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DIFFERENTIAL ABILITY SCALES – SECOND EDITION (NEURO)PSYCHOLOGICAL PREDICTORS OF MATH PERFORMANCE FOR TYPICAL CHILDREN AND CHILDREN WITH MATH DISABILITIES

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Concerns about the ability-achievement discrepancy method for specific learning disability (SLD) determination led to alternative research-based methods, such as failure to respond to intervention. Neither of these *regulatory* methods address the *statutory* SLD definition, which explicitly includes a deficit in *basic psychological processes*. Examining neuropsychological processing differences among typical children and children with math SLD, commonality analyses revealed that *Differential Ability Scales – Second Edition* (DAS-II) predictors accounted for more achievement variance in typical children (46% to 58%) than in children with math SLD (33% to 50%), with substantial loss of predictive validity when General Conceptual Ability was used instead of subcomponent scores. Results suggest that differences in typical predictor-outcome relationships may provide a foundation for developing specific cognitive and academic interventions for children with math SLD. © 2008 Wiley Periodicals, Inc.

Intelligence test interpretation remains one of the most controversial and divisive issues in psychological assessment. Although examining a child's *level of performance* using a global intelligence score (e.g., IQ) interpretation has been steadfastly advocated by some (e.g., Watkins, Glutting, & Lei, 2007), others have heuristically and empirically challenged this practice (e.g., Hale, Fiorello, Kavanagh, Holdnack, & Aloe, 2007), suggesting that global IQ scores may have limited utility in clinical practice (Fiorello, Hale, Holdnack, Kavanagh, Terrell, & Long, 2007). At least since Thurstone (1938), many researchers have emphasized individual components of intelligence, with this multifactorial view dominating the field in recent times (Daniel, 1997). As a result, several authorities (e.g., Groth-Marnat, Gallagher, Hale, & Kaplan, 2000; Hale & Fiorello, 2004; Kamphaus, 2001; Kaufman, 1994; Lezak, 1995; Miller, 2007; Miller & Hale, 2008; Prifitera, Weiss, & Saklofske, 1998; Sattler, 2001) offer methods and tables to assist practitioners in examining cognitive subtest or factor scores, a technique often referred to as *profile analysis* of a child's cognitive or neuropsychological *pattern of performance.*

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Level of Performance Interpretation: Fact or Fancy?

Those who advocate interpreting a child's *level* of performance have insisted that intellectual or cognitive ability tests simply measure global intelligence or psychometric *g* (Spearman, 1927). The positive manifold among subtests (Brody, 1997) supports use of *g*'s proxy, global IQ, which has excellent reliability and validity (Jensen, 1998) and strong predictive validity (e.g., Ceci & Williams, 1997; Gottfredson, 1997; Neisser et al., 1996). Additional support for IQ interpretation has come from arguments that intelligence subtest profiles are so unreliable (Canivez & Watkins, 1998, 1999, 2001; Macmann & Barnett, 1997) and invalid (Gresham & Witt, 1997; Reschly & Gresham, 1989), that practitioners have been admonished to "just say no" to subtest analysis (McDermott, Fantuzzo, & Glutting, 1990). In addition, significant profile variability base rates are so high that variability is the norm, not the exception (Fiorello, Hale, McGrath, Ryan, & Quinn, 2001; Glutting, McDermott, Watkins, Kush, & Konold, 1997; Hale et al., 2007; Kahana, Youngstrom, & Glutting, 2002), albeit these researchers offer very different conclusions regarding the meaning of profile variability.

The strongest attacks on subtest profile analysis have been based on techniques that statistically control for IQ variance, and then explore the utility of factors, subtests, or profiles, which typically yield little additional diagnostic information (e.g., Glutting, Watkins, Konold, & McDermott, 2006; Glutting, Youngstrom, Ward, Ward, & Hale, 1997; Kahana et al., 2002; Maller & McDermott, 1997; McDermott & Glutting, 1997; Watkins & Glutting, 2000; Watkins et al., 2007; Youngstrom, Kogos, & Glutting, 1999). The implicit conclusion offered by this research group is that it is unscientific and irresponsible to interpret anything beyond global IQ. These conclusions are made explicit by others, who argue that IQ, *g*, and intelligence are virtually synonymous and that global ability should be used in educational, occupational, social, and political decisions and policy (e.g., Gottfredson, 1997; Herrnstein & Murray, 1994).

Despite these redundant findings, there is clear and convincing evidence that the measures and/or statistical methods used in these studies do not support the authors' conclusions or claims. For instance, in *The Bell Curve*, Herrnstein and Murray (1994) reported racial differences in "intelligence," yet their measure primarily tapped prior learning (Roberts, Goff, Anjoul, Kyllonen, Pallier, & Stankov, 2000), suggesting that results could be explained by racial achievement—not intelligence—differences (see Hale & Fiorello, 2001). Equally problematic is the use of hierarchical regression methods for evaluating the "incremental validity" of subtest, factor, or profile differences beyond the global IQ. As has been demonstrated elsewhere (Fiorello et al., 2001, 2007; Fiorello, Hale, & Snyder, 2006; Hale et al., 2007; Hale & Fiorello, 2001, 2004; Hale, Fiorello, Kavanagh, Hoeppner, & Gaither, 2001), hierarchical regression analyses that use global IQ scores in the same analysis as lower-order factor and subtest scores are inappropriate because the global (e.g., IQ) and subcomponent (e.g., factor, subtest profile, variability group) scores are derived from the same subtest scores. The subtest and/or factor scores account for all the variance of the global score. This precludes their inclusion in the same regression equation (Pedhazur, 1997), and is a fatal flaw in the research cited in the previous paragraph.

To correct for the dubious results and unwarranted conclusions of the incremental validity studies, data partitioning using regression commonality analysis (see Pedhazur, 1997) allows for calculation of the unique and shared variance that each multicollinear predictor contributes to the dependent variable. In a series of Wechsler Intelligence Scale for Children, 3rd. and 4th editions (WISC-III and WISC-IV) studies, Fiorello, Hale, and colleagues (see Fiorello et al., 2001, 2007; Hale et al., 2001, 2007, 2008; Hale, Fiorello, Sherman, & Bertin, 2002) demonstrated that there is little shared factor/subtest variance in the prediction of IQ, achievement, neuropsychological, and behavioral domains among typical children with variable profiles and those with disabilities, with the loss of predictive validity substantial when one interprets global over subcomponent scores in clinical populations (see Hale et al., 2007; 2008). If the shared variance among predictors, or true *g*, is typically less than 10% for a vast majority of the population, including those with variable profiles and disabilities, then we have spent the last 100 years reifying a construct that is no longer useful in clinical practice (Fiorello et al., 2001). In addition, because unique and shared variance among predictors of achievement and neuropsychological functioning vary among different populations (Hale et al., 2001, 2007, 2008; Hale, Hoeppner, & Fiorello, 2002), subcomponent score interpretation would appear to be warranted if empirical methods are developed to interpret a child's cognitive profile or *pattern of performance*.

Pattern of Performance Interpretation: Empirical Evaluation of Profile Analysis

Although it is widely used in clinical practice (Pfeiffer, Reddy, Kletzel, Schmelzer, & Boyor, 2000), the term "profile analysis" is, unfortunately, used to describe at least three different methods for analyzing subtest scores. One method compares the examinee's subtest score pattern to one or more subtest profiles found in standardization or clinical samples, such as attention-deficit/hyperactivity disorder (ADHD; Mayes & Calhoun, 2006) or reading disability (Fiorello et al., 2006). These patterns may reflect only small subtest score variations (see Glutting, McDermott, Prifitera, & McGrath, 1994; Glutting, McGrath, Kamphaus, & McDermott, 1992; Holland & McDermott, 1996), thereby limiting their discriminant validity. Moreover, this method assumes clinical samples to be homogeneous, whereas in practice it is commonly found that children identified with such disabilities as ADHD or reading disability have very diverse cognitive profiles and form distinctive subgroups. Collapsing them into one clinical group has the effect of attenuating, or even eliminating, statistically significant and valid cognitive profiles found within the group. The second approach, ipsative analysis, is especially problematic because disparate abilities are collapsed into a mean score (Hale & Fiorello, 2004), and then *g* is removed from the analysis by comparing each score to that mean (McDermott, Fantuzzo, Glutting, Watkins, & Baggaley, 1992).

A third type of profile analysis requires delineation and verification of the examinee's scores on validated groups (i.e., factors, scales, or clusters) of subtests as possibly reflecting different cognitive functions, taking both level and pattern of performance into account (Hale et al., 2007). Advocated in this article, this form of profile analysis is similar to the methods suggested by Elliott (2007), Hale and Fiorello (2004), Kaufman (1994), Miller (2007), Sattler (2001), and the authors of the Cattell-Horn-Carroll (CHC) Cross-Battery Approach (e.g., Flanagan & McGrew, 1997; Flanagan, McGrew, and Ortiz, 2000; Flanagan & Ortiz, 2001; Flanagan, Ortiz, & Alfonso, 2007; McGrew, 1997; McGrew & Flanagan, 1998; Woodcock, 1990, 1993) based in part on the massive review and analysis of factor-analytic studies by Carroll (1993, 1997). The Cross-Battery application of CHC theory has been challenged (e.g., Watkins, Youngstrom, & Glutting, 2002) and defended (e.g., Ortiz & Flanagan, 2002a, 2002b), with some offering a moderate position for applying CHC theory to clinical practice (e.g., Fiorello & Primerano, 2005; Hale & Fiorello, 2002). It is worth noting that the apparent convergence of CHC and current neuropsychological theories (Fiorello, Hale, Snyder, Forrest, & Teodori, 2008; Hale & Fiorello, 2004) provides crucial construct validity support for both positions.

Similar to the neuropsychological process approach, the Cognitive Hypothesis Testing (CHT; Hale & Fiorello, 2004) approach to profile analysis is essential practice because neuropsychological and neuroimaging research has demonstrated that children with disabilities not only have difficulty learning in the classroom, they also have specific learning *deficits* (Castellanos et al., 2002; Francis, Shaywitz, Stuebing, Shaywitz, & Fletcher, 1996) that are likely due to differences in brain structure and/or function (see Basso, Burgio, & Caporali, 2000; Berninger, 2002; Cao, Bitan, Chou, Burman, & Booth, 2006; Casanova, Christensen, Giedd, Rumsey, Garver, & Postel, 2005; Castellanos et al., 2002; Collins & Rourke, 2003; Demb, Boynton, & Heeger, 1998; Eden, VanMeter, Rumsey, Maison, & Zeffiro, 1996; Fiez & Petersen, 1998; Filipek, 1999; Fine, Semrud-Clikeman, Keith, Stapleton, & Hynd, 2007; Fleischner, 1994; Geary, Hoard, and Hamson, 1999; Isaacs, Edmonds, Lucas, & Gadian, 2001; Leonard, Lombardino, Giess, & King, 2005; Mazzocco, 2001; Naglieri & Bornstein, 2003; Nicholson & Fawcett, 2001; Njiokiktjien, de Rijke, & Jonkman, 2001; Pugh et al., 2000; Richards et al., 2006; Ruff et al., 2003; Semrud-Clikeman & Pliszka, 2005; Shaywitz, Lyon, & Shaywitz, 2006; Stein, 2001; Tallal, 2006; Zadina, Corey, & Casbergue, 2006). If verified through CHT, examining a child's neuropsychological *pattern* of performance provides practitioners with the insight into individual differences in cognition, learning, and behavior essential for accurate differential diagnosis and effective individualized instruction (Hale & Fiorello, 2004).

Using Empirical Profile Analysis to Predict Math Skills

We do not have a different brain for intelligence, neuropsychological functioning, achievement, and acting within the environment (Hale et al., 2007). This fact, combined with the evidence cited above, suggests that empirical profile analysis is warranted and necessary when predicting a child's mathematics achievement and other important outcomes. Although children with math learning disabilities (MLD) may score similarly to peers on global measures, they often show cognitive strengths and weaknesses (Proctor, Floyd, & Shaver, 2005), consistent with the Individuals with Disabilities Education Act (IDEA) statutory requirements that affected individuals display a deficit in the basic psychological processes in the presence of cognitive integrities (Hale, Kaufman, Naglieri, & Kavale, 2006). Several studies have begun to examine such cognitive patterns of performance, with results providing a foundation for empirical profile analysis.

For their WISC-III SLD commonality study, Hale et al. (2001) showed that crystallized (Gc), quantitative/fluid (Gq/Gf), and memory (Gsm-WM) were strong predictors of math computation skills, but there was some unique visual (Gv) variance and shared variance between Processing Speed (Gs), Gq/Gf, and Gv. Further subtest analysis in Hale et al. (2002) revealed that most math computation variance was accounted for by the six WISC-III Verbal and two Processing Speed subtests, with some contribution by Block Design. The Wechsler Individual Achievement Test (WIAT) Math Reasoning (MR) results were similar, with measures of Gv and Gq/Gf playing an even larger role. For the WISC-IV/WIAT-II Math Composite commonality analysis, Hale et al. (2007) found Gc and Gf to be the strongest predictors, and this predictive validity was enhanced by their combination with Gsm-WM. Gs provided a substantial, unique contribution, and it shared variance with other predictors as well.

Also working within CHC theory, Floyd, Evans, and McGrew (2003) used structural equation modeling to show that Woodcock-Johnson III (WJ III; Woodcock, McGrew, & Mather, 2001) specific cognitive abilities predicted math achievement better than general cognitive ability in the standardization data. Similar to earlier large-scale studies (McGrew, Flanagan, Keith, & Vanderwood, 1997), complex relationships among CHC factors and math achievement domains were found for different age levels (Floyd et al., 2003). They found that Gc, Gf, Gsm, Gsm-WM, and Gs were moderate to strong predictors, with Long-term Retrieval (Glr) and Auditory Processing (Ga) demonstrating moderate relationships at younger ages. Gc's importance increased with age, and was more related to MR, which would be consistent with the notion that Gc reflects both prior knowledge and language development/facility (Hale & Fiorello, 2004). Similar to the Hale et al. (2002) findings, Floyd et al. (2003) found Gf or novel problem solving skills to be consistently related to math achievement. Gs was related to calculation skills more than MR, and Glr and Ga were predictive of math achievement for young children. Although Gsm appears to be an important predictor of math performance, not all children with math difficulties experience deficits in this area (Proctor et al., 2005). In addition to supporting CHC component analyses over general ability, these findings also reflect the dynamic nature of mathematics development during childhood, validating the need for individual assessment for children with MLD.

Empirical Examination of the Differential Ability Scales

The recently revised Differential Abilities Scales-Second Edition (DAS-II; Elliott, 2007) and its predecessor are popular measures of intellectual and cognitive functioning among school psychology practitioners and have excellent technical qualities (Dumont, Willis, & Sattler, 2001; Elliott, 2007; Platt, Kamphaus, Keltgen, & Gilliland, 1991). The Verbal (Gc), Nonverbal Reasoning (Gf), and Spatial (Gv) abilities factor structure hypothesized for the DAS and DAS-II Core subtests has been validated using large standardization samples (Elliott, 1990, 2007); children with cultural, linguistic, or racial differences (DiCerbo & Barona, 2000; Keith, Quirk, Schartzer, & Elliott, 1999; Riccio, Ross, Boan, Jemison, & Houston, 1997); and children with developmental and learning disabilities (Dumont, Cruse, Price, & Whelley, 1996; Elliott, 2001; Gibney, McIntosh, Dean, & Dunham, 2002; Hughes & McIntosh, 2002; Kercher & Sandoval, 1991; McIntosh & Gridley, 1993; Shapiro, Buckhalt, & Herod, 1995). The structure is also supported by independent exploratory and confirmatory factor analysis (Daleo et al., 1999; Dunham, McIntosh, & Gridley, 2002; Keith, 1990). The *DAS-II Introductory and Technical Handbook* (Elliott, 2007) provides evidence that the Core subtest factor structure remains unchanged from the original DAS. In addition, there are two new Working Memory and Processing Speed factors derived from the Diagnostic subtests, adding to the clinical utility of this instrument.

Despite the apparent clinical utility of the DAS-II Core and Diagnostic measures, some academics have used the dubious hierarchical statistical techniques described earlier to admonish practitioners to interpret only General Conceptual Ability (GCA) scores in predicting academic achievement (Youngstrom et al., 1999). Kahana et al. (2002) reported that discrepancy or subtest data did not yield significant improvement beyond GCA in the prediction of achievement domains, but again, the GCA was force entered into the regression equation first, followed by a dummy-coded discrepancy variable, thereby violating basic regression requirements because these variables are not statistically independent (see Hale et al., 2007). Not surprisingly, similar methods provided similar results when comparing ipsative and normative analysis of DAS subtests (McDermott & Glutting, 1997). This academic group also appeared to show that children with unique DAS profiles do not differ from matched controls on meaningful outcome criteria, such as special education placement, academic performance, and behavior ratings (Glutting, McDermott, Konold, Snelbaker, & Watkins, 1998), but these results also suffer methodological problems related to matching participants on GCA (see Hale et al., 2007). Finally, consistent with the Wechsler studies reported earlier, Kahana et al. reported that approximately 80% of the DAS standardization sample had one or more statistically significant between-ability scores, with the authors concluding that profile analysis is unwarranted. However, this is an illogical conclusion, equivalent to saying that because individual differences in visual acuity are so common that detailed eye examinations are unwarranted. Instead, this suggests that cognitive and intellectual diversity are the norm – not the exception – and that this diversity requires examination of both level *and* pattern of child performance.

Present Study Purpose

This interpretation debate is not trivial. Many school psychologists (see Pfeiffer et al., 2000) and neuropsychologists (see Kaplan, 1988; Lezak, 1995; Miller & Hale, in press) routinely analyze patterns of factor, scale, cluster, or subtest scores to determine individual cognitive strengths and deficits. If global IQ scores are largely irrelevant and subtests or groups of subtests (e.g., factors, indices, scales, clusters) yield relevant diagnostic information for typical and clinical populations (see Fiorello et al., 2001, 2007; Hale et al., 2001, 2002, 2007), then clinicians should be strongly encouraged to examine individual cognitive strengths and weaknesses as reflected by patterns of performance, and verify findings with other data sources in an attempt to achieve concurrent, predictive, and treatment validity (e.g., CHT; Hale & Fiorello, 2004). Not only can this type of profile analysis aid in differential diagnosis of learning and other disabilities, and ensure that children with SLD meet the statutory *and* regulatory requirements under IDEA (2004), but it could also serve as a foundation for developing individualized interventions for differentiated instruction following identification (Fiorello et al., 2006; Hale, 2006; Hale et al., 2006; Hale, Naglieri, Kaufman, & Kavale, 2004; Kavale, Kaufman, Naglieri, & Hale, 2005; Mather & Gregg, 2006). In clinical populations, subcomponent (i.e., factor/subtests) predictors account for much more achievement variance than does global intelligence (Hale et al., 2007), with the loss of variance so great that failure to conduct empirical profile analysis might be considered irresponsible and unscientific.

This regression commonality analysis study was undertaken to examine the unique and shared variance components among DAS-II CHC factors in the prediction of WIAT-II Numerical Operations (NO) and Math Reasoning (MR) skills for the normative sample and for children with MLD. If DAS-II CHC factors contribute mostly shared variance (that is, shared across all factors) in predicting math achievement scores, then a global ability or GCA interpretation would be warranted. However, if the underlying CHC factors provided large amounts of unique variance in predicting achievement domains (suggesting adequate interpretive specificity), or numerous shared variance components below the global level, then empirical profile analysis would be necessary to examine the unique strengths and deficits of individual children. It was predicted that unique CHC factor contributions to math achievement would be substantial across samples, but that different patterns of unique and shared variance would emerge for the normative and MLD groups, suggesting that profile analysis beyond global GCA is necessary when examining math achievement competency and disability.

Method

Participants

The participants were drawn from the DAS-II standardization sample of 3,480 children aged 2 years 6 months to 17 years 11 months, described in depth in the DAS-II *Introductory and Technical Handbook* (Elliott, 2007). The DAS-II standardization sample was carefully chosen to be representative of the general U.S. population according to the October 2002 Census for race, ethnicity, parent education level, and geographic region. The DAS-II/WIAT-II Linking Sample data of 413 children aged 6 to 17 years included 371 typical children and 42 children identified as having MLD according to school district and psychometric data (see Elliott, 2007). Although male and female representation was comparable in the Typical Group (52% female), a majority of the children in the MLD Group were male (64%). For the Typical Group racial breakdown, 59% were Caucasian, 20% were Latino American, 16% were African American, and 5% were Asian/Other. In the MLD Group, 52% were Caucasian, 24% were African American, 14% were Latino American, and 10% were Asian/Other. The Typical Group mean age was approximately 11 years, 6 months (mean [M] = 11.49, standard deviation [SD] = 3.58), whereas the MLD group was younger on average ($M = 9.69$, $SD = 2.00$). The mean Typical Group DAS-II GCA was solidly average ($M = 100.21$, $SD = 13.23$), but the MLD Group had a low average mean GCA score ($M = 89.39$, $SD = 10.60$). Further information regarding the samples can be found in the *DAS-II Introductory and Technical Manual* (Elliott, 2007).

Instrumentation

The DAS-II (Elliott, 2007) is an individual test of cognitive ability. The School-Age Battery (ages 7 years through 17 years, 11 months) includes six Core and eight Diagnostic subtests. The Core subtests yield a GCA score and three subcomponent Cluster scores: Verbal Ability (Word Definitions [WD] and Verbal Similarities [SI] subtests), Nonverbal Reasoning Ability (Matrices [MA] and Sequential and Quantitative Reasoning [SQ] subtests), and Spatial Ability (Recall of Designs [RD] and Pattern Construction [PC] subtests). The subtests have evidence of sufficient reliability (mean [Item Response Theory]-based reliabilities: WD = .83, SI = .80, MA = .85, SQ = .92, RD = .87, PC = .96) and considerable evidence of internal and external validity (see Elliott, 2007). The Cluster and GCA scores are reported as standard scores (*SS; M* = 100, *SD* = 15). The Verbal Ability Cluster (VE) primarily measures crystallized intelligence (Gc), the Nonverbal Reasoning Ability Cluster (NV) primarily measures fluid reasoning (Gf), and the Spatial Ability Cluster (SP) primarily measures visual-spatial abilities (Gv) (Elliott, 2007). Based on confirmatory factor analyses reported in Elliott (2007), the three Core Clusters, and three additional Cluster scores derived from the Diagnostic subtests were used as predictors in this study. Two Diagnostic cluster scores are provided in the manual – the Working Memory Cluster (WM; Gsm; Recall of Digits Backward [DB] and the Recall of Sequential Order [SO] subtests) and the Processing Speed cluster (PS; Gs; Speed of Information Processing [IP] and Rapid Naming [RN] subtests). As in the case of the Core subtests, the Diagnostic subtests show evidence of good reliability (mean IRT-based reliabilities: DB = .91, SO = .93, IP = .91, RN = .81). The Visual-Verbal Memory factor (Glr measure) includes only one subtest, the Recall of Objects-Immediate subtest score (ROI). Although the Elliott (2007) CFA results suggest separate interpretation of ROI, results should be interpreted with caution.

The WIAT-II (Psychological Corporation, 2002) is an individual test of academic achievement. It was standardized on 2,950 students aged 4 to 19 years, and the normative sample closely represented the October 1998 Census information on race, ethnicity, geographic region, and parent education level. The mathematics subtests are NO; (a test of math calculation skills) and MR (a test of math problem-solving skills), and are reported as *SS*. NO (average split-half reliability = .91) and MR (average split-half reliability = .92) are reliable and have adequate content-, construct-, and criterion-related evidence of validity (Psychological Corporation, 2002).

Procedure

The archival DAS-II/WIAT-II Linking Sample and MLD Sample (Elliott, 2007) data sets were obtained from Harcourt Assessment and uploaded to SPSS 15.0. Descriptive data and correlational analyses were performed separately for the Typical and MLD groups to develop group profiles. Multiple regression analyses were performed using the WIAT-II NO and MR subtests as dependent variables in separate regression equations, and the DAS-II factors (Verbal [VE], Nonverbal Reasoning [NR], Spatial [SP], Working Memory [WM], Processing Speed [PS], and Verbal-Visual Memory [VVM]) as predictors. The ROI subtest was converted to a *SS* to foster interpretability.

Commonality equations were written using standard variance partitioning procedures described by Pedhazur (1997). This technique allows for the examination of the proportion of dependent variable variance (i.e., NO and MR scores) that is accounted for by unique and shared predictor variance (e.g., DAS-II factor scores). To conduct the six-predictor commonality analysis, equations were entered into a SPSS syntax file using compute commands. For each dependent variable, force-entry multiple regression equations were computed with all possible combinations of predictors to acquire the required R^2 components for the commonality computations. These R^2 values were entered into a new data file with each being a new variable. The compute statements were applied

Table 1
Descriptive Statistics for Typical Children and Those with Math Disabilities

	Typical		Math LD			
Measure	*M*	*SD*	*M*	*SD*	*F*	*p*
DAS-II Factors						
Verbal	100.49	13.91	95.79	13.88	4.32	.038
Nonverbal Reasoning	100.47	13.24	88.26	10.99	33.14	<.001
Spatial	99.42	13.45	89.48	10.50	21.47	<.001
Working Memory	100.52	13.59	88.74	13.05	28.61	<.001
Processing Speed	101.66	14.51	86.07	14.16	43.79	<.001
Visual-Verbal Memory	98.18	16.23	92.04	18.03	5.30	.022
WIAT-II Math Subtests						
Math Composite	102.76	17.85	78.40	11.63	74.53	<.001
Numerical Operations	102.32	16.41	81.29	13.67	64.00	<.001
Math Reasoning	102.70	16.26	79.88	10.97	78.59	<.001

Note. LD: learning disability; DAS-II: Differential Ability Scales – Second Edition; WIAT-II: Wechsler Individual Achievement Test.

to this new data file to acquire the unique and common variance components of the commonality analysis. Only commonalities exceeding .01 are reported, as these indicate significant amounts of interpretable dependent variable variance.

Results and Discussion

The Typical Group had average DAS-II cognitive factor and achievement scores, but only the VE and VVM *SS* values were in the average range for the MLD group, with all other scores low average (see Table 1). This pattern shows that children with MLD struggle with NR, SP, WM, and PS, possibly reflecting difficulty with right hemisphere and frontal executive functions, which would be consistent with Rourke's (1995) theory that children with MLD have white matter dysfunction that leads to difficulty with global, holistic, and implicit processing of nonverbal *and* verbal content (see Bryan & Hale, 2001).

Typical Group

Typical Group zero order correlations were strong for the DAS-II Clusters and the WIAT-II math subtest scores (see Table 2). The VE correlations with math achievement were high, indicating that the expected Gc relationship with math outcomes, but also the NR/Gf and SP/Gv relationships with math outcomes were strong. MR correlations were relatively higher than those obtained for NO, except in the area of PS, where the reverse was true.

For the Typical Group commonality analyses (see Table 3), the factorial complexity of the DAS-II in the prediction of math achievement was clearly evident. DAS-II predictors remarkably accounted for 46% of NO and 58% of MR variance, which is substantial, especially when one considers that some response-to-intervention (RTI) proponents argue that intelligence testing is largely irrelevant (e.g., Reschly, 2005). For both math analyses, there was substantial unique variance (11% for NO; 14% for MR), suggesting some factor specificity for interpretation; whereas only 2% of math variance could be accounted for by the shared variance among all six predictors. It could be argued that the Core factor commonality ($C_{VE/NR/SP}$) is a more appropriate measure of general intelligence, but it accounted for only 3% of NO and 4% of MR variance. As has been suggested elsewhere (Fiorello et al., 2001, 2007; Hale & Fiorello, 2004; Hale et al., 2001, 2002, 2006, 2007), these data suggest

Table 2
Zero-order Correlations for DAS-II Predictors and WIAT-II Math Scores for Typical Group

Measure	Numerical Operations	Math Reasoning
Verbal	.514**	.601**
Word Definitions	.482**	.551**
Verbal Similarities	.454**	.550**
Nonverbal Reasoning	.561**	.615**
Matrices	.450**	.487**
Seq. & Quant. Reasoning	.566**	.634**
Spatial	.549**	.618**
Pattern Construction	.543**	.609**
Recall of Designs	.426**	.492**
Working Memory	.474**	.559**
Recall of Digits–Backward	.437**	.482**
Recall of Seq. Order	.378**	.474**
Processing Speed	.296**	.260**
Speed of Info. Processing	.251**	.197**
Rapid Naming	.246**	.240**
Visual-Verbal Memory (ROI)	.321**	.355**

Note. DAS-II: Differential Ability Scales – Second Edition; WIAT-II: Wechsler Individual Achievement Test; Seq.: sequential; Quant.: quantitative; Info.: information; ROI: Recall of Objects–Immediate.
$^{**}p < .01$.

that practitioners should not emphasize global GCA, and instead interpret factor scores and their interrelationships in developing hypotheses regarding individual strengths and weaknesses, which are subsequently evaluated for concurrent, ecological, and treatment validity (e.g., CHT; Hale & Fiorello, 2004).

For total variance explained, the Core factors explained the most total math variance (range 26% for VE/Gc prediction of NO to 38% for SP/Gv prediction of MR). However, the diagnostic WM/Gsm factor was also a strong predictor, with unique and shared components accounting for 23% of NO and 31% of MR variance. WM/Gsm shared considerable variance with the VE/Gc and NR/Gf factors, possibly suggesting that their combination reflects executive control of these robust Core predictors of math achievement or the working memory necessary for higher level processing, which is entirely consistent with our previous WISC-III findings (Hale et al., 2002) and our knowledge of dorsolateral prefrontal cortex functioning (e.g., Lichter & Cummings, 2001; Hale, Fiorello, & Brown, 2005). Both the PS/Gs and VVM/Glr factors contributed smaller amounts of variance, with virtually no unique variance, suggesting that they have limited predictive validity of math performance without examining their relationships with other factors.

For unique variance, the strongest predictors were VE/Gc, reflective of quantitative knowledge and math fact storage; NR/Gf, necessary for novel problem solving and exploring math algorithms; and SP/Gv, likely necessary for attention to operands, column alignment in multistep problems, and estimation skills (see Hale et al., 2002; Mazzocco, 2001). Gc has been a consistent predictor of math performance (Floyd et al., 2003; Hale et al., 2001, 2002, 2007), but it likely reflects computational knowledge and language facility, because it is a stronger predictor of the auditory-verbal MR subtest than the visual-motor NO subtest. As has been shown elsewhere (Floyd et al., 2003; Hale et al., 2001, 2002), Gf appears to be a strong predictor of math competency, and it is typically deficient in children with MLD (Hale et al., 2002, 2007; Proctor et al., 2005). Although Gv has limited utility

Table 3
DAS-II Factor Predictors of WIAT-II Math Performance for Typical Children

	DAS-II Factor/CHC Classification					
Component	VE/Gc	NR/Gf	SP/Gv	WM/Gsm	PS/Gs	ROI/Glr
	DAS-II/WIAT-II Numerical Operations ($R^2_{Total} = .458$)					
U_{VE}	.030					
U_{NR}		.030				
U_{SP}			.032			
U_{WM}				.009		
U_{PS}					.007	
U_{ROI}						.001
$C_{VE/NR}$	.021	.021				
$C_{NR/SP}$		.036	.036			
$C_{NR/WM}$		.011		.011		
$C_{VE/NR/SP}$	.034	.034	.034			
$C_{VE/NR/WM}$	.022	.022		.022		
$C_{NR/SP/WM}$		.021	.021	.021		
$C_{VE/NR/SP/WM}$	.052	.052	.052	.052		
$C_{VE/NR/SP/WM/ROI}$	.024	.024	.024	.024		.024
$C_{ALL(g)}$	.019	.019	.019	.019	.019	.019
UNIQUE	.030	.030	.032	.009	.007	.001
SHARED	.234	.284	.269	.216	.080	.102
TOTAL	.264	.314	.301	.225	.087	.103
	DAS-II/WIAT-II Math Reasoning ($R^2_{Total} = .579$)					
U_{VE}	.046					
U_{NR}		.018				
U_{SP}			.049			
U_{WM}				.021		
U_{PS}					.000	
U_{ROI}						.002
$C_{VE/NR}$	.027	.027				
$C_{VE/SP}$	.010		.010			
$C_{VE/WM}$	.013			.013		
$C_{NR/SP}$		.039	.039			
$C_{NR/WM}$		.016		.016		
$C_{VE/NR/SP}$	.044	.044	.044			
$C_{VE/NR/WM}$	.033	.033		.033		
$C_{NR/SP/WM}$		.030	.030	.030		
$C_{VE/NR/SP/WM}$	.074	.074	.074	.074		
$C_{VE/NR/SP/WM/ROI}$	.035	.035	.035	.035		.035
$C_{ALL(g)}$	.022	.022	.022	.022	.022	.022
UNIQUE	.046	.018	.049	.021	.000	.002
SHARED	.315	.360	.333	.291	.067	.124
TOTAL	.361	.378	.382	.312	.067	.126

Note. Commonalities < .01 omitted. DAS-II: Differential Ability Scales – Second Edition; WIAT-II: Wechsler Individual Achievement Test; VE: Verbal Ability; Gc: Crystallized Ability; NR: Nonverbal Reasoning Ability; Gf: Fluid Reasoning; SP: Spatial Ability; Gv: Visualization; WM: Working Memory Ability; Gsm: Short-term Memory; PS: Processing Speed; Gs: Speediness; ROI: Recall of Objects-Immediate; Glr: Long-term Memory Encoding/Retrieval.

in predicting math performance in typical populations (e.g., Floyd et al., 2003), it predicts math performance in disabled populations (Hale et al., 2001; Proctor et al., 2005), suggesting that the underlying psychological processes on Gv subtests are more relevant for predicting math than the apparent visual/nonverbal content. Consistent with previous research (Floyd et al., 2003; Hale et al., 2002), unique WM/Gsm demands were not essential for NO performance, but they played a larger role in MR, attesting to the executive requirements necessary to keep information in memory and manipulate it when solving math word problems. In contrast to individuals with math difficulties (Hale et al., 2001, 2007; Proctor et al., 2005), PS/Gs played only a minor role in predicting Typical Group math performance.

Interestingly, NR/Gf unique variance was less for MR than NO, which at first glance is the opposite of what would be expected given our knowledge of fluid abilities and quantitative reasoning (Flanagan, Ortiz, Alfonso, & Mascolo, 2002). However, this pattern makes sense when one examines the NR/Gf commonalities, where shared variance among NR/Gf and WM/Gsm becomes important. Because these two DAS-II factors likely reflect right frontal activity (e.g., novel problem solving), particularly dorsolateral executive functions (e.g., working memory), they must work with each other to govern more posterior neuropsychological functions reflected in Gc and Gv in the prediction of MR. In fact, this hypothesis is entirely consistent with the NR/Gf, SP/Gv, and WM/Gsm commonality, which could reflect frontal (e.g., WM/Gsm-NR/Gf) and right hemisphere (e.g., NR/Gf-SP/Gv) systems and the white matter integrity known to be critical for math computation and problem-solving skills (Rourke, 1995). As for the prediction of NO, unique NR/Gf variance could reflect the sequential processing demands of the Sequential and Quantitative Reasoning subtest (Elliott, 2007) necessary to carry out math computation steps (e.g., Hale et al., 2002).

The SP/Gv cluster was a stronger predictor of math performance than has been previously reported (e.g., Floyd et al., 2003), possibly because the Recall of Designs graphomotor requirements are necessary for written math problems. The SP/Gv results were similar to those obtained in Hale et al. (2002), where Gv skills played a greater role in predicting auditory-verbal MR than visual-motor calculation skills, which seems counterintuitive. Although not diagnostic in isolation, Gv is also a fairly consistent weakness in children with math difficulties or disabilities (Hale et al., 2001; Proctor et al., 2005). Obviously, this could be related to the global, holistic, and implicit right hemisphere processing demands often impaired in many children with "nonverbal" learning disabilities (e.g., Rourke, 1995). However, Pattern Construction, like the WISC-IV Block Design subtest, is likely related to right (global) and left (local) hemispheric functions (e.g., Schatz, Ballantyne, & Trauner, 2000), and graphomotor skills are also related to right (e.g., spatial-global) and left (e.g., detail-directional-motor) hemisphere functions (see Hale & Fiorello, 2004), so interpreting SP/Gv as a uniform measure of right hemisphere functions would be erroneous. As suggested by Hale et al. (2001), this consistent finding suggests that the *psychological processes* tapped by this cluster (e.g., analysis and synthesis) may be more important in predicting math achievement than the observable input (e.g., auditory-visual) or output (e.g., verbal-motor) demands, consistent with the neuropsychological literature that supports interpretation of underlying neuropsychological processes over observable behaviors (see Hale & Fiorello, 2004).

Higher level commonalities are difficult to interpret (Pedhazur, 1997), but it is interesting that there was a $C_{VE/NR/SP/WM/VVM}$. This commonality did not include PS/Gs and it was the only VVM/Glr commonality (below *g*) that was significant. Perhaps this commonality reflects the integrity of the memory system in general, such as hippocampal functioning, or memory retrieval of math facts from long-term memory, which is thought to be primarily a right frontal function (see Tulving & Markowitsch, 1997).

Similar to previous study results (e.g., Floyd et al., 2003; Geary & Hoard, 2001; Hale et al., 2001, 2002, 2007; Proctor et al., 2005), these findings suggest that multiple neuropsychological

Table 4
Zero-orderCcorrelations for DAS-II Predictors and WIAT-II Math Scores for Children with Math Disabilities

	Numerical Operations	Math Reasoning
Verbal	.354*	.456**
Word Definitions	.367*	.462**
Verbal Similarities	.255	.354*
Nonverbal Reasoning	.263	.418**
Matrices	.214	.331*
Seq. & Quant. Reasoning	.259	.405**
Spatial	.308*	.652**
Pattern Construction	.297	.605**
Recall of Designs	.242	.546**
Working Memory	.318*	.425**
Recall of Digits-Backward	.279	.249
Recall of Seq. Order	.216	.455**
Processing Speed	.478**	.247
Speed of Info. Processing	.412**	.328*
Rapid Naming	.418**	.111
Visual-Verbal Memory (ROI)	.321*	.261

Note. DAS-II: Differential Ability Scales – Second Edition; WIAT-II: Wechsler Individual Achievement Test; Seq.: sequential; Quant.: quantitative; Info.: information; ROI: Recall of Objects-Immediate.
$^{*}p < .05$; $^{**}p < .01$.

functions involving frontal, left, and right hemisphere systems are necessary for math performance and that these functions differ in the prediction of math computation and reasoning skills, consistent with the cognitive and neuropsychological literature on math competence and disability (e.g., Geary & Hoard, 2001; Hale & Fiorello, 2004; Hale et al., 2002; Mazzocco, 2001; Proctor et al., 2005). In addition, commonalities crossed over the traditional verbal-nonverbal dichotomy, attesting to the value of exploring the underlying psychological processes associated with these measures instead of focusing solely on the stimulus-input and response-output during psychological evaluation (Hale & Fiorello, 2004).

MLD Group

Table 4 presents the zero-order correlations among the DAS-II and WIAT-II math scores for children with MLD. Although math subtests were more related to Core than to diagnostic subtests, several were nonsignificant, and NO correlations were particularly low. Unlike the Typical Group correlations, which tended to be consistent across math subtests, some interesting differences were found for the MLD Group. For instance, the Rapid Naming subtest correlation was considerably stronger for NO than MR, but the opposite was true for Recall of Sequential Order. An examination of DAS-II factor versus subtest correlations with math scores revealed an interesting phenomenon – namely, that correlations tended to be lower for factors than for subtests, which is not uncommon in disabled populations (see Hale et al., 2007). For instance, the PS/Gs factor correlation with the MR was nonsignificant ($r = .25$), whereas the PS/Gs Speed of Information Processing subtest correlation was significant ($r = .33$) because the other PS/Gs subtest, Rapid Naming, had a very low correlation with MR ($r = .11$).

This apparently perplexing finding is further demonstrated in Table 5, where forced entry multiple regression analyses revealed that the most variance is accounted for by the 11 subtests as

Table 5
Total Math VarianceAaccounted for by Global, Composite, and Subtest Predictors

	Numerical Operations		Math Reasoning	
Predictor	Variance	%Loss	Variance	%Loss
Typical Group				
Subtests	.493	—	.620	—
6 Factors	.458	−7%	.579	−7%
GCA	.428	−13%	.541	−13%
Math Learning Disability Group				
Subtests	.387	—	.541	—
6 Factors	.326	−16%	.499	−8%
GCA	.171	−56%	.431	−20%

Note. %Loss = Amount of math variance lost as compared to the most variance explained by the *Differential Ability Scales – Second Edition* (DAS-II) predictor combinations. GCA: General Cognitive Ability.

predictors, followed by the factor scores, and finally the GCA, with decrements especially evident for the MLD Group. For instance, only 16% of the NO variance is lost when one interprets factors over subtests in this group, but more than half (56%) of the variance is lost when one interprets the GCA only. This dramatic loss of variance was also found in the Hale et al. (2007, 2008) WISC-IV SLD study, suggesting that the predictive validity of intellectual and/or cognitive measures is significantly reduced when one interprets global IQ over subcomponent scores. As a result, collapsing disparate subtest scores into composites may obscure important individual differences that may have diagnostic implications. Although subtest-level interpretation is questionable without corroborating evidence, including data obtained through hypothesis-testing measures and environmental sources (e.g., CHT; Hale & Fiorello, 2004), these data suggest that consideration of differential processing demands on subtests may be informative for children with MLD if hypotheses derived from them are substantiated and validated over time. It should be noted that the DAS-II subtests were developed to have high reliability and specificity (even within their respective Clusters) (Elliott, 2007), so it is perhaps not surprising that they should show effects such as those reported here.

For the MLD commonality analyses (see Table 6), higher order commonalities and R^2_{Total} values were lower than those obtained for the Typical Group, perhaps due to the level (i.e., factor) of interpretation noted in Table 5. For NO and MR, the unique predictor contributions totaled 16% and 20%, respectively, higher than the results found for the Typical Group, but only 1% of math variance was explained by the six-way commonality (g) for both NO and MR. Even the $C_{VE/NR/SP}$, which could be considered as an alternative measure of g, accounted for only 3% of the MR and virtually *none* of the NO variance ($C_{VE/NR/SP} = .004$).

Consistent with previous research on children with SLD (e.g., Hale et al., 2007, 2008), DAS-II predictor relationships with math outcomes were different for children with MLD than for typical children, suggesting that these children experience developmental deficits that require individualized instruction, not similar strategies at greater intensities, as has been suggested by some RTI advocates (e.g., Barnett, Daly, Jones, & Lentz, 2004; Reschly, 2005). For instance, whereas NR/Gf, SP/Gv, and WM/Gsm processes, presumed to be related to right hemisphere and frontal lobe functioning (see Hale & Fiorello, 2004) played an important role in Typical Group NO performance, they contributed little to the prediction of MLD Group NO performance. From a neuropsychological perspective, these findings are interpreted to indicate that, when solving math problems, typical children are

Table 6
DAS-II Factor Predictors of WIAT-II Math Performance for Children with Math Disabilities

Variance Component	VE/Gc	NR/Gf	SP/Gv	WM/Gsm	PS/Gs	ROI/Glr
	DAS-II Factor/CHC Classification					
DAS-II/WIAT-II Numerical Operations ($R^2_{Total} = .326$)						
U_{VE}	.042					
U_{NR}		.007				
U_{SP}			.000			
U_{WM}				.005		
U_{PS}					.096	
U_{ROI}						.008
$C_{VE/PS/PS}$	.014				.014	
$C_{PS/ROI}$					.020	.020
$C_{WM/PS/ROI}$				.015	.015	.015
$C_{ALL(g)}$	.011	.011	.011	.011	.011	.011
UNIQUE	.042	.007	.000	.005	.096	.008
SHARED	.083	.062	.095	.096	.132	.095
TOTAL	.125	.069	.095	.101	.228	.103
DAS-II/WIAT-II Math Reasoning ($R^2_{Total} = .499$)						
U_{VE}	.042					
U_{NR}		.005				
U_{SP}			.132			
U_{WM}				.017		
U_{PS}					.001	
U_{ROI}						.001
$C_{VE/SP}$	.060		.060			
$C_{NR/SP}$		.031	.031			
$C_{SP/WM}$			.023	.023		
$C_{VE/NR/SP}$	.031	.031	.031			
$C_{NR/SP/WM}$		.034	.034	.034		
$C_{SP/WM/ROI}$			.010	.010		.010
$C_{VE/NR/SP/WM}$	.018	.018	.018	.018		
$C_{ALL(g)}$	.011	.011	.011	.011	.011	.011
UNIQUE	.042	.005	.132	.017	.001	.001
SHARED	.166	.170	.293	.163	.060	.067
TOTAL	.208	.175	.425	.180	.061	.068

Note. Commonalities < .01 omitted. DAS-II: Differential Ability Scales – Second Edition; WIAT-II: Wechsler Individual Achievement Test; VE: Verbal Ability; Gc: Crystallized Ability; NR: Nonverbal Reasoning Ability; Gf: Fluid Reasoning; SP: Spatial Ability; Gv: Visualization; WM: Working Memory Ability; Gsm: Short-term Memory; PS: Processing Speed; Gs: Speediness; ROI: Recall of Objects-Immediate; Glr: Long-term Memory Encoding/Retrieval.

much more likely to use multiple brain areas simultaneously than are children with MLD. During math performance, children with MLD might rely on specific cognitive functions or strategies (e.g., finger counting instead of retrieving math facts) (Geary et al., 1999). They might also have difficulty integrating different brain functions via the corpus callosum (Smith & Rourke, 1995) and/or have general white matter dysfunction commonly reported in children with MLD (Rourke, 1995), which would be consistent with their poor performance on NR/Gf and SP/Gv clusters.

For math computation skills, the children with MLD primarily used VE/Gc and PS/Gs skills, but only the former factor was in the average range relative to normative data. Certainly, the VE/Gc relationship is expected, as prior quantitative knowledge and overall left hemisphere functions are related to acquisition of math facts and algorithms (e.g., Flanagan et al., 2002; Floyd et al., 2003; Hale & Fiorello, 2004; Hale et al., 2001, 2002, 2007), but the PS/Gs findings are at first somewhat perplexing given the relative lack of importance in Typical Group math performance. Similar PS findings for children with SLD have been reported using the Wechsler scales (Calhoun & Mayes, 2005; Hale et al. 2001, 2007), so this interesting finding appears to be consistent across instruments and samples.

Perhaps these VE/Gc and PS/Gs findings combined suggest that children with MLD are mostly reliant on what they know, and do not attempt to solve (or are unsuccessful at solving) more complex problems (e.g., Gf) beyond their very low level of math competency. Given their lower mean PS/Gs scores, this could suggest that children with MLD have difficulty quickly and efficiently accessing math facts and algorithms, and this interferes with their success on multistep tasks. As speeded performance is related to automaticity, this finding would also be consistent with the frequent observation that these children use more immature calculation strategies (Geary & Hoard, 2001). This finding combined with the absence of Gf and Gsm-WM variance in the MLD group may indicate that children with MLD have difficulty carrying out sequential computation steps in math algorithms, and doing so quickly and efficiently. In fact, PS measures may have more to do with *processing and decision* speed than speeded motor performance (e.g., Kennedy, Clement, & Curtiss, 2003), which would be related to cingulate and cerebellar functions (see Ivry, 1997; Lichter & Cummings, 2001), not motor ones. Another possibility is that PS tasks in general are a sign of the overall integrity of brain functioning (e.g., Calhoun & Mayes, 2005; van der Heijden & Donders, 2003). These hypotheses fit nicely with the assumption that children with MLD have difficulty integrating different brain systems and functions described earlier, and attest to the importance of teaching multistep computation skills, math fact and algorithm knowledge to automaticity, and problem-solving skills (e.g., Gf, inductive and deductive reasoning) to children with MLD.

The SP/Gv unique and shared variance components are noticeably absent for visual-motor NO performance in children with MLD, but were important for predicting auditory-verbal MR performance, again suggesting that *psychological processes* are more important than observable input or output demands (Hale & Fiorello, 2004; Hale et al., 2006, 2007, 2008). This might indicate that some children with MLD attempt to solve math word problems by visualizing the content, but have difficulty using perceptual analysis and synthesis skills successfully to translate verbal content to written algorithms for subsequent problem solving, which would be consistent with the Hale et al. (2001) findings where Block Design predicted word problem performance. As SP/Gv shared variance with Gf for the MLD group, both of which were below average, the combined deficit results in poor math problem-solving skills (Gv for analysis and synthesis, Gf for problem solving). As a result, working memory demands would be high as students attempt to retrieve linguistic, math fact, and math algorithm information from long-term memory, which would be consistent with the $C_{SP/WM/POI}$ and $C_{VE/NR/SP/WM}$ MR findings.

Implications

A growing body of evidence supports a multifactorial representation of (neuro)psychological processes, not a unitary global score representative of a child's intellectual potential (Fiorello et al., 2007; Hale et al., 2007, 2008). This evidence, combined with widespread criticism of ability-achievement discrepancy (e.g., Hale et al., 2006), has led many evaluators to abandon the discrepancy approach for determining SLD. Although some authors have advocated using an RTI approach to determine SLD (Reschly, 2005), nonresponsiveness can be the result of many possible causes, only one of them being SLD (Hale, 2006; Mather & Gregg, 2006). In addition, this approach does not address the IDEA SLD definition, one that requires identification of a child's specific (neuro)psychological processing deficits that, in the presence of other processing integrities, resulted in the SLD (Fiorello et al., 2006; Hale et al., 2006).

This study was an attempt to explore these processing integrities and deficits in children with MLD and compare their findings to those of typical children. Given the complexity of findings, and differences between groups, this study demonstrates that children with MLD may need specific instruction in math problem solving (e.g., fluid reasoning), carrying out computational steps (e.g., sequential processing and working memory), analysis and synthesis of math word problems (e.g., spatial-holistic processes), learning and accessing math facts and algorithms (e.g., long-term memory encoding, storage, and retrieval), efficiency in problem solving (e.g., fluency and automaticity), or some combination of these processes, depending on the child. This focus on remediating (neuro)psychological processes associated with math competency, or using compensatory techniques to overcome processing deficits, could lead to better math performance for children with MLD (Hale & Fiorello, 2004).

It is the *pattern* of performance that can guide idiographic interpretation and lead to individualized intervention efforts for children with MLD, and this information is avoided or minimized if practitioners focus solely on the child's overall level of performance or GCA. Given the findings reported here, including the substantial loss of predictive validity when global scores are interpreted (e.g., Hale et al., 2007, 2008), it is clearly time to move beyond global score interpretation for children with high incidence disabilities (Fiorello et al., 2007), as this merely reifies a construct that is of little use in clinical practice (Fiorello et al., 2001). Practitioners should "just say no" to the "one size fits all" approach to cognitive, neuropsychological, and academic assessment and intervention suggested by some RTI proponents (e.g., Barnett et al., 2004), as sufficient data exist to warrant the valid use of empirical profile analysis, especially if one ensures that results have sufficient concurrent, ecological, and treatment validity using the CHT model (Hale & Fiorello, 2004). Although systematic RTI efforts should be undertaken for any child with learning difficulties, nonresponders should be provided with a comprehensive evaluation using well-standardized tools such as the DAS-II in an attempt to delineate the child's (neuro)psychological processing assets and deficits. Not only will this ensure that IDEA statutory and regulatory requirements are met before SLD identification (e.g., Hale et al., 2006), but it will also provide a foundation from which to develop individualized interventions designed to meet the needs of children with MLD.

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