Colloquium Talk Presented in the Centre of Methods and Policy Application in the Social Sciences (COMPASS) University of Auckland, March 1, 2019

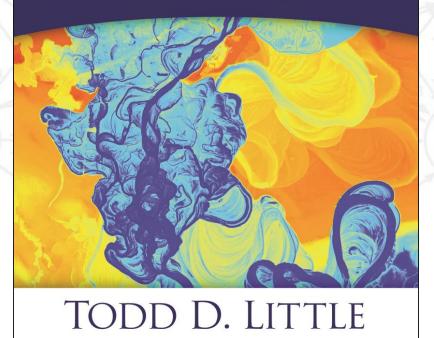
Modeling Ecological and Contextual Effects in the Social Sciences

Todd D. Little Founder and co-Director, IMMAP Director & Founder, Stats Camp (Statscamp.org)





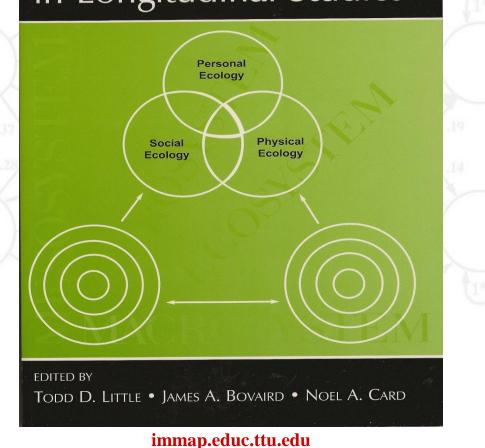
Longitudinal Structural Equation Modeling



Context



Modeling Contextual Effects in Longitudinal Studies



Context



The circumstances in which an event occurs; a setting.

- The set of features that influences the performance or the outcome of a process
- The conditions that are relevant to an event, fact, etc.
 - From contextus a putting together
 - From contexere to interweave, braid
 - circumstances, times, conditions, situation, ambience, frame of reference, background, framework, relation, connection
- Ecology
 - The relationship between organisms and their environment.

Context



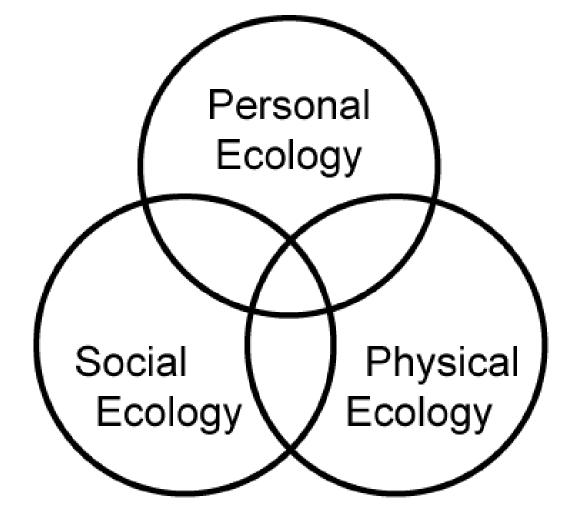


Figure 2.5. Overlapping Ecologies of Human Development

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Social Ecology



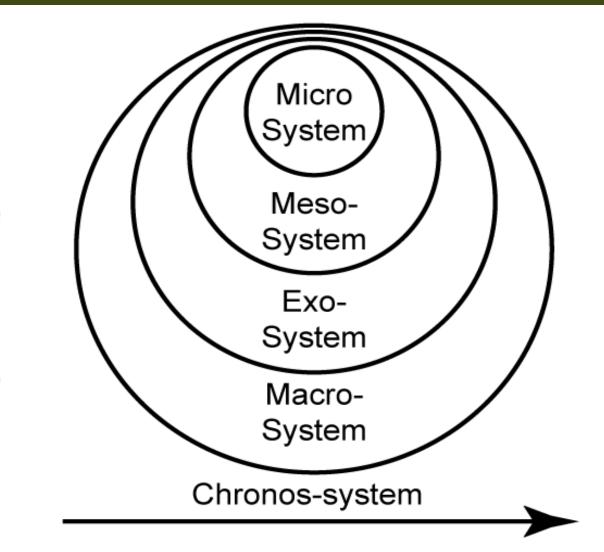


Figure 2.6. Bronfrenbrenner's hierarchy of the Social Ecology immap.educ.ttu.edu

Physical Ecology



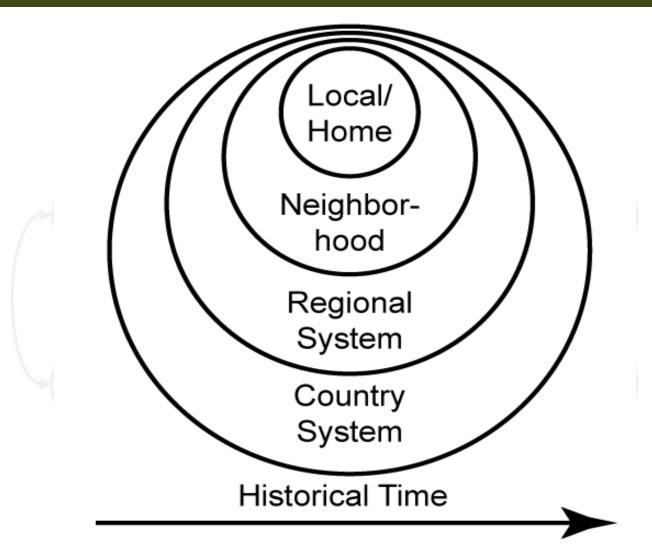


Figure 2.7. Widaman's hierarchy of the Physical Ecology immap.educ.ttu.edu

Personal Ecology



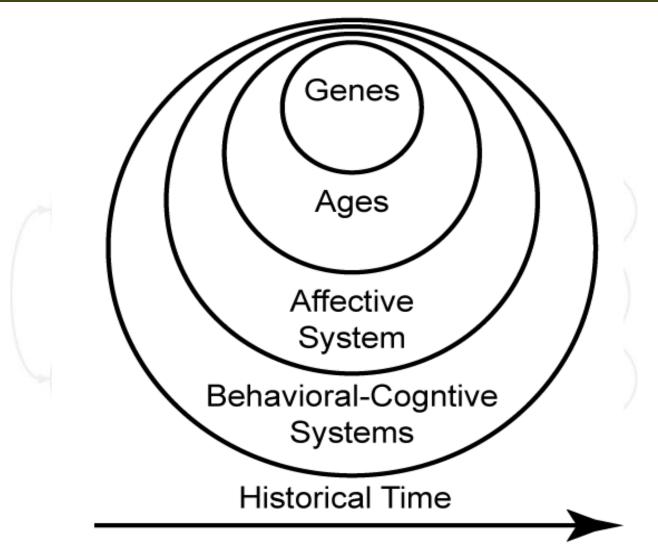


Figure 2.8. Little's hierarchy of the Personal Ecology immap.educ.ttu.edu

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offuences the individual directly

- Varies at the level of the individual and influences the individual directly
 Indirect (mediated) effects
 - X varies at the level of the individual and influences the individual through its effect on an intervening variable, M
- **Mediating effects**
- Distal context influences proximal context which influences the individual Moderating effects
 - Interactive influences that change the strength of any of the above effects
 - Discrete vs. Continuous
- **Reciprocal effects and feedback loops**
 - Cross-time associations that can express as indirect, mediated/mediating, or moderated/moderating.
- **Hierarchically nested effects**
 - Larger units of context that can have direct, indirect, mediating, or moderating effects or be mediated and or moderated.

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Contexts as Statistical Relationships

Direct effects

Context and Measurement

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"Whatever exists at all exists in some amount. To know it thoroughly involves knowing its quantity as well as its quality"E. L. Thorndike (1918)

We should measure persons and contexts well

- Measures should be appropriate for the construct
 - Contexts should be quantified (borrow from sociology, for example)
 - Developmental measures should address change
 - The tragic legacy of test-retest reliability
- Measures and analyses should not be haphazard
 - Avoid: "Hey, this new method is cool, let's try it on this data?"
 - Question -> Measurement -> Statistical Model
 - Avoid short forms of existing scales (use intentionally missing design)

 ('allure of the bloated specific' idea)
 - Develop or modify to make sure the measurement tool is right
 - Take time to refine and pilot measures (even well-established ones). immap.educ.ttu.edu

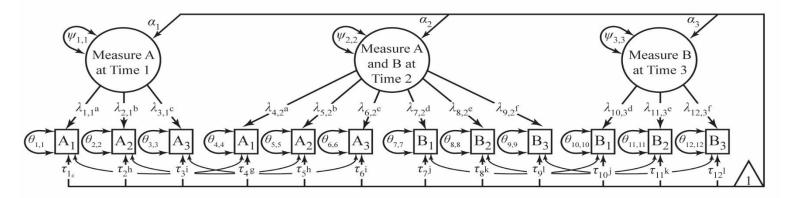
Context of Measurement



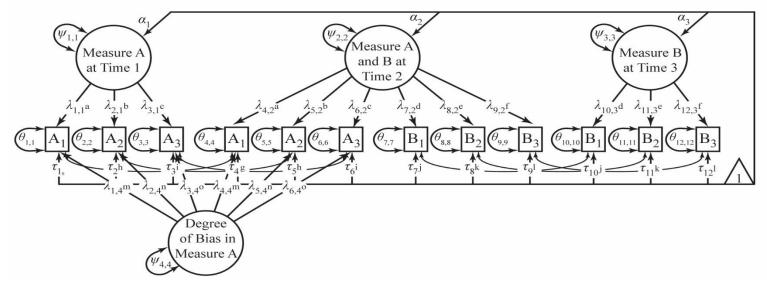
- Homotypic vs. heterotypic expressions across ages
 - e.g., Aggression
- **Surface (proximal) structure vs. deep (ultimate) structure of behavior**
- e.g., helping as resource-directed behavior
 Typological (subgroups) differences
- Identification issues and procedures
 - Muthen's m-Plus, Nagin's Proc Traj, Bergman's Sleipner
- n-adic (dyadic, triadic, etc.) overlay on all of the various modeling approaches
 - e.g., SRM, APIM, Siena



A) Establishing comparability of different measures of the same construct over time: No bias



B) Establishing comparability of different measures of the same construct over time: Bias corrected



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Context of Change



Interindividual differences vs. Intraindividal differences

Ergodicity conundrum

Associations (within and between time)

- Covariances and Correlations vs. Regressions
- Direct and Indirect effects
 - Auto-regressive vs. Cross-lagged
 - 1st-order vs. higher-order
- Linear vs. non-linear
- **Means and Variances**
- **Mediation vs. Moderation vs. Additive Effects**
- B = f(age) vs. $\Delta = f(time)$

Appropriate Time and Intervals

- Age in years, months, days.
- **Experiential time: Amount of time something is experienced**
 - Years of schooling, length of relationship, amount of practice
- Calibrate on beginning of event, measure time experienced
 Episodic time: Time of onset of a life event
 - Toilet trained, driver license, puberty, birth of child, retirement
 - Early onset, on-time, late onset: used to classify or calibrate.
 - Time since onset or time from normative or expected occurrence.
- **Measurement Intervals (rate and span)**
 - How fast is the developmental process?
 - Intervals must be equal to or less than expected processes of change
 - Measurement occasions must span the expected period of change
 - Cyclical processes
 - E.g., schooling studies at yearly intervals vs. half-year intervals

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Transforming to Episodic Time

$\begin{bmatrix} -\psi_{A'} + \theta_{A'} - B' & -B' \\ -\psi_{A'} + \theta_{A'} - B' & -A' \\ -\psi_{A'} + \theta_{A'} - B' & -A' \\ -\psi_{A'} + \theta_{A'} - \theta_{A'} \end{bmatrix}$
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	Dat	a Coll	ection V	Vave Cr	ossed v	with Ep	pisode O	ccuran	ce		
Pattern	Wav	e1 V	Wave 2	Wave	3 Wa	we 4	Wave 5	Wave	6		
Pattern 1	Р)	P + 1	P+2	2 P	9 + 3	P+4	P +	5		
Pattern 2	Р-	1	Р	P + 1	l P	+2	P+3	P +	4		
Pattern 3	Р-	2	P - 1	Р	Р	$^{2} + 1$	P+2	P +	3		
Pattern 4	Р-	3	P - 2	P - 1	l	Р	P + 1	P +	2		
Pattern 5	Р-	4	P - 3	P - 2	2 1	? - 1	Р	P +	1		
Pattern 6	Р-	5	P - 4	P - 3	3 1	P - 2	P - 1	Р	,		
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	P - 5	P - 4	P - 3	P - 2	P - 1	Р	P + 1	P+2	P+3	P+4	P + 5
Pattern 1						W1	W2	W3	W4	W5	W6
Pattern 2					W1	W2	W3	W4	W5	W6	
Pattern 3				W1	W2	W3	W4	W5	W6		
Pattern 4			W1	W2	W3	W4	W5	W6			
Pattern 5		W1	W2	W3	W4	W5	W6				
Pattern 6	W1	W2	W3	W4	W5	W6					

Transforming to Accelerated Longitudinal



	Age i	n years;m	onths for	each coh	ort at	each	asses	smen	t									
Age/Cohort	-	4 Mos	8 Mos	12 Mos		Mos		Mos										
Age 11 yrs	11;0	11;4	11;8	12;0	1	12;4	1	2;8										
Age 12 yrs	12;0	12;4	12;8	13;0	1	13;4	1	3;8										
Age 13 yrs	13;0	13;4	13;8	14;0	1	14;4	1	4;8										
Age 14 yrs	14;0	14;4	14;8	15;0	1	15;4	1	5;8										
Age 15 yrs	15;0	15;4	15;8	16;0	1	16;4	1	6;8										
Age 16 yrs	16;0	16;4	16;8	17;0	1	17;4	1	7;8										
					F	ull sp	oan of	the a	ges co	overed	d							
	11;0 11;4	11;8 12;0) 12;4 12	2;8 13;0	13;4	13;8	14;0	14;4	14;8	15;0	15;4	15;8	16;0	16;4	16;8	17;0	17;4	17;8
Age 11 yrs	W1 W2	W3 W4	W5 W	/6														
Age 12 yrs		W1	W2 W	/3 W4	W5	W6												
Age 13 yrs				W1	W2	W3	W4	W5	W6									
Age 14 yrs							W1	W2	W3	W4	W5	W6						
Age 15 yrs										W1	W2	W3	W4	W5	W6			
Age 16 yrs													W1	W2	W3	W4	W5	W6

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Validity Threats in Longitudinal Work



Threats to Validity

Maturation

- In pre-post experiment effects may be due to maturation not the treatment
- Most longitudinal studies, maturation is the focus.
- Regression to the mean
 - Only applicable with measurement error
- Instrumentation effects (factorial invariance)
- Test-retest effects (ugh)
- Selection Effects
 - Sample Selectivity vs. Selective Attrition

Age, Cohort, and Time of Measurement are confounded

Sequential designs attempt to unconfound these.

The Sequential Designs

Cohort (Birth Time of Measurement	Time of Measurement							
Year) 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008	3 2009 202	10						
∞ 1975 21 22 23 24 25 26 27 28 29 30 31 32 33	34 35	5						
5 1975 21 22 23 24 25 26 27 28 29 30 31 32 33 5 1976 20 21 22 23 24 25 26 27 28 29 30 31 32 33	33 34	4						
$\frac{1977}{51978}$ $\frac{19}{18}$ $\frac{20}{19}$ $\frac{21}{20}$ $\frac{22}{21}$ $\frac{22}{21}$ $C_{20}h_{20}$ rt_{4}^{5} Sequential $\frac{30}{29}$ $\frac{31}{30}$	32 33	3						
$\frac{1}{5}$ 1978 18 19 20 21 20 21 20 24 025 4 025 4 20 30	31 32	2						
(5) 1979 17 18 19 20 21 22 23 24 25 26 27 28 29	30 3	1						
1980 16 17 18 19 20 21 22 23 24 25 26 27 28	29 30	_						
1981 15 $17 18 19 20 21 22 23 24 25 26 27$	28 29	9						
1982 14 14 14 14 18 19 20 21 22 23 24 25 26	27 28	8						
1983 13 14 15 16 17 18 19 20 21 22 23 24 25	26 27							
1984 1Sequential ⁶ 1 7 18 19 20 21 22 23 24	25 20	6						
1985 [1] 124 13 14 15 16 17 $\mathbf{P}_{\mathbf{M}} d^{9}_{\mathbf{M}} a^{2}_{\mathbf{M}} \mathbf{C}_{\mathbf{M}} d^{2}_{\mathbf{M}} \mathbf{A}^{2}_{\mathbf{M}} \mathbf{A}^{2}_{\mathbf{M}}$	a^{23}							
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2 1986 10 11 12 13 14 15 16 UT I USSTOCULUTINA 1987 9 10 11 12 13 14 15 16 17 18 19 20 21	22 23							
	21 22	2						
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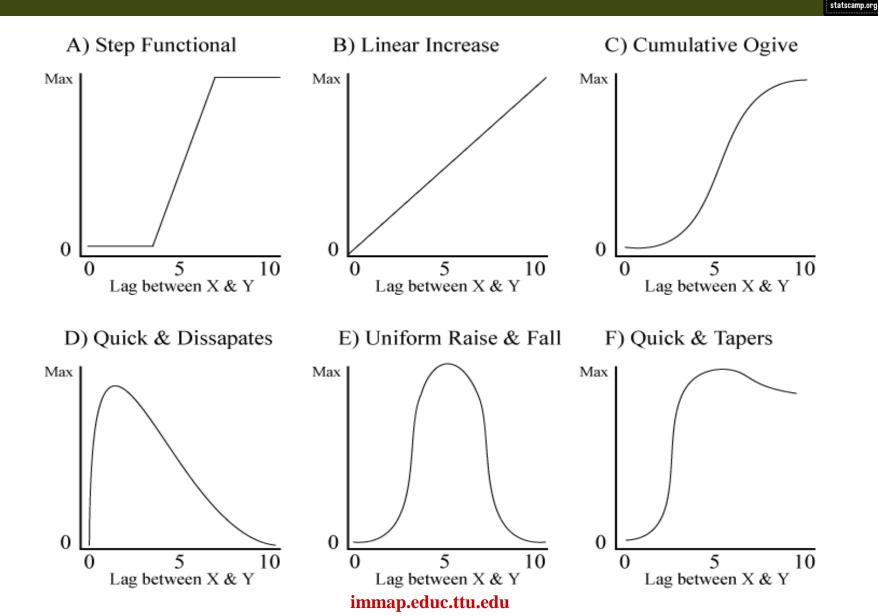
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- **Changes (and causes) take time to Unfold**
- The ability to detect the effect depends on the measurement interval
- The ability to model the shape of the effect requires adequate sampling of time intervals.
- The ability to model the optimal effect requires knowing the shape in order to pick the optimal (peak) interval.
- Lag within Occasion: the Lag as Moderator Model

Types of Change Effects



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Lag as Moderator (LAM) Models

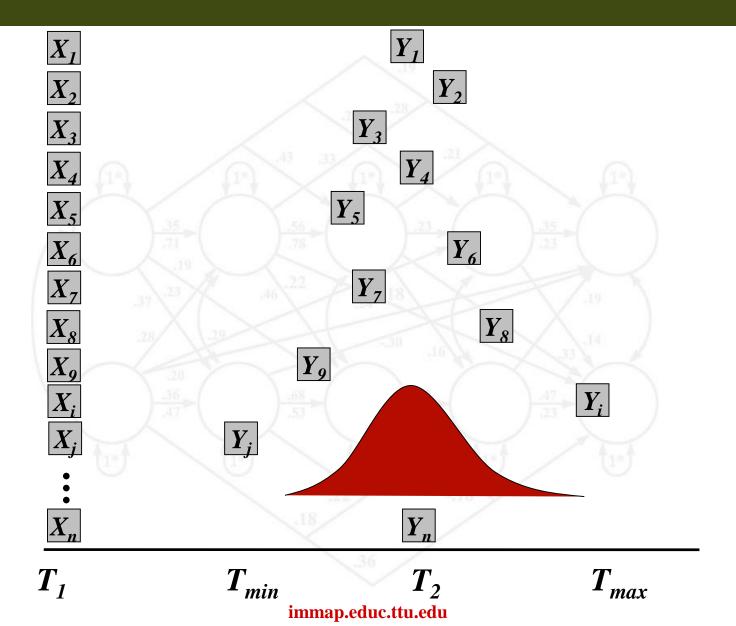


One possible way to address the issue of lag choice is to treat lag as a moderator

Following this approach lag is treated as a continuous variable that can vary across individuals

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Variable Actual Assessments



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$$\hat{Y}_{i} = b_{0} + b_{1}X_{i} + b_{2}Lag_{i} + b_{3}X_{i} \times Lag_{i}$$

- X_i is the focal predictor of outcome Y_i
- Lag_i can vary across persons
- b_1 describes the effect of X_i on Y_i when Lag_i is zero
- b_2 describes the effect of Lag_i on Y_i when X_i is zero
- b_3 describes change in the $X_i \to Y_i$ relationship as a function of Lag_i

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Data are from the Early Head Start (EHS) Research and Evaluation study (N = 1,823)

Data were collected at Time 1 when the focal children were approximately 14 months of age and again at Time 2 when the children were approximately 24 months of age

The average lag between Time 1 and Time 2 observations was 10.3 months with values ranging from 3.0 to 17.3 months

Measures:

- The Home Observation for the Measurement of the Environment (HOME) assessed the quality of stimulation in the home at Time 1.
- The Mental Development Index (MDI) from the Bayley Scales of Infant Development measured developmental status of children at Time 2.

HOME predicting MDI

 $MDI_{T2} = b_o + b_1 HOME_{T1} + b_2 Lag + b_3 (HOME_{T1} x Lag)$



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Implications of LAM Models

Lag is embraced

•LAM models allow us to model, not ignore, interactions
Selecting Lag is critical

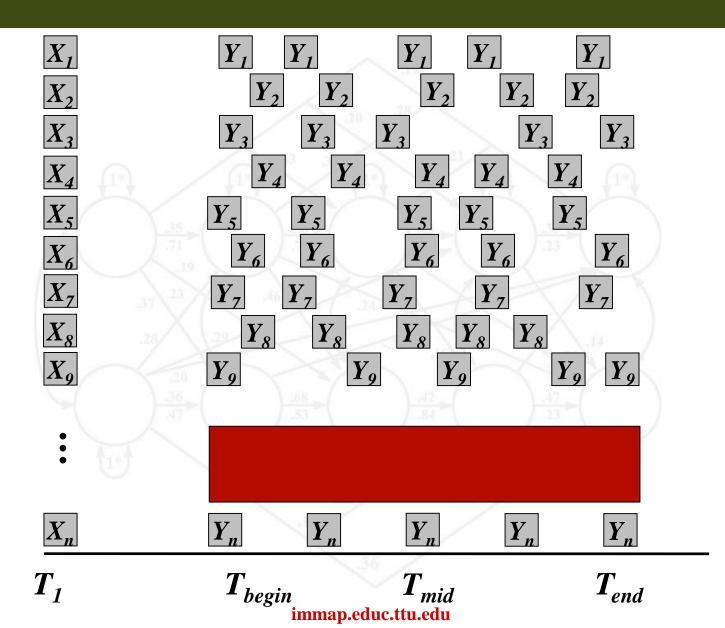
Sampling only a single lag may limit generalizability
 Theory Building

LAM models may yield a better understanding of relationships and richer theory regarding those relationships

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Randomly Distributed Assessment





Multilevel Structures



- Observations at one level are nested within observations at another and so on.
- Number of levels theoretically limitless, bounded by practicality (and software).
 - Random sampling at each level.
- Multilevel vs. multiple-group structures
- Lowest level observations are *not* independent—possible biases in parameter estimates, standard errors, and test of model fit.
 - Goal is to model *both* within- and between-cluster relationship.
- Examples:
 - Students within classrooms
 - Times of measurement within persons



- Finding meaning in the massively multivariate world
 - Open system versus closed system
 - Verisimilitude versus Causality
 - Justification and Social Justice
- Optimizing the relations between theory and data
 - Having a dialog between theory and data
 - I am the driver, data are my co-pilot
 - Never let data get in the way of good theory
 - Never let theory get in the way of good data
 - Data are my focus group

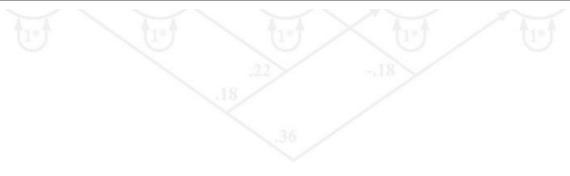
Characteristics of Good Models

Evaluation

Kommensuration



I DO SEEK	DEPICT	LEAP
Intuition	Describe	Logical and internally consistent
— ·	Explain	Empirically testable (falsifiable)
Design	Predict	Accounts for extant findings
Operationalization	Improve	Parsimonious (sufficient
S pecification	Change	verisimilitude)
Estimation	Test	



Wesearch Instead of Mesearch



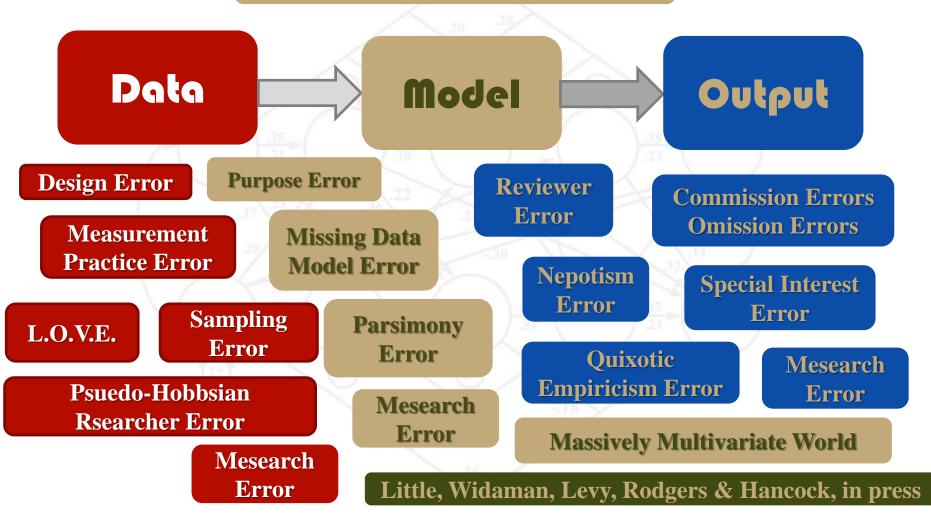
The Ubiquity of Errors



GIGO, FUDSI, P-Hacking, Harking, Larking, >50 Shades of Grey, SOL



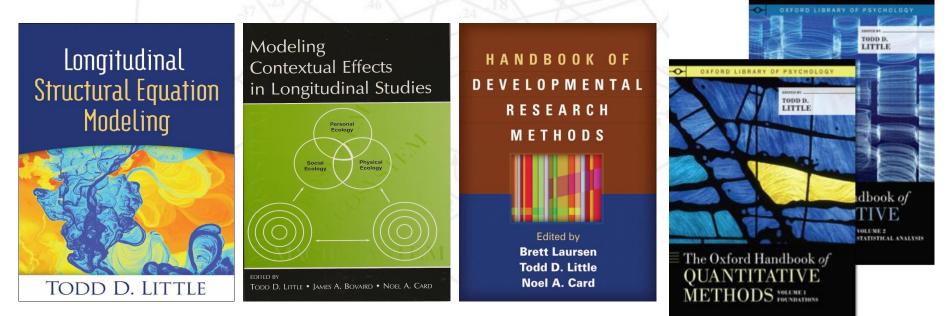
Error Types I, II, III, IV, S, M ... ?



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Design and Measurement Issues

- STATS CAMP
- Not all "advances" in developmental research are analysis based: we need to (re)start with the basics!
- The Ubiquity of Error
- Measurement, Measurement, Measurement
- My sources, each of which highlights design and measurement:



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(re) focus on Measurement

- Rethink Likert scales
 - Our great-great-great-great academic progenitors used them!
- Take advantage of touch screen technology and software
 - Using "rulers" and "sliders" is now easy and efficient
- Develop measures/procedures that are sensitive to change
 - Retrospective Pretest Posttest Design
 - Direct change Assessment

"Whatever exists at all exists in some amount. To know it thoroughly involves knowing its quantity as well as its quality"

- E. L. Thorndike (1918)

I am curious about science.

Strongly Disagree

Before the program

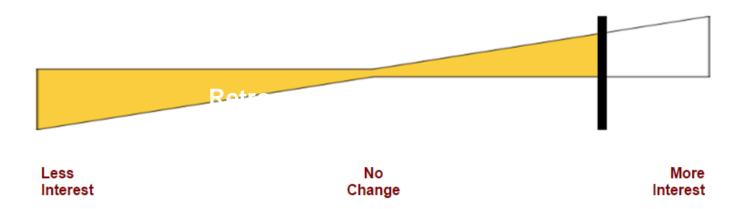
At this time





Visual Analog Scaling

I am curious about technology.



Preview Link – Qualtrics

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Recommended readings



Little, T.D. (2013). Longitudinal Structural Equation Modeling. New York, NY: Guilford Press

Duh.

Card, N. A., & Little, T. D. (2007). Longitudinal modeling of developmental processes. *International Journal of Behavioral Development*, *31*, *297-302*

 Introduction to special issue, but first part identifies basic issues in longitudinal modeling and then points you to the innovations covered in the special issue.
 Little, T. D., Card, N. A., Preacher, K. J., & McConnell, E. (2009). Modeling

longitudinal data from research on adolescence. In R. Lerner & L. Steinberg (Eds.)., Handbook of Adolescent Psychology (4th Ed., pp 15-54). Wiley.

Provides a broad summary of the three classes of techniques
 Card, N. A., Little, T. D., & Bovaird, J. A. (2007). Modeling ecological and contextual effects in longitudinal studies of human development. In T. D. Little, J. A., Bovaird, & N. A. Card (Eds.), *Modeling contextual effects in longitudinal studies* (pp. 1-11). Mahwah, NJ: LEA

Introduction to our book that points you to a lot of really great chapters covering many of these issues in detail

Recommended readings



- Little, T. D., Widaman, K. F., Levy, R., Rodgers, J. L., & Handcock,G. R. (in press). Error, error, in my model, who's the fairest ofthem all. *Research on Human Development*.
- Little, T. D., Gorrall, B. K., Panko, P. & Jacob D. Curtis, J. D. (in press). Modern practices to improve human developmental research. *Research on Human Development*.
- Little, T. D. (2017). Methodological considerations for research on ethnopolitical violence. *Development and Psychopathology*, 29, 71-77.
- Little, T. D. (2015). Methodological practice as matters of justice, justification, and the pursuit of verisimilitude. *Research in Human Development*, *12*, 268-273.