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

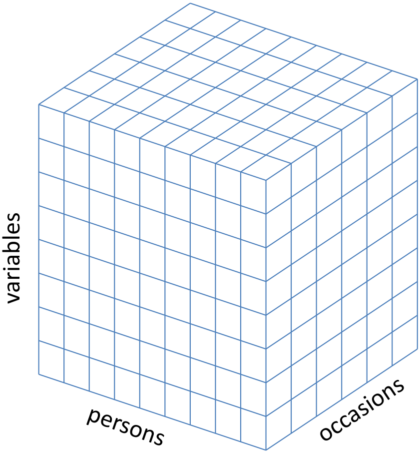
(Part 1)

Ellen L. Hamaker
Utrecht University
e.l.hamaker@uu.nl

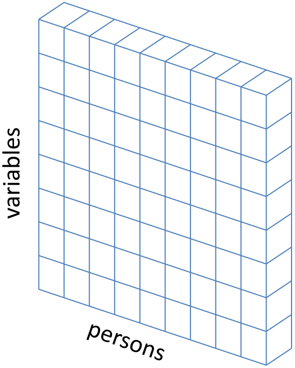
Tihomir Asparouhov & Bengt Muthén
Muthén & Muthén

PSMG, March 14, 2017

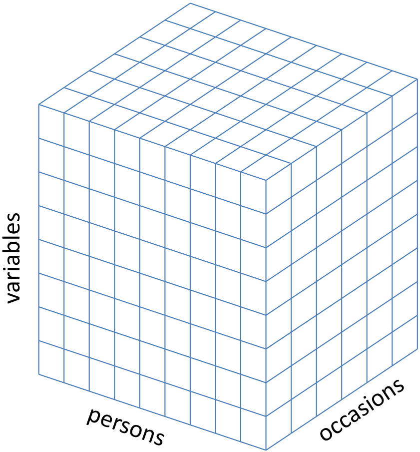
Cattell's data box



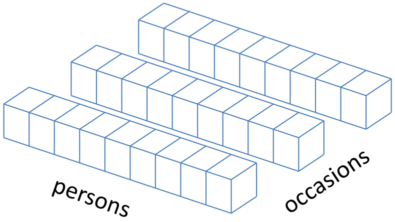
Cross-sectional research: N is large, T=1



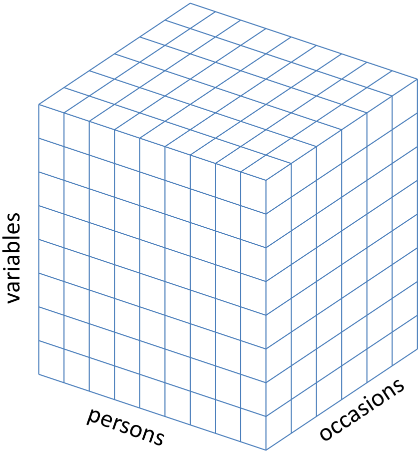
Cattell's data box



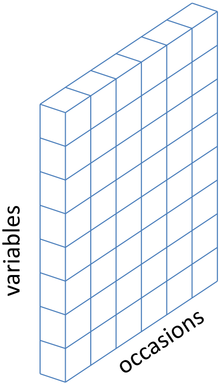
Panel research: N is large, T is small



Cattell's data box

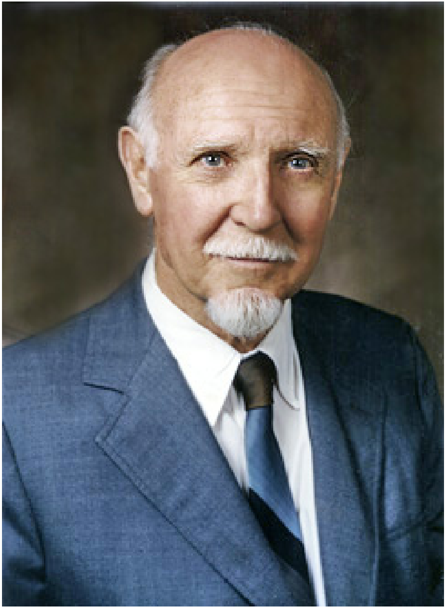


Time series data: N=1 and T is large



Time series analysis: Looking at the movie

Pioneers of idiographic research in psychology



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

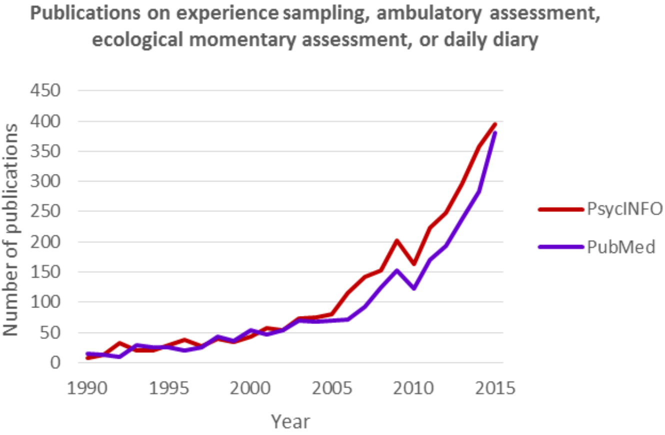
Data structure:

- 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

- **Modeling the dynamics of ILD**
- Separating between-person and within-person variance
- Application 1: Daily negative affect and depressive symptomatology
- Application 2: Intervention study with ESM
- Conclusion

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

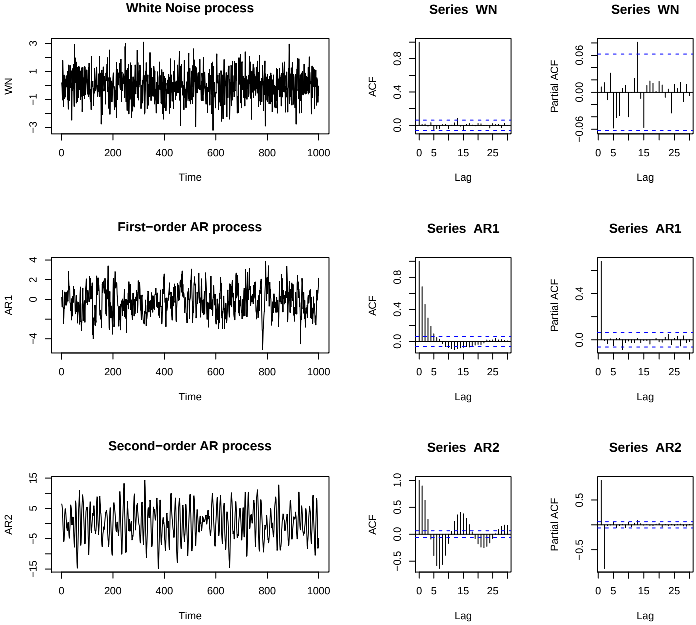
Y	Y at lag 1	Y at lag 2
y_1		
y_2	y_1	
y_3	y_2	y_1
y_4	y_3	y_2
y_5	y_4	y_3
y_6	y_5	y_4
y_7	y_6	y_5
y_8	y_7	y_6
$\dots$	$\dots$	$\dots$
y_T	y_{T-1}	y_{T-2}
	y_T	y_{T-1}
		y_T

Partial autocorrelation function (PACF)

Partial autocorrelation at lag k: The correlation between y_t and y_{t-k} after **removing the effect of the intermediate observations** (i.e., y_{t-1} to y_{t-k+1}).

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
$\dots$	$\dots$	$\dots$
y_T	y_{T-1}	y_{T-2}
	y_T	y_{T-1}
		y_T

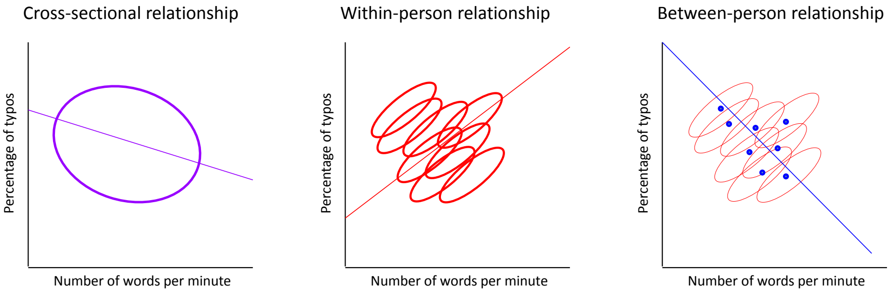
Sequence, ACF and PACF



Outline

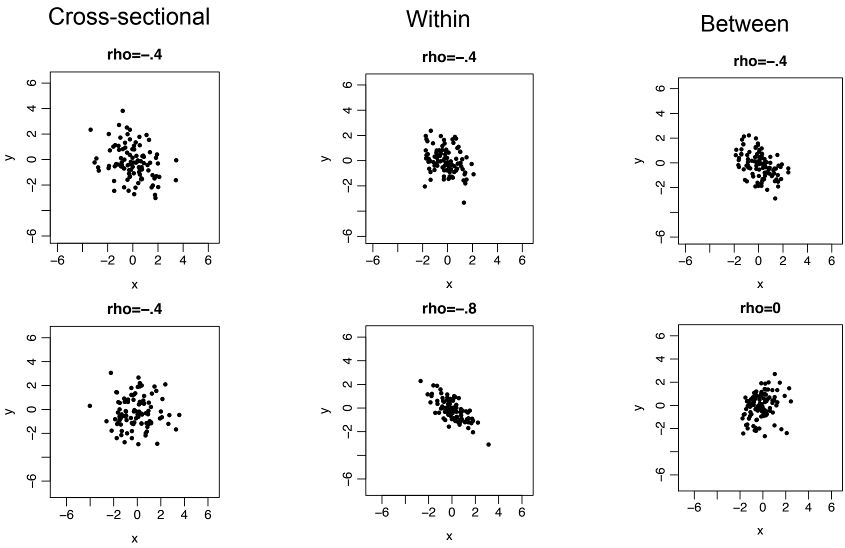
- Modeling the dynamics of ILD
- **Separating between-person and within-person variance**
- Application 1: Daily negative affect and depressive symptomatology
- Application 2: Intervention study with ESM
- Conclusion

A fundamental problem in a nutshell



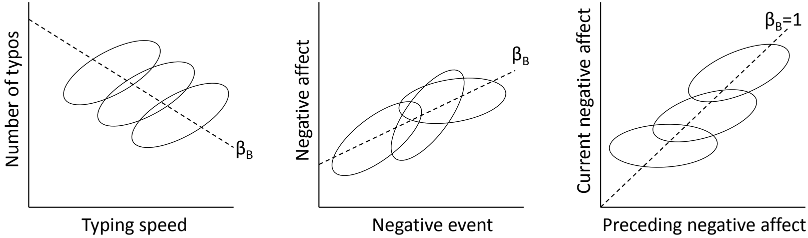
Taken from Hamaker (2012).

Three perspectives on data



Taken from Hamaker (2012).

Between-person differences in within-person slopes



Taken from Hamaker and Grasman (2014).

In conclusion: To study within-person processes we need

- (intensive) **longitudinal** data
- to **decompose** observed variance into within and between
- to consider **individual differences** in within-person dynamics

Outline

- Modeling the dynamics of ILD
- Separating between-person and within-person variance
- **Application 1: Daily negative affect and depressive symptomatology**
- Application 2: Intervention study with ESM
- Conclusion

Data: Daily measurements of negative affect (NA)

Data come from the **COGITO study** of the MPI in Berlin (based on Hamaker et al., in preparation).

Here we consider the **younger sample**:

- aged 20-31
- 101 individuals
- 100 daily measurements of negative affect (NA)

Decomposition into a between part and a within part

$$NA_{it} = \mu_i + NA^*_{it}$$

where

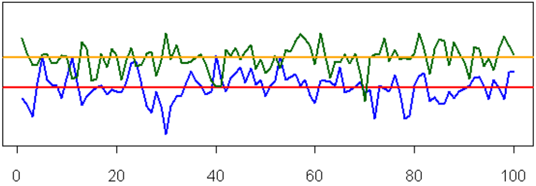
- Between part: μ_i is the individual's **mean** (i.e., baseline, trait, equilibrium)
- Within-part: NA^*_{it} is the **within-person centered** (cluster-mean centered) score

Between versus within

Here, the **intraclass correlation** is:

$$\frac{\sigma^2_{between}}{\sigma^2_{between} + \sigma^2_{within}} = .64$$

meaning there is about twice as much variability between people as there is within people in these data.



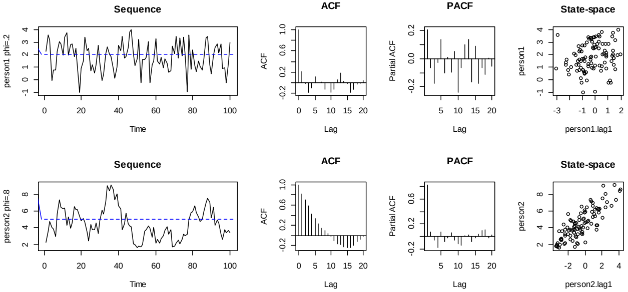
Univariate multilevel AR(1) model

Autoregressive part:

$$NA^*_{it} = \phi_i NA^*_{i,t-1} + \zeta_{it}$$

where

- ϕ_i is the **autoregressive parameter** (i.e., inertia, carry-over)
- ζ_{it} is the **innovation** (residual, disturbance, dynamic error) (with $\zeta_{it} \sim N(0, \sigma^2_\zeta)$)



Univariate multilevel AR(1) model

Within level: AR(1) with random ϕ_i

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

Parameters estimated at this level: residual variance σ^2

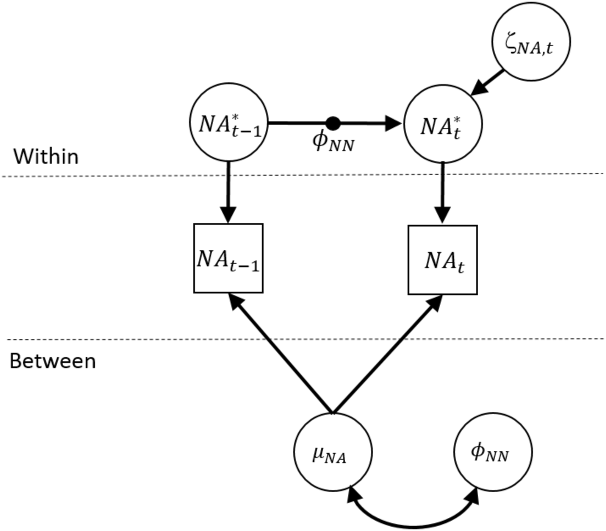
Between level: fixed and random effects

$$\begin{aligned} \mu_i &= \gamma_\mu + u_{0i} \\ \phi_i &= \gamma_\phi + u_{1i} \end{aligned} \qquad \begin{bmatrix} u_{0i} \\ u_{1i} \end{bmatrix} \sim MN \left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \psi_{11} & \\ \psi_{21} & \psi_{22} \end{bmatrix} \right]$$

Parameters estimated at this level:

- fixed effects (means): γ_μ and γ_ϕ
- random effects (variances): ψ_{11} and ψ_{22}
- relation between random effects (covariance): ψ_{21}

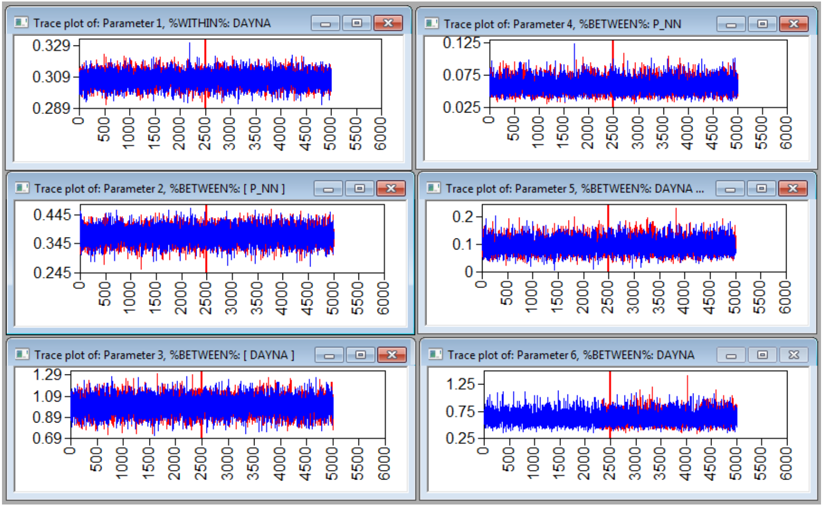
Univariate multilevel AR(1) model



Mplus input

```
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      =   dayNA;
lagged      =   dayNA(1);
tinterval   =   sessdate(1);
missing     =   all(-999);

ANALYSIS:   TYPE = twolevel random;
            estimator = bayes;
            proc = 2;
            biter= (5000);
            bseed = 526;
            thin = 10;

MODEL:
    %WITHIN%
    p_nn | dayNA ON dayNA&1;

    %BETWEEN%
    p_nn WITH dayNA;
```

Mplus results: Trace plots



Mplus results: Parameter estimates

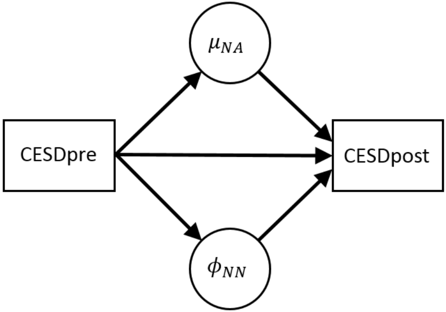
MODEL RESULTS

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
Residual Variances						
DAYNA	0.307	0.004	0.000	0.299	0.316	*
Between Level						
P_NN WITH						
DAYNA	0.093	0.025	0.000	0.051	0.146	*
Means						
DAYNA	0.998	0.082	0.000	0.844	1.163	*
P_NN	0.377	0.027	0.000	0.323	0.426	*
Variances						
DAYNA	0.617	0.118	0.000	0.434	0.887	*
P_NN	0.057	0.010	0.000	0.041	0.082	*

Dynamic multilevel mediation model

Within level: AR(1) with random ϕ_i

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



Between level: Mediation model

$$\begin{aligned} \mu_i &= \gamma_\mu + \gamma_{01} CESDpre_i + u_{0i} \\ \phi_i &= \gamma_\phi + \gamma_{11} CESDpre_i + u_{1i} \\ CESDpost_i &= \gamma_{20} + \gamma_{21} CESDpre_i + \gamma_{22}\mu_i + \gamma_{23}\phi_i + u_{2i} \end{aligned}$$

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      =   dayNA CESDpre CESDpost;
between     =   CESDpre CESDpost;
lagged      =   dayNA(1);
tinterval   =   sessdate(1);
missing     =   all(-999);

DEFINE: CENTER CESDpre CESDpost (GRANDMEAN);

ANALYSIS:   TYPE IS TWOLEVEL random;
            estimator=bayes; proc=2;
            fbiter=5000; bseed=1956; thin=10;

MODEL:
    %WITHIN%
    p_nn | dayNA ON dayNA&1;

    %BETWEEN%
    p_nn dayNA ON CESDpre (a1-a2);
    CESDpost ON p_nn dayNA CESDpre (b1-b3);

model constraint:
  new (ab_p_nn); ab_p_nn=a1*b1;    ! MEDIATED PATH THROUGH AR PARAMETER
  new (ab_dayNA); ab_dayNA=a2*b2; ! MEDIATED PATH THROUGH WITHIN-PERSON MEAN
```

Mplus output mediation model

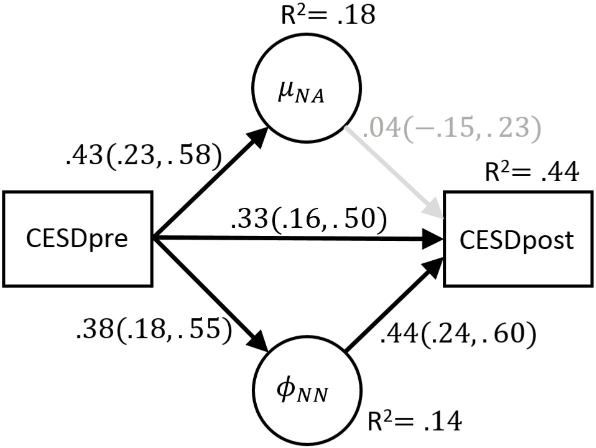
```
MODEL RESULTS

                                Posterior  One-Tailed         95% C.I.
                    Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%  Significance

Within Level

 Residual Variances
    DAYNA              0.307       0.004      0.000       0.299       0.316      *

Between Level

 P_NN       ON
    CESDPRE            0.254       0.071      0.000       0.118       0.397      *

 CESDPOST   ON
    P_NN               0.698       0.164      0.000       0.385       1.020      *

 DAYNA      ON
    CESDPRE            1.018       0.257      0.000       0.509       1.505      *

 CESDPOST   ON
    DAYNA              0.017       0.044      0.351      -0.071       0.103
    CESDPRE            0.364       0.100      0.000       0.170       0.560      *
```

Mplus output mediation model

(continued)

```
 Means
    CESDPRE            0.000      0.035      0.499     -0.067      0.068

 Intercepts
    CESDPOST          -0.281      0.069      0.000     -0.416     -0.144      *
    DAYNA              1.002      0.076      0.000      0.854      1.157      *
    P_NN               0.378      0.025      0.000      0.327      0.426      *

 Variances
    CESDPRE            0.119      0.017      0.000      0.091      0.159      *

 Residual Variances
    CESDPOST           0.081      0.013      0.000      0.060      0.111      *
    DAYNA              0.552      0.094      0.000      0.400      0.768      *
    P_NN               0.047      0.009      0.000      0.033      0.067      *

New/Additional Parameters
    AB_P_NN            0.174      0.066      0.000      0.067      0.321      *
    AB_DAYNA           0.016      0.046      0.351     -0.069      0.115
```

Mediation model: Standardized results



Random variance (cf. Jongerling et al., 2015)

Within level: AR(1) with random ϕ_i

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

Where ζ is the **innovation**, consisting of:

- external influences
- reactivity to external influences

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)

Hence, we allow for a **random innovation variance** using a log normal distribution.

Random innovation variance

Within level: AR(1) with random ϕ_i

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

Between level: fixed and random effects

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

```
MODEL:
    %WITHIN%
    p_nn | dayNA ON dayNA&1;
    logRVNA | dayNA;

    %BETWEEN%
    p_nn WITH logRVNA dayNA;
    logRVNA WITH dayNA;
```

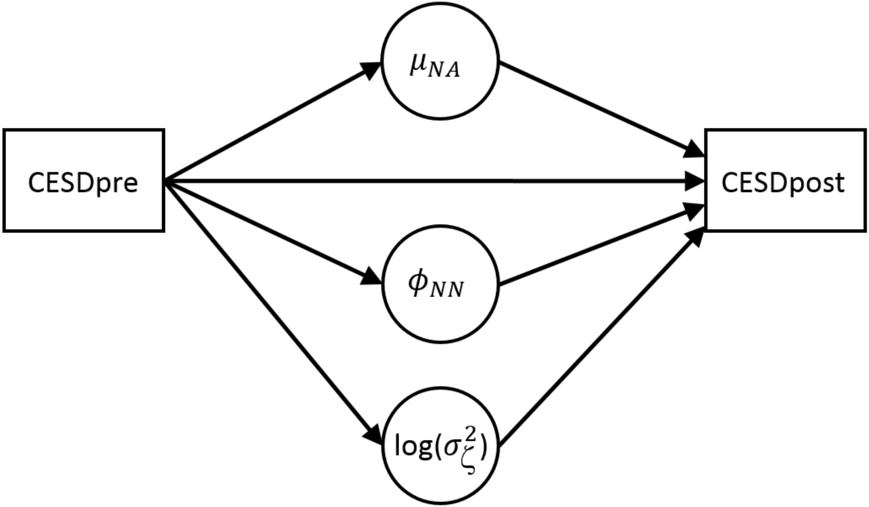
Mplus results

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
Between Level						
P_NN WITH						
LOGRVNA	0.082	0.035	0.004	0.021	0.160	*
DAYNA	0.065	0.022	0.001	0.027	0.114	*
LOGRVNA WITH						
DAYNA	0.563	0.113	0.000	0.379	0.819	*
Means						
DAYNA	0.977	0.075	0.000	0.829	1.123	*
P_NN	0.406	0.026	0.000	0.355	0.456	*
LOGRVNA	-1.663	0.118	0.000	-1.905	-1.433	*
Variances						
DAYNA	0.543	0.086	0.000	0.408	0.737	*
P_NN	0.058	0.010	0.000	0.042	0.081	*
LOGRVNA	1.382	0.216	0.000	1.046	1.892	*

Mplus results (cf. Schuurman et al., 2016)

```
STDYX Standardization

                                Posterior  One-Tailed         95% C.I.
                    Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%  Significance

Within-Level Standardized Estimates Averaged Over Clusters

 P_NN | DAYNA ON
    DAYNA&1            0.405       0.010      0.000       0.385       0.425      *

 LOGRVNA |
    DAYNA              0.783       0.008      0.000       0.767       0.797      *

Between Level

 P_NN     WITH
    LOGRVNA            0.294       0.105      0.004       0.079       0.488      *
    DAYNA              0.370       0.101      0.001       0.156       0.553      *

 LOGRVNA  WITH
    DAYNA              0.654       0.061      0.000       0.516       0.756      *

(...)

R-SQUARE

Within-Level R-Square Averaged Across Clusters

                                Posterior  One-Tailed         95% C.I.
    Variable        Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%

    DAYNA              0.217       0.008      0.000       0.203       0.233
```

Mediation model with random innovation variance



Mediation model with random innovation variance

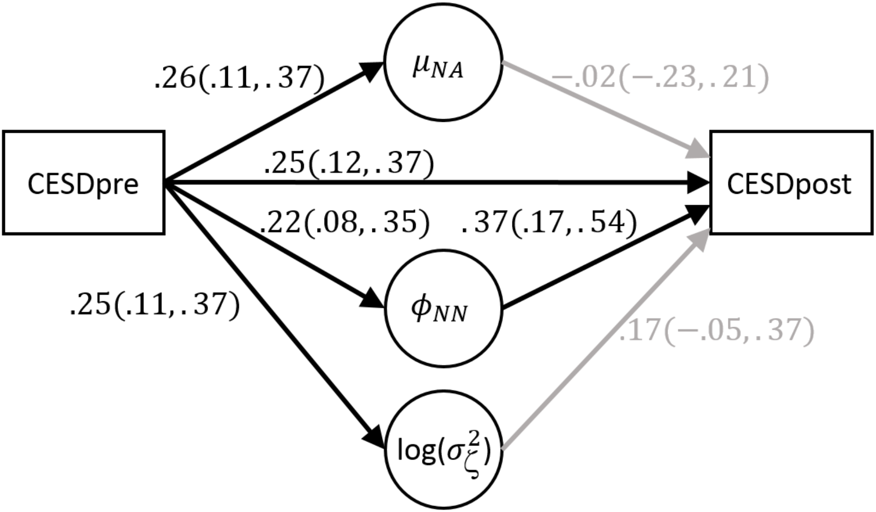
```
MODEL RESULTS

                                Posterior  One-Tailed         95% C.I.
                    Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%  Significance

Within Level

Between Level

 P_NN       ON
    CESDPRE            0.213       0.070      0.002       0.074       0.350      *

 LOGRVNA    ON
    CESDPRE            1.193       0.326      0.000       0.556       1.837      *

 CESDPOST   ON
    P_NN               0.569       0.158      0.000       0.258       0.876      *
    LOGRVNA            0.053       0.035      0.062      -0.016       0.124

 DAYNA      ON
    CESDPRE            0.780       0.231      0.000       0.332       1.252      *

 CESDPOST   ON
    DAYNA             -0.010       0.058      0.438      -0.126       0.104
    CESDPRE            0.378       0.099      0.000       0.181       0.570      *
```

Mediation model with random innovation variance

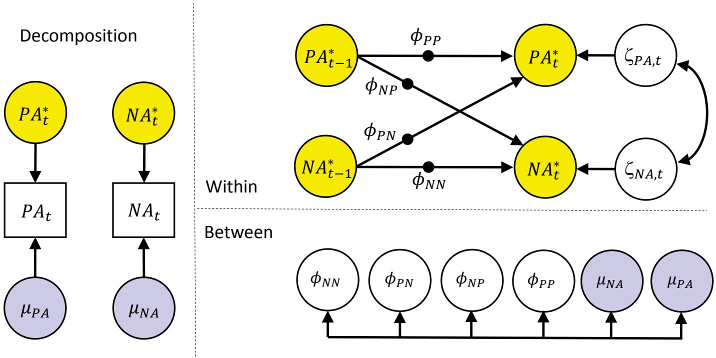
MODEL RESULTS

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
(...)						
Intercepts						
CESDPOST	-0.134	0.119	0.133	-0.362	0.103	
DAYNA	0.972	0.069	0.000	0.833	1.107	*
P_NN	0.406	0.025	0.000	0.358	0.456	*
LOGRVNA	-1.664	0.109	0.000	-1.874	-1.446	*
Residual Variances						
CESDPOST	0.086	0.014	0.000	0.064	0.117	*
DAYNA	0.459	0.075	0.000	0.345	0.633	*
P_NN	0.049	0.009	0.000	0.035	0.069	*
LOGRVNA	1.165	0.176	0.000	0.891	1.579	*
New/Additional Parameters						
AB_P_NN	0.116	0.053	0.002	0.033	0.238	*
AB_DAYNA	-0.007	0.047	0.438	-0.103	0.088	
AB_LOGRV	0.060	0.047	0.062	-0.017	0.168	

Mediation model with random innovation variance



Bivariate model: Multilevel vector AR(1) model



Bivariate model: Mplus code

```
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;
lagged      =   dayPA(1) dayNA(1);
tinterval   =   sessdate(1);
missing     =   all(-999);

ANALYSIS:   TYPE IS TWOLEVEL random; estimator=bayes;
            proc = 2; fbiter= 5000; bseed = 2359; thin = 10;

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;

    %BETWEEN%
    dayPA WITH dayNA;

    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;
```

Mplus results: Fixed, random, and standardized

```
 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      *

[...]

STDYX Standardization

                                Posterior  One-Tailed         95% C.I.
                    Estimate       S.D.      P-Value   Lower 2.5%  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      *
```

Outline

- Modeling the dynamics of ILD
- Separating between-person and within-person variance
- Application 1: Daily negative affect and depressive symptomatology
- **Application 2: Intervention study**
- Conclusion

Intervention study with ESM

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

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

Here we use data 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.

Here we analyze 117 participants, where 56 received a **mindfulness training** between the two phases, and 61 served as **controls**.

Treatment effect on the within-person mean

Decomposition into a between part and a within part

$$\text{Pre-treatment phase:} \quad y_{1it} = \mu_{1i} + y^*_{1it}$$
$$\text{Post-treatment phase:} \quad y_{2it} = \mu_{2i} + y^*_{2it}$$

Between level

$$\mu_{1i} = \alpha_1 + \beta_1 Group_i + u_{1i}$$
$$\mu_{2i} = \alpha_2 + \mu_{1i} + \beta_2 Group_i + u_{2i}$$

- β_1 are initial differences between the groups
- α_2 is the effect of time
- β_2 is the effect of treatment

```
MODEL:
    %WITHIN%
    na_pre WITH na_post@0;

    %BETWEEN%
    na_pre ON Group;
    na_post ON na_pre@1 Group;
    na_pre WITH na_post;
```

Mplus results

```
                                Posterior  One-Tailed         95% C.I.
                    Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%  Significance

Within Level

 NA_PRE   WITH
    NA_POST            0.000       0.000      1.000       0.000       0.000

 Variances
    NA_PRE             0.639       0.012      0.000       0.616       0.662      *
    NA_POST            0.483       0.009      0.000       0.466       0.501      *

Between Level

 NA_PRE     ON
    GROUP             -0.005       0.136      0.484      -0.292       0.249

 NA_POST    ON
    NA_PRE             1.000       0.000      0.000       1.000       1.000
    GROUP             -0.320       0.108      0.002      -0.539      -0.112      *

 NA_PRE   WITH
    NA_POST           -0.157       0.046      0.000      -0.262      -0.082      *

 Intercepts
    NA_PRE             2.019       0.095      0.000       1.837       2.210      *
    NA_POST            0.006       0.077      0.472      -0.148       0.155

 Residual Variances
    NA_PRE             0.524       0.078      0.000       0.402       0.706      *
    NA_POST            0.324       0.050      0.000       0.247       0.439      *
```

Treatment effect on autoregression

Within level

Pre-treatment phase: $y^*_{1it} = \phi_{1i} y^*_{1it} + \zeta_{it}$

Post-treatment phase: $y^*_{2it} = \phi_{2i} y^*_{2it} + \zeta_{it}$

Between level: Pre-treatment phase

$\mu_{1i} = \alpha_1 + \beta_1 Group_i + u_{1i}$ $\qquad$ $\phi_{1i} = \gamma_1 + \delta_1 Group_i + v_{1i}$

We expect β_1 and δ_1 to be zero.

Between level: Post-treatment phase

$\mu_{2i} = \alpha_2 + \mu_{1i} + \beta_2 Group_i + u_{2i}$ $\qquad$ $\phi_{2i} = \gamma_2 + \phi_{1i} + \delta_2 Group_i + v_{2i}$

- α_2 and γ_2 represent the effects of time
- β_2 and δ_2 represent the effects of treatment

Mplus results

```
Between Level

 PHI2       ON
    PHI1              1.000       0.000      0.000       1.000       1.000

 PHI2       ON
    GROUP            -0.056       0.042      0.095      -0.141       0.025

 PA_PRE     ON
    GROUP            -0.199       0.150      0.090      -0.497       0.094

 PA_POST    ON
    PA_PRE            1.000       0.000      0.000       1.000       1.000
    GROUP             0.481       0.122      0.000       0.246       0.736      *

 Means
    PHI1              0.465       0.019      0.000       0.427       0.504      *

 Intercepts
    PA_PRE            3.824       0.102      0.000       3.628       4.031      *
    PA_POST          -0.067       0.085      0.208      -0.239       0.104
    PHI2              0.002       0.032      0.481      -0.062       0.060

 Variances
    PHI1              0.019       0.004      0.000       0.013       0.030      *

 Residual Variances
    PA_PRE            0.632       0.093      0.000       0.472       0.846      *
    PA_POST           0.356       0.059      0.000       0.264       0.493      *
    PHI2              0.017       0.007      0.000       0.006       0.033      *
```

Mplus results (with fixed change in ϕ)

```
Between Level

 PHI2       ON
    PHI1               1.000       0.000      0.000       1.000       1.000

 PHI1       ON
    GROUP              0.049       0.045      0.140      -0.041       0.139

 PHI2       ON
    GROUP             -0.067       0.032      0.023      -0.132      -0.001      *

 NA_PRE     ON
    GROUP             -0.046       0.126      0.361      -0.308       0.189

 NA_POST    ON
    NA_PRE             1.000       0.000      0.000       1.000       1.000
    GROUP             -0.280       0.104      0.002      -0.477      -0.070      *

 Intercepts
    NA_PRE             2.007       0.088      0.000       1.839       2.180      *
    NA_POST            0.014       0.072      0.421      -0.125       0.152
    PHI1               0.445       0.032      0.000       0.381       0.506      *
    PHI2              -0.013       0.022      0.280      -0.055       0.032

 Residual Variances
    NA_PRE             0.449       0.068      0.000       0.339       0.603      *
    NA_POST            0.257       0.043      0.000       0.189       0.356      *
    PHI1               0.042       0.007      0.000       0.031       0.059      *
    PHI2               0.001       0.000      0.000       0.001       0.001
```

Outline

- Modeling the dynamics of ILD
- Separating between-person and within-person variance
- Application 1: Daily negative affect and depressive symptomatology
- Application 2: Intervention study with ESM
- **Conclusion**

Conclusion

- DSEM in Mplus version 8 offers many new modeling opportunities for analyzing ILD
- There are many additional options not covered here
- We are working on regime-switching extensions
- We (the research community) need to gain new knowledge about these models

References

- Asparouhov, Hamaker & Muthén (2017). Dynamic latent class analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 24*, 257-269.
- Asparouhov, Hamaker & Muthén (in preparation). Dynamic structural equation models.
- 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 (in preparation). 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.
- Hamaker & Wichers (2017). No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science, 26*, 10-15.
- 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.
- Schuurman, Ferrer, de Boer-Sonnenschein & Hamaker (2016). How to compare cross-lagged associations in a multilevel autoregressive model. *Psychological Methods, 21*, 206-221.