

First-Order Confirmatory Factor Analysis (CFA)

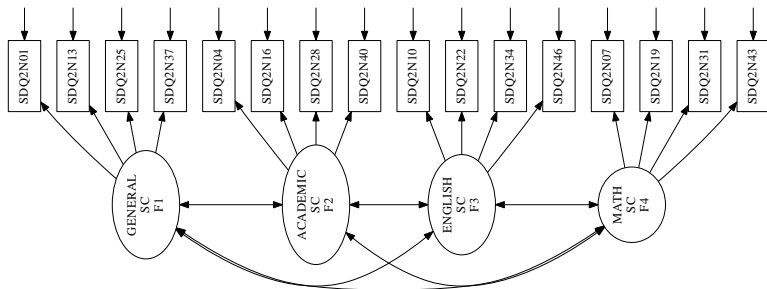


Part 2 of the material is based on the Chapter 3 of the book Byrne, Barbara M. (2012). Structural Equation Modeling with Mplus. It gives a typical example of the **single-group analyses** of SEM: testing the **factorial validity** of a **theoretical construct**.

- ▶ **Hypothesis:** self-concept (SC) is a multidimensional construct composed of four factors:
 - ▶ General SC (GSC)
 - ▶ Academic SC (ASC)
 - ▶ English SC (ESC)
 - ▶ Mathematics SC (MSC)
- ▶ **Data:** 16 variables from grade 7 children (N=265)
- ▶ **Alternative hypotheses:** 1) SC has two factors (GSC, ASC), 2) SC is unidimensional (only one SC factor).

Hypothesized four-factor CFA model (graph)

Fig. 3.1 (p.44) (redrawn)



Hypothesized four-factor CFA model

Assumptions:

- ▶ four correlated SC factors
- ▶ 16 observed variables
- ▶ each loads on one and only one factor
- ▶ residuals of observed variables uncorrelated

The corresponding matrices include three types of parameters:

- ▶ # = parameter to be (freely) estimated
- ▶ 0 = parameter fixed to 0.0 (restrictions to model)
- ▶ 1 = parameter fixed to 1.0 (latent variable scaling, model identification)

Altogether to be estimated:

- ▶ 12 factor loadings (first of each congeneric set fixed)
- ▶ 16 observed variable residual variances
- ▶ 4 factor variances
- ▶ 6 factor covariances (two-headed arrows in the graph)

■ 38 parameters (+ 16 observed variable intercepts, ignored)



Hypothesized four-factor CFA model (matrices)

1) Factor loadings: (LAMBDA)

Variable	Factors			
	GSC (F1)	ASC (F2)	ESC (F3)	MSC (F4)
SDQ2N01	1	0	0	0
SDQ2N13	#	0	0	0
SDQ2N25	#	0	0	0
SDQ2N37	#	0	0	0
SDQ2N04	0	1	0	0
SDQ2N16	0	#	0	0
SDQ2N28	0	#	0	0
SDQ2N40	0	#	0	0
SDQ2N10	0	0	1	0
SDQ2N22	0	0	#	0
SDQ2N34	0	0	#	0
SDQ2N46	0	0	#	0
SDQ2N07	0	0	0	1
SDQ2N19	0	0	0	#
SDQ2N31	0	0	0	#
SDQ2N43	0	0	0	#

2) Factor variance-covariance matrix: (PSI)

GSC	#			
ASC	#	#		
ESC	#	#	#	
MSC	#	#	#	#



Hypothesized four-factor CFA model (matrices)

3) (Measurement) Error variance-covariance matrix: (THETA)

SDQ2N01	#																		
SDQ2N13	0	#																	
SDQ2N25	0	0	#																
SDQ2N37	0	0	0	#															
SDQ2N04	0	0	0	0	#														
SDQ2N16	0	0	0	0	0	#													
SDQ2N28	0	0	0	0	0	0	#												
SDQ2N40	0	0	0	0	0	0	0	#											
SDQ2N10	0	0	0	0	0	0	0	0	#										
SDQ2N22	0	0	0	0	0	0	0	0	0	#									
SDQ2N34	0	0	0	0	0	0	0	0	0	0	#								
SDQ2N46	0	0	0	0	0	0	0	0	0	0	0	#							
SDQ2N07	0	0	0	0	0	0	0	0	0	0	0	0	0	#					
SDQ2N19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	#			
SDQ2N31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	#		
SDQ2N43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	#	



Hypothesized four-factor CFA model (input file)

ASC7INDM.INP

TITLE: CFA of Academic SC Structure for Grade 7 Adolescents
(Byrne 2012, p. 56)

DATA:

FILE IS "ASC7INDM.DAT";
FORMAT IS 40F1.0,X,6F2.0;

VARIABLE:

NAMES ARE

SPPCN08 SPPCN18 SPPCN28 SPPCN38 SPPCN48 SPPCN58 SPPCN01 SPPCN11
SPPCN21 SPPCN31 SPPCN41 SPPCN51 SPPCN06 SPPCN16 SPPCN26 SPPCN36
SPPCN46 SPPCN56 SPPCN03 SPPCN13 SPPCN23 SPPCN33 SPPCN43 SPPCN53

SDQ2N01 SDQ2N13 SDQ2N25 SDQ2N37 SDQ2N04 SDQ2N16 SDQ2N28 SDQ2N40
SDQ2N10 SDQ2N22 SDQ2N34 SDQ2N46 SDQ2N07 SDQ2N19 SDQ2N31 SDQ2N43

MASTENG1 MASTMAT1 TENG1 TMAT1 SENG1 SMAT1;

USEVARIABLES ARE

SDQ2N01 SDQ2N13 SDQ2N25 SDQ2N37 SDQ2N04 SDQ2N16 SDQ2N28 SDQ2N40
SDQ2N10 SDQ2N22 SDQ2N34 SDQ2N46 SDQ2N07 SDQ2N19 SDQ2N31 SDQ2N43;

ANALYSIS:

TYPE IS GENERAL;
ESTIMATOR IS ML;
ITERATIONS = 1000;
CONVERGENCE = 0.00005;

MODEL:

F1 by SDQ2N01-SDQ2N37;
F2 by SDQ2N04-SDQ2N40;
F3 by SDQ2N10-SDQ2N46;
F4 by SDQ2N07-SDQ2N43;

OUTPUT: SAMPSTAT MODINDICES STANDARDIZED TECH1;



Some comments and points of the analysis (p.64–)

Assessment of the model

- ▶ primary interest: the extent to which a model fits the data
- ▶ several criteria for a) model as a whole, b) parameter estimates

Model fitting

- ▶ Let Σ be the population covariance matrix, \mathbf{S} the sample covariance matrix and θ the vector of model parameters.
- ▶ Now, $\Sigma(\theta)$ is the restricted covariance matrix implied by the model (the specified structure).
- ▶ Null hypothesis $H_0 : \Sigma = \Sigma(\theta)$, i.e., the postulated model holds in the population
- ▶ We hope *not* to reject H_0 (cf. traditional procedures).

Statistical significance

- ▶ As always, merely a starting point, not a result as such!
- ▶ Practical significance is important (values of estimates, effect sizes, confidence intervals etc.)



Hypothesized four-factor CFA model (selected output)

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	265

Number of dependent variables	16
Number of independent variables	0
Number of continuous latent variables	4

Observed dependent variables

Continuous

SDQ2N01	SDQ2N13	SDQ2N25	SDQ2N37	SDQ2N04	SDQ2N16
SDQ2N28	SDQ2N40	SDQ2N10	SDQ2N22	SDQ2N34	SDQ2N46
SDQ2N07	SDQ2N19	SDQ2N31	SDQ2N43		

Continuous latent variables

F1	F2	F3	F4
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Estimator	ML
Information matrix	OBSERVED
Maximum number of iterations	1000
Convergence criterion	0.500D-04
Maximum number of steepest descent iterations	20



Hypothesized four-factor CFA model (selected output)

TESTS OF MODEL FIT

Chi-Square Test of Model Fit

Value	159.112
Degrees of Freedom	98
P-Value	0.0001

Chi-Square Test of Model Fit for the Baseline Model

Value	1703.155
Degrees of Freedom	120
P-Value	0.0000

CFI/TLI

CFI	0.961
TLI	0.953

Loglikelihood

H0 Value	-6562.678
H1 Value	-6483.122

Information Criteria

Number of Free Parameters	54
Akaike (AIC)	13233.356
Bayesian (BIC)	13426.661
Sample-Size Adjusted BIC	13255.453
$(n^* = (n + 2) / 24)$	

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.049	
90 Percent C.I.	0.034	0.062
Probability RMSEA \leq .05	0.556	

SRMR (Standardized Root Mean Square Residual)

Value	0.045
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Some comments and points of the analysis

Estimation process

- ▶ minimize the discrepancy (residual) between \mathbf{S} and $\Sigma(\theta)$

The goodness-of-fit statistics

Chi-Square Test of Model Fit

- ▶ traditional Likelihood Ratio Test statistic, expressed as a chi-square (χ^2) statistic
- ▶ p -value represents the likelihood of obtaining a χ^2 value that exceeds the χ^2 value when H_0 is true, so the higher the p , the closer the fit.
- ▶ always reported but rarely used as the sole index of model fit

Here, $\chi^2 = 159.112$, with 98 degrees of freedom (df) and a p -value of less than 0.0001 suggests that the fit of the data to the model is not adequate and H_0 should be rejected. However, χ^2 is quite sensitive to sample size (it is based on large sample theory) and

- nonnormal data. It is still important in model comparisons.



Some comments and points of the analysis



Chi-Square Test of Model Fit for the Baseline Model

- ▶ Usually the so called "null model", but in Mplus a slight difference: in addition to the variances, also the means of the observed items are included (although they may not be relevant in the model).
- ▶ In any baseline case, the observed items are assumed uncorrelated (no structure). The point: χ^2 value of the H_0 is much less than the value for the baseline, that is, the model is superior to the unstructured baseline model. (But this is not a remarkable or surprising result, it is just a good start.)

Some comments and points of the analysis (p.69–)

Alternative (subjective) indices of fit: more pragmatic approach, e.g. Comparative Fit Index (CFI), Tucker–Lewis Fit Index (TLI), Akaike's Information Criterion (AIC), Bayes Information Criterion (BIC). First two represent the most typical incremental indices measuring the proportionate improvement in fit with *nested* models. The latter two are predictive or parsimony-corrected criteria for *non-nested* models.

A careful consideration of these is essential when fitting models. Use of multiple indices highly recommended. Here, only four, perhaps the most typical ones. **Warning:** model may fit well, and still be incorrectly specified! These are merely giving information on the model's lack of fit. Researcher must know if the model is plausible or not.

Therefore the assessment of model adequacy must be based on multiple criteria that take into account a) theoretical, b)

- statistical, and c) practical considerations!

Some comments and points of the analysis

- ▶ CFI:
 - ▶ compares the hypothesized (H) and the baseline model (B):
 - ▶ $CFI = 1 - [(\chi_H^2 - df_H) / (\chi_B^2 - df_B)]$
 - ▶ range: $[0, 1]$, well-fitting models have $CFI > 0.95$
- ▶ TLI:
 - ▶ quite similar as CFI, but nonnormed (may extend $[0, 1]$):
 - ▶ $TLI = [(\chi_B^2 / df_B) - (\chi_H^2 / df_H)] / [(\chi_B^2 / df_B) - 1]$
 - ▶ includes a penalty function for overly complex models (H)
 - ▶ well-fitting models have TLI close to 1

The Loglikelihood values (H_0 for H, H_1 for B) are used in computation of information criteria AIC and BIC. AIC is the more commonly used one in SEM (they are quite similar):

$$AIC = -2(\text{loglikelihood}) + 2a,$$

where loglikelihood refers to the H_0 value and a is the number of estimated parameters (again including observed item intercepts in Mplus). Smaller value indicates a good fit when comparing across

- different models or samples.



Some comments and points of the analysis (p.72–)

The last two fit indices are RMSEA and SRMR, both absolute ones, sometimes termed "absolute misfit indices". They do not compare models, but depend only on determining how well the model fits the data. Therefore these decrease as the fit improves. Values of RMSEA less than 0.05 indicate good fit, 0.08 to 0.10 mediocre/reasonable fit, and greater than 0.10 poor fit.

RMSEA is sensitive to the number of estimated parameters (model complexity). Routine use of RMSEA is strongly recommended in literature. Here: 0.049 (with a 90 % C.I. [0.034, 0.062]), indicating a good precision.

SRMR represents the average residual value of the fit (standardized, i.e., range [0, 1]). In well-fitting models, it will be small, less than 0.05. Here: 0.045, that is, model explains the correlations to within an average error of 0.045.

■ RMSEA: Root Mean Square Error Of Approximation

■ SRMR: Standardized Root Mean Square Residual



Some comments and points of the analysis (p.77–)



Assessment of parameter estimates

1) appropriateness, 2) statistical significance

- ▶ Parameter estimates should exhibit the correct sign and size, and be consistent with the underlying theory.
- ▶ Any estimates falling outside the admissible range indicate that a) model is wrong or b) input matrix lacks sufficient information.
- ▶ Standard errors of parameters should not be excessively large or small.
- ▶ Assuming that the sample size is adequate, nonsignificant parameters (except the error variances) should be deleted from the model.

Hypothesized four-factor CFA model (selected output)

MODEL RESULTS

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
(factor loadings)					
F1	BY				
	SDQ2N01	fixed: 1.000	0.000	999.000	999.000
	SDQ2N13	1.083	0.156	6.939	0.000
	SDQ2N25	0.851	0.125	6.806	0.000
	SDQ2N37	0.934	0.141	6.607	0.000
F2	BY				
	SDQ2N04	1.000	0.000	999.000	999.000
	SDQ2N16	1.279	0.151	8.489	0.000
	SDQ2N28	1.247	0.155	8.022	0.000
	SDQ2N40	1.259	0.159	7.913	0.000
F3	BY				
	SDQ2N10	1.000	0.000	999.000	999.000
	SDQ2N22	0.889	0.104	8.561	0.000
	SDQ2N34	0.670	0.148	4.541	0.000
	SDQ2N46	0.843	0.118	7.160	0.000
F4	BY				
	SDQ2N07	1.000	0.000	999.000	999.000
	SDQ2N19	0.841	0.058	14.447	0.000
	SDQ2N31	0.952	0.048	19.905	0.000
	SDQ2N43	0.655	0.050	13.182	0.000
(factor covariances)					
F2	WITH				
F1		0.415	0.078	5.325	0.000
F3	WITH				
F1		0.355	0.072	4.928	0.000
F2		0.464	0.080	5.825	0.000
F4	WITH				
F1		0.635	0.117	5.437	0.000
F2		0.873	0.134	6.507	0.000
F3		0.331	0.100	3.309	0.001



Hypothesized four-factor CFA model (selected output)

Intercepts				
SDQ2N01	4.408	0.083	53.312	0.000
SDQ2N13	5.004	0.083	60.087	0.000
SDQ2N25	5.098	0.075	67.766	0.000
SDQ2N37	4.826	0.070	68.758	0.000
SDQ2N04	4.521	0.086	52.630	0.000
SDQ2N16	4.649	0.076	61.116	0.000
SDQ2N28	4.691	0.082	57.419	0.000
SDQ2N40	4.977	0.083	59.717	0.000
SDQ2N10	4.623	0.071	65.454	0.000
SDQ2N22	5.377	0.067	80.384	0.000
SDQ2N34	3.891	0.104	37.256	0.000
SDQ2N46	5.268	0.080	66.253	0.000
SDQ2N07	4.321	0.109	39.560	0.000
SDQ2N19	4.543	0.104	43.738	0.000
SDQ2N31	4.740	0.096	49.225	0.000
SDQ2N43	4.977	0.086	57.961	0.000

Variances				
F1	0.613	0.141	4.342	0.000
F2	0.561	0.126	4.449	0.000
F3	0.668	0.116	5.744	0.000
F4	2.307	0.272	8.483	0.000

Residual Variances				
SDQ2N01	1.198	0.130	9.228	0.000
SDQ2N13	1.119	0.124	9.000	0.000
SDQ2N25	1.056	0.109	9.675	0.000
SDQ2N37	0.771	0.089	8.621	0.000
SDQ2N04	1.394	0.128	10.890	0.000
SDQ2N16	0.616	0.070	8.856	0.000
SDQ2N28	0.896	0.092	9.739	0.000
SDQ2N40	0.952	0.095	10.061	0.000
SDQ2N10	0.653	0.082	7.926	0.000
SDQ2N22	0.657	0.076	8.703	0.000
SDQ2N34	2.590	0.233	11.093	0.000
SDQ2N46	1.201	0.118	10.164	0.000
SDQ2N07	0.854	0.098	8.729	0.000
SDQ2N19	1.228	0.125	9.808	0.000
SDQ2N31	0.365	0.065	5.581	0.000
SDQ2N43	0.964	0.093	10.410	0.000



Some comments and points of the analysis (p.81–)

Standardized estimates

Mplus offers three types of standardization: STDYX, STDY and STD. These correspond to various ways of conceptualizing standardization (there is no one right choice!). In this respect, SEM programs vary. Hence: check, compare and verify that particular parameter values are consistent with the literature, if you want to replicate some known results! (Here, I follow Byrne and consider only the STDYX option).

Two aspects of standardized values (compared with the unstandardized solution):

- ▶ parameters reported earlier as 1.0 have now new values
- ▶ factor variances are now reported as 1.0 (no matter which STD option is used)



Hypothesized four-factor CFA model (selected output)

STANDARDIZED MODEL RESULTS - STDYX Standardization

		Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
F1	BY				
	SDQ2N01	0.582	0.055	10.613	0.000
	SDQ2N13	0.626	0.050	12.426	0.000
	SDQ2N25	0.544	0.056	9.644	0.000
	SDQ2N37	0.640	0.051	12.608	0.000
F2	BY				
	SDQ2N04	0.536	0.048	11.143	0.000
	SDQ2N16	0.774	0.031	24.983	0.000
	SDQ2N28	0.703	0.037	19.071	0.000
	SDQ2N40	0.695	0.036	19.043	0.000
F3	BY				
	SDQ2N10	0.711	0.044	16.167	0.000
	SDQ2N22	0.668	0.046	14.447	0.000
	SDQ2N34	0.322	0.064	5.002	0.000
	SDQ2N46	0.532	0.054	9.873	0.000
F4	BY				
	SDQ2N07	0.854	0.020	41.953	0.000
	SDQ2N19	0.755	0.030	24.825	0.000
	SDQ2N31	0.923	0.016	59.292	0.000
	SDQ2N43	0.712	0.033	21.287	0.000
F2	WITH				
F1		0.707	0.057	12.421	0.000
F3	WITH				
F1		0.555	0.072	7.733	0.000
F2		0.758	0.052	14.652	0.000
F4	WITH				
F1		0.534	0.061	8.756	0.000
F2		0.767	0.038	20.291	0.000
F3		0.266	0.073	3.652	0.000



Hypothesized four-factor CFA model (selected output)

Intercepts				
SDQ2N01	3.275	0.155	21.135	0.000
SDQ2N13	3.691	0.172	21.498	0.000
SDQ2N25	4.163	0.191	21.798	0.000
SDQ2N37	4.224	0.193	21.831	0.000
SDQ2N04	3.233	0.153	21.092	0.000
SDQ2N16	3.754	0.174	21.544	0.000
SDQ2N28	3.527	0.165	21.368	0.000
SDQ2N40	3.668	0.171	21.481	0.000
SDQ2N10	4.021	0.185	21.718	0.000
SDQ2N22	4.938	0.223	22.132	0.000
SDQ2N34	2.289	0.117	19.584	0.000
SDQ2N46	4.070	0.187	21.746	0.000
SDQ2N07	2.430	0.122	19.898	0.000
SDQ2N19	2.687	0.132	20.372	0.000
SDQ2N31	3.024	0.145	20.854	0.000
SDQ2N43	3.561	0.166	21.396	0.000

Variances				
F1	fixed:	1.000	0.000	999.000
F2		1.000	0.000	999.000
F3		1.000	0.000	999.000
F4		1.000	0.000	999.000

Residual Variances				
SDQ2N01	0.661	0.064	10.366	0.000
SDQ2N13	0.609	0.063	9.665	0.000
SDQ2N25	0.704	0.061	11.467	0.000
SDQ2N37	0.591	0.065	9.096	0.000
SDQ2N04	0.713	0.051	13.847	0.000
SDQ2N16	0.402	0.048	8.381	0.000
SDQ2N28	0.506	0.052	9.784	0.000
SDQ2N40	0.517	0.051	10.195	0.000
SDQ2N10	0.494	0.063	7.905	0.000
SDQ2N22	0.554	0.062	8.987	0.000
SDQ2N34	0.896	0.042	21.583	0.000
SDQ2N46	0.717	0.057	12.493	0.000
SDQ2N07	0.270	0.035	7.763	0.000
SDQ2N19	0.429	0.046	9.341	0.000
SDQ2N31	0.148	0.029	5.170	0.000
SDQ2N43	0.493	0.048	10.351	0.000



Some comments and points of the analysis (p.82–)

R^2 values

When standardized estimates are requested, R^2 values for the dependent variables are reported.

- ▶ R^2 is the proportion of variance accounted for by its related factor (*communality* in factor analytic terms).
- ▶ SDQ2N34 is the weakest indicator ($R^2 = 1 - 0.896 = 0.104$).

R-SQUARE				
Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
SDQ2N01	0.339	0.064	5.307	0.000
SDQ2N13	0.391	0.063	6.213	0.000
SDQ2N25	0.296	0.061	4.822	0.000
SDQ2N37	0.409	0.065	6.304	0.000
SDQ2N04	0.287	0.051	5.572	0.000
SDQ2N16	0.598	0.048	12.492	0.000
SDQ2N28	0.494	0.052	9.535	0.000
SDQ2N40	0.483	0.051	9.522	0.000
SDQ2N10	0.506	0.063	8.083	0.000
SDQ2N22	0.446	0.062	7.224	0.000
SDQ2N34	0.104	0.042	2.501	0.012
SDQ2N46	0.283	0.057	4.936	0.000
SDQ2N07	0.730	0.035	20.976	0.000
SDQ2N19	0.571	0.046	12.412	0.000
SDQ2N31	0.852	0.029	29.646	0.000
SDQ2N43	0.507	0.048	10.643	0.000



Some comments and points of the analysis (p.82–)

Model misspecification and Modification Indices (MI)

The function of MIs is to identify badly chosen parameter constraints (e.g. those fixed to a value of 0.00).

MIs are used to help answering to these questions:

- ▶ "What if a parameter would be freely estimated?"
- ▶ "How much would χ^2 value of the model decrease?"
- ▶ "Would the drop be significant?"
- ▶ "Would it lead to a better fitting model?"

A clue is given by the corresponding EPC (Expected Parameter Change) values. Again substantive knowledge and reasoning is required.

By default, Mplus reports only those parameters having $MI \geq 10$.



Some comments and points of the analysis (p.87–)

Here, we have four suggestions: one factor loading and three *residual* covariances (note: observed variables in CFA are always dependent variables; their (co)variances are not eligible for estimation).

MODEL MODIFICATION INDICES			M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
BY Statements						
F2	BY	SDQ2N07	11.251	-0.563	-0.422	-0.237
WITH Statements						
SDQ2N25	WITH	SDQ2N01	17.054	0.359	0.359	0.319
SDQ2N31	WITH	SDQ2N07	10.696	0.305	0.305	0.546
SDQ2N31	WITH	SDQ2N19	17.819	-0.331	-0.331	-0.495

The factor loading (F2 BY SDQ2N07) represents a **cross-loading** that could be added. The problem is that from a substantive perspective, the EPC value has a wrong sign! (The relation should be positive, not negative.) Thus it would be questionable to free this parameter for estimation, no matter the MI and EPC.



Some comments and points of the analysis (p.87–)

Overall: the residual covariances seem to be rather small and not worthy of inclusion in a subsequently specified model. Remember the topic of scientific parsimony: avoid too many parameters and hence too complex models! **First of all: model must be substantively meaningful.**

In general, model respecification is commonly conducted in SEM. (We will get back to this issue many times!) However, it is important to realize that when we move to so called *Post Hoc* analyses, they will then be framed within *exploratory*, not anymore confirmatory modeling approach! Post hoc model fitting is also called *specification searches* (detection of misfitting parameters in the originally hypothesized model). Combination of 1) substantive and 2) statistical aspects is required (always in this order!).

"When to stop fitting a model?" – a good question...

