A Simulation Study on the Performance of a Longitudinal Multilevel CTC(M-1) Model using MplusAutomation

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February 10, 2012

Outline

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Complex Measurement Desgins
Different Methods → Different Models
Longitudinal Multilevel CTC(M-1) Model
Simulation Design
Results of the Simulation Study
Summary & Discussion
Reference

Multitrait-Multimethod Multioccasion (MTMM-MO)

- different methods are used to assess different traits on different occasions of measurement
- advantages of longitudinal MTMM designs:
  - study the stability and change of constructs and methods effects
  - evaluate the psychometric properties of an instrument at each occasion of measurement and across occasions of measurement
  - use more information to assess a construct
  - test the generalizability of different method effects
  - use covariates in order to explain method effects
  - test theoretical assumptions
  - analyze the discriminant and convergent validity

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interchangeable & structurally different methods

interchangeable methods

- *randomly* selected methods out of a common set of equivalent methods
- implies at least a two stage sampling procedure (target → raters) = multilevel data structure
- e.g., colleague ratings, peer ratings, customer ratings

structurally different methods

- fixed (not random) methods (rater) for a particular target
- stem out of different rater populations
- e.g., self-ratings, teacher rating, supervisor rating

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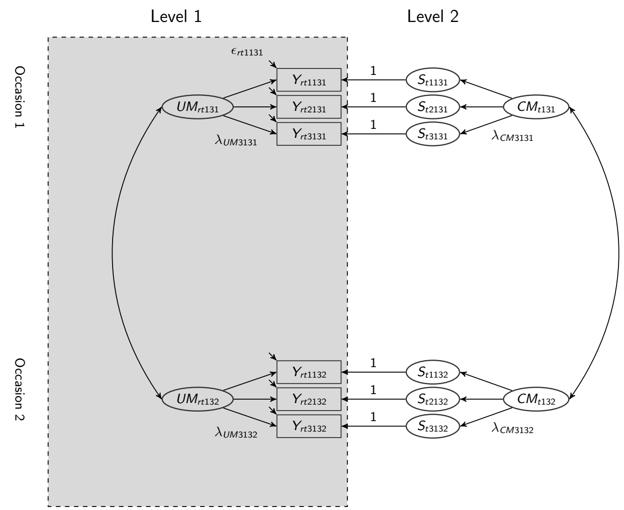
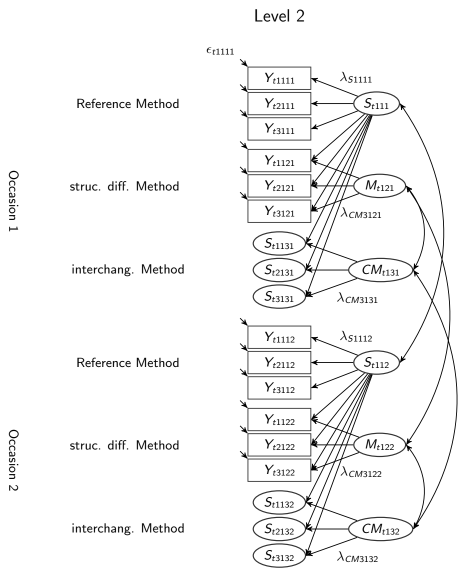
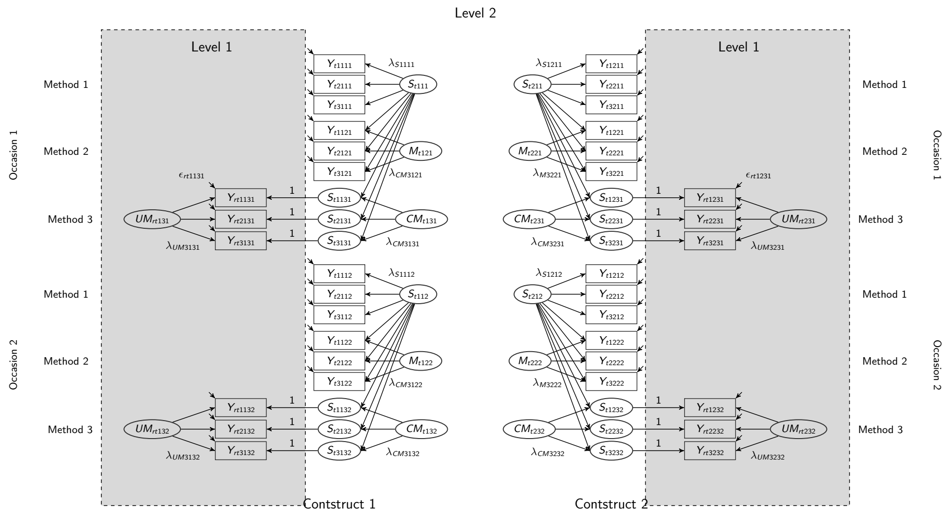
Measurement model for interchanegable methods



Measurement model for structurally different methods



CSCM-1-COM Model



Consistency and method specificity

Consistency

- amount of true variance of a non-reference indicator that can be explained by the reference method
- $\sqrt{\text{consistency}}$ = indicator of convergent validity

Method Specificity

- amount of true variance of a non-reference indicator that can *not* be explained by the reference method
- 2 method effects = 2 coefficients
- common method specificity: amount of true variance of an indicator of the exchangeable method that reflects the common view of the exchangeable method but is independent of the reference method
- unique method specificity: amount of true variance of an indicator of the exchangeable method that reflects neither the common view of exchangeable methods nor the reference method

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Simulation Design

- a 2x2x3x4x3 simulation design with 96 conditions à 500 replications (48 conditions were excluded for identification reasons)
- 48000 datasets with 200 to 10000 observations
  - consistency (high vs. low)
  - number of methods (2 vs. 3)
  - number of measurement occasions (2 to 4)
  - number of level-one units (2, 5, 10, 20)
  - number of level-two units (100, 250, 500)
  - all models assumed strict measurement invariance (c.f. Widaman & Reise, 1997)

Simulation Implementation

- clusters of conditions were assigned to 27 computers and simulated simultaneously
- software: Mplus, R Gui, R-Package MplusAutomation
- duration of estimation: 3 days

Consistency vs. Method Specificity

Table: Consistency and Method Specificity

	low consistency	high consistency
consistency	.3	.6
unique method specificity	.25	.1
common method specificity	.25	.1
total method specificity	.5	.2

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Coefficients for Parameter Bias

Parameter Estimation Bias

= standardized indicator of parameter bias

$$peb = \frac{M_p - e_p}{e_p} \tag{1}$$

cutoff-value: peb $<$ .10

Standard Error Bias

= standardized indicator of standard-error bias

$$seb = \frac{M_{SE} - SD_p}{SD_p} \tag{2}$$

cutoff-value: seb $<$ .10

Relevant Biases

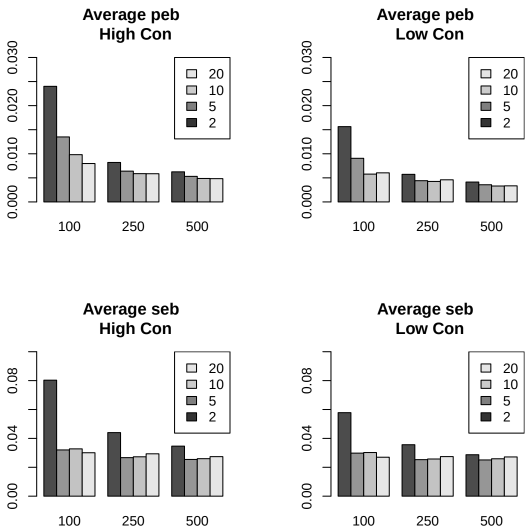
peb

- the peb did not exceed the cutoff of .1 in any condition

seb

- the seb exceeded the cutoff of .1 in 3 of the low consistency and 4 of the high consistency conditions
- in all of the 7 conditions the seb of the common method loadings exceeded .1
- in 4 of the 7 conditions the seb of the unique method loadings exceeded .1
- in 1 of the 7 conditions the seb of the level-one latent variances exceeded .1
- all of the 7 conditions had only 2 level-one units

Average peb and seb



Estimation Problems

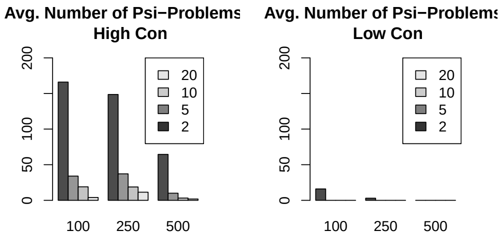
Ψ-problems

- latent covariance matrix Ψ is not positive-definite or there are linear dependencies in the data
- not necessarily an actual problem
- encountered in 37 of 96 conditions (38.5 %)
- 32 of these 37 were high consistency conditions

Θ-Problems

- negative residual variances
- indicate real problems in estimation
- happened in a single replication of one condtion

Ψ-Problems



- most problems occur with 2 level-one units
- at worst, 333 replications resulted in Ψ-problems

Ψ-Problems

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
nL1	1	42098.34	42098.34	12.61	0.0009
nL2	1	13332.11	13332.11	3.99	0.0521
Methods	1	22148.46	22148.46	6.63	0.0135
Occasions	1	23097.20	23097.20	6.92	0.0118
Residuals	43	143611.56	3339.80		

Table: ANOVA for the Psi-problems of the high consistency conditions

- Ψ-problems occur most often in high consistency situations
- smaller samples (especially less level-one units) lead to estimation problems
- more complex models lead to estimation problems
- most Ψ-problems pertain to partial correlations of method or common method factors exceeding 1 when controlling for all other latent variables

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Summary & Discussion

- Parameter biases (peb and seb) are mostly within acceptable ranges
- common and unique method loadings are associated with the largest parameter biases
- Ψ-problems occur very often in high consistency conditions with 2 level-one units

Summary & Discussion

- low convergent validities are the case in most empirical settings
- more measurement occasions grant stability in model estimation
- model requires large sample sizes (min. 100 level-two and 5 level-one units)
- replication of the findings of Julian (2001) and Maas & Hox (2005)!
- number of level-one units is extremely important
- generally: the more complex the model, the larger the required sample

Thank You!

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Reference

Geiser, C. (2009). *Multitrait-Multimethod-Multioccasion Modeling.* München, Germany: AVM.

Eid, M., & Diener, E. (Eds.) (2006). *Handbook of multimethod measurement in psychology.* Washington, DC: American Psychological Association.

Eid, M., Nussbeck, F., Geiser, C., Cole, D., Gollwitzer, M., & Lischetzke, T. (2008). Structural equation modeling of multitrait-multimethod data: Different models for different types of methods. *Psychological Methods*, *13*, 230-253.

Steyer, R. (1989). Models of classical psychometric test theory as stochastic measurement models: Representation, uniqueness, meaningfulness, identifiability, and testability. *Methodika*, *3* ,25 - 60.

Steyer, R., & Eid, M. (2001). *Messen und Testen* (2., korrigierte Auflage; 1. Auflage: 1993). Berlin: Springer.

$$S_{tij1l} \equiv E(Y_{tij1l}|p_T, p_{TS_l}), \tag{3}$$
$$S_{rtij2l} \equiv E(Y_{rtij2l}|p_T, p_{TS_l}, p_R, p_{RS_l}), \tag{4}$$
$$S_{tijkl} \equiv E(Y_{tijkl}|p_T, p_{TS_l}) \quad ,\forall k \neq 1,2, \tag{5}$$
$$E_{tij1l} \equiv Y_{tij1l} - E(Y_{tij1l}|p_T, p_{TS_l}), \tag{6}$$
$$E_{rtij2l} \equiv Y_{rtij2l} - E(Y_{rtij2l}|p_T, p_{TS_l}, p_R, p_{RS_l}), \tag{7}$$
$$E_{tijkl} \equiv Y_{tijkl} - E(Y_{tijkl}|p_T, p_{TS_l}) \quad ,\forall k \neq 1,2, \tag{8}$$
$$S_{tij2l} \equiv E\left[E(Y_{rtij2l}|p_T, p_{TS_l}, p_R, p_{RS_l})|p_T, p_{TS_l}\right], \tag{9}$$
$$UM_{rtij2l} \equiv S_{rtij2l} - E(S_{rtij2l}|p_T, p_{TS_l}), \tag{10}$$
$$CM_{tij2l} \equiv S_{tij2l} - E(S_{tij2l}|S_{tij1l}), \tag{11}$$
$$M_{tijkl} \equiv S_{tijkl} - E(S_{tijkl}|S_{tij1l}) \quad ,\forall k \neq 1,2, \tag{12}$$

$$Y_{tij1l} = S_{tij1l} + E_{tij1l}, \tag{13}$$
$$Y_{tijkl} = \alpha_{tijkl} + \lambda_{Sijkl} S_{tij1l} + \lambda_{Mijkl} M_{tjkl} + E_{tijkl}, \forall k \neq 1,2, \tag{14}$$
$$Y_{rtij2l} = \alpha_{tij2l} + \lambda_{Sij2l} S_{tij1l} + \lambda_{CMij2l} CM_{tj2l} + \lambda_{UMij2l} UM_{rtj2l} + E_{rtij2l}. \tag{15}$$
$$\tag{16}$$

$$Var(Y_{tij1l}) = Var(S_{tij1l}) + Var(E_{tij1l}), \tag{17}$$
$$Var(Y_{tijkl}) = \lambda^2_{Sijkl} Var(S_{tij1l}) + \lambda^2_{Mijkl} Var(M_{tjkl}) + Var(E_{tijkl}), \forall k \neq 1,2, \tag{18}$$
$$Var(Y_{rtij2l}) = \lambda^2_{Sij2l} Var(S_{tij1l}) + \lambda^2_{CMij2l} Var(CM_{tj2l}) + \lambda^2_{UMij2l} Var(UM_{rtj2l}) + Var(E_{rtij2l}). \tag{19}$$

$$CON(Y_{tij1l}) = \frac{Var(S_{tij1l})}{Var(Y_{tij1l})}, \tag{20}$$
$$CON(Y_{tijkl}) = \frac{\lambda^2_{Sijkl} Var(S_{tij1l})}{Var(Y_{tijkl})} \quad ,\forall k \neq 1,2, \tag{21}$$
$$CON(Y_{rtij2l}) = \frac{\lambda^2_{Sij2l} Var(S_{tij1l})}{Var(Y_{rtij2l})}. \tag{22}$$

$$MS(Y_{tijkl}) = \frac{\lambda^2_{Mijkl} Var(M_{tjkl})}{Var(Y_{tijkl})}, \quad \forall k \neq 1,2, \tag{23}$$
$$CMS(Y_{rtij2l}) = \frac{\lambda^2_{CMij2l} Var(CM_{tj2l})}{Var(Y_{rtij2l})}, \tag{24}$$
$$UMS(Y_{rtij2l}) = \frac{\lambda^2_{UMij2l} Var(UM_{rtj2l})}{Var(Y_{rtij2l})}. \tag{25}$$

	M peb	SD peb	M seb	SD seb
UM Loadings	0.001	0.001	0.033	0.022
Latent Covariances	0.011	0.004	0.028	0.006
Latent Variances	0.002	0.002	0.027	0.010
Residual Variances	0.002	0.003	0.024	0.005

Table: Bias for level-one parameters of the low consistency condition

	M peb	SD peb	M seb	SD seb
State Loadings	0.002	0.001	0.029	0.010
CM Loadings	0.001	0.002	0.036	0.027
M Loadings	0.001	0.001	0.029	0.012
Latent Covariances	0.015	0.007	0.027	0.006
Latent Means	0.004	0.003	0.028	0.014
Intercepts	0.002	0.001	0.025	0.012
Latent Variances	0.005	0.004	0.027	0.006
Residual Variances	0.005	0.002	0.028	0.006

Table: Bias for level-two parameters of the low consistency condition

Overview of Parameter Bias

	M peb	SD peb	M seb	SD seb
UM Loadings	0.003	0.004	0.037	0.030
Latent Covariances	0.023	0.008	0.029	0.009
Latent Variances	0.003	0.003	0.032	0.016
Residual Variances	0.002	0.003	0.025	0.006

Table: Bias for level-one parameters of the high consistency condition

	M peb	SD peb	M seb	SD seb
State Loadings	0.001	0.001	0.027	0.009
CM Loadings	0.004	0.008	0.049	0.044
M Loadings	0.002	0.001	0.042	0.013
Latent Covariances	0.020	0.005	0.028	0.007
Latent Means	0.004	0.003	0.027	0.014
Intercepts	0.002	0.001	0.025	0.012
Latent Variances	0.006	0.004	0.030	0.008
Residual Variances	0.005	0.002	0.028	0.006

Table: Bias for level-two parameters of the high consistency condition

Causes of peb and seb

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
nL1	1	0.00	0.00	5.17	0.0280
nL2	1	0.00	0.00	32.23	0.0000
Methods	1	0.00	0.00	2.66	0.1104
Occasions	1	0.00	0.00	1.46	0.2335
Residuals	43	0.00	0.00		

Table: ANOVA for the peb of the low consistency conditions

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
nL1	1	0.00	0.00	3.71	0.0608
nL2	1	0.00	0.00	6.33	0.0157
Methods	1	0.00	0.00	0.01	0.9342
Occasions	1	0.00	0.00	0.02	0.9014
Residuals	43	0.00	0.00		

Table: ANOVA for the seb of the low consistency conditions

Causes of peb and seb

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
nL1	1	0.00	0.00	7.73	0.0080
nL2	1	0.00	0.00	25.81	0.0000
Methods	1	0.00	0.00	2.09	0.1557
Occasions	1	0.00	0.00	2.20	0.1457
Residuals	43	0.00	0.00		

Table: ANOVA for the peb of the high consistency conditions

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
nL1	1	0.00	0.00	7.61	0.0085
nL2	1	0.00	0.00	7.88	0.0075
Methods	1	0.00	0.00	0.52	0.4767
Occasions	1	0.00	0.00	0.21	0.6505
Residuals	43	0.00	0.00		

Table: ANOVA for the seb of the high consistency conditions