

Joint Modeling of Longitudinal Multivariate Outcomes

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Evidence for Understanding Aging in Systems of Variables

Levels of analysis (from populations to an individual)

1. Inter-Cohort Differences

- Aggregate effects of broad contextual differences in same age / different birth cohort groups

2. Population mean trends

- Aggregate BP (or WP) age trends

3. Between-person differences in age

- Factor and regression decomposition models

4. Correlation of between-person differences in within-person rates of change

- Multivariate growth curve models

5. Correlated within-person variability

- Correlations among SD within-person

6. Coupled within-person processes

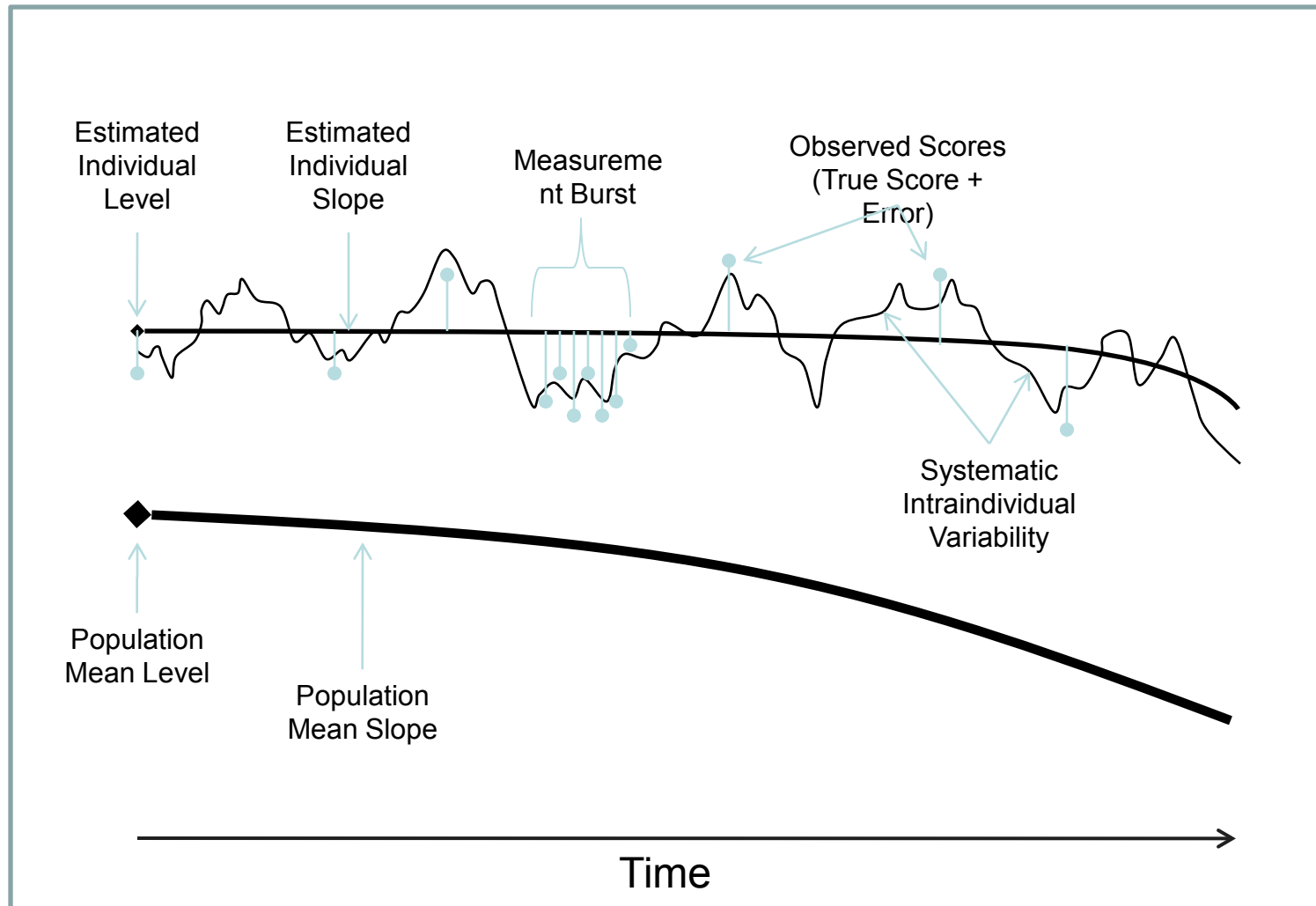
- Within-person correlation, dynamic factor analysis

Note. Available time-scale often decreases across these levels of analysis

Hierarchy of Evidence for Understanding Developmental and Aging-Related Processes

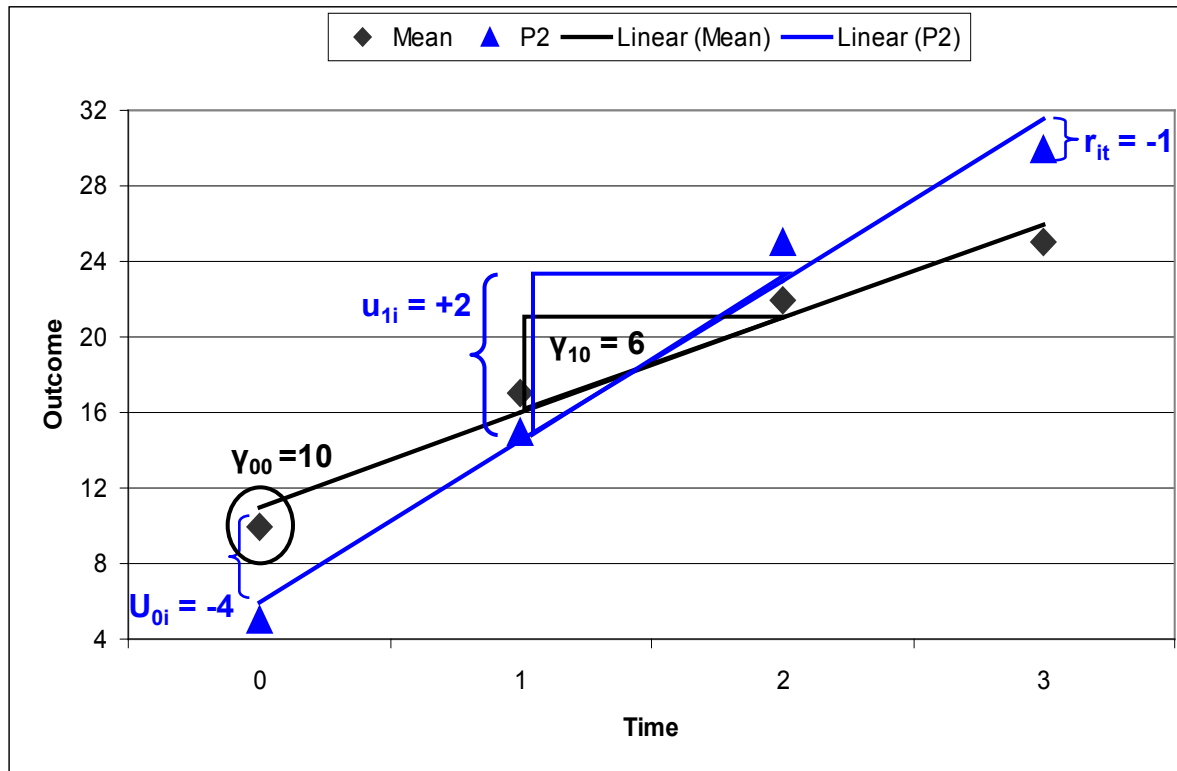
- Attributes of the hierarchy
 - Each successive level refers to distinct inferences related to different levels of aggregation and abstraction
 - Populations—Between Persons—Within Persons
 - Generalizability and inferential limitations
 - Interpretation of any particular level requires attention to prior levels in the hierarchy
 - Time scale usually decreases from population trends to within-person covariation
 - Different processes and predictors of between-person and within-person variation likely to be different across levels
 - Methodological sophistication increases across levels
 - Sensitivity of results (i.e., cross-validation) to different design and analysis attributes is likely to increase across levels
 - Disciplinary emphases
 - Population (Demography/Sociology) to Individual (Psychology) sciences

Theoretical decomposition of an individual's observed scores.



Mixed Linear Model: Fixed & Random Effects

$$Y_{it} = \underbrace{(Y_{00} + U_{0i})}_{\substack{\text{Sample} \\ \text{Intercept}}} + \underbrace{(Y_{10} \text{Time}_{it} + U_{1i} \text{Time}_{it})}_{\substack{\text{Sample} \\ \text{Slope}}} + \underbrace{r_{it}}_{\substack{\text{error for} \\ \text{person } i \\ \text{at time } t}}$$



Reasons for Joint Analysis of Outcomes

- Tests of multivariate hypotheses
 - Does a covariate predict similar change in a set of related outcomes?
- Association of change over time
 - Structure of individual change and variation across different outcomes
 - Evaluation of common factor model
- Evaluation of joint and independent effects of a set of predictors on a set of outcomes

Models for Correlated, Coupled, and Conditional Change

- Separate outcome variables
 - e.g., Change in multiple cognitive abilities
 - Parallel growth models
 - Evaluation of factor model of intercepts, slopes, & residuals
- Same outcome measured on different (identifiable, non-exchangeable) but related individuals (e.g., dyads)
 - e.g. Spouse outcomes (occur at same time); e.g. Sibling outcomes (occur at different ages)
- Time-varying ‘covariate’ and an ‘outcome’
 - Examine conditional prediction at Level 1
 - Conditional growth model
- Multiple indicator factor models
 - Factor-Level Parallel Growth



Multivariate Relations of Change

- Correlated Random Intercepts
 - Is level (at the centering point) for DV1 related to level for DV2 across persons?
- Correlated Random Slopes
 - Is magnitude of change on DV1 related to magnitude of change on DV2 across persons?
- Correlated/Coupled Residuals
 - After accounting for systematic individual change, do DV1 and DV2 vary together over time within-persons?
- Time-Varying Predictors
 - Does TV1 predict intraindividual variation in DV1? Does IV1 moderate time-varying effects of TV1 on DV1?
 - TV covariate vs Conditional growth model

These associations describe unexplained heterogeneity conditional on the time structure of the model (e.g., time in study, age, time to death, time to diagnosis)


Multivariate: Multiple Outcomes

Example: Cognitive Aging

(time centered at Occasion 1: Initial Status)

- Correlated random **intercepts**
 - Are individual differences in level of memory performance related to processing speed and spatial abilities at the initial measurement occasion?
- Correlated random **slopes**
 - Are rates of change in memory, speed, and spatial abilities related?
- Correlated **residuals** (coupling)
 - Is occasion-specific variation (i.e, higher/lower than predicted by growth model) in memory performance related to speed or spatial ability?

Within-Person (WP) vs. Between-Person (BP) Variance

- BP-WP outcomes similar
 - Stress and Health
 - **BP**: People who are more stressed have worse health
 - **BP**: People who exhibit an increase in stress also have an increase in health problems
 - **WP**: On days that people experience more stress, they are likely to report more symptoms of poor health
- BP-WP outcomes different
 - Exercise and Blood Pressure
 - **BP**: People who exercise  have lower blood pressure
 - **WP**: During periods of exercise, blood pressure is higher
- Cross-level (BP-WP) developmental interaction

Multivariate: Dyad and Family Data

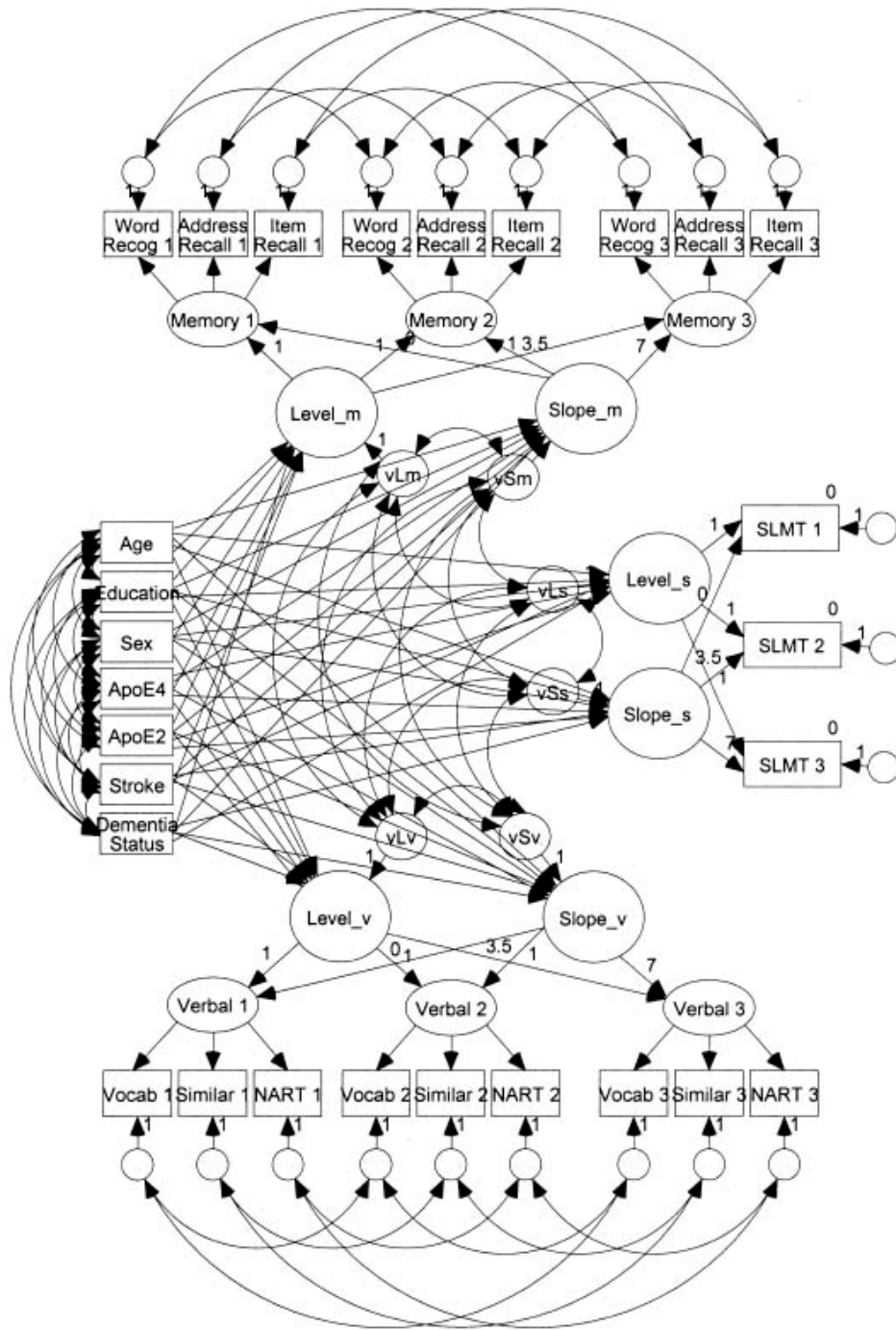
Example: Stress in Mothers and Fathers

(time centered at child=5 years old)

- Correlated random **intercepts**
 - Is Mom's level of stress when their child is 5 related to Dad's level of stress when their child is 5?
- Correlated random **slopes**
 - Is Mom's rate of change in stress related to Dad's rate of change in stress as the child grows older?
- Correlated **residuals** (coupling)
 - If Mom has more stress than predicted at a given age, does Dad also have more stress than predicted at a given age?

SEM Figures: Multivariate Relationships Among Developmental Functions (McArdle, 1988)

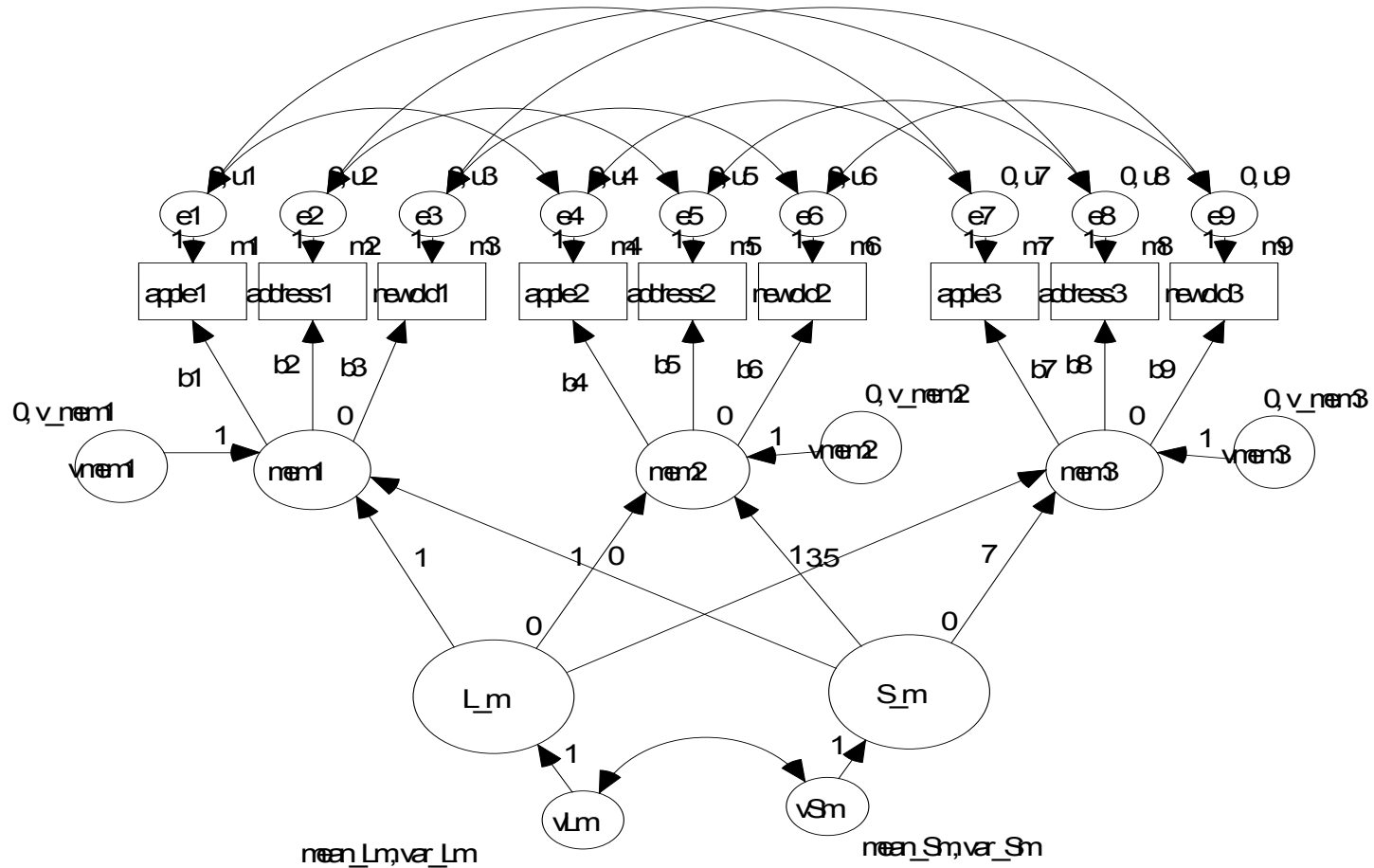
- Three General Models
 - Multiple Correlated Growth Curves
 - Estimation of covariation among levels, slopes, and time-specific residuals (random effects)
 - Curve-of-Factors
 - LGM based on measurement model (i.e., second-order LGM)
 - Factor-of-Curves
 - Evaluation of factor structure of covariance among levels and slopes



- Multivariate LGM with factors as outcomes

- Hofer, S. M., Christensen, H., MacKinnon, A. J., Korten, A. E., Jorm, A. F., Henderson, A. S., & Eastaer, S. (2002). Change in cognitive functioning associated with apoE genotype in a community sample of older adults. *Psychology and Aging*, 17, 194-208.

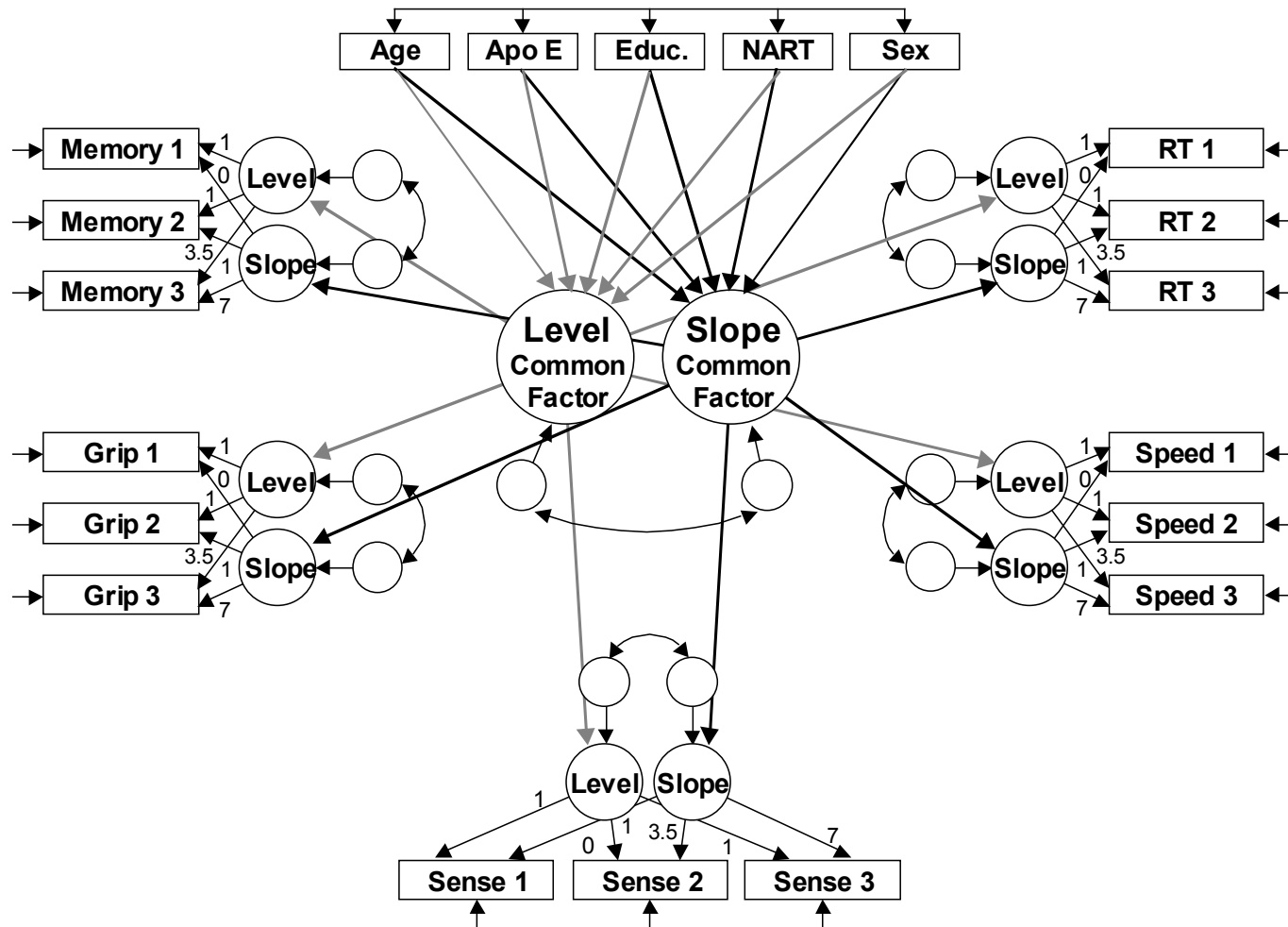
Curve-of-Factors



Factor-of-Curves

Christensen, Mackinnon, Korten, Hofer, & Jorm (2004).

The Canberra Longitudinal Study: Design, aims, methodology, outcomes, and recent empirical investigations. *Aging, Neuropsychology, and Cognition*, 11, 169-195.



Mplus: Bivariate parallel growth model

MODEL



i_y s_y | y1-y5 AT time1-time5;

i_x s_x | x1-x5 AT time1-time5;

! Random effects variances/covariances for int and slopes estimated by default

i_y ON age80 female age80fem;

s_y ON age80 female age80fem;

i_x ON age80 female age80fem;

s_x ON age80 female age80fem;



i_y WITH i_x; ! correlated intercepts and linear slopes

i_y WITH s_x;

s_y WITH i_x;

s_y WITH s_x;

y1 WITH x1(1); ! within-person covariance

y2 WITH x2(1);

y3 WITH x3(1);

y4 WITH x4(1);

y5 WITH x5(1);



y1(2); !homogeneous residual variances

y2(2);

y3(2);

y4(2);

y5(2);



x1(3); !homogeneous residual variances

x2(3);

x3(3);

x4(3);

x5(3);

Multivariate modeling of two associated cognitive outcomes in a longitudinal study

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Abstract. Longitudinal studies of Alzheimer's disease provide information about cognitive decline and predictors of this decline. However, overall cognitive function is comprised of many underlying processes, each of which may respond differently over time and may be affected by different predictors. In addition to studying how these processes decline independently, one might also be interested in how the processes decline together. Multivariate growth models, an extension and modification of random effects models, provide a means of dealing with these issues and enable assessing the association between the processes of interest. This technique allows for separate random effects and predictors for each process in the same model, thereby providing simultaneous estimates of the model parameters and variability for each process. We can then determine if factors associated with decline in one process are also associated with decline in another process and the extent to which the processes differ. We provide data that include information on two underlying processes of cognitive function, namely memory and executive function, to illustrate this methodology.

Multivariate Data Structure for MLM: “Double Stacked” into 3 levels



OutcomeY	DV	DV1	DV2	Wave
Y_{i11}	1	1	0	1
Y_{i21}	1	1	0	2
Y_{i31}	1	1	0	3
Y_{i41}	1	1	0	4
Y_{i51}	1	1	0	5
Y_{i61}	1	1	0	6
Y_{i12}	2	0	1	1
Y_{i22}	2	0	1	2
Y_{i32}	2	0	1	3
Y_{i42}	2	0	1	4
Y_{i52}	2	0	1	5
Y_{i62}	2	0	1	6

1. Stack two DVs into a single Y
2. Create an indicator for which DV is which (1,2)
3. Create a dummy variable for each
DV1= (1,0)
DV2= (0,1)
4. Keep all other variables

Multivariate Model as 3 Levels:

L3=Person, L2=Time, L1=DV

L1: $Y_{tik} = \beta_{0i1}(DV1) + \beta_{0i2}(DV2)$ If DV=1, β_{0i1} are active
 If DV=2, β_{0i2} are active

L2: $\beta_{0i1} = \delta_{0i1} + \delta_{1i1} \text{time}_{ti1} + r_{ti1}$
 $\beta_{0i2} = \delta_{0i2} + \delta_{1i2} \text{time}_{ti2} + r_{ti2}$

L3: $\delta_{0i1} = \gamma_{001} + \gamma_{011} \text{Age}_i + U_{0i1}$
 $\delta_{1i1} = \gamma_{101} + U_{1i1}$ } Intercept and slope for DV1

$\delta_{0i2} = \gamma_{002} + \gamma_{012} \text{Age}_i + U_{0i2}$
 $\delta_{1i2} = \gamma_{102} + U_{1i2}$ } Intercept and slope for DV2

Multivariate Model as 2 Levels:

L3=Person, L2=Time, L1=DV

Level 1 and 2 (Within-Person, across DV):

$$Y_{tik} = \beta_{0i1} (DV1) + \beta_{1i1} (\text{time}_{it})(DV1) + r_{ti1}(DV1) + \beta_{0i2} (DV2) + \beta_{1i2} (\text{time}_{it})(DV2) + r_{ti2}(DV2)$$

Level 3 (Between-Person):

$$\begin{aligned} \beta_{0i1} &= Y_{001} + Y_{011}(\text{Age}_i) + U_{0i1} \\ \beta_{1i1} &= Y_{101} + U_{1i1} \\ \beta_{0i2} &= Y_{002} + Y_{011}(\text{Age}_i) + U_{0i2} \\ \beta_{1i2} &= Y_{102} + U_{1i2} \end{aligned}$$

} Intercept and slope for DV1
 } Intercept and slope for DV2

Univariate Multilevel Model: Segmentation of Error Variance



G Matrix (RANDOM)

Between-Person Variance

Assume correlation between
intercept and slope (Type=UN)

	Intercept	Slope
Intercept	v_{11}	
Slope	c_{21}	v_{22}

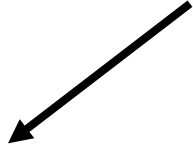
R Matrix (REPEATED)

Within-Person Variance

Assume residual variances equal
over time with no covariances
(Type=VC)

	Residual
Residual	v_{11}

Multivariate Multilevel Model: Segmentation of Error Variance



G Matrix (RANDOM) Between-Person Variance

Estimate variances for intercepts and slopes **for each DV**, and correlations among everything (Type=UN)

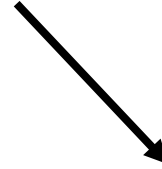
	Int DV1	Int DV2	Slope DV1	Slope DV2
Int DV1	i_1			
Int DV2	r_{21}	i_2		
Slope DV1	r_{31}	r_{32}	s_1	
Slope DV2	r_{41}	r_{42}	r_{43}	s_2

**Intercept
Variances**

**Slope
Variances**

**Correlations
among Intercepts
and Slopes**

Multivariate Multilevel Model: Segmentation of Error Variance



	Res DV1	Res DV2
Res DV1	v_{11}	
Res DV2	r_{21}	v_{22}

Residual variances for each DV

Correlation among residuals

R Matrix (REPEATED)

Within-Person Variance

Assume residual variances equal over time **WITHIN EACH DV**, but residuals can be correlated with each other using TYPE=UN

= **specific covariance**
remaining after accounting for
the effects of time

Parallel Growth Models

- Model different outcomes simultaneously by specifying a joint distribution of random effects
- Problem: High dimensionality of joint random effects models often leads to computational problems
 - Number of outcomes
 - Number of random effects per outcome
- Solution: Perform estimation on all possible combinations of “bivariate” models
 - Equivalent to maximizing a pseudo-likelihood function of the full joint likelihood (Fieuws & Verbeke, 2006)

Pairwise Modeling Approach

- Analysis steps (Fieuws & Verbeke, 2006)
 - Estimate models for all possible pairwise combinations
 - Compute average estimates (e.g., variances) for each outcome
 - Additional step is needed to correctly compute standard errors of estimates
 - Loss of efficiency $< 10\%$ for parameters that are shared in the joint model
 - Compute and report standardized effects for intercepts, slopes, and residual covariances

Australian Child to Adult Development Study (ACAD)

- The epidemiological cohort (n=578) was recruited in 1990 from all health, education and family agencies that provide services to children with mental retardation of all levels
 - Psychiatric interview
 - Medical and genetic history
 - Cognitive assessment
- Because registration with disability services is gateway to state-funded services, ascertainment of moderate, severe, and profound ID is likely complete.

Australian Child to Adult Development Study

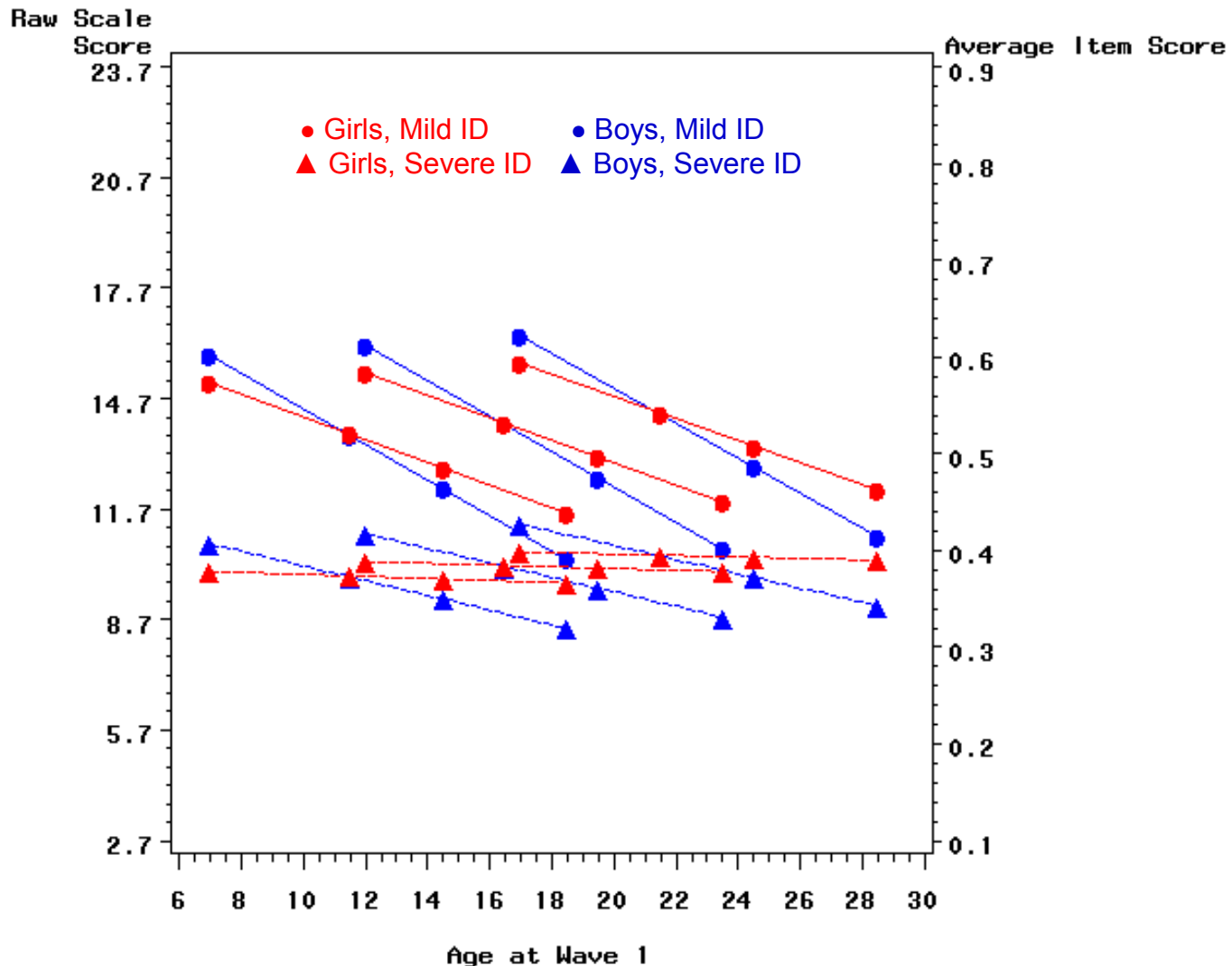
Developmental Behavior Checklist Subscales

- **Disruptive / Antisocial** (27 items) :
 - manipulates, abusive, tantrums, irritable, kicks, hits, noisy, lies, steals, hides
- **Self-Absorbed** (31 items) :
 - eats non-food, preoccupied with trivial items, hums, grunts
- **Communication disturbance** (13 items) :
 - echolalia, perseveration, talks to self, talks in whispers
- **Anxiety** (9 items) :
 - separation anxiety, distressed if alone, fears, phobias, cries easily
- **Social relating** (10 items) :
 - doesn't show affection, resists cuddling, aloof, doesn't respond to other's feelings

Aims: ACAD Multivariate Analysis

- Functional form and variation in change
 - Are there systematic individual differences in rates of change in psychopathology?
- Prediction of change
 - Do individual differences in Sex, IQ status, and Age account for differences in the pattern of change?
- Association of rates of change and occasion-specific variation across types of psychopathology
 - To what degree are rates of change in distinct types of psychopathology correlated?
 - To what degree are time-specific deviations in psychopathology factors correlated within individuals?
- Common factor models of change
 - Can correlated intercepts, linear slopes, and within-person correlations in psychopathology be explained by a common factor model?

Predicted Plot of Disruptive/Antisocial Behavior by Time with Predictors Age, Sex, and IQ2



Predicted Plot of Social Relating Problems by Time with Predictors Age, Sex, and IQ

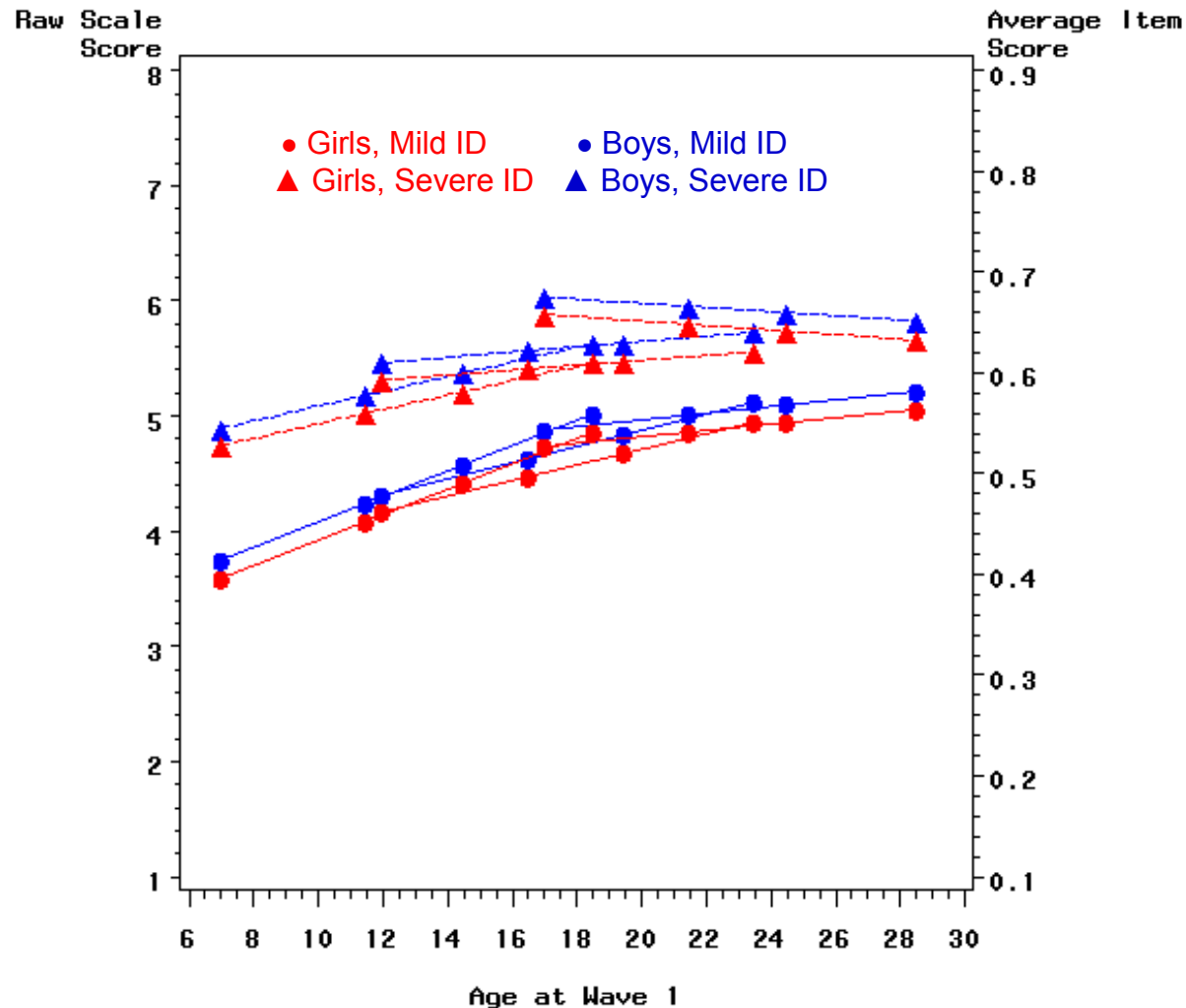


Table 3. Random Effects Correlation Estimates for DBC Subscales

DBC subscale	Subscale correlation: Conditional on age and age/gender/IQ					
	Level		Slope		Occasion-specific residual	
	Age only	Age/gender/ IQ	Age only	Age/gender/ IQ	Age only	Age/gender/ IQ
Anxiety with						
Communication Disturbance	.50	.49	.53	.52	.39	.39
Disruptive	.50	.48	.47	.44	.42	.42
Self-Absorbed	.37	.47	.46	.43	.38	.38
Social Relating	.46	.50	.39	.44	.31	.31
Communication Disturbance with						
Disruptive	.60	.57	.80	.81	.50	.50
Self-Absorbed	.46	.64	.85	.83	.52	.52
Social Relating	.42	.52	.56	.57	.40	.40
Disruptive with						
Self-Absorbed	.42	.62	.87	.88	.61	.61
Social Relating	.34	.43	.57	.62	.39	.39
Self-Absorbed with						
Social Relating	.67	.66	.56	.57	.45	.46

Note. All associations were statistically significant at the $p < .01$ level. DBC = Developmental Behavior Checklist.

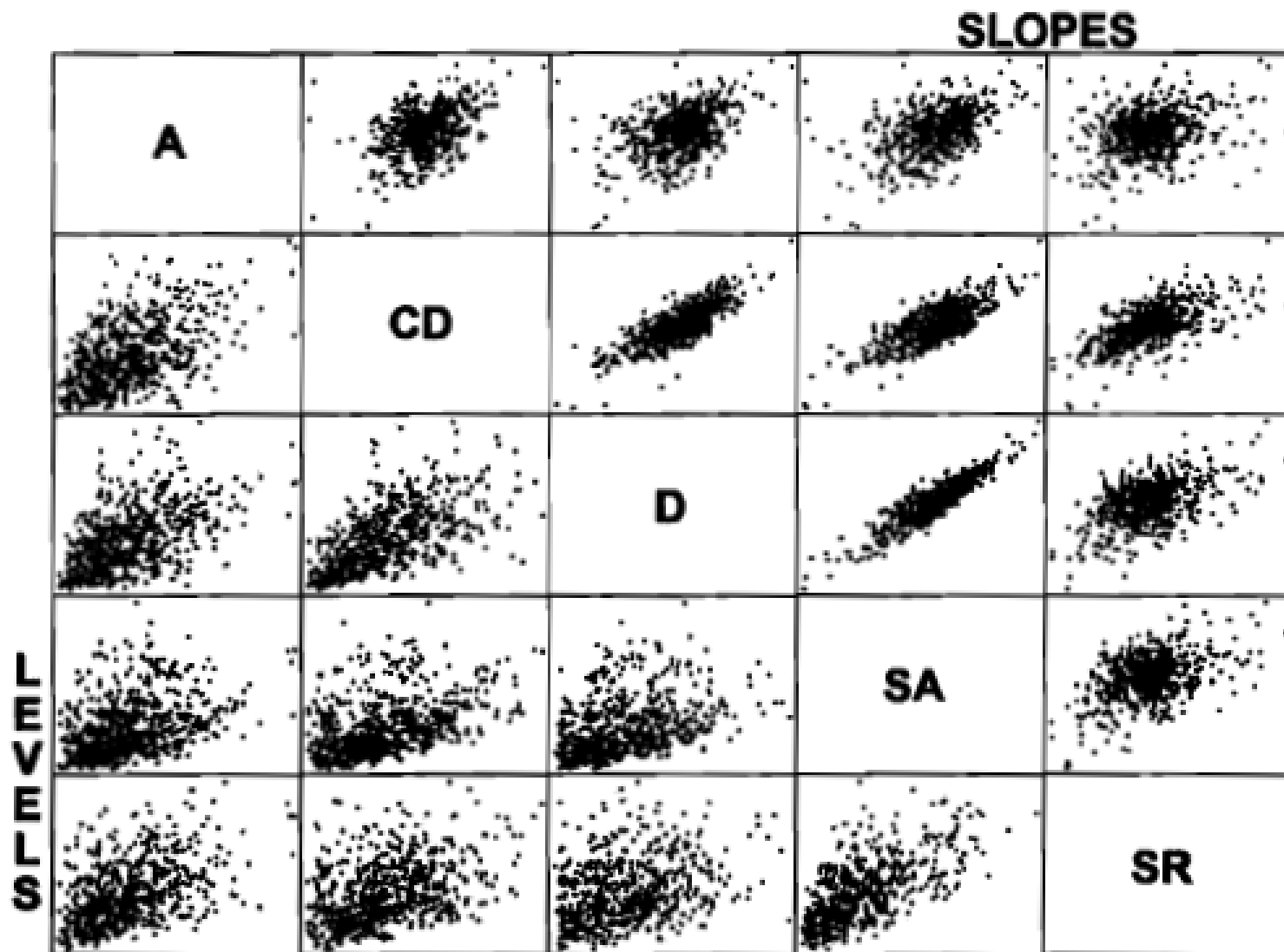


Figure 1. Scatterplots for level-level and slope-slope correlations across Developmental Behavior Checklist (DBC) subscales. A = Anxiety, CD = Communication Disturbances, D = Disruptive, SA = Self-Absorbed, SR = Social Relating.

Correlations of Levels and Slopes

- Correlations between the levels of the DBC subscales can be seen as the underlying dimensional foundation of previous research reporting higher rates of diagnostic comorbidity (Dekker & Koot, 2003; Emerson, 2003).
- Children who show increases or decreases over time on one subscale tend to exhibit similar changes (relative to other children) on another.
 - The strongest relationships however, were consistently between the Disruptive, Self-Absorbed, and Communication Disturbance subscales.
 - Changes in Anxiety were the least correlated with the other scales, although even changes on this scale were significantly correlated with the others.

Evaluation of Common Factor Models

- Secondary factor analysis of model-based intercepts, slopes, and residuals
- Whether or not a common factor model provides a fit to the data has more to do with the general pattern (i.e., consistency) of covariation than to the magnitude of correlation among DBC subscales.

Mplus: Common factor model with input pairwise correlation matrix

TITLE: Common Factor Model of DBC

DATA: FILE IS DBC_Rcorr.txt;
TYPE IS corr;
NOBS IS 506;

VARIABLE: NAMES ARE
A CD D SA SR;

USEVAR =
A CD D SA SR;

ANALYSIS: TYPE=;

MODEL:
F1 by A CD D SA SR;

OUTPUT: STANDARDIZED MOD;

Table 4. Confirmatory Factor Analysis of the Intercepts, Slopes, and Occasion-Specific Residuals



DBC ^a subscale	Level		Slope		Occasion-specific residual	
	Factor loading	<i>R</i> ²	Factor loading	<i>R</i> ²	Factor loading	<i>R</i> ²
Anxiety	.62	.38	.50	.25	.53	.28
Communication						
Disturbance	.76	.57	.88	.78	.67	.46
Disruptive	.71	.51	.93	.87	.76	.57
Self-Absorbed	.86	.74	.94	.88	.79	.62
Social Relating	.73	.53	.64	.41	.56	.32

Note. *R*² is the proportion of total variance explained in the indicator variable by the common factor.

^aDevelopmental Behavior Checklist.

- Fit to a common factor model was marginal for level and rate of change in DBC subscales (i.e., there were correlations among subscales that were not sufficiently accounted for by the factor model).
- Correlations among occasion-specific residuals were found to be sufficiently consistent with a common factor model.
- The common factor model of residuals provides indirect evidence for common covariation among “state-like” transient behavioral and emotional disturbances across different features of psychopathology.

Summary of ACAD Results

- All DBC subscales moderately correlated across initial status (intercepts), rates of change (slopes), and residuals (within-person correlation)
- The magnitude of the correlations ranged from
 - .45 to .71 for initial levels  
 - .42 to .90 for linear slopes
 - .32 to .62 for within-person residuals
 - Highest correlations were consistently found among scales for Disruptive, Self-absorbed, and Communication Disturbance behaviors.
- Provides evidence for moderate commonality of individual initial status and change patterns in distinct features of psychopathology
 - Evidence for common factor of time-specific variation in emotional and behavioral disturbance

Multivariate Growth Models

- Multivariate growth models can be fit in either MLM or SEM software – estimation of multiple growth curves and covariance among intercepts, slopes, and residuals
 - For SEM equivalence to MLM: Residual variances and covariances are constrained to be equal across time
- Flexibility in estimating unique time-specific residuals and residual covariance structures
 - Model estimates are sensitive to residual variance/covariance structure (Grimm & Widaman, 2009)

Selected References

Multivariate Growth Curves

- Duncan, T. E., Duncan, S. C., Strycker, L. A., Li, F., & Alpert, A. (1999). *An introduction to latent variable growth curve modeling: Concepts, issues, and applications*. Mahwah, NJ: Erlbaum.
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- McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In J. R. Nesselroade & R. B. Cattell, (Eds.). *The handbook of multivariate experimental psychology* (Volume 2, pp. 561-564). New York: Plenum Press.
- Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. London: Oxford University Press.
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Multivariate Outcomes vs. Time-Varying Covariates

- Multivariate Outcomes: Random Effects Model for Variances/Covariances
 - Relations among model-based BP and WP parameters for intercepts (BP), slopes (BP), and residuals (WP)
 - Does not permit tests of moderation of “association” (and accompanying random effects) except in multiple-group models
- Time-Varying Predictors: Fixed Effects Model for Means
 - No direct mapping to parallel growth model in regards to slope-slope associations
 - Permits direct tests of moderation of IV-DV regression

- Time-varying covariates can be introduced to the level-1 model,

$$y_{kit} = \beta_{0ki} + \beta_{1ki} \textit{time}_{it} + \beta_{2ki} z_{it} + r_{kit}$$

- where the effect of a time-varying covariate, β_{2ki} , is a function of a fixed and possibly random effect.

Use and Interpretation

- Moderated TVx
 - Why do some people have higher or lower regressions of TVx on the DV?
- Impact of trend in TVx
 - Estimate of “time” slope is conditional on holding TVx constant and adjusted (residualized) for time slope of TVx.

Parameters in TV Predictors MLM vs. Parameters in Multivariate Models

1. Multivariate: correlation among random intercepts (BP correlation between levels)

TV \approx BP fixed effect if BPx is grand mean at centering point

TV \neq BP fixed effect if BPx is person-mean-centered

2. Multivariate: correlation among random slopes (BP correlation among rates of change)

3. Multivariate: correlation among residuals (WP correlation among residual time-specific deviations)

TV \neq WP correlation except when time trend on DV1 is modeled

Slope covariance is unmodeled and adjusted for when time trend on DV1 is modeled

Bivariate DCSM (Ferrer & McArdle, 2010)

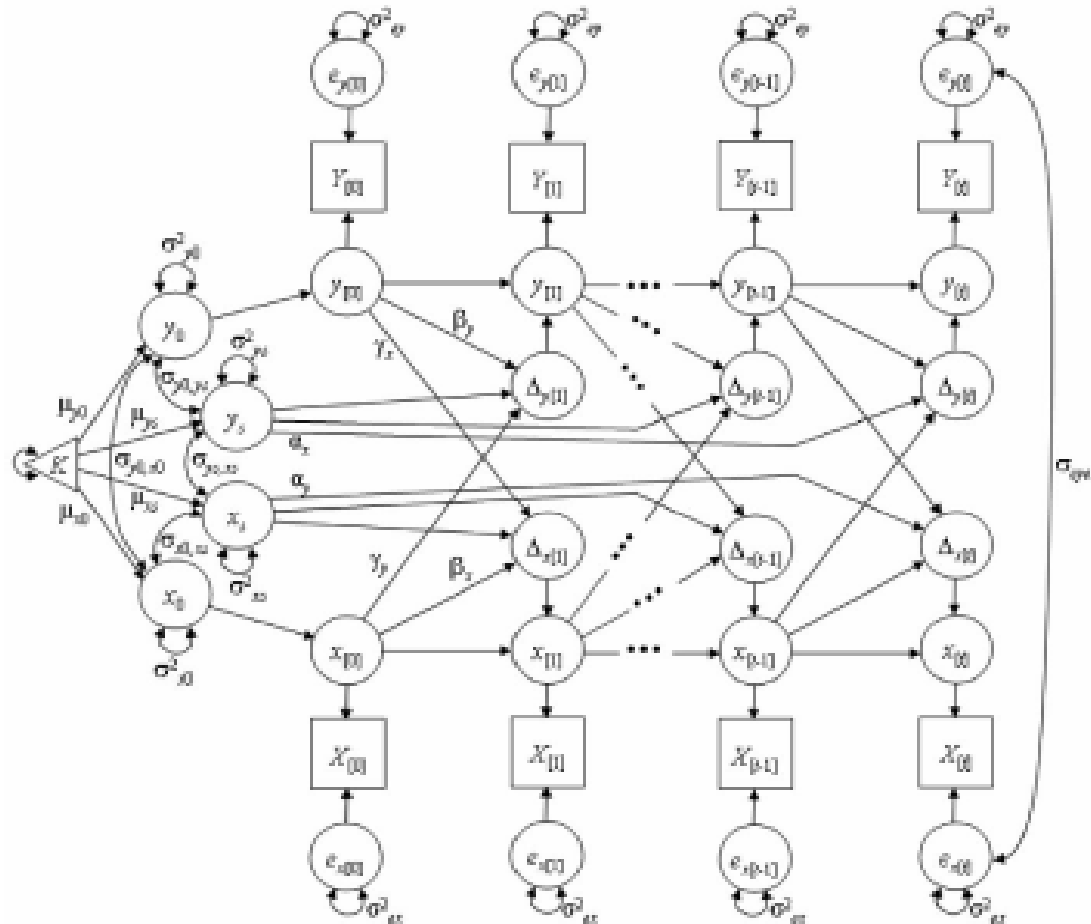


Fig. 1. Path diagram of a bivariate latent change score model. Squares represent observed variables, circles represent latent (or unobserved) variables, and the triangle represents a constant. Single-headed arrows indicate regression coefficients, intercepts, or means; double-headed arrows indicate variances and covariances. For each repeated assessment, a latent variable (Δ_y) is created to indicate latent changes. These latent changes are the main specification feature of LCS models.

Complexities

- Centering of TVx in longitudinal studies
- Sensitivity of parallel/TVx approaches to alternative time structures
- Sensitivity of parallel/TVx approaches to different error structures

Importance of Direct Observation of Within-Person Changes

- Aging-related changes reflect developmental and pathological processes (and their interaction)
 - External forces influence the gradually unfolding (involutional) developmental processes within individuals
- Causal period for aging-related changes may be very long
 - Patterns of early development may be predictive of later changes (lifespan development perspective)
 - Interaction of multiple causal influences
 - Accumulation of risk / protective factors
 - Age-specific causal action (delayed action)
- Selection (mortality) is a natural population dynamic and is only accessible in longitudinal studies
 - Causal processes obscured if selection is not taken into account

Examining Processes of Change in Aging Individuals

- Goal: To model overall pattern and predictors of **within-person change** and **between-person differences in change**
 - Separate effects WP change and BP age-related differences
 - Evaluate whether WP and BP effects lead to the same inference
- **Multiple time-dependent processes** are likely to be responsible for observed changes
 - Examination of **alternative time structures** (event-centered) and **time-varying covariation**

Correlation and Coupling of Cognitive Functions: Einstein Aging Study

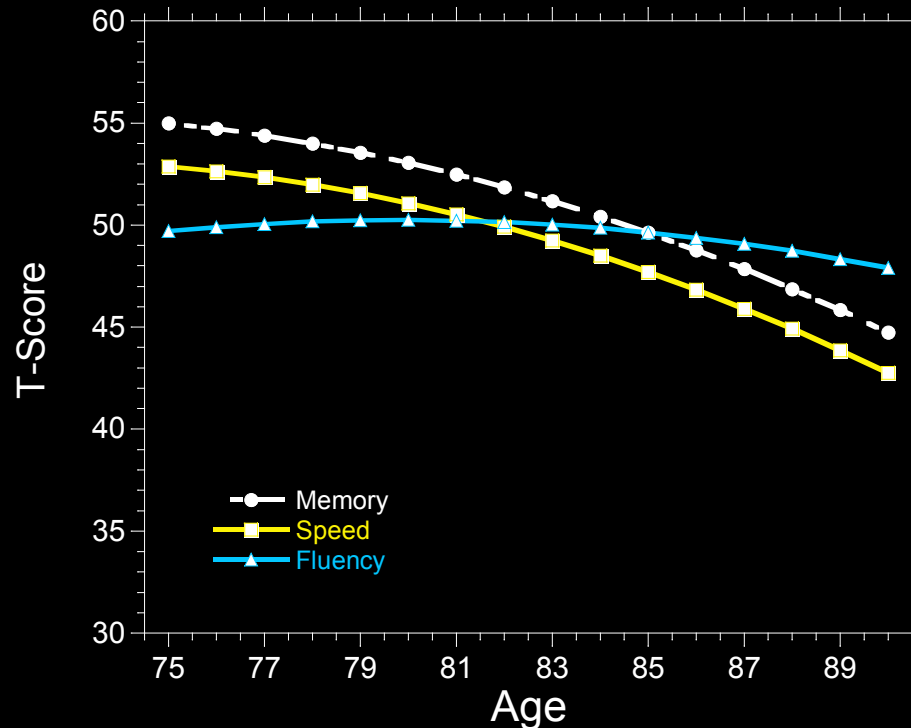
- 389 healthy older adults (ages 75-90)
- Annual Testing (2-15 years)
- 25% developed dementia (Preclinical)
 - 70% AD
 - 21% Vascular
 - 9% other (e.g., Lewy Body disease)
- 75% not develop dementia (NonDemented)

Sliwinski, M. J., Hofer, S. M., & Hall, C. (2003). Correlated and coupled cognitive change in older adults with and without clinical dementia. *Psychology and Aging, 18*, 672-683.

NonDemented

Random (Slope) Effects

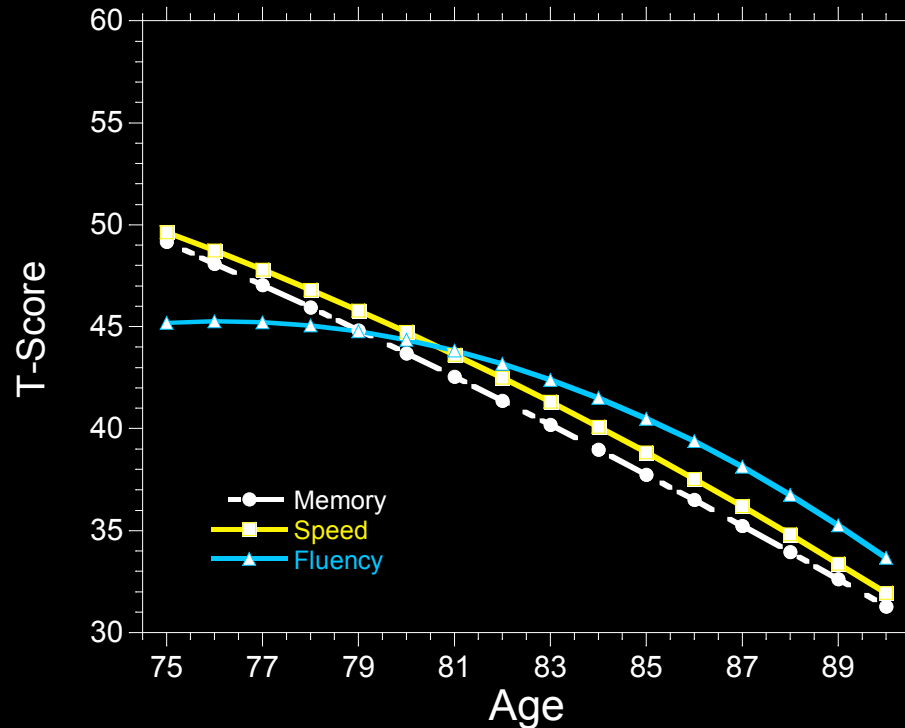
	Memory	Speed	Fluency
Memory	.31		
Speed	.48	.29	
Fluency	.42	.34	.09



Preclinical

Random (Slope) Effects

	Memory	Speed	Fluency
Memory	.51		
Speed	.54	.44	
Fluency	.66	.86	.77

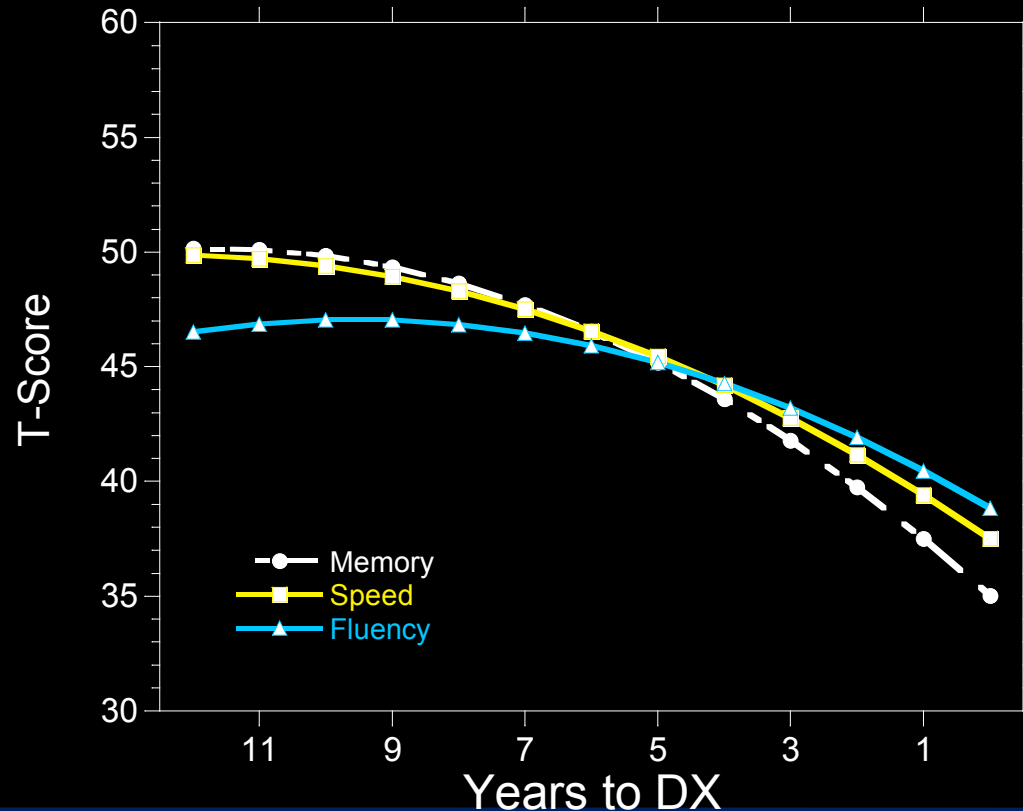


Fixed Effects: PreDx Sample

$$memory_{ij} = \beta_0 + \beta_3(YrsDx_{ij}) + \beta_6(YrsDx_{ij}^2) + U_{0j} + U_{3j}(YrsDx_{ij}) + e_{memory.ij}$$

$$speed_{ij} = \beta_1 + \beta_4(YrsDx_{ij}) + \beta_7(YrsDx_{ij}^2) + U_{1j} + U_{4j}(YrsDx_{ij}) + e_{speed.ij}$$

$$fluency_{ij} = \beta_2 + \beta_5(YrsDx_{ij}) + \beta_8(YrsDx_{ij}^2) + U_{2j} + U_{5j}(YrsDx_{ij}) + e_{fluency.ij}$$



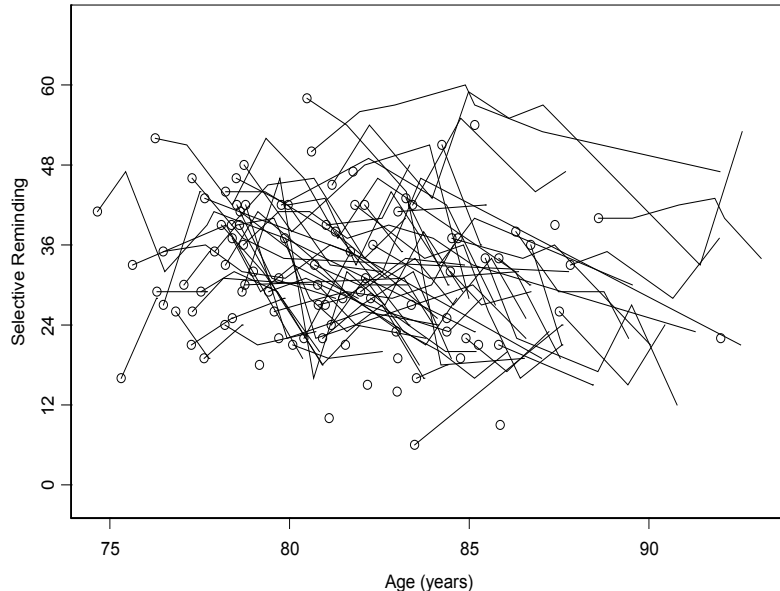
Correlated Rates of Change: Disease Processes

(Sliwinski ,Hofer, & Hall, 2003)

Correlated Age-Based Change

	Memory	Speed	Fluency
Memory	.51		
Speed	.54	.44	
Fluency	.66	.86	.77

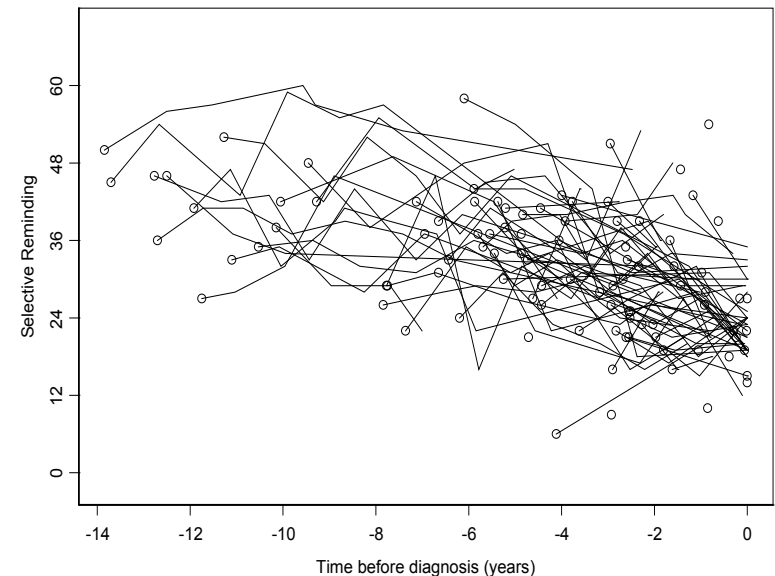
Var(Rate of Change)=0.51



Correlated Disease-Based Change

	Memory	Speed	Fluency
Memory	.10		
Speed	.0	.01	
Fluency	.0	.0	.44

Var(Rate of Change)=0.10



Distance to/from a Common Event

- Is appropriate if a **distinct process** is responsible for the pattern of and individual differences in change
- Distinction between **moderation** and **time structure**:
 - Time in Study Model: Predictors of Age and Time to Diagnosis: Initial status and rate of change are driven by unknown forces, but vary by age and time to diagnosis
 - Time to Diagnosis Model: Predictor of Age: Initial status and rate of change are driven by disease progression, but vary by age
- Other examples: Time to first marriage, Time to divorce, Time to dropout, Time since treatment
- Model only includes those who have experienced the event

Alternative Metrics of Time-Dependent Processes

- Time in Study as Time
 - Individual differences are organized around the mean level and change for a given **time from the start of observation** and change with time from start of observation
- Chronological Age as Time
 - Individual differences are organized around the mean level for a given **time from birth** and change with time since birth
- Proximity to Death as Time
 - Individual differences are organized around the mean level for a given **time to death** and change with time to death
- Disease Progression as Time
 - Individual differences are organized around the mean level for a given **time to/from diagnosis** and change with time to/from diagnosis
- Events (e.g., retirement, widowhood, stressor) as Time
 - Individual differences are organized around the mean level for a given **time to/from event** and change with time to/from event

Incomplete Data in Studies of Aging: Mortality as a Distinct Process

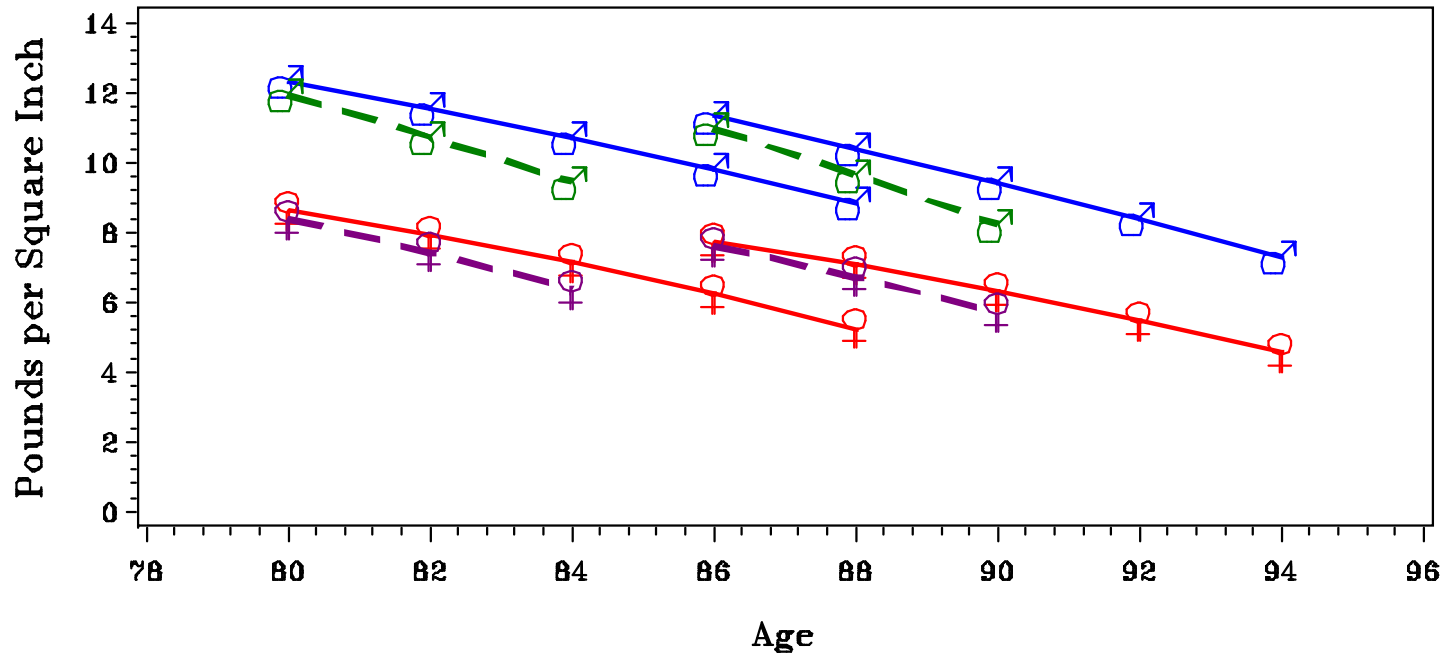
- At the population level, causal influences on individual change and likelihood of missingness are likely to be complex (e.g., dementia, morbidity)
- Naïve statistical treatments (MI/ML-MAR) treat death and other types of dropout as ignorable (MAR)
 - Inference to a single “immortal” population
- Inferences to defined populations: Conditional ML/MI approaches
 - Permit a more accurate description of aging-related change as a joint function of age and age at death (and interaction)
 - Inferences defined as conditional on the probability of surviving and/or remaining in the study

Kurland, B. F., Johnson, L. L., Eggleston, B. L., & Diehr, P. H. (2009). Longitudinal data with follow-up truncated by death: Match the analysis method to research aims. *Statistical Science*, 24, 211–222.

Longitudinal Changes in Physical Functional Performance: OCTO-Twin

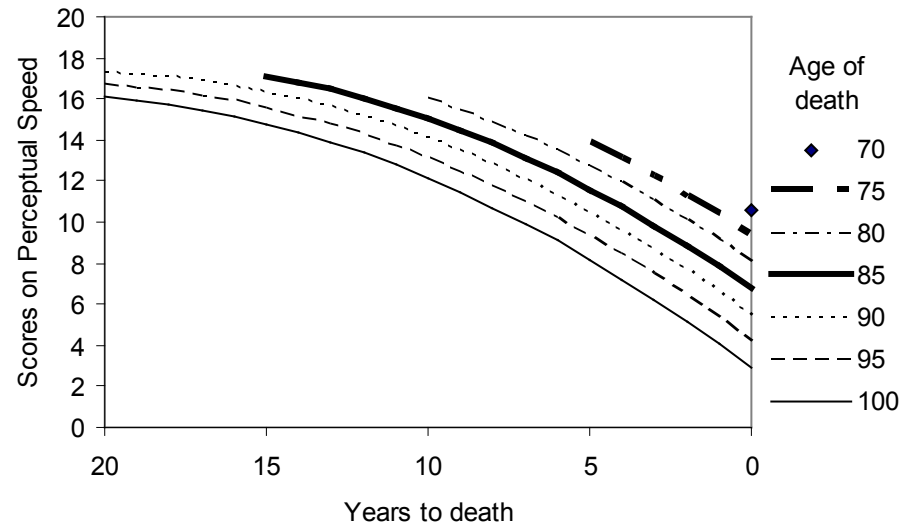
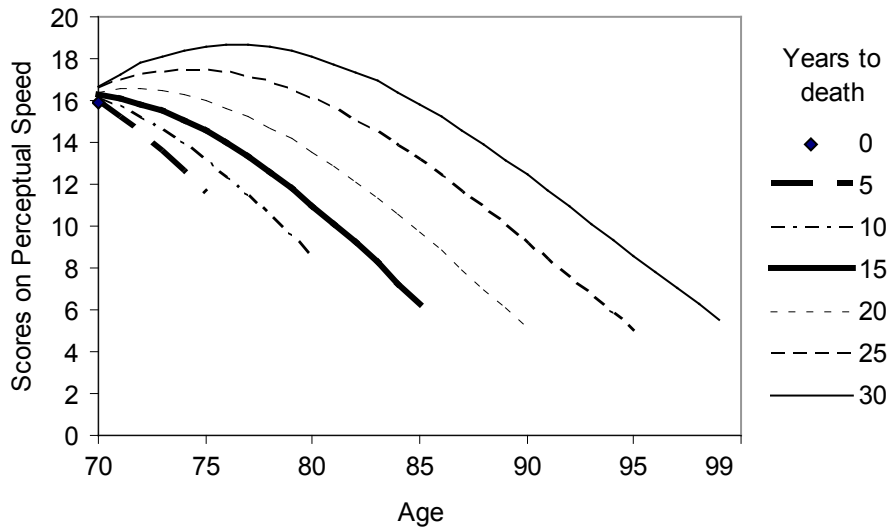
Predicted Grip Strength
Covariates of Initial Age and Years to Death (YTD)

- ♂♂♂ Age 80, Man, 10 YTD
- ♀♀♀ Age 80, Woman, 10 YTD
- ♂♂♂ Age 80, Man, 7 YTD
- ♀♀♀ Age 80, Woman, 7 YTD
- ♂♂♂ Age 86, Man, 10 YTD
- ♀♀♀ Age 86, Woman, 10 YTD
- ♂♂♂ Age 86, Man, 7 YTD
- ♀♀♀ Age 86, Woman, 7 YTD



Proctor, D. N., Fauth, E. B., Hoffman, L., Hofer, S. M., Berg, S., & Johansson, B. (2006). Longitudinal changes in physical functional performance among the oldest old: Insight from a study of Swedish twins. *Aging Clinical and Experimental Research*, 18, 517-530.

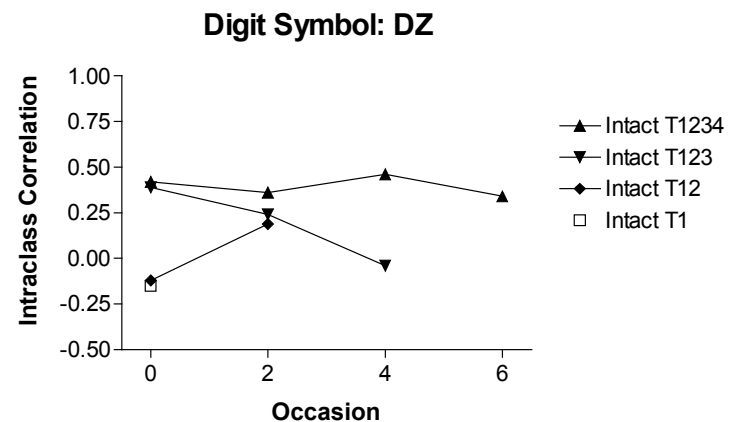
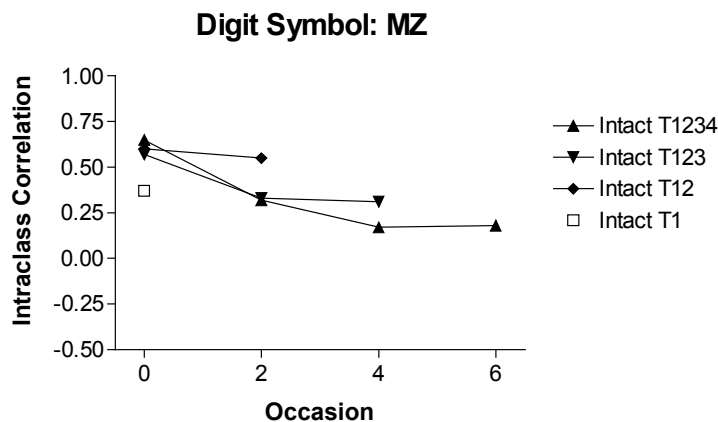
Cognitive Change as a Function of Age and Mortality in the Oldest Old: Gothenburg H70 Study



Thorvaldsson, V., Hofer, S. M., & Johansson, B. (2006). Ageing and late life terminal decline: A comparison of alternative modeling approaches. *European Psychologist*, 11, 196-203.

Effects of Differential Mortality on Estimates of Heritability: OCTO-Twin

- Multivariate LGM analysis of MZ and DZ twins
- Weak and often negative intraclass correlations among rates of change in cognitive outcomes
 - Indicates greater differential change within twin pairs than occurs on average across twin pairs



Johansson, B., Hofer, S. M., Allaire, J. C., Maldonado-Molina, M., Piccinin, A. M., Berg, S., Pedersen, N., & McClearn, G. E. (2004). Change in memory and cognitive functioning in the oldest-old: The effects of proximity to death in genetically related individuals over a six-year period. *Psychology and Aging, 19*, 145-156.

Explanatory Theories of Development and Aging

- Interindividual differences are complex functions of
 - Initial individual differences
 - Intraindividual change and covariation
 - Population selection
- Must seek comprehensive, developmental theories that combine both BP and WP sources of variance
 - BP differences are important modifiers of WP process
 - WP processes are important components of BP differences
- Evaluation of multiple-process models
 - The challenge is to understand aging-related changes with age in the context of morbidity, comorbidity, and mortality.