Received: 29 August 2017 | Accepted: 20 November 2017
DOI: 10.1002/pits.22096

WILEY

RESEARCH ARTICLE

Investigating the theoretical structure of the DAS-II core battery at school age using Bayesian structural equation modeling

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Abstract
Bayesian structural equation modeling (BSEM) was used to investigate the latent structure of the Differential Ability Scales—Second Edition core battery using the standardization sample normative data for ages 7–17. Results revealed plausibility of a three-factor model, consistent with publisher theory, expressed as either a higher-order (HO) or a bifactor (BF) model. The results also revealed an alternative structure with the best model fit, a two-factor BF model with Matrices (MA) and Sequential and Quantitative Reasoning (SQ) loading on *g* only with no respective group factor loading. This was only the second study to use BSEM to investigate the structure of a commercial ability test and the first to use a large normative sample and the specification of both approximate zero cross-loadings and correlated residual terms. It is believed that the results produced from the current study will advance the field's understanding of not only the factor structure of the DAS-II core battery but also the potential utility of BSEM in psychometric investigations of intelligence test structures.

KEYWORDS
Bayesian structural equation modeling, bifactor model, confirmatory factor analysis, Differential Abilities Scales, Second Edition, intelligence, structural validity

The Differential Ability Scales—Second Edition (DAS–II; Elliott, 2007a) is an individually administered test of cognitive ability for children and adolescents ages 2–17 years. The DAS–II is divided into three levels: Lower Early Years (ages 2:6 through 3:5), Upper Early Years (3:6 through 6:11), and School Age (7:0 through 7:11). At school age, the DAS-II contains six core subtests that yield three first-order composite scores referred to as *cluster* scores (Verbal Ability, Nonverbal Reasoning Ability, and Spatial Ability) as well as a full-scale General Conceptual Ability (GCA) score thought to reflect psychometric *g* (Spearman, 1927). There are also 10 diagnostic subtests that contribute the measurement of two additional cluster scores (Working Memory and Processing Speed). These cluster scores can be used by examiners to supplement the core battery. However, none of these supplemental measures contribute to the measurement of the GCA or the three primary clusters, nor can they be exchanged for any of the core battery measures. It is also noted that the Early Years battery features different core and diagnostic subtest configurations and not all school-age clusters are available.[1] According to the *Introductory and Technical Handbook* (Elliott, 2007b; hereafter referred to as the "Technical Handbook"), this is the result of being unable to measure certain constructs well (e.g., Processing Speed, Working Memory) at younger ages.

1.1 | Factor structure of the DAS–II

To validate the DAS–II at school age, the test publisher relied exclusively on confirmatory factor analysis (CFA) using maximum-likelihood (ML) estimation to appraise the six subtest core battery and structure for normative participants ages 7–17.[2] Four oblique (correlated) factors models ranging from one to three factors (one model was a variant of the two-factor model with cross-loading permitted) were specified and evaluated for adequacy. Fit statistics reported in the Technical Handbook indicate that a three-factor model consistent with publisher theory fit the standardization sample data well though the factor loadings for this model were not presented.

Similar analyses were also conducted to evaluate different configurations of the core and diagnostic measures at school age. For these analyses, the normative sample was split into two groups (6:0–12:11 and 6:0–17:11) with a 14 subtest configuration used at ages 6–12 and a 12 subtest configuration used at ages 6–17. Although a seven-factor model was retained for ages 6–12, it was suggested that a six-factor model best fit the normative data for ages 6–17. The Technical Handbook indicates that both structural models are *likely* consistent with the Cattell–Horn–Carroll theory of cognitive abilities (CHC; Schneider & McGrew, 2012); however, several first-order factors were specified (e.g., Auditory Processing, Visual–Verbal Memory, and Verbal Short-Term Memory) that were not available for scoring and interpretation in the actual DAS-II. 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 reflecting factors that are underidentified. Although the inclusion of singlet variables is possible in CFA, they should not be interpreted as latent factors because they do not contain any shared common variance (Brown, 2015).

Since its publication, independent factor analytic investigations of the DAS–II structure have been scarce. In one of the two studies that could be located, Keith, Low, Reynolds, Patel, and Ridley (2010) used CFA to investigate the age invariance of the DAS–II full test battery (20 subtests). The measurement model was derived from the normative data from participants ages 5–8. As previously mentioned, this is the only age bracket at which the Early Years and School-Age batteries are co-normed. Rival models were evaluated, containing different mixtures of correlated errors ($n = 10$), cross-loadings ($n = 10$), and additional post-hoc modifications with a separate validation sample ($n = 5$). Despite these modifications, the fit statistics for many of the models were indistinguishable. Nevertheless, a measurement model was selected and tested. Keith et al. (2010) explained that the subtests not administered in other age groups were treated as latent variables using the reference variable approach suggested by McArdle (1994). As described by Keith et al. (2010), "This method allows the researcher to keep the full model as the comparison model" (p. 688). In this procedure, subtests that are not administered at an age level are treated as latent variables, while constraining their parameters and loadings to be equal to the values obtained for the age group at which they are administered (ages 5–8). Ultimately, a six-factor, CHC-based, higher-order (HO) model (Crystallized Ability, Fluid Reasoning, Visual Processing, Long-Term Retrieval, Short-Term Memory, and Processing Speed) was found to be invariant across the instrument. It should be noted that the final validation model for ages 4–17 required the specification of additional parameters, including correlated residual terms not only for subtests (e.g., Copying and Recall of Designs), but also group factors (Visual Processing [Spatial Ability] and Fluid Reasoning [Nonverbal Reasoning]). The analysis also incorporated a theoretically inconsistent cross-loading (i.e., Verbal Comprehension was found to load on Crystallized Ability and Fluid Reasoning).

[1] Several Early Years measures have restricted age bands that preclude them from being administered at school age. However, both batteries are co-normed at ages 5:0 through 8:11, permitting "out of level" testing for examinees in that age bracket.

[2] It appears additional exploratory analyses were conducted by the project team (see p. 157, Elliot, 2007b); however, description and results of these procedures are not presented in the Technical Handbook.

Given these departures from desired simple structure and the incorporation of out-of-range measures across the age span, the practical implications of these findings are unclear.

Considering that the models produced from the core battery CFA analyses were not presented in the Technical Handbook, users of the DAS–II electing to administer and interpret the core battery may be tempted to extrapolate from the CFA analyses from the full DAS–II battery. However, results furnished by a recent exploratory factor analytic (EFA) of the DAS–II core battery structure suggest this practice may be problematic. Canivez and McGill (2016) used principal axis factoring with promax rotation followed by the Schmid–Leiman Orthogonalization (Schmid & Leiman, 1957) to disclose an approximate exploratory bifactor (BF) structure of the DAS–II core battery. Whereas empirical extraction criteria suggested that DAS–II was a one-factor test, a forced three-factor extraction produced subtest alignment consistent with that proposed within the Technical Handbook. Nevertheless, the variance accounted for by the three group factors (Verbal, Nonverbal, and Spatial) was consistently small suggesting the DAS–II may be overfactored (Frazier & Youngstrom, 2007). Specifically, once variance was apportioned to higher- and lower-order constructs, as recommended by Carroll (1993, 1995), most of the variance in the DAS–II subtests was sourced to *g*, rendering the Nonverbal factor ill-defined (i.e., contained less than two salient subtest loadings).

Historically, two basic factor analytic techniques have been used to evaluate the internal structure of intelligence tests: EFA and CFA. Although EFA and CFA have been used to provide insight on the DAS–II structure, the results of these investigations have not clarified what the DAS–II core battery measures. Whereas EFA results suggest that the core battery may be overfactored and mostly reflects general intelligence, CFA investigations using various combinations of the core and diagnostic subtests have provided evidence to support the three group factors posited for the core battery model. The invariance results produced by Keith et al. (2010) suggest that the relationships among DAS–II variables may be more complex than the simple structure portrayed in the CFAs reported in the Technical Handbook (i.e., no cross-loading or correlated residuals). Gorsuch (1983) and others (Carroll, 1985; Horn, 1989) suggest that when different methods of factor analysis converge upon the same solution then greater confidence may be engendered in the instrument's factor structure. These discrepant results suggest that additional analyses of the DAS–II factor structure may be worthwhile.

It is worth pointing out that there are important differences between EFA and CFA. EFA models are weakly specified. CFA models are more flexible, requiring the researcher to specify all relevant aspects of the model a priori. Within the factor analytic literature, it is frequently suggested that EFA is preferred when the relationship among variables is less understood and CFA is a better method for formal model testing.[3] Nevertheless, both methods have limitations. EFA procedures can underestimate the number of factors and may produce solutions that oversimplify data (Mulaik, 2010). CFA may be able to detect previously omitted variance; however, as models become more complex as the researcher adjusts the model there is a threat of capitalizing on chance and retaining a model that may not generalize to other samples (MacCallum, Roznowski, & Necowitz, 1992). As a result, “researchers are often left with the dilemma of whether to keep meaningful alternatives untested or to risk overfitting their model to the data” (Golay, Reverte, Rossier, Favez, & Lecerf, 2013, p. 498). Horn (1989) also recognized an additional limitation of CFA methodology as it relates to cognitive ability.

> *At the present juncture of history in the study of human abilities, it is probably overly idealistic to expect to fit confirmatory models to data that well represent the complexities of human cognitive functioning: too much is unknown. Even when we can, a priori, specify a multiple-variable model that fits data in a general way—with chi-square three or four times as large as the number of degrees of freedom (df)—we cannot anticipate all the small loadings that must be in a model for a particular sampling of variables and subjects if the model is to “truly fit data” (p. 39). Horn continued, “The statistical demands of structure equation theory are stringent. If there is tinkering with results to get a model to fit, the statistical theory, and thus the basis for strong inference, goes out the window (p. 39).*

[3] In practice, the line between EFA and CFA is less clear. For instance, one can use EFA in a confirmatory context and CFA in an exploratory fashion. Thus, it is better to think of EFA and CFA more generally as techniques for conducting factor analysis. Whether an approach is *exploratory* or *confirmatory* depends on its application.

Horn (1989) also explained that when there is excessive model tinkering then "… one should not give any greater credence to results from modeling analyses than one can give to results from comparably executed factor analytic studies of the older variety"(e.g., EFA) (p. 40). Bayesian structural equation modeling (BSEM) represents a methodological procedure that can provide a useful, and perhaps even elegant, solution for researchers faced with the dilemma of considerable post hoc model adjusting—what Horn described as "tinkering"—by permitting the specification of small-variance cross-loadings (and correlated residuals) that come close to zero but are not fixed at zero. This methodological procedure attempts to incorporate aspects of both EFA and CFA and may well overcome limitations of both methodologies.

1.2 | Bayesian structural equation modeling

BSEM is based upon Bayes' theorem, a mathematical proof created by Thomas Bayes, an 18th century theologian, that has been recently rediscovered by applied measurement researchers following the arrival of microcomputers with sufficient processing capabilities, the creation of statistical software capable of performing complex Bayesian modeling, and greater confidence in Bayesian estimation that challenges many assumptions of traditional Gaussian statistics (Brown, 2015; Kaplan & Depaoli, 2013). One of the most famous—but until recently, secret—uses of Bayesian methodology was to decipher the German enigma code during the Second World War (Stone, 2013). However, the application of Bayesian methodology to understand applied cognitive measurement issues is in its infancy. To date, within the fields of psychometrics and intelligence research there has been only one application of Bayesian estimation. Golay et al. (2013) used the procedure to acquire further insight into the French WISC–IV theoretical structure. Application of BSEM revealed that a five-factor CHC-based direct hierarchical (BF) model best fit the data produced from a clinical sample ($N = 249$) of French-speaking Swiss children. However, in their application of BSEM, Golay et al. (2013) did not include estimation of small variance correlated residuals, potentially important features of the BSEM technology (Muthén & Asparouhov, 2012). The present study seeks to extend use of BSEM to a different measure of cognitive ability to help understand its factor structure and apply other aspects of the BSEM model not included in previous analyses (e.g., simultaneous estimation of approximate zero cross-loadings and approximate zero correlated error terms).

BSEM holds promise for the understanding of the latent structure of assessment instruments used within many fields including psychology, health, business, and education (Muthén & Asparouhov, 2012). It portends to better reflect substantive theory and overcome some of the limitations of traditional (i.e., termed frequentist) exploratory and confirmatory factor analytic procedures (Brown, 2015). One of the major limitations of classical ML CFA estimation is the need to often apply overly strict constraints to represent hypotheses about latent structure, leading to the rejection of a tested model and a subsequent series of model modifications that may capitalize on chance (MacCallum et al., 1992; Marsh et al., 2009). This is noticeable in the requirement to fix cross-loadings to zero and estimate only selected residual correlations that are specified a priori. Although EFA freely yields cross-loadings, it limits the researcher to a decision regarding how many factors should be extracted and retained, and hypothesized factor complexity (i.e., how to best determine simple structure where each subtest score loads on a single factor). With EFA, the assignment of indicators to particular factors is not necessarily specified a priori by the researcher as it is with CFA; instead, data are allowed to "speak for themselves" within the factor analytic algorithm assigning the location of major factor loadings and cross-loadings (Carroll, 1985; Gorsuch, 1983). In some respects BSEM attempts to incorporate aspects of both exploratory and confirmatory factor analytic methods (Golay et al., 2013).

BSEM has the capacity to specify not only cross-loadings, but also correlated residuals using priors that come close to, but are not fixed at, zero. Because of this, Bayesian estimation may permit an otherwise nonidentified model to be identified. The practice of estimating all correlated residuals is currently a topic of debate with some suggesting it should be avoided (Stromeyer, Miller, Sriramachandramurthy, & DeMartino, 2015) and others contending that it better clarifies an instrument's structure (Muthén & Asparouhov, 2012). Stromeyer et al. (2015) criticized the use of simultaneous estimation of small but informative correlated error terms; however, Asparouhov, Muthén, and Morin (2015) suggested that Stromeyer et al. (2015) may have misapprehended the approach and provided additional guidelines for the use of small variance correlated residuals. Asparouhov et al. (2015) concluded that instead of adding *statistical*

TABLE 1 Summary of ML CFA, BSEM, and EFA characteristics

Characteristics	ML CFA	BSEM	Traditional EFA
Theory	Frequentist	Bayes	Frequentist
Parameters	Constants	Variables	Constants
Cross-loadings	Exact zeros	Estimated via informative priors (zero mean and small variance)	Freely estimated
Major loading	Freely estimated	Diffuse noninformative priors (zero mean and infinite variance)	Freely estimated
Correlated residuals	Specified requiring a degree of freedom	Informative priors (zero mean and small variance)	Not available
Model modification	Multiple indices with improvement made one parameter at a time	All parameters freed and simultaneously estimated. Use of DIC in Mplus and additional indices (i.e., LOO; WAIC) in other statistical applications	Typically not used but some are available
Parameter estimates	Typically assumed to be normally distributed (not all cases)	Does not assume a normal distribution but that has implications for bias and variance in resulting estimates	Typically assumed to be normally distributed (not in all cases)
Sample size	Requires large sample size	Sample size less of a concern and can work with small sample sizes. With small sample sizes the prior dominates, which decreases variance and increases bias. With larger samples sizes the influence on the posterior is diminished making estimates similar to those produced by ML CFA	Requires large sample size

noise to the model as Stromeyer et al. (2015) suggested, the use of correlated residuals can be used to improve upon an understanding of a structural or measurement model. Despite Asparouhov's et al.'s (2015) clarification regarding how to properly estimate correlated residuals, generalized apprehension about its use remains, notably that its inclusion may result in models with limited theoretical meaning (Rindskopf, 2012) and cumbersome additional computations that does little to improve structural clarity (Stromeyer et al., 2015). Whereas the specification of informative, small variance, cross-loading is generally better accepted, the function of correlated residuals remains an issue that requires further examination, discussion, and modeling via simulation (e.g., Asparouhov et al., 2015; Brown, 2015; Stromeyer et al., 2015).

A summary of the general characteristics of BSEM relative to ML CFA and EFA is presented in Table 1, whereas more specific details regarding Bayesian estimation are provided in the forthcoming section.

1.3 | Bayesian estimation

Bayesian analysis uses a distribution known as a *prior* and views parameters as variables instead of constants (Muthén & Asparouhov, 2012; Zyphur & Oswald, 2015). The selection of a prior may be predicated upon theory, pilot studies, or results from EFA studies (Gelman et al., 2004; Stone, 2013). With BSEM, data inform about a parameter and modify a prior into a posterior that produces a Bayesian estimate (often a median value). There are three different distributions associated with Bayesian estimation: the prior, the posterior, and the likelihood (Gelman et al., 2014; Gelman, Meng, & Stern, 1996). The likelihood is the distribution of data given a parameter value. The posterior reflects a distribution that lies in between a prior and the likelihood. Within this context, priors can be either diffuse (i.e., noninformative) or informative. A noninformative prior usually has a normal distribution with a large variance, although it could theoretically also have a uniform distribution. A large variance reflects a high degree of uncertainty in the parameter value.

When the prior variance is large, the likelihood contributes more information to the formation of the posterior and the estimate is closer to the ML estimate (Muthen & Asparouhov, 2012).

1.4 | Markov chain Monte Carlo (MCMC)

Bayesian estimation utilizes MCMC (Edwards, 2010; Green, 1995; Link & Eaton, 2012) algorithms to iteratively draw random samples from the posterior distribution of the model parameters. Mplus uses the Gibbs algorithm (Cassella & George, 1992) to undertake MCMC sampling. When a model is run in BSEM one of the first characteristics to observe is whether the model converges. Convergence of the MCMC algorithm is evaluated by monitoring the potential scale reduction (PSR) convergence criterion (Gelman & Rubin, 1992; Gelman et al., 2014). The first half of the MCMC chains is discarded as the burn-in phase, whereas the second half is used to estimate the posterior distribution (Muthén & Asparouhov, 2012). During the first half it is not uncommon for the PSR to fluctuate before stabilizing in the second half of the algorithm. The PSR criterion compares within- and between-chain variation of parameter estimates. A PSR of <1.10 indicates an acceptable convergence level, whereas a PSR of 1.00 is considered perfect model convergence (Kaplan & Depaoli, 2013). Convergence of the MCMC algorithm may also be assessed by monitoring the posterior distribution through trace and autocorrelation plots (Muthén & Muthén, 1998–2017). Convergence is considered attained when there is an absence of rapid up-and-down fluctuations and an absence of trends over time (Kaplan & Depaoli, 2013). If a model does not converge then it is appropriate to increase the number of iterations (I) first by two (2I) and then by four (4I, Muthén & Asparouhov, 2012). Once model convergence has been established it is then appropriate to move to an investigation of model fit with the data and consideration of which model might be preferred.

1.5 | Model fit and comparison

Posterior predictive checking is used to determine model fit with data. Although researchers have used the posterior predictive *P*-value (PPp) value as a model comparison tool, it is most appropriately used for checking whether a particular model suggests that the modeled data are similar to data that are actually observed (Gelman, Meng, & Stern, 1996). There are additional model comparison tools that may be utilized to compare models. These include leave-one-out cross-validation (LOO), the widely applicable information criterion (WAIC), and the deviance information criterion (DIC; Levy, 2011; Vehtari, Gelman, & Gabry, 2017). LOO and WAIC are generally infrequently utilized by statisticians and applied researchers because of their additional programming and computational complexity. Currently, Mplus offers users DIC and Bayesian information criterion (BIC; Muthén & Muthén, 1998–2015). BIC is appropriate only when informative priors (i.e., small variance cross-loading or correlated residuals) are *not* specified (Muthén & Asparouhov, 2012). LOO and WAIC are available in other statistical applications such as R (R Developmental Core Team, 2017) but not in Mplus at the present time. This generally leaves one model fit index, DIC, to determine which model is to be preferred (Muthén & Asparouhov, 2012). With BSEM, however, the need to adjust model parameters and rely upon multiple modification indices the way they are adjusted in ML CFA tends to be obviated by the simultaneous estimation of all cross-loadings and correlated error terms. Finally, because all relationships among indicators and factors are estimated simultaneously, this may eliminate the need for the comparison of many slightly different models.

1.6 | Posterior predictive checking

The range in values of PPp is from 0 to 1, with a value of .50 considered perfect model fit (Gelman et al., 1996; Muthén & Asparouhov, 2012). Values of less than .10, or greater than .90, suggest a poor model fit with data. As with *P*-values in a frequentist analysis, the sampling distribution of a PPp under a true null hypothesis is uniform between 0 and 1 (Gelman et al., 1996). In practice, PPp seems to have lighter tails under the null than frequentist *P*-values, but any value between .10 and .90 is considered almost equally likely under the null. Like a frequentist *P*-value, it only signals something is wrong with a model when a PPp estimate is at an extreme tail. In other words, if PPp is less than .10 then the model rarely fits the observed data as well as data simulated under that model's parameters; thus, it is to be concluded that the data are not very consistent with the model. Stated another way, PPp values indicate that model is able to make predictions that are similar to the observations made about the model.

1.7 | Deviance information criteria

The DIC is the test statistic available in Mplus to compare among models and determine which model is preferred. Much like frequentist test statistics, the DIC is to be interpreted in the same way as other ML CFA information criterion fit statistics (i.e., AIC and BIC). This suggests that lower values are generally preferred although theoretical convergence is also important to consider.

1.8 | Purpose of the current study

The present investigation sought to apply BSEM to the DAS–II standardization sample data to understand better the core battery factor structure for ages 7–17. The application of BSEM to the DAS–II factor structure presents an opportunity to compare the procedure across different types of structural models (oblique, HO, BF). The present study will also serve as a comparative test of BSEM relative to results produced from frequentist exploratory (i.e., Canivez & McGill, 2016) and confirmatory factor analytic methods (i.e., Technical Handbook, Elliott, 2007b; Keith et al., 2010) for the measurement instrument. This is also the first BSEM study of a cognitive ability test taking advantage of a large sample size and the use of correlated residuals; thus, it is believed that the results produced from the current study will be instructive for advancing the field's understanding of not only the factor structure of the DAS-II core battery but also the potential utility of BSEM in psychometric investigations of intelligence test structures.

2 | METHOD

2.1 | Participants

Participants were drawn from the DAS–II standardization sample and included a total of 2,188 individuals ranging in age from 7 to 17:11 years. The standardization sample was obtained using stratified proportional sampling across demographic variables of age, sex, race/ethnicity, parent educational level, and geographic region. Details of demographic characteristics and close approximation to population characteristics are provided in the Technical Handbook (Elliott, 2007b).

2.2 | Instrument

The DAS–II is an individually administered test of intelligence that includes six core subtests across the 7–17:11 age range and a mixture of 10 supplemental diagnostic subtests. At this age range the DAS–II core subtests combine to form a GCA score as well as three primary cognitive clusters at the first-order level, each composed of two subtests. The clusters include Verbal, Nonverbal, and Spatial. Supplemental diagnostic subtests are also available, which can be combined to form additional first-order clusters (e.g., working memory, processing speed) but these measures are not utilized to calculate the HO GCA or the three primary cognitive clusters. As previously noted, the Early Years battery contains different combinations of core subtests and cluster scores. For the sake of parsimony, the present study is focused specifically on the core battery at school age as it is at that age that the DAS–II structure is most consistent.

2.3 | Procedure and analyses

The DAS–II standardization sample participant raw data for the six core, age 7–17:11 subtests were obtained from the test publisher. Bayesian structural equation modeling was used to investigate two- and three-factor (oblique, HO, BF) models from the DAS–II, which included a test of the three-factor HO structure furnished in the Technical Handbook. Additionally, a derivation of a two-factor BF structure was investigated where the two nonverbal subtests (Matrices [MA] and Sequential and Quantitative Reasoning [SQ]) loaded only on *g*. This model was tested post hoc and after observing that the two- and three-BF structures had subtests (MA and SQ) with approximate zero loadings on the nonverbal group factor.

Mplus 8.0 (Muthén & Muthén, 1998–2017) was used for Bayesian estimation. Three different BSEM procedures were invoked to test each of the models: (1) an analysis *without* cross-loadings or correlated residuals; (2) an analysis where all cross-loading are simultaneously estimated; and (3) and an analysis where all cross-loadings *and* correlated residuals are simultaneously estimated.

A prior mean of 0 and variance of .01 was established for cross-loadings. For the cross-loadings this resulted in a range of −.20 to .20 for the resulting cross-loading estimates. If the model failed to converge then a prior cross-loading variance of .001 was specified. This reduced the range of the cross-loadings estimates from −.06 to .06. An Inverse-Wishart prior variance of .01 was selected for specification of residual prior variance (Asparouhov & Muthén, 2010).

Three MCMC chains were utilized and iterations were established at 150,000 with the first 75,000 being discarded as the burn-in phase. A model was determined to have attained convergence under two conditions: (1) a PSR value stabilizing on a value less than 1.10; and (2) a satisfactory Kolmogorov–Smirnov distribution (i.e., no discrepant posterior distributions in the different MCMC chains; Muthén & Muthén, 1998–2017). In cases where the model failed to converge using 150,000 iterations then the number of iterations was increased to 250,000. Generally, it is appropriate to increase iterations (I) by a factor of two (i.e., I, I2, then I4; Muthén & Muthén, 1998–2017) but this is dependent upon computing power. If the model converged then the next step was to investigate the PPp. As previously noted, a perfect fit of the model to the data is a PPp of .50 with values <.10 or >.90 considered poor model fit meriting model rejection. Following acceptable model fit with these data via the PPp, the DIC was referenced as the main index to compare competing models. Finally, models were examined in relation to theoretical plausibility as guided by the prevailing literature base.

Omega-hierarchical (ω_{H}) and omega-hierarchical subscale (ω_{HS}) coefficients (Reise, 2012; Rodriguez et al., 2016) were estimated as model-based reliability estimates of the latent factors (Gignac & Watkins, 2013) for both the BF and HO models. Although omega coefficients have been referred to as model-based reliability estimates, they may also be conceived of as validity estimates as they present data regarding the plausibility of interpreting general and group factors (Gustafsson & Aberg-Bengtsson, 2010). Omega coefficients should at a minimum exceed .50, but .75 would be preferred (Reise, 2012; Reise, Bonifay, & Haviland, 2013). Additionally, Hancock and Mueller (2001) suggested use of an index of construct reliability or replicability (called *H*) that reflects the proportion of variability in the construct that is explained by its own indicators and furnishes an estimate of the reliability of the underlying factor. High *H*-values (>.80) suggest a well-defined latent variable that portends to be stable across studies. Rodriquez et al. (2016) indicated that it is difficult to specify group factors within a single instrument and it should only be done when *H*-values are higher than .70. Further, when *H*-values are large, it might be useful to utilize a weighted composite score instead of unit-weighted composite score. The percentage of uncontaminated correlations (PUCs) was also referenced. PUC determines the potential bias associated with forcing multidimensional data into a unidimensional model. When explained common variance (ECV) and PUC are both greater than .70, then the relative bias will be slight and the common variance might best be considered unidimensional (Rodriquez et al., 2016). Omega-hierarchical and omega-hierarchical subscale coefficients, PUC, and *H* were estimated using Watkin's (2013) Omega program. To estimate these values in the HO models, the group factors needed to be residualized of general factor variance.

3 | RESULTS

Table 2 presents the results of BSEM of the DAS–II investigating the two- and three-factor oblique, HO, and BF models under three conditions: (1) without small variance priors as identified by the “a” model versions; (2) with small

TABLE 2 Comparison of model fit for the DAS-II core battery ages 7–17 using Bayesian structural equation modeling

Models	Number of Free Parameters	Posterior Predictive P-Value (PPP)	Difference Between Observed and Replicated χ^2 95% CrI Lower 2.5%	Upper 2.5%	DIC	pD
1. Single factor (*g*)	18	.000	327.114	364.872	31,902.352	18.116
2a. Two-factor oblique	19	.000	32.459	70.882	31,608.850	18.994
2b. Two-factor oblique (with cross-loadings .01)	25	.001	50.473	103.480	31,635.589	20.912
2c. Two-factor oblique (cross-loadings and correlated residuals .01)	40	.500	−20.558	20.566	31,553.384	15.302
3a. Two-factor higher order	20	.000	16.227	55.776	31,594.712	20.354
3b. Two-factor higher order (cross-loadings .001)	26	.000	22.503	63.462	31,601.397	19.686
3c. Two-factor higher order (xload/corr resd .001; *I* = 250k; Table SA4)	41	.500	−20.702	20.445	31,554.280	16.227
4a. Two-factor bifactor	23	.475	−19.705	19.802	31,557.689	19.196
4b. Two-factor bifactor (xload .001 Table 4)	29	.539	−21.158	18.862	31,554.227	17.146
4c. Two-factor bifactor (xload/resd corr .001; *I* = 250k)[a]		Model	Did not	Converge[a]		
5a. Two-factor bifactor MA and SQ on *g* only	20	.385	−16.952	21.401	31,560.490	19.897
5b. Two-factor bifactor MA and SQ on *g* only (cross-loadings .01; Table SA1)	28	.507	−20.894	19.514	31,561.036	23.211
5c. Two-factor bifactor MA and SQ on *g* only (xload and corr res .01; Table 5)	43	.499	−20.532	20.655	31,546.422	8.318
6a. Three-factor oblique	21	.358	−16.651	23.073	31,562.399	20.854
6b. Three-factor oblique (with cross-loadings .01)	33	.458	−19.659	20.276	31,560.556	21.537
6c. Three-factor oblique (xload and corr residual .01; Table SA2)[b]	48	.499	−20.620	20.289	31,543.577	5.483
7a. Three-factor higher order	21	.353	−16.289	23.101	31,562.034	20.266
7b. Three-factor higher order (cross-loadings .001; Table SA3)	33	.464	−19.530	19.080	31,559.694	20.926
7c. Three-factor higher order (xload and corr residual .001)	48	.501	−20.672	20.668	31,561.587	23.546
8a. Three-factor bifactor	21	.354	−16.812	22.217	31,561.803	20.504
8b. Three-factor bifactor (with cross-loadings .001; Table 3)	33	.508	−20.115	18.786	31,559.564	21.828
8c. Three-factor bifactor (xload and corr resid .001; *I* = 250k)[a]		Model	Did not	Converge[a]		

Note. PPP = posterior predictive *P*-value; CrI = credibility interval; DIC = deviance information criterion; pD = estimated number of parameters; MA = Matrices; SQ = Sequential & Quantitative Reasoning; *g* = general intelligence; *I* = Iterations.

[a]Kolmogorov–Smirnov distribution test indicates model noncovergence.

[b]CI for saliently loading verbal subtests contains values > 1.00.

variance priors for cross-loadings only, as identified by the "b" model versions; and (3) with small variance priors for cross-loadings and correlated residuals, as identified by the "c" model versions. A single factor (*g*) model was also investigated. When BSEM does not utilize small variance, informative priors for cross-loadings or correlated residuals (i.e., all "a" models from Table 2), then the model is said to be akin to a frequentist ML CFA.

All of the models (see Table 2) examined, except for models 1 (single factor), 2a, and 2b (two-factor oblique), and 3a and 3b (two-factor HO), fit these data well according to an examination of the PPp (PPp > .10). When investigating the PPp, it is further noted that several of the models displayed near perfect fit with these data (.50; see models 2c, 3c, 5c, 6c, and 7c; Table 2). This was most commonly found when both cross-loadings and correlated residuals were specified (two exceptions were the BF models [i.e., 5b and 8b] in which only cross-loadings were specified). These latter two models failed to converge when correlated residuals were estimated.

Although the PPp value should be used to determine how well the data fit the model, DIC along with theoretical considerations should be used to compare models and determine which model is preferred (Asparouhov et al., 2015; Brown, 2015). Improvements in model fit both within (i.e., models "a" to "c") and between (i.e., 1 through 8) models was determined by examining the DIC (with models that had a PPp > .10). All models with PPp > .10 demonstrated a slightly lower DIC when cross-loadings were incorporated, except for models 3b and 5b. In those two cases the "a" version (that did not incorporate cross-loadings or correlated residuals) was preferred to the models that incorporated small variance cross-loadings.

When correlated residuals, along with cross-loadings, were incorporated, five of the models (2c, two-factor oblique; 3c, two-factor HO; 5c, two-factor BF with MA and SQ on *g* only; 6c, three-factor oblique; 7c three-factor HO) then demonstrated perfect fit with these data (PPp = .499 or .500). However, the two- and three-factor BF models (4c and 8c) failed to converge when specifying correlated residuals. Additionally, the three-factor HO (model 7c) demonstrated a slightly higher DIC when all residuals were correlated. The three remaining models (two oblique [2c]; three HO [3c]; two BF plus MA and SQ on *g* only [5c]; and three-factor oblique [6c]) demonstrated a lower DIC, indicative of improved model fit, when both correlated residuals and cross-loadings were specified. Additionally, examining the publisher's proposed three-factor HO model versus a three-factor BF model revealed nearly identical DIC when no cross-loadings (model "a" versions) or when cross-loadings (model "b" versions) were specified. This is consistent with ML CFA research that suggests that just identified models have nearly identical fit whether a HO or BF model is specified (Brown, 2015; also see McGill & Dombrowski, 2017 for an applied example).

3.1 | Pattern of subtest loadings

An investigation of the pattern of subtest loadings was informative. Within the two- and three-factor BF models (8b and 4b) the group nonverbal factor loadings were near zero for all BF models (Tables 3 and 4) suggesting that once the two subtests were residualized of their general factor variance the two subtests had negligible group factor variance. This finding similarly occurred when the "a" model versions without informative cross-loadings or correlated residuals were included with the BF models, although the "a" model version had lower *g* loadings for MA and SQ compared to the "b" model version. Thus, the decision was made to test a derivation of the two-factor BF model where MA and SQ loaded only on *g* [two BF plus MA and SQ on *g* only (model 5 (a–c); Tables 5 and SA1)]. With the exception of the three oblique factors model (6c; Table SA2), the two BF plus SQ and MA on *g* only model (model 5c; Table 5) had the lowest DIC when both cross-loadings and correlated errors were specified. Although the oblique model (Table SA2) had a lower DIC, it was deemed to be theoretically inferior as tests of cognitive ability are generally presumed to have a hierarchical latent ability factor, presumably general intelligence (Carroll, 1993; Gorsuch, 1983). An examination of the three-factor HO model (Table SA3), which included cross-loadings, suggested that all subtests were aligned with theoretically proposed factors. This did not occur with its three-factor BF counterpart (Table 2) wherein MA and SQ had approximate zero loadings on the nonverbal group factor once general ability was residualized. The two-factor HO model (Table SA4) with both cross-loadings and correlated residuals produced loadings consistent with theoretically proposed factors.

TABLE 3 Three-factor bifactor BSEM with cross-loadings and small variance (.001) priors

Loading Estimates (Median)	General									
	g		Verbal		Nonverbal		Spatial			
	b	S^2	*b*	S^2	*b*	S^2	*b*	S^2		
Subtest	[95% CI]		[95% CI]		[95% CI]		[95% CI]		h^2	u^2
Word definitions	**.658 [.621**	**.433 .694]**	**.467 [.419**	**.218 .511]**	.000 [−.061	.000 .061]	−.004 [−.056	.000 .047]	.653	.347
Verbal similarities	**.665 [.628**	**.442 .701]**	**.467 [.419**	**.218 .511]**	.000 [−.062	.000 .060]	−.002 [−.054	.000 .049]	.662	.338
Matrices	**.766 [.731**	**.587 .796]**	−.004 [−.055	.000 .045]	**−.020 [−.215**	**.000 .196]**	.014 [−.045	.000 .071]	.601	.399
Sequential and Quantitative	**.810 [.777**	**.656 .840]**	.017 [−.036	.000 .067]	**−.020 [−.215**	**.000 .197]**	−.007 [−.064	.000 .050]	.671	.329
Pattern construction	**.714 [.681**	**.510 .748]**	−.027 [−.075	.001 .020]	.000 [−.063	.000 .063]	**.302 [.222**	**.091 .363]**	.604	.396
Recall of designs	**.639 [.602**	**.408 .676]**	.016 [−.032	.000 .063]	.000 [−.060	.000 .062]	**.302 [.223**	**.091 .363]**	.501	.499
									.615	.385
ECV[a]		.822		.118		.000		.049	.991[a]	
Total variance		.506		.073		.000		.030		
ω_H / ω_{HS}		.835		.263		.000		.118		
H		.869		.358		.001		.167		
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_H = omega-hierarchical (general factor); ω_{HS} = omega-hierarchical subscale (group factors); BSEM = Bayesian structural equation modeling; CI = confidence interval; *g* = general intelligence.
[a]Does not total to 100% due to use of median parameter estimates. Loadings in bold were freely estimated. Other loadings were estimated with small (.001) variance priors.

Examination of variance apportionment along with omega statistics, *H* and PUC—presented at the bottom of Tables 2 through 5 and Tables SA1 through SA4—all converge to suggest that the general factor absorbed a considerable proportion of both total and common variance across all HO and BF models. Across all BF and HO models investigated, the ECV of the general factor ranged from .663 to .823. Individual group ECV ranged from .000 to .218. The general factor similarly accounted for a considerably higher proportion of total variance ranging from .442 to .508 than did the group factors. Group factor total variance ranged from .000 to .145.

Omega hierarchical and omega hierarchical subscale coefficients suggested that interpretation of the DAS–II should reside primarily at the HO or general (GCA) level, whether a BF or HO was referenced, with omega hierarchical ranging from .711 to .838. Omega hierarchical subscale ranged from .000 to .274, again supporting primary emphasis on general factor interpretation. When looking at PUC in combination with the ECV of the general factor, it is evident that the DAS–II is dominated by a general factor. Similarly, the high *H* values (>.80) also suggests a dominant general factor that portends to be stable across studies. Thus, consistent with other frequentist EFA and CFA studies (e.g., Bodin, Pardini, Burns, & Stevens, 2009; Canivez, 2014; Canivez & McGill, 2016; Canivez, Watkins, & Dombrowski, 2016, 2017; DiStefano & Dombrowski, 2006; Dombrowski, 2013, 2014a, 2017b; Dombrowski, Watkins, & Brogan, 2009; Dombrowski, Canivez, & Watkins, 2017; Dombrowski, Canivez, Watkins, & Beaujean, 2015; Dombrowski, McGill, & Canivez, 2017a, 2017b; Watkins & Beaujean, 2014) and consistent with Frazier and Youngstrom (2007), the DAS–II appears to be an instrument dominated by a general factor.

TABLE 4 Two-factor bifactor BSEM with cross-loadings and small variance (.01) priors

	General							
	g		Verbal		Nonverbal			
	b	S^2	*b*	S^2	*b*	S^2		
Subtest	[95% CI]		[95% CI]		[95% CI]		h^2	u^2
Word definitions	**.652**	**.425**	**.476**	**.227**	.000	.000	.652	.348
	[.613	**.691]**	**[.423**	**.521]**	[−.05	.051]		
Verbal similarities	**.659**	**.434**	**.476**	**.227**	.002	.000	.661	.339
	[.620	**.698]**	**[.423**	**.521]**	[−.048	.053]		
Matrices	**.763**	**.582**	.004	.000	**.016**	**.000**	.587	.413
	[.730	**.799]**	[−.056	.059]	**[−.107**	**.152]**		
Sequential and Quantitative	**.825**	**.681**	.007	.000	**−.053**	**.003**	.690	.310
	[.787	**.869]**	[−.053	.064]	**[−.242**	**.207]**		
Pattern construction	**.715**	**.511**	−.021	.000	**.225**	**.051**	.572	.428
	[.651	**.758]**	[−.069	.030]	**[−.028**	**.564]**		
Recall of designs	**.646**	**.417**	.031	.000	**.353**	**.125**	.546	.454
	[.582	**.710]**	[−.044	.066]	**[−.048**	**.053]**		
ECV[a]		.823		.122		.048	.993	
Total variance		.508		.076		.030	.614	.386
ω_H / ω_{HS}		.838		.274		.039		
H		.872		.369		.166		
PUC		.533						

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_H = omega-hierarchical (general factor); ω_{HS} = omega-hierarchical subscale (group factors); BSEM = Bayesian structural equation modeling; CI = confidence interval; g = general intelligence.
[a]Does not total to 100% due to use of median parameter estimates. Loadings in bold were freely estimated. Other loadings were estimated with small (.01) variance priors.

4 | DISCUSSION

The present study permitted a comparison of BSEM across different types of structural models (oblique, HO, BF). It also furnished information about possible alternative structures (i.e., two BF plus MA and SQ on *g* only; Model 5, Tables 5 and SA1) for the DAS–II that were not described in the Technical Handbook nor observed within Canivez and McGill's (2016) EFA-SL or Keith et al.'s (2010) studies.

One of the more potentially useful capabilities of BSEM (Asparouhov et al., 2015; Muthén & Muthén, 1998–2017) is that it permits the simultaneous estimation of cross-loadings and correlated error terms using small variance priors. This would not be possible on a six subtest instrument, such as the DAS–II, using classical ML CFA estimation. The attempt to estimate this many parameters in frequentist CFA would simply lead to an unidentified model. With ML CFA most cross-loadings have to be fixed at zero to achieve model identification and most error terms remain uncorrelated for that same reason. But, this may not reflect the researcher's hypothesis or even the structural reality of a cognitive ability instrument that often has overlapping, highly correlated constructs (Carroll, 1993; Gorsuch, 1983; Horn, 1989). Unnecessarily strict models and inappropriate zero cross-loadings could contribute to poor model fit, distorted factors, inflated loadings, and biased correlations (Asparouhov & Muthén, 2009; Brown, 2015; Marsh et al., 2009). McCrae et al. (2008) recognized this concern within the personality structural validity research literature and posited that ML CFA was overly restrictive (i.e., independent cluster assumption requiring an indicator to load only one factor and disregard cross-loadings) leading to correlations among the factors that tend to be overestimated.

BSEM offers the potential of an elegant solution to this problem that accounts for both cross-loadings and correlated residuals through simultaneous estimation. It may also be considered a hybrid estimation procedure in between

TABLE 5 Two-factor bifactor BSEM MA and SQ on *g* only with cross-loadings and correlated residuals (.01)

	General							
	g		Verbal		Nonverbal			
	b	S^2	*b*	S^2	*b*	S^2		
Subtest	[95% CI]		[95% CI]		[95% CI]		h^2	u^2
Word definitions	**.607 [.441**	**.368 .733]**	**.612 [.464**	**.375 .703]**	.037 [−.144	.001 .209]	.754	.246
Verbal similarities	**.621 [.454**	**.386 .747]**	**.612 [.463**	**.375 .703]**	.028 [−.156	.001 .203]	.771	.229
Matrices	**.839 [.652**	**.704 .930]**	−.029 [−.212	.001 .157]	−.018 [−.200	.000 .161]	.722	.278
Sequential and Quantitative	**.866 [.697**	**.750 .940]**	−.012 [−.200	.000 .168]	−.021 [−.209	.003 .161]	.767	.233
Pattern construction	**.658 [.501**	**.433 .782]**	.037 [−.140	.001 .212]	**.550 [−.046**	**.330 .646]**	.748	.252
Recall of designs	**.590 [.395**	**.348 .740]**	.042 [−.144	.002 .217]	**.550 [−.046**	**.330 .647]**	.664	.336
ECV[a]		675		.170		.137	.983	
Total variance		.498		.126		.101	.725	.275
ω_H / ω_{HS}		.800		.428		.358		
H		.887		.545		.464		
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_H = omega-hierarchical (general factor); ω_{HS} = omega-hierarchical subscale (group factors); BSEM = Bayesian structural equation modeling; CI = confidence interval; MA = Matrices; SQ = Sequential and Quantitative Reasoning; *g* = general intelligence.
[a]Does not total to 100% due to use of median parameter estimates. Loadings in bold were freely estimated. Other loadings were estimated with small (.01) variance priors.

EFA and CFA. It is noted, however, that the specification of all correlated residual terms represents a novel approach to structural modeling that is not yet fully embraced by the statistical community (Rindskopf, 2012; Stromeyer et al., 2015). The incorporation of all correlated residuals terms within BSEM deserves further study and debate but has potential to help clarify more complex elements of an instrument's internal structure (Asparouhov et al., 2015).

Within this study, the inclusion of correlated residuals improved model fit in some cases, (e.g., models 2c, 3c, and 5c) as determined by PPp values suggesting that the model nearly perfectly fit these data, and produced lower DIC scores. However, there were also cases where incorporation of correlated errors produced models that failed to converge (the two- and three-factor BF models, 4c and 8c), failed to yield a lower DIC (model 7c, three-factor HO), or did not enhance structural clarity based on the patterns of loadings, as the loadings were essentially the same whether or not correlated residuals were incorporated. In those cases, the more parsimonious model (cross-loadings only or no incorporation of cross-loadings) may be favored. For instance, model (5c; Table 5) produced a DIC that was lower than all models except model 6c (three-factor oblique model; Table SA2) but it is unknown whether any structural clarity or theoretical gains could be made by choosing the correlated errors version (Model 5c; Table 5) over its cross-loading only counterpart (Model 5b; Table SA1).

Also, theoretical considerations must be accounted for. Although model 6c (three-factor oblique) produced the lowest DIC, and one could indeed offer a statistical defense for an oblique model, at present oblique models do not reflect the consensual theoretical conceptualization for measures of cognitive abilities (Carroll, 1993; Dombrowski, 2015; Gignac, 2016; Gignac & Watkins, 2013). Therefore, oblique models were incorporated for pedagogical reasons because

BSEM has only been used once before in the professional literature to understand cognitive ability instruments (i.e., Golay et al., 2013).

Moving next to an understanding of the three-factor structure posited in the Technical Handbook, the three-factor HO (cross-loadings only; Table SA3) and the three-factor BF (cross-loadings only; Table 3) models demonstrated a nearly identical DIC. This is not surprising. As occurs with ML CFA estimation, in BSEM estimation when a just identified model is investigated, fit indices are virtually identical (Brown, 2015). When correlated residuals where incorporated both the two- and three-factor BF models failed to converge. When correlated residuals were specified for the HO models, the two-factor HO model saw improved model fit, whereas the three-factor HO model evidenced a reduced model fit as noted by an increase in DIC. In the case of model 5c (two BF plus MA and SQ on *g* only; Table 5), the incorporation of correlated residuals improved model fit with these data and lowered DIC. However, the pattern of subtest loadings was essentially the same as when cross-loadings only approach was specified (Table SA1). Across all models investigated, parameter estimates for correlated residuals were not statistically significant. This information is important in its own right and along with inclusion of cross-loadings (all were nonsignificant) suggested that the subtests may be statistically homogenous as posited in the Technical Handbook.

The results of this study indicate that the DAS–II six core subtest battery may be conceptualized not only as a three-factor HO model, as indicated in the Technical Handbook (although the standardized loadings associated with this model were not reported), but also as a three-factor BF model. With both models, the incorporation of cross-loadings improved model fit with these data. However, the incorporation of correlated residuals caused the three-factor BF model (and two-factor BF model) to fail to converge.

In addition to being conceptualized as a three-factor HO model (Table SA3) or three-factor BF model (Table 3), the DAS–II may be conceptualized as a two-factor BF model with two of its subtests (MA and SQ; Tables 5 and SA1) loading on *g* only. If one ascribes to a BF conceptualization of intelligence, then this hybrid BF model appears plausible: the three-factor BF model produced loadings–; MA and SQ– close to zero on their theoretically posited group factor. Whether a two- (Tables 5 and SA1) or three-factor BF (Table 3) model is investigated MA and SQ load on their respective group factors at close to zero, but have high general factor loadings. If the choice is for a BF model, then the hybrid approach (i.e., Model 5a–c; Tables 5 and SA1) is viable as having MA and SQ load on *g* only improves structural clarity. When correlated residuals were included, this model produced the lowest DIC and affirmed a lack of relationship among the error terms for the DAS–II, a finding that is important in its own right.

Regardless of whether a BF or HO model is adopted omega statistics suggest that the DAS–II is an instrument dominated by general ability. This was similarly supported by H and PUC. The finding is also consistent with prior findings from Canivez and McGill (2016) who cautioned about moving beyond interpretation of the general factor even though they found evidence for three group factors consistent with that posited in the Technical Handbook when force extracting that model in their EFA analyses.

Similar to Golay et al. (2013), the present results suggest the use of BSEM appears to be a viable option for the investigation of the structure of cognitive ability instruments. With the DAS–II it produced results that appear theoretically plausible and in fact offered an alternative structure (two BF plus MA and SQ on *g* only; Model 5a–c) that was not described within the Technical Handbook nor described within the extant DAS-II factor analytic research (Canivez & McGill, 2016; Keith et al., 2010). Within the present study, the inclusion of small variance cross-loadings appeared to aide in theoretical interpretation of the DAS–II structure. The inclusion of correlated residuals did not necessarily improve the structural clarity of the model beyond the use of cross-loadings, lowered DIC in some cases, and failed to permit the model to converge in others. But, it did offer additional insight into the DAS–II structure by demonstrating that subtests were not confounded by error terms that were correlated and that cross-loadings do not detract from the core battery's structural clarity as none were statistically significant.

Whereas cross-loadings are familiar to the structural validity researcher who encounters them when using EFA, the use of correlated residuals may well require further explication, scrutiny, and debate. Questions remain about whether its use improves structural clarity, introduces statistical noise, or may be exploited for the sole purpose of improving model fit. Because of this it is suggested that guidelines be established. However, the specification of correlated residuals may be of benefit. Unlike with ML CFA that permits only the specification of just a few correlated residuals often guided by theory, with BSEM the model identification issues are less of a concern and portend to uncover relationships that were not specified. Keep in mind, however, that BSEM is not a panacea for model identification issues, and is not the only option to the structural validity mountain top. This study demonstrated that BF models still experience identification problems when correlated residuals were specified quite possibility due to the inclusion of additional parameters that had to be estimated. This study's findings regarding the DAS–II support either a three-factor HO or three-factor BF structure. This study also lends support for an alternative two-factor BF structure where MA and SQ load only on the general factor.

Limitations include the need for further research on the use of BSEM. There has only been one prior study using BSEM for cognitive ability and just a handful investigating psychology, health, and management (De Bondt, Van Petegem, 2015; Fong & Ho, 2013, 2014; Stromeyer et al., 2015; Zyphur & Oswald, 2015). Although proponents of BSEM may claim that BSEM is devoid of statistical fishing expeditions, this may not be entirely true. A researcher still needs to specify in advance the selection of a prior and avoid the temptation to search for improved model fit just for its own sake. The results of this study showed that it was indeed possible to simultaneously estimate all cross-loadings to evaluate the nature of the constructs measured by each subtest scores. Thus BSEM avoided resorting to many comparisons that may capitalize on chance and potentially bias the estimation of the model parameters. The most controversial aspect of BSEM is the use of correlated residuals. There are researchers who raise concerns about their use (Stromeyer et al., 2015). On the other hand, Muthén and Asparouhov (2012) and Asparouhov et al. (2015) contend that if used appropriately then the specification of correlated residuals may enhance the understanding of an instrument's structure. Additional discussion and debate of this topic is necessary.

In totality, the use of BSEM on the six core subtest DAS–II structure offered additional insight into the structure of the DAS–II not previously uncovered by the use of ML CFA within the Technical Handbook nor within the exploratory and Schmid–Leiman procedures used by Canivez and McGill (2016). As a result, a follow-up ML CFA study comparing the various two- and three-factor structures, including the two BF plus MA and SQ on *g* only, may be worthwhile. Both Carroll (1993) and Horn (1989), whose work guided the development of CHC theory, a theory that undergirds the DAS-II, acknowledge that scientific validation requires convergent evidence from different procedures and sources of data.

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REFERENCES

Asparouhov, T., & Muthen, B. (2009). Exploratory structure equation modeling. *Structural Equation Modeling*, *16*, 397–438. https://doi.org/10.1080/10705510903008204

Asparouhov, T., & Muthén, B. (2010). *Bayesian analysis using Mplus: Technical implementation*. Retrieved from https://www.statmodel.com/download/Bayes3.pdf

Asparouhov, T., Muthén, B., & Morin, A. J. S. (2015). Bayesian structural equation modeling with cross-loadings and residual covariances: Comments on Stromeyer et al. (2015). *Journal of Management*, *41*, 1561–1577.

Bodin, D., Pardini, D. A., Burns, T. G., & Stevens, A. B. (2009). Higher order factor structure of the WISC–IV in a clinical neuropsychological sample. *Child Neuropsychology*, *15*, 417–424.

Brown, T. A. (2015). *Confirmatory factor analysis for the applied researcher*. New York: Guilford Press.

Canivez, G. L., & McGill, R. J. (2016). Factor structure of the Differential Ability Scales—Second Edition: Exploratory and hierarchical factor analysis with the core subtests. *Psychological Assessment*, *28*, 1475–1488. https://doi.org/10.1037/pas0000279

Canivez, G. L., Watkins, M. W., & Dombrowski, S. C. (2016). Factor structure of the Wechsler Intelligence Scale for Children–Fifth Edition: Exploratory factor analyses with the 16 primary and secondary subtests. *Psychological Assessment*, *28*, 975–986. https://doi.org/10.1037/pas0000238

Canivez, G. L., Watkins, M. W., & Dombrowski, S. C. (2017). Structural validity of the Wechsler Intelligence Scale for Children–Fifth Edition: Confirmatory factor analyses with the 16 primary and secondary subtests. *Psychological Assessment*, *29*, 458–472. https://doi.org/10.1037/pas0000358

Canivez, G. L. (2014). Review of the Wechsler Preschool and Primary Scale of Intelligence–Fourth Edition. In J. F. Carlson, K. F. Geisinger, & J. L. Jonson (Eds.), *The nineteenth mental measurements yearbook* (pp. 732–737). Lincoln, NE: Buros Institute of Mental Measurements.

Carroll, J. B. (1985). Exploratory factor analysis: A tutorial. In D. K. Detterman (Ed.), *Current topics in human intelligence, Vol. 1: Research methodology* (pp. 25–58). Norwood, NJ: Ablex.

Carroll, J. B. (1993). *Human cognitive abilities*. Cambridge, England: Cambridge University Press.

Carroll, J. B. (1995). On methodology in the study of cognitive abilities. *Multivariate Behavioral Research*, *30*, 429–452. https://doi.org/10.1207/s15327906mbr3003_6

Casella, G., & George, E. I. (1992). Explaining the Gibbs sampler. *The American Statistician*, *46*, 167–174.

De Bondt, N., & Van Petegem, P. (2015). Psychometric evaluation of the Overexcitability Questionnaire-Two applying Bayesian structural equation modeling (BSEM) and multiple-group BSEM-based alignment with approximate measurement invariance. *Frontiers in Psychology*, *6*, 1–17, https://doi.org/10.3389/fpsyg.2015.01963

DiStefano, C., & Dombrowski, S. C. (2006). Investigating the theoretical structure of the Stanford–Binet–Fifth Edition. *Journal of Psychoeducational Assessment*, *24*, 123–136.

Dombrowski, S. C. (2013). Investigating the structure of the WJ–III Cognitive at school age. *School Psychology Quarterly*, *28*, 154–169. https://doi.org/10.1037/spq0000010

Dombrowski, S. C. (2014a). Exploratory bifactor analysis of the WJ–III Cognitive in adulthood via the Schmid–Leiman procedure. *Journal of Psychoeducational Assessment*, *32*, 330–341. https://doi.org/10.1177/0734282913508243

Dombrowski, S. C. (2014b). Investigating the structure of the WJ–III Cognitive in early school age through two exploratory bifactor analysis procedures. *Journal of Psychoeducational Assessment*, *32*, 483–494. https://doi.org/10.1177/0734282914530838

Dombrowski, S. C. (2015). *Psychoeducational assessment and report writing*. New York: Springer Science.

Dombrowski, S. C., Canivez, G. L., & Watkins, M. W. (2017). Factor structure of the 10 WISC–V primary subtests in four standardization age groups. *Contemporary School Psychology*. Advance online publication. https://doi.org/10.1007/s40688-017-0125-2

Dombrowski, S. C., Canivez, G. L., Watkins, M. W., & Beaujean, A. (2015). Exploratory bifactor analysis of the Wechsler Intelligence Scale for Children–Fifth Edition with the 16 primary and secondary subtests. *Intelligence*, *53*, 194–201. https://doi.org/10.1016/j.intell.2015.10.009

Dombrowski, S. C., McGill, R. J., & Canivez, G. L. (2017a). Exploratory and hierarchical factor analysis of the WJ IV Cognitive at school age. *Psychological Assessment*, *29*, 294–407. https://doi.org/10.1037/pas0000350

Dombrowski, S. C., McGill, R. J., & Canivez, G. L. (2017b). Exploratory and hierarchical factor analysis of the WJ IV Full Test battery. *School Psychology Quarterly*. https://doi.org/10.1037/spq0000221

Dombrowski, S. C., Watkins, M. W., & Brogan, M. J. (2009). An exploratory investigation of Factor structure of the Reynolds Intellectual Assessment Scales (RIAS). *Journal of Psychoeducational Assessment*, *27*, 279–286. https://doi.org/10.1177/0734282909333179

Edwards, M. C. (2010). A Markov chain Monte Carlo approach to confirmatory item factor analysis. *Psychometrika*, *75*, 474–497.

Elliott, C. D. (2007a). *Differential Ability Scales* (2nd ed.). San Antonio, TX: Harcourt Assessment.

Elliott, C. D. (2007b). *Differential Ability Scales–2nd ed.: Introductory and technical handbook*. San Antonio, TX: Harcourt Assessment.

Fong, T. C., & Ho, R. T. (2013). Factor analyses of the Hospital Anxiety and Depression Scale: A Bayesian structural equation modeling approach. *Quality of Life Research*, *22*, 2857–2863.

Fong, T. C., & Ho, R. T. (2014). Testing gender invariance of the Hospital Anxiety and Depression Scale using the classical approach and Bayesian approach. *Quality of Life Research*, *23*, 1421–1426. https://doi.org/10.1007/s11136-013-0594-3

Frazier, T. W., & Youngstrom, E. A. (2007). Historical increase in the number of factors measured by commercial tests of cognitive ability: Are we overfactoring? *Intelligence*, *35*, 169—182. https://doi.org/10.1016/j.intell.2006.07.002

Gelman, A., & Rubin, D. (1992). Inference from iterative simulation using multiple sequences (with discussion). *Statistical. Science*, *7*, 457–511.

Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2004). *Bayesian data analysis* (2nd ed.). Boca Raton: Chapman and Hall/CRC.

Gelman, A., Meng, X.-L., & Stern, H. S. (1996). Posterior predictive assessment of model fitness via realized discrepancies. *Statistica Sinica*, *6*, 733–807.

Gignac, G. E. (2016). The higher-order model imposes a proportionality constraint: That is why the bi-factor model tends to fit better. *Intelligence*, *55*, 57–68. https://doi.org/10.1016/j.intell.2016.01.006

Gignac, G. E., & Watkins, M. W. (2013). Bifactor modeling and the estimation of model-based reliability in the WAIS-IV. *Multivariate Behavioral Research*, *48*, 639–662.

Golay, P., Reverte, I., Rossier, J., Favez, N., & Lecerf, T. (2013). Further insights on the French WISC–IV factor structure through Bayesian structural equation modeling. *Psychological Assessment*, *25*, 496–508. https://doi.org/10.1037/a0030676

Gorsuch, R. L. (1983). *Factor analysis* (2nd ed.). Hillsdale, NJ: Erlbaum.

Green, P. J. (1995). Reversible jump Markov chain Monte Carlo computation and Bayesian model determination. *Biometrika*, *82*, 711–732.

Gustafsson, J.-E., & Åberg-Bengtsson, L. (2010). Unidimensionality and interpretability of psychological instruments. In S. Embretson (Ed.), *Measuring psychological constructs: Advances in model-based approaches* (pp. 97–121). Washington, DC: American Psychological Association.

Hancock, G. R., & Mueller, R. O. (2001). Rethinking construct reliability within latent variable systems In R. Cudeck, S. du Toit, & D. Sorbom (Eds.), *Structural equation modeling: Present and future* (pp. 195–216). Lincolnwood, IL: Scientific Software International.

Horn, J. (1989). Models of intelligence. In R. L. Linn (Ed.), *Intelligence: Measurement, theory, and public policy* (pp. 29–75). Urbana, IL: University of Illinois Press.

Kaplan, D., & Depaoli, S. (2013). Bayesian statistical methods. In T. Little (Ed.), *The Oxford handbook of quantitative methods* (Vol. *1*, pp. 407–437). New York: Oxford University Press.

Keith, T. Z., Low, J. A., Reynolds, M. R., Patel, P. G., & Ridley, K. P. (2010). Higher-order factor structure of the Differential Ability Scales-II: Consistency across 4 to 17. *Psychology in the Schools*, *47*, 676–697. https://doi.org/10.1002/pits.20498

Link, W. A., & Eaton, M. J. (2012). On thinning of chains in MCMC. *Methods in Ecology and Evolution*, *3*, 112–115. https://doi.org/10.1111/j.2041-210X.2011.00131.x

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structures analysis: The problem of capitalizing on chance. *Psychological Bulletin*, *111*, 490–504. https://doi.org/10.1037//0033-2909.111.3.490

Marsh, H. W., Muthén, B., Asparouhov, A., Ldtke, O., Robitzsch, A., Morin, A. J. S., & Trautwein, U. (2009). Exploratory structural equation modeling, integrating CFA and EFA: Application to students' evaluations of university teaching. *Structural Equation Modeling*, *16*, 439–476. https://doi.org/10.1080/10705510903008220

McArdle, J. J. (1994). Structural factor analysis experiments with incomplete data. *Multivariate Behavioral Research*, *29*, 409–454. https://doi.org/10.1207/s15327906mbr2904_5

McCrae, R. R., Yamagata, S., Jang, K. L., Riemann, R., Ando, J., Ono, Y., … Spinath, F. M. (2008). Substance and artifact in the higher-order factors of the Big Five. *Journal of Personality and Social Psychology*, *95*, 442–455. https://doi.org/10.1037/0022-3514.95.2.442

McGill, R. J., & Dombrowski, S. C. (2017). What does the WRAML2 core battery measure? Utilizing exploratory and confirmatory techniques to disclose higher-order structure. *Assessment*. Advance online publication. https://doi.org/10.1177/1073191116677799

Mulaik, S. A. (2010). *Foundations of factor analysis* (2nd ed.). Boca Raton, FL: CRC Press.

Muthén, B., & Asparouhov, T. (2012). Bayesian structural equation modeling: A more flexible representation of substantive theory. *Psychological Method*, *17*, 313–335. https://doi.org/10.1037/a0026802

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus User's Guide* (7th ed.). Los Angeles, CA: Muthén & Muthén.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL Retrieved from https://www.R-project.org/

Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*, 667–696. https://doi.org/10.1080/00273171.2012.715555

Reise, S. P., Bonifay, W. E., & Haviland, M. G. (2013). Scoring and modeling psychological measures in the presence of multidimensionality. *Journal of Personality Assessment*, *95*, 129–140. https://doi.org/10.1080/00223891.2012.725437

Rindskopf, D. (2012). Next steps in Bayesian structural equation models: Comments on, variations of, and extensions to Muthen and Asparouhov (2012). *Psychological Methods*, *17*, 336–339.

Rodriguez, A., Reise, S. P., & Haviland, M. G. (2016). Applying bifactor statistical indices in the evaluation of psychological measures. *Journal of Personality Assessment*, *98*, 223–237.

Schmid, J., & Leiman, J. M. (1957). The development of hierarchical factor solutions. *Psychometrika*, *22*, 53–61. https://doi.org/10.1007/BF02289209

Schneider, W. J., & McGrew, K. S. (2012). The Cattell-Horn-Carroll model of intelligence. In D. P. Flanagan & P. L. Harrison (Eds.), *Contemporary intellectual assessment: Theories, tests, and issues* (3rd ed., pp. 99–144). New York: Guilford Press.

Spearman, C. (1927). *The abilities of man*. New York, NY: Cambridge University Press.

Stone, J. V. (2013). Bayes' rule: A tutorial introduction to Bayesian analysis. Sebtel Press: Sheffield, UK.

Stromeyer, W. R., Miller, J. W., Sriramachandramurthy, R., & DeMartino, R. (2015). The prowess and pitfalls of Bayesian structural equation modeling: Important considerations for management research. *Journal of Management*, *41*, 491–520.

Vehtari, A., & Gelman, A. J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*, 1413–1432.

Watkins, M. W. (2013). *Omega [Computer software]*. Phoenix, AZ: Ed & Psych Associates.

Watkins, M. W., & Beaujean, A. A. (2014). Bifactor structure of the Wechsler Preschool and Primary Scale of Intelligence–Fourth edition. *School Psychology Quarterly*, *29*, 52–63. https://doi.org/10.1037/spq0000038

Zyphur, M. J., & Oswald, F. L. (2015). Bayesian estimation and inference: A user's guide. *Journal of Management*, *41*, 390–420. https://doi.org/10.1177/0149206313501200

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How to cite this article: Dombrowski SC, Golay P, McGill RJ, Canivez GL. Investigating the theoretical structure of the DAS-II core battery at school age using Bayesian structural equation modeling. *Psychol Schs*. 2018;55:190–207. https://doi.org/10.1002/pits.22096

Online Supplement

Investigating the Theoretical Structure of the DAS-II Core Battery at School Age using Bayesian Structural Equation Modeling

By S. C. Dombrowski et al.

Table A1

Two Factor Bifactor BSEM with Cross-Loadings and Small Variance (.01) Priors.

	General							
	g		Verbal		Nonverbal			
Subtest	*b* [95% CI]	S^2	*b* [95% CI]	S^2	*b* [95% CI]	S^2	h^2	u^2
Word Definitions	**.652**	**.425**	**.476**	**.227**	.000	.000	.652	.348
	[.613	**.691]**	**[.423**	**.521]**	[-.05	.051]		
Verbal Similarities	**.659**	**.434**	**.476**	**.227**	.002	.000	.661	.339
	[.620	**.698]**	**[.423**	**.521]**	[-.048	.053]		
Matrices	**.763**	**.582**	.004	.000	**.016**	**.000**	.587	.413
	[.730	**.799]**	[-.056	.059]	**[-.107**	**.152]**		
Sequential & Quantitative	**.825**	**.681**	.007	.000	**-.053**	**.003**	.690	.310
	[.787	**.869]**	[-.053	.064]	**[-.242**	**.207]**		
Pattern Construction	**.715**	**.511**	-.021	.000	**.225**	**.051**	.572	.428
	[.651	**.758]**	[-.069	.030]	**[-.028**	**.564]**		
Recall of Designs	**.646**	**.417**	.031	.000	**.353**	**.125**	.546	.454
	[.582	**.710]**	[-.044	.066]	**[-.048**	**.053]**		
ECV*		.823		.122		.048	.993	
Total Variance		.508		.076		.030	.614	.386
ω_H / ω_{HS}		.838		.274		.039		
H		.872		.369		.166		
PUC		.533						

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_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors). BSEM=Bayesian Structural Equation Modeling, CI=Confidence Interval, *g* = general intelligence. *Does not total to 100% due to use of median parameter estimates. Loadings in bold were freely estimated. Other loadings were estimated with small (0.01) variance priors.

Table A2

Two Factor Bifactor BSEM (MA & SQ on g only) with Cross-Loadings and Small Variance (.01) Priors.

	General							
	G		Verbal		Spatial			
	b	S^2	*b*	S^2	*b*	S^2		
Subtest	[95% CI]		[95% CI]		[95% CI]		h^2	u^2
Word Definitions	**.661**	**.437**	**.469**	**.220**	.003	.000	.653	.347
	[.571	**.723]**	**[.356**	**.567]**	[-.126	.126]		
Verbal Similarities	**.654**	**.428**	**.469**	**.220**	.008	.000	.662	.338
	[.577	**.730]**	**[.356**	**.567]**	[-.120	.130]		
Matrices	**.761**	**.579**	.003	.000	.036	.001	.601	.399
	[.714	**.821]**	[-.130	.133]	[-.145	.181]		
Sequential & Quantitative	**.630**	**.397**	.005	.000	-.025	.001	.671	.329
	[.773	**.901]**	[-.143	.143]	[-.210	.120]		
Pattern Construction	**.708**	**.501**	-.025	.001	**.314**	**.099**	.604	.396
	[.646	**.761]**	[-.141	.096]	**[.182**	**.419]**		
Recall of Designs	**.630**	**.397**	.035	.001	**.314**	**.099**	.501	.499
	[.567	**.681]**	[-.074	.150]	**[.183**	**.419]**		
							.615	.385
ECV*		.742		.120		.054	.915*	
Total Variance		.456		.074		.033		
ω_H / ω_{HS}		.808		.266		.128		
H		.839		.361		.179		
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_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors). BSEM=Bayesian Structural Equation Modeling, CI=Confidence Interval, MA=Matrices, SQ= Sequential & Quantitative Reasoning, *g* = general intelligence. *Does not total to 100% due to use of median parameter estimates. Loadings in bold were freely estimated. Other loadings were estimated with small (0.01) variance priors.

Table A3 Three Factor Oblique with Informative Cross Loadings and Correlated Residuals (.001)

Loading estimates (median)	Verbal		Nonverbal		Spatial			
	b	S^2	*b*	S^2	*b*	S^2		
Subtest	[95% CI]		[95% CI]		[95% CI]		h^2	u^2
Word Definitions	**.878**	**.771**	-.003	.000	-.005	.000	.766	.234
	[.672	**1.103]**	[.637	1.102]	[.614	1.092]		
Verbal Similarities	**.863**	**.745**	.011	.000	.003	.000	.763	.237
	[.604	**1.052]**	[.584	1.054]	[.493	1.025]		
Matrices	-.008	.000	**.880**	**.774**	-.006	.000	.764	.236
	[-.199	.157]	**[-.193**	**.158]**	[-.184	.152]		
Sequential & Quantitative	.018	.000	**.837**	**.701**	.017	.000	.748	.252
	[-.167	.196]	**[-.167**	**.183]**	[-.160	.163]		
Pattern Construction	-.004	.000	.005	.000	**.873**	**.762**	.771	.229
	[-.201	.164]	[-.161	.175]	**[-.180**	**.166]**		
Recall of Designs	.009	.000	.008	.000	**.791**	**.626**	.652	.348
	[-.167	.178]	[-.169	.181]	**[-.150**	**.194]**		
ECV*		.340		.330		.311	.981	
Total Variance		.253		.246		.231	.730	.270
Factor Intercorrelations								
Verbal	*1*							
Nonverbal	*0.671*		1					
Spatial	*0.585*		.705		1			

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, CI=Confidence Interval. *Does not total to 100% due to use of median parameter estimates. Loadings in bold were freely estimated. Other loadings were estimated with small (0.001) variance priors.

Table A4 Two factor Higher Order with Cross-loadings and Correlated Residuals (.001) 250K Iterations

Loading estimates (median)	General* g		Verbal		Residualized Verbal		Nonverbal		Residualized Nonverbal			
Subtest	*b* [95% CI]	S^2	*b* [95% CI]	S^2	*b*	S^2	*b* [95% CI]	S^2	*b*	S^2	h^2	u^2
Word Definitions	**.723**	**.523**	**.870**	**.757**	*.487*	*.237*	.000	.000			.760	.240
			[.740	**.878]**			[-.046	.048]				
Verbal Similarities	**.726**	**.528**	**.874**	**.764**	*.489*	*.239*	.000	.000			.767	.233
			[.742	**.885]**			[-.047	.050]				
Matrices	**.648**	**.420**	.000	.000			**.804**	**.646**	*.478*	*.228*	.648	.352
			[-.052	.038]			**[.705**	**.841]**				
Sequential & Quantitative	**.662**	**.438**	.000	.000			**.821**	**.674**	*.492*	*.242*	.680	.320
			[-.030	.062]			**[.739**	**.875]**				
Pattern Construction	**.623**	**.388**	.001	.000			**.773**	**.598**	*.459*	*.211*	.599	.401
			[-.066	.022]			**[-.048**	**.047]**				
Recall of Designs	**.596**	**.355**	.004	.000			**.739**	**.546**	*.437*	*.191*	.546	.454
			[-.029	.060]			**[-.047**	**.049]**				
ECV		.663				.119				.218	1.00	
Total Variance		.442				.079				.145	.667	.333
ω_H / ω_{HS}**		.711				.270				.305		
H		.830				.385				.528		
PUC		.533										
Second Order Loadings (median)												
Verbal	**.831**											
	[.649	**.992]**										
Nonverbal	**.806**											
	[.648	**.991]**										

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_H = Omega-hierarchical (general factor), ω_{HS} = Omega-hierarchical subscale (group factors), *g* = general intelligence. Omega estimates based on residualized group factor loadings. Loadings in bold were freely estimated. Other loadings were estimated with small (0.001) variance priors. Residualized using the following formula: $\sqrt{R^2 - (g\ loading)^2}$ *Calculated using the path tracing rules. **Used residualized estimates to calculate omega.