Factor Structure of the Differential Ability Scales-Second Edition Core Subtests:

Standardization Sample Confirmatory Factor Analyses

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Standardization data from the *Differential Ability Scales, Second Edition (DAS-II)*.

Abstract

The present study examined the factor structure of the Differential Ability Scales–Second Edition (DAS–II; Elliott, 2007a) core subtests from the standardization sample via confirmatory factor analysis (CFA) using methods (bifactor modeling and variance partitioning) and procedures (robust model estimation due to non-normal subtest score distributions) recommended but not included in the DAS–II *Introductory and Technical Handbook* (Elliott, 2007b). CFAs were conducted with the three DAS–II standardization sample age groups (Lower Early Years [Ages 2:6–3:5], Upper Early Years [Ages 3:6–6:11], School–Age [Ages 7:0–17:11]) using standardization sample raw data provided by NCS Pearson, Inc. Although most DAS–II core subtests were properly associated with the theoretically proposed group factors, both the higher-order and bifactor models indicated that the g factor accounted for large portions of total and common variance while the group factors (Verbal, Nonverbal, Spatial) accounted for small portions of total and common variance. The DAS–II core battery provides strong measurement of general intelligence and clinical interpretation should be primarily, if not exclusively, at that level.

Keywords: DAS–II, confirmatory factor analysis, higher–order structure, bifactor structure, structural validity

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The Differential Ability Scales-Second Edition (DAS–II; Elliott, 2007a) is a popular

battery of cognitive tests to assess intelligence of children and adolescents ages 2-17 years and

while becoming somewhat dated (the norms are now over 12 years old), is still currently used by

practitioners and included in omnibus interpretive systems such as Cross-Battery Assessment.

The DAS–II is a revision of the DAS (Elliott, 1990), an adaptation of the British Ability Scales

(Elliott, Murray, & Pearson, 1979) that was standardized for use in the United States. There are

three age related levels: Lower Early Years (ages 2:6 through 3:5); Upper Early Years (3:6

through 6:11); and School-Age (7:0 through 17:11), and the three levels contain different

configurations of 10 core subtests appropriate for each age. These subtests combine to yield a

General Conceptual Ability score (GCA), a higher-order composite score thought to measure

psychometric *g* (Spearman, 1927). There are also three first-order composite scores called *cluster*

scores (Verbal Ability [V], Nonverbal Reasoning Ability [NV], and Spatial Ability [SP]) that are

hypothesized to reflect more specific and diverse aptitudes. Additionally, the DAS–II provides

users with nine supplementary subtests across the various age brackets, which contribute to the

measurement of three diagnostic cluster scores (Processing Speed, Working Memory, and

School Readiness). However, these indicators do not contribute to the measurement of the GCA

or the three primary cluster scores and thus were not the focus of the present investigation.

Although the *Introductory and Technical Handbook* (Elliott, 2007b) indicated that the

DAS–II development was not driven by a single theory of cognitive ability, the content and

structure of the DAS–II was heavily influenced by the Cattell-Horn-Carroll model of cognitive

abilities (CHC; Carroll, 1993; 2003; Cattell & Horn, 1978; Horn, 1991; Schneider & McGrew,

2018). This model also served to guide assessment of DAS–II structural validity and serves as the primary method for score interpretation.

The *Introductory and Technical Handbook* suggests that users should interpret DAS–II scores in a stepwise fashion beginning with the GCA and then proceed to more specific measures (e.g., clusters and subtests). However, Elliott (2007b) suggested that the profile of strengths and weaknesses generated at the cluster and subtest levels *is of more value* than the information provided by the GCA, especially in cases where considerable variability across the cluster scores is observed and detailed procedures for evaluating scatter among the cluster and subtest scores are outlined in the *Introductory and Technical Handbook*. According to Elliott (2007b), "the most satisfactory description of a child's abilities is nearly always at the level of profile analysis" (p. 87). However, such prescriptive statements are rarely justified in applied practice and require adherence to standards of empirical evidence (Marley & Levin, 2011). More recently, McGill, Dombrowski, and Canivez (2018) reported on the absence of supportive evidence and negative evidence for such profile analyses since the seminal review by Watkins (2000).

Interpretation of test scores and comparisons must be guided by strong replicated empirical evidence deriving from structural validity, relationships with external variables including incremental validity, and diagnostic and treatment utility, as noted in the *Standards for Educational and Psychological Testing* (AERA, APA, & NCME, 2014). An important starting point for such evidence resides in the test structure as structural validity is a requisite property of broader construct validity (Keith & Kranzler, 1999).

The DAS–II *Introductory and Technical Handbook* did not report results of exploratory factor analysis (EFA) in examining construct validity nor was there disclosure of proportions of variance accounted for by the higher-order g factor and the proposed first–order group factors, subtest g loadings, subtest specificity estimates, or incremental predictive validity estimates for

the factors and subtest scores. Without this information, clinicians are unable to independently determine the relative importance of factor and subtest scores relative to the GCA score. Factor or subtest scores that fail to capture meaningful portions of non-*g* true score variance will likely be of limited clinical utility. The omission of incremental predictive validity results is particularly troubling because users are encouraged to interpret the DAS–II beyond the GCA level but DAS–II cluster scores, like all such scores, conflate general intelligence variance and group factor variance. Youngstrom, Kogos, and Glutting (1999) examined the incremental validity of the original DAS found that interpretation beyond the GCA was not supported.

Structural Validity Investigations of the DAS–II

Confirmatory factor analyses (CFA) of the DAS–II hierarchical structure were reported in the DAS–II *Introductory and Technical Handbook* (Elliott, 2007b), and Figures 8.1, 8.2, 8.3, and 8.4 illustrate the standardized validation models for the seven core and diagnostic subtests (ages 2:6-3:5) featuring two first–order factors, 11 core and diagnostic subtests (ages 4:0-5:11) with five first–order factors, 14 core and diagnostic subtests (ages 6:0–12:11) with seven first-order factors, and 12 core and diagnostic subtests featuring six first–order factors, respectively. In these models, several first–order factors not available in the actual DAS–II were specified (e.g., Auditory Processing, Visual-Verbal Memory, and Verbal Short-Term Memory). In addition, the Auditory Processing and Visual-Verbal Memory factors in the final validation models for ages 6–17 were each produced from a single indicator and reflect an empirically underidentified dimension. Although the inclusion of single indicator variables is possible in CFA, variables assessed by a single measure should not be interpreted as factors due to the fact that they do not possess any shared variance from multiple indicators (Brown, 2015).

Keith et al. (2010) examined measurement invariance of the DAS–II core and diagnostic subtest structure and reported support for a six–factor hierarchical model that corresponded

closely with CHC theory with general intelligence at the apex. However, the final validation

model required the specification of a cross–loading for the Verbal Comprehension measure on

Crystallized Ability and Fluid Reasoning factors. Although Keith et al. (2010) provided the

results of residualized subtest factor loadings in their DAS–II CFA analyses, the clinical utility

of these results are limited due to the fact they were derived from a hypothesized first–order

latent structure that deviates significantly from the structure suggested in the *Introductory and*

Technical Handbook (Elliott, 2007b). Neither Elliott (2007b) nor Keith et al. (2010) reported

univariate or multivariate skewness or kurtosis estimates among the scales used as indicators in

their CFA models which could have implications for proper model estimation if data were non-

normally distributed[1]. Also missing from CFAs conducted by Elliott and Keith et al. were

comparisons of rival bifactor structures as explanations of DAS–II.

Until recently, independent factor analytic investigations of the DAS–II, as well as the

validation study results reported in the *Introductory and Technical Handbook,* relied singularly

on application of CFA procedures to various configurations of the core and supplementary

subtests to produce different hierarchical models consistent with CHC theory. However, use of

these results to ascertain what the core battery measures is problematic as those models are not

structurally equivalent (Cattell, 1978). In recognition of these limitations, McGill and Canivez

(2016) conducted hierarchical EFA and variance decomposition using the Schmid and Leiman

(1957) procedure. Canivez and McGill found that while the DAS–II core subtests measured the

general intelligence dimension (estimated by the GCA) well, as evidenced by high omega-

hierarchical (ω_H) coefficients, the DAS–II group factors (V, NV, SP) did *not* contribute sufficient

portions of unique variance as evidenced by low and inadequate omega-hierarchical subscale

(ω_{HS}) coefficients. These results suggest that clinical interpretation of the DAS–II should likely

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[1] The estimation method used by Keith and colleagues was not disclosed.

be restricted to the GCA level and any interpretation of other scores or comparisons beyond the GCA should be done with caution and in light of additional external validation evidence.

To further elaborate on the DAS–II structure, Dombrowski, McGill, Canivez, and Peterson (2019) utilized similar EFA procedures to examine the total battery using the standardization sample data from the 5- to 8-year-old age range to determine the degree to which the DAS–II theoretical structure proposed in the *Introductory and Technical Handbook*, later refined by Keith et al. (2010), could be replicated. Results suggested a six-factor solution that was generally consistent with the CHC-based structure suggested by the publisher, with desired simple structure attained. However, two subtests (Picture Similarities and Early Number Concepts) did not saliently load on any group factors. Dombrowski, McGill, and Morgan (2019) used Monte Carlo simulation by resampling the standardization sample correlation matrices 1,000 times and analyzed the structure of the DAS-II total battery using maximum likelihood CFA. Both studies generally supported the theoretical structure posited in the *Introductory and Technical Handbook*. However, like Canivez and McGill (2016), large portions of subtest variance across both studies was apportioned to the general intelligence dimension resulting in a large ω_H coefficient, but small portions of unique variance was apportioned to the first-order group factors as evidenced by the small ω_{HS} coefficients, indicating inadequate unique measurement by the group factors.

Alternatively, Dombrowski, Golay, McGill, and Canivez (2018) used Bayesian structural equation modeling (BSEM) to examine the latent factor structure from the DAS–II core subtests using the 7 to 17 years age range standardization sample raw data. This allowed the estimation of small, nonzero parameters often set to zero in traditional CFA that can inflate factor covariances and potentially distort model results. Results revealed the plausibility of the hypothesized three-factor model, consistent with publisher theory, expressed as either a higher-order (HO) or a

bifactor (BF; Holzinger & Swineford, 1937) model. However, best BSEM model fit was obtained from an alternative structure, a two-group factor (V, SP) bifactor (BF) model with Matrices (MA) and Sequential & Quantitative Reasoning (SQ) loading on g only and no NV group factor. As with Canivez and McGill (2016), Dombrowski et al. (2019), and Dombrowski, McGill & Morgan (2019), the general intelligence factor dominated subtest variance and had high omega-hierarchical (ω_H) coefficients, but the DAS–II group factors (V, NV, SP) did not contribute sufficient portions of unique variance as shown by low and inadequate omega-hierarchical subscale (ω_{HS}) coefficients.

Although the latent structure of the DAS–II core subtests was examined via CFA in the *Introductory and Technical Handbook*, the standardized solutions for these analyses were not provided nor were alternative, rival models (e.g., bifactor) evaluated. Inspection of the goodness-of-fit results in Table 8.4 indicated that a three–factor hierarchical model provided the most optimal solution for the core subtests across the age spans with fairly robust improvements in fit when compared to competing one factor and hierarchical two–factor models. Generally, CFA have supported a hierarchical model with general intelligence at the apex and three first–order factors for the core subtests, but bifactor structure has thus far only been examined by Dombrowski et al (2018) using a recently rediscovered approach to latent variable modeling and those results did not support a three-factor structure for the core tests.

Purpose of the Current Study

Confirmatory factor analyses for the DAS–II core subtests reported in the *Introductory and Technical Handbook* are not sufficiently explicated, did not recognize or account for non-normal distributions, and did not disclose portions of variance accounted for by the various factors. Further, Elliott did not provide standardized parameter estimates for the core subtest

models nor did he examine rival bifactor model representations, which might provide better and more parsimonious fit to the standardization sample data. Accordingly, the purpose of the present investigation is to extend the results of the Canivez and McGill (2016) EFA study and to address the limitations of CFA reported in the DAS–II *Introductory and Technical Handbook*. Specifically, the present study examined the factor structure of the DAS–II core subtests through CFA and disclosure of variance contributions of latent factors using the normative sample raw data across the three test levels (i.e., Lower Early Years, Upper Early Years, and School-Age). It is believed that the results furnished by the present investigation will be instructive for determining how the DAS–II core battery should be interpreted in clinical practice.

Method

Participants

Participants were members of the DAS–II standardization sample and included a total of 3,460 individuals ranging in age from 2–17 years. Age groups included Lower Early Years 2:6–3:5 year-olds ($N = 352$)*,* Upper Early Years 3:6–6:11 year-olds ($N = 920$)*,* and School-Age 7:0–17:11 year-olds ($N = 2,188$). Detailed demographic characteristics are provided in the DAS–II *Introductory and Technical Handbook* book (Elliott, 2007b). The standardization sample was obtained using stratified proportional sampling across key demographic variables of age, sex, race/ethnicity, parent educational level, and geographic region; and examination of the demographic results reported in the *Introductory and Technical Handbook* reveal a close correspondence across the stratification variables to the October 2002 U.S. census estimates.

Table A1 (see online supplement) presents DAS–II Core Subtest correlation matrices and descriptive statistics for the three DAS–II age groups indicating some departure from normal distribution (Onwuegbuzie & Daniel, 2002; West, Finch, & Curran, 1995). Univariate skewness estimates from the three age groups ranged from -0.911 to 0.733. Univariate kurtosis estimates

from the three age groups, however, ranged from 0.556 to 3.195. Mardia's (1970) multivariate

kurtosis estimates for the Lower Early Years Ages 2:6 to 3:5 sample (Z = 11.37), Upper Early

Years Ages 3:6 to 6:11 sample (Z = 26.49), and the School-Age Ages 7:0 to 17:11 sample (Z =

33.86) indicated statistically significant (p < .05) multivariate non-normality for all three age

groups (Cain, Zhang, & Yuan, 2017) that has implications for CFA model estimation and fit

statistics.

Instrument

The DAS–II uses different combinations of the 10 core subtests to produce the GCA

score at different points of the age span. Whereas the GCA score is composed of four subtests at

ages 2:6 through 3:5, six core subtests are used from ages 3:6 through 17:11. The core subtests

combine to form three primary cognitive clusters at the first–order level and each is composed of

two subtests. Verbal (V) Ability and Nonverbal (NV) Reasoning Ability clusters are provided for

all ages, but an additional Spatial (SP) Ability cluster is available from ages 3:6 through 17:11.

Additional combinations of supplemental diagnostic subtests are provided, which can be

combined to yield additional first–order clusters (e.g., Working Memory, Processing Speed, and

School Readiness); however, these measures are not utilized to calculate the higher–order GCA

composite or its lower–order cognitive clusters. Additionally, the diagnostic measures cannot be

used to substitute for the core subtests.

Procedure and Analyses

NCS Pearson, Inc. provided standardization sample raw data for independent analyses.

EFA models suggested by Canivez and McGill (2016) and those promoted by Elliott (2007b) and

the publisher (see Table 8.4, p. 159) were examined and compared. Whereas Elliott only reported

oblique models for the core subtests, the present study examined oblique, higher-order, *and*

bifactor structures to determine fit to these data.

Confirmatory factor analyses (CFA) with maximum likelihood estimation were conducted using EQS 6.3 (Bentler & Wu, 2016). Each of the three latent group factors produced by DAS–II core subtests (V, NV, SP) have only two observed indicators and thus are empirically underidentified. Consequently, to ensure identification of CFA bifactor models, those subtests were constrained to equality (Little, Lindenberger, & Nesselroade, 1999). Given the significant multivariate kurtosis observed in all three age groups, robust maximum likelihood estimation with the Satorra and Bentler (S-B; 2001) corrected chi-square was applied. Byrne (2006, p. 138) indicated "the S-B χ^2 has been shown to be the most reliable test statistic for evaluating mean and covariance structure models under various distributions and sample sizes." Because Elliott (2007b) did not disclose univariate or multivariate normality estimates nor apply the S-B corrected χ^2, present results may differ from those presented in the *Introductory and Technical Handbook.* Some models reported in Table 8.4 (p. 159) included cross-loading the Picture Similarities and Matrices subtests on multiple factors, but these were not presently examined given problems of cross-loading and its abandoning of desired simple structure. It should be noted that previous EFA studies (Canivez & McGill, 2016; Dombrowski, Golay et al., 2018, Dombrowski et al., 2019) *did not* support specification of this parameter; while Keith et al. (2010) did not include cross loadings of Picture Similarities and Matrices subtests in initial calibration, reference variable, or final validation CFA models. Furthermore, those parameters deviate from the theoretical structure of the test which is based upon desired simple structure.

Given that the large sample size could unduly influence the χ^2 value (Kline, 2016), approximate fit indices were used to aid model evaluation and selection. While criterion values for approximate fit indices are not universally accepted (McDonald, 2010), the comparative fit index (CFI), Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA) were used to evaluate overall global model fit. Higher values indicated better fit for

the CFI and TLI whereas lower values indicated better fit for the RMSEA. Combinatorial heuristics of Hu and Bentler (1999) were applied where CFI and TLI $\geq$ .90 and RMSEA $\leq$ .08 were criteria for adequate model fit; whereas CFI and TLI $\geq$ .95 and RMSEA $\leq$ .06 were criteria for well-fitting models. Marsh, Hau, and Wen (2004) however, cautioned overgeneralizing such heuristics that could result in the incorrect rejection of an acceptable model (Type I error). The Akaike Information Criterion (AIC) was also considered. Because AIC does not have a meaningful scale, the model with the smallest AIC value was preferred as most likely to replicate (Kline, 2016). Superior models required adequate to good overall fit *and* indication of meaningfully better fit (ΔCFI > .01, ΔRMSEA > .015, ΔAIC > 10) than alternative models (Burnham & Anderson, 2004; Cheung & Rensvold, 2002; Chen, 2007). Local fit was also considered in addition to global fit as models should never be retained "solely on global fit testing" (Kline, 2016, p. 461). Statistical power sufficient to detect even small differences is provided by the large sample size as well as more precise model parameter estimates.

Coefficients omega-hierarchical (ω_H) and omega-hierarchical subscale (ω_{HS}) were estimated and provide a model-based estimate of the proportion of true score variance that would be obtained in a unit-weighted score composed of subtests associated with a specific factor (Reise, 2012; Rodriguez, Reise, & Haviland, 2016a, b; Watkins, 2017). The ω_H coefficient is the unique general intelligence factor variability estimate with variability from the group factors removed. The ω_{HS} coefficient is the unique group factor variability estimate with variability from all other group *and* general factors removed (Brunner, Nagy, & Wilhelm, 2012; Reise, 2012). Omega estimates (ω_H and ω_{HS}) are calculated from CFA bifactor solutions or decomposed variance estimates from higher-order models and were obtained using the *Omega* program (Watkins, 2013), which is based on the works of Zinbarg, Revelle, Yovel, and Li (2005) and Zinbarg, Yovel, Revelle, and McDonald (2006) and the Brunner et al. (2012) tutorial. While

standards for omega coefficients acceptability for clinical use are not universally accepted, it has

been suggested that ω_H and ω_{HS} coefficients should exceed .50, but .75 might be preferred

(Reise, 2012; Reise, Bonifay, & Haviland, 2013; Rodriguez et al., 2016a, b). Reise et al. (2013)

and Rodriguez et al. (2016a, b) illustrated meaningful attribution of indicators to latent general or

group factor measurement when the majority of unique variability was present in the factor and

thus the minimum criterion of .50. The Hancock and Mueller (2001) construct reliability or

construct replicability coefficient (*H*) supplemented omega coefficients and estimated the latent

construct adequacy represented by the indicators, using a criterion value of .70 (Hancock &

Mueller, 2001; Rodriguez et al., 2016). *H* coefficients were produced by the *Omega* program

(Watkins, 2013).

Results

Lower Early Years (Ages 2:6-3:5)

Table 1 presents fit statistics for the only two models that could be tested. Both

unidimensional *g* (Model 1, see Figure 1) and the oblique V & NV (Model 2, see Figure 2)

models fit the standardization data well. No statistically significant or meaningful differences

between these two models were noted in fit statistics, so given the extremely high V-NV

covariance (.936), the unidimensional *g* model was determined the best representation for

parsimonious explanation of DAS–II measurement for this age group. Higher-order and bifactor

models would be mathematically equivalent to Model 2.

Upper Early Years (Ages 3:6-6:11)

Table 1 presents fit statistics for models tested for the Ages 3:6-6:11 age group. The

combinatorial heuristics of Hu and Bentler (1999) indicated that Model 1 (*g*) was inadequate

with too low TLI and too high RMSEA. Model 2 (oblique V and NV) provided adequate fit to

standardization sample data, but Model 3 (oblique V, NV, SP) fit the standardization sample data

well and better than Model 2 (higher TLI and CFI and lower RMSEA and AIC). However, given the significant covariance among the three group factors, it was necessary to explicate higher-order and bifactor representations of that model. Model 4 (higher-order with V and NV) produced adequate to good fit but contained a local fit problem of linear dependence of the lower-order Verbal factor disturbance that needed to be fixed to zero to allow model estimation. Model 5a (bifactor with V and NV) provided better fit than Model 4 (higher TLI and CFI and lower RMSEA and AIC), but Matrices and Picture Similarities subtests had negative standardized path coefficients on the NV group factor so was respecified as Model 5b (as per Dombrowski et al., 2018) with Matrices (MAT) and Picture Similarities (PS) subtests containing only standardized g path coefficients and no NV group factor standardized path coefficients. Due to only having two indicators per group factor, Model 6 (higher-order [see Figure 3] & bifactor [see Figure 4] representations with V, NV, and SP) were mathematically equivalent and both provided good fits to standardization sample data, and neither produced local fit problems. As such, both higher-order (Figure 3) and bifactor (Figure 4) representations of Model 6 are further explicated in Table 2 and Table 3 to illustrate decomposed sources of variance and model-based reliability estimates.

The general intelligence dimension accounted for most of the DAS–II subtest variance and substantially smaller portions of subtest variance were uniquely associated with the three DAS–II group factors (V, NV, SP). Omega-hierarchical and omega-hierarchical subscale coefficients estimated using bifactor results from Table 4 found the ω_H coefficient for general intelligence (.748) was high and indicated a unit-weighted composite score based on the six subtest indicators would account for 74.8% true score variance. The ω_{HS} coefficients for the three DAS–II group factors (V, NV, SP) were considerably lower ranging from .072 (NV) to .210 (V). Thus, unit-weighted composite scores for the three DAS–II first-order factors possess

too little unique true score variance to recommend confident clinical interpretation (Reise, 2012; Reise et al., 2013). Table 4 also presents *H* coefficients that reflect correlations between the latent factors and optimally weighted composite scores (Rodriguez et al., 2016). The *H* coefficient for the general factor (.785) indicated the general factor was well defined by the six DAS–II subtest indicators, but the *H* coefficients for the three DAS–II group factors ranged from .096 to .281 and thus were not adequately defined by their subtest indicators. Results were identical or nearly identical for the higher-order representation of DAS–II (see Table 3).

School-Age (Ages 7:0-17:11)

Table 2 presents fit statistics for tested models for the Ages 7:0-17:11 age group. Examination of fit statistics indicated that Model 1 (*g*) was inadequate (too low TLI and CFA, too high RMSEA). Model 2 (oblique V and NV) provided adequate to good fit but Model 3 (oblique V, NV, SP) fit the standardization sample data well and was superior to Models 1 and 2 (higher TLI and CFI and lower RMSEA and AIC). Due to significant covariance of the three group factors (V, NV, SP), higher-order and bifactor models were necessary. Model 4 (higher-order with V and NV) produced good fit but contained a local fit problem where the NV and *g* factors were linearly dependent on other parameters. Model 5 (bifactor with V and NV) fit the standardization sample data well and was superior to Model 4 (higher TLI and CFI and lower RMSEA and AIC), but also contained local fit problems where Matrices (MAT) and Sequential & Quantitative Reasoning (SQR) subtests had small negative path coefficients (-.01 and -.05, respectively) on the NV group factor. Due to only having two indicators per group factor, Model 6 (higher-order [see Figure 5] & bifactor [see Figure 6] representations with V, NV, and SP) were mathematically equivalent and provided good fit to standardization sample data. The higher-order version of Model 6 contained a local fit problem of a standardized path coefficient of 1.0 between *g* and NV (see Figure 5) and the bifactor version of Model 6 contained a local fit

problem of standardized path coefficients of 0 between the NV group factor and MAT and SQR subtests. As a result, the NV group factor was deleted from the bifactor model and Model 7 (see Figure 7) estimated to represent a bifactor model with only the V and SP group factors and MAT and SQR subtests contained only standardized path coefficients with *g*. Both higher-order (Figure 5) and bifactor (Figure 6 and 7) representations of Models 6 and 7 are further explicated in Table 4 (higher-order) and Table 5 (bifactor) to illustrate decomposed sources of variance and model-based validity estimates.

In both the higher-order and bifactor versions of Model 6, the general intelligence dimension accounted for most of the DAS–II subtest variance and substantially smaller portions of subtest variance were uniquely associated with the three DAS–II group factors (V, NV, SP). Omega-hierarchical and omega-hierarchical subscale coefficients estimated using bifactor results from Table 5 found the ω_H coefficient for general intelligence (.834) was high and indicated a unit-weighted composite score based on the six subtest indicators would account for 83.4% true score variance. The ω_{HS} coefficients for the three DAS–II group factors (V, NV, SP) were considerably lower ranging from .000 (NV) to .268 (V). Thus, unit-weighted composite scores for the three DAS–II first-order factors possess too little unique true score variance to recommend clinical interpretation (Reise, 2012; Reise et al., 2013). Table 5 also presents *H* coefficients that reflect correlations between the latent factors and optimally weighted composite scores (Rodriguez et al., 2016). The *H* coefficient for the general factor (.871) indicated the general factor was well defined by the six DAS–II subtest indicators and essentially unidimensional, but the *H* coefficients for the three group factors ranged from .000 to .365 and thus were not adequately defined by their subtest indicators. Results were nearly identical for the higher-order representation of DAS–II (see Table 4).

Discussion

The present study provided an independent analysis of the factor structure of the DAS–II core subtests with the three age groups in the standardization sample using best practice CFA methods. The DAS–II *Introductory and Technical Handbook* (Elliott, 2007b) does not report the CFA procedures and analyses necessary to adequately support reported construct validity. Lack of disclosure of univariate and multivariate non-normality among DAS–II core subtests in the standardization sample and apparent lack of robust model estimation in CFA reported in the DAS–II *Introductory and Technical Handbook* resulted in misestimation of model fit statistics and parameter estimates. Further, the lack of reporting portions of variance captured by the various dimensions prohibits users of the DAS–II from determining which scores contain sufficient unique true score variance necessary for individual decision making. The present study attempted to overcome these shortcomings using the standardization sample raw data provided by NCS Pearson, Inc. for independent assessment.

Results of the present study paralleled quite well the EFA results from the DAS–II core subtests reported by Canivez and McGill (2016) that indicated that the DAS–II core subtests measured general intelligence well, and while the subtests generally had associations with theoretically linked first-order factors (V, NV, SP), the *unique* contributions of true score variance in the first-order group factors were universally low, prohibiting confident individual clinical interpretation. The present CFA results for the three DAS–II age groups (Lower Early Years [Ages 2:6–3:5], Upper Early Years [Ages 3:6–6:11], School–Age [Ages 7:0–17:11]) showed that while most subtests were generally aligned with their theoretical first-order group factors (V, NV, SP), most of the reliable subtest variance was associated with an overall, general intelligence factor (*g*), regardless of model expression (higher-order versus bifactor). The dominance of the general intelligence factor and the limited unique measurement of the three group factors is evidenced by the subtest variance apportions where the general factor accounted

for more than 6.84 times as much common subtest variance (Ages 3:6 to 6:11) and 6.88 times as

much common subtest variance (Ages 7:0–17:11) as any individual DAS–II group factor and

about 3 times as much common subtest variance (Ages 3:6 to 6:11) and about 4.7 times as much

common subtest variance (Ages 7:0–17:11) as all three DAS–II group factors combined. Similar

results were reported by Cucina and Howardson (2017) with the original DAS (Elliott, 1990).

The omega coefficients (ω_H and ω_{HS}) and construct reliability or construct replicability

coefficients (*H*) from CFA results of the bifactor models (and higher-order models) indicated

that while the broad *g* factor allows for confident individual interpretation of the GCA, the ω_{HS}

and *H* estimates for the three DAS–II group factors were unacceptably low (see Tables 3 through

6), and thus extremely limited for measuring unique cognitive constructs (Brunner et al, 2012;

Hancock & Mueller, 2001; Reise, 2012; Rodriguez et al., 2016) supposedly quantified by the

DAS–II cluster scores. Most disconcerting is the observation that for ages 7:0 to 17:11, the NV

factor appears completely absent (a result suggested by Dombrowski et al., 2018), yet a

Nonverbal Reasoning Ability cluster score is provided for interpretation by the publisher. Such

results indicate "to interpret subscale scores as representing the precise measurement of some

latent variable that is unique or different from the general factor, clearly, is misguided"

(Rodriguez et al., 2016, p. 225). Had variance apportions been reported in the DAS–II

Introductory and Technical Handbook, this problem would have been disclosed and users of the

DAS–II would be better able to decide if there was little to nothing to report beyond the GCA[2].

The present results, like those reported by Cucina and Howardson (2017) with the

original DAS, challenge the CHC-inspired interpretive model preferred by the test publisher

model in that the portions of unique variance conveyed by the broad ability clusters (V, NV, SP)

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[2] Standardized path coefficients between NV and *g* reported in the *Introductory and Technical Handbook* ranged form .93-.99 suggesting those constructs may be redundant.

are quite small and thus likely to be of little consequence but the variance contributed by *g* is quite large and of primary importance. Thus, it appears these results provide ample support for Carroll's conceptualization of the structure of intelligence but not Cattell and Horn or McGrew who have deemphasized psychometric *g* and focused on the group factors (Horn & Blankson, 2005; Horn & Noll, 1997; McGrew, 2018). An additional theoretical implication is the preference for the bifactor model when there is an attempt to estimate or account for domain-specific abilities (Murray & Johnson, 2013), something explicitly done with DAS–II interpretations of V, NV, and SP scores and their comparisons. Users of the DAS–II must consider the empirical *evidence* of how well the group factor cluster scores (domain-specific) *uniquely* measure their represented construct independent of the general intelligence (*g*) factor (GCA) score (Chen, Hayes, Carver, Laurenceau, & Zhang, 2012; Chen, West, & Sousa, 2006). Bifactor models contain a general factor but permit multidimensionality, which some consider an advantage relative to the higher-order model for determining the group factor contributions independent of the general intelligence factor (Reise, Moore, & Haviland, 2010).

Reynolds & Keith (2013) have questioned the appropriateness of the bifactor model and stated that "we believe that higher-order models are theoretically more defensible, more consistent with relevant intelligence theory (e.g., Jensen, 1998), than are less constrained hierarchical [bifactor] models" (p. 66). However, Gignac (2006, 2008) argued, in comparing bifactor and higher-order models, that general intelligence is the most substantive factor of a battery of cognitive tests so *g* should be modeled *directly* and that it is the higher-order model that requires explicit theoretical justification for the full mediation of general intelligence by the group factors. Carroll (1993, 1995) empirically illustrated that variation in subtest scores reflect both general *and* a more specific group factor variances. So, while subtest scores may appear reliable, in the majority of cases that reliability estimate is primarily due to the influence of the

general factor and *not* the specific group factor (Caretta & Ree, 2001). Others have argued that

Spearman's (1927) and Carroll's (1993) conceptualizations of intelligence are better represented

by the bifactor model (Beaujean, 2015; Frisby & Beaujean, 2015; Brunner et al., 2012; Gignac,

2006, 2008; Gignac & Watkins, 2013; Gustafsson & Balke, 1993). For example, Beaujean

(2015) suggests that Spearman's conception of general intelligence was of a factor "that was

directly involved in all cognitive performances, not indirectly involved through, or mediated by,

other factors" (p. 130) and also noted that "Carroll was explicit in noting that a bi-factor model

best represents his theory" (p. 130).

The question of whether the general factor of intelligence *actually* represents a legitimate

psychological dimension continues to be adjudicated and there are respected intelligence

scholars that contend that *g* is nothing more than a statistical artifact. Recently, Kovacs and

Conway (2016, 2019a, 2019b) presented their process overlap theory (POT) which argues for

combination of, and attempts to merge, psychometric aspects of intelligence with cognitive

psychology and neuroscience. They suggest that *g* is an emergent property (not the cause) of

domain-general executive functions. Their effort was to provide a unified theory for general

intelligence but Gottfredson (2016) pointed out a number of misconceptions and misattributions

of *g* theory noting "the *g* theory they portray is not the one to which *g* theorists actually

subscribe" (p. 210). Gottfredson (2016) welcomed the attempt to merge the disparate fields but

illustrated how Kovacs and Conway are consistent with *g* theory, and not contrary to it, based on

different levels of analysis.

Even so, the substantially greater total and common variance associated with general

intelligence among DAS–II core subtests is a result that has been observed in numerous other

studies examining the latent factor structure of intelligence or cognitive ability tests using both

EFA and CFA procedures (Bodin et al., 2009; Canivez, 2008, 2014b; Canivez et al., 2009;

Canivez & Watkins, 2010a, 2010b; Canivez et al., 2016, 2017; DiStefano and Dombrowski, 2006; Dombrowski, 2013, 2014a, 2014b; Dombrowski & Watkins, 2013; Dombrowski et al., 2009; Gignac & Watkins, 2013; Nelson & Canivez, 2012; Nelson, et al., 2007; Nelson et al., 2013; Watkins, 2006; 2010; Watkins & Beaujean, 2014; Watkins et al., 2013; Watkins et al., 2006). These results continue to support the dominance of psychometric *g* and are consistent with the literature regarding the practical importance of general intelligence (Deary, 2013; Gottfredson, 2008; Jensen, 1998; Lubinski, 2000, Ree, Carretta, & Green, 2003). While it appears that in the case of highly gifted (precocious) individuals there are additional effects of spatial abilities and intraindividual differences (higher verbal or higher quantitative abilities) related to excelling in humanities or science, technology, engineering, and math (STEM) domains (Kell, Lubinski, & Benbow, 2013; Kell, Lubinski, Benbow, & Steiger, 2013; Lubinski, 2016; Makel, Kell, Lubinski, Putallaz, & Benbow, 2016) such that *g* accounts for *less* variance in these circumstances, *g* still typically accounts for the most variance. This phenomenon is described by Spearman's law of diminishing returns, which was specifically examined in the DAS-II by Reynolds, Hajovsky, Niileksela, and Keith (2011), and they did indeed find that there was less *g* variance related to most subtests in the high versus low ability group, but for most subtests there was still *more g* variance than broad ability variance associated with most DAS–II subtests. As such the principal interpretation of DAS–II core subtests should be of the GCA, the estimate of *g*; although, perhaps in intellectually gifted individuals, other factors might be of value. The dominance of *g* variance captured by the DAS–II core subtests is a likely reason that methods to determine how many factors to extract and retain in EFA such as parallel analysis and minimum average partials suggest the DAS–II might be sufficiently represented by only one factor and the inability to locate the posited NV factor consistently in the present results (Crawford et al., 2010).

Relatedly, the confidence intervals provided for the DAS–II factor scores are considerably smaller (due to conflated general intelligence variance) than they might be if only the *unique* true score variance of the factor scores was used. The poor incremental validity provided by intelligence test group factors in accounting for meaningful portions of achievement variance beyond that provided by the omnibus composite IQ score in many contemporary intelligence tests (e.g., Canivez, 2013; Glutting, Watkins, Konold, & McDermott, 2006; McGill, 2015) may be the result of small amounts of unique variance captured by first–order factors as observed in the present study. Youngstrom, Kogos, and Glutting (1999) found in the assessment of incremental validity of the DAS factor scores, as predictors of achievement beyond the GCA, that interpretation of broad factor scores was not supported. While incremental validity of DAS–II cluster scores above and beyond the GCA does not yet appear to have been investigated, it is hard to imagine these specific group factors would provide useful incremental information when predicting performance in academic achievement or relations with other external criteria given the current results.

Another problem for DAS–II interpretation is the recommended practice of identification of factor based cognitive strengths and weaknesses through ipsative comparisons because analyses of DAS–II factor score differences at the observed score level conflate *g* variance and specific group factor (Verbal, Nonverbal, Spatial) variance. The same is true of analyses of subtest-based processing strengths and weaknesses. Because it is not possible to disaggregate these sources of variance for individuals it is impossible to know how much of the variance in performance is due to the general factor, specific group factor, or the narrow subtest ability. These concerns are in addition to the long-standing problems identified for ipsative score comparisons (McDermott, Fantuzzo, & Glutting, 1990; McDermott, Fantuzzo, Glutting, Watkins, & Baggaley, 1992; McDermott & Glutting, 1997) and suggest that these interpretive

practices should probably be eschewed. Additionally, the longitudinal stability of such PSWs (see Watkins & Canivez, 2004) or diagnostic and treatment utility of such DAS–II PSWs in particular, has yet to be demonstrated. Although these types of profile analysis methods remain popular in clinical practice, compelling empirical support for the validity of these practices is presently lacking (e.g., Glutting, Watkins, & Youngstrom, 2003; Macmann & Barnett, 1997; McDermott, Fantuzzo, & Glutting, 1990; McDermott, et al., 1992; McDermott & Glutting, 1997; Miciak et al., 2014; McGill et al., 2018; Watkins, 2000; Watkins, Glutting, & Lei, 2007).

Finally, it should be noted that these results are not unique to the DAS–II. As a result, a host of independent CFA and EFA studies of other major tests of intelligence such as the WISC–IV (Bodin, Pardini, Burns, & Stevens, 2009; Canivez, 2014b; Keith, 2005; Watkins, 2006, 2010; Watkins, Wilson, Kotz, Carbone, & Babula, 2006), WISC–V (Canivez, Watkins, & Dombrowski, 2016, 2017, Canivez, McGill, Dombrowski, Watkins, Pritchard, & Jacobson, 2018; Dombrowski, Canivez, & Watkins, 2017), WAIS-IV (Canivez & Watkins, 2010a, b; Nelson, Canivez, & Watkins, 2013), WPPSI–IV (Watkins & Beaujean, 2014), WJ III (Cucina & Howardson, 2017; Dombrowski, 2013, 2014a, 2014b; Dombrowski & Watkins, 2013; Strickland, Watkins, & Caterino, 2015), WJ IV (Dombrowski, McGill, & Canivez, 2017, 2018a, b), SB-5 (Canivez, 2008; DiStefano & Dombrowski, 2006), KABC (Cucina & Howardson, 2017), KABC-2 (McGill & Dombrowski, 2018), KAIT (Cucina & Howardson, 2017), and RIAS (Dombrowski, Watkins, & Brogan, 2009; Nelson & Canivez, 2012; Nelson, Canivez, Lindstrom, & Hatt, 2007) have reached similar conclusions about what our commercial ability tests measure. We encourage practitioners to consider these results along with the psychometric meta-analysis conducted by Dombrowski, McGill and Morgan (2019) when making decisions about how these measures should be interpreted and utilized in clinical practice.

Limitations

The results of the present study pertain only to the latent factor structure of the DAS–II core subtests and do not fully test all aspects of construct validity. In fact, as emphasized by Bonifay, Lane, and Reise (2017), bifactor (and other structures) must be examined for adequacy against external criteria in theoretical validation. Latent profile analysis might be useful to determine if the DAS–II is able to identify various diagnostic groups that might be expected to differ from normative samples. As previously mentioned, studies examining relations of DAS–II scores with external criteria such as examinations of incremental predictive validity (Youngstrom et al., 1999) or effects of extreme cluster score variability on DAS–II prediction of academic achievement (Kotz, Watkins, & McDermott, 2008) should also be conducted. In addition to observed scores, DAS–II latent factor scores could also be examined for contributions to the explanation of academic achievement (see Kranzler, Benson, & Floyd, 2015; Glutting et al., 2006). Diagnostic utility of DAS–II cluster scores should also be examined to determine if they offer utility for correct classification of individuals within specific groups or differential treatment response (see Canivez, 2013b).

Conclusions

The present CFA results reinforce the admonition of extreme caution for any interpretations of DAS–II scores beyond the GCA (Canivez & McGill, 2016; Dombrowski et al., 2018, 2019), including assessments for PSW. Due to the very small portions of unique true score variance provided cluster scores and the inability to locate the NV score consistently across the age span of the test, such scores and their comparisons are potentially misleading. Better measurement of posited DAS–II first-order dimensions as distinct from g will likely require the creation and inclusion of more or better indicators as has been suggested with other general intelligence tests (Canivez, Watkins, & Dombrowski, 2016, 2017; Dombrowski, McGill, & Canivez, 2017, 2018a, b). These results, in addition to the advantages of bifactor modeling in

aiding our understanding of test structure (Canivez, 2016; Cucina & Byle, 2017; Reise, 2012;

Gignac, 2008), indicate that comparisons of bifactor and higher-order representations are likely

needed to fully understand what cognitive tests like the DAS–II measure. Given "the ultimate

responsibility for appropriate test use and interpretation lies predominantly with the test user"

(AERA et al., 2014, p. 141), consideration of the present results and other independent DAS–II

studies allow users to "know what their tests can do and act accordingly" (Weiner, 1989, p. 829).

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Table 1

CFA Fit statistics for DAS–II Core Subtests for the Total Standardization Samples

Measurement Models	S-B χ^2	df	p	TLI	CFI	RMSEA	RMSEA 90% CI	AIC
Ages 2:6 to 3:5 (N = 352)								
1 One factor (g)	**1.94**	**2**	**.3786**	**1.000**	**1.000**	**.000**	**[.000, .105]**	**9,992.94**
2 Two oblique factors (V, NV)	0.66	1	.4170	1.000	1.000	.000	[.000, .131]	9,993.71
Ages 3:6 to 6:11 (N = 920)								
1 One factor (g)	91.16	9	.0001	.835	.901	.100	[.081, .118]	39,670.84
2 Two oblique factors (V, NV)	36.33	8	.0001	.936	.966	.062	[.042, .083]	39,608.50
3 Three oblique factors (V, NV, SP)	4.36	6	.6287	1.000	1.000	.000	[.000, .036]	39,573.54
4[1] Higher-Order (V, NV)	31.78	7	.0001	.936	.970	.062	[.041, .085]	39,610.50
5a[2] Bifactor (V, NV)	3.61	4	.4616	1.000	1.000	.000	[.000, .048]	39,578.87
5b[3] Bifactor (V, NV)	6.76	7	.4544	1.000	1.000	.000	[.000, .040]	39,578.51
6[4] Higher-Order & Bifactor (V, NV, SP)	**4.36**	**6**	**.6287**	**1.000**	**1.000**	**.000**	**[.000, .036]**	**39,573.54**
Ages 7:0 to 17:11 (N = 2,188)								
1 One factor (g)	326.63	9	.0001	.781	.868	.127	[.115, .139]	92,378.96
2 Two oblique factors (V, NV)	76.30	8	.0001	.939	.968	.062	[.050, .075]	92,821.48
3 Three oblique factors (V, NV, SP)	9.03	6	.1721	.997	.999	.015	[.000, .034]	92,036.27
4[5] Higher-Order (V, NV)	51.90	7	.0001	.960	.981	.054	[.041, .068]	92,088.29
5[6] Bifactor (V, NV)	2.92	4	.5710	1.000	1.000	.000	[.000, .028]	92,035.95
6[7] Higher-Order & Bifactor (V, NV, SP)	9.03	6	.1716	.997	.999	.015	[.000, .034]	92,036.29
7[8] Bifactor (V, SP)	**8.97**	**7**	**.2552**	**.998**	**.999**	**.011**	**[.000, .030]**	**92,038.29**

Note. S-B = Satorra-Bentler, TLI = Tucker–Lewis Index, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation, AIC = Akaike's Information Criterion, g = general intelligence, V = Verbal, NV = Nonverbal, SP = Spatial. [1]Factor 2 (Verbal) disturbance was linearly dependent on other parameters so EQS set disturbance variance to zero for model estimation. [2]Matrices and Picture Similarities subtests had negative path coefficients on the NV group factor. [3]Model respecified with Matrices and Picture Similarities subtests with only g paths and no NV group factor paths. [4]Higher-order model AIC presented in table, Bifactor model AIC was slightly higher at 39,579.54 but not meaningfully different. [5]EQS condition code noted the NV and g factors were linearly dependent on other parameters. [6]Matrices and Sequential & Quantitative Reasoning subtests had small negative path coefficients (-.01 and -.05, respectively) on NV group factor. [7]Higher-order model AIC presented in table, Bifactor model AIC was slightly higher at 92,042.29 54 but not meaningfully different than higher-order model, and MA and SQ group factor standardized path values were 0 and thus not statistically significant. [8]Bifactor model respecified with Matrices and Sequential & Quantitative Reasoning subtests having only g paths and no NV group factor paths (equivalent to removing Matrices and Sequential & Quantitative Reasoning subtests NV group factor paths in model 5).

Table 2

Sources of Variance in the DAS–II Core Subtests for the Total Standardization Sample Ages 3:6 to 6:11 (N = 920)
According to a CFA Higher-Order Model (Figure 3)

DAS–II Subtest	General		Verbal		Nonverbal		Spatial		h^2	u^2	ECV
	b	S^2	b	S^2	b	S^2	b	S^2			
Verbal Comprehension	.627	.393	.405	.164					.557	.443	.706
Naming Vocabulary	.623	.388	.402	.162					.550	.450	.706
Picture Similarities	.641	.411			.242	.059			.469	.531	.875
Matrices	.542	.294			.205	.042			.336	.664	.875
Pattern Construction	.670	.449					.437	.191	.640	.360	.702
Copying	.550	.303					.359	.129	.431	.569	.701
Total Variance		.373		.054		.017		.052	.497	.503	
ECV		.750		.109		.034		.107			
ω		.831		.713		.572		.696			
ω_H / ω_{HS}		.748		.210		.072		.208			
Relative ω		.900		.294		.125		.299			
Factor correlation		.865		.458		.267		.456			
H		.785		.280		.096		.277			
PUC		.800									

Note. b = standardized loading of subtest on factor, S^2 = variance explained in the subtest, h^2 = communality, u^2 = uniqueness, ECV = explained common variance, ω = Omega, ω_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), H = construct reliability or replicability index, PUC = percentage of uncontaminated correlations.

Table 3

Sources of Variance in the DAS–II Core Subtests for the Total Standardization Sample Ages 3:6 to 6:11 (N = 920) According to a CFA Bifactor Model (Figure 4)

DAS–II Subtest	General		Verbal		Nonverbal		Spatial		h^2	u^2	ECV
	b	S^2	b	S^2	b	S^2	b	S^2			
Verbal Comprehension	.627	.393	.400	.160					.553	.447	.711
Naming Vocabulary	.623	.388	.408	.166					.555	.445	.700
Picture Similarities	.641	.411			.226	.051			.462	.538	.889
Matrices	.542	.294			.222	.049			.343	.657	.856
Pattern Construction	.670	.449					.392	.154	.603	.397	.745
Copying	.550	.303					.399	.159	.462	.538	.655
Total Variance		.373		.054		.017		.052	.496	.504	
ECV		.752		.110		.034		.105			
ω		.831		.713		.572		.693			
ωH / ωHS		.748		.210		.072		.205			
Relative ω		.900		.295		.125		.296			
Factor correlation		.865		.458		.268		.453			
H		.785		.281		.096		.271			
PUC		.800									

Note. b = standardized loading of subtest on factor, S^2 = variance explained in the subtest, h^2 = communality, u^2 = uniqueness, ECV = explained common variance, ω = Omega, ωH = Omega-hierarchical (general factor), ωHS = Omega-hierarchical subscale (group factors), H = construct reliability or replicability index, PUC = percentage of uncontaminated correlations.

Table 4

Sources of Variance in the DAS–II Core Subtests for the Total Standardization Sample Ages 7:0 to 17:11 (N = 2,188) According to a CFA Higher-Order Model (Figure 5)

DAS–II Subtest	General		Verbal		Nonverbal		Spatial		h^2	u^2	ECV
	b	S^2	b	S^2	b	S^2	b	S^2			
Word Definitions	.654	.428	.469	.220					.648	.352	.660
Verbal Similarities	.662	.438	.473	.224					.662	.338	.662
Matrices	.772	.596			.004	.000			.596	.404	.999
Seq. & Quant. Reasoning	.820	.672			.024	.001			.673	.327	.999
Pattern Construction	.705	.497					.334	.112	.609	.391	.817
Recall of Designs	.638	.407					.302	.091	.498	.502	.817
Total Variance		.506		.074		.000		.034	.614	.386	
ECV		.824		.120		.000		.055			
ω		.893		.791		.776		.712			
ω_H / ω_{HS}		.834		.268		.000		.130			
Relative ω		.933		.339		.000		.183			
Factor correlation		.913		.518		.015		.361			
H		.871		.363		.001		.184			
PUC		.800									

Note. b = standardized loading of subtest on factor, S^2 = variance explained in the subtest, h^2 = communality, u^2 = uniqueness, ECV = explained common variance, ω = Omega, ω_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), H = construct reliability or replicability index, PUC = percentage of uncontaminated correlations.

Table 5

Sources of Variance in the DAS–II Core Subtests for the Total Standardization Sample Ages 7:0 to 17:11 (N = 2,188)
According to a CFA Bifactor Model (Figure 6)

DAS–II Subtest	General		Verbal		Nonverbal		Spatial		h^2	u^2	ECV
	b	S^2	b	S^2	b	S^2	b	S^2			
Word Definitions	.655	.429	.472	.223					.652	.348	.658
Verbal Similarities	.662	.438	.469	.220					.658	.342	.666
Matrices	.772	.596			.000	.000			.596	.404	.999
Seq. & Quant. Reasoning	.820	.672			.000	.000			.672	.328	.999
Pattern Construction	.705	.497					.319	.102	.599	.401	.830
Recall of Designs	.638	.407					.320	.102	.509	.491	.799
Total Variance		.507		.074		.000		.034	.614	.386	
ECV		.825		.120		.000		.055			
ω		.893		.792		.776		.713			
ω_H / ω_{HS}		.834		.268		.000		.132			
Relative ω		.933		.338		.000		.185			
Factor correlation		.913		.517		.000		.363			
H		.871		.363		.000		.185			
PUC		.800									

Note. b = standardized loading of subtest on factor, S^2 = variance explained in the subtest, h^2 = communality, u^2 = uniqueness, ECV = explained common variance, ω = Omega, ω_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), *H* = construct reliability or replicability index, PUC = percentage of uncontaminated correlations.
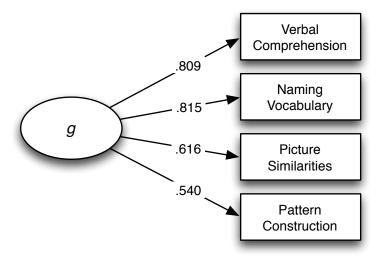
Figure 1. Unidimensional measurement model with standardized coefficients, for the 4 DAS–II core subtests for ages 2:6 to 3:5, $N = 352$. All standardized coefficients statistically significant, $p < .05$.
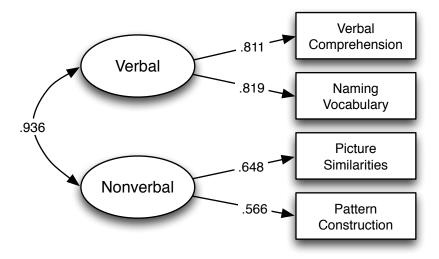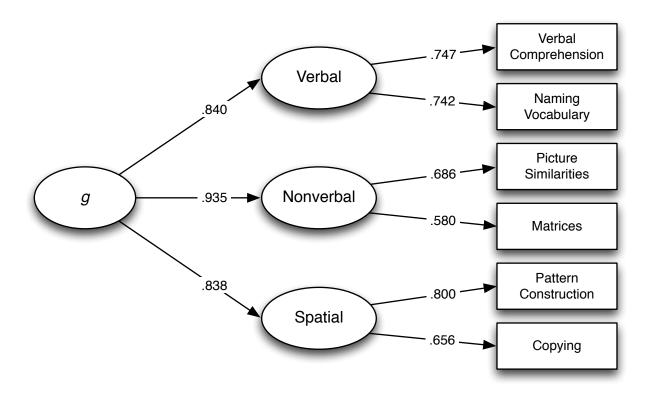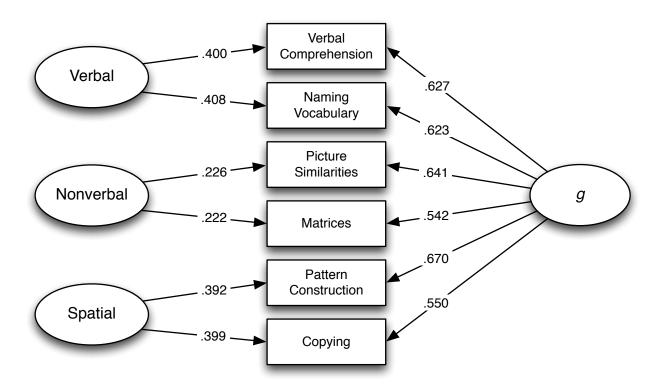

Figure 2. Two oblique factors measurement model with standardized coefficients, for the 4 DAS–II core subtests for ages 2:6 to 3:5, $N = 352$. All standardized coefficients statistically significant, $p < .05$.

Figure 3. Higher-order measurement model with standardized coefficients, for the 6 DAS–II core subtests for ages 3:6 to 6:11, *N* = 920. All standardized coefficients statistically significant, *p* < .05.
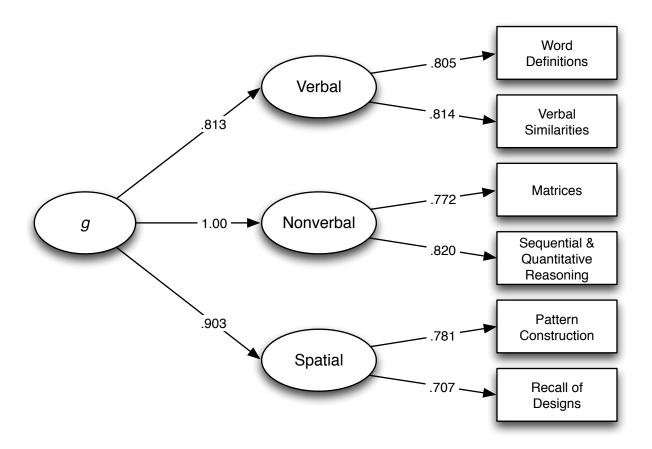
Figure 4. Bifactor measurement model with standardized coefficients, for the 6 DAS–II core subtests for ages 3:6 to 6:11, *N* = 920. All standardized coefficients statistically significant, *p* < .05.

Figure 5. Higher-order measurement model with standardized coefficients, for the 6 DAS–II core subtests for ages 7:0 to 17:11, *N* = 2,188. All standardized coefficients statistically significant, *p* < .05.
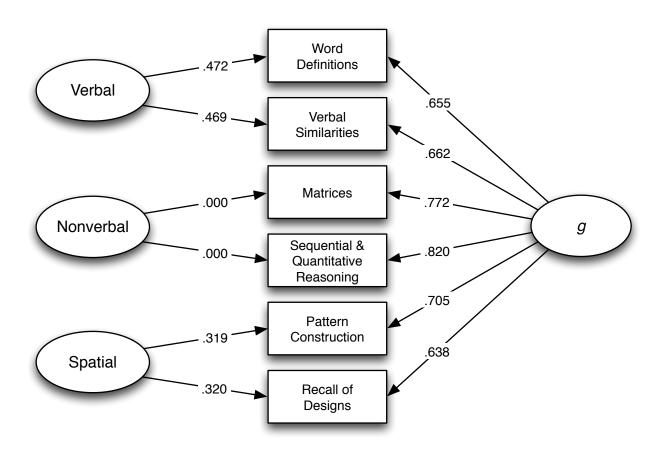
Figure 6. Bifactor measurement model with standardized coefficients, for the 6 DAS–II core subtests for ages 7:0 to 17:11, *N* = 2,188. All standardized coefficients statistically significant, *p* < .05 except Nonverbal to Matrices and Nonverbal to Sequential & Quantitative Reasoning paths.
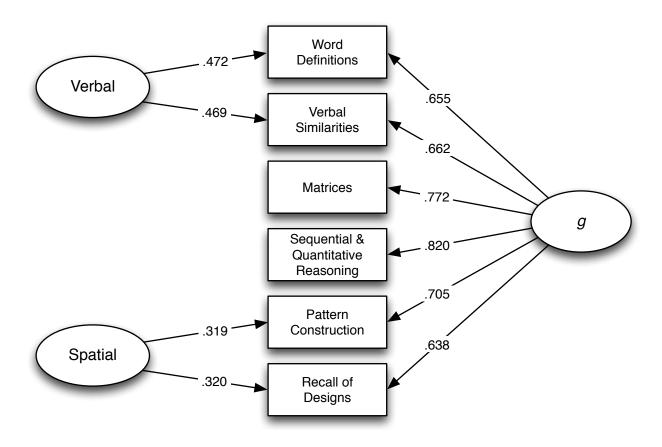
Figure 7. Final bifactor measurement model with standardized coefficients, for the 6 DAS–II core subtests for ages 7:0 to 17:11, $N = 2,188$. All standardized coefficients statistically significant, $p < .05$.