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The Factor Structure of ADHD – Different Models, Analyses and Informants in a Bifactor Framework

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Abstract The methodological approach of exploratory structural equation modelling (ESEM) has only been applied once to the construct of Attention-deficit/hyperactivity disorder (ADHD). We decided to compare bifactor models based on confirmatory factor analyses (Bi-CFA) and exploratory equation modeling (Bi-ESEM) only, as there is a growing support of a bifactor structure of ADHD. To examine the factorial validity of the construct we compared three possible bifactor models. One model with two specific factors (inattention and hyperactivity/impulsivity), another model with three specific factors (inattention, hyperactivity and impulsivity) and an alternative, incomplete model with one general ADHD and two specific factors (inattention and impulsivity). We used parent- (N = 1386; Age: M = 11.70, SD = 3.18; Sex: 74.5 % male) and teacher-ratings (N = 110; Age: M = 11.27, SD = 3.04; Sex: 77.5 % male) from clinically referred children between the age of 6 and 18. The results indicate that both methods lead to equally good model fit and for both informants the reliable variance of the specific factor hyperactivity is almost completely explained by the general factor. However, in the teacher condition cross-loadings seem to be of particular importance. Across both methods and informants covariation among ADHD symptom items can be in most part attributed to a general ADHD factor as well as to three (inattention, hyperactivity and impulsivity) or two (inattention and impulsivity) weakly defined specific factors. Further research regarding associations between the specific factors of ADHD and other disorders (e.g. conduct disorder) should be conducted.

Keywords Parent-report · Teacher-report · Bifactor factor analysis · ADHD · Symptom dimensions · Exploratory equation modelling

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Introduction

Depending on the diagnostic classification system, attention-deficit/hyperactivity disorder (ADHD) consists of two (according to the Diagnostic and Statistical Manual of Mental Disorders 5th ed., DSM-5; American Psychiatric Association 2013) separable dimensions (inattention - IN and hyperactivity/impulsivity - HY/IM) or three (according to the International Classification of Diseases and Related Health Problems, ICD-10; World Health Organization 2004) separable dimensions (IN, hyperactivity - HY and impulsivity - IM). Furthermore, both classification systems categorize ADHD by adding up symptoms within the dimensions, indicating that there is more communality within the separable dimensions (IN, HY, IM or HY/IM) than in the general construct (ADHD).

The traditional approach to examine the factor structure of a construct such as ADHD is to conduct confirmatory factor analyses (CFA) with correlated factor models. With this method it is possible to test an a priori defined structure such as those described by DSM-5 and ICD-10. Most studies using CFAs with correlated factor models have favored the DSM-5 model due to small differences in model fit and its greater parsimony

(Willcutt et al. 2012). However, in recent studies bifactor models have been used to shed new light on the factor structure of ADHD. Bifactor models are applied within a CFA framework and examine the presence of a general factor (g-factor) and further test, if meaningful specific factors coexist alongside the g-factor (Reise 2012; Chen et al. 2012; Chen et al. 2006). In a bifactor model the general factor is associated with all items whereas the specific factors (IN, HY/IM or IN, HY and IM) are only linked to their respective items. All factors are uncorrelated, which implies that the specific factors explain further variance over and above the general factor. Thus, in ADHD bifactor models we examine whether two (IN and HY/IM) or three specific dimensions (IN, HY and IM) can be identified that exist over and above the general ADHD factor. Almost all studies examining ADHD with bifactor models concluded that they displayed better model fit than CFA models with correlated factors and that a bifactor model with two specific factors (IN and HY/IM) represents the most adequate model (see Table 1 in Arias et al. 2016). Furthermore, the results indicated that the general factor contains much more reliable variance than the specific factors which shows the importance of the general factor, meaning the communality of all items compared to those captured by the subscales. However, almost all of those previously mentioned studies delivered results in which at least one of the specific factors was improperly defined, meaning that at least one specific factor displayed negative, and or nonsignificant item loadings. Negative or nonsignificant item loadings on a specific factor imply that the items do not have a meaningful or even a counter-intuitive association with their respective factor, and therefore these items do not belong to the defined construct. This problem mostly concerned items from the HY dimension (Caci et al. 2013; Morin et al. 2013; Toplak et al. 2009; Toplak et al. 2012; Ullebø et al. 2012; Rodenacker et al. 2016). These results may indicate, that hyperactivity should only be regarded as part of a general ADHD dimension and there may not be a strong empirical foundation for a specific hyperactivity factor beyond this general ADHD spectrum. Therefore, in two recent studies an alternative model without a specific HY factor was proposed (Ullebø et al. 2012; Rodenacker et al. 2016). In both studies the HY items displayed negative or nonsignificant loadings and/or convergence problems which appeared presumably due to a lack of variance of the specific HY factor. These findings were the reason to omit the HY factor from the model. This alternative, incomplete bifactor model (Bi-CFA-Inc) with one general ADHD factor and only two specific factors (IN and IM) showed equally well model fit compared to bifactor models with two specific factors (IN and HY/IM) and three specific factors (IN, HY and IM), however, it was more parsimonious and displayed a better structure of the item loadings (no negative or nonsignificant loadings).

Since the CFA approach has been criticized for its assumption of constraining cross-loadings to zero which may not represent a realistic proposition, exploratory structural equation modeling has been developed (Marsh et al. 2014; Morin et al. 2016). It combines the advantages of several approaches and appears to be the most advanced method to explore different sources of construct-relevant multidimensionality. In bifactor exploratory structural equation models (Bi-ESEM) the multidimensionality in terms of the existence of a g-factor is assessed (advantage of Bi-CFA models), a priori model specifications are considered (advantage of CFA models) and the fallible nature of indicators, meaning cross-loadings are allowed (advantage of EFA models; Marsh et al. 2014; Morin et al. 2013, 2016). ADHD is in particular predestined to be assessed with Bi-ESEM models as it is defined as a multidimensional construct and therefore certain items most probably also assess adjacent constructs. However, since the empirical evidence is greatly in favor of Bi-CFA models compared to CFA models with correlated factors we compared Bi-CFA models to Bi-ESEM models only. So far, we are aware of only one study which used this new

Table 1 Sample sizes, means and standard deviations (SDs; in parentheses)

	FBB-parent	FBB-teacher
Total sample N	1386	1100
Gender - %Male	74.5	77.5
Age - Mean (SD)	11.70 (3.18)	11.27 (3.04)
ADHD – Mean (SD)	1.36 (0.67)	1.17 (0.71)
IN	1.60 (0.74)	1.42 (0.78)
HY	0.99 (0.80)	0.80 (0.86)
IM	1.30 (0.90)	1.07 (0.98)
HY/IM	1.13 (0.77)	0.92 (0.84)
With ADHD N	838	721
Gender - %Male	85.1	86.0
Age - Mean (SD)	10.69 (2.76)	10.50 (2.70)
ADHD – Mean (SD)	1.60 (0.59)	1.34 (0.69)
IN	1.81 (0.65)	1.58 (0.74)
HY	1.25 (0.78)	0.99 (0.88)
IM	1.56 (0.85)	1.24 (0.98)
HY/IM	1.39 (0.72)	1.10 (0.85)
With other diagnoses N	548	379
Gender - %Male	58.2	61.5
Age - Mean (SD)	13.24 (3.17)	12.72 (3.11)
ADHD – Mean (SD)	1.01 (0.63)	0.85 (0.64)
IN	1.27 (0.75)	1.13 (0.79)
HY	0.60 (0.66)	0.45 (0.67)
IM	0.91 (0.82)	0.73 (0.87)
HY/IM	0.74 (0.67)	0.57 (0.70)

FBB-parent parent-report, *FBB-teacher* Teacher-report, *ADHD* Total scale, *IN* Inattention scale (DSM and ICD), *HY* Hyperactivity scale (ICD), *IM* Impulsivity scale (ICD), *HY/IM* Hyperactivity-Impulsivity scale (DSM) methodological approach with ADHD (Arias et al. 2016). The researchers found that in preschool children (4–6 years of age) a BI-ESEM model with three specific factors (IN, HY and IM) fit the data best. A model with three separate specific factors has been already reported by using conventional CFA bifactor models (Morin et al. 2013; Wagner et al. 2015; Gibbins et al. 2012). However, this was rather the exception.

We compared Bi-CFA to Bi-ESEM models with one general factor and either two (IN and HY/IM), three (IN, HY and IM) or two specific factors (IN and IM according to an alternative, incomplete bifactor model). All tested models are depicted in Fig. 1. The hypotheses were: 1) all conventional bifactor models with a specific HY or a specific HY/IM factor (Bi-CFA-2 and Bi-CFA-3) have shortcomings in terms of negative or non-significant loadings whereas the incomplete bifactor models are adequate (Bi-CFA-Inc.). 2) Bi-ESEM models (Bi-ESEM-2 and Bi-ESEM-3) display better model fit compared to Bi-CFA models as they also consider the fallible nature of the indicators.

In light of the existing literature on the factor structure of ADHD we want to stress two more points. First, since ADHD is meanwhile conceptualized as dimensional rather than a categorical in nature (e.g. Marcus and Barry 2011) patients fulfilling the diagnostic criteria of ADHD as well as patients with other diagnosis (e.g. Oppositional Defiant Disorder) but with elevated levels of ADHD symptoms were included in this study. And second, we want to emphasize that the current study is one of the very few studies in which the factor structure of ADHD was assessed with bifactor models in a large sample of clinically referred children and adolescents covering a large age range (6–18 years) and considering parent ratings as well as teacher ratings.

Methods

Measures

The German parent- and teacher-rating scale used to assess ADHD symptoms in children and adolescents is part of the Diagnostik-System für psychische Störungen nach ICD-10 und DSM-IV für Kinder und Jugendliche - II (DISYPS-II; Döpfner et al. 2008), which is a well-evaluated and commonly used questionnaire to aid clinicians in assessing ADHD. It is identical for parents and teacher and is here referred to as FBB-parent and FBB-teacher. For the parent-report previous exploratory factor analyses have indicated that a two factor structure (DSM-5) seems to be most adequate for the German items of FBB-ADHS and scale-score reliability coefficients (Cronbach's α) have indicated sufficiently high values for the respective subscales of the (range α = .78–.95; Döpfner et al. 2008).

The parent- and teacher-rated scales can be applied to children aged between 6 and 18 years. The questionnaire consists of 20 items that capture the 18 DSM-5 as well as the 18 ICD-10 criteria. Items are rated on a 4-point Likert scale ranging from 0 = not at all to 3 = very much. Depending on the diagnostic classification system the questionnaire consists of two (IN and HY/IMP in DSM-5) or three (IN, HY and IM in ICD-10) subscales as well as a total score scale.

For this study the item "talks excessively", which is part of the HY dimension in DSM-5, was added to the IM scale as indicated in ICD-10. However, for comparison with previous studies, we only included the 18 items that assess ADHD symptomology according to DSM-5 (items B14 "extreme internal restlessness" and B15 "permanently extremely restless" were excluded for the current analyses).

Samples and Procedure

We used a clinical sample which consisted of children who were referred to the child and adolescent psychotherapy outpatient unit of the Department of Child and Adolescent Psychiatry, Psychosomatics and Psychotherapy at the University Hospital of Cologne, Germany. Clinical diagnoses were based on semistructured clinical interviews of the parents and the patients. Diagnostic criteria were checked by using diagnostic checklists based on DSM IV and ICD-10 (Döpfner et al. 2008).

All participants of our study had to be diagnosed with at least one mental disorder. Further, we limited our sample to children between 6 and 18 years whose parents and/or teachers had completed the FBB-parent or FBB-teacher questionnaire. Our total sample consisted of 1424 children (Age: M = 11.73, SD = 3.19; Sex: 74.2 % male), of which 1386 parent-reports (Age: M = 11.70, SD = 3.18; Sex: 74.5 % male) and 1100 teacher-reports (Age: M = 11.27, SD = 3.04; Sex: 77.5 % male) had been completed. For 1062 children both forms were available and for 324 only the parent-report and 38 only the teacher-report had been completed. Out of the total sample (N = 1424) 53.2 % of the children had been diagnosed with a primary diagnosis of ADHD (F90 or F98.8) and 46.8 % had other diagnoses. Those included 21.6 % conduct disorders (F91 or F92), 4.8 % emotional and behavioral disorders (F93) and 6.6 % with anxiety disorders (F40). In total 60.4 % of our sample had been diagnosed with primary or secondary ADHD. Of those children 25.1 % had a F90.0 diagnosis which can be considered the combined type in DSM-IV, 30 % had been diagnosed with a F90.1 which is ADHD with ODD/CD and 5.3 % can be considered the inattentive type in DSM-IV (F90.8, F90.9 or F98.8). Further sample statistics regarding scale means and standard deviations are depicted in Table 1. 49 % of the questioned parents lived together and 48 % were separated. 20 % of the mothers worked full-time, 32 % part-time and 22 % stayed at home. For the fathers, 66 % worked full-time and for 13 % their occupation was unknown. 37 % of the parents reported a psychiatric disorder in the family.

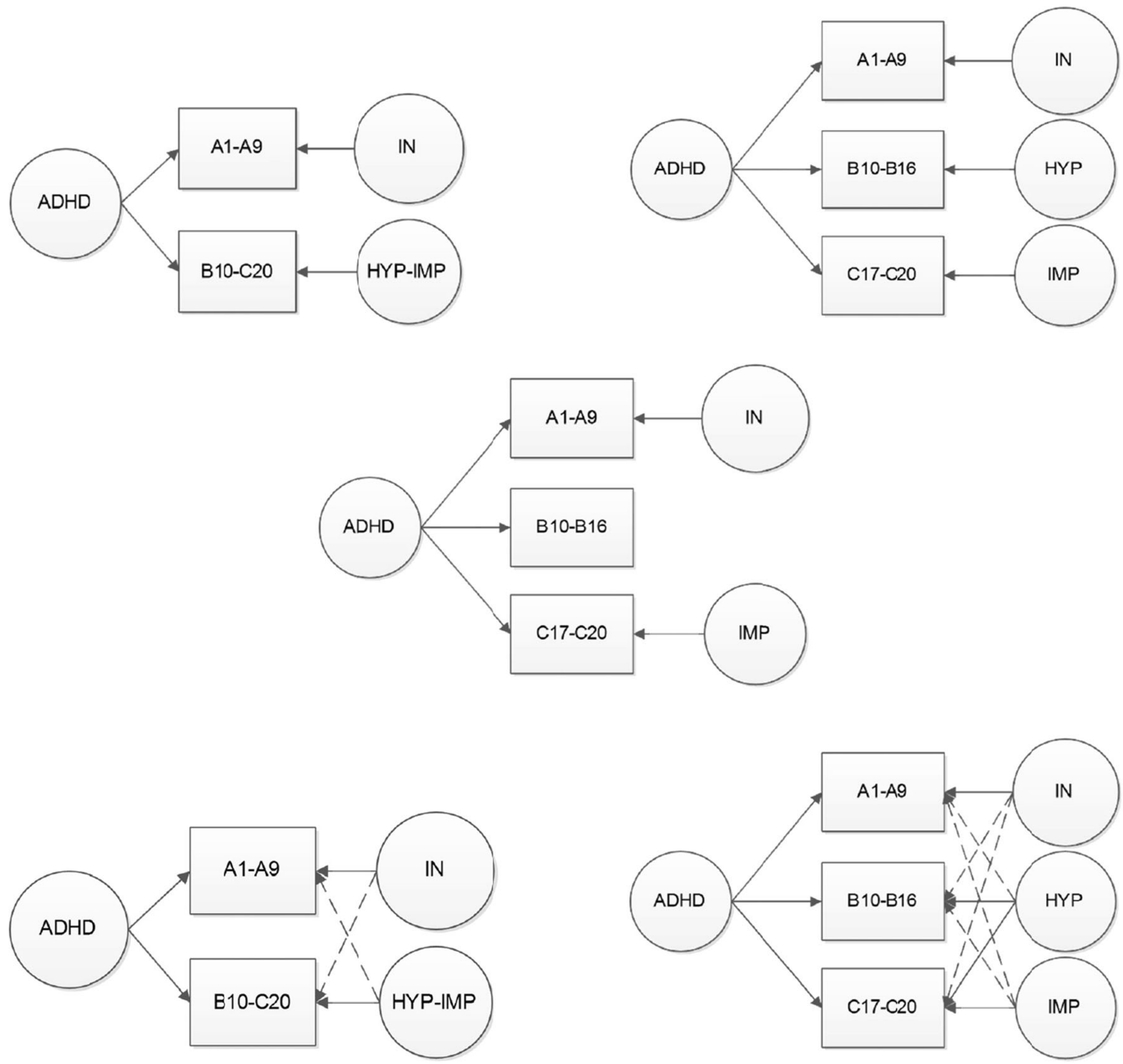

Fig. 1 Tested bifactor models. 1) Bi-CFA-2 (upper left), 2) Bi-CFA-3 (upper right), 3) Bi-CFA-Incomplete (central), Bi-ESEM-2 (lower left) and Bi-ESEM-3 (lower right); residual covariances between item 7 and 9 not shown; items B14 and B15 have been excluded from the analyses (see methods)

Statistical Analyses

All models were estimated with Mplus 7 (Muthén and Muthén 1998–2012). Due to the ordinal structure of our data (4-point Likert scale) we used the mean- and variance-adjusted weighted least squares estimator (WLSMV) and used the recommended default strategy (pairwise deletion) (Asparouhov and Muthén 2010) (FBB - parents =2.8–4.4 % missing and FBB - teachers =22.9–25.8 % missing). As χ^2 is sensitive to sample size, we predominantly relied on the Root Mean Square Error of Approximation (RMSEA) and the Comparative Fit Index (CFI) to assess model fit. Model fit is considered to be good when RMSEA values are equal or below .05 and the CFI at levels of .95 and higher, whereas adequate fit is achieved when RMSEA values are below .08, and CFI values above .90 (Hu and Bentler 1999).

We specified all Bi-CFA models according to a bifactor structure (one general and several orthogonal specific factors). The models consisted of two specific factors (Bi-CFA-2), three specific factors (Bi-CFA-3) or according to an incomplete bifactor model two specific factors (Bi-CFA-Inc). To set the metric we chose the variables B13 (Runs/Climbs) for the general factor (ADHD) and A4 (Does not Finish work) for the specific factor IN as indicator variables (item loading set to 1) in all tested models. Item C19 (Often interrupts) was chosen for the specific factor HY/IM in the Bi-CFA-2 model and for the IM factor in Bi-CFA-3 and the incomplete model as indicator variable. Regarding the HY factor of the Bi-CFA-3 model we chose item B13 (Runs/Climbs) as indicator variable. By choosing indicator variables, instead of fixing the variance of the factors to 1, we are able to estimate the factor variance. For the Bi-ESEM models (Marsh et al. 2014; Morin et al. 2016) the same bifactor structures were considered as described above. We used the orthogonal target rotation and allowed all loadings to be freely estimated with regard to the general factor. All cross-loadings of the specific factors were set to be close to zero, while all corresponding item loadings were freely estimated with regard to their respective scale.

For all models eminent areas of strain were investigated by modifications indices (MI; Brown 2006). We thereby followed the recommendations of Byrne (Byrne 2012). First, when considering MIs, they should have a substantive impact on model fit (indicated by $\Delta\chi^2$ DIFFTEST function Mplus) and must outstand the remaining MIs. Second, the areas of strain must be theoretically explainable and third, one must consider model parsimony, meaning researchers should not conduct more than 4 adjustments.

To compare model based composite reliability scores we computed Omega and OmegaH. Omega is defined by the variance accounted for by all (i.e., general and specific) factors that underlie a scale score, whereas OmegaH by the variance accounted for by a specific target construct (general or specific factor only; Zinbarg et al. 2005). It has been recommended that OmegaH values should at minimum be .50 but .75 would be preferred. For further details see the works by Reise and colleagues (Reise 2012; Reise et al. 2013).

Results

In preliminary examinations of eminent areas of strain one covariance was detected. In all Bi-CFA models we found very high residual covariances (MIs ≈ 200–600) between item A7 (loses things) and A9 (often forgetful) and by allowing the residuals of these items to covary model fit ($\Delta\chi^2$ DIFFTEST function) (Asparouhov and Muthén 2006) improved significantly ($p < .001$). For the parent-report the Bi-CFA-2 model improved by $\Delta\chi^2(1) = 261.901$, the Bi-CFA-3 by $\Delta\chi^2(1) = 259.936$ and the Bi-CFA-Inc. by $\Delta\chi^2(1) = 261.291$. For the teacher-report Bi-CFA-2 improved by $\Delta\chi^2(1) = 205.073$ and Bi-CFA-Inc. by $\Delta\chi^2(1) = 207.282$ (Bi-CFA-3 did not converge). For the Bi-ESEM models the picture was not as straight forward. In the parent condition the Bi-ESEM-2 improved by $\Delta\chi^2(1) = 168.341$ and for the Bi-ESEM-3 model fit only improved by $\Delta\chi^2(1) = 32.191$. In the teacher condition this was confirmed as the Bi-ESEM-2 model improved $\Delta\chi^2(1) = 145.892$, however, the Bi-ESEM-3 model did not ($\Delta\chi^2(1) = 1.041$, $p = .308$). This was a point of discussion but we decided to allow them to covary due to their similar content.

All models had in common that they demonstrated a well-defined general factor (OmegaH = .781–.796) and weakly defined specific factors (OmegaH = .012–.525; Table 2). Independently of the utilized method (CFA or ESEM) the models with one general and two specific factors (IN and HY/IM) always comprised an improperly defined HY/IM factor, showing negative or nonsignificant item loadings. Further, all models shared that mostly items of the IN dimension had weaker item loadings on the general and highest on the specific factor (Table 2) compared to the other dimensions. Consequently, in comparison to the specific factors the IN factors also displayed the highest composite reliability values (OmegaH = .498–.525).

Looking at the Bi-CFA models, model fit of all models did not differ considerably within both perspectives. The highest difference in RMSEA was between the FBB-parent Bi-CFA-2 model and the FBB-parent Bi-CFA-3 model (ΔRMSEA = .002). For the teacher-report the Bi-CFA-3 model showed no convergence and is therefore not included in Table 2. Analyzing the item loadings and factor variances several short-comings in the Bi-CFA-2 and −3 models are to be noted. In the Bi-CFA-2 (FBB-parent and FBB-teacher) model all hyperactivity items of the HY/IM dimension loading on the corresponding specific factor are nonsignificant. When this dimension is separated into two factors (FBB-parent Bi-CFA-3 model) the variance of the HY factor turns nonsignificant. This means that the specific factor does not contribute substantially to the model once the general factor has been taken into consideration. In contrast, the Bi-CFA-Inc. models displayed for both informants marginally worse model fit but no nonsignificant item loadings or factor variances.

Presuming that the Bi-ESEM models are most adequate for this construct as it allows cross-loadings and tests for a general factor we assumed that these models would present the best model fit. However, they did not improve model fit substantially and the results were partially contradicting across informants (Table 3).

First, the Bi-ESEM-2 model and the Bi-ESEM-Inc. model yielded in the exact same model fit and almost the same item loadings. Therefore we chose to report the results as Bi-ESEM-2 (two specific factors IN and HY/IM) and Bi-ESEM-3 (three specific factors IN, HY and IM) only. That both model specifications, either according to Bi-ESEM-2 or according to an incomplete Bi-ESEM model, yielded to the same solution is astonishing because it underlines the dissimilarity of the factors HY and IM. In the Bi-ESEM-2 model the structure of item loadings is to be interpreted as an improperly defined factor (due to negative or nonsignificant loadings of the HY items) whereas in the Bi-ESEM-Inc. model it would represent a theory confirm model specification as it is assumed that HY items do not covary significantly with a specific factor.

For both raters the Bi-ESEM-2 model did not point to the existence of a specific HY factor as all loadings are around zero although they were allowed to freely load on that factor. In the Bi-ESEM-3 models there appears to be some reliable variance accounted for by the specific HY factor which is indicated by significant item loadings. However, when taking OmegaH values of the specific HY factor into account the

Table 2 Bi-CFA models - Standardized item loadings FBB-parent and FBB-teacher

Nr.	Item	FBB-parent										FBB-teacher[a]					
		Bi-CFA-2			Bi-CFA-3				Bi-CFA-Inc.			Bi-CFA-2			Bi-CFA-Inc.		
		AD	IN	HY/IM	AD	IN	HY	IM	AD	IN	IM	AD	IN	HY/IM	AD	IN	IM
A1	Careless	.38	.65		.38	.65			.38	.65		.42	.60		.42	.60	
A2	Attention	.64	.51		.64	.50			.64	.50		.61	.62		.60	.62	
A3	Not listening	.59	.40		.60	.39			.60	.39		.49	.49		.49	.49	
A4	Finishing	.51	.70		.51	.70			.51	.70		.48	.76		.47	.76	
A5	Disorganized	.43	.62		.43	.61			.43	.61		.48	.71		.47	.71	
A6	Unmotivated	.52	.62		.52	.62			.52	.62		.53	.59		.52	.60	
A7	Loses things	.38	.50		.39	.49			.37	.49		.51	.46		.51	.47	
A8	Distracted	.69	.47		.69	.47			.69	.47		.76	.41		.75	.42	
A9	Forgetful	.41	.52		.41	.52			.41	.52		.40	.55		.40	.55	
B10	Fidgets	.83		-.11	.80		.22		.81			.85		**.03**	.85		
B11	Leaves seat	.82		**-.08**	.79		.34		.81			.94		**.02**	.94		
B12	Play quietly	.80		**.00**	.82		**-.08**		.81			.83		**.06**	.83		
B13	Runs/climbs	.85		**-.02**	.85		**.12**		.86			.95		**.00**	.94		
B16	Motor	.67		**.10**	.70		**-.13**		.69			.83		.13	.85		
C17	Blurts out	.65		.48	.64			.48	.64		.48	.71		.59	.74		.56
C18	Awaiting	.74		.48	.73			.50	.73		.50	.71		.64	.74		.61
C19	Interrupts	.77		.48	.76			.50	.76		.51	.78		.49	.80		.46
C20	Talks	.57		.50	.57			.51	.56		.51	.68		.46	.69		.44
	Variance[b]	.73	.50	.23	.72	.49	**.01**	.25	.74	.49	.26	.90	.58	.24	.89	.58	.21
	S.E.	.021	.025	.032	.024	.026	**.011**	.023	.020	.025	.023	.014	.029	.034	.014	.029	.020
	Omega	.958	.924	.942	.959	.924	.905	.905	.958	.924	.904	.971	.935	.970	.971	.935	.949
	OmegaH	.782	.505	.068	.781	.498	.012	.317	.782	.500	.320	.790	.515	.097	.796	.525	.312
	χ^2(df)[c]	499.51 (116)			477.35 (116)				505.78 (121)			495.57 (116)			457.26 (121)		
	RMSEA	.049			.047				.048			.055			.050		
	CFI	.987			.988				.987			.991			.992		

AD general ADHD factor; Nonsignificant ($p < .01$) loadings are printed in bold letters, *Omega* the proportion of total score variance that can be attributed to all common factors, *OmegaH* the proportion of total score variance that can be attributed to a single common factor, *RMSEA* Root Mean Square Error of Approximation, *CFI* Comparative Fit Index

[a] the FBB-teacher Bi-CFA-3 model did not converge

[b] Variance refers to the unstandardized factor variance and significance was $p < .01$; [c] All χ^2 estimates are significant p < .01

Table 3 Bi-ESEM - Standardized item loadings FBB-parent and FBB-teacher

Nr.	Item	FBB							FBB-teacher						
		Bi-ESEM-2			Bi-ESEM-3				Bi-ESEM-2			Bi-ESEM-3			
		AD	IN	HY/IM	AD	IN	HY	IM	AD	IN	HY/IM	AD	IN	HY	IM
A1	Careless	.38	.65	**.01**	.40	.64	**-.07**	**-.00**	.40	.62	**.05**	.46	.57	**-.11**	**-.02**
A2	Attention	.66	.49	-.09	.70	.44	-.09	-.01	.57	.65	.10	.72	.49	-.24	-.14
A3	Not listening	.60	.39	**.00**	.60	.38	**.06**	**.01**	.50	.48	**-.08**	.53	.44	**.03**	-.13
A4	Finishing	.51	.71	**.02**	.52	.69	**-.01**	**.00**	.47	.76	**-.04**	.57	.66	-.13	-.19
A5	Disorganized	.43	.61	**.00**	.43	.62	**.07**	**.00**	.50	.69	-.13	.50	.69	**.03**	-.09
A6	Unmotivated	.53	.62	**-.01**	.56	.58	-.15	**-.03**	.51	.61	**.04**	.56	.56	**-.06**	**-.02**
A7	Loses things	.38	.50	**.02**	.36	.53	.12	**.04**	.52	.46	**-.05**	.40	.64	.28	.18
A8	Distracted	.69	.47	**.03**	.71	.44	**-.05**	**.00**	.72	.45	.14	.76	.39	**-.01**	**.06**
A9	Forgetful	.39	.54	.07	.37	.57	.15	.09	.42	.53	-.12	.32	.69	.25	.10
B10	Fidgets	.83	**-.01**	**-.08**	.81	**-.01**	.19	-.08	.83	.09	**.03**	.80	.08	.24	**.03**
B11	Leaves seat	.82	**-.01**	**-.05**	.82	**-.02**	**.11**	-.07	.94	**-.01**	**-.04**	.87	**.01**	.36	**-.01**
B12	Play quietly	.78	**.06**	**.06**	.75	.07	.24	.06	.81	.07	**.03**	.75	.10	.29	.09
B13	Runs/climbs	.87	-.07	**.03**	.83	**-.05**	.29	**.04**	.97	**-.05**	-.10	.86	**.00**	.44	**-.01**
B16	Motor	.66	**.00**	.14	.59	**.06**	.41	.18	.83	**.03**	**.07**	.76	.07	.32	.15
C17	Blurts out	.61	.06	.54	.59	.08	.16	.57	.77	-.08	.52	.77	-.09	.08	.51
C18	Awaiting	.72	**.00**	.50	.76	**-.04**	**-.06**	.45	.77	-.08	.57	.78	-.11	**.04**	.53
C19	Interrupts	.75	**.02**	.51	.79	**-.03**	**-.06**	.46	.80	**.02**	.46	.83	-.04	**.02**	.40
C20	Talks	.57	**-.03**	.51	.56	**-.03**	.09	.50	.69	**.02**	.44	.73	**-.03**	**-.00**	.38
	Omega	.958[a]	.924[a]	.942[a]	.959	.925	.902	.908	.971[a]	.934[a]	.969[a]	.971	.938	.942	.947
	OmegaH	.776[a]	.501[a]	.090[a]	.775	.487	.086	.319	.797[a]	.527[a]	.064[a]	.793	.498	.134	.243
	χ^2(df)[b]	537.14 (101)			388.13 (86)				372.14 (101)			265.29 (86)			
	RMSEA	.056			.050				.049			.044			
	CFI	.986			.990				.993			.996			

AD general ADHD factor; Non significant (p < .01) loadings are printed in bold letters, *Omega* the proportion of total score variance that can be attributed to all common factors, *OmegaH* the proportion of total score variance that can be attributed to a single common factor, *RMSEA* Root Mean Square Error of Approximation, *CFI* Comparative Fit Index

[a] OmegaH was estimated according to two DSM-5 conform specific factors (IN and HY/IM)

[b] All χ^2 estimates are significant $p < .01$

impact appears neglectable. It is impressive that no high cross-loadings (< .20) could be observed meaning the items show very little overlap between the different constructs after the g-factor has been taken into consideration.

Comparing the results of both methods (CFA and ESEM) model fit were mostly comparable. More precisely, model fit slightly worsened with regard to RMSEA in the parent-report and slightly improved in the teacher-report across all models. On the other hand CFI stayed almost equal under all conditions (methods, models and informants). Generally, comparable fit indices between both methods and no meaningful cross-loadings in the ESEM models would argue for the more parsimonious Bi-CFA models and therein for the Bi-CFA-Inc. model which displays the most comprehensible structure of item loadings. However, the solutions of both methods showed very good model fit, ESEM assumption are more realistic and in the teacher condition the cross-loadings appeared to be essential in order to estimate the model (no convergence for the Bi-CFA-3 model in the teacher condition).

Discussion

We tested several models of ADHD within a bifactor framework with two types of analyses (CFA vs. ESEM) and two informants (parents and teachers). We pursued the goal to compare the general model fit of several ADHD models and furthermore, we tried to find out if one or more dimensions remain weakly or improperly defined.

All previous studies which incorporated bifactor models have argued in favor of a bifactor structure of ADHD (Caci et al. 2013; Gibbins et al. 2012; Morin et al. 2013; Normand et al. 2012; Toplak et al. 2009; Toplak et al. 2012; Ullebø et al. 2012; Rodenacker et al. 2016). Further, they have indicated that the general factor contains much higher item loadings (and therein higher composite reliability scores) compared to the specific factors. Therefore, ADHD appears to be rather unidimensional with a strong general and weakly defined and, more importantly, unrelated specific factors. Nevertheless, the question remains, which model is most suitable therein also statistically sound and if they include improperly defined factors, is there an alternative model which represents ADHD equally well or better?

Two recent studies (Ullebø et al. 2012; Rodenacker et al. 2016) have proposed such an alternative model. It consists of one general factor and two specific factors (IN and IM) and was also under examination in this study. Further, we wanted to add a more advanced types of analyses (Bi-ESEM; Marsh et al. 2014; Morin et al. 2016) to the picture. Bi-ESEM models combine the advantages of several approaches, those of CFAs (a priori specification of a model), of EFAs (fallibility of the items/allowing cross-loadings) and bifactor models (the consideration of a general factor and specific uncorrelated factors). Therein we wanted to examine if this advanced approach would confirm the proposed incomplete bifactor model or if models with two (IN and HY/IM) or three (IN, HY and IM) specific factors would fit better.

In our results all models across both types of analyses and informants had a strong general factor and weakly defined specific factors in common which is consistent with previous studies (Caci et al. 2013; Gibbins et al. 2012; Normand et al. 2012; Toplak et al. 2009; Toplak et al. 2012; Rodenacker et al. 2016). Looking at the CFA results only, we would conclude, that the HY items do not contain meaningful amount of specific variance above the variance shared with all items (the general factor). The incomplete model incorporates this idea by omitting the specific factor from the model. This model showed comparable fit indices to the Bi-CFA-2 and Bi-CFA-3 models and was more parsimonious and displayed a more statistically sound structure of item loadings.

Assessing Bi-ESEM models with regard to ADHD for the first time, we presumed that model fit would improve. However, allowing cross-loadings did not improve model fit in all perspectives. Nevertheless, the results of this more advanced method also hint into a similar direction than the results of the Bi-CFA models. First, OmegaH values of the g-factor do not change in a meaningful manner which confirms the identified strong g-factor. Second, although there are no eminent cross-loadings to be observed (< .20) it becomes clear, that the allowance of cross-loadings is of particular importance to estimate the model, at least in the teacher condition (Bi-ESEM-3). This may be a result of the fixation of the cross-loadings to zero which may inflate the item loadings on the general factor in Bi-CFA models (Morin et al. 2016). And third, although cross-loadings may be important for specification purposes the results clearly state that the dimensions HY and IM are separable dimensions (indicated by negative loadings of the HY items in the Bi-ESEM-2 model and better model fit of the Bi-ESEM-3 models) and the specific variance attributed to both factors does not appear to be meaningful (OmegaH < .50). The differences in the amount of reliable variance accounted for the specific IN and IM factors must also be seen in relation the number of items each factor consists of. An equal number of items would facilitate this comparison.

Conclusions and Future Directions

Due to the inconsistency of the subtypes over time DSM-5 is now using the term representations instead of subtypes, as representations may change over time (Lahey et al. 2005; Willcutt et al. 2012). However, this change over time may also be interpreted as a shift of symptomatology within the general factor, which is different from the specific factors, as they are uncorrelated and, therefore, should represent distinct constructs. Therefore we agree with DSM-5 and other researchers

(Caci et al. 2013) to refrain from diagnosing subtypes. This assumption is in line with our conclusion that a bifactor model is not equal to DSM-5 which rather represents a higher order or correlated factor model.

Further, the OmegaH values clearly indicate that there is a strong general factor and several weak specific factors, presumably there is only one reliable specific factor (IN). Clinicians should therefore use total scale scores to assess ADHD instead of adding up symptoms within the separate dimensions. First, simply adding up items does not help to distinguish variance of the general factor from variance of the specific factors. Second, the impact of the specific factors appears to be neglectable and therefore it would not be useful to build subscale scores either.

However, to test whether the specific factors are still useful dimensions, OmegaH is definitely not an exclusive criterion. External criteria appear to be much more valid for answering this question. Therefore, future studies, such as those conducted by Burns and colleagues (Lee et al. 2015; Burns et al. 2014) should test whether well-known associations between the specific factors and external criteria (e.g. between academic impairment and IN; Willcutt et al. 2012) prevail in a bifactor specification of ADHD.

For scientists researching on ADHD and related disorders it may be interesting to look at associations between constructs (Beauchaine 2015). In Bi-ESEM models which incorporate items of related constructs, e.g. ADHD and oppositional defiant disorder (ODD) / conduct disorder (CD) or sluggish cognitive tempo (SCT) the meaning of specific factors may be of more importance (Burns et al. 2014; Lee et al. 2015; Garner et al. 2014). Overall, it is important to keep in mind what bifactor models implicate. In bifactor models all factors are orthogonal and should therefore be interpreted as separate constructs. This means that e.g. the inattention captured by the general factor (ADHD) is something else than the inattention captured by the specific IN factor.

In recent bifactor studies, ADHD and SCT were examined within one model (Garner et al. 2014; Lee et al. 2015). SCT refers to attentional symptoms such as daydreaming, hypoactivity, and staring/fogginess which are not captured by ADHD criteria (Becker et al. 2016). The results of both studies supported the idea of separable constructs (non-orthogonal bifactor model fitted best) but also showed high correlations between SCT and the specific IN factor. However, in Lee et al. (2015) a model with a combined general ADHD/SCT and two specific factors, SCT/IN and HY/IM showed equal model fit compared to the preferred model with correlations between the g-factor and SCT as well as IN and SCT (non-orthogonal bifactor). Since both models appear to represent the constructs in an adequate manner, we recommend further research and theoretical discussion regarding the general and the specific IN and SCT factors in a bifactor framework. For ADHD and ODD/CD Burns et al. (2014) and Lee et al. (2015) were able to show that variance in the ODD items is partly explained by a general factor (named disruptive behavior) but also by a distinct ODD dimension over and above the general factor. All three studies show that bifactor modelling can aid in answering different questions with regard to related constructs.

Limitations

There are certain limitations to be considered. First, the results only apply to the German translation of the diagnostic criteria of ADHD. Nevertheless, many studies with Bi-CFA models from other cultures indicate similar results with regard to improperly defined factors in bifactor models with two specific factors – IN and HY/IM (Caci et al. 2013; Toplak et al. 2009; Toplak et al. 2012; Ullebø et al. 2012).

Second, the sample consisted of clinical referred children between 6 and 18 years only and 60 % of them had been diagnosed with ADHD. The other 40 % of the sample was assessed with the questionnaires (FBB-parents and FBB-teachers) because the semistructured interview indicated elevated ADHD symptoms. To capture the whole range of the spectrum of ADHD we also included children with a subclinical level of ADHD and a different primary diagnosis. Third, the subtype distribution may also be of interest as an overrepresentation of a particular subtype might bias the findings with relation to the general ADHD construct. Because diagnoses were based on ICD-10, subtypes of DSM-IV were not directly available and could only be inferred from ICD-10 diagnoses. However, previous research has shown that negative and or nonsignificant item loadings has been found across different types of samples (see table in Arias et al. 2016). Further, it would be interesting to test whether our incomplete model can be replicated in field samples and combined samples as well as with adults and across different methods (e.g. interviews).

Nevertheless, our results add to the growing literature that support an orthogonal bifactor structure of ADHD with a strong general factor and weakly defined specific factors. In contrast to previous studies we also considered an ADHD bifactor model with only two specific factors (IN and IM) which showed to be most adequate alongside a model with three specific factors (IN, HY and IM).

Compliance with Ethical Standards

Conflict of Interest Anja Görtz-Dorten and Manfred Döpfner are authors of the German ADHD and ODD/CD rating scale (FBB-ADHS and FBB-SSV). The authors receive royalties from the publisher (Hogrefe). Klaas Rodenacker and Christopher Hautmann are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this manuscript.

Experiment Participants All procedures performed were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all participants included in the study.

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