. Lane, and James S. McGinley
University of North Carolina at Chapel Hill

Objective: Although recent statistical and computational developments allow for the empirical testing of psychological theories in ways not previously possible, one particularly vexing challenge remains: how to optimally model the prospective, reciprocal relations between 2 constructs as they developmentally unfold over time. Several analytic methods currently exist that attempt to model these types of relations, and each approach is successful to varying degrees. However, none provide the unambiguous separation over time of between-person and within-person components of stability and change, components that are often hypothesized to exist in the psychological sciences. Our goal in this article is to propose and demonstrate a novel extension of the multivariate latent curve model to allow for the disaggregation of these effects. **Method:** We begin with a review of the standard latent curve models and describe how these primarily capture between-person differences in change. We then extend this model to allow for regression structures among the time-specific residuals to capture within-person differences in change. **Results:** We demonstrate this model using an artificial data set generated to mimic the developmental relation between alcohol use and depressive symptomatology spanning 5 repeated measures. **Conclusions:** We obtain a specificity of results from the proposed analytic strategy that is not available from other existing methodologies. We conclude with potential limitations of our approach and directions for future research.

Keywords: latent curve models, growth models, structural equation modeling, disaggregation of effects

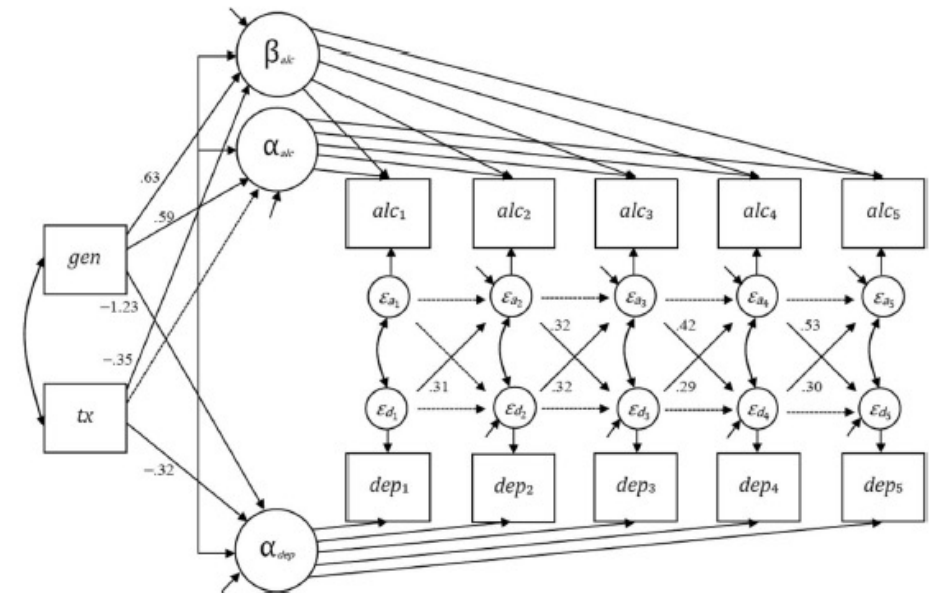
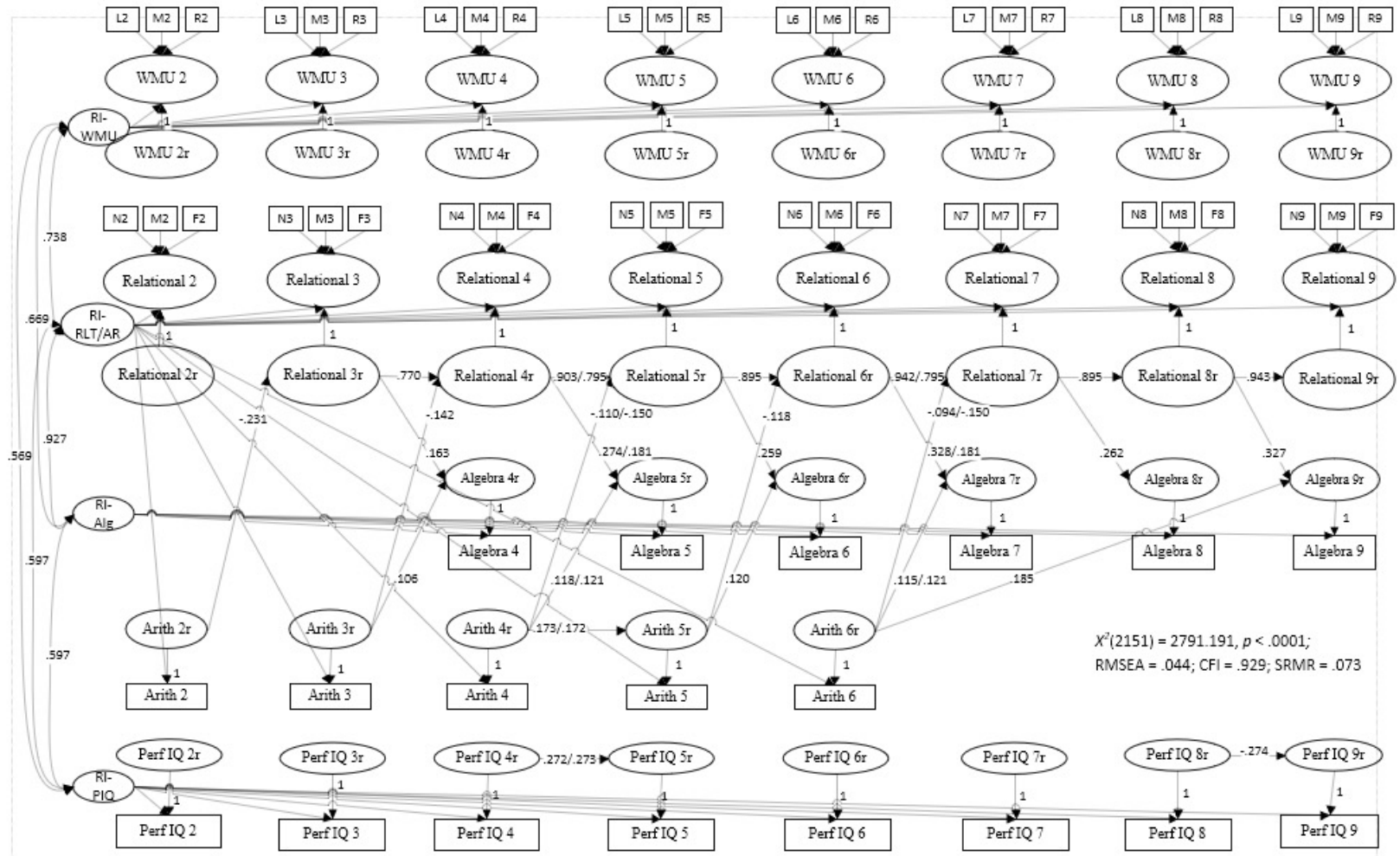


Figure 8. Final model results for artificial data set corresponding to a bivariate conditional latent curve model with structured residuals for five repeated measures. All numerical values are standardized and are significant at $p < .05$; regression coefficients for binary covariates are partially standardized; dashed lines are estimated but nonsignificant. Full results are in Table 1. *alc* = alcohol use; *dep* = depression; *gen* = gender; *tx* = treatment group.

MODEL RE-SPECIFIED



See Lee, Ng, & Bull (2018) Dev Psych



MODEL SPECIFICATION

MODEL:

!Specify latent measure

R1 BY NPpct1r FMpct1r (RM) FNpct1r (RN);

R2 BY NPpct2r FMpct2r (RM) FNpct2r (RN);

R3 BY NPpct3r FMpct3r (RM) FNpct3r (RN);

R4 BY NPpct4r FMpct4r (RM) FNpct4r (RN);

[NPpct1r - NPpct4r] (IP);

[FMpct1r - FMpct4r] (IM);

[FNpct1r - FNpct4r] (IN);

! Create Random intercepts/growth terms

i_r s_r | R1@0 R2@1 R3* R4*; i_r WITH s_r*;

! create "phantom factors" to define the time-specific residuals;

R1res BY R1@1;R2res BY R2@1;R3res BY R3@1;R4res BY R4@1;

!Estimate variance of phantoms

[R1-R4@0];R1-R4@0;[R1res-R4res@0];R1res;R2res-R4res (1);

!Specify AutoRegression between phantoms

R2res-R4res PON R1res-R3res;

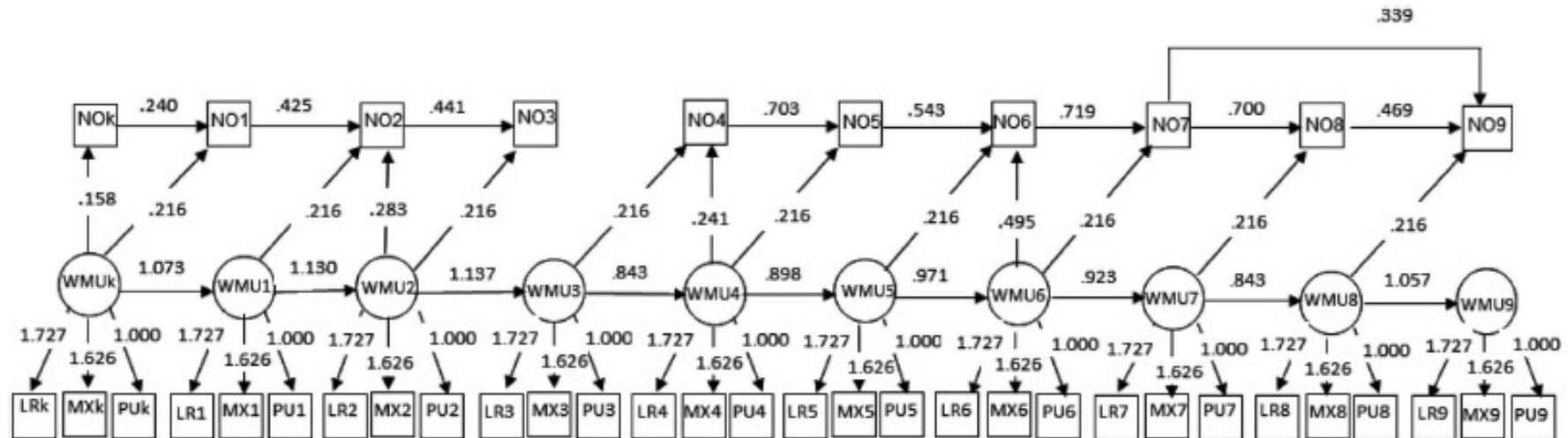
Developmental Changes in Working Memory, Updating, and Math Achievement

ACCELERATED DESIGN

Kerry Lee and Rebecca Bull
Nanyang Technological University

Children with higher working memory or updating (WMU) capacity perform better in math. What is less clear is whether and how this relation varies with grade. Children ($N = 673$, kindergarten to Grade 9) participated in a 4-year cross-sequential study. Data from 3 WMU (Listening Recall, Mr. X, and an updating task) and a standardized math task (Numerical Operations) showed strong cross-sectional correlations at each of the 10 grades, but particularly at Grades 1 and 2. Cross-lagged autoregressive analysis showed invariance in the predictive relations between WMU and subsequent math performance, but the importance of domain-specific knowledge increased with grade. Latent growth modeling showed that higher WMU capacity at kindergarten predicted higher math growth rates, averaged across all grades, but WMU growth rate was invariant across grades. Socioeconomic status, but not gender, explained variance in WMU at kindergarten. Implications for WM training are discussed.

Keywords: executive functioning, academic performance, working memory, updating, math





MODEL SPECIFICATION

VARIABLE:

USEVARIABLES ARE NORw1r NORw2r NORw3r NORw4r;

GROUPING =

level (0 = K2 2 = P2 4 = P4 6 = P6);

MODEL:

!Autoregression

NORw4r ON NORw3r;

NORw3r ON NORw2r;

NORw2r ON NORw1r;

Model K2:

NORw4r ON NORw3r (1); NORw3r ON NORw2r; NORw2r ON
NORw1r;

Model P2:

NORw4r ON NORw3r (5); NORw3r ON NORw2r; NORw2r ON
NORw1r (1);

Model P4:

NORw4r ON NORw3r (9); NORw3r ON NORw2r; NORw2r ON
NORw1r (5);

MODEL P6:

NORw4r ON NORw3r ; NORw3r ON NORw2r; NORw2r ON
NORw1r (9);

An abstract graphic consisting of several overlapping, irregular white polygons and lines on a black background. The shapes are interconnected, creating a complex, layered geometric pattern. The lines vary in length and orientation, some forming closed shapes while others are open or partially cut off by the edges of the frame.

SOME PRACTICAL
CONSIDERATIONS

ALTERNATIVES FOR CROSS-SECTIONAL DATA

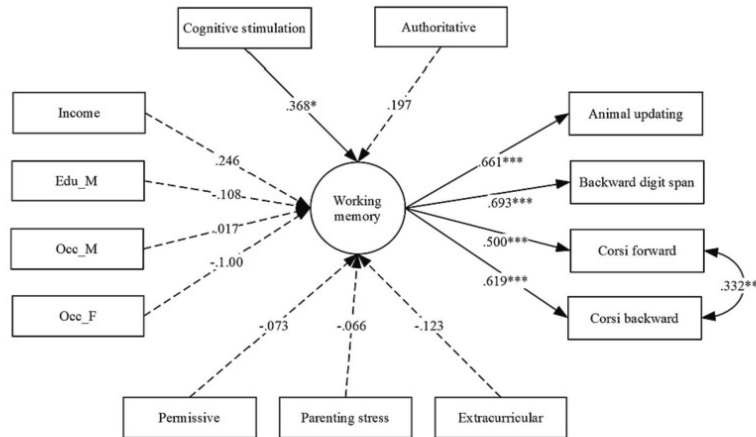


Fig. 3. The role of SES and parenting-related factors on WM.
 Note. Edu_M = mothers' education; Occ_M = mothers' occupation; Occ_F = fathers' occupation; Path coefficients refer to standardised values. Covariances between the explanatory variables were specified in the model but were not depicted here.

Socioeconomic status and parenting-related differences in preschoolers' working memory

Xiaozhi Gao^a, Kerry Lee^{b,*}, Kannika Permpoonputtana^{b,***}

^a Department of Early Childhood Education and Centre for Educational and Developmental Sciences, The Education University of Hong Kong, Hong Kong, China
^b National Institute for Child and Family Development, Mahidol University, Thailand

Table 3
 The moderating role of SES on parenting-related factors on WM.

Income			Edu_M		
Tested models	β	<i>p</i>	Tested models	β	<i>p</i>
Income	0.247	0.006	Edu_M	-0.095	0.450
Cognitive stimulation	0.340	0.001	Cognitive stimulation	0.368	0.013
Authoritative	0.086	0.415	Authoritative	0.209	0.136
Permissive	-0.015	0.878	Permissive	-0.048	0.661
Parenting stress	-0.018	0.860	Parenting stress	-0.106	0.331
Extracurricular	-0.098	0.376	Extracurricular	-0.055	0.622
Cognitive stimulation × income	-0.165	0.097	Cognitive stimulation × Edu_M	-0.012	0.910
Authoritative × income	0.019	0.829	Authoritative × Edu_M	-0.066	0.607
Permissive × income	0.021	0.795	Permissive × Edu_M	0.223	0.028
Parenting stress × income	-0.207	0.034	Parenting stress × Edu_M	-0.212	0.044
Extracurricular × income	0.026	0.750	Extracurricular × Edu_M	0.003	0.979

Occ_F			Occ_M		
Tested models	β	<i>p</i>	Tested models	β	<i>p</i>
Occ_F	0.072	0.617	Occ_M	0.074	0.517
Cognitive stimulation	0.306	0.029	Cognitive stimulation	0.282	0.043
Authoritative	0.171	0.215	Authoritative	0.149	0.174
Permissive	-0.043	0.707	Permissive	-0.059	0.578
Parenting stress	-0.055	0.620	Parenting stress	-0.099	0.364
Extracurricular	-0.072	0.540	Extracurricular	-0.026	0.810
Cognitive stimulation × Occ_F	-0.079	0.536	Cognitive stimulation × Occ_M	-0.267	0.043
Authoritative × Occ_F	-0.043	0.777	Authoritative × Occ_M	0.069	0.667
Permissive × Occ_F	0.090	0.451	Permissive × Occ_M	0.013	0.918
Parenting stress × Occ_F	-0.129	0.239	Parenting stress × Occ_M	-0.151	0.217
Extracurricular × Occ_F	0.059	0.529	Extracurricular × Occ_M	-0.031	0.732

Model fit of each interaction model						
Tested models	χ^2	df	<i>p</i>	CFI	<i>R</i> ²	RMSEA
Income as a moderator	42.848	34	0.142	0.958	0.320	0.040
Edu_M as a moderator	41.599	34	0.174	0.952	0.291	0.040
Occ_F as a moderator	44.940	34	0.099	0.922	0.237	0.049
Occ_M as a moderator	64.225	34	0.001	0.839	0.275	0.080
Parenting stress × Income constrained ¹	48.182	35	0.068	0.937	0.288	0.049
Permissive parenting × Edu_M constrained ¹	47.245	35	0.081	0.923	0.258	0.050
Parenting stress × Edu_M constrained ¹	45.902	35	0.103	0.931	0.258	0.047
Cognitive stimulation × Occ_M constrained ¹	69.363	35	0.001	0.817	0.246	0.084

Model comparison results				
Tested models (specified versus freed)	$\Delta\chi^2$	df	<i>p</i>	FDR adjusted <i>p</i>
Parenting stress × Income constrained	5.340	1	0.021	0.031
Permissive parenting × Edu_M constrained	5.646	1	0.017	0.031
Parenting stress × Edu_M constrained	4.303	1	0.038	0.038
Cognitive stimulation × Occ_M constrained	5.138	1	0.023	0.031

Note. ¹ The noted parameter was constrained to null. Edu_M = mothers' education; Edu_F = fathers' education; Occ_M = mothers' occupation; Occ_F = fathers' occupation; WM = working memory. FDR = False discovery rate adjusted using the Benjamini-Hochberg method.

RUNNING A MULTI-WAVE LONGITUDINAL STUDY

Funding and duration

- Typically expensive
- Estimate double the amount of time needed
- Consider accelerated, planned missing, intensive multiple time point designs if theoretically defensible

Forming and managing a team

- Admin support
- Small full time team supported by part-timers

Recruitment – keeping participants engaged

- Performance reports, briefings, compensation, address needs & benefits



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