UNIVERSITY OF SOUTHERN QUEENSLAND

EXAMINING THE UTILITY OF A CLUSTERING METHOD FOR ANALYSING PSYCHOLOGICAL TEST DATA

A Dissertation submitted by

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ABSTRACT

The belief that certain disorders will produce specific patterns of cognitive strengths and weaknesses on psychological testing is pervasive and entrenched in the area of clinical neuropsychology, both with respect to expectations regarding the behaviour of individuals and clinical groups. However, there is little support in the literature for such a belief. To the contrary, studies examining patterns of cognitive performance in different clinical samples without exception find more than one pattern of test scores. Lange (2000) in his comprehensive analysis of WAIS-R/WMS-R data for a large sample of mixed clinical cases found that three to five profiles described variations in test performances within clinical diagnoses. Lange went on to show that these profiles occurred with approximately equal frequency in all diagnostic groups. He additionally found four profiles in an exploratory analysis of WAIS-III/WMS-III data from a similar sample. The goals of the current dissertation were to: a) replicate Lange's findings in a larger clinical sample; b) extend the scope of these findings to a wider array of psychological tests; and c) develop a method to classify individual cases in terms of their psychological test profile.

The first study assessed 849 cases with a variety of neurological and psychiatric diagnoses using hierarchical cluster and K-Means analysis. Four WAIS-III/WMS-III profiles were identified that included approximately equal numbers of cases from the sample. Two of these profiles were uniquely related to two of Lange's profiles, while the remaining two demonstrated relationships with more than one of Lange's clusters.

The second study expanded the neuropsychological test battery employed in the analysis to include the Trail Making Test, Boston Naming Test, Wisconsin Card Sorting Test, Controlled Oral Word Association Test, and Word Lists from the WMS-III reducing the number of clinical cases to 420. In order to compensate for the impact

of the reduced number of cases and increased number of variables on potential cluster stability, the number of test score variables was reduced using factor analysis. In this manner the 22 variables were reduced to six factor scores, which were then analysed with hierarchical cluster and K-Means analysis yielding five cognitive profiles.

The third study examined the potential clinical utility of the five cognitive profiles by developing a single case methodology for allocating individual cases to cognitive profiles. This was achieved using a combination of a multivariate outlier statistic, the Mahalanobis Distance, and equations derived from a discriminant function analysis. This combination resulted in classification accuracies exceeding 88% when predicting the profile membership based upon the K-Means analysis. The potential utility of this method was illustrated with three age-, education-, gender-, and diagnostically-matched cases that demonstrated different cognitive test profiles.

The implications of the small number of cognitive profiles that characterise test performance in a diverse sample of neurological and psychiatric cases as well as the clinical utility of an accurate classification method at the individual case level was discussed. The role of such a classification system in the design of individualised rehabilitation programmes was also highlighted. This research raises the intriguing possibility of developing a typology based on human behaviour rather than a medical nosology. In effect, replacing the medical diagnosis so ill-suited to encompassing the complexities of human behaviour, with a more appropriate "psychological diagnosis" based on cognitive test performance.

CERTIFICATION OF DISSERTATION

I certify that the ideas, experimental work, results, analyses, software and conclusions reported in this dissertation are entirely my own effort, except where otherwise acknowledged. I also certify that the work is original and has not previously been submitted for any other award, except where otherwise acknowledged.

_____ _____

Sharron Dawes Date

ENDORSEMENT

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Dr. Graeme Senior Date

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ABBREVIATIONS

AD	Auditory Delayed - Standard Score
AI	Auditory Immediate - Standard Score
ANOXIC	Anoxic Injury
ARD	Auditory Recognition Delayed - Standard Score
AUD	Auditory Delayed Memory
BNT	Boston Naming Test
COG NOS	Cognitive Impairment Not Otherwise Specified
COWAT	Controlled Oral Word Association Test – FAS version
CVD	Cerebrovascular Disorders
DAD	Auditory Delayed - Deviation Score
DAI	Auditory Immediate - Deviation Score
DARD	Auditory Recognition Delayed - Deviation Score
DAT	Alzheimer's Dementia
DBD	Block Design - Deviation Score
DDS	Digit Symbol Coding - Deviation Score
DEM	Other Dementia
DEP	Depression
DFA	Discriminant Function Analysis
DIN	Information - Deviation Score
DMR	Matrix Reasoning - Deviation Score
DPC	Picture Completion - Deviation Score
DrugEtoh	Drug/Alcohol Abuse
DS_i	Deviation Score i
DSI	Similarities - Deviation Score
DSS	Symbol Search - Deviation Score
DVD	Visual Delayed - Deviation Score
DVI	Visual Immediate - Deviation Score
DVO	Vocabulary - Deviation Score
DWM	Working Memory – Deviation Score
ENCEP	Encephalitis
GEN MED	General Medical Condition
Hi	Hierarchical Cluster i
HNRB	Halstead-Reitan Neuropsychological Battery
HYDRO	Hydrocephalus
K*i*	K-Means Cluster i
L_i	Lange K-Mean Profile i
LNNB	Luria-Nebraska Neuropsychological Battery
MD	Mahalanobis Distance
MD_i	Mahalanobis Distance calculated for Cluster i.
MEN RET	Mental Retardation
MID	Multi-Infarct Dementia
MMPI	Minnesota Multiphasic Personality Inventory
MMPI-2	Minnesota Multiphasic Personality Inventory – 2^{nd} edition
MS	Multiple Sclerosis
N	Number of Cases
NIL	No Diagnosis
Other	Other Disorders
PD	Parkinson's Disease
PO	Perceptual Organisation - Standard Score

ABBREVIATIONS (cont)

PS	Processing Speed - Standard Score
PSYCH	Psychiatric Disorder
SD	Standard Deviation
SLE	Systemic Lupus Erythematosus
ssBD	Block Design - Scaled Score
ssDS	Digit Symbol Coding - Scaled Score
ssIN	Information - Scaled Score
ssMR	Matrix Reasoning - Scaled Score
ssPC	Picture Completion - Scaled Score
ssSI	Similarities - Scaled Score
ssSS	Symbol Search - Scaled Score
ssVO	Vocabulary - Scaled Score
SZ	Seizure Disorder
TBI	Traumatic Brain Injury
TLE	Temporal Lobe Epilepsy
TOXIC	Toxic Exposure
TMT	Trail Making Test
TMT-A	Trail Making Test – Part A
TMT-B	Trail Making Test – Part B
TMT-B min A	Trail Making Test – Part B minus Part A
TUMOUR	Tumour
VC	Verbal Comprehension - Standard Score
VD	Visual Delayed - Standard Score
VI	Visual Immediate - Standard Score
VIS	Visual Memory
WAIS-III	Wechsler Adult Intelligence Scale - Third Edition
WAIS-R	Wechsler Adult Intelligence Scale – Revised Edition
WCST	Wisconsin Card Sort Test
WCST: Pers. Err	Wisconsin Card Sort Test: Perseverative Errors
WCST: Cat. Com	Wisconsin Card Sort Test: Categories Completed
WISC-III	Wechsler Intelligence Scale for Children - Third Edition
WL-I	Word Lists I - Scaled Score
WL-II	Word Lists II - Scaled Score
WM	Working Memory - Standard Score
WMS-III	Wechsler Memory Scale - Third Edition
WMS-R	Wechsler Memory Scale – Revised Edition

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CHAPTER 1

1.0 INTRODUCTION

1.1 Background

The role of neuropsychological assessment is to examine change in cognition and emotion in individuals after brain dysfunction related to trauma, psychiatric or neurological disorders, or disease (Franzen, 2000). By indicating the clients strengths and weaknesses revealed in their test scores, neuropsychologists are then able to make predictions about how these changes may affect the client's life (Bennett, 2001). These findings should ultimately be integrated into rehabilitation planning for that individual (Schatz, Hughes, & Chute, 2001). Often however, the rehabilitation programmes available to a client are not modified to account for the demonstrated cognitive strengths and weaknesses revealed through the assessment process. This is reflected in the tendency for cognitive rehabilitation strategies to be structured around types of illness or mechanisms of injury, i.e. different programs for stroke patients, those with traumatic brain injuries, or Alzheimer's disease. However, when the client's strengths and weakness are considered in terms of guiding intervention strategies, rehabilitation that is tailored to the specific client's needs has proven beneficial (Engelberts, Klein, Ader et al., 2002).

Clinicians employ a battery of tests in neuropsychological assessment to determine the individual's current level of functioning for a wide range of cognitive abilities. In doing so, they are attempting to classify the status of brain-behaviour relationships for a specific individual. Ironically, most of the research in this area is soundly placed within studies of groups, either groups of people with a particular diagnosis or groups of tests and their ability to classify. It is these studies that reveal the brain-behaviour relationships, which clinicians then use as the basis for their assumptions regarding patterns of test performance for the individual case. The

difficulty with this is that clinicians may rely blindly upon these brain-behaviour relationships revealed through group studies to make inferences regarding a particular individual, based upon the assumption that the individual came from the same diagnostic group. In the vast majority of such studies, the patterns of test performance, described as characteristic of a particular condition or disorder, are based upon measures of central tendency such as group means without consideration of the degree to which the individuals in the group are represented by mean scores. Therefore, these group mean studies fail to consider the possible heterogeneity of patterns of performance by individuals within a certain diagnostic group.

This is perhaps most readily understood with regard to the mean performance for the co-standardisation sample (weighted N = 1250) of the third edition of the Wechsler Adult Intelligence Scale (WAIS-III, Wechsler, 1997a) or Wechsler Memory Scale (WMS-III, Wechsler, 1997b). By definition the mean score on each of the thirteen WAIS-III subtests is 10 with a standard deviation of three. The mean performance for a "normal" group is therefore 10 on each test. If this is depicted graphically, the mean scaled score for the standardisation sample is a flat line representing 10 on every subtest. For example, in the WAIS-R standardisation sample not a single subject generated the same score on all subtests (Matarazzo & Priftera, 1989). Assumptions regarding expected patterns of individual's test scores based upon group studies are powerful and pervasive in clinical practice. This problem can only be redressed by the application of appropriate multivariate methodologies that are sensitive to the behaviour of individuals within groups.

1.2 Neuropsychological Research, Tests and Profile Analysis

Neuropsychology often attempts to utilise subject classification based on multivariate data to assist in the analysis of many test profiles. Such profile analysis is used to analyse the differences between cognitive profiles of groups and individuals

on a set of specific measures (Tabachnick & Fidell, 1996), with multivariate analysis of variance, cluster analysis, factor analysis, or structural equation modelling demonstrating utility in this regard. The assessment of the profiles that are obtained from such multivariate analyses attempt to group individuals or scores according to their degree of relatedness. Thus individuals may be grouped together based upon similar strengths and weaknesses in test score patterns. The profiles are usually derived through configural rules (Greene, 2000), formulae (Moses & Pritchard, 1996), or algorithms (Zimmerman, 1998).

Research utilising these methods in examining modal profiles include the Halstead-Reitan Neuropsychological Battery (HRNB) in both adults (Moses, Pritchard, & Adams, 1996) and children (Livingston et al., 1997), the Wechsler Adult Intelligence Scale – Revised (WAIS-R, Burgess, 1991; Crawford & Allan, 1994; Moses & Pritchard, 1996), the Wechsler Intelligence Scale for Children – 3rd edition (WISC-III, Cramer, 1998), the Luria-Nebraska Neuropsychological Battery (LNNB, G. Goldstein, Shelly, M^{c}Cue, & Kane, 1987), and the first (Giannetti, Johnson, Klingler, & Williams, 1978; Goldberg, 1972) and second editions (MMPI-2) of the Minnesota Multiphasic Personality Inventory (Greene, 2000) . This type of analysis is often undertaken to categorise cognitive performances on these tests in both clinical and control groups to assess differences in performances.

The profiles of each of these tests were developed in different ways. Modal profile analysis was used to assess the HRNB (Livingston et al., 1997; Moses et al., 1996), a method which utilises a clustering algorithm to eliminate the effect of magnitude during the analysis and then restores elevations once the profile types are identified. The profile clustering indicated that there were 18 modal profile types for subjects with a variety of clinical diagnoses. The clustering of subjects was achieved by converting raw test scores to age- and education-adjusted t-scores, which were

then cluster analysed, and these were then placed into a principle components factor analysis to assess the most frequently occurring profile. Once this was determined, the typal uniqueness of each individual was assessed by the Simple Distance Probability Statistic to allocate each person to only one of the profiles.

The LNNB was assessed using cluster and ipsative profile analysis (G. Goldstein et al., 1987), a method in which cluster analysis was used to allocate cases to a limited number of profiles based on the statistical significance differences between test score fluctuations. The results of this study indicated a four-cluster solution to the LNNB based upon hierarchical cluster analysis with squared Euclidean distance as the distance metric. The four profiles were then analysed to assess whether they were related to clinical diagnosis, which proved not to be the case.

The MMPI and its more recent revision, the MMPI-2, are probably the most well recognised personality inventories that have employed profile analysis. In the traditional approach, the individual's profile is coded based upon configural rules, which are associated with interpretative statements. The codetypes are determined by assessing which of the t-scores are elevated, indicating the highest two, or less commonly three, scales from among 10 basic scales. This codetype is then matched to one of the 45 patterns associated with specific interpretative statements (Greene, 2000). This seems to be a gross underutilisation of the data, when it is considered that there are more than 200 scales available for interpretation. With a focus on only two scales, this could hardly be presented as a multivariate approach.

An alternative approach to comparing individual MMPI profiles to group patterns was proposed by Goldberg (1972). He developed predictor indices that utilised the point-biserial correlations between scores to develop simple composites of scale scores with the use of cut-off scores as prediction functions. He found that these composite scores based on individual profiles were good at discriminating between

group profiles. Goldberg's results were confirmed in a study by Gianetti et al. (1978) who utilised the omega-squared statistic to determine the amount of variance accounted for between profiles. While Goldberg's equations were found to have high hit-rates (65.5%) in terms of discriminating groups, they were still not good at predicting diagnosis from individual profiles.

WAIS-R profile analysis has been analysed using modal profiles (Moses & Pritchard, 1996), cluster analysis (Clark, Crockett, Klonoff, & MacDonald, 1983) and Mahalanobis distance (Burgess, 1991; Crawford & Allan, 1994). Burgess (1991) analysed the WAIS-R factor structure and utilised Mahalanobis distance to assess for deviance within the profiles. Crawford and Allen (1994) indicated that the profiles that Burgess found were stable and independent of one another. Moses and Pritchard found that differences in the modal profiles, derived from ipsative Q-type principle components analysis on the WAIS-R were mainly attributable to profile elevation, and that this accounted for 65.9% of the difference in the profiles. They also found that the subtest profiles were better at aligning with only one of the modal profiles but that the factor profiles tended to align with more than one modal profile.

1.2.1 Assessment and Prototypical Patterns of Performance

The belief that certain disorders will produce specific patterns of cognitive strengths and weaknesses on testing is ubiquitous in the area of neuropsychology, both in determination of the individual's dysfunction (Lezak, 1995) and in the diagnostic process (Golden, 1990). Lezak (1995) asserts that individuals with differing diagnoses exhibit different profiles of scores, and that individuals with the same disorder exhibit similar test score profiles. Indeed this type of knowledge, in which large organic impairments or disorders have been studied, is stressed by Arbit and Zager (1978) as critical to understanding the nature of a client's current cognitive functioning.

Heinrichs and Zakzanis (1998) indicate that neuropsychological research has traditionally used matching strategies to demonstrate selectivity of deficit, which leads to inherent problems associated with misattribution of deficits to some disorders, related to age of onset and educational issues. For example, they note that within schizophrenia, the use of age and education matched controls may lead to spuriously low estimates of generalised abilities related to the nature of the illness and its age of onset in late adolescence to early adulthood. This may lead to low estimates of abilities and confound any reported findings of deficits that are attributable to the disorder of schizophrenia. This belief has been perpetuated by researchers claiming distinct profiles of performance for traumatic brain injury (Al-Adawi, Powell, & Greenwood, 1998), multiple sclerosis (Andrade et al., 1999), dementia of the Alzheimer's type (Johnstone, Hogg, Schopp, Kapila, & Edwards, 2002), Parkinson's disease (Woods & Troester, 2003), substance abuse (Di Sclafani, Tolou-Shams, Price, & Fein, 2002; Ornstein et al., 2000) but especially in schizophrenia and other types of mental illness (Addington, Addington, & Gasbarre, 2001; Mojtabai et al., 2000; Moritz et al., 2002; Riley et al., 2000; Zakzanis, Andrikopoulos, Young, Campbell, & Sethian, 2003). Implicitly, clinicians attempt to match their client's pattern of test scores to hypothetical prototypical models that they have built up through clinical experience or from the research literature.

For example, many authors (Axelrod, Fichtenberg, Liethen, Czarnota, & Stucky, 2002; Crawford, Garthwaite, Johnson, Mychalkiw, & Moore, 1997; Dikmen, Machamer, & Temkin, 2001; Jacobus Donders, Tulsky, & Zhu, 2001; D. C. Fisher, Ledbetter, Cohen, Marmor, & Tulsky, 2000; Franzen, 2000; Haut & Shutty, 1992; Kersel, Marsh, Havill, & Sleigh, 2001) indicate that the main deficits that are found in both mild, and moderate to severe traumatic brain injury profiles, are related to memory, attention/concentration and processing speed, with other authors adding

problems in reasoning and executive functioning (Franzen, 2000; Greve et al., 2002; Iverson, 2000). These poor performances have been found with numerous tests including the Wechsler scales, (e.g. Jacobus Donders et al., 2001; D. C. Fisher et al., 2000), list learning tasks (Kersel et al., 2001), executive functioning (Greve et al., 2002; Wiegner & Donders, 1999b) and speeded tasks (Dikmen et al., 2001). These authors however, describe these patterns and make their inferences based upon group means and give little to no indication of the behaviour of individuals within the group. This has been recognised by researchers such as Crawford et al. (1997), who in discussing their findings that only one of their clusters fit the "prototypical subtest pattern…..in which Arithmetic and Digit Span are the most severely effected Verbal subtests and Digit Symbol is the most severely effected Performance subtest" (p.255) of a closed head injury.

Parkinson's disease is most often characterised by a pattern of executive functioning deficits (Farina et al., 2000; Green et al., 2002; Libon et al., 2001; Tomer, Fisher, Giladi, & Aharon-Peretz, 2002; Woods & Troester, 2003). These deficits are usually related to poor performances on tests which are purported to measure frontal lobe functioning, like the Wisconsin Card Sort Test (WCST, Farina et al., 2000; Green et al., 2002; Tomer et al., 2002; Woods & Troester, 2003), Boston Naming Test (BNT) and tests of verbal fluency (Libon et al., 2001). Other deficits that are common in the literature on Parkinson's disease are observed on visuo-constructional and memory tasks, especially in individuals at risk of dementia (Farina et al., 2000; Woods & Troester, 2003). However, all of these studies again used group means to characterise the deficits and without assessment of performances on other neuropsychological domains (e.g. verbal and visual abilities, speed and attention).

One of the most common deficits that are described in temporal lobe epilepsy (TLE) is that of confrontation naming (Bell et al., 2002; Seidenberg et al., 1998),

usually measured by the Boston Naming Test (BNT). Other deficits that are commonly associated with TLE are those of memory, especially on verbal tasks (Seidenberg et al., 1998; Wilde et al., 2001), attention, and speed of processing (Engelberts, Klein, Ader et al., 2002; Engelberts, Klein, van der Ploeg et al., 2002; Moore & Baker, 2002). All of these studies, again, usually test only the specific cognitive domains of interest (e.g. memory) and determine profiles based on group means.

Schizophrenia research is also plagued with these kinds of generalist statements in the overabundance of literature regarding this disorder. The most common deficit that people with schizophrenia are documented as having, regardless of chronicity, type, or symptomatology, lies with executive functions (Albus et al., 2002; Allen, Goldstein, & Aldarondo, 1999; Bilder et al., 2000; Dinn, Harris, Aycicegi, Greene, & Andover, 2002; Everett, Lavoie, Gagnon, & Gosselin, 2001; Gambini, Campana, Garghentini, & Scarone, 2003; Gerald Goldstein, Allen, & Seaton, 1998; Gonzalez-Hernandez, Pita-Alcorta, Cedeno, Dias-Cosmas, & Figueredo-Rodriguez, 2003; Gooding & Tallent, 2002; Grawe & Levander, 2001; R. Heinrichs & Awad, 1993; R. W. Heinrichs & Zakzanis, 1998; Hill, Ragland, Gur, & Gur, 2001, 2002; Joober et al., 2002; Kremen, Seidman, Faraone, & Tsuang, 2001; McBride et al., 2002; Riley et al., 2000; Seaton, Goldstein, & Allen, 2001; Seidman et al., 2002; Suhr & Spitznagel, 2001; Zakzanis et al., 2003). The next most common deficits reported are in memory and attention (Addington et al., 2001; Gerald Goldstein, Beers, & Shemansky, 1996; Holthausen et al., 2002; Mojtabai et al., 2000; O'Leary et al., 2000; Smith et al., 1998). Some authors have also indicated a generalised overall decline in functioning (Allen et al., 1999; Gerald Goldstein et al., 1996; R. Heinrichs & Awad, 1993; R. W. Heinrichs & Zakzanis, 1998; Hill et al., 2001, 2002; Moritz et al., 2002; Seidman et al., 2002; Zakzanis et al., 2003), while

others have noted normal functioning in schizophrenia, albeit that such individuals usually had higher levels of premorbid functioning (Holthausen et al., 2002; Kremen, Seidman, Faraone, Toomey, & Tsuang, 2000; Seaton et al., 2001). Dinn et al. (2002) suggest that the varied range of deficits in schizophrenia may be related to the extent to which the client experiences negative or positive symptoms. Heinrichs and Zakzanis (1998) in their quantitative review of 204 studies that assessed the deficits of schizophrenia concluded that any discerning deficits of schizophrenia tended to be reflected against a global deficit in cognitive functioning. The diverse array of deficits noted in schizophrenia is testament to the fact that this disorder, by no means, has a single prototypical pattern of performance.

The Wechsler Scales (both Intelligence and Memory) are among the most common tests of cognitive functioning administered in neuropsychological, clinical, and forensic settings (Butler, Retzlaff, & Vanderploeg, 1991; Camara, Nathan, & Puente, 2000; Lees-Haley, Smith, Williams, & Dunn, 1996; Piotrowski & Keller, 1989; Sharpley & Pain, 1988; K. Sullivan & Bowden, 1997). Consequently, statements regarding Wechsler profiles characteristic of specific diagnoses abound in the research literature (Lange, 2000), including such diverse diagnostic groups as autism and schizophrenia (Boelte, Rudolf, & Poustka, 2002), traumatic brain injury (D. C. Fisher et al., 2000) and alcoholic women (E. V. Sullivan, Fama, Rosenbloom, & Pfefferbaum, 2002), to name a few.

This research illustrates the same exclusive focus on group means at the expense of individual cases which bias clinicians' expectations regarding psychological test patterns. The myth of specific profiles of performance on the WAIS-III and WMS-III based on brain pathology continues to be perpetuated by authors such as Hawkins (1998). In his article, Hawkins analysed the profiles of mean scores obtained from each of the clinical samples from the WAIS-III and WMS-

III Technical manual (The Psychological Corporation, 1997). Based on the means of these small groups of patients, Hawkins indicates that the traumatic brain injury profile will exhibit poor processing speed and poor memory, especially visual memory. He then asserts that poorer performance in these areas, and especially in processing speed will have good "diagnostic-specific utility" when diagnosing traumatic brain injury. This author goes on to illustrate further differences in group patterns based on the means of other diagnostic groups from the Technical Manual.

The assumptions that certain types of brain pathology result in certain profiles of scores on tests (i.e. brain test behaviour relationships) manifest clinically in psychological test reports that include statements such as: "the obtained pattern of test scores is consistent with the traumatic brain injury Mr. Y sustained". This assertion is logically based upon three assumptions. Firstly that there is a particular pattern of cognitive functioning that is found following a particular neurological injury (e.g. traumatic brain injury). As has been discussed above, this assumption is perpetuated by the research literature where means and standard deviations are provided for groups with different diagnoses. In psychological reports, this manifests in such statements as "traumatic brain injury commonly produces deficits in the efficiency of learning, attentional abilities, and speed of processing".

This leads to the second assumption where the writer's statement directly indicates that the test data in the particular case has been compared to the results of others with the same diagnosis. The statement "consistent with" directly indicates that a comparison has been made with others who have "sustained a traumatic brain injury". While this is not an impossible task, the vast majority of clinicians would use only normative data in their statistical analysis of test scores. Technically, such a comparison with norms can only indicate inconsistency with normalcy, not consistency with a group with whom no comparison has been made.

The third assumption that the writer in this example has also made is that the only relevant event that affects test scores is the traumatic brain injury, and may be ignoring such things as a pre-existing learning disability, a lifelong history of substance abuse, or a seizure disorder. That is not to say that all individuals must have other contributing conditions, but presumably in saying that the test scores are consistent with a traumatic brain injury, the clinician must be assuming that the profile is **NOT** consistent with any other cause or explanation. To not do so is to suffer from confirmatory bias, where the clinician seeks only confirmatory information and does not examine disconfirming evidence (Wedding & Faust, 1989). Perhaps most surprising of all is that there is little support in the literature for any of these assumptions (Lange, 2000).

1.2.2 Examination of Lange (2000) Profiles of WAIS-R/WMS-R Performance

The current research is based extensively on and extends the doctoral dissertation of Dr. Rael Lange (2000). Lange examined the statistical basis for prototypical patterns of cognitive functioning in differing psychiatric and neurological diagnoses. He utilised cluster analysis to examine the presence of patterns of cognitive test performance on the WAIS-R and WMS-R for 1367 clinical cases comprising seven diagnostic groups: pharmacologically treated seizure disorder; surgically treated seizure disorder; traumatic brain injury; alcohol abuse; psychiatric disorder; dementia; and cerebrovascular disorder. Lange found that no single pattern was characteristic of test performance in any of the seven diagnostic groups. In fact each group generated between three and five cognitive profiles, a finding that contradicted any assumption that one specific pattern of relative cognitive strengths and weaknesses characterises the effect of a particular disorder. For example, the profile of scores described by Hawkins (1998) regarding traumatic brain injury having a pattern of scores reflecting poor processing speed and poor memory, was found in

only 9.4% Lange's sample. Therefore 90.6% of subjects in Lange's traumatic brain injured group did not have both poor memory and poor speed of processing but reflected a weakness in only memory and normal performance on speed of processing (58.5%) or relative strengths or normal memory with poor performances on processing speed (32.1%).

Lange (2000) also found that the different patterns derived were not specific to their respective diagnostic groups. Rather the same profile of scores, were repeatedly found in each of the clinical groups. For example, a cognitive pattern derived from his alcohol abuse sample correlated highly with patterns identified in other diagnostic groups: .95 with psychiatric; .94 with dementia; .90 with traumatic brain injury; .84 with cerebrovascular disease; .71 with pharmacologically treated seizure disorder; and .62 with surgically treated seizure disorder.

Because Lange (2000) found no empirical basis for distinct diagnostic profiles, he analysed all 1367 clinical cases treating them as one large clinical group. This time he derived three distinct and robust profiles. Lange described the three patterns in terms of the general areas of cognitive strength and weakness that they typified and referred to them as "cognitive clusters":

Cognitive Cluster 1 – Characterised by individuals displaying relative cognitive strengths in verbal and visuospatial abilities, with a relative weakness in overall memory functioning.

Cognitive Cluster 2 - Characterised by individuals displaying relative cognitive strengths in visuospatial abilities, attentional, and overall memory abilities, with a relative weakness in verbal abilities.

Cognitive Cluster 3 - Characterised by individuals displaying relative cognitive strengths in verbal and memory abilities, with a relative weakness in visuospatial abilities.

Interestingly, these cognitive clusters represent strengths and weaknesses that reflect the inherent factor structure of the tests administered. Not surprisingly, this suggests that the number of patterns of performance characterised by a particular group of tests is a function of the number of different abilities assessed by these tests. This idea was further supported by Lange's preliminary analysis of a small data set of 254 cases who were administered the WAIS-III and WMS-III. Cluster analysis, which revealed the presence of four cognitive profiles within this small sample:

Cognitive Cluster 1 – Relative cognitive strengths in of verbal and auditory memory, with relative weaknesses in processing speed, attentional and visuospatial abilities.

Cognitive Cluster 2 - Relative cognitive strengths in verbal and visuospatial abilities, with a relative weakness in overall memory functioning.

Cognitive Cluster 3 - Relative cognitive strength in overall memory functioning, with relative weaknesses in verbal and visuospatial abilities.

Cognitive Cluster 4 - Relative cognitive strength in visuospatial ability with a relative weakness in verbal ability.

Analysis of WAIS-III and WMS-III data generated one more profile than was found with WAIS-R/WMS-R data. This is likely due to the greater factorial complexity (five factors) of the third editions of these popular batteries compared to their revised versions (four factors). Cluster analysis was central to Lange's approach to deriving cognitive profiles and is discussed in greater detail below.

1.3 Statistical Methodologies Utilised

1.3.1 Cluster Analysis

Cluster analysis is used to describe a number of statistical techniques that explore subgroups within multivariate data (Lange, Iverson, Senior, & Chelune, 2002). Essentially it is used to objectively group individuals on the basis of their

convergence and divergence to particular criteria and therefore defining groups or clusters of people with homogenous profiles (Davison, Gasser, & Ding, 1996; G. Goldstein et al., 1987). Overall and colleagues (Atlas & Overall, 1994; Overall & Magee, 1992) indicate that the major use of clustering procedures in the behavioural sciences is to deduce the divergent core groups that are represented in samples.

There are a large variety of methods and measures that may be used in cluster analysis. In their comprehensive overview of clustering techniques, Lange et al. (2002) describe each of the clustering methods, proximity measures, standardisation of scores, ways to determine the number of clusters, and the internal validation of cluster solutions. While it is beyond the scope of the current research to comprehensively evaluate these methods here, consideration of some of the issues relating to the determination of cluster analytic methods, measures, and decisions will be briefly discussed.

Perhaps the most commonly administered cluster analytic method within the area of neuropsychology is Ward's method using squared Euclidian distance as the distance metric (Cheng & Milligan, 1995; Jacques Donders, 1996; N. J. Fisher et al., 1996; Greve et al., 2002; Haut & Shutty, 1992; R. Heinrichs & Awad, 1993; Hill et al., 2002; Kixmiller, Williams, Gatten, & Dean, 1994; Schear, 1987; Wiegner & Donders, 1999a). However there have been some criticisms levelled at this approach. For example, Romesburg (1984) indicated that many authors who utilise this approach are lulled into a false sense of security that the clusters they are deriving are well-defined as indicated by the cluster tree. The nature of the cluster tree is actually an artefact of the way that it is calculated using sums of squares and may result in a mathematically contrived tree. Romesburg also indicated that the use of Ward's method is limited in that it implies a hierarchical method of clustering which does not allow reallocation of cases throughout the partitioning. This means that if cases are

inappropriately added to a cluster early in the partitioning process, it cannot be corrected at a later stage. Donders (1996) argued that this type of agglomerative clustering technique is susceptible to fusion errors within the clustering process and therefore this method should only be used to indicate how many clusters are to be specified for the iterative K-Means procedure. Other problems with this method are its sensitivity to outliers (Kaufman & Rousseeuw, 1990) and its tendency to produce clusters of equal size (Lange et al., 2002).

Many authors have utilised cluster analysis to examine case profiles and report finding three to four clusters (Jacques Donders & Warschausky, 1997; Greve et al., 2002; Haut & Shutty, 1992). Often the findings of these authors, however, are not based upon distinct profiles with differing shapes but rather tend to reflect the same pattern with differing levels of magnitude such as high, average and low scorers (Jacques Donders, 1996; Haut & Shutty, 1992; Kaufman & Rousseeuw, 1990; Schear, 1987; Suhr & Spitznagel, 2001). Crawford et al. (1997) argued that the successful detection of noteworthy subgroups would enhance neuropsychological comprehension of disorders and aid clinical management. However, finding clusters based on performance levels does little to enhance the understanding or management of disorders. Therefore caution needs to be taken when utilising cluster analysis lest a solution that has no clinical or research significance is produced (Davison et al., 1996).

Another problem seen with the use of cluster analysis in the research literature is that of small sample sizes, notably those with less than 100 cases (Greve et al., 2002; Haut & Shutty, 1992; Nestor, Kimble, Berman, & Haycock, 2002; Suhr & Spitznagel, 2001; Walzer, Herrmann, & Wallesch, 1997). Meehl (1995) believed that the use of taxometric research tools like cluster analysis, should involve larger samples of at least 300 cases or more, noting that psychological researchers who do

not have sample sizes of at least this size employed with valid measuring tools should move on to other ideas.

Everitt (1974) indicated that another source of error in cluster analysis findings is the number of variables in the analysis and suggested the use of a small number of principle components instead of all variables. This approach that has been utilised to advantage by some authors (Wiegner & Donders, 1999a).

The current studies will generally employ methods of analysis similar to those of Lange (2000) and recommended by Lange et al. (2002) designed to reduce the number of assumptions imposed in order to derive clusters and to minimise the vulnerabilities of particular methods by employing a stage process to cluster determination. The use of average linkage hierarchical cluster analysis using Pearson correlation will be used initially to determine the number of clusters in a data set, a task to which this method is well suited. The number of clusters will be chosen based upon inspection of inverse scree plot, dendrogram and inconsistency matrix of the hierarchical cluster output. The number of clusters required would then be required of a K-Means analysis using random seed points. Examination of the representativeness of the cluster solution would then be included in the final stage.

1.3.2 Goodness of Fit Measures

The evaluation of the adequacy of many models includes the use of various goodness-of-fit statistics. These statistics assess how well the model actually accounts for the scores that are produced on the various tests. Cramer (1998) indicated a number of fit indices for use. These include: chi-square statistic, chi-squared divided by the degrees of freedom, non-normed fit index, the comparative fit index, the root mean square residual, the average absolute standardised residual, the root mean square error of approximation, and the Tucker-Lewis index. All of these

statistics indicate whether or not the factor model is a good fit to the individual and group scores.

Multivariate outliers are cases that produce an atypical pattern of scores when two or more variables are considered in conjunction with one another and may indicate both Type I and Type II errors (Tabachnick & Fidell, 1996). There are a number of different outlier statistics. The MD, which assesses how far the individual's score is from the centroid of the population from which the observation was drawn, is often used in multivariate statistics and has been used previously in the assessment of WAIS-R profiles (Burgess, 1991; Crawford & Allan, 1994). Burgess (1991) found that the Mahalanobis distance was most sensitive to within factor differences and less sensitive to between factor differences on the WAIS-R. It is a good measure when assessing if an individual profile fits a group profile, as abnormalities are identified in subtest profiles that are not usually identified by other methods (Burgess, 1991). Bacon (1995) found that the hit rate of the Mahalanobis distance for identifying outliers was very high when the majority correlation was higher than the outlier correlation, and recommends its use in these situations.

Comrey's D (Comrey, 1985) is another outlier statistic that was purported to be better at detecting outliers that distort the correlation coefficient than the MD. Rasmussen (1988) used a Monte Carlo simulation technique to compare these two methods and found that the Mahalanobis distance was preferable to Comrey's D because it had a higher hit rate for identifying outliers with the same false alarm rate, and that the average correlations produced after the Mahalanobis distance were closer to the population correlations.

The maximum likelihood approach was introduced by Bacon (1995), and compares the correlational estimates for each individual case to that of the group. He compared the maximum likelihood approach to the Mahalanobis distance and

Comrey's D, and found that the maximum likelihood approach was more robust across measures but that it did not perform as well as the Mahalanobis distance in situations where the majority correlation was higher than the outlier correlation, but better when the majority and outlier correlations were reversed.

The Simple Distance Probability statistic is another statistic utilised in this manner and assesses the probability that a subject belongs only to the cluster that is assigned to and not to any of the other clusters (Livingston et al., 1997). The subject is assigned to the clusters by the MAXR rule, which is the degree to which the subjects' profiles were similar to the final modal profiles. As the value of the Simple Distance Probability approaches one, the closer the individual's profile is a fit to that cluster.

Another statistic used to measure the fit of an individual profile to group profiles is the Euclidean distance squared which minimises the straight-line distance between two points, between all cases in a cluster (G. Goldstein et al., 1987) and generalised to space (Harris, 1955). This measure is sensitive to both level and pattern considerations within clusters, and clusters by level when a large amount of variability in the level of the data is shown (G. Goldstein et al., 1987).

Goldberg (1972) utilised the point-biserial correlation to determine the difference between his first stage predictor indices, which are three-scale composite scores established by stepwise multiple regression, to the dichotomous criterion classification to assess whether the predictor indices were true measures of the criteria. This allowed the point-biserial correlation coefficients to be measures of how well the predictor indices fitted the individual and group profiles of the MMPI, and how well they discriminated between the groups.

All of these measures of fit and outliers have specific purposes and situations in which they appear to outperform the others. The Mahalanobis distance appears to

be one of the most commonly used of these outlier indices and appears to be one of the best in assessing the match between an individual profile and a group profile. Accordingly, Mahalanobis distance will be utilised in the current studies as the metric of choice in examining the relationship between individual and cluster profiles.

1.4 Purpose of Research

The main aims of this research are threefold. The first is to examine the findings of Lange (2000) with regard to WAIS-III and WMS-III data. Lange's study with the third edition Wechsler scales was exploratory in nature and will be more formally evaluated in the first study with a larger related clinical database.

The second study is designed to extend Lange's finding beyond the scope of the Wechsler scales, while the Wechsler batteries are quite extensive there are a number of cognitive areas, which would be omitted or inadequately evaluated if these tests alone were used. Lange's failure to discriminate between different diagnostic groups may have been a consequence of using only WAIS-R and WMS-R data. It is possible that the cognitive domains on which his diagnostic groups dissociate were not evaluated with these two batteries. To examine this possibility, a database of clinical cases with a larger number of psychological tests will be submitted to cluster analysis to determine the number of underlying cognitive profiles. These profiles will then be examined, in the manner employed by Lange, to examine the degree to which these cognitive profiles recur in different diagnostic groups.

The third study has a much more applied focus. The implications of Lange's research are that diagnosis does not systematically alter patterns of cognitive strengths and weaknesses. If this is the case, it raises the question as to what role psychological test patterns can play in the evaluation of cognitive functioning. As multiple but a finite number of distinct patterns have been repeatedly observed, the potential for a behavioural classification system which groups individuals according to their

common strengths and weaknesses is apparent. Rather than a medical diagnosis, this is akin to a psychological diagnosis in which intervention strategies are applied to individuals with the same or similar psychological diagnoses. While this is well beyond the scope of the current research, a critical first step must be the development of a statistically sound and accurate system for classifying patterns of test performance. Only after such a system has been developed, can clinicians and researchers alike examine the potential utility of psychological classification to the judicious application and design of treatment programmes. Development and demonstration of the accuracy of such a classification system is the focus of the third study.

1.5 Overview of Dissertation

1.5.1 Chapter 2: Study 1 - Replication and Verification of Lange (2000) WAIS-III/WMS-III Profiles

Validation of Lange's (2000) provisional findings regarding the WAIS-III and WMS-III and examining the implications for clinical practice form the basis of the second chapter. The first study aims to replicate Lange's (2000) findings of the four cognitive clusters for the WAIS-III/WMS-III using a more extensive database of cases from clinical practices the United States of America. The procedures for cluster analysis developed by Lange (2000) and the strategies recommended by Lange et al. (2002) will be generally employed with some minor modifications. The degree to which these newly derived cognitive clusters replicate those found by Lange (2000) will then be considered by correlational analysis with the clinical implications being explored briefly.

1.5.2 Chapter 3: Study 2 - Examination of Prototypical Cognitive Patterns in an expanded neuropsychological battery using cluster analysis

The third chapter will present the second study, which will expand Lange's research by increasing the number of cognitive tests and factorial complexity of the test battery to examine whether or not this generates a larger number of profiles. One implication of this study is that the overly simplistic assumptions regarding the robustness of brain-behaviour-test relationships may be even less tenable in a test battery that is more characteristic of those employed by clinicians. Alternatively, the patterns of distinct cognitive functioning related to diagnosis that eluded Lange, may be more apparent in profiles composed of more varied domains of cognitive functioning. The tests that will be added to the WAIS-III and the WMS-III will cover a number of cognitive constructs including speed of processing, executive functioning, verbal fluency, and visual organisation and processing. The addition of the extra measures is designed to increase the robustness of the cognitive clusters, as they will become more pronounced and therefore more useful in clinical practice.

1.5.3 Chapter 4: Study 3 - Clinical Utility of the Derived Clusters from an Expanded Neuropsychological Battery

The fourth chapter of the dissertation will then assess the accuracy and clinical utility of the cognitive clusters from the second study. The third study therefore will aim to test the robustness of the cognitive clusters, and determine the applicability of a multivariate analytical system to individual clinical cases. The goal is to essentially develop a method of analysis that examines whether or not the group clusters can be effectively applied at the individual case level. This will be assessed by the use of the multivariate outlier statistic, Mahalanobis distance, to determine to which cognitive cluster or clusters a particular case would be assigned. If successful, this would allow clinicians to classify individual cases according to a particular cognitive profile,

which takes into account the psychometric properties and interrelationships of the tests utilised. Such a classification system would better reflect the complexity of human behaviour and permit grouping of individuals based upon the communality of their behaviour rather than the disease process or mechanics of their injury.

1.5.4 Chapter 5: Case Study Examples

The fifth chapter will illustrate and demonstrate the method developed in the third study through the use of demographically and diagnostically matched cases. In particular, this will emphasise the diversity of behavioural changes in individuals who would be characteristically grouped according to their neurological diagnosis. With these examples it is hoped that the reader will gain a greater understanding of not only how the method is employed with individual cases but the potential for describing and testing clinical hypotheses.

1.5.5 Chapter 6: General Discussion

This chapter will summarise the findings from the three studies and will discuss their conclusions in terms of theoretical and practical considerations. This chapter will also highlight implications for future research and address limitations in the dissertation.

CHAPTER 2

2.0 REPLICATION AND VERIFICATION OF LANGE (2000) WAIS-III/WMS-III PROFILES

2.1 Overview

Lange (2000) found that no one cognitive profile based on WAIS-R and WMS-R test data was characteristic of any particular diagnosis. Rather he found that a small number of cognitive patterns recurred in all diagnostic groups. Additionally, Lange also examined potential cognitive patterns in a sample of 254 individuals who had been administered the WAIS-III and WMS-III. Given his small sample size, this aspect of his research could be considered only exploratory in nature and was designed to consider whether the profiles derived for the revised editions were also found for the third editions. Perhaps because of the increased factor complexity of the third editions, Lange's exploratory analyses revealed one more cognitive profile than was observed following his analysis of clinical data from the revised editions. This chapter will seek to replicate and clarify these cognitive profiles identified by Lange in a similar clinical sample administered the WAIS-III and WMS-III. Because both Lange's findings and the method he employed are of critical importance to the studies conducted in the current research, his study will be described in some detail.

Lange's sample was drawn from the case files of the Cleveland Clinic Foundation, Ohio, USA, consisted of nine diagnostic groups: traumatic brain injury (9.5%); seizure disorders (26.7%); probable dementia of the Alzheimer's type (9.5%); other dementias (9.8%); drug and alcohol abuse (5.5%); psychiatric disorders (7.5%); stroke (6.7%); other cerebrovascular disorders (19.6%); and tumour (5.2%). The sample consisted of 141 males (55.5%) and 113 females (44.5%), with a mean age of 49.91 years (sd = 17.21) and a mean education of 13.32 years (sd = 3.01), and was

comprised of three ethnic groups (Caucasian: 89.7%, African-American: 9.1%, and Hispanic: 1.2%).

Lange analysed their performances across eight measures from the WAIS-III (Vocabulary, Information, Similarities, Picture Completion, Block Design, Matrix Reasoning, Digit Symbol and Symbol Search) and eight indices from the WMS-III (Auditory Immediate, Visual Immediate, Immediate Memory, Auditory Delayed, Visual Delayed, Auditory Recognition Delayed, General Memory and Working Memory). In order to represent all measures on the same scaling system, the WMS-III indices were converted from Standard Scores to Scaled Scores comparable to the WAIS-III subtests. All scores were then converted to deviation scores. Deviations scores are computed as the difference between each test scaled score and the mean of scaled scores for each individual. In this way, scores are presented relative to the mean performance level for each case and diminish the effects of profile magnitude but leave profile configuration unaltered. As the goal of his study and cluster analysis procedure was to cluster the profiles according to shape and not magnitude, the use of these scores was critical.

After the conversion of all scores to deviation scores, Lange performed a hierarchical cluster analysis on the WAIS-III/WMS-III Mixed Diagnostic sample utilising between groups' average linkage as the clustering algorithm, and the Pearson Product moment correlation as the proximity measure. He concluded that the data were best described by a four cluster solution based upon examination of the inverse scree plot, the dendrogram, and rejection of clusters containing less than 5% of the sample (Everitt, 1974; Morris, Blushfield, & Satz, 1981). Lange then applied a K-Means analysis designating four clusters as indicated by the prior hierarchical analyses and utilised a nearest centroid clustering algorithm beginning with random seed points and using squared Euclidean distance as the proximity measure.

The hierarchical cluster analysis represents one method for determining clusters, a method well suited to the delineation of the number of clusters in a data set. The K-Means analysis, particularly using random seed points, represents a second approach to clustering this same data but is reliant upon specification of the number of clusters to be derived. Once the number of clusters can be confidently designated, K-Means analysis is particularly well suited to allocating cases appropriately to clusters, as individual cases can be repeatedly re-assigned to more appropriate clusters throughout the iterative process. Table 2.1 presents the correlations between the clusters identified in Lange's K-Means analysis. Notably there are no significant correlations among the K-Means clusters, indicating that the derived profiles are statistically independent.

Table 2.1
Correlations Lange's K-Means Analysis

	K-Means Analysis			
	K1	K2	K3	K4
K1	1.00			
K2	.06	1.00		
K3	.27	-.79	1.00	
K4	-.39	-.12	-.10	1.00

Lange depicted and characterised each of the profiles according to the factor structure of the WAIS-III/WMS-III sample. Relative strengths were indicated by scores that fell more than one standard deviation above the mean, and relative weaknesses, reflected in scores more than one standard deviation below the mean. He described Profile 1 as having strengths in the areas of verbal comprehension (VC), and delayed recall of verbal information (AD, ARD), and weaknesses in the ability to perceptually organise visual information (PO), process information rapidly (PS), and attend to information (WM). Profile 2 included individuals with relative cognitive strengths in their abilities to comprehend verbal material (VC) and perceptually organise visual stimuli (PO), but who demonstrated a relative cognitive weakness in

their overall memory abilities (AI, VI, IM, AD, VD, GM). Lange's third profile was characterised by individuals with a relative cognitive strength in their ability to recall and recognise information after a delay (GM, ARD), and particularly with verbally presented information (AD), but who has a relative cognitive weakness in their ability to perceptually organise visual stimuli (PO), and attend to information (WM). His fourth profile was characterised by a relative cognitive strength in the ability to reason abstractly when the stimuli is visually mediated (Matrix Reasoning), with a relative cognitive weakness in the ability to verbally comprehend information (VC).

Lange's evaluation of WAIS-III/WMS-III data must be considered exploratory due to the small sample size (N<300). The focus of this chapter therefore was to more formally examine cognitive profiles utilising data from the WAIS-III and WMS-III in a larger mixed diagnostic sample drawn from the same clinical setting. The replicability of Lange's findings can then be considered through comparison with the profiles found in this new sample.

2.2 Method

2.2.1 Cases

The mixed diagnostic sample consisted of 854 cases who had been administered the WAIS-III and WMS-III. The cases were drawn from the archives of the Department of Psychiatry and Psychology (Neuropsychology) at the Cleveland Clinic Foundation. Cases included individuals from 12 diagnostic groups, including cerebrovascular disorders (n = 111, 13.0%), probable dementia of the Alzheimer's type (n = 52, 6.1%), multi-infarct dementia (n = 92, 10.7%), other dementias (n = 65, 7.6%), drug and alcohol abuse (n = 40, 4.7%), Parkinson's disease (n = 32, 3.7%), psychiatric disorders (n = 25, 2.9%), seizure disorders (n = 199, 23.2%), traumatic brain injury (n = 76, 8.9%), tumour (n = 38, 4.4%), other disorders (n = 92, 10.7%), and no diagnosis attributable (n = 35, 4.1%).

The "other disorders" diagnostic category consists of diagnoses with too few subjects to be classified individually or whose diagnosis was not recorded. The diagnostic categories in this group were anoxia (n = 2, 0.2%), cognitive impairment not otherwise specified (n = 39, 4.6%), encephalitis (n = 9, 1.1%), general medical (n = 10, 1.2%), hydrocephalus (n = 2, 0.2%), mental retardation (n = 2, 0.2%), multiple sclerosis (n = 7, 0.8%), systemic lupus erythematosus (n = 3, 0.4%), toxic exposure (n = 4, 0.5%), infantile cerebral sphingolipidosis (n = 1, 0.1%), and no diagnosis attributable (n = 13, 1.5%). All subjects had been referred for neuropsychological assessment as part of routine medical management and/or rehabilitation, and were chosen for inclusion in this study based on the following criteria suggested by Lange (2000).

1. Individuals had been administered sufficient subtests of the WAIS-III and the WMS-III for the purposes of analysis.
2. All cases received an ICD-9 (International Classification of Disease – 9th Edition) diagnosis.
3. Cases were excluded if they had received more than one neurological or psychiatric diagnosis.

The characteristics of this sample along with psychological test scores are presented in Table 2.2 and stratified by diagnostic group in Appendix A (Table A.1).

Table 2.2
Descriptive Statistics of the WAIS-III/WMS-III Mixed Diagnostic Sample

	Measures	Cases	%	
Gender	Male	44 8	52.3	
	Female	409	47.7	
Ethnicity	Caucasian	771	90.0	
	African-American	71	8.3	
	Hispanic	15	1.8	
Diagnostic Group	CVD	111	13.0	
	Alzheimer's Dementia	52	6.1	
	Multi-Infarct Dementia	92	10.7	
	Other Dementia	65	7.6	
	Parkinson's Disease	32	3.7	
	Drug and ETOH Abuse	40	4.7	
	Psychiatric Disorder	25	2.9	
	Seizure Disorder	199	23.2	
	Tumour	38	4.4	
	Traumatic Brain Injury	76	8.9	
	Other Disorders	92	10.7	
	No Diagnosis Attributable	35	4.1	
		Mean	SD	Range
Demographics	Age (years)	48.90	17.36	15-92
	Education (years)	13.29	2.96	3-20
WAIS-III	Verbal Comprehension	95.45	16.12	50-145
Factor Scores	Perceptual Organisation	93.06	16.90	56-150
	Processing Speed	87.58	15.69	54-137
WAIS-III	Vocabulary	9.32	3.30	1-18
Selected	Similarities	8.91	3.12	1-18
Subtests	Information	9.36	3.20	1-19
	Picture Completion	8.42	3.27	1-18
	Block Design	8.69	3.22	1-19
	Matrix Reasoning	9.53	3.30	1-18
	Digit Symbol Coding	7.35	3.14	1-19
	Symbol Search	7.99	3.23	1-18
WMS-III	Auditory Immediate	90.22	18.24	47-146
Indices	Visual Immediate	86.76	17.26	45-142
	Immediate Memory	86.15	19.63	45-146
	Auditory Delayed	90.71	18.92	46-140
	Visual Delayed	87.36	17.99	50-140
	Aud. Recog. Delayed	93.26	18.18	55-140
	General Memory	88.14	19.82	45-150
	Working Memory	89.76	16.99	49-141

2.2.2 Cognitive Measures

The cognitive measures for this analysis included data obtained from the administration of the WAIS-III and the WMS-III. The WAIS-III consists of 13

subtests, which measure a variety of cognitive abilities. These subtests include: Vocabulary (VO), Similarities (SI), Information (IN), Comprehension (CO), Arithmetic (AR), Digit Span (DSP), Letter-Number Sequencing (LNS), Picture Arrangement (PA), Picture Completion (PC), Block Design (BD), Matrix Reasoning (MR), Symbol Search (SS), and Digit Symbol-Coding (DSY). While the traditional Full Scale IQ, Verbal IQ and Performance IQ differentiation is retained within the WAIS-III, in the context of clinical neuropsychology, however, greater significance is placed on the Index scores. These indices include Verbal Comprehension (VC, composed of VO, SI, and IN), Working Memory (WM, composed of AR, DSP, and LNS), Perceptual Organisation (PO, composed of PC, BD, and MR), and Processing Speed (PS, composed of DSY and SS). Administration of the test in its entirety is not necessary to generate the IQ Composites and/or the Index scores. Nonetheless, it is necessary to administer all 13 subtests if both IQs and Index scores are desired.

The data utilised in this study does not include all WAIS-III subtests. At the Cleveland Clinic only those subtests that contribute to the VC, PO, and PS indices are routinely administered. The WM index appears on both the WAIS-III and WMS-III and it is the score from the latter test battery that is used to assess the construct of Working Memory. Consequently, only eight of the 13 WAIS-III subtests were required for the purposes of this study (VO, SI, IN, PC, MR, BD, DSY and SS) as was the case in the Lange (2000) study.

The WMS-III consists of 17 subtests, which include 10 core subtests (Logical Memory I and II, Faces I and II, Verbal Paired Associates I and II, Family Pictures I and II, Letter-Number Sequencing and Spatial Span), and seven optional subtests (Word Lists I and II, Visual Reproduction I and II, Mental Control, Information and Orientation, and Digit Span). The 10 core subtests measure various aspects of memory performance and when combined, generate eight memory indices: Auditory

Immediate (AI, composed of Logical Memory I and Verbal Paired Associates I); Visual Immediate (VI, composed of Faces I and Family Pictures I); Immediate Memory (IM composed of Auditory Immediate and Visual Immediate); Auditory Delayed (AD, composed of Logical Memory II and Verbal Paired Associates II); Visual Delayed (VD, composed of Faces II and Family Pictures II); Auditory Recognition Delayed (ARD, composed of the recognition trials of Logical Memory II and Verbal Paired Associates II); General Memory (GM, composed of Auditory delayed, Visual Delayed, and Auditory Recognition Delayed); and the Working Memory factor (WM, composed of Letter-Number Sequencing and Spatial Span). The data utilised in this study consisted of all the WMS-III indices, with the exclusion of the combined composites, Immediate Memory and General Memory. These indices were omitted as they represent the algebraic sum of indices already included in the study. Thus in the current study only six of the eight measures used by Lange were utilised (AI, VI, AD, VD, ARD, WM) omitting the redundant IM and GM composites.

All WAIS-III and WMS-III subtests were administered according to standardised instructions by experienced psychometricians. The initial data derived for the current study consisted of age adjusted scaled scores (mean = 10, standard deviation = 3) from the eight WAIS-III subtests. The six WMS-III index scores initially existed as standard scores (mean = 100, standard deviation = 15). These scores were converted to scaled scores (retaining two decimal places), utilising a simple linear transformation and then represented as deviation scores (see Equation 1).

$$\text{Scaled Score} = ((X - 100) / 15) * 3 + 10 \quad [1]$$

Deviation scores were chosen so as to minimise the effect of the score magnitude on the cluster analysis. Lange (2000) indicated the use of deviation score

over other transformations like z-scores, as other transformations tended to flatten the magnitude of the profile. As magnitude is of interest a deviation score transformation was most appropriate. The deviation score adjustments were completed by initially computing the mean scaled score for the individual based on all eight WAIS-III and six WMS-III scaled scores and then the deviation scores was computed by subtracting the mean score for the case from each of the 14 variables (see Equation 2) in the analysis as illustrated below.

DS_i = Scaled $Score_i$ – Individual Mean [2]

WAIS-III Vocabulary = 11

Individual's mean score for the 14 measures = 10.5

Calculation of Deviation Score = 11.0 - 10.5 = +0.5

The individual's Deviation Score for Vocabulary = + 0.5

2.2.3 Cluster Analysis

MATLAB 6.5.1 (The MathWorks Inc., 2003) was chosen as the statistical package for performing all cluster analyses due to its greater number of diagnostic algorithms for determining the clusterability of data. As per Lange (2000) hierarchical cluster analysis was conducted using between groups average linkage as the clustering algorithm, and the Pearson Product moment correlation as the proximity measure. Determination of the number of clusters was achieved through examination of the inverse scree plots, dendrograms, and inconsistency matrix between cluster solutions in the hierarchical cluster analysis. Once the number of likely clusters had been established, the K-Means cluster method was then computed using the Squared-Euclidean distance as the distance metric, to establish the final cluster solution. This final solution was determined based on assessment of the cluster centroid means, silhouette plots and iteration statistics. The syntax files from the analysis are shown in Appendix B.

2.3 Analysis and Results

2.3.1 Cluster Analysis

The cophenet correlation of a hierarchical cluster analysis indicates the correlation between the linking of the objects within the cluster tree and the distances between objects in the distance vector (Romesburg, 1984). Romesburg (1984) indicates that the cophenet correlation signifies the concordance of how much the clustering method distorts the data on the way to a solution. He suggests that the closer the cophenetic correlation is to concordance ($r_{xy} = 1.0$) the less the data is distorted but with no real guidelines for what is acceptable. The cophenet correlation of .52 for the hierarchical cluster analysis conducted using MATLAB 6.5.1 indicated that the data was considered to be approaching concordance. Therefore, the hierarchical cluster analysis solution was computed. Examination of the inverse scree plot in Appendix C (Figure C.1) indicated an initial adjustment of the curve at an eight-cluster solution (marker B); however, this was more noticeable at a four-cluster solution (marker A). The dendrogram (Figure C.2) also revealed a number of likely solutions, with anywhere from a four (marker C) to an eight-cluster (marker D) solution likely in this data set. The four-factor solution was deemed as the most stable and representative.

A four-cluster solution was then designated in the K-Means analysis using random seed points and the clusters were derived. The silhouette plot, which is used to determine the amount of overlap between the clusters, was consulted for the K-Means analysis. Silhouette plots signify little overlap between clusters if the majority of scores are greater than .6. As shown in Appendix D (Figure D.1), the silhouette plot indicates some overlap between the clusters as the majority of scores fall below the cut of .6. The mean deviation scores for the four profiles generated by the K-Means analyses are presented in Table 2.3.

Table 2.3
Mean WAIS-III and WMS-III Deviation Scores for K-Means (K) Solutions

	K-Means Analysis			
Subtest	K1	K2	K3	K4
AI	-0.53	-2.10	1.45	0.01
AD	-0.11	-2.63	1.83	0.17
ARD	0.51	-1.74	1.53	0.91
VI	-0.27	-2.40	1.04	-2.16
VD	-0.18	-2.47	1.16	-1.97
WM	-0.02	0.61	-1.35	-0.94
VO	-0.65	1.19	0.70	2.41
SI	-0.65	0.78	0.25	1.67
IN	-0.59	1.08	0.50	2.79
PC	0.27	1.31	-1.35	-0.13
BD	0.36	2.58	-1.59	-0.18
MR	0.98	2.78	-0.25	1.03
DSY	0.15	0.19	-2.21	-2.22
SS	0.73	0.84	-1.70	-1.39
N	213	216	197	231

2.3.2 Independence of Cluster Solutions

The K-Means clusters were then correlated to ascertain the level of independence of the four derived profiles (as shown in Table 2.4). Only significant positive correlations are of relevance in this matrix as they signal a high degree of similarity. Negative correlations, regardless of how significant their association, indicate an inverse pattern and signal dissimilarity. There were no significant positive correlations among the four clusters indicating that the profiles they represent are essentially independent.

Table 2.4
K-Means Cluster Solution Within-Group Correlation Matrix

	K-Means Analysis			
	K1	K2	K3	K4
K1	1.00			
K2	.33	1.00		
K3	-.46	-.69	1.00	
K4	-.30	.38	.32	1.00

2.4 Examination of Profile Membership

Based on the above results, it is apparent that there were at least four common cognitive profiles identified within the mixed diagnostic sample, with each of the clusters approximately equal in size (range: 23.0% to 27.0%). Lange (2000) found that his cognitive profiles recurred across all his diagnostic groups, which is also the case in the current study. Table 2.5 presents the distribution of each cluster within each of the 12 main diagnostic groups comprising the mixed diagnostic sample. While some profiles were less represented in some diagnostic categories (e.g. Parkinson's disease: Profile 1, n = 6.3%), other profiles indicated larger diagnostic group membership (e.g. Parkinson's disease: Profile 1, n = 56.3%). However, all four cognitive profiles included individuals from all diagnostic groups.

Table 2.5
Percentage of Cases in Different Diagnostic Categories (K-Means)

Diagnosis	Profile 1	Profile 2	Profile 3	Profile 4	N
CVD	23.4	19.8	27.9	28.8	111
DAT	25.0	34.6	9.6	30.8	52
MID	17.4	22.8	26.1	33.7	92
DEM	20.0	26.2	30.8	23.1	65
PD	6.3	9.4	28.1	56.3	32
DrugEtoh	27.5	20.0	20.0	32.5	40
PSYCH	28.0	16.0	28.0	28.0	25
SZ	31.2	34.7	15.6	18.6	199
TUMOUR	28.9	15.8	34.2	21.1	38
TBI	38.2	21.1	17.1	23.7	76
Other	21.7	20.7	28.3	29.3	92
NIL	8.6	37.1	28.6	25.7	35
N	213	216	197	231	

These results support Lange's assertion of the absence of a single prototypical pattern of cognitive functioning that is representative of any particular diagnostic group. If a single unique cognitive pattern of functioning exists for each diagnostic group, then the current analysis should have generated at least 12 cognitive profiles.

However, this was not the case with only four patterns underlying the patterns of performance in these 857 cases.

2.5 Profile Characteristics

The four cluster profiles are presented graphically in Figures 2.1 to 2.4. These depict the mean deviation scores for each of the cognitive profiles across the eight WAIS-III subtests and six WMS-III indices. To facilitate consideration of the profiles, the measures have been arranged according to the factor structure of the WAIS-III and WMS-III. These include verbal abilities (VC: VO, SI, IN), visuospatial abilities (PO: PC, BD, MR), speed of information processing (PS: DSY, SS), attentional abilities (WM), Auditory memory (AUD: AI, AD, ARD), and visual memory (VIS: VI, VD) (Tulsky & Price, 2003).

Profile 1 (Figure 2.1) is characterised by homogenous scores on all cognitive domains as all deviation scores fall within one deviation point of the mean. Individuals in this profile therefore, have no reported relative cognitive strengths or weaknesses.

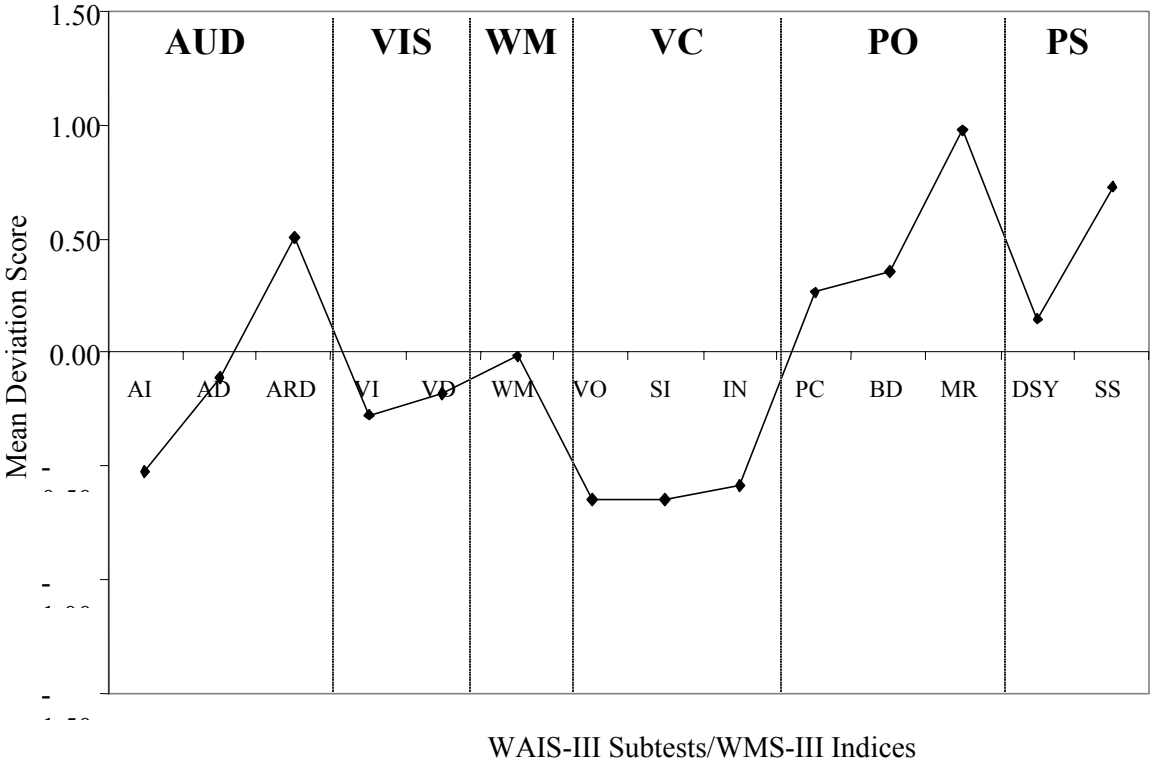

Figure 2.1 Profile 1 – High Verbal, Low Processing Speed, Visual Memory, Attention

The character of Profile 2 (Figure 2.2) demonstrates cognitive weaknesses in overall memory, as indicated by poor scores on all WMS-III memory scores (AUD, VIS). However, this profile shows relative cognitive strengths in the areas of verbal knowledge (VC) and overall visual abilities (PO) with average scores in processing speed (PS) and working memory/attentional abilities (WM).

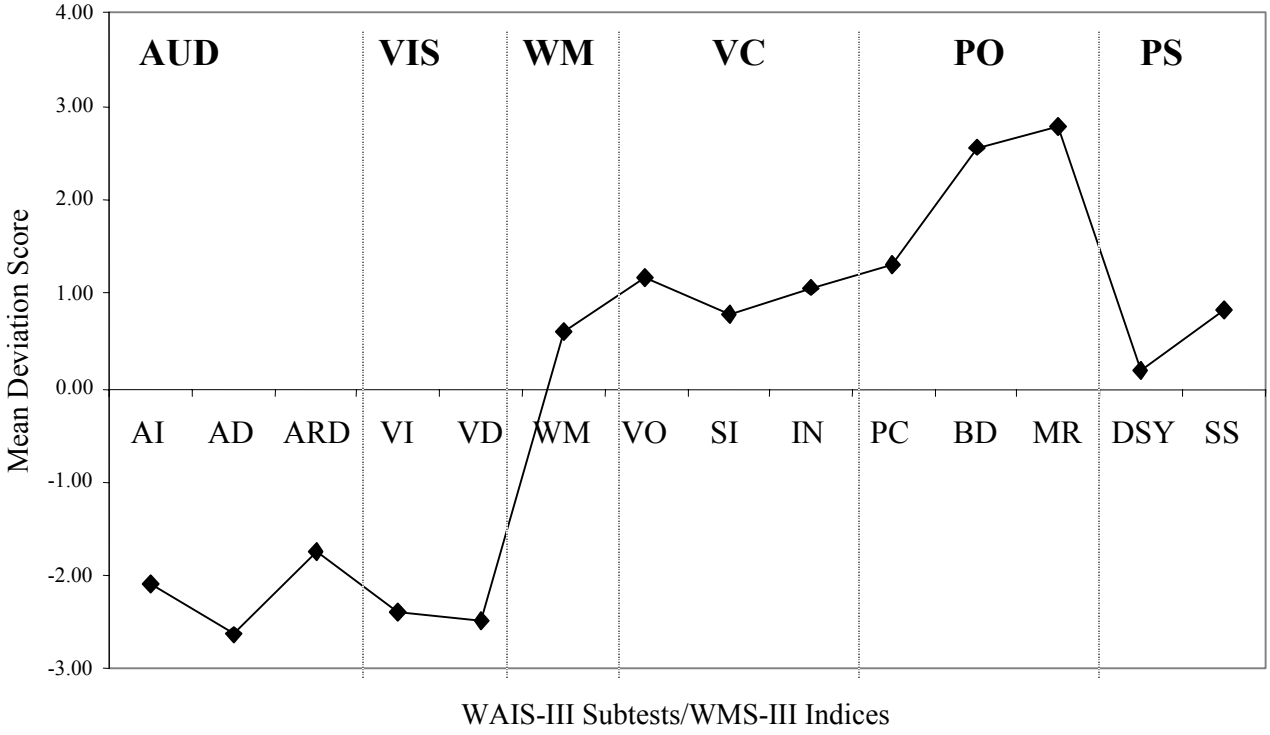

Figure 2.2 Profile 2 – High Visual Abilities, Low Visual Memory

The pattern of performance indicated by Profile 3 (Figure 2.3), shows elevations on all the WMS-III memory scores (AUD, VIS). Individuals in this profile are inclined to have a relative cognitive weakness in their ability to attend and concentrate (WM). Another area of cognitive weakness appears to be in their visual abilities, not only in their visuospatial abilities (DPC and DBD), but also their ability to complete visual tasks quickly and accurately (PS).

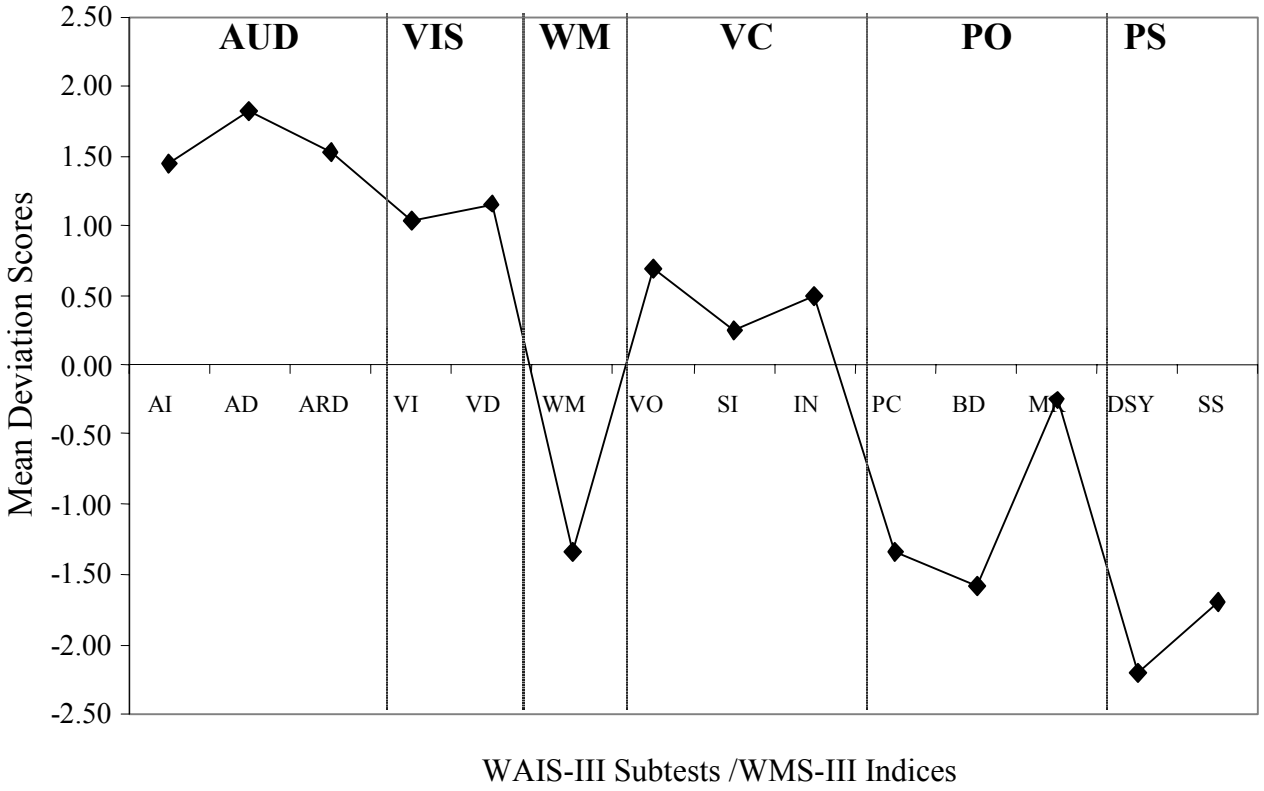

Figure 2.3 Profile 3 – High Visual and Verbal, Low Memory

Profile 4 (Figure 2.4) can be typified by deficits in Visual Memory (VIS) and in their abilities to quickly and accurately process visual information (PS). Individuals in this profile appear to have a relative cognitive strength in their general verbal comprehension abilities (VC).

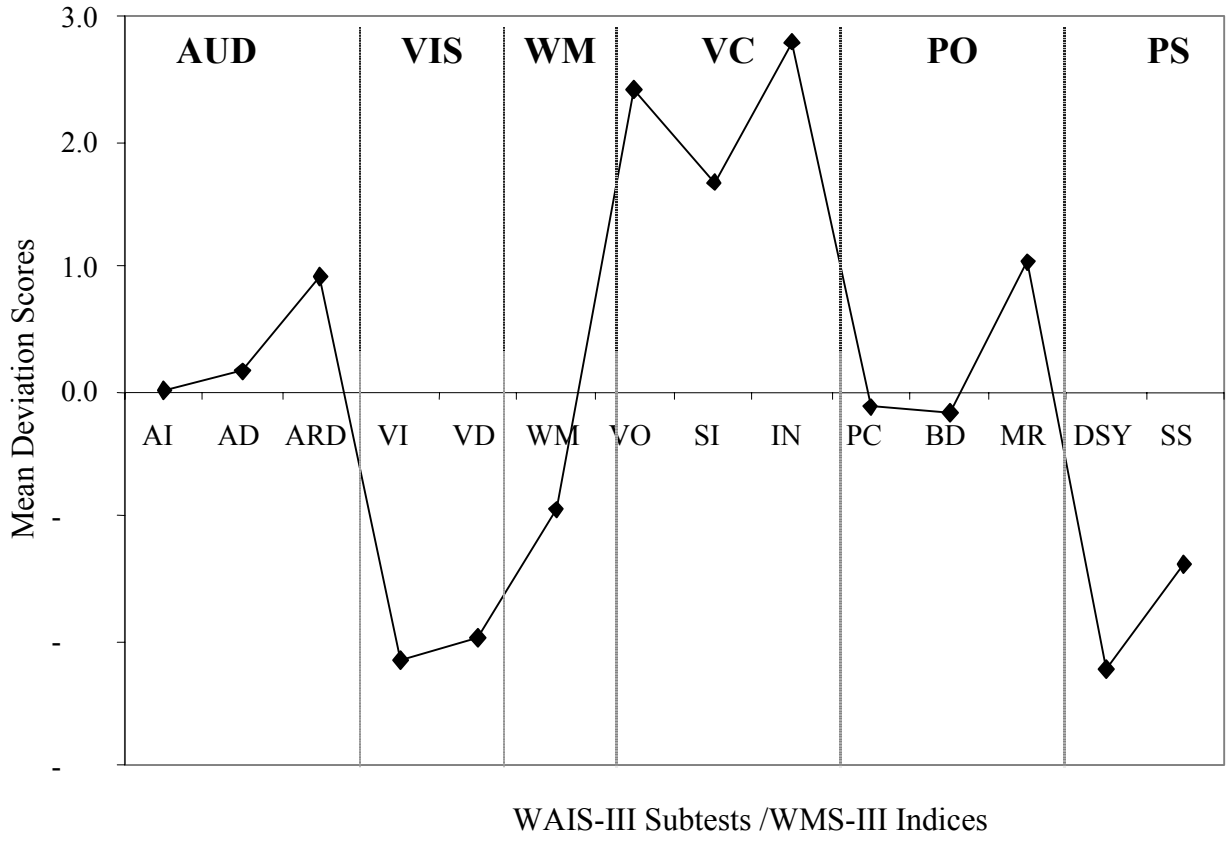

Figure 2.4 Profile 4 – High Memory, Low Attention and Processing Speed

2.6 Comparison of Cognitive Profiles With Those Identified by Lange (2000)

Of additional interest to this study was the relationship of the four cognitive profiles identified by Lange (2000) from his sample of 254 subjects with those derived from the 857 subjects in the current study. This was undertaken by correlating (see Table 2.6) the profiles derived from the current K-Means analysis with those derived by Lange on those measures common to the two studies.

Table 2.6
Correlations Between Cluster profiles: Lange (2000) & Current Study

Current Study	Lange (2000) K-Means Clusters			
	L1	L2	L3	L4
K1	-.51	.19	-.23	.72**
K2	-.15	.96**	-.83	-.02
K3	.77**	-.52	.66*	-.10
K4	.83**	.60*	-.13	-.46

*p<.05. **p<.01 Only significant positive correlations are indicated

Examination of Table 2.6 indicates that all four profiles identified by Lange (2000) are significantly and highly correlated with the four profiles identified in the current study (range: r = .66 to r = .96). It is also notable, however, that two of Lange's profiles (L1 and L2) correlated with more than one of the current profiles (K3 and K4, and K2 and K4 respectively). This indicates that the two largest clusters found by Lange, each bear strong similarities to two of the four clusters found in the current study. For the purposes of graphic representation, clusters from the current study have been depicted in Figures 2.5 through 2.8 along with the Lange clusters with which they are most highly correlated.

While the current study cannot be said to have completely replicated Lange's findings it is certainly the case that at least four profiles consistently emerge from clinical data of the type employed in these analyses. Given the small N in Lange's original study and the demonstrated independence of the clusters derived with the current larger sample, it is likely that the similarity of some Lange's clusters to more than one in the current study is an artefact of the instability of the original clusters. Regardless, these findings are consistent with Lange's (2000) results, and provide further support for the absence of prototypical patterns of cognitive functioning within diagnostic groups when using the new third edition Wechsler scales.

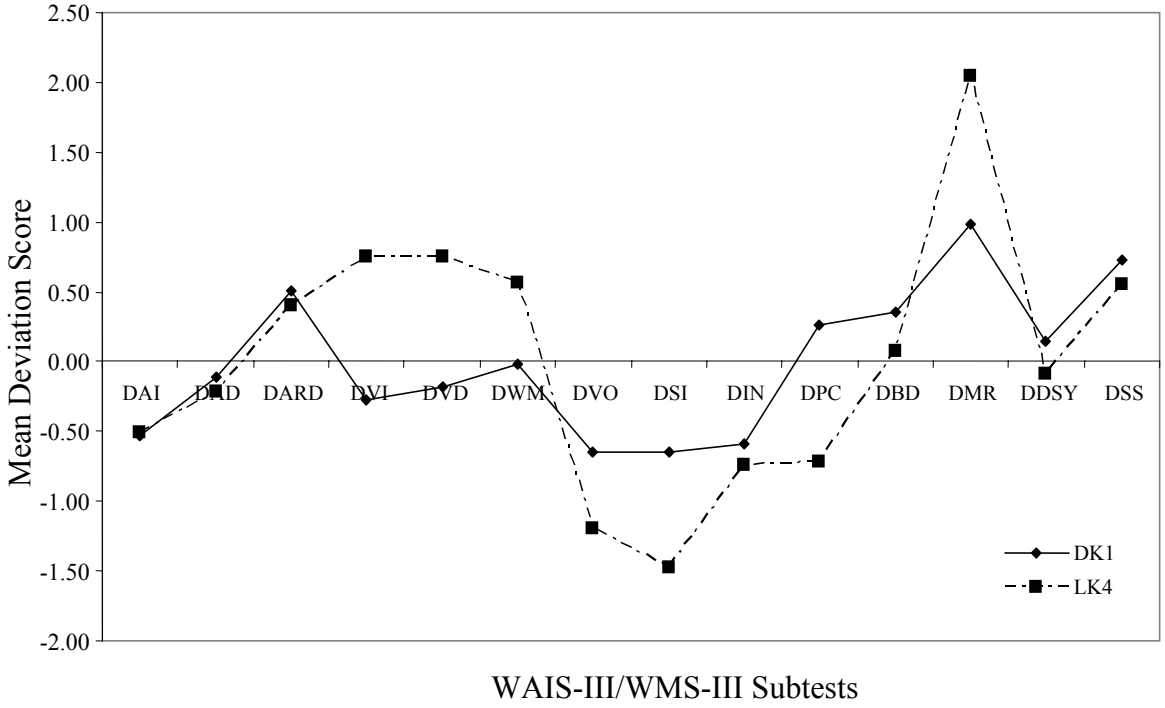

Figure 2.5 Corresponding Cognitive Profiles: Current Profile 1 and Lange Profile 1 (r=.84, p<.05)

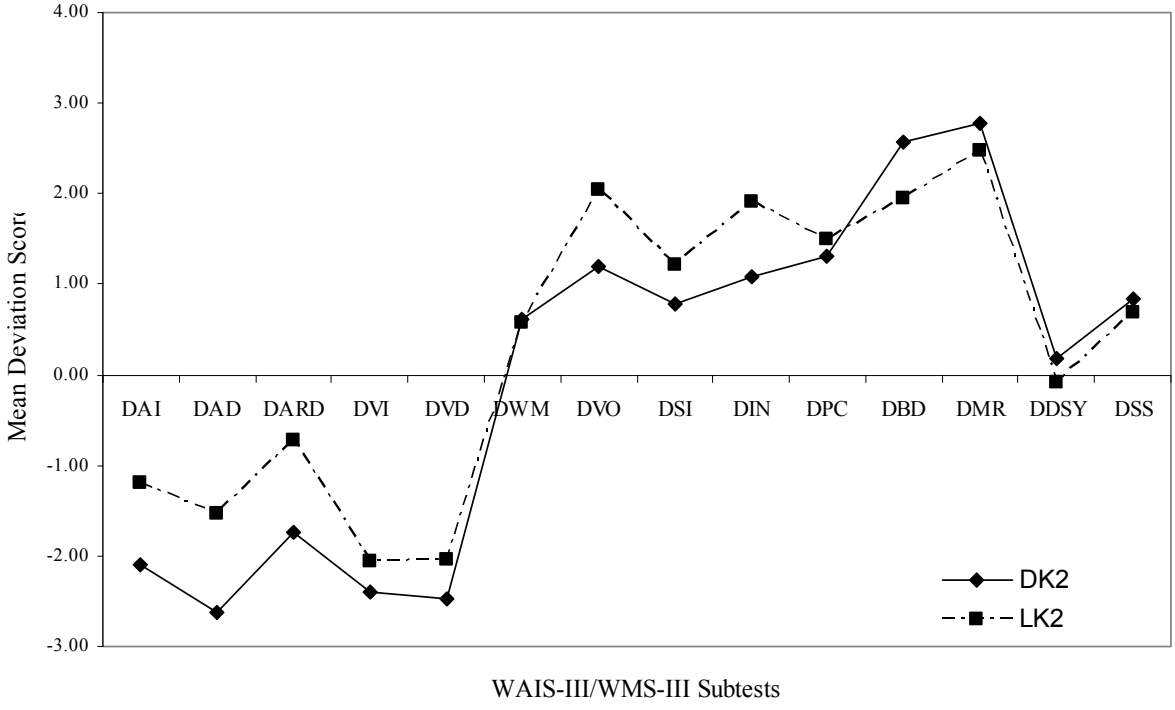

Figure 2.6 Corresponding Cognitive Profiles: Current Profile 2 and Lange Profile 2 (r=.96, p<.05)

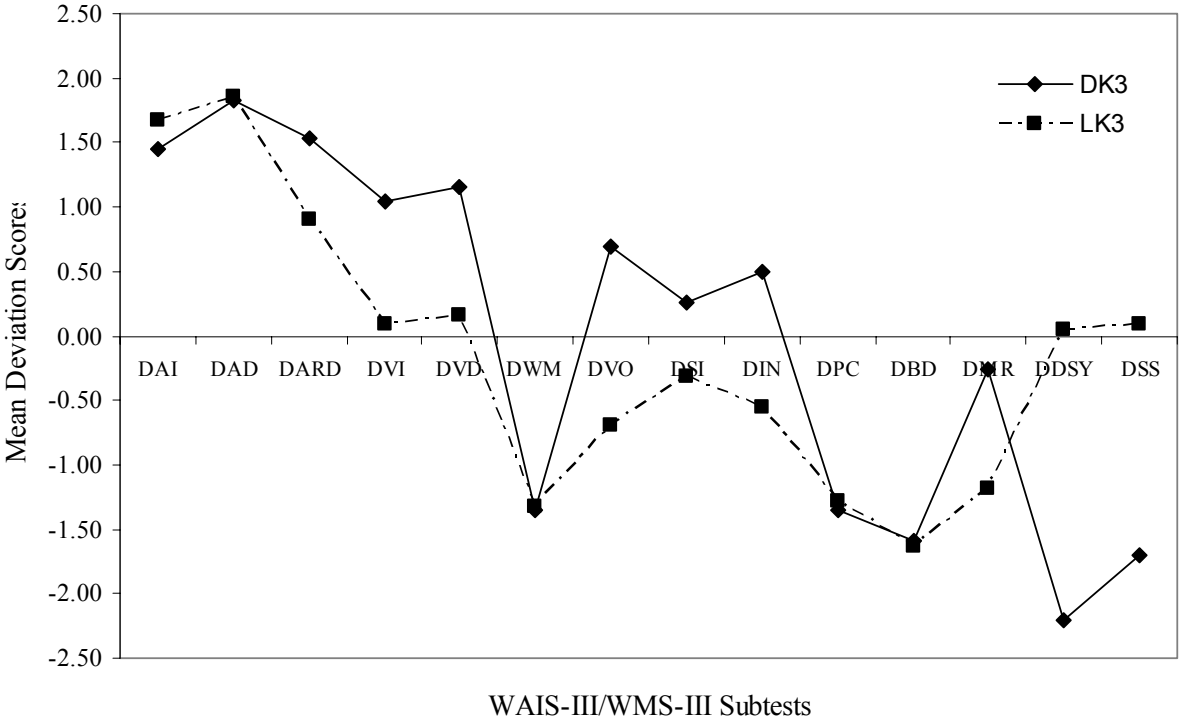

Figure 2.7 Corresponding Cognitive Profiles: Current Profile 3 and Lange Profile 3 (r=.66, p<.05)

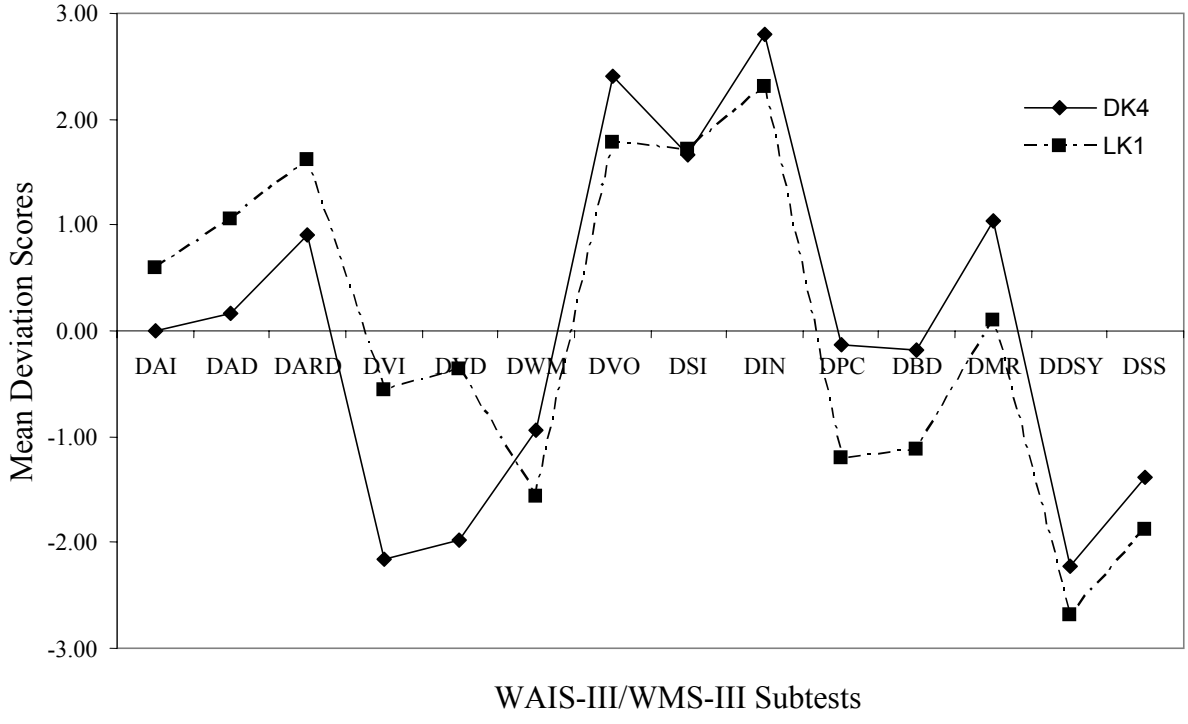

Figure 2.8 Corresponding Cognitive Profiles: Current Profile 4 and Lange Profile 1 (r=.83, p<.05)

2.7 Summary

The current study replicated Lange's earlier finding of four common profiles identified in WAIS-III/WMS-III data, which are considered to represent stable patterns of cognitive performance in this sample. Two of the current profiles were found to be highly similar to profiles identified by Lange, reflecting a high degree of stability within these profiles derived from the WAIS-III and WMS-III mixed diagnostic sample. The other two profiles were not as highly correlated, but this is believed to be an artefact of Lange's small sample size, and his inclusion of immediate and delayed memory indices in the analysis. As with Lange (2000), the distribution of these four profiles across the different diagnostic groups was too widespread to support any assumptions regarding unique or prototypical cognitive patterns for any of the diagnoses examined.

While the Wechsler scales reflect an extensive evaluation of cognitive functioning, it is possible that the small number of clusters observed and their frequency within all of the diagnostic groups resulted from the absence of cognitive constructs in the battery of tests upon which the diagnostic groups would dissociate. It is possible that the Wechsler Scales just do not assess all of the cognitive domains upon which different diagnostic groups dissociate. This concern will be further explored in the next chapter where a number of other common measures used in neuropsychological assessments will be added to the battery of tests examined to broaden the spectrum of cognitive constructs assessed. This will permit not only a more robust examination of the issues raised by Lange (2000) and in the current study, but also better reflect the diversity and types of tests routinely employed by clinicians in neuropsychological assessments.

CHAPTER 3

3.0 EXAMINATION OF PROTOTYPICAL COGNITIVE PATTERNS IN AN EXPANDED NEUROPSYCHOLOGICAL BATTERY USING CLUSTER ANALYSIS

3.1 Overview

In Chapter 2, cluster analysis was used to identify commonly occurring patterns of cognitive functioning within a mixed diagnostic sample using data from the WAIS-III and the WMS-III. The results of these analyses indicated that there were at least four cognitive profiles identified within this sample. The factor structure of the Wechsler batteries, however, does not reflect all of the relevant cognitive domains commonly assessed by neuropsychologists. For example, naming ability, verbal fluency, flexibility of mental set, and ability to alter problem-solving behaviour based upon feedback are capabilities routinely examined in a clinical assessment that do not appear on either the WAIS-III or WMS-III. One concern is that the four clusters identified in the previous study may not adequately sample from sufficiently distinct cognitive tasks to differentiate between different clinical diagnoses. In other words, the limitation in cluster complexity may have resulted from limitations in the complexity of these tests. The addition of further tests designed to increase the range of cognitive abilities assessed should aid in the determination of whether or not the relatively small numbers of cluster profiles is intrinsic to the individuals being assessed or the tests employed for that purpose.

This was achieved through the addition of a number of neuropsychological tests designed to assess verbal fluency (Controlled Oral Word Association Test), object naming (Boston Naming Test), learning efficiency (WMS-III Word Lists), graphomotor speed and mental flexibility (Trail Making Test), and rule discrimination based upon positive and negative feedback (Wisconsin Card Sorting Test).

3.2 Method

3.2.1 Cases

Cases incorporated in the neuropsychological mixed diagnostic sample consisted of 420 individuals gathered from the archives of the Department of Psychiatry and Psychology (Neuropsychology) at the Cleveland Clinic Foundation, Ohio, USA. Cases included individuals from twelve diagnostic categories, including cerebrovascular disorders (n = 40, 9.5%), probable dementia of the Alzheimer's type (n = 14, 3.3%), multi-infarct dementia (n = 26, 6.2%), other dementias (n = 32, 7.6%), drug and alcohol abuse (n = 11, 3.6%), Parkinson's disease (n = 8, 1.9%), psychiatric disorders (n = 12, 3.9%), seizure disorders (n = 158, 37.6%), traumatic brain injury (n = 39, 9.3%), tumour (n = 22, 5.2%), other disorders (n = 43, 10.2%), and no diagnosis attributable (n = 15, 3.6%). The "other disorders" diagnostic category consisted of diagnoses with too few cases to be categorized individually or whose diagnosis was not indicated. The diagnostic categories included, anoxia (n = 1, 0.2%), cognitive impairment not otherwise specified (n = 21, 5.0%), encephalitis (n = 6, 1.4%), general medical (n = 4, 1.0%), hydrocephalus (n = 1, 0.2%), multiple sclerosis (n = 5, 1.2%), toxic exposure (n = 1, 0.2%), and no diagnosis attributed (n = 4, 1.0%). All cases had been referred for neuropsychological assessment as part of usual medical management and/or rehabilitation, and were chosen for inclusion in this study based on the following criteria:

1. Each case had been administered the WAIS-III, the WMS-III (including Word Lists I and Word Lists II), Controlled Oral Word Association Test – FAS version, Boston Naming Test, Wisconsin Card Sorting Test, and the Trail Making Test - Part A and Part B, as part of a larger neuropsychological test battery, to ascertain their level of cognitive functioning resulting from neurological or psychiatric dysfunction.

2. All cases had sufficient information supplied to permit classification into a particular diagnostic group. This was achieved through the use of an electronic database, which included ICD-9 codes, and information supplied by the referring Neuropsychologist and/or brief hospital notes.
3. To augment the homogeneity within the diagnostic groups, individuals were not included in the analysis if they could be classified into more than one neurological or psychiatric disorder.

Further characteristics of this sample are presented in Table 3.1, Table 3.2 and Appendix A (Table A.2).

Table 3.1
Characteristics of the Neuropsychological Mixed Diagnostic Sample

Gender/Ethnicity	Cases	%	
Male	246	58.6	
Female	174	41.4	
Caucasian	387	93.1	
African-American	27	6.4	
Hispanic	6	1.4	
Diagnostic Group			
CVD	40	9.5	
DAT	14	3.3	
MID	26	6.2	
DEM	32	7.6	
PD	8	1.9	
DrugEtoh	11	3.6	
PSYCH	8	3.9	
SZ	158	37.6	
TUMOUR	22	5.2	
TBI	39	9.3	
Other	43	10.2	
NIL	15	3.6	
Demographics	Mean	SD	Range
Age (years)	43.33	15.27	16-81
Education (years)	13.49	3.81	3-20

3.2.2 Cognitive Measures

The cognitive measures for this analysis included data obtained from the administration of the WAIS-III and the WMS-III (as detailed in Chapter 2), with the

addition of the supplemental test of Word Lists I and II from the WMS-III, the Controlled Oral Word Association Test – FAS version (COWAT), the Boston Naming Test (BNT), the Wisconsin Card Sort Test (WCST), and the Trail Making Test (TMT).

Word Lists I from the WMS-III is an auditory verbal list-learning task that requires the person to learn 12 words over four trials (Word Lists I – Total score) (Wechsler, 1997b). He or she is then asked to learn and recall a second list of 12 words (List B), followed by free recall of the first list of words (Immediate Recall). After a 25 to 35 minute delay the client is again asked to recall as many of the words from the first list again (Word Lists II – Total). A test of word list recognition is then conducted using the 12 target words and 12 foils. The two scores that have been chosen for this analysis are the Total words learned over the four learning trials (Word Lists I), and the total words recalled after the 25 to 35 minute delay (Word Lists II).

The COWAT (Benton, 1976) is a test of verbal fluency where the person must say as many words as possible (excluding proper nouns) starting with the letters F, A, or S in turn. This is completed over three one minute trials with the dependent variable being the total number of words generated (Gladsjo, Miller, & Heaton, 1999). Norms utilised in the standardisation of the COWAT scores were those presented by Gladsjo et al.

The BNT is part of the Boston Diagnostic Aphasia Examination (Kaplan, 2001) and assesses the respondent's ability to name 60 objects presented as simple line drawings. The dependent variable is the total number of correctly named objects either with no cues or with semantic cues provided by the examiner as normed by Kaplan.

The Wisconsin Card Sort Test (Heaton, 1981) is an executive functioning test where the patient must determine the rules necessary to sort a series of cards when

only given feedback as to whether the category selected was correct or incorrect. The test has a total of 128 trials, with 3 categories (Colour, Number, Shape), which are to be sorted twice. There are a number of indices that may be determined from the WCST, however for the purpose of this analysis only two were chosen. These were the number of correct categories that the client was able to sort and the number of perseverative errors made whilst performing the task (Heaton, 1981).

The Trail Making Test (Army Individual Test Battery, 1944) is a paper and pencil test that consists of two trials. The first (Part A) is a test of graphomotor speed, attention and sequencing (Spreen & Strauss, 1998), where the person is required to draw lines in order between the numbers 1 through 25, distributed over a page. The second (Part B) is a test of mental flexibility, attention and sequencing (Spreen & Strauss), where the respondent is required to draw lines between the numbers one to thirteen and the letters "A" to "L", alternating between the numbers and the letters (eg, 1-A-2-B, etc) in numerical and alphabetical order. The two variables that were chosen from this test were the time to completion for Part A, and the discrepancy between the time taken to complete Part A, and the time taken to complete Part B. The discrepancy score between trials A and B was chosen to reflect the additional component of alternating between mental sets without the confounding influence of slowed graphomotor output which is theoretically subtracted with Part A.

The WAIS-III, WMS-III, WCST, BNT, COWAT, and TMT, were administered in the standardised manner by experienced psychometricians trained in psychological and neuropsychological test administration. Scores obtained from the WAIS-III for analysis consisted of Scaled Scores from the eight subtests (VO, IN, SI, BD, MR, PC, SS, DSY). The WMS-III index scores (AI, VI, AD, VD, ARD, and WM) were scaled as Standard Scores with a mean of 100 and a standard deviation of 15. In order to facilitate comparison and ensure that no measure was allocated a

greater weighting due to a larger score distribution, the WMS-III index scores were adjusted to the common Scaled Score system. It should be stressed that these different scaling systems are all just representations of scores standardised to the normal distribution. The decision to convert all scores to Scaled Scores was both arbitrary and pragmatic and intended to present data throughout this dissertation in a format or language with which most clinicians are very familiar. It is anticipated that the findings and implications of this research will be more readily appreciated if presented in the form in which this type of data is customarily encountered.

Data for the Word Lists subtest were also provided as Scaled Scores. The other tests, WCST, BNT, and COWAT initially consisted of raw scores, which were then standardised using normative data to Scaled Scores using the following formula:

$$\frac{\left(X - \overline{X}\right)}{sd} \times 3 + 10 \qquad [2]$$

Where: X = the observed score

$\overline{X}$ = the mean score for demographically adjusted norms

sd = standard deviation for demographically adjusted norms

For Example:

A 29-year-old client produces a BNT raw score of 52. Age-adjusted norms indicate a mean of 55.8 and a standard deviation of 3.8 for this age group. This raw score is converted to a Scaled Score of 7.0 through Equation 3:

$$\frac{\left(52 - 55.8\right)}{3.8} \times 3 + 10 = 7.0$$

TMT scores were converted in the same manner but included reversal of the sign to reflect the fact that the dependent variable was time for completion. Scaled scores greater than 10 indicate performance above the mean, while those below 10 indicate below average performance. With dependent variables such as time and number of errors, below average performance would generate values greater than 10

as longer than average times or more than an average number of errors indicate below average performance. To ensure that all Scaled Scores indicate the same level of performance, the sign of the numerator in Equation 3 is therefore reversed. Perseverative error scores from the WCST were treated in the same manner.

Deviation scores were not utilised in this or subsequent analyses. In Lange's original work deviation scores were computed to eliminate the effects of magnitude to specifically focus the analysis on profile shape (Lange, 2000). This made sense in the context of his research. However, the purpose of the current study was to widen the range of cognitive measures in an effort to better emulate the types of clinical analyses conducted by clinicians. Clinicians attend to both magnitude and profile when interpreting test scores and accordingly, it was deemed appropriate to permit the influence of magnitude to be reintroduced into the analysis.

3.2.3 Statistical Analysis

Once the WMS-III indices, WCST, BNT, COWAT and TMT raw scores were transformed in the above manner, scores from all the tests were then subjected to a Principle Axis Factoring utilising Oblimin rotation followed by cluster analysis. The decision to perform a factor analysis prior to clustering was based upon concerns regarding the consequences of increasing the number of dependent variables in the cluster analysis. With the inclusion of more variables, cluster analysis becomes increasingly vulnerable to producing questionable clusters whose origins are tenuous (Everitt, 1974). The role of factor analysis here was to reduce the complexity of the database to produce a smaller number of more representative and stable measures. These factor scores were then used as the dependent variables in the cluster analysis conducted using MATLAB 6.5.1

Determination of the number of clusters was the same as described in the previous chapter (assessment of inverse scree plots, dendrogram and inconsistency

matrix from the hierarchical cluster analysis). Once the number of likely clusters had been established, the K-Means cluster method was then utilised to establish the final cluster solution, with careful attention paid to the cluster centroid means, silhouette plots and iteration statistics.

3.3 Analysis and Results

The means, standard deviations, and range of test scores for the total sample are presented in Table 3.2. Where necessary these scores were then converted into Scaled Scores to ensure all measures were represented on the same scaling system. It is these Scaled Scores that were then submitted to factor analysis.

Table 3.2
Test Scores for the Mixed Diagnostic Sample

Tests	Mean	SD	Range
WAIS-III Selected Subtests			
Vocabulary	9.41	3.27	1-18
Similarities	9.07	3.00	1-18
Information	9.47	3.18	2-19
Picture Completion	8.68	3.22	1-18
Block Design	8.97	3.04	1-19
Matrix Reasoning	9.78	3.24	2-18
Digit Symbol Coding	7.61	3.08	1-19
Symbol Search	8.30	3.07	1-18
WMS-III Indices			
Auditory Immediate	91.43	17.98	47-146
Visual Immediate	87.87	17.48	45-142
Auditory Delayed	91.75	18.82	46-140
Visual Delayed	88.56	18.00	50-140
Aud. Recog. Delayed	94.08	17.85	55-140
Working Memory	91.26	16.37	49-141
Word Lists I (Scaled Score)	7.56	3.58	1-17
Word Lists II (Scaled Score)	7.66	3.58	1-16
Trail Making Test			
Part-A (sec)	45.99	33.32	8-300
Part-B (sec)	124.36	83.00	30-300
Part-B minus Part A (sec)	78.37	64.64	-63-292
Wisconsin Card Sort Test			
Categories Achieved	4.07	3.14	0-6
Perseverative Errors	23.52	17.68	3-114
Controlled Oral Word Assoc. Test			
Total Words	30.22	13.76	1-68
Boston Naming Test			
Total	49.21	10.20	1-60

3.3.1 Factor Analysis

An exploratory principal axis analysis with oblimin rotation was performed on the scaled scores for the entire sample. The initial factor solution of four factors accounted for 68.1% of the variance. The eigenvalues, percent variance, cumulative percent variance, and factor loadings of the four factors based on the rotated component matrix are presented in Table 3.3. However, due to all memory scores being grouped on Factor 1 (AI, AD, ARD, Word Lists I and II, VI and VD Indices), and with processing speed and attention (DSY, SS, TMT-A, TMT-B min A, COWAT, and WM), and visuospatial abilities (PC, BD, and MR) being grouped on Factor 4, a more interpretable solution was sought. The other two factors produced from this initial analysis were Factor 2, comprising of the executive functioning tasks (TMT-B min A; WCST: Categories Completed and Perseverative Errors), and Factor 3, which encompassed the verbal ability tasks (VO, IN, SI, COWAT and BNT).

Factor 1 and Factor 4 included the majority of items from the test (i.e., seven and nine items, respectively). While loadings for these two factors were only moderate (range: 0.31 to 0.86), only Factor 1 was well defined. Two items were loaded on two factors (i.e., TMT-B min A - Factor 2 = 0.47 and Factor 2 = -0.31, and Matrix Reasoning - Factor 3 = 0.33 and Factor 4 = 0.37). This factor structure was considered suboptimal as it combined measures that have consistently been demonstrated to have differential vulnerabilities to neuropathology. Consequently other factor solutions were explored for their greater utility and interpretability. Note that while this is imposing a higher order structure on the data, the purpose of the factor analysis was to reduce the number of variables entered into the cluster analysis. The value of this data reduction would be undermined if the reduced data did not adequately represent how clinicians utilise and interpret these tests.

Table 3.3
Initial Factor Structure of the Test Battery.

	Factor			
Subtest	1	2	3	4
TMT-A				-.562
TMT-B min A		.472		-.311
WCST: Pers. Errors		.812		
WCST: Cat. Com		.869		
COWAT – Total				-.305
BNT			.691	
WL-I	.609			
WLII	.700			
AI	.765			
AD	.862			
ARD	.699			
VI	.729			
VD	.736			
WM				-.460
VO			.846	
SI			.715	
IN			.883	
PC				-.349
BD				-.484
MR			.327	-.373
DSY				-.759
SS				-.787
Eigenvalues	10.01	3.17	1.65	1.16
% Variance	45.48	9.87	7.50	5.28
Cum.%Variance	45.48	55.35	63.85	68.12

N = 420 Pers. Err. = Perseverative errors; Cat. Com = Categories Completed; Total = Total words; % Variance = Percent Variance; Cum.%Variance = Cumulative Percent Variance.

A six-factor final solution provided the least number of factors, which produced a clinically meaningful organisation of test scores. This factor analysis accounted for 75.20% of the variance. The eigenvalues, percent variance, cumulative percent variance, and factor loadings of the six factors based on the rotated component matrix are presented in Table 3.4. Items with factor loadings of less than .30 have been suppressed in the table to better illustrate the factor structure. This solution only produced one variable that was loaded on two factors (i.e. COWAT – Total: Factor 2 = -.32 and Factor 4 = -.31). However, all other factors were well defined.

Table 3.4
Final Rotated Factor Structure of the Test Battery.

	Factor					
Subtest	1	2	3	4	5	6
TMT-A				-.464		
TMT-B min A		.438				
WCST: Pers. Errors		.813				
WCST: Cat. Com		.886				
COWAT – Total			-.315	-.314		
BNT			-.620			
WL-I	.560					
WLII	.682					
AI	.946					
AD	.956					
ARD	.703					
VI					.882	
VD					.878	
WM				-.346		
VO			-.925			
SI			-.706			
IN			-.863			
PC						-.516
BD						-.856
MR						-.544
DSY				-.857		
SS				-.646		
Eigenvalues	10.01	3.17	1.65	1.16	0.81	0.74
% Variance	45.48	9.87	7.50	5.28	3.70	3.38
Cum.%Variance	45.48	55.35	63.85	68.12	71.82	75.20

N = 420 Pers. Err. = Perseverative errors; Cat. Com = Categories Completed; Total = Total words; % Variance = Percent Variance; Cum.%Variance = Cumulative Percent Variance.

Factor 1 included all tests related to verbal memory (AI, AD, ARD, Word Lists I and II subtests). Factor 2 included tests related to executive functioning (TMT: Part B minus A, WCST: Categories Completed and Perseverative Errors), with Factor 3 producing the traditional WAIS-III verbal comprehension factor (VO, SI, and IN), which included the tests of verbal fluency (COWAT) and naming (BNT). The fourth factor comprised tests of speed of information processing, and working memory/attentional abilities (DSY, SS, WM, TMT-A, and COWAT). The last two factors appeared to be related to immediate and delayed visual memory (VI and VD), and visuospatial abilities (PC, BD, and MR) respectively. The six-factor solution

factor scores were retained from this analysis and were then used as the dependent variables in the cluster analysis. Table 3.5 presents the unstandardised coefficients and constants for the derivation of the factor scores.

Table 3.5
Unstandardardised Coefficients and Factor Scores

Test	Unstandardised Coefficients					
	Verbal Memory	Visual Memory	Executive Functioning	Speed & Attention	Verbal Ability	Visual Ability
TMT-A	.001	.000	-.002	-.009	-.004	-.005
TMT-B min A	.002	-.003	.015	-.007	.002	-.005
WCST: Pers. Errors	-.003	.001	.071	.007	.000	-.005
WCST: Cat. Com	.007	.000	.103	.003	.007	-.001
COWAT – Total	.003	.007	-.004	-.016	-.009	.007
BNT	.002	.001	-.007	-.004	-.015	-.008
WL-I	.037	.008	.013	-.016	.013	.011
WLII	.030	.005	.000	-.002	-.003	.009
AI	.116	-.010	-.003	.008	-.024	-.025
AD	.080	.006	-.011	.024	.004	.018
ARD	.023	.001	.004	-.008	.000	.008
VI	-.001	.087	.006	-.006	-.001	.011
VD	.019	.191	-.007	.005	.003	.001
WM	.000	-.013	.019	-.045	-.002	-.035
VO	.006	.003	-.003	.008	-.144	.025
SI	-.003	.005	.001	-.002	-.057	-.016
IN	-.003	-.006	.000	.015	-.084	-.016
PC	-.005	-.001	.003	-.001	-.008	-.044
BD	-.005	-.009	.003	-.001	.001	-.175
MR	.003	-.003	.016	-.004	-.006	-.068
DSY	.000	.007	.006	-.174	.009	.018
SS	.004	.006	.003	-.098	.000	-.039
Constant	-2.521	-2.076	-1.701	2.533	2.903	3.069

3.3.2 Group Mean Behaviour

Traditionally, diagnostically based groups have been assessed on the basis of mean scores. By way of illustration, the cases from the mixed diagnostic sample with traumatic brain injury (Figure 3.1), seizure disorder (Figure 3.2), and Parkinson's

disease (Figure 3.3) have been separately combined and group means were generated for each of the factor scores and depicted graphically. Consistent with the expectations in the research literature based upon group means, the mean factor scores for traumatic brain injury indicated a trend towards lower attentional and speed of processing abilities. The mean factor scores for the seizure disorder group reflected poorer memory and the mean scores for the Parkinson's disease group indicated poor executive functioning and visuo-constructional abilities. While this bears little relevance to the analyses undertaken it does illustrate that if only the means were presented for these groups they would resemble the expected patterns derived from similar representations in the literature.

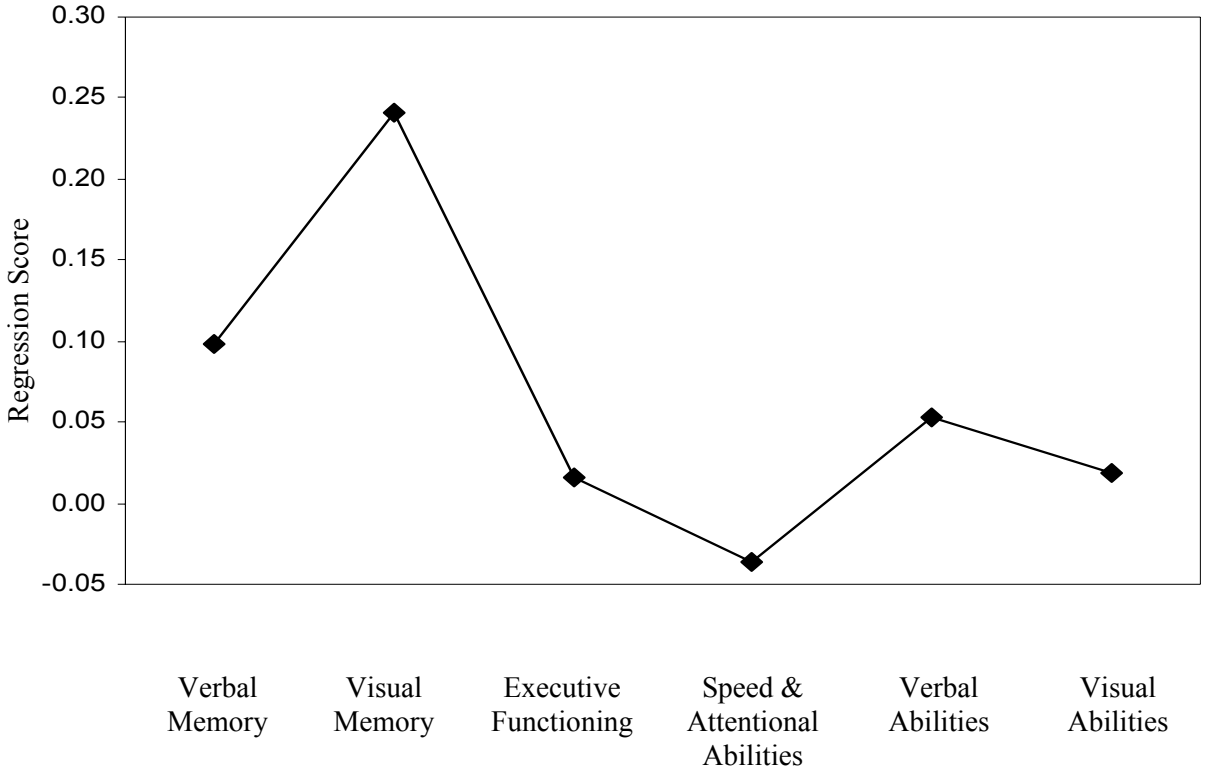

Figure 3.1 Neuropsychological Battery Mean Factor Scores: Traumatic Brain Injury

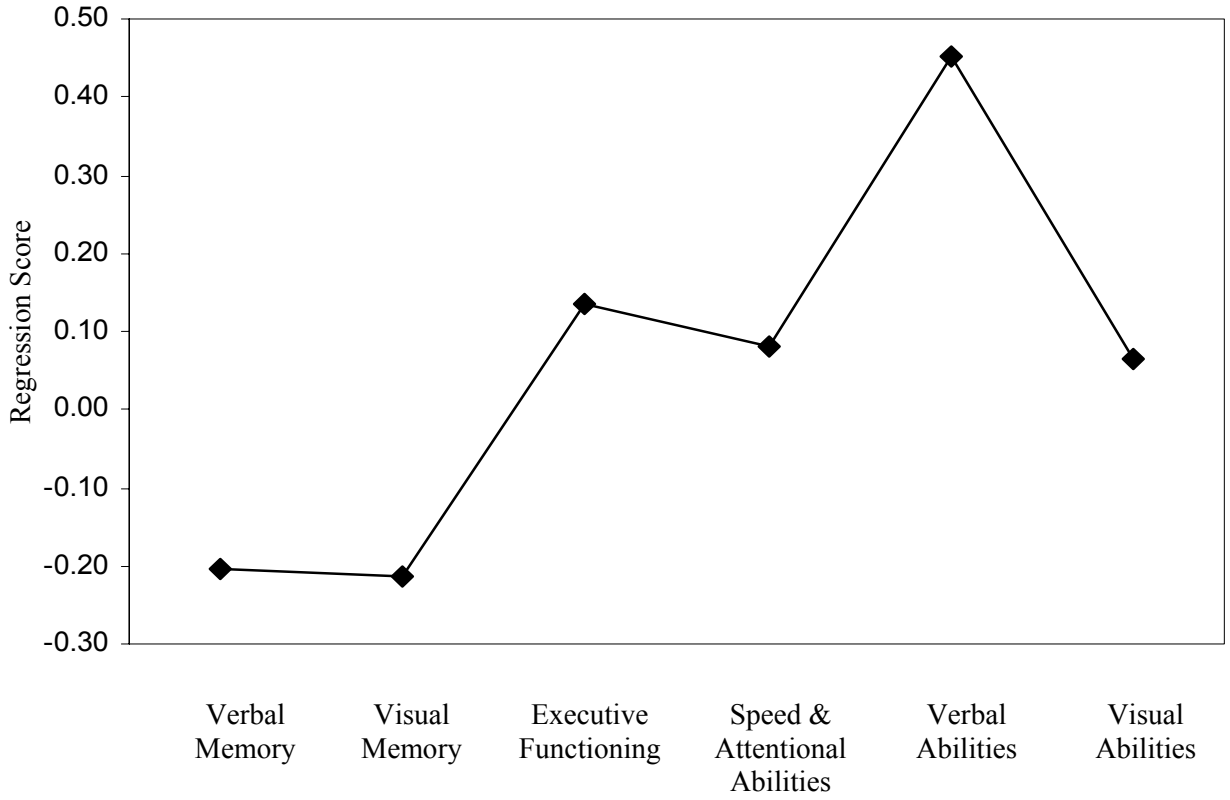

Figure 3.2 Neuropsychological Battery Mean Factor Scores: Seizure Disorder

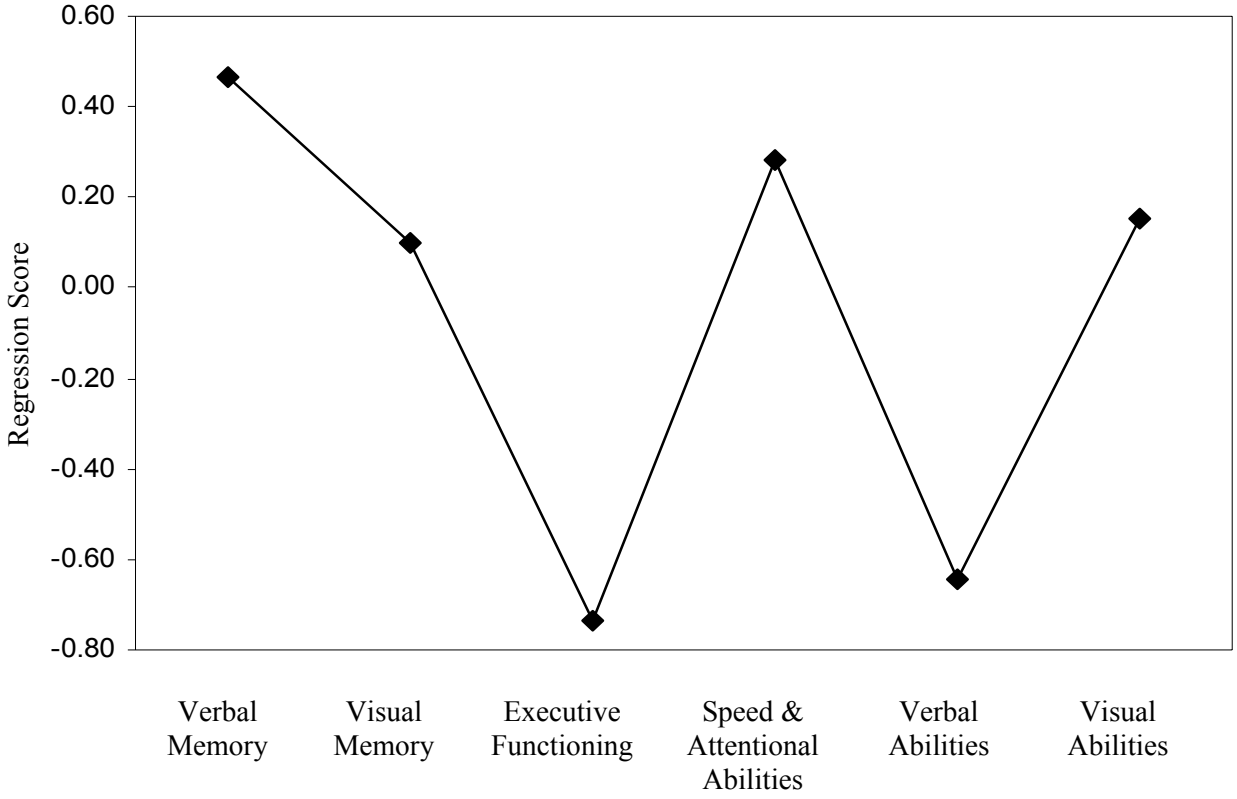

Figure 3.3 Neuropsychological Battery Mean Factor Scores: Parkinson's Disease

3.3.3 Hierarchical and K-Means Cluster Analysis of the Mixed Diagnostic Sample

The cophenet correlation of the hierarchical cluster analysis indicated that the data was clusterable (C = .72) and the hierarchical cluster analysis solution was computed. Following computation of the hierarchical cluster analysis (N = 420), examination of the inverse scree plot indicated an initial adjustment of the curve at a three-cluster solution (marker A), however, this was more noticeable at a five or seven-cluster solution (marker B and C). The dendrogram also revealed a number of likely solutions, with anywhere from a two (marker D) to a twelve-cluster (marker E) solution likely in this data set (see Appendix E, Figures E.1 and E.2).

A five-cluster solution was selected as the most appropriate outcome, for this data set, based on the indicators from the scree plot, and dendrogram. The silhouette plot, shown in Appendix F (Figure F.1), indicated that the solution was not ideal due to overlap between the clusters, indicated by the majority of cases not falling over 0.6. A K-Means analysis was then conducted using random seed points and designating a five-cluster solution. The mean factor regression scores for the five profiles generated by the K-Means analyses are presented in Table 3.6.

Table 3.6
Mean Factor Regression Scores for the K-Means (K) Solutions

	K-Means Analysis				
Factor	K1	K2	K3	K4	K5
Verbal Memory	-0.197	1.081	-0.543	-1.107	0.497
Executive Function	0.663	0.702	-1.053	-0.881	-0.121
Verbal Abilities	0.234	-0.981	-0.329	1.137	-0.068
Speed and Attention	-0.197	-0.905	0.130	1.124	0.129
Visual Memory	-0.374	0.983	-0.501	-0.949	0.676
Visual Abilities	-0.442	-0.811	0.033	1.152	0.402
N = 420	109	97	56	82	76

3.3.4 Independence of Cluster Solutions

The pattern of scores for each of the clusters was then investigated for independence. This was done by examining the correlations between each of the five

patterns of scores identified. Table 3.7 presents the inter-correlation matrix for the five profiles identified by the K-Means analyses.

Table 3.7
Correlation Matrix: K-Means Analysis (K)

	K-Means Analysis				
	K1	K2	K3	K4	K5
K1	1.00				
K2	.09	1.00			
K3	-.70	-.74	1.00		
K4	-.18	-1.00	.80	1.00	
K5	-.84	.45	.21	-.36	1.00

*p<.05. Only significant positive correlations are indicated

As indicated by Table 3.6 the only statistically significant within-group correlations found between any of the five patterns identified by the K-Means analysis were negative correlations. As negative correlations are indicative of dissimilarity (the reverse pattern) and not similarity, these five profiles identified by the K-Means analysis represent independent patterns of cognitive performance.

3.4 Examination of Profile Membership

The degree to which any of the five clusters were associated with a specific clinical diagnosis was examined by evaluating the frequency of each of the clusters in the different diagnostic groups that comprised the mixed diagnostic sample.

Table 3.8 indicates how many individuals from each of the 12 diagnostic categories are present in each of the five cognitive profiles. While some profiles were under-represented in some diagnostic categories (e.g. Tumour: Cluster 4, n = 4.5%), other profiles indicated larger diagnostic group membership (e.g. Tumour: Cluster 2, n = 40.9%). Some of the diagnostic groups such as CVD and Psychiatric disorders were spread fairly evenly across all five profiles. Every cluster contained members from every diagnostic group except for Cluster 4. This cluster did not include any cases diagnosed with Substance Abuse or Parkinson's disease. However, it should be noted that the sample size of these particular groups was very small.

Table 3.8
Percentage of Cases with Each Cluster in Different Diagnostic Categories

Diagnosis	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	N
CVD	17.5	20.0	25.0	15.0	22.5	40
DAT	7.1	28.6	28.6	21.4	14.3	14
MID	15.4	7.7	23.1	23.1	30.8	26
DEM	21.9	15.6	15.6	15.6	31.3	32
PD	12.5	25.0	37.5	0.0	25.0	8
DrugEtoh	9.1	63.6	18.2	0.0	9.1	11
PSYCH	16.7	33.3	16.7	16.7	16.7	12
SZ	40.5	12.0	8.9	24.1	14.6	158
TUMOUR	18.2	40.9	9.1	4.5	27.3	22
TBI	20.5	35.9	10.3	25.6	7.7	39
Other	18.6	44.2	2.3	18.6	16.3	43
NIL	13.3	26.7	20.0	20.0	20.0	15

These results provide further support for the assertion that no unique or prototypical patterns of psychological test scores are characteristic of particular diagnostic groups. If test score patterns were uniquely associated with diagnoses then 12-clusters should have been specified by the cluster analysis, with each of these containing only the participants from a single diagnostic category. However, this was clearly not the case with five clusters appearing frequently in most of the diagnostic groups comprising the sample.

3.5 Profile Characteristics

The five profiles from the K-Means analysis are presented graphically in Figures 3.4 to 3.8. These graphs indicate the mean regression scores retained from the final six-factor solution for each of the cognitive profile. A factor score falling outside the average mean score range specifies a strength or weakness in any one profile. As these factor scores are normalised with a mean of 0 and a standard deviation of 1, scores of more than +.67 and less than -.67 reflect strengths and weaknesses respectively. These scores were chosen as they correspond to the 25th and the 75th percentiles respectively.

Profile 1 (Cluster 1, n=109) may be characterised as a flat profile as there are no indicated strengths or weaknesses. The character of Profile 2 (Cluster 2, n=97)

demonstrated relative cognitive strengths in the areas of visual and verbal memory, and executive functioning, with relative cognitive weaknesses in speed and attentional, verbal, and visual abilities. Therefore, Profile 2 has very defined strengths and weaknesses with no mean performances.

The pattern of performance indicated by Profile 3 (Cluster 3, n=56) showed no relative strengths and only one weakness in the area of executive functioning. On the whole, people in this profile tend to display a relatively stable profile falling within mean range scores.

Profile 4 (Cluster 4, n=82) can be typified by relative cognitive strengths in the areas of speed and attentional, verbal, and visual abilities, with relative cognitive weaknesses in visual and verbal memory, and executive functioning. Therefore, Profile 4 had very defined strengths and weaknesses with no average performances. It is also noted that this profile reflects the reverse pattern from that of Profile 2. These two profiles are noted to occur with reasonably equal frequency within most diagnostic groups.

The pattern of performance that typified Profile 5 (Cluster 5, n=76) indicated strength in the area of visual memory, with no other strengths or weaknesses noted. Therefore, all other scores fall within the mean range of functioning.

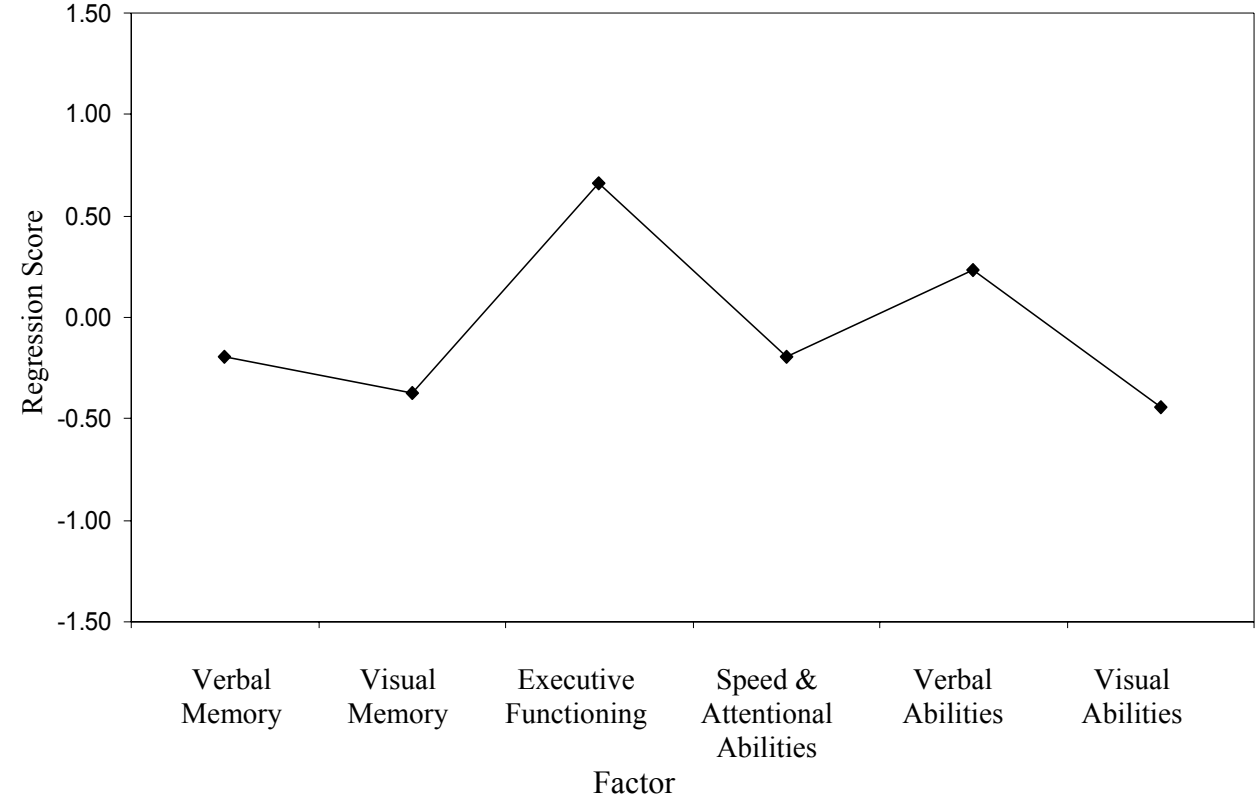

Figure 3.4 Mixed Diagnostic Sample: Profile 1

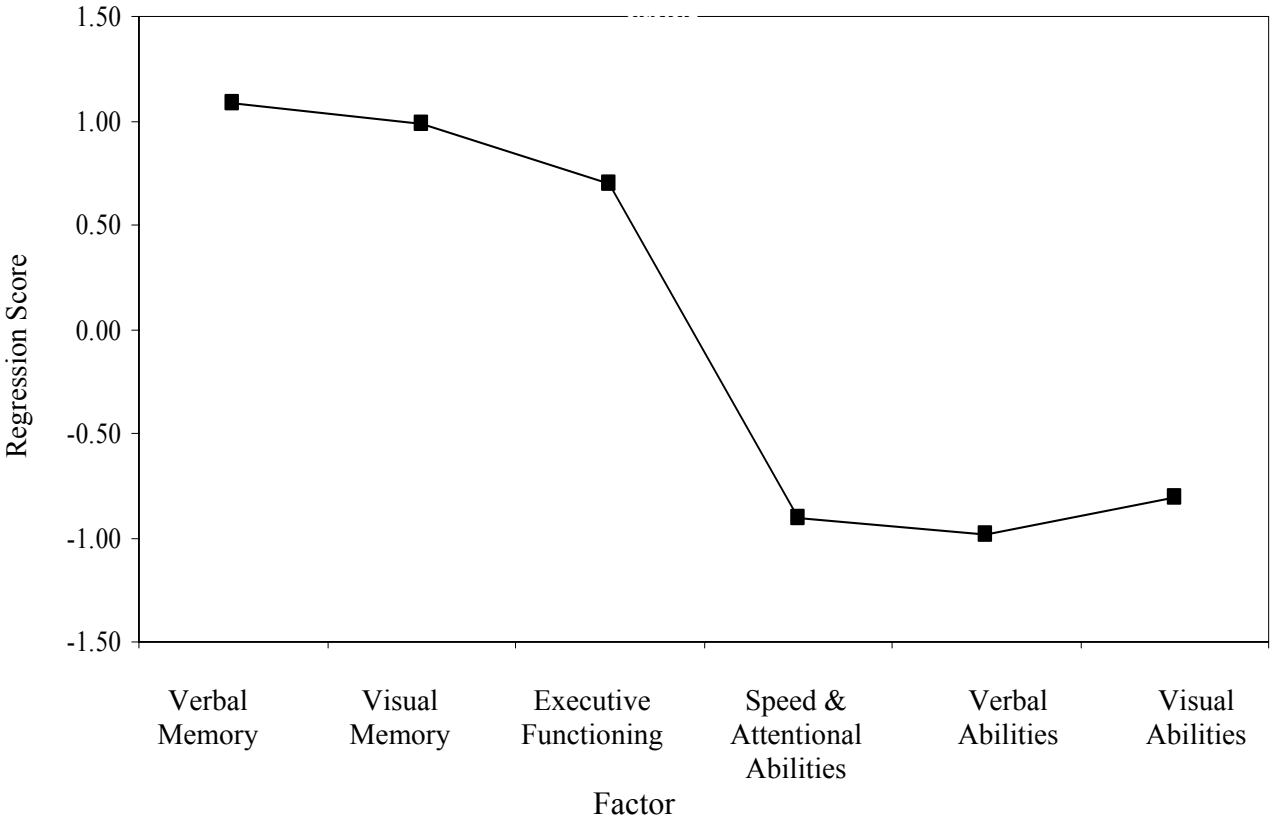

Figure 3.5 Mixed Diagnostic Sample: Profile 2

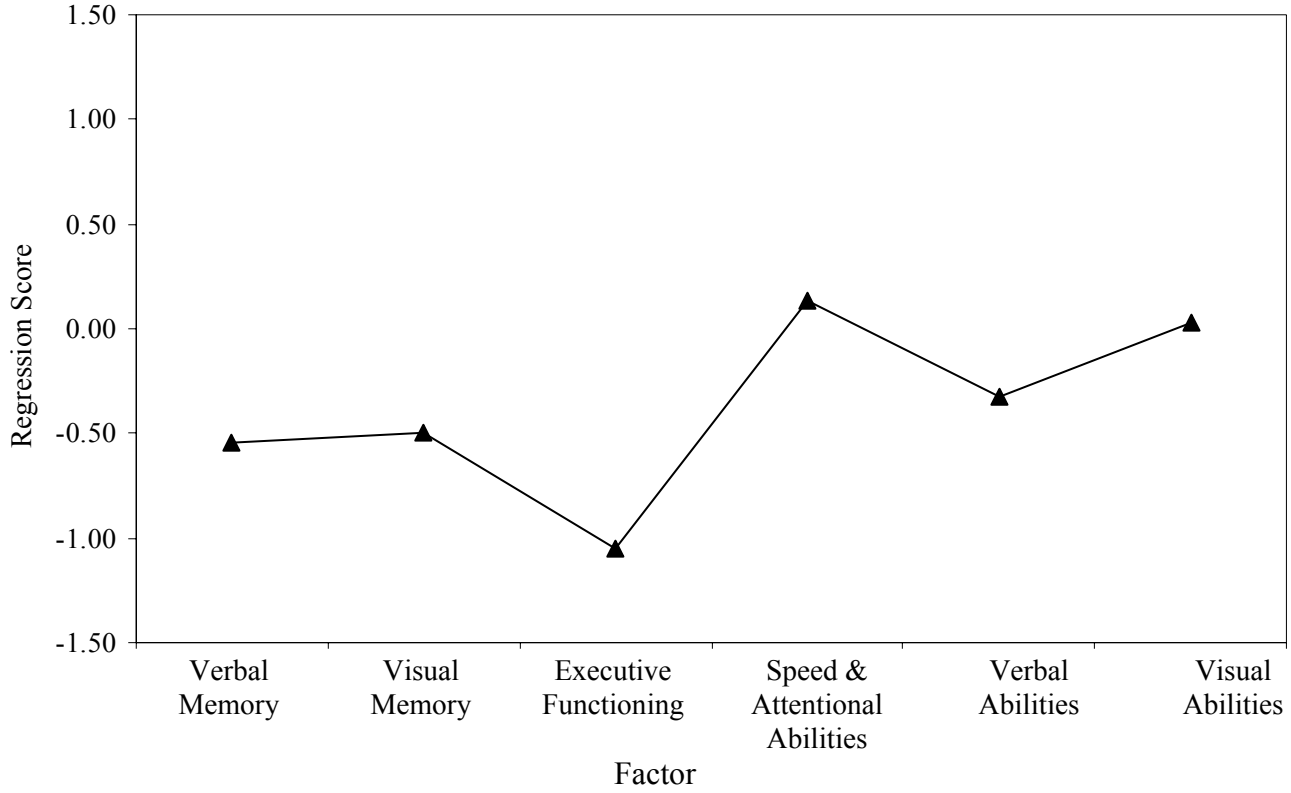

Figure 3.6 Mixed Diagnostic Sample: Profile 3

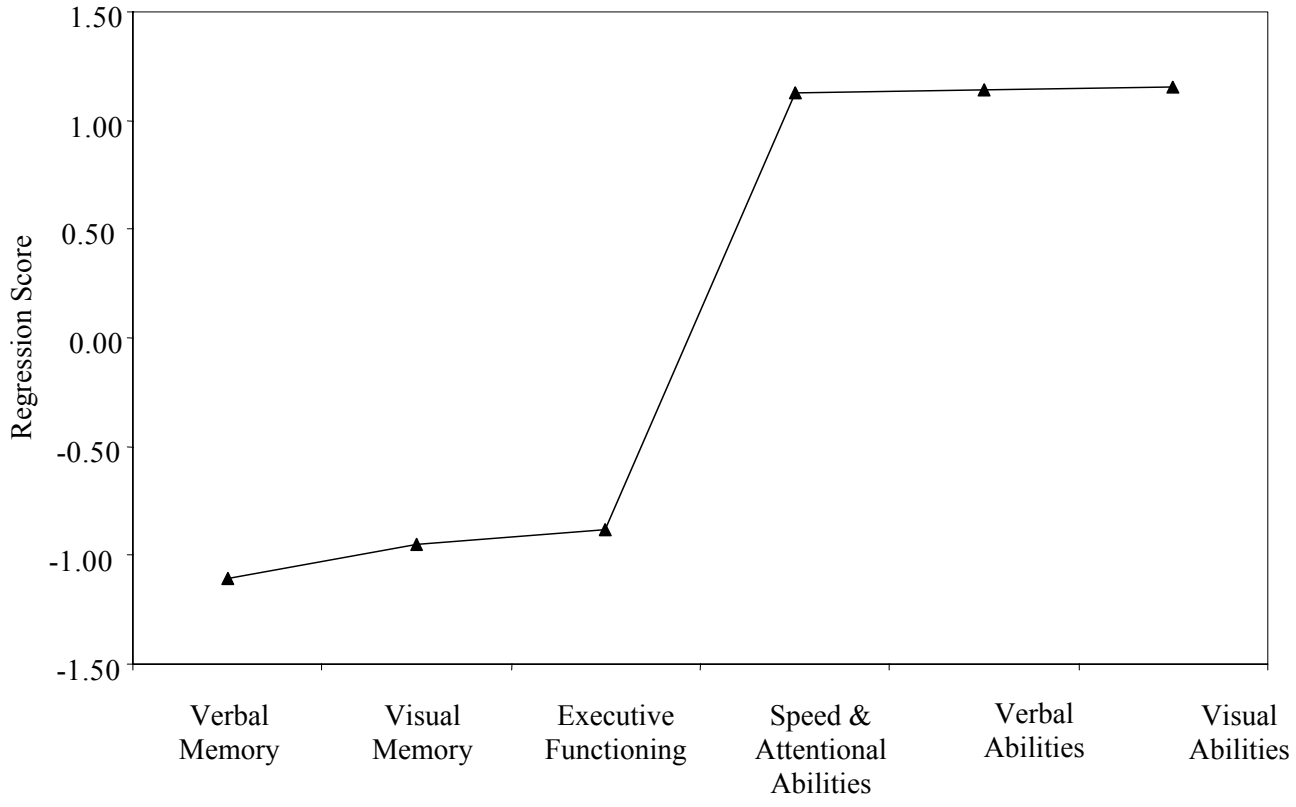

Figure 3.7 Mixed Diagnostic Sample: Profile 4

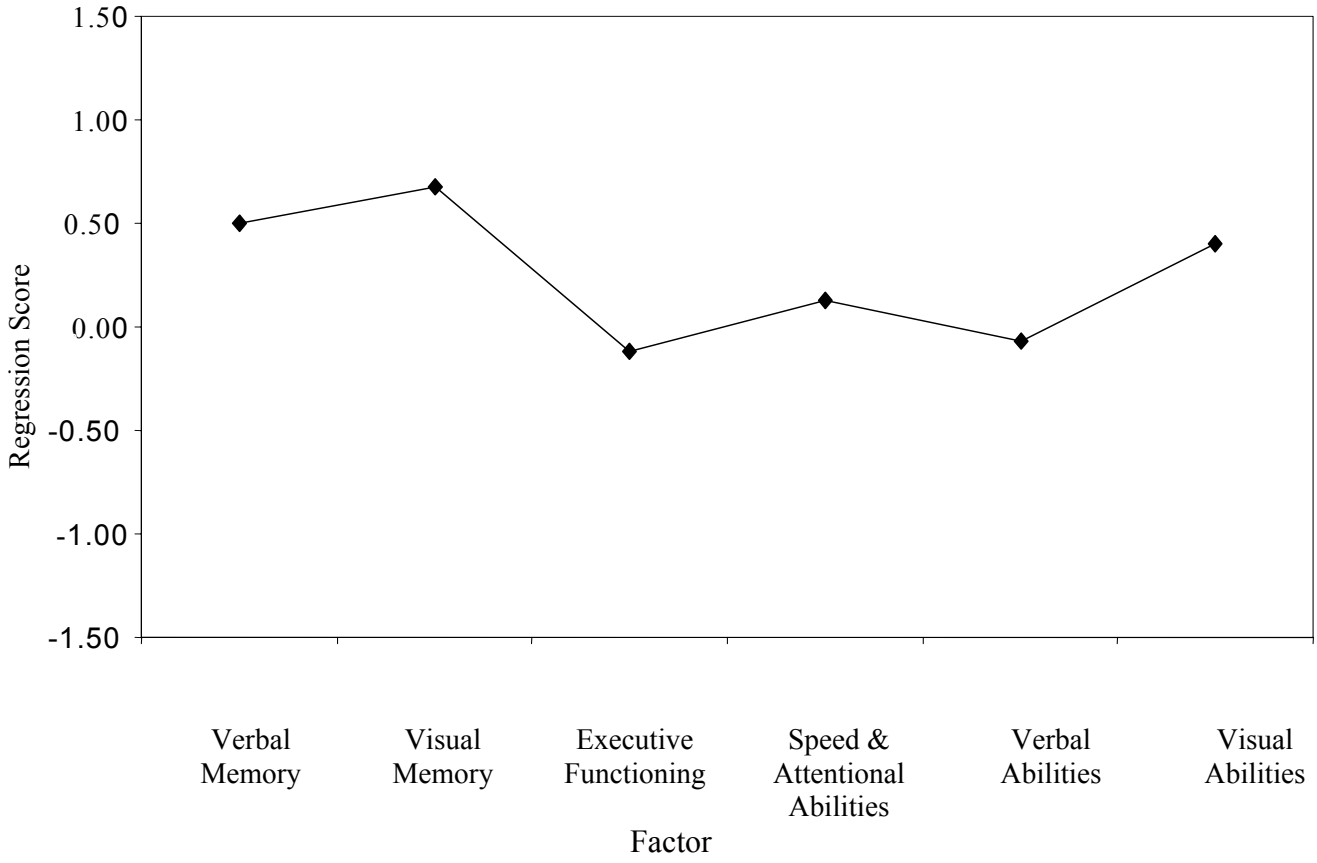

Figure 3.8 Mixed Diagnostic Sample: Profile 5

3.6 Impact of Group Means on Diagnostic Patterns

Traditionally most research is conducted with mean profile scores on different diagnosis, with no recognition of the differing trends in scores for individuals within the diagnostic group. Consideration will now be given to the some of the diagnoses within the analysis with the expectation that mean scores for each of the diagnoses would be similar to the profiles that are reported in the literature.

For example, the literature regarding traumatic brain injury indicates that the main deficits suffered from those with mild to moderate or severe injuries are within the factors of attention and speed of processing (Axelrod et al., 2002; Crawford et al., 1997; Dikmen et al., 2001; Jacobus Donders et al., 2001; D. C. Fisher et al., 2000; Franzen, 2000; Haut & Shutty, 1992; Kersel et al., 2001). As was shown graphically (Figure 3.1), the lowest scores for this diagnostic group were in their attention and

speeded factor scores, therefore indicating support for the current literature in the area. However it is noted that within this diagnostic group, only 35.9% of cases fell within the cluster that indicated poor abilities in these areas. It is noted that 25.6% of the cases with traumatic brain injury were indicated to have strength in these areas as they fell within the fourth cluster.

Another example of the misleading nature of patterns of performance inferred from group means can be seen with the sub-sample of cases with seizure disorders. The literature indicates that the main areas of deficit for this diagnostic group are within the factors of memory (see Seidenberg et al., 1998; Wilde et al., 2001). When graphically presented earlier (Figure 3.2), the lowest scores for this diagnostic group were shown within the areas of verbal and visual memory. However the cluster analysis showed that only 24.1% of the cases with this disorder were allocated to the cluster that showed cognitive weaknesses in this area, with the rest of the cases (75.9%) demonstrating scores within the average range or higher.

Parkinson's disease is usually typified by weaknesses in the areas of executive functioning and visuo-constructional abilities (see Farina et al., 2000; Woods & Troester, 2003). When group means were graphed for this sample (Figure 3.3) these findings were substantiated. However, the cluster analysis indicated that no profile showed this pattern of performance and that the PD group fell within clusters showing deficits and strengths in other areas. However, it is noted that the largest group of PD cases (37.5%), but by no means the majority, were allocated to Cluster 3, which was defined by a weakness in executive functioning.

3.7 Summary

Neuropsychological data from a mixed clinical sample of 420 cases was factor analysed using principle axis factoring to reduce the number of variables from 22 to six. This was done to reduce the complexity of the database and enhance the

clustering of the sample. The hierarchical cluster analysis indicated that there were any where between two and twelve possible clusters. After consideration of the clustering diagnostics including the dendrogram, and inverse scree plot, a five-profile solution was sought, and was considered to represent stable patterns of cognitive performance in this sample. These clusters appeared independent of each other as shown by the lack of statistically significant positive correlations between the cluster scores. The implications of these findings are that the relatedness amongst cases in the sample is best characterised by the pattern of relative cognitive strengths and weaknesses they demonstrate on psychological tests rather than the medical diagnosis they have received. In order for this information to be utilised to greatest effect by clinicians a method of categorising individual cases to cognitive patterns must be developed. The method and efficacy of such a classification system is explored in the next chapter.

CHAPTER 4

4.0 CLINICAL UTILITY OF PROTOTYPICAL COGNITIVE PATTERNS IN A MIXED DIAGNOSTIC SAMPLE

4.1 Overview

In Chapter 3, cluster analysis was used to identify commonly occurring patterns of cognitive functioning within a mixed diagnostic sample using the WAIS-III, WMS-III and other neuropsychological tests. The results of these analyses indicated that there were at least five cognitive profiles identified within this sample. This strongly indicated that a small number of cognitive test patterns account for much of the variance in the mixed diagnostic sample.

While sophisticated multivariate statistical analyses of large groups of data are well suited to exploring the patterns that underlie both medical conditions and psychological tests, they cannot be employed in the single case world of the clinician. The findings of this and prior studies warn clinicians that assumptions regarding prototypical patterns of test performance associated with different medical diagnoses are without empirical support. Instead clinicians should be focusing on the pattern of cognitive strengths and weaknesses revealed in cognitive test patterns and recognise that these are both consistent and finite. Realistically, this information is cold comfort and contributes little more than a clinical warning unless a method for accurately classifying individual cases to one of the five cognitive profiles can be devised. This is addressed in the current chapter through the use of an outlier metric, Mahalanobis distance (MD).

Mahalanobis distance permits the multivariate comparison of any single case with each of the five identified cognitive profiles. It was chosen over other metrics for its ability to accommodate means, variance, test reliabilities and intercorrelations in

its computation, all parameters that must be considered in interpreting psychological tests data.

Traditionally, significant MDs are used for the complementary process of excluding cases that are not characteristic of a group as statistical outliers. Here the principle is reversed with a non-significant Mahalanobis distance indicating a failure to reject the null-hypothesis and potential assignment of the case to that cognitive profile. Diagrammatically this is depicted in Figures 4.1 and 4.2. Figure 4.1 shows the best-case scenario with regard to the outcome of the clustering procedure. That is, that there is no overlap between any of the clusters and that they are truly independent of each other. Figure 4.2, on the other hand illustrates the far more likely situation where there is overlap between the clusters indicating some independence. The greater the amount of overlap between clusters the less likely it will be that clinical cases can be allocated to only one cluster. However, if there is a low amount of overlap, the clustering solution and method may still be clinically meaningful dependent upon the actual proportion of cases that can be uniquely classified.

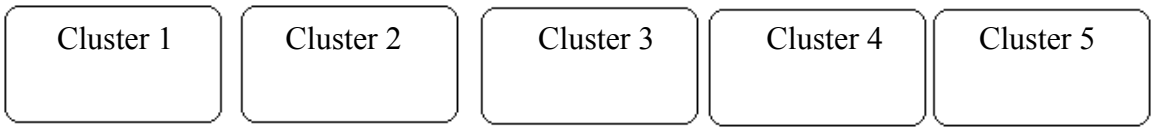

Figure 4.1 Best-Case Scenario for Clustering Solution: No Overlap

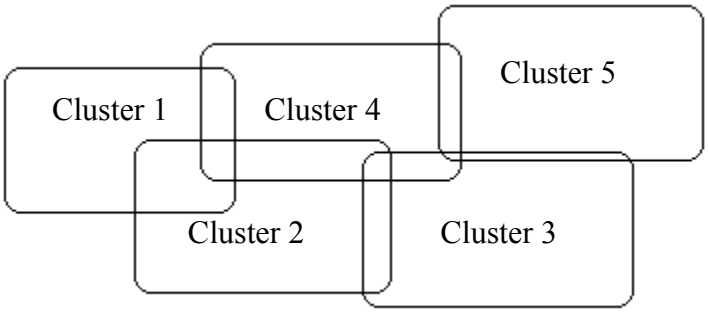

Figure 4.2 Most likely Scenario for Clustering Solution: Overlap between clusters.

This study sought first to examine the amount of overlap between each of the clusters by use of Mahalanobis distance as a means of classifying which cases fall into which cluster - a single case approach. The Mahalanobis distance classification was then compared to the cluster membership indicated by the cluster analysis performed in the previous chapter - a group based approach. Discriminant function analysis was employed to determine the accuracy of the Mahalanobis distance approach in predicting membership indicated by the cluster analysis. With sufficient classification accuracy, the algorithms derived from the discriminant function analysis would then be explicated as a specific method of single case classification to cognitive profiles of psychological test performance.

4.2 Method

4.2.1 Cases

As the purpose of the current study was to develop a single-case based method of classification to determine cognitive profile membership derived from the earlier cluster analysis, the same sample of 420 mixed diagnostic cases analysed in the previous chapter was employed here.

4.2.2 Cognitive Measures

The six factor scores derived for each of the 420 cases from the factor analysis conducted in the previous study were used along with the mean factor scores derived from the K-Means analysis presented earlier in Table 3.5.

4.2.3 Statistical Analysis

The Mahalanobis distance was calculated using matrix algebra in MATLAB 6.5.1 with the following4:

$$MD_k = \left(X - \overline{X}_k\right)' s_k^{-1} \left(X - \overline{X}_k\right) \qquad [3]$$

Where:

k = number of the cluster profile

X = factor scores for each individual case

$\overline{X}_k$ = mean factor scores for cluster k

s_k^{-1} = inverse covariance matrix for cluster k

For each case, five Mahalanobis distance scores were generated, one for each cluster and tested against the χ^2 distribution for significance. Statistically significant ($p<.05$) Mahalanobis distance scores indicate that the case should be viewed as a multivariate outlier with regard to the cognitive cluster to which the case is being compared. If the χ^2 statistic indicated that the Mahalanobis distance was non-significant then the case must be considered to have potentially come from that cluster.

These Mahalanobis distance scores were then submitted in a Discriminant Function Analysis using SPSS version 11.5 to predict the classification of the clinical cases based upon the cluster analysis procedures.

4.3 Analysis and Results

4.3.1 Mahalanobis Distance

The Mahalanobis distance was calculated between each case and the factor centroids of each of the five clusters. The inverse covariance matrices were computed using the standard deviations, reliabilities, and inter-correlations of the factor scores for each cluster and are presented in Tables 4.1 through 4.5.

Table 4.1
Inverse Covariance Matrix for Cluster K1 (N=109)

	Verbal Memory	Visual Memory	Executive Functioning	Speed/ Attention	Verbal Abilities	Visual Abilities
Verbal Memory	3.57	-0.91	-0.06	0.17	1.19	-0.38
Visual Memory	-0.91	3.70	-1.27	0.63	0.01	-0.19
Exec. Funct.	-0.06	-1.27	8.52	0.05	-0.29	1.24
Speed/Attention	0.17	0.63	0.05	2.86	0.94	-0.48
Verbal Abilities	1.19	0.01	-0.29	0.94	3.06	-0.84
Visual Abilities	-0.38	-0.19	1.24	-0.48	-0.84	3.33

Table 4.2
Inverse Covariance Matrix for Cluster K2 (N=97)

	Verbal Memory	Visual Memory	Executive Functioning	Speed/ Attention	Verbal Abilities	Visual Abilities
Verbal Memory	3.71	-1.33	-0.13	0.08	1.19	-0.16
Visual Memory	-1.33	2.70	0.09	0.29	-0.42	-0.65
Exec. Funct.	-0.13	0.09	5.62	0.20	0.37	1.04
Speed/Attention	0.08	0.29	0.20	2.68	0.16	-0.65
Verbal Abilities	1.19	-0.42	0.37	0.16	3.04	-0.25
Visual Abilities	-0.16	-0.65	1.04	-0.65	-0.25	2.97

Table 4.3
Inverse Covariance Matrix for Cluster K3 (N=56)

	Verbal Memory	Visual Memory	Executive Functioning	Speed/ Attention	Verbal Abilities	Visual Abilities
Verbal Memory	3.68	-1.19	-0.36	-0.05	-0.17	-0.82
Visual Memory	-1.19	3.21	0.12	0.59	0.29	-0.57
Exec. Funct.	-0.36	0.12	3.55	0.86	0.05	-0.33
Speed/Attention	-0.05	0.59	0.86	2.77	0.41	-1.53
Verbal Abilities	-0.17	0.29	0.05	0.41	2.98	-0.85
Visual Abilities	-0.82	-0.57	-0.33	-1.53	-0.85	4.08

Table 4.4
Inverse Covariance Matrix for Cluster K4 (N=82)

	Verbal Memory	Visual Memory	Executive Functioning	Speed/ Attention	Verbal Abilities	Visual Abilities
Verbal Memory	3.41	-1.51	0.50	-0.18	1.22	0.16
Visual Memory	-1.51	4.12	-0.57	1.35	0.47	-1.22
Exec. Funct.	0.50	-0.57	1.76	0.07	-0.31	1.01
Speed/Attention	-0.18	1.35	0.07	4.42	0.17	-2.84
Verbal Abilities	1.22	0.47	-0.31	0.17	3.29	-1.36
Visual Abilities	0.16	-1.22	1.01	-2.84	-1.36	5.61

Table 4.5
Inverse Covariance Matrix for Cluster K5 (N=76)

	Verbal Memory	Visual Memory	Executive Functioning	Speed/ Attention	Verbal Abilities	Visual Abilities
Verbal Memory	6.49	-1.31	0.54	0.19	1.38	-0.07
Visual Memory	-1.31	3.06	0.20	0.46	-0.02	0.21
Exec. Funct.	0.54	0.20	2.26	-0.36	-0.12	0.42
Speed/Attention	0.19	0.46	-0.36	2.75	1.02	-0.66
Verbal Abilities	1.38	-0.02	-0.12	1.02	2.85	-0.81
Visual Abilities	-0.07	0.21	0.42	-0.66	-0.81	3.86

The Mahalanobis distance for each case, by each cluster, with the original cluster membership, are illustrated for the first 20 cases in Table 4.6. The computations and cluster allocation for all 420 cases can be found in Appendix G. χ^2 statistics were calculated and used to assess if individual cases were outliers relative to each of the five clusters derived from the K-Means analysis. The amount of overlap between the clusters was determined by how many cases had more than one non-significant Mahalanobis distance and therefore fitted into more than one cluster. The percentage of cases that generated significant Mahalanobis distance scores for all five cases indicating non-fit with any cluster was small (4.1%, N=17). One hundred and fifty cases (35.7%) generated only one non-significant MD, indicating allocation to only one cluster. Of these cases, 148 (98.6%) were correctly allocated by the Mahalanobis distance to the cluster in which they were originally placed by the K-Means analysis. The remaining 253 cases were considered fits for two clusters (n=120, 28.6%), three clusters (n=95, 22.6%), four clusters (n=34, 8.1%), or five clusters (n=4, 1.0%), with 232 (91.7%) cases being correctly allocated by the Mahalanobis distance scores to the cluster that they were originally assigned by the K-Means analysis. While this result was certainly promising, with only one-third of cases being allocated to only a single profile this method alone would be insufficient to provide clinicians with a useful tool for classification. Consequently, a more

sophisticated method of classification using Mahalanobis distance scores in a discriminant functions analysis was examined.

Table 4.6
Mahalanobis Distance Scores for each case and K-Means derived cluster (Initial 20 Cases)

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
1	64.59	.00	108.15	.00	63.61	.00	11.12	.08	81.84	.00	4
2	66.41	.00	98.34	.00	53.68	.00	14.00	.03	77.41	.00	4
3	91.25	.00	94.73	.00	36.42	.00	9.38	.15	58.27	.00	4
4	50.86	.00	83.57	.00	36.15	.00	4.41	.62	59.02	.00	4
5	55.55	.00	53.03	.00	23.84	.00	10.92	.09	27.13	.00	4
6	37.21	.00	75.78	.00	39.03	.00	5.62	.47	52.20	.00	4
7	36.36	.00	68.46	.00	29.79	.00	3.48	.75	46.65	.00	4
8	32.61	.00	57.78	.00	20.14	.00	1.68	.95	32.65	.00	4
9	40.22	.00	60.25	.00	17.38	.01	6.50	.37	40.53	.00	4
10	18.42	.01	34.83	.00	10.74	.10	1.62	.95	16.15	.01	4
11	18.15	.01	36.88	.00	9.03	.17	3.49	.75	16.16	.01	4
12	11.29	.08	31.67	.00	9.62	.14	2.15	.91	15.72	.02	4
13	19.50	.00	23.72	.00	10.82	.09	9.24	.16	9.15	.17	5
14	13.06	.04	25.19	.00	3.23	.78	5.15	.53	10.84	.09	3
15	7.81	.25	22.22	.00	6.34	.39	5.39	.49	8.40	.21	1
16	10.37	.11	28.35	.00	17.94	.01	11.51	.07	10.34	.11	1
17	23.75	.00	43.94	.00	14.89	.02	2.59	.86	26.36	.00	4
18	49.33	.00	67.84	.00	17.43	.01	6.86	.33	42.81	.00	4
19	17.16	.01	39.06	.00	16.35	.01	5.78	.45	19.33	.00	4
20	7.77	.26	25.43	.00	12.28	.06	4.34	.63	10.71	.10	4

4.4 Discriminant Function Analysis

A direct discriminant function analysis (using SPSS version 11.5) was performed using the Mahalanobis distance scores generated from each case for each of the five clusters to predict cluster membership determined through the K-Means analysis. No cases were excluded. The tests of equality of group means were all significant indicating that all variables should be included in the discriminant function analysis (MD_{K1}: λ =.61, F(4,415)=65.19,p<.01; MD_{K2}: λ =.33, F(4,415)=209.61,p<.01; MD_{K3}: λ =.61, F(4,415)=67.37,p<.01; MD_{K4}: λ =.40, F(4,415)=155.25,p<.01; MD_{K5}, λ =.67, F(4,415)=50.72,p<.01). The sample size criteria was well met with a ratio of 90 cases to each independent variable (Hair,

Anderson, Tatham, & Black, 1998). The Box's M test for the assumption of homogeneity of covariance matrices, although significant ($F(60,245387)=21.02, p<.01$) and therefore indicating violation of this assumption, still indicated a probable robust solution due to the large N.

The amount of variance in the dependant variable accounted for by each of the discriminant functions is indicated below in Table 4.7. Wilks' lambda indicated that each of these functions was significant (Functions 1 through 4: $\lambda = .06$, $\chi^2(20) = 1173.19$, $p<.01$; Functions 2 through 4: $\lambda = .31$, $\chi^2(12)=491.83$, $p<.01$; Functions 3 through 4: $\lambda = .52$, $\chi^2(6)=273.84$, $p<.01$; Function 4: $\lambda = .75$, $\chi^2(2)=122.06$, $p<.01$).

Table 4.7
Summary of Canonical Discriminant Functions

Function	Eigenvalue	% of Variance	Canonical Correlation
1	4.19	73.9	.90
2	.69	12.2	.64
3	.44	7.8	.55
4	.34	6.1	.51

The unstandardised discriminant coefficients are shown in Table 4.8 and are used to calculate the discriminant scores that allow the direct comparison of cases on each function (Hair et al., 1998). The more similar the discriminant scores, the more likely those cases are to be allocated to a particular cluster.

Table 4.8
Unstandardised Canonical Discriminant Function Coefficients

	Function			
	1	2	3	4
MD_1	-0.027	-0.015	0.101	0.038
MD_2	0.099	-0.016	-0.106	0.046
MD_3	-0.038	0.147	0.031	0.081
MD_4	-0.051	-0.121	-0.093	-0.002
MD_5	-0.002	0.006	0.080	-0.157
Constant	-0.090	-0.072	-0.084	-0.635

However, when attempting to classify a case into a cluster, Hair, et al. (1998) suggests utilising the classification function, Fisher's linear discriminant function. This allows the calculation of a classification score for a case into each of the different clusters where the highest classification score signifies membership within that cluster. Fisher's classification function coefficients are shown in Table 4.9 and are presented as equations in Equations 5 through 9. The highest obtained score from the equations indicates the cluster that an individual case will fall into.

Table 4.9
Fisher's Classification Function Coefficients

	Function				
	1	2	3	4	5
MD_1	-0.399	-0.149	-0.290	-0.329	-0.259
MD_2	0.728	0.310	0.778	0.936	0.730
MD_3	-0.071	0.091	-0.431	-0.052	-0.062
MD_4	0.921	0.905	0.992	0.559	0.992
MD_5	-0.455	-0.364	-0.338	-0.431	-0.656
Constant	-9.683	-13.434	-11.709	-15.463	-10.943

$$K1 = -9.683 - 0.399*MD_1 + 0.728*MD_2 - 0.071*MD_3 + 0.927*MD_4 - 0.455*MD_5 \quad [5]$$

$$K2 = -13.434 - 0.149*MD_1 + 0.31*MD_2 + 0.091*MD_3 + 0.905*MD_4 - 0.364*MD_5 \quad [6]$$

$$K3 = -11.709 - 0.29*MD_1 + 0.778*MD_2 - 0.431*MD_3 + 0.992*MD_4 - 0.338*MD_5 \quad [7]$$

$$K4 = -15.463 - 0.329*MD_1 + 0.936*MD_2 - 0.052*MD_3 + 0.559*MD_4 - 0.431*MD_5 \quad [8]$$

$$K5 = -10.943 - 0.259*MD_1 + 0.73*MD_2 - 0.062*MD_3 + 0.992*MD_4 - 0.656*MD_5 \quad [9]$$

The results of this analysis indicated that 88.3% of cases could be correctly classified according to the K-Means analysis using the above equations with individual cluster accuracy rates varying from 80 to 94% (see Table 4.10).

Table 4.10
Predicted Group Membership versus Actual Group Membership

Actual Group Membership	Predicted Group Membership									
	1		2		3		4		5	
	N	%	N	%	N	%	N	%	N	%
1	102	93.58	4	3.67	3	2.75	0	0.00	0	0.00
2	5	5.15	87	89.69	0	0.00	0	0.00	5	5.15
3	3	5.36	0	0.00	48	85.71	2	3.57	3	5.36
4	3	3.66	0	0.00	4	4.88	73	89.02	2	2.44
5	14	18.42	1	1.32	0	0.00	0	0.00	61	80.26

These findings indicate that through the use of algorithms derived through discriminant function analysis the Mahalanobis distance scores can be employed to accurately classify from 80% to 94% of the clinical cases to a single cognitive cluster. This represents a substantial improvement over the 35% of cases accurately classified using only a non-significant Mahalanobis distance score.

4.5 Summary

This study attempted to develop a clinically useful method for allocating clinical cases to cognitive profiles. This was done by computing Mahalanobis distance scores for each of the 420 cases compared to the five identified cognitive profiles using the six factor scores derived in Study 2. While it was clear that using Mahalanobis distance as a multivariate outlier statistic was successful in correctly allocating the majority of cases (90.5%) to their assigned cognitive profile based on cluster analysis, the alarmingly high percentage of cases (60.2%) that were allocated to more than one cluster threatened to severely limit the clinical applicability of this method.

Discriminant function analysis was utilised to derive a multivariate approach to using the Mahalanobis distance scores to predict cognitive profile classification, which proved to be very effective in allocating individual cases to their correct

cognitive profile, with a mean accuracy of 88.3%, which ranged from a low of 80% to a high of 94%. Such a high rate of correct classification indicates that the Mahalanobis distance scores from each case to the cluster centroids holds substantial promise as a means of determining which cluster profile best applies to each clinical case. The next chapter will illustrate the potential utility of this method in interpreting the data from clinical cases.

CHAPTER 5

5.0 EXAMPLES OF THE CLINICAL UTILITY OF PROTOTYPICAL COGNITIVE PATTERNS IN A MIXED DIAGNOSTIC SAMPLE

5.1 Overview

The previous two chapters have devised and then empirically tested the validity of a new method for the classification of cases into cognitive patterns. This chapter will demonstrate the step-by-step procedure utilised to examine specific cases. In the last chapter, five equations (Equations 5 through 9) were derived from the discriminant function analysis that allowed the classification of cases into one of the five clusters.

The basis of the method is to compute factor scores from the Scaled Scores of each test using the factor score regression equations generated from Study 2 (see Table 3.5). Then Mahalanobis distance scores must be computed for each case by comparing the case to each of the cognitive profiles identified through cluster analysis in Study 2. Once computed, these MDs are then placed into the discriminant function equations derived from Study 3 (Equations 5 through 9), to determine to which cognitive cluster or profile the case is most similar. These steps will be illustrated in detail through the use of three case studies.

5.2 Case Study 1

5.2.1 Demographics and Test Scores

This case study involves an 18-year-old female with 12 years of education. She was assessed after being diagnosed with temporal lobe epilepsy. In the cluster analysis from Study 2, this case was indicated to fall into cluster 1. Her scores on the relevant tests are shown in Table 5.1.

Table 5.1
Case Study 1: 18 year-old female – Test Scores

WAIS-III Selected Subtests	Raw Score	Standard Score	Scaled Score
Vocabulary			6.00
Similarities			9.00
Information			5.00
Picture Completion			9.00
Block Design			10.00
Matrix Reasoning			10.00
Digit Symbol Coding			7.00
Symbol Search			11.00
WMS-III Indices			
Auditory Immediate		89	7.80
Visual Immediate		88	7.60
Auditory Delayed		92	8.40
Visual Delayed		94	8.80
Aud. Recog. Delayed		85	7.00
Working Memory		102	10.40
Word Lists I (Scaled Score)			5.00
Word Lists II (Scaled Score)			6.00
Trail Making Test			
Part-A (sec)	43		-.50
Part-B (sec)	53		
Part-B minus Part A (sec)	10		14.73
Wisconsin Card Sort Test			
Categories Achieved	5		9.08
Perseverative Errors	15		9.29
Controlled Oral Word Assoc. Test			
Total Words	41		9.69
Boston Naming Test			
Total	55		-.11

5.2.2 Computation of Factor Scores

The factor scores for this client are derived using Table 3.5 presented in Chapter 3. Each of these regression equations uses the scaled scores for all of the tests to compute each of the six factor scores. The computed factor scores for Case 1 are presented in Table 5.2.

Table 5.2
Case Study 1: Scaled Scores, Unstandardardised Coefficients and Factor Scores

Test	Scaled Scores	Unstandardised Coefficients					
		Verbal Memory	Visual Memory	Executive Functioning	Speed & Attention	Verbal Ability	Visual Ability
TMT: Part A	-0.50	.001	.000	-.002	-.009	-.004	-.005
TMT: B minus A	14.73	.002	-.003	.015	-.007	.002	-.005
WCST: Pers. Errors	9.29	-.003	.001	.071	.007	.000	-.005
WCST: Cat. Com	9.08	.007	.000	.103	.003	.007	-.001
COWAT – Total	9.69	.003	.007	-.004	-.016	-.009	.007
BNT	-0.11	.002	.001	-.007	-.004	-.015	-.008
WL-I	7.80	.037	.008	.013	-.016	.013	.011
WLII	8.40	.030	.005	.000	-.002	-.003	.009
AI	7.00	.116	-.010	-.003	.008	-.024	-.025
AD	7.60	.080	.006	-.011	.024	.004	.018
ARD	8.80	.023	.001	.004	-.008	.000	.008
VI	10.00	-.001	.087	.006	-.006	-.001	.011
VD	6.00	.019	.191	-.007	.005	.003	.001
WM	9.00	.000	-.013	.019	-.045	-.002	-.035
VO	5.00	.006	.003	-.003	.008	-.144	.025
SI	9.00	-.003	.005	.001	-.002	-.057	-.016
IN	10.00	-.003	-.006	.000	.015	-.084	-.016
PC	10.00	-.005	-.001	.003	-.001	-.008	-.044
BD	7.00	-.005	-.009	.003	-.001	.001	-.175
MR	11.00	.003	-.003	.016	-.004	-.006	-.068
DSY	5.00	.000	.007	.006	-.174	.009	.018
SS	6.00	.004	.006	.003	-.098	.000	-.039
Constant		-2.521	-2.076	-1.701	2.533	2.903	3.069
Factor Score		-.209	.231	.518	-.230	.956	-.312

The Scaled Scores for each test are multiplied by the unstandardised coefficients (indicated in the columns) and summed to compute each factor score. For example, as shown in Equation 10, the Verbal Memory factor Score is computed for Case 1 as:

Verbal Memory = -2.52069 + (-.50*.00146) + (14.73*.00155) + (9.29*-.00345) + [10]
(9.08*.00731) + (9.69*.00256) + (-.11*.00164) + (7.80*.11558) + (7.60*-.00056) +
(8.40*.07973) + (8.80*.01861) + (7.00*.02287) + (1.40*-.00050) + (5.00*.03706) +
(6.00*.03014) + (6.00*.00632) + (9.00*-.00340) + (5.00*-.00349) + (9.00*-.00516) +
(1.00*-.00459) + (1.00*.00324) + (7.00*.00034) + (11.00*.00356) = -.209

These computations may seem intimidating but are readily calculated in seconds with statistical or spreadsheet software. The six computed Factor Scores are then used to generate Mahalanobis distance scores for each of the five cognitive clusters.

5.2.3 Derivation of Mahalanobis Distances

The next step in the analysis is the calculation of Mahalanobis distance scores for each of the cognitive profiles or clusters derived from the K-Means analysis in Study 2. This is most easily performed as matrix multiplication in statistical software packages or Microsoft Excel. As indicated in the Mahalanobis distance formula (Equation 4) provided on page 69 of Chapter 4, two matrices need to be computed: the inverse covariance matrix discrepancy matrix between the six factor scores from Case 1 and the six factor centroids for each of the five clusters. Table 5.3 depicts the computation of the discrepancy matrix:

Table 5.3
Case Study 1 Discrepancy Matrix Computations

	Factor Score	K1	K2	K3	K4	K5	C-K1	C-K2	C-K3	C-K4	C-K5
Verbal Memory	-.21	-.20	1.08	-.54	-1.11	.50	-.01	-1.29	.33	.90	-.71
Visual Memory	.23	-.37	.98	-.50	-.95	.68	.61	-.75	.73	1.18	-.44
Executive Functioning	.52	.66	.70	-1.05	-.88	-.12	-.14	-.18	1.57	1.40	.64
Speed & Attention	-.23	-.20	-.91	.13	1.12	.13	-.03	.68	-.36	-1.35	-.36
Verbal Abilities	.96	.23	-.98	-.33	1.14	-.07	.72	1.94	1.28	-.18	1.02
Visual Abilities	-.31	-.44	-.81	.03	1.15	.40	.13	.50	-.35	-1.46	-.71

Each of the Mahalanobis distance scores for the five cognitive clusters are simply computed using matrix multiplication of the case discrepancy matrix [X], the transposed matrix [X]', and the inverse covariance matrix [S^{-1}] for each cluster presented in Tables 4.1 through 4.5 in Chapter 4. The resultant matrix algebra and the computed Mahalanobis distance scores for each cluster are presented below:

$MD_1 = 3.17$

[X]'		[S^{-1}]							[X]					
-.01	x	3.57	-.91	-.06	.17	1.19	-.38	x	-.01	.61	-.14	-.03	.72	.13
.61		-.91	3.7	-1.27	.63	.01	-.19							
-.14		-.06	-1.27	8.52	.05	-.29	1.24							
-.03		.17	.63	.05	2.86	.94	-.48							
.72		1.19	.01	-.29	.94	3.06	-.84							
.13		-.38	-.19	1.24	-.48	-.84	3.33							

$MD_2 = 13.14$

[X]'		[S^{-1}]							[X]					
-1.29	x	3.71	-1.33	-.13	.08	1.19	-.16	x	-1.29	-.75	-.18	.68	1.94	.50
-.75		-1.33	2.7	.09	.29	-.42	-.65							
-.18		-.13	.09	5.62	.2	.37	1.04							
.68		.08	.29	.2	2.68	.16	-.65							
1.94		1.19	-.42	.37	.16	3.04	-.25							
.50		-.16	-.65	1.04	-.65	-.25	2.97							

$MD_3 = 16.13$

[X]'		[S^{-1}]							[X]					
.33	x	3.68	-1.19	-.36	-.05	-.17	-.82	x	.33	.73	1.57	-.36	1.28	-.35
.73		-1.19	3.21	.12	.59	.29	-.57							
1.57		-.36	.12	3.55	.86	.05	-.33							
-.36		-.05	.59	.86	2.77	.41	-1.53							
1.28		-.17	.29	.05	.41	2.98	-.85							
-.35		-.82	-.57	-.33	-1.53	-.85	4.08							

$MD_4 = 11.52$

[X]'		[S^{-1}]							[X]					
.90	x	3.41	-1.51	.50	-.18	1.22	.16	x	.90	1.18	1.40	-1.35	-.18	-1.46
1.18		-1.51	4.12	-.57	1.35	.47	-1.22							
1.40		.50	-.57	1.76	.07	-.31	1.01							
-1.35		-.18	1.35	.07	4.42	.17	-2.84							
-.18		1.22	.47	-.31	.17	3.29	-1.36							
-1.46		.16	-1.22	1.01	-2.84	-1.36	5.61							

$MD_5 = 6.68$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} -.71 \\ -.44 \\ .64 \\ -.36 \\ 1.02 \\ -.71 \end{bmatrix} \times \begin{bmatrix} 6.49 & -1.31 & .54 & .19 & 1.38 & -.07 \\ -1.31 & 3.06 & .20 & .46 & -.02 & .21 \\ .54 & .20 & 2.26 & -.36 & -.12 & .42 \\ .19 & .46 & -.36 & 2.75 & 1.02 & -.66 \\ 1.38 & -.02 & -.12 & 1.02 & 2.85 & -.81 \\ -.07 & .21 & .42 & -.66 & -.81 & 3.86 \end{bmatrix} \times \begin{bmatrix} -.71 & -.44 & .64 & -.36 & 1.02 & -.71 \end{bmatrix}$$

5.2.4 Derivation of Fisher's Equations

Each of these Mahalanobis distances was then placed into the five Fisher equations derived from the discriminant function analysis, as shown in Table 5.4. The highest ranked value in table indicates the cluster to which the individual's case is most similar, in this case, Cluster 1.

Table 5.4
Case Study 1: Fisher Equation Scores

Cluster	MD Scores	Fisher's Classification Function Coefficients					Score
		1	2	3	4	5	
K1	3.17	-.40	-.15	-.29	-.33	-.26	5.11*
K2	13.14	.73	.31	.78	.94	.73	-.37
K3	16.13	-.07	.09	-.43	-.05	-.06	-.19
K4	11.52	.92	.91	.99	.56	.99	-1.49
K5	6.68	-.46	-.36	-.34	-.43	-.66	3.87
Constant		-9.68	-13.43	-11.71	-15.46	-10.94	

*Indicates highest score; MD = Mahalanobis distance

The Mahalanobis distance scores for each cluster are multiplied by the unstandardised coefficients (indicated in the columns) and summed to compute each Fisher Equation score. For example, as shown in Equation 11, the Fisher Equation Score for Cluster 1 is computed for Case 1 as:

$$K_{1F} = -9.683 - .399*3.17 + .728*13.14 - .071*16.13 + .927*11.52 - .455*6.68 = 5.11 \quad [11]$$

5.2.5 Summary for Case 1

The highest score from these equations is for function 1 indicating that Case 1 should be classified as having a cognitive profile most consistent with Cluster 1. Accordingly, her pattern of scores should indicate an Average profile overall with no

specific strengths or weaknesses. Figure 5.1 shows Case 1's profile plotted against the profile of Cluster 1. As shown in Figure 5.1, this case certainly seems to fit this profile.

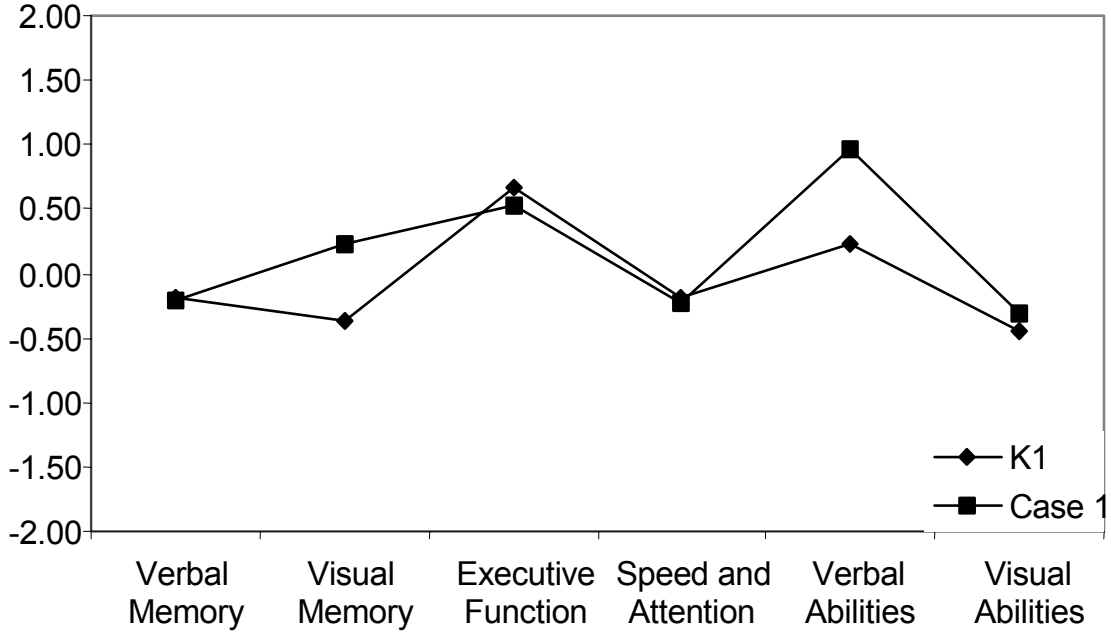

Figure 5.1 Neuropsychological Battery Mixed Diagnostic Sample: Profile 1 and Case 1

Note that while Cluster 1 indicates no specific strengths or weaknesses, the actual score distributions indicate a strength in Verbal abilities (i.e. a standardised score of greater than .67). It is not the intent of this classification system to ignore or replace individual variation but rather to permit grouping of individuals in a fundamentally more meaningful way based upon their relative cognitive strengths and weaknesses. The implications of Case 1's classification are that she is most similar to other cases where there is, in general, no systematic pattern of strengths and weaknesses.

5.3 Case Study 2

5.3.1 Demographics and Test Scores

This case study involves a 22-year-old female with 12 years of education. She was tested following her diagnosis of temporal lobe epilepsy. Case 2 was chosen as an

age, education and diagnosis match to Case 1 but was allocated in the cluster analysis to cluster 3. Her scores on psychological testing are shown in Table 5.5.

Table 5.5
Case Study 2: 22-year-old female – Test Scores

WAIS-III Selected Subtests	Raw*	Standard Score*	Scaled Score
Vocabulary			5.00
Similarities			6.00
Information			5.00
Picture Completion			9.00
Block Design			11.00
Matrix Reasoning			9.00
Digit Symbol Coding			8.00
Symbol Search			10.00
WMS-III Indices			
Auditory Immediate		80	6.00
Visual Immediate		71	4.20
Auditory Delayed		58	1.60
Visual Delayed		65	3.00
Aud. Recog. Delayed		85	7.00
Working Memory		81	6.20
Word Lists I (Scaled Score)			8.00
Word Lists II (Scaled Score)			8.00
Trail Making Test			
Part-A (sec)	23		9.50
Part-B (sec)	73		
Part-B minus Part A (sec)	53		8.17
Wisconsin Card Sort Test			
Categories Achieved	0		-2.46
Perseverative Errors	51		-1.29
Controlled Oral Word Assoc. Test			
Total Words	28		6.05
Boston Naming Test			
Total	44		.68

5.3.2 Computation of Factor Scores

The factor scores for this client are derived using Table 3.5 presented in Chapter 3. As in the previous case study, each of these regression equations used the scaled scores for all of the tests to compute each of the six factor scores. The computed factor scores for Case 2 are presented in Table 5.6.

Table 5.6
Case Study 2: Scaled Scores, Unstandardardised Coefficients and Factor Scores

Test	Scaled Scores	Unstandardised Coefficients					
		Verbal Memory	Visual Memory	Executive Functioning	Speed & Attention	Verbal Ability	Visual Ability
TMT: Part A	9.50	.001	.000	-.002	-.009	-.004	-.005
TMT: B minus A	8.17	.002	-.003	.015	-.007	.002	-.005
WCST: Pers. Errors	-1.29	-.003	.001	.071	.007	.000	-.005
WCST: Cat. Com	-2.46	.007	.000	.103	.003	.007	-.001
COWAT – Total	6.05	.003	.007	-.004	-.016	-.009	.007
BNT	0.68	.002	.001	-.007	-.004	-.015	-.008
WL-I	6.00	.037	.008	.013	-.016	.013	.011
WLII	1.60	.030	.005	.000	-.002	-.003	.009
AI	7.00	.116	-.010	-.003	.008	-.024	-.025
AD	4.20	.080	.006	-.011	.024	.004	.018
ARD	3.00	.023	.001	.004	-.008	.000	.008
VI	6.00	-.001	.087	.006	-.006	-.001	.011
VD	5.00	.019	.191	-.007	.005	.003	.001
WM	6.00	.000	-.013	.019	-.045	-.002	-.035
VO	5.00	.006	.003	-.003	.008	-.144	.025
SI	9.00	-.003	.005	.001	-.002	-.057	-.016
IN	11.00	-.003	-.006	.000	.015	-.084	-.016
PC	9.00	-.005	-.001	.003	-.001	-.008	-.044
BD	8.00	-.005	-.009	.003	-.001	.001	-.175
MR	10.00	.003	-.003	.016	-.004	-.006	-.068
DSY	8.00	.000	.007	.006	-.174	.009	.018
SS	8.00	.004	.006	.003	-.098	.000	-.039
Constant		-2.521	-2.076	-1.701	2.533	2.903	3.069
Factor Score		-.957	-1.154	-1.499	-.452	1.208	-.258

The Scaled Scores for each test are multiplied by the unstandardised coefficients (indicated in the columns) and summed to compute each factor score. The six computed Factor Scores are then used to generate Mahalanobis distance scores for each of the five cognitive clusters.

5.3.3 Derivation of Mahalanobis Distances

Next the Mahalanobis distance scores were computed for each of the cognitive profiles derived from the K-Means analysis in Study 2. Table 5.7 depicts the computation of the discrepancy matrix between the factor scores from Case 2 and the six factor centroids from each of the five clusters.

Table 5.7
Case Study 2: Discrepancy Matrix Computations

	Factor Score	K1	K2	K3	K4	K5	C-K1	C-K2	C-K3	C-K4	C-K5
Verbal Memory	-.96	-.20	1.08	-.54	-1.11	.50	-.76	-2.04	-.41	.15	-1.45
Visual Memory	-1.15	-.37	.98	-.50	-.95	.68	-.78	-2.14	-.65	-.21	-1.83
Executive Functioning	-1.50	.66	.70	-1.05	-.88	-.12	-2.16	-2.20	-.45	-.62	-1.38
Speed & Attention	-.45	-.20	-.91	.13	1.12	.13	-.25	.45	-.58	-1.58	-.58
Verbal Abilities	1.21	.23	-.98	-.33	1.14	-.07	.97	2.19	1.54	.07	1.28
Visual Abilities	-.26	-.44	-.81	.03	1.15	.40	.18	.55	-.29	-1.41	-.66

The Mahalanobis distance scores for the five cognitive clusters are simply computed using matrix multiplication of the case discrepancy matrix [X], the transposed matrix [X]', and the inverse covariance matrix for each cluster presented in Tables 4.1 through 4.5 in Chapter 4. [S^{-1}] The resultant matrix algebra and the computed Mahalanobis distance scores for each cluster are presented below:

$MD_1 = 40.06$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} -.76 \\ -.78 \\ -2.16 \\ -.25 \\ .97 \\ .18 \end{bmatrix} \times \begin{bmatrix} 3.57 & -.91 & -.06 & .17 & 1.19 & -.38 \\ -.91 & 3.7 & -1.27 & .63 & .01 & -.19 \\ -.06 & -1.27 & 8.52 & .05 & -.29 & 1.24 \\ .17 & .63 & .05 & 2.86 & .94 & -.48 \\ 1.19 & .01 & -.29 & .94 & 3.06 & -.84 \\ -.38 & -.19 & 1.24 & -.48 & -.84 & 3.33 \end{bmatrix} \times \begin{bmatrix} -.76 & -.78 & -2.16 & -.25 & .97 & .18 \end{bmatrix}$$

$MD_2 = 46.54$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} -2.04 \\ -2.14 \\ -2.20 \\ .45 \\ 2.19 \\ .55 \end{bmatrix} \times \begin{bmatrix} 3.71 & -1.33 & -.13 & .08 & 1.19 & -.16 \\ -1.33 & 2.7 & .09 & .29 & -.42 & -.65 \\ -.13 & .09 & 5.62 & .2 & .37 & 1.04 \\ .08 & .29 & .2 & 2.68 & .16 & -.65 \\ 1.19 & -.42 & .37 & .16 & 3.04 & -.25 \\ -.16 & -.65 & 1.04 & -.65 & -.25 & 2.97 \end{bmatrix} \times \begin{bmatrix} -2.04 & -2.14 & -2.20 & .45 & 2.19 & .55 \end{bmatrix}$$

$MD_3 = 9.79$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} -.41 \\ -.65 \\ -.45 \\ -.58 \\ 1.54 \\ -.29 \end{bmatrix} \times \begin{bmatrix} 3.68 & -1.19 & -.36 & -.05 & -.17 & -.82 \\ -1.19 & 3.21 & .12 & .59 & .29 & -.57 \\ -.36 & .12 & 3.55 & .86 & .05 & -.33 \\ -.05 & .59 & .86 & 2.77 & .41 & -1.53 \\ -.17 & .29 & .05 & .41 & 2.98 & -.85 \\ -.82 & -.57 & -.33 & -1.53 & -.85 & 4.08 \end{bmatrix} \times \begin{bmatrix} -.41 & -.65 & -.45 & -.58 & 1.54 & -.29 \end{bmatrix}$$

$MD_4 = 12.66$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} .15 \\ -.21 \\ -.62 \\ -1.58 \\ .07 \\ -1.41 \end{bmatrix} \times \begin{bmatrix} 3.41 & -1.51 & .50 & -.18 & 1.22 & .16 \\ -1.51 & 4.12 & -.57 & 1.35 & .47 & -1.22 \\ .50 & -.57 & 1.76 & .07 & -.31 & 1.01 \\ -.18 & 1.35 & .07 & 4.42 & .17 & -2.84 \\ 1.22 & .47 & -.31 & .17 & 3.29 & -1.36 \\ .16 & -1.22 & 1.01 & -2.84 & -1.36 & 5.61 \end{bmatrix} \times \begin{bmatrix} .15 & -.21 & -.62 & -1.58 & .07 & -1.41 \end{bmatrix}$$

$MD_5 = 28.33$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} -1.45 \\ -1.83 \\ -1.38 \\ -.58 \\ 1.28 \\ -.66 \end{bmatrix} \times \begin{bmatrix} 6.49 & -1.31 & .54 & .19 & 1.38 & -.07 \\ -1.31 & 3.06 & .20 & .46 & -.02 & .21 \\ .54 & .20 & 2.26 & -.36 & -.12 & .42 \\ .19 & .46 & -.36 & 2.75 & 1.02 & -.66 \\ 1.38 & -.02 & -.12 & 1.02 & 2.85 & -.81 \\ -.07 & .21 & .42 & -.66 & -.81 & 3.86 \end{bmatrix} \times \begin{bmatrix} -1.45 & -1.83 & -1.38 & -.58 & 1.28 & -.66 \end{bmatrix}$$

5.3.4 Derivation of Fisher's Equations

As in Case 1, the Mahalanobis distance scores from each of the clusters were then placed into the five Fisher equations derived from the discriminant function analysis. The Mahalanobis distance scores for each cluster are multiplied by the

unstandardised coefficients (indicated in the columns) and summed to compute each Fisher Equation score, as shown in Table 5.8.

Table 5.8
Case Study 2: Fisher Equation Scores

Cluster	MD Scores	Fisher's Classification Function Coefficients					Score
		1	2	3	4	5	
K1	40.06	-.40	-.15	-.29	-.33	-.26	6.37
K2	46.54	.73	.31	.78	.94	.73	-2.94
K3	9.79	-.07	.09	-.43	-.05	-.06	11.65*
K4	12.66	.92	.91	.99	.56	.99	9.28
K5	28.33	-.46	-.36	-.34	-.43	-.66	6.03
Constant		-9.68	-13.43	-11.71	-15.46	-10.94	

*Indicates highest score; MD = Mahalanobis distance

5.3.5 Summary for Case 2

The highest score from these equations is from Cluster 3 indicating that Case 2 falls into the third cluster as derived from the K-Means analysis. Accordingly, her pattern of scores should indicate no specific strengths and a weakness in the area of executive functioning. This person's profile of scores indicates weaknesses in executive functioning and in both memory scores, with strength in her verbal abilities. Again, while more strengths and weaknesses are indicated by the individual case data, the third cognitive cluster bears the greatest resemblance to the pattern illustrated in Case 2.

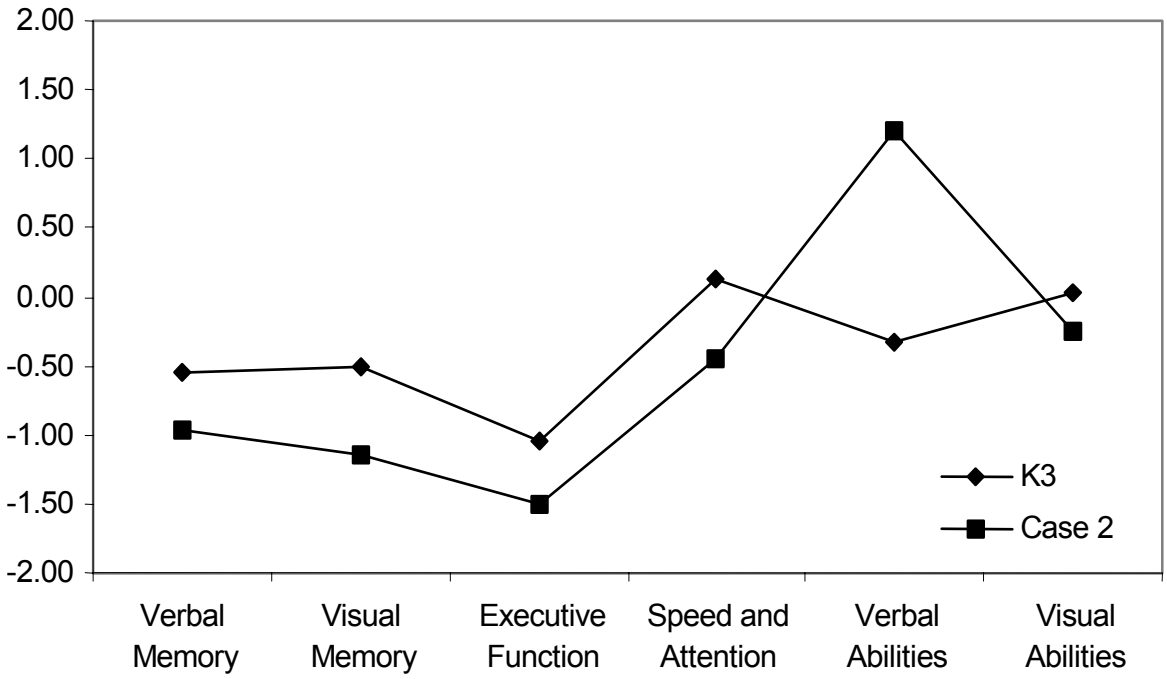

Figure 5.2 Neuropsychological Battery Mixed Diagnostic Sample: Profile 3 and Case 2

5.4 Case Study 3

5.4.1 Demographics and Test Scores

This case study again involves a 22-year-old female with 12 years of education. Also tested following a diagnosis of temporal lobe epilepsy. Notably, this case study's demographics and aetiology match the previous two cases. Again, if diagnosis has a substantial impact upon test performance a high degree of similarity in her test scores would be expected with both cases 1 and 2. However, this case was allocated to Cluster 4 in the K-Means analysis. Case study 3's scores on the psychological tests are shown in Table 5.9.

Table 5.9
Case Study 3: 22-year-old female – Test Scores

WAIS-III Selected Subtests	Raw*	Standard Score*	Scaled Score
Vocabulary			5.00
Similarities			7.00
Information			5.00
Picture Completion			8.00
Block Design			11.00
Matrix Reasoning			6.00
Digit Symbol Coding			7.00
Symbol Search			9.00
WMS-III Indices			
Auditory Immediate		59	1.80
Visual Immediate		65	3.00
Auditory Delayed		52	.40
Visual Delayed		78	5.60
Aud. Recog. Delayed		75	5.00
Working Memory		85	7.00
Word Lists I (Scaled Score)			5.00
Word Lists II (Scaled Score)			6.00
Trail Making Test			
Part-A (sec)	26		8.00
Part-B (sec)	67		
Part-B minus Part A (sec)	41		9.52
Wisconsin Card Sort Test			
Categories Achieved	3		4.46
Perseverative Errors	35		3.41
Controlled Oral Word Assoc. Test			
Total Words	26		5.59
Boston Naming Test			
Total	4		-30.89

5.4.2 Computation of Factor Scores

The factor scores for this client were again derived using Table 3.5 presented in Chapter 3. Each of these regression equations utilised the scaled scores from all of the tests to compute each of the six factor scores. The computed factor scores for Case 3 are presented in Table 5.10.

Table 5.10
Case Study 3: Scaled Scores, Unstandardardised Coefficients and Factor Scores

Test	Scaled Scores	Unstandardised Coefficients					
		Verbal Memory	Visual Memory	Executive Functioning	Speed & Attention	Verbal Ability	Visual Ability
TMT: Part A	8.00	.001	.000	-.002	-.009	-.004	-.005
TMT: B minus A	9.52	.002	-.003	.015	-.007	.002	-.005
WCST: Pers. Errors	3.41	-.003	.001	.071	.007	.000	-.005
WCST: Cat. Com	4.46	.007	.000	.103	.003	.007	-.001
COWAT – Total	5.59	.003	.007	-.004	-.016	-.009	.007
BNT	-30.89	.002	.001	-.007	-.004	-.015	-.008
WL-I	1.80	.037	.008	.013	-.016	.013	.011
WLII	0.40	.030	.005	.000	-.002	-.003	.009
AI	5.00	.116	-.010	-.003	.008	-.024	-.025
AD	3.00	.080	.006	-.011	.024	.004	.018
ARD	5.60	.023	.001	.004	-.008	.000	.008
VI	7.00	-.001	.087	.006	-.006	-.001	.011
VD	5.00	.019	.191	-.007	.005	.003	.001
WM	7.00	.000	-.013	.019	-.045	-.002	-.035
VO	5.00	.006	.003	-.003	.008	-.144	.025
SI	8.00	-.003	.005	.001	-.002	-.057	-.016
IN	11.00	-.003	-.006	.000	.015	-.084	-.016
PC	6.00	-.005	-.001	.003	-.001	-.008	-.044
BD	7.00	-.005	-.009	.003	-.001	.001	-.175
MR	9.00	.003	-.003	.016	-.004	-.006	-.068
DSY	5.00	.000	.007	.006	-.174	.009	.018
SS	6.00	.004	.006	.003	-.098	.000	-.039
Constant		-2.521	-2.076	-1.701	2.533	2.903	3.069
Factor Score		-1.731	-.818	-.288	-.011	1.779	.182

As in the previous case analyses the Scaled Scores for each test are multiplied by the unstandardised coefficients (indicated in the columns) and summed to compute each factor score.

5.4.3 Derivation of Mahalanobis Distances

The Mahalanobis distance scores for each of the cognitive profiles are then computed using the scores derived from the K-Means analysis in Study 2. The

calculation of the discrepancy matrix between the factor scores from Case 3 and the six factor centroids from each of the five clusters is shown in Table 5.11.

Table 5.11
Case Study 3: Discrepancy Matrix Computations

	Factor Score	K1	K2	K3	K4	K5	C-K1	C-K2	C-K3	C-K4	C-K5
Verbal Memory	-1.73	-.20	1.08	-.54	-1.11	.50	-1.53	-2.81	-1.19	-.62	-2.23
Visual Memory	-.82	-.37	.98	-.50	-.95	.68	-.44	-1.80	-.32	.13	-1.49
Executive Functioning	-.29	.66	.70	-1.05	-.88	-.12	-.95	-.99	.77	.59	-.17
Speed & Attention	-.01	-.20	-.91	.13	1.12	.13	.19	.89	-.14	-1.14	-.14
Verbal Abilities	1.78	.23	-.98	-.33	1.14	-.07	1.55	2.76	2.11	.64	1.85
Visual Abilities	.18	-.44	-.81	.03	1.15	.40	.62	.99	.15	-.97	-.22

Ensuing from this same process as indicated by the computations in both Cases 1 and 2, the Mahalanobis distance scores for the five cognitive clusters are again computed utilising the matrix multiplication of the case discrepancy matrix X, the transposed matrix X', and the inverse covariance matrix for each cluster which were presented in Tables 4.1 through 4.5 in Chapter 4, as indicated by the previous case analyses. Presented below are the resultant matrix algebra and the computed Mahalanobis distance scores for each cluster for Case 3:

$MD_1 = 16.18$

$$[X]' \times [S^{-1}] \times [X]$$

$$\begin{bmatrix} -1.53 \\ -.44 \\ -.95 \\ .19 \\ 1.55 \\ .62 \end{bmatrix} \times \begin{bmatrix} 3.57 & -.91 & -.06 & .17 & 1.19 & -.38 \\ -.91 & 3.7 & -1.27 & .63 & .01 & -.19 \\ -.06 & -1.27 & 8.52 & .05 & -.29 & 1.24 \\ .17 & .63 & .05 & 2.86 & .94 & -.48 \\ 1.19 & .01 & -.29 & .94 & 3.06 & -.84 \\ -.38 & -.19 & 1.24 & -.48 & -.84 & 3.33 \end{bmatrix} \times \begin{bmatrix} -1.53 & -.44 & -.95 & .19 & 1.55 & .62 \end{bmatrix}$$

$MD_2 = 39.39$

[X]'	x	$[S^{-1}]$						x	[X]					
-2.81		3.71	-1.33	-.13	.08	1.19	-.16		-2.81	-1.80	-.99	.89	2.76	.99
-1.80		-1.33	2.7	.09	.29	-.42	-.65							
-.99		-.13	.09	5.62	.2	.37	1.04							
.89		.08	.29	.2	2.68	.16	-.65							
2.76		1.19	-.42	.37	.16	3.04	-.25							
.99		-.16	-.65	1.04	-.65	-.25	2.97							

$MD_3 = 20.73$

[X]'	x	$[S^{-1}]$						x	[X]					
-1.19		3.68	-1.19	-.36	-.05	-.17	-.82		-1.19	-.32	.77	-.14	2.11	.15
-.32		-1.19	3.21	.12	.59	.29	-.57							
.77		-.36	.12	3.55	.86	.05	-.33							
-.14		-.05	.59	.86	2.77	.41	-1.53							
2.11		-.17	.29	.05	.41	2.98	-.85							
.15		-.82	-.57	-.33	-1.53	-.85	4.08							

$MD_4 = 6.79$

[X]'	x	$[S^{-1}]$						x	[X]					
-.62		3.41	-1.51	.50	-.18	1.22	.16		-.62	.13	.59	-1.14	.64	-.97
.13		-1.51	4.12	-.57	1.35	.47	-1.22							
.59		.50	-.57	1.76	.07	-.31	1.01							
-1.14		-.18	1.35	.07	4.42	.17	-2.84							
.64		1.22	.47	-.31	.17	3.29	-1.36							
-.97		.16	-1.22	1.01	-2.84	-1.36	5.61							

$MD_5 = 30.14$

[X]'	x	$[S^{-1}]$						x	[X]					
-2.23		6.49	-1.31	.54	.19	1.38	-.07		-2.23	-1.49	-.17	-.14	1.85	-.22
-1.49		-1.31	3.06	.20	.46	-.02	.21							
-.17		.54	.20	2.26	-.36	-.12	.42							
-.14		.19	.46	-.36	2.75	1.02	-.66							
1.85		1.38	-.02	-.12	1.02	2.85	-.81							
-.22		-.07	.21	.42	-.66	-.81	3.86							

5.4.4 Derivation of Fisher's Equations

As in Cases 1 and 2, the five Fisher equations derived from the discriminant function analysis were computed using the Mahalanobis distance scores from each of the clusters. Again the unstandardised coefficients (indicated in the columns) are

multiplied by the Mahalanobis distance scores for each cluster and summed to compute each Fisher Equation score.

Table 5.12
Case Study 3: Fisher Equation Scores

Cluster	MD Scores	Fisher's Classification Function Coefficients					Score
		1	2	3	4	5	
K1	16.18	-.40	-.15	-.29	-.33	-.26	3.64
K2	39.39	.73	.31	.78	.94	.73	-6.58
K3	20.73	-.07	.09	-.43	-.05	-.06	1.85
K4	6.79	.92	.91	.99	.56	.99	5.81*
K5	30.14	-.46	-.36	-.34	-.43	-.66	-.70
Constant		-9.68	-13.43	-11.71	-15.46	-1.94	

*Indicates highest score; MD = Mahalanobis distance

5.3.5 Summary for Case 3

The highest score from these equations is from function 4 indicating that Case 3 is most similar to cognitive cluster four consistent with the results of the K-Means analysis. Her pattern of scores should be typified by relative cognitive strengths in the areas of speed and attentional, verbal, and visual abilities, with relative cognitive weaknesses in visual and verbal memory, and executive functioning. Case study 3's performance profile indicates a weakness in memory (both verbal and visual) and a defined strength in her verbal abilities. Her executive functioning, speed and attentional abilities, and visual abilities were all average. Again, this case study does not fit the profile perfectly, nor would it be expected to, but is more similar to this profile than any of the others, and is notably different from the other two matched cases (see Figure 5.3).

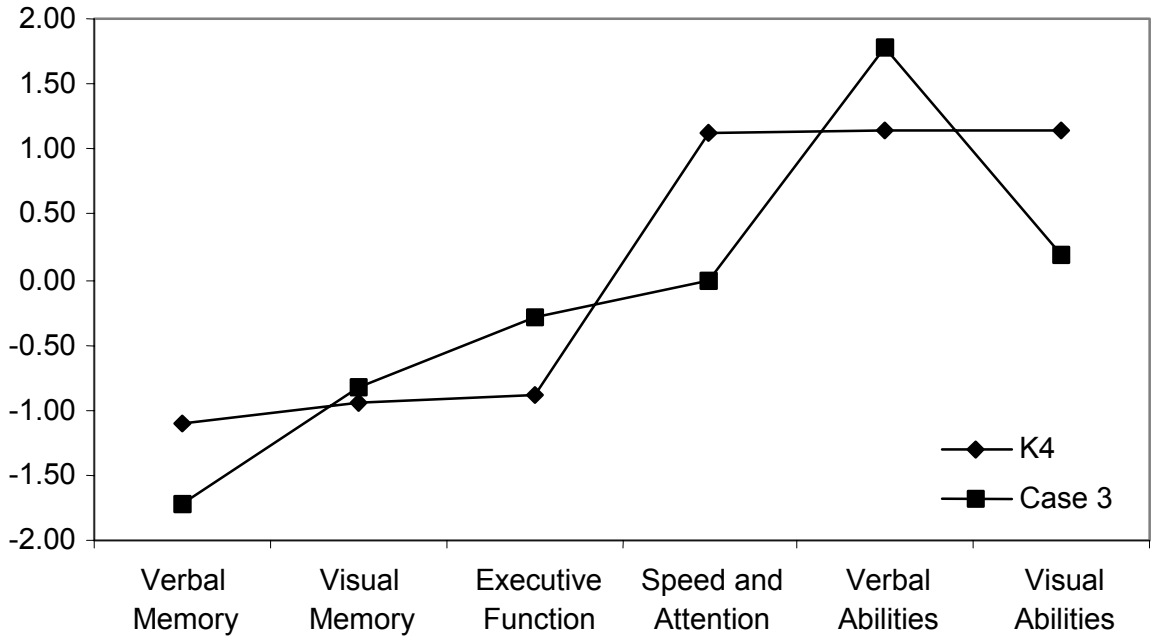

Figure 5.3 Neuropsychological Battery Mixed Diagnostic Sample: Profile 4 and Case 3

5.4.5 Comparison of Cases

It is noted and of particular relevance here is that all cases were approximately the same age (between 18 and 22), had the same educational level (12 years) and most importantly were diagnosed with the same condition (Seizure disorder). If medical diagnosis was a salient contributing factor with regard to changes in behaviour as represented by scores on cognitive tests, then we would have expected the profiles for the three cases to be similar. As can be seen in Figure 5.4 their profiles are quite different, especially with regard to memory and executive functioning, and based upon both group-based cluster analysis and individually-based Mahalanobis distance scores have been allocated to distinctly different patterns of cognitive test performance.

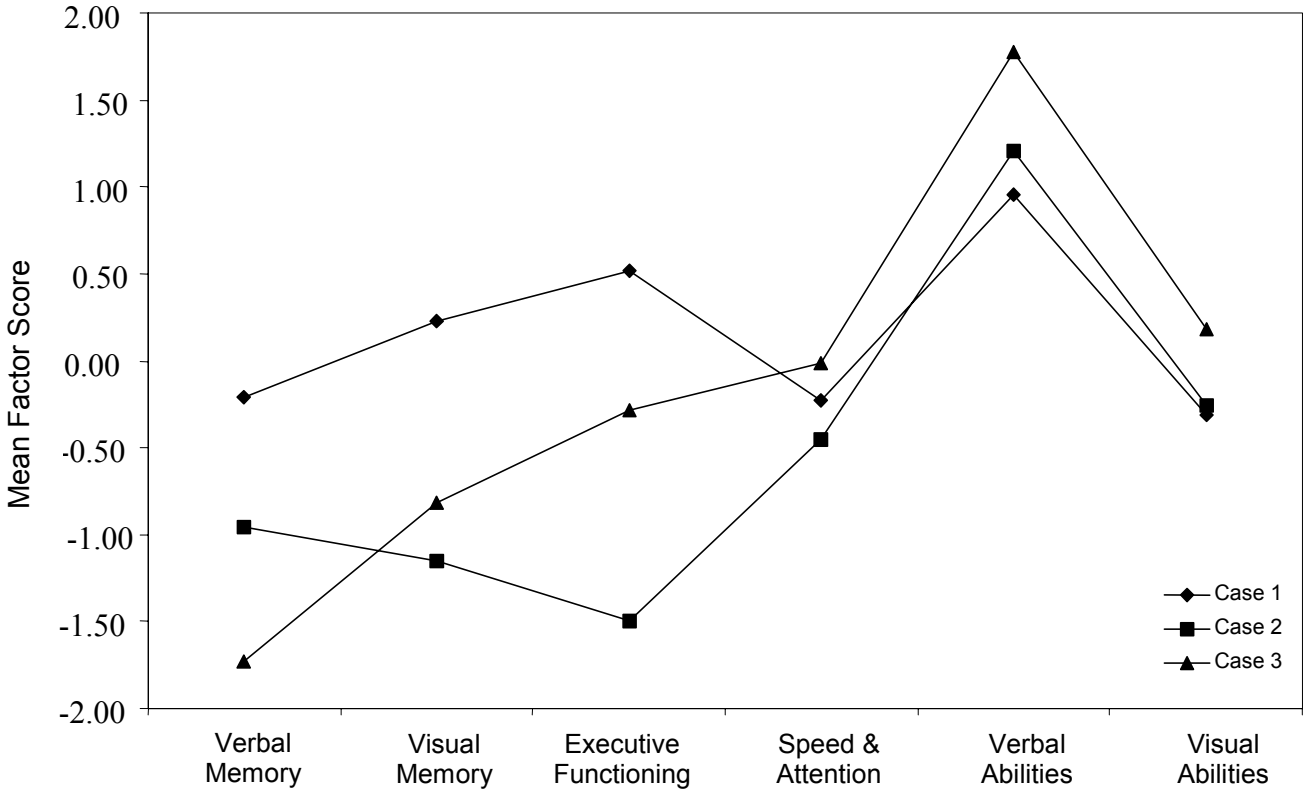

Figure 5.4 Neuropsychological Battery Mixed Diagnostic Sample: Cases 1 through 3

5.4.6 Overall Summary of Case Studies

Three case studies have been examined to demonstrate the clinical utility of this new method for the classification of cases into cognitive patterns. The case studies were matched as closely as possible for age, education, gender, and diagnosis with each of the three cases being female, aged between 18 and 22 years of age, had 12 years of education and were diagnosed with temporal lobe epilepsy. By matching the three cases, the systematic effects of demographic variables on normative data were eliminated as potential confounding variables. The presence of the same diagnosis in all three cases would, in the opinion of this researcher, lead many clinicians to expect similar patterns of cognitive test performance, and would have assured all three as cases in any study examining the effects of temporal lobe epilepsy on cognition, reflect the assumptions of homogeneity of test performance based upon the same diagnosis.

These cases were evaluated in terms of their original allocation to cognitive profiles in the K-Means analysis, the determination of their best fit to a cognitive cluster using the Mahalanobis distance score method of analysis developed in this research, and to each other. These methods determined that although all three case studies were demographically and diagnostically matched, they each were classified into different cognitive profiles. Case one was classified as a cluster one type, case two a type three cluster, and case three most resembled the cluster four profile.

It is notable that each case was not a perfect match for the cluster to which it was allocated. This is as it should be. The centroids that form the basis of the Mahalanobis distance analysis account for the reliability and inter-correlations of measures and indicate the likelihood that a particular case could have come from a particular cluster. To expect that any case should exactly mimic the behaviour of a group of similar cases would be to make the same mistake that is perpetrated repeatedly in the research literature when only group profiles are presented in clinical studies. The role of the cluster profiles is not to force individual profiles into a particular profile associated with a rigid interpretation, but rather to classify or group cases together according to their actual underlying behavioural similarity. It is hoped that this empirical approach to classification may prove to be a basis for an empirically validated “psychological diagnosis” to supplant the “medical diagnosis” model which, at least with regards to cognitive abilities, demonstrably does not group individuals together based upon their common relative cognitive strengths and weaknesses.

CHAPTER 6

6.0 GENERAL DISCUSSION, CONCLUSIONS AND IMPLICATIONS FOR CLINICAL PRACTICE

6.1 Overview

The foundations of this dissertation arose from the work conducted by Lange (2000) who utilised WAIS-R/WMS-R data from a large mixed neuropsychological sample. His findings indicated that there were no prototypical patterns of cognitive function associated with any of the neurological or psychiatric diagnostic groups he examined. Instead, Lange found that there were at least three to five different patterns of performance that were found across each of the seven different diagnostic groups that he investigated in his sample of approximately 1370 cases. Each of these profiles indicated varying patterns of strengths and weaknesses across the subtests of the WAIS-R/WMS-R. Lange concluded his research with an exploratory analysis a small sample of cases that had been administered the WAIS-III/WMS-III and while deriving one further cognitive profile confirmed that these profiles occur frequently across all the diagnostic groups investigated.

The goal of the current research was to not only expand Lange's findings to the third editions of the Wechsler scales but to also examine the influence on the cognitive profiles of a wider range of cognitive measures. It was also intended that, if the degree of classification accuracy permitted, a method would be developed which would allow clinicians to directly employ the findings of this research in classifying individual cases according to their relative cognitive strengths and weaknesses.

6.2 General Discussion and Summary of Results

6.2.1 Study One

Lange's (2000) exploratory cluster analysis of a small sample of patients'

WAIS-III and WMS-III scores derived a four cluster solution for this data. Meehl (1995) argued that when employing taxometric research tools like cluster analysis, sample sizes of greater than 300 cases should be used. Consistent with this caveat, Lange suggested that future research would need to further investigate his preliminary WAIS-III/WMS-III findings.

The first study of this dissertation achieved this goal. A much larger sample of 849 cases with a variety of neurological or psychiatric diagnoses was subjected to hierarchical and K-Means analyses to determine and allocate cases to a number of clusters. As with Lange's study, study one indicated four profiles from the hierarchical cluster analysis which when subjected to a K-Means analysis occurred with approximately equal frequency in the sample. The four clusters were qualitatively described as:

Profile 1 exhibited no relative cognitive strengths or weaknesses in any of the cognitive domains measured.

Profile 2 contained individuals that exhibited a relative cognitive weakness in their overall memory abilities and relative cognitive strengths in their verbal knowledge and overall visual abilities.

Profile 3 displayed relative cognitive strengths in their overall memory abilities and cognitive weaknesses in attention, visuospatial abilities, and processing speed.

Profile 4 had individuals with a relative cognitive strength in their ability to comprehend and express themselves verbally but demonstrated relative cognitive weaknesses in remembering visually presented material and processing visual information rapidly.

These current and more robust profiles were then correlated to Lange's (2000) WAIS-III/WMS-III profiles. It was found that two of the profiles from the current

analysis correlated extremely high with two of the cluster profiles described by Lange. Lange's two largest clusters, however, each correlated with two of the current profiles indicating a lack of one-to-one correspondence between the four profiles across the two studies. This was not entirely unexpected as the majority of cases were allocated to Lange's first two clusters, which probably, due to his relatively small sample size, reduced the representativeness of his profiles. Lange had also included the WMS-III indices of immediate and delayed memory in his analysis and utilised a rule that indicated clusters with N's less than 5% of the sample should be considered to be outlier clusters and therefore removed from the analysis. The cluster profiles derived from the current analysis are more robust, due to the larger sample size and therefore more likely to be representative of the types of diverse profiles inherent in the diagnostic groups from which they were formed. Previous cluster analytic findings from Wechsler scales have indicated that there are usually between three to five profiles (Crawford et al., 1997; Jacques Donders, 1996; Jacques Donders & Warschausky, 1997; Gerald Goldstein et al., 1998) and this has certainly been the case in both Lange's original study and the replication conducted here.

6.2.2 Study Two

The second aim of this dissertation was to expand the battery employed in the analysis (e.g. TMT, BNT, COWAT, etc.), and thereby increase the generalisability and utility of the findings from study one. Study 2 explored the idea that with more tests the findings may be more robust. The tests that were added to the analysis were limited by the archival data supplied. Following Everitt's (1974) suggestion to assist in the feasibility of the cluster analysis, the data were subjected to a principle axis factoring with six factors produced. The regression scores from the Principle Components analysis were then used in the cluster analysis. The hierarchical analysis with Pearson's Product Moment Correlation used as the distance metric indicated

anywhere between a two to twelve cluster solution with a five-cluster solution selected as the most appropriate outcome based on clustering diagnostics of the analysis and this was then sought from the K-Means analysis.

The five cluster profiles from this analysis were described according to their factor scores as follows:

Profile 1 was an "Average" profile with no indicated strengths or weaknesses. The character of Profile 2 indicated very defined relative cognitive strengths in the areas of visual and verbal memory, and executive functioning, with relative cognitive weaknesses in speed and attentional, verbal, and visual abilities.

A single weakness in the area of executive functioning with no strengths characterised Profile 3. The fourth profile derived from the cluster analysis was the opposite of that indicated in profile 2 and had relative cognitive strengths in the areas of speed and attentional, verbal, and visual abilities, with relative cognitive weaknesses in visual and verbal memory, and executive functioning. Profile 5 showed a single strength in the area of visual memory, with no weaknesses noted.

6.2.3 Study Three

The third study was conducted to ascertain the clinical utility of the clustering solution. The solution derived from the cluster analysis may be arbitrary unless proven to show well-defined clusters with little overlap. Mahalanobis distance was employed to ascertain the amount of overlap between the clusters. It was thought that by calculating the Mahalanobis distance from each of the cluster centroids (mean scores for each of the clusters) to the individual scores of each of the cases, that amount of overlap between each of the clusters in the solution would then be able to be tested. The MD, which assesses how far the individual's score is from the centroid of the population from which the observation was drawn, is often used in multivariate

statistics and has been previously used in the assessment of WAIS-R profiles (Burgess, 1991; Crawford & Allan, 1994).

The Mahalanobis distance was calculated utilising matrix algebra for each of the cases to the centroids of each of the clusters, yielding five MDs per case. Each of these was then examined for significance using the Chi-square statistic. If the resultant Mahalanobis distance was significant, the case was considered an outlier from that particular cluster and unlikely to have come from that grouping. If the Mahalanobis distance was non-significant than the case was deemed to have come from that cluster. These preliminary analyses indicated that approximately 91% of cases returned non-significant MDs for the clusters to which they were allocated in the cluster analysis. Unfortunately, the percentage of cases for which only one cluster was indicated was close to only one in three cases. This indicated that while the correct cluster was certainly most likely to be indicated, the degree of overlap between clusters with regard to their Mahalanobis distance scores was too great to permit accurate classification to only one cluster. The difficulty here was considered to be the use of statistical significance ($p<.05$) as the criterion for indicating cluster membership or exclusion.

In an attempt to find a more effective criterion for classification, the Mahalanobis distance scores were submitted to a discriminant function analysis to predict cluster membership indicated by the K-Means analysis. This proved to be much more effective in accurately indicating not only the correct cluster, but provided a heuristic for classifying each case to only one cluster.

It was found that approximately 88% of cases were correctly attributed to the clusters from the K-Means analysis with little overlap between the clusters (in terms of incorrect classification to another cluster). Such a high rate of correct classification indicates that the Mahalanobis distance from each of the cluster centroids to each

case's factor regression scores appears can be used with a high degree of accuracy to allocate individual cases to cluster profiles. Due to the good discrimination of the cases by their Mahalanobis distance scores in the discriminant function analysis, a method for formally analysing and classifying cognitive test data was devised.

6.2.4 Case Studies

The application and clinical potential of the method was demonstrated in Chapter 5. Three case studies were chosen on the basis of being as closely matched in terms of age, education, gender, race and diagnosis as possible. The three cases were all female, Caucasian, aged between 18 and 22 years of age, and had 12 years of education. Each of the cases was diagnosed with having temporal lobe epilepsy.

Each case was presented in step-by-step fashion demonstrating how an individual case can be analysed and allocated to one of the five cognitive profiles. Their scaled scores on each test were placed into the regression equations to obtain six factor scores from which Mahalanobis distance scores are computed using the centroids and inverse covariance matrices derived for each cluster identified in Study 2. The Mahalanobis distance scores were then entered into the five Fisher's equations derived from the Discriminant Function Analysis. The equation that produced the highest positive result indicated the cluster/cognitive profile to which the case is most closely associated. Of greatest interest was that each case, despite virtually identical age, ethnicity, gender, education, and diagnosis was found to match with a different cluster. These case studies highlight the fact that any assumptions regarding underlying common patterns of cognitive performance based upon their similarity in diagnosis is without merit. The three clusters to which the cases were allocated were characterised by:

Case 1 fell into Cluster Profile 1 indicating an average profile with no indicated relative strengths or weaknesses. Case 2 was associated with Cluster Profile

3, which indicated a single relative weakness in the area of executive functioning with no relative strengths. Case 3 was more related to Cluster Profile 4 and demonstrated relative cognitive strengths in the areas of speed, attentional, verbal, and visual abilities, with relative cognitive weaknesses in visual and verbal memory, and executive functioning.

Of course, each case did not exactly match their respective cluster profiles but demonstrated strengths and weaknesses that were most similar to the clusters to which they were allocated. The method itself may, at first glance, seem intimidating but can be readily computed in seconds with standard statistical or spreadsheet software that can perform matrix algebra.

6.2.5 Issues Regarding Cluster Analysis:

In cluster analysis, the selection of analysis method and parameters associated with the clustering process is critical to the meaningfulness of the groups derived. Previous cluster analytic studies utilising neuropsychological data have often used the Ward's method of agglomeration with the Squared Euclidian distance as the proximity metric (Jacques Donders, 1996; Kixmiller et al., 1994; Schear, 1987). However, most of these studies have produced profiles that are overly influenced by performance level and poorly reflect the actual strengths and weaknesses of the patients. This may lead to the production of solutions that have little or no significance to clinicians and/or researchers (Davison et al., 1996). The difficulty with Ward's method and any other single approach to cluster analysis lies in their respective vulnerabilities in one or more aspects of deriving clusters. Lange (2000) adopted a two-stage clustering approach, which effectively employed two analyses of the data utilising the strengths of each approach to compensate for their weaknesses. For example, hierarchical analysis is well suited to determining the number of clusters but does less well in actually allocating cases to clusters because of the inability of

these methods to reallocate cases at a later point in the analysis process. In contrast, K-Means analysis is well suited to flexibly allocating cases to clusters and can readily reallocate cases to better clusters later in the process. The difficulty with K-Means analysis is that it cannot determine the number of clusters to derive. Together these two distinct approaches complement each other well: hierarchical analysis to determine the number of clusters, followed by K-Means analysis to allocate cases to clusters. It is this two-fold approach, which was similar to that utilised by Lange (2000) and in the current studies.

A further issue to consider was the decisions regarding types of scores submitted for cluster analysis. Lange (2000) utilised deviation scores in all of his analyses in order to eliminate the influence of test score magnitude upon the clustering process. This approach was used here only in Study 1 for the purposes of replicating Lange's findings. All other cluster analyses used factor scores generated through factor analysis. Lange utilised deviation scores in order to eliminate test score magnitude from his cluster solutions. While this made sense in the context of his research, the goal here was to produce profiles, which would be more representative of the types of test performances found in clinical settings. These must of course include the influence of test score magnitude. The greater difficulty in the current studies was the inclusion of more variables to be analysed and the consequences that has upon cluster stability. In order to address these issues in a way that permitted a balance between clinical representativeness and the needs to reduce method or statistical artefacts, the decision was made to reduce the number of variables in the analysis through factor analysis and to not employ deviation scores, permitting magnitude to again influence cluster solutions. The use of the Pearson Product Moment correlation as the distance metric in the hierarchical analysis ensured that the

pattern of test scores would still influence the clustering solution as this has been shown to be the most sensitive to profile shape (Lange et al., 2002).

6.2.6 Issues Regarding Test Selection:

The tests chosen for the analysis, for example, the Wechsler scales, are some of the most frequently used within the area of neuropsychology (Butler et al., 1991; Camara et al., 2000; K. Sullivan & Bowden, 1997). As the data utilised in the analyses were archival there were some limitations with test selection however. The tests in the analysis were chosen so as to cover a wide range of cognitive domains and were thought to be typical of the types of batteries employed within the area. However, it must be acknowledged that the selection of tests for analysis was largely opportunistic. As the cases were derived from one very large clinical setting in the United States of America, the expectation was that uniform testing practices would be more likely than if cases were drawn from multiple settings and countries. Unfortunately, test selection changes with the publication of new measures, changes in professional personnel, new innovations in the literature, and the changing needs of the clients assessed and the purposes of their assessments. Nowhere is this more evident than when considering the reduction in sample size with the inclusion of each additional measure into the samples. The use of the third editions of the Wechsler Scales automatically reduced the sample to assessments conducted after the introduction of these measures. While there may be an abundance of data for the revised editions, use of those cases would limit the applicability of the current research to current clinical practice. When only the third editions of the Wechsler scales were chosen, 849 cases out of a potential database of 1050 cases were available. With the each additional test that was added to the analysis, the available database fell to 420 cases. For example with the addition of the Controlled Oral Word

Association Test, then Trail Making Test, Wisconsin Card Sort Test, and Word Lists, the available number of cases was 815, 744, 633, and 420 respectively.

Ultimately, the selection of tests was based upon the principle of examining as wide a range of cognitive functions as possible utilising the most commonly employed measures in clinical practice without reducing the sample size to a point where it would undermine the multivariate analyses. It is hoped that those who would have liked to see different combinations of measures or a greater focus on a particular cognitive domain will find these studies useful as a template for their own investigations.

A second issue regarding the test score data submitted for cluster analysis that may seem to deviate from clinical expectations was the decision to utilise factor scores. Clinically, factor scores or indices are composites of a small number of measures that have been identified through factor analysis as sharing substantial underlying variance. For example, the verbal comprehension index of the WAIS-III is comprised of the Vocabulary, Similarities, and Information subtests. This approach, however, generates statistical difficulties, which appear to be frequently ignored by clinicians, namely the consequences to reliability of combining different numbers of tests all with differing internal consistency. This leads to those composites, which are under-represented in the database having lower reliability and greater error variance. In the current studies, the factor analysis clearly indicates different numbers of tests with substantial loadings for the different factors. The use of all measures to produce factor scores ensured that the same number of measures were utilised to generate all factor scores. The only difference lay in the weightings each measure is given in any particular factor score. These weightings are, of course, based upon the factor loadings. With regard to this particular issue, the advantages in this approach seemed to far outweigh the consequences of deviating from customary clinical practice.

6.2.7 Conclusions

This research has updated and expanded the scope of previous research conducted by (Lange, 2000). His battery of tests was expanded to incorporate other tests commonly used in assessments by neuropsychologists in their testing of clients with brain dysfunction. The utility of these findings were then assessed, and a new method of classifying cognitive test score profiles was developed. The potential implications for such a classification system are many and include classification of individuals into groups based upon their relative cognitive strengths and weaknesses to better allocate valuable rehabilitation resources to individuals who are most likely to benefit from them, to a new way of considering diagnosis that is better suited to the cognitive and behavioural measures psychologists routinely employ.

6.3 Limitations and Future Research

As with any research, there are limitations that must be acknowledged and considered before judicious application of the research findings can be undertaken. The main limitation of this research is the use of archival data, which limited the choice of tests for analysis. When using archival data, researchers must work within the limits of what is provided. Although the prospective battery of test choice was large with data for approximately 13 different tests available, the attrition of cases with each additional test to the sample resulted in only seven tests being retained before the sample size would have become too small. The consequence of this limitation is that the findings of this research will have less direct application for clinicians and researchers who do not employ the tests used here. There is simply no way around this. The current findings will be of potential substantial value to the Cleveland Clinic Foundation from which the samples were derived and less so to those whose test batteries deviate from the tests used in the current analysis. There are implications, of course, for the use of fixed versus flexible cognitive test batteries.

The analysis and method derived in the current research can be applied to any combination of tests scores, but it is the "fixed batteries" with their systematic administration of the same tests, that will most likely benefit from these methods. Any clinician who wishes to apply these findings to their own "flexible" battery will need to compile sample sizes in excess of 300 before being able to realistically apply the individual case method to their own clients.

Another problem linked to the use of archival data is that some cognitive domains may not have been measured as effectively as they might have if other tests had been available. Again, this will always be the case in neuropsychology, and it is hoped that the impact of the poor psychometric properties of some measures is offset by the computation of factor scores.

A further consideration is the sometimes, small numbers of cases in particular diagnostic groups comprising the mixed sample. The concern here is that some of the diagnoses may have been under-represented in Study 2, while others were over-represented. For example, of the total number of cases in Study 2, approximately 37% were diagnosed with having a seizure disorder while approximately 2% diagnosed with having Parkinson's disease. The attrition of diagnostic groups of cases as the analysis progressed however could not be changed due to the use of archival data. However, it must also be acknowledged that compelling evidence has been provided both in Lange's original study (Lange, 2000) and in the current research that diagnosis has little influence on the pattern of cognitive test scores, or if it does, is so varied that it cannot be systematically employed to aid in decision making regarding psychological assessment. Consistently, prototypical patterns of cognitive test performance related to medical diagnosis have been conspicuous in their absence. While there may have been insufficient numbers of cases in particular diagnostic groups to determine the full diversity of their cognitive profiles, the fact that the

number is not “one” is undiminished. The focus of this research has been to develop a classification system based upon cognitive test scores and this has been achieved regardless of the representativeness of some of the diagnostic groups.

Future research implications that have arisen from this dissertation are varied. The first and perhaps most immediate need is to develop a computerised scoring tool to perform the more algebraically demanding aspects of the classification system. It will be important for clinicians to be able to easily calculate the profile and the cluster to which a single case should be allocated. The second is for an expanded battery of tests to be used that have been specifically designed to assess a comprehensive set of cognitive domains. Test batteries such as the Halstead-Reitan Neuropsychological Battery and Luria-Nebraska Neuropsychological Battery, would be particularly useful in this regard.

Another area for future research would be to evaluate the accuracy of the current discriminant functions in a different clinical sample. With any regression equations, shrinkage and its consequent impact upon classification accuracy must be examined. Also it will be important to consider the potential role of “psychological diagnosis” for clinical areas traditionally relying heavily upon medical diagnosis such as rehabilitation, clinical diagnosis, and medicolegal assessment. Ultimately, this system for accurately classifying cases into cognitive profiles must be evaluated in the crucible of clinical practice to determine what explicit role such a classification system can play in enhancing clinical decision-making.

6.4 Conclusions and Implications for Clinical Practice

This dissertation has outlined a new method of case analysis that may be able to assist in the classification of individuals according to their relative cognitive strengths and weaknesses. This has immediate implications for rehabilitation in that a better match between the intervention strategies and the actual abilities of the client

can be examined and used to apply limited rehabilitative resources. All too often it seems that brain-injured individuals are rehabilitated along with others who have sustained similar injuries, i.e. their medical diagnosis. However, the different patterns reflect different cognitive strengths and weaknesses, which may reflect the underlying neuroanatomical or neurophysiological impairment or alternatively the natural progression of the disease process. Grouping individuals according to their cognitive profiles would indicate that those with memory impairments regardless of aetiology should be allocated similar resources and tasks. Consider the three cases demonstrated in Chapter 5, and whether or not they would have received similar treatment based upon their medical diagnosis when they each demonstrated distinct and different patterns of relative cognitive strengths and weaknesses. It is hoped that rehabilitative resources allocated in this way would lead to an increase in the productivity and profitability of the rehabilitation facilities as well.

It is important to recognise another potential role of these research findings. In addition to classifying an individual according to their relative cognitive strengths and weaknesses, use of this system also serves to warn clinicians of premature closure in their diagnostic decision-making. It is hoped that this research can convince clinicians that assumptions regarding profiles and diagnosis must be considered at the very least suspect. If so, this in its own right would be a major contribution if it prevented clinicians from making the mistake of asserting that a client who reported a traumatic brain injury but did not demonstrate reduced rate of information processing or attentional difficulties either did not sustain such an injury or did not suffer from its negative consequences. The educative value of this research is to instruct clinicians in the wide variety of relative cognitive strengths and weaknesses present in any diagnostic group. Assertions of single prototypical patterns associated with a

particular diagnosis do not serve either the client or the profession and have no empirical basis.

In conclusion, a new method of analysing cognitive test data has been developed that can accurately classify individual cases according to their relative cognitive strengths and weaknesses. It is hoped that this new method will facilitate clinicians in making more reasoned and empirically supported inferences regarding their client's cognitive abilities and perhaps contribute to the development of a system of psychological diagnosis to supplant the medical diagnoses which so poorly capture the diversity of human behaviour.

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APPENDIX A

Means and Standard Deviations for 12 Diagnostic Groups

Table A.1
Means and SDs of the Diagnostic Groups for the WAIS-III/WMS-III Scores

	CVD	DEM	DAT	DrugEtoh	MID	NIL
Age/Ed						
Age	58.79	57.43	64.71	43.59	64.95	42.76
	(13.44)	(15.04)	(11.55)	(13.97)	(11.38)	(15.34)
Education	13.15	13.02	13.35	14.99	12.68	14.46
	(3.09)	(3.48)	(4.06)	(3.35)	(3.30)	(2.58)
WMS-III	Indices					
AI	90.96	88.83	79.46	100.60	83.37	91.06
	(18.29)	(15.25)	(20.70)	(17.56)	(15.49)	(15.23)
VI	85.63	88.02	78.71	94.95	79.95	88.23
	(14.18)	(18.96)	(15.93)	(14.81)	(13.92)	(16.68)
IM	85.86	86.02	74.60	97.38	77.99	87.57
	(17.58)	(18.78)	(21.34)	(18.00)	(15.81)	(17.91)
AD	92.12	89.37	79.40	100.55	85.29	91.57
	(18.50)	(17.58)	(20.94)	(17.09)	(17.22)	(16.05)
VD	86.68	88.78	78.31	97.50	81.83	89.57
	(14.90)	(19.08)	(19.04)	(13.55)	(15.10)	(16.92)
ARD	95.95	91.77	83.08	103.63	89.53	94.14
	(17.16)	(17.17)	(18.79)	(15.40)	(16.12)	(19.72)
GM	89.15	87.74	76.12	100.23	82.08	89.69
	(17.67)	(19.52)	(22.46)	(17.44)	(16.16)	(18.26)
WM	89.76	87.12	81.81	99.43	84.30	91.37
	(15.94)	(14.09)	(19.81)	(14.46)	(15.81)	(18.16)
WAIS-III	Subtests					
VO	9.58	9.18	9.13	12.18	8.82	9.34
	(3.03)	(3.08)	(2.76)	(2.70)	(2.91)	(3.45)
SI	9.06	8.65	8.56	10.93	8.18	9.34
	(2.89)	(3.28)	(3.42)	(2.80)	(2.75)	(3.28)
IN	9.46	9.54	8.63	12.25	8.62	10.11
	(3.06)	(3.00)	(2.85)	(2.27)	(3.16)	(3.03)
PC	8.03	8.09	6.73	10.15	7.34	8.80
	(3.11)	(3.39)	(3.19)	(3.20)	(2.74)	(3.49)
BD	8.53	8.06	6.87	10.03	7.40	9.17
	(2.91)	(3.00)	(3.33)	(3.34)	(3.13)	(3.47)
MR	9.33	9.12	7.58	11.43	8.39	9.69
	(2.88)	(3.30)	(3.23)	(3.04)	(2.69)	(3.79)
DSY	7.03	7.08	6.75	8.88	6.01	7.74
	(3.06)	(3.09)	(3.51)	(3.04)	(2.56)	(3.31)
SS	7.82	8.00	6.71	10.20	6.45	8.51
	(3.19)	(3.26)	(3.57)	(3.29)	(2.90)	(3.16)

Table A.1 (cont.)
Means and SDs of the Diagnostic Groups for the WAIS-III/WMS-III Scores

	Other	PSYCH	SZ	TBI	TUMOUR	PD
Age/Ed						
Age	44.85	41.64	35.19	41.25	39.87	69.91
	(13.82)	(12.03)	(11.99)	(12.89)	(13.53)	(11.65)
Education	13.59	13.32	12.87	13.36	13.76	13.53
	(2.76)	(2.94)	(2.35)	(2.53)	(2.75)	(2.27)
WMS-III	Indices					
AI	94.23	95.32	88.40	92.26	98.84	94.34
	(21.32)	(15.38)	(16.14)	(19.13)	(13.91)	(21.87)
VI	91.17	92.88	83.97	91.53	95.29	87.34
	(19.35)	(21.04)	(16.86)	(17.77)	(17.22)	(14.31)
IM	91.25	92.64	83.53	90.28	96.66	88.38
	(22.91)	(21.21)	(17.49)	(20.63)	(17.75)	(20.02)
AD	95.16	97.04	87.96	92.51	98.32	95.31
	(20.91)	(17.01)	(17.83)	(18.36)	(16.57)	(20.80)
VD	90.91	93.76	84.23	90.74	96.34	87.97
	(20.03)	(18.88)	(16.89)	(19.64)	(19.15)	(17.40)
ARD	96.25	97.20	90.63	94.67	97.76	96.25
	(20.91)	(17.97)	(16.73)	(19.15)	(12.82)	(22.25)
GM	92.60	95.20	84.85	90.67	96.89	91.44
	(22.66)	(19.40)	(17.79)	(20.89)	(18.42)	(22.05)
WM	94.71	92.20	88.67	91.13	96.03	89.97
	(19.70)	(16.94)	(16.20)	(16.18)	(14.32)	(16.28)
WAIS-III	Subtests					
VO	10.01	10.40	7.94	9.37	10.66	10.78
	(3.47)	(3.62)	(3.14)	(3.44)	(3.22)	(3.01)
SI	9.08	10.08	8.35	8.89	9.76	9.75
	(3.50)	(3.05)	(2.72)	(3.53)	(2.69)	(3.45)
IN	9.91	9.60	8.35	9.55	10.26	10.53
	(3.52)	(3.03)	(2.97)	(3.26)	(3.31)	(3.04)
PC	8.49	9.40	8.76	8.72	9.34	8.81
	(3.35)	(3.57)	(3.31)	(3.18)	(2.93)	(2.90)
BD	9.32	9.12	9.04	9.58	9.68	7.47
	(3.51)	(3.44)	(2.89)	(3.10)	(2.94)	(3.19)
MR	10.43	10.56	9.41	10.21	11.21	8.72
	(3.51)	(3.07)	(3.20)	(3.29)	(3.27)	(3.31)
DSY	7.88	8.16	7.47	7.83	8.26	6.25
	(3.56)	(3.64)	(2.97)	(2.89)	(3.06)	(2.71)
SS	8.22	9.04	8.13	8.61	8.71	7.19
	(3.39)	(3.19)	(3.30)	(3.00)	(2.99)	(2.83)

Table A.2
Means and SDs of the Diagnostic Groups Test Scores

	CVD	DEM	DAT	DrugEtoh	MID	NIL
Age/Ed						
AGE	57.00	60.79	51.91	43.36	59.23	41.00
	(12.05)	(8.43)	(16.67)	(13.60)	(11.10)	(12.10)
EDN	13.63	13.93	14.38	14.45	14.35	15.40
	(2.87)	(4.81)	(3.03)	(1.63)	(3.59)	(3.07)
Other Neuropsychological Tests						
TMT-A Time	41.38	45.64	44.13	29.73	57.85	44.20
	(12.45)	(25.91)	(18.01)	(9.83v	(33.49)	(28.75)
TMT-B	120.38	133.57	127.28	81.18	164.46	98.93
Time	(55.59)	(84.55)	(76.40)	(30.05)	(81.06)	(67.08)
TMT-B min	79.00	87.93	83.16	51.45	106.62	54.73
TMT-A Time	(49.95)	(70.10)	(65.89)	(23.53)	(66.68)	(43.16)
WCST Pers.	24.93	30.64	25.50	12.45	30.27	19.27
Err.	(16.69)	(20.89)	(18.18)	(10.96)	(18.12)	(10.92)
WCST Cat.	3.40	3.29	3.69	5.27	3.15	3.87
Completed	(2.16)	(2.37)	(2.43)	(1.56)	(2.26)	(2.26)
COWAT	33.53	31.64	28.38	37.09	27.50	32.07
Total	(13.19)	(13.47)	(11.94)	(5.58)	(11.68)	(13.23)
BNT	51.05	47.64	52.69	56.36	50.42	51.80
	(7.68)	(8.32)	(5.69)	(1.63)	(11.38)	(10.28)
WMS-III	Indices					
AI	92.85	92.57	89.91	100.09	85.73	87.33
	(18.33)	(21.28)	(14.36)	(16.19)	(17.04)	(15.28)
VI	87.98	86.14	87.84	96.36	82.54	86.20
	(12.67)	(20.06)	(17.51)	(15.91)	(16.07)	(14.00)
AD	92.48	89.79	89.25	98.64	87.85	88.33
	(19.27)	(23.88)	(16.49)	(17.44)	(19.43)	(14.28)
VD	90.55	86.57	87.50	98.27	84.08	88.40
	(15.36)	(23.89)	(17.23)	(14.53)	(15.72)	(16.27)
ARD	94.50	92.50	95.00	103.64	92.12	91.33
	(16.12)	(19.49)	(15.81)	(16.14)	(16.26)	(16.31)
WM	95.93	90.93	91.34	99.73	89.31	87.07
	(17.07)	(18.13)	(11.06)	(10.29)	(15.43)	(19.52)
WMS-III	Subtests					
Word Lists	7.88	7.93	7.56	9.00	6.73	7.07
Total SS	(3.47)	(4.39)	(3.37)	(4.00)	(3.49)	(3.47)
Word Lists	8.78	8.43	8.75	9.36	8.08	8.60
Delay	(3.12)	(3.18)	(2.79)	(3.04)	(2.91)	(2.80)

Table A.2 (cont.)
Means and SDs of the Diagnostic Groups Test Scores

	CVD	DEM	DAT	DrugEtoh	MID	NIL
WAIS-III	Subtests					
VO	10.05	10.21	9.97	11.64	10.23	9.67
	(2.71)	(2.46)	(2.67)	(2.06)	(2.52)	(3.74)
SI	9.48	10.71	9.53	11.36	9.12	10.07
	(2.91)	(2.09)	(2.71)	(2.46)	(2.57)	(4.13)
IN	10.38	9.71	10.66	11.91	10.27	10.47
	(2.94)	(3.27)	(2.57)	(1.76)	(3.07)	(3.16)
PC	9.33	8.36	8.78	9.82	7.77	8.87
	(3.05)	(3.23)	(3.33)	(3.09)	(2.82)	(2.33)
BD	9.75	8.64	8.88	9.64	8.73	8.40
	(2.83)	(2.34)	(2.93)	(3.44)	(2.93)	(3.20)
MR	10.40	8.86	10.03	10.91	9.00	9.67
	(2.79)	(3.01)	(3.20)	(2.07)	(2.35)	(4.10)
DSY	7.98	8.79	7.78	8.55	6.31	7.67
	(2.85)	(3.19)	(3.01)	(2.16)	(2.60)	(3.64)
SS	9.40	8.64	9.28	9.91	6.96	8.40
	(2.67)	(2.73)	(3.29)	(2.88)	(2.89)	(3.62)

Table A.2 (cont.)
Means and SDs of the Diagnostic Groups Test Scores

	Other	PD	PSYCH	SZ	TBI	TUMOUR
Age/Ed						
AGE	42.51	61.00	44.00	34.70	42.51	36.82
	(12.05)	(13.27)	(9.34)	(11.91)	(13.08)	(10.69)
EDN	14.07	13.50	12.75	12.68	13.41	14.14
	(2.98)	(1.69)	(2.26)	(2.27)	(2.66)	(2.61)
Other Neuropsychological Tests						
TMT-A Time	34.79	60.88	37.42	39.25	36.85	32.68
	(14.30)	(42.85)	(20.03)	(23.66)	(24.58)	(16.82)
TMT-B	94.67	154.25	110.50	100.16	108.54	75.36
Time	(54.80)	(93.26)	(74.66)	(69.03)	(77.81)	(35.39)
TMT-B min	59.88	93.38	73.08	60.91	71.69	42.68
TMT-A Time.	(50.04)	(68.80)	(58.31)	(55.94)	(59.51)	(28.18)
WCST Pers	17.53	29.13	31.08	20.78	21.28	17.55
Err.	(16.36)	(12.51)	(21.84)	(18.26)	(15.50)	(14.47)
WCST Cat.	4.91	2.13	3.75	4.42	4.13	4.95
Completed	(1.67)	(2.03)	(1.86)	(1.92)	(2.32)	(1.79)
COWAT	35.58	30.88	29.33	27.85	33.08	33.41
Total	(16.03)	(8.87)	(9.45)	(11.28)	(11.28)	(11.04)
BNT	53.09	54.63	52.75	46.00	48.85	53.45
	(6.30)	(5.37)	(6.50)	(10.06)	(12.64)	(4.92)
WMS-III	Indices					
AI	96.05	102.63	95.25	87.90	91.56	99.05
	(22.04)	(16.39)	(16.35)	(15.47)	(18.61)	(12.51)
VI	91.05	89.00	88.58	83.72	92.44	91.27
	(17.85)	(12.96)	(21.80)	(16.74)	(18.83)	(15.73)
AD	97.56	103.38	95.75	87.25	94.00	97.45
	(21.05)	(17.99)	(19.90)	(17.39)	(18.18)	(15.38)
VD	91.00	89.13	86.75	83.90	91.26	94.00
	(17.07)	(13.63)	(20.69)	(16.61)	(21.13)	(19.24)
ARD	97.91	100.63	95.42	90.09	97.18	98.64
	(21.55)	(13.74)	(19.82)	(16.19)	(18.52)	(11.87)
WM	97.79	96.13	86.00	89.98	92.67	96.45
	(17.82)	(14.75)	(10.94)	(16.05)	(16.64)	(16.19)
WMS-III	Subtests					
Word Lists	8.53	7.88	7.08	7.64	8.15	9.68
Total SS	(3.90)	(2.42)	(4.27)	(2.99)	(4.21)	(3.75)
Word Lists	9.63	8.25	8.00	7.63	8.38	9.77
Delay	(3.35)	(3.58)	(2.59)	(2.88)	(3.22)	(3.13)

Table A.2 (cont.)
Means and SDs of the Diagnostic Groups Test Scores

	Other	PD	PSYCH	SZ	TBI	TUMOUR
WAIS-III	Subtests					
VO	10.47	11.25	9.75	7.83	9.21	11.00
	(3.22)	(1.16)	(3.17)	(2.91)	(3.71)	(2.99)
SI	9.84	10.63	9.25	8.27	8.72	10.18
	(3.28)	(2.07)	(2.09)	(2.56)	(3.69)	(2.38)
IN	10.88	10.88	9.25	8.24	9.38	10.91
	(3.30)	(2.47)	(2.45)	(2.86)	(3.42)	(3.48)
PC	9.23	9.13	7.92	8.90	9.08	9.64
	(3.21)	(2.36)	(3.09)	(3.38)	(2.89)	(2.82)
BD	9.60	8.75	8.92	9.13	9.28	10.55
	(2.85)	(1.98)	(2.75)	(2.75)	(2.93)	(3.13)
MR	10.56	9.00	10.33	9.56	10.05	11.50
	(3.22)	(1.51)	(2.71)	(3.20)	(3.26)	(3.66)
DSY	8.44	7.00	7.50	7.64	7.95	8.68
	(3.44)	(2.20)	(3.45)	(2.88)	(3.12)	(3.24)
SS	8.77	7.63	8.92	8.20	8.49	9.23
	(3.35)	(2.56)	(3.26)	(2.89)	(2.90)	(3.07)

APPENDIX B

Example Syntax from SPSS and MATLAB Analyses

STUDY 1

B.1.1 SPSS 11.5: Syntax for Deviation Scores

B.1.1.1 Conversion of Standard Scores from WMS-III to Scaled Scores: E.g. Conversion of Working Memory score.

```
COMPUTE ssWM = (WM-100)/15*3+10
EXECUTE .
```

B.1.1.2 Computation of deviation scores: E.g. Computation of Symbol Search Deviation Score.

```
COMPUTE dss = ssss-meanss .
EXECUTE .
```

B.1.1.3 Computation of Descriptives and Frequencies:

```
DESCRIPTIVES
  VARIABLES=dai dvi dad dvd dard dwm dvo dsi din dpc dbd dmr ddsy dss age edn
  /STATISTICS=MEAN STDDEV MIN MAX .
FREQUENCIES
  VARIABLES=sex race no1diag
  /ORDER=  ANALYSIS .
```

B.1.1.4 Hierarchical Cluster Analysis:

```
Y = pdist(X,'correlation');
squareform(Y);
Z=linkage(Y,'average');
dendrogram(Z);
C=cophenet(Z,Y)
I=inconsistent(Z);
T=cluster(Z,5);
size(X)
idx5=kmeans(X,5,'distance','sqeuclidean','display','iter');
[silh5,h]=silhouette(X,idx5,'sqeuclidean');
mean(silh5)
```

B.1.1.5 K-Means Analysis:

```
Idx4=kmeans(X,4,'distance','sqeuclidean','display','iter');
[silh4,h]=silhouette(X,idx4,'sqeuclidean');
mean(silh5)
```

STUDY 2

B.1.1 STUDY 2 SPSS Syntax: Scaled Score Transformation e.g. COWAT

```
   fastot (0 thru 12=2)  (13 thru 14=3)  (15 thru 17=4)  (18 thru 20=5)  (21 thru
  2=6)  (26 thru 28=7)  (29 thru 32=8)  (33 thru 36=9)  (37 thru 41=10)  (42
  thru 45=11)  (46 thru 49=12.)  (50 thru 53=13)  (54 thru 57=14)  (58 thru
  62=15)  (63 thru 66=16)  (67 thru 72=17)  (73 thru 77=18)  (78 thru
  Highest=19)  INTO  issfasto .
EXECUTE .
RECODE
```

```
IF (agegpfas = 1) ssfas = ((xbar3fas - 14.06) / 3.82)* 3 + 10 .
EXECUTE .
```

B.1.2 STUDY 2 SPSS Syntax: Factor Analysis

```
FACTOR
  /VARIABLES sstmta ssbmina sswperer sswcats ssfas ssbnt ssai ssvi ssad ssvd
  ssard sswm ssvo sssi ssin sspc ssbd ssmr ssdsy ssss lst_ldss wltotss
 /MISSING LISTWISE /ANALYSIS sstmta ssbmina sswperer sswcats ssfas ssbnt ssai
  ssvi ssad ssvd ssard sswm ssvo sssi ssin sspc ssbd ssmr ssdsy ssss lst_ldss
  wltotss
  /PRINT INITIAL CORRELATION SIG DET KMO ROTATION
  /FORMAT BLANK(.35)
  /PLOT EIGEN
  /CRITERIA FACTORS(6) ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25) DELTA(0)
  /ROTATION OBLIMIN
  /METHOD=CORRELATION .
FREQUENCIES
  VARIABLES=verb_mem exec_fn verbabil speed_wm vis_mem vis_abil
  /STATISTICS=STDDEV VARIANCE RANGE MINIMUM MAXIMUM SEMEAN
MEAN SKEWNESS
  SESKEW KURTOSIS SEKURT
  /ORDER=  ANALYSIS .
DESCRIPTIVES
  VARIABLES=verb_mem exec_fn verbabil speed_wm vis_mem vis_abil
  /STATISTICS=MEAN .
CORRELATIONS
  /VARIABLES=verb_mem exec_fn verbabil speed_wm vis_mem vis_abil
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE .
```

B.1.3 STUDY 2 MATLAB 6.5.1: Syntax Cluster Analysis

```
Y = pdist(X,'correlation');
squareform(Y);
Z=linkage(Y,'average');
dendrogram(Z);
C=cophenet(Z,Y)
I=inconsistent(Z);
T=cluster(Z,5);
size(X)
idx5=kmeans(X,5,'distance','sqeuclidean','display','iter');
[silh5,h]=silhouette(X,idx5,'sqeuclidean');
mean(silh5)
```

B.1.4 STUDY 3 MATLAB 6.5.1: Syntax Mahalanobis Distance Calculations

```
data=clipboarddata;
cov1=clipboarddata;
```

```
cov2=clipboarddata;
cov3=clipboarddata;
cov4=clipboarddata;
cov3=clipboarddata;
mean1=clipboarddata;
mean2=clipboarddata;
mean3=clipboarddata;
mean4=clipboarddata;
mean5=clipboarddata;
incov1=inv(cov1);
incov2=inv(cov2);
incov3=inv(cov3);
incov4=inv(cov4);
incov5=inv(cov5);
for row=1:size(data,1),
Q1 = data(row,:) - mean1';
M1(row) = Q1*incov1*Q1';
end
for row=1:size(data,1),
Q2 = data(row,:) - mean2';
M2(row) = Q2*incov2*Q2';
end
for row=1:size(data,1),
Q3 = data(row,:) - mean3';
M3(row) = Q3*incov3*Q3';
end
for row=1:size(data,1),
Q4 = data(row,:) - mean4';
M4(row) = Q4*incov4*Q4';
end
for row=1:size(data,1),
Q5 = data(row,:) - mean5';
M5(row) = Q5*incov5*Q5';
end
```

APPENDIX C

Hierarchical Cluster Analysis for Mixed Diagnostic Sample: WAIS-III/WMS-III

Scree Plot, Dendrogram, and Inconsistency Matrix

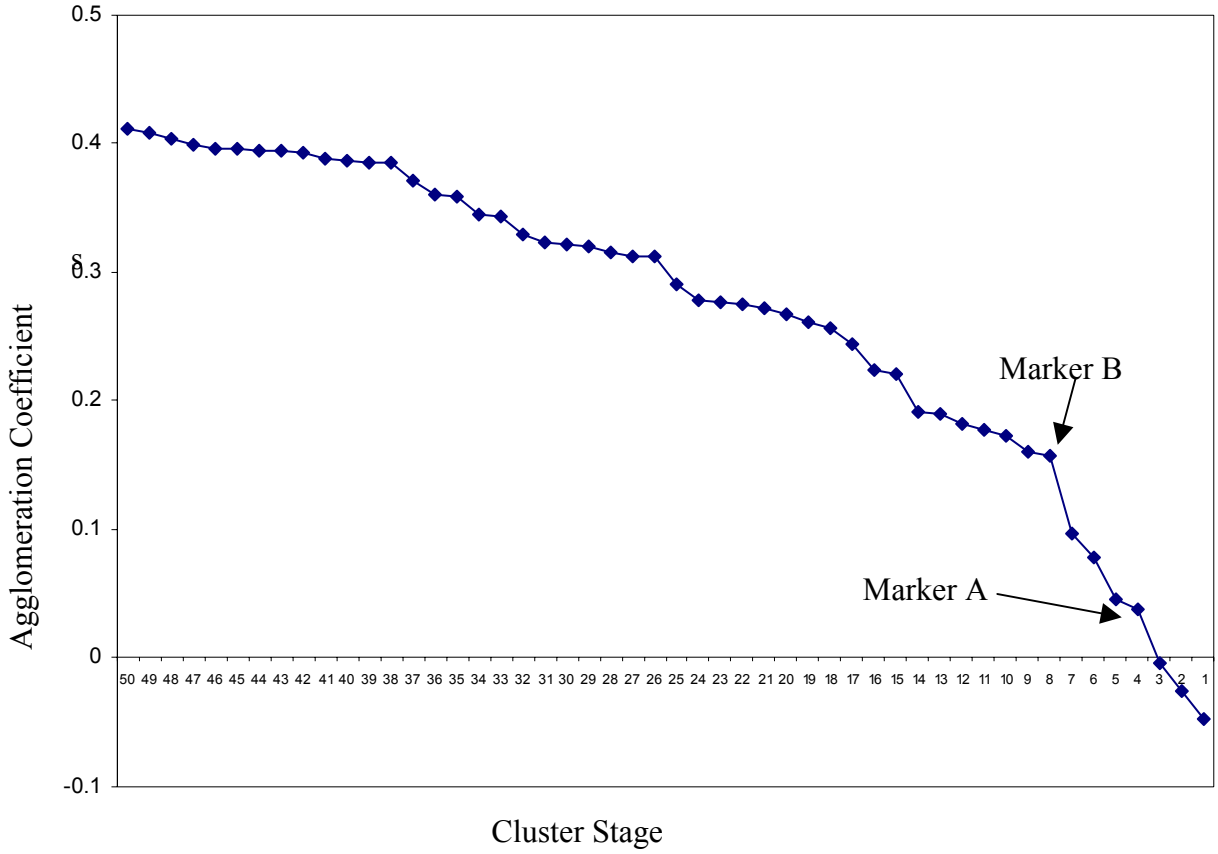

Figure C.1 Study 1: Inverse Scree Plot from cluster analysis.

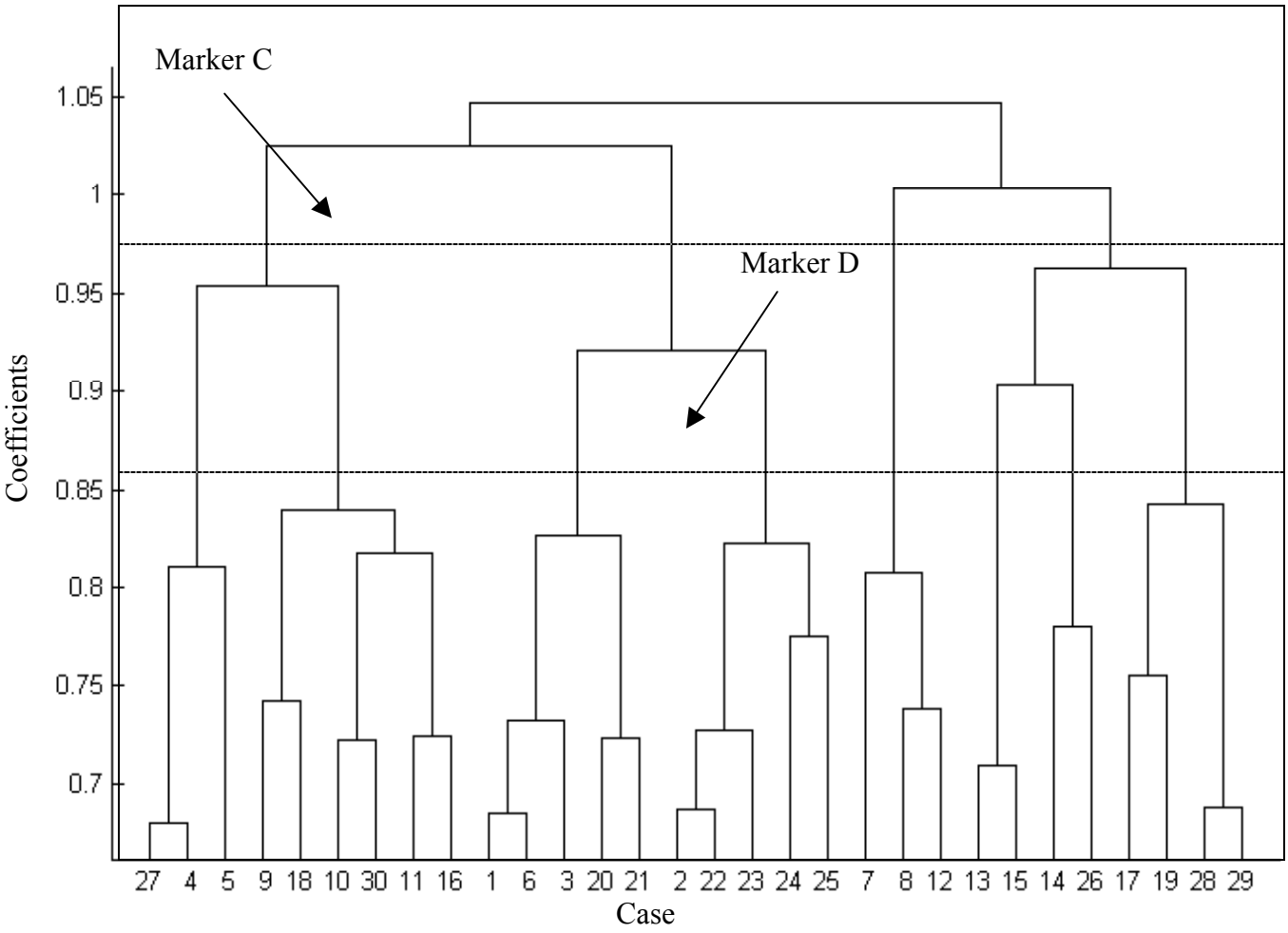

Figure C.2 Study 1: Dendrogram from cluster analysis.

APPENDIX D

K-Means Analysis for Mixed Diagnostic Sample: WAIS-III/WMS-III

Silhouette Plot

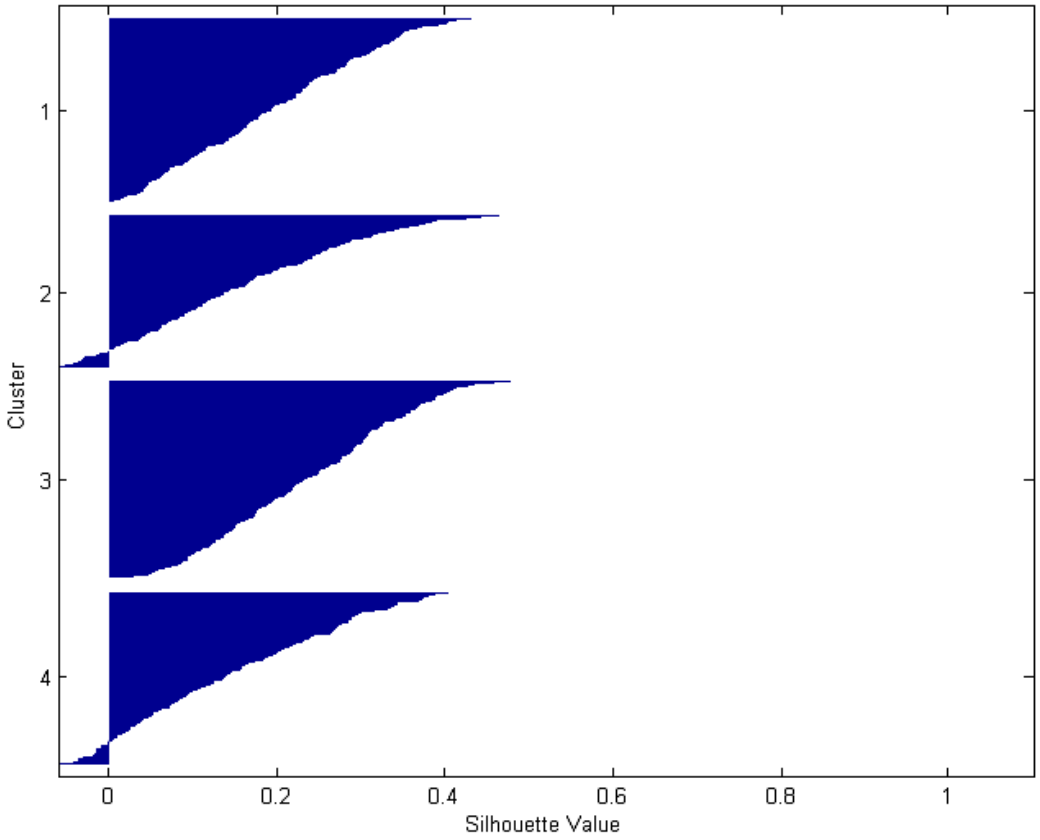

Figure D.1 Study 1: Silhouette Plot from K-Means analysis

APPENDIX E

Hierarchical Cluster Analysis for Mixed Diagnostic Sample: WAIS-III/WMS-III and Assorted Neuropsychological Tests

Inverse Scree Plot, Dendrogram and Inconsistency Matrix

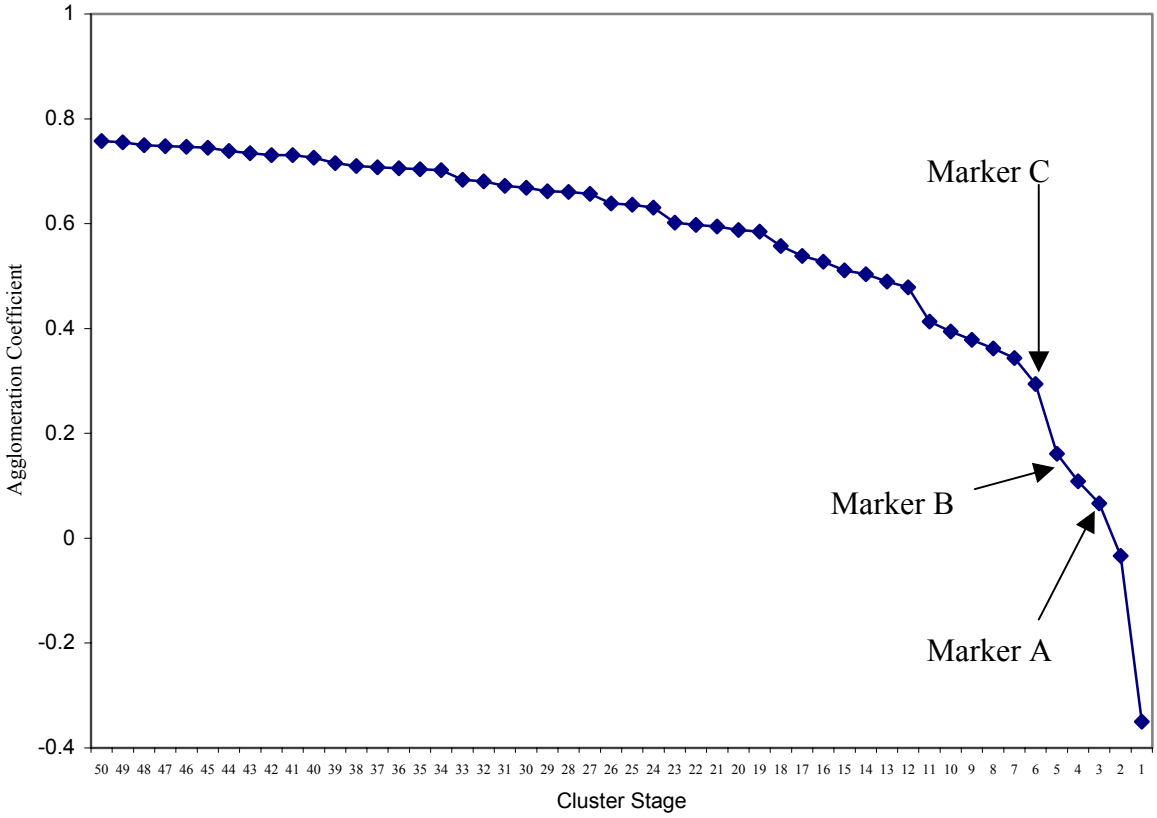

Figure E.1 Study 2: Inverse Scree Plot from cluster analysis.

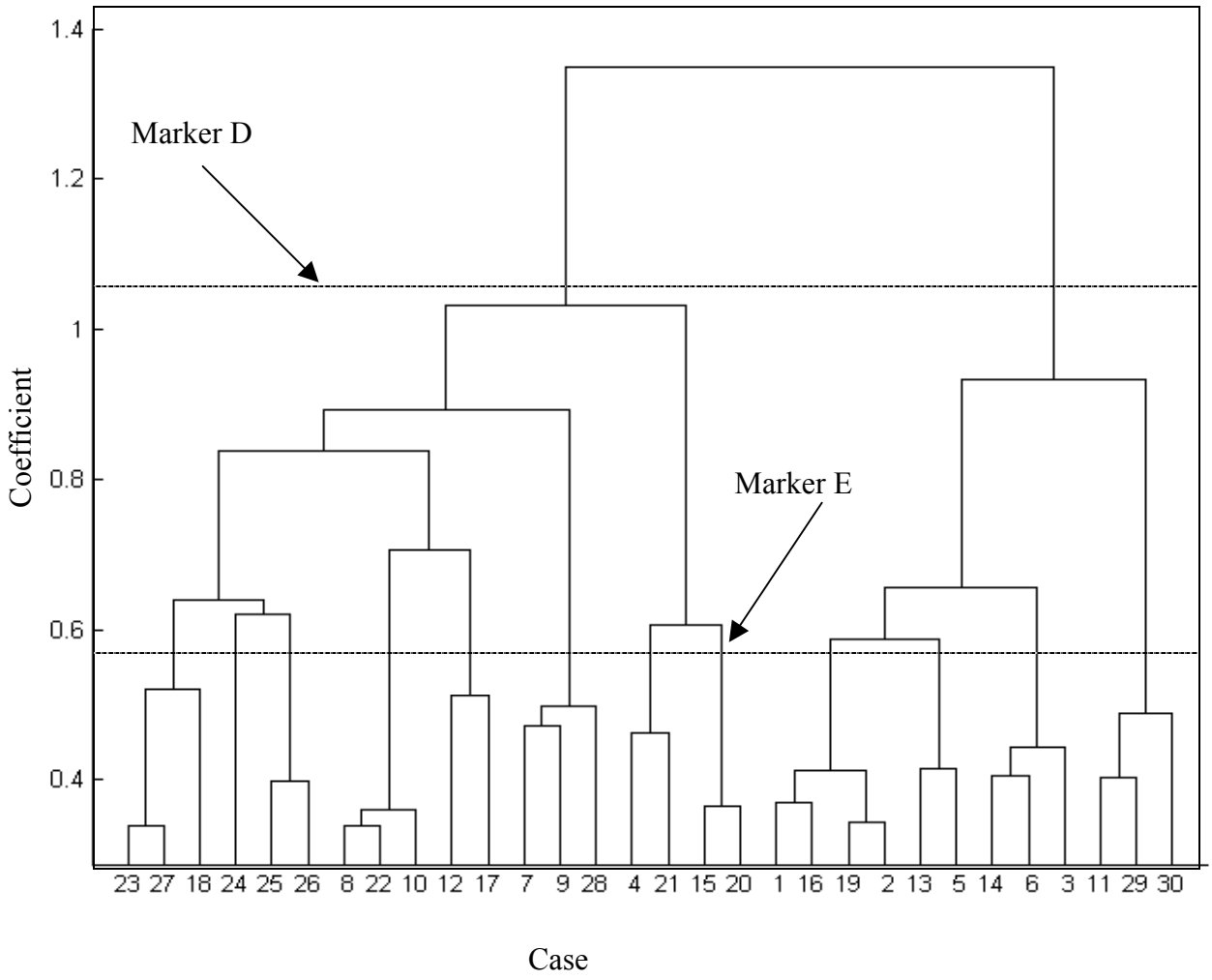

Figure E.2 Study 2: Dendrogram from cluster analysis.

Table E
First 40 Cases MATLAB 6.5.1Inconsistency Matrix

Length Mean	Length Standard Deviation	Number of Links	Inconsistency Coefficient
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	2.00	0.71
0.00	0.00	1.00	0.00
0.00	0.00	2.00	0.71
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.00	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.00	0.00	2.00	0.71
0.01	0.00	1.00	0.00
0.01	0.00	2.00	0.71
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	2.00	0.71
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.01	0.00	2.00	0.71
0.01	0.00	2.00	0.71
0.01	0.01	2.00	0.71
0.01	0.00	1.00	0.00
0.01	0.00	1.00	0.00
0.00	0.00	1.00	0.00

APPENDIX F

K-Means Analysis for Mixed Diagnostic Sample: WAIS-III/WMS-III and Assorted Neuropsychological Tests

Silhouette Plot

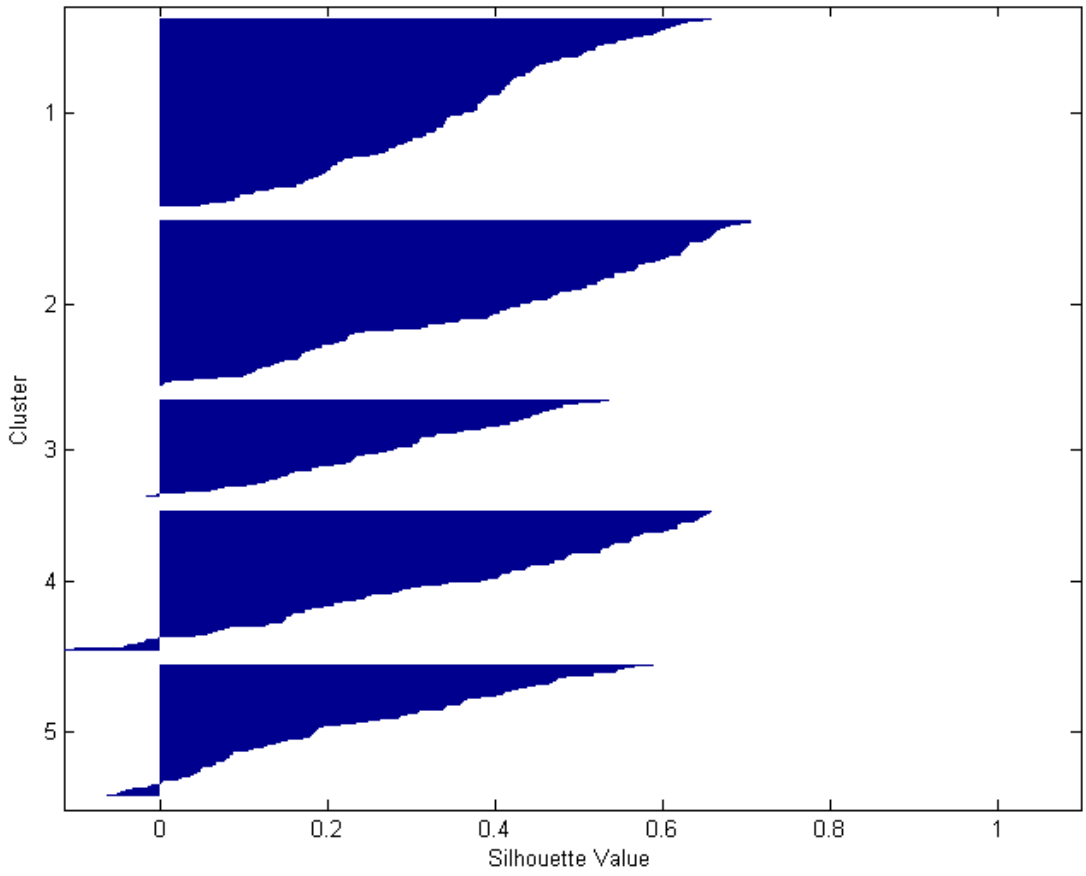

Figure F.1 Study 2: Silhouette plot from K-Means analysis.

APPENDIX G

Mahalanobis Distance for Mixed Diagnostic Sample

Table G

Mahalanobis distance Scores for each case and K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
1	64.59	.00	108.15	.00	63.61	.00	11.12	.08	81.84	.00	4
2	66.41	.00	98.34	.00	53.68	.00	14.00	.03	77.41	.00	4
3	91.25	.00	94.73	.00	36.42	.00	9.38	.15	58.27	.00	4
4	50.86	.00	83.57	.00	36.15	.00	4.41	.62	59.02	.00	4
5	55.55	.00	53.03	.00	23.84	.00	10.92	.09	27.13	.00	4
6	37.21	.00	75.78	.00	39.03	.00	5.62	.47	52.20	.00	4
7	36.36	.00	68.46	.00	29.79	.00	3.48	.75	46.65	.00	4
8	32.61	.00	57.78	.00	20.14	.00	1.68	.95	32.65	.00	4
9	40.22	.00	60.25	.00	17.38	.01	6.50	.37	40.53	.00	4
10	18.42	.01	34.83	.00	10.74	.10	1.62	.95	16.15	.01	4
11	18.15	.01	36.88	.00	9.03	.17	3.49	.75	16.16	.01	4
12	11.29	.08	31.67	.00	9.62	.14	2.15	.91	15.72	.02	4
13	19.50	.00	23.72	.00	10.82	.09	9.24	.16	9.15	.17	5
14	13.06	.04	25.19	.00	3.23	.78	5.15	.53	10.84	.09	3
15	7.81	.25	22.22	.00	6.34	.39	5.39	.49	8.40	.21	1
16	10.37	.11	28.35	.00	17.94	.01	11.51	.07	10.34	.11	1
17	23.75	.00	43.94	.00	14.89	.02	2.59	.86	26.36	.00	4
18	49.33	.00	67.84	.00	17.43	.01	6.86	.33	42.81	.00	4
19	17.16	.01	39.06	.00	16.35	.01	5.78	.45	19.33	.00	4
20	7.77	.26	25.43	.00	12.28	.06	4.34	.63	10.71	.10	4
21	5.32	.50	13.51	.04	9.81	.13	6.90	.33	2.40	.88	5
22	13.99	.03	30.47	.00	8.90	.18	3.87	.69	17.08	.01	4
23	46.76	.00	62.54	.00	10.07	.12	7.34	.29	41.66	.00	4
24	40.94	.00	47.41	.00	7.25	.30	21.52	.00	48.28	.00	3
25	21.28	.00	25.88	.00	0.62	1.00	8.79	.19	18.66	.00	3
26	25.28	.00	36.48	.00	6.60	.36	13.17	.04	34.87	.00	3
27	15.67	.02	37.80	.00	11.69	.07	7.82	.25	22.24	.00	4
28	16.52	.01	39.08	.00	10.70	.10	3.19	.78	28.87	.00	4
29	15.61	.02	35.57	.00	10.03	.12	5.42	.49	23.54	.00	4
30	9.58	.14	24.97	.00	5.33	.50	8.28	.22	10.87	.09	3
31	13.90	.03	20.62	.00	3.78	.71	8.86	.18	13.33	.04	3
32	17.67	.01	29.26	.00	13.38	.04	19.33	.00	25.20	.00	3
33	17.86	.01	25.61	.00	8.90	.18	6.55	.36	7.39	.29	5
34	10.50	.11	24.83	.00	10.22	.12	4.50	.61	11.20	.08	4
35	41.35	.00	36.54	.00	10.04	.12	6.46	.37	13.64	.03	4
36	25.30	.00	36.19	.00	4.92	.55	1.92	.93	12.23	.06	4
37	18.69	.00	29.54	.00	8.49	.20	6.93	.33	7.10	.31	5
38	9.02	.17	17.61	.01	8.31	.22	9.53	.15	5.10	.53	1
39	25.98	.00	43.49	.00	14.96	.02	3.86	.70	25.65	.00	4
40	12.71	.05	21.54	.00	8.50	.20	5.49	.48	6.37	.38	5
41	11.33	.08	19.66	.00	3.21	.78	5.07	.54	7.38	.29	3
42	7.02	.32	16.47	.01	4.74	.58	6.71	.35	5.52	.48	1

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
43	15.75	.02	36.16	.00	15.51	.02	4.83	.57	14.46	.02	4
44	20.45	.00	29.98	.00	9.44	.15	5.83	.44	9.82	.13	4
45	18.67	.00	50.06	.00	18.92	.00	6.80	.34	22.35	.00	4
46	12.35	.05	33.75	.00	18.77	.00	11.27	.08	9.33	.16	4
47	14.71	.02	21.84	.00	8.37	.21	4.80	.57	4.19	.65	5
48	94.14	.00	92.97	.00	31.25	.00	12.88	.04	38.52	.00	4
49	61.85	.00	66.45	.00	16.18	.01	8.25	.22	23.83	.00	4
50	22.41	.00	31.01	.00	4.34	.63	2.48	.87	9.28	.16	4
51	59.90	.00	75.16	.00	18.32	.01	5.17	.52	41.55	.00	4
52	61.06	.00	66.56	.00	8.83	.18	8.20	.22	38.41	.00	4
53	40.06	.00	46.54	.00	9.79	.13	12.66	.05	28.33	.00	3
54	26.51	.00	30.78	.00	3.21	.78	5.91	.43	14.83	.02	3
55	36.49	.00	29.09	.00	7.47	.28	16.82	.01	17.24	.01	3
56	16.07	.01	18.94	.00	1.87	.93	7.56	.27	12.05	.06	3
57	16.60	.01	23.38	.00	4.64	.59	3.61	.73	9.01	.17	3
58	41.61	.00	58.37	.00	23.44	.00	5.80	.45	46.86	.00	4
59	26.98	.00	44.54	.00	12.49	.05	4.50	.61	16.52	.01	4
60	21.75	.00	28.19	.00	7.83	.25	4.08	.67	8.08	.23	4
61	10.53	.10	17.51	.01	12.00	.06	8.48	.21	4.58	.60	5
62	16.87	.01	17.77	.01	5.93	.43	6.84	.34	2.76	.84	5
63	60.89	.00	77.40	.00	18.80	.00	3.24	.78	43.40	.00	4
64	48.21	.00	62.66	.00	14.30	.03	1.18	.98	31.29	.00	4
65	38.25	.00	52.51	.00	16.60	.01	3.61	.73	31.21	.00	4
66	27.65	.00	34.60	.00	7.45	.28	3.64	.73	12.85	.05	4
67	32.78	.00	54.71	.00	25.18	.00	3.69	.72	34.86	.00	4
68	45.31	.00	69.10	.00	23.49	.00	3.78	.71	36.19	.00	4
69	26.66	.00	42.38	.00	6.71	.35	1.83	.93	23.28	.00	4
70	11.51	.07	29.22	.00	8.31	.22	7.80	.25	13.71	.03	3
71	10.14	.12	15.35	.02	4.22	.65	6.73	.35	6.46	.37	3
72	13.78	.03	41.13	.00	15.47	.02	3.08	.80	17.61	.01	4
73	50.67	.00	47.38	.00	5.19	.52	10.22	.12	26.84	.00	3
74	41.22	.00	49.34	.00	4.56	.60	14.71	.02	36.77	.00	3
75	41.46	.00	59.97	.00	14.13	.03	8.97	.18	36.38	.00	4
76	34.52	.00	42.88	.00	6.19	.40	3.31	.77	14.79	.02	4
77	32.93	.00	25.56	.00	3.70	.72	9.30	.16	5.33	.50	3
78	24.73	.00	33.13	.00	6.19	.40	1.56	.96	10.30	.11	4
79	13.06	.04	26.85	.00	13.68	.03	6.85	.33	6.67	.35	5
80	36.38	.00	56.47	.00	25.75	.00	10.18	.12	26.66	.00	4
81	36.79	.00	42.59	.00	6.47	.37	7.13	.31	14.03	.03	3
82	20.15	.00	39.01	.00	10.04	.12	9.69	.14	17.46	.01	4
83	20.95	.00	33.72	.00	11.68	.07	7.53	.27	9.20	.16	4
84	24.72	.00	26.88	.00	4.24	.64	13.91	.03	21.06	.00	3
85	53.59	.00	56.87	.00	8.41	.21	6.91	.33	21.42	.00	4
86	60.33	.00	53.17	.00	3.71	.72	10.96	.09	24.37	.00	3
87	27.09	.00	24.37	.00	4.66	.59	8.53	.20	5.76	.45	3

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
88	28.57	.00	23.31	.00	1.34	.97	10.20	.12	12.21	.06	3
89	52.38	.00	55.39	.00	10.35	.11	6.22	.40	30.47	.00	4
90	65.68	.00	51.52	.00	10.03	.12	11.50	.07	26.89	.00	3
91	52.50	.00	62.49	.00	13.08	.04	2.83	.83	37.22	.00	4
92	80.17	.00	78.84	.00	22.99	.00	6.99	.32	44.51	.00	4
93	49.33	.00	62.53	.00	19.64	.00	8.34	.21	35.40	.00	4
94	57.83	.00	55.60	.00	9.84	.13	4.25	.64	20.83	.00	4
95	25.30	.00	39.26	.00	8.15	.23	6.43	.38	12.33	.05	4
96	83.73	.00	77.13	.00	18.16	.01	5.09	.53	34.09	.00	4
97	56.46	.00	63.45	.00	9.74	.14	3.03	.81	29.11	.00	4
98	52.18	.00	50.18	.00	6.19	.40	5.04	.54	15.98	.01	3
99	62.40	.00	55.36	.00	10.00	.12	6.28	.39	18.36	.01	4
100	45.84	.00	37.15	.00	5.69	.46	6.31	.39	11.04	.09	3
101	22.60	.00	33.95	.00	4.04	.67	3.72	.71	11.71	.07	4
102	31.45	.00	33.80	.00	6.42	.38	8.25	.22	9.28	.16	3
103	46.02	.00	32.57	.00	7.14	.31	10.31	.11	6.71	.35	5
104	16.51	.01	16.75	.01	2.07	.91	9.46	.15	9.98	.13	3
105	28.28	.00	18.35	.01	8.33	.22	13.28	.04	3.06	.80	5
106	28.72	.00	23.53	.00	1.99	.92	10.60	.10	10.05	.12	3
107	77.38	.00	64.43	.00	8.90	.18	7.35	.29	22.01	.00	3
108	36.68	.00	30.09	.00	3.56	.74	11.44	.08	10.15	.12	3
109	63.36	.00	59.41	.00	8.68	.19	5.38	.50	31.04	.00	4
110	80.88	.00	77.26	.00	9.55	.14	21.32	.00	50.35	.00	3
111	24.39	.00	42.02	.00	6.74	.35	5.43	.49	29.00	.00	4
112	74.97	.00	83.96	.00	18.51	.01	50.31	.00	81.34	.00	3
113	45.56	.00	39.22	.00	5.32	.50	13.55	.04	25.01	.00	3
114	26.13	.00	32.62	.00	2.19	.90	6.40	.38	15.20	.02	3
115	47.51	.00	48.72	.00	5.81	.44	22.52	.00	45.82	.00	3
116	30.70	.00	32.35	.00	7.21	.30	15.66	.02	23.90	.00	3
117	42.78	.00	30.30	.00	4.24	.64	12.44	.05	8.82	.18	3
118	37.05	.00	28.20	.00	5.81	.44	8.17	.23	4.77	.57	5
119	12.23	.06	19.05	.00	3.09	.80	6.45	.37	4.47	.61	3
120	14.37	.03	25.06	.00	6.54	.37	13.30	.04	16.78	.01	3
121	83.87	.00	126.88	.00	72.76	.00	13.19	.04	91.78	.00	4
122	81.99	.00	99.28	.00	42.80	.00	8.98	.17	58.42	.00	4
123	54.18	.00	79.95	.00	34.60	.00	5.97	.43	42.88	.00	4
124	30.14	.00	58.02	.00	23.29	.00	2.96	.81	37.87	.00	4
125	45.05	.00	62.52	.00	30.84	.00	7.86	.25	31.70	.00	4
126	116.99	.00	131.77	.00	51.87	.00	10.87	.09	80.03	.00	4
127	59.61	.00	69.65	.00	34.43	.00	9.83	.13	50.00	.00	4
128	74.78	.00	53.64	.00	15.88	.01	12.85	.05	24.18	.00	4
129	37.77	.00	32.61	.00	14.92	.02	22.65	.00	13.30	.04	5
130	16.18	.01	39.39	.00	20.73	.00	6.79	.34	30.14	.00	4
131	16.48	.01	46.61	.00	28.29	.00	3.55	.74	25.80	.00	4
132	14.38	.03	45.33	.00	27.72	.00	6.96	.32	31.94	.00	4

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
133	18.61	.00	40.09	.00	29.74	.00	7.93	.24	28.00	.00	4
134	12.62	.05	38.84	.00	26.14	.00	5.26	.51	28.77	.00	4
135	13.72	.03	43.72	.00	28.03	.00	4.54	.60	25.89	.00	4
136	7.96	.24	28.37	.00	19.61	.00	12.26	.06	19.85	.00	1
137	11.33	.08	31.82	.00	32.23	.00	12.39	.05	22.94	.00	1
138	6.80	.34	25.73	.00	15.11	.02	8.79	.19	22.59	.00	1
139	5.58	.47	21.27	.00	15.30	.02	9.31	.16	13.25	.04	1
140	6.66	.35	30.44	.00	24.04	.00	6.79	.34	17.71	.01	1
141	10.61	.10	21.85	.00	19.49	.00	10.82	.09	6.47	.37	5
142	4.25	.64	19.76	.00	22.71	.00	14.19	.03	22.23	.00	1
143	11.42	.08	33.04	.00	24.25	.00	32.02	.00	15.97	.01	1
144	5.30	.51	16.89	.01	6.44	.38	10.50	.11	8.34	.21	1
145	8.12	.23	23.61	.00	28.14	.00	15.15	.02	18.10	.01	1
146	6.75	.34	20.09	.00	19.91	.00	16.84	.01	18.20	.01	1
147	3.52	.74	11.76	.07	25.45	.00	20.20	.00	18.20	.01	1
148	6.96	.32	17.37	.01	22.39	.00	18.24	.01	10.17	.12	1
149	1.50	.96	14.77	.02	17.42	.01	11.40	.08	9.92	.13	1
150	8.39	.21	29.30	.00	16.01	.01	20.04	.00	20.24	.00	1
151	10.29	.11	27.21	.00	33.53	.00	21.20	.00	38.29	.00	1
152	26.18	.00	56.09	.00	45.24	.00	9.37	.15	35.46	.00	4
153	4.40	.62	20.24	.00	17.08	.01	9.44	.15	10.59	.10	1
154	6.44	.38	17.02	.01	10.16	.12	11.08	.09	11.13	.08	1
155	9.55	.14	30.49	.00	16.91	.01	3.98	.68	15.87	.01	4
156	5.29	.51	18.49	.01	21.28	.00	14.49	.02	26.90	.00	1
157	3.37	.76	13.51	.04	16.92	.01	16.71	.01	12.62	.05	1
158	1.74	.94	13.73	.03	12.25	.06	7.55	.27	5.01	.54	1
159	6.77	.34	23.88	.00	24.27	.00	16.31	.01	19.10	.00	1
160	1.49	.96	14.52	.02	17.82	.01	11.12	.08	7.95	.24	1
161	3.53	.74	16.09	.01	21.53	.00	17.23	.01	15.96	.01	1
162	14.18	.03	31.92	.00	10.07	.12	14.94	.02	31.10	.00	3
163	6.58	.36	28.92	.00	15.57	.02	12.42	.05	13.88	.03	1
164	13.37	.04	37.71	.00	25.52	.00	6.60	.36	32.54	.00	4
165	6.02	.42	28.56	.00	18.02	.01	4.70	.58	20.25	.00	1
166	7.01	.32	23.39	.00	8.65	.19	11.53	.07	21.00	.00	1
167	5.41	.49	19.12	.00	8.86	.18	8.70	.19	21.64	.00	1
168	9.15	.17	17.88	.01	11.04	.09	15.77	.02	19.95	.00	1
169	4.34	.63	12.93	.04	4.64	.59	8.28	.22	7.73	.26	1
170	7.18	.30	21.54	.00	20.33	.00	18.25	.01	27.61	.00	1
171	6.59	.36	17.07	.01	14.14	.03	13.01	.04	15.76	.02	1
172	2.26	.89	13.03	.04	10.09	.12	7.31	.29	5.44	.49	1
173	3.94	.69	11.51	.07	19.44	.00	18.15	.01	22.25	.00	1
174	3.84	.70	11.31	.08	19.98	.00	16.67	.01	19.42	.00	1
175	15.37	.02	39.01	.00	34.05	.00	16.95	.01	43.59	.00	1
176	8.92	.18	29.58	.00	28.74	.00	15.46	.02	32.35	.00	1
177	6.88	.33	17.79	.01	31.35	.00	25.63	.00	28.35	.00	1

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
178	5.37	.50	18.42	.01	21.58	.00	10.28	.11	6.90	.33	1
179	4.02	.67	19.09	.00	22.89	.00	13.60	.03	13.13	.04	1
180	5.13	.53	20.43	.00	19.53	.00	13.12	.04	9.78	.13	1
181	2.75	.84	15.29	.02	16.18	.01	10.36	.11	9.87	.13	1
182	0.83	.99	12.32	.06	10.91	.09	9.17	.16	7.09	.31	1
183	5.52	.48	14.19	.03	17.96	.01	10.84	.09	3.43	.75	5
184	7.47	.28	19.51	.00	5.96	.43	10.49	.11	22.57	.00	1
185	5.52	.48	21.38	.00	16.93	.01	16.57	.01	9.58	.14	1
186	5.15	.52	17.15	.01	13.11	.04	16.71	.01	10.11	.12	1
187	5.31	.51	19.07	.00	14.42	.03	12.64	.05	6.34	.39	1
188	4.19	.65	13.10	.04	13.28	.04	8.68	.19	2.37	.88	5
189	3.94	.68	19.31	.00	15.36	.02	13.09	.04	14.03	.03	1
190	4.44	.62	21.10	.00	12.69	.05	13.20	.04	9.17	.16	1
191	5.72	.46	17.36	.01	19.38	.00	11.06	.09	5.57	.47	1
192	18.81	.00	44.55	.00	25.26	.00	3.95	.68	30.85	.00	4
193	3.46	.75	13.78	.03	27.25	.00	17.37	.01	12.19	.06	1
194	17.11	.01	21.26	.00	22.80	.00	23.17	.00	8.19	.22	5
195	26.12	.00	23.52	.00	3.68	.72	18.73	.00	28.12	.00	3
196	12.16	.06	17.65	.01	5.74	.45	11.06	.09	5.17	.52	5
197	38.46	.00	22.81	.00	20.37	.00	28.65	.00	8.42	.21	5
198	10.18	.12	13.29	.04	11.08	.09	12.81	.05	3.78	.71	5
199	15.15	.02	15.55	.02	23.39	.00	33.57	.00	12.20	.06	5
200	41.15	.00	28.85	.00	5.40	.49	15.12	.02	11.86	.07	3
201	18.13	.01	12.31	.06	7.79	.25	14.95	.02	5.36	.50	5
202	31.71	.00	26.47	.00	6.76	.34	19.62	.00	21.15	.00	3
203	11.98	.06	11.52	.07	10.74	.10	17.95	.01	4.58	.60	5
204	21.60	.00	16.75	.01	13.86	.03	18.24	.01	4.49	.61	5
205	40.75	.00	32.53	.00	8.90	.18	25.70	.00	33.61	.00	3
206	12.87	.05	9.44	.15	5.21	.52	12.48	.05	7.16	.31	5
207	60.29	.00	24.52	.00	15.44	.02	24.58	.00	5.93	.43	5
208	27.99	.00	16.81	.01	19.46	.00	24.39	.00	10.39	.11	5
209	27.85	.00	13.15	.04	8.96	.18	17.08	.01	2.81	.83	5
210	40.58	.00	20.58	.00	10.48	.11	16.71	.01	3.57	.73	5
211	28.49	.00	14.14	.03	5.83	.44	13.45	.04	2.89	.82	5
212	27.79	.00	8.28	.22	17.64	.01	26.88	.00	8.50	.20	2
213	36.60	.00	12.09	.06	16.81	.01	25.37	.00	9.39	.15	2
214	24.90	.00	6.60	.36	15.56	.02	24.36	.00	7.92	.24	2
215	31.03	.00	8.23	.22	24.53	.00	28.63	.00	11.82	.07	2
216	56.21	.00	22.38	.00	23.57	.00	32.72	.00	9.97	.13	5
217	25.63	.00	9.25	.16	15.41	.02	21.51	.00	3.33	.77	5
218	40.27	.00	13.35	.04	17.69	.01	25.43	.00	6.16	.41	5
219	14.33	.03	10.50	.10	9.15	.17	16.75	.01	3.86	.70	5
220	17.96	.01	9.09	.17	17.33	.01	19.80	.00	4.12	.66	5
221	47.06	.00	12.58	.05	40.77	.00	48.33	.00	26.70	.00	2
222	18.80	.00	15.70	.02	8.37	.21	9.77	.13	3.63	.73	5

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
223	37.39	.00	10.20	.12	45.56	.00	45.84	.00	17.29	.01	2
224	20.23	.00	12.81	.05	6.80	.34	11.72	.07	1.51	.96	5
225	20.61	.00	9.01	.17	10.77	.10	16.32	.01	3.19	.78	5
226	27.50	.00	11.41	.08	16.16	.01	20.81	.00	3.93	.69	5
227	58.08	.00	16.24	.01	60.52	.00	58.98	.00	44.69	.00	2
228	17.24	.01	15.58	.02	10.65	.10	12.85	.05	3.07	.80	5
229	29.72	.00	15.93	.01	10.89	.09	15.45	.02	2.51	.87	5
230	30.90	.00	13.08	.04	13.51	.04	19.14	.00	3.62	.73	5
231	36.93	.00	8.99	.17	42.48	.00	43.31	.00	24.17	.00	2
232	21.25	.00	20.23	.00	4.20	.65	13.97	.03	12.76	.05	3
233	32.00	.00	19.76	.00	4.77	.57	15.78	.01	10.74	.10	3
234	42.01	.00	25.01	.00	5.81	.44	19.52	.00	16.14	.01	3
235	37.09	.00	24.73	.00	13.70	.03	19.26	.00	9.54	.15	5
236	46.44	.00	23.90	.00	9.02	.17	16.35	.01	5.93	.43	5
237	34.24	.00	18.44	.01	10.55	.10	17.79	.01	8.76	.19	5
238	33.54	.00	14.07	.03	10.31	.11	20.16	.00	5.91	.43	5
239	39.34	.00	21.11	.00	12.19	.06	21.47	.00	12.86	.05	2
240	27.05	.00	9.88	.13	9.44	.15	17.38	.01	3.50	.74	5
241	54.22	.00	15.90	.01	26.28	.00	34.71	.00	10.36	.11	2
242	44.88	.00	35.69	.00	7.98	.24	26.52	.00	34.80	.00	3
243	65.23	.00	29.64	.00	17.95	.01	22.82	.00	9.89	.13	5
244	42.54	.00	22.93	.00	6.96	.32	16.37	.01	6.64	.36	5
245	39.78	.00	32.91	.00	5.21	.52	14.07	.03	14.86	.02	3
246	34.89	.00	19.69	.00	18.48	.01	23.28	.00	13.80	.03	2
247	50.63	.00	33.62	.00	9.01	.17	25.25	.00	20.28	.00	3
248	27.38	.00	12.39	.05	29.53	.00	34.40	.00	11.27	.08	5
249	64.11	.00	34.51	.00	16.22	.01	23.62	.00	13.79	.03	5
250	3.17	.79	13.14	.04	16.13	.01	11.52	.07	6.68	.35	1
251	4.43	.62	16.88	.01	16.13	.01	17.45	.01	11.59	.07	1
252	2.64	.85	7.53	.27	9.00	.17	13.11	.04	11.72	.07	1
253	4.48	.61	15.14	.02	18.50	.01	15.76	.02	6.31	.39	1
254	3.47	.75	10.02	.12	22.05	.00	15.26	.02	9.72	.14	1
255	1.79	.94	8.75	.19	15.43	.02	12.65	.05	12.47	.05	1
256	5.67	.46	14.22	.03	21.43	.00	20.19	.00	9.70	.14	1
257	2.10	.91	8.12	.23	18.83	.00	14.87	.02	6.81	.34	1
258	4.12	.66	10.02	.12	21.77	.00	19.83	.00	12.54	.05	1
259	5.12	.53	13.53	.04	21.90	.00	21.46	.00	14.13	.03	1
260	3.51	.74	7.22	.30	18.25	.01	15.32	.02	6.42	.38	1
261	19.34	.00	4.67	.59	47.54	.00	40.19	.00	23.48	.00	2
262	10.90	.09	23.36	.00	31.39	.00	29.93	.00	27.61	.00	1
263	23.47	.00	26.91	.00	14.47	.02	25.13	.00	29.90	.00	1
264	10.34	.11	11.05	.09	34.42	.00	29.86	.00	21.07	.00	1
265	2.28	.89	6.75	.35	21.76	.00	17.71	.01	9.32	.16	1
266	13.12	.04	3.93	.69	35.08	.00	32.11	.00	19.49	.00	2
267	9.91	.13	4.26	.64	31.68	.00	31.12	.00	21.59	.00	2

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
268	24.34	.00	10.26	.11	54.67	.00	46.30	.00	43.60	.00	2
269	4.88	.56	7.12	.31	11.93	.06	18.10	.01	9.47	.15	1
270	14.38	.03	2.22	.90	33.84	.00	31.94	.00	24.87	.00	2
271	4.67	.59	10.01	.12	16.28	.01	12.78	.05	11.28	.08	1
272	12.15	.06	5.45	.49	14.57	.02	24.46	.00	18.89	.00	2
273	33.50	.00	8.66	.19	43.34	.00	44.46	.00	31.27	.00	2
274	5.71	.46	4.34	.63	12.12	.06	16.81	.01	13.14	.04	1
275	2.71	.84	6.98	.32	20.08	.00	17.19	.01	9.45	.15	1
276	5.41	.49	9.73	.14	16.96	.01	20.58	.00	13.70	.03	1
277	4.23	.65	6.17	.40	17.49	.01	18.60	.00	14.31	.03	1
278	6.07	.42	2.71	.84	22.18	.00	21.19	.00	15.19	.02	2
279	7.34	.29	1.39	.97	17.55	.01	20.86	.00	12.24	.06	2
280	6.39	.38	4.47	.61	19.80	.00	19.22	.00	13.50	.04	2
281	7.41	.28	4.27	.64	23.67	.00	24.39	.00	21.00	.00	2
282	7.30	.29	2.02	.92	24.20	.00	24.05	.00	14.70	.02	2
283	10.00	.12	2.26	.89	21.83	.00	24.25	.00	15.64	.02	2
284	13.97	.03	4.81	.57	30.94	.00	30.72	.00	18.06	.01	2
285	12.40	.05	5.88	.44	19.98	.00	27.73	.00	23.06	.00	2
286	16.53	.01	5.32	.50	25.92	.00	29.10	.00	25.60	.00	2
287	10.73	.10	4.24	.64	25.65	.00	27.20	.00	24.66	.00	2
288	13.55	.04	4.76	.58	27.76	.00	29.95	.00	18.62	.00	2
289	15.60	.02	5.34	.50	24.07	.00	27.65	.00	20.65	.00	2
290	26.02	.00	5.84	.44	33.00	.00	36.70	.00	29.98	.00	2
291	24.12	.00	5.48	.48	36.54	.00	39.73	.00	33.40	.00	2
292	5.69	.46	9.65	.14	22.40	.00	20.24	.00	21.10	.00	1
293	3.16	.79	6.55	.36	19.85	.00	15.62	.02	5.07	.53	1
294	13.22	.04	15.71	.02	39.79	.00	38.20	.00	20.69	.00	1
295	3.16	.79	5.64	.47	16.91	.01	14.71	.02	3.77	.71	1
296	2.04	.92	4.53	.61	14.79	.02	15.27	.02	10.44	.11	1
297	3.92	.69	4.34	.63	18.87	.00	18.60	.00	10.23	.12	1
298	4.71	.58	7.87	.25	27.41	.00	26.60	.00	17.61	.01	1
299	5.52	.48	8.36	.21	31.22	.00	25.74	.00	14.10	.03	1
300	4.93	.55	3.55	.74	24.73	.00	20.85	.00	8.62	.20	2
301	10.80	.09	3.09	.80	30.92	.00	27.79	.00	9.41	.15	2
302	8.27	.22	1.99	.92	24.46	.00	22.87	.00	7.16	.31	2
303	22.39	.00	14.13	.03	44.96	.00	46.12	.00	49.36	.00	1
304	10.48	.11	3.69	.72	35.83	.00	31.27	.00	18.81	.00	2
305	14.76	.02	5.19	.52	44.41	.00	38.30	.00	24.78	.00	2
306	7.07	.31	3.90	.69	14.51	.02	17.71	.01	10.08	.12	2
307	12.51	.05	9.71	.14	31.88	.00	37.02	.00	19.31	.00	2
308	6.28	.39	2.78	.84	20.76	.00	21.37	.00	13.78	.03	2
309	17.08	.01	3.04	.80	32.45	.00	31.12	.00	13.49	.04	2
310	4.71	.58	2.75	.84	15.78	.01	15.90	.01	6.28	.39	2
311	44.05	.00	14.81	.02	55.57	.00	59.85	.00	58.07	.00	2
312	15.45	.02	4.55	.60	27.11	.00	32.64	.00	21.48	.00	2

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
313	9.63	.14	5.37	.50	21.73	.00	25.34	.00	13.70	.03	2
314	29.82	.00	4.73	.58	46.98	.00	41.34	.00	30.65	.00	2
315	17.39	.01	2.52	.87	27.24	.00	31.99	.00	20.29	.00	2
316	10.74	.10	6.69	.35	16.93	.01	19.40	.00	5.01	.54	5
317	17.63	.01	4.12	.66	25.82	.00	30.03	.00	12.78	.05	2
318	20.13	.00	5.24	.51	24.16	.00	31.12	.00	13.29	.04	2
319	12.17	.06	9.79	.13	18.13	.01	21.71	.00	6.87	.33	5
320	11.21	.08	7.29	.29	15.43	.02	23.60	.00	12.62	.05	2
321	12.59	.05	3.09	.80	17.25	.01	21.42	.00	6.75	.35	2
322	8.85	.18	13.20	.04	19.46	.00	25.76	.00	21.24	.00	1
323	20.41	.00	9.47	.15	37.06	.00	41.44	.00	33.00	.00	2
324	3.74	.71	7.51	.28	13.40	.04	15.42	.02	5.46	.49	1
325	11.62	.07	3.27	.77	27.62	.00	28.59	.00	17.03	.01	2
326	7.19	.30	4.68	.59	15.12	.02	17.84	.01	5.19	.52	2
327	3.14	.79	10.69	.10	11.80	.07	12.71	.05	4.48	.61	1
328	7.61	.27	4.77	.57	16.17	.01	18.19	.01	6.30	.39	2
329	3.62	.73	10.11	.12	11.51	.07	11.24	.08	2.51	.87	5
330	4.94	.55	13.24	.04	19.53	.00	15.62	.02	5.70	.46	1
331	13.61	.03	6.12	.41	29.68	.00	30.67	.00	13.96	.03	2
332	19.67	.00	4.03	.67	31.47	.00	35.39	.00	20.81	.00	2
333	11.17	.08	7.41	.28	26.75	.00	25.81	.00	9.21	.16	2
334	15.22	.02	7.89	.25	36.36	.00	35.13	.00	15.83	.01	2
335	12.67	.05	2.17	.90	25.28	.00	24.33	.00	8.61	.20	2
336	11.83	.07	3.42	.75	27.56	.00	29.53	.00	15.39	.02	2
337	45.65	.00	12.25	.06	60.86	.00	53.50	.00	48.76	.00	2
338	20.27	.00	6.63	.36	18.33	.01	27.80	.00	16.24	.01	2
339	5.96	.43	12.61	.05	22.94	.00	16.11	.01	7.96	.24	1
340	13.21	.04	2.24	.90	33.33	.00	31.39	.00	16.82	.01	2
341	13.60	.03	0.98	.99	33.56	.00	30.12	.00	18.31	.01	2
342	21.33	.00	2.83	.83	41.95	.00	37.80	.00	28.32	.00	2
343	11.13	.08	6.35	.38	29.24	.00	30.46	.00	11.38	.08	2
344	11.18	.08	7.33	.29	27.36	.00	25.58	.00	6.57	.36	5
345	13.66	.03	2.91	.82	31.92	.00	30.27	.00	12.48	.05	2
346	16.65	.01	0.99	.99	31.34	.00	30.11	.00	13.77	.03	2
347	20.81	.00	5.00	.54	29.66	.00	32.51	.00	11.27	.08	2
348	16.94	.01	1.64	.95	23.98	.00	25.76	.00	9.19	.16	2
349	15.03	.02	1.50	.96	25.58	.00	26.44	.00	11.40	.08	2
350	23.18	.00	3.22	.78	33.41	.00	32.49	.00	13.67	.03	2
351	15.67	.02	5.72	.46	32.33	.00	28.82	.00	9.55	.14	2
352	12.34	.05	1.51	.96	22.16	.00	22.63	.00	7.84	.25	2
353	19.78	.00	2.87	.83	33.31	.00	31.57	.00	15.68	.02	2
354	10.28	.11	3.59	.73	24.05	.00	23.91	.00	5.74	.45	2
355	27.27	.00	4.35	.63	49.28	.00	43.19	.00	26.83	.00	2
356	18.57	.00	4.19	.65	23.46	.00	29.02	.00	16.74	.01	2
357	22.65	.00	3.19	.78	31.47	.00	32.65	.00	17.39	.01	2

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
358	20.24	.00	4.56	.60	25.95	.00	30.34	.00	13.08	.04	2
359	28.50	.00	3.92	.69	37.48	.00	39.28	.00	24.23	.00	2
360	12.21	.06	2.65	.85	28.78	.00	28.68	.00	13.82	.03	2
361	2.80	.83	6.78	.34	21.19	.00	18.38	.01	7.90	.25	1
362	4.97	.55	8.49	.20	30.06	.00	26.07	.00	15.69	.02	1
363	16.27	.01	3.53	.74	33.22	.00	30.78	.00	18.12	.01	2
364	25.48	.00	3.80	.70	34.05	.00	35.56	.00	21.58	.00	2
365	10.79	.09	18.48	.01	25.07	.00	16.93	.01	6.81	.34	5
366	10.06	.12	6.08	.41	11.55	.07	21.38	.00	10.04	.12	2
367	15.43	.02	1.03	.98	30.03	.00	28.54	.00	16.08	.01	2
368	15.84	.01	3.69	.72	41.08	.00	34.45	.00	22.11	.00	2
369	37.75	.00	7.34	.29	51.22	.00	48.44	.00	33.46	.00	2
370	31.32	.00	8.62	.20	61.21	.00	52.21	.00	39.73	.00	2
371	18.82	.00	11.76	.07	29.33	.00	27.99	.00	9.37	.15	5
372	30.23	.00	11.74	.07	67.59	.00	51.68	.00	44.95	.00	2
373	7.11	.31	1.99	.92	17.60	.01	17.85	.01	4.94	.55	2
374	42.86	.00	12.52	.05	61.54	.00	53.23	.00	35.88	.00	2
375	14.15	.03	18.60	.00	16.36	.01	16.66	.01	19.53	.00	1
376	5.12	.53	8.43	.21	9.81	.13	12.82	.05	8.49	.20	1
377	11.04	.09	11.32	.08	15.04	.02	17.83	.01	7.51	.28	5
378	3.38	.76	9.97	.13	16.22	.01	12.40	.05	4.77	.57	1
379	5.54	.48	14.90	.02	11.26	.08	14.55	.02	10.19	.12	1
380	5.66	.46	13.99	.03	24.80	.00	21.87	.00	17.36	.01	1
381	10.04	.12	11.27	.08	18.96	.00	25.35	.00	14.70	.02	1
382	8.40	.21	12.57	.05	13.42	.04	17.60	.01	9.26	.16	1
383	6.14	.41	7.78	.25	10.74	.10	16.91	.01	12.10	.06	1
384	8.88	.18	15.33	.02	11.88	.06	15.55	.02	8.67	.19	1
385	3.78	.71	5.15	.52	9.43	.15	13.33	.04	5.62	.47	1
386	5.93	.43	13.56	.03	15.80	.01	18.11	.01	11.17	.08	1
387	3.21	.78	10.78	.10	12.76	.05	10.49	.11	2.69	.85	5
388	17.01	.01	13.64	.03	6.82	.34	16.80	.01	11.66	.07	3
389	11.15	.08	9.64	.14	7.82	.25	15.20	.02	9.55	.14	3
390	3.26	.78	10.40	.11	20.03	.00	16.95	.01	9.02	.17	1
391	11.27	.08	9.81	.13	15.79	.01	20.19	.00	10.74	.10	5
392	15.91	.01	9.81	.13	30.05	.00	33.63	.00	16.64	.01	2
393	2.24	.90	12.04	.06	14.46	.02	14.03	.03	9.76	.14	1
394	2.89	.82	10.17	.12	17.37	.01	13.02	.04	4.32	.63	1
395	3.99	.68	6.71	.35	15.69	.02	17.33	.01	13.54	.04	1
396	12.48	.05	10.93	.09	28.87	.00	29.57	.00	15.14	.02	2
397	10.56	.10	10.16	.12	11.22	.08	14.32	.03	2.56	.86	5
398	12.89	.04	10.13	.12	26.09	.00	25.03	.00	6.48	.37	5
399	4.57	.60	9.89	.13	13.48	.04	13.20	.04	3.43	.75	5
400	16.95	.01	11.86	.07	32.02	.00	31.90	.00	21.68	.00	2
401	8.16	.23	9.33	.16	24.28	.00	24.13	.00	7.27	.30	5
402	19.84	.00	21.91	.00	16.38	.01	20.00	.00	8.72	.19	5

Table G (cont.)
Mahalanobis distance for each case for each K-Means derived cluster

Case	K1	p=	K2	p=	K3	p=	K4	p=	K5	p=	Cluster
403	14.76	.02	17.73	.01	4.23	.65	10.06	.12	5.81	.45	3
404	9.63	.14	16.00	.01	16.02	.01	12.88	.04	3.50	.74	5
405	8.36	.21	15.14	.02	11.08	.09	11.39	.08	3.19	.79	5
406	4.45	.62	9.46	.15	18.29	.01	14.62	.02	4.69	.58	1
407	7.43	.28	12.63	.05	17.04	.01	17.81	.01	7.02	.32	5
408	14.77	.02	12.03	.06	30.43	.00	31.80	.00	7.48	.28	5
409	11.58	.07	6.84	.34	23.14	.00	22.43	.00	4.16	.66	5
410	19.58	.00	9.79	.13	26.82	.00	26.24	.00	7.97	.24	5
411	20.48	.00	17.19	.01	36.67	.00	38.57	.00	23.41	.00	2
412	43.20	.00	39.51	.00	8.81	.18	32.49	.00	45.98	.00	3
413	20.67	.00	12.94	.04	31.73	.00	34.17	.00	10.24	.12	5
414	7.65	.27	18.09	.01	18.41	.01	20.52	.00	15.20	.02	1
415	5.69	.46	12.97	.04	9.35	.15	9.33	.16	3.40	.76	5
416	11.54	.07	22.55	.00	13.48	.04	19.53	.00	8.90	.18	5
417	29.73	.00	32.07	.00	6.45	.37	20.97	.00	28.50	.00	3
418	8.02	.24	15.24	.02	10.05	.12	12.84	.05	4.77	.57	5
419	4.99	.55	11.10	.09	9.37	.15	10.71	.10	3.08	.80	5
420	8.53	.20	13.24	.04	7.87	.25	15.67	.02	8.78	.19	1