Dynamic Structural Equation Modeling of Intensive Longitudinal Data Using Mplus Version 8

Parts 1 and 2

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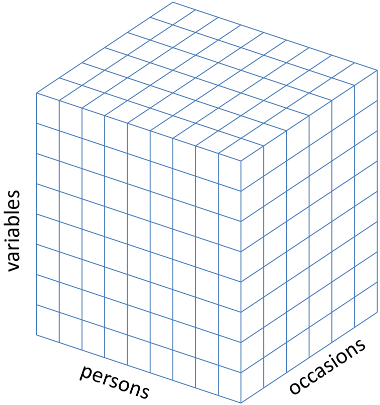
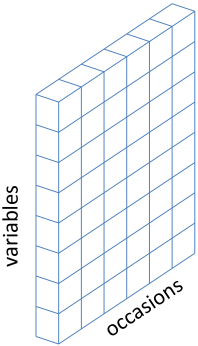
Cattell's data box



Time series data: N=1 and T is large



Idiographic (N=1) research in psychology

N=1 research has included:

- Cattell's P-technique: factor analysis of N=1 data
- Dynamic factor analysis: considering lagged relationships
- Measurement burst design: multiple waves of intensive measurements
- Intervention research: ABAB design etc.

Critique of this kind of research:

- within-person fluctuations are just **noise**
- results are **not generalizable**
- no one has these data

New technology

Smart phones

Smart glasses

Secure continuous remote alcohol monitor (SCRAM)

Smart watches

Activity trackers

Intensive longitudinal data

Different forms of intensive longitudinal data:

- daily diary (DD); self-report end-of-day
- experience sampling method (ESM); self-report of subjective experience
- ecological momentary assessment (EMA); healthcare related self-report
- ambulatory assessment (AA); physiological measurements
- event-based measurements; self-report after a particular event
- observational measurements; expert rater

For more info on **methodology**, check out:

- Seminar of Tamlin Conner and Joshua Smyth on YouTube (https://www.youtube.com/watch?v=nQBBVp9vBIQ)
- Society for Ambulatory Assessment (http://www.saa2009.org/)
- Life Data (https://www.lifedatacorp.com/)
- Quantified Self (http://quantifiedself.com/)

Characteristics of these kind of data

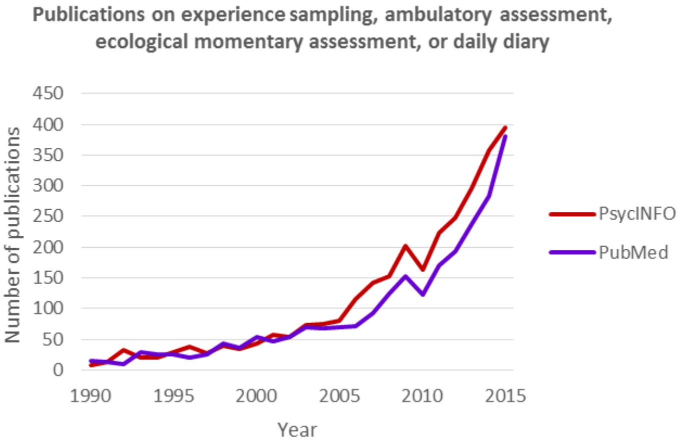
Data structure:

- one or more measurements per day
- typically for multiple days
- sometimes multiple waves (i.e., Nesselroade's measurement-burst design)

Advantages of ESM, EMA and AA

- no recall bias
- high ecological validity
- physiological measures over a large time span
- monitoring of symptoms and behavior, with new possibilities for feedback and intervention (e-Health and m-Health)
- window into the dynamics of processes

A paradigm shift



Taken from Hamaker and Wichers (2017)

Outline

- **Time series analysis**
- Multilevel time series analysis
- DSEM application 1: Multilevel VAR(1) model
- DSEM application 2: Mediation
- DSEM application 3: Random innovation variance
- DSEM application 4: Intervention study
- DSEM application 5: Latent variable model
- Discussion

What is time series analysis?

Time series analysis is a class of techniques that is used in econometrics, seismology, meteorology, control engineering, and signal processing.

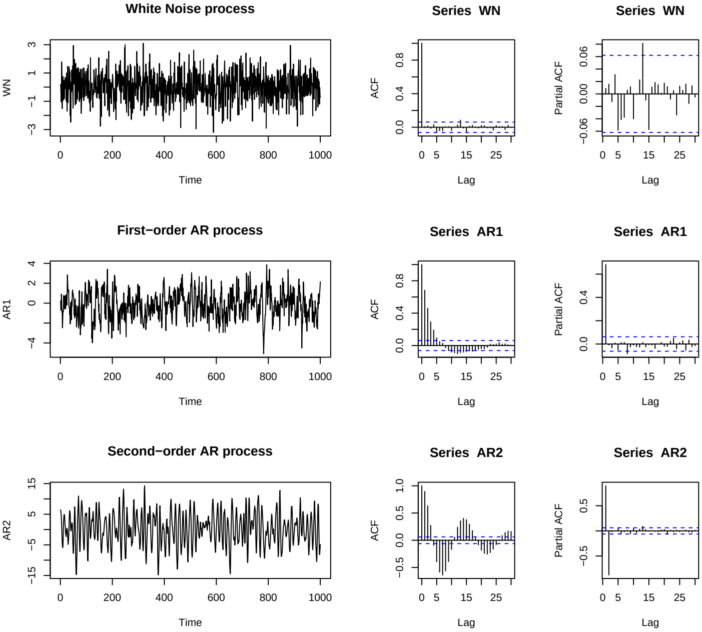
Main characteristics:

- N=1 technique
- T is large (say $>$50)
- concerned with *trends*, *cycles* and *autocorrelation structure* (i.e., serial dependency)
- goal: forecasting ($\neq$ prediction)

Lags

Y	Y at lag 1	Y at lag 2
y_1		
y_2	y_1	
y_3	y_2	y_1
y_4	y_3	y_2
y_5	y_4	y_3
y_6	y_5	y_4
y_7	y_6	y_5
y_8	y_7	y_6
$\dots$	$\dots$	$\dots$
y_T	y_{T-1}	y_{T-2}
	y_T	y_{T-1}
		y_T

Sequence, ACF and PACF



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Lagged relationships in multilevel data

If we have **time series data from multiple individuals**, we may want to study:

- individual differences in lagged relationships between a variable and itself: **autoregression**
- individual differences in lagged relationship between different variables: **cross-lagged relationships**

If we use multilevel modeling for this, we could refer to it as **multilevel time series analysis**, or **dynamic multilevel modeling**.

Creating lagged predictors

ID	$\mathbf{y_{it}}$	$\mathbf{y_{it-1}}$	$\mathbf{x_{it-1}}$
1	$\mathbf{y_{11}}$	–	–
1	$\mathbf{y_{12}}$	$\mathbf{y_{11}}$	$\mathbf{x_{11}}$
1	$\mathbf{y_{13}}$	$\mathbf{y_{12}}$	$\mathbf{x_{12}}$
1	...	...	...
1	$\mathbf{y_{1T}}$	$\mathbf{y_{1T-1}}$	$\mathbf{x_{1T-1}}$
2	$\mathbf{y_{21}}$	–	–
2	$\mathbf{y_{22}}$	$\mathbf{y_{21}}$	$\mathbf{x_{21}}$
2	$\mathbf{y_{23}}$	$\mathbf{y_{22}}$	$\mathbf{x_{22}}$
2	...	...	...
2	$\mathbf{y_{2T}}$	y_{2T-1}	$\mathbf{x_{2T-1}}$
...	...	...	...
N	$\mathbf{y_{N1}}$	–	–
N	$\mathbf{y_{N2}}$	$\mathbf{y_{N1}}$	$\mathbf{x_{N1}}$
N	$\mathbf{y_{N3}}$	$\mathbf{y_{N2}}$	$\mathbf{x_{N2}}$
N	...	...	...
N	$\mathbf{y_{NT}}$	$\mathbf{y_{NT-1}}$	$\mathbf{x_{NT-1}}$

Inertia research based on multilevel AR(1) models

Level 1 model:

$$NA_{it} = c_i + \phi_i NA_{i,t-1} + \zeta_{it}$$

Level 2 model:

$$c_i = \gamma_{00} + u_{0i}$$
$$\phi_i = \gamma_{01} + u_{1i}$$

This research line was initiated by **Suls, Green and Hillis (1998)**, and continued by the group of **Kuppens.**

The focus is on individual differences in the **autoregressive parameter** ϕ_i (=inertia, carry-over, regulatory weakness), which is shown to be:

- positively related to current depression, neuroticism, and being female
- predictive of later depression (Kuppens and Koval)

Dynamic networks based on multilevel VAR(1) models

Level 1 model:

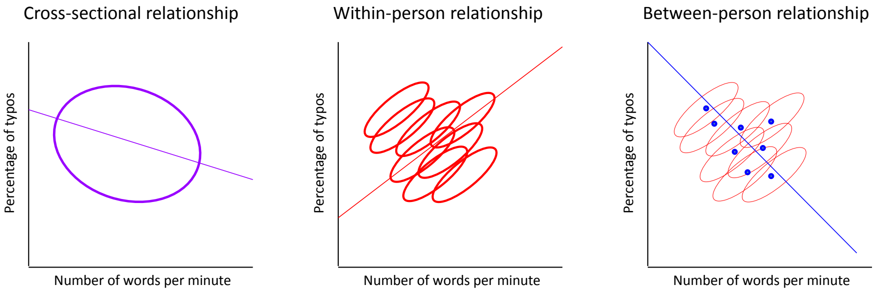
$$
\begin{aligned}
&y_{1it} = c_{1i} + \phi_{11i} y_{1it-1} + \cdots + \phi_{1ki} y_{kit-1} + \zeta_{1it} \\
&y_{2it} = c_{2i} + \phi_{21i} y_{1it-1} + \cdots + \phi_{2ki} y_{kit-1} + \zeta_{2it} \\
&\ldots \\
&y_{kit} = c_{ki} + \phi_{k1i} y_{1it-1} + \cdots + \phi_{kki} y_{kit-1} + \zeta_{kit}
\end{aligned}
$$

Initiated by **Bringmann et al. (2013)**, and further popularized by the software from **Sacha Epskamp.**

The focus is on **cross-lagged parameters** between variables (=nodes; typically symptoms), and on measures based on these (e.g., centrality).

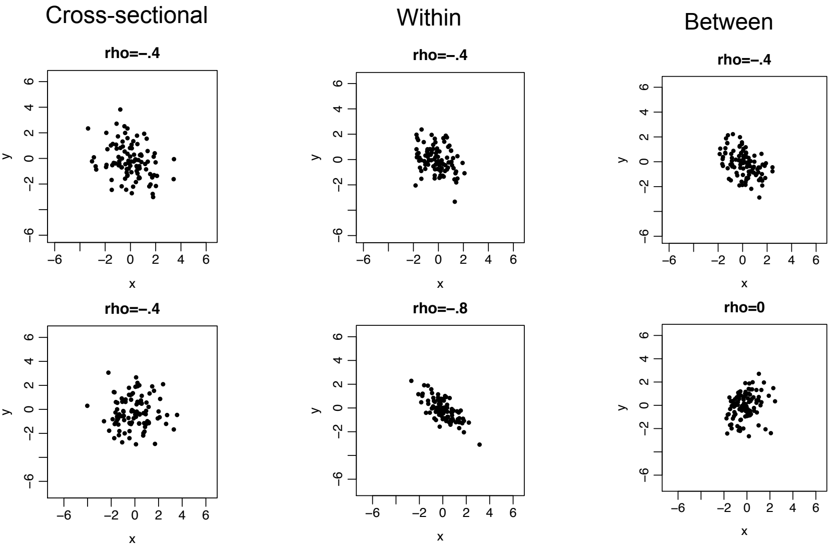
Main idea is that **stronger connections** lead to an **increased risk** of developing and maintaining psychopathology.

A fundamental problem in a nutshell



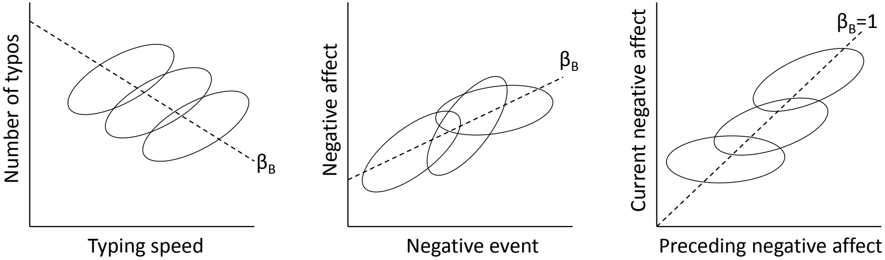
Taken from Hamaker (2012).

Three perspectives on data



Taken from Hamaker (2012).

Within-person slopes



Taken from Hamaker and Grasman (2014).

The **within-person slope** can:

- differ from the between-person slope
- differ across individuals (i.e., random slope)
- be an autoregression

When **estimating** the multilevel AR(1) model, we can decide to:

- **not center** the lagged predictor (NC)
- center with the **sample mean** $\bar{y}_{\cdot i}$
- center with the **estimated mean from an empty multilevel model** $\hat{\mu}_i$
- center with the **true mean** μ_i (in case of simulations)

Sample size		**Bias**				**CR**$_{.95}$			
N	T	NC	C($\bar{y}_{\cdot i}$)	C($\hat{\mu}_i$)	C(μ_i)	NC	C($\bar{y}_{\cdot i}$)	C($\hat{\mu}_i$)	C(μ_i)
20	20	.002	-.072	-.069	-.068	.928	.762	.785	.787
	50	.000	-.027	-.027	-.026	.940	.900	.901	.898
	100	.000	-.013	-.013	-.013	.932	.932	.932	.932
50	20	.005	-.071	-.069	-.067	.893	.480	.512	.518
	50	.001	-.027	-.026	-.026	.936	.800	.804	.805
	100	.000	-.013	-.013	-.013	.946	.902	.902	.903
100	20	.006	-.070	-.068	-.066	.892	.196	.227	.242
	50	.001	-.027	-.027	-.027	.930	.623	.630	.637
	100	.000	-.013	-.013	-.013	.930	.851	.854	.851

Disadvantages of using regular multilevel software

If we are interested in **dynamic multilevel modeling**, we may run into the following problems/limitation when using **standard multilevel software**:

- **negative bias in autoregression** when centering the lagged predictor (Nickell's bias)
- only **one outcome variable** (thus, separate models for multivariate outcomes)
- only **observed variables** (no measurement error, moving average terms, factor models)
- **missing data** result in many missing cases
- **unequally spaced** observations

Dynamic structural equation modeling (DSEM) in Mplus tackles all these problems.

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Data: Daily measurements affect

Data come from the **COGITO study** of the MPI in Berlin; goal is to study aging using a younger and older sample.

Analyses here are based on Hamaker et al. (under revision).

Characteristics of the **younger** and **older sample**:

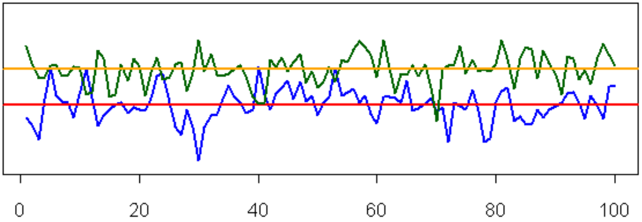
- aged 20-31; aged 65-80
- 101 individuals; 103 individuals
- about 100 daily measurements of positive affect (PA) and negative affect (NA)

Decomposition into a between part and a within part

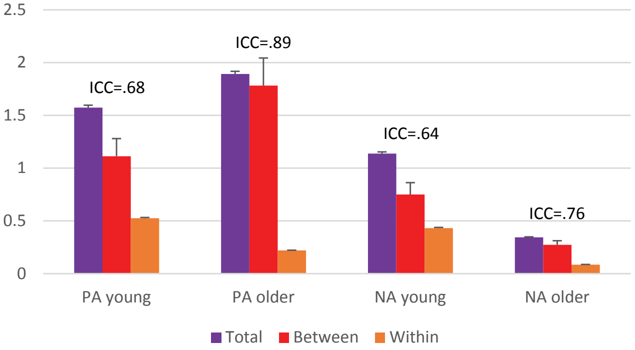
$$PA_{it} = \mu_{PA,i} + PA_{it}^{(w)}$$
$$NA_{it} = \mu_{NA,i} + NA_{it}^{(w)}$$

where

- $\mu_{PA,i}$ and $\mu_{NA,i}$ are the individual's **means** on PA and NA (i.e., baseline, trait, or equilibrium scores) $\Rightarrow$ between-person part
- $PA_{it}^{(w)}$ and $NA_{it}^{(w)}$ are the **within-person centered** (cluster-mean centered) scores $\Rightarrow$ within-person part



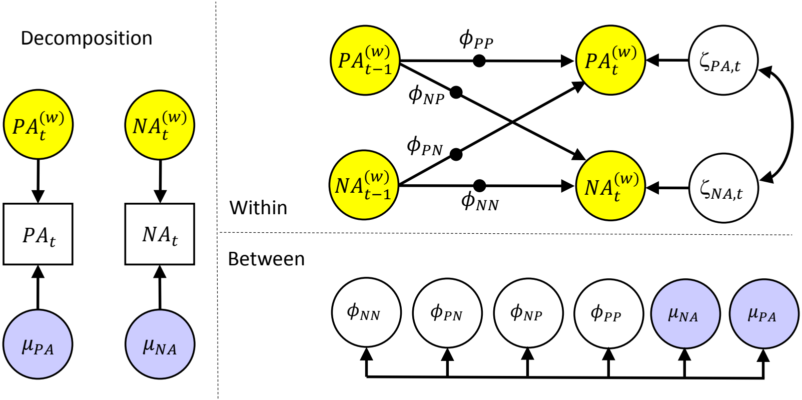
Total, between-, and within-person variance



Intraclass correlation:

$$\frac{\sigma^2_{between}}{\sigma^2_{between}+\sigma^2_{within}} = \frac{\sigma^2_{between}}{\sigma^2_{total}}$$

Bivariate model: Multilevel vector AR(1) model



Within-person level model

Lagged within-person model:

$$PA_{it}^{(w)} = \phi_{PP,i} PA_{i,t-1}^{(w)} + \phi_{PN,i} NA_{i,t-1}^{(w)} + \zeta_{PA,it}$$
$$NA_{it}^{(w)} = \phi_{NN,i} NA_{i,t-1}^{(w)} + \phi_{NP,i} PA_{i,t-1}^{(w)} + \zeta_{NA,it}$$

where

- $\phi_{PP,i}$ is the **autoregressive parameter** for PA (i.e., inertia, carry-over)
- $\phi_{NN,i}$ is the **autoregressive parameter** for NA (i.e., inertia, carry-over)
- $\phi_{PN,i}$ is the **cross-lagged parameter** for NA to PA (i.e., spill-over)
- $\phi_{NP,i}$ is the **cross-lagged parameter** for PA to NA (i.e., spill-over)
- $\zeta_{PA,it}$ is the **innovation** for PA (residual, disturbance, dynamic error)
- $\zeta_{NA,it}$ is the **innovation** for NA (residual, disturbance, dynamic error)

Parameters estimated at this level are the residual variances and covariance:

$$\begin{bmatrix} \zeta_{PA,it} \\ \zeta_{NA,it} \end{bmatrix} \sim MN \left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \theta_{11} & \\ \theta_{21} & \theta_{22} \end{bmatrix} \right]$$

Between-person level model

Between level: fixed and random effects

$$\mu_{PA,i} = \gamma_P + u_{P,i}$$
$$\mu_{NA,i} = \gamma_N + u_{N,i}$$
$$\phi_{PP,i} = \gamma_{PP} + u_{PP,i}$$
$$\phi_{PN,i} = \gamma_{PN} + u_{PN,i}$$
$$\phi_{NP,i} = \gamma_{NP} + u_{NP,i}$$
$$\phi_{NN,i} = \gamma_{NN} + u_{NN,i}$$

The u's are assumed to be **multivariate normally distributed** (i.e., $\boldsymbol{u} \sim MN(\mathbf{0}, \boldsymbol{\Psi})$).

Parameters estimated at this level are:

- 6 fixed effects (i.e., γ's)
- 6 variances for random effects (i.e., diagonal elements of $\boldsymbol{\Psi}$: variances of the u's)
- 15 covariances between the random effects (i.e., off-diagonal elements in $\boldsymbol{\Psi}$)

Bivariate model: Mplus code

Data are in **long format** (i.e., each record is an occasion within a person; multiple records per person).

Lagged variables are **created in Mplus** (using the LAGGED command).

```
VARIABLE:    NAMES = id sessdate
             na1 na2 na3 na4 na5 na6 na7 na8 na9 na10
             pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
             sessionNr age_pre sex CESDpre CESDpost dayNA dayPA older;

             CLUSTER = id; ! Specify the person id variable
             USEVAR = dayPA dayNA; ! Specify which variables are used in the model
             MISSING = ALL(-999);
             LAGGED = dayPA(1) dayNA(1); ! This creates lagged variables
             TINTERVAL = sessdate(1); ! This is to account for unequal intervals

ANALYSIS:    TYPE = TWOLEVEL RANDOM; ! This allows for random slopes
             ESTIMATOR = BAYES; ! DSEM requires Bayesian estimation
             PROC = 2; ! Using 2 processors makes it faster
             BITER = (5000); ! This implies at least 5000 iterations are used
             THIN = 10; ! Thinning helps with getting more stable results
```

Bivariate model: Mplus code

```
MODEL:      %WITHIN% ! Specify the random lagged relationships
            p_pp | dayPA ON dayPA&1;
            p_pn | dayPA ON dayNA&1;
            p_np | dayNA ON dayPA&1;
            p_nn | dayNA ON dayNA&1;

            %BETWEEN% ! Allow all 6 random effects to be correlated
            p_pp WITH p_pn-p_nn dayPA dayNA;
            p_pn WITH p_np-p_nn dayPA dayNA;
            p_np WITH p_nn dayPA dayNA;
            p_nn WITH dayPA dayNA;
            dayPA WITH dayNA;

OUTPUT:     TECH1 TECH8 STDYX;

PLOT:       TYPE = PLOT3;
            FACTORS = ALL;
```

Mplus results: Within-person (younger sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
DAYNA WITH						
DAYPA	-0.069	0.004	0.000	-0.076	-0.061	*
Residual Variances						
DAYPA	0.414	0.006	0.000	0.403	0.426	*
DAYNA	0.302	0.004	0.000	0.294	0.311	*

Mplus results: Between-person (younger sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
...						
Means						
DAYPA	3.090	0.110	0.000	2.875	3.308	*
DAYNA	0.977	0.077	0.000	0.826	1.128	*
P_PP	0.334	0.026	0.000	0.283	0.387	*
P_PN	0.050	0.022	0.016	0.006	0.093	*
P_NP	0.038	0.015	0.006	0.008	0.068	*
P_NN	0.370	0.027	0.000	0.315	0.423	*
Variances						
DAYPA	1.178	0.189	0.000	0.886	1.618	*
DAYNA	0.595	0.101	0.000	0.443	0.832	*
P_PP	0.055	0.010	0.000	0.039	0.079	*
P_PN	0.024	0.006	0.000	0.014	0.039	*
P_NP	0.013	0.003	0.000	0.008	0.021	*
P_NN	0.062	0.012	0.000	0.044	0.089	*

Comparing cross-lagged parameters

Standardization in multilevel models is a **tricky issue.**

Schuurman, Ferrer, Boer-Sonnenschein and Hamaker (2016) discuss four forms of **standardization in multilevel models**, using:

- total variance (i.e., grand standardization)
- between-person variance (i.e., between standardization)
- average within-person variance
- within-person variance (i.e., within standardization)

Conclusion: last form is most meaningful, as it **parallels standardizing when N=1.**

Standardized fixed effect should be the **average standardized within-person effect.**

Mplus standardized results (younger sample)

STDYX Standardization

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within-Level Standardized Estimates Averaged Over Clusters						
P_PP | DAYPA ON						
DAYPA&1	0.335	0.011	0.000	0.312	0.358	*
P_PN | DAYPA ON						
DAYNA&1	0.034	0.013	0.006	0.008	0.059	*
P_NP | DAYNA ON						
DAYPA&1	0.038	0.011	0.000	0.017	0.059	*
P_NN | DAYNA ON						
DAYNA&1	0.370	0.012	0.000	0.347	0.394	*
DAYNA WITH						
DAYPA	-0.194	0.010	0.000	-0.213	-0.175	*
Residual Variances						
DAYPA	0.816	0.008	0.000	0.799	0.832	*
DAYNA	0.792	0.008	0.000	0.775	0.808	*

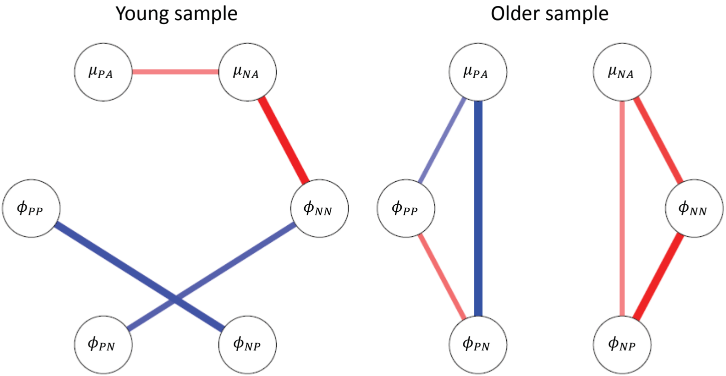
Mplus standardized results (younger sample)

Within-Level R-Square Averaged Across Clusters

Variable	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%
DAYPA	0.184	0.008	0.000	0.168	0.201
DAYNA	0.208	0.008	0.000	0.192	0.225

Between-person level: Correlated random effects

To **represent the correlation matrices** of the 6 random effects in each group, we can use the network representation (with qgraph from Sacha Epskamp in R):



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Including level 2 predictor and outcome

Depression was measured prior to the ILD phase and afterwards, using the CESD; we include these measures at the between-person level as a **predictor** and an **outcome.**

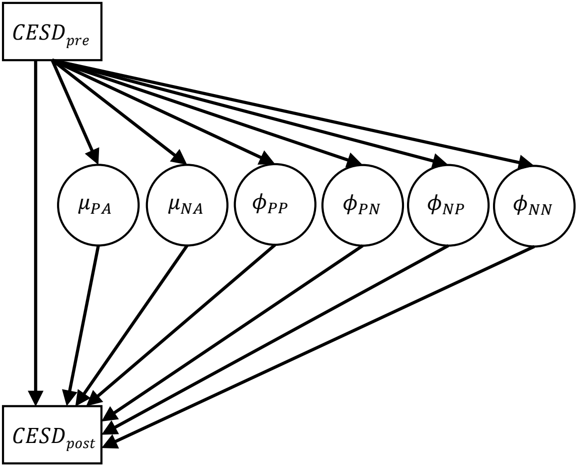
Between level: Including a level 2 predictor

$$
\begin{aligned}
\mu_{PA,i} &= \gamma_{00} + \gamma_{01} CESDpre_i + u_{0i} \\
\mu_{NA,i} &= \gamma_{10} + \gamma_{11} CESDpre_i + u_{1i} \\
\phi_{PP,i} &= \gamma_{20} + \gamma_{21} CESDpre_i + u_{2i} \\
\phi_{PN,i} &= \gamma_{30} + \gamma_{31} CESDpre_i + u_{3i} \\
\phi_{NN,i} &= \gamma_{40} + \gamma_{41} CESDpre_i + u_{4i} \\
\phi_{NP,i} &= \gamma_{50} + \gamma_{51} CESDpre_i + u_{5i}
\end{aligned}
$$

Between level: Including a level 2 outcome

$$
\begin{aligned}
CESDpost_i = {} & \gamma_{60} + \gamma_{61} CESDpre_i + \gamma_{62} \mu_{PA,i} + \gamma_{63} \mu_{NA,i} \\
& + \gamma_{64} \phi_{PP,i} + \gamma_{65} \phi_{PN,i} + \gamma_{66} \phi_{NN,i} + \gamma_{67} \phi_{NP,i} + u_{6i}
\end{aligned}
$$

Dynamic mediation model



Mplus input mediation model

```
VARIABLE:     NAMES = id sessdate
              na1 na2 na3 na4 na5 na6 na7 na8 na9 na10
              pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
              sessionNr age_pre sex CESDpre CESDpost dayNA dayPA older;
              CLUSTER = id;
              USEVAR = dayPA dayNA CESDpre CESDpost; ! Plus level 2 variables
              BETWEEN = CESDpre CESDpost; ! Specify these as level 2 variables
              LAGGED = dayPA(1) dayNA(1);
              TINTERVAL = sessdate(1);
              MISSING = ALL(-999);

DEFINE:       CENTER CESDpre CESDpost (GRANDMEAN);! Grand mean centering

ANALYSIS:     TYPE = TWOLEVEL RANDOM;
              ESTIMATOR = BAYES;
              PROCESSORS = 2;
              BITER = (5000);
              THIN = 10;
```

Bivariate model: Mplus code

```
MODEL:                 %WITHIN% ! Same as before
                       p_pp | dayPA ON dayPA&1;
                       p_pn | dayPA ON dayNA&1;
                       p_np | dayNA ON dayPA&1;
                       p_nn | dayNA ON dayNA&1;

                       %BETWEEN% ! Mediation model with parameter names
                       p_pp-p_nn dayPA dayNA ON CESDpre (a1-a6);
                       CESDpost ON p_pp-p_nn dayPA dayNA CESDpre (b1-b7);

MODEL CONSTRAINT:      ! Compute the indirect effects
                       new (ab_p_pp); ab_p_pp=a1*b1;
                       new (ab_p_pn); ab_p_pn=a2*b2;
                       new (ab_p_np); ab_p_np=a3*b3;
                       new (ab_p_nn); ab_p_nn=a4*b4;
                       new (ab_dayPA); ab_dayPA=a5*b5;
                       new (ab_dayNA); ab_dayNA=a6*b6;

OUTPUT:                TECH1 TECH8 STDYX;

PLOT:                  TYPE = PLOT3;
                       FACTOR =ALL;
```

Mplus output mediation model (younger sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
New/Additional Parameters						
AB_P_PP	0.010	0.025	0.266	-0.028	0.076	
AB_P_PN	-0.002	0.032	0.439	-0.074	0.062	
AB_P_NP	-0.004	0.037	0.401	-0.089	0.067	
AB_P_NN	0.195	0.070	0.000	0.081	0.359	*
AB_DAYPA	0.049	0.035	0.029	-0.001	0.135	
AB_DAYNA	0.028	0.043	0.234	-0.052	0.119	

Mplus output mediation model (older sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
New/Additional Parameters						
AB_P_PP	0.005	0.016	0.302	-0.018	0.049	
AB_P_PN	-0.004	0.025	0.396	-0.061	0.045	
AB_P_NP	0.012	0.027	0.268	-0.035	0.076	
AB_P_NN	-0.036	0.038	0.112	-0.130	0.025	
AB_DAYPA	0.028	0.038	0.209	-0.042	0.110	
AB_DAYNA	0.027	0.036	0.194	-0.040	0.108	

Outline

- Time series analysis
- Multilevel time series analysis
- DSEM application 1: Multilevel VAR(1) model
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- **DSEM application 3: Random innovation variance**
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- DSEM application 5: Latent variable model
- Discussion

Random innovation variance (univariately)

Within level: AR(1) with random ϕ_i

$$NA_{it}^{(w)} = \phi_i NA_{i,t-1}^{(w)} + \zeta_{it} \qquad \zeta_{it} \sim N(0, \sigma_i^2)$$

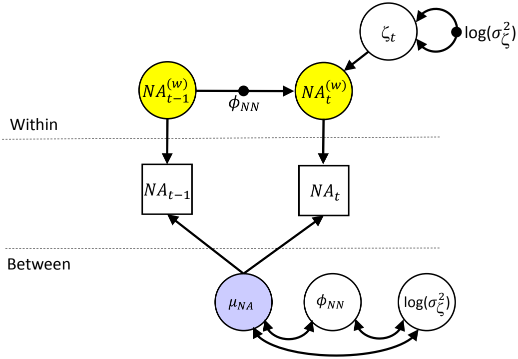
Between level: fixed and random effects

$$\begin{aligned} \mu_i &= \gamma_\mu + u_{0i} \\ \phi_i &= \gamma_\phi + u_{1i} \\ \log(\sigma_i^2) &= \gamma_{\log(\sigma^2)} + u_{2i} \end{aligned} \qquad \begin{bmatrix} u_{0i} \\ u_{1i} \\ u_{2i} \end{bmatrix} \sim MN \left[\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi_{11} & & \\ \psi_{21} & \psi_{22} & \\ \psi_{31} & \psi_{32} & \psi_{33} \end{bmatrix} \right]$$

Reasons to assume **individual differences** for σ^2:

- individuals may differ with respect to the **variability in exposure** to external factors
- individuals may differ with respect to their **reactivity** to external influences (see reward experience and stress sensitivity research)

Random variance in a univariate model



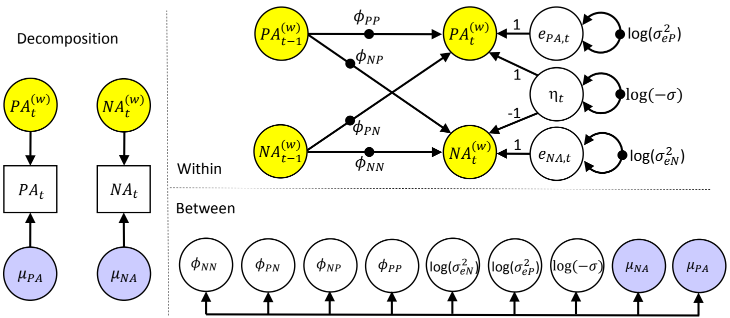
MODEL:

```
%WITHIN%
p_nn | dayNA ON dayNA&1;
logIV | dayNA;

%BETWEEN%
p_nn WITH dayNA logIV;
dayNA WITH logIV;
```

Random innovation variances and covariance

In the bivariate case, we want **random innovation variances** AND **random innovation covariance**; the latter is modeled with **an additional factor** η_t:



Where:

- -η_t is the shared part (we assume a negative covariance)
- $e_{PA,t}$ and $e_{NA,t}$ are the unique parts

Mplus code: Within model

```
MODEL:      %WITHIN%
            p_pp | dayPA ON dayPA&1;
            p_pn | dayPA ON dayNA&1;
            p_np | dayNA ON dayPA&1;
            p_nn | dayNA ON dayNA&1;

            ! Create latent variable that represents negative covariance
            NCov BY dayPA@1 dayNA@-1;

            ! Create random (log) variances
            logvarPA | dayPA;
            logvarNA | dayNA;
            logNCov | NCov;

            %BETWEEN%
            p_pp-p_nn WITH p_pn-p_nn logvarPA logvarNA logNCov dayPA dayNA;
            logvarPA WITH logvarNA logNCov dayPA dayNA;
            logvarNA WITH logNCov dayPA dayNA;
            logNCov WITH dayPA dayNA;
            dayPA WITH dayNA;

OUTPUT:     TECH1 TECH8 STDYX FSCOMPARISON;
```

Mplus results

Effect	Younger	Older
direct	**0.290 [0.062,0.522]**	**0.585 [0.076,1.206]**
mediated by μ_{PA}	*0.058 [-0.011,0.154]*	*0.054 [-0.018,0.147]*
mediated by μ_{NA}	*0.024 [-0.062,0.130]*	*0.011 [-0.022,0.070]*
mediated by ϕ_{PP}	*0.003 [-0.032,0.050]*	*0.003 [-0.020,0.043]*
mediated by ϕ_{PN}	*0.000 [-0.053,0.061]*	*-0.003 [-0.106,0.097]*
mediated by ϕ_{NP}	*-0.019 [-0.178,0.087]*	*-0.048 [-0.691,0.470]*
mediated by ϕ_{NN}	**0.127 [0.036,0.258]**	*-0.011 [-0.069,0.020]*
mediated by $log(\sigma^2_{eP})$	*0.000 [-0.059,0.055]*	*-0.046 [-0.127,0.007]*
mediated by $log(\sigma^2_{eN})$	*-0.009 [-0.103,0.076]*	*0.079 [-0.015,0.212]*
mediated by $log(-\sigma)$	**0.072 [0.004,0.185]**	*0.029 [-0.035,0.122]*

Hence:

- **higher CESDpre** is associated with **higher CESDpost** (both samples)
- **higher CESDpre** is **indirectly** associated with **higher CESDpost** (younger sample) through the **autoregression of NA** and the negative **covariance between the innovations**

Mediation through logNCov

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
LOGNCOV ON						
CESDPRE	0.959	0.436	0.016	0.079	1.786	*
CESDPOST ON						
P_PP	-0.212	0.186	0.120	-0.583	0.147	
P_PN	-0.346	0.336	0.149	-0.998	0.313	
P_NP	-0.576	0.984	0.265	-2.581	1.325	
P_NN	0.560	0.173	0.001	0.225	0.907	*
LOGVARPA	0.005	0.048	0.454	-0.089	0.098	
LOGVARNA	-0.008	0.034	0.406	-0.075	0.059	
LOGNCOV	0.077	0.031	0.007	0.017	0.138	*

Conclusion: **Higher CESDpre** is associated with **more negative common variance** (i.e., covariance).

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Intervention study with ESM

When **ESM** is used in a **randomized controlled trial**, we can investigate whether treatment affects symptoms through changing:

- means
- dynamics (e.g., autoregression)
- variability

Here we use negative affect (NA) from individuals with a **history of depression** and current residual depressive symptoms (Geschwind et al., 2011).

Each ESM period consisted of 6 days, 10 beeps per day.

We analyze data from 117 participants; 56 received a **mindfulness training** between the two phases, and 61 served as **controls**.

Data setup

Phase	Meas	Y
1	1	31
1	2	45
1	3	42
1	4	38
1	5	51
1	6	34
2	1	16
2	2	31
2	3	34
2	4	28
2	5	19
2	6	22

Phase	Meas	Y1	Y2
1	1	31	
1	2	45	
1	3	42	
1	4	38	
1	5	51	
1	6	34	
2	1		16
2	2		31
2	3		34
2	4		28
2	5		19
2	6		22

Treatment effect on the within-person mean

We use $NA1_{it}$ and $NA2_{it}$ as **two separate variables**!

Decomposition into a between part and a within part

$$\text{Pre-treatment phase: } NA1_{it} = \mu_{1i} + NA1_{it}^{(w)}$$
$$\text{Post-treatment phase: } NA2_{it} = \mu_{2i} + NA2_{it}^{(w)}$$

Between level

$$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{1i}$$
$$\mu_{2i} = \gamma_{10} + \mu_{1i} + \gamma_{11} Group_i + u_{2i}$$

- γ_{01} is the **initial difference** between the groups
- γ_{10} is the **effect of time**
- γ_{11} is the **effect of treatment**

Note: $\mu_{2i} - \mu_{1i} = \gamma_{10} + \gamma_{11} Group_i + u_{2i}$.

Mplus input

```
MODEL:    %WITHIN%
          NA1 WITH NA2@0;

          %BETWEEN%
          NA1 ON Group;
          NA2 ON NA1@1 Group;
          NA1 WITH NA2;
```

Note: When $NA1_{it}$ is observed, $NA2_{it}$ is missing, and vice versa; hence, we fix their within-person **covariance to zero.**

Mplus results: Within

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
NA1 WITH						
NA2	0.000	0.000	1.000	0.000	0.000	
Variances						
NA1	0.631	0.012	0.000	0.607	0.656	*
NA2	0.472	0.009	0.000	0.454	0.490	*

Mplus results: Between

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
NA1 ON						
GROUP	-0.031	0.136	0.408	-0.304	0.234	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.280	0.110	0.003	-0.500	-0.074	*
Intercepts						
NA1	2.028	0.093	0.000	1.849	2.213	*
NA2	-0.027	0.076	0.345	-0.175	0.122	
Residual Variances						
NA1	0.520	0.074	0.000	0.398	0.683	*
NA2	0.316	0.049	0.000	0.237	0.431	*

Conclusion:

- No initial differences between the groups
- Significant (negative) change in NA due to treatment
- No change due to time

Treatment and time effects on autoregression

Within level: AR(1) processes

Pre-treatment phase: $NA1_{it}^{(w)} = \phi_{1i} NA1_{it-1}^{(w)} + \zeta 1_{it}$

Post-treatment phase: $NA2_{it}^{(w)} = \phi_{2i} NA2_{it-1}^{(w)} + \zeta 2_{it}$

Between level: Pre-treatment phase

$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{0i}$

$\phi_{1i} = \gamma_{10} + \gamma_{11} Group_i + u_{1i}$

We expect γ_{01} and γ_{11} to be zero.

Between level: Post-treatment phase

$\mu_{2i} = \gamma_{20} + \mu_{1i} + \gamma_{21} Group_i + u_{2i}$ or: $\Delta\mu_i = \gamma_{20} + \gamma_{21} Group_i + u_{2i}$

$\phi_{2i} = \gamma_{30} + \phi_{1i} + \gamma_{31} Group_i + u_{3i}$ or: $\Delta\phi_i = \gamma_{30} + \gamma_{31} Group_i + u_{3i}$

Where: γ_{20} and γ_{30} represent the **effects of time** and: γ_{21} and γ_{31} represent the **effects of treatment**

Mplus results (all effects random)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
PHI2 ON						
PHI1	1.000	0.000	0.000	1.000	1.000	
PHI1 ON						
GROUP	0.052	0.047	0.130	-0.039	0.142	
PHI2 ON						
GROUP	-0.077	0.066	0.119	-0.209	0.057	
NA1 ON						
GROUP	-0.079	0.134	0.284	-0.340	0.183	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.246	0.105	0.010	-0.457	-0.038	*
Intercepts						
NA1	2.008	0.092	0.000	1.831	2.190	*
NA2	-0.005	0.071	0.470	-0.148	0.136	
PHI1	0.454	0.034	0.000	0.390	0.522	*
PHI2	-0.092	0.047	0.022	-0.185	-0.004	*

Mplus results with: phi2@0;

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
PHI2 ON						
PHI1	1.000	0.000	0.000	1.000	1.000	
PHI1 ON						
GROUP	0.075	0.049	0.053	-0.014	0.174	
PHI2 ON						
GROUP	-0.070	0.033	0.014	-0.137	-0.005	*
NA1 ON						
GROUP	-0.071	0.132	0.302	-0.327	0.192	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.247	0.105	0.010	-0.454	-0.043	*
Intercepts						
NA1	2.012	0.090	0.000	1.837	2.194	*
NA2	-0.010	0.071	0.442	-0.152	0.133	
PHI1	0.425	0.034	0.000	0.356	0.491	*
PHI2	-0.019	0.022	0.199	-0.062	0.026	

Including a level 1 predictor

Let $UP1_{it}$ and $UP2_{it}$ be variables for phases 1 and 2, that indicate whether something emotionally charged happened **since the previous beep** (positive scores is Pleasant event, negative score is Unpleasant event).

Within level

Pre-treatment phase: $NA1_{it}^{(w)} = \phi_{1i} NA1_{it-1}^{(w)} + \beta_{1i} UP1_{it}^{(w)} + \zeta_{1it}$

Post-treatment phase: $NA2_{it}^{(w)} = \phi_{2i} NA2_{it-1}^{(w)} + \beta_{2i} UP2_{it}^{(w)} + \zeta_{2it}$

where:

- ϕ_{1i} and ϕ_{2i} represent carry-over
- β_{1i} and β_{2i} represent reactivity/sensitivity

Note that we have **concurrent regressions** in this model (i.e., β_{1i} and β_{2i}).

Including a level 1 predictor

Group is a predictor at the between level:

Between level: Pre-treatment phase

$$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{0i}$$
$$\phi_{1i} = \gamma_{10} + \gamma_{11} Group_i + u_{1i}$$
$$\beta_{1i} = \gamma_{20} + \gamma_{21} Group_i + u_{2i}$$

where γ_{00}, γ_{10}, and γ_{20} are expected to be zero.

The **change** in mean, carry-over, and reactivity is modeled as:

Between level: Post-treatment phase

$$\mu_{2i} = \gamma_{30} + \mu_{1i} + \gamma_{31} Group_i + u_{3i} \quad \text{or:} \quad \Delta\mu_i = \gamma_{30} + \gamma_{31} Group_i + u_{3i}$$
$$\phi_{2i} = \gamma_{40} + \phi_{1i} + \gamma_{41} Group_i + u_{4i} \quad \text{or:} \quad \Delta\phi_i = \gamma_{40} + \gamma_{41} Group_i + u_{4i}$$
$$\beta_{2i} = \gamma_{50} + \beta_{1i} + \gamma_{51} Group_i + u_{5i} \quad \text{or:} \quad \Delta\beta_i = \gamma_{50} + \gamma_{51} Group_i + u_{5i}$$

where

- γ_{30}, γ_{40}, and γ_{50} represent **change due to time**
- γ_{31}, γ_{41}, and γ_{51} represent **change due to treatment**

Mplus input: Centering within predictors

```
VARIABLE:   NAMES = ID Time PrePost Group pa1 pa2 na1 na2
            PDLA1 PDLA2 up1 up2 ham1 ham2;
            CLUSTER = ID;
            USEVAR = na1 na2 up1 up2 Group;
            LAGGED = na1(1) na2(1);
            BETWEEN = Group;
            WITHIN = up1 up2;
            TINTERVAL = Time(1);
            MISSING = ALL(-999);

DEFINE:     CENTER up1 up2 (GROUPMEAN);
```

Note that the **concurrent predictors** UP1 and UP2 are:

- defined as **within-level variables**
- centered per person (i.e., group mean centering using **sample means** rather than latent means)

This is to allow for **lag zero (concurrent) regressions** when the **predictor has missings.**

Mplus input: Within and between model

Note: The within-person predictor has missings; by asking for the variances, Mplus treats it as a y-variable, which is allowed to have missings.

```
MODEL:
          %WITHIN%
          phi1 | na1 ON na1&1;
          beta1 | na1 ON up1;
          phi2 | na2 ON na2&1;
          beta2 | na2 ON up2;

          na1-up1 WITH na2-up2@0;
          up1; up2;

          %BETWEEN%
          na1 phi1 beta1 ON Group;
          na2 ON na1@1 Group;
          phi2 ON phi1@1 Group;
          beta2 ON beta1@1 Group;
```

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
Between Level						
PHI2 ON						
PHI1	1.000	0.000	0.000	1.000	1.000	
BETA2 ON						
BETA1	1.000	0.000	0.000	1.000	1.000	
PHI1 ON						
GROUP	0.050	0.046	0.119	-0.035	0.144	
BETA1 ON						
GROUP	0.001	0.019	0.470	-0.034	0.041	
PHI2 ON						
GROUP	-0.077	0.068	0.123	-0.214	0.053	
BETA2 ON						
GROUP	-0.016	0.026	0.264	-0.069	0.032	
NA1 ON						
GROUP	-0.070	0.134	0.297	-0.340	0.180	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.255	0.105	0.007	-0.463	-0.059	*

Mplus output: Intercepts and random effects

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
Intercepts						
NA1	2.012	0.091	0.000	1.835	2.189	*
NA2	-0.014	0.071	0.422	-0.155	0.126	
PHI1	0.423	0.033	0.000	0.357	0.487	*
BETA1	-0.123	0.013	0.000	-0.150	-0.097	*
PHI2	-0.082	0.047	0.039	-0.173	0.011	
BETA2	0.005	0.018	0.388	-0.027	0.041	
Residual Variances						
NA1	0.466	0.070	0.000	0.355	0.632	*
NA2	0.268	0.042	0.000	0.199	0.359	*
PHI1	0.038	0.008	0.000	0.026	0.056	*
BETA1	0.006	0.001	0.000	0.004	0.009	*
PHI2	0.078	0.016	0.000	0.051	0.114	*
BETA2	0.008	0.003	0.000	0.005	0.015	*

Conclusion:

- means of μ_{1i}, ϕ_{1i}, and β_{1i} deviate from zero
- no change due to time (intercepts for μ_{2i}, ϕ_{2i}, and β_{2i} are zero)

Mplus output: Standardized regressions

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within-Level Standardized Estimates Averaged Over Clusters						
PHI1 | NA1 ON						
NA1&1	0.449	0.014	0.000	0.419	0.475	*
BETA1 | NA1 ON						
UP1	-0.254	0.013	0.000	-0.279	-0.229	*
PHI2 | NA2 ON						
NA2&1	0.328	0.016	0.000	0.297	0.358	*
BETA2 | NA2 ON						
UP2	-0.259	0.015	0.000	-0.287	-0.230	*

Conclusion:

- the standardized parameters are standardized per person first
- the standardized parameters for the post treatment phase are for the "total" parameter (e.g., $\phi_{2i} = \gamma_{40} + \phi_{1i} + \gamma_{41} Group_i + u_{4i}$)

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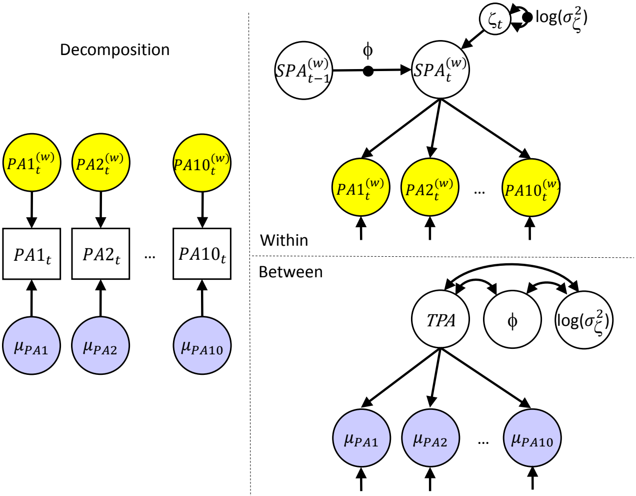
- **DSEM application 5: Latent variable model**
- Discussion

Using the 10 indicators of PA from the COGITO study, we can specify a multilevel factor model:



Multilevel latent AR(1) model

Decomposition

$$\mathbf{y}_{it} = \boldsymbol{\mu}_i + \mathbf{y}_{it}^{(w)}$$

Within level: State positive affect

$$\mathbf{y}_{it}^{(w)} = \boldsymbol{\Lambda}^{(w)} SPA_{it} + \boldsymbol{\epsilon}_i^{(w)} \qquad \boldsymbol{\epsilon}_i^{(w)} \sim MN(0, \boldsymbol{\Theta})$$

$$SPA_{it} = \phi_i SPA_{i,t-1} + \zeta_{it}^{(w)} \qquad \zeta_{it}^{(w)} \sim N(0, \sigma^2_{\zeta,i})$$

Between level: Trait positive affect

$$\boldsymbol{\mu}_i = \boldsymbol{\nu} + \boldsymbol{\Lambda} TPA_i + \boldsymbol{\epsilon}_i$$

$$\begin{bmatrix} TPA_i \\ \phi_i \\ log(\sigma^2_{\zeta,i}) \end{bmatrix} = \begin{bmatrix} \gamma_{TPA} \\ \gamma_{\phi} \\ \gamma_{logVar} \end{bmatrix} + \begin{bmatrix} u_{TPA,i} \\ u_{\phi,i} \\ u_{logVar,i} \end{bmatrix}$$

Mplus input latent AR(1) model

```
VARIABLE:    NAMES = id sessdate na1 na2 na3 na4 na5 na6 na7 na8 na9 na10
             pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
             sessionNr age_pre sex CESDpre CESDpost dayNA dayPA older;
             CLUSTER = id;
             USEVAR = pa1-pa10 sessdate;
             TINTERVAL = sessdate(1);
             MISSING = ALL(-999);

ANALYSIS:    TYPE = TWOLEVEL RANDOM; ESTIMATOR = BAYES;
             PROCESSORS = 2; BITER = (5000); THIN = 10;

MODEL:       %WITHIN%
             SPA BY pa1-pa10 (&1 LW1-LW10);
             phi | SPA ON SPA&1;
             logVSPA | SPA;

             %BETWEEN%
             PAB BY pa1-pa10 (LB1-LB10);
             PAB WITH phi logVSPA;
             phi WITH logVSPA;
```

Note: We are now making a **latent lagged variable**; this is done in the **MODEL command** (using: (&1)), rather than in the **VARIABLE command**.

Extra: Computing differences in factor loadings

A key question here is whether there is **weak factorial invariance across the levels**: Are the state-like, within-person fluctuations taking place on the same underlying dimension as the one on which the trait-like, between-person differences are located?

```
MODEL CONSTRAINT:    new (difL2); difL2=LB2-LW2;
                     new (difL3); difL3=LB3-LW3;
                     new (difL4); difL4=LB4-LW4;
                     new (difL5); difL5=LB5-LW5;
                     new (difL6); difL6=LB6-LW6;
                     new (difL7); difL7=LB7-LW7;
                     new (difL8); difL8=LB8-LW8;
                     new (difL9); difL9=LB9-LW9;
                     new (difL10); difL10=LB10-LW10;
```

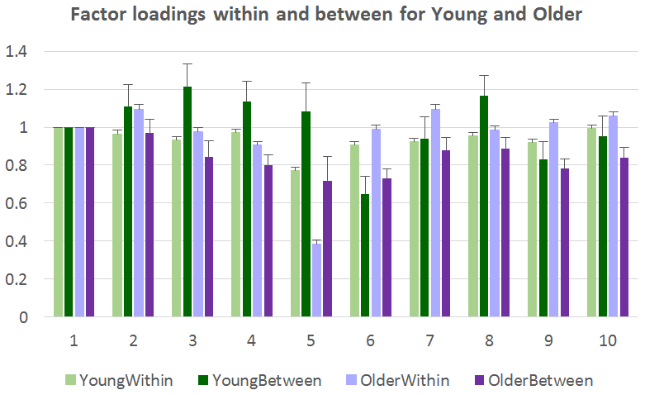
This will **compute the differences in each iteration** of the MCMC sampler; hence, we get **posterior distributions** for these quantities.

Results for differences in factor loadings

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
New/Additional Parameters						
DIFL2	-0.106	0.076	0.090	-0.242	0.060	
DIFL3	-0.118	0.089	0.101	-0.277	0.069	
DIFL4	-0.095	0.060	0.077	-0.199	0.037	
DIFL5	0.361	0.129	0.002	0.117	0.621	*
DIFL6	-0.246	0.057	0.001	-0.346	-0.121	*
DIFL7	-0.202	0.076	0.009	-0.334	-0.037	*
DIFL8	-0.080	0.061	0.107	-0.187	0.053	
DIFL9	-0.223	0.054	0.000	-0.315	-0.101	*
DIFL10	-0.199	0.060	0.003	-0.305	-0.066	*

Conclusion: 5 out of 10 factor loadings show evidence for being different across levels.

Factor loadings within-between for young-older



Items: 1) enthusiastic; 2) excited; 3) strong; 4) interested; 5) proud; 6) alert; 7) inspired; 8) determined; 9) attentive; 10) active

Mplus output: R-square within and between

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%
Within-Level R-Square Averaged Across Clusters					
PA1	0.291	0.009	0.000	0.273	0.310
PA2	0.314	0.010	0.000	0.293	0.333
PA3	0.252	0.010	0.000	0.233	0.272
PA4	0.302	0.010	0.000	0.282	0.323
PA5	0.057	0.007	0.000	0.045	0.071
PA6	0.305	0.010	0.000	0.285	0.325
PA7	0.260	0.010	0.000	0.241	0.282
PA8	0.273	0.010	0.000	0.254	0.294
PA9	0.366	0.010	0.000	0.346	0.386
PA10	0.339	0.010	0.000	0.319	0.360
SPA	0.549	0.012	0.000	0.525	0.573
Between Level					
PA1	0.767	0.045	0.000	0.664	0.843
PA2	0.844	0.031	0.000	0.775	0.895
PA3	0.614	0.064	0.000	0.474	0.728
PA4	0.876	0.025	0.000	0.819	0.916
PA5	0.295	0.077	0.000	0.149	0.450
PA6	0.872	0.027	0.000	0.811	0.914
PA7	0.835	0.033	0.000	0.757	0.889
PA8	0.947	0.013	0.000	0.917	0.966
PA9	0.975	0.008	0.000	0.957	0.986
PA10	0.935	0.015	0.000	0.900	0.958

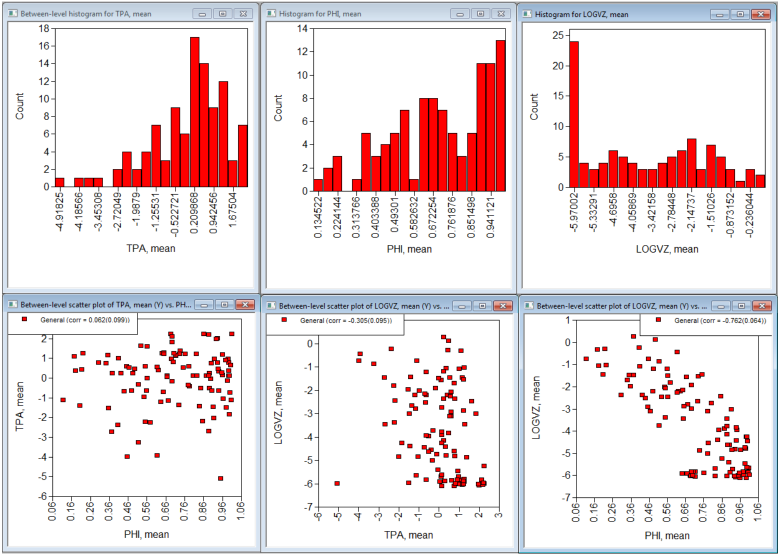
Mplus output: Correlations at between level

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
TPA WITH						
PHI	0.067	0.110	0.263	-0.146	0.285	
LOGVZ	-0.303	0.096	0.002	-0.473	-0.100	*
PHI WITH						
LOGVZ	-0.728	0.063	0.000	-0.828	-0.584	*

Conclusion:

- trait level of PA and carry-over in state PA are **not related**
- trait level of PA is **negatively related** to innovation variance of state PA: higher trait PA is associated with smaller innovation variance
- carry-over in state PA is **negative related** to innovation variance in state PA: higher autoregression is associated with smaller innovation variance

Mplus output: Between-level plots



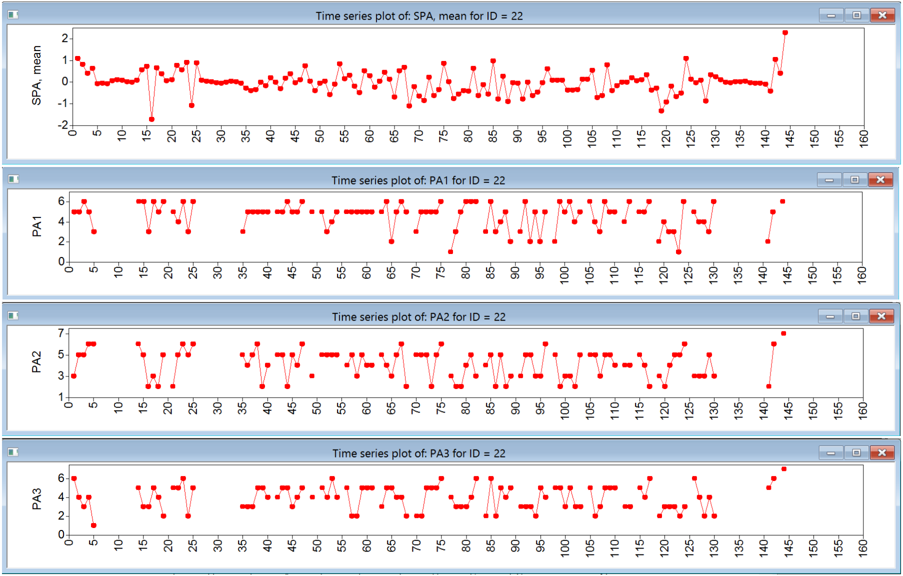
Mplus output: Estimated factor scores for ϕ_i

Using the statement:

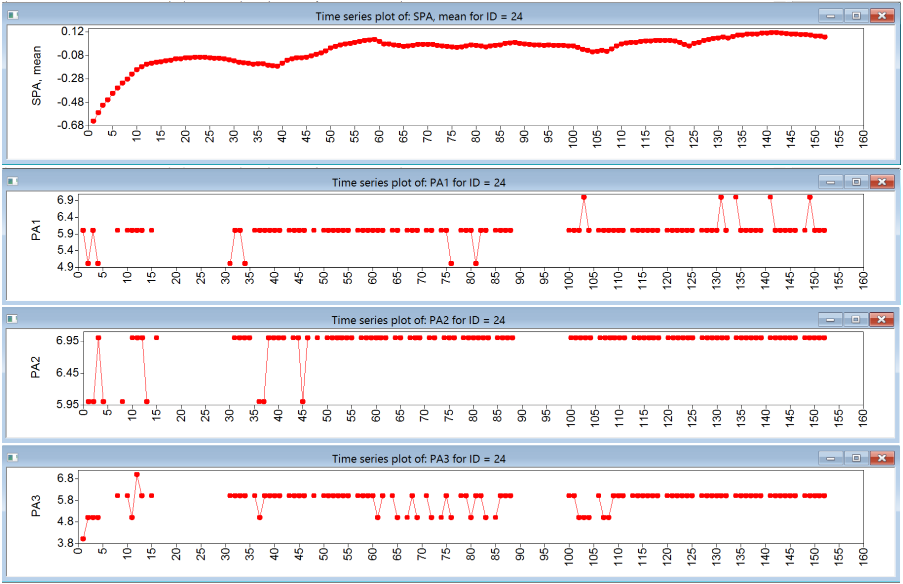
OUTPUT: TECH1 TECH8 STDYX FSCOMPARISON;
PLOT: TYPE = PLOT3; FACTOR = ALL(1000);

Ranking	Cluster	Factor Score	Ranking	Cluster	Factor Score	Ranking	Cluster	Factor Score
1	144	1.000	2	99	0.999	3	193	0.996
4	156	0.994	5	132	0.989	6	151	0.989
7	166	0.988	8	181	0.985	9	90	0.981
10	53	0.979	11	87	0.969	12	112	0.968
13	168	0.966	14	39	0.965	15	6	0.958
16	157	0.949	17	94	0.942	18	58	0.941
19	190	0.938	20	171	0.936	21	9	0.931
22	142	0.926	23	163	0.924	24	1	0.904
...								
94	174	0.359	95	41	0.325	96	70	0.323
97	124	0.302	98	177	0.219	99	95	0.212
100	49	0.207	101	44	0.195	102	115	0.189
103	22	0.126						

Estimated factor scores for SPA and observed scores



Estimated factor scores for SPA and observed scores



Multilevel latent AR(2) model

Decomposition

$$\mathbf{y}_{it} = \boldsymbol{\mu}_i + \mathbf{y}_{it}^{(w)}$$

Within level:

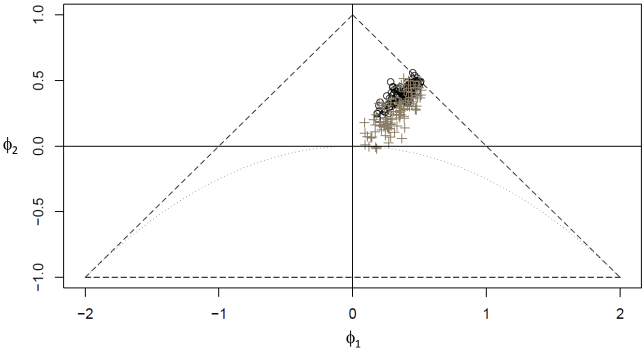
$$\mathbf{y}_{it}^{(w)} = \boldsymbol{\Lambda}^{(w)} SPA_{it} + \boldsymbol{\epsilon}_i^{(w)}$$

$$SPA_{it} = \phi_{1i} SPA_{i,t-1} + \phi_{2i} SPA_{i,t-2} + \zeta_{it}^{(w)}$$

Between level:

$$\boldsymbol{\mu}_i = \boldsymbol{\nu} + \boldsymbol{\Lambda} SPA_i + \boldsymbol{\epsilon}_i$$

$$\begin{bmatrix} \eta_i \\ \phi_{1i} \\ \phi_{2i} \\ log(\sigma^2_\zeta) \end{bmatrix} = \begin{bmatrix} \gamma_\eta \\ \gamma_{\phi 1} \\ \gamma_{\phi 2} \\ \gamma_{logVar} \end{bmatrix} + \begin{bmatrix} u_{\eta,i} \\ u_{\phi 1,i} \\ u_{\phi 2,i} \\ u_{logVar,i} \end{bmatrix}$$



Scatter plot of **estimated autoregressive parameters** (i.e., ϕ_{1i} and ϕ_{2i}):

- values inside the **triangle** imply **stationary processes**
- values below the **curve** imply **oscillating processes**

Outline

- Time series analysis
- Multilevel time series analysis
- DSEM application 1: Multilevel VAR(1) model
- DSEM application 2: Mediation
- DSEM application 3: Random innovation variance
- DSEM application 4: Intervention study
- DSEM application 5: Latent variable model
- **Discussion**

Strengths of DSEM in Mplus

Compared to standard multilevel software:

- **Multiple outcome variables**: this allows for correlated residuals and correlated random effects
- **Unequal time interval**: can be handled by choosing a grid for inserting missings
- **Outcomes** at between-person level
- **Person-mean centering** integral part of model estimation (solves Nickell's bias)
- **Latent variables**: allows for measurement error to be split off and for moving average terms
- **Cross-classified models**: allows for random effects of time
- **Random variance**: allows for individual difference in variability

Compared to other Bayesian software (e.g., WinBUGS, jags, Stan):

- **Easy to use** due to tailor-made code
- **Default uninformative priors** for parameters (even for small variances)
- **Fast** (which makes a difference in case of Bayes)

Other recent developments:

- mlVAR (Epskamp, Deserno and Bringmann)
- ctsem (Driver, Voelkle and Oud)
- open Mx (Boker, Neale, et al.)
- DynR (Ou, Hunter and Chow)
- BOUM (Oravecz, Tuerlinckx and Vanderkerckhove)
- GIMME (Gates and Molenaar)
- ...

Future options Mplus will offer:

- **Regime-switching models**: allows for a process to switch between distinct states
- **Residual dynamic modeling**: allows for easy combination of time trends and residual lagged relationships
- ...

Suggested readings

- Bringmann, Vissers, Wichers, Geschwind, Kuppens, Peeters, Borsboom & Tuerlinckx (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS ONE, 8*, e60188, 1-13.
- Hamaker (2012). Why researchers should think "within-person": A paradigmatic rationale. In M. R. Mehl & T. S. Conner (Eds.). *Handbook of Research Methods for Studying Daily Life*, 43-61. New York, NY: Guilford Publications.
- Hamaker, Asparouhov, Brose, Schmiedek & Muthén (submitted). At the frontiers of modeling intensive longitudinal data: Dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research*.
- Hamaker & Grasman (2015). To center or not to center? Investigating inertia with a multilevel autoregressive model. *Frontiers in Psychology, 5*, 1492.
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- Jongerling, Laurenceau & Hamaker (2015). A multilevel AR(1) model: Allowing for inter-individual differences in trait-scores, inertia, and innovation variance. *Multivariate Behavioral Research, 50*, 334-349.

Suggested readings

- Koval, Kuppens, Allen & Sheeber (2012). Getting stuck in depression: The roles of rumination and emotional inertia. *Cognition & Emotion, 26*, 1412-1427.
- Kuppens, Allen & Sheeber (2010). Emotional inertia and psychological maladjustment. *Psychological Science, 21*, 984-991.
- Kuppens, Sheeber, Yap, Whittle, Simmons & Allen (2012). Emotional inertia prospectively predicts the onset of depressive Multilevel AR(1) model 33 disorder in adolescence. *Emotion, 12*, 283-289.
- Schuurman, Ferrer, de Boer-Sonnenschein & Hamaker (2016). How to compare cross-lagged associations in a multilevel autoregressive model. *Psychological Methods, 21*, 206-221.
- Suls, Green & Hillis (1998). Emotional reactivity to everyday problems, affective inertia, and neuroticism. *Personality and Social Psychology Bulletin, 24*, 127-136.