Block-Wise Model Fit for Structural Equation Models with Experience Sampling Data

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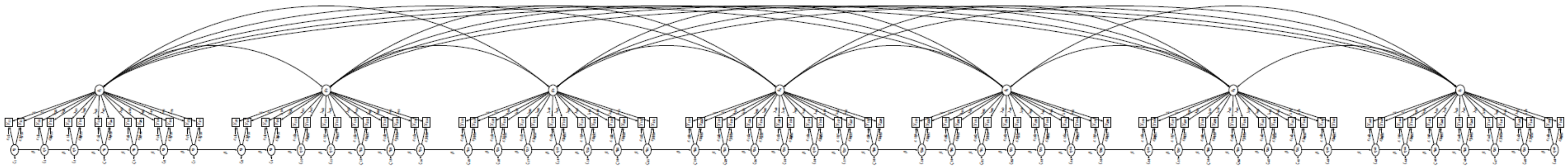
SEM for Experience Sampling Data

Starting point: Research questions regarding the (in)stability of psychological constructs

$\Rightarrow$ Latent state trait (LST) theory

$$Y_{11} = \underbrace{\lambda_{T11} \cdot \theta}_{\text{Stable influence}} + \underbrace{\lambda_{O11} \cdot \zeta_1}_{\text{Situation-specific influence}} + \underbrace{\epsilon_{11}}_{\text{measurement error}}$$

$\Rightarrow$ Very large models with experience sampling data:



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Fit evaluation for Experience Sampling SEMs

Problem: Common fit indices in SEM are less reliable for models with many manifest variables

- χ^2 estimated are inflated
- CFI and TLI tend to get worse
- RMSEA improves with more manifest variables

(e.g. Moshagen, 2012; Shi et al., 2019; Kenny & McCoach, 2003)

Alternative: Block-wise fit evaluation

- (Co)Variances of entire SEM are estimated together
- Smaller blocks of the covariance matrix (for each day) are used to calculate block-wise fit indices
- Advantages:
  - Model restrictions across days can be included
  - We can use common cut-offs to evaluate model fit

	day 1	day 2	day 3	...
day1	χ^2_1, RMSEA_1, CFI_1, TLI_1			
day2		χ^2_2, RMSEA_2, CFI_2, TLI_2		
day3			χ^2_3, RMSEA_3, CFI_3, TLI_3	
$\vdots$				$\ddots$

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Block-wise Fit Evaluation

(1) Overall Model is estimated (with ML)

(2) K blocks are extracted from the model-implied and empirical (co)ovariance Matrices $\hat{\Sigma}$ and S.

- K = Number of blocks, e.g. days in an Experience Sampling Study

(3) Common fit indices are calculated with adjusted formulas for common indices

$$\chi^2 = \left(\log\left|\hat{\Sigma}\right| + \mathrm{tr}\left(\hat{\Sigma}^{-1} S\right) - \log|S| - q + (\bar{x} - \hat{\mu})^{\mathrm{T}} \hat{\Sigma}^{-1} (\bar{x} - \hat{\mu}) \right) \cdot N$$

$$\Downarrow$$

$$\chi_k^2 = \left(\log\left|\hat{\Sigma}_k\right| + \mathrm{tr}\left(\hat{\Sigma}_k{}^{-1} S_k\right) - \log|S_k| - q_k + (\bar{x}_k - \hat{\mu}_k)^{\mathrm{T}} \hat{\Sigma}_k^{-1} (\bar{x}_k - \hat{\mu}_k) \right) \cdot N$$

q_k = number of observed variables per block

$$\mathrm{RMSEA}_k = \frac{\sqrt{\chi_k^2 - \mathrm{df}_k}}{\sqrt{\mathrm{df}_k \cdot N}}$$

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Block-wise Fit Evaluation

Degrees of freedom = observed parameters – estimated parameters

Easy to split between blocks

Unclear how to split between blocks

Alternative: simulate block-wise df_k

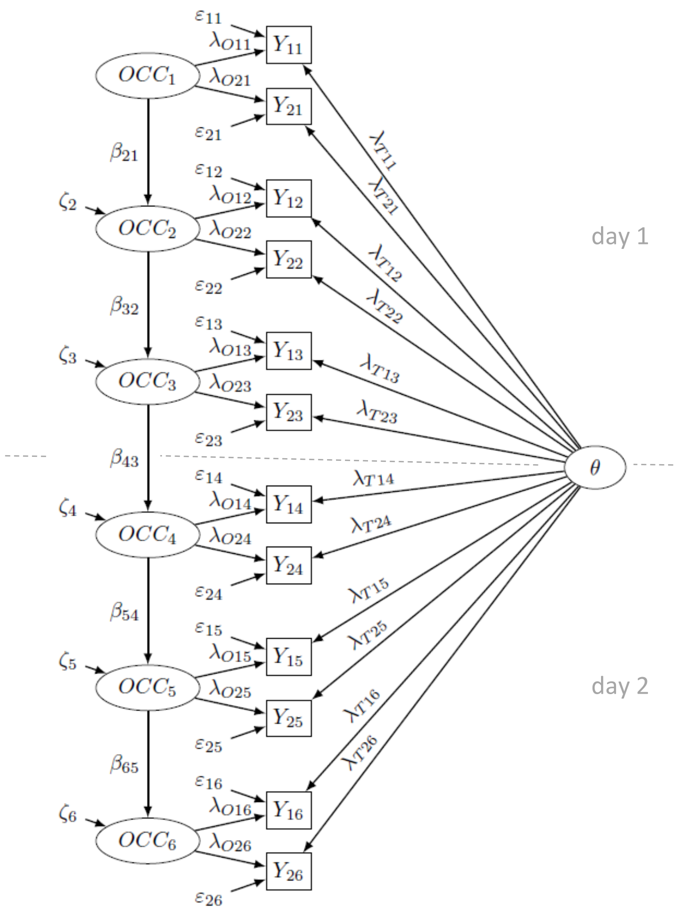
$df = E(\chi^2)$

$\Rightarrow$ Under H_0, the mean χ^2-value should be equal to the df

$\Rightarrow$ We can compute block-wise χ^2_k

$\Rightarrow$ with many simulated datasets: $df_k = M(\chi^2_k)$

$\Rightarrow$ simulation study: χ^2_k are χ^2 distributed with df_k degrees of freedom



Multistate-Singletrait model with autoregressive paths

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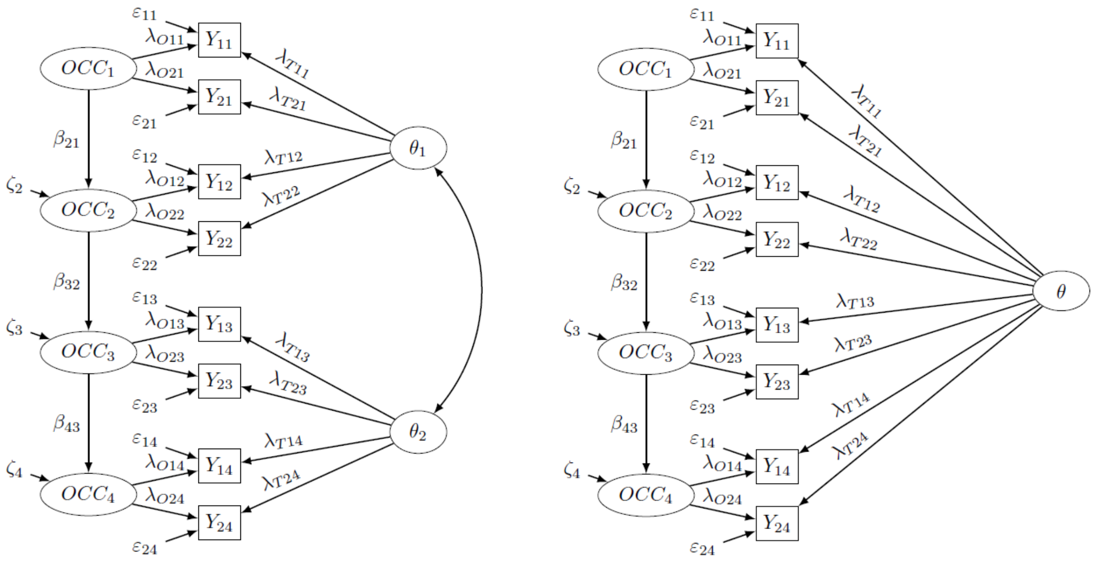
Simulation Study 1: Method

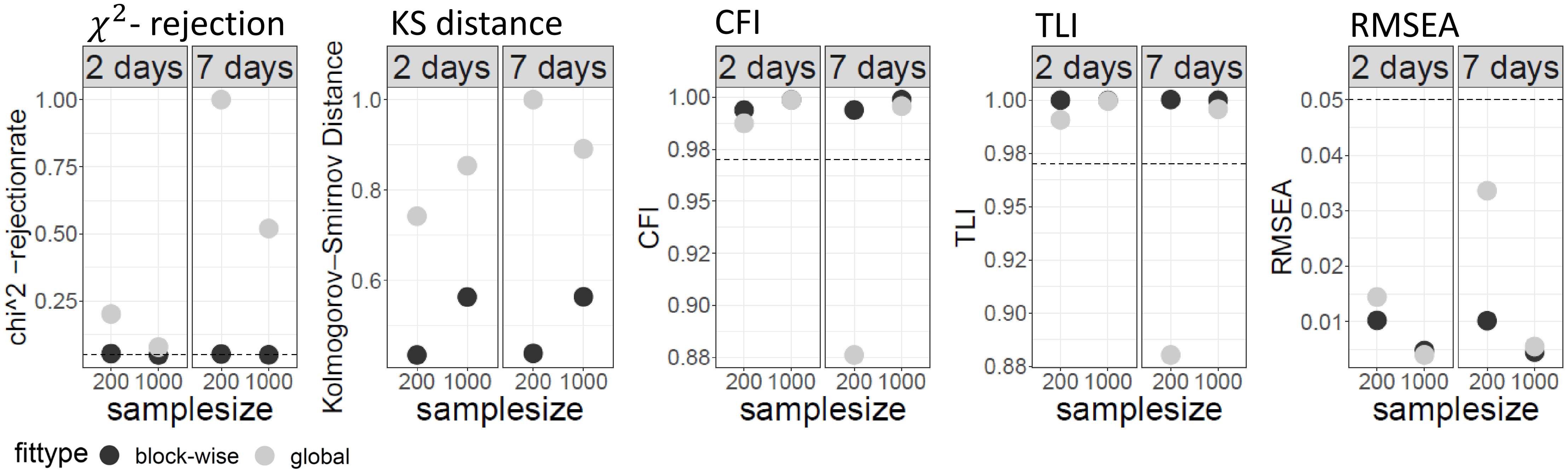
Can block-wise fit evaluation better identify correctly specified models than global fit evaluation?

Design:

- 2 model sizes: 2 days (28 manifest variables), 7 days (98 manifest variables)
- 2 sample sizes: 200, 1000
- 2 models: day-specific traits LST model, singletrait LST model



Simulation Study 1: Results



Most likely experience sampling scenario: 7 days, N = 200

$\Rightarrow$ global indices reject perfect models

$\Rightarrow$ block-wise fit correctly identifies perfect models

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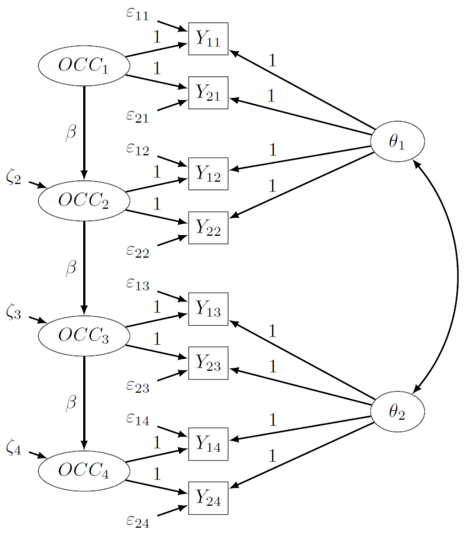
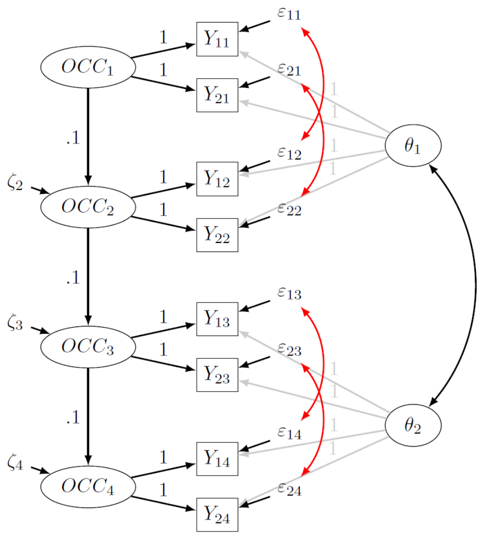
Simulation Study 2: Method

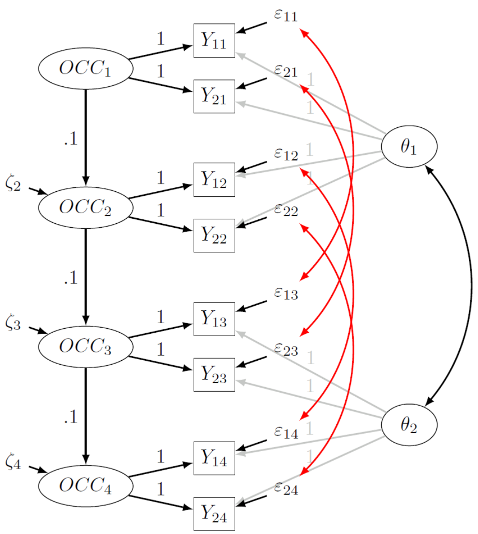
Can block-wise fit evaluation correctly identify misspecified models?

Design: 2 (model size) x 2 (sample size) x 2 (model) x **6 (misspecifications)**





residual correlations
within days ($r = .15$; $r = .40$)



residual correlations
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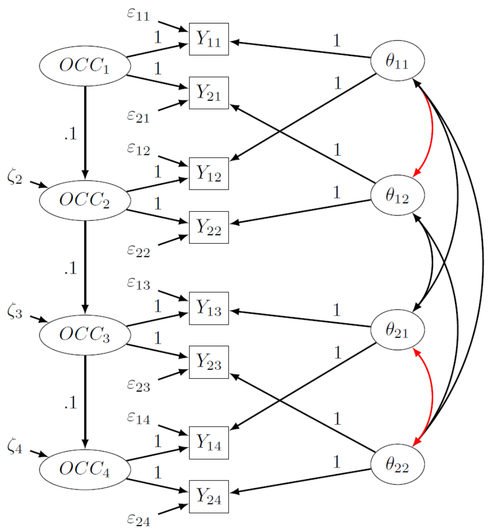

Structural misspecification
($r = .90$; $r = .60$)

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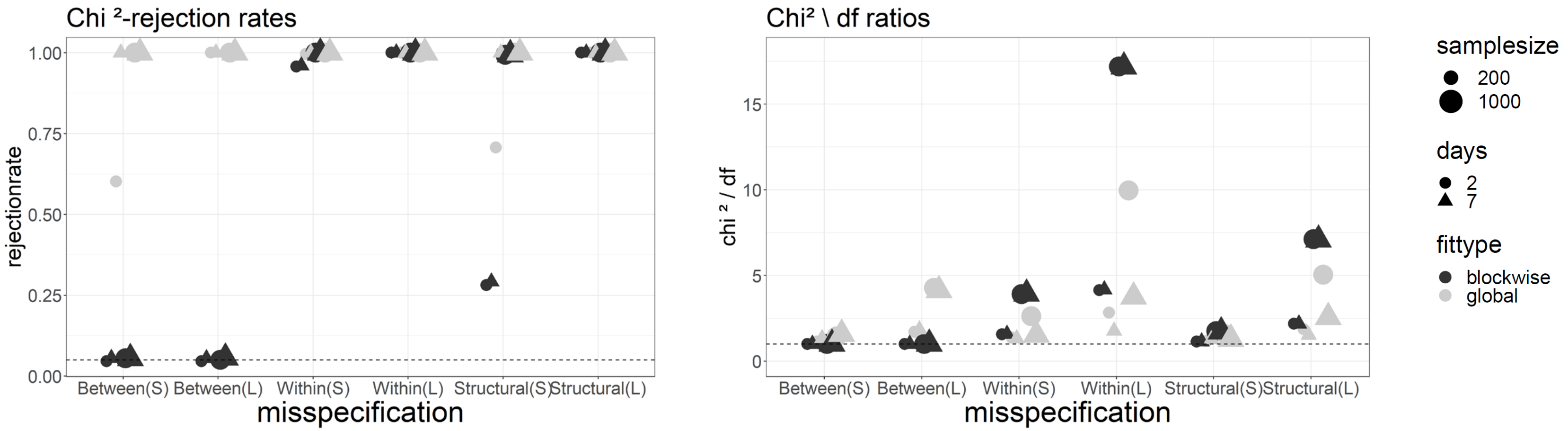
Simulation study 2: Results



Global χ^2 and block-wise χ^2_k

- High rejection rates
- No effect of the number of days

Block-wise χ^2_k (and other indices)

- Cannot detect misspecification between days

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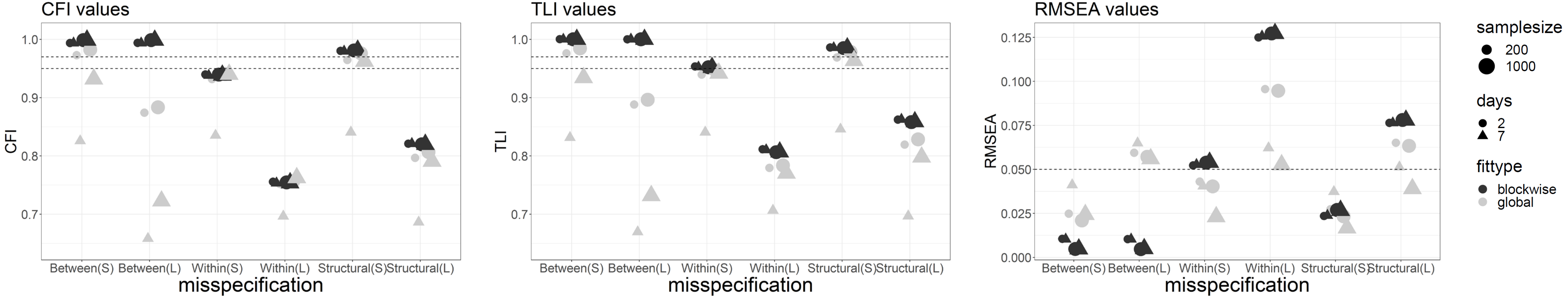
Simulation Study 2: Results



Global CFI and TLI

- Strongly affected by number of days (d = 0.87)
- values for 7 days and N = 200 systematically lower

Block-wise CFI_k and TLI_k

- Not affected by numbers of days (p = .51)

Global RMSEA

- Would let us conclude that (strongly) misspecified models are acceptable

Block-wise $RMSEA_k$

- Generally indicates worse fit

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Discussion

For typical experience sampling data (e.g. 7 days, N = 200), block-wise fit

- can better identify well-fitting models than global evaluation
- is not affected by the number of days, i.e. manifest variables

$\Rightarrow$ For LST models (and other SEM) with experience sampling data, we recommend block-wise fit evaluation

Limitations and Future Research

- Block-wise fit cannot detect misspecification purely between days
- Missing data is common, FIML should be implemented for block-wise fit calculation

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Thank you for your attention!

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