Please use the following citation when referencing this work:
McGill, R. J., & Busse, R. T. (2015). Incremental validity of the WJ III COG: Limited predictive effects beyond the GIA-E. *School Psychology Quarterly, 30,* 353-365. doi: 10.1037/spq0000094

Incremental Validity of the WJ-III COG: Limited Predictive Effects Beyond the GIA-E

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The authors thank Kevin McGrew and Fredrick Schrank for making data from the WJ-III standardization sample available for this research. The standard score dataset analyzed in this study was used with permission from the Woodcock-Muñoz Foundation.

The authors also thank Randy Floyd for reviewing an earlier version of this manuscript.

Preliminary versions of this research were presented at the 2014 annual conventions of the National Association of School Psychologists and the American Psychological Association.

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Abstract

This study is an examination of the incremental validity of Cattell-Horn-Carroll (CHC) broad clusters from the Woodcock-Johnson III Tests of Cognitive Abilities (WJ-III COG) for predicting scores on the Woodcock-Johnson III Tests of Achievement (WJ-III ACH). The participants were children and adolescents, ages 6-18, (N = 4,722) drawn from the WJ-III standardization sample. The sample was nationally stratified and proportional to U.S. census estimates for race/ethnicity, parent education level, and geographic region. Hierarchical multiple regression analyses were used to assess for cluster-level effects after controlling for the variance accounted for by the General Intellectual Ability-Extended (GIA-E) composite score. The results were interpreted using the $R^2/\Delta R^2$ statistic as the effect size indicator. Consistent with previous studies, the GIA-E accounted for statistically and clinically significant portions of WJ-III ACH cluster score variance, with R^2 values ranging from .29 to .56. CHC cluster scores collectively provided statistically significant incremental variance beyond the GIA-E in all of the regression models, although the effect sizes were consistently negligible to small (Average ΔR^2_{CHC} = .06), with significant effects observed only in the Oral Expression model (ΔR^2_{CHC} = .23). Individually, the WJ-III COG cluster scores accounted for mostly small portions of achievement variance across the prediction models, with a large effect found for the Comprehension-Knowledge cluster in the Oral Expression model (ΔR^2_{Gc} = .23). The potential clinical and theoretical implications of these results are discussed.

Keywords: WJ-III COG, Incremental Validity, CHC, Predictive Validity

Incremental Validity of the WJ-III COG: Limited Predictive Effects Beyond the GIA

Although scientists and philosophers have written about the intellectual capabilities of the human brain for over 2,000 years, it is just within the past half century that intelligence tests have been modified to account for advances in cognitive and neuropsychological theory. To account for these advances, contemporary intelligence tests have been designed to appraise examinee performance at multiple levels (e.g., subtest, composite, full scale), providing examiners with many options for making inferences about the status of an individual's cognitive functioning (Canivez, 2013b). Due to the size of test batteries, significant effort is required to obtain all of the available scores on most IQ tests. Examiners who undertake these efforts often operate under the assumption that interpretation of lower order composite scores provides them with additional diagnostic or treatment advantages that are not provided by the full scale IQ score (Glutting, Watkins, Konold, & McDermott, 2006).

Intelligence testing research has been impacted over the last 20 years as a result of the rise of the Cattell-Horn-Carroll (CHC) model of cognitive abilities. CHC theory has been used to provide a theoretical and empirical foundation for understanding cognitive abilities and how they relate to academic learning (Keith & Reynolds, 2010; McGrew & Wendling, 2010). Although several tests reference CHC theory within their technical and interpretive manuals, the Woodcock-Johnson III Tests of Cognitive Abilities (WJ-III COG; Woodcock, McGrew, & Mather, 2001c) was the first test to utilize CHC specifically as its foundation. Additionally, the WJ-III COG was the first test that purported to measure all of the proposed broad cognitive abilities in the most recent iteration of the CHC model (Schneider & McGrew, 2012). Accordingly, the WJ-III COG has been utilized as the primary instrument for validating many of the refinements to CHC theory in the empirical literature since its publication over a decade ago.

Consistent with popular diagnostic interpretive frameworks (e.g., Flanagan, Ortiz, & Alfonso, 2013), the WJ-III COG examiner manual (Mather & Woodcock, 2001) encourages primary interpretation at the broad ability level (e.g., CHC-related cluster scores). Because predicting achievement and other related important life outcomes are a chief function of intelligence tests (Canivez, 2013a; Gottfredson, 1997), examining relationships between WJ-III COG cluster scores and external achievement measures is an important criterion for appraising the validity of interpretive recommendations. These examinations are also critically important for evaluating the tenability of several models that have been proposed (e.g., Fiorello, Hale, & Snyder, 2006; Flanagan, Alfonso, & Mascolo, 2011) for use in the identification of specific learning disabilities (SLD) in children and adolescents. These and similar models utilize lower-order scores, such as the WJ-III COG broad ability clusters, as a critical component for determining whether or not an individual has a learning disability.

Shortly after the publication of the WJ-III COG, Evans, Floyd, McGrew, and Leforgee (2001) utilized multiple regression to examine predictive relationships between WJ-III COG CHC clusters and standardized reading measures. Their analyses provided evidence for differential predictive effects across the age span for specific CHC clusters. These results were later replicated for predicting mathematics (Floyd, Evans, & McGrew, 2003) and writing outcomes (Floyd, McGrew, & Evans, 2008). However, the potential effects of the common variance shared by mental measures (i.e., Spearman, 1904) were not controlled for in these studies, which is a significant limitation given the results of several recent factor analytic studies (e.g., Dombrowski, 2013; Dombrowksi & Watkins, 2013; Floyd, McGrew, Barry, Rafael, & Rogers, 2009) that have indicated that many of the lower order measures on the WJ-III COG are saturated with large amounts of common variance. To investigate the tenability of the recommendation for practitioners to interpret primarily at the broad ability level, it is necessary to examine the incremental predictive validity provided by these measures after controlling for the effects of variance already accounted for by the full scale score.

Incremental Validity of Intelligence Test Measures

According to Hunsley (2003), incremental validity is the "extent to which a measure adds to the prediction of a criterion beyond what can be predicted with other data" (p. 443). Incremental validity is rooted in the scientific law of parsimony which states "what can be explained by fewer principles is needlessly explained by more" (Jones, 1952, p. 620). When applied to intelligence tests, interpretation of the full scale score is more parsimonious than interpretation at the cluster or broad ability level. Thus, to interpret primarily at the broad ability level, practitioners should have a compelling reason for doing so.

Hierarchical multiple regression analysis is a well-established statistical procedure for assessing incremental validity in the social sciences and has been successfully applied in the technical literature in studies utilizing cognitive assessment data (Canivez, 2013b). In this procedure, the full scale score is entered first into a regression equation followed by the lower order factor or cluster scores to predict a criterion achievement variable. This entry technique allows for the predictive effects of the cluster scores to be assessed while controlling for the effects of the full scale score and operates conceptually in very much the same way as the Schmid and Leiman technique (1957) for residualizing variance in exploratory factor analysis.

Incremental validity studies using hierarchical multiple regression analysis have been conducted on various iterations of the Wechsler scales (Canivez, 2013a; Glutting et al., 2006; Glutting, Youngstrom, Ward, Ward, & Hale, 1997; Nelson, Canivez, & Watkins, 2013), the Cognitive Assessment System (Canivez, 2011), the Differential Ability Scales (Youngstrom, Kogos, & Glutting, 1999), the Reynolds Intellectual Assessment Scales (Nelson & Canivez, 2012), and the Kaufman Assessment Battery for Children-Second Edition (McGill & Busse, 2013). Across these studies, it was consistently demonstrated that the omnibus full scale score on intelligence tests accounted for most of the reliable achievement variance in the regression models and that little additional incremental variance was accounted for by factor scores after controlling for the predictive effects of the general factor. However, a comprehensive assessment of the incremental validity of the WJ-III COG, or its previous iterations, has yet to be conducted.

To address this gap in the literature, we examined the incremental validity of the WJ-III COG CHC cluster scores in accounting for Woodcock-Johnson III Tests of Achievement (WJ-III ACH; Woodcock, McGrew, & Mather, 2001b) test scores beyond that already accounted for by the General Intellectual Ability-Extended (GIA-E) composite. Given the relationships that have been established between the WJ-III COG CHC clusters and achievement in regression studies and the large amounts of specific variance found in some CHC clusters in principal component analysis studies (e.g., Floyd et al., 2009), it was expected that incremental validity would be demonstrated on the WJ-III COG. The current study is an extension of previous research and will potentially provide practitioners with additional information regarding correct interpretation of the WJ-III COG, and its forthcoming revision, in clinical/school-based practice (the test authors for the forthcoming WJ-IV COG have confirmed that that the new measure will retain the seven factor CHC-based interpretive structure).

Method

Participants

The participants were children and adolescents ages 6-0 to 18-11 (N = 4,722) drawn from the standardization sample for the WJ-III COG and the WJ-III ACH (WJ-III; Woodcock, McGrew, & Mather, 2001a). Table 1 presents the relative proportions across demographics for sex, race, ethnicity, region, community type, and parent education level for the sample along with comparable 2005 U.S. census estimates. The participants ranged in grade from kindergarten to grade 12 with a mean age of 11.48 (*SD* = 3.51).

Measurement Instruments

Woodcock-Johnson III Tests of Cognitive Abilities. The WJ-III COG is a multidimensional test of general intelligence for ages 2 to 90 years. The measure is comprised of 20 subtests, 14 of which contribute to the measurement of seven CHC-based broad cluster scores: *Comprehension-Knowledge* (Gc), *Fluid Reasoning* (Gf), *Auditory Processing* (Ga), *Visual-Spatial Thinking* (Gv), *Short-Term Memory* (Gsm), *Long-Term Retrieval* (Glr), and *Processing Speed* (Gs). All of the CHC clusters are differentially weighted according to their relative *g* loadings and then combined to form the GIA-E composite. All variables on the WJ-III COG are expressed as standard scores with a mean of 100 and a standard deviation of 15. In contrast to other measures, WJ-III standard scores are derived from the Rasch model of measurement and are anchored to a reference scale referred to as the *W* scale (Jaffe, 2009). The total norming sample (*N* = 8,818) is stratified according to region, community type, sex, and race, and is nationally representative based upon 2000 U.S. census estimates. Extensive normative and psychometric data can be found in the WJ-III technical manuals (McGrew, Schrank, & Woodcock, 2007; McGrew & Woodcock, 2001). Mean internal consistency estimates for the included ages in this study ranged from .78 to .95 for the factor scores. The mean internal consistency estimate for the GIA-E was .97. Validity evidence is provided in several forms in the technical manual and independent reviews are available (e.g., Cizek, 2003; Sandoval, 2003).

Woodcock-Johnson III Tests of Achievement. The WJ III-ACH is a comprehensive academic assessment battery designed to measure five academic domains: Reading, Written Language, Mathematics, Oral Language, and Academic Knowledge. The WJ-III ACH is comprised of 22 subtests that combine to provide 17 broad clusters and a total achievement composite score. Broad clusters are expressed as standard scores with a mean of 100 and a standard deviation of 15. Mean internal consistency estimates for the included ages in this study ranged from .82 to .96 for the composite and broad scores that were assessed. Additional technical information for the WJ-III ACH can be found in the WJ-III technical manuals (McGrew et al., 2007; McGrew & Woodcock, 2001).

Procedure

According to the WJ-III technical manual, all school-aged participants in the WJ-III dataset were administered measures from the WJ-III COG and the WJ-III ACH by trained examiners under the direct supervision of a standardization project member. According to one of the test authors, the WJ-III standardization procedures were developed to better approximate the selective testing approach favored by many clinicians (K. S. McGrew, personal communication, November 22, 2010).

Data Analysis

Hierarchical multiple regression analyses were conducted to assess the proportions of WJ-III ACH cluster score variance accounted for by the observed WJ-III COG GIA-E and CHC cluster scores. The WJ-III COG GIA-E was entered into the first block, and the CHC cluster scores were entered jointly into the second block of the SPSS version 21 linear regression analysis. CHC cluster effects also were individually assessed by entering each cluster alone into the second block of the regression equation. WJ-III ACH analyses included the Broad Reading, Basic Reading Skills, Reading Comprehension, Broad Mathematics, Math Reasoning, Math Calculation Skills, Broad Written Language, Basic Writing Skills, and Written Expression, Oral Expression, and Listening Comprehension cluster scores as criterion variables. The change in the WJ-III ACH achievement variance predicted by the CHC cluster scores in the second block of the regression model provided an estimate of the incremental prediction beyond the GIA-E in the first block of the model. According to Pedhazur (1997), these variance partitioning procedures are appropriate given the predictive nature of the current study.

It is important to consider order of entry when utilizing HMRA to assess the incremental effects of IVs due to the fact that the R^2 statistic is derived from the predictive effects of the model as a whole. As a result, reverse entry of the IVs, in this case entering the clusters first, would result in the clusters accounting for approximately the same variance proportions that were attributed to the GIA-E in the present study. Consequently, the GIA-E would provide little incremental prediction in most circumstances. Hale and colleagues (2007) argued that order of entry arbitrarily determines whether scores such as the GIA mean everything or nothing. However, order of entry is not an arbitrary process and must be determined *a priori* according to expected theoretical relationships between the variables and causal priority (Pedhazur, 1997). According to Cohen et al. (2003), "this is the *only* basis on which variance partitioning can proceed with correlated IVs" (p. 158). Contemporary intelligence theory (e.g., CHC) and the WJ-III COG structural model support entering the GIA-E prior to the clusters due to the fact that the cluster scores are both theoretically and statistically subordinate to the GIA-E. Reverse entry conflicts with existing intelligence theory and violates the scientific law of parsimony (Canivez, 2013b; Schneider, 2008).

The results were interpreted using the resulting R^2 statistic as an effect size. Guidelines for interpreting R^2 as an effect size are found in Cohen (1988); they are "small," .01; "medium," .09; and "large," .25. The critical coefficient in hierarchical multiple regression analysis is the incremental squared multiple correlation coefficient (ΔR^2). The ΔR^2 represents the amount of variance that is explained by an independent variable (IV) after controlling for the effects of IVs previously entered in the regression equation. At present there are no conventional guidelines for interpreting the ΔR^2 coefficient, thus Cohen's interpretive framework for R^2 was applied.

Missing data analysis. Due to the standardization procedures described in the technical manual, missing data analysis was completed to determine the amount of missing data in the sample utilized in the current study. Across the variables utilized, 15% to 55% of the cases contained missing data. Little's test for Missing Completely at Random (MCAR) was statistically significant across the sample χ^2 (2,581) = 3593.42, $p < .001$, indicating that the MCAR hypothesis may not be tenable. Enders (2010) recommended comparing obtained parameter estimates with those that are generated from a validated estimation technique (e.g., maximum likelihood) prior to utilizing imputed values for data analysis. If negligible differences between the two sets of estimates are observed, it would make little sense to analyze estimated values as the current study was designed to be predictive in nature with observed-level data. Post-estimation means for the study variables were compared to the means calculated from the standardization sample. Hedge's *g* values ranged from -.03 to .02 across the variables, indicating that the estimation parameters were commensurate with those obtained from the original sample. Due to the large sample size and the predictive nature of the study, data analysis was completed utilizing listwise deletion procedures.

Collinearity. Collinearity is a broad term that refers to a potential threat to validity in multiple regression research that is introduced when a prediction model utilizes IVs that are significantly correlated (Pedhazur, 1997). Collinearity is commonly assessed using one or more of several indicators available in most statistical programs. The most commonly used indicators are the tolerance index, variance inflation factor (VIF), and condition index. The VIF, condition, and tolerance values for the WJ-III COG IVs used in the Broad Reading, Broad Mathematics, and Broad Written Language prediction models can be found in Table A (available as a supplementary resource online). Evidence for collinearity was found in all of the prediction models. VIF values ranged from 2.06 to 68.37. Tolerance indices for the IVs ranged from .015 to .485. Specifically, VIF and tolerance values for the GIA-E and Comprehension-Knowledge cluster exceeded critical levels in each of the prediction models. These results are consistent with the fact that the Comprehension-Knowledge cluster possesses the highest *g* loading of all the CHC measures on the WJ-III COG (McGrew & Woodcock, 2001).

Despite these results, it should be noted that, according to several theorists, collinearity is not an issue in predictive studies that are limited to interpreting the R^2 statistic (e.g., Cohen, Cohen, West, & Aiken, 2003, Pedhazur, 1982; Tabachnick & Fiddell, 2007), nor does interpretation of the R^2 coefficient in the face of collinearity violate any statistical rules of thumb (Berry, 1993). Furthermore, collinearity does not invalidate the use of hierarchical multiple regression analysis to detect improvements in R^2 such as those provided by the CHC cluster scores beyond the GIA-E score (Dana & Dawes, 2007; Schneider, 2008). According to Canivez (2013a), this redundancy is precisely the problem that practitioners must confront when simultaneously interpreting full scale and factor-level scores on intelligence tests such as the WJ-III COG. Additionally, Yin and Fan (2001) found that the $R^2/\Delta R^2$ statistic was a stable estimate of the population parameter in a simulation study on the impact of collinearity on regression coefficients once the sample size/number of IVs (N/P) ratio exceeded 100. In the current study, N/P ratios exceeded 200 in all of the regression models.

Results

The means, standard deviations, skewness, and kurtosis statistics for all of the WJ-III cognitive and achievement variables are listed in Table 2. The mean (99.99 to 101.38) and standard deviation ranges (14.62 to 16.08) for the cognitive and achievement variables generally reflect values that would be expected for normally distributed standard score variables. Skewness values provided evidence of normally distributed symmetry for all the variables, ranging from -0.41 to 0.11. Additionally, inspection of the residual plots of the data indicated that the regression models utilized in this study met the assumptions for homoscedasticity of the residuals.

WJ-III ACH Cluster Scores

Table 3 presents the results from hierarchical multiple regression analyses for the WJ-III ACH cluster scores. In order to account for potential inflationary effects resulting from multiple statistical comparisons, the Type I error rate was estimated using the guidelines in Cohen et al. (2003). It was determined that the investigation-wise error rate, with α set at .05, was in the vicinity of .14. To control for the increase in Type I error, the statistical significance of $R^2/\Delta R^2$ was evaluated after adjusting the critical α level using the Bonferroni correction for multiple comparisons (Mundform, Perett, Schaffer, Piconne, & Rooseboom, 2006). The GIA-E accounted for statistically significant (investigation-wise, $p < .006$) portions of each of the WJ-III ACH cluster scores. Across the 11 regression models utilized to predict Broad Reading, Basic Reading, Reading Comprehension, Broad Mathematics, Math Calculation, Math Reasoning, Broad Written Language, Basic Writing, Written Expression, Oral Expression, and Listening Comprehension Skills on the WJ-III ACH, the GIA-E accounted for 29% (Math Calculation Skills) to 56% (Listening Comprehension; *Mdn* = 46%) of the criterion variable variance. The R^2 values that corresponded to those variance increments all indicate large effects using Cohen's interpretive guidelines.

CHC clusters entered jointly into the second block of the regression equations accounted for 2% (Math Reasoning) to 23% (Oral Expression; *Mdn* = 5%) of the incremental variance. The ΔR^2 values that corresponded to those variance increments indicated small to large effects. The incremental variance coefficients attributed to individual CHC clusters ranged from 0% to 23%, with only the Comprehension-Knowledge cluster in the Oral Expression model (ΔR^2_{Gc} = .23) accounting for more than 5% of achievement variance. Although ANOVA-based tests of significance indicated that the CHC clusters on the WJ-III COG contributed significant portions of incremental achievement variance beyond the effects of the GIA-E, effect size estimates were only significant at the practical level of interpretation in the Oral Expression model (ΔR^2_{CHC} = .23). A post hoc power analysis revealed that for each of the IVs, $R^2/\Delta R^2$ effect sizes of less than .01 could be reliably detected with α set at .006, at a power of greater than .93 in all of the regression models.

Discussion

We examined the incremental validity of WJ-III COG CHC-based cluster scores in accounting for achievement outcomes beyond the GIA-E in a sample of 4,722 children and adolescents. Hierarchical multiple regression analyses were used to determine the extent to which CHC cluster scores provided meaningful improvements in predicting achievement scores beyond the GIA-E.

For the most part, the CHC clusters accounted for negligible to small effects on the WJ-III ACH. These variance coefficients were discrepant from the estimated effects of the GIA-E, which accounted for large achievement effects across all of the criterion variables. These results are fairly consistent with those that have been obtained from other cognitive measures and samples (e.g., Canivez, 2013a; Glutting et al., 2006; Glutting et al., 1997; Watkins, Glutting, & Lei, 2007; Youngstrom et al., 1999). However, large cluster-level effects were obtained in the Oral Expression model. This is the first incremental validity investigation with normative cognitive assessment data in which such significant factor-level effects have been observed.

Oral Expression

In predicting Oral Expression outcomes, the CHC clusters jointly accounted for an increase in predictive variance that was consistent with a large effect size estimate ($\Delta R^2{}_{CHC}$ = .23). Factor-level effects of this magnitude have not previously been reported in the technical literature. At the individual level of analysis, the Comprehension-Knowledge cluster alone accounted for almost all of the additional Oral Expression variance ($\Delta R^2{}_{Gc}$ = .23). Interestingly, several other clusters contributed additional predictive power in increments that exceeded chance factors due to rounding errors (e.g., $\Delta R^2{}_{Gf}$ = .03, $\Delta R^2{}_{Gsm}$ = .04, $\Delta R^2{}_{Gs}$ = .03). These results indicate that some of the individual-level variance might have been absorbed when the clusters were entered jointly into the regression equation. Such suppressor effects have been noted in other hierarchical multiple regression designs (Cohen, et al., 2003).

Whereas the implications from these findings indicate incremental validity of the CHC factors for the prediction of norm-referenced Oral Expression outcomes on the WJ-III ACH, the results are tempered by the potential confound of construct overlap between the predictors and the criterion measure. According to Mather, Wendling, and Woodcock (2001), the Oral

Expression cluster "measures linguistic competency and vocabulary knowledge" (p. 127) and is implicated as being a measure of Crystallized Ability (Gc). Therefore, the predictive effects attributed to the Comprehension-Knowledge (Gc) factor should be viewed with caution.

Interpreting R^2 as an Effect Size Indicator

The study results also indicate that strict interpretation of variance coefficients using effect size guidelines may obfuscate the potential identification of significant findings in certain circumstances. To illustrate, in the Math Calculation Skills model, the CHC cluster scores accounted for 6% additional achievement variance. Interpretation of the variance coefficient alone indicates that this finding is not clinically significant, however when the weaker effects associated with the general factor are taken into account, the cluster scores actually accounted for an additional 17% of the variance predicted by the regression model as a whole. Similar results have been obtained in incremental validity investigations with clinical samples (e.g., Nelson & Canivez, 2012). Thus, when weaker general factor effects are obtained, it is possible for factor-level scores to provide for significant predictive effects even though the variance coefficients associated with those variables remain small to negligible.

Implications for Clinical Interpretation

When considering why the CHC clusters generally failed to account for meaningful achievement variance beyond the GIA-E, it is important to remember that all factor-level scores on intelligence tests are comprised of various mixtures of common, unique, and error variances. The results from this study indicate that in most circumstances, when the common variance is removed from the subordinate clusters there is little reliable unique variance left that is useful for predicting norm-referenced achievement on the WJ-III ACH. These findings were interesting given the factor analytic results obtained by Floyd et al. (2009) that indicated many of the CHC factor clusters contained large amounts of specific variance. Interestingly, a recent exploratory bifactor modeling study conducted by Dombrowksi (2014) found strong omega coefficients associated with general factor whereas weaker omega coefficients (.038 to .517) were found for the seven CHC-clusters, suggesting that the clusters contain much smaller portions of specific variance associated with their latent constructs than previously thought.

Although the clusters accounted for more variance than has generally been observed in other incremental validity investigations using standardization data, critical levels were exceeded in only one of the prediction models. Unfortunately, the potential contaminator effects that were noted for that model (Oral Expression) raise questions about the tenability of those findings. As it relates to clinical practice, it is worth noting that several individual clusters accounted for 2% to 5% of additional predictive variance beyond the general factor. Whereas these variance coefficients were not indicative of significant effects, clinical interpretation of those scores may benefit school psychologists engaged in high stakes evaluations (e.g., SLD assessments), where the maximization of achievement prediction is essential (Keith, 2006). Ultimately, the decision as to whether the additional variance provided by the CHC-based clusters is worth the additional administration time that is needed to obtain them is a value judgment that will vary from one clinician to another. When making clinical decisions, we encourage school psychologists to consider Weiner's advice to assessors to "(a) know what their tests can do and (b) act accordingly" (1989, p. 829).

Potential Implications for PSW Methods of SLD Identification

The results from the current study have implications that are relevant for evaluating the practical validity of models that require practitioners to evaluate relationships between an individual's profile of cognitive strengths and weaknesses and achievement markers (PSW) for the purposes of SLD Identification. In the CHC-based PSW model advocated by Flanagan et al., (2011), SLD is established when there a link between a normative cognitive deficit in a CHC/neuropsychological domain and a concomitant deficit in a relevant area of achievement, with remaining psychoeducational abilities falling within expected ranges. Although a full scale IQ score can be utilized as evidence to demonstrate a pattern of cognitive behavior not related to the deficit area of concern, in the PSW model, primary interpretation is to occur at the narrow and broad ability levels of the CHC model. The results from the current study indicate that practitioners who interpret CHC cluster scores on the WJ-III COG, without accounting for the effects of the GIA-E risk overestimating the predictive effects of various CHC-related abilities (Glutting, et al., 2006). As previously discussed, all of the CHC-clusters on the WJ-III COG contain common variance associated with the GIA-E, unfortunately, the task complexity inherent in all cognitive measures makes it difficult to identify “pure” factors of individual differences (Carroll, 1976). Whereas it may be possible for practitioners to account for general factor effects when interpreting primarily at the broad ability level, contemporary PSW models have yet to provide a mechanism for doing so. As Horn (1991) cautioned long ago, attempting to disentangle the different features of cognition is akin to “slicing smoke.”

Future Directions

Incremental validity researchers have largely relied on archived standardization data to assess the predictive effects of cognitive test scores. This is problematic given that the two incremental validity studies (Nelson & Canivez, 2012; Nelson et al., 2013) that have been conducted using data obtained from clinical samples have found significantly diminished effects associated with the general factor with greater portions of achievement variance accounted for by factor-level scores. As a reviewer noted in an earlier version of this manuscript, research is needed to determine how well these results generalize to other samples and clinical contexts as well as to the recently revised version of the Woodcock-Johnson assessment series.

There are many questions related to the incremental validity of intelligence test data that have yet to be explored. We believe that it is critical to continue examining the predictive utility of cognitive test data at all levels of inference. For instance, many contemporary measures such as the WJ-III COG report multiple IQ indicators (e.g., brief or short versions, nonverbal ability composites), as an alternative to a more comprehensive IQ composite. Additional research is needed to explore the stability of prediction across these indicators. Also, an examination of these effects across various demographic groups may provide useful information for evaluating the predictive effects of factor-level scores for students with culturally and linguistically diverse backgrounds. To our knowledge, such an examination has yet to take place.

Additionally, it is important to note that, whereas the cognitive variables consistently accounted for large portions of achievement variance, approximately half of the variance in the WJ-III ACH variables was left unpredicted in many of the regression models. More research is needed to identify the relevant variables (e.g., Cattell, 1971) that may account for the unexplained variance in the current study.

Limitations

This study is not without limitations that should be considered when interpreting the results. First, it is important to remember that this study was designed to be predictive in nature, which limits the explanatory inferences that can be drawn from the data. According to Pedhazur (1997), predictive studies are concerned primarily with determining the most optimal variables or set of variables for predicting an external criterion with a specific sample, whereas in explanatory investigations the goal of the research is to shed light on a relationship with results that will generalize to the population. Whereas this necessarily limits the generalizability of our findings, it is worth noting that the present study utilized a large, nationally stratified, standardization sample that has been employed by other researchers (e.g., Floyd et al., 2009; Keith & Reynolds, 2010; Taub, Floyd, Keith, & McGrew, 2008) over the last decade to assess the psychometric validity of the WJ-III COG and to extend the CHC literature base. Nevertheless, given the stark differences that have been obtained between validity studies using hierarchical multiple regression analysis and those utilizing other methods (e.g., structural equation modeling), the potential confound of method variance also must be considered when interpreting these results. Accordingly, additional research examining the generalizability of these findings using alternative methodologies is needed.

Additionally, although we have made frequent references to *g* and the "general factor" throughout this article, it is important to highlight that many questions remain as to whether *g* reflects an actual latent ability or is merely a statistical artifact resulting from the tendency for all tests of mental ability to be positively correlated (Spearman, 1904). Ironically, CHC theory is actually a synthesis of competing theories that took opposite sides on this issue. Whereas Horn (1991) rejected the notion of *g*, Carroll (1993) believed there was sufficient evidence to conclude that positive manifold was the result of a higher-order general intelligence factor. A more detailed discussion is beyond the scope of the present article and readers are referred to Schneider and McGrew (2012) for an excellent discussion of the issue.

Conclusion

The results of this study do not support the omnibus recommendation in the WJ-III COG examiner manual (Mather & Woodcock, 2001), or other interpretive resources (e.g., Wendling, Mather, & Schrank, 2009) that the CHC cluster scores should be the primary point of interpretation with this instrument. In contrast, the results indicate that the GIA-E should be given the greatest interpretive weight because it accounted for the largest amount of variance across achievement indicators on the WJ-III ACH. The GIA-E consistently accounted for greater portions of achievement variance than that accounted for by the CHC cluster scores. Therefore, clinicians who forego interpreting the GIA-E in favor of the cluster scores may risk over-interpretation of the measurement instrument. Additional research with the soon to be published WJ-IV COG will be important in determining whether the CHC cluster scores provide useful clinical information beyond the GIA-E. Such information is vital to assist in guiding empirically supported interpretation of data obtained from this instrument.

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Table 1

Demographic Information for the Study Sample (N = 4,722)

Variable	*n*	Percent of Sample	Percent of U.S. Population
Sex			
Male	2382	50.4	51.2
Female	2340	49.6	48.8
Race			
European American	3702	78.4	78.5
African American	684	14.5	16.1
Asian American	241	5.1	4.1
Native American	95	2.0	1.3
Hispanic/Latino/Chicano			
Yes	567	12.0	18.7
No	4155	88.0	81.3
Census Region			
Northeast	1133	24.0	17.8
Midwest	978	20.7	22.3
South	1487	31.5	35.9
West	1124	23.8	24.0
Community Size			
Large City	2800	59.3	68.3
Suburban	1025	21.7	10.7
Rural	897	19.0	21.0
Type of School			
Public	4099	86.8	86.5
Private	571	12.1	11.3
Home	52	1.1	2.2
Foreign Born			
No	4486	95.0	94.3
Yes	236	5.0	5.7
Father's Education			
Less than High School	527	11.7	13.3
High School	1507	33.5	31.8
More than High School	2465	54.8	54.9
Not Available	223		
Mother's Education			
Less than High School	432	9.6	10.9
High School	1485	33.0	29.5
More than High School	2583	57.4	59.6
Not Available	222		

Table 2

Univariate Descriptive Statistics for WJ-III Cognitive-Achievement Variables

Variables	*N*	*M*	*SD*	Skewness	Kurtosis
GIA-E	2130	100.36	14.94	-0.12	0.39
Comprehension-Knowledge	2903	100.85	14.86	-0.40	0.53
Fluid Reasoning	3253	100.30	15.45	-0.34	0.32
Auditory Processing	3435	100.25	15.64	0.11	0.40
Visual-Spatial Thinking	2775	100.36	14.62	-0.15	0.37
Long-Term Retrieval	3078	100.16	14.88	0.03	0.34
Short-Term Memory	3746	100.74	15.49	-0.07	0.48
Processing Speed	3326	99.99	15.11	-0.07	0.47
Broad Reading	3845	101.38	15.26	-0.36	0.99
Basic Reading Skills	4028	100.94	15.00	-0.35	0.57
Reading Comprehension	3217	101.15	15.53	-0.37	1.12
Broad Mathematics	3954	100.76	15.70	-0.20	0.68
Math Calculation Skills	3961	100.19	15.63	-0.25	0.70
Math Reasoning	3647	100.31	15.82	-0.11	0.40
Broad Written Language	3877	100.51	15.44	-0.41	1.07
Basic Writing Skills	3311	100.59	14.74	-0.13	0.36
Written Expression	3890	101.13	15.10	-0.32	0.90
Oral Expression	3183	100.06	15.30	-0.11	0.43
Listening Comprehension	3831	100.00	16.08	-0.27	0.46

Note. GIA-E = General Intellectual Ability Composite. Obtained values rounded to the nearest hundredth.

Table 3

Incremental Contribution of Observed Woodcock-Johnson III Tests of Cognitive Abilities CHC Cluster Scores in Predicting Woodcock-Johnson III Tests of Achievement Cluster Scores Beyond the GIA-E.

	Broad Reading (n = 2,059)[b]			Basic Reading Skills (n = 2,129)[b]			Reading Comprehension (n = 1,813)[b]		
Predictor	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]
GIA-E	.55*	-	55%	.46*	-	46%	.54*	-	54%
CHC Cluster Scores (df = 7)[a]	.60	.06*	6%	.49	.03*	3%	.60	.06*	6%
Comprehension-Knowledge	.57	.02*	2%	.47	.01*	1%	.59	.05*	5%
Fluid Reasoning	.57	.02*	2%	.48	.02*	2%	.54	.01*	1%
Auditory Processing	.55	.00	0%	.46	.00	0%	.54	.00	0%
Visual-Spatial Thinking	.55	.01*	1%	.46	.00*	0%	.54	.00*	0%
Long-Term Retrieval	.55	.00	0%	.46	.00	0%	.54	.00*	0%
Short-Term Memory	.55	.00	0%	.46	.00*	0%	.55	.01*	1%
Processing Speed	.56	.01*	1%	.46	.00	0%	.54	.00	0%
	Broad Mathematics (n = 2,106)[b]			Math Calculation Skills (n = 2,106)[b]			Math Reasoning (n = 2,127)[b]		
	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]
GIA-E	.46*	-	46%	.29*	-	29%	.54*	-	54%
CHC Cluster Scores (df = 7)[a]	.49	.03*	3%	.35	.06*	6%	.56	.02*	2%
Comprehension-Knowledge	.46	.00	0%	.29	.00	0%	.54	.01*	1%
Fluid Reasoning	.46	.00*	0%	.29	.00	0%	.54	.01*	1%
Auditory Processing	.46	.01*	1%	.29	.00	0%	.55	.01*	1%
Visual-Spatial Thinking	.46	.00	0%	.29	.00	0%	.54	.00	0%
Long-Term Retrieval	.46	.00	0%	.29	.00	0%	.54	.00	0%
Short-Term Memory	.46	.00	0%	.29	.00	0%	.54	.00*	0%
Processing Speed	.47	.01*	1%	.33	.04*	4%	.54	.00	0%
	Broad Written Language (n = 2,062)[b]			Basic Writing Skills (n = 2,110)[b]			Written Expression (n = 2,063)[b]		
	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]
GIA-E	.46*	-	46%	.41*	-	41%	.41*	-	41%
CHC Cluster Scores (df = 7)[a]	.51	.05*	5%	.43	.03*	3%	.47	.06*	6%
Comprehension-Knowledge	.46	.01*	1%	.41	.01*	1%	.41	.00*	0%
Fluid Reasoning	.46	.01*	1%	.41	.01*	1%	.42	.01*	1%
Auditory Processing	.46	.00	0%	.41	.00	0%	.41	.00*	0%
Visual-Spatial Thinking	.46	.00*	0%	.41	.00*	0%	.41	.00	0%
Long-Term Retrieval	.46	.00	0%	.41	.00	0%	.41	.00	0%

Short-Term Memory	.46	.00	0%	.41	.00	0%	.41	.00	0%
Processing Speed	.47	.02*	2%	.51	.01*	1%	.43	.02*	2%

	Oral Expression (n = 2,126)[b]			Listening Comprehension (n = 2,130)[b]		
	R^2	ΔR^2	Increment (%)[c]	R^2	ΔR^2	Increment (%)[c]
GIA-E	.47*	-	47%	.56*	-	56%
CHC Cluster Scores (df = 7)[a]	.70	.23*	23%	.61	.05*	5%
Comprehension-Knowledge	.70	.23*	23%	.59	.02*	2%
Fluid Reasoning	.50	.03*	3%	.57	.01*	1%
Auditory Processing	.47	.00	0%	.56	.00	0%
Visual-Spatial Thinking	.48	.01*	1%	.57	.00*	0%
Long-Term Retrieval	.47	.00	0%	.56	.00	0%
Short-Term Memory	.51	.04*	4%	.58	.01*	1%
Processing Speed	.50	.03*	3%	.56	.00	0%

Note. GIA-E = General Intellectual Ability composite score. CHC = Cattell-Horn-Carroll cognitive cluster scores. All coefficients rounded to nearest hundredth, may not equate due to rounding.

[a]Degrees of freedom reflects controlling for the effects of the GIA-E.

[b]Indicates valid cases listwise.

[c]Represents proportion of variance accounted for by variables at their entry point into regression equation. $R^2/\Delta R^2$ values multiplied by 100.

*Investigation-wise, $p < .006$.