Understanding the time course of interventions - a memory strategy example

March, 2018

Charles Driver

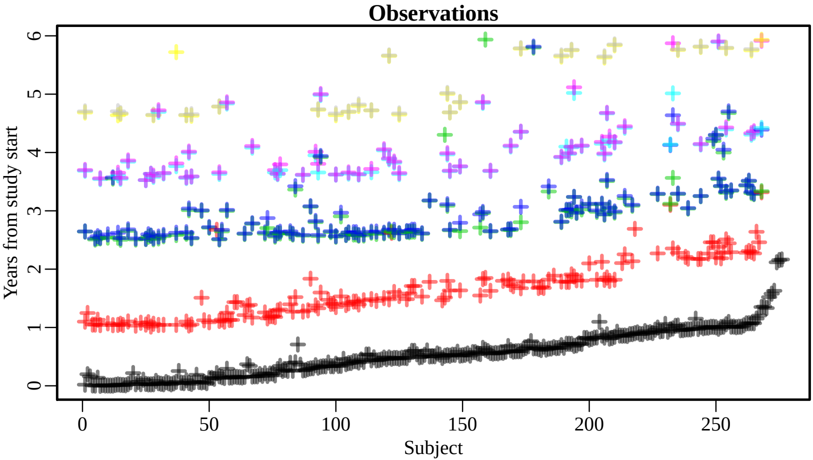
Max Planck Institute for Human Development

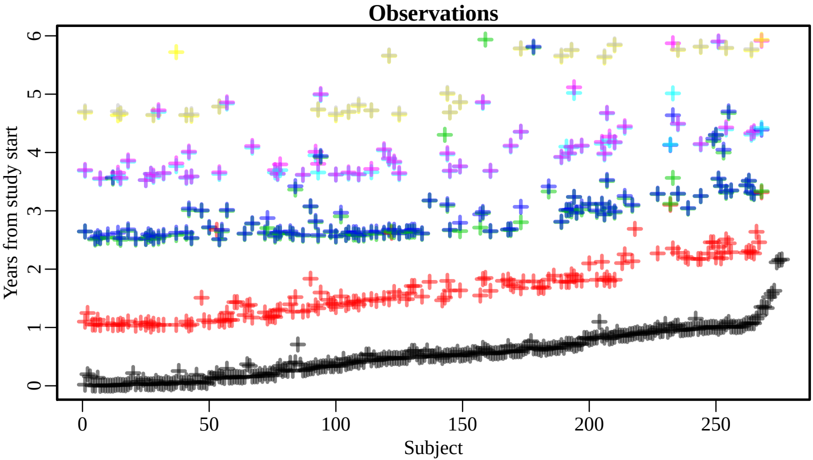
- Change in associative and recognition memory across the adult age range, particularly with regards to strategy use.

- Change in associative and recognition memory across the adult age range, particularly with regards to strategy use.
- Longitudinal study with 5 waves – though actually 8 waves!

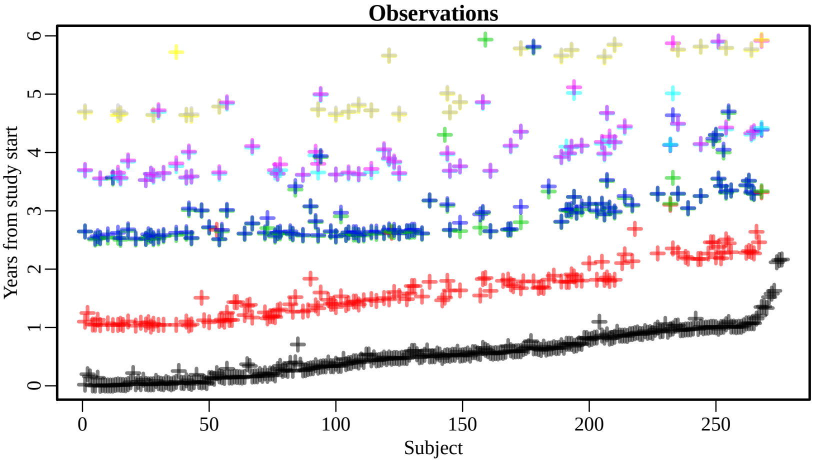
- Change in associative and recognition memory across the adult age range, particularly with regards to strategy use.
- Longitudinal study with 5 waves – though actually 8 waves!
- Within wave, participants shown two lists of 26 word pairs, and tested on recognition of individual words (items) and pairs of words (associations).

book running

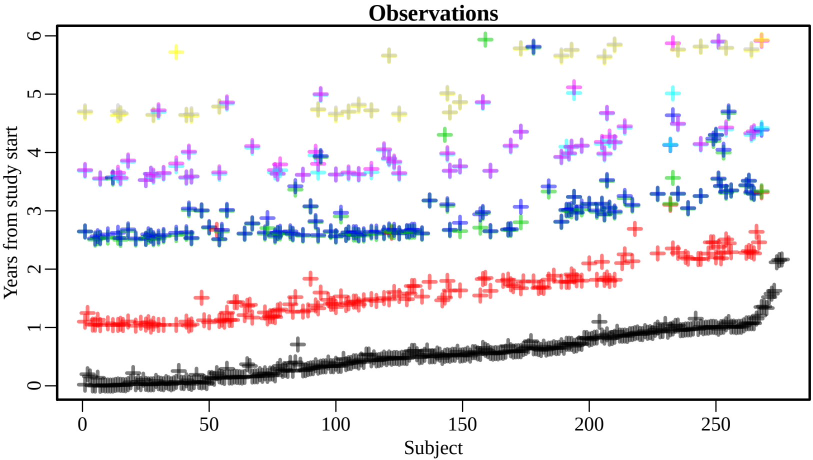

Observations
Years from study start
0
1
2
3
4
5
6
Subject
0
50
100
150
200
250



- Before each of the 3 waves with the short, 2 week interval, deep encoding intervention:



- Before each of the 3 waves with the short, 2 week interval, deep encoding intervention:
  - Participants asked to generate, for each pair, a sentence relating the two words to each other during the study portion, and use that sentence to aid recognition of words and pairs.

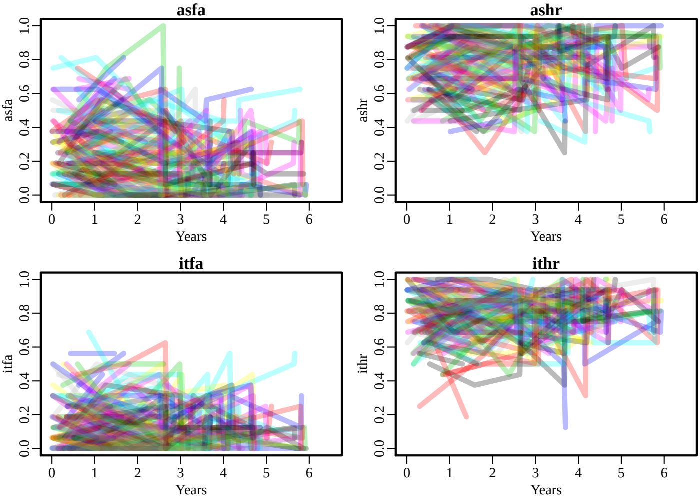


- Before each of the 3 waves with the short, 2 week interval, deep encoding intervention:
  - Participants asked to generate, for each pair, a sentence relating the two words to each other during the study portion, and use that sentence to aid recognition of words and pairs.
- Individual variation in timing too...

Research questions

- Does the intervention have lasting effects?

- Does the intervention have lasting effects?
- How do the covariates moderate the findings?


asfa
ashr
itfa
ithr
Years
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5
6

- Subject level latent dynamics driven by stochastic differential equation:

$$\mathrm{d}\boldsymbol{\eta}(t) = \left(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\boldsymbol{\chi}(t)\right)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Subject level latent dynamics driven by stochastic differential equation:

$$\mathrm{d}\boldsymbol{\eta}(t) = \Big(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\chi(t)\Big)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Observations for each subject are described by:

$$\mathbf{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\epsilon}(t) \quad \text{where } \boldsymbol{\epsilon}(t) \sim \mathrm{N}(\mathbf{0}_c, \boldsymbol{\Theta}) \tag{2}$$

- Subject level latent dynamics driven by stochastic differential equation:

$$\mathrm{d}\boldsymbol{\eta}(t) = \left(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\boldsymbol{\chi}(t)\right)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Observations for each subject are described by:

$$\mathbf{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\epsilon}(t) \quad \text{where } \boldsymbol{\epsilon}(t) \sim \mathrm{N}(\mathbf{0}_c, \boldsymbol{\Theta}) \tag{2}$$

- Possible via:

- Subject level latent dynamics driven by stochastic differential equation:

$$\mathrm{d}\boldsymbol{\eta}(t) = \left(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\boldsymbol{\chi}(t)\right)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Observations for each subject are described by:

$$\mathbf{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\epsilon}(t) \quad \text{where } \boldsymbol{\epsilon}(t) \sim \mathrm{N}(\mathbf{0}_c, \boldsymbol{\Theta}) \tag{2}$$

- Possible via:
    - wide, SEM approach.

- Subject level latent dynamics driven by stochastic differential equation:

$$\mathrm{d}\boldsymbol{\eta}(t) = \Big(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\chi(t)\Big)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Observations for each subject are described by:

$$\mathbf{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\epsilon}(t) \quad \text{where } \boldsymbol{\epsilon}(t) \sim \mathrm{N}(\mathbf{0}_c, \boldsymbol{\Theta}) \tag{2}$$

- Possible via:
  - wide, SEM approach.
  - long, Kalman-filter.

- Subject level latent dynamics driven by stochastic differential equation:

$$\mathrm{d}\boldsymbol{\eta}(t) = \left(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\boldsymbol{\chi}(t)\right)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Observations for each subject are described by:

$$\mathbf{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\epsilon}(t) \quad \text{where } \boldsymbol{\epsilon}(t) \sim \mathrm{N}(\mathbf{0}_c, \boldsymbol{\Theta}) \tag{2}$$

- Possible via:
  - wide, SEM approach.
  - long, Kalman-filter.
- Frequentist SEM allows individual variation in intercepts,

- Subject level latent dynamics driven by stochastic differential equation:

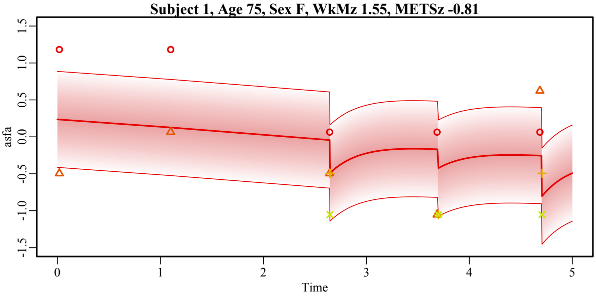
$$\mathrm{d}\boldsymbol{\eta}(t) = \left(\mathbf{A}\boldsymbol{\eta}(t) + \mathbf{b} + \mathbf{M}\boldsymbol{\chi}(t)\right)\mathrm{d}t + \mathbf{G}\mathrm{d}\mathbf{W}(t) \tag{1}$$

- Observations for each subject are described by:

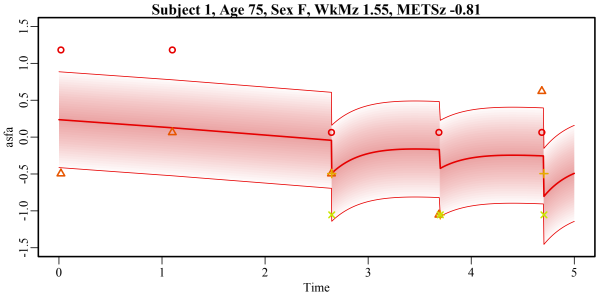
$$\mathbf{y}(t) = \boldsymbol{\Lambda}\boldsymbol{\eta}(t) + \boldsymbol{\tau} + \boldsymbol{\epsilon}(t) \quad \text{where } \boldsymbol{\epsilon}(t) \sim \mathrm{N}(\mathbf{0}_c, \boldsymbol{\Theta}) \tag{2}$$

- Possible via:
  - wide, SEM approach.
  - long, Kalman-filter.
- Frequentist SEM allows individual variation in intercepts,
- With Bayesian formulation, everything can vary.

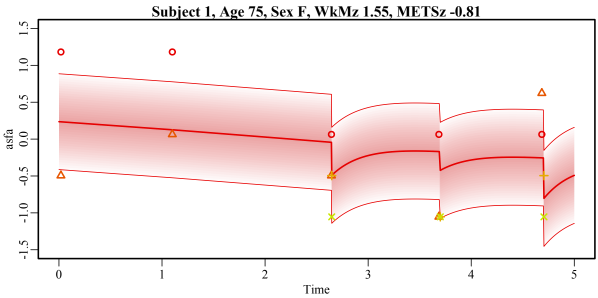
- Four latent memory factors asfa, ashr, itfa, ithr, each measured by two noisy indicators per wave.



- Four latent memory factors asfa, ashr, itfa, ithr, each measured by two noisy indicators per wave.
- Change over time in these latent factors is modelled with an initial intercept, a linear slope, and a stochastic portion to account for meaningful but unpredictable (according to our model) change.



- Four latent memory factors asfa, ashr, itfa, ithr, each measured by two noisy indicators per wave.
- Change over time in these latent factors is modelled with an initial intercept, a linear slope, and a stochastic portion to account for meaningful but unpredictable (according to our model) change.
- On top of this, we estimate an intervention process, and the effect of this process on each of the four memory factors.

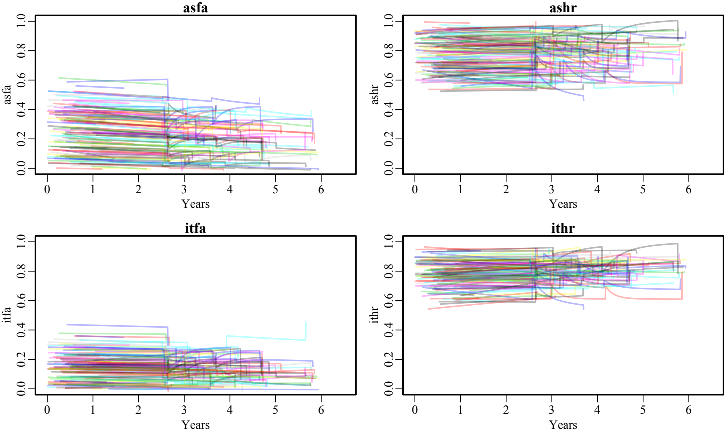


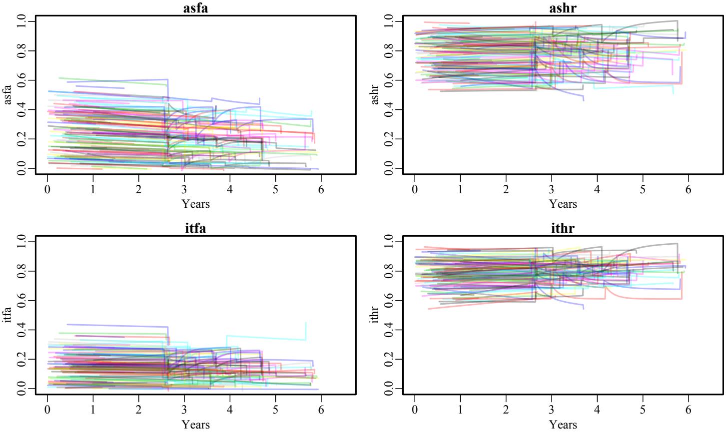
What do we gain with such an approach to interventions?

- Continuous time accounts for variability in time interval between observations.

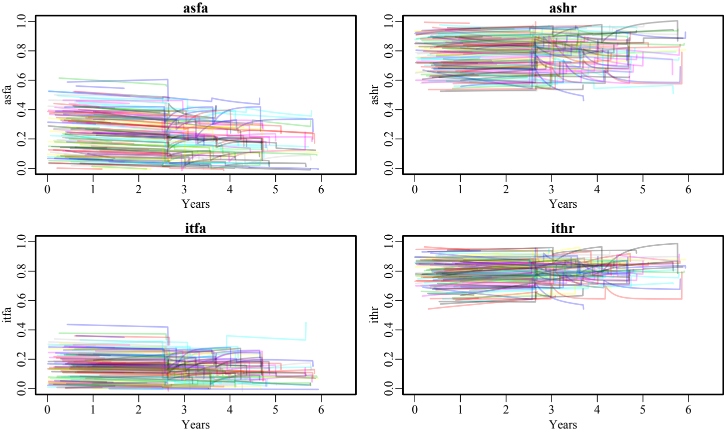
- Continuous time accounts for variability in time interval between observations.
- Intervention as dynamic process allows estimating unknown shape / persistence parameters.

- Continuous time accounts for variability in time interval between observations.
- Intervention as dynamic process allows estimating unknown shape / persistence parameters.
- Hierarchical approach accounts for, allows understanding of, individual variability.

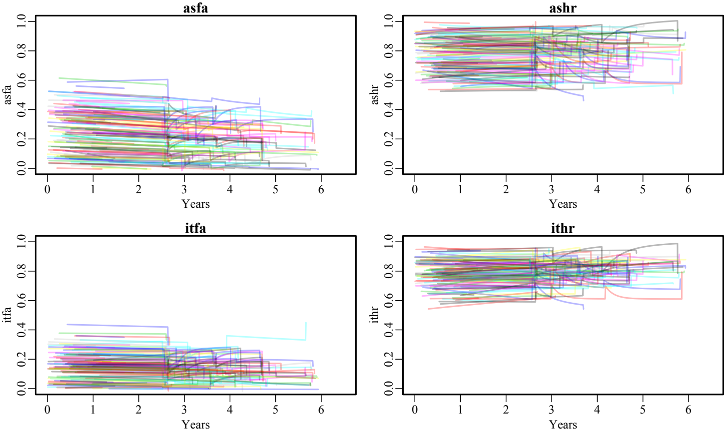

asfa
ashr
itfa
ithr
Years
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5
6



- Sig. intervention improvement for asfa, ashr, itfa.

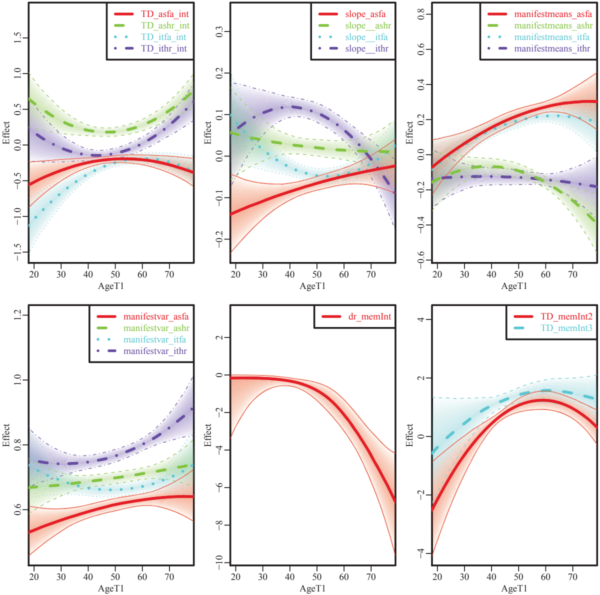


- Sig. intervention improvement for asfa, ashr, itfa.
- Unclear if intervention effect persists across years – probably not in general.

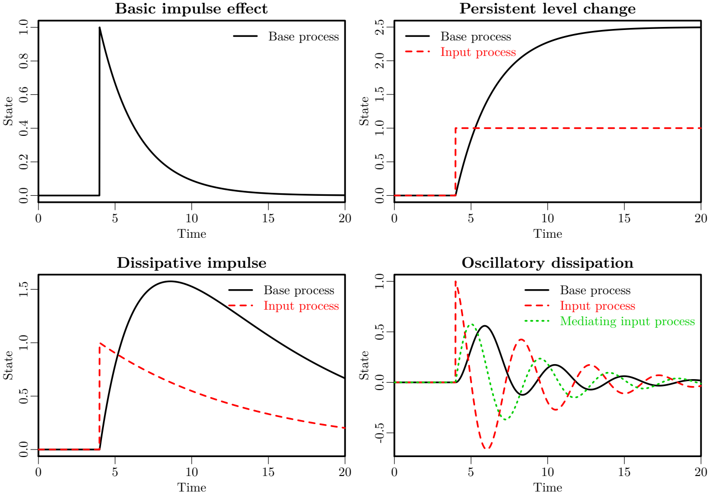


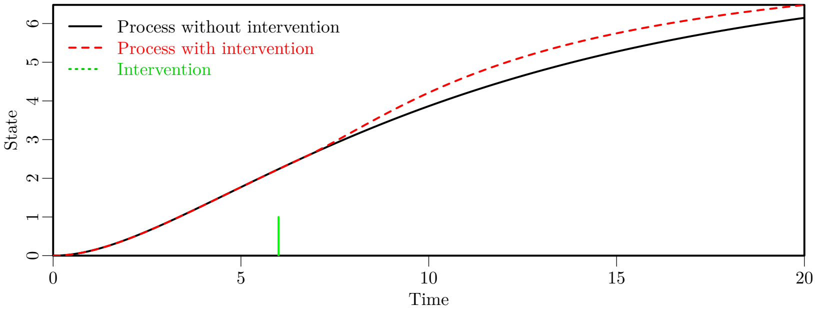
- Sig. intervention improvement for asfa, ashr, itfa.
- Unclear if intervention effect persists across years – probably not in general.
- Intervention gives greater gains for worse performers.

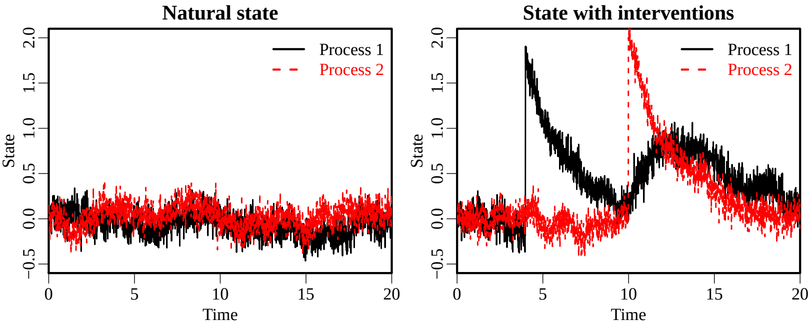
Individual differences - age effects



Discussion points - different shapes of intervention effect




Process without intervention
Process with intervention
Intervention
State
Time
0
1
2
3
4
5
6
0
5
10
15
20


Natural state
State with interventions
Process 1
Process 2
State
Time
2.0
1.5
1.0
0.5
0.0
−0.5
0
5
10
15
20

- Fits are better than saturated covariance structure.

- Fits are better than saturated covariance structure.
- Are there formalised approaches for model fit with person specific mean and or covariance?

- Fits are better than saturated covariance structure.
- Are there formalised approaches for model fit with person specific mean and or covariance?
- Is absolute fit actually important?

- The effect of interventions can change in time, and across people.

- The effect of interventions can change in time, and across people.
- Analyses and plots via ctsem R package.

- The effect of interventions can change in time, and across people.
- Analyses and plots via ctsem R package.
- Chapter: Understanding the time course of interventions with continuous time dynamic models.

- The effect of interventions can change in time, and across people.
- Analyses and plots via ctsem R package.
- Chapter: Understanding the time course of interventions with continuous time dynamic models.
- Thanks!