CORE PROFILE TYPES FOR THE COGNITIVE ASSESSMENT SYSTEM AND WOODCOCK-JOHNSON TESTS OF ACHIEVEMENT-REVISED: THEIR DEVELOPMENT AND APPLICATION IN DESCRIBING LOW PERFORMING STUDENTS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

Margaret E. Ronning, M.A.

* * * * *

The Ohio State University 2004

Dissertation Committee:

Approved by

Associate Professor Antoinette Miranda, Adviser

Associate Professor Wendy Naumann

Assistant Professor Laurice Joseph

Adviser College of Education

ABSTRACT

The present study was conducted in two phases. Phase 1 involved the development of ability/achievement normative taxonomies for reading and mathematics using the multivariate techniques of cluster analysis. The core profiles that emerged provide important comparisons for evaluating individual profiles, as well as add to the information explaining common variability in the child population. The taxonomies were based upon 711 children in the 8 to 17 year old portion of the standardization sample of the Cognitive Assessment System (CAS) who were co-administered the Woodcock-Johnson Tests of Achievement –Revised (WJ-R ACH). Ability/reading and ability/math normative taxonomies were developed from the Planning, Attention, Simultaneous, and Successive scales of the CAS in conjunction with four reading and three math WJ-R ACH subscales. Eight reading and five math clusters were identified and described using demographics and overall ability and achievement levels. In Phase 2, the prevalence of students with low reading and math achievement in each cluster was examined. Ramifications for intervention planning are discussed.

Dedicated to my parents, Lawrence and Ann Ronning.

ACKNOWLEDGMENTS

This dissertation and degree would not have been possible without the help and assistance of many individuals. I wish to thank my dissertation committee members: Dr. Wendy Naumann and Dr. Laurice Joseph, for their support and contributions to this document. I am greatly indebted to my adviser, Dr. Antoinette Miranda; her belief in me has been endless. I am privileged to have been her student throughout my graduate career.

I would like to thank my parents, Lawrence and Ann Ronning, who instilled in me the belief that I could do anything. I am appreciative of the love and support I have received from my brothers, sister, sisters-in-law, nieces, nephew, and friends throughout my doctoral program.

I am grateful to the Muskingum Valley Educational Service Center for their support during this endeavor, particularly Gwyn Wagstaff for her editorial assistance and constant understanding. I am exceedingly thankful to Dr. Michael Fuller for his continual support and guidance throughout my time in this profession.

I am particularly thankful to Riverside Publishing Company for the use of the Cognitive Assessment System/Woodcock-Johnson-Revised Achievement data that made this study possible. Finally, I wish to thank Dr. Jack Naglieri for his input and support in the early formation of this document.

VITA

January 28, 1952	Born - Parkersburg, West Virginia
1973	B.G.S., Ohio University Athens, Ohio
1992	M.A., The Ohio State University Columbus, Ohio
1992 - 1993	School Psychology Intern Muskingum County Board of Education Zanesville, Ohio
1994 - 1998	School Psychologist Muskingum Valley Educational Service Center Zanesville, Ohio
1998 - 1999	Graduate Teaching Assistant School Psychology Program The Ohio State University Columbus, Ohio
1999 - Present	School Psychologist Data Services Department Muskingum Valley Educational Service Center Zanesville, Ohio

PUBLICATIONS

Naglieri, J. A., & Ronning, M. E. (2000). The relationship between general ability using the Naglieri Nonverbal Ability Test (NNAT) and Stanford Achievement Test (SAT) reading achievement. *Journal of Psychoeducational Assessment*, *18*, 230-239. Naglieri, J. A., & Ronning, M. E. (2000). Comparison of White, African American, Hispanic, and Asian children on the Naglieri Nonverbal Ability Test. *Psychological Assessment, 12, 328-334.*

FIELDS OF STUDY

Major Field: Education

Specialization: School Psychology

Departmental Minor: Quantitative Psychology - Psychometric/Data Analysis

TABLE OF CONTENTS

Page

Abst	ract	ii
Dedi	ication	iii
Ackı	nowledgments	iv
Vita	<i>C</i>	v
List	of Tables	X
List	of Figures	xi
2150	····	
Chap	pters:	
1.	Introduction	1
	Purpose of Present Study	7
	Objectives	7
	Significance of Study	
	Limitations of Study	
	Definition of Terms	9
2.	Review of Literature	
	PASS Theory and the Cognitive Assessment System	
	PASS and Reading Achievement	
	PASS and Math Achievement	
	Profile Analysis	
	Subtest Profile Analysis	
	Cluster Analysis	
	Normative Profiles	
	Conclusions	
3.	Methodology	
	Participants	

	Instruments	39
	Cognitive Assessment System (CAS)	39
	PASS Scales	40
	Reliability of the CAS	42
	Validity of the CAS	43
	Woodcock-Johnson Tests of Achievement-Revised (WJ-R ACH)	46
	Reliability of the WJ-R ACH	47
	Validity of the WJ-R ACH	48
	WJ-R ACH Subtests	49
	Data Analysis	51
	Phase 1	51
	Sample	51
	Variables	52
	Procedure	53
	Hierarchical Agglomerative Clustering Step	54
	Iterative Partitioning Step	55
	Phase 2	57
4.	Results	59
	Phase 1: Reading Analysis (PASS/RD)	59
	Hierarchical Agglomerative Cluster Analysis	59
	K-means Iterative Partitioning	61
	PASS/RD Eight Core Profile Types	61
	Phase 1: Math Analysis (PASS/Math)	67
	Hierarchical Agglomerative Cluster Analysis	67
	K-means Iterative Partitioning	69
	PASS/Math Five Core Profile Types	70
	Phase 2: Low Reading Group	74
	Phase 2: Low Math Group	76
5.	Discussion	79
	Level as a Key Profiling Component	79
	Shape as a Key Profiling Component	81
	Reading	81
	Math	82
	Demographic Characteristics	83
	Utilization of Core Profile Types	86
	Limitations and Future Research	87

Appendices	
Appendix A: Letter of Permission For Data Usage	
Appendix B: Dendrograms	
List of References	

LIST OF TABLES

Table	F	'age
3.1	Demographic characteristics for the sample of 8 to 17 year olds from the CAS standardization sample administered the WJ-R Tests of Achievement ($N = 711$)	38
4.1	Prevalence, homogeneity, and names of the PASS/RD core profile type	62
4.2	PASS/RD Cluster means and standard deviations profile type	63
4.3	Prevalence, homogeneity, and names of the PASS/Math core profile type	70
4.4	PASS/Math Cluster means and standard deviations profile type	71
4.5	Demographic prevalences of the Low Reading group	74
4.6	Demographic prevalences of the Low Math group	77

LIST OF FIGURES

Figure

Page

4.1	PASS/RD plot of the t-statistic by proposed cluster partitions	60
4.2	PASS/RD core profile type standard scores by clustering variables	63
4.3	PASS/Math plot of the t-statistic by proposed cluster partitions	68
4.4	PASS/Math core profile type standard scores by clustering variables	71
A.1	Letter of permission for the use of Riverside Publishing Company data	90
B .1	PASS/RD dendrogram	92
B.2	PASS/Math dendrogram	93

CHAPTER 1

INTRODUCTION

In education, the passage of legislation such as the Education for All Handicapped Children Act of 1975 (EAHCA) and the recent revisions of the Individuals with Disabilities Education Act (IDEA, 1997) put an emphasis on individual children and their unique needs. Administratively necessary standards continue to be developed for comparison with assessment results so that students may be classified, placed in special programs, remediated, or provided early interventions appropriately (Braden, 2003; Prasse, 2002; Sattler, 2001, chap.3). These practices have come under increasing criticism for not meeting the needs of all children (Braden, 2002). Eventually, the federal government passed the No Child Left Behind Act of 2001 (NCLB Act) that requires that all children be served regardless of their uniqueness or difference in learning capabilities. This has left educators, parents, and students struggling to find ways to provide education for all students.

Traditionally, decisions involving low-achieving students have been made based upon some standard that was established prior to evaluation efforts (e.g., mental retardation classification, state-defined special education criteria). Although these evaluations have many components, educators and psychologists often use ability and achievement test scores to inform this decision-making process. Therefore, the quality of the method of test interpretation and score comparison is crucial to the decision-making process and the formation of a suitable educational plan.

Test interpretations are typically based upon some combination of clinical judgment and statistical results. Clinical judgment relies heavily upon the expertise and training of the individual clinician and is an important component of test interpretation (American Educational Research Association [AERA], American Psychological Association [APA], & National Council on Measurement in Education [NCME], 1999; Ekstrom, Elmore, & Schafer, 1997). However, its importance varies depending upon the philosophy of the test administrator. It may supersede test results or, at the other extreme, may only play a role in the determination of the accuracy of responses. When clinical judgment is the primary means of test interpretation, the clinician's determinations take precedence over the relationship of test scores to standards (e.g., did the discrepancy score meet a state standard for eligibility for a learning disability program) or the performance of others (e.g., was this performance significantly different from the standardization sample). Proponents of this method of test interpretation maintain that the uniqueness of an individual can only be captured by the clinician and not by the test scores. The clinician must improve the information derived from an assessment; they must integrate test results with other sources of information to make a clinical judgment as to why the student performed in such a manner during the standardized administration of the test (Cronbach, 1990; Kaufman, 1994; Stone, 1995). Thus, from this viewpoint it is the process of making the clinical judgment that is most valuable to the test interpretation, rather than the actual score values.

2

Other methods of interpretation involve the use of clinical judgment in conjunction with a variety of test score transformations and comparisons. This may involve adherence to empirically derived cut scores, calculation of difference scores, or the development of a profile of scores.

The development and use of cut scores is often applied to the use of tests in regulating programs or determining classifications, and involves some mandated regulation of services and monies. Cut scores are validated through prediction and the setting of an acceptable criterion, a yardstick against which the accuracy of predictions is determined (AERA et al., 1999; Cronbach, 1990). Examples of such criterions include: index of academic achievement, state proficiency test score standards, performance standards for specialized training, job performance criteria, professional licensure standards, psychiatric diagnoses, and ratings (Anastasi & Urbina, 1997; Braden, 2002, 2003). Utilizing this method of test interpretation, the clinician administers a test and compares performance to the appropriate cut score(s). It is the relationship between the score and the criterion that primarily determines the decision.

Another test interpretation method involves the use of difference scores, particularly in psychoeducational testing. As necessitated by this approach, a criterion is set for the acceptable level of performance differences (American Psychiatric Association, 2000; IDEA, 1997; Kirby & Williams, 1991; Stone, 1995). The most familiar example of this method involves the difference or discrepancy score between IQ and academic achievement for the identification of learning disability. Although this use of test scores is frequently disputed (Sattler & Ryan, 2001; Stuebing et al., 2002), it continues to play a prevalent role in classification and test interpretation. For example, the manuals for the Wechsler Intelligence Test for Children – Third Edition (WISC-III; Wechsler, 1991), Kaufman Assessment Battery for Children (K-ABC; Kaufman & Kaufman, 1983), and the Cognitive Assessment System (CAS; Naglieri & Das, 1997a) provide the information necessary to evaluate the achievement/IQ difference. State and federal regulations (e.g., IDEA, 1997) and publications, such as the Diagnostic and Statistical Manual of Mental Disorders – Fourth Edition – Text Revision (DSM-IV-TR; American Psychiatric Association, 2000), utilize this approach to determine if a learning disability placement or diagnosis is warranted.

Difference scores are also computed for other comparisons to show treatment or intervention effectiveness. These comparisons may involve a basic pretest/posttest scenario or an ongoing monitoring of progress. Examples include the score differences involved in the test-train-test paradigm (Sattler & Saflofske, 2001) and curriculum-based measurement (Shinn, 2002). Score differences may involve very specific situations such as the monitoring of neurological recovery or deterioration (Havey, 2002; Naglieri & Das, 1997b). Beyond typical test score situations, difference scores are used in problem solving when making behavioral comparisons between an identified and typical student. A comparison standard is defined for an acceptable difference in performance as represented by behavioral observation scores between a child and typical peer (Tilly, 2002). When considering difference scores, it is the difference between the scores that is of primary importance to the professional when relating test interpretations and subsequent decisions.

4

A final method of test interpretation to be considered is profile analysis. This expression encompasses a variety of techniques and practices attempting to make sense of the score variations of individuals or groups. Studies and discussions of specific methodologies involving profile analysis continue to appear in the literature (Gustafsson & Snow, 1997; Keith, 2000). Subtest profile analysis (Kaufman, 1994), configural frequency analysis (Stanton & Reynolds, 2000), multidimensional scaling (Davison, Gasser, & Ding, 1996), modal profile analysis (Pritchard, Livingston, Reynolds, & Moses, 2000), and cluster analysis (Aldenderfer & Blashfield, 1984; Donders, 1996; Wilhoit & McCallum, 2002) are a few of the methods resulting in a profile of scores. In all of these situations, it is the overall pattern of scores rather than the individual differences on singular measures that is important to the decision-making process.

Of these methods of profile analysis, cluster analysis is a multivariate technique that shows promise for the development of useful descriptions of individuals and groups of students. It allows for the development of normative typologies (e.g., core profiles for a measure) (Donders, 1999; Glutting & McDermott, 1990; Glutting, McDermott, Prifitera, & McGrath, 1994) and subgroup typologies (e.g., core profiles for special education populations) (Kavale & Forness, 1987; Maller & McDermott, 1997; Shapiro, Buckhalt, & Herod, 1995; Ward, Ward, Glutting, & Hatt, 1999). Multivariate typologies have been developed using a variety of measures of cognition such as the Wechsler scales (Donders, 1996; Glutting & McDermott, 1990; Konold, Glutting, McDermott, Kush, & Watkins 1999), Differential Ability Scales (Holland & McDermott, 1996), Comprehensive Test of Nonverbal Intelligence (Drossman, Maller, & McDermott, 2001), Woodcock-Johnson Psychoeducational Battery-Revised (Konold, Glutting, & McDermott, 1997), and Universal Nonverbal Intelligence Test (Wilhoit & McCallum, 2002). These taxonomies, involving only intellectual ability, have been the most widespread. However, as psychoeducational evaluations usually involve ability and achievement measures, it is important to include in a normative taxonomy variables from both domains. In recent years testing companies have been co-norming or co-administering cognitive and intelligence measures with achievement measures in order to improve score comparison statistics. Examples include the co-normed WISC-III and Wechsler Individual Achievement Test (WIAT; Wechsler, 1992) as well as the co-administered CAS and Woodcock-Johnson Tests of Achievement – Revised (WJ-R ACH; Woodcock & Johnson, 1989). Thus, these types of data have become more readily available to researchers interested in developing intelligence/achievement typologies.

With the drive to serve all students and the increasing body of knowledge of multivariate techniques to guide interpretation, professionals are now in a unique position to begin identifying groups of students based upon common profile characteristics who may benefit from similar interventions. In order to use multivariate profile analysis for academic decision-making on a programmatic or individual basis, it is necessary to first identify normative profiles. These profiles can then be used to determine the uniqueness of a profile or the extent to which an intervention might be effective for a group.

A final consideration is that the taxonomy resulting from any technique is only as useful as the measures upon which it was built. Therefore, utilizing a recently developed, theoretically based measure of cognitive processing, such as the Cognitive Assessment System (CAS), strengthens the interpretation of the profiles and resultant intervention strategy development.

Purpose of the Present Study

The scope of the present study was influenced by current federal legislation as well as the availability of improved data and more complex analysis methods. First, a recent federal regulation, NCLB (2001), has charged schools with the need to bring all students to a high level of achievement in mathematics and reading. Therefore, the present study focuses on mathematics and reading achievement. Second, the development of multivariate techniques allows for the creation of valuable information (i.e., normative core profile types) that can inform test interpretation efforts and is available for use in decisions concerning district and individual intervention plans. Therefore, cluster analysis was used to develop normative typologies for reading and math. Third, the existence of co-administered data for the CAS and the Woodcock-Johnson Tests of Achievement -Revised (WJ-R ACH), a commonly used academic achievement battery, makes a substantial, representative data set available for the development of core profile types. These core profile types aid in test interpretation by serving as normative comparisons. Thus, the present study applied the multivariate techniques of cluster analysis to the CAS/WJ-R ACH sample to create core profile types for reading and for mathematics. In addition, this taxonomy was used to describe students with low math and reading achievement.

Objectives

The objectives are as follows:

1. Identify core profile types for the CAS PASS scales and WJ-R ACH reading achievement subscales.

2. Identify core profile types for the CAS PASS scales and WJ-R ACH mathematics achievement.

3. To describe the prevalence of the reading core profiles within a group of students with a Broad Reading cluster score greater than or equal to one standard deviation below the mean.

4. To describe the prevalence of the math core profiles within a group of students with a Broad Mathematics cluster score greater than or equal to one standard deviation below the mean.

Significance of Study

The present study applied the multivariate techniques of cluster analysis to the CAS/WJ-R ACH sample to create core profile types for reading and for mathematics. By establishing normative profiles, clinicians will have the tools to compare individual student profiles on a multivariate basis. In addition, this taxonomy was used to describe students with low math and reading achievement. This information has implications for improving the development of specific interventions for individual students. Moreover, normative taxonomies can aid in program planning for broad interventions within classrooms.

Limitations of Study

In the development of this study, two primary assumptions were made. First, cognitive functioning can be measured. Second, achievement is different from cognitive functioning. With this in mind, there are a number of limitations of this study. This

investigation involved students between the ages of 8 to 17 who were administered the CAS and WJ-R ACH. Therefore, inferences to other groups can only be made with similarly aged subjects. In addition, other cognitive or intelligence tests as well as achievement tests may yield different results due to theoretical differences in construction.

Definition of Terms

<u>cluster centroid</u> - the mean value of all variables utilized in the cluster analysis for the subjects contained in the cluster

<u>cluster</u> - the group of individuals who are maximally similar to each other and minimally similar to members of other clusters in a solution

<u>cluster analysis</u> - a multivariate data reduction technique used to create clusters of individuals who are most similar to each other and maximally dissimilar to those in other clusters in terms of the clustering variables; cluster parameters are unknown prior to the classification through cluster analysis

<u>cluster seeds</u> - the starting points for clusters to be developed using nonhierarchical methods

<u>complete coverage</u> – occurs when the resulting clusters are formed from a representative sample of the population of interest which is particularly important for a normative typology/taxonomy

core profiles – the most common profiles that are reflective of a population

<u>dendrogram</u> - a tree-like graphical representation of the steps showing clusters being combined step-by-step in hierarchical cluster analysis; the tree starts with each entity in its own cluster (i.e., a branch) and results in all entities combined into one cluster at the extreme right

<u>dispersion</u> – a cluster property; the amount of scatter of the cases around the centroid in the clustering space

<u>Euclidean distance</u> – a similarity measure that is essentially the length of a straight line between two clusters

<u>hierarchical agglomerative methods</u> - a clustering procedure that starts with individuals in their own cluster, determines cluster similarities, merges the two most similar clusters, and repeats this process until all individuals are fused into one cluster; one pass is made through the set of cases

<u>iterative partitioning</u> - clustering method in which there is a pre-determined number of clusters; multiple passes through the cases allow for the re-assignment of cases to clusters until there are no new assignments

<u>k-means clustering algorithm</u> – an iterative partitioning method that represents each cluster by its center

<u>level</u> – a cluster property; the general position of the cluster in space (i.e., the centroid scores are in the high, middle, or low portion of the range)

<u>normative typology</u> – the resultant set of clusters from an analysis of a representative sample drawn from the population of interest (e.g., test's standardization sample)

profile – a set of scores that represent an individual or group

profile analysis. (i.e., subtest analysis, scatter analysis) – practice of interpreting patterns of test-score elevation and depression as derived for a given individual

<u>shape</u> – a cluster property; the arrangement of points in cluster space (i.e., score highs and lows)

<u>similarity</u> – a measure of the likeness of cases to be included in the cluster analysis; distance measures have been the most frequently used in the social sciences

stopping rules - algorithms for selecting the number of clusters which best represents the underlying structure of the dataset

<u>subtest analysis</u> – common profile analysis practice used in psychoeducational test interpretation involving a comparison of subtest scores to determine strengths and weaknesses

 $\underline{taxonomy}$ – an empirical classification; often used in the biological sciences but interchanged with the term typology

<u>typology</u> – a theoretical or conceptual classification of entities; often used in the social sciences but interchanged with the term taxonomy

weighting - the manipulation of a clustering variable's value so that it plays a greater or lesser role in the measurement of similarity between cases

11

CHAPTER 2

REVIEW OF THE LITERATURE

In this chapter an overview of the literature concerning PASS theory, the Cognitive Assessment System, and their relationship to reading and math achievement is presented. Although there are various approaches to test interpretation as overviewed in Chapter 1, this study focuses on profile analysis. Therefore, subtest profile analysis, the Naglieri profile analysis procedure, and cluster analysis are reviewed.

PASS Theory and the Cognitive Assessment System

Tests of intelligence have played a part in predicting school success since the turn of the century. The various batteries have a number of similar characteristics. Neisser et al. (1996) stated that intelligence test scores are fairly stable and predict academic achievement moderately well, accounting for about 25% of the variance. Intelligence test batteries differ in other ways, such as the theoretical underpinnings and appropriate uses of the test, as well as the types of questions utilized (Anastasi & Urbina, 1997; Neisser et al., 1996). A recent addition to the intelligence testing arena, the Cognitive Assessment System (Naglieri & Das, 1997a), is based on the Planning, Attention, Simultaneous and Successive processes (PASS) theory of cognitive functioning as originated by Das, Kirby and Jarman (1979). Of great importance to the authors was to move away from conventional intelligence tests, such as the Wechsler scales (i.e., WISC-III, Wechsler Adult Intelligence Scale-III [WAIS-III], and Wechsler Preschool and Primary Scale of Intelligence – Revised [WPPSI-R]) and Stanford-Binet Intelligence Scale: Fourth Edition (SB:IV) which are updates of tests developed in the early 1900's. Their goal was to develop a theory-based, multidimensional view of intelligence with constructs built on contemporary research in human cognition.

The theoretical foundation of the PASS theory of cognitive processing is A. R. Luria's research in the fields of neuropsychology, information processing, and cognitive psychology (Das, Kirby, & Jarman, 1979; Das, Naglieri, & Kirby, 1994; Naglieri & Das, 1990, 1997b, 1997c). Luria divides human cognitive processes into three primary functional units. Maintaining appropriate cortical tone, or attention, to allow for adequate vigilance and discrimination between stimuli is the primary function of the first unit. The second unit is responsible for obtaining, elaborating upon, and storing information using successive and simultaneous processes. The third functional unit is relied upon for programming as well as the regulation and control of mental activity (i.e., executive functioning or planning).

Cognition is a dynamic process that works within the context of the individual's knowledge base, responds to their experiences, and is subject to developmental variations (Das, Naglieri, & Kirby, 1994; Neisser, et al., 1996). When considering the measurement of cognitive processes, Das, Naglieri, and Kirby (1994) make the point that "effective processing is accomplished through the integration of knowledge with planning, attention, simultaneous, and successive processes as demanded by the particular task" (p. 19). Although these processes are interrelated and nonstop, they are not equally involved

in all tasks. For that reason, CAS tasks for planning, attention, simultaneous, and successive processing were developed to adhere to PASS theory and predominantly require a specific cognitive process (Das, Naglieri, & Kirby, 1994; Naglieri, 1999; Naglieri & Das, 1997b).

The changing contribution of the cognitive processes suggests that a pattern of strengths or weaknesses in PASS processes would have differential impact upon various academic tasks (e.g., reading a passage or calculating one's taxes). Therefore, the CAS offers a unique opportunity to examine the relative contributions of cognitive processes to reading and mathematics achievement. The achievement areas of reading and math require a wide variety of cognitive skills. Therefore, difficulties in bringing these skills to bear upon academic tasks can produce learning problems in one or more areas. For example, normal classroom performance requires attention skills and controlled levels of arousal. Difficulty with attention and arousal can disrupt classroom behavior generally and lead to broad academic problems (Kirby & Williams, 1991; Sattler, Weyandt, & Roberts, 2002). Inappropriate attention may disrupt planning, which in turn could disrupt simultaneous and successive processing, and achievement. In addition, one or both of the processing skills (simultaneous and successive) may be weak, producing a particular type of learning problem across achievement areas. Poor successive processing may affect word analysis in reading, resulting in overemphasis upon visual cues in spelling and an inability to follow a plan in problem solving (Naglieri, 1999).

One of the most important practical uses of an IQ test is making the connection between assessment results and intervention (Naglieri and Das, 1997b; Sattler, 2001, chap. 1). This emphasis is clearly apparent in books focused upon the PASS theory and

the CAS such as *Learning Problems: A Cognitive Approach* (Kirby & Williams, 1991), Assessment of Cognitive Processes: The PASS Theory of Intelligence (Das, Naglieri, & Kirby, 1994), and Essentials of CAS Assessment (Naglieri, 1999). The relationship between IQ and instruction is often conceptualized within the context of an aptitude by treatment interaction (ATI). ATI assumes that the variation in a person's cognitive ability can have relevance to the type of instruction provided (Cronbach & Snow, 1977). The idea of using intelligence test scores for the purpose of instructional decision-making has had considerable intuitive appeal for some time. Unfortunately, researchers have found that tests of general intelligence have not been useful for providing effective aptitude by treatment interactions (ATIs) for evaluating how children best learn, or for determining how a particular child's style of learning is different from the styles of other children (Esters, Ittenbach, & Han, 1997; Gresham & Witt, 1997). In contrast, Snow (1986) concluded that students low in ability generally respond poorly to instruction and those high in ability respond well, showing an aptitude by treatment interaction. Others support that ATIs can be demonstrated and used appropriately (Peterson, 1988; Shute & Towle, 2003; Snow, 1992)

The limited support for ATI led Peterson (1988) to suggest that an aptitude approach based on cognitive processes could hold more hope for success. One method that fits the process by treatment interaction (PTI) model is the dynamic assessment approach designed to measure a child's learning potential (Elliott, 2003; Lidz, 1991). Another application of this approach involves utilizing PASS theory to drive intervention planning (Kirby & Williams, 1991; Naglieri & Ashman, 1999; Naglieri & Pickering, 2003). Similarly, methods that link information about a child's PASS characteristics with interventions in order to improve educational outcomes have been described in detail (Naglieri, 1997b; Naglieri, 2001b; Naglieri, 2002). The PASS Remedial Program (PREP; Das & Kendrick, 1997; Das, 1999), the Planning Facilitation Method (Naglieri, 1999), and the MAthematics Strategy Training for Educational Remediation (MASTER; Van Luit & Naglieri, 1999) are related to the PASS theory and appear to have promising utility. In the CAS manual, Naglieri and Das (1997b) report some attempts to obtain ATI evidence to substantiate intervention methods using this instrument. Methods included the PASS Remedial Program (PREP), planning facilitation, and process-based instruction (PBI).

Most recently Naglieri and Pickering (2003) published a set of intervention handouts for use with a classroom, small group or individual child. It includes a brief questionnaire based upon the CAS to evaluate student strengths and weaknesses with respect to the PASS theory. Teachers and parents can choose from the almost 50 interventions with reproducible handouts to use with elementary to high school students.

PASS and Reading Achievement

Even before the introduction of the CAS, the relationship between PASS processes and reading achievement was being explored. Initially, the relationship between simultaneous and successive processing and reading achievement were the focus of investigators' attention (Kirby & Das, 1977; Leong, 1984; Stoiber, Bracken, & Gissal, 1983). In time, the contribution of the planning process upon reading performance was added to the research surrounding the cognitive demands of reading achievement. Early studies found that reading was significantly related to both successive and simultaneous processes (i.e., the integration of the reading stimuli in either a sequential or simultaneous manner) (Das & Mensink, 1989; Das, Snart & Mulcahy, 1982; Kirby and Das, 1977; Leong, 1980). Simultaneous and successive processing tasks have correlated significantly with measures of reading comprehension (Kirby, 1982; Kirby & Robinson, 1987; Leong, 1984; McRae, 1986), reading decoding (Cummins & Das, 1980; Das & Cummins, 1982; Das, Cummins, Kirby & Jarman, 1979), and performance in college level English courses (Wachs & Harris, 1986). These findings suggest that high reading achievement necessitates adequate skill development in both simultaneous and successive processing and neither by itself is sufficient (Kirby & Das, 1977).

A study by Cummins and Das in 1977 was an exception to these early studies. These investigators used a sample of 3rd grade children to investigate the relationship of simultaneous and successive processing and reading decoding and comprehension. Results revealed significant main effects for simultaneous processing in reading decoding and comprehension. The main effect for successive processing, however, was not significant for reading decoding or comprehension. Another study found that simultaneous processing contributed more to early reading than successive processing (Shinn-Strieker, House, & Klink, 1989).

In an attempt to understand the fine discriminations between simultaneoussequential processing and reading achievement, Cummins and Das (1978) point out that, at different developmental levels, and between different groups, the role of simultaneous and successive processing in linguistic functioning may vary. For instance, successive processing may be particularly important for mastering initial reading decoding skills while simultaneous processing may be more significantly related to fluent reading or advanced levels of reading. Using this rationale in a second study, Das and Cummins (1978) studied these processes with a sample of youths classified as educable mentally retarded (EMR). Their findings provide further support for the importance of successive processing in the reading performance of low-achieving individuals, particularly in the development of decoding skills. Kirby and Robinson (1987) concluded that simultaneous processing was involved in direct lexical access and semantic processing whereas successive processing was involved in graphophonic decoding and syntactic analysis.

Planning and attention have also been shown to correlate significantly with reading (Das et al., 1982; Parrila, Das, Kendrick, Papadopoulos, & Kirby, 1999). Planning has been related to reading decoding and reading comprehension in studies with elementary school-aged students and was reported to become more highly correlated with reading achievement as students matured (Leong, Cheng & Das, 1985; Naglieri & Das, 1987). Ramey's study (as cited in Das et al., 1994) with high school students also supported the importance of planning with a variety of reading tasks.

Recent studies suggest that the CAS is beginning to be used by professionals outside the psychoeducational community (Solan, Shelley-Tremblay, Ficarra, Silverman, & Larson, 2003; Steinman, Steinman, & Garzia, 1998). For example, Solan et al. (2003) report a connection between attention and reading that has been of interest to the optometric community. These investigators used the Attention scale of the CAS to evaluate changes in the children's ability to sustain and direct their attention before and after vision/attention therapy. Their findings suggest that the CAS scores can be used to help direct intervention even outside the direct psychoeducational domain.

In a recent study designed to explore the relationships between PASS processes and various measures of phonological processes and basic reading, Joseph, McCachran & Naglieri (2003) studied a group of primary students who had been referred for reading problems. The students were assessed using the CAS, the Comprehensive Test of Phonological Processing (CTOPP; Wagner, Torgesen, and Rashotte, 1999), and the basic reading subtests of the Woodcock-Johnson Battery of Achievement-III (WJ-III; Woodcock, McGrew, & Mather, 2000). Using repeated ANOVAs, the authors reported that the students scored significantly lower on the Planning and Successive scales of the CAS, which is contrary to scores expected for normally achieving students. Multiple correlation coefficients revealed significant relationships between successive processing and phonological memory as well as successive and simultaneous processing and phonological awareness. In connection with basic reading skills, simultaneous processing was significantly related to letter-word identification and word attack. In addition, planning was related to word attack skills. Phonological awareness was strongly related to basic reading skills, while phonological memory lacked this relationship. The authors suggest that measures of phonological processing (e.g., CTOPP) as well as psychological processes (e.g., CAS) should be included in the testing scheme to more clearly understand the underlying processes related to children's reading difficulties.

The links between reading and the cognitive processing components continue to be substantiated and clarified. However, the differential effects of remediation and intervention are becoming the primary focus of many of these studies. For example, Crawford and Snart (1994) used a small group of gifted/learning-disabled students to investigate the effectiveness of instruction and verbal mediation in improving reading skills as well as successive cognitive processing.

Lidz and Greenberg (1997) utilized a process treatment interaction (PTI) procedure for both reading and math entitled the Cognitive Assessment System/Group Dynamic Modification (CAS/GDM). They used a pretest-intervene-posttest format with groups of first graders. The authors reported a stronger relationship between reading and cognitive processes for posttest scores. In addition, lower performing students made greater gains than their higher performing peers.

Parrila et al. (1999) studied the cognitive makeup of poor readers in the first grade and their reaction to specific interventions. Two groups were formed; one received the PREP remediation program (Pass Reading Enhancement Program; Das, 1999; Das & Kendrick, 1997) while the contrast group participated in a meaning-based program. The authors stressed that while both groups improved there was greater improvement in the PREP group who did not receive direct phonological coding instruction. PREP allows children to develop their own strategies for cognitive processing.

PASS and Math Achievement

Although not as prominent in the literature, the connections between PASS theory and mathematics achievement have been well documented. The progression of studies is similar to PASS and reading achievement in that they initially focused on successive and simultaneous processes, then incorporated planning and attention, and finally, expanded to include treatment effectiveness as the primary focus of investigations. Simultaneous and successive processing tasks have correlated significantly with measures of mathematics (Garafalo, 1986; Naglieri & Das, 1987; Naglieri & Gottling, 1997). Wachs & Harris (1986) demonstrated that simultaneous processing strategies correlated significantly with mathematics proficiency (i.e., math portion of the Scholastic Aptitude Test) for a sample of college undergraduates. This finding supported the contention by Luria (1966) that mathematics achievement is more closely related to simultaneous processing rather than successive processing due to the highly spatial nature of mathematics. Findings by a number of early researchers support this relationship between mathematics tasks and simultaneous processing (Das & Cummins, 1978; Mwamwenda, Dash & Das, 1985).

Planning and achievement have also correlated significantly with measures of math achievement. For example, Garafalo (1986) investigated the relationship of math computation, problem solving, and quantitative ability with the successive and simultaneous processing. Results indicate that quantitative ability and problem solving were significantly related to the simultaneous factor whereas computation was more closely related to the planning factor. Garafalo concluded that the belief that problem solving and quantitative ability require an understanding of mathematical and logical relationships (i.e., simultaneous processing) and computation is more related to the regulation and monitoring of behavior (i.e., planning) is substantiated.

Naglieri and Das (1987) examined the simultaneous, successive and planning processes from a developmental perspective. Math achievement was most strongly related to simultaneous processing and planning at a second grade level. For the sixth graders, simultaneous, successive, and planning showed a strong association with mathematics achievement. By the 10th grade level, the relationship of successive processing to math nearly increased to the level of simultaneous processing.

Planning was the focus of two studies of mathematics instruction and PASS processes (Naglieri & Gottling, 1995, 1997). Low- and high-planning groups of elementary learning disabled students were identified. A cognitive-based intervention focused on improving planning processing (i.e., planning facilitation method) was provided. After attempting to solve 54 math problems in 10 minutes, students were engaged in discussions involving self-reflection designed to facilitate the child's awareness of their need for planfulness. It is important to note that this intervention may be used with the entire class or with small groups. In addition, no mathematics instruction or feedback on correct solutions was given during the discussion sessions. While all students showed improvement, those in the low-planning group showed higher gains than their peers. The connection between planning and math achievement was substantiated and the effectiveness of the intervention shown. This work was supported by a second study that involved middle school special education students (Naglieri & Johnson, 2000). Cognitive strategy instruction provided in a classroom setting was effective in improving math performance, particularly for those with low planning skills.

In 1999, Van Luit and Naglieri explored the usefulness of a cognitive strategy program with learning disabled and mild mentally retarded 9 to 14 year old Dutch students. One group of students participated in the MAthematics Strategy Training for Educational Remediation (MASTER) program while the comparison group received standard remedial instruction in their classroom. Although there was not a direct measurement of planning, the MASTER program targets problem-solving and strategy

22

formation and supports the usefulness of improving cognitive strategies as a means to academic interventions. They found that the students who had been a part of the MASTER training program achieved significantly better on math tasks than the comparison groups. This improvement was attributed to their employment of effective strategies for the solution of math problems.

A second study which utilized the MASTER program involved a group of Dutch math learning disabled students (Kroesbergen, Van Luit, and Naglieri, 2003). The results indicated that cognitive processes are related to certain areas of mathematics. For example, attention and successive processing are important to success with math word problems. However, they did not find that students with a weakness in planning showed greater improvement than students without this cognitive weakness as expected (Naglieri & Gottling, 1995, 1997; Naglieri & Johnson, 2000). The authors suggest that this lack of a differential effect may be due to the fact that MASTER is not as focused on planning intervention as the planning facilitation methods used in the previous studies. This suggests that the MASTER program may be a valuable tool for intervention of low performing math students. However, if improved planning is the goal, the planning facilitation method utilized by Naglieri & Gottling (1995, 1997) and Naglieri & Johnson (2000) may be more appropriate.

Finally, Joseph and Hunter (2001) studied the influence of planning on math achievement. The subjects, three eighth grade students with similar math achievement but diverse planning abilities, were selected. Instruction on the use of a cue card strategy for solving fraction problems was provided. The two students with adequate planning showed significant improvement when working with fractions; the student with low

23

planning processing scores did not improve as much as his peers. The authors suggest that the low-planner had more difficulty maintaining a consistent use of the cue card strategy. They stress the importance of tailoring interventions to individuals with differing levels of motivation and self-efficacy.

Profile Analysis

Subtest profile analysis

Subtest profile analysis has been referred to as scatter analysis (Rapaport, Gill, and Schafer, 1945/1946), score pattern analysis (Anastasi & Urbina, 1997), and, generally, as profile analysis or subtest analysis. Wechsler (1958) presented his ideas concerning the interpretation of subtest patterns with respect to mental illness diagnosis. As a strong proponent of the centrality of professional judgment in clinical practice, he maintained that experience, study, and personal beliefs lead to a set of profiles that are used by the clinician to inform their work. Each profile is believed to result in particular behavioral patterns. Therefore, Wechsler's ideas were influential in adding impetus to interpreting subtest patterns and the creation of meaningful profiles to aid in test interpretation.

On the surface, subtest profile analysis is the evaluation of the peaks and valleys of subtest scores. Various sources give detailed directions, as well as supporting interpretation tables, and suggestions for building a subtest profile for specific measures (Elliott, 1990; Kaufman, 1990, 1994; Naglieri & Das, 1997b; Rosenthal & Kamphaus, 1988; Sattler, 2001). This process begins with the computation of difference scores for the subtests, yielding a pattern of high and low scores. The statistical significance of these
differences must be determined so that chance variations do not influence the interpretation. In addition, the uniqueness of the difference can be determined when compared to tables of general population differences. In addition, Pfeiffer, Reddy, Kletzel, Schmelzer, and Boyer (2000) found that practitioners (i.e., 89% of a nationwide sample of practicing school psychologists) considered subtest profile analysis valuable in their work.

Some methodologies utilize a univariate approach in that they compare single scores to a mean score for an individual or group of individuals. However, the univariate approach frequently increases error rates by making multiple comparisons to one achievement score (e.g., comparing the WISC-III FSIQ as well as the VIQ and PIQ to a broad reading achievement score).

The subtest analysis procedures have become increasingly controversial. Some of the arguments against this means of test interpretation have been that the profiles are unstable and unreliable, are based upon technically indefensible practices, and are not diagnostically useful (Greenway & Milne, 1999; Macmann & Barnett, 1997; McDermott, Fantuzzo, Glutting, Watkins, & Baggaley, 1992; Spreen & Haaf, 1986; Watkins, 2000). Watkins (2000) noted that much of the work with profile analysis has moved from the subtest level to the scale or composite level of analysis. However, subtest analysis continues to be presented in textbooks (Kaufman, Lichtenberger, & Naglieri, 1999; Sattler, 2001) and test manuals (Elliot, 1990; Wechsler, 1997). In addition, subtest profile analysis continues to be widely used particularly in psychoeducational work (Pfeiffer et al., 2000).

25

Naglieri (1993) shifted attention from the subtest level of analysis to the more reliable index level of interpretation with the WISC-III (i.e., that level that results from the combined influence of two or more subtests). Kaufman, et al. (1999) referred to this approach as Naglieri's index-level analysis. Of particular relevance to the current study was Naglieri's (1999, 2000) extension to the creation of a profile of cognitive strengths and weaknesses from the PASS scores of the CAS. The author distinguishes between a relative weakness (RW), a cognitive weakness (CW), and a cognitive weakness accompanied by a similarly low academic test score (CWAW). A relative weakness (RW) occurs when a child is found to have a PASS scale score that is significantly lower than their mean PASS scores (i.e., the ipsative method promoted in Kaufman's 1994 book, *Intelligent Testing with the WISC-III*). When a child has a RW and the lowest score falls below the identified average range, they fall within the group with a cognitive weakness (CW). A final profile emerges when a child with a CW also has an academic test score that is similar to their low PASS scale score (CWAW).

Naglieri (2000) applied this methodology to a portion of the standardization sample of the CAS who were also administered the WJ-R ACH. The relative weakness criteria did not differentiate between regular and poor performing students. The CW group obtained lower achievement scores and was more apt to have been identified and placed in special education settings. The CWAW profile may be useful for intervention planning in specific academic areas. These results suggest that utilizing scaled scores may have utility in the development of profiles to be used for intervention planning.

<u>Cluster analysis</u>

Classifying objects or persons is a basic activity that has been used by man to simplify and manage their environment. However, cluster analysis as a scientific activity is relatively new, since the early 1900's. The introduction of fast computers and the publication of Sokal and Sneath's Principles of Numerical Taxonomy (1963) accelerated the development of cluster analysis as a separate methodology (Aldenderfer & Blashfield, 1984; Bailey, 1984). Parallel development has occurred in many fields of study (e.g., engineering, biology, psychology, education) resulting in domain-specific nomenclature and methodologies. Cluster analysis has been referred to as "O-analysis" (Tryon & Bailey, 1970; psychology), "Q analysis" (psychology), "numerical taxonomy" (Sokal & Sneath, 1963; biology), "inverse factor analysis", and typology. R. C. Tryon (1939) and R. B. Cattell (1949) were early psychologists who brought this methodology to the social sciences. The approach to analyses can be exploratory (i.e., no pre-established groups) or confirmatory (i.e., validate known attributes). Cluster analysis continues to be a developing methodology and remains primarily exploratory in nature (Bailey, 1984; Everitt, 1997).

As exploratory analysis, cluster analytic techniques are used when no configurations have been identified a priori. They make no assumptions as to the number of groups, pre-determined structure, or group characteristics (Johnson & Wichern, 2002). It is a mixture of revealing the "natural" structure within the data while simultaneously imposing a structure on the data (Anderberg, 1973).

Aldenderfer and Blashfield (1984) stated that cluster analysis is "a multivariate statistical procedure that starts with a data set containing information about a sample of

entities and attempts to reorganize these entities into relatively homogeneous groups" (p. 7). Therefore, score variations are compared on more than a correlational (linear) basis as they are sensitive to shape, level, and dispersion of all profiling variables. Cluster analysis most often refers to a subject by variable matrix with classifying subjects as the goal. Ultimately, the goal is to illuminate a set of clusters that reduce the data to useful categories. This means of interpreting scores takes more than a single variable into account simultaneously, which makes members of the group similar in terms of all variables considered and maximally dissimilar to other groups' members.

Topics common to cluster analysis procedures include selection of the sample and variables, determination of an appropriate similarity measure and clustering algorithms, and validation and description of the resulting clusters (Aldenderfer & Blashfield, 1984; Anderberg, 1973; Everitt, 1993; Hair & Black, 2002; Sneath & Sokel, 1973). By using clustering techniques one would expect to find groups of individuals whose profiles are similar and amenable to intervention. Each profile is defined by its level (its position in the score continuum), shape (where highs and lows occur) and scatter (distribution of scores around the mean). These topics have been carefully addressed in the psychoeducational studies involving intelligence and achievement measures (Donders, 1996; Drossman, et al., 2001; Glutting, et al., 1994).

Normative Profiles

The profile analysis techniques that had been widely used within psychoeducational testing were often used without knowledge of whether a profile is typical of others in the population of interest. Therefore, test interpretation has expanded to include cluster analysis as a means of providing normative information and a multivariate means of creating profiles. In the 1980's and early 1990's, investigators such as McDermott, Glutting, Watkins, and Donders began exploring the usefulness of cluster analysis in the creation of normative taxonomies of various test instruments. More specific profiling (e.g., learning disabled population profiles is being promoted in the absence of appropriate comparisons with normal population variation.

One of these early studies focused on the development of core profile types for the Wechsler Intelligence Scales for Children-Revised (WISC-R; Wechsler, 1974). McDermott, Glutting, Jones, Watkins, & Kush (1989) used the entire national standardization sample excluding severely emotionally disturbed children and institutionalized children with mental deficiency. The variables included in the profiling steps were 11 WISC-R subtests (i.e., five Verbal, five Performance, and Digit Span). A number of variables were also used as internal and external criteria to substantiate and describe the resulting clusters. These included the Full Scale, Verbal, and Performance IQs, age, sex, ethnicity, head-of-household's occupational status, parental educational level, child's birth order, and the number of children in the family. For the cluster analysis procedures, they chose to use Ward's minimum-variance algorithm. Their investigation yielded a seven-cluster solution with FSIQ variations being the primary distinguishing characteristic. However, they point out that these profiles have configurations that are similar within the upper and lower levels of ability.

A number of additional studies have been conducted to create normative typologies for a number of the other Wechsler scales. As Glutting, McDermott, and their colleagues did much of this work, similar aforementioned methodology was applied. For example, typologies have been developed for the Wechsler Adult Intelligence Scale – Revised (WAIS-R; Wechsler, 1981) (McDermott, Glutting, Jones, & Noonan, 1989), Wechsler Preschool and Primary Scale of Intelligence (WPPSI; Wechsler, 1967)(Glutting & McDermott, 1990), and the WISC-III (Konold et al., 1999).

In 1992, Glutting, McGrath, Kamphaus, & McDermott used the school-age portion of the standardization sample of the Kaufman Assessment Battery for Children (K-ABC; Kaufman & Kaufman, 1983). The subtests for the Sequential and Simultaneous scales were used as clustering variables, resulting in eight core profile types. Beyond constructing the typology, the authors used it to explore the subtest patterns of special populations (e.g., learning disabled, emotionally disturbed) and locate children with unusual subtest patterns.

Donders (1996) extended the work with the WISC-III to the creation of a taxonomy based on the entire 2,200 children in the standardization sample. In contrast to the previous work, the four factor index scores (i.e., Verbal Comprehension, Perceptual Organization, Freedom from Distractibility, and Processing Speed) were used as the clustering variables. Using a two-stage clustering procedure, Ward's agglomerative clustering followed by *k*-means iterative partitioning, a five-cluster solution emerged. Three clusters were primarily identified by levels of performance, while the remaining showed pattern distinctiveness. Donders (1998, 1999) has done similar work with the Children's Category Test (CCT; Boll, 1993) and the California Verbal Learning Test-Children's Version (CVLT-C; Delis, Kramer, Kaplan, & Ober, 1994).

Donders (1998) determined core profile subtypes for the Children's Category Test standardization sample using subtest error scores. This instrument is used to evaluate complex cognitive processes and is sensitive to cerebral impairment. He points out that in order to interpret scores from clinical settings it is necessary to identify common subtypes. Donders cluster analyzed the 320 sets of scores in the CCT-1 (ages 5 - 8) and the 600 in the CCT – 2 (ages 9 - 16) in the standardization sample.

Donders (1999) used *z* scores for a variety of quantitative and qualitative variables from the CVLT-C standardization sample to provide a normative taxonomy. He identified five core clusters using a two-stage cluster analysis. First-stage analysis used the Ward's minimum variance algorithm and squared Euclidean distance for the similarity method.

Holland and McDermott (1996) identified the cognitive subtest profiles (ability profiles) from the standard scores on the nine cognitive subtests (core and diagnostic) that make up the school-age version of the Differential Ability Scales (DAS). They used Wards's minimum-variance in a three-stage clustering process. They ended with seven core profile types.

Drossman, et al. (2001) derived core profiles from the general education subsample of the Comprehensive Test of Nonverbal Intelligence (CTONI; Hammill, Pearson, & Wiederholt, 1997). Standard scores on the six subtests were used in the cluster analyses. They used a three-stage cluster analysis procedure (i.e., multistage Ward's minimum-variance cluster analysis). The cluster analysis resulted in the formation of three core profile types for the CTONI primarily distinguishable by level. The second phase involved an evaluation of the percentages of unique profiles for a learning disabled

31

sample. These profiles lacked variation in shape and there were no significant differences in the learning-disabled sample profiles; therefore, interpretation of the CTONI taxonomy was not supported in this study.

Wilhoit and McCallum (2002) sought to determine the common subtest profiles for the Standard and Extended Batteries of the Universal Nonverbal Intelligence Test (UNIT; Bracken & McCallum, 1998). In addition, they wanted to give practitioners the information to interpret UNIT from a multivariate perspective. The authors stated that they followed Glutting, McDermott, and Konold (1997) procedures. A seven-cluster solution for the Extended Battery and a six-cluster solution for the Standard Battery were obtained. These taxonomies support the underlying factor structure and provide a usable method of determining the uniqueness of obtained profiles when compared to the normative typology.

There have been a number of additional investigations using samples of special populations (e.g., learning disabled, attention deficit, traumatic brain injured). When available, the researchers have compared the learning disabled profiles with the profiles from the normative typology. Maller and McDermott (1997) studied learning-disabled college students using the WAIS-R. The majority (93.8%) matched profiles from the normative typology. The authors suggest that profile comparisons utilizing the WAIS-R may need to be reconsidered in light of their findings. Glutting, et al. (1992) made a similar comparison between special education students and the normative typology of the K-ABC. In addition, the authors used the normative typology to identify unusual patterns

in both regular and special education students. The authors present an overall summary of these studies as supporting the position that the utility of exceptional profiles types is still unsubstantiated.

In other instances, the investigators did not compare their profiles to a normative taxonomy, thereby clouding the interpretation of cluster membership. Studies have involved closed-head-injured subjects (Crawford, Garthwaite, Johnson, Mychalkiw, & Moore, 1997; Williams, Gridley, & Fitzhugh-Bell, 1992), preschoolers with cognitive delays (Hughes & McIntosh, 2002), learning disabilities (D'Amato, Dean, & Rhodes, 1998; Glutting et al., 1992), schizotypy dimensions (Barrantes-Vidal, et al., 2002), and poor readers versus dyslexic children (Tyler & Elliott, 1988). Another approach was taken by Buly and Valencia (2002) to use cluster analysis to sort students who failed a state reading assessment into meaningful groups. This information was used to allow for more differentiated instructional strategies. Finally, Bonafina, Newcorn, McKay, Koda, & Halperin (2000) developed a four-cluster solution of referred Attention Deficit/Hyperactivity Disorder (ADHD) students with and without a reading disability.

In the psychoeducational domain, the literature extending cluster analysis to more than a measure of intelligence is limited. However, practitioners commonly use a combination of ability and achievement measures. The discrepancy between ability and achievement is taken to mean that something unusual may be affecting a child's performance in the classroom. Therefore, a normative taxonomy that includes both ability and achievement scores can be a valuable tool to assess when profiles are indeed unusual and determine the common profiles that may be representative of underachieving children.

33

Two investigations of this type have been completed. Glutting, McDermott, Prifitera, & McGrath (1994) used subjects from the linking sample of the WISC-III and the WIAT who took similar sets of subtests (i.e., children from 8 years, 9 months through 16 years, 11 months). This allowed for the development of a taxonomy of core WISC-III/WIAT profiles that may be used to test multivariate IQ-achievement discrepancies. The authors used the standardized scores from the WISC-III factor Indexes (i.e., Verbal Comprehension Index [VCI], Perceptual Organization Index [POI], Freedom from Distractibility Index [FDI], and Processing Speed Index [PSI]) and WIAT composites (i.e., Reading, Mathematics, Language, and Writing). They used a multi step clustering procedure with a combination of agglomerative and iterative partitioning methods. Ward's method, having the best internal criteria, produced the best overall taxonomy of ability and achievement profiles. Six core profile types were formed and described using unusual score differences and distinct demographic prevalence.

Glutting, et al. (1994) indicate that the WISC-III/WIAT core profiles can illuminate how ability and academic achievement covary and relate to other external characteristics. In addition, they offered two methods of profile comparison that enable the practitioner to evaluate the clinical uniqueness and relevance of an individual's performance. One is designed for everyday practice and is therefore more accessible, while the other is mathematically rigorous but impractical for everyday application.

A second study involving the development of normative profiles for aptitude and achievement was conducted by Konold et al. (1997). In this investigation four scales from the cognitive portion and four from the achievement portion of the Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R; Woodcock & Johnson, 1989) were used. These included the Reading, Mathematics, Written Language, and Knowledge aptitude scales as well as the Broad Reading, Broad Mathematics, Broad Written Language, and Broad Knowledge achievement scales. A stratified quota system was used to select subjects in Grades 1 through 12 participating in the standardization of the WJ-R. A multistage clustering procedure with agglomerative stages as well as an iterative partitioning stage was conducted. An eight-cluster solution was deemed most appropriate and described using external characteristics. Similar to the Glutting et al. (1994) study, a reasonable method for profile comparison was presented. This research supports the premise that a multivariate typology allows for more robust aptitude or ability with achievement comparisons.

Conclusions

This chapter provided an overview of PASS theory, the Cognitive Assessment System, and their relationship to reading and math achievement. In addition, profile analysis was discussed, specifically the areas of subtest profile analysis, the Naglieri alternate procedures, and cluster analysis.

Although there have been a number of methods of creating profiles from test results, a number of points appear to be most salient to this investigation. Ipsative subtest analysis is limited in scope and statistical rigor. The use of scaled or index scores improves the reliability of the scores used to build those profiles. Finally, cluster analysis appears to be a promising means of identifying normative groups as well as provide a backdrop for individual or group comparisons. The CAS and WJ-R ACH afford the researcher and practitioner a test built upon a theory of cognitive functioning and a wellused achievement battery. The continued attempts to find viable interventions based upon cognitive processing strengths and weaknesses provide opportunities to study the viability of the taxonomy. This foundation lends support for the connections to be made from the profiles to uses of the profiles in practice (e.g., intervention planning, program criteria).

CHAPTER 3

METHODOLOGY

Participants

The samples for this study were drawn from the 1600 participants in the CAS standardization sample that were administered the WJ-R ACH concurrently.¹ This subset of the total standardization sample was provided by the publisher of the CAS and WJ-R ACH (see Figure A.1, Appendix). The demographic characteristics correspond closely to the U.S. population based on gender, race, Hispanic origin, geographical region, community setting, handicapping condition, and parental educational attainment (Naglieri & Das, 1997).

Administration instructions and materials for the CAS subtests were divided into age appropriate partitions (i.e., ages 5 to 7 and 8 to 17). This design feature allowed for the continuous assessment of the theoretical constructs of interest without items being too complicated for younger children or too simple for the older partition. In order to ensure that subtests used the same administration format and materials, the 8 to 17 year old

¹Copyright © 1997 by the Riverside Publishing Company. All rights reserved. Reproduced from the "Das Naglieri Cognitive Assessment System" by Jack Naglieri and J.P. Das, with permission of the publisher.

		Ν	%	US% *
Region	Midwest	170	23.9%	25.2%
	Northeast	135	19.0%	18.7%
	South	249	35.0%	34.2%
	West	157	22.1%	21.9%
Gender	Female	352	49.5%	48.6%
	Male	359	50.5%	51.4%
Parental Education Levels	<hs< td=""><td>127</td><td>17.9%</td><td>20.3%</td></hs<>	127	17.9%	20.3%
	HS	211	29.7%	28.6%
	Some College	171	24.1%	28.7%
	4 or more years	202	28.4%	22.5%
	of college			
Race	White	558	79.6%	76.9%
	Black	89	12.0%	13.5%
	Other	64	8.4%	9.6%
Hispanic Origin	Hispanic	73	10.0%	11.4%
	Non-Hispanic	638	90.0%	88.6%
Community Setting	Urban/Suburban	522	72.6%	75.2%
	Rural	189	27.4%	24.8%

Table 3.1: Demographic characteristics for the sample of 8 to 17 year olds from the CAS standardization sample administered the WJ-R Tests of Achievement (N = 711)

* U. S. population percentages are from the U. S. Bureau of the Census, 1992

partition was used in this study (see Table 3.1). Three of the age groups (i.e., 8, 9, and 10 year old groups) were over-represented in this subset. Therefore, one half of each group was randomly selected and omitted. In addition, subjects with data missing for one of the clustering variables were eliminated prior to the analyses so that only complete subject profiles would affect the outcome. Special education students were included in the sample in order to more accurately reflect the variation of scores in the total population. The resulting subsample of 711 subjects adequately represents the U.S. population according to the 1990 U.S. census reports (see Table 3.1).

Instruments

Cognitive Assessment System (CAS)

The CAS is based on the Planning, Attention, Simultaneous, and Successive (PASS) processing theory of cognitive functioning, as originated by Das, Kirby and Jarman (1979). According to the PASS theory, there are four fundamental processes involved in human cognitive functioning: (a) planning processes, (b) attention processes, (c) simultaneous processes, and (d) successive processes.

The CAS is structured on three levels: the Full Scale; the cognitive processing (PASS) scales; and the subtests. The Full Scale (FS) is an overall indicator of the child's cognitive functioning with a mean of 100 and a standard deviation of 15. The average internal consistency reliability for the Standard Battery is .96 (Naglieri & Das, 1997). The PASS scales represent the individual's functioning on subtests designed to predominantly involve one of the four cognitive processes and contribute equally to the FS score. These scales have high reliability and are most closely tied to the theoretical basis of the CAS. At the most basic level, the individual subtests make up the PASS scales with a mean of 10 and a standard deviation of 3. Although each subtest has distinctive content they were not intended to measure unique constructs (Naglieri, 1999). These subtest scores can be combined to create a Basic Battery with eight subtests or a Standard Battery with 12 subtests.

PASS Scales

In the following explanations of the PASS scales, the subtests appropriate for 8 to 17 year olds are described.

Planning Scale (PLAN). Planning is the cognitive process involved in executive functioning (i.e., determining, selecting, and using efficient solutions). This scale consists of three subtests designed to measure planning. Matching Numbers requires the child to identify two identical numbers in a row of numbers. The numbers increase in length from one to seven digits across four pages. The child must devise a plan of attack to efficiently complete as many rows as possible within the given time limit. Planned Codes presents two pages with a distinct set of codes shown in a legend at the top of each page. The legend shows how the letters (i.e., A, B, C, and D) correspond to certain codes (i.e., OX, XX, OO, XO, respectively). Rows and columns of letters above empty boxes fill the rest of each page. The goal is for the child to find an efficient means of placing the appropriate code beneath each letter. The third subtest, Planned Connections, requires the child to develop an efficient strategy to connect numbers in sequence or numbers and letters in an alternating sequential order. The average internal consistency reliability for the Planning scale of the Standard Battery is .88 (Naglieri & Das, 1997).

<u>Attention Scale</u> (ATT). The subtests comprising the Attention Scale demand that the child resist distraction and maintain appropriately directed attention to the completion of specific tasks. For the Expressive Attention subtest, the child must read color words orally, identify the color of a series of rectangles, and name the color of the ink in which words are printed. The distractor is the difference between the word and the color of the ink (e.g., RED printed in green ink). Number Detection consists of pages of numbers that are printed in various fonts (e.g., outline). Children are given a stimulus (e.g., 1, 2 and 3 in a normal font) and are required to find all numbers that match the number as well as the font. The last attention task, Receptive Attention, involves underlining pairs of matching letters in multiple rows of stimuli. The first item requires that the letters match physical appearances (e.g., R, R) while the subsequent item demands that they have the same name (e.g., r, R). For the Attention Scale, the average internal consistency reliability for the Standard Battery is .88 (Naglieri & Das, 1997).

Simultaneous Scale (SIM). Simultaneous processing involves interrelating component parts to arrive at a correct solution. The three tasks designed for the Simultaneous Scale require verbal and nonverbal synthesis of separate components into an organized group. Nonverbal Matrices was designed using the standard progressive matrix format. The child is presented with interrelated geometric shapes, must determine the relationships present, and then choose the multiple choice selection that correctly completes the analogy presented. Verbal-Spatial Relations requires the individual to answer a question describing the spatial relationships of a specific drawing that has been presented to the child with five distracter drawings. Figure Memory is the final simultaneous task presented to the child. The examinee is shown a geometric figure for five seconds. From memory, the child is required to find and trace that figure in a more complex drawing. The average internal consistency reliability for the Simultaneous Scale for the Standard Battery is .93 (Naglieri & Das, 1997).

<u>Successive Scale</u> (SUC). The tasks that make up the Successive Scale require the examinee to arrange stimuli into an explicit serial order. The result is a chain-like progression with elements that are only related to the preceding element. During the

Word Series subtest the child is required to repeat a series of words in the same order as presented. For the Sentence Repetition task the examinee must repeat sentences, after a single reading, in which the content words are replaced with color words. The final successive subtest for 8 to 17 year olds is Sentence Questions. Increasingly complex sentences made up of color words are read to the child. The child must answer a question concerning that sentence. The average internal consistency reliability for the Successive scale of the Standard Battery is .93 (Naglieri & Das, 1997).

<u>Reliability of the CAS</u>

In evaluating the reliability of the CAS, the authors report in the CAS manual (1997) estimates of the internal consistency, test-retest, and standard error of measurement. Internal consistency reliability is an estimate of the extent to which test items are homogeneous as they are designed to draw upon a unidimensional construct (e.g., planning processes). At the subtest level the split-half method was used for the Simultaneous and Successive subtests. In contrast, due to the time component involved in the Planning and Attention subtests, test-retest reliability was used. The average reliability coefficients range from .75 (Matching Numbers) to .89 (Nonverbal Matrices and Figure Memory). For the PASS scale and Full Scale standard scores the reliability coefficients were calculated using Nunnally and Bernstein's formula for the reliability of linear combinations (1994). These coefficients range from .84 for the Attention Scale of the Basic Battery to .96 for the Standard Battery Full Scale. These coefficients fell above the criterions suggested by Bracken (1987) for acceptable levels of test reliability.

Test-retest reliability was examined for a subsample of the CAS standardization sample. This was conducted over 9 to 73 day periods. The average stability coefficients for subtests ranged from .67 for Verbal-Spatial Relations to .80 for Planned Codes and Sentence Repetition. For the PASS scale and Full Scale standard scores, the average stability coefficients ranged from .77 for the Simultaneous Scale of the Basic Battery to .91 for the Standard Battery Full Scale.

The third estimate used to determine the CAS 's reliability was the standard error of measurement (*SEM*) that is calculated from the reliability coefficients and standard deviations (SD) of the subtest or scale scores under consideration. The subtests are standardized to a mean of 10 and SD of 3. The average subtest *SEM* 's ranged from 1.0 for Nonverbal Matrices to 1.5 for Matching Numbers, Planned Connections, Expressive Attention, Number Detection, and Receptive Attention. For the PASS and FS scores, mean of 100 and SD of 15, the *SEM* 's ranged from 3.1 for the Standard Battery Full Scale to 6.2 for the Basic Battery Attention Scale.

Validity of the CAS

Content validity is the degree to which the CAS items or tasks are representative of the domain of content (i.e., PASS). A review of the literature and expert professional judgments determined the universe of content to be sampled through the use of this instrument. To operationalize the content, task analysis, pilot item development, field testing, statistical analyses, and standardization investigations were conducted (Naglieri & Das, 1997). Throughout this process, a central aim of the test developers was to adhere to the theory upon which the test was built (Naglieri, 1999). Criterion-related validity has been referred to as empirical validity, statistical validity, and predictive validity (Nunnally and Bernstein, 1994). Regardless of the title, evidence that demonstrates that test scores are systematically related to one or more outcome criteria support specific uses of the measure and are considered evidence of test validity. The authors approached this validation process by concentrating on studies of (a) the CAS and tests of achievement, (b) CAS and tests of intelligence, and (c) PASS scores for exceptional students.

Predictive validity was reported for academic achievement from the study of the subsample of standardization subjects who were concurrently administered the WJ-R ACH. The CAS Full Scale correlation with the WJ-R ACH Skills cluster, an overall measure of achievement, was .73 while correlations between the PASS scales for the Standard Battery and the WJ-R ACH cluster scores ranged from .50 to .67. These values are similar to other relationships between cognitive abilities and achievement lending support for the use of the CAS in predicting achievement (Naglieri & Das, 1997).

Studies relating the CAS to other tests of intelligence involved the *Wechsler Preschool and Primary Scale of Intelligence-Revised* (WPPSI-R) and the Wechsler Intelligence Scale for Children – Third Edition (WISC-III). These studies supported previous findings that the Simultaneous and Successive Scales were most related to the WPPSI-R Verbal and Performance Scales and the WISC-III scores (Naglieri & Das, 1997). In addition, the Planning and Attention Scales were less well correlated lending support to the test developers' intention to capture new areas of cognitive processing.

PASS performances for exceptional children involved studies of subjects who were mentally retarded, learning disabled, traumatic brain injured, gifted, attentiondeficit/hyperactive, reading disabled, and seriously emotionally disturbed. The findings of these studies lend support to the utility of the CAS for determining differences among these various populations (Das & Naglieri, 1996; Gutentag, Naglieri, & Yeates, 1998; Kirby, Booth, & Das, 1996; Naglieri, 1999, 2001a).

Finally, construct validity evidence supports the theoretical constructs upon which a test is constructed (i.e., PASS theory of cognitive processing). First, the age progression of raw scores across ages was addressed, as this is a primary means of construct validation for intelligence tests. As expected, Planned Connections and Speech Rate decreased with age while all other subtest raw scores increased (Naglieri & Das, 1997). Secondly, each subtest was correlated with the PASS scale scores after its removal from the PASS scale where it is normally included. The subtests typically correlated highest with the scale of which they are a part and lower on the remaining scales. Finally, exploratory and confirmatory factor analyses were conducted to analyze the test's underlying structure. The fit of the PASS model and comparison of the model with alternatives was accomplished using confirmatory analyses. Principal components, principal factor, and maximum-likelihood methods were used for the exploratory analyses. Support for both a three- and four-factor solution emerged with the combining of the closely related Planning and Attention scales. However, Naglieri and Das (1997) emphasize that planning and attention processing are theoretically distinct and should not be ignored simply due to the results of a portion of the factor solutions.

Woodcock-Johnson Tests of Achievement - Revised (WJ-R ACH)

The Woodcock-Johnson Tests of Achievement – Revised (Woodcock & Johnson, 1989) is a nationally standardized, individually administered achievement test created with parallel forms matched in content (i.e., Form A and Form B) for use with subjects 2 to 95 years of age. Each form consists of 18 subtests, nine representing the Standard Battery and nine representing the Supplemental Battery. The supplemental subtests result in scores from five administered tests and four score derivations. Each subtest was designed to measure a specific aspect of scholastic achievement (i.e., reading, mathematics, written language, or knowledge). In addition, five cluster scores were derived for the Standard Battery and six for the Supplemental Battery.

The standardization of the WJ-R ACH was accomplished in conjunction with the development of the total Woodcock-Johnson Psycho-Educational Battery – Revised (Woodcock & Johnson, 1989). The sample consists of 6,359 participants from over 100 diverse U. S. communities. The test developers used a stratified sampling design to obtain a representative group similar to the United States population with regard to census region, community size, sex, race, Hispanic origin, funding of college or university, type of college or university, education of adults, occupational status of adults, and occupation of adults in the labor force. The authors reported that the distribution of subjects approximated the exact U. S. population distributions for all 10 variables based on a comparison with the 1980 and later U. S. census reports (Woodcock & Mather, 1989, 1990).

<u>Reliability of the WJ-R ACH</u>

As test scores always involve some error variance, test reliability is used to determine the amount of variance that may be encountered and is generally represented as a correlation coefficient. McGrew, Werder, & Woodcock (1991) report estimates of the WJ-R ACH reliability using split-half, standard error of measurement, test-retest, alternate-form, and interrater reliability. They suggest that the desired level for test reliabilities is at or above .80 for subtests and at or above .90 for cluster scores. The splithalf procedure, as a measure of internal consistency, was calculated at each age level for all achievement tests, except Writing Fluency and Handwriting. The tests were split according to item number, grouping odd and even items for the split. All median reliabilities for the 16 test scores for Forms A and B exceeded the .80 level. All median reliabilities for the cluster scores were above the .90 level.

Standard error of measurement (*SEM*) is used as an indicator of the precision of scores and is calculated from the reliability coefficient and standard deviation in W scale units, a transformation of Rasch model scores. The *SEMs* for the WJ-R ACH scores are provided in the WJ-R Technical Manual, Tables C and D (McGrew et al., 1991).

A third measure of reliability reported is test-retest, an indication of test stability. Although a number of metrics were discussed and reported for the repeated measures studies, the authors indicate that the age-corrected correlations are the statistic typically reported as test-retest reliability (McGrew et al., 1991). For the four clusters reported, the median test-retest correlations were from .86 to .92. For the 12 achievement tests reported the median correlation was in the range of .80 to .89.

Validity of the WJ-RACH

The authors of the Woodcock-Johnson-R Achievement Test stressed content validity and concurrent validity as the most important types to address in the validation of achievement measures. To ensure adequate content validity for the WJ-R ACH outside experts (i.e., teachers, curriculum specialists) were consulted in the preparation of the items for the 18 achievement areas. The areas fall within the broader domains of reading, mathematics, written language, as well as the content areas of science, humanities, and social studies. Assessment questions were based on a broad sampling of the content areas with careful attention to the scope, sequence, and difficulty of each item. Rigorous criteria were created based on latent-trait theory and the Rasch model in order to select the most appropriate items for inclusion in the achievement subtests.

Concurrent validity is an estimate of how well one test's scores relate to scores, collected at the same time, from a test believed to measure the same construct. McGrew et al. (1991) reported a portion of the concurrent validity studies completed for the WJ-R ACH. The studies and resultant correlations with the Basic Achievement Skills Individual Screener (BASIS), Kaufman Assessment Battery for Children (K-ABC), Kaufman Test of Educational Achievement (K-TEA), Peabody Individual Achievement Test (PIAT), Test of Written Language (TOWL), Picture Story Language Test (PSLT), Metropolitan Achievement Test – Sixth Edition (MAT6), and Wide Range Achievement Test – Revised (WRAT-R) were described. From the validation studies, the authors report that the WJ-R ACH compares well with many of the currently used psychoeducational instruments, thereby lending support for the concurrent validity of this test (McGrew et al., 1991).

WJ-R ACH Subtests

Seven subtests were used in the present study and are described below. Letter-Word Identification, Passage Comprehension, Word Attack and Reading Vocabulary were used in the reading analyses while Calculation, Applied Problems, and Quantitative Concepts were used in the math analyses.

Letter-Word Identification (LWID). This subtest involves the identification, as opposed to the recognition, of letters or words in isolation. Knowledge of the meaning of the stimulus words or previous exposure is not required. Presenting words that appear with decreasing frequency in written English controls the difficulty of the items. The median internal consistency reliability for the 8 to 17 portion of the standardization sample is .93.

Passage Comprehension (PC). The initial items for Passage Comprehension are presented in a multiple-choice format, requiring the subject to read a phrase and point to the picture that it represents. However, the majority of the items in this subtest use a modified cloze procedure involving the presentation of sentences or paragraphs with a missing significant word. It is assumed that the reader must understand the passage in order to provide the correct word and is therefore measuring comprehension (McKenna & Robinson, 1983; Woodcock, 1997). The examinee must use vocabulary and comprehension skills to state a word to appropriately complete the sentence. The median internal consistency reliability for the 8 to 17 year old cohort is .87.

<u>Word Attack</u> (WA). The Word Attack items are made up of nonsense words or low-frequency English words that are linguistically logical but unfamiliar. The subject must use phonic and structural analysis skills to pronounce the increasingly difficult words. The median internal consistency reliability for this subtest is .91.

<u>Reading Vocabulary</u> (RV). This subtest has two distinct parts. In Part A, the child is required to supply a one-word synonym to a printed word. In Part B, the child must produce an antonym to the stimulus word. The median internal consistency reliability is .93.

<u>Calculation</u> (CALC). The calculation problems are presented to the child in a traditional format within the Subject Response Booklet. The problems may require one or more mathematical calculations (e.g., addition, division, geometry, calculus) and involve decimals, fractions, or whole numbers to complete correctly. The median internal consistency reliability is .93.

<u>Applied Problems</u> (AP). In this subtest the problems are more practical and require rather simple calculations. However, the child is required to recognize pertinent information, ignore extraneous information, and determine a correct procedure to follow. Initial items require simple counting and have pictorial stimuli whereas later items are entirely word problems. The median internal consistency reliability is .91.

<u>Quantitative Concepts</u> (QC). Quantitative Concepts was designed to measure the examinee's knowledge of mathematical concepts and vocabulary (e.g., shapes, signs). Calculations and application decisions are not necessary for the completion of subtest items. The median internal consistency reliability is .86.

Data Analysis

In order to satisfy the objectives of this study data analyses were conducted in phases. Phase 1 involved the creation of CAS/reading and CAS/math core profile types to address Objectives 1 and 2. Phase 2 focused on Objectives 3 and 4 by exploring the prevalence of the core profile types in low performing reading and mathematics subjects.

<u>Phase 1</u>

Cluster analysis was used to identify core profile types for the CAS PASS scales in combination with WJ-R ACH subscales. Cluster analysis is a group of multivariate techniques whose purpose is to discover the underlying structure for a group of observations such that each group's members are maximally similar to one another and maximally dissimilar to other groups' members (Hair & Black, 2000). It is distinct from classification activities such as discriminant analysis in that there is not a known set of profiles for the particular data being explored a priori (Johnson & Wichern, 2002). Therefore, cluster analysis was the appropriate technique for distinguishing the core profile types found in the cognitive processing and achievement scores for a nationally representative sample of subjects.

Sample. The previously described sample of standardization participants (n = 711) was used for the cluster analyses. An important issue is the concept of complete coverage if the purpose is to infer that the resulting clusters represent the population (Blashfield & Draguns, 1976; Hair & Black, 2000; Overall, Gibson, & Novy, 1993). In this case, the purpose is to create core profile types that represent the 8 to 17 year olds in the United States. Complete coverage was accomplished by using a representative sample

of 8 to 17 year olds, including previously identified special education students. In addition, no outliers were removed to maintain complete representation of the population.

<u>Variables</u>. In order to capture both cognitive processing and achievement, scores that added unique information to the cluster analysis were included. From the CAS, the PASS scale scores were used as they were designed to reflect four unique cognitive processing constructs and have the greatest interpretive utility (Naglieri, 1999). The Standard Battery scores, based upon 12 subtests, were utilized in this cluster analysis as opposed to the Basic Battery scores (i.e., based upon eight subtests).

Particular cognitive processes have been linked with specific achievement skills in books and research aimed at cognitively-based interventions (Kirby & Williams, 1991; Pressley & Woloshyn, 1995; Naglieri & Gottling, 1997). Therefore, the WJ-R ACH subtests, which measure specific aspects of achievement, were considered the best variables for use in this study. Consequently, the clustering variables for the reading analysis were the Planning, Attention, Simultaneous, and Successive standard scale scores from the Standard Battery of the CAS; and, the Letter-Word Identification (LWID), Passage Comprehension (PC), Word Attack (WA), and Reading Vocabulary (RV) subtests from the WJ-R ACH. Similarly, the clustering variables for the math analysis were the Planning, Attention, Simultaneous, and Successive standard scale scores from the Standard Battery of the CAS; and, the Calculation (CALC), Applied Problems (AP), and Quantitative Concepts (QC) subtests from the WJ-R ACH.

When choosing variables it is necessary to consider their units of measurement (Aldenderfer & Blashfield, 1984). The consistency of standardization of the CAS and WJ-R ACH variables to a mean of 100 and standard deviation of 15 will negate any

difficulties that differences in metrics can create in the clustering process. Therefore, standardization was not a necessary step for these analyses.

Giving differential weights to variables is another issue that must be determined a priori (Aldenderfer & Blashfield, 1984; Anderberg, 1973). Because the units for the different variables are combined to achieve a single measure of distance, the influence of each variable must be considered from more than an equalization of the scaling perspective. Weighting a variable is in effect multiplying the contribution of each variable to the proximity measure by its assigned weight. The PASS scales and reading achievement variables were equally weighted (i.e., 1.0); hence, the effect of cognitive processing and achievement were balanced as both contribute equally (i.e., four variables) to the clustering process. However, math achievement is represented by only three variables versus the four PASS variables. Therefore, in order to equalize the effect of academics and cognitive processing on the resulting cluster solutions it was necessary to equalize their contributions. This was accomplished by assigning weights of 1.0 to the three achievement subtests and .75 to the four PASS scales.

Procedure. Cluster analysis methods vary depending upon the discipline from which they originated and the rules used to determine group formation (Aldenderfer & Blashfield, 1984). However, the use of a combination of hierarchical agglomerative and iterative partitioning methods are commonly seen in the social sciences (Aldenderfer & Blashfield, 1984; Hair & Black, 2000; Milligan & Sokol, 1980) and more specifically in work with normative typologies based upon psychometric variables (Donders, 1998; Drossman, et al., 2001; Wilhoit & McCallum, 2002). This approach was followed in the analyses for this investigation. Therefore, a multi-step clustering process was used to sort the 711 score profiles according to the cluster components of shape, level, and dispersion with the use of the ClustanGraphics (Clustan Limited, 2003) software.

<u>Hierarchical Agglomerative Clustering Step</u>. A hierarchical agglomerative technique was used to establish the number of clusters and describe the cluster centers. Hierarchical agglomerative methods begin with each subject in a separate cluster and sequentially combine the clusters, reducing the number of clusters at each step by one until only one cluster remains. This results in n-1 fusions (i.e., clustering steps) that are represented as a tree or "dendrogram". From the dendrogram and associated fusion statistics, the appropriate cluster partitions are identified and their cluster centers are described in terms of the clustering variable values.

A subject by variable data matrix was subjected to the Cluster Data process in ClustanGraphics (Clustan Limited, 2003) to complete the hierarchical agglomerative analyses. Squared Euclidean distance was chosen as the most appropriate similarity measure. Technically, squared Euclidean distance is a measure of dissimilarity (i.e., the smaller the value the greater the similarity of the two entities). The clustering methodology chosen was Ward's (1963) method (i.e., Increase in Sum of Squares, Wishart, 2003), which is also referred to as Ward's Minimum Variance method. This combination of similarity measure and clustering method have been shown to perform well in comparison to alternative methods (Glutting et al., 1994; Milligan & Cooper, 1987; Morey, Blashfield, & Skinner, 1983), produce reliable results, and are sensitive to both profile level and pattern (Aldenderfer & Blashfield, 1984; Everitt, 1993). In this method, the Euclidean Sum of Squares (ESS) for a cluster is the weighted sum of the

54

squared Euclidean distances between the cases and the cluster mean. Entities are joined at successive steps when they result in the smallest or minimum increase in the ESS.

Determination of the number of clusters that best define the underlying typological structure of the data must be made. First, a study of the fusion values between clustering steps was examined using the Best Cut procedure (Wishart, 2003). The output indicates which cluster partitions are significant at the .05 level, their Realised Deviates, and t-statistics from the Upper Tail Rule (Wishart, 2003). This procedure examines the fusion values at each step in the clustering process to identify any atypical jumps in the fusion statistic as an indication of a sizeable loss of homogeneity. The level preceding this jump indicates the appropriate number of cases (Aldenderfer & Blashfield, 1984; D'Amato, et al., 1998; Hair & Black, 2000; Wishart, 2003). Secondly, ClustanGraphics (Clustan Limited, 2003) provides a procedure, Bootstrap Validation, which compares the obtained tree of clusters with a series of trees generated at random from the same data. At each partition the absolute difference of the deviation of the fusion statistic (ESS) is calculated from the data and the randomly generated data (e.g., $|ESS_{Data} - ESS_{Random}| =$ Absolute Difference). The goal is to identify the partitions of the data that are most distant from random; hence, the largest absolute deviation. These are considered to be the best solutions for the data under consideration. The means of the best solutions were used as seeds (i.e., starting points) for the second stage of the clustering process.

<u>Iterative Partitioning Step</u>. Agglomerative techniques are unable to offset poor initial partitioning as they only make one pass through the data. In other words, once a subject's profile has been added to a cluster, it is not reassigned even if, in the end, it would be more appropriately placed in another cluster (Everitt, 1993). The stability of agglomerative solutions has also been suspect (Aldenderfer & Blashfield, 1984; Gordon, 1996). The stability of a solution may be affected by the order of cases in the data matrix and the omission of even a few cases. These issues were addressed by subjecting the data to iterative partitioning cluster analyses.

Iterative partitioning methods divide the data into a number of clusters that are specified a priori and continue to make sweeps through the data until no further improvements can be made on cluster assignment. K-means passes, also known as the nearest centroid sorting pass or the reassignment pass, was used. Each case is placed into a cluster according to the one with which it shares the closest centroid (i.e., mean values of the cases on the clustering variables). Using running means, new centroids are computed for a cluster as a new subject is added and subject profiles are then checked to see if re-assignment is necessary. This procedure has performed well in a number of studies involving psychometric variables (Fuerst & Rourke, 1995; Glutting, et al, 1994; Holland & McDermott, 1996).

FocalPoint Clustering (Wishart, 2000), a detailed k-means analysis program, was designed for use within ClustanGraphics (Clustan Limited, 2003) and provided additional control of method parameters. It is the iterative partitioning method used to optimize the cluster models in this study. FocalPoint compiles a range of solutions from a specified number of trials so that the solution least affected by serial order of cases can be determined. From the six starting options available in ClustanGraphics (Clustan Limited, 2003), the cluster means from the hierarchical solution were used as starting points (i.e., seeds) for the k-means process. Using starting seeds greatly improves the performance of all k-means methods (Milligan & Hirtle, 2003). Random trials were set at 500 so that the

56

order that cases are considered for re-assignment will vary. The Running Means option was selected so that FocalPoint would re-calculate the cluster means each time a case moved from one cluster to another. Details for the "top" solutions, those with the lowest ESS values, were retained from the 500 trials. For each "top" solution the reproducibility (i.e., percent of the 500 trials) and its overlap with other "top" solutions were calculated.

As part of the validation process, resulting clusters will be described using both the internal criteria (i.e., clustering variables, CAS FS, and WJ-R ACH cluster scores) as well as external criteria (e.g., gender, special education status, race). In addition, the Tryon's homogeneity coefficient, *H*, was computed to indicate the "tightness of fit" for each cluster (i.e., the relative cohesion of variance) (Blashfield & Aldenderfer, 1988; Tryon & Bailey, 1970). In order to have acceptable internal profile cohesion, the homogeneity coefficient must be \geq .60 which has been established with other typologies (Glutting & McDermott, 1990; Glutting, McGrath, Kamphaus, & McDermott, 1992; Holland & McDermott, 1996).

<u>Phase 2</u>

As stated previously, Phase 2 focused on Objectives 3 and 4 by exploring the prevalence of the core profile types in low performing reading and mathematics subjects. From the 711 subjects included in the Phase 1 analyses, two subsamples (i.e., Low Reading and Low Math) were selected. Students were placed in the Low Reading group if their WJ-R ACH Broad Reading Cluster score fell at or below one standard deviation below the mean. Therefore, any student with a Broad Reading Cluster score of 85 or less was included in this portion of the study. Similarly, the Broad Math Cluster score was used to determine those subjects that were considered to be Low Math students. From the cluster assignments obtained from Phase 1 analyses, frequencies and percentages of Low Reading and Low Math students were obtained for the respective clusters. The groups were further described using external variables.

CHAPTER 4

RESULTS

Phase 1: Reading Analysis (PASS/RD)

The multi-step clustering process (i.e., hierarchical agglomerative analysis followed by k-means iterative partitioning) was used to sort the 711 reading score profiles according to shape, level, and dispersion with the use of the ClustanGraphics (Clustan Limited, 2003) software. The resulting core profile types are described using the clustering variables (i.e., internal variables) and external demographic variables. Significant differences between the number of individuals found in the total sample and the number of individuals observed in each cluster were determined (See Appendix B).

Hierarchical Agglomerative Cluster Analysis

A data matrix of 711 subjects by the PASS/RD clustering variables (i.e., four PASS scales and four WJ-R ACH reading subscales) was submitted to hierarchical agglomerative analysis. It was performed using ClustanGraphics' (Clustan Limited, 2003) squared Euclidean distance as the similarity measure and the Increase in Sum of Squares methodology (i.e., Ward's minimum variance procedure, 1963). In order to determine the most appropriate clustering solution, the Best Cut and Bootstrap Validation procedures



Figure 4.1: PASS/RD plot of the t-statistic by proposed cluster partitions.

were evaluated. From the Best Cut procedure, appropriate cluster partitions are indicated by jumps in the t-statistic, reflecting a jump in the fusion values. In Figure 4.1, jumps may be seen at the five- and eight-cluster solutions. The five- and eight-cluster solutions were significant at .05 on an Upper Tail Test with 709 degrees of freedom (t-statistics of 52.26 and 26.81 respectively). The Realised Deviates were 1.96 for the five-cluster solution and 1.01 for the eight-cluster solution.

The second method used to determine the best number of clusters for the PASS/RD data was the Bootstrap Validation procedure (Clustan Limited, 2003). Ward's method of minimizing the Euclidean sum of squares was employed and 120 random trials without replacement were conducted. From this comparison of proposed partitions of the data with the confidence intervals generated from the randomly permuted data, the
absolute difference for the eight-cluster solution was 1413.9 and for the five-cluster solution was 686.8. As the eight-clusters represented the greatest departure from randomness, it was deemed the best partitioning of the PASS/RD data and was selected as a reasonable starting point for further analyses.

K-means Iterative Partitioning

FocalPoint k-means clustering was conducted on the eight-cluster solution in order to further define the cluster model. Cluster means from the agglomerative hierarchical procedure partitions were utilized as initial starting points for FocalPoint analyses. Each of the 500 trials used a different, random order of subject entry into the model. Each trial was terminated when the relocation of profiles from one cluster to another failed to result in a decrease in the Error Sums of Squares statistic (i.e., failed to improve the within-cluster homogeneities). For the eight-cluster solutions, 498 of the trials yielded the same cluster assignments for a reproducibility of 99.6%. This cluster model was deemed the best PASS/RD eight-cluster solution.

PASS/RD Eight Core Profile Types

In this section the eight PASS/RD core profile types are described with reference to internal as well as external variables. The population prevalence, within-type homogeneity (*H*), and descriptive names for each PASS/RD cluster type are provided in

Drofile		%	Within-type	
Type	Ν	Population	Homogeneity	Descriptive Name (Acronym)
Type		Prevalence	(H)	
1	99	13.9%	0.79	Ave PA/Hi Ave SS & ACH (RD1)
2	111	15.6%	0.80	Average/High Average; PA>SS (RD2)
3	72	10.1%	0.78	Average; High Average LWID, WA (RD3)
4	85	12.0%	0.64	High Average/Superior (RD4)
5	122	17.2%	0.83	Average (RD5)
6	108	15.2%	0.81	Low Average/Average; PA>SS (RD6)
7	87	12.2%	0.78	Low Average (RD7)
8	27	3.8%	0.74	Low/Very Low(RD8)

Table 4.1: Prevalence, homogeneity, and names of the PASS/RD core profile types

Table 4.1. All within-type homogeneities met the a priori criterion of \geq .60. Profile 5, average PASS and reading achievement, was the most prevalent while the lowest performing group, RD8, was the least prevalent. Clustering variable means and deviations are presented. These data are graphically represented.

		Total	RD1	RD2	RD3	RD4	RD5	RD6	RD7	RD8
	n	(711)	(99)	(111)	(72)	(85)	(122)	(108)	(87)	(27)
DLAN	Μ	99.2	99.4	112.8	101.2	115.2	92.1	98.8	82.0	77.0
PLAN	SD	14.7	10.1	8.5	8.6	11.4	9.4	9.7	9.9	7.6
	Μ	99.4	97.8	115.3	102.0	114.0	91.4	99.7	81.0	79.8
AII	SD	15.0	10.2	8.7	10.5	11.1	9.9	8.4	9.6	9.3
SIM	Μ	99.8	110.4	104.5	97.2	119.9	98.9	91.6	82.9	76.6
311/1	SD	15.6	10.4	10.7	11.3	11.7	9.1	10.9	10.7	8.3
SUC	Μ	98.7	108.4	99.5	101.1	114.3	101.4	87.3	87.2	73.9
300	SD	14.8	9.7	11.4	10.2	10.5	10.2	10.4	12.4	13.8
LWID	Μ	103.0	114.9	105.3	111.5	125.7	100.7	91.6	86.1	65.3
	SD	16.6	8.5	7.6	10.3	12.7	7.0	7.4	7.6	8.6
DC	Μ	105.4	120.2	111.6	102.4	125.0	104.7	94.4	89.1	71.3
FC	SD	16.4	9.4	10.0	8.5	13.5	8.8	7.4	6.9	12.4
W 7 A	Μ	101.5	109.2	102.9	121.8	128.8	97.5	87.5	83.1	61.9
W A	SD	19.3	9.7	9.2	10.7	12.1	7.1	10.4	10.8	13.1
DV	Μ	104.1	119.7	109.2	101.3	125.4	103.3	92.3	88.3	66.7
ĸν	SD	17.2	9.9	8.9	9.4	15.2	7.6	8.8	9.2	9.4

Table 4.2: PASS/RD Cluster means and standard deviations



Figure 4.2: PASS/RD core profile type standard scores by clustering variables

The eight core profile types based on all 711 children were presented in Table 4.1, Table 4.2, and Figure 4.2. In the following sections they are described in terms of the prevalence in the population, PASS and reading achievement levels, and prevalence trends for demographics. Only prevalences that were statistically significant different from expected are reported.

Reading Cluster 1: RD1 (prevalence = 13.9%; FS = 105, SD = 7.0). This profile type (N = 99) had the expected frequencies by gender and community setting. Approximately 69% of parents had college experience, 23 % completed high school, and the remaining 8% had less than a high school education. Parental education was, in general, higher than expected. The majority (i.e., 92.9%) of the subjects was White, 3% were Black, and 4% fell within the Other racial category. Similarly only 4% were of Hispanic origin. This resulted in fewer non-Whites than were expected from the population prevalences. With regard to the PASS processes, the Planning and Attention fell within the average range while the Simultaneous and Successive scales fell at the juncture of the average/high average ranges. In terms of their performance on the achievement measures, Passage Comprehension and Reading Vocabulary fell within the superior range with LWID in the high average range and Word Attack in the average range.

<u>Reading Cluster 2: RD2</u> (prevalence = 15.6%; FS = 110, SD = 7.1). Of the 111 subjects with this profile, 66.7% were females and only 33.3% were males. This overrepresentation of females in this cluster is the only significant demographic for this cluster. Percentages by parental educational level, race, Hispanic origin, and community setting were not significantly different from expected. Planning and Attention process scores and Passage Comprehension achievement scores fell within the high average range. In contrast, the Simultaneous and Successive scale scores and LWID, WA, and RV were in the average range.

<u>Reading Cluster 3: RD3</u> (prevalence = 10.1%; FS = 100, SD = 8.0). This profile type was comprised of 72 children with a mean age of 13.6 years, the oldest average age for any of the reading clusters. As to gender, race, community setting, and parental educational attainment RD3 subjects were not remarkably different from expected. All PASS process scores as well as PC and RV fell in the middle average range. In contrast, LWID and WA were in the high average and superior range respectively.

<u>Reading Cluster 4: RD4</u> (prevalence = 12.0%; FS = 120, SD = 7.9). This profile type (N = 85) was comprised of the appropriate balance of males and females. A large proportion (i.e., 83.6%) of parents had some college experience while 16.5% had a high school or less education. The majority of the subjects were White (i.e., 87.1%) or Other (i.e., 11.8%). Only 2.4% were of Hispanic origin. This profile type had the highest overall mean scores of all eight profiles. With regard to the PASS processes, Planning. Attention, and Successive fell within the high average range while the Simultaneous scale score mean fell at the juncture of the high average/superior ranges. In terms of their performance on the achievement measures, all four of the subtest scores fell in the superior range.

<u>Reading Cluster 5: RD5</u> (prevalence = 17.2%; FS = 94, SD = 7.0). This was the largest cluster with 122 subjects. In addition, it had the youngest average age at 11.6 years old. A larger than expected proportion were male (59.8%). Only 44.3% of parents had some college experience while a higher than expected percentage (40.2 %)

completed high school. All clustering variable score means for PASS as well as reading achievement fell within the average range. Therefore, RD5 was a young, average group with more males than expected.

<u>Reading Cluster 6: RD6</u> (prevalence = 15.2%; FS = 92, SD = 6.9). This profile (N = 108) was typified by a lower parental educational level with only 39.8% with college experience. The race of subjects was White (68.5%), Black (18.5%) and Other (i.e., 13.0%) resulting in more non-Whites than expected. This profile type had average Planning, Attention, and Simultaneous process as well as LWI, PC, and RV scores. However, the Successive processing mean and Word Attack achievement scores fell within the low average range.

<u>Reading Cluster 7: RD7</u> (prevalence = 12.2%; FS = 77.6, SD = 6.8). This profile type (N = 87) was comprised of individuals from families with a higher than expected percentage of parents with some college experience. Of the subjects in this cluster 23% were Black, 72.4% were White and 4.6% were in the Other category resulting in more Black individuals than expected. With regard to the PASS processes, the Planning, Attention, Simultaneous, and Successive scores fell within the low average range. In terms of their performance on the achievement measures, all four of the subtest score means also fell in the low average range.

<u>Reading Cluster 8: RD8</u> (prevalence = 3.8%; FS = 69.3, SD = 7.9). This was the smallest cluster with 27 subjects. The largest proportion of the parents had less than a high school education (i.e., 59.3%) and none of the parents were college educated. However, 25.9% had some college experience and 14.8% had a high school diploma. The majority of the subjects were Black (i.e., 51.9%) with 44.4% Whites and 3.7% in the Other racial groups. RD8 was the only cluster with significantly different representation on a community setting variable with more rural students being represented. Planning, Simultaneous, and Successive process scores fell within the low range with Attention at the juncture of the low average/low ranges. Achievement scores were lowest for this cluster with LWI, WA, and RV falling within the very low range and PC in the low range.

Phase 1: Math Analysis (PASS/Math)

The multi-step clustering process (i.e., hierarchical agglomerative analysis followed by k-means iterative partitioning) was used to sort the 711 subjects according to their PASS and math scores. The resulting core profile types are described using the clustering variables (i.e., internal variables) and external demographic variables.

Hierarchical Agglomerative Cluster Analysis

A data matrix of 711 subjects by the PASS/Math clustering variables was submitted to hierarchical agglomerative analysis. The squared Euclidean distance was used as the similarity measure with the Increase in Sum of Squares methodology. The three math subscales were weighted 1.0 while the four PASS scales were each assigned a weight of .75 so that both achievement and cognitive processing contributed equally to the creation of profile types. In order to determine the most appropriate clustering solution, the Best Cut and Bootstrap Validation procedures were evaluated.



Figure 4.3: PASS/Math plot of the t-statistic by proposed cluster partitions.

From the Best Cut procedure, appropriate cluster partitions are indicated by jumps in the t-statistic, reflecting a jump in the fusion values. In Figure 4.3, jumps may be seen at the five and seven cluster solutions. The five and seven cluster solutions were significant at .05 on an Upper Tail Test with 709 degrees of freedom (t-statistics of 46.16 and 23.65 respectively). The Realised Deviates were 1.73 for the five-cluster solution and 0.89 for the seven-cluster solution.

The Bootstrap Validation procedure (Clustan Limited, 2003) was also used to determine the best number of clusters for the PASS/Math data. Ward's method of minimizing the Euclidean sum of squares was employed and 120 random trials without replacement were conducted. From this comparison of proposed partitions of the data with the randomly permuted data, the absolute difference for the five-cluster solution was 1732.5 and for the seven-cluster solution was 1651.2. As the departures from randomness were not greatly different, both the five and seven cluster solutions were selected as starting points for further analyses.

<u>K-means Iterative Partitioning</u>

FocalPoint k-means clustering was conducted on the five and seven cluster solutions in order to further define a cluster model. Cluster means from the agglomerative hierarchical procedure partitions were utilized as initial starting points. Each of the 500 trials used a different, random order of subject entry into the model. For the seven-cluster solution, the best reproducibility obtained was 17.0% (85 of the 500 trials). However, for the five-cluster solutions, 410 of the trials yielded the same cluster assignments in Solution 2 for a reproducibility of 82.0%. In addition, the overlap (i.e., degree to which subjects fall within the same cluster) with the Top Solution, having the lowest ESS, was 99.3% (n = 72) indicating few differences between them. When comparing Solution 2 with the Top Solution, the differences in cluster means for the PASS, calculation, applied problems, and quantitative concepts scales ranged from 0 to 0.58 indicating few differences in subject assignment. These two solutions accounted for 482 of the 500 trials resulting in a combined reproducibility of 96.4%. Therefore, the five-cluster model was considered the best classification of the subjects into core profile types for the PASS/Math data.

Drofila		%	Within-type	
Turne	Ν	Population Homogene		Descriptive Name (Acronym)
Type		Prevalence	(H)	
1	215	30.2%	0.78	Average (MTH1)
2	105	14.8%	0.68	Borderline Low/Low Average (MTH2)
3	171	24.1%	0.78	Hi Ave PA & Ave SS & ACH PA>SS (MTH3)
4	120	16.9%	0.75	PA <ss (mth4)<="" ach="" average="" high="" td="" with=""></ss>
5	100	14.1%	0.66	High Average/Superior (MTH5)

Table 4.3: Prevalence, homogeneity, and names of the PASS/Math core profile types

PASS/Math Five Core Profile Types

Internal as well as external variables for the five PASS/Math core profile types are described. Table 4.3 provides the population prevalence, within-type homogeneity (*H*), and descriptive names for each PASS/Math cluster type. All within-type homogeneities met the a priori criterion of \geq .60. MTH1, average PASS and math achievement, was the most prevalent while the highest performing group, Profile 5, was



Figure 4.4: PASS/Math core profile type standard scores by clustering variables

		Total	MTH1	МТН2	МТИЗ	MTH/	MTH5
		10tai	(215)	(105)	(171)	(120)	(100)
n		(711)	(215)	(105)	(171)	(120)	(100)
	Μ	99.2	93.8	81.5	110.2	96.8	113.7
PLAN	SD	14.7	9.8	10.6	10.1	9.6	10.6
	Μ	99.4	94.2	81.8	111.4	95.3	113.0
ATT	SD	15.0	10.8	10.2	10.2	9.9	11.0
	Μ	99.8	93.7	80.5	103.6	107.3	118.6
SIM	SD	15.6	10.6	10.6	10.3	11.1	11.9
	Μ	98.7	93.9	83.8	102.1	103.7	112.6
SUC	SD	14.8	11.9	14.4	11.3	11.4	11.9
	Μ	103.5	96.0	78.1	106.7	115.8	126.1
CALC	SD	18.0	9.0	11.6	8.8	11.1	14.0
	Μ	104.0	96.5	82.9	104.8	115.7	127.1
AP	SD	15.9	7.0	10.2	8.1	8.5	10.4
	Μ	100.1	91.8	77.5	102.8	110.0	125.4
QC	SD	17.4	7.6	9.7	9.0	11.3	13.8

Table 4.4: PASS/Math cluster means and standard deviations

the least prevalent. Clustering variable means and deviations are presented. These data are graphically represented in Figure 4.4.

The five core profile types based on all 711 children were presented in Table 4.3, Table 4.4, and Figure 4.4. In the following sections they are described in terms of the prevalence in the population, PASS and math achievement levels, and prevalence trends for demographics. Only a statistically significant difference from expected prevalence was reported.

<u>Math Cluster 1: MTH1</u> (prevalence = 30.2%; FS = 91.5, SD = 7.0): This profile type (N = 215) was the largest math cluster. Approximately 40.9% of parents had college experience while 35.3 % completed high school while the remaining 23.7% had less than a high school education. This cluster had the largest proportion of subjects of Hispanic origin (15.3%). All clustering scores for both PASS and math achievement variables fell within the average range.

<u>Math Cluster 2:MTH2</u> (prevalence = 14.8%; FS = 75.9, SD = 8.9): Of the 105 subjects with this profile, the educational levels of their parents had the highest percentage with less than a high school diploma (i.e., 39.0%) and the lowest percentage of parents with four or more years of college experience. A larger proportion of subjects (i.e., 29.5%) were in the Black racial group than was expected (12.0%) while the Other proportion (i.e., 4.8%) was lower than the 8.4% expected. This cluster had the lowest overall performance in all areas. All four of the cognitive processing scores fell within the low average range. In math achievement the Calculation and Quantitative Concepts scores fell in the low range with Applied Problems in the low average range. <u>Math Cluster 3: MTH3</u> (prevalence = 24.1%; FS = 108.4, SD = 6.9): This profile type was comprised of 171 children with the highest percentage of females (i.e., 67.8%) and only 32.2% males. Other demographic characteristics were not significantly different from expected numbers. This group had average math achievement scores as well as the Successive and Simultaneous processing scales. Planning and Attention process scores fell within the high average range.

<u>Math Cluster 4: MTH4</u> (prevalence = 16.9%; FS = 100.8, SD = 8.4): This profile type (N = 120) was comprised of 66.7% males, the highest percentage of all math clusters, and 33.3% females. The average age of the subjects was 11.5 years old, the youngest grouping. The proportion of parents with some college experience was 59.1%, while 40.9% had a high school or less education. The majority of the subjects were White (i.e., 88.3%) with only 5.0% Black and 6.7% Other. With regard to the PASS processes, all four fell within the average range. In terms of their performance on the achievement measures, all three of the math subtest scores fell in the high average range.

<u>Math Cluster 5: MTH5</u> (prevalence = 14.1%; FS = 118.6, SD = 8.6): This was the smallest cluster with 100 subjects. Parental educational levels were highest for this group with 80% having some college experience. The majority of the subjects were White (i.e., 82.0%) with 2.0% Blacks and 16.0% in the Other racial category. A smaller proportion of Hispanic origin subjects (3.0%) were represented in this cluster compared to the 10% in the total sample. There were more urban/suburban subjects (83.0%) than expected (72.6%). This profile type had the highest overall mean scores of all five profiles. All PASS processes fell within the high average. In terms of their performance on the achievement measures, all three of the math scores fell in the superior range.

73

		Total		RE	RD6		RD7		08
		%	n	%	n	%	n	%	n
Low Readers		100.0	81	17.3	14	49.4	40	33.3	27
Gondor	Female	34.6	28	35.7	5	32.5	13	37.0	10
Gender	Male	65.4	53	64.3	9	67.5	27	63.0	17
	White	66.7	54	85.7	12	75.0	30	44.4	12
Race	Black	27.2	22	0.0	0	20.0	8	51.9	14
	Other	6.2	5	14.3	2	5.0	2	3.7	1
Hispanic	Hispanic	16.0	13	21.4	3	17.5	7	11.1	3
Origin	Non-Hispanic	84.0	68	78.6	11	82.5	33	88.9	24
Community	Rural	37.0	30	35.7	5	27.5	11	51.9	14
Setting	Urban/Suburban	63.0	51	64.3	9	72.5	29	48.1	13
Dorontol	<hs< td=""><td>48.1</td><td>39</td><td>42.9</td><td>6</td><td>42.5</td><td>17</td><td>59.3</td><td>16</td></hs<>	48.1	39	42.9	6	42.5	17	59.3	16
Educational	HS	22.2	18	28.6	4	25.0	10	14.8	4
Loval	1-3 College	19.8	16	21.4	3	15.0	6	25.9	7
Level	4+ College	9.9	8	7.1	1	17.5	7	0.0	0
Educational Programs	Regular Program	45.7	37	50.0	7	60.0	24	22.2	6
	LD	33.3	27	50.0	7	32.5	13	25.9	7
	MR	18.5	15	0.0	0	2.5	1	51.9	14
	SED	2.5	2	0.0	0	5.0	2	0.0	0

 Table 4.5: Demographic prevalences of the Low Reading group

Note: RD6 - Ave PA/ Low Ave-Ave SS & ACH; RD 7 - Low Ave PASS/ Low Ave ACH; RD 8 - Low PASS/ Very Low ACH

Phase 2: Low Reading Group

The goal of Objective 3 was to describe the prevalence of the reading core profile types within a group of students with overall poor reading performance. From the 711 subjects included in the Phase 1 analyses, students were placed in the Low Reading group if their WJ-R ACH Broad Reading Cluster score fell at or below one standard deviation below the mean (see Table 4.5). Therefore, any student with a Broad Reading Cluster score of 85 or less was included in this portion of the study. From the cluster assignments obtained from Phase 1 analyses, frequencies and percentages of Low Reading students were obtained for the respective clusters. The groups were further described using external variables.

Of the eight reading core profile types, the Low Reading group fell within three types primarily due to the level of reading achievement dictated by each cluster. Of the 81 subjects in the Low Reading group, the largest proportion fell within RD7 (49.4%), the cluster with all low average PASS and reading achievement scores. Another 33.3% of the Low Reading group subjects were members of RD8, the low PASS and very low reading achievement cluster. The remaining 17.3% were found in RD6, characterized by average Planning and Attention processes as well as low average Simultaneous and Successive processes and reading achievement.

Cluster membership varied somewhat based on a number of external variables (see Table 4.5). Males were over-represented in the Low Reading group (i.e., approximately 66%), which was mirrored in all three-core profile types. In terms of race and Hispanic origin, Black youth were over-represented in RD8 and under represented in RD6 (i.e., no Black subjects were assigned to this cluster). In contrast, Hispanic subjects with poor reading skills were under represented in RD8 and over-represented in RD6. From the proportions found in the Low Reading sample, it was expected that urban youth would comprise 63% of each profile. However, RD8 had approximately equal rural and urban/suburban representation. On the other hand, RD7 was comprised of nearly 75% urban subjects (i.e., 72.5%). The parents of students represented in RD8 were somewhat less well educated, while the parents of those in RD7 had the highest educational attainment. Previously identified special education students in the Low Reading group

were of three types: learning disabled (LD), mentally retarded (MR), and seriously emotionally disturbed (SED). All but one of the 15 MR students were found in RD8 while the SED students were both placed in RD7. The highest proportion of LD students was found in RD7 with the remaining students evenly distributed between RD6 and 8.

Phase 2: Low Math Group

The goal of Objective 4 is to describe students with overall poor mathematics performance by their prevalence within the PASS/Math core profile types. From the 711 subjects included in the Phase 1 analyses, students were placed in the Low Math group if their WJ-R ACH Broad Math Cluster score fell at or below one standard deviation below the mean. Therefore, any student with a Broad Math Cluster score of 85 or less was included in this portion of the study. Frequencies and percentages of Low Math students,

		Total		MT	H1	MTH2		
		%	n	%	n	%	n	
Low Math		100.0	95	15.8	15	84.2	80	
Gandar	Female	40.0	38	40.0	6	40.0	32	
Gender	Male	60.0	57	60.0	9	60.0	48	
	White	68.4	65	80.0	12	66.3	53	
Race	Black	26.3	25	6.7	1	30.0	24	
	Other	5.3	5	13.3	2	3.8	3	
Hispanic	Hispanic	11.6	11	13.3	2	11.3	9	
Origin	Non-Hispanic	88.4	84	86.7	13	88.8	71	
Community	Rural	35.8	34	26.7	4	37.5	30	
Setting	Urban/Suburban	64.2	61	73.3	11	62.5	50	
Dorontol	<hs< td=""><td>37.9</td><td>36</td><td>13.3</td><td>2</td><td>42.5</td><td>34</td></hs<>	37.9	36	13.3	2	42.5	34	
Educational	HS	25.3	24	46.7	7	21.3	17	
Lovel	1-3 College	28.4	27	33.3	5	27.5	22	
Level	4+ College	8.4	8	6.7	1	8.8	7	
	Regular Program	52.6	50	80.0	12	47.5	38	
Educational	LD	27.4	26	20.0	3	28.8	23	
Programs	MR	15.8	15	0.0	0	18.8	15	
	SED	4.2	4	0.0	0	5.0	4	

Table 4.6: Demographic prevalences of the Low Math group

Note: RD1 – Average PASS & ACH; RD2 – Borderline low/Low average PASS & ACH

separated by PASS/Math profile types were obtained for the respective clusters. The groups were further described using external variables (see Table 4.6).

Similar to the Low Reading group, the Low Math group fell within only two of the five profile types primarily due to the level of math achievement dictated by each cluster. Of the 95 subjects in the Low Math group, the largest proportion fell within MTH2 (84.2%), the borderline low/low average PASS and math achievement cluster. The remaining 15.8% of the Low Math group subjects were members of MTH1, the average PASS and math achievement cluster.

When considering the external variables, membership in the two clusters varied somewhat (see Table 4.6). The gender proportions found in the Low Math group were the

same for both profiles. MTH1 had higher numbers of Whites and Other subjects than expected, while a slightly higher proportion of Blacks were found in MTH2. From the proportions found in the Low Reading sample, urban/suburban subjects were somewhat over-represented in MTH1. Parental educational levels were distributed in a similar manner to the total Low Math group with approximately 63% with less than high school or high school education. Of greatest interest were the distributions of previously identified special education students. Similar to the Low Reading group there were learning disabled (LD), mentally retarded (MR), and seriously emotionally disturbed (SED) students represented. All of the MR and SED students along with the majority of LD students were found in MTH2.

CHAPTER 5

DISCUSSION

This study applied the multivariate techniques of cluster analysis to the CAS/WJ-R ACH sample to create core profile types for reading and for mathematics. In addition, this typology was used to describe students with low math and reading achievement. Level as a key profiling component, cognitive processing and profile shape, demographic characteristics, and utilization of core profile types are discussed in this chapter.

Level as a Key Profiling Component

One of the primary benefits of cluster analysis is the development of groups on the basis of level, shape, and dispersion from a multivariate perspective. Each of the components adds to the separation of the clusters. However, in many of the normative typologies involving intelligence and achievement tests, level has been found to be a primary differentiating component for some portion of the clusters. Level, as a profiling component, involves the location of a profile within the score continuum (e.g., superior, average, or low range of performance). Therefore, it was expected that some of the resulting core types would have a flat profile with scores falling at one level of the continuum. Three of the eight reading profiles (i.e., RD4, RD7, and RD8) are differentiated primarily on the basis of level of performance and encompass 28% of the representative sample. The RD4 profile had the highest overall performance with high average PASS processes and superior reading achievement scores. Low average performances on both cognitive and achievement measures were found in RD7. Low to very low PASS and reading achievement performances were characteristic of the RD8 profile.

The cluster analytic procedures produced three of the five math profiles (i.e., MTH1, MTH2, and MTH5) which were relatively flat in terms of the level of cluster means. The MTH1 profile had scores that fell within the lower portion of the average range for PASS processes and math achievement scales. The lowest performing students with PASS and math achievement scores in the low to low average range were clustered in MTH2. A third core profile type, MTH5, was comprised of the highest performing students with high average PASS process scores and superior math achievement scores. These profiles made up approximately 49% of the total sample.

These findings support the conviction that some normative profiles will be without distinguishing shapes. From the work on determining the cognitive demands of math and reading from a PASS perspective, tasks have been found to have differing cognitive demands. For example, a reading decoding task may rely heavily on the successive process; therefore, the successive processing level will be a limitation on performance. When an individual has a flat cognitive profile this connection between successive processing and reading decoding will not be evident. Therefore, these profiles do not confirm or refute the connections between specific cognitive processes and specific academic tasks.

80

Shape as a Key Profiling Component

Differences in profile shape (i.e., the peaks and valleys of profiling variable scores) were evident in the remaining PASS/RD and PASS/Math core profile types. The prevalence (i.e., 72% for reading and 51% for math) of these profiles suggests that more differentiated instruction may be necessary for significant portions of the population.

Reading. The literature has suggested a strong connection between successive and simultaneous processes and reading performance. Three of the reading clusters appear to support this association. Two of the reading clusters, RD1 and RD5, have a similar pattern of performance; the simultaneous and successive processing scores (SS) were higher than their planning and attention scores (PA) (PA<SS). The RD1 profile had middle average planning and attention with borderline high average successive and simultaneous scores. PA scores at the low average/average juncture and SS scores at the middle average range were characteristic of the RD5 profile. Reading achievement followed the SS scores. The reading achievements for RD1 and RD5 profiles were high average and middle average respectively. Similarly, the RD6 reading achievement scores followed their performance on the SS scales. However, their pattern of cognitive processes was reversed (PA>SS). Middle average planning and attention with low average/average successive, simultaneous, and reading achievement scores characterized the students in the RD6 cluster.

The remaining two clusters, RD2 and RD3, were less consistent with the suggestion that successive and simultaneous cognitive processes primarily influence reading achievement in general. The RD2 profile exhibited the PA>SS pattern with high average PA processes and middle average SS scores. However, the reading achievement

scores were not as well aligned with the SS score levels. Reading comprehension (RC) and reading vocabulary (RV) fell at the average/high average juncture while letter-word identification (LWID) and word attack (WA) scores were in the middle average range. This core profile supports the more specific connection between successive and simultaneous processes and basic reading skills (i.e., LWID and WA). RD3, on the other hand, had middle average PASS, reading comprehension, and reading vocabulary scores. However, these students had high average letter-word identification skills and superior word attack skills. The patterns of RD2 and RD3 suggest that there is a differential effect of simultaneous and successive processing as readers improve and move into the average and above range.

<u>Math</u>. The two remaining PASS/Math clusters, MTH3 and MTH4, were distinguished by their pattern of PASS and math achievement scores as opposed to a difference in score mean levels. The MTH3 profile exhibited the PA>SS pattern with high average PA processes and middle average SS scores. Their math achievement scores, middle average range, were similar to the SS scores, which supports studies indicating that successive and simultaneous are important cognitive processes for the completion of math tasks. The final cluster, MTH4, showed a different pattern of scores with higher than expected math achievement scores. Although all PASS scores were within the average range, simultaneous and successive processes were higher than the planning and attention processes (PA<SS). All three math achievement scores fell within the high average range. An unexpected finding of the present study is that no core profile type emerged supporting the importance of planning in math achievement.

82

Demographic Characteristics

Demographic characteristics of individuals were studied with respect to gender, parental educational levels, race, Hispanic origin, type of educational programming, and community setting. This information was mixed in its support for the resulting taxonomies found in this study.

Parental educational level is considered to have a significant relationship to a student's academic performances. Therefore, children whose parents progressed in school through high school or a lower grade would be expected to perform at a lower level than those children of parents with a college education. The reading and math core profile types identified in the Low Reading and Low Math groups both supported this contention. The three PASS/RD profiles in the Low Reading group were over-represented by parents with a high school or less than high school education (70.3%). Similarly, parental educational levels were over-represented at the high school and less than high school levels for the Low Math core profile types (63.2%).

Gender has been linked to differences in both reading and math performance. Boys are believed to be poorer readers while girls tend to dislike math activities. In the core profile types gender was significantly different for a number of reading and math clusters. RD2 and MTH3 were over-represented by girls while RD5 and MTH4 had more boys than expected. Both of the profiles with more girls than expected had PA>SS patterns with PC and RV as the only academic variables to follow planning and attention. For the girls, there was some evidence in RD2 of higher reading comprehension and vocabulary skills. However, RD5 did not support the contention that boys would be overrepresented in the lowest performing core profiles (i.e., RD6, RD7, and RD8). In contrast, the pattern in math supported an over-representation of boys in a high average math skills core profile type (i.e., RD5). Girls were over-represented in a math core profile with average performances and the number of girls was not significantly different from expected in the lowest performing math cluster (MTH2). In the normative taxonomy, a clear gender pattern of performance was not evidenced.

When considering low performing math students (i.e., Broad math scores of less than or equal to 85; Low Math group), MTH1 and MTH2 were the only profiles represented for this 8 to 17 year old sample. Consistent with the normative taxonomy, there were no significant differences in the numbers of boys and girls from the frequencies in the sample. This again seems surprising as the perception that girls underachieve in mathematics persists in the educational community, particularly with regards to high school students. One expectation, however, was supported in the cluster taxonomy with regard to boys and reading achievement. In all three clusters found in the Low Reading group, boys were over-represented (i.e., approximately 65% boys).

Gender differences with respect to the normative taxonomies are not clearly in line with current perceptions. This may be due to misconceptions or performance following expectation by significant adults. Trends in gender research (i.e., "boy turn") are moving towards a greater focus on boys' issues in the classroom (Weaver-Hightower, 2003). It seems that a balanced approach, with attention to the issues of both boys and girls, is a sensible middle ground. When examining instructional strategies and interventions for low performing math students, the context and implementation of an intervention may need to be more sensitive to gender issues (e.g., opportunities for teacher-student interaction or increased presence of male educators in the classroom

84

The disproportionate numbers of minority students, particularly Black students, performing at lower academic levels than their White counterparts were evidenced in the normative taxonomy for both reading and math. Black students were over-represented in MTH2, RD6, RD7, and RD8, the lowest performing math and reading clusters. In addition, White students were over-represented in the highest performing reading core profile types(i.e., RD1 and RD4). In the area of mathematics, Blacks were significantly under-represented in the highest performing clusters (i.e., MTH4 and MTH5). When controlling for individual and parental characteristics (e.g., parental literacy, low birth weight status, family income), this gap is reduced considerably. These core profile type characteristics indicate that at the time of testing, early 1990's, Black students were in greater jeopardy of poor math and reading performances than their White classmates.

Class placement substantiated the core profile types. RD 7 and RD8 were characterized by the poorest reading performances. As expected, these clusters had 100% of the students with mental retardation (MR) with the remaining MR students in RD7. In mathematics, 100% of the MR students were found in MTH2, the lowest performing group. Interestingly, RD7 and RD8 accounted for 9.7% of regular education students while 8.8% of the students in MTH2 were in a regular program. These students may represent a portion of the 8 to 17 year old population in need of assistance who are missed in our current system.

With regard to learning-disabled students (LD), the expectations have been clouded by trends in service provision for this category of special education students. In the area of reading, 85.4% of the LD students are found in RD6, RD7, and RD8. The majority of LD students were found in clusters MTH1 and MTH2 (i.e., 90.3%). Although

the expectation is not as clear cut for LD students, it is not surprising that these students were found in the same clusters as the Low Math and Low Reading group students.

Utilization of Core Profile Types

The PASS/RD and PASS/Math core profile types developed in this study have a number of possible uses. In that many assessments within the school and private setting still utilize a measure of intelligence and academic performance, these taxonomies can serve as comparisons for individual students when determining the uniqueness of a child's profile. The multivariate nature of these profiles allows the use of a multivariate comparison, such as that suggested by Glutting et al.(1994). When used with a theoretically-based measure of cognition, the unusual profile may add important information to the decision making process as to cognitive strengths and weaknesses. Hence, the course of action to be taken on behalf of the student can be guided by an improved comparison and improving cognitive interventions.

The core profile types developed in this study can also be used for developing programmatic changes with interventions designed for large groups of struggling students without prior testing. For example, an intervention found to be effective for students with MTH2 might be integrated into the curriculum to reach large numbers of struggling students as it was found in 14.8% of the normative sample. A planning facilitation method of intervention (Naglieri & Gottling, 1995, 1997; Naglieri & Johnson, 2000) may provide benefits for all students with greater impact on those falling in MTH2. Lidz and Greenberg's (1997) work on Cognitive Assessment System/Group Dynamic Modification (CAS/GDM) supports the notion that utilizing cognitive interventions as a classroom

86

procedure to address the lower performing portion of the population may be beneficial. On the other hand, an intervention for RD8, found in 3.8% of the sample, may only be necessary after additional testing suggests the individual fits the profile (i.e., RD8) for which the intervention has been found effective.

Finally, the prevalence of the normative profiles may inform those working with specific populations. For example, in both the Low Reading and Low Math groups the parental educational levels were lower than expected. Although this is often taken for granted, it may inform practices for engaging the community in intervention efforts. Opportunities for adult reading and math nights would be worth further investigation.

Limitations and Future Research

The use of the multivariate techniques involved in cluster analysis appears to hold promise in creating a comparable set of normative taxonomies that can be used to make educational and psychological decisions. Clinical judgment will always be necessary when dealing with individuals; however, the better the statistical conclusions, the less cloudy the clinician's judgments will be (Garb, 2003).

The parameters of this study must be taken into consideration when using these taxonomies. The WJ-R ACH has undergone some revision and subsequently been standardized. However, the subtests chosen have remained in the achievement battery. Validating these taxonomies with the new Woodcock-Johnson battery would lend support to the initial core profile types. In addition, the Low Reading and Low Math students were selected using a broad reading score calculated from their performance on the various subtests. It should be noted that numerous children with one or two low scores may not have been considered to be low performing. However, many of these children may experience difficulty in reading or mathematics in the classroom.

Future efforts to utilize these profiles in intervention efforts would lend support to the typal structure of this representative sample. In addition, a normative taxonomy of just the PASS scales of the CAS would add to the body of literature being formed with respect to the development of current intelligence test taxonomies. Comparison of the normative typology formed in this study with Naglieri's profile analysis results may shed more light on the interconnections between PASS processes and achievement. In addition, using multivariate profile comparisons to profile subjects from previously conducted intervention studies using the taxonomy derived in this work, may help clarify the potential use of the interventions.

APPENDIX A

LETTER OF PERMISSION FOR DATA USAGE



May 20, 2003

#C030015

Ms. Margaret Ronning Muskingum Valley Educational Service Center 205 N. Seventh Street Zanesville, OH 43701

Dear Ms. Ronning

The Riverside Publishing Company hereby grants you permission to use the CAS in your research study entitled "Core Profile Types for the Cognitive Assessment System and the Woodcock-Johnson® Revised Tests of Achievement Subtests."

You may use the materials referenced herein for the purpose stated above solely and may only be used under the following conditions:

- There will be no deletions, additions, or other changes to the material without the prior written permission of The Riverside Publishing Company. All materials received from Riverside shall be returned.
- 2. The permission granted is non-exclusive and is not transferable to other persons or institutions.
- 3 The permission is limited to the material as identified above.
- 4. Credit will be given for the material as follows:

"Copyright © 1997 by The Riverside Publishing Company. All rights reserved. Reproduced from the "Das Naglieri Cognitive Assessment System" by Jack Naglieri and J.P, with permission of the publisher.

4 Please forward two (2) copies of the publication to: Janet A. Wiedemann, The Riverside Publishing Company, 425 Spring Lake Drive, Itasca, IL 60143-2079.

Sincerely hita. Wednam

Janet A. Wiedemann Permissions Manager

Figure A.1: Letter of permission for the use of Riverside Publishing Company data.

425 Spring Lake Drive

lusca, Illinois

60143-2079

800.323.9540 customer service

800.767.8420 general

www.riverpub.com

APPENDIX B

CLUSTER DENDROGRAMS



Figure B.1: PASS/RD dendrogram



Figure B.2: PASS/Math dendrogram

LIST OF REFERENCES

- Aldenderfer, M. S., & Blashfield, R. K. (1984). *Cluster analysis* (Sage University Paper series on Quantitative Applications in the Social Sciences, No. 07-102). Beverly Hills, CA: Sage.
- American Educational Research Association, American Psychological Association, & National Council on Measurement in Education. (1999). *Standards for educational and psychological testing*. Washington, DC: American Educational Research Association.
- American Psychiatric Association (2000). *Diagnostic and statistical manual of mental disorders* (4th ed., Text Revision), Washington, DC: Author.
- Anastasi, A., & Urbina, S. (1997). *Psychological testing* (7th ed.). Upper Saddle River, NJ: Prentice Hall.
- Anderberg, M. R. (1973). Cluster analysis for applications. New York: Academic Press.
- Bailey, K. D. (1984). Typologies and taxonomies: An introduction to classification techniques (Sage University Paper series on Quantitative Applications in the Social Sciences, No. 07-044). Thousand Oaks, CA: Sage.
- Barrantes-Vidal, N., Fananás, L., Rosa, A., Caparrós, B., Riba, M. D., & Obiold, J. E. (2002). Neurocognitive, behavioural and neurodevelopmental correlates of schizotypy clusters in adolescents from the general population. *Schizophrenia Research*, 61, 293-302.
- Blashfield, R. K., & Aldenderfer, M. S. (1988). The methods and problems of cluster analysis. In J. R. Nesselroade & R. B. Cattell (eds.), *Handbook of multivariate experimental psychology* (2nd ed., pp. 447-473). New York: Plenum Press.
- Blashfield, R. K., & Draguns, J. G. (1976). Evaluative criteria for psychiatric classification. *Journal of Abnormal Psychology*, 85, 140-150.
- Boll, T. (1993). Children's Category Test. San Antonio, TX: Psychological Corporation.

- Bonafina, M. A., Newcorn, J. H., McKay, K. E., Koda, V. H., & Halperin, J. M. (2000). ADHD and reading disabilities: A cluster analytic approach for distinguishing subgroups. *Journal of Learning Disabilities*, 33, 297-307.
- Bracken, B. A. (1987). Limitations of preschool instruments and standards for minimal levels of technical adequacy. *Journal of Psychoeducational Assessment*, 5, 313-326.
- Bracken, B. A., & McCallum, R. S. (1998). Universal Nonverbal Intelligence Test: Examiner's Manual. Itasca, IL: Riverside Publishing.
- Braden, J. P. (2002). Best practices for school psychologists in educational accountability: High stakes testing and education reform. In A. Thomas &: J. Grimes (Eds.), *Best practices in school psychology IV: Vol. 1*. Bethesda, MD: The National Association of School Psychologists.
- Braden, J. P. (2003). Psychological assessment in school settings. In I. B. Weiner (Series Ed.) & J. R. Graham & J. A. Naglieri (Vol. Eds.), *Handbook of psychology: Vol.* 10. Assessment Psychology (pp. 261-290). New York: Wiley.
- Buly, M. R., & Valencia, S. W. (2002). Below the bar: Profiles of students who fail state reading assessments. *Educational Evaluation and Policy Analysis*, 24 (3), 219-239.
- Cattell, R. B. (1949). r_p and other coefficients of pattern similarity. *Psychometrika*, 14(4), 279-298.
- Clustan Limited. (2003). *ClustanGraphics* (Version 6.04) [Computer software]. Edinburgh, Scotland: Author.
- Crawford, J. R., Garthwaite, P. H., Johnson, D. A., Mychalkiw, B., & Moore, J. W. (1997). WAIS-R subtest pattern clusters in closed-head-injured and healthy samples. *The Clinical Neuropsychologist*, *11*, 249-257.
- Crawford, S., & Snart, F. (1994). Process-based remediation of decoding in gifted LD students: Three case studies. *Roeper Review*, *16*, 247-252.
- Cronbach, L. J. (1990). Essentials of psychological testing. New York: Harper & Row.
- Cronbach, L. J., & Snow, R. E. (1977). *Aptitudes and instructional methods*. New York: Irvington.
- Cummins, J. P., & Das, J. P. (1977). Cognitive processing and reading difficulties: A framework for research. *Alberta Journal of Educational Research*, 23, 245-256.

- Cummins, J. P., & Das, J. P. (1978). Simultaneous and successive syntheses and linguistic processes. *International Journal of Psychology*, *13*, 129-138.
- Cummins, J. P., & Das, J. P. (1980). Cognitive processing, academic achievement, and WISC-R performance in EMR children. *Journal of Consulting & Clinical Psychology*, 48, 777-779.
- D'Amato, R. C., Dean, R. S., & Rhodes, R. L. (1998). Subtyping children's learning disabilities with neuropsychological, intellectual, and achievement measures. *International Journal of Neuroscience*, *96*, 107-125.
- Das, J. P. (1999). A neo-Lurian approach to assessment and remediation. *Neuropsychology Review*, 9(2), 107-116.
- Das, J. P., & Cummins, J. (1978). Academic performance and cognitive processes in EMR children. *American Journal of Mental Deficiency*, 83, 197-199.
- Das, J. P., & Cummins, J. P. (1982). Language processing and reading disability. Advances in Learning & Behavioral Difficulties, 1, 3-24.
- Das, J. P., Cummins, J., Kirby, J. R., & Jarman, R. F. (1979). Simultaneous and successive processes, language and mental abilities. *Canadian Psychological Review*, 20, 1-11.
- Das, J. P., & Kendrick, M. (1997). PASS Reading Enhancement Program: A short manual for teachers. *Journal of Cognitive Education*, *5*, 193-208.
- Das, J. P., Kirby, J. R., & Jarman, R. F. (1979). Simultaneous and successive cognitive processes. New York: Academic Press.
- Das, J. P., & Mensink, D. (1989). K-ABC simultaneous-sequential scales and prediction of achievement in reading and mathematics. *Journal of Psychoeducational Assessment*, 7, 103-111.
- Das, J. P., & Naglieri, J. A. (1996). Mental retardation and assessment of cognitive processes. In J. W. Jacobson & J. A. Mulick (Eds.), *Manual of diagnosis and professional practice in mental retardation* (pp. 115-126), Washington, DC: American Psychological Association.
- Das, J. P., Naglieri, J. A., & Kirby, J. R. (1994). Assessment of cognitive processes: The PASS theory of intelligence Boston: Allyn & Bacon.
- Das, J. P., Snart, F., & Mulcahy, R. F. (1982). Reading disability and its relation to information integration. In J. P. Das, R. F. Mulcahy, & A. E. Wall (Eds.), *Theory* and research in learning disabilities. New York: Plenum.
- Davison, M. L., Gasser, M., & Ding, S. (1996). Identifying major profile patterns in a population: An exploratory study of WAIS and GATB patterns. *Psychological Assessment*, 8, 26-31.
- Delis, D. C., Kramer, J. H., Kaplan, E., & Ober, A. (1994). *California Verbal Learning Test-Children's Version*. San Antonio, TX: Psychological Corporation.
- Donders, J. (1996). Cluster subtypes in the WISC-III standardization sample: Analysis of factor index scores. *Psychological Assessment*, 8, 312-318.
- Donders, J. (1998). Cluster subtypes in the Children's Category Test standardization sample. *Child Neuropsychology*, *4*, 178-186.
- Donders, J. (1999). Cluster subtypes in the standardization sample of the California Verbal Learning Test-Children's Version. *Developmental Neuropsychology*, 16, 163-175.
- Drossman, E. R., Maller, S. J., & McDermott, P. A. (2001). Core profiles of school-aged examinees from the national standardization sample of the Comprehensive Test of Nonverbal Intelligence. *School Psychology Review*, 30, 586-598.
- Ekstrom, R. B., Elmore, P. B., & Schafer, W. D. (1997). Standards for educational and psychological tests and testing professionals. In R. F. Dillon (Ed.), *Handbook on testing* (pp. 39-64). Westport, CT: Greenwood.
- Elliott, C. D. (1990). *Differential Ability Scales (DAS) administration and scoring manual*. San Antonio, TX: Psychological Corporation.
- Elliott, J. (2003). Dynamic assessment in educational settings: realising potential. *Educational Review*, 55, 15-32.
- Esters, I. G., Ittenbach, R. F., & Han, K. (1997). Today's IQ tests: Are they really better than their historical predecessors?. *School Psychology Review*, *26*, 211-224.
- Everitt, B. S. (1993). *Cluster analysis* (3rd ed.). New York: Wiley.
- Everitt, B. S. (1997). Cluster analysis. In J. P. Keeves (Ed.), *Educational research*, *methodology, and measurement: An international handbook* (2nd ed.). New York: Elsevier Science.
- Garb, H. N. (2003). Clinical judgment and mechanical prediction. In I. B. Weiner (Series Ed.) & J. R. Graham & J. A. Naglieri (Vol. Eds.), *Handbook of Psychology: Vol.* 10. Assessment Psychology (pp. 27-42). New York: Wiley.

- Garofalo, J. (1986). Simultaneous synthesis, regulation, and arithmetical performance. *Journal of Psychoeducational Assessment*, 4, 229-238.
- Glutting, J. J., & McDermott, P. A. (1990). Patterns and prevalence of core profile types in the WPPSI standardization sample. *School Psychology Review*, 19, 471-491.
- Glutting, J. J., McDermott, P. A., & Konold, T. R. (1997). Ontology, structure, and diagnostic benefits of a normative subtest taxonomy from the WISC-III standardization sample. In D. P. Flanagan, J. L. Genshaft, & P. L. Harrison (Eds.), *Contemporary intellectual assessment: Theories, tests, and issues* (pp. 349-372). New York: Guilford.
- Glutting, J. J., McDermott, P. A., Prifitera, A., & McGrath, E. A. (1994). Core profile types for the WISC-III and WIAT: Their development and application in identifying multivariate IQ-achievement discrepancies. *School Psychology Review*, 23, 619-639.
- Glutting, J. J., McDermott, P. A., Watkins, M. W., Kush, J. C., & Konold, T. R. (1997). The base rate problem and its consequences for interpreting children's ability profiles. *School Psychology Review*, 26, 176-188.
- Glutting, J. J., McGrath, E. A., Kamphaus, R W., & McDermott, P. A. (1992). Taxonomy and validity of subtest profiles in the Kaufman Assessment Battery for Children. *Journal of Special Education*, 26, 85-115.
- Gordon, A. D., (1996). Hierarchical classification. In P. Arabie, L. Hubert, & G. De Soete (Eds.), *Clustering and classification* (pp. 65-121). River Edge, NJ: World Scientific Press.
- Greenway, P., & Milne, L. (1999). Relationship between psychopathology, learning disabilities, or both and WISC-III subtest scatter in adolescents. *Psychology in the Schools*, *36*(2), 103-108.
- Gresham, F. M., & Witt, J. C. (1997). Utility of intelligence tests for treatment planning, classification, and placement decisions: Recent empirical findings and future directions. *School Psychology Quarterly*, 12, 249-267.
- Gustafsson, J., & Snow, R. E. (1997). Ability profiles. In R. F. Dillon (Ed.), *Handbook* on testing (pp. 107-135). Westport, CT: Greenwood.
- Gutentag, S., Naglieri, J. A., & Yeates, K. O. (1998). Performance of children with traumatic brain injury on the Cognitive Assessment System. *Assessment*, *5*, 263-272.

- Hair, J. F., & Black, W. C. (2000). Cluster analysis. In L. A. Grimm & P. R. Yarnold (Eds.), *Reading and understanding more multivariate statistics*. Washington, DC: American Psychological Association.
- Hammill, D. D., Pearson, N. A., & Wiederholt, J. L. (1997). *The Comprehensive Test of Nonverbal Intelligence*. Austin, TX: PRO-ED.
- Havey, J. M. (2002). Best practices in working with students with traumatic brain injury. In A. Thomas & J. Grimes (Eds.), *Best practices in school psychology IV: Vol. 2*. Bethesda, MD: The National Association of School Psychologists.
- Holland, A. M., & McDermott, P. A. (1996). Discovering core profile types in the school-age standardization sample of the Differential Ability Scales. *Journal of Psychoeducational Assessment*, (14), 131-146.
- Hughes, T. L., & McIntosh, D. E. (2002). Differential Ability Scales: Profiles of preschoolers with cognitive delay. *Psychology in the Schools, 39*, 19-29.

Individuals with Disabilities Education Act, 20 U.S.C. Ch. 33, Sec. 1400, (1997).

- Johnson, R. A., & Wichern, D. W. (2002). *Applied multivariate statistical analysis* (5th ed.). Upper Saddle River, NJ: Prentice-Hall.
- Joseph, L. M., McCachran, M. E., & Naglieri, J. A. (2003). PASS cognitive processes, phonological processes, and basic reading performance for a sample of referred primary-grade children. *Journal of Research in Reading*, *26*(3), 304-314.
- Joseph, L. M.& Hunter, A. D. (2001). Differential application of a cue card strategy for solving fraction problems: exploring instructional utility of the cognitive assessment system. *Child Study Journal*, 31(2), 123-136.
- Kaufman, A. S. (1990). *Assessing adolescent and adult intelligence*. Boston: Allyn and Bacon.
- Kaufman, A. S. (1994). Intelligent testing with the WISC-III. New York: Wiley.
- Kaufman, A., & Kaufman, N. (1983). Kaufman Assessment Battery for Children. Circle Pines, MN: American Guidance Service.
- Kaufman, A. S., Lichtenberger, E. O., & Naglieri, J. A. (1999). Intelligence testing in the schools. In C. R. Reynolds, & T. B. Gutkin (Eds.), *The Handbook of School Psychology* (3rd ed., pp. 307-349). New York: Wiley.

- Kavale, K. A., & Forness, S. R. (1987). The far side of heterogeneity: A critical analysis of empirical subtyping research in learning disabilities. *Journal of Learning Disabilities*, 20(6), 374-382.
- Keith, T. Z. (Ed.). (2000). Research methods for profile analysis [Special issue]. School Psychology Quarterly, 15(4).
- Kirby, J. R. (1982). Cognitive processes, school achievement, and comprehension of ambiguous sentences. *Journal of Psycholinguistic Research*, 11, 485-499.
- Kirby, J. R., Booth, C. A., & Das, J. P. (1996). Cognitive processes and IQ in reading disability. *Journal of Special Education*, 29(4), 442-446.
- Kirby, J. R., & Das, J. P. (1977). Reading achievement, IQ, and simultaneous-successive processing. *Journal of Educational Psychology*, 69, 564-570.
- Kirby, J. R., & Robinson, G. L. (1987). Simultaneous and successive processing in reading disabled children. *Journal of Learning Disabilities*, 20, 243-252.
- Kirby, J. R., & Williams, N. H. (1991). Learning problems: A cognitive approach. Toronto: Kagan and Woo.
- Konold, T. R., Glutting, J. J., & McDermott, P. A. (1997). The development and applied utility of a normative aptitude-achievement taxonomy for the Woodcock-Johnson Psycho-educational Battery-Revised. *The Journal of Special Education*, 31, 212-232.
- Konold, T. R., Glutting, J. J., McDermott, P. A., Kush, J. C., & Watkins, M. M. (1999). Structure and diagnostic benefits of a normative subtest taxonomy developed from the WISC-III standardization sample. *Journal of School Psychology*, 37, 29-48.
- Kroesbergen, E. H., Van Luit, J. E. H. & Naglieri, J. A. (2003). Mathematical learning difficulties and PASS cognitive processes. *Journal of Learning Disabilities*, 36(6), 574-582.
- Leong, C. K. (1980). Cognitive patterns of "retarded" and below-average readers. *Contemporary Educational Psychology*, *5*, 101-117.
- Leong, C. K. (1984). Cognitive processing, language awareness, and reading in Grade 2 and Grade 4 children. *Contemporary Educational Psychology*, *9*, 369-383.
- Leong, C. K., Cheng, S. C., & Das, J. P. (1985). Simultaneous-successive syntheses and planning in Chinese readers. *International Journal of Psychology*, 20, 19-31.

- Lidz, C. S. (1991). *Practitioner's guide to dynamic assessment*. New York: Guilford Press.
- Lidz, C. S., & Greenberg, K. H. (1997). Criterion validity of a group dynamic assessment procedure with rural first grade regular education students. *Journal of Cognitive Education*, *6*, 89-99.
- Macmann, G. M., & Barnett, D. W. (1997). Myth of the master detective: Reliability of interpretations for Kaufman's "intelligent testing" approach to the WISC-III. *School Psychology Quarterly, 12*, 197-234.
- Maller, S. J., & McDermott, P. A. (1997). WAIS-R profile analysis for college students with learning disabilities. *School Psychology Review*, *26*, 575-585.
- McDermott, P. A., Fantuzzo, J. W., Glutting, J. J., Watkins, M. W., & Baggaley, A. R. (1992). Illusions of meaning in the ipsative assessment of children's ability. *The Journal of Special Education*, 25, 504-526.
- McDermott, P. A., Glutting, J. J., Jones, J. N., & Noonan, J. V. (1989). Typology and prevailing composition of core profiles in the WAIS-R standardization sample. *Psychological Assessment*, *1*, 118-125.
- McDermott, P. A., Glutting, J. J., Jones, J. N., Watkins, M. W., & Kush, J. (1989). Core profile types in the WICS-R national sample structure, membership, and applications. *Psychological Assessment: A Journal of Counsulting and Clinical Psychology*, 1, 292-299.
- McGrew, K. S., Werder, J. K., & Woodcock, R. W. (1991). *WJ-R Technical Manual*. Allen, TX: DLM.
- McRae, S. G. (1986). Sequential-simultaneous processing and reading skills in primary grade children. *Journal of Learning Disabilities*, 19, 509-511.
- Milligan, G. W., & Cooper, M. C. (1987). Methodology review: Clustering methods. *Applied Psychological Measurement*, 11 (4), 329-354.
- Milligan, G. W., & Hirtle, S. C. (2003). Clustering and classification methods. In I. B. Weiner (Series Ed.) & J. A. Schinka & W. F. Velicer (Vol. Eds.), *Handbook of psychology: Vol. 2. Research Methods in Psychology* (pp. 165-186). New York: Wiley.
- Milligan, G. W., & Sokol, L. M. (1980). A two-stage clustering algorithm with robust recovery characteristics. *Educational & Psychological Measurement*, 40, 755-759.

- Morey, L. C., Blashfield, R. K., & Skinner, H. A. (1983). A comparison of cluster analysis techniques within a sequential validation framework. *Multivariate Behavioral Research*, *18*, 309-329.
- Mwamwenda, T., Dash, U. N., & Das, J. P. (1984). A relationship between simultaneoussuccessive synthesis and concrete operational thought. *International Journal of Psychology*, 19, 547-563.
- Naglieri, J. A. (1993). Pairwise and ipsative comparisons of WISC-III IQ and index scores. *Psychological Assessment*, *5*, 113-116.
- Naglieri, J. A. (1999). Essentials of CAS assessment. New York: Wiley.
- Naglieri, J. A. (2000). Can profile analysis of ability test scores work? An illustration using the PASS theory and CAS with an unselected cohort. *School Psychology Quarterly*, *15*, 419-433.
- Naglieri, J. A. (2001a). Understanding intelligence, giftedness and creativity using the PASS theory. *Roeper Review*, 23, 151-156.
- Naglieri, J. A. (2001b). Using the Cognitive Assessment System (CAS) with learningdisabled children. In A. S. Kaufman & N. L. Kaufman (Eds.), Specific Learning Disabilities and difficulties in children and adolescents (pp. 141-177). United Kingdom: Cambridge University Press.
- Naglieri, J. A. (2002). Best practices in interventions for school psychologists: A cognitive approach to problem solving. In A. Thomas &: J. Grimes (Eds.), Best practices in school psychology IV: Vol. 2. Bethesda, MD: The National Association of School Psychologists.
- Naglieri, J. A., & Ashman, A. F. (1999). Making the connection between PASS and intervention. In J. A. Naglieri (Ed.), *Essentials of CAS assessment*. New York: John Wiley.
- Naglieri, J. A., & Das, J. P. (1987). Construct and criterion-related validity of planning, simultaneous, and successive cognitive processing tasks. *Journal of Psychoeducational Assessment, 5*, 353-363.
- Naglieri, J. A., & Das, J. P. (1990). Planning, attention, simultaneous, and successive cognitive processes as a model for intelligence. *Journal of Psychoeducational Assessment*, *8*, 303-337.
- Naglieri, J. A., & Das, J. P. (1997a). Cognitive Assessment System. Itasca, IL: Riverside.

- Naglieri, J. A., & Das, J. P. (1997b). Cognitive Assessment System: Interpretive handbook. Itasca, IL: Riverside.
- Naglieri, J. A., & Gottling, S. H. (1995). A study of planning and mathematics instruction for students with learning disabilities. *Psychological Reports*, *76*(*3*), 1343-1354.
- Naglieri, J. A., & Gottling, S. H. (1997). Mathematics instruction and PASS cognitive processes: an intervention study. *Journal of Learning Disabilities 30*(5), 513-520.
- Naglieri, J. A., & Johnson, D. (2000). Effectiveness of a cognitive strategy intervention in improving arithmetic computation based on the PASS theory. *Journal of Learning Disabilities 33(6)*, 591-597.
- Naglieri, J. A., & Pickering, E. B. (2003). *Helping children learn: Intervention handouts* for use in school and at home. Baltimore: Paul H. Brookes.
- Neisser, U., Boodoo, G., Bouchard, T. J., Jr., Boykin, A. W., Brody, N., Ceci, S. J., Halpern, D. F., Loehlin, J. C., Perloff, R., Sternberg, R. J., & Urbina, S. (1996). Intelligence: Knowns and unknowns. *American Psychologist*, 51(2). 77-101.
- No Child Left Behind Act. Public Law 107-110 (2001).
- Parrila, R. K., Kendrick, M. E., Papadopoulos, T. C. & Kirby, J. R. (1999). Efficacy of cognitive reading remediation program for at-risk children in grade 1. *Developmental Disabilities Bulletin*, 27(2), 1-31.
- Peterson, P. L. (1988). Selecting students and services for compensatory education: Lessons from aptitude-treatment interaction research.
- Pfeiffer, S. I., Reddy, L. A., Kletzel, J. E., Schmelzer, E. R., & Boyer, L. M. (2000). The practitioner's view of IQ testing and profile analysis. *School Psychology Quarterly*, 15, 376-385.
- Prasse, D. P. (2002). Best practices in school psychology and the law. In A. Thomas &: J. Grimes (Eds.), *Best practices in school psychology IV: Vol. 1*. Bethesda, MD: The National Association of School Psychologists.
- Pressley, M., & Woloshyn, V. E. (1995). Cognitive Strategy Instruction that Really Improves Children's Academic Performance. Brookline Books, Cambridge, MA.
- Pritchard, D. A., Livingston, R. B., Reynolds, C. R., & Moses, J. A., Jr. (2000). Modal profiles for the WISC-III. School Psychology Quarterly, 15, 400-418.
- Rapaport, D., Gill, M., & Schafer, R. (1945/1946). *Diagnostic psychological testing*. Chicago: YearBook

- Rosenthal, B. L., & Kamphaus, R. W. (1988). Interpretive tables for test scatter on the Stanford-Binet Intelligence Scale: Fourth Edition. *Journal of Psychoeducational Assessment*, 6, 359-370.
- Sattler, J. M. (2001). Assessment of children: Cognitive applications (4th ed.). San Diego, CA: Jerome M. Sattler.
- Sattler, J. M., & Ryan, J. J. (2001). Wechsler Adult Intelligence Scale-III (WAIS-III): Description. In J. M. Sattler (Ed.), Assessment of children: Cognitive applications (4th ed.). San Diego, CA: Jerome M. Sattler.
- Sattler, J. M., & Saflofske, D. H. (2001). Interpreting the WISC-III. In J. M. Sattler (Ed.), Assessment of children: Cognitive applications (4th ed.). San Diego, CA: Jerome M. Sattler.
- Sattler, J. M., Weyandt, L., & Roberts, M. A. (2002). Attention-Deficit/Hyperactivity disorder. In J. M. Sattler (Ed.), *Assessment of children: Behavioral and clinical applications* (4th ed.). San Diego, CA: Jerome M. Sattler.
- Shapiro, S. K., Buckhalt, J. A., & Herod, L. A. (1995). Evaluation of learning-disabled students with the Differential Ability Scales (DAS). *Journal of School Psychology*, 35, 247-263.
- Shinn, M. R. (2002). Best practices in using curriculum-based measurement in a problem-solving model. In A. Thomas &: J. Grimes (Eds.), *Best practices in school psychology IV: Vol. 1*. Bethesda, MD: The National Association of School Psychologists.
- Shinn-Strieker, T., House, G., & Klink, B. (1989). The roles of cognitive processing and language development in emergent literacy. *RASE: Remedial & Special Education*, 10 (5), 43-50.
- Shute, V., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist*, 38(2), 105-114.
- Sneath, P. H., & Sokal, R. R. (1973). Numerical Taxonomy. San Francisco: Freeman.
- Snow, R. E. (1986). Individual differences and the design of educational programs. *American Psychologist, 41*, 1029-1039.
- Snow, R. E. (1992). Aptitude theory: Yesterday, today, and tomorrow. *Educational Psychologist*, 27, 5-32.

- Solan, H.A., Shelley-Tremblay, J., Ficarra, A., Silverman, M., & Larson, S. (2003). Effect of attention therapy on reading comprehension. *Journal of Learning Disabilities*, 36(3), 556-563.
- Sokal, R. R., & Sneath, P. H. (1963). *The Principles of Numerical Taxonomy*. San Francisco: Freeman.
- Spreen, O., & Haaf, R. G. (1986). Empirically derived learning disability subtypes: A replication attempt and longitudinal patterns over 15 years. *Journal of Learning Disabilities*, 19, 170-180.
- Stanton, H. C., & Reynolds, C. R. (2000). Configural frequency analysis as a method of determining Wechsler profile types. School Psychology Quarterly, 15, 434-448.
- Steinman, S. B., Steinman, B. A., & Garzia, R. P. (1998). Vision and attention II: Is visual attention a mechanism through which a deficient magnocellular pathway might cause a reading disability? *Optometry and Vision Science*, 75, 674-681.
- Stoiber, K. C., Bracken, B. A., & Gissal, T. J. (1983). Cognitive processing styles in reading-disabled and a matched group of normal children. *Journal of Psychoeducational Assessment*, 1, 219-233.
- Stone, B. J. (1995). Best practices in the use of standardized assessments. In A. Thomas & J. Grimes (Eds.), *Best practices in school psychology-III* (pp. 841-848).
 Washington, DC: The National Association of School Psychologists.
- Stuebing, K. K., Fletcher, J. M., LeDoux, J. M., Lyon, G. R., Shaywitz, S. E., & Shaywitz, B. A. (2002). Validity of IQ-discrepancy classifications of reading disabilities: A meta-analysis. *American Educational Research Journal*, 39, 469-518.
- Tilly, W. D., III (2002). Best practices in school psychology as a problem-solving enterprise. In A. Thomas &: J. Grimes (Eds.), *Best practices in school psychology IV: Vol. 1*. Bethesda, MD: The National Association of School Psychologists.
- Tryon, R. C. (1939). *Cluster Analysis; correlation profile and orthometric (factor) analysis for the isolation of unities in mind and personality.* Ann Arbor, MI: Edwards Brothers.
- Tryon, R. C., & Bailey, D. E. (1970). Cluster Analysis. New York: McGraw-Hill.
- Tyler, S., & Elliott, C. D. (1988). Cognitive profiles of groups of poor readers and dyslexic children on the British Ability Scales. *British Journal of Psychology*, 79, 493-508.

- U. S. Bureau of the Census. (1992). 1990 Census of population and housing: Summary population and housing characteristics, United States. Washington, DC: Author.
- U.S. Office of Education (1975). Education for All Handicapped Children Act. Public Law No. 94-142. November 29, 1975.
- Van Luit, J. E. H., & Naglieri, J. A. (1999). Effectiveness of the MASTER program for teaching special children multiplication and division. *Journal of Learning Disabilities*, 32, 98-107.
- Wachs, M. C., & Harris, M. (1986). Simultaneous and successive processing in university students: Contribution to academic performance. *Journal of Psychoeducational Assessment*, 4, 103-112.
- Wagner, R. K., Torgesen, J., & Rashotte, C. A. (1999). *Comprehensive Test of Phonological Processing*. Austin, TX: PROED.
- Ward, J. H. (1963). Hierarchical grouping to optimize an objective function. *American Statistical Journal*, *58*, 236-244.
- Ward, T. J., Ward, S. B., Glutting, J. J., & Hatt, C. V. (1999). Exceptional LD profile types for the WISC-III and WIAT. *School Psychology Review*, 28, 629-643.
- Watkins, M. W. (2000). Cognitive profile analysis: A shared professional myth. *School Psychology Quarterly*, 15, 465-479.
- Weaver-Hightower, M. (2003). The "boy turn" in research on gender and education. *Review of Educational Research*, *73*, 471-498.
- Wechsler, D. (1958). *The measurement and appraisal of adult intelligence* (4th ed.). Baltimore: Williams & Wilkins.
- Wechsler, D. (1967). *Wechsler Preschool and Primary Scale of Intelligence*. New York: Psychological Corporation.
- Wechsler, D. (1991). *Wechsler Intelligence Test for Children-Third Edition*. San Antonio: Psychological Corporation.
- Wechsler, D. (1992). *Wechsler Individual Achievement Test*. San Antonio, TX: Psychological Corporation.
- Wechsler, D. (1997). *Wechsler Adult Intelligence Scale-Third Edition*. San Antonio: Psychological Corporation.

- Wilhoit, B. E., & McCallum, R. S. (2002). Profile analysis of the Universal Nonverbal Intelligence Test standardization sample. *School Psychology Review*, *31*, 263-281.
- Williams, D. L., Gridley, B. E., & Fitzhugh-Bell, K. (1992). Cluster analysis of children and adolescents with brain damage and learning disabilities using neuropsychological, psychoeducational, and sociobehavioral variables. *Journal of Learning Disabilities*, 25, 290-299.
- Wishart, D. (2000). *FocalPoint Clustering User Guide*. Edinburgh, Scotland: Clustan Limited.
- Wishart, D. (2003). *ClustanGraphics Primer: A Guide to Cluster Analysis* (2nd ed.). Edinburgh, Scotland: Clustan Limited.
- Woodcock, R. W. (1997). Woodcock Diagnostic Reading Battery. Chicago: Riverside.
- Woodcock, R. W., & Johnson, M. B. (1989). Woodcock-Johnson Revised Tests of Achievement: Standard and Supplemental Batteries. Itasca, IL: Riverside Publishing.
- Woodcock, R. W., & Mather, N. (1989, 1990). WJ-R Tests of Achievement: Examiner's Manual. In R. W. Woodcock & M. B. Johnson, *Woodcock-Johnson Psycho-Educational Battery-Revised*. Allen, TX: DLM Teaching Resources.
- Woodcock, R. W., McGrew, K. S., & Mather, N. (2000). Woodcock-Johnson Psychoeducational Tests of Achievement-III. Itasca, IL: Riverside.