A PROFILE ANALYSIS OF DIAGNOSTIC DATA FROM COLLEGE STUDENTS EXPERIENCING MATH DIFFICULTY

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By

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

A PROFILE ANALYSIS OF DIAGNOSTIC
DATA FROM COLLEGE STUDENTS
EXPERIENCING MATH DIFFICULTIES

presented by Sean M. McGlaughlin,

a candidate for the degree of doctor of philosophy

and hereby certify that, in their opinion, it is worthy of acceptance.

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Professor Gregory Holliday

Professor Andrew Knoop

Professor Kathryn Chval

DEDICATION

I would like to dedicate this to my wife, Tammy Eigenheer, who is my soul mate and is the rock that is always by my side. I would like to also dedicate this book to my son, Caelen, you are the joy in my life and I am so very blessed to have you. I love you both very much.

I would also like to thank my father, mother, and grandparents for instilling in me values that allowed me to pursue my dreams and reach for the stars.

Finally, I want to thank all of the individuals above as well as the rest of my family and friends who continually “bothered” me to get this dissertation finished.

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ABSTRACT

Level, shape and scatter are three characteristics of profiles that determine the specific focus of profile analysis procedures. In this study, three methods of profile analysis that emphasize each of these characteristics are analyzed: cluster analysis (which distinguishes profiles by level), modal profile analysis (which distinguishes profiles by shape) and configural frequency analysis (which distinguishes profiles by scatter). Within a group of college student’s struggling with mathematics, these three profile analysis methods are used to form three distinct subtype grouping schemes. The profile subgroups resulting from each of the three profile analysis methods are compared to previously identified clinical subgroups. Results indicate that the best method to correspond with clinical subgroups is cluster analysis, which emphasizes level.

CHAPTER ONE

Introduction

The Importance of Mathematics Education Today

According to Geary and Hoard (2005), approximately five to eight percent of students are affected with mathematics disabilities. It is well known that now, more than ever, students need help in understanding mathematics, especially in a rapidly evolving world. Obtaining a job that does not require some degree of mathematical skills is virtually impossible, and for that reason, understanding mathematics disabilities is important (National Commission on Mathematics and Science Teaching for the Twenty-First Century, 2000).

Many college students experience difficulties in mathematics. College Algebra and other introductory mathematics courses cause students to experience a great deal of difficulty. Failure to meet the basic math requirements set by colleges can impede progress in earning degrees. Some students are not identified as requiring special services for math during secondary school.

Understanding students' struggles with mathematics at the college level is key to helping students earlier rather than later. While the focus of this research study is aimed at comparing and contrasting three profile analysis methods, utilizing the information gained from this study to help understand college students struggling with mathematics will be an important secondary benefit to this research.

The Hurdle that is College Algebra

College Algebra and other preliminary algebra courses are becoming difficult hurdles for some students. In some cases, this hurdle seems insurmountable (Blum, 2007; Knoop, 2003; McGlaughlin, Knoop & Holliday, 2005; Walker, 2008). Even in the late 1980s, educators were recognizing that in post-secondary education, mathematics is serving as a "gatekeeper that filters many students out of careers they might otherwise pursue" (National Research Council, 1989). This trend does not appear to have changed (McGlaughlin et al., 2005; National Research Council, 2001; Riccomini, 2005; Sullivan, 2005).

According to Weinstein (2004), students in a college algebra course studied for that class between five and 15 hours a week, with most students falling in the range of eight to 12 hours. Half of the students in the same class reported working regularly with peers or tutors. College students not succeeding have to continually enroll in the same course, change education plans and many drop out of college (Blum, 2007; Knoop, 2003). In fact, Walker (2008) reports that in her essential meta-analysis of literature, as many as 30 to 50 percent of students in distance education drop out after their first attempt taking college algebra; whereas, five to 15 percent dropout after a first attempt at on-campus courses (Walker, 2008). In fact, Walker (2008) reports that College Algebra has essentially become the “general education quantitative literacy requirement” for bachelors’ degrees (p. 37).

Research designed to understand students’ struggles with mathematics has the potential to assist them in overcoming these difficulties. Many students can succeed with the appropriate accommodation; yet, there are some that may not ever overcome the hurdle through accommodations, and may be better served by taking alternate classes that correspond with their choice of major. Research must be conducted to help identify specific characteristics of groups of students struggling in math.

By identifying these common characteristics, researchers and practitioners can then identify specific strategies aimed at helping those same students improve deficits and utilize strengths toward better performance in mathematics (McGlaughlin et al., 2005). There are several different statistical methods to subtype information. Most of these are derived from profile analysis procedures. When different methods of profile analysis are chosen, the methodology can emphasize different information.

Information gained from this study can help to determine what method(s) of profile analysis best categorize(s) students based on their exhibited profile patterns or individual strengths and weaknesses. These profile patterns will be best described by referring to profile characteristics of “level”, “shape” and “scatter” (Aldenderfer & Blashfield, 1984; Pritchard, Livingston, Reynolds & Moses, 2000; Stanton & Reynolds, 2000).

Statement of the Problem

Educators and clinicians attempt to help individuals who are having difficulty in math. Before this can be effective, a preliminary step is to utilize different classification methods to help understand what makes individuals similar or different in their math strengths and weaknesses.

While many clinicians utilize the Diagnostic and Statistical Manual-Fourth Edition Text Revision (DSM-IV TR), some researchers use DSM-IV categories when conducting research. Others use statistics to derive subtypes of individuals. The DSM-IV is designed to categorize mental health problems based on characteristics exhibited by individuals. The book is designed to provide criteria for diagnosing mental health disorders based on exhibited characteristics, and then clinicians can utilize information for treatment planning based on the diagnosis of an individual. Further, this information can then be utilized to communicate about individuals with particular disorders as these diagnoses now provide common terminology that allow more simple identification of the common characteristics that groups of individuals may share.

While some utilize the DSM-IV categories to conduct research, other researchers utilize statistical measures to determine patterns of scores that exist. One way to determine patterns of scores is profile analysis. Profile analysis is a statistical method of grouping individuals into categories based on similarities and differences on chosen measures of performance (Aldenderfer & Blashfield, 1984). There are several forms of analyzing students' profiles, each of which utilize different means to analyze data and each of which have unique strengths and weaknesses. Researchers can utilize the information collected given the scores on the measures chosen as well as the particular profile analysis method chosen. Eventually, these methods employ statistical procedures to determine subtypes of individuals, and utilize these patterns of scores to describe individuals within these subtypes (Aldenderfer & Blashfield, 1984; Pritchard, Livingston, Reynolds & Moses, 2000; Stanton & Reynolds, 2000).

Three types of profile analysis will be utilized to determine which comprehensive set of subgroupings best corresponds to pre-existing clinical subgroups. To determine an optimal subset of profiles extracted from a profile analysis method, one must consider the important profile characteristics pertaining to level, shape, and scatter (Aldenderfer & Blashfield, 1984; Davison & Kuang, 2000; Jobson, 1996). "Level", (sometimes called profile elevations) represents the means of each of the variables in the analysis. "Scatter" represents the degree of dispersion around the mean of each variable. “Shape” represents the pattern of peaks and valleys across the variables. Because, level, scatter and shape are the major ways that guide how profiles are grouped, three methods of profile analysis that seem to correspond with level, scatter and shape are used (Aldenderfer & Blashfield, 1984; Davison & Kuang, 2000; Hair & Black, 2000).

By utilizing cluster analysis (Aldenderfer & Blashfield, 1984; Davison & Kuang, 2000), modal profile analysis (Pritchard, et al., 2000), and configural frequency analysis (Stanton & Reynolds, 2000), the issues of level, shape and scatter can be explored, and eventually all three can be compared with respect to their ability to determine which of these profile grouping methods fits best with clinically determined subgroups. Partitioning individuals in four categories of clinical diagnoses best represents the major difficulties leading to mathematics difficulties. These major areas are: affective disorders; learning disorders; attention deficit disorders; and no diagnoses or no disorders. Then, these four diagnoses made through a college diagnostic clinic can be compared with each of the empirically derived subgroups (using profile analysis) to determine which method best corresponds with the clinical diagnoses.

Important questions can be derived from this data. First, do any of the methods of profile analysis correspond with DSM-IV, clinically derived subtests? The problem can be best stated as: Using diagnostic data from a large group of college students who experience various degrees of math difficulties, to what extent can a statistical profile analysis procedure align with DSM-IV subgroups determined by clinical judgment? When three types of profile analysis procedures are applied to the same diagnostic data, which method most closely resembles clinically determined categories?

Purpose of the Study

The purpose of this study is to evaluate the homogeneity of clinically determined categories of students who have math difficulties by using profile analysis procedures applied to relevant diagnostic data. This study systematically compares each profile analysis methodology applied to the same data set (Pritchard et al., 2000; Stanton & Reynolds, 2000).

Significance of the Study

Subgroups identified through profile analysis categorize individuals based upon their common characteristics and differences. For example, Group A may be identified by a certain set of characteristics—one of which is that they have common differences from Group B.

Identifying individuals' patterns of strengths and weaknesses by clustering them into groups can help provide a general knowledge base or heuristic for each individual within each group. An example of heuristics is represented in professional psychologists' use of the Diagnostic and Statistical Manual (DSM). The DSM traditionally identifies individuals with certain disorders according to common characteristics. Thus, a person who is identified as having bipolar disorder is characterized by generalizations such as having significantly elevated and significantly deflated periods of self-esteem.

Just as the DSM allows for common characteristics to be discussed amongst clinical subtypes, profile analysis can provide the same information amongst commonalities found within profiles obtained statistically (Mayes & Calhoun, 2004). While the utility of profile analysis in helping to understand and identify diagnoses has been long debated in school psychology, it is clear that some profile types have been found consistently within the field allowing for individuals to then be grouped based on commonalities (Mayes & Calhoun, 2004; McDermott, Fantuzzo, & Glutting, 1990; Pritchard et al., 2000; Stanton & Reynolds, 2000). In fact, Mayes and Calhoun, 2004 indicate that among diagnostic subtype groups, differences found utilizing methods of profile analysis have been found among students with attention deficit hyperactivity disorder (ADHD), emotional disturbance, autism, high functioning autism, schizophrenia, reading disorder (RD), math disorder (MD) and both RD and MD. From these created profiles, characteristics about these individuals can be determined and methods of intervention that work for these individuals can be discussed (Mayes & Calhoun, 2004; Stanton & Reynolds, 2000; Ward, Ward, Glutting & Hatt, 1999).

By comparing three methods that separate issues of level, shape and scatter in profile analysis, this study aims to find a corresponding statistical heuristic that aligns with already derived clinical subtypes. Overall, these comparisons might help to determine an optimal method of profile analysis that corresponds best with the clinical diagnoses. Having methods that statistically align with clinical diagnoses is important because this would actually allow for research on subtypes to closely align statistical and clinical groupings and generalize these findings in a more practical way.

This study also significantly contributes to existing literature due to the sample of the population that is being examined. In this instance, the sample consists of individuals attending college that are having difficulty particularly in Math. Further, many studies utilize other forms of subtyping LD instead of DSM-IV criteria (Fuchs & Fuchs, 2006). In this instance, DSM-IV criteria are utilized to compare and contrast the clinical subtypes with the statistical subtyping.

In addition, this study utilizes all of the information obtained to aid in determining an optimal statistical method to learn about individuals’ struggling with mathematics. By understanding this information, commonalities among individuals experiencing math difficulty may best be explained by one of the methods of profile analysis or some combination of any/all of the methods. This information is potentially valuable, as it could help determine which remedies may be most appropriate for students struggling with math.

Overview of the Research Question

Initially, the three profile analysis methods chosen have been designed to emphasize the three major characteristics used to determine differences among profiles: level, shape and scatter. The three methods of profile analysis are then compared with the clinical subgroups to determine the degree of congruence. Hence, the primary research question can be stated as follows:

What is the optimum method of profile analysis, the results of which best align with clinical subgroups determined from DSM-IV TR criteria? This can be explored by examining the following major and alternative research hypotheses:

Major: Within each of the three profile analysis methods, the distribution of participants across profile subgroups is not significantly related to clinically derived diagnostic groups.

Alternative 1: The distribution of participants across profile subgroups, determined through cluster analysis, is significantly related to clinically determined diagnostic groups.

Alternative 2: The distribution of participants across profile subgroups, determined through modal profile analysis, is significantly related to clinically determined diagnostic groups.

Alternative 3: The distribution of participants across profile subgroups, determined through configural frequency analysis, is significantly related to clinically determined diagnostic groups.

CHAPTER TWO

Review of Related Literature

Diagnosing Learning Disabilities

According to the Diagnostic and Statistical Manual Fourth Edition-Text Revision (DSM-IV TR; 2000), a learning disability is “characterized by academic functioning that is substantially below that expected given the person’s chronological age, measured intelligence, and age-appropriate education” (p. 39). The DSM-IV TR lists three major learning disabilities. These are a mathematics disorder (MD), reading disorder (RD), and disorder of written expression (WD). However, there is also a category known as Not Otherwise Specified, or NOS. Often, students get diagnoses under this category with discrepancies in areas such as working memory, processing speed, and academic fluency.

Given this definition, one can be diagnosed with a learning disability based on a number of different criteria. For instance, what is defined as a substantial difference? Different research and different psychologists utilize different methods to determine if one is learning disabled or is not. This is unfortunate because it makes comparing and contrasting general and specific learning disabilities difficult. For purposes of this paper, common definitions used by researchers are given for students with mathematics disorder. However, it must be noted that as the knowledge and understanding of researchers and practitioners continue to change, these definitions continue to change with that knowledge. Learning disabilities are not as simple as the DSM-IV definition might seem.

Mathematics Disabilities—Primary and Secondary Age Students

Geary and Hoard (2005) indicate that five to eight percent of school age children have some form of MD. Further, they state that many of these children have comorbid disorders, especially in the areas of reading and attention-deficit hyperactivity disorders.

MD is identified in several ways among researchers. Geary and Hoard (2005) indicate that there is not a common procedure on identifying students with learning disabilities amongst researchers. Some utilize methods such as scores on a standardized achievement test below the 25th to 30th percentiles combined with a higher IQ score are most common. Another common method is to define students who score below the 25th and 30th percentiles on standardized achievement tests alone as being MD. There are less common methods, but Geary and Hoard (2005) clarify that the 5 to 8 percent of school age children identified refers to the former of the two methods listed above and that the latter method is likely to include more than 5 to 8 percent of school age children. When possible and information was readily assessable, methods utilized to determine MD students are described below.

Given that research on MD is often discussed in the framework of comparison with other disabilities, this section focuses on research with RD/MD combined, RD alone, nonverbal learning disabilities, memory and ADHD fields separately.

The Reading Disorder/Math Disorder (RD/MD) Relationship

Reading Disorders (RD) and Math Disorders (MD) have high comorbidity rates and share some similarities (Fuchs & Fuchs, 2002; Geary & Hoard, 2005; Light & Defries, 1995). Kulak (1993) points out some of the similarities of people with RD and MD. In particular, she discusses two ways in which these two disabilities are similar. First, several students with these disabilities have delays in skill automaticity. Automaticity is learning a skill to the point that the skill becomes automatic or second nature. An example of automaticity in mathematics is the expectation that students memorize multiplication tables. Second, both groups have delays when recalling or remembering the information. Among both groups of disabilities are students who have subtype profiles that are qualitatively different and not delayed. That is, some people with RD and MD are delayed in that they are performing at a level that is developmentally behind their peers, yet still along the same normal developmental path. Others are qualitatively different and not just behind developmentally.

Comparisons are often made between students with RD alone, MD alone, and combined reading/mathematics disorders (RD/MD) to establish shared attributes and those that are not (Benton, 2001; Fuchs & Fuchs, 2002; Rourke, 1993; Shafrir, Greene, 2001; & Siegel, 1994). Groups of normally achieving (NA) peers are often used in comparisons. Several of these findings shed light on unique difficulties math students have.

Shafrir and Siegel (1994) examine these three groups in an adult and adolescent population. Students qualify as RD if they fall below the 25th percentile on the WRAT-R reading subtest and above 30th percentile on the arithmetic subtest. Students who scored below the 25th percentile on the arithmetic subtest and above the 30th percentile on the reading subtest constituted the MD group. Students who scored below the 25th percentile on both measures made up the MD/RD group. Those considered as NA scored above the 30th percentile on both measures. The WISC-R and WAIS-R are used to determine that students fall within the low average to very superior ranges and are not slow learners. Using analysis of variance to examine differences among the group, they find that individuals with MD and MD/RD display a visual-spatial deficit when compared to their RD and NA peers.

Jordan and Hanich (2000) found that when students solved four types of problems (number facts, story problems, place value, and written calculation) the MD/RD group performed significantly worse on the tasks compared to NA peers. Further, the MD group only did worse at complex story problems when compared to the NA group. The RD group performed similarly to the NA group. Overall, both the MD/RD and MD groups significantly under performed the other two groups on mathematics related tasks.

Benton (2001) studied children with RD, MD, and RD/MD subtypes of LD on the Wisconsin Card Sorting Test, Tower of London, and Verbal Fluency tests. The Wisconsin Card Sorting Test assesses a person's ability to form abstract concepts. On this test, the subject sees four cards and determines a pattern by sorting the cards. Patterns can be identified on the cards from very simple concepts such as color or can be more difficult such as by shapes and or sizes. They are informed if they are correct or incorrect and progress until all cards have been shown or the subject completes the 6 potential way to group the cards (Spreen & Straus, 1991). The Tower of London is a nonverbal planning and problem test. In this test, subjects must look at a picture of the objects placed in a pattern on the right and in the fewest moves possible create that exact picture. The Verbal Fluency test determines a person's ability to produce words based on a letter of the alphabet or category.

According to Benton (2001), MD students perform worse on three of four Tower of London tasks. In addition, children with MD differ in their executive function patterns compared to their RD and RD/MD counterparts. Davis, Parr, and Lan (1997) find similar nonverbal strengths while comparing students with RD and students with MD. Interestingly, when examining students with learning disabilities in first and second grade, Geary (1990) found that those who are improving are ones with closer to normal developmental profiles. However, those who were not improving or seemed stuck at the same ability level had unique developmental patterns. This could suggest a reason for continued difficulties for these students with more unique developmental profiles.

RD/MD and Nonverbal Learning Disabilities

Fleischner and Manheimer (1997) identify two main reasons students struggle with mathematics. First, some students have comprehension problems with reading. Second, some students have difficulties in nonverbal reasoning and/or primary mathematics knowledge. Rourke and his colleagues have contributed much to the field of learning disabilities by studying nonverbal learning disabilities and their relationship to reading and mathematics disorders from a neurological perspective.

Rourke (1993) uses a plethora of assessment measures such as the Wechsler Intelligence Scale for Children (WISC), Wide Range Achievement Test (WRAT), and the Woodcock Johnson Psychoeducational Battery. He used various revisions of each of these tests as his studies span a number of years. Among the three main groups, he points out certain similarities between the group with RD and MD, stating that the group with RD typically has verbal deficits while the group with MD typically has nonverbal deficits, as measured by the discrepancy between VIQ and PIQ measures on the WISC-R. He states that “Older group [RD] children exhibit normal levels of performance on visual-spatial-organizational, psychomotor, and tactile-perceptual tasks; Group [MD] children have outstanding difficulties on such tasks” (p. 220).

For additional details related to differences between RD and MD, the interested reader is referred to several publications on RD and MD (Rourke & Del Dotto, 1994; Rourke & Fuerst, 1996). Rourke later changed the name of the MD group to NLD, or nonverbal learning disabilities. For the purposes of this paper, Rourke’s NLD group is referred to by his initial identification of MD.

The term “older” refers to children who are between 9 and 14 years old, while “younger” refers to children who are 7 and 8 years old. Rourke found that older MD students exhibited average to above average scores in the areas of psycholinguistics. Also, older MD children had more difficulty with novel, complex, and meaningful material when compared to the RD group. The older MD group “exhibits profound problems on nonverbal problem-solving tasks” (Rourke & Fuerst, 1996, p. 283). Further these students have difficulty learning these tasks when given feedback, even though, it would be expected that they could do this based upon their ability measures. Younger groups resemble older children in the MD group with the exception of psycholinguistic skills, which appear to be lower than that of older children, especially when rote memorization is required. In Rourke and Del Dotto (1994), they claim that these results can be generalized to adults.

More recent research continues to corroborate Rourke’s seminal findings. It is more and more common to see individuals discussed on the basis of the neurological processing (e.g. nonverbal learning disabilities) more so than calling it a mathematics disorder (Fuchs, Compton, Fuchs, Paulsen, Bryant, & Hamlett, 2005; Forrest, 2004;

Hendriksen, Keuhlers, Feron, Wassenberg, Jolles, & Viles, 2007).

Stability of subtypes means that a person's profile of multi-test battery scores does not differ when assessed again on the same or similar measures. Some have questioned the stability among some of the groups studied by Rourke and colleagues, suggesting that there may not be as much stability in students who do not have more pervasive disorders (Branch, Cohen, & Hynd, 1995; Silver et al., 1999). Thus, a person's scores on a mathematics achievement measure would be similar when tested again. According to Silver et al., (1999), visuo-spatial deficits may be the core deficit for students with isolated mathematics disorders, yet subtype stability is worse for the arithmetic only group. Jordan (1995) found three subtypes of mathematics disabilities among which are the visuo-spatial deficits, similar to the nonverbal deficit discussed by Rourke. Geary (1994) and Geary and Hoard (2005) discuss other subtypes commonly found in the literature.

Memory and MD

Geary (1994) describes semantic memory deficits and procedural deficits, both of which could be related to some sort of underlying memory deficit. Semantic memory deficits are those, which cause difficulties in fact retrieval and learning facts to the point of automaticity. Procedural deficits are those that are considered to be more problematic and pervasive. These types of difficulties for students cause faulty procedures that are learned with errors, and these students are more likely to use inappropriate development procedures. They appear to struggle with remembering the appropriate ways to complete certain problems. An oversimplified example of a faulty procedure might be to learn that a plus sign means to subtract instead of add.

Greene (2001) examines metamemory and other functional skills such as strategy generalization in 10 to 14 year-old children. These children are divided into four groups- NA, RD, MD, and RD/MD. Disabilities are determined by having 15-point (or more) discrepancies between the particular subtest and the other WRAT-R subtests. Thus, a person with RD scores 15 points lower (or more) than their arithmetic score is identified as having RD. For the RD/MD group, both the reading and mathematics achievement scores fall in the borderline range. She uses a metamemory instrument which has subtests that require a student to estimate their own memory, understand categorization, understand memory problems and find solutions to those memory problems, memorize pairs of words, and estimate the amount of time it would take to memorize a string of six of words. Using analyses of variance to compare the groups, Greene found those students with RD and MD performed worst of all the groups on the metamemory instruments. Although a combination of RD and MD causes the students to show poorer performance, no interaction effects are noted in the study. Further, students with MD were noted to have the poorest transfer of skills from instruction and practice to actually attempting the various mathematical tasks, essentially their application and generalization of math skills to the real world is poor.

Swanson investigated working memory and its effect on mathematics disorder over a long period of time (Swanson, 1993; Swanson, 1994; Swanson, 2006 & Swanson & Beebe-Frankenberger, 2006). Swanson (1993, 1994) investigated working memory in learning disabled and non-learning disabled children. He defines working memory as “the system of limited capacity for the temporary maintenance and manipulation of information” (Swanson, 1994, p. 190). Students are defined as having learning disabilities either by having scores that are one-half standard deviation below the mean or by having scores on the Wide Range Achievement Test-Revised (WRAT-R) that are below the 25th percentile for their age. It is important to note that while some of these students may be learning disabled, there is the possibility that some of these students could also be slow learners.

Normal achieving students are identified as having scores equal to or above the 50th percentile for their age. Students are excluded in both cases if their scores are due to “retardation, poor teaching, or cultural deprivation” (Swanson, 1994, p. 192). He used a variety of memory measures and found that students with learning disabilities have particular difficulties in several areas of working memory compared to normally achieving peers.

Further, Swanson (1994) found similar results and demonstrated that the differences in verbal working memory are not as discrepant from NA as are students considered to be slow learners, but were nonetheless discrepant. McLean and Hitch (1999) found that students with arithmetic difficulties were impaired on areas of spatial working memory and executive processing. More currently, Swanson & Beebe-Frankenberger (2004) note the effects of working memory still presently indicating that among first graders, working memory continues to be a major factor in children’s mathematical performance.

Walsh, Lowenthal, and Thompson (1989) evaluated scores from the WJ-Cognitive Battery to determine clusters of students between the ages of 5 and 14. These students were identified as LD based upon Public Law 94-142. Although, the purpose of the study was to determine the usefulness of the WJ-Cognitive Battery, findings suggested that the students demonstrated significant deficiencies in memory, especially short-term memory. In fact, these are the only areas that the mean score for subtests did not fall in the average range. These scores were significantly below the norm group for the measure. All of the subjects performed below average in achievement and were significantly below the norm group.

Geary et al., (1999) investigated first graders’ digit span scores, and found that “average IQ children with low arithmetic achievement scores have difficulties retaining information in working memory while engaging in a counting task” (p. 235). Furthermore, they demonstrated that students with both MD and RD and students with RD only exhibited higher numbers of retrieval errors than just the RD group alone. However, they also indicated that this might not necessarily be a working memory deficit, but might be a deficit in attentional capacity.

Retrieval and reaction time can be linked to working memory as well. Hayes, Hynd, and Wisenbaker (1986) found that students with learning disabilities had difficulty building facts into automaticity. In fact, they indicated that groups of learning disabled students as compared to normal achieving pairs had more difficulty in recalling basic facts and thus made more errors. In addition, these students were more variable when making those errors. Geary, Brown, and Samaranayake (1991) and Geary, Hoard, Byrd-Craven and De Soto (2004) find similar results in groups of first and second graders that are studied ten months after a previous study. When comparing NA and MD students, NA students were not as likely to rely on counting procedures, a less than optimum strategy when building automaticity, and are more likely to rely on memory for recalling basic facts in addition and subtraction. MD students still relied on the counting procedures and not on memory. According to Geary et al., (1991), this poor working memory not only affected retrieval, but it can also lead to errors in procedure such as counting errors - which can lead to memorization of wrong facts, e.g. 7 + 6 = 12. All of these compounded can cause difficulty for students struggling with math.

Beaujean, McGlaughlin, and Knoop (2003) examined college students with mathematics difficulties and found that there were specific tasks that are associated with number facility besides math-related items. These tasks include mental chronometric tasks, processing speed, and working memory.

In studies designed to look at the effects of time on students with and without MD, Alster (1997) and Jordan and Mantani (1997) demonstrated that students with MD in grades 3 through high school did better on tasks when their retrieval ability was not timed. Thus, both studies demonstrated that when doing algebraic and word problems, students who had MD performed more poorly as compared to the non-MD group when time was involved, but scored very close to the non-MD group when there is no time limit. Both studies inferred that some short-term memory and semantic memory difficulties might be the reason that timed tests discriminated between the groups. Jordan and Mantani (1997) demonstrated that this was especially true for people with specific mathematics difficulties instead of general academic difficulties.

There are several studies designed to identify groupings under the various subtypes of learning disabilities. However, several of these studies utilize clinical procedures to classify students. Clinical procedures vary based on the referring clinic. In this instance, however, clinical procedures included a clinical interview and appropriate psychological tests implemented, scored, and interpreted. Eventually based on this data, diagnoses were made. Empirical methods used to classify students are rare in the literature on math disabilities. Further, most of these studies that do apply empirical methods to classify data focus on younger populations, and there is some conflicting evidence regarding the stability of subtypes within the various groups that are studied. As one gets older, it is reasonable to assume that skills become less variable and have likely stabilized in terms of both strengths and weaknesses. For instance, it is very easy for college students to discuss what they know as their strengths and weaknesses. College students typically do not choose to major in an area they dislike or in which they are weak, but instead choose to major in an area they like or in which they are proficient.

Several of the studies specifically address struggles experienced by students with mathematics disorders. These struggles include memory deficits evidenced through such things as recalling information and remembering the procedures to gain information. According to Rourke and his colleagues, these struggles have demonstrated nonverbal/visual-spatial difficulties. Although learning disability studies demonstrate an obvious explanation for why students experience math difficulties, there are many reasons why students struggle in math. Assuming a person has to have a learning disability to struggle can be misleading, because there are several other reasons a person may struggle with mathematics. Such reasons include poor motivation, anxiety surrounding math or tests, attention difficulties, or low intellectual ability.

ADHD and MD

Some researchers include students with attention-deficit disorders in their analyses and discussion when studying LD subtypes. (Hendriksen et al., 2007; Hurley, 1997; Marshall, Schafer, O'Donnell, Elliott, & Handwerk, 1999; Rourke, 1993). While 3 percent of children in the United States have learning disabilities, approximately 35 percent of children with AD/HD have difficulties learning (Woodrich, 2000). Mayes, Calhoun, and Crowell (2000) studied a sample of 8 to 16-year olds with ADHD and non-ADHD. The group is set up to be as similar to those referred to clinics as possible. They found that the proportion of LD among ADHD students was significantly higher than the sample of students without ADHD. Mathematics had the second highest comorbidity with approximately 33 percent of the students with ADHD having MD diagnoses. This study defines LD by using a procedure found in the Wechsler Individual Achievement Test (WIAT) manual that uses a significant discrepancy at the .05 level between a student's FSIQ and WIAT subtest score (Mayes, Calhoun, & Crowell, 2000).

Sometimes research is completed using students with ADHD to see what their profiles look like against students with LD. At other times, studies addressed the comorbidity of these two disorders (Barbaresi, Katusic, Colligan, Bagniewski & Weaver, 2006; Riccio, Gonzalez & Hynd, 1994). According to Riccio et al., (1994) the comorbidity of ADHD and LD is so high that the two may be indistinguishable. This trend continues to be seen (Del'Homme, Kim, Loo, Yang & Smalley, 2007). Although, it can be argued if the two are indistinguishable or not, the point that ADHD concerns affect achievement must be explored when analyzing students struggling in math.

Marshall et al., (1999) examined MD and ADHD subtypes to investigate patterns in poor arithmetic performance among ADHD subtypes. To examine differences in 8 to 12 year olds with ADHD with and without hyperactivity as part of their diagnosis, these researchers used the Woodcock Johnson – Psycho Educational Battery-Revised (WJ-R) Math Calculation, Applied Problems, Letter-Word Identification, and Passage Comprehension subtests along with the Wechsler Intelligence Scale-Revised Edition (WISC-R) or Wechsler Intelligence Scale-Third Edition (WISC-III), Diagnostic and Statistical Manual for Mental Disorders-Third Edition (DSM-III), and educational criteria. Using records from the students' school files, the participants in this study were determined to have one of the two types of ADHD by either determining that they are diagnosed by the doctor or diagnosed as Other Health Impaired in the school system. Results indicated that students with ADHD without hyperactivity had more difficulty with arithmetic calculation than students with AD/HD and hyperactivity. Further differences were noted between these two groups in terms of the WISC’s Verbal Intelligence Quotient (VIQ), Performance Intelligence Quotient (PIQ), and math problems in general, but not reading problems.

In the previous study, Mayes et al., (2000) evaluated groups of students that conformed to one of four groups: LD and ADHD, LD without ADHD, ADHD without LD, and no LD or ADHD. They found that attention affects all three of the groups of students with disabilities, and that students with ADHD had significantly more learning problems than the group without ADHD or LD. Among the three groups with disability diagnoses, attention problems were most prevalent in those with combined LD and ADHD followed by those with ADHD only and LD, respectively. Thus, the presence of ADHD with LD exacerbated the difficulties with attention, and thus, learning became more difficult. Mayes Calhoun, and Crowell (2000) conducted a similar study examining WISC-III profiles of children among the four groups. Again, they found difficulties in tasks pertaining to attention. In particular, they found that all groups of LD and ADHD children had significant discrepancies between the Freedom from Distractibility (FD) factor score on the WISC-III. This difference was not present for the students without disabilities.

Mathematics Disabilities and College Age Students

Many students who have suffered from learning disabilities in high school have lower aspirations for attending college compared to students without learning disabilities. While these students with learning disabilities may be hesitant to go to college, some students are attending college without an identified learning disability and are struggling in math (Walker, 2008).

At the time this dissertation project began, literature was scarce regarding college students with mathematics difficulty. McGlaughlin, Knoop, and Holliday (2005) examined the extensive amount of literature previously discussed to examine if findings based on elementary and secondary age students is applicable to students at the college level. Utilizing a multiple analysis of variance to compare commonly noted difficulties at these levels, they found statistically significant results that distinguished groups of students diagnosed with MD as opposed to those with ND on reading comprehension (WJ-III Passage Comprehension), nonverbal reasoning (WAIS-III PIQ), and Working Memory (WMS-III WM and WJ-III Math Fluency). No statistically significant results distinguished the two groups when attention deficit concerns were noted.

While literature on college students struggling in math is still scarce, published studies are starting to analyze each of the separate issues discussed in McGlaughlin et al., (2005). While these issues have been discussed earlier, the general findings of these studies related to college students are presented below. Utilizing cluster analysis, Osmon, Smerz, Braun and Plambeck (2006) identified three subtypes of college students struggling with mathematics. The three subgroups after controlling for variations in g (general intelligence) were a spatial functioning subgroup, an executive functioning subgroup, and a combined double functioning group. Cirino, Morris and Morris (2007) indicated that nearly 30 percent of variance in math calculation and 50 percent of variance in math reasoning scores of struggling college students could be determined by semantic retrieval and visuospatial skills.

Methods of Profile Analysis

The emphasis of this study is on profile analysis methods and their tendency to group data based on level, shape and scatter. Therefore, the pertinent issues among the three types of profile analysis methodology, including their strengths and weaknesses, must be addressed.

Cluster Analysis

According to Hair and Black (2000), cluster analysis is a procedure that categorizes objects, people, or data (hereafter called elements) based on certain characteristics that make them similar. Cluster analysis is used to empirically determine which elements belong in what group by maximizing the between-cluster variance relative to the within-cluster variance (Dillon & Goldstein, 1984). Cluster analysis classifies elements into groups based on their similarities on multivariate data sets (Gore, 2000). The procedure examines differences among the elements when determining cluster membership. Further, cluster analysis is similar to discriminate analysis except that it is not concerned with the optimum variables to discriminate elements in a group, which already are considered to be similar a priori by the researcher. Thus, cluster analysis is used to create groups of elements based upon similarities and differences on observed variables.

The two major types of cluster analysis are hierarchical and k-means (or nonhierarchical) cluster analysis. Hierarchical analysis can provide direction for where to begin the analysis for k-means procedures. Hierarchical analysis procedures utilize all of the variables on which objects are measured and then combines this data using a specified measure of similarity, dissimilarity, or both (Hair & Black, 2000). Examples of similarity include distance measures. Using these procedures, all subject scores are analyzed in terms of who is most similar or dissimilar. Sometimes procedures use a combination of similar and dissimilar measures to determine whom to combine into a group. This determination is made and the two subjects that are most alike according to the statistical procedure are combined. This process continues until the combination has been made that result in only one cluster. For example, suppose there are five subjects in a sample, each of whom has a score on one test. Initially, two people would be combined, which would yield four cluster groups- one group of two and three groups with one individual in each group. Then, those four groups are combined to make three. These three groups may consist of two groups of two subjects who were most similar and one group consisting of one subject. All combinations are statistically derived based on the most similar individuals being combined in groupings. Eventually, the process is completed when there is only one group. No matter how many individuals are in the data set, the hierarchical procedure will always end with one cluster group and proceed from each individual as a group to one cluster, with every step in between being accounted for by a new combination of clusters. In the group of five elements discussed earlier, hierarchical procedures combines to make a group of four clusters, then a group of three clusters, a group of two clusters, and eventually one. With a sample of ten subjects, the groupings would proceed from nine clusters, then to eight, and so forth until just one cluster was created.

It is important to note that there is several statistical measures one can apply to determine similarities and/or dissimilarities among groups. Correlation coefficients, distance measures, association coefficients, and probabilistic similarity coefficients can be used. Depending on the measure one chooses to determine clusters, results can vary based on statistical principles associated with the statistical measure chosen (Aldenderfer & Blashfield, 1984; Jobson, 1996).

Once the hierarchical procedure is run, the results can be used to narrow the field to determine a statistically optimum number of clusters. A preliminary analysis to check for the statistically optimum number of clusters is conducted. This can be done by graphing Amalgamation coefficients against the number of clusters formed at each stage in the hierarchical procedure. An Amalgamation coefficient represents the within-group variance. Within-group variance measures the similarity between the members of a particular cluster or group. Thus, the larger the number, people in the cluster group are more similar. The Amalgamation coefficients are graphed against the number of clusters formed to look for a marked flattening. Essentially, this procedure is analogous to the scree plot in factor analysis (Aldenderfer & Blashfield, 1984). Also, statistics known as the Pseudo-t, Pseudo-F, and Cubic Clustering Criterion can also be used to help determine optimal number of clusters (Sarle, 1983).

K-means analyses, or iterative partitioning methods, are two-stage cluster analyses. This procedure calls for the researcher to determine beforehand the number of clusters that will be tested, or the estimated centers of a specified number of clusters. Using either the number of clusters to compute the centers or the estimated centers of a number of clusters, the analysis begins. These estimated centers are called seed points. Once this step is complete, the computer assigns data points to each of the clusters' seed points, and thus, the seed points become centroids. Seed points and centroids are very similar, a seed point is a predetermined center based upon the estimations of the researcher; whereas, centroids represent the mean position of items in a group that change as members enter and leave groupings. The centroids are not computed until running an entire iteration. Then, the centroids are recomputed (Aldenderfer & Blashfield, 1984).

Thus, as the data has been run through one time, there may be a need to reassign some data points as they might fit better into clusters with newly computed centroids. K-means refers to the types of passes made through the data and is unique in that it allows for data points to be assigned into or out of clusters based upon the center points computed throughout the process. Thus, the uniqueness of k-means passes occurs after a centroid is computed. A k-means pass is the reassignment of cases to clusters with the nearest centroid or center point of data. There are two types of k-means passes: combinatorial or noncombinatorial. In combinatorial, the data is recalculated when a new member is added or removed. In noncombinatorial, the data is all recomputed after an entire run through of the data and all cases are assigned to a group. K-means passes allow for members that are once a part of a cluster to be removed because they no longer are similar to that cluster (Aldenderfer & Blashfield, 1984; Jobson, 1996).

As the computer cycles through all the data, cases are reassigned to the cluster they fit best by using shortest distance computed from the centroid of the cluster. The procedure is only complete after an entire iteration is completed and individuals and/or groups have remained stable or there is little or no movement among groups. The final cluster centers are computed and then Euclidean distances give indications of how different each cluster is from the other clusters (Aldenderfer & Blashfield, 1984; Jobson, 1996).

When using cluster analysis, one must choose whether or not to use hierarchical or non-hierarchical procedures.

According to Hair and Black (2000), larger pools of data require non-hierarchical analyses because hierarchical procedures are more sensitive, and hence are likely to make more flaws with this type of data. Further, they state that hierarchical analyses are more sensitive to outliers and that the procedures can be misleading due to less than optimal early connections. Gore (2000) suggests that a major flaw of hierarchical analyses is that “once an object is clustered in hierarchical methods, it cannot be reassigned to a ‘better fitting’ cluster at some subsequent stage of the process” (p. 313). Because hierarchical analyses are more sensitive to outliers as well as larger data sets and are unable to reassign subjects, a non-hierarchical or k-means analysis is used in the final process of analyzing and refining the data. Furthermore, a k-means analysis fits better with the theory and research questions analyzed in this study when compared with hierarchical analysis.

Because of some of the flaws of running k-means analysis exclusively (such as determining the number of clusters that would be optimal), hierarchical cluster analysis is used to provide information on an optimum number of clusters to use in the k-means procedure. The hierarchical analysis is used to determine an appropriate number to enter in the k-means procedure. Statistical packages available on computers are typically needed to conduct a cluster analysis, as hand calculations would be tedious and cumbersome.

Modal Profile Analysis

Modal Profile Analysis (MPA) is a statistical procedure that determines similarities and differences among groups of people by determining which profile patterns (or shapes) of subtest scores occur most frequently in a multi-test battery. Essentially, individuals' patterns of scores or profiles are compared with other individuals' profiles and this comparison determines the most frequently occurring profile patterns (Pritchard, Livingston, Reynolds, & Moses, 2000; Skinner, 1977, 1978, 1979; Skinner & Jackson, 1977; Skinner & Lei, 1980).

When completing data analysis, if scores are not on the same scale, they should be standardized because not all obtained scores share the same metric. For example, Personality Assessment Inventory scores are measured using T scores with means of 50 and standard deviations of 10;

whereas, WAIS-III, WJ-III, and WMS-III scores all have standard scores of 100 and means of 15. These standardized z scores allow for all variables to be evaluated using the same metric. Once this is completed, relatively flat profiles are removed. Flat profiles occur when there is little to no variation in individuals’ relative profiles and hence, their shape is flat. Researchers define what is considered a flat profile differently depending on the nature of their analysis and the data being used (Pritchard et al., 2000).

Once flat profiles are removed, correlational data among all participants results in a participant-by-participant matrix. This matrix is then submitted to factor analysis. Analyzing the factor analysis results, one can determine the number of modal profiles and the characteristics of those modal profiles (Pritchard, Livingston, Reynolds, & Moses, 2000; Skinner, 1977, 1978, 1979; Skinner & Jackson, 1977; Skinner & Lei, 1980).

Once the modal profiles are determined, individuals are identified who load positively and negatively on each factor. Positive loadings are separated from the negative loadings to form two subgroups of a factor. The positive factor loadings are the modal profiles and the negative factor loadings are the mirror image of that modal profile, but are still called modal profiles. Using these positively and negatively loading participants, one can compute the average scores for all subjects within each variable and obtain the shapes of these profiles. To ensure that the average scores best reflect the data, individuals' scores are weighted. Thus, if one person loads .95 and another .74, the person with the .95 weighs more heavily into the final average score that is used to construct the modal profile for the group (Pritchard et al., 2000).

Configural Frequency Analysis

Configural frequency analysis (CFA) is a multivariate statistical procedure used to interpret data, the purpose of which is to determine patterns that occur more or less frequently than would be expected by chance (Stanton & Reynolds, 2000; von Eye, 2002; von Eye, 1990; von Eye, Spiel, & Wood, 1996). Typically, CFA is used to interpret categorical data. Categorical data is information or qualitative data used to compare information based on categories. Male vs. female or republican vs. democrat are both categorical type comparisons. The procedure can be manipulated to analyze data that was not originally categorical. For example, WAIS-III examinees can be categorized as having either a weakness or not having a weakness in a specified area (Stanton & Reynolds, 2000).

When using CFA procedures, “types” and “antitypes” are statistically derived. Types are those configurations of scores, which indicate patterns that are more likely than would be expected by chance; whereas, antitypes are those configurations of scores that are less likely than would be expected by chance. These types and antitypes are derived based upon loglinear methods, which determine approximate proportion estimates of what are typical or expected frequencies. In some cases, researchers can forgo using the loglinear method to determine expected frequency and indicate their own percentages based on standardization or control group data that has already been collected (Stanton & Reynolds, 2000; von Eye, 2002).

Stanton and Reynolds (2000) indicate that they apply CFA from a perspective that more closely resembles clinical practice instead of how CFA has been previously researched. They claim they are taking an approach more akin to what clinicians apply in practice. They are analyzing people’s relative profiles to determine areas of weakness and from that, they determine their subtypes. They argue that this is similar to clinicians who determine diagnoses based upon scores (e.g. a person with a significantly higher IQ than achievement area has a relative weakness in that achievement area and can be diagnosed with a learning disability). The current study is designed to utilize CFA in a manner similar to procedures used by Stanton and Reynolds.

Stanton and Reynolds (2000) argue that comparisons of strengths and weaknesses would be optimum in their data set, but explain that adequate sample size would be needed to do this. In their study, sample size is also small and hence, only analysis of weaknesses and non-weaknesses are explored.

A weakness is defined as scores that are one standard deviation or more below the participant’s own mean. A non-weakness is any score tat does not meet the definition of a weakness. These scores are all relatively determined and the researcher utilizes each participants’ own mean to determine if their score is coded as a one (weakness) or zero (non-weakness).

Methods of Profile Analysis and Relevant Research

Because there is little to no research on mathematics disabilities with MPA or CFA procedures, their particular strengths and weaknesses are analyzed using research pertaining to the methodology itself, or research done analyzing other data (e.g. IQ score analyses).

Cluster Analysis

To date, studies have defined subtypes of learning disabilities using DSM-IV TR diagnoses and/or other non-traditional means to categorize and then compare students based upon these categories. Although these are perfectly acceptable ways to categorize and compare students, there are statistical ways to categorize and compare students on scores. Studies that use cluster analysis to compare students with learning disabilities, specifically mathematics disabilities, are examined.

Several studies examine participants with all three disorders, RD, MD, and WD. Using a myriad of statistical procedures such as analysis of variance and factor analysis, participants are compared on measures to determine what distinguishes them from other subjects and separates them from normal achieving peers (Geary, Hoard, &

Hamson, 1999; Hurley, 1997; Shoemaker, 1993; Silver, Pennett, Black, Fair, & Balise, 1999). Interestingly, many studies looking for subtypes in the LD population also find groups of students labeled as LD that actually have more normal subtype profiles (Hurley, 1997; Kulak, 1993; Shoemaker, 1993; Silver et al., 1999).

Hurley (1997) examined groups of students with LD and without LD while subtyping each group using the Woodcock-Johnson-Revised Edition (WJ-R) Cognitive and Achievement measures. From these groupings, she discusses three main subtypes, one in the non-LD group and two in the LD group. She identifies these subtypes as two with profiles more similar to normal achievers (an LD group and a non-LD group) as well as one LD group with verbal deficits. Hurley examines the subtypes of the groups prior to performing the analysis. Thus, her subtypes already existed when analyses were run. The comparisons that were made have to be examined with the understanding that she had defined subtypes a priori.

Using hierarchical cluster analysis, Ward, Ward, Glutting, and Hatt (1999) derive a five-cluster solution of students based on WISC-III and the Wechsler Individual Achievement Test-Second Edition (WIAT-II) scores. Using an ability-achievement discrepancy model, 201 subjects are selected from a large urban school district’s referrals for one year. These subjects met the criteria for a learning disability and are selected for this procedure. No significant differences are noted on aspects such as race and gender between all the referrals, and the 201 who met the qualifications to be included in their study. Five cluster groups are derived from this study.

Among the five clusters identified by Ward et al. (1999), two cluster groups score close to normal achieving peers and are identified as difficult to describe. Two cluster groups have ability-achievement discrepancies, which are significant at the .05 level. All members of this cluster have average FSIQs. The other cluster group with significant ability-achievement discrepancies demonstrates, on average, 31-point discrepancies between the VIQ and PIQ, which are considered unusual in the general population. The final group is identified as having suppressed scores in all areas including FSIQ, and was labeled as slow learners.

Maller and McDermott (1997) examined 194 college students with LD attending a Southwestern university. They ranged in age from 17 to 25 and had approximately equal numbers of male and female participants. Only 9 percent of the population studied represented minority populations. LD Diagnoses of LD were determined based on WAIS-R and WJ discrepancies. The subtypes found in the college students with LD are similar to those found in the standardization sample of the WAIS-R. Among these categories include students with WAIS-R profiles that are overall high in all areas; overall above average with a higher VIQ than PIQ; overall above average; slightly above average in all areas with VIQ higher than PIQ; average; slightly below average with a higher digit symbol copy score; slightly below average in all areas; below average; low; and unique. The unique profiles consisted of 6 percent of the population. Based upon this data, most of the college students' subtypes fell into one of the profiles already identified in the normal population.

Using the WISC-III, Yuan (1999) used k-means cluster analysis to determine subtypes of LD profiles on the WISC-III for white, non-Hispanic students in grades K through 8. A criterion of 1.5 standard deviations between a standardized ability and achievement measure is used to determine if the students meet requirements for LD. Further, their disorder defines as not being caused by environmental, cultural, or economic disadvantages, and the discrepancy is unable to be corrected through regular education programs and/or visual or hearing aids. These determinations are made at school by IEP teams. For this research, the achievement measures chosen varied, but the tests were accepted standardized methods within the school. However, all participants selected were given a WISC-III. This research yielded several important findings. First, the group of LD students performed relatively highly on Object Assembly, Picture Completion, Picture Arrangement, and Block Design. They scored relatively poorly on Digit Span, Arithmetic, and Coding. Furthermore, nearly 50 percent have significant discrepancies between VIQ and PIQ, of which 18 percent are uncommon to the general population.

Bender and Golden (1990) use hierarchical cluster analysis to classify 57 students with LD into groups. Classification was based on their scores on the WISC-R, WJ, Piers-Harris Children’s Self-Concept Scale, Walker Problem Behavior Identification Checklist, and the Weller-Strauser Adaptive Behavior Scale. These children are in grades three through nine and are randomly selected from 43 different class rosters for the perceptually or neurologically impaired. There are 37 boys, 20 girls, and approximately 12 percent were from minority populations.

Based on their results, Bender and Golden (1990) find a five-cluster solution. In this solution, 37 percent of the subjects had fairly flat profiles in that they have no significant strengths or weaknesses. Roughly 25 percent of the subjects formed a group with visually based deficits. Interestingly, this group also has the highest scores on the acting out behaviors with the exception of one cluster that is behaviorally disordered. Approximately 23 percent of the group had language-based deficiencies. Bender and Golden (1990) describe a fourth cluster of approximately six percent of the subjects as the “I’m OK” group (p. 188). This group appears to have deficits of both visual and verbal reasoning, especially in the verbal reasoning area, but scores the highest on the behavioral indicators. Thus, although their scores are low, they appear to have relatively adaptive behaviors. The final cluster is a group of students with scores above everyone else in terms of academic measures, but below everyone in terms of behavior measures. These students make up the group of behaviorally disordered students.

Thus far the discussion has focused on applying cluster analysis procedures to determine subtypes of individuals based upon their performance on various instruments. Using this information helps gain insight into particular strengths and weaknesses of individuals and groups of individuals with mathematics difficulties. However, it is also important to examine strengths and weaknesses among the methodology itself.

Strengths and Weaknesses of the Cluster Analysis Approach. Researchers who have used this procedure point out several strengths and weaknesses. According to Hair and Black (2000), cluster analysis allows for "identifying latent patterns suggesting useful groupings (clusters) of objects that are not discernible through other multivariate techniques" (p. 200).

Researchers always examine weaknesses and/or limitations based upon their analyses. Limitations noted by researchers in applying this method include the idea that a common rule of thumb must be followed when selecting the number of variables to analyze. This rule is 10 subjects for every variable in the analysis. Thus, if someone wants to use 20 variables, he or she needs 200 subjects. Given this rule, this standard becomes difficult to meet with too many variables (Aldenderfer & Blashfield, 1984).

Another limitation of cluster analysis procedures is that it is still poorly understood. Different decisions and types of analysis can lead to very different results. As long as someone explains their decision trees and why they made the choices they did, this is a surmountable limitation of the technique, but it must be noted. Further, while the number of studies utilizing cluster analysis has grown, no clear-cut published guidance is available to help researchers determine all of the strengths and weaknesses of particular procedures (Aldenderfer & Blashfield, 1984; Hair & Black, 2000).

Modal Profile Analysis (MPA)

Moses and Pritchard (1996) utilize Modal Profile Analysis (MPA) with adults using the Halstead-Reitan Neuropsychological Battery. In this article, they did not provide a detailed description of all of the 18 modal profiles they found. Instead, they refer to future articles to explain more about the typologies found through their analyses.

Livingston, Pritchard, Moses, Haak, Marshall, and Gray (1997) applied MPA procedures to the Halstead-Reitan Neuropsychological Battery for Children with children ages

9 to 14. While extensive, their modal profiles are explained here because they explain, in detail, the results of their performance in simple terms that can be understood.

After an extensive neuropsychological evaluation with pertinent psychological data, Livingston et al., (1997) determined 8 subtypes existed in their data of children. These children presented because they were having behavior, academic, or both types of difficulty.

Livingston et al.,(1997) describe Modal Profile group 1a as individuals with had low-average IQ with consistent VIQ and PIQ scores and also had low-average achievement scores. Their math scores were lower than their language based scores. Modal Profile 1b (the mirror image of 1a) had average range intelligence, with PIQ greater than VIQ and achievement scores that were at the “low-end” of average (p. 475).

Livingston et al., (1997) describe Modal Profile 2a as having comparable VIQ and PIQ scores that are average, as well as consistent achievement scores that are average. They appear to be the least impaired groups. Modal Profile 2b had “a pattern of mild to moderate deficits involving motor speed, tactual performance, nonverbal auditory perception, and abstract concept formation" (p 475). They performed "at the low end of the Average range, with similar Performance and Verbal IQs" (p. 475).

Livingston et al., (1997) describe Modal Profile 3a as having average intelligence with PIQ well above VIQ, and achievement scores being low average with spelling being the lowest. Many students with ADHD fell within this group. Modal Profile 3b has average intelligence with comparable VIQ and PIQ scores and average achievement scores.

Livingston et al., (1997) describe Modal Profile 4a as having similar VIQ and PIQ that both fell at the "low-end" of average, as well as low average achievement scores (p. 475). A disproportionate number of males fall in this category. 4b was described as having average IQ scores; both VIQ and PIQ were similar. However, they point out that this was the only group where VIQ was "several points higher than PIQ (i.e., approximately 4 points) (p. 476). Their achievement scores were in the low average range. There was an overrepresentation of females in this group.

Henceforth, Livingston et al., (1997) describe 4 more modal profiles that and they do not describe the mirror image profiles in these instances. Modal Profile 5 is characterized by students with similar PIQ and VIQs falling at the “low-end” of average, with low average achievement scores (p. 476). Again, there is an overrepresentation of females in this group. They describe Modal Profile 6 as having “moderate to severe deficits across a variety of language and auditory based measures” with attention and concentration noted as possible weaknesses as well (p. 476). They describe Modal Profile 7 as having lower end average range IQ, with PIQ much higher than VIQ. Their achievement scores are in the low average range. Finally, they describe Modal Profile 8 as being “characterized by moderate deficits in abstract reasoning and language based abilities” with “relative strengths in nonverbal auditory perception and spatial memory” (p. 476). Their IQ scores were in the low average range, with PIQ much higher than VIQ. They had the poorest performance on IQ measures of all groups.

Moses and Pritchard (1996) chose MPA to analyze data from the Wechsler Adult Intelligence Scale-Revised (WAIS-R) to determine the amount of variance that is explained by profile shape, elevation and scatter. They analyzed this data in terms of both subtest profiles and factor profiles. They determined that between 48.1% (subtest profiles) and 65.9% (factor profiles) of the variance could be described based on profile elevations, with scatter accounting for much less (below 10%). While understanding the importance of profile level, they sought to determine the role of profile shape. They were able to distinguish 100% of the factor profiles correlated with one of four main profile patterns/shapes, which they found using MPA.

Pritchard, Livingston, Reynolds and Moses (2000) used MPA to help determine normative typologies for classifying students on the WISC-III. Applying this procedure with the WISC-III normative population, they determined four modal profiles. The four modal profiles are Elevated Processing Speed (average to high average Verbal Comprehension-VC, Perceptual Organization-PO, and Freedom From Distractibility-FD with Depressed Processing Speed-PS), Depressed Processing Speed (average to high average VC, PO, and FD with low average PS), VC > PO and Elevated FD (average VC > low average PO with high average FD, and average PS), and PO > VC and Depressed FD (average VC < high average PO, average FD, and average PS).

McGlaughlin, Knoop, and Margulies (2008) applied MPA to WAIS-III profiles in college students who were having difficulty with mathematics. They found two unique profiles as well as four similar modal profiles to those found in the Pritchard et al., (2000) study. The two additional subtypes found include elevated Perceptual Organization (PO) and Working Memory (WM) and Depressed PO and WM. Elevated PO & WM consisted of VC and PS approximately one standard deviation below PO and WM scores; whereas Depressed PO & WM consisted of PO & WM approximately one standard deviation above VC & PS. It is important to note that the WM is the adult equivalent to the WISC-III FD score. Of the 31 college students eventually diagnosed with MD from this group, 16 or more than half fell in this new modal profile group. Of the other 15, 8 fell in the VC > PO elevated FD (WM in the WAIS-III) group, providing evidence that some students who struggle with math did not have a unique profile.

Strengths and Weaknesses of the MPA Approach. Researchers who have utilized this procedure point out several strengths and weaknesses. Among the strengths noted is the emphasis on profile shape that is an essential feature of MPA. Thus, when researchers are most interested in shape alone, this might be the method of choice.

The fact that MPA can take into account the influence of shape alone is a strength, but so too is the fact that it can take into account all three issues important in profile analysis: level, shape, and scatter. Depending on decisions made, one can differentiate between two of the concepts (e.g. the influence of level vs. shape) (Skinner, 1978; Skinner & Lei, 1980).

Another strength is the fact that the method uses a person-centered approach (Davison & Kuang, 2000). This means that instead of looking at mean scores, each person’s data is analyzed statistically and correlated in a way that makes each person’s contributions weigh more into the statistical procedures. This method differs from procedures such as analysis of variance, where means are compared.

According to Kim, Frisby, and Davison (2004) and Davison and Kuang (2000), MPA may not be an adequate procedure when sample sizes are large. This is because the data sets become so large that it is very difficult to complete the procedures without splitting the data into two or more manageable datasets. Also, they indicate that it does not provide information in terms of both level and shape, and hence may not be as comprehensive as would be necessary.

Configural Frequency Analysis

Stanton and Reynolds (2000) select CFA to determine whether or not relationships exist among participants as units of analysis. They examined scores from the WISC-R standardization sample to determine the frequency of occurrence/base rate of an individual's coded profile configuration and compared it to a sample of students with learning disabilities.

Utilizing the subtests on the WISC-R, they determine profile patterns using systems of 0s and 1s to determine where weaknesses are, and code those patterns accordingly (1 for weakness, 0 for nonweakness). Then, they determine the percentage of times these particular profiles exist and compared the two groups (LD and Standardization Group). Examining this data, they determine which profile types on the WISC-R are types and which are antitypes (see previous discussion). The standardization/normative group is the expected frequencies and the LD group was the observed frequencies. From this data, they determined that two types existed. These types were students who had weaknesses on Arithmetic and Coding together and Arithmetic, Coding, and Digit Span together. Hence, these two profiles occurred more than would be expected compared to the standardization sample.

In a series in the journal *Applied Psychology: An International Review*, von Eye, Spiel, & Wood, 1996 write a lead article pertaining to CFA in applied research. From this article and several other researchers' commentary, issues pertinent to CFA research (as well as strengths and weaknesses of the model) are discussed.

Bergman (1996) and Krauth (1996) have argued about the usefulness of defining antitypes. Both agree that interpreting antitypes has suffered and is not nearly as prevalent as interpreting types. However, they disagree on whether or not interpreting them is useful. Bergman (1996) argues that it is useful to interpret antitypes and that they are central to CFA. Krauth (1996) states that "the concept of an antitype seems to be without any interesting interpretation"(p. 335). He argues that antitypes inherently exist when types are present and hence, one must only utilize the information gained from types (von Eye, Spiel, & Wood, 1996). Von Eye, Spiel, and Wood, 1996 reply to both, siding with Bergman. Basically, their reply explains a 2 x 2 analysis explaining that while one type might exist, an antitype does not inherently exist because a type is present. They focus on the fact that a type and/or antitype can statistically exist without the other being present and warn practitioners that claiming the existence of a type/antitype does not necessarily mean the other exists statistically.

Strengths and Weaknesses of the CFA Approach. Researchers who have analyzed this procedure discuss several strengths and weaknesses. Among the strengths noted is the inherent face validity that comes with applying this procedure. Stanton and Reynolds (2000) explain this strength as being what the researcher is always doing in the clinic. He or she is taking and analyzing the data to determine strengths and weaknesses and then determine from this profile of strengths and weaknesses what should be implemented and/or what diagnoses are given, and thus, the approach is very person centered (Bergman, 1996; von Eye et al, 1996).

Von Eye et al., summarize five strengths of cluster analysis. These are:

> 1. It allows one to analy[z]e data from a wide range of research designs; 2. it is available in both non-parametric and parametric variants; 3. it is easy

to calculate . . . and to teach (Aikin et al., 1990); 4. it allows researchers to pursue the person-oriented approach; and 5. it does not pose greater demands on the sample size than other multivariate methods. (p. 323)

Depending on the data and analyses used, the fact that a researcher is taking continuous data and narrowing it to categorical data is both a strength and a limitation (von Eye et al., 1996; Bergman, 1996). When categorical data is analyzed in this way it becomes similar to how clinical data is used and hence it is a strength. (von Eye et al., 1996). This is a weakness because at times, the data can be reduced to something too simplistic. Hence, important statistical power is lost when taking data and narrowing it to 2 or 3 choices (e.g. categorizing as strength/weakness). This is because the researcher has lost much of the variance inherent in the data when data is dichotomized (Bergman, 1996; Jensen, 1992; McDermott, Fantuzzo, & Glutting, 1990). Another way to look at this issue is the manageability of the data. According to Stanton and Reynolds (2000), an analysis of all possible scaled scores on the 19 subtests of the WISC-R would lead to 116,490,258,219 possible combinations (the 19 possible scores on the WISC-R to the 11th power). By simplifying this data to weakness/nonweakness, they narrowed the choices to two and hence, 2 to the 11th power or 2,048 choices. It is more manageable to compare 2,048 possible combinations than 116,490,258,219!

According to Bergman (1996), Krauth (1996), and von Eye et al., (1996) the fact that antitypes yield limited information is another weakness. Another limitation is the tediousness of calculations utilizing this method. Furthermore, some of these calculations are done by hand and hence, it is much easier to make a mistake in calculation (Stanton & Reynolds, 2000; von Eye et al.,1996).

Current Study

McGlaughlin (2004) compared clinical subtypes classified (using interviews to arrive at a DSM-IV diagnosis) with statistical subtypes classified utilizing a combination of hierarchical and nonhierarchical cluster analysis techniques. These statistical subtypes were determined utilizing the Wechsler Adult Intelligence Scale-Third Edition (WAIS-III) Verbal and Performance IQs, Wechsler Memory Scale-Third Edition (WMS-III) General

Memory score, Woodcock Johnson Achievement Battery-Third Edition (WJ-III.) Broad Reading, Calculation, Math Fluency, and Applied Problem scores, Personality Assessment Inventory (PAI) Anxiety score, Cognometer Working Memory Speed and Working Memory Capacity scores, Computer Based Academic Assessment System (CAAS) reaction time standard deviation trial two score, Conners' Adult AD/HD Rating Scales (CAARS) Total ADHD Index, and a clinically derived math exposure score. Clinical subtypes were affective disorders, attention-deficit disorders, learning disorders, and no diagnoses. Statistical subtypes were not similar. The two statistically derived clustered groups from this data included high average achievers and average achievers, where both groups exhibited relative discrepancies in math scores when compared to other observed data. These findings appeared to emphasize differences among level and results may have been a function of the actual method chosen to analyze the data. For that reason, two other types of profile analysis are used to analyze this same data set, because these two methods emphasize different profile characteristics. Through comparing and contrasting the differing patterns of subgroups identified by these three methods, the results should provide a clearer picture of which data analytic method(s) is more accurate in corresponding most closely to DSM-IV clinical diagnoses as determined by interview methods alone. From this research, individuals working with students struggling in college algebra can have a working knowledge base to help identify, and most importantly, help remediate these difficulties.

CHAPTER THREE

Method

Participants

Participants with Math Difficulties

The 207 participants in this study consisted of undergraduate and graduate students at a large Midwestern university who referred themselves to an on-campus assessment and consultation clinic for a diagnostic evaluation associated with difficulties experienced in math courses. The goal of the project is to help struggling students in mathematics gain an understanding of their difficulties and when appropriate, receive accommodations for whatever disability they might have through the university Office of Disability Services. For students who do not meet eligibility requirements for having a disability, recommendations are made to help them accommodate to their math difficulties. Occasionally intake data is missing for particular students. This occurs for a number of reasons, such as client/examiner failure to read a form properly, client/examiner failure to remember to report or ask information, or time constraints of the client. Of the two hundred and seven participants, seventyfive students are selected from this group because they did not have any missing data on variables that are used to classify the students. Participants ranged in age from 18 to 44, with a mean age of approximately 20 years. Each participant completed an average of 17 courses. The mean high school GPA for the sample is 3.18, with a range of 1.50 to 4.00. The mean college GPA is 2.82, with a range of 1.00 to 4.00. Of the 75 selected participants, 49 are female and 26 are male. Sixty-four are Caucasian, nine are African American, one is Hispanic and one is Native American.

Control Group Participants

The control group consisted of sixty undergraduate students at the same university who were given the same psychoeducational test battery and clinical interview as the participants in the clinical group. Participants were recruited from general education undergraduate courses. All control group participants met the following criteria: (a) they did not report math difficulties, (b) they had previously earned college credit for College Algebra, (c) they did not have a documented learning disorder, and (d) they did not have academic majors in a math-related field (e.g., math education, statistics, computer science and engineering). Of the sixty undergraduate students tested, fifty-five students are selected because they did not have any missing data for comparison purposes with the math difficulty group. Participants ranged in age from 19 to 24, with a mean age of 20.6 years. The mean high school GPA for the control group is 3.73, with a range of 2.88 to 4.33 (note: the age over 4.0 is due to AP/advance classes receiving higher weights at some high schools). The mean college GPA is 3.35 with a range of 2.30 to 4.00. Of the 55 selected participants, 48 participants are Caucasian, four are African American, and two are Asian American and one Arab American. Forty-seven are female and eight are male.

The control group did differ in examination in a few ways that are pertinent to this study, where CFA is concerned. While reiterated among the CFA portions of this analysis, the control group was not given The Computer-Based Academic Assessment System and/or math exposure scores. At the time the control group participated in the study, the CAAS had malfunctioned and a replacement was not available. They did not give math exposure scores because examiners did not include this as a part of their shortened structured interview.

Measures

Clinical Interview: Math Exposure Score

A structured clinical interview with each client is standard procedure at the Assessment and Consultation Clinic. For the purposes of this study, information was gathered on each participant’s background experience in math. Each client explained what math classes they had taken previously in middle school and high school. From inspection of these courses, a highest math exposure score was assigned. The highest math exposure score was derived from an ordinal scale that ranges from 0 to 9. These values reflect the remedial to advanced math courses that could be taken in most high schools in the state of Missouri. The math exposure score for each participant consisted of the number associated with the most advanced math class taken in high school. The ordinal scale consisted of 10 levels and is as follows: 0 = no math experience, 1 = Consumer Mathematics, General Mathematics, and/or GED Mathematics, 2 = Accounting and/or Business Math, 3 = Pre-Algebra, 4 = Algebra I, 5 = Geometry, 6 = Algebra II and/or Probability/Statistics, 7 = Trigonometry and/or

PreCalculus, 8 = Discrete Mathematics and/or other advanced math courses, and 9 = Calculus.

Wechsler Adult Intelligence Scale-Third Edition (WAIS-III)

The Wechsler Adult Intelligence Scale-Third Edition (WAIS-III) is a well-known and frequently used standardized and individually administered measure of general intelligence. It contains 13 subtests, which yields 4 index scores, a Verbal IQ (VIQ)score, a Performance IQ (PIQ)score, and a Full Scale IQ score. The VIQ score reflects an individual’s ability to answer questions and utilize verbal and memory skills to solve novel tasks. The PIQ score measures an individual’s ability to solve novel nonverbal or visual tasks such as completing parts to missing pictures and solving puzzle designs. Most subtests that make up the VIQ and PIQ scores enter into the Full Scale IQ score (FSIQ). Only the VIQ and PIQ are used in this analysis. The WAIS-III’s VIQ measure is a composite score derived from six subtest scores and the PIQ is a composite score derived from five subtest scores. According to the WAIS-III/ WMS III Technical Manual (The Psychological Corporation, 1997), the average split-half reliability for the VIQ and PIQ is .97 and .94

respectively. According to The Psychological Corporation (1997) the test-retest stability coefficients for VIQ, broken down by age groupings, range from .94 to .97. The test-retest stability coefficients for PIQ, broken down by age groupings, range from .88 to .92. Other measures on which criterion-related validity coefficients with the WAIS-III VIQ and PIQ have been reported include the Wechsler Adult Intelligence Scale-Revised (WAIS-R) FSIQ (.84 and .86, respectively), the Wechsler Intelligence Scale for Children-Third Edition (WISC-III) FSIQ (.88 and .77, respectively), and the Stanford Binet-Fourth Edition (SB-IV) Composite score (.78 and .89, respectively).

Wechsler Memory Scale-Third Edition (WMS-III)

The Wechsler Memory Scale-Third Edition (WMS-III) is a multidimensional memory scale, which measures both immediate and delayed memory of both verbal and nonverbal content for persons between the ages of 18 and 89. Further, general memory composite scores and subscale scale scores for each memory domain are provided. For this study, the General Memory score is used. The General Memory score is made up of the Auditory Delayed, Auditory Recognition Delayed, and Visual Delayed subtests. The average split-half reliability for the WMS-III General Memory (GM) score is .91. The test-retest stability for WMS-III General Memory score ranges from .87 to .88 depending upon age (The Psychological Corporation, 1997). The reported criterion-related validity for the WMS-III General Memory score reports correlation coefficients of .67 with the Wechsler Memory Scale-Revised Edition (WMS-R) General Memory and .67 with the Children's Memory Scale (CMS) General Memory score (The Psychological Corporation, 1997).

Woodcock Johnson Achievement Battery-Third Edition (WJ-III ACH)

The Woodcock Johnson Achievement Battery-Third Edition (WJ-III ACH) is a standardized individually administered achievement test that measures academic skills in reading, math, language usage, writing, and general knowledge. The WJ-III ACH consists of four broad area scores, each of which consists of 3 subtests. The WJ-III ACH is available in two psychometrically equivalent Forms (Form A or Form B). For the purposes of this assessment, only the Broad Reading area score (BR), and the three subtests, which comprise the Broad Math area score, Math Fluency (MF), Calculation (Calc), and Applied Problems (AP) scores, are used. Forms A and B of the instrument are administered in this study. According to McGrew and Woodcock (2001), the median split-half reliability coefficients for are .94 for Broad Reading, .90 for Math Fluency, .86 for Calculation and .93 for Applied Problems. Due to the speeded nature of the Math Fluency test, reliability estimates are computed using Rasch-analysis procedures, due to the inappropriateness of the split-half reliability procedure. Criterion-referenced correlation coefficients for Broad Reading are .76 with the Reading Composite score on the Kaufman Test of Educational Achievement (K-TEA) and .67 with the Reading Composite on the Wechsler Individual Achievement Test (WIAT). The coefficients for Broad Mathematics (BM) are .66 with the Mathematics Composite on the K-TEA and .70 with the Mathematics Composite on the WIAT. No specific validity studies are reported for the three component subtests of the BM area score, which is why the BM validity measure is reported.

Personality Assessment Inventory (PAI)

The Personality Assessment Inventory (PAI) is a 344-item self-report personality inventory that is standardized and used on participants 18 years and over and is designed for use regarding clinical diagnosis, treatment planning, and psychopathological screenings. It can be administered in a group or individual format. The PAI consists of 11 clinical scales, five treatment scales, and two interpersonal scales. For the purposes of this study, the Anxiety (ANX) subscale is used. Respondents are then asked to indicate their level of agreement from response options aligned on a four-point Likert scale. Response options include “false”, “somewhat true”, “mainly true”, and “very true”. Respondents are informed there are no right or wrong answers and that this is just their opinion of themselves. According to Morey (1991), the anxiety scale “items focus on phenomenology and observable signs of anxiety with an emphasis on assessment across different response modalities” (p. 2). The anxiety scale has such questions as: “it’s often hard for me to enjoy myself because I am worrying about things” and “I don’t worry about things that I can’t control.” (Morey, 1991, p. 179). Items measure constructs in the cognitive, affective, and physiological domains. The reported internal consistency estimate for the anxiety subscale is reported as a Cronbach alpha of .90. Test-retest stability is reported as .88. Several criterion-related validity estimates are cited for the PAI anxiety subscale, which range from correlation coefficients of .12 on the Fear Survey Schedule to .76 on the Minnesota Multiphasic Personality Inventory (MMPI).

Cognometer

According to Cognitive Diagnostics, Inc., (1995), the Cognometer is an experimental computer-based neuro-cognitive assessment tool. It is designed to provide data on intra-individual profiles (strengths/weaknesses) among subtests as well as treatment considerations for participants who are involved with the instrument. It is administered to one individual at a time and requires a student to sit down and complete 8 subtests on the computer. For each test, items appear on the screen and the examinee must respond by pressing an arrow key on the computer keyboard. These subtests consist of: Simple Reaction Time, Perceptual Reflexes and Thresholds, Cognitive Choice Reaction Time, Working Memory Speed and Efficiency, Inspection Time, Immediate Memory, Visual-Spatial Reflexes, Working Memory Capacity and Delayed Memory. The Cognometer records an individual's reaction times on each item in milliseconds. For each subtest, a mean and standard deviation of reaction times is computed.

From these subtests, memory, attention, speed, motor reflexes, and perceptual threshold scores are calculated. For purposes of the current study, two individual subtest scores were used. These are the Working Memory Speed (WMS) and Working Memory Capacity (WMC) subtests. In the WMS test, participants look at a cue word next to a picture. If the cue word describes the picture, they click yes and if not, they click no. A yes response corresponds with the left arrow key on the computer; whereas a no response corresponds with a right click on the arrow key. However, if a tone is heard at the same time that an item is presented (called a reversal cue), the participant is to provide the opposite answer. For example, if the word “dog” appears next to a picture of a dog, and the tone (reversal cue) is heard, then the examinee must indicate “no”. Participants are given a trial period to learn the test and then are given several items in the actual test. In the WMC, a participant sees varying numbers of letters for a few seconds and then sees another group of varying numbers of letters. The participant clicks the right arrow button for yes and the left arrow button for no. A yes response indicates that a letter in the first group is in the second; whereas, a no response indicates no letters in the first group appear in the second group. According to Cognitive Diagnostics, Inc. (1995), the reliability of the Cognometer in general is high under repeated measures designs. No specific coefficients are listed or given for the entire battery or specific subtests. No validity information is reported.

The Computer-Based Academic Assessment System (CAAS)

According to Cisero, Royer, Merchant III, and Jackson (1997), the CAAS is an assessment battery where stimuli presented on the computer that examines responses made by the examinee by either a microphone or button that is pressed. The CAAS permits researchers to design their own tasks in math and reading for computer administration and assessment of reaction time. For this study, a Triple Multiplication subtest was designed to measure mathematics fluency for three single or double digit multiplicands yielding products equal to or less than 100. Each subject is administered two trials consisting of 20 triple multiplication problems within each trial. Each problem consists of series of three single or double-digit numbers whose product is equal to or less than 100(e.g., 2 x 4 x 8 = ___ and 4 x 12 x 2 = ___). Within each trial, problems are balanced for difficulty so that one trial does not result in more difficult problems than others (e.g., 1 x 2 x 0 is easier than 2 x 12 x 3).

Four sample items and 20 test items per trial are administered to the subject, who says the answer into a microphone. As the subject says the answer into the microphone, the program emits a “clicking” sound indicating that the microphone was registered the vocal response. The computer then records the reaction time in milliseconds between the appearance of the problem on the screen and the respondent’s first vocal utterance. As the subject vocalizes the answer, the examiner indicates the correctness or incorrectness of the answer by pressing a corresponding button on an attached response pad. In the rare instance that the microphone fails to record the subject’s response, a “clicking” sound will not be heard after the examinee vocalizes the response. In this instance, the examiner can press both buttons simultaneously, which then deletes the item from the results. After the examiner records the correctness/incorrectness of the response, the next item is presented. For this subtest, mean reaction time and standard deviations of those times as well as the percentage of actual test items that were answered correctly represent subjects' scores. For the purposes of this analysis, the standard deviation time of Trial 2 (RTSD2) is utilized. The standard deviation is analyzed because individuals' with lower ability typically have higher standard deviations than higher ability students (Cisero et al., 1997).

Conners' Adult AD/HD Rating Scales (CAARS)

The CAARS is a 66-item self-report scale that measures symptoms of inattention, hyperactivity, impulsivity, and poor self-concept in adults over the age of 18. Four factor scores are derived from these constructs, including Inattention/Memory Problems, Hyperactivity/Restlessness, Impulsivity/Emotional Lability, and Problems with Self-Concept. Also, three Attention Deficit/Hyperactivity Disorder (AD/HD) scales are generated, including DSM-IV Inattentive Symptoms, DSM-IV Hyperactive-Impulsive Symptoms, and DSM-IV AD/HD Symptoms. In addition, Total AD/HD Index scores and Inconsistency Index scores are measured. For these scales, respondents answer a variety of items on four-point Likert scale (0-never, 1-seldom or rarely, 2-often or frequently, and 3 very much or very frequently). For this analysis, the DSM-IV Total AD/HD Symptoms scale scores are used. This scale consists of the DSM-IV Inattention Symptoms and DSM-IV Hyperactive-Impulsive Symptoms scales. Respondents whose T scores are below forty (meaning few reported symptoms) are considered to fall in the low range, respondents whose T scores are between forty and fifty-fall in the average range, respondents whose T scores fall between 60 and 69 are considered at-risk, and respondents whose T scores fall above 70 are considered to have clinically significant symptoms. For the CAARS, coefficient alphas range from .86 to .92, and the median test-retest reliability for the four factors is .89. Criterion validity is assessed on the basis of comparisons of matched samples of individuals with and without AD/HD (Erhardt, Epstein, Conners, Parker, & Sitarenios, 1999).

Procedure

Selection of Participants

All participants were evaluated at the university Assessment and Consultation clinic (ACC). A school psychology program graduate student under the supervision of a licensed psychologist evaluated each participant.

Participants are identified for evaluation in one of three ways. First, some students saw posted flyers or were informed by others. Second, based upon a prior student having been evaluated or some previous knowledge, some academic advisors at the university at which the student attends would recommend that advisees contact the clinic to inquire about the possibility of testing. Third, instructors and/or administrators in the mathematics department would encourage some students to participate. Once the participant demonstrated a need for assessment in a preliminary interview with either the ACC head psychologist or a post-graduate school psychology student, he or she is assigned a case manager who completed the assessment. As long as they were struggling with a math or math-related class, or struggled with math in general, and could provide the appropriate documentation (e.g., poor grades or low ACT/SAT scores in math), students were evaluated.

Evaluation

The complete evaluation battery requires 8 to 10 hours of completion time for each subject. The battery is usually administered in two to three testing sessions, each lasting

2 to 4 hours. Breaking up the assessment is done to eliminate mental and physical fatigue, as well as to accommodate for the schedules of both the evaluator and participant. The assessment procedure consisted of an initial interview, which lasted approximately 30 minutes. During this interview, informed consent is first obtained from each subject. Next, self-report measures (e.g., PAI and CAARS) were explained and given to subjects to take home. Information is obtained from the subject about a myriad of measures including the subjects’ opinions about their math performance in elementary and high school as well as their recent performance in college mathematics. Subjects also indicated their perceived difficulties of learning basic mathematics skills in elementary school, high school, and also at a functional level (e.g. keeping a checkbook balanced). After the initial interview, the evaluator gave the individually administered tests. The order of tests varied based upon the available time for the assessment procedure that day and the evaluator’s discretion. To be considered eligible for evaluation, the students needed to present evidence of having difficulties in mathematics courses. If a student did not have difficulties in math, they are referred to other sources of

help. The students are assessed by one of three school psychology program graduate students, working under a licensed psychologist who reviewed all information and had final approval in the designation of the final diagnosis.

The assessment procedure consisted of an interview that solicited relevant information, which included previous math problems in school, prior grades in math courses in middle school, high school, and college, as well as information pertaining to perceived difficulty with several math procedures completed both in school and out of school. Symptoms of AD/HD and other diagnoses are assessed as well during the interview. After the interview, all clients are administered the WAIS-III, WMS-III, WJ-III, PAI, CAARS, Barkley Scales, Conners' Continuous Performance Test (CPT), Cognometer, and CAAS. For purposes of this analysis, the CPT was not included in the analysis.

Based upon these assessments, a variety of clinical judgments were made utilizing DSM-IV TR criteria to determine each participant's diagnoses. These diagnoses are learning disorders, attention-deficit disorders, or anxiety/depressive disorders. Among the 75 participants, 26 received no diagnosis based on DSM-IV criteria. Table 1 denotes the four major categories of diagnoses and then, further delineates the subtypes of those diagnoses that are described in the results section.

Clinical Diagnoses

For each of the diagnoses made in the assessment procedure, the DSM-IV TR criteria are utilized. These criteria are described below.

ADHD. According to the DSM-IV TR (2000) AD/HD Predominantly Inattentive is characterized by six or more of nine inattention criteria being met for a period of six months or longer that are maladaptive for the person in more than one setting. These inattention symptoms can include failing to pay attention or giving close attention to detail, difficulty sustaining attention, not listening, avoiding tasks that require sustained mental effort, or being forgetful in daily activities. AD/HD Predominantly Hyperactive-Impulsive Type is characterized by six or more of nine hyperactive-impulsive characteristics being met for a period of six months or longer that are maladaptive for the person in one or more settings. These hyperactive-impulsive symptoms can include such things as often being fidgety or squirming, often leaving seats when it is not appropriate to do so, blurting out answers, always being active as if being “driven by a motor”, and often talking excessively. AD/HD Combined Type is simply meeting both the inattentive and hyperactive-compulsive criteria. AD/HD NOS is characterized by meeting some of the above criteria but not all of the above criteria in any of the categories, yet the AD/HD is still significantly impacting the individual (DSM-IV TR, 2000).

Affective Disorders. Generalized Anxiety Disorder (GAD) is characterized by anxiety and worry that is so excessive that it interrupts one’s daily functioning. The anxiety/worry is difficult to control and has to include at least “three additional symptoms from a list that includes restlessness, being easily fatigued, difficulty concentrating, irritability, muscle tension, and disturbing sleep” (DSM-IV TR, 2000, p. 472). Further, these symptoms are not caused by the use of a substance or medication that might elicit these effects and/or another disorder relating to another DSM-IV TR disorder. Dysthymic Disorder or Dysthymia is characterized by a depressed mood that has lasted for at least two years and is present more days than not observed by ones’ self and/or others. At least two symptoms among overeating/poor appetite, sleep disturbances/oversleeping, fatigue, poor self-esteem, poor concentration, and feelings of hopelessness must be present. No major depressive episodes have been present and the symptoms cannot be better explained by other impairments such as other disorders or DSM-IV TR diagnoses (DSM-IV TR, 2000). PTSD is persistently re-experiencing symptoms of a traumatic event in way that is maladaptive for more than one month and causes clinically significant distress (see DSM-IV TR, 2000, p. 468 for specific examples of this). These symptoms result in at least three symptoms that were not present before experiencing the trauma. Some examples include persistent efforts to avoid thoughts and feelings about the event and/or displaying a restricted range of affect. Also two symptoms of increased arousal should also be present. These might be such things as difficulty falling or staying asleep or difficulty concentrating (DSM-IV TR, 2000).

Learning Disorders. According to the DSM-IV TR (2000), “[l]earning disorders are diagnosed when the individual’s achievement on individually administered standardized tests in reading, mathematics, or written expression is substantially below what is expected for age, schooling, and level of intelligence” (p. 49). There is some flexibility in what constitutes “substantially below”.

However, this is typically between one and 2 standard deviations. One must also rule out the effects that other disorders might also have on determining disorders such as vision, hearing, and/or “lack of opportunity, poor teaching, or cultural factors” (DSM-IV TR, 2000, p. 51). Learning Disorders, NOS are for individuals who do not meet the criteria for any specific disorder listed in the DSM-IV TR, but do exhibit significant difficulties in areas that are inhibiting their ability to perform academically (DSM-IV, TR, 2000).

No Diagnoses. Individuals who did not receive a diagnosis because they did not meet DSM-IV, TR (2000) criteria are considered no disorder or no diagnosis.

Data Analysis

Profile analysis is the name given to a class of statistical procedures that classify individuals according to similarities and differences in their scores on a multivariate dataset. (Aldenderfer & Blashfield, 1984). Three forms of profile analysis used to analyze the data in this study are cluster analysis, modal profile analysis, and configural frequency analysis.

Cluster Analysis

For this analysis, both hierarchical and k-means cluster analyses were utilized together to determine an optimum cluster solution for the data (see discussion in previous literature review).

To run both types of data, hierarchical cluster analysis was used to determine the optimum number of clusters. Once the hierarchical procedure is run through SPSS version 11.0, the results can be used to narrow the field to determine an optimum number of clusters. A preliminary analysis to check for an optimum number of clusters is conducted. This can be done by graphing Amalgamation coefficients against the number of clusters formed at each stage in the hierarchical procedure. Essentially, this procedure is analogous to the scree plot in factor analysis (Aldenderfer & Blashfield, 1984).

An Amalgamation coefficient represents the within-group variance. Within-group variance measures the similarity between the members of a particular cluster or group. However, it is reasonable to expect that these numbers would always increase, as adding individuals will add to within-group variance. Thus, the Amalgamation coefficients are graphed against the number of clusters formed to look for a marked flattening. A marked flattening of the Amalgamation coefficients means that the addition of new members does not significantly increase the within-cluster variance. Thus, the optimal number of clusters is represented by the number of clusters present at the beginning of the flattening coefficient trend line (Aldenderfer & Blashfield, 1984).

To check preliminary analyses, the Cubic Clustering Criterion, Pseudo-F and Pseudo-T are statistics that can provide further evidence beyond the Amalgamation coefficient to confirm the optimal number of clusters. SPSS does not provide statistical measures to determine optimum clusters beyond the method discussed previously. Thus, a quick procedure using SAS data analysis software was run. Using the same methodology and choices as was used in SPSS, SAS procedures were run to obtain statistics that would guide the selection of an optimum number of clusters. The Cubic Clustering Criterion (CCC), Pseudo-F, and Pseudo-T statistics are computed to examine the optimum levels.

The Pseudo-F is similar to a one-way ANOVA utilizing an F-test to compare the between subjects variance to the total variance. Between groups variance in cluster analysis reflects the extent to which cluster groups differ from each other. Within subjects variance reflects the extent to which elements within the groups are similar. The total variance is the between subjects variance combined with within subject variance. Although the pseudo-F test is similar to one-way ANOVA, the significance levels for this statistic are not important. Instead, Pseudo-F is used to determine an optimum number of clusters by looking at the F values. A "traditional" F value is the ratio of mean square between groups over mean square within groups. The highest F value is considered indicative of the best cluster solution (Jobson, 1996; Sarle, 1983).

Adjustments to the Pseudo-F have to be made because of the number of F tests that are completed to determine an optimum number of clusters. This statistic is used to test each possible cluster solution with the previous cluster solution to determine the optimum number of clusters. Thus, this analysis for optimum number of clusters increases the chances for Type I error. To account for this increased chance of Type I error, Bonferroni adjustments are made (Sarle, 1983).

The Pseudo-t is analogous to a t-test. Again, it is called a pseudo-t test because of the amount of instances in which pairs of clusters need to be compared. All possible cluster groups are compared to determine optimum clusters. As such, the 15-cluster group is compared with the 14-cluster group, the 14- cluster group with the 13-cluster group and so on until each possible cluster has been compared with the surrounding possible clusters. Once each comparison has been made, the researcher examines the data to determine where marked numerical jumps occur. Where the highest numerical jump occurs, the researcher selects the higher of those two cluster solutions as optimal. For example, to carry out our 15 tests above, if only one marked jump occurs between 11 and ten clusters, the 11-cluster solution would represent the optimal cluster solution for the data set. Because comparisons are completed numerous times, Bonferroni adjustments are made to account for the increased chances of type I error (Sarle, 1983).

The Cubic Clustering Criterion (CCC) is derived using the adjusted R-squared and the expected R-squared. The R-squared value measures the goodness-of-fit of a measure. For this analysis, the R-squared indicates the proportion of the variance that can be explained by a given cluster solution. The expected R-squared is the estimated value of R-Squared. Adjusted R-squared is the actual value of R-squared that is adjusted due to the biased nature of R-squared to overestimate the variance explained by the cluster groups. This statistic is a way to control for the chance of R-squared being abnormally large due to the amount of tests conducted to find out the optimum number of clusters. Thus, using the CCC is another statistic to determine optimum number of clusters. The higher the value, the better the cluster solution is at explaining the data in terms of subtypes when compared to other cluster solutions. As values increase, this indicates a better likelihood that this cluster solution is different from having no cluster solution at all. As values go down, are lower or decrease, it reflects similarity to a condition of having no cluster groupings within the dataset. (Sarle, 1983).

K-Means Cluster Procedure. After determination of a statistically derived number of appropriate clusters, the seed points are entered into SPSS version 11.0 and the k-means procedure is used to analyze the data. Using these results, the assignment of subjects across clusters is then compared to the groupings as determined by clinical diagnoses to analyze the degree to which cluster membership corresponds with the clinical interview subgroup diagnoses.

Modal Profile Analysis (MPA)

Modal Profile Analysis (MPA) is a statistical procedure that determines similarities and differences among groups of people by determining which profile patterns (or shapes) of subtest scores occur most frequently in a multi-variable dataset (Pritchard et al., 2000). For each participant, standardized z scores (on all test scores in the dataset) are computed using SPSS 11.0 and relatively flat profiles are removed. These z scores are computed for all persons relative to the distribution within a particular test. Flat profiles occur when all of a person's scores are equal to or less than one-half standard deviation from the mean on all subtests. If all of a participant's profile scores are no more than 0.5 (or one-half) standard deviation different from the mean of each test's distribution, they are removed from the dataset and considered to be flat profiles. Since the purpose of MPA is to determine shapes that occur most frequently, it is important to remove these flat profiles since they add little variation to the data.

After the flat profiles have been removed, individuals' scores on all subtests are intercorrelated with the other individuals' scores using SPSS version 11.0. These results in a participant-by-participant intercorrelation matrix that is then submitted to principal components analysis and rotated using a varimax criterion to maximize loadings on one factor. These analyses were completed on SPSS version 11.0. (Pritchard et al, 2000).

From the results of the principal components analysis ran in SPSS, the profile shape that is characteristic of individuals who load positively and negatively on each factor becomes the "modal profile". The positive and negative loadings for each factor are both modal profiles and are mirror images of each other. So, a two-factor solution actually has 4 modal profiles. From these positively and negatively loading participants, the average raw scores for all subjects within each test variable can be computed by hand or using any spreadsheet or statistics package. The results of these average raw scores can be graphed, which provides a visual representation of the shape of these profiles. To ensure that the average raw scores best reflect the data, individuals' scores are weighted based on loadings. Thus, if one person's factor loading is .95 and another's loading is .74, the person with the .95 weighs more heavily into the final average score than does the person with the .74 score. This use of the different weighted scores is used to construct the modal profile for the group (Pritchard et al., 2000).

Due to their large sample size, Pritchard et al., (2000) split the data in half. However, this is not the case for this data set. Thus, there is no need to correlate groups and re-weight scores and form new modal profile scores as they demonstrated in their seminal article on MPA (See Pritchard et al., 2000 for details of this procedure). The next step is to compare the final modal profiles with individual scores through Pearson product-moment correlations. When this is done, an arbitrary critical value of 0.65 is used as a criterion level to determine if individuals are retained within a modal profile or dropped and not classified in this procedure. Pritchard et al., (2000) call this the MAXR criterion.

Configural Frequency Analysis (CFA)

Configural frequency analysis (CFA) is a multivariate statistical procedure used to interpret data, the purpose of which is to determine patterns that occur more or less frequently than would be expected by chance (Stanton & Reynolds, 2000; von Eye, 2002; von Eye, 1990; von Eye, Spiel, & Wood, 1996). All of the test battery data collected for this profile analysis method has been recoded based upon a weakness/nonweakness status and coded as either 1s or 0s. To do this, all participant standard test scores were converted to standardized z scores so relative weaknesses or ipsative profile weaknesses can be determined.

After this conversion, the mean score of each participant, relative to themselves, is computed and then each individual z score is compared to that individual’s mean z score. Any z score that is greater than or equal to one below the mean is coded a “1” (weakness) and any z score of -.9999 to +.9999 when compared to the mean is coded “0” or nonweakness. On the attention deficit scales, anxiety scales, and Cognometer and CAAS data, the definitions for “weakness” and “nonweakness” are reversed. On these measures, a weakness is actually one standard deviation above the mean since higher scores indicate clinically undesirable difficulties. With other scales, lower scores are indicative of difficulties. So for these scores where difficulty or weakness is actually a positive z score, the same procedure is used only that scores of plus one or greater (when compared to the mean) are coded as a one or weakness and any score of +.9999 to -.9999 is coded as a zero or nonweakness.

After these are completed, profiles codes are listed out based on each test battery's code. Each battery has a designated position (i.e., first, second, third, etc.) in the code string for each participant. Suppose, for example, that the WAIS-III verbal intelligence score is first, and the WJ-III mathematics fluency score is fifth in the code string. Hence, a person may be 10000000000, coded as having a weakness only on the WAIS-III verbal intelligence scale, a person coded 00001000000 has a weakness only in the mathematics fluency scale, or a person may be coded as 10001000000, meaning that they have weaknesses in WAIS-III verbal intelligence and WJ-III mathematics fluency.

Once the data has been coded in this manner for all 75 participants, then the frequency of each profile is compared to expected frequencies. Expected frequencies can be derived utilizing a control group of real data or loglinear methods, which can be used to estimate the proportions. However, in this instance, a control group has been analyzed and this group can be utilized as expected frequencies to compare with the mathematically struggling group's observed frequencies (Stanton & Reynolds, 2000; von

Eye, 2002; von Eye, 1990; von Eye, Spiel, & Wood, 1996). Because the control group was derived from the same population (college students at the same university), comparisons can be made from this “normative” group instead of using loglinear methods that estimate parameters. Then, the percentages for expected and observed frequencies are compared using the statistical test between two proportions (Dryer, 1979, p.384). This test produces a z-statistic that can be interpreted using one-tailed test critical values and comparing them at the $p < .05$ level (or z greater than or equal to 1.65). This means that the chances of this happening by chance alone are unlikely. One-tailed values are used because only weaknesses are being considered in this analysis. If analyses examined both strengths and weaknesses, a two-tailed measure would be used (Stanton & Reynolds, 2000).

To control for Type I error, Bonferroni adjustments are made for the amount of actual profiles that are being analyzed. For example, if 20 profiles exist, the alpha level of .05 divided by 20 to determine a new adjusted alpha level. In the analysis between the control and math struggling groups, Bonferroni adjustments are made 42 times for the 42 profiles being directly compared between the two groups (Stanton & Reynolds, 2000; von Eye, 2002).

From these z-statistics that are computed, types and antitypes can be determined. If a profile percentage is statistically significantly less than would be expected in the population, then it is classified as an antitype. If a profile percentage is statistically significantly more than would be expected in the population it is a type. For example, assume Group A has weakness only in the area of math calculation in 54 percent of their profiles; whereas, the Control Group has only 14 percent of their profiles with this weakness. When comparing Group A and the control group, a statistically significant difference is noted. Then, this profile of math calculation as a weakness is considered to be an antitype. Simply reversing the Group A and Control Group percentages to 14 and 54, respectively, and assuming the difference is still significant would be indicative of a Type (von Eye, 2002).

The entire test battery was not administered to participants in the control group. Thus, information from math exposure score and CAAS data was not available. For these particular profiles, all strength and weakness patterns that involved any of these were compared utilizing a log-frequency model that uses the actual cells to estimate expected cells. After this is computed, these scores are then entered in place of the control group frequencies and compared utilizing the Pearson χ^2 component test (von Eye, 2002). According to von Eye (2002), there are several tests that can be chosen; however, the component test is chosen because it is the most conservative of available tests (von Eye, 2002). Again, Bonferroni adjustments are made because this test is completed 15 times to control for error.

Determination of Optimal Statistical Method

In selecting the optimal statistical method for determining subtypes of individuals that correspond best with clinical subtypes, two separate analyses are run utilizing chi-squared analysis. For the first analysis, an optimal solution from each of the three profile analysis procedures will be compared to the clinical subtypes assigned to each individual at the clinic. This is accomplished through computing the percentages of individuals within each clinical category that correspond with each of the statistically derived profile analysis methods' optimal solutions.

Given the clinical diagnoses, Four logical clinical subtypes of people are identified: (1)”no diagnosis”, or those individuals who presented with difficulties but had no clinical diagnosis after diagnostic evaluation; (2) “math difficulties”, or those individuals that presented with math difficulties and after diagnostic evaluation were given clinical diagnoses of Math Disorder or LDNOS diagnoses related to mathematical difficulties; (3) “memory/attention related difficulties”, or those individuals who presented with math difficulties and after diagnostic evaluation were given diagnoses related to memory, attention, and/or hyperactivity concerns; and (4) “social/emotional difficulties”, or those individuals who presented with math difficulties and after diagnostic evaluation were identified as having difficulties such as anxiety/depression. By separating the clinical diagnoses into these 4 categories, the clinical subtypes can be compared to the profile analysis subtypes to see which match up best - by analyzing the percentages of people within each profile grouping solution that have given diagnoses.

For example, an outcome that would reflect 100 percent congruence would be one in which the profile solution yields four subgroups. Within each of these four subgroups, 100 percent of the participants within each subgroup would correspond to the same individuals assigned to each of the four clinical diagnoses. Here, profile subgroup one would include all participants who were assigned mathematics based diagnoses, profile subgroup two would include all participants who were assigned memory related diagnoses, and so on. Although this ideal situation is not likely to occur as perfectly as described here, the profile method that partitions the highest percentages of each of the four clinical diagnoses within its empirically derived subgroupings would be chosen as the optimal method. All clinical subtypes are based upon the pattern of scores an individual participant had on each of the measures, taken with clinical information and applied to DSM-IV TR criteria. Together, all of the clinical information is utilized to determine the clinical diagnosis given at the time of the participants' evaluation.

Statistically, each of the profile extraction methods will divide the total sample into mutually exclusive subgroups. By comparing the clinical diagnoses that each participant received within each statistically defined subgroup, one can determine which profile extraction method best aligns with the subgrouping method derived from clinical diagnostic decision-making alone. This can be achieved statistically by running chi-squared ratio analysis.

For example, in the chart below, the horizontal headings at the top refers to the subgroups extracted from the profile method. The far left column refers to the diagnostic subgroups.

Suppose Profile Extraction Method 1

identifies 3 subgroups:

	Subgroup 1	Subgroup 2	Subgroup 3
Diagnosis 1	10	2	1
Diagnosis 2	8	15	0
Diagnosis 3	1	3	13

This table will be computed for each of the three profile analysis methods. The method that yields the largest chi-square value (which in turn would yield the smallest probability) is the best solution. A significant chi-square value means that the empirically determined profile configuration is not independent of clinical diagnostic membership.

Upon completing these chi-squared analyses, it became apparent that configural frequency analysis and modal profile analysis results may have been too cumbersome. So, to compare all three methods consistently with the same statistical analysis applied to each form of profile extraction and to further determine which statistical methods best correspond with clinical diagnoses, each of the four sets of diagnoses are analyzed further. First, the clinically DSM-labeled subgroups are aligned individually vs. the other three groups so that there are 4 groupings for comparison:

-No Diagnosis Group vs. Other Three Diagnosis Groups

-ADHD Group vs. Other Three Diagnosis Groups

-Affective Disorders Group vs. Other Three Diagnosis Groups

-Learning Disabilities Group vs. Other Three Diagnosis Groups.

Among these four groupings, one is comparing the amount of participants who share a profile with at least one other member to the amount of members who do not share a profile with another individual. These four comparisons are completed three separate times, one for each of the types of profile analysis that are completed.

An example of one of these twelve comparisons that need to take place is below:

	Share Profile	Do Not Share Profile
ADHD	12	3
All Other Diagnoses	49	11

Once these twelve comparisons are created, chi-squared analyses are completed to determine if any of the relationships are statistically significant. If results are significant, an exact probability of the table can also be calculated.

A final analysis for the three remaining methods of profile analysis is completed to compare with three other 2 x 2 comparisons. In these 2 x 2 comparisons, mathematics disorder alone is compared to all other diagnoses and non-diagnoses. Each time, the number of individuals who share a profile with at least one other member is compared with the number of members who did not share a profile with one other member.

CHAPTER FOUR

Results

Data Screening

Before analysis is run, several procedures were completed to check for outliers and basic assumptions that must be met for multivariate analyses. Although checking for outliers is the preferred practice, all outliers for these data are accepted as extreme values because the participants reported with academic difficulties. In this type of research, it is reasonable to assume their difficulties may be due to extreme scores. Because the sample is not representative of the general population (only persons who struggle in math are included), some extreme outliers of both univariate and multivariate types might be expected. Outliers of both types are expected because the sample consists of students who are having difficulties and thus, one would reasonably expect that the students might have extreme values on one or multiple measures. Thus, this data should be generalized only to college students struggling with math and not to the general population. For that reason, outliers were not deleted. However, if univariate outliers do exist, data transformation must take place to ensure precision of the estimation of the regression weights. When the data was checked for outliers, no univariate or multivariate outliers existed.

The four main assumptions of multivariate analysis are normality, linearity, homoscadasticity, and independence of observations. To check for these assumptions, probability plots are examined in SPSS. Probability plots are used to compare actual with expected normal values.

Normality

The first assumption is that each variable in the analysis is normally distributed, or meets the requirements of normality. All variables are plotted against a normal curve and appear normal. Further, the kurtosis and skewness numerical values are checked and also appear normal. For this data set, all variables meet the assumption of normality.

Linearity

Second, participants' scores on the assessment data are checked to determine if the data meets the requirements of linearity. To check for the assumption of linearity, actual scores and predicted scores are compared on a bivariate scatter plot. If the plotted data points resemble the shape of a line via visual inspection, then the assumption of linearity is met.

Homoscadasticity

Third, the assumption of homoscadasticity is met when the data points fall near equally on both sides of the expected line of best fit. For all variables in this data set, visual inspection indicates that the assumptions of linearity and homoscadasticity are met.

Independence of Observations.

The fourth and final assumption is that participants' responses did not influence other responses on the assessment. This is known as independence of observations, and is assumed for this data analysis.

Clinical Diagnoses

Nineteen received AD/HD diagnoses (Two Not Otherwise Specified, or NOS; 12 Inattentive; Four Combined Type; One Hyperactive). Twelve received affective disorders (Five Generalized Anxiety Disorder; Six Dysthymic Disorder; One

Post Traumatic Stress Disorder (PTSD)). Thirty received learning disability diagnoses (10 mathematics disorders; 2 writing disorders; 1 reading disorder; and 17 NOS).

Cluster Analysis Results

Optimal Cluster Decision

A hierarchical cluster analyses was run to check for the optimal number of clusters to investigate in subsequent k-means analysis. The amalgamation coefficients plotted against the number of clusters formed at each stage in the hierarchical analysis are shown in Fig. 1. In Fig. 1, each red box represents the number of clusters. The x-axis represents the amalgamation coefficient. As this method is similar to a scree plot, and is meant only as an initial indicator, this is a visual inspection. The CCC, pseudo-F and pseudo-t analyses will help to determine if this visual inspection is correct or if the number of clusters needs to be revised. Visually, no apparent marked flattening occurs, however there is flattening beginning to occur from five to four clusters all the way to two to one clusters. The biggest change or most marked flattening appears from two to one cluster(s), preliminarily indicating two-clusters as the best fit.

Statistical analysis of the CCC, Pseudo-F, and Pseudo-t also indicates the presence of a two-cluster solution as optimum. Visual representations of the CCC, Pseudo-F, and Pseudo-t statistics are shown in Figures 2, 3, and 4. Milligan and Cooper (1985) state the largest value for CCC is indicative of the optimal number of clusters. For this data, CCC = 10.5, at 2 clusters, is the largest value and indicates that 2 clusters may be an optimum solution. Jobson (1996) states that the largest Pseudo-F value indicates the optimum cluster solution for the data. For this data, the highest Pseudo-F = 14.1 is found at 2 clusters and indicative of an optimum cluster solution. With the pseudo-t, the larger jumps between numbers are indicative of possible cluster solutions. So, the higher number of clusters in the two is selected (Jobson, 1996).

For example, if the largest jump occurs between 12 and 11 clusters, the higher number of clusters is selected, (e.g., in this example 12 is the higher number). In this data set, the largest jump occurs between one and two clusters, indicating that two clusters is optimum. SAS recommends using the statistical procedures in coordination with each other to determine the optimum number of clusters. Based upon the initial indicators and the corroborating evidence with the statistical measures of the CCC, Pseudo-F and Pseudo-t, the two-cluster solution is selected as optimum for analysis (Sarle, 1983).

Two-Cluster Solution

The number of individuals within each cluster, variable means within each cluster, and variable standard deviations within each of the clusters of the two-cluster solution are described in Table 2. In the two-cluster solution, the procedure divides the participants into two groups, and these two groups appear to be distinguished by level. The first group (n=32) has high performers and the second group (n=43) scores below the first group on all assessment measures. The difference between Cluster Group One and Cluster Group Two on WAIS-III VIQ is 14 points, and the difference between Cluster Group One and Cluster Group Two WAIS-III PIQ scores is 11 points. Cluster Group One’s scores are approximately ten points higher on each of the WJ-III achievement scores. General Memory scores are more similar across the two groups, however Group One scored five points higher. Group Two scores lower on Working Memory Speed and Working Memory Capacity scores and the Reaction Time Standard Deviation-Second Trial (RTSD2)score.

A higher number on the Cognometer and RTSD2 measures equates to poorer performance. The difference in scores for these measures is approximately 285 milliseconds for the WMS, 130 milliseconds for the WMC, and 2.6 seconds for the RTSD. Better scores in the areas of WMC and WMS indicate that they have better developed abilities to both hold and quickly recall information in working memory speed and capacity.

On the measure of anxiety, Cluster Group Two scored nearly 10 points higher than Cluster Group One, and is overall in the at-risk range of developing disorders related to anxiety. Cluster Group One fell in the average range on the measure of anxiety. AD/HD total symptoms are nearly equal and the difference is not significant, with Cluster Group One scoring three points lower. Lastly, both groups have near equal math exposure scores, with Cluster Group One being slightly more exposed almost one point higher, than Cluster Group Two. Essentially, Cluster Group One scores average to above average on several of the scores while the other group scores closer to average on most of the measures. Thus, Cluster Group One is referred to as “High Performers with Mathematical Discrepancies” (HP) and Cluster Group Two is referred to as “Average

Performers with Mathematical Discrepancies" (AP). The means and standard deviations for each of the variables are shown in Table 2.

In each cluster, subjects are assigned distances from the centroids. A centroid is the average point, three dimensionally, among the cluster groupings. These centroids continually change as members are added to cluster groups. Those subjects who are closest to the most prototypical member of a cluster group have the lowest distance from the center of the cluster. Means for each of the subtests after the clusters are formed give the best indication of where the cluster centroids are located (Aldenderfer & Blashfield, 1984). The means of each of the subtests included in the analysis are given in Table 2. An ideal member is the person who most closely identifies the scores that made up that cluster group. Scores of ideal members in the AP and HP group are given in Table 3.

When comparing the two groups, the cluster analysis procedure maximizes the difference between the conglomerate groups of scores. Thus, significant differences between the groups are expected, as this is the goal of the procedure, however this does not necessarily mean all the differences in variable means between cluster groups are statistically significant. SPSS compares the mean scores of all variables in both cluster groups using a One Way ANOVA. In this analysis, all the scores are significantly different from each other except the CAARS DSM-IV ADHD Total Symptoms scale, the Math Exposure Score, and the WMS-III General Memory scale. It is important to reiterate that this analysis is only to be used for descriptive purposes, as cluster analysis is designed to maximize differences. Thus, this is discussed to describe which of the variables are helping differentiate the groups.

Stability of Cluster Solution (Reliability)

McIntyre and Blashfield (1980) suggested a modified split-half sampling technique to estimate internal stability. They suggested using the same centroids as is computed in the original analysis, but recommended application to a split sample. Thus, to determine if the clusters have internal stability, the data is randomly split into two subgroups using SPSS. Using SPSS, the computer splits the group into two randomly selected subgroups with 53 percent (40 members)in one subgroup and 47 percent (35 members)in a second subgroup. The two-cluster group membership is generally replicated over both subsamples. The means of the clusters are similar in the split half samples. The distribution of the cases is similar; yet, more people appear in the high performing group in one of the two split half samples. The split half means of the HP and AP groups are given in Tables 4 and 5. Overall, the two-cluster solution split half analysis yields similar results to the analysis on the entire sample. In comparing the original analysis with the full group to the split-half analysis, only 4 members (2 from HP and 2 from AP) switch groups.

Modal Profile Analysis Results

Results of the MPA on the psychological assessment data produced six factors, which yielded twelve clusters of participants (i.e., a profile and its “mirror image” for each factor). Six clusters represented positive factor loadings, and six clusters represented negative factor loadings or mirror images of the positive factor loadings. Figures 5, 6, 7, 8, 9, and 10 represent the shapes of the modal profile groups with scores that need to be inverted so that all mean Z scores above 0 indicate positive or more desired performance and where all mean Z scores below 0 indicate negative or less desired performance.

Synopses of Modal Profile Types

In modal profile analysis, flat profiles must be removed. In this analysis no profiles were flat and so, all 75 participants remain for MPA. Utilizing MPA to group the factor index scores produced twelve modal profiles. Of the 75 participants, approximately 16% were assigned to MP 1a (n = 12), (b) 9% were assigned to MP 1b (n = 9), (c) 13.3% were assigned to MP 2a (n = 10), (d) 9.3% were assigned to MP 2b (n = 7), (e) 9.3% were assigned to MP 3a (n = 7), (f) 8% were assigned to MP 3b (n = 6); and (g) 6.7% were assigned to MP 4a (n = 5), (h) 6.7% were assigned to MP 4b (n = 5), (i) 5.3% were assigned to MP 5a (n = 4), (j) 5.3% were assigned to MP 5b (n = 4), (k) 2.7% were assigned to MP 6a (n = 2), and (k) 5.3% were assigned to 6b (n = 4). The modal profile groups are described below.

MP 1a. This group is at or below average in all areas except PIQ and General Memory. The weakest areas are in the WJ-III math fluency and the RTSD scores which are nearly one SD below the mean. So, when processing math facts they have difficulty quickly solving simple math problems and show wide variation in their response times. For example, they may answer 3 x 5 x 1 very quickly and 2 x 2 x 8 very slowly.

MP 1b. This group is at or above average in all areas except general memory. They have above average skills and their strongest skills are in completing simple math problems efficiently (WJ-III MF) and in completing the CAAS tri-level multiplication problem with little variation.

MP 2a. WJ-III Calculation and Applied Problems and the RTSD scores are slightly above average; whereas, the rest of the scores are below average. These individuals have more than one-half standard deviation below average scores in the area of VIQ, PIQ, WMS-III General Memory, and WJ-III Broad Reading scores. The General Memory and Cognometer Working Memory Speed and Working Memory Capacity scores are over one SD below average. Interestingly, these individuals had higher math exposure scores.

MP 2b. Individuals in this group score average to above average in all areas except WJ-III Calculation and Applied Problems, which are below average. They have high average scores(more than one SD above the mean) in the areas of WJ-III Broad Reading and Cognometer Working Memory Speed and Working Memory Capacity.

MP 3a. There is nearly a one SD difference between VIQ and PIQ, favoring VIQ. All scores except for WJ-III Broad Reading are below average. In fact, PIQ, WJ-III

Calculation, PAI Anxiety, and CAARS ADHD scores fall nearly one SD below average and appear to be areas of significant difficulty for these students.

MP 3b. There is nearly a one SD difference between VIQ and PIQ, favoring VIQ. Only WJ-III Broad Reading, Math Fluency and the CAAS RTSD scores are below average. The rest of the scores for these individuals are above average. Both Calculation and Applied Problems are above the mean 1.5 and 2.0 SD above the mean respectively. Overall, it appears processing mathematics quickly and efficiently when time constraints are involved is the most difficult thing for these individuals.

MP 4a. While both VIQ and PIQ are above average, there is nearly a one SD difference between VIQ and PIQ, favoring VIQ. Math scores on the WJ-III and reaction time measures on the Cognometer and CAAS are at least 0.5 SD above the mean and the Anxiety and ADHD scales are both elevated and nearly one SD above the mean.

MP 4b. These individuals have most scores below average but are not exhibiting significant signs of anxiety and/or ADHD as the scores are nearly one-half to one standard deviation below the mean. The capacity of Working Memory Capacity score on the Cognometer is above average, while the Working Memory Speed and CAAS RTSD scores are both well below average.

MP 5a. These individuals have more math exposure than is typical. Most scores in this group are between one-half SD above and one-half SD below the mean. Strengths for this group above one-half SD above the mean are the Working Memory Speed and Working Memory Capacity, while the CAAS RTSD is more than one-half SD below the mean.

MP 5b. These individuals have relatively low exposure to mathematics before college. They are exhibiting little signs of anxiety and/or ADHD symptoms (approximately 0.75 SD above the mean). They have WMS-III General Memory and CAAS RTSD scores well above one-half SD above the mean. The rest of the scores for individuals in this group fall between one-half SD above and one-half SD below the mean.

MP 6a. There is over one SD difference between the PIQ and VIQ, favoring PIQ. WJ-III Broad Reading corresponds with the VIQ scores, which is well below average. Math Fluency is more than one-half SD below the mean.

MP 6b. For this group, there is nearly a one SD difference between VIQ and PIQ, favoring VIQ. The WJ-III Broad Reading score is similar to the VIQ score and well above average at nearly one SD above the mean. The WJ-III

Math Fluency is also nearly one SD above the mean. These individuals also do not appear to exhibit significant signs of difficulty in the areas of anxiety and ADHD.

Configural Frequency Analysis Results

Before the configural frequency analysis takes place, it is important to review how the terms type and antitype are defined. Types are those configurations of scores, which indicate patterns that are more likely than would be expected by chance; whereas, antitypes are those configurations of scores that are less likely than would be expected by chance (Stanton and Reynolds, 2000; von Eye, 2002). In this analysis, of the 130 individuals examined in both the math difficulty group and control group, 57 total profiles existed. Of those 57 profiles, 42 could be compared among the groups because these profiles could potentially exist among the control group. Fifteen of the profiles are compared to the logarithmic estimates. These individuals had profiles that contained at least one score for the CAAS and/or math exposure measures. As the control group was not administered the CAAS or math exposure measures, this comparison could not be made among the groups. As a result, the math struggling group is compared to logarithmic estimates.

Control Group Comparison

In this analysis, the control group can be used as the population estimate. Hence the group experiencing math difficulties is compared to those expected proportions derived from the control group. In this comparison, if the group experiencing math difficulties has lower proportions of individuals with no strengths and weaknesses than the control group, then it is a potential antitype. Results indicate that when comparing the two groups, the tests of proportional statistical value $z=-3.48$ $p < .001$. Because this test was completed 42 times for the 42 different profile types that existed, Bonferroni adjustments were made so that the .05 level divided by 42 became .0012. This statistic was still significantly below the new threshold with those adjustments. Because the difference was significant after Bonferroni adjustments, it is the only identified type or antitype among the control and math difficulty groups.

Synopses of Types/Antitypes. Remembering that an antitype for this data is a profile that exists among the math struggling group that is not seen as often in the control group, only one antitype was indicated. This antitype was in the no strengths and/or weaknesses category. In this category, the control group had nearly 45.45 percent of total individuals with no strengths/weaknesses as opposed to the math difficulty group, which only had 17.33 percent of its individuals identified as having no strengths or weaknesses.

Logarithmic Comparison

Logarithmic comparisons are made for the 15 profiles that could not be compared with the control group. This is because the control group was not given the CAAS or math exposure measures. When comparing the individuals struggling with mathematics with the logarithmic estimates of the sample, results indicated of the 15 profiles, the profiles of 11 single individuals were antitypes when compared to the logarithmic estimates. All of these individuals had the same χ^2 value (χ^2 = 26.54; p <.000). Because the test was completed 15 times, (i.e., once for each existing profile), Bonferroni adjustments were made the significance value .003. Thus, these values are significant (Stanton & Reynolds, 2000; von Eye, 2002).

Synopses of Type/Antitype. There were 11 individuals who were identified as antitypes, each with unique profile scatter patterns. Each of the patterns listed below reflects the scores that each person had as a weakness. The 11 identified weakness patterns are as follows:

Person 1. WJ-III Broad Reading and CAAS Trial 2 Reaction Time Standard Deviation

Person 2. Math exposure

Person 3. PAI Anxiety and Math Exposure

Person 4. WJ-III Applied Problems, WJ-III Math Fluency and Math Exposure

Person 5. PAI Anxiety, CAARS DSM-IV Total and Math Exposure

Person 6. WMS-III General Memory and CAAS Trial 2 Reaction Time Standard Deviation

Person 7. WJ-III Calculation, Cognometer Working Memory Speed and CAAS Trial 2 Reaction Time Standard Deviation

Person 8. WMS-III General Memory, PAI Anxiety, Cognometer Working Memory Speed, Cognometer Working Memory Capacity, and CAAS Trial 2 Reaction Time Standard Deviation

Person 9. PAI Anxiety, CAARS DSM-IV Total, Cognometer Working Memory Speed and CAAS Trial 2 Reaction Time Standard Deviation

Person 10. Cognometer Working Memory Speed and Trial 2 Reaction Time Standard Deviation

Person 11. WMS-III General Memory and WJ-III Broad Reading and CAAS Trial 2 Reaction Time Standard Deviation

Clinical Diagnoses vs. Profile Membership

Attention Deficit/Hyperactivity Disorder (AD/HD)

Overall, 19 clients are diagnosed as having AD/HD. When these results are compared to the distribution of persons resulting from the cluster analysis, 13 are in the Average Performers with Mathematical Discrepancy group (AP) group and 6 are in the High Average Performers with Mathematical Discrepancy group (HP) groups. When these results are compared to the distribution of persons resulting from the Modal Profile Analysis, nearly half or nine individuals are in MP 1A, three in MP 2A and MP 4A, two in MP 1B and one in MP 5A and MP 6A. When these results are compared to the distribution of persons resulting from the Configural Frequency Analysis, the CFA control group comparison of the 13 individuals with no strengths or weaknesses identified as an antitype, four had ADHD diagnoses. Among the single profiles identified as antitypes through logarithmically estimating the population comparisons, three individuals had ADHD diagnoses.

Affective Disorders

In all, twelve participants are identified as having affective disorders. When these results are compared to the distribution of persons resulting from the cluster analysis, ten participants fall in the AP group and two fall in the HP group. When these results are compared to the distribution of persons resulting from the Modal Profile Analysis, results indicated that one-third or four of the individuals with affective disorders fall in MP 1A, one-quarter or three fall in group MP 2A, two fall in MP 4A and one falls in MP 2B, MP 3A and MP 5A. When these results are compared to the distribution of persons resulting from the Configural Frequency Analysis, CFA control group comparison results indicate that of the 13 individuals identified as having no strengths or weaknesses, an antitype, none had affective disorders. In the CFA logarithmic antitype individuals identified, two had affective disorders.

Learning Disorders

Overall, there were 28 individuals identified with learning disabilities LD. When these results are compared to the distribution of persons resulting from the cluster analysis, 10 individuals had Mathematics Disorder (MD) and 18 had other learning disorders (OLD). Of the ten individuals with MD, cluster analysis results produced nine individuals in the AP group and one in the HP group. Of the 18 individuals with OLD, cluster analysis produced 14 individuals in the AP group and four in the HP group. When these results are compared to the distribution of persons resulting from the Modal Profile Analysis, four individuals are in MP 3A, two in MP 1A and MP 2B and one in MP 4B and MP 6B. Amongst the OLD, MPA had at least one LDNOS in all six of the modal profiles and their mirror images, with the most, five, existing in MP 2A. When these results are compared to the distribution of persons resulting from the Configural Frequency Analysis, neither of the two comparisons, control or logarithmic, resulted in any profile that contained an individual with MD. For OLD, the antitype identified by the control group had 3 individuals with OLD, while the antitypes identified by the logarithmic comparison resulted in only one with an OLD.

No Diagnoses

Twenty-six people are identified as having no DSM-IV diagnosis at all. When these results are compared to the distribution of persons resulting from the cluster analysis, 18 fall in the HP group and 8 fall in the AP group. When these results are compared to the distribution of persons resulting from the Modal Profile Analysis, very high percentages (over 75%) of the individuals in MP 1B and 5B are identified as having no diagnosis and only MP 4A and 6A had only diagnoses. Every other modal profile grouping had at least one individual with no diagnosis. When these results are compared to the distribution of persons resulting from the Configural Frequency Analysis, six of the individuals with no strengths or weaknesses are identified as having no diagnosis. When comparing the remaining individuals logarithmically, five had no diagnosis.

Comparing the Three Methods

Initially, Pearson chi-squared analyses were run as a means for comparing the congruence between the distributions of participants from the three profile analysis methods when compared to the distribution of participants among clinically diagnosed groups. Overall results for the Pearson chi-squared analyses for cluster analyses were a $\chi^2 = 15.210$, $p < 0.002$, for modal profile analysis were a $\chi^2 = 45.949$, $p < 0.066$, for configural frequency analysis logarithmic were a $\chi^2 = 1.752$, $p < 0.625$ and for configural frequency analysis normative group were a $\chi^2 = 2.591$, $p < 0.459$. Crosstabulation tables for each of these 4 methods are included in Tables 6, 7, 8 and 9. Because the three methods did not produce equal number of subgroupings, this could bias the results of the original method of comparison. So, to keep the analyses consistent, all analyses are reduced to the 2 x 2 tables.

Results of the Pearson chi-squared tests for all three specifically comparing cluster analysis, MPA and CFA and the number of individuals who share diagnoses among the profile groupings are not significant. However, it must be pointed out that in the case of cluster analysis, the chi-squared analysis is unnecessary. A visual inspection of the table indicates a perfect match. A perfect match means that all individuals within a diagnostic group share a profile with at least one other member and none of the individuals have unique or nonshared profiles. The chi-squared cross tabulation for cluster analysis is included as Table 10

Finally, to compare the individuals specifically with mathematics disorder, four other chi-squared analyses were run. One significant result occurred within the cluster analysis tests. The results for the Pearson chi-squared analysis when comparing participants with MD to all other diagnoses and non-diagnoses are a $\chi^2 = 6.588$, $p < 0.01$. Crosstabulation tables for this significant measure are in Table 11.

CHAPTER FIVE

Discussion

The main purpose of this study is to determine which method of applying profile analysis yields empirically determined subtypes that are most congruent with diagnostic subtypes determined primarily by clinical interviews of college students experiencing math difficulties. Four main diagnostic subtypes appear from clinical interviews. These four main subtypes are AD/HD disorders, affective disorders, learning disorders, and no diagnosis.

These methods are chosen because of their different emphases on level, scatter and shape. By purposely picking the three methods to emphasize one of these characteristics, this research also helps to shed light on which profile extraction method yield results that might best fit clinically derived subtypes.

The Best Fit to the Clinical Diagnoses

What is the optimum method of profile analysis, the results of which best align with clinical subgroups determined from DSM-IV TR criteria? This can be explored by examining the following major and alternative research hypotheses:

This was explored by examining the following major and alternative research hypotheses:

Major: Within each of the three profile analysis methods, the distribution of participants across profile subgroups is not significantly related to clinically determined diagnostic groups.

Alternative 1: The distribution of participants across profile subgroups, determined through cluster analysis, is significantly related to clinically determined diagnostic groups.

Alternative 2: The distribution of participants across profile subgroups, determined through modal profile analysis, is significantly related to clinically determined diagnostic groups.

Alternative 3: The distribution of participants across profile subgroups, determined through configural frequency analysis, is significantly related to clinically determined diagnostic groups.

To test each of the three alternative hypotheses, individuals who shared a profile with at least one other member were compared with members who did not share a profile with one other member. This was done for each of the profile methods. Within the three methods, these comparisons were made for each of the four diagnostic subtypes compared individually to the other three combined diagnostic subtypes (e.g. ADHD vs. all other groups; LD vs. all other groups; Affective Disorders vs. all other groups; and ND vs. all other groups.) This created twelve 2 x 2 tables, four within each profile method.

Results indicated that in this study the Major hypothesis is rejected and the first alternative hypothesis is accepted. The best fit to the diagnoses is the cluster analysis procedure, which emphasizes level.

Statistical Subtypes within the Method of Best Fit

Cluster Analysis Subtypes

The optimal solution is the cluster analysis procedure. Results of the chi-squared analysis indicated that the portioning of individuals based on this profile measure is unlikely due to chance. Also, there was a perfect match as seen through visual inspection of the chi-squared cross tabulation table relating to shared diagnoses and profile types (Table 11). Further, of all the shared profile vs. diagnoses analyses, only cluster analysis produced a significant chi-squared. Again, the portioning of individuals with math disorder compared to those who did not have math diagnoses is unlikely due to chance. Both of these significant results support cluster analysis as the best fit of empirical to clinical subtypes. Cluster analysis resulted in two groups.

While both groups' profiles demonstrated mathematics discrepancies, the distinction was in their performance overall or in their overall elevations. The optimal solution is a two-cluster solution of students who were high performing with mathematics discrepancies and average performing with mathematics discrepancies.

High Performers with Mathematics Discrepancies (HP). Members of the HP subtype typically have above average VIQs, PIQs, and BR scores. The GM score falls in the average range. Their scores on the three mathematics achievement measures on the WJ-III are in the average range and are approximately 6 to 20 points discrepant from their IQ scores. These math scores fall near 100 and above. Both PAI Anxiety and DSM-IV AD/HD Total Symptoms fall in the average range. Because the Cognometer WMS and WMC as well as the CAAS RTSD2 scores are relatively new to research, it is difficult to determine the range that would be considered typical. What can be stated is that the HP group outperforms the AP group on all of these chronometric measures. Thus, the HP group is better at quickly recalling information in the WMS subtest, is better at keeping information in working memory in the WMC subtest, and has less variable times when recalling triplicate multiplication problems in the CAAS subtests. These results coincide with some preliminary work done by other researchers. Beaujean, Knoop, and McGlaughlin (2003) found that the chronometric data is a reliable predictor of diagnostic categories, where members with diagnoses perform worse than those without diagnoses, on average. Overall, the members of the HP subtype score better on all aspects when compared to the AP achievers.

Average Performers with Mathematics Discrepancies (AP). Members of the AP subtype typically have average VIQs, PIQs, GM, and BR scores. Their scores on the three mathematics achievement measures on the WJ-III are in the average range and are approximately 5 to 14 points discrepant from their IQ scores. These math scores fall near 100 and below. PAI Anxiety scores fall in the at-risk range, while DSM-IV AD/HD Total Symptoms fall in the average range. Again, their scores on WMS, WMC, and CAAS RTSD 2 are worse than the HP group, where, on average, the AP group is worse at quickly recalling information from working memory and keeping information in working memory. Further, they are less able to consistently complete triplicate multiplication problems. Overall, the members of the AP subtype score worse on all aspects when compared to the HP achievers.

Overall, these subtypes appear similar to the results found in Kulak (1993) in that some students with difficulties/disorders are delayed or behind their peers, yet are in the same progression. However, there is not a subtype of students that are qualitatively different as was found in the same study.

Learning Disorders. Approximately two-thirds of the individuals identified as having no diagnoses are members of the HP subtype. One-third appears in AP. 22.2 percent of the people diagnosed are in the HP group; whereas, 77.8 percent of the people diagnosed are in the AP group. Intuitively, these results make sense for many reasons. First, to be diagnosed with an affective disorder, one must have evidence of significant distress in life. Higher scores on the anxiety measure are one example of evidence of distress. The fact that AP students score 10 points higher and thus, are considered more anxious and stressed, will result in more subjects from this subtype being identified with affective disorders.

Second, to be diagnosed with learning disorders, one must not only have discrepant scores between achievement and IQ measures (a relative weakness), but also one must demonstrate a performance “below that expected given the person’s chronological age” (DSM-IV TR, 2000). In clinical terms, this is referred to as a normative weakness. For this reason, it is more likely that those in the AP group would meet the criteria of both relative and normative weakness. This is because, on average, their scores fall at the lower end of what is typical. Thus, this group is more likely to have individuals whose scores fall far enough below average to be considered a normative weakness. Members in the HP group are less likely to have these normative weakness scores as their average scores are nearly 10 points higher. However, it is reasonable to assume that some of those diagnosed fall in the HP group as it is possible for them to meet the requirements of relative and normative weakness.

Third, the fact that ND appears more in the HP group than the AP group spurs from the two main diagnoses discussed above. For instance, even if one has a relative weakness in mathematics, as is demonstrated by the IQ-achievement discrepancy in both groups, the criteria for normative weakness is less likely to be met in the HP group and thus, they are less likely to be diagnosed. This does not mean that mathematics is not problematic for them, it simply demonstrates the criteria for the DSM-IV are not met; thus, diagnosis is not made. Further, having lower anxiety scores makes it less likely that diagnoses are made in the area of affective disorders.

AD/HD. Average scores for both AP and HP are nearly equal; thus, one would expect that AD/HD diagnoses would be nearly equal in both groups. However, this is not the case. Nearly two-thirds of the AD/HD diagnoses are in the AP group. Thus, an important question generated from this study is why the groups' AD/HD diagnoses are not more evenly spread.

Woodrich (2000) points out that while only three percent of children in the United States have LD, approximately 35 percent of children with AD/HD have difficulties learning. Thus, a possible answer may be that it is more likely that those with AD/HD would have suppressed scores in the academic achievement areas. Mayes et al., (2000) found evidence that support the findings of Woodrich for 8 to 16 year olds, and concluded that MD had the second highest comorbidity with AD/HD of the three main LD types. Riccio et al., (1994) state that LD and AD/HD may be indistinguishable. These results certainly do not support that the two are indistinguishable, but they do support that individuals with AD/HD are more likely to be in the AP group, and the AP group did have lower achievement scores as well as a higher probability of diagnosis.

This may be one possible answer as to why AD/HD individuals are not more evenly spread. Another answer may be evidenced in the findings of Mayes et al., (1998). They showed that AD/HD groups are more likely to have a significant discrepancy between VIQ and PIQ scores and FD on the WISC-III. The FD task on the WISC-III is similar to the Working Memory Index score on the WAIS-III. Two important findings are evident when looking at Working Memory and AD/HD. First, both the WMS-III and WAIS-III Working Memory scores could be significantly predicted based on cluster membership. Further analysis on these scores indicates that the WMS-III and WAIS-III Working Memory scores are in fact discrepant from both groups' IQ scores. Second, the Cognometer WMC and WMS scores are both lower in the AP group than in the HP group. Thus, AP group members appear to have worse working memory scores than HP group members. Discrepant scores in both groups provide some evidence as to why subjects identified with AD/HD appear in both groups. The fact that AD/HD appears more in the AP group might be understood as exhibiting greater distress as evidenced by more suppressed scores in all areas tested.

Memory. WMS-III General Memory scores were essentially equal in both groups. Results from several studies involving memory support the conclusion that memory processes are lower for those with mathematics difficulties than normally achieving peers and peers with other disabilities (Geary, 1993; Geary, 1999; Greene, 2001; Swanson, 1993; Swanson, 1994). This study supports the finding that the memory scores of the HP are better than the AP in terms of the WMS-III General Memory scores. However, this difference is minimal and could be explained by error alone. That being said, the Cognometer and CAAS scores, which also measure working memory speed, capacity, and working memory as it relates to mathematics, are all different as well. Because the subtests on these mental chronometric tasks are not normed to date, it is difficult to state if one group falls in a particular category. However, the differences are significant from one another and do indicate that when examining working memory, one can see that the differences are apparent. Further, when externally validating the two subtypes, the working memory measure was significantly different between the two groups as well. This lends support to memory functioning being worse for individuals in the AP group when compared to the HP group.

Nonverbal Discrepancies. When examining nonverbal deficits as evidenced in work by Rourke and colleagues (Rourke, 1993; Rourke & Del Dotto, 1994; Rourke & Fuerst, 1996), results support that those more likely to be diagnosed with mathematics disorders are those in the AP group. Further, those in the AP group scores in the PIQ were, on average, one standard deviation lower than those in the HP group; however, there was no support that their scores were discrepant from the VIQ. That is the results did not show any nonverbal weakness in either group as might be expected based upon the work of Rourke and his colleagues. This must be noted with caution, as these profiles are based upon group average scores so that does not mean that the nonverbal deficits do not exist on individual bases. Instead, these scores are not noted when looking at the average of the entire clusters as conglomerates.

Diagnosed vs. Not Diagnosed. While the results of this study are far from perfect, it helps to reframe one’s thinking of aligning the cluster clinical subtypes with each of the four diagnostic subtypes. Instead, visual examination of Table 12 demonstrates that nearly 80 percent of the participants diagnosed with a disorder are in the AP group and nearly 70 percent of participants with no diagnosis appear in the HP group.

Limitations & Delimitations

Limitiations

Clinical Procedure. Some limitations exist related to gaining information for the study through the clinical procedure. Clinic personnel diagnose individuals in this process. Thus, the reliability of these diagnoses can be called into question. Although clinic personnel use the

DSM-IV TR and follow its procedure, there are limitations inherent in all clinic diagnoses, especially since several researchers were working in collaboration with one supervisor of the project. Using the DSM-IV TR criteria, one follows general categorization procedures. In the DSM-IV TR, it specifically calls for using clinical judgment and one is not always required to have statistically significant differences for diagnosis. There are times people are diagnosed with the same disorder, when in fact the two individuals look very different.

To explore this issue, the means of the four diagnostic subtypes are presented in Table 13. Overall, exploration of this table indicates that the four major diagnoses correspond with criteria in the DSM-IV TR (e.g. high ANX scores, AD/HD scores, discrepant LD scores). However, on average, these scores are not in the clinically significant ranges for affective disorders and attention deficit disorders. Furthermore, the LD scores, while discrepant, do not meet the one and one-half standard deviation criterion. The important point is that these scores are on average and thus, clinical judgment can affect if these scores fall at the appropriate cutoffs. Thus, on average, the scores do not meet the criteria. This is another possible explanation for why some individuals might be in the HP group instead of the AP group, which is a limitation of the procedure.

Finally, because there are practical considerations when testing college students at a university based clinic such as students not coming for all sessions, students not completing testing, examiners choosing to ignore pieces of information for several reasons and a myriad of other issues that arise clinically, the sample size was cut tremendously by incomplete data. This small number of cases presented limitations in methodology.

Methodology. The sample size in this distribution is somewhat smaller presenting limitations on the analyses itself. First and foremost, the researcher had to choose which variables made the most sense as to what to include. While these decisions were not taken lightly, there is no way of determining if those measures that are chosen are any better than other measures available. Ideally, including more information or a scientific way to determine which subtests and measures should have been included would be better ways to make sure those subtests and measures that were chosen were best.

Limitations in comparing and contrasting the method also exist. When making comparisons among the four subtypes and three profile analysis methods, 15 separate Pearson chi-squared analyses were run and overall, the comparison was cumbersome. Further, the small sample size may have affected results within the Pearson chi-squared analyses.

Delimitations

One of the major delimitation of this study is that all participants examined in this dataset presented with mathematics difficulties. Thus, this study generalizes poorly to the population as a whole and is only able to generalize to individuals on a college campus who report mathematics difficulties.

Another delimitation is the choice of grouping students to four major diagnosis levels. There could have been several choices to group participants to study them more efficiently or obtain different results. Participants could have been compared using a diagnosis vs. non-diagnosis model. Students could have been compared via math diagnosis vs. other diagnosis vs. non-diagnosis. Each of the groupings of individual diagnoses could have been studied separately and compared. Regardless, the four major subtypes chosen actually contain individuals that might have different profiles. For example, an individual with anxiety and an individual with depression may look very different both clinically and statistically when profiles compared. For simplicity sake, the groupings were made; however, these decisions could have affected the outcomes.

Profile Analysis. Within the methods of profile analysis, several limitations are present especially related to the choices made in analyzing the dataset.

As was discussed earlier, subtype profiles can be described in three ways: level, scatter, and shape (Aldenderfer & Blashfield, 1984; Davison & Kuang, 2000; Jobson, 1996). Different choices within methods emphasize may only emphasize one of the three. For example, in the case of the hierarchical analysis performed for this study, Ward’s method emphasizes clusters that are equal in number (Aldenderfer & Blashfield, 1984). Further, “a common problem associated with the use of the Ward’s method is that the clusters found by this method can be biased toward overall elevation” or level. As was seen in the cluster portion of this analysis, the shape of the clusters is relatively the same and the analysis focuses on differences in level or elevation. There are determinations in cluster analysis that could have been used to emphasize shape and scatter instead of using the separate methods modal profile analysis and configural frequency analysis to emphasize the two (Aldenderfer & Blashfield, 1984).

This particular study automatically uses techniques to externally validate the clusters and give further evidence that the cluster groups are good explanations of the data; however, this cannot be assumed as a method that naturally explains the data when compared to other methods. In fact, different disciplines emphasize different questions and ways to get answers. One discipline may be interested in clustering procedures from one angle, while another is interested in another method of clustering. For these reasons, future research might be aimed at comparing and contrasting the various methods of profile analysis as well as exploring various decisions that can be made within one method (Aldenderfer & Blashfield, 1984; Hair & Black, 2000; Jobson, 1996, von Eye, 2002).

Within cluster analysis, there are limitations to the iterative procedure as well. First, the selection of the number of clusters is an important part of performing this method. By using hierarchical methods, the choice of two clusters is affected by all the limitations discussed previously. There may also be reason to believe another heuristic to choose the initial partition could be as good as the one chosen. In fact, a major limitation of the k-means analysis is that it is impossible to actually complete all the possible iterations that could be done with a given data set. That is, even a supercomputer could not complete the process of figuring out all possible combinations and therefore, it can never be known with any certainty that the cluster grouping chosen is actually optimum (Aldenderfer & Blashfield, 1984). Aldenderfer and Blashfield (1984) stated, “for 15 cases and 3 clusters, this approach requires the examination of 217,945,728,000 unique partitions, clearly beyond the capacity of modern computers” (p. 46).

Future Research

Originally, it would be simplistic to assume that each of the four main types of diagnoses might lead a four-cluster solution that aligned with clinical diagnoses. This was not the case. The level differences among extracted profiles appear to play the largest role in this study. The results as presented above demonstrate that the AP group and HP group had similar profiles, with the HP group manifesting overall better scores or higher levels of scores. From this, several potential questions arise.

First, are these results similar to groups of adults outside of the college setting? Second, are these results similar for people presenting with different problems at the college setting? Third, are people with disabilities more similar than they are different, and thus, is lumping all individuals with LD an appropriate way to examine data? Finally, what can be learned about the chronometric measures added information to the diagnostic process? These are simply a few questions that follow from the research. There are certainly several more areas that can be explored.

Overall, the findings presented demonstrate most of the people presenting with mathematics difficulties seemingly had reason to be there. For the most part, math scores are discrepant from ability, and math appeared to be a relative weakness for these individuals. Thus, it appears that their concerns are real and validated statistically. However, this does not mean they have diagnosable disorders. In some instances they do, however in others they do not. These instances are the result of scores that fall in the significantly below average range and are then considered normative weakness. Yet, the DSM-IV TR clearly states that a normative weakness is but one criterion when diagnosing, and many in the HP group did not meet this criterion. This does not mean that students are not struggling at mathematics? Future research should not only concentrate on what can be done to help students with disorders, but also on those who may not meet the criteria for a mathematics disability or other disorders affecting math performance.

Secondary information that will be very useful from this research will include answers to the following questions: What are the methods/combination of methods for determining statistical subtypes that best explain individual and/or group characteristics of those students' struggling with college level mathematics? What can be gained from this information to help individuals who work with college aged students struggling in mathematics?

Conclusions

Through this entire process, issues of level, shape and scatter have been the most important in determining the subtypes in each method.

While, shape and scatter have their place statistically and much can be gained from these two methods, especially statistically, the most parsimonious form of profile analysis that matches with clinical subtypes appears to be best described by cluster analysis, the method where choices that were made emphasized level.

Clinical and statistical subtypes have some commonalities, but to be able to truly derive a statistical method that matches with clinical subtypes may in fact be improbable, if not, impossible. Statistical analyses and clinical analyses do not match for the simple fact that they are seeking to address two different concerns. Clinically, clinicians are practically trying to help people who are struggling. Statistically, researchers are trying to find the best fit of information to participants, regardless of their struggles. Just the utilization and difference in how individuals are described, people vs. participants give some insight into this information.

Statistically, level was the most important profile characteristic in this study. There were two groups: high achievers and low achievers both with math discrepancies. Participants identified clinically with mathematics disorder could exist in either group, but were more likely in the average performing group.

Interestingly, clinically, level was important as well. Individuals could be identified among either group but were more likely to be identified in the average achiever group. This is because with both groups having discrepancies, it was easiest for these individuals discrepancy to be significantly below average and discrepant from their ability. High achievers, on average, had higher levels and thus, there might still be a discrepancy, but this discrepancy is more likely to lead to simple average achievement and hence, fails to meet the significantly below average DSM-IV TR criteria for math disorder.

Overall, all of the individuals participating in this study were struggling with mathematics at the college level. Statistical subtypes and clinical subtypes exist. Each of these statistical and clinical subtypes, regardless of whether they match, can help to shed light on the problems faced by college students struggling with math. Unless more is done to analyze the trends for these students, college algebra will continue to be the gatekeeper for students trying to earn a college degree.

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Table 1

DSM-IV Clinical Diagnoses and Related Subtypes

DSM-IV Diagnosis	n
Overall Learning Disorders	30
Learning Disorders	12
Math Disorder	10
Writing Disorder	2
Reading Disorder	1
LDNOS	18
Auditory Memory	4
Visual Memory	5
Working Memory	2
General Memory	2
Processing Speed	3
Attention	2
ADHD	19
Inattentive	12
Hyperactive	1
Combined	4
NOS	2
Affective Disorders	12
Dysthymia	5
PTSD	2
GAD	4
Social Phobia	1
No Diagnosis	26

Table 2

Two Cluster Solution: High vs. Average Performers with Math Discrepancies (MD)

	High Performer w/MD[d]		Avg. Performer w/MD[e]	
Variable	*M*	SD	*M*	SD
WAIS-III VIQ[a]	118.69	8.80	104.67	8.53
WAIS-III PIQ[a]	114.66	9.49	103.26	9.81
WMS-III Gen Memory[a]	106.34	9.86	101.49	9.79
WJ-III Broad Reading[a]	111.28	12.11	99.05	10.76
WJ-III Calculation[a]	108.66	13.19	98.02	11.00
WJ-III App Problems[a]	102.81	9.33	93.77	5.28
WJ-III Math Fluency[a]	98.81	11.65	90.14	10.47
Math Exposure Score	6.41	1.72	5.65	1.70
PAI Anxiety[b]	54.03	12.34	64.63	13.80
CAARS ADHD[b]	57.44	12.79	60.26	13.26
Cognometer WMS[c]	1213.06	197.21	1501.51	219.58
Cognometer WMC[c]	956.00	214.40	1085.91	210.58
CAAS Trial 2 RTSD[c]	3.83	2.00	6.14	2.42

[a]Means =100 and SD = 15. [b]Means = 50 and SD = 10 (higher scores indicate poor performance).[c]Cognometer Scores in milliseconds; CAAS scores in seconds (higher scores indicate poorer performance).[d]n=32. [e]n=43.

Table 3

Prototypical Scores of One Member for Average and High Performers with Math Discrepancies (AP w/MD; HP w/MD)

Variable	HP w/MD	AP w/MD
WAIS-III VIQ[a]	105	116
WAIS-III PIQ[a]	100	121
WMS-III Gen Memory[a]	112	98
WJ-III Broad Reading[a]	93	110
WJ-III Calculation[a]	99	104
WJ-III App Problems[a]	93	110
WJ-III Math Fluency[a]	95	92
Math Exposure Score	6	7
PAI Anxiety[b]	57	40
CAARS ADHD[b]	55	58
Cognometer WMS[c]	1470	1170
Cognometer WMC[c]	851	860
CAAS Trial 2 RTSD[c]	7.62	1.83

[a]Means =100 and SD = 15. [b]Means = 50 and SD = 10 (higher scores indicate greater difficulty).[c]Cognometer Scores in milliseconds; CAAS scores in seconds (higher scores indicate poorer performance).

Table 4

High vs. Average Performers w/ Mathematics Discrepancies (Split-Half One)

Variable	High Performer w/MD[d] *M*	High Performer w/MD[d] SD	Avg. Performer w/MD[e] *M*	Avg. Performer w/MD[e] SD
WAIS-III VIQ[a]	119.47	10.54	104.70	8.50
WAIS-III PIQ[a]	114.65	10.39	102.83	10.01
WMS-III Gen Memory[a]	105.65	10.85	101.65	9.91
WJ-III Broad Reading[a]	113.65	9.81	98.70	11.38
WJ-III Calculation[a]	106.65	13.27	97.65	12.08
WJ-III App Problems[a]	100.35	7.35	93.39	5.28
WJ-III Math Fluency[a]	96.71	11.88	91.87	11.84
Math Exposure Score	5.94	1.68	5.83	1.97
PAI Anxiety[b]	52.41	12.09	65.39	16.11
CAARS ADHD[b]	54.94	12.55	57.78	13.79
Cognometer WMS[c]	1172.24	211.85	1511.83	372.42
Cognometer WMC[c]	901.06	224.59	1034.87	179.99
CAAS Trial 2 RTSD[c]	3.66	1.99	6.65	2.32

[a]Means =100 and SD = 15. [b]Means = 50; SD = 10 (higher scores indicate poor performance). Cognometer Scores in milliseconds; CAAS scores in seconds (higher scores indicate poorer performance). [d]n=17. [e]n=23.

Table 5

High vs. Average Performers w/ Mathematics Discrepancies (Split-Half Two)

	High Performer w/MD[d]		Avg. Performer w/MD[e]	
Variable	*M*	SD	*M*	SD
WAIS-III VIQ[a]	117.80	6.57	104.65	8.78
WAIS-III PIQ[a]	114.67	8.72	103.75	9.80
WMS-III Gen Memory[a]	107.13	8.92	101.30	9.91
WJ-III Broad Reading[a]	108.60	14.15	99.45	10.27
WJ-III Calculation[a]	110.93	13.17	98.45	9.90
WJ-III App Problems[a]	105.60	10.74	94.20	4.75
WJ-III Math Fluency[a]	101.20	11.30	88.15	8.49
Math Exposure Score	6.93	1.67	5.45	1.36
PAI Anxiety[b]	55.87	12.77	63.75	10.91
CAARS ADHD[b]	60.27	12.89	63.10	12.35
Cognometer WMS[c]	1259.33	174.66	1489.65	226.63
Cognometer WMC[c]	1018.27	190.57	1143.45	232.37
CAAS Trial 2 RTSD[c]	4.02	2.06	6.16	2.57

[a]Means =100 and SD = 15. [b]Means = 50; SD = 10 (higher scores indicate poor performance). Cognometer Scores in milliseconds; CAAS scores in seconds (higher scores indicate poorer performance). [d]n=15. [e]n=20.

Table 6

Chi-Squared Analysis Cluster Group Frequency Crosstabulation

	Cluster Group	
DSM-IV Diagnosis	AP w/MD	HP w/MD
No Diagnosis	18	8
Learning Disabilities	4	21
ADHD	6	9
Affective Disorders	3	6

Note. AP w/MD=Average Performers with Math discrepancy. HP w/MD= High Performers with Math discrepancy.

Table 7

Chi-Squared Analysis Modal Profile Analysis (MPA) Crosstabulation Frequencies

	MPA Group											
DSM-IV Diagnosis	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
No Diagnosis	1	6	2	3	1	5	0	2	1	3	0	2
Learning Disabilities	3	1	5	3	4	0	1	3	1	1	1	2
ADHD	5	2	3	0	0	1	2	0	1	0	1	0
Affective Disorders	3	0	0	1	2	0	2	0	1	0	0	0

Note. a indicates the image and b represents the mirror image.

Table 8

Chi-Squared Cross Tabulation-Configural Frequency Analysis (CFA) Logarithmic Comparison

	CFA Group	
DSM-IV Diagnosis	No Classification	Type/ Antitype
No Diagnosis	21	5
Learning Disabilities	23	2
ADHD	12	3
Affective Disorders	8	1

Table 9

Chi-Squared Cross Tabulation-Configural Frequency Analysis Control Group

	CFA Group	
DSM-IV Diagnosis	No Classification	Type/ Antitype
No Diagnosis	20	6
Learning Disabilities	21	4
ADHD	12	3
Affective Disorders	9	0

Table 10

Chi-Squared Cross Tabulation-Cluster *Analysis Shared vs. Not Shared Profiles*

DSM-IV Diagnosis	Shared	Not Shared
No Diagnosis	26	0
Learning Disabilities	25	0
ADHD	15	0
Affective Disorders	9	0

Note. Shared indicates number of persons within the DSM-IV Diagnosis group who shared a cluster with at least one other person in the diagnosis group; Nonshared indicates number of persons within the DSM-IV Diagnosis group who do not share a cluster with at least one other person in the diagnosis group.

Table 11

Chi-Squared Cross Tabulation-Cluster Analysis Math Disorders Shared vs. Not Shared

DSM-IV Diagnosis	Shared	Not Shared
Math Disorders	9	1
All other Disorders	65	0

Note. Shared indicates number of persons within the DSM-IV Diagnosis group who shared a cluster with at least one other person in the diagnosis group; Nonshared indicates number of persons within the DSM-IV Diagnosis group who do not share a cluster with at least one other person in the diagnosis group.

Table 12

Number of Participants for Each Cluster identified as having any DSM-IV Diagnosis

DSM-IV Diagnosis	AP w/MD[a]	HP w/MD[b]
Learning Disorders	10	2
Math Disorder	9	1
Writing Disorder	0	1
Reading Disorder	1	0
LDNOS	15	3
Auditory Memory	4	0
Visual Memory	3	2
Working Memory	2	0
General Memory	2	0
Processing Speed	2	1
Attention	2	0
ADHD	13	6
Inattentive	9	3
Hyperactive	1	0
Combined	3	1
NOS	0	2
Affective Disorders	10	2
Dysthymia	5	0
PTSD	1	1
GAD	3	1
Social Phobia	1	0
No Diagnosis	8	18

Note. AP w/MD: Average Performers with Math Discrepancies and HP w/MD: High Performers with Math Discrepancies. [a]n=43. [b]n=32.

Table 13

Four Diagnostic Subtypes Means

Variable	ND[d]	LD[e]	ADHD[f]	Aff Dx[g]
WAIS-III VIQ[a]	112.52	108.31	113.07	107.75
WAIS-III PIQ[a]	111.07	104.77	110.93	104.13
WMS-III Gen Memory[a]	107.04	100.85	100.07	106.75
WJ-III Broad Reading[a]	106.59	103.62	101.79	102.88
WJ-III Calculation[a]	108.96	94.96	106.50	98.75
WJ-III App Problems[a]	100.78	94.12	100.14	94.00
WJ-III Math Fluency[a]	97.15	89.65	93.57	96.75
Math Exposure Score	6.00	5.69	6.00	6.75
PAI Anxiety[b]	52.22	60.65	63.36	65.00
CAARS ADHD[b]	53.11	58.23	68.64	65.00
Cognometer WMS[c]	1311.89	1459.27	1348.64	1392.50
Cognometer WMC[c]	1020.19	1058.96	1028.50	1392.50
CAAS Trial 2 RTSD[c]	4.42	6.41	4.39	6.37

[a]Means =100 and SD = 15. [b]Means = 50; SD = 10 (higher scores indicate poor performance). Cognometer Scores in milliseconds; CAAS scores in seconds (higher scores indicate poorer performance). [d]n=26. [e]n=25. [f]n=15. [g]n=9.

Figure Caption

Figure 1. Number of Clusters and Amalgamation Coefficients for Hierarchical Cluster Analysis.

Figure 2. Graphic of Pseudo-F Statistic for Hierarchical Cluster Analysis.

Figure 3. Graphic of Pseudo-t^2 for Hierarchical Cluster Analysis.

Figure 4. Graphic of Cubic Clustering Criterion (CCC) for Hierarchical Cluster Analysis.

Figure 5. Shapes of Modal Profile Groups 1a and 1b.

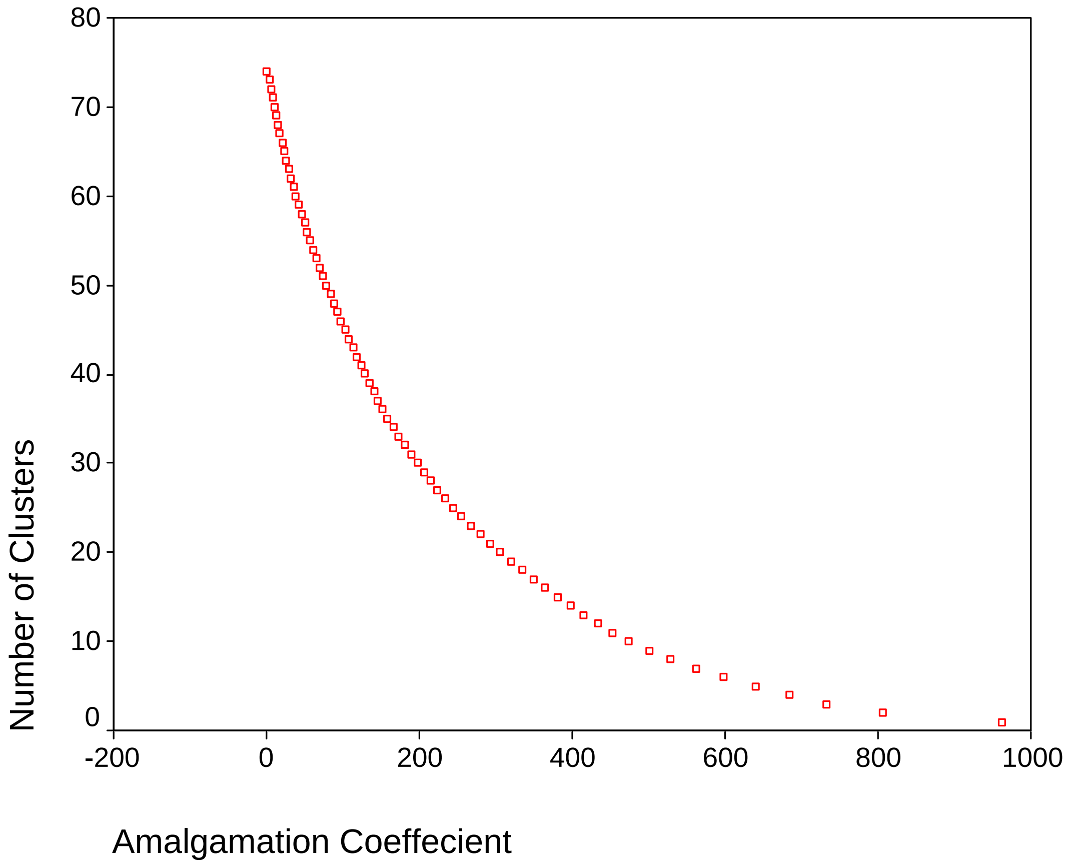
Figure 6. Shapes of Modal Profile Groups 2a and 2b.

Figure 7. Shapes of Modal Profile Groups 3a and 3b.

Figure 8. Shapes of Modal Profile Groups 4a and 4b.

Figure 9. Shapes of Modal Profile Groups 5a and 5b.

Figure 10. Shapes of Modal Profiles Groups 6a and 6b.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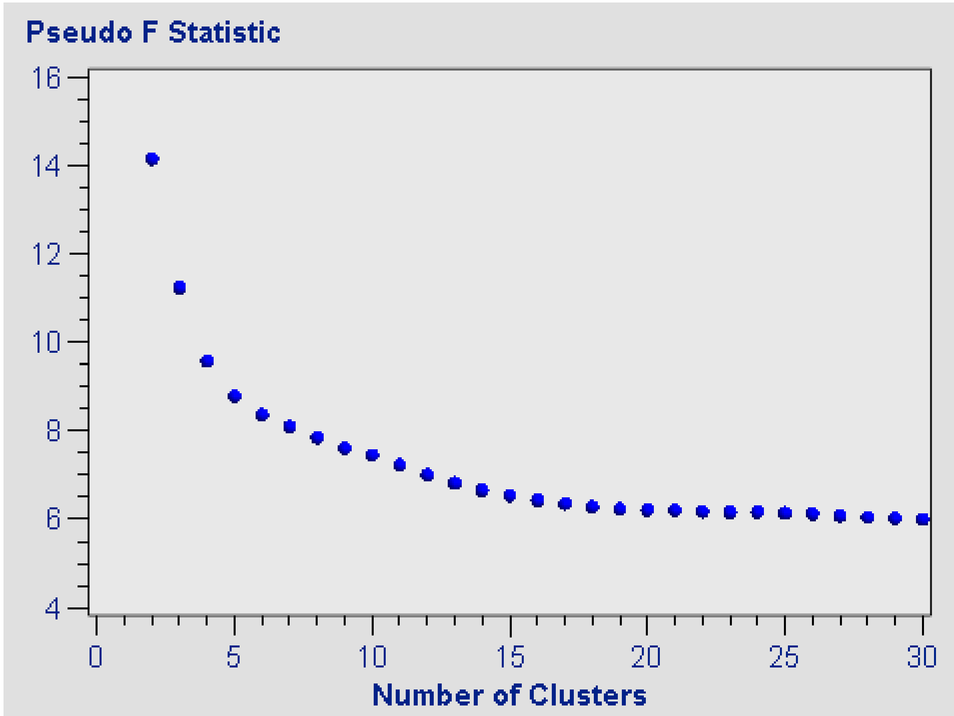
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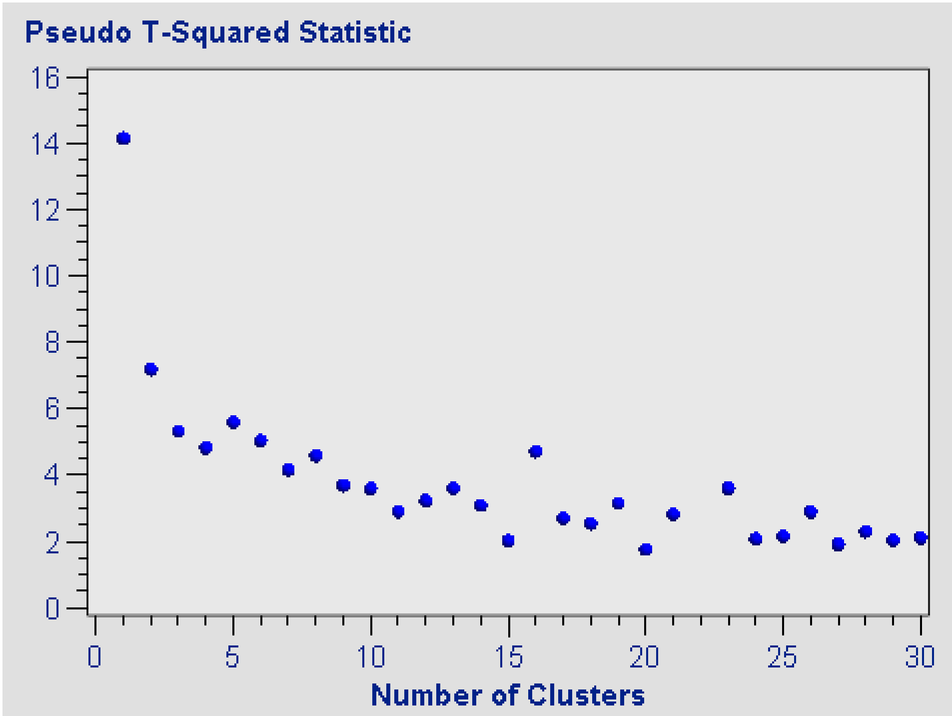
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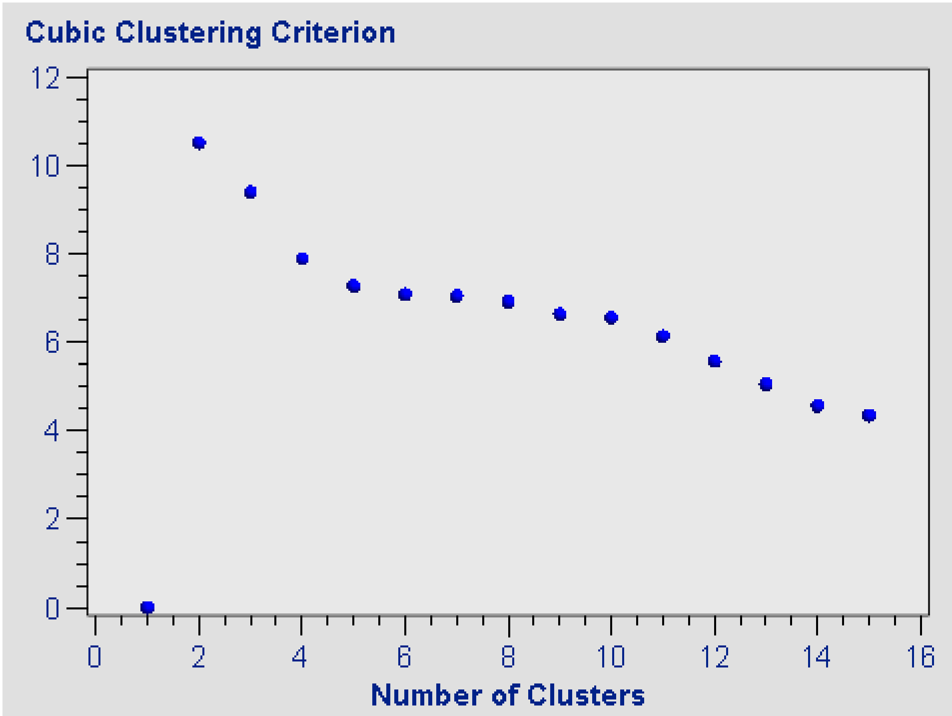
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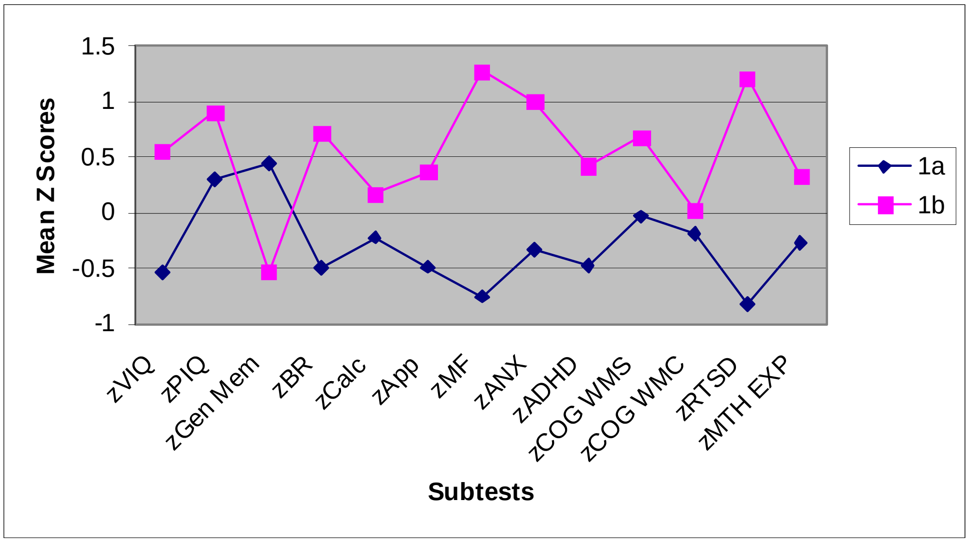
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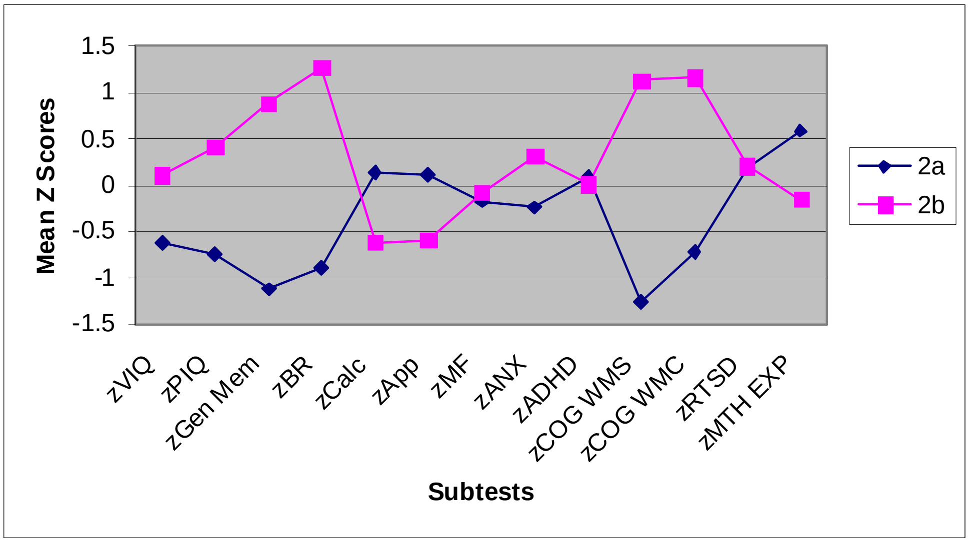
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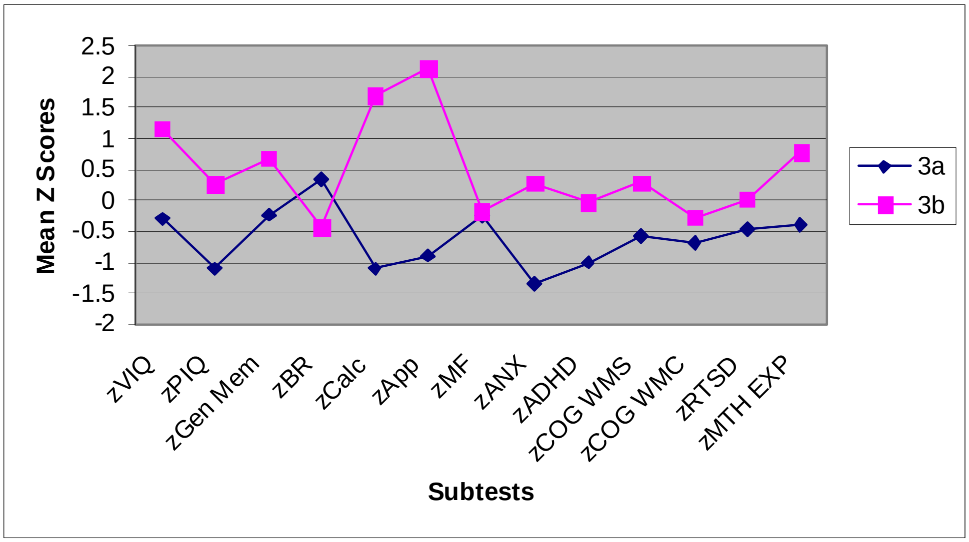
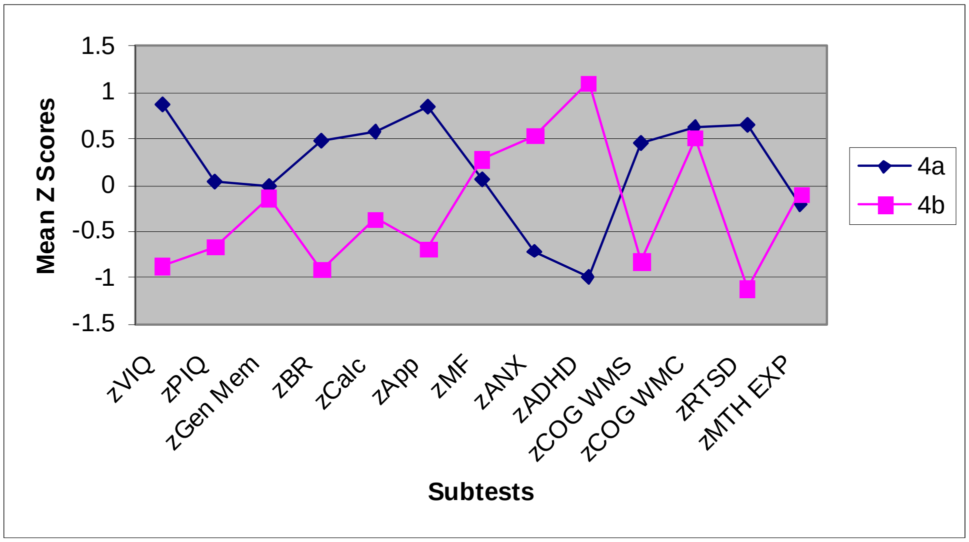
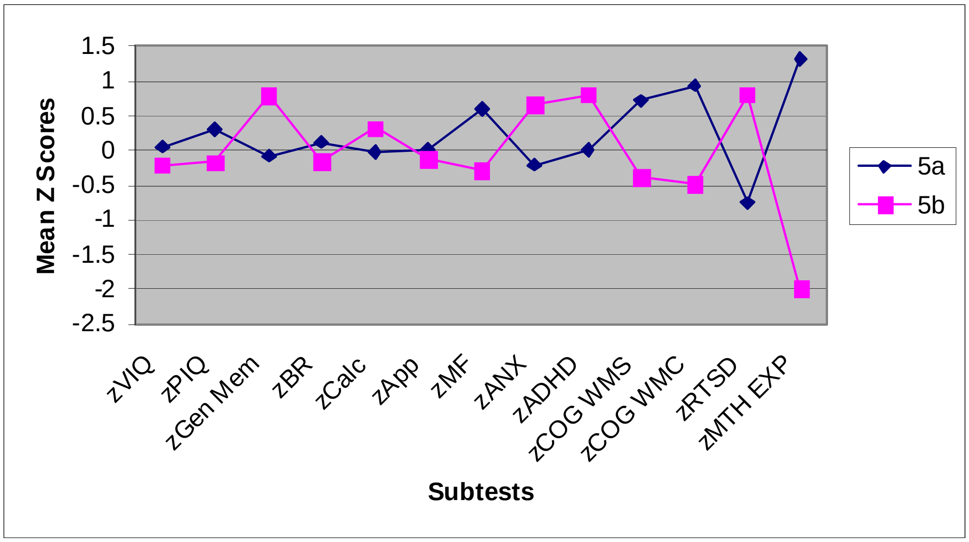
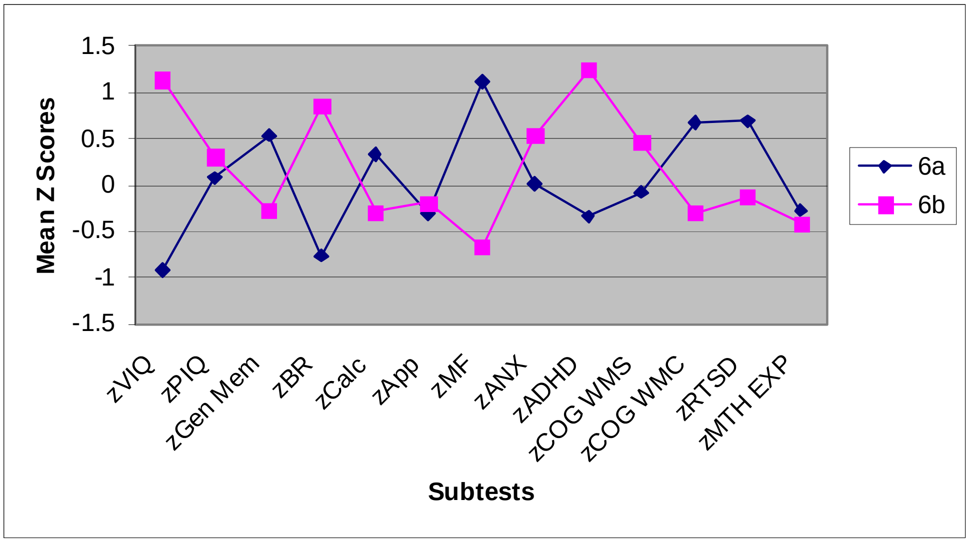
zADHD
zCOG WMS
zCOG WMC
zRTSD
zMTH EXP
Subtests
2a
2b


Mean Z Scores
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
zVIQ
zPIQ
zGen Mem
zBR
zCalc
zApp
zMF
zANX
zADHD
zCOG WMS
zCOG WMC
zRTSD
zMTH EXP
Subtests
3a
3b


Mean Z Scores
1.5
1
0.5
0
-0.5
-1
-1.5
zVIQ
zPIQ
zGen Mem
zBR
zCalc
zApp
zMF
zANX
zADHD
zCOG WMS
zCOG WMC
zRTSD
zMTH EXP
Subtests
4a
4b


1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
Mean Z Scores
zVIQ
zPIQ
zGen Mem
zBR
zCalc
zApp
zMF
zANX
zADHD
zCOG WMS
zCOG WMC
zRTSD
zMTH EXP
Subtests
5a
5b


1.5
1
0.5
0
-0.5
-1
-1.5
Mean Z Scores
zVIQ
zPIQ
zGen Mem
zBR
zCalc
zApp
zMF
zANX
zADHD
zCOG WMS
zCOG WMC
zRTSD
zMTH EXP
Subtests
6a
6b

VITA

Sean Michael McGlaughlin was born in Kansas City, Missouri on February 15, 1977. He is the son of George M. McGlaughlin and Vicki L. Sallaz. He was raised in Kansas City and graduated from North Kansas City High School. He then attended Missouri State University where he majored in Middle School Education with a minor in Psychology. He earned his bachelors of science degree from Missouri State University in December 1999. Sean entered the school psychology program at the University of Missouri in December 2000. He earned his Master of Arts in School Psychology in December 2004. He was accepted as a pre-doctoral intern at the Nebraska Internship Consortium in Professional Psychology. He completed his internship in August 2005. Sean earned his Ph.D. at the University of Missouri in December 2008. He is a practicing school psychologist in the Omaha Public Schools and has been with the district since 2004. He has a post-doctoral fellowship appointment in the Omaha Public Schools to begin in January 2009.