

Longitudinal Model Selection in Applied Research: Tips and Tricks for Matching Model Choice to Theory

Ethan M. McCormick, Ph.D.

Postdoctoral Fellow (Dr. Rogier Kievit)
Donders Institute at the RadboudUMC

@McCormickNeuro
ethan.mccormick@radboudumc.nl
<https://mccormickneuro.github.io/>

Acknowledgements: A Village



THE UNIVERSITY
of NORTH CAROLINA
at CHAPEL HILL



Universiteit
Leiden



UNIVERSITY OF
MARYLAND



UNIVERSITY OF
OREGON



Erasmus
University
Rotterdam
Erasmus



Radboudumc

DONDERS
INSTITUTE *α*

MONASH
University



HARVARD
UNIVERSITY



NIH
National Institute
of Mental Health

NIH
National Institute
on Drug Abuse



European
Research
Council

NIH
National Institute
of Mental Health

Selecting a Longitudinal Modeling Approach

- Overwhelming number of ways to model repeated measures data
 - Often told “use theory”, but not *how* to do that
- Different frameworks*
 - Mixed-effects & structural equation models
 - A lot of historical baggage
- Need a conceptual decision tree to adjudicate between model choices
 - Access to training in many methods

Longitudinal Primer + Codebook

The Hitchhiker's Guide to Longitudinal ...

About

Introduction

Canonical Models

Time Structure

The Shape of Development

Covariates and Distal Outcomes

Nested Data

Datasets

Published with bookdown

☰ 🔍 A ✎ i

The Hitchhiker's Guide to Longitudinal Models



Mills, & Jennifer H. Pfeifer

The following document is a code companion to [The Hitchhiker's Guide to Longitudinal Models: A Primer on Model Selection for Repeated-Measures Methods](https://doi.org/10.31234/osf.io/ga4qz), <https://osf.io/bn6yu/>.

Some general notes about this code companion:

- We believe in the importance of using real data in our examples of longitudinal models. However, some of the models we discuss can not yet be fit using publicly-available neuroimaging data (most

Longitudinal Modeling in Pre-collected Data

- Matching models to theory is often complicated by the need to use pre-existing data sources
 - Other people have made decisions for you
- But with more datasets becoming publicly available, there may be options in the future

Using large, publicly available data sets to study adolescent development: opportunities and challenges

Rogier A. Kievit^{2,3}, Ethan M. McCormick^{2,3,a},
Delia Fuhrmann^{1,4,a}, Marie K. Deserno^{5,6,a} and Amy Orben^{1,a}

Longitudinal Modeling in Pre-collected Data

- Matching models to theory is often complicated by the need to use pre-existing data sources
 - Other people have made decisions for you
- But with more datasets becoming publicly available, there may be options here in the future
- Sometimes we have to work within constraints
 - Occasionally can turn these into a strength
 - Might be able to take intentional subsamples

Matching Models and Theory

- Often, we fit standard models because “that’s how they are done” without interrogating the assumptions different model specifications impose
 - Our goal is to peel back those assumptions and ask if they make sense for testing a particular theory
 - Also (hopefully) help make better theories
- But...perfect should not be the enemy of the good
 - Sometimes we must make compromises
 - Important to be transparent about those

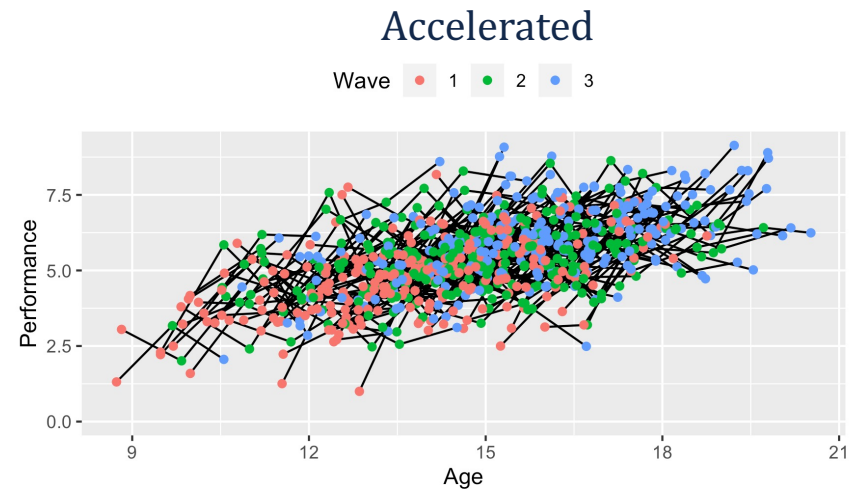
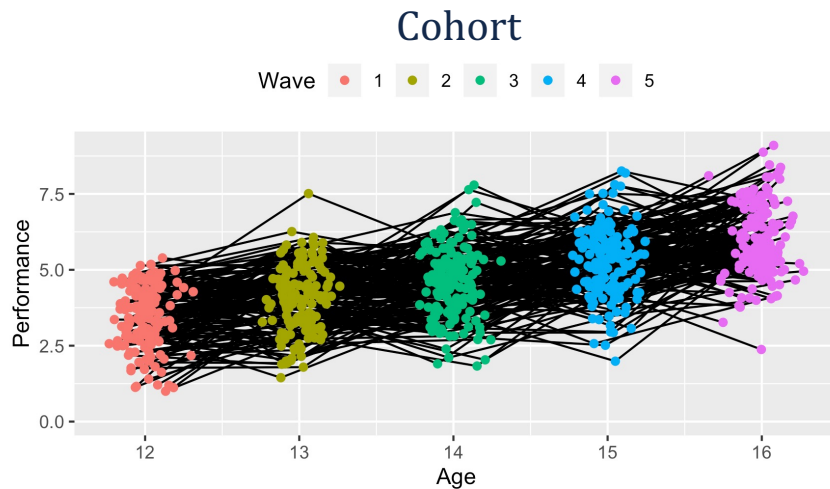
Outline for the Rest of the Talk

- 3 use cases
 - Assessment designs and longitudinal model selection
 - Cohort vs accelerated studies
 - Uncovering sensitive periods
 - Linear and nonlinear effects
 - Understanding brain-behavior relationships
 - Exogenous and endogenous predictors
- Conclusions and Next Steps

Assessment designs and longitudinal model selection

Use-Case 1: Assessment Designs

- Cohort- vs Accelerated Longitudinal Designs



Use-Case 1: Assessment Designs

- Cohort- vs Accelerated Longitudinal Designs
 - Historically,
 - Cohort designs → SEM methods
 - Accelerated designs → MEM-based methods

Use-Case 1: SEM vs. MEM growth models

Mixed-Effect Data & Model

- Linear Model:

$$y_{ti} = \underbrace{\gamma_{00} + \gamma_{10}Time_{ti}}_{\text{fixed effects}} + \underbrace{u_{0i} + u_{1i}Time_{ti}}_{\text{random effects}} + r_{ti}$$

- Time is an observed covariate
 - Model treats it like *any other* covariate
 - Allows for individually-varying values

Executive Function Data: Long Format

id	wave	dlpfc
1	0	-0.184
1	1	1.129
1	2	-0.840
1	3	0.472
2	0	0.801
2	1	1.129
2	2	0.801
2	3	1.457
3	0	0.472
3	1	1.129
3	2	0.144
3	3	0.144

Use-Case 1: SEM vs. MEM growth models

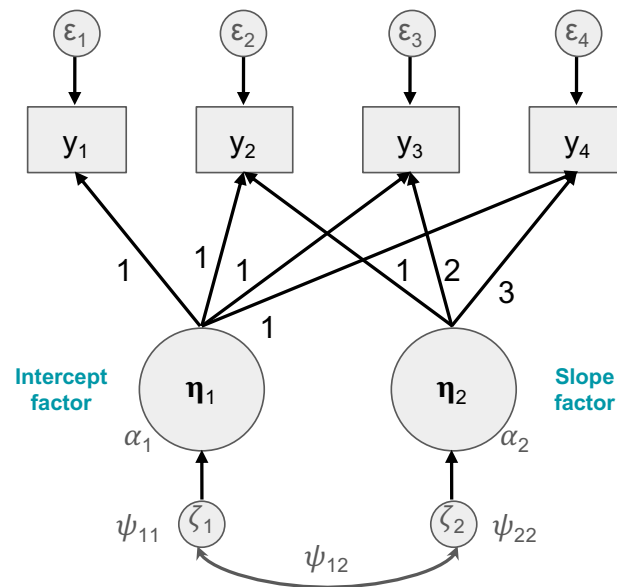
SEM Data & Model

- Linear Model:

$$\mathbf{y}_i = \mathbf{A}\boldsymbol{\eta}_i + \boldsymbol{\varepsilon}_i$$

$$\boldsymbol{\eta}_i = \boldsymbol{\alpha} + \boldsymbol{\zeta}_i$$

- Time is hard-coded into the factor-loading matrix
 - Repeated measures are separate variables
 - Need to group variables into time-bins*



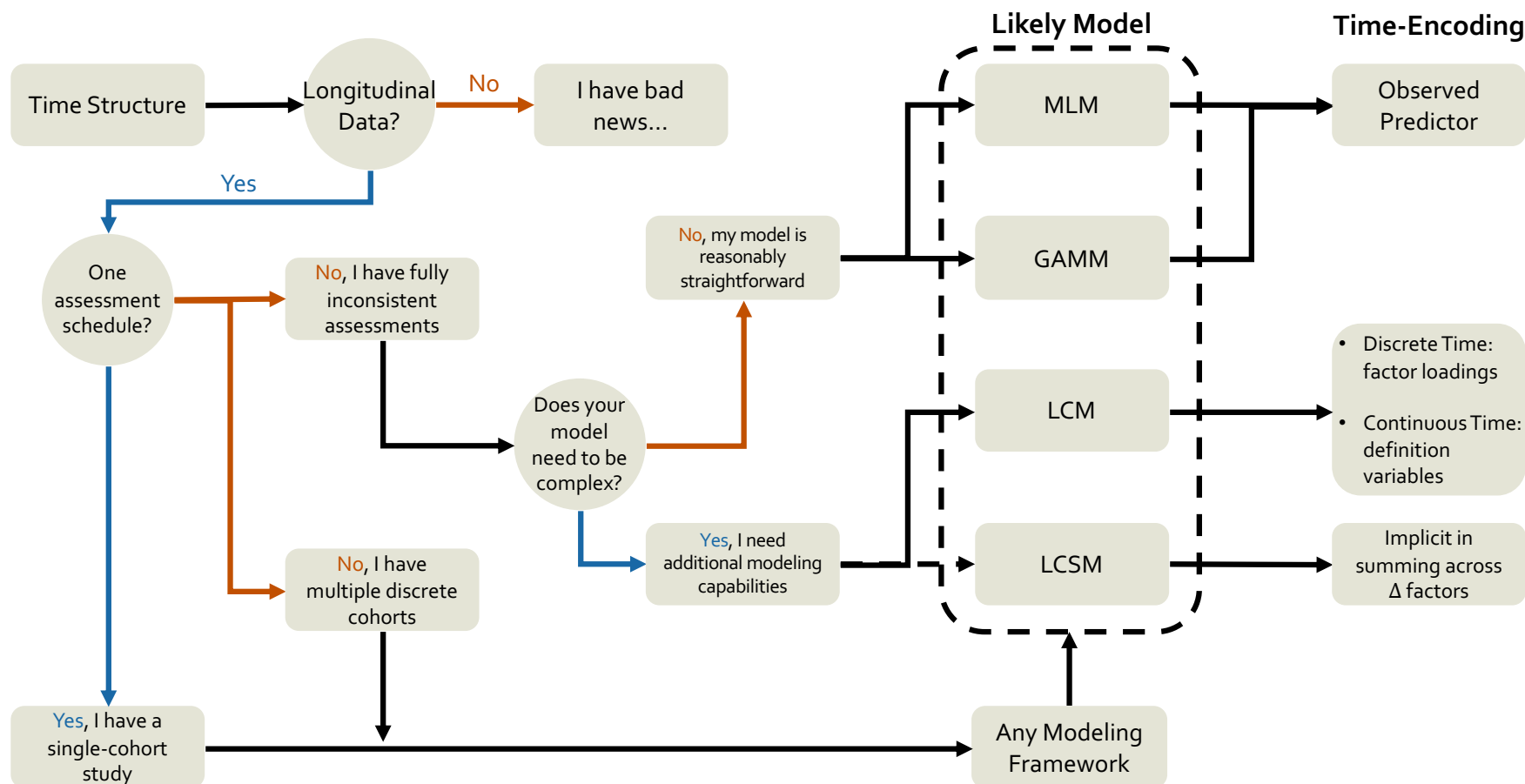
Executive Function Data: Wide Format

id	dlpfc1	dlpfc2	dlpfc3	dlpfc4
1	-0.184	1.129	-0.840	0.472
2	0.801	1.129	0.801	1.457
3	0.472	1.129	0.144	0.144
4	0.472	0.472	0.472	0.472
5	-0.840	2.114	2.442	2.442

Use-Case 1: Assessment Designs

- Modern methods
 - Can allow for individually-varying assessment in SEMs with definition variables through Mplus or OpenMx
- But in general, accelerated designs are still modeled primarily with mixed-effects models
- Main theoretical distinction: how much age-variation can you compress before the model is mis-specified?

Use-Case 1: Assessment Designs Heuristic Map



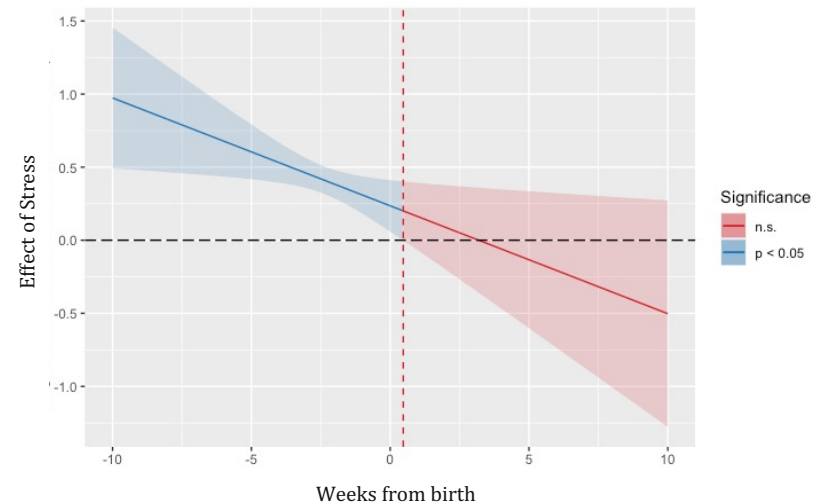
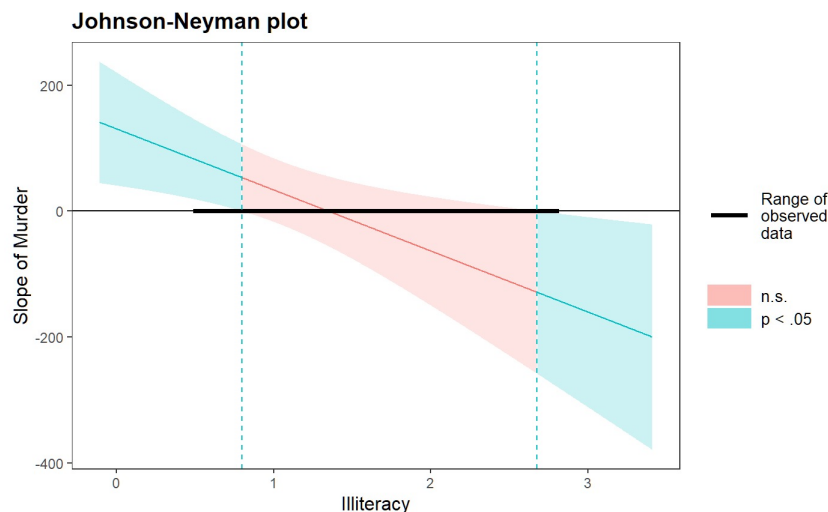
Uncovering Sensitive Periods

Use-Case 2: Sensitive Periods

- Sensitive periods
 - A window of development where the organism is differentially- (usually hyper-) sensitive to a particular environmental* input
 - Especially abundant in the peri-natal period
- Main theoretical question: Do we believe that the effects of predictors should be consistent across development?
 - Practical concerns: how to include in our models

Use-Case 2: Modeling Interactions for Sensitive Periods

- Modeling sensitive periods are fundamentally about interactions (e.g., maternal stress and PFC pruning)
 - Main effect: Holding age constant, there is an effect of maternal stress (β_{stress})
 - Interaction: The effect of maternal stress depends (in part) on the age of the offspring ($\beta_{\text{stress} \times \text{age}}$)



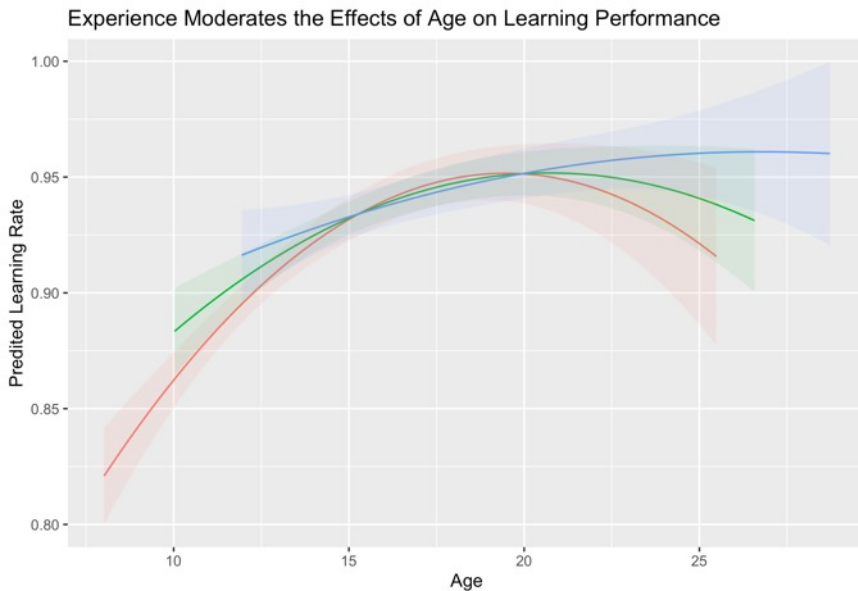
Use-Case 2: Modeling Interactions for Sensitive Periods

- Simple tests for sensitive periods
 - In the prior example, we have a bilinear interaction (β_{stress} changes linearly over age)
 - Quadratic/cubic effects
 - The effect of age itself changes across age in some fashion

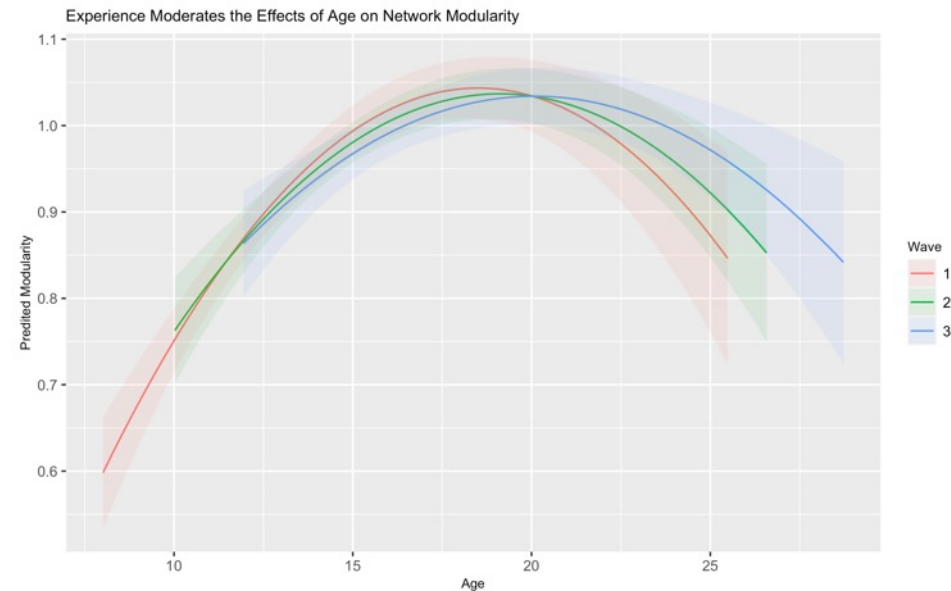
Testing Interactions: An Empirical Example

Interaction Models

Learning Rate



Network Modularity

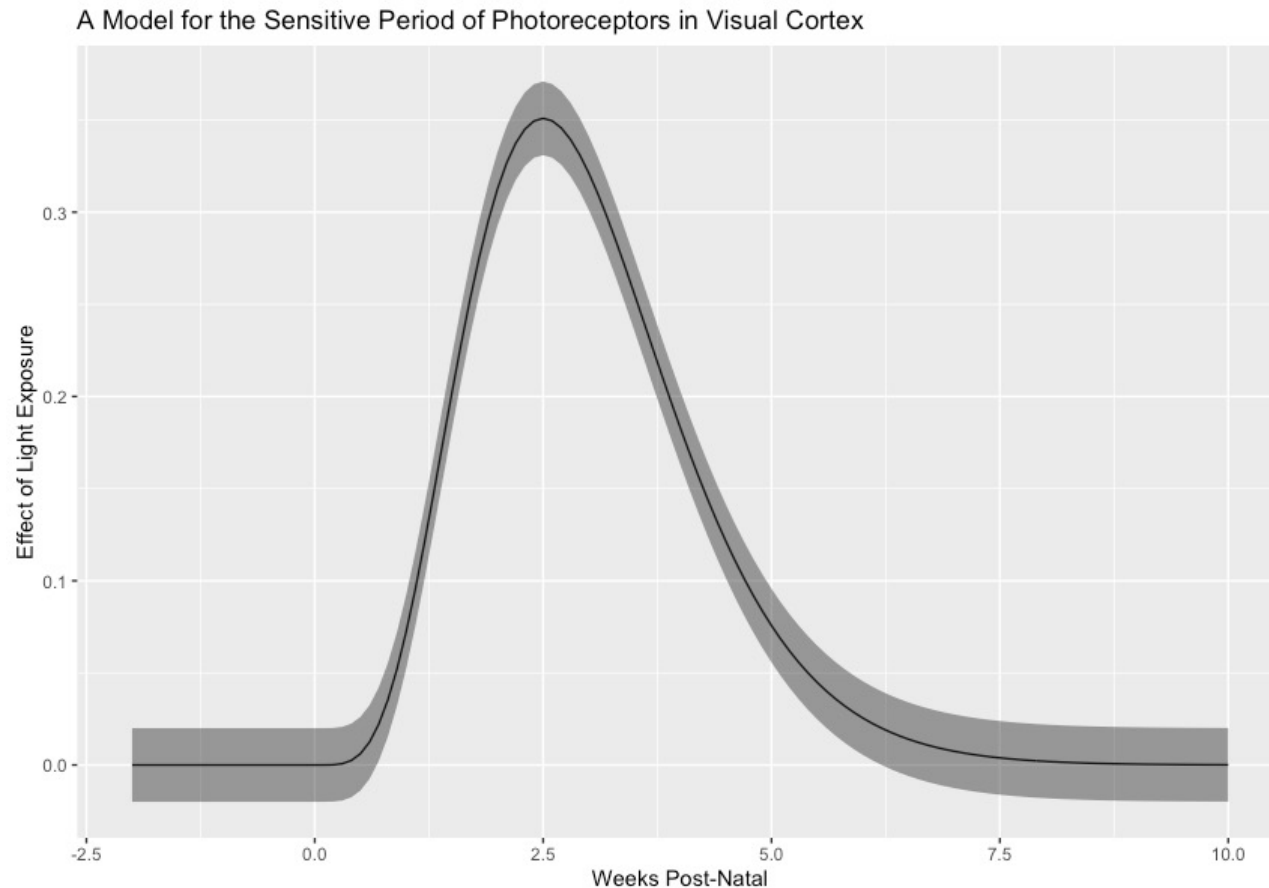


Use-Case 2: Modeling Interactions for Sensitive Periods

- Simple tests for sensitive periods
 - In the prior example, we have a bilinear interaction (β_{stress} changes linearly over age)
 - Quadratic/cubic effects
 - The effect of age itself changes across age in some fashion
 - Generally requires that we pre-specify the sensitive period relationship
 - Can be limiting if the effects are truly nonlinear

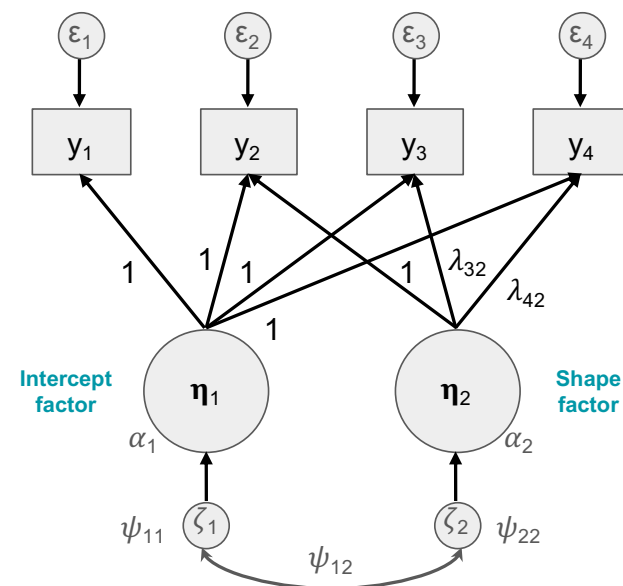
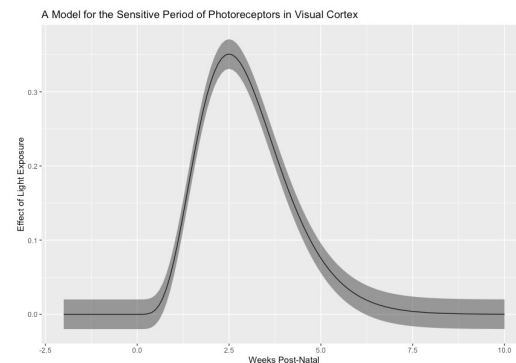
Use-Case 2: Nonlinear Interactions for Sensitive Periods

- Nonlinear tests for sensitive periods



Use-Case 2: Nonlinear Interactions for Sensitive Periods

- Nonlinear tests for sensitive periods
 - Generalized additive models
 - Spline-based approach
 - Allows naturally for nonlinear interactions
 - Fixed versus random effects
 - Latent Basis models
 - Free-factor loadings
 - Including predictors of shape factor



Use-Case 2: Nonlinear Interactions for Sensitive Periods

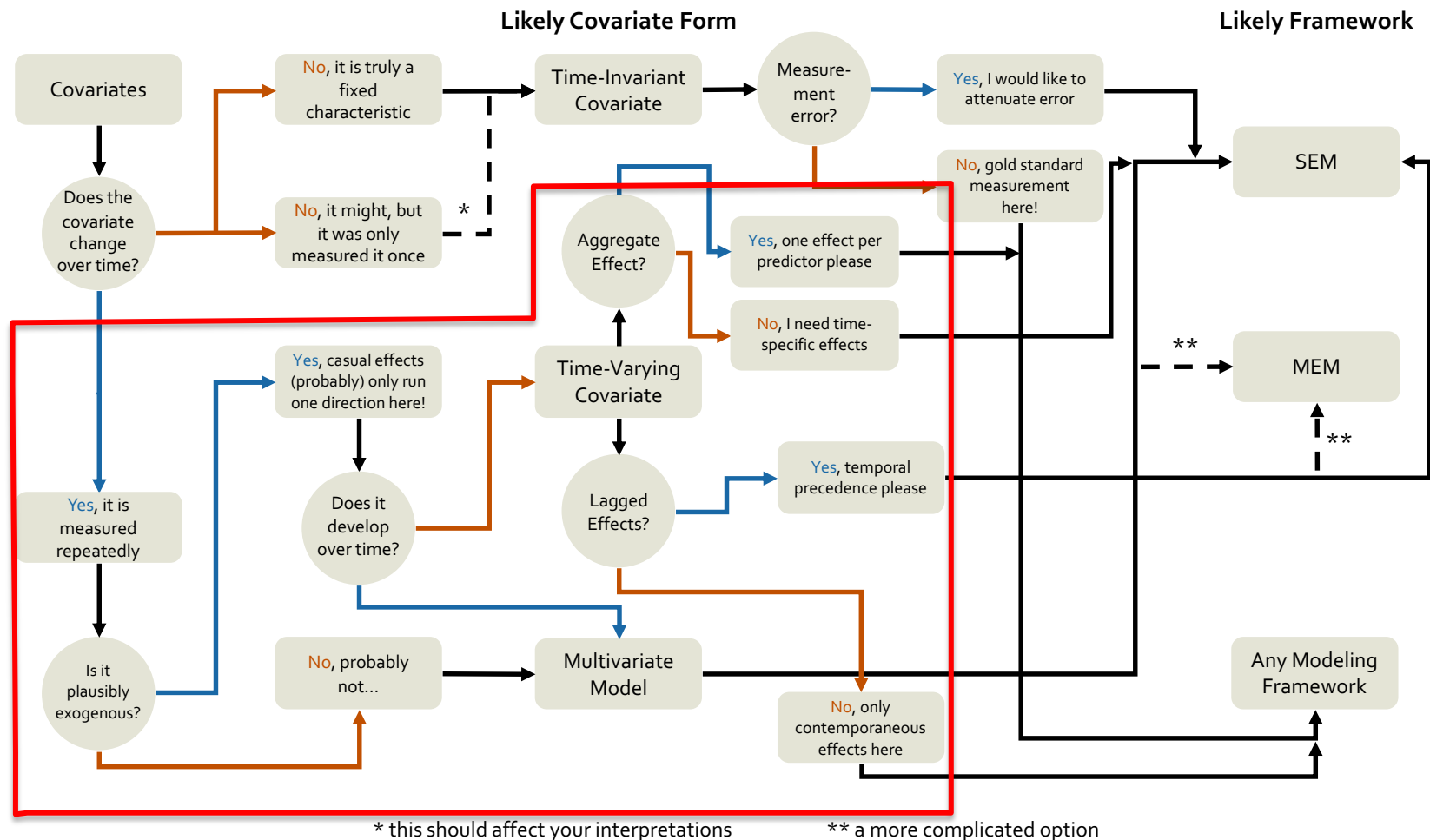
- Nonlinear tests for sensitive periods
 - Often require many more timepoints to model
 - Can benefit from accelerated designs with a fixed effect
- Differential Coupling
 - Require us to move away from univariate (i.e., single-outcome models)
 - How do two (or more) constructs travel together through time?

Understanding brain-behavior relationships

Use-Case 3: Brain-Behavior Relationships

- Brain-Behavior Relationships
 - Fundamentally about testing causal explanations for *why* we see particular developmental trajectories
 - Time-invariant Effects
 - Explain stable between-person differences
 - Time-varying Effects
 - Can explain within-person processes
 - Can be exogenous or endogenous

Use-Case 3: Brain-Behavior Relationships Heuristic Map



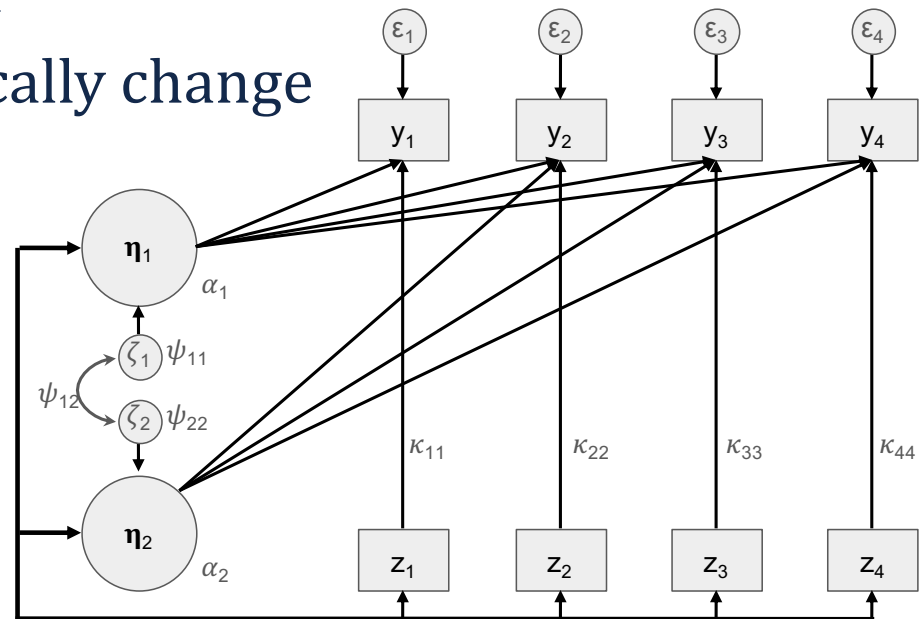
Use-Case 3: TVC-Models

- Exogenous Time-varying Covariates
 - Only one causal direction
 - TVC “fixed and known”
 - Typically, a univariate model
 - MEM or SEM will work
 - TVC does not systematically change

MLM Equation

$$y_{ti} = \gamma_{00} + \gamma_{10}Time_{ti} + \gamma_{20}TVC_{ti} + u_{0i} + u_{1i}Time_{ti} + r_{ti}$$

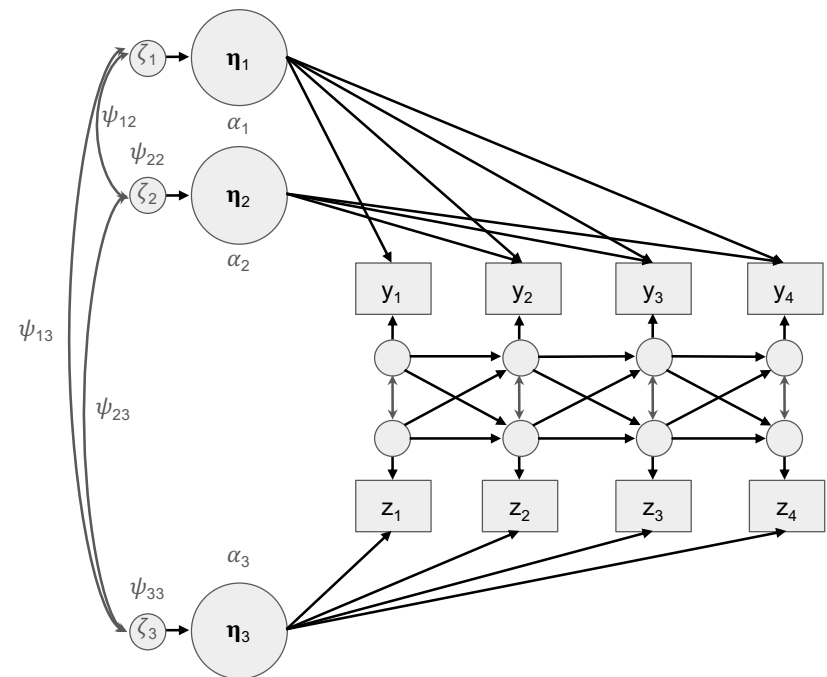
SEM Diagram



Use-Case 3: Multivariate Models

- Endogenous (Multivariate) Time-varying Effects
 - Reciprocal relationships over time
 - TVC assumed measured with error
 - Real limitations for MEMs
 - SEMs predominate
 - Different functional forms

SEM Diagram



Use-Case 3: Within- and Between-Person Effects

- TICs only explain between-person variance, but TVCs can explain both within- and between variance
 - To separate out these effects, we need to do a little extra work
- MEMs
 - Centering of predictors by extracting the means
- SEMs
 - Structured residuals

Conclusions and Next Steps

Conclusions and Next Steps

- Longitudinal model selection is complex and there are rarely 100% “right” answers
 - We should strive to be better but know that there are inherent limitations
- Understanding model assumptions gives us more reliable estimates of the effects of interest
 - Constrains our conclusions
- “Working out the terms of moral justification is an unending task.”
 - Also works for matching models to theory



Conclusions and Next Steps

- More in-depth exploration of these topics: Preprint
 - Including links to lots of primary sources
- Hands on code applications of these models: Online codebook companion
 - Primarily in R but some (future) resources for Mplus/SAS
- Additional training in advanced topics: Flux Pre-conference (details to come)

Especial thanks to these lovely people



THE UNIVERSITY
of NORTH CAROLINA
at CHAPEL HILL



Universiteit
Leiden



UNIVERSITY OF
MARYLAND



UNIVERSITY OF
OREGON



Erasmus
University
Rotterdam

Erasmus



Radboudumc

DONDERS
INSTITUTE



MONASH
University



HARVARD
UNIVERSITY



National Institute
of Mental Health



National Institute
on Drug Abuse



European
Research
Council



National Institute
of Mental Health

Questions?



@McCormickNeuro



ethan.mccormick@radboudumc.nl



<https://mccormickneuro.github.io/>