

Quantitative Data Analysis II

SOC 781

SEM brief overview

Today we will...

- SEM brief overview

Why SEM?

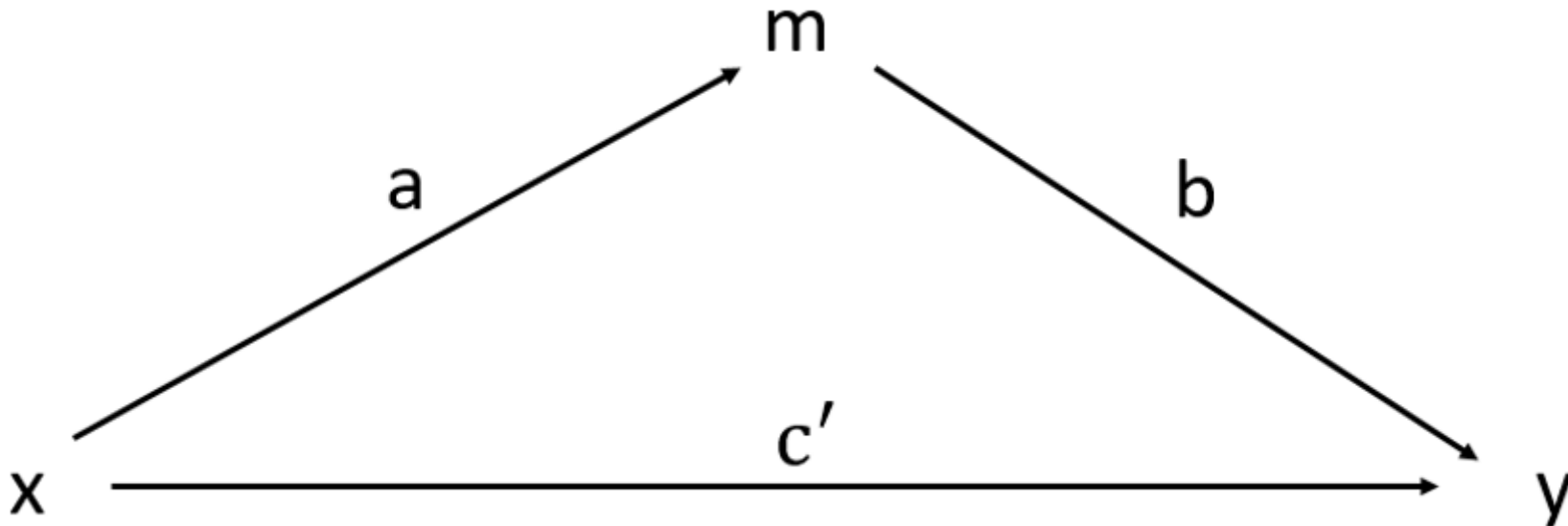
- Enables more complex RQs
 - can handle multiple outcomes (i.e., multivariate modeling)
 - compensates for measurement error in variables
- Four common SEM techniques
 - path analysis
 - confirmatory factor analysis
 - latent variable structural model
 - growth curve

SEM basics

- Relies on covariance matrices
 - matrix algebra
- MANY assumptions
 - model specific
- MANY parameters
 - heavily technical

Path analysis

- Recall mediation techniques for LRM
 - Barron-Kenny approach
 - outdated and limited to continuous outcomes
- m is a mediator because it lies “in the path” from x to y



Path analysis

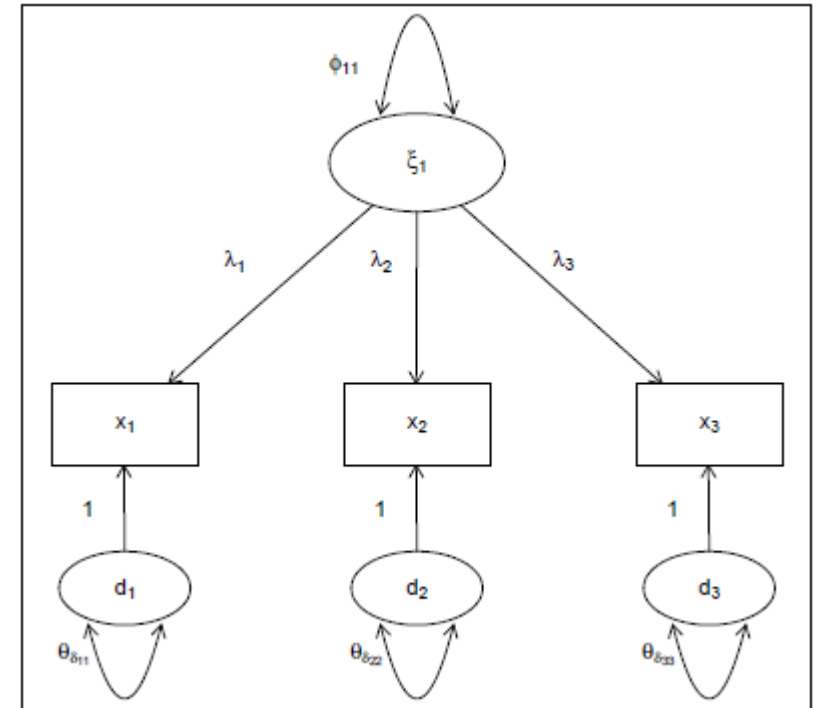
- Requires decomposition of total effect of x on y
 - direct and indirect effects through m
- Sobel's method assume normality of sampling distribution
 - typically, not met with samples < 1000
- Bigger problems with BK approach
 - countervailing mediators and confounders
 - sometimes dealt with using [bootstrapping](#)
- Path analysis can overcome these limitations
 - because SEMs...

Structural Equation Models

- Use observed variables, x and y , as measures of
 - latent variables ξ and η
- ξ are latent exogenous variables
- η are latent endogenous variables
- Measurement models link x and y to ξ and η
- Theory used to “structure” un/constrained parameters
 - with their own sets of assumptions, but
 - less restrictive than univariate model or sequential univariate models
 - kind of like mlogit vs sequential blrm models

Measurement Models

- Not only useful for addressing error biases
 - also, for reliability: precise/consistent
 - and, for validity: do items measure what is intended?
- latent variable (“factor”)
 - inter-item correlation between variables
 - shared variance of a set of variables



Factor Analysis

- Exploratory Factor Analysis (EFA)
 - (1) limiting number of factors to extract, (2) rotation method (orthogonal/oblique), (3) allowing items to load on limited number of factors
- Confirmatory Factor Analysis (CFA)
 - derived from theory
 - pre-specified and tested
- EFA-CFA
 - more of a continuum vs dichotomy

Factor Analysis

- Reliability (ideally $R^2 > 0.75$)
 - function of all arrows to x , not just from one factor
- Validity: only possible with multiple items
 - similarity/clusters in standardized loadings
 - distinct clusters suggest distinct factors

Single vs multigroup analysis

- Traditional regression limited to...
 - interaction terms or stratified models
 - limitations: group parameters or ignored shared error variance
- SEM allows
 - all parameters to be freely estimated within each group
 - enables significant difference test

Latent Class Analysis vs Growth Curve Modeling

- LCA and GCM both used to model patterns over time (longitudinal)
 - LCA also used for different purposes (e.g., latent profile analysis)
 - special case of SEM for categorical outcomes
- GCM and HLM approaches are equivalent
 - SEM is multivariate and more flexible but with costs
- LCA and GCM can be combined in same model
 - lots of different (hybridized and extended) approaches

CFA example: domain satisfaction

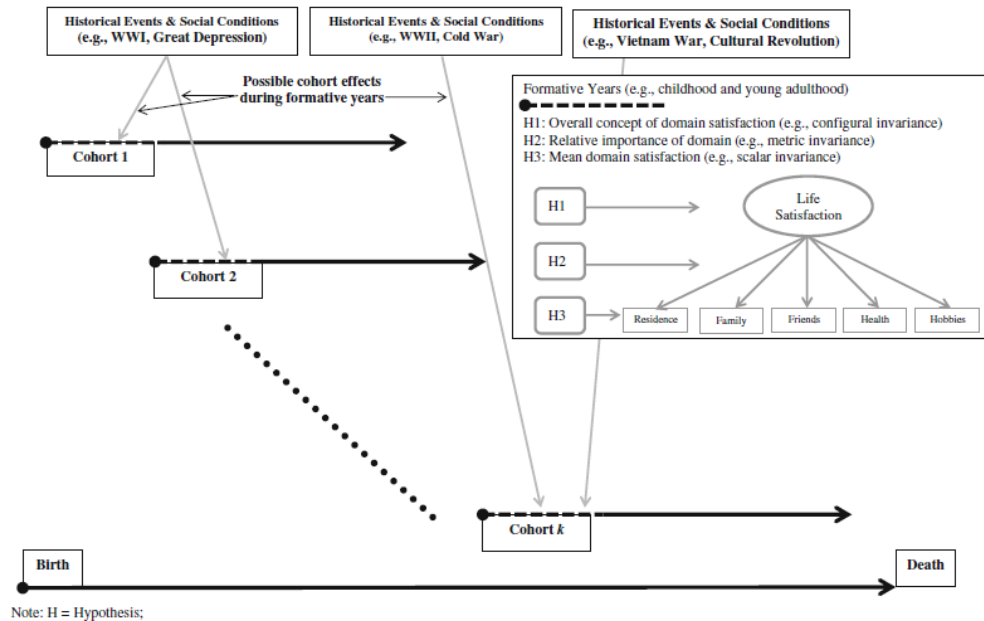


Fig. 1 Simplified life course model of possible cohort effects on domain satisfaction through life experiences during formative years

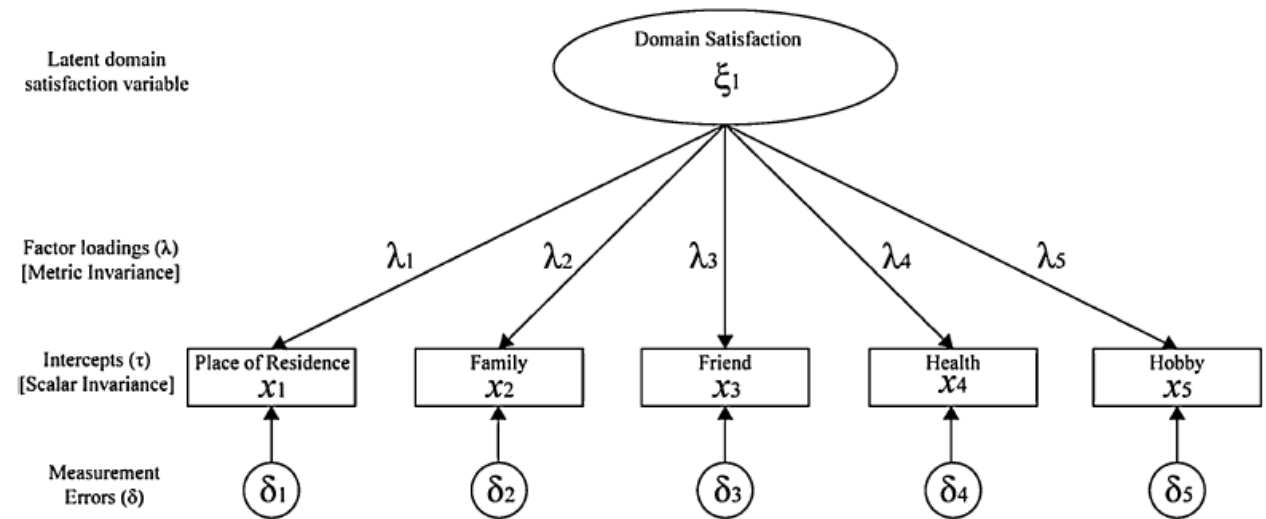
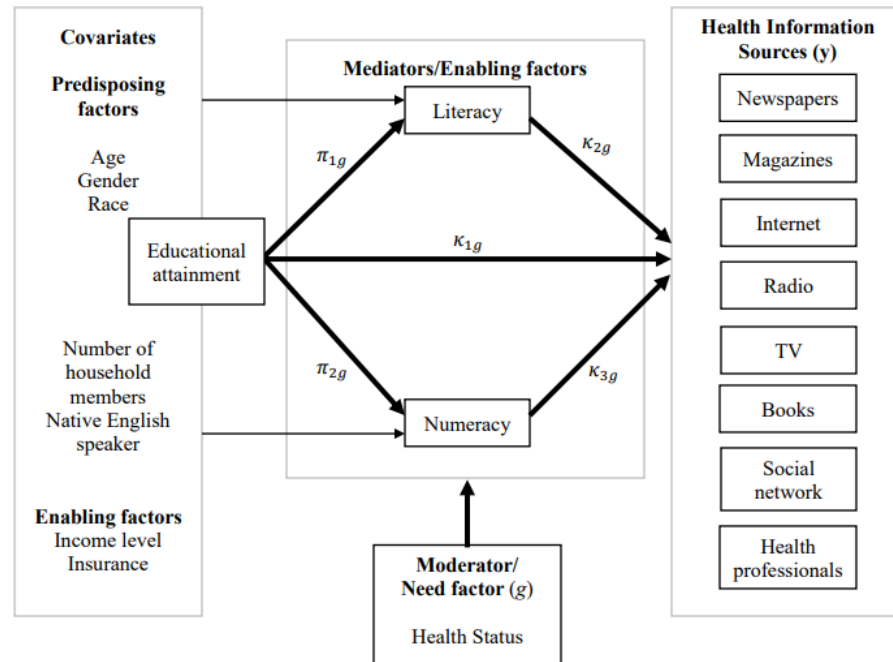


Fig. 2 One factor measurement model of domain satisfaction with five quality of life domain indicators

Multi-group Path Analyses: moderated mediation

Figure 2: Simplified Path Diagram of the Final Model



Note: Straight line = regression paths; bold lines indicate research questions; all variables in each box with gray lines were allowed to be correlated. For the notation (i.e., Greek letters), see the methods section; (g) groups indicator (fair/poor health vs. good or better health)

Table 3a: Estimated Coefficients from Path Models with a Probit Link Function

Fair/Poor health group			Good or better health group		
Education	Literacy ID = 0.590	Newspapers	Education	Literacy ID = 0.401*	Newspapers
	0.065			0.184*	
Education	Numeracy ID = -0.601	Newspapers	Education	Numeracy ID = -0.479*	Newspapers
	0.757*			0.722*	
		-0.791			-0.663*
Education	Literacy ID = 1.187*	Magazines	Education	Literacy ID = 0.954*	Magazines
	0.036			0.170	
Education	Numeracy ID = -1.082*	Magazines	Education	Numeracy ID = -0.980*	Magazines
	0.757*			0.722*	
		-1.426*			-1.357*
Education	Literacy ID = 0.648	Internet	Education	Literacy ID = 0.744*	Internet
	0.802*			0.516*	
Education	Numeracy ID = -0.240	Internet	Education	Numeracy ID = -0.547*	Internet
	0.757*			0.722*	
		-0.316			-0.757*
Education	Literacy ID = -0.084	Radio	Education	Literacy ID = -0.160	Radio
	0.039			0.181*	
Education	Numeracy ID = 0.037	Radio	Education	Numeracy ID = 0.062	Radio
	0.757*			0.722*	
		0.048			0.086

* $p < 0.05$; ID = indirect/mediation effect; solid line indicates statistical significance; gray line indicates non-significance; all models were adjusted for covariates, and correlations between literacy and numeracy

Growth Curve Analyses: latent trajectories



Social Science & Medicine 66 (2008) 849–861



Trajectories of functional health: The ‘long arm’ of childhood health and socioeconomic factors[☆]

Steven Haas*

Arizona State University, School of Social and Family Dynamics, P.O. Box 873701, Tempe, AZ 85287-3701, USA

Available online 26 December 2007

Table 2
Model fit indices and curve parameters for unconditional latent growth curves of functional limitations under various functional forms (HRS 1994–2002)

	Model fit indices				Growth curve parameters					
	X^2 (df)	BIC	CFI	RMSEA	Intercept		Linear term ^a		Quadratic term	
					Mean	Variance	Mean	Variance	Mean	Variance
Linear model	464.89 (14)	331.67	0.99	0.06	1.87	5.00	0.07	0.04	—	—
Freely-estimated model	407.74 (11)	305.42	0.99	0.06	1.90	5.00	0.59	2.27	—	—
Quadratic model	114.62 (10)	21.60	1.00	0.03	1.92	4.83	0.02	0.14	0.01	0.00

Notes: $BIC = X^2 - (\ln(N) \times df)$.
All models assume constant error variances.
^a for freely estimated model this represents the total change over the period rather than a linear slope.

Latent Class Analyses: finite-mixture models

Life Course Pathways of Economic Hardship and Mobility and Midlife Trajectories of Health

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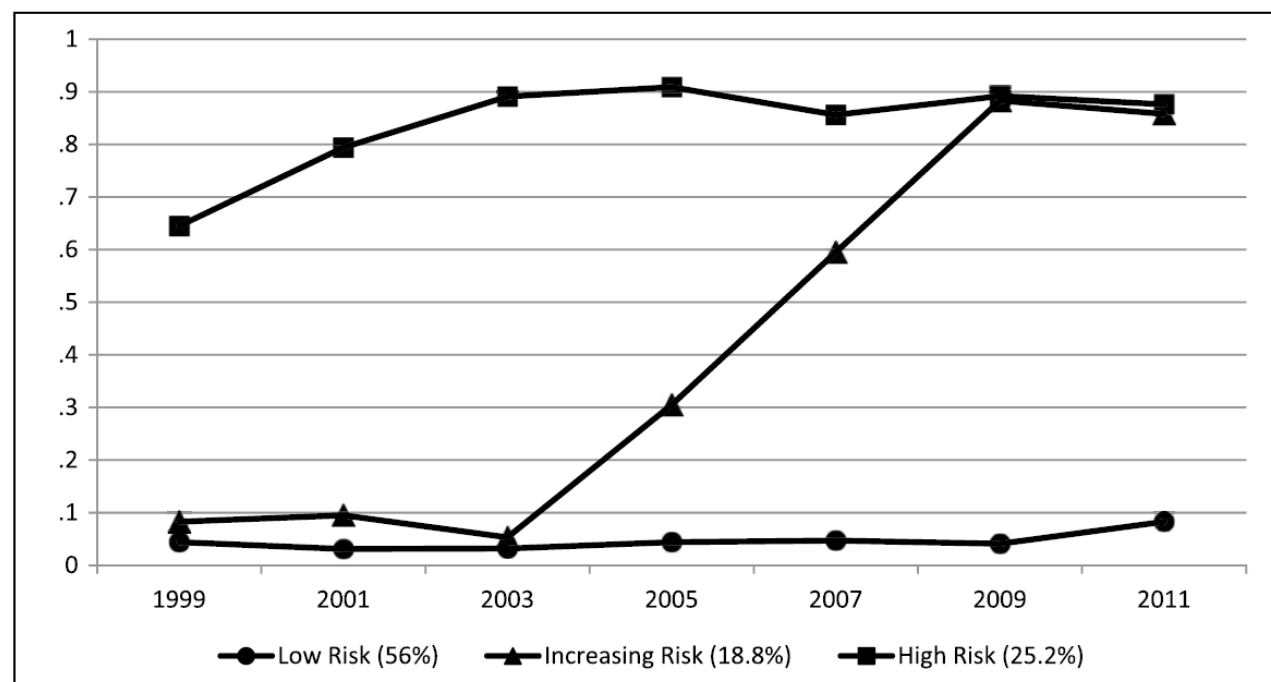


Figure 2. Item-response Probabilities for a Three-class Longitudinal Latent Class Model of Health Risk Trajectories, by Class and Year (Panel Study of Income Dynamics, 1999–2011).

Hybridized and Extended: [survival analyses](#)

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doi:10.1093/geront/gns164

Body Mass Trajectories and Mortality Among Older Adults: A Joint Growth Mixture–Discrete-Time Survival Analysis

Anna Zajacova, PhD^{1,*} and Jennifer Ailshire, PhD^{2,3}

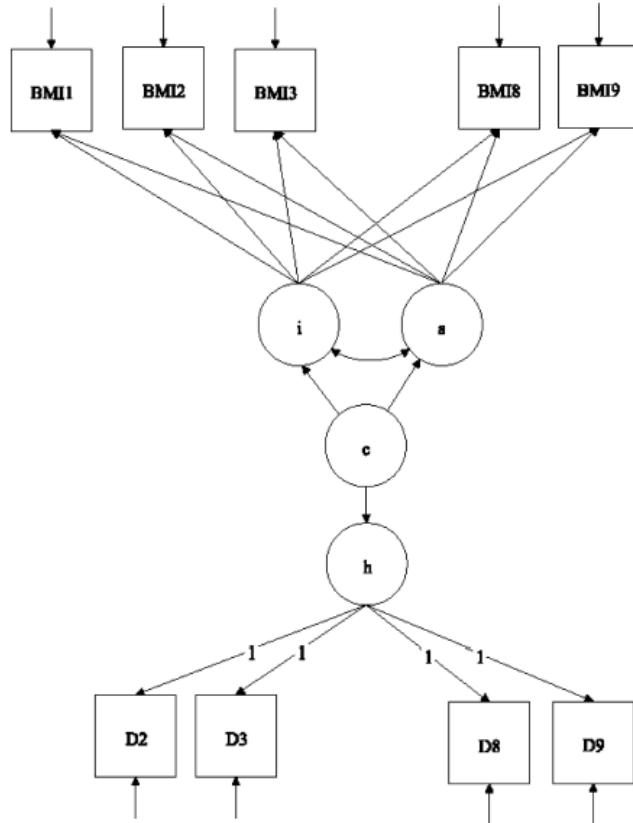
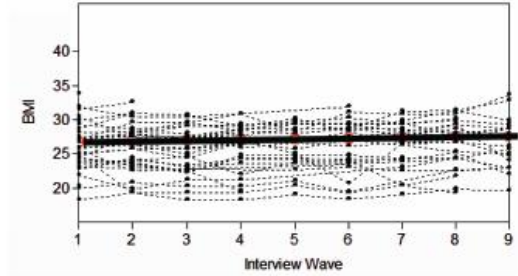
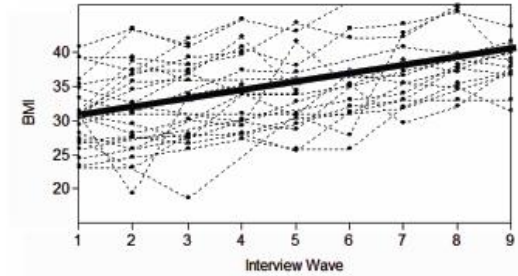


Figure 1. Schematic diagram of the joint growth mixture–discrete-time survival model. Note: BMI1–BMI9 are the observed BMI values; D2–D9 are vital status indicators, coded 0 if the respondent was alive through the end of a given time interval, 1 if the respondent died in the time interval, and missing if the respondent died previously or attrited. The means of the latent growth factors for the BMI trajectories, i and s , are allowed to vary across the trajectory classes, c . The mortality hazard h is modeled as a function of the class membership via a logistic regression model.

Panel A. Stable overweight class (92.9%)



Panel B. Obese gaining class (2.8%)



Panel C. Obese losing class (4.3%)

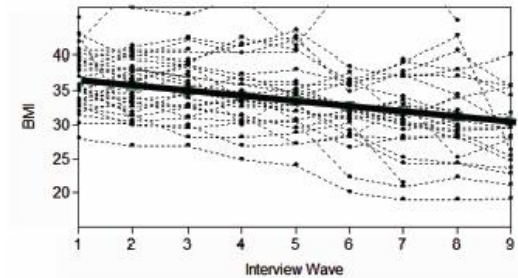


Figure 2. Three classes of BMI trajectories for men—estimated trajectory for each class and a random sample of observed individual trajectories. Panel A: Stable overweight class (92.9%); Panel B: Obese gaining class (2.8%); Panel C: Obese losing class (4.3%). Note: Results for women are visually nearly indistinguishable. The estimated sample trajectories and sample proportions for both genders are summarized in Figure 3.

Methods in Gerontology

Section Editors: *Anthony R. Bardo* and
Kenneth Carl Land

Age-Period-Cohort Models

Big Data

Cross-Sectional and Longitudinal Studies

Dyad/Triad Studies

Ethnography

Experimental Studies and Observational Studies

False Negative/False Positive

Hierarchical Models

Item Response Theory and Modeling

Latent Class Analysis

Life Course Perspective

Likert Scale

Missing Data Concepts

Mobile Data Collection with Smartphones

Narrative Analysis

Qualitative Research/Quantitative Research

Recruitment and Retention in Aging Research

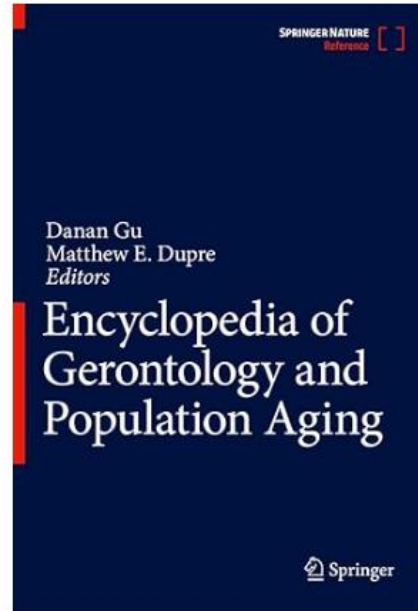
Repeated Cross-Sectional Design

Selective Bias in Longitudinal Studies

Semiparametric Methods

Structural Equation Models

Survival Analysis



- Focus on where your RQs rest
 - can't master all
 - but be broadly familiar
- Collaborate when needed
 - network outside expertise
- Published \neq right
 - refer to solid sources and multiple examples
 - see reference lists in resources I provided
- SEM has huge scope
 - [Ken Bollen](#) and [Shawn Bauldry](#) for sociology
 - can get easily lost in psychometric literature