On the Many "Claims" and Applications of the Latent Variable

Science is an attempt to exploit this contact between our minds and the world, and science is also motivated by the limitations that result from our relations to the world; we need science because much of the world is not accessible to ordinary **observation**. Science works by taking theoretical ideas and trying to find ways **to expose them to observation**. The scientific strategy is to construe ideas, to embed them in surrounding conceptual frameworks, and to develop them, in such a way that this exposure is possible even in the case of the most general and ambitious hypotheses about the universe. (Godfrey-Smith, 2003, p. 161)

Godfrey-Smith, P. (2003). *Theory and reality. An introduction to the philosophy of science*. Chicago: The University of Chicago Press.

Thinking about the Latent Variable from Three Perspectives

- Mathematical model (e.g., SEM, MLM, IRT)
- Theoretical model
  - Classical test theory (i.e., true-score, reliability)
  - Psychological concepts (e.g., g-intelligence, traits)
  - Construct validity – nomological (stochastological*) networks
- Philosophical connections
  - Levels/units of analysis
    - Particles, molecules, cells, organ tissues, brain/nervous system, cognition, personality, social interaction, and culture.
  - Empiricism/positivism, operationalism, naturalism, realism

Kinds of Mathematical Latent Variables

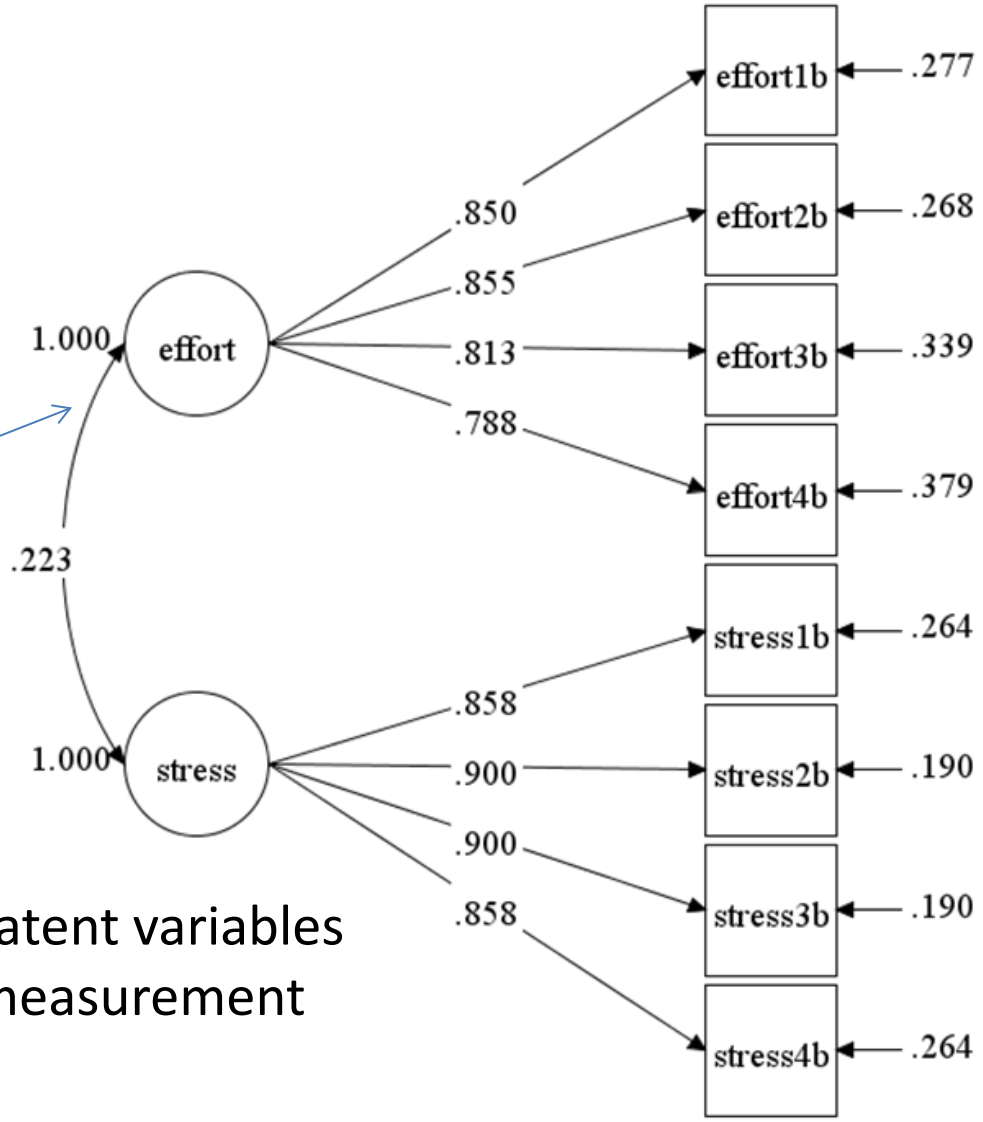
1. Principal component (not a latent variable)
2. Common factor model
3. Reflective measurement
4. Formative measurement
5. Various SEM (higher-order, bi-factor, MTMM)
6. Latent-class and latent profile analysis
7. IRT
8. Latent variables in longitudinal data (e.g., change)
9. Latent variables in MLM (random and contextual variables)
10. Network analysis of personality (Borsboom et al.)

Common Factor Model

$$\hat{\rho}_{X_i X_i} = \frac{\left(\sum \hat{\lambda}_i\right)^2 \hat{\phi}}{\left(\sum \hat{\lambda}_i\right)^2 \hat{\phi} + \sum \hat{\theta}_{ii}}$$

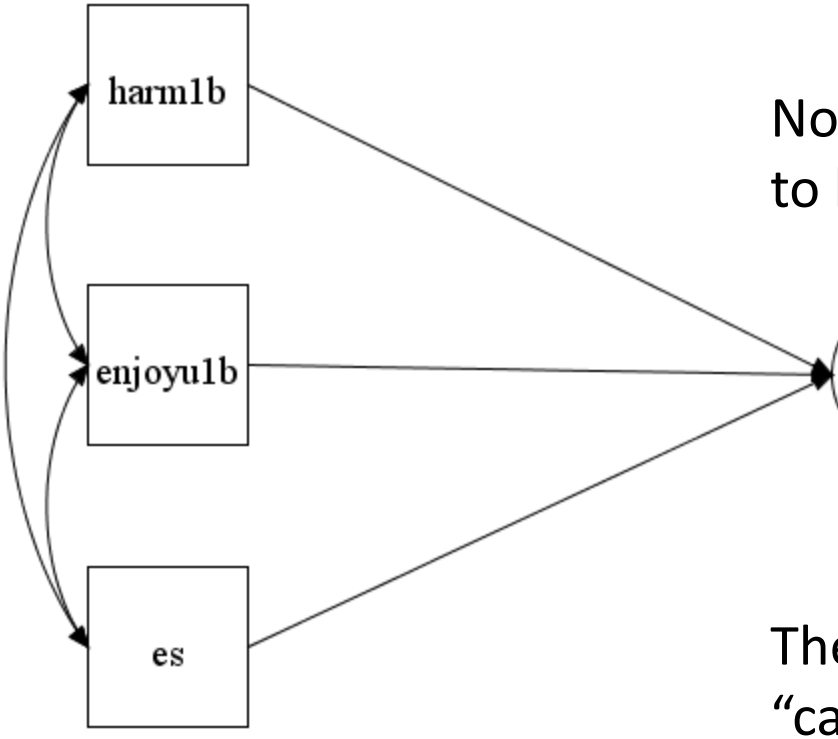
In Kline (Raykov, 1997, 2004)

Reliability of Effort = .896



Note arrows going from latent variables to indicators: Reflective measurement with effect indicators

Formative Measurement



Note arrows going from indicators to latent variable

Residual ($1 - R^2$)

These indicators are referred to as "causal indicators"

Bollen, K. A., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. Psychological Bulletin, 110, 305–314.

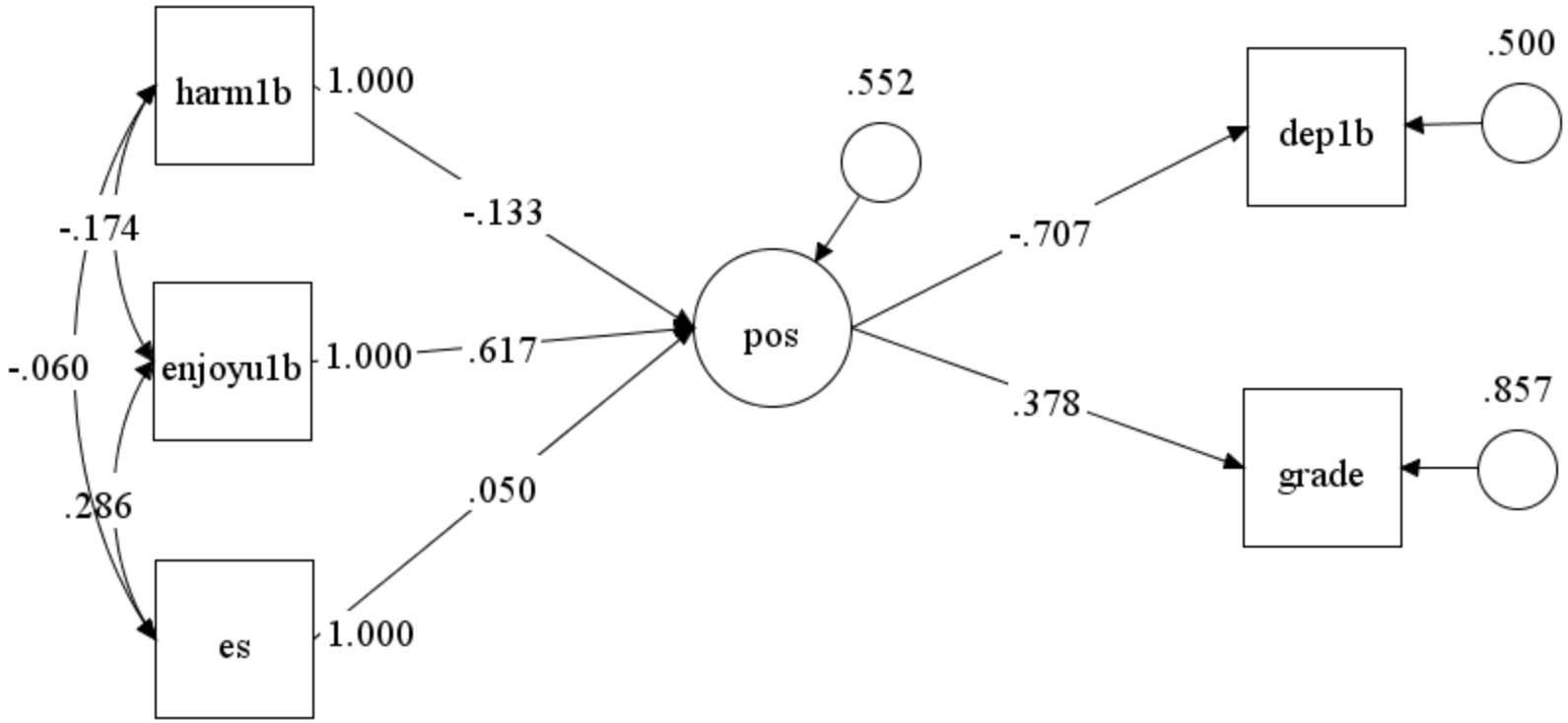
Other Examples of LVs with Causal Indicators

1. Social Interaction
   - Time spent with family, with friends, with coworkers
2. Quality of Life
   - Health, happiness, economic status
3. SES
   - Education, income, occupational prestige
4. Exposure to discrimination
   - Race, sex, age, disabilities
5. Stress
   - Job loss, divorce, death in family, injury

Deciding to Use Formative Measurement

- Causal indicators not necessarily correlated with other indicators (implications for CTT and Cronbach's alpha)
- Effect/reflective indicator can be deleted without changing meaning of LV, removing a causal indicator can change meaning
- Imagine a shift in the latent variable: does it lead to a shift in all indicators? (if yes, then effect/reflective indicators)
- Alternatively, a shift if one causal indicator would lead to a shift in the latent variable
- Vanishing Tetrad test (Bollen)

Formative Measurement



$\chi^2_{(2)} = 6.638$, $p < .05$, RMSEA = .083, CFI = .960

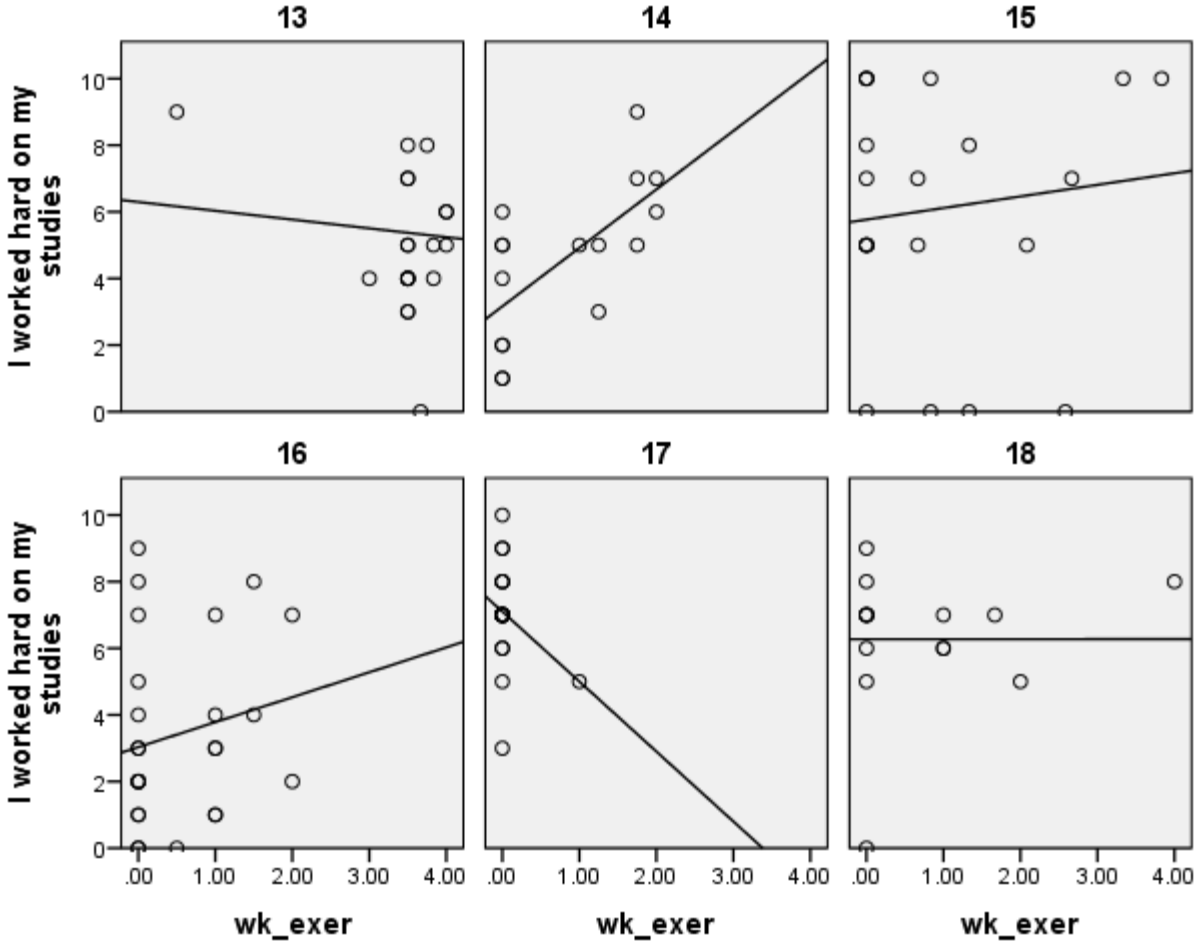
Formative Measurement

STDYX Standardization

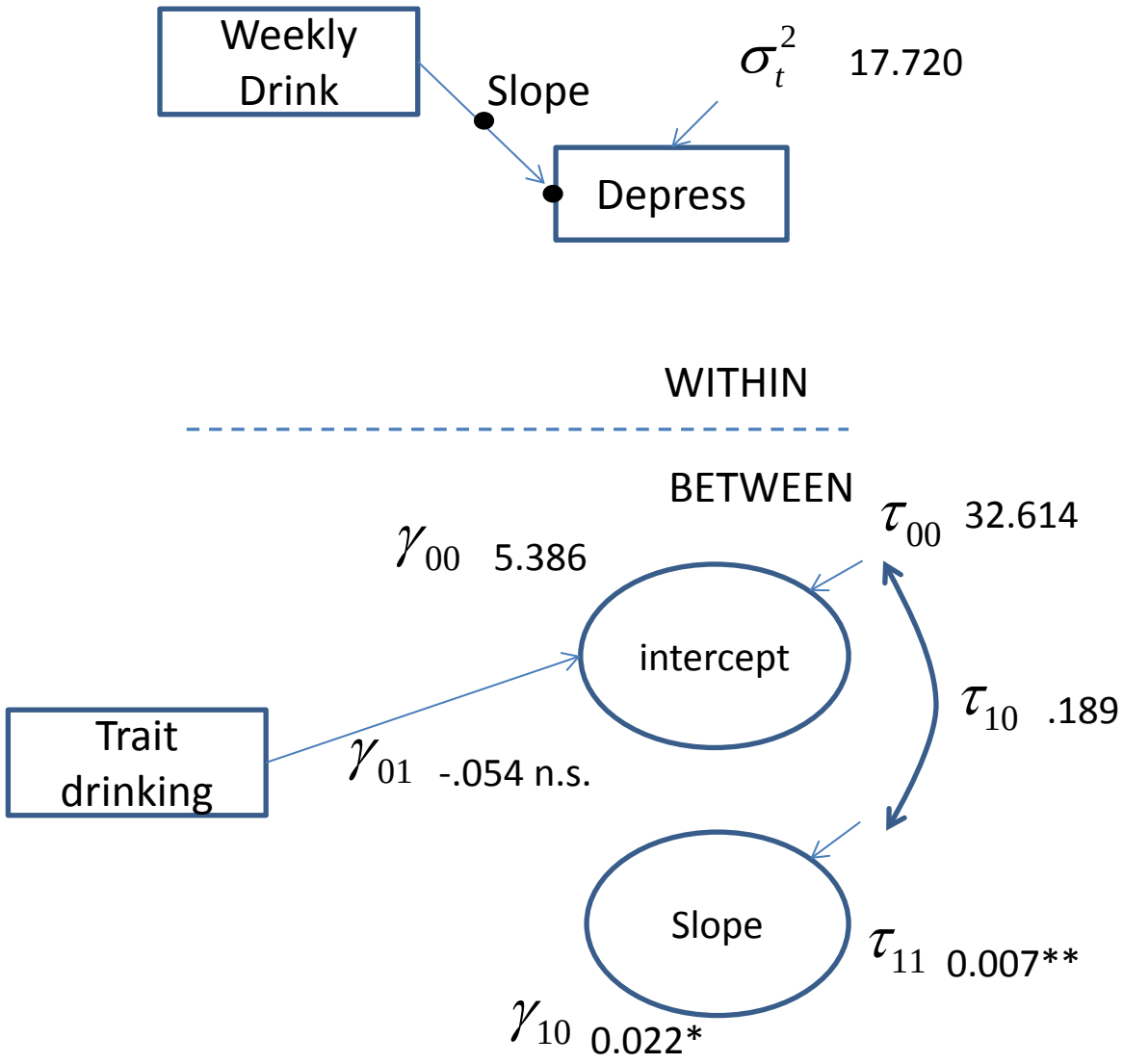
	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
POS BY				
GRADE	0.378	0.062	6.056	0.000
DEP1B	-0.707	0.082	-8.670	0.000
POS ON				
ES	0.050	0.070	0.719	0.472
ENJOYU1B	0.617	0.085	7.292	0.000
HARM1B	-0.133	0.066	-2.009	0.045
ES WITH				
ENJOYU1B	0.286	0.050	5.679	0.000
HARM1B	-0.060	0.055	-1.092	0.275
ENJOYU1B WITH				
HARM1B	-0.174	0.053	-3.282	0.001

MLM of Diary Data – SEM Approach

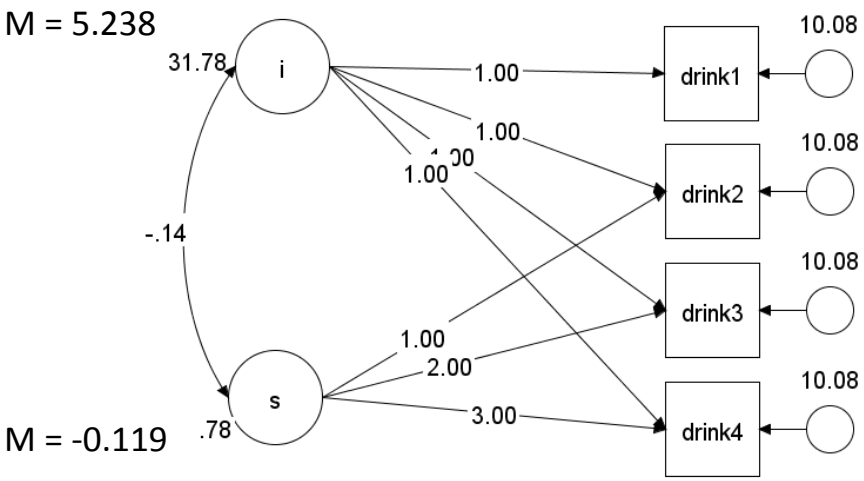
Notice the variation in the intercepts and the slopes

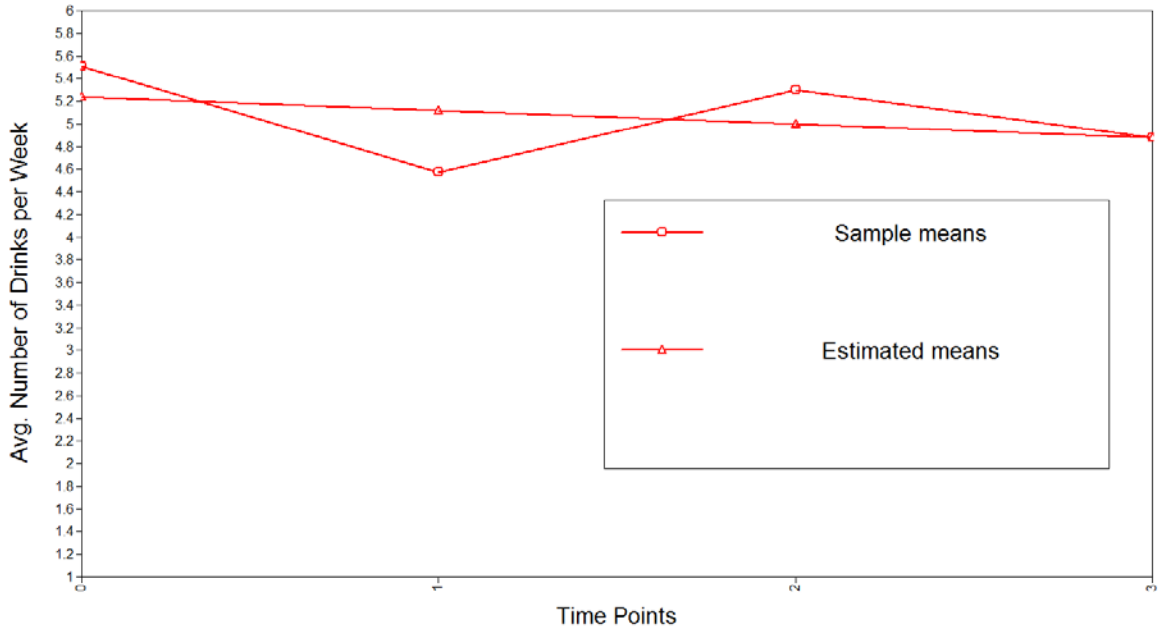


MLM of Diary Data – SEM Approach



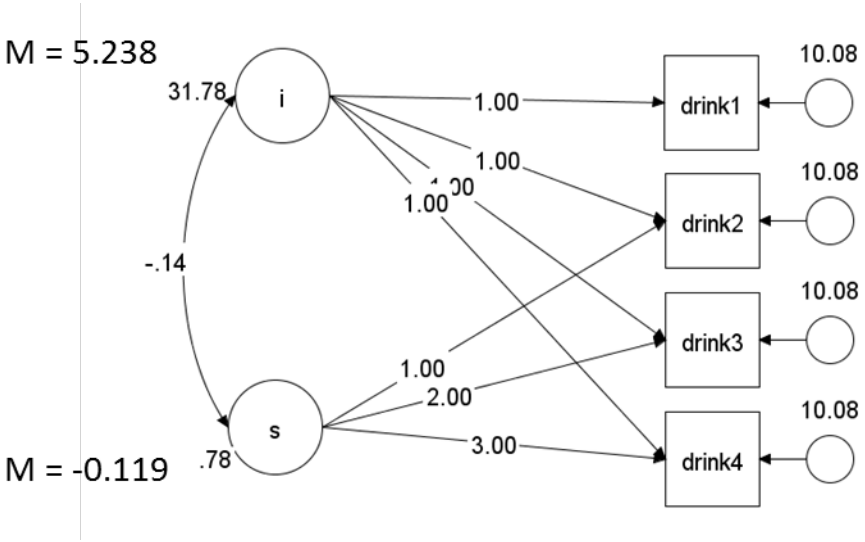
Latent Growth Modeling



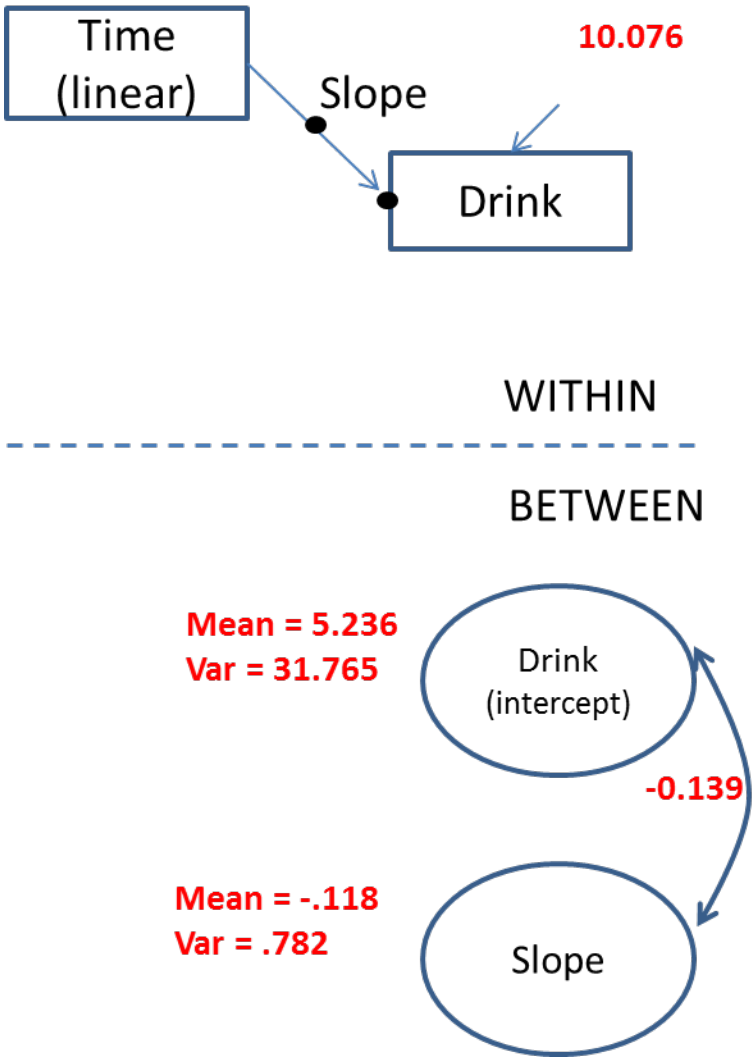


LGM vs. MLM of Longitudinal Data

LGM



MLM



Principal Components Analysis

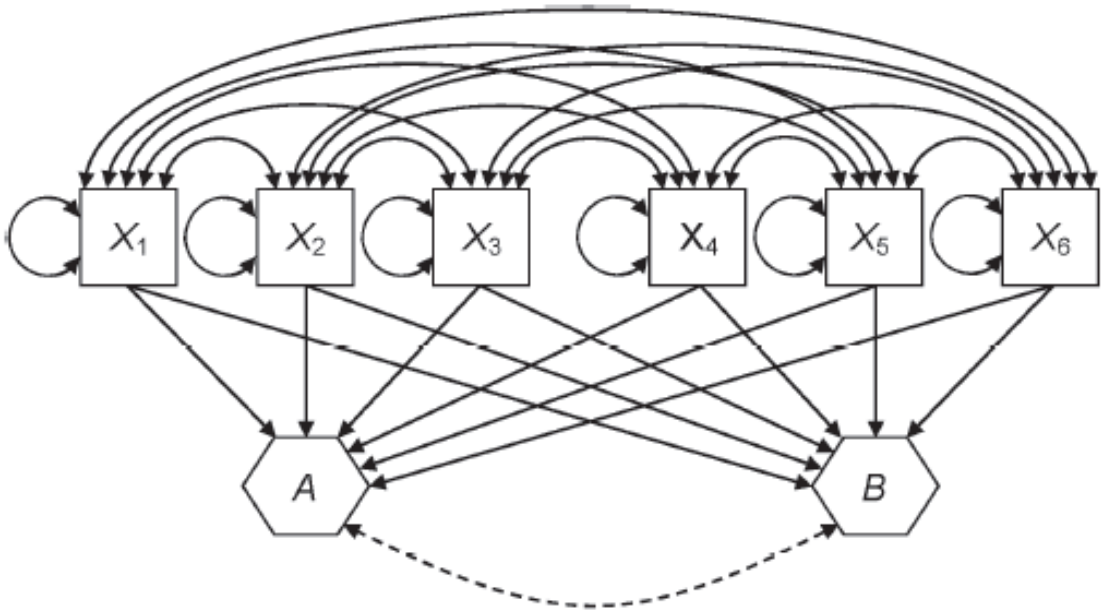


Figure 6.3 Conceptual representation of principal components analysis for 6 indicators and 2 composites (components).

Kline, R. B. (2013). Exploratory and confirmatory factor analysis. In Y. Petscher & C. Schatsschneider (Eds.), Applied quantitative analysis in the social sciences (pp. 171-207). New York: Routledge. (Chap. 6, print proof)