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Identifying Students With Learning Disabilities: Composite Profile Analysis Using the Cognitive Assessment System

Leesa V. Huang[1], Achilles N. Bardos[2], and Rik Carl D'Amato[3]

Abstract

The detection of cognitive patterns in children with learning disabilities (LD) has been a priority in the identification process. Subtest profile analysis from traditional cognitive assessment has drawn sharp criticism for inaccurate identification and weak connections to educational planning. Therefore, the purpose of this study is to use a new generation of cognitive tests with megacluster analysis to augment diagnosis and the instructional process. The Cognitive Assessment System uses a contemporary theoretical model in which composite scores, instead of subtest scores, are used for profile analysis. Ten core profiles from a regular education sample (N = 1,692) and 12 profiles from a sample of students with LD (N = 367) were found. The majority of the LD profiles were unique compared with profiles obtained from the general education sample. The implications of this study substantiate the usefulness of profile analysis on composite scores as a critical element in LD determination.

Keywords

profile analysis; specific learning disabilities

With nearly 3 million school-age students in the United States identified as having a specific learning disability (LD), this population comprises virtually half of all students with disabilities (U.S. Department of Education, 2006). Given that the incidence of LD is the highest of 13 disabilities recognized by the Individuals with Disabilities Education Act (IDEA) of 2004, a tremendous amount of controversy surrounds this category, especially the manner in which they are identified. The search for the most accurate, reliable, and valid methods of identifying children with LD continues to elude professionals.

There are two models of LD identification that have received attention recently, the comprehensive psychological evaluation approach and the response to intervention (RTI) approach.

[1]California State University, Chico
[2]University of Northern Colorado, Greeley
[3]University of Macau, Macau SAR, China

Corresponding author:
Leesa V. Huang, Assistant Professor Pupil Personnel Services Program, Department of Psychology (Zip 0234), California State University, Chico, CA 95929-0234
Email: lvhuang@exchange.csuchico.edu

Proponents of both sides have passionately advocated for their own model, which has created separation in the field of education. Instead, Hale, Kaufman, Naglieri, and Kavale (2006) have recommended a "methodology [which] incorporates the best aspects of both the RTI and comprehensive evaluation perspectives to forge a balanced practice model that ensures diagnostic accuracy and optimizes educational outcomes for children with LD" (p. 753). The operationalization and implementation of this combined approach proves to be a monumental task as both models present their own set of challenges to the accurate classification of LD.

It is the intent of this article to provide additional support and evidence for the use of a comprehensive cognitive assessment approach. It is commonly accepted that LD can be caused by myriad neurological and/or information processing disorders (National Association of School Psychologists, 2007). If poor academic achievement is displayed, LD is suspected, and a student will be referred for a comprehensive special education evaluation to determine the cause of the difficulties. The underpinning belief of the cognitive assessment approach is that variation in cognitive processing skills is correlated to academic performance. However, conventional intelligence tests have failed to identify those critical factors for the accurate classification of LD. This lack of precision in differential diagnosis for LD has been affected by two matters: the slow development of theory-based intelligence measures and ineffective interpretation methods.

In the beginning, test developers such as Binet, Terman, and Wechsler were directed by a general, unitary view of intelligence, which dominated the first half of the century of the history of intelligence testing (Kamphaus, Winsor, Rowe, & Kim, 2005). Their chief concern was that tests were being developed without a formal theory of intelligence, even though numerous theories have emerged to offer more thorough explanations of the complex phenomena of intelligence (Sattler, 2001). The gradual evolutions of intelligence theory and subsequent slow operationalization into cognitive measures have contributed to the unreliability and variability of LD identification procedures.

Another factor affecting the accuracy of identifying students with LD relates to the interpretation methods of IQ tests. Educators have used various methods to interpret intelligence test results as indicators of potential LD (Kamphaus et al., 2005). The first method that has received considerable attention has been the use of the global scores. Even though global scores provided the most statistically reliable summary of an individual's performance, it cannot detect cognitive assets and difficulties that adequately explain or discriminate children's academic performance (Kaufman & Lichtenberger, 2000), including those with LD.

The next level of interpretation after the global score is both intra- and interindividual profile analyses on subtests. This method has emerged as an empirical procedure of examining student performance to complement the global score. For intraindividual profile analysis, it is the practice of examining an individual's unique pattern of strengths and weaknesses among subtests (Kaufman & Lichtenberger, 2000). However, numerous research studies have concluded that subtest profile analysis demonstrates inadequate reliability and validity (see Watkins, Glutting, & Youngstrom, 2005 for further discussion).

Concerning interindividual profile analysis, Wilhoit and McCallum (2002) defined this as an approach that "examines a profile pattern produced on a given scale for a given individual and compares it with the patterns of scores on the same scales from other individuals" (p. 264). The use of normative interpretations for interindividual profile analysis has far superior technical adequacies and thereby sidesteps the statistical pitfalls experienced by intraindividual profile analysis (Bray, Kehle, & Hintze, 1998). Though several studies have successfully identified students of exceptional samples (Naglieri, 2000; Stanton & Reynolds, 2000), the major limitation in these research findings was that profiles identified only a very small portion, approximately 10%, of students with LD. The importance of profiling individuals with LD may lead to more detailed understanding of the nature of LD and thus may assist in improving definitions used to classify individuals.

In the midst of the controversy regarding measures and interpretive methods, additional criticisms began to focus intensively on the connection of diagnosis and intervention. Critics have been increasingly vocal that traditional IQ testing results do not provide functional information for developing strategies to improve students' learning (President's Commission on Excellence in Special Education, 2002; Reschly & Ysseldyke, 2002). Without understanding *why* a student struggles in learning, any efforts to remediate those difficulties are at best, limited in success. By answering the *why* question using cognitive assessment practices, practitioners will be able to determine an accurate diagnosis, which then leads to relevant and targeted intervention for individuals in the third tier as advocated by Hale et al. (2006).

Unlike the traditional psychological assessment model for identifying LD, the RTI model is currently conceptualized as a multitiered intervention model of increasing intensity (Tilly, 2003). According to Tilly (2003), quality instruction can be provided for all students in the general educational setting as part of Tier 1 services. At the next level in Tier 2, approximately 15% of all students could be recommended for individualized educational support services because of poor classroom performance. A small percentage of students who fail to demonstrate expected improvements could then be referred to Tier 3 for intensive treatment and subsequently classified as LD because of lack of progress (Fuchs, Mock, Morgan, & Young, 2003). Despite the strong principles and practices of RTI, this model fails to consider alternative rationale as to why children are unsuccessful (Hale et. al., 2006).

For this study, the first purpose was to identify cognitive patterns using profile analysis on composite scores instead of subtest scores. The second purpose of this study is to compare group pattern profiles between the regular education and LD samples. Furthermore, this study compared individual profiles of students with LD with group profiles obtained from the general education sample to determine the uniqueness of the individual profile.

Method

Participants

Two samples were used for the study. First, a general education sample, including those who were not identified with any disabilities and who received no special services, was extracted from the standardization population of the Cognitive Assessment Scale (CAS; Naglieri & Das, 1997). The number of participants used for the general education sample was 1,692 and ranged in age from 5 years, 0 months to 17 years, 11 months (mean [M] = 9.14 ± 3.70 years). The second sample included students identified as LD using the discrepancy model. This sample was composed of five separate subgroups. The first two subgroups were obtained from the standardization population and CAS validity studies (Naglieri & Das, 1997). The third, fourth, and fifth subgroups were taken from the research conducted by Brams (1999), Johnson (2001), and N. Politikos, A. N. Bardos, and D. T. Cooke (personal communication, 2003).

Consent was granted by the Riverside Publishing Company and aforementioned researchers. Demographic data are listed in Tables 1 and 2, respectively. The number of participants used for the sample of students with LD was 367 and ranged in age from 5 years, 0 months to 17 years, 11 months (M = 9.34 ± 2.92).

Instrumentation

The CAS is a norm-referenced, individually administered test to measure cognitive processes. It is intended for children and adolescents between the ages of 5 years and 17 years, 11 months. Naglieri and Das (1997) developed the CAS using a total of 12 subtests, to measure the Planning, Attention, Successive, and Simultaneous (PASS) theory of cognitive neuropsychological

Table 1. Size (*N*) and Percentage of Demographic Information for the General Education Sample

Sample Descriptor	*N*	Percentage
Gender		
Female	863	51.00
Male	829	49.00
Race		
White	1321	78.07
Black	211	12.47
Asian	57	3.37
Other	96	5.67
Native American	7	0.41
Parent educational level		
Did not complete high school	340	20.09
High school diploma	529	31.26
Some college	477	28.19
College degree	346	20.45

Table 2. Size (*N*) and Percentage of Demographic Information for the Learning Disability Sample

Sample Descriptor	*N*	Percentage
Gender		
Female	139	37.87
Male	228	62.13
Race		
White	273	74.39
Black	35	9.54
Asian	9	2.45
Other	49	13.35
Native American	1	0.27

abilities derived from A. S. Luria's work. The formal operationalization of the PASS model resulted in the CAS being arranged into three separate, yet interrelated levels of scores: individual subtests, PASS cognitive processes scales' scores, Full Scale score (Naglieri, 2000). Table 3 lists the subtests arranged under the corresponding composite scale.

The Standard Battery incorporates all 12 subtests with 3 subtests for each PASS process and was given to all participants in both general education and LD samples. Each subtest generates a scaled score ($M = 10$; standard deviation [SD] = 3). Each of the four PASS scale scores ($M = 100$; $SD = 15$) is the combination of the subtests included in each respective scale. Finally, the Full Scale score ($M = 100$; $SD = 15$) is the aggregate total of the four PASS cognitive processes scales, which are equally weighed.

The test–retest reliability of the CAS was at least .75 for all PASS scores across all ages. The internal consistency reliability coefficients for the Full Scale score averaged .96 across all age groups. For the PASS composite scores, reliability coefficients ranged from .84 to .93. Average reliabilities for the 12 subtests ranged from .64 to .93. Table 3 lists reliability coefficients for the PASS scores as well as the subtests obtained.

Numerous validity procedures were used. For construct-related validity, the theoretical premise of the CAS was constructed on a four-factor model and confirmatory factor analyses (CFA) results yielded Goodness of Fit and Adjusted Goodness of Fit Indices, both of which were more than .90 for a three- or four-factor model. Content validity was established using both task

Table 3. Cognitive Assessment System (CAS) Composite and Subtest Scales With Internal Consistency Reliability Coefficients From the Manual and Present Study Samples

Composite Scales (Subtests)	Manual	General Education	Learning Disability
Planning (matching numbers, planned codes, planned connections)	.88	.83	.79
Simultaneous (nonverbal matrices, verbal–spatial relations, figure memory)	.88	.91	.77
Attention (expressive attention, number detection, receptive attention)	.93	.87	.90
Successive (word series, sentence repetition, speech rate [5-7], or sentence questions [8-17])	.93	.85	.91

analysis and experimental examination during the development of tasks and items. Finally, criterion validity was established through correlations for CAS Standard Battery Full Scale and PASS scale scores with Woodcock–Johnson Psycho-Educational Tests of Achievement–Revised (WJ-R; Woodcock & Johnson, 1989) cluster and subtest scores ($p < .01$; Naglieri & Das, 1997).

Data Analysis

Cluster analysis methodology allows large numbers of individuals to be sorted or grouped according to similar variables, and in this research study, performance on the CAS. The advantage of cluster analysis rests in its ability to determine or predict the membership of an individual based on the defined variables. Frequently, the researcher will discover that cluster analysis is not a singular application of a technique to a data set but rather, a series of steps with results often dependent on previous step (Everitt, 1993). McDermott (1998) advocates a megaclustering or multistage Euclidean grouping (MEG) in which the process of cluster analysis advances in three stages. Unlike one- or two-step cluster analysis, the MEG process can detect misclassifications and significantly improve cluster uniformity through statistical homogeneity indicators and multiple steps (McDermott, 1998).

To derive profile types from these two samples, three separate cluster analyses were performed as delineated in Drossman, Maller, and McDermott (2001) and McDermott (1998). In the *first stage*, the sample is separated into a specified number of mutually exclusive blocks. A minimum-variance cluster analysis was applied separately to each block. The results of this first stage were verified by randomly assigning the regular education population to the same number blocks and rerunning the minimum-variance cluster analysis. The results of the first stage analysis were combined to form a similarity matrix of squared Euclidean distances and submitted for the *second stage* minimum-variance cluster analysis. The *third stage* analysis involved the use of *k*-means iterative partitioning, which allows for misplaced data to be relocated into the correct cluster.

To determine the uniqueness of LD group profiles as compared with the general education group profiles, a similarity coefficient was used. The formula for group-to-group comparison, r_p, is

$$r_p = \frac{4K - \sum w_j d_j^2}{4K + \sum w_j d_j^2}.$$

Table 4. Final Cluster Solution Means for General Education (GE) Sample

Cluster	*N*	Sample Prevalence (%)	PASS	Mean	Standard Deviation
GE1	153	9.04	Planning	119.7	8.06
			Simultaneous	117.9	8.25
			Attention	118.8	9.00
			Successive	114.8	8.63
GE2	137	8.10	Planning	115.7	8.45
			Simultaneous	103.2	8.82
			Attention	120.5	6.77
			Successive	101.7	7.16
GE3	161	9.52	Planning	105.1	9.65
			Simultaneous	113.9	6.61
			Attention	96.31	6.96
			Successive	116.9	7.47
GE4	170	10.05	Planning	103.2	6.98
			Simultaneous	98.82	5.87
			Attention	107.0	7.08
			Successive	113.0	6.88
GE5	167	9.87	Planning	100.4	7.12
			Simultaneous	113.9	7.40
			Attention	106.4	7.04
			Successive	100.1	6.32
GE6	155	9.16	Planning	111.3	7.68
			Simultaneous	102.2	6.41
			Attention	106.4	7.28
			Successive	88.54	7.86
GE7	189	11.17	Planning	101.8	8.04
			Simultaneous	86.41	7.00
			Attention	98.81	7.90
			Successive	98.54	6.84
GE8	240	14.18	Planning	86.62	7.41
			Simultaneous	100.7	8.09
			Attention	87.36	7.71
			Successive	102.8	7.40
GE9	187	11.05	Planning	92.70	7.23
			Simultaneous	91.83	7.89
			Attention	96.06	7.96
			Successive	81.81	7.17
GE10	133	7.86	Planning	78.89	8.58
			Simultaneous	81.76	8.13
			Attention	81.04	9.21
			Successive	81.13	10.06

Note: PASS = planning, attention, successive, and simultaneous.

An r_p value of +1 indicates complete resemblance between the profiles, whereas −1 indicates complete dissimilarity (Cattell, 1949; Tatsuoka, 1988). A solid r_p cutoff point of <.40 has been advocated by several researchers (Konold, Glutting, McDermott, Kush, & Watson, 1999; McDermott, Glutting, Jones, & Noonan, 1989). After examining the cluster profile patterns with regard to shape and level and because of the high numbers of clusters, an r_p cutoff point of .30 appeared to be more appropriate for this study in order to achieve the maximum amount of dissimilarity.

Table 5. Twelve-Cluster Solution With Means for Learning Disability Sample

Cluster	*N*	Sample Prevalence (%)	PASS	Means	Standard Deviation
SLD1	14	3.81	Planning	99.2	10.30
			Simultaneous	114.6	8.71
			Attention	98.6	8.25
			Successive	117.8	8.45
SLD2	31	8.45	Planning	112.4	7.59
			Simultaneous	105.7	9.35
			Attention	117.0	6.74
			Successive	98.3	7.83
SLD3	36	9.81	Planning	101.3	7.87
			Simultaneous	100.0	7.19
			Attention	103.2	6.51
			Successive	102.2	6.76
SLD4	22	6.00	Planning	98.7	6.24
			Simultaneous	104.8	5.59
			Attention	101.7	5.62
			Successive	89.7	7.05
SLD5	45	12.26	Planning	94.7	5.43
			Simultaneous	94.8	6.64
			Attention	94.9	5.20
			Successive	100.2	5.64
SLD6	20	5.45	Planning	86.2	5.38
			Simultaneous	103.2	5.66
			Attention	96.5	7.17
			Successive	84.8	7.03
SLD7	15	4.09	Planning	87.2	6.27
			Simultaneous	96.9	5.37
			Attention	79.6	5.51
			Successive	84.7	6.97
SLD8	15	4.09	Planning	82.2	4.84
			Simultaneous	83.8	5.53
			Attention	7.3	5.45
			Successive	98.1	5.73
SLD9	66	17.98	Planning	84.8	8.16
			Simultaneous	95.8	7.45
			Attention	81.3	6.62
			Successive	96.7	7.10
SLD10	29	7.90	Planning	87.5	7.90
			Simultaneous	83.1	6.83
			Attention	90.6	7.42
			Successive	74.6	7.87
SLD11	26	7.08	Planning	78.0	7.67
			Simultaneous	75.5	7.55
			Attention	76.1	7.31
			Successive	89.6	4.78
SLD12	48	13.08	Planning	76.4	7.42
			Simultaneous	81.2	10.30
			Attention	71.3	6.12
			Successive	79.0	7.23

Note: SLD = specific learning disability; PASS = planning, attention, simultaneous, and successive.

A second similarity coefficient was needed to determine the uniqueness of individual profiles when compared with a group profile. Tatsuoka (1988) modified Cattell's original r_p equation to consider the correlation between clusters. The formula is presented as follows:

$$r_{p(k;i)} = \frac{C_P - \chi^2_{ik}}{C_P + \chi^2_{ik}}.$$

This equation's components include p variables (Planning, Simultaneous Processing, Attention, and Successive Processing), k groups (clusters from the regular education sample), and i individuals (individuals with LD). "C_p is the median of chi-square distribution with p degrees of freedom" (Tatsuoka, 1988, p. 377). The variable χ^2_{ik}, is the square Euclidean distances while taking into account the correlation between variables. The r_p cutoff point used for this study is .15.

Results

General Education Clusters

The general education sample ($N = 1{,}692$) was separated into nine age blocks prior to submitting data to Stage 1 of three-stage cluster analysis. To determine the initial number of clusters to continue onto the second stage, three statistical criteria need to be met. First, Mojena's stopping rule provides a coefficient that determines the optimal number of clusters with values between two and three considered to be adequate (Mojena, 1977). Second, the pseudo F statistic is used to determine how much distance is between all clusters, whereas the pseudo T^2 values indicate the distance between two clusters prior to combining together. The pseudo F statistic should be higher than the pseudo T^2 for the solution to be valid (Duda & Hart, 1973). The final criterion, R^2 coefficient, indicates the between-cluster variance. The minimum acceptable value used for this study was .6 to reduce the variance due to chance or error (Ward, 1963).

From the first stage, 74 clusters were manually selected based on these three statistical criteria and then input into a 74×74 similarity matrix for a second round of cluster analysis. To determine the final number of clusters in the second stage, the only pseudo F/pseudo T^2 and R^2 criteria were required as described above. The 10-cluster solution fit the aforementioned criteria and therefore underwent the third stage of MEG cluster analysis to relocate misclassified profiles.

The average within-cluster homogeneity coefficient, H, was used to determine the uniformity of the clusters (Tryon & Bailey, 1970). The closer to 1.00 the H value is, the more homogenous the clusters are; a minimum acceptable value of H was set at .6 (Konold et al., 1999; McDermott et al., 1989). The 10-cluster solution met this criterion with a mean H value of .64. In addition, the results of the data provided the r_p for comparisons of group profiles within the regular education sample. This statistical procedure reevaluated the results to validate the overall integrity of the 10-cluster solution. The average r_p coefficients for the 10 clusters derived from the regular education population were all negative (r_p mean = −.67). This signifies that each of the group profiles was dissimilar from the other nine group profiles.

Clusters of Individuals With LD

The sample containing students with LD ($N = 367$) was separated into two age blocks and subsequently submitted to first stage minimum-variance cluster analysis. The same procedure and statistical criteria used with the general education sample were also applied to the LD sample. This first stage generated 18 clusters, which were then inputted into an 18×18 similarity matrix for a second round of hierarchical cluster analysis. A 12-cluster solution met all statistical criteria and completed the final stage of MEG with a mean H value of 0.70. The r_p results indicated that the profiles obtained within the sample of individuals with LD were all negative (r_p mean = −.74) signifying that each of the group profiles was dissimilar from the other 11 group profiles.

Profile Comparisons

Tatsuoka's (1988) method for determining similarity was used to compare between clusters (e.g., cluster-to-cluster) as well as individual profiles with clusters. Group profile comparison was used to determine the uniqueness of the profiles found within the LD sample. Each of the 12 LD profiles was compared against all 10 profiles obtained from the general education sample. Four profiles from the LD sample matched four profiles from the general education sample. The remaining eight group profiles from the sample of individuals with LD did not match any of the general education profiles and therefore were determined to be unique.

The next step was to compare an individual's profile against the group profiles of the general education population. Composite scores from individuals identified with LD were compared against the general education profiles. Approximately 35% (N = 131) were found to match 1 of the 10 group profiles from the general education sample. Thus, 236 individual profiles or more than 65% were considered to be unique because these did not match any of the 10 group profiles derived from the general education sample.

Discussion

A longstanding assumption has been that those individuals with LD have different neuropsychological patterns, which explain academic weaknesses and difficulties. In an effort to provide evidence supporting the profile analysis interpretive method for LD identification, the present study attempted to demonstrate the diagnostic utility of the profile analysis on the CAS composite scales as an alternative to subtest profile analysis. For cognitive assessment to be deemed useful, tools need to discriminate between the exceptional and general education samples in addition to the ability to answer the question of *why* a student struggles. By answering the *why*, not only is cognitive assessment assisting in the more accurate identification of children with LD but also will provide valuable information on which to base and design educational interventions.

The existence of 10 profiles within the general education sample supports the notion that various groups of individuals exhibit different patterns of learning strengths and weaknesses. Likewise, the 12 LD profiles confirm the heterogeneous makeup of this category (i.e., children with any combination of reading, writing, or math LD) and seem to validate the practice of subtyping children with LD. The extraction of these core profiles is important for several reasons. First, the presence of various patterns of the PASS cognitive processes provides initial, yet promising evidence that interpretation at the composite level using the CAS is useful for the cognitive assessment approach for identifying LD in children. Continuous research is needed to reinforce these results through the use of multiple profile analysis techniques. Furthermore, to provide stronger evidence that composite-level profile analysis is superior to subtest profile analysis, however, future studies should focus on comparing the use of composite and subtest scores. Second, this study provides practitioners a useful resource to compare and determine the uniqueness of an individual's profile pattern to differentiate between students needing long-term intensive educational planning in general education or special education. Finally, the likelihood of unsubstantiated claims or recommendations from clinical samples can be reduced because there is a normative comparison revealed by the results of this study.

In comparing group profiles obtained from the general education and LD samples, eight profiles found from the sample of individuals with LD differed from the regular education profiles. When compared individually, approximately 65% of the LD profiles were unique. Both results offer evidence for the moderate discriminative power of profile analysis when used on the CAS composite scores. That is, a student with a true LD has a relatively high chance of being accurately identified when using profile analysis on composite scores. However, practitioners are reminded that the determination of a unique profile is only one piece of evidence collected within a comprehensive assessment for LD identification (Salvia, Ysseldyke, & Bolt, 2007). Despite these high hit rates, a complete diagnostic accuracy study including measures of sensitivity, specificity, positive and negative predictive power should be conducted to further validate these results.

Interestingly, four group profiles from the sample of students with LD matched four profiles from the regular education sample. This phenomenon has occurred in other research (D'Amato, Dean, & Rhodes, 1998). The overlap could be caused by those who have been misdiagnosed as LD and inappropriately placed into special education. Finally, this analysis of a student provides information about how a student learns best and also provides the rationale as to why a student struggles.

Summary

Using a theoretically driven instrument and psychometrically sound techniques can enhance a practitioner's ability to draw meaningful conclusions from evaluation results (Flanagan & Ortiz, 2002). Additionally, revealing cognitive processing patterns within individuals will lead to more accurate identification and more successful attempts to understand how students learn. The findings of this study support that the CAS can provide reliable, valid, and functional information regarding students' cognitive processing in relation to achievement. After reviewing the results, the analysis has provided evidence for the use of the PASS theory and it appears that it has sufficient applications for diagnosis for students suspected of having a LD.

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