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To the Graduate Council:

I am submitting herewith a dissertation written by Kerry Towler entitled "An Investigation of Automaticity in Learning Disabled (LD) and Non-Clinical Adults." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Psychology.

Teresa A. Hutchens, Joel F. Lubar, Major Professor

We have read this dissertation and recommend its acceptance:

Debora R. Baldwin, Tara S. Wass

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Joel F. Lubar, Co-Major Professor

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and recommend its acceptance:

Debora R. Baldwin

Tara S. Wass

Accepted for the Council:

Vice Chancelor and Dean of
Graduate Studies

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2006b
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An Investigation of Automaticity in Learning Disabled (LD) and Non-Clinical Adults

A Dissertation

Presented for the Doctor of Philosophy Degree

The University of Tennessee, Knoxville

Kerry Towler

December 2006

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ABSTRACT

Dyslexia research has implicated phonetic dysfunction in the phoneme-grapheme associations which underlie reading skills. Expert readers of normal developmental etiology have required less mental effort, faster processing speed, and reduced focal attention when applying reading subskills. Readers with dysphonia and poorly automatized reading subskills have required more time, mental effort, and attention. Dyslexia automaticity deficit has been attributed to left hemisphere neuro-cortical disruptions of the underlying neurological substrata that support developmental acquisition of reading subskills. Effects of inefficiently automatized phoneme-grapheme skills accumulate over time resulting in poor reading skills that are detrimental to academic achievement.

Using neuropsychological methodology, adults with dysphonetic dyslexia were selected for automaticity investigation via psychometrics and quantitative electroencephalography. Clinical group inclusion criteria included a current Learning Disability (LD) diagnosis in the reading skills domain and dysphonia evidence. LD and non-clinical (NC) adult volunteers were characterized by phonetic ability after administration of selected subtests of Woodcock Johnson, Revised, Achievement Tests, namely, Word Attack, Letter-Word Identification, and Passage Comprehension. Neuropsychological automaticity tasks included Rapid Automatized Naming, Rapid Alternating Stimuli, and Color-Word Stroop. Response time and Stroop-effect data were recorded. Passive electroencephalographic data collection technique allowed access to remnant cortical activity after the performance of automaticity tasks. Active task

electroencephalographic data was collected during the performance of Congruent and Incongruent Stroop subtests.

Automaticity in this LD sample was characterized by slower response times and comparable cortical activation to NC group; the LD group required more time, but used similar cortical activation to achieve the same outcome of the NC group. Response time data, related to speed of processing, demonstrated that the LD participants required more time to complete the neuropsychological tasks; however the differences of some response time results disappeared when covaried with age. Electrophysiological data, reflecting cortical activation and mental effort, demonstrated comparable between group activations during both the passive and active recording tasks for left frontal and temporal cortical target locations. Some support was found for the semantic processing interpretation for the Color-Word Stroop.

TABLE OF CONTENTS

CHAPTER ONE..... 1

Introduction..... 1

Diagnostic Models..... 3

Model Foundations..... 3

The Discrepancy Model..... 4

The Neuropsychological Model..... 7

Synopsis..... 8

Dyslexia..... 9

Cognitive Deficits..... 9

Theories of Etiology..... 13

Neuroimaging Evidence..... 16

Quantitative Electroencephalography..... 17

Cognitive Automatization..... 24

Automaticity..... 24

Tests of Automaticity..... 30

Automaticity and Neurophysiology..... 34

Automaticity and QEEG..... 38

Statement of the Problem..... 42

Research Hypotheses..... 43

CHAPTER TWO..... 46

Methodology..... 46

Participants..... 46

Recruitment..... 46

Procedures..... 48

Psychometric Measures..... 49

EEG Recording..... 56

CHAPTER THREE..... 60

Results..... 60

Participants..... 61

Non-Clinical Sample..... 61

Learning Disability Sample..... 61

Data Analysis..... 65

Psychometric Measurement..... 65

Exploratory Analysis..... 67

Automaticity Measures..... 67

Additional Analyses..... 75

EEG Recording..... 77

CHAPTER FOUR..... 85

Discussion..... 85

Overview..... 85

Group Criteria Comparisons..... 86

Automaticity..... 90

Psychometric Measures..... 90

The First Hypothesis..... 91

Response Times..... 91

Evaluation of First Hypothesis..... 96

Electrophysiological Measures..... 97

QEEG Baselines..... 99

The Second Hypothesis..... 100

Passive Recordings..... 101

Evaluation of the Second Hypothesis..... 105

The Third Hypothesis..... 107

Active Recordings..... 107

Evaluation of the Third Hypothesis..... 108

Semantic Abilities and Stroop..... 108

Study Limitations and Future Directions..... 109

Limitations of the Present Investigation..... 109

Implications for Clinical Applications..... 112

Implications for Future Research..... 113

Concluding Comments..... 116

REFERENCES..... 119

APPENDICES..... 136

VITA..... 159

LIST OF TABLES

Table 1: Profile of Mood States (POMS): Group Comparisons of Subscale Scores.. 62

Table 2: Mean Age Comparisons..... 64

Table 3: Psychometrics: Group Mean Scores Comparisons..... 66

Table 4: Psychometrics: Subtyped LD Group Mean Scores Comparisons 68

Table 5: Omnibus Tests for Response Time Data by Task 70

Table 6: Rapid Automatized Naming (RAN): Group Mean Response-Time Comparisons 71

Table 7: Rapid Alternating Stimuli (RAS): Group Mean Response-Time Comparisons..... 73

Table 8: Color-Word Stroop: Group Mean Comparisons..... 74

Table 9: Response Times Correlations with Age: Rapid Automatized Naming and Color-Word Stroop Subtests..... 76

Table 10: Multivariate Analysis of Variance (MANOVA): Tests for Baseline Group Effects at Electrodes F7 and T5 by Waveform..... 79

Table 11: Multivariate Analysis of Variance (MANOVA): Tests of Group Effects for Passively Collected Data..... 82

Table 12: Multivariate Analysis of Variance (MANOVA): Tests of Group Effects by Task for Active Tasks..... 84

Table 13: Future Research with the Incongruent-Task: The Posterior Attention System (PAS) and the Posterior Parietal Electrodes 115

Table G-1: Baselines: Descriptive Statistics of Group Data..... 153

Table H-1: Passive Tasks: Descriptive Statistics of Group Data..... 155

Table H-2: Passive Tasks: Descriptive Statistics of Color-Word Stroop Subtest Data..... 156

Table I-1: Active Tasks: Descriptive Statistics of Group Data..... 158

LIST OF FIGURES

Figure 1: RAN and RAS Stimulus Elements: Colors, Objects, Numbers, Letters, and Words..... 52

Figure 2: Traditional Stroop Stimuli: Congruent and Incongruent, respectively..... 54

Figure 3: The Stroop Stimuli Organized into Block Format for Naming Tasks..... 55

Figure 4: Future Research with the Incongruent-Task..... 117

ABBREVIATIONS

AAS	Anterior Attention System
ADHD	Attention Deficit Hyperactivity Disorder
ANOVA	Analysis of Variance
BRNL	UT Brain Research and Neuropsychology Laboratory
C-WS	Color-Word Stroop
DSM-IV	Diagnostic and Statistical Manual of Mental Disorders – Fourth Edition
EEG	Electroencephalography
EC	Eyes-Closed baseline
EO	Eyes-Opened baseline
EP/ERP	Evoked/Event-Related Potentials
fMRI	functional Magnetic Resonance Imaging
FSIQ	Full Scale Intelligence Quotient
FZ, CZ, PZ	Central-midline electrodes
HZ	Hertz
IDEA(-R)	Individuals with Disabilities in Education Act
IQ	Intelligence Quotient
LD	Learning Disability
M	Mean
MEG	Magnetoencephalography
MANCOVA	Multivariate Analysis of Covarianc
MANOVA	Multivariate Analysis of Variance

MRI	Magnetic Resonance Imaging
NALD	Neuropsychological Assessment of Learning Disabilities checklist
ODS	UT Office of Disability Services
PET	Positron Emission Tomography
PAS	Posterior Attention System
PIQ	Performance Intelligence Quotient
POMS-R	Profile of Mood States-Revised
PPVT-III	Peabody Picture Vocabulary Test – Third Edition
QEEG	Quantitative Electroencephalography
RDM	Regression Discrepancy Model
RAN	Rapid Automatized Naming
RAS	Rapid Alternating Stimuli
SD	Standard Deviation
SDM	Simple Discrepancy Model
SS	Standard Scores
TAC	The Assessment Center
TNWASC	Tennessee Wesleyan's Academic Success Center
VIQ	Verbal Intelligence Quotient
WJ-R-A	Woodcock Johnson Psychoeducational Battery-Revised, Tests of Achievement

CHAPTER ONE

Introduction

Historically, learning disabilities (LD) definitions reflected the context of investigative practices but did not demonstrate consistent diagnostic efficacy. Defining LD has been as difficult today as it was 30 years ago (Lyon, et al., 2001). Federal law, The Education of All Handicapped Children Act (Federal Register, 1976), attempted to combine neurological foundations with psychometric practice to systematize LD identification; this mandate of 1975 was a part of the provision of a free and appropriate education in the least restrictive environment for all children (Harwell, 2001). Children with learning difficulties were often classified as retarded or minimally brain damaged, alluding to the neurological nature of the myriad problems of learning disabilities.

Federal legislation on LD identification was initially influenced by prevailing assessment practices, which included intelligence testing (IQ) testing (Berninger, 2001). The consequence to policy was a rule-based approach to LD diagnosis called discrepancy analysis. This formulation eased implementation within an organizational structure whose assessment professionals had little neurological/clinical training. The effect was poorly validated psychometric identification methods which have resulted in the over identification of individuals with learning problems (Fletcher, et al., 1998). Heterogeneous samples have challenged the internal validity of empirical study, which has complicated the use of both psychometrics and brain-imaging technology for examination of learning disabilities. Professionals from all aspects of the field have called for change to improve empirical validation and, ultimately, meet the needs of all students

(Berninger, 2001; Fetcher, et al., 2001; Francis, Fletcher, Shaywitz, Shaywitz, & Rourke, 1996; Morgan, Singer-Harris, Bernstein, & Waber, 2000).

Much of the research in learning disabilities has been based upon reading disability, which has been investigated more thoroughly than other LD domains because it is the most common and pervasive academic issue (Bigler, Lajiness-O'Neill, & Howes, 1998; Fletcher, et al., 1998; Harwell, 2001). The term dyslexia, a formal term for the dysfunctional reading, has been applied to a broad range of potential dysfunctions of expressive, written, or reading function. The cognitive deficits associated with dyslexia have been thought to reside in any number of basic nonacademic subskills, such as accuracy in the perception of language sounds, visual discrimination of graphemes, and visual letter/word association, all of which contribute to reading as an academic skill. Component subskills have been shown to develop differently or less efficiently due to clinical differences in neural organization (Hynd & Semrud Clikeman, 1989; Wolf, Bowers, & Biddle, 2000).

With a large portion of the left hemisphere of the brain implicated in language function, numerous component sources of neural dysfunction have the potential to create functional deficits. Diagnostics based solely upon psychometric discrepancies would thus be problematic. The automatization of reading subskills has been shown to be a serial sequence of component cortical subskills, any of which can disrupt the reading process if dysfunctional (Berninger, 2001; Wolf, Bally, & Morris, 1986). The specific processing deficit has been shown to determine the specific behavior as it has been manifested in the numerous component skills of reading behavior. The literature base

resulting from imprecise diagnostic practices has presented challenges for group heterogeneity and interpretation in research.

The neuropsychological identification of dyslexia has been an appropriate response to the current methodological inconsistency, in part, because of the focus on individual skills. Clinical methodologies, brain imaging, and scientist-practitioners have provided evidence for this position (e.g. Allen, 2002; Gaddes & Edgell, 1994; Hebben & Milberg, 2002); however, the converging body of data has not been integrated easily into entrenched educational assessment practices. Future diagnostic practices including the education and application of neuropsychological LD identification techniques has been projected. Other areas of potential impact on learning disability diagnosis are also projected to include effective identification and subsequent classification of domain specific LD subtype definitions and the access to inexpensive brain imaging methods.

Diagnostic Models

Model Foundations

Federal law, P.L. 94–142, provided definitional guidance for LD identification by forwarding the primary criterion of a chronic discrepancy between intellectual potential and academic achievement (Federal Register, 1976). Exclusionary criteria were added to insure that the achievement deficits which were the result of mental retardation, limited instruction, sensory handicap (i.e. visual, auditory, or motor), and emotional disturbance were not diagnosed as learning disabilities nor inappropriately served within the categorical LD model (Mercer, Jordan, Allsopp, & Mercer, 1996). Definitions used in the diagnostic process of LD/dyslexia have left room for interpretation making the process less than efficacious (Fletcher, et. Al., 2001).

Individuals with Disabilities in Education Act (IDEA) (1990) was a response to state specific interpretation of the Federal model. This mandate, IDEA and IDEA-R, encouraged the use of the term *specific* learning disabilities because of the continued requirement that the diagnostic definition include the specific manifestation and the underlying specific skills deficit. Diagnoses included both the associated expressive or receptive skills deficits and their resultant manifestations in reading, writing, and mathematics (Harwell, 2001). The functional abnormality in the perceptual, comprehensive, verbal or nonverbal domains, were defined as constitutional to the individual.

Two models of practice have emerged in formal assessment of learning disabilities: neuropsychological assessment and discrepancy analysis. Neuropsychological assessment has a history of specific skills identification and has an efficacious platform for dyslexia identification. The majority of states with formal LD identification criteria, however, have utilized discrepancy analysis.

The Discrepancy Model

Discrepancy models were constructed on the function of the intelligence quotient (IQ) as an ability measure to predict academic success while presuming that academic skills difficulties were effectively demonstrated by a measure of achievement. Federal LD identification requirements have been met in many states by subtracting an achievement score from a test of ability like that of IQ. In this model, subtracting a standard reading or math achievement score from an IQ score, a simple discrepancy, has come to be diagnostic of the dysfunction (Mercer, et al., 1996; Warner, Dede, Garvan, & Conway, 2002). The discrepancy was designed originally to reflect magnitude of need

and has since been used exclusively in some states' interpretations of the mandate. The problem in this has been an absence of differential diagnosis, i.e. discriminating those with a learning disability forms other types of reading problems. Rates of LD diagnosis have soared (Harwell, 2001). Students who are served by LD programs, in fact, may need services in a different model appropriate to the source of the individual reading problem.

Discrepancy criteria for diagnostics have varied between states and even between school districts (Gaddes & Edgell, 1994; Harwell, 2001; Morgan, et al., 2000; Peterson & Shinn, 2002). A child identified with dyslexia in Tennessee may not be identified similarly in another state. Increasingly, researcher-practitioners have defined the insufficiency of the discrepancy approach in terms of children being misidentified (Berninger, 2001; Fletcher, et al., 1998; Fletcher, et al., 2001; Francis, et al., 1996; Morgan, et al., 2001; Warner, et al., 2002).

The Simple Discrepancy Model (SDM) emerged as a common practice (Peterson & Shinn, 2002). Unfortunately, this formula has not accounted for the correlation of the IQ and achievement measures or their range of reliability (Van de Broeck, 2002). In addition, this model has failed to require identification of the cognitive processing deficit underlying achievement difficulties and the requisite magnitude of the discrepancy has been variable between states (Peterson & Shinn, 2002).

The Regression Discrepancy Model (RDM) extended the basic model and remains another application of the discrepancy theory (Peterson & Shinn, 2002). This method applied the principles of the discrepancy between academic achievement scores and IQ testing, but also employed principles of statistical regression to identify the

magnitude of the deficit. Through statistical regression techniques, standard scores of intellectual ability (IQ) and achievement are regressed to reveal an expected achievement score (Evans, 1993). The expected achievement score, based upon its statistically predicted relationship to IQ, is compared to the obtained achievement score. If falling outside a preset statistical limit, such as 2-standard deviations (SD), considering the measurement error distribution about the discrepancy, then it is deemed severe enough to warrant placement. Statistical phenomena inherent to regression methodology, in particular, regression-to-the mean and the high correlation between IQ and achievement, is carefully attended (Evans, 1993; Fletcher, et al. 1998).

The use of standardized cognitive measurement in LD discrepancy methods was based on a foundational premise that such measure was a valid reflection of intellectual ability (Francis, et al., 1996). The history of intelligence testing is rich with such study; however, the composite IQ score without internal consistency and internal reliability checks, has interpretive difficulty. One of the many chronic problems with discriminating achievement difficulties has been in the use of IQ scores with statistically different constituent scores. Often, sufficient analyses have not been done to investigate the component score differences. Thus, because of the deviation intelligence quotient's recombinant nature, the Full Scale IQ (FSIQ) may not be valid to predict global ability (Kaufman & Lichtenberger, 1999; Reitan & Wolfson, 1996). For example, significant differences between and within the global components, such as the Verbal IQ (VIQ) and Performance IQ (PIQ), have been shown to be integral to some types of cognitive deficits, including learning disabilities. The absence of internal validity requirements has challenged the very foundation on which the discrepancy model was built. An additional

criticism of RDM has been its inherent manipulation of the error term during regression calculations (Van de Broeck, 2002). The error term, a mathematical representation of measurement error, when calculated according to parametric assumptions, could influence the predicted achievement score, and could inappropriately suggest achievement deficits.

LD discrepancy identification has inversely fostered the idea that all learning discrepancies have a basis in neural functionality, which is not the case. Without the use of discriminately applied reliable assessment tools and the concurrent use of exclusionary criteria, overidentification, i.e. false positives, creates heterogeneity within a single diagnostic (sub) type. Thus, the SDM and RDM has affected efficacious intervention planning and characterization of heterogeneous learning disability samples.

The Neuropsychological Model

The neuropsychological model was predicated upon the idea that cognitive, academic processing and non-academic cognitive abilities are neurologically supported. For years, neuropsychological sampling of behavior included the use of psychometrics and provided inferences about CNS integrity (e.g., Hebben & Milberg, 2002). From a background of historic inferences, contemporary study has shown real-time, functional relationships between neural substrates and specific academic skills. Direct neural measurement, which differentiates academic tasks, has supported the efficacy of this model. Neuropsychological evaluation procedures and assessment instruments have discriminated students with learning difficulties from normally-achieving peers, mild from severe learning disabilities, and students with LD from other poor achievers (Hutchens, 1988; Morgan, et al., 2000). Systematic and comprehensive evaluation has

included developmental, academic, medical and education histories through clinical methodology to establish an evidentiary pattern of specific processing deficits (Allen, 2002; Berninger, 2001). The sampling of behavior and information provided from many sources and settings has proven essential for ecological validation of skills strengths and weaknesses. Such data have provided insight into the clinical evaluation of the developmental qualitative differences in emergent types of academic deficits.

These differences in the origins of academic deficits may be found in the exclusionary criteria identified by federal mandate. Variables for exclusion were identified because of their negative impact upon achievement; however, they have been shown to be of different etiology compared to developmental learning disabilities (e.g., lack of instructional opportunity, depression, anxiety, etc.). Formal assessment of cognitive ability and academic achievement may be analyzed beyond a simple score comparison and has the potential to identify specific deficits in academic and specific nonacademic cognitive processing underlying the academic area of need. The neuropsychological model has provided discriminate evaluation of skills and processes that remove the ambiguity from LD identification. It has proven to be a superior diagnostic process whereby differential diagnosis in LD identification reflects a true skill deficit (Allen, 2002; Berninger, 2001; Gaddes & Edgell, 1994).

Synopsis

Two methods of differential diagnosis, the discrepancy approach and the neuropsychological approach, have been used to meet federal requirements for LD identification. The discrepancy approach, an inferential educational model, has been applied as a general representation of federal law that relies predominantly on subtracting

standard achievement scores from standard IQ scores for diagnostic purposes. The neuropsychological method, by contrast, has used a cognitive processing model requiring the identification of the nonacademic cognitive deficit that produced an academic problem. These two diagnostic methods are not mutually exclusive. Each has used similar diagnostic elements to discriminate between samples of non-clinical and learning disability, however, the former represents a mechanical practice while the latter a comprehensive, differential approach. The majority of states with formal LD identification criteria have utilized discrepancy analysis (Mercer, et al., 1996; Warner, et al. 2002).

Increasingly, researcher-practitioners have acknowledged the insufficiency of the discrepancy approach in terms of children either being missed or misidentified (Berninger, 2001; Fletcher, et al., 1998; Fletcher, et al., 2001; Francis, et al., 1996; Harwell, 2001; Morgan, et al., 2001; Warner, et al., 2002). Neuropsychological methodology has proved a superior diagnostic process whereby LD identification reflects a true skill deficit (Allen, 2002; Berninger, 2001; Gaddes & Edgell, 1994). Alternative diagnostic approaches have been necessitated for better LD subtype specific identification and domain specific treatment (Fletcher, et al. 1998). Increasing the homogeneity of subgroups of LD in research is posited to yield data on common psychometric patterns and neuroanatomical correlations.

Dyslexia

Cognitive Deficits

The cognitive deficits associated with dyslexia have been shown to be developmentally persistent, leaving a legacy of impaired processes that can be observed

in complex cognitive demands such as those required for academic achievement (Hutchens, 1988; Meyer, Wood, Hart, & Felton, 1998). Core features of dyslexia have included poor, slow word identification and decreased reading comprehension. (van der Leij & van Daal, 1999). The acquisition of the knowledge of the sequential nature of speech, the rhythmic alteration between vowels and consonants, and the connection of phonological information to visual components of the written word may not be well developed in individuals with dyslexia (Post, Foorman, & Hiscock, 1997). The cognitive skills of those with reading disability can be developed with age and maturity, which is consistent with expected normal skill development, however these skills are not built with a similar potential. Academic and reading skills are built upon information processing resources that have constructed phoneme-grapheme relationships and automatized skills; ultimately, these have provided foundation for more complex processing tasks. Basic lower-order processes, such as automatized phoneme-grapheme subskills, have been impaired for individuals with dyslexia and have comprised the corrupted building blocks of more complex information processing components, such as metacognitive skills, identified as deficit areas in people with LD (Berninger, 2001; Helland & Asbjornsen, 2000; Hutchens, 1988). Basic automatized processing skills have provided for the development of executive functions for self-regulation of attention processes during learning (Berninger, 2001) and strategies of control for stimulus inputs/organization (Hutchens, 1988). Deficits resulting from impaired processes throughout development have had lifelong impacts (Felton, Naylor, & Wood, 1990; Meyer, et al., 1998).

Reading related academic skills have been described in terms of lower-order and higher-order processes (van der Leij & van Daal, 1999). Lower-order, or bottom-up processing, has been described as emphasizing the analysis of information derived from stimuli (Matlin, 2003; van der Leij & van Daal, 1999). These processes are activated during word and object recognition after the incoming stimulus information has passed through the sensory receptors. Coding subskills, utilized at the bottom level of cortical processing, are applied to information that is then forwarded for increasing levels of organizational complexity. Higher-order, or top-down processing, has been described as emphasizing the influence of concepts, expectations, and memory on word and object recognition, as well as, other cognitive processes (Matlin, 2003). Prior learning and experience, in effect, have been shown to play a role in word recognition by providing the historical organizational context for understanding. Word recognition skills have been shown to be reliant upon bottom-up processing early in learning; as skills are mastered and a repertoire is built, less time and energy is thought to be spent in the lower level processes (Wolf, et al., 1986).

Reading skills mastery has resulted from lower level processes that have been automated such that little effort is used for recognition; thus, the higher order processes have been provided with resources for better comprehension (van der Leij & van Daal, 1999). Another benefit of skills mastery has been shown in speed of processing elements; increased retrieval speed is correlated with increased automatization of reading skills (Wolf, Bally, & Morris, 1986). Top-down processing may be constrained, in people diagnosed with dyslexia, by deficits in bottom-up processing. Subskills supporting reading or other cognitive activities may not have been efficiently coded due to

neurological subtrait abnormalities that are suspected to underlie basic information processes (i.e. bottom-up related). As Berninger (2001) stated, functional systems operate best when component processes have developed at similar levels and rates. An underdeveloped component process of a functional system may have hampered the ability to orchestrate the components in functional synchrony. Imperfectly automatized phoneme-grapheme decoding skills in the functional system supporting reading skills has been posited to interfere with reading fluency.

Students diagnosed with dyslexia have been shown to be sensitive to increases in both task demand and cognitive complexity in reading related tasks (Hutchens, 1988; Morgan, et al., 2000; van der Leij & van Daal, 1999). Performance has distinguished between individuals with dyslexia and their normal achieving peers, especially when choice and multiple subprocess integration have been part of task demands (Wolf, Bowers, & Biddle, 2000). Accordingly, individuals with dyslexia may be required to work harder than normally achieving peers to achieve a similar behavioral effect, particularly in situations of high task demand. The result has been eroded comprehension skills promoted by the inability to manipulate the sound structure of speech (D'Angiulli & Siegel, 2003) and poor automatization of word recognition skills (van der Leij & van Daal, 1999).

Whereas normally-achieving individuals have been expected to reap the benefits of cognitive skills practice, (i.e. increased speed of processing, reduced energy expenditure, and decreased attention requirements) people diagnosed with dyslexia have been hypothesized to perform some simple, familiar tasks in a slower, more variable fashion (Hutchens, 1988). For example, early automatization of decoding skills (e.g.,

phonetic, semantic, and visual) have been thought to be necessary for fluency and sophistication of reading ability (Chall, 1983). Phonological awareness skills have been shown to predict later reading ability (Wolf, et al., 1986) although inconsistently (Hurford, et. Al,1994). Decoding visual stimuli and associating corresponding linguistic labels (i.e. grapheme-phoneme learning) became efficient with time and practice; eventually, conscious attention processes originally tapped during learning are released in normal language processing, (van der Leij & van Daal, 1999). Early development of phonological skills has been shown to be predictive of reading ability in a normal distribution of children (Meyer, et al., 1998; Wolf, et al., 1986) while, conversely, automatization failure of these reading subskills may be demonstrated by slow, laborious, and halting reading behavior (Hutchens, 1988).

Theories of Etiology

Three major theories have been developed to explain behavioral deficits in dyslexic individuals: phonological, cerebellar, and magnocellular (see Ramus, et al., 2003 for review). The phonological theory has described the basic phonological subskill deficit as being responsible for automatization failure. The cerebellar theory has attempted to explain the co-occurrence of fine motor and balance deficits in many dyslexia diagnoses. The magnocellular deficit has pursued pre-cortical neural pathway influences as sources of visual data stream corruption prior to cortical patterning for subskill automatization. These three theories have found support through research.

The phonological theory has made a connection between cognitive phonological deficit and behavioral dysfunction. Neurological connections have been based on the assumption that the disorder is physiological (Hynd, & Semruld-Clikeman, 1989).

Proponents for the phonological theory have suggested that a left hemispheric, peri-sylvian structural abnormality is responsible for a disruption of the normal grapheme-phoneme learning association. The assumption has been that the neural dysfunction lies in brain areas subserving phonological representation and/or connections between phonological and orthographic representations (Ramus, et al., 2003). This theory has importance as two thirds of dyslexic children have reportedly had difficulty with complex phonological processing (Ackerman, Dykman, Oglesby, & Newton, 1994).

Gaddes and Edgell (1994) reported that histological studies have shown instances of normal right hemisphere neural structure with left hemisphere abnormal white matter in dyslexics. The white matter abnormality has been thought to be indicative of a disordered neural migration particular to the peri-sylvian area. If structure determines function, then Galaburda (1984) suggested that a result of this left hemispheric abnormality is acquired anomalous lateralization, indicating that the left hemisphere was unable to acquire the 'normal' specificity of language function due to the structural distortions. A related view has suggested that the phonological insufficiency, accrued over the course of development and not inconsistent with the above, may be the result of a basic auditory deficit (Ramus, et al., 2003).

An alternate supposition has been referred to as the automaticity/cerebellar theory of dyslexia (Ramus, et al., 2003). The cerebellum has been shown to play a role in two areas of concern to dyslexic research: motor control and automatization. Articulate speech requires muscular control; if this process is delayed or dysfunctional, then the subsequent phoneme-grapheme learning could be affected. Phoneme-grapheme learning could be impacted by weakness in automatization, which ordinarily has promoted easy

access and low resource usage in performance of overlearned tasks such as found in speech and reading. Support for this hypothesis has been demonstrated in brain imaging studies. Posner and Raichle (1997) demonstrated cerebellar activation during tasks of reading nouns and verbs aloud. Cerebellar metabolic and activation differences have been demonstrated in individuals with dyslexia when compared to normal controls (Nicolson, et al., 1999). Support for this hypothesis also has been found in poor balance performance during cognitively loaded tasks (Nicolson & Fawcett, 1990). More current research, however, has identified cerebellar deficits in reading disabled only if they have attention deficits concomitant with hyperactivity (Raberger & Wimmer, 2003).

The final major theory attempting to explain reading related deficits has been called the magnocellular theory. Ramus, et al. (2003) called this "…a unifying theory that attempts to integrate…" (p. 843) not only the scope of the previous two theories but also other sensory deficits, such as visual and auditory. The most general view of this theory has proposed that the visual system that has been divided into two pathways, the magnocellular and parvocellular, has been selectively disrupted in the magnocelluar division. This disruption has been postulated to be responsible for a visual speed-of-processing deficit associated with the visual information that passes through the lateral geniculate body (Gaddes & Edgell, 1994). Support for this theory has been reported by Richards (2001); fMRI studies have demonstrated differential task-related functional activation between individuals with dyslexia and those with normal reading ability in the magnocellular system. From the retina through the lateral geniculate where corruption has been thought to occur, this information is passed into the cerebellum, and, therefore,

all potential behavioral outcomes are affected when utilizing the affected neural data stream.

Neuroimaging Evidence

Magnetic resonance imaging, (MRI/functional MRI) has been the method of choice for language research seeking to correlate behavior with brain structure. Most imaging LD research has focused on dyslexia and has implicated left hemisphere abnormalities (Bigler, et al., 1998). Richards (2001) provided a limited summary of MRI and positron emission tomography (PET) findings specific to differences found between those with and without dyslexia diagnoses. Left hemisphere areas implicated in adults with dyslexia for reading tasks have included the angular gyrus, inferior parietal area, prefrontal cortex, occipital lobe, and the insula. Areas implicated in phonological tasks have included Wernicke's area, left angular gyrus, striate cortex, Broca's area, left cerebellum, left thalamus, the striatum, and the insula. Positron emission tomography (PET) studies have demonstrated focal increases in activation in the prefrontal and the medial temporal cortices and have been interpreted as either inefficient processing or activation of compensatory pathways. Ultimately, blood flow studies have implicated either widespread left hemispheric cortical activation differences or differences limited to the posterior left hemisphere (Collins & Rourke, 2003). Also, MRI studies have suggested that the posterior region around the left angular gyrus is dysfunctional in dyslexia (Richards, 2001).

Magnetoencephalography (MEG) studies have reported abnormal functional connectivity for reading in the left ventral visual association and left temporoparietal cortices (Richards, 2001). Helenius, et al. (2002), using MEG, have suggested that a

small sample of Finnish adults with dyslexia demonstrated delayed semantic activation during reading tasks. The delayed activation has been attributed to the planum temporal, and may have reflected difficulty in sound processing. They speculated that the large left hemisphere peak along the posterior temporal plane may represent an aberrant auditory response that activates larger poorly specialized neural populations. Functional magnetic resonance imaging ($_f$MRI) studies have demonstrated left hemisphere activation asymmetry for phonological tasks with those diagnosed with dyslexia overactivating inferior frontal gyrus and underactivating posterior regions that included Wernicke's and the angular gyrus (Richards, 2001). Neuroimaging has demonstrated the importance of the angular gyrus in dyslexia research, however, the nature of its involvement has not been resolved (Collins & Rourke, 2003). Other studies have demonstrated a general reduction of brain activation found in individuals with dyslexia compared to individuals of normal reading ability.

Quantitative Electroencephalography

The electrophysiological literature has provided mixed results relating functional brain relationships to dysfunctional behaviors with LD definitional ambiguity a likely concern (Bigler, et al., 1998; Collins & Rourke, 2003). EEG methods that have been used for dyslexia research have included evoked potentials (EP) or event-related potentials (ERP) and quantitative electroencephalography (QEEG). EP/ERP have been used as measures of cognitive processing efficiency (Bigler, et al., 1998). QEEG has been used to measure real time functional cortical activity/relationships during cognitive activities. Both have been considered non-invasive techniques for measuring brain activity.

ERP waveforms have been classified according to positive or negative peaks and latency, which is post-stimulus time measured for each waveform phenomenon. Each peak, the amplitude, and latency is interpreted as a specific aspect of brain function in response to a specific stimulus. In a review of ERP studies with both children and adults with LD, Collins and Rourke (2003) suggested that mixed results of the representative studies with children prior to1994 were due to heterogeneity in dyslexic samples.

In a review of ERP literature, Collins and Rourke (2003) reported results suggesting that children with dyslexia required more processing time in evaluating stimuli when compared to controls. Their evaluation of developmental ERP literature suggested evidence of functional brain deficits present at birth that have been shown to extend into adulthood. ERP research with dyslexia-at-risk infants has suggested that they process auditory verbal stimuli inefficiently resulting in fuzzy or less precise sound representation of temporal features (i.e. duration) in speech sounds thus predicting the impediment of normal development of timing and perceptual cues of language (Leppanen, et al., 2002). Rubin and Johnson (2002) used ERP to evaluate college students with and without dyslexia and suggested that the semantic processing abilities of the dyslexia group were not as efficient. Unfortunately, Bigler, et al. (1998) have reported that ERP research has provided mixed results in reporting dyslexic differences in the P300 (P3) wave, commonly thought to be associated with cognitive functioning such as that involving language. Some studies have reported hemispheric differences with visually presented verbal material while others have not. Ultimately, the results of these studies have been difficult to replicate and have demonstrated methodological inconsistencies. For example, Bigler, et al. (1998) noted that ERP's vary with age, but

most of the studies reviewed did not attempt to control for this variable. For research to be useful in diagnostic practices, uniformity across studies has been identified as useful in direct comparison of data across the developmental period (Collins & Rourke, 2003).

QEEG data has been computerized and has allowed the digitization and statistical analysis of spectral data utilizing electrical waveform spectra (e.g. 1 hz to 31 hz), (Nuwer, 2003). EEG methods have been considered to have good temporal resolution, but poor spatial localization compared to structural imaging methods. However, EEG has been shown to be sensitive to focal increases in brain electrical activation and amplitude of neural activation during cognitive tasks (Harmony, et al., 1996; Richards, 2001). Consequently, EEG may be more functionally related to the task of reading due to the integration of processes across multiple neural structures. As late as 2003, clinical use of QEEG has been suggested to be worthy of further exploration in clinical research but usefully problematic in the clinical domain (Nuwer, 2003).

A goal of QEEG research has been to demonstrate differential skill lateralization based upon the breakdown of component waveforms into their respective frequencies (Bigler, et al., 1998). Traditionally the broadband frequencies have been defined as delta, 1 to 3.5 Hz, theta, 4 to 7.5 Hz, alpha, 8 to 13 Hz, low beta, 13 to 20.5 Hz, and high beta, 21 to 32 Hz. However, studies have utilized different strategies of analysis including single hertz and subgrouping (e.g. alpha broken into low and high bands). Delta, a low power, high amplitude waveform, has been associated with sleep, cognitive deterioration, brain damage, and internal processing attention (Harmony, et al., 1996). The square-topped waveform known as theta has been associated with attention, cognitive readiness, effortful engagement, and memory encoding (Bigler, et al., 1998; Klimesch, et. Al.,

2001). Alpha has been associated with a resting state, inverse relationship to attention, cognitive memory performance, and focal decrease in activation, such as that found in depression (Faber & Zelinkova, 1996; Klimesch, 1997; Niedermeyer, 1993; Tomarken, Davidson, Wheeler, & Doss, 1992). Finally, low and high beta, highly desynchronized low amplitude waveforms, have been associated with focal activity during cognition (Harmony, et al., 1996; Niedermeyer, 1993). In general, studies based upon clinical samples have attempted to demonstrate abnormal asymmetry or focal activation in participants with dyslexia and those without. The objective has been to identify specific abnormal spectral waveforms that are parallel to brain activity found in anatomical and structural imaging research (Bigler, et al., 1998; Mattson, Sheer, & Fletcher, 1992; Rippon & Brunswick, 2000).

A number of studies have demonstrated hemispheric asymmetry between clinical and non-clinical groups during reading or word tasks (Byring, 1986; Duffy, Denckla, Bartels, & Sandini, 1980; Duffy & McAnulty, 1990; Rumsey, Coppola, Denckla, Hamburger, & Kruesi, 1989). In a group of boys who demonstrated criteria for specific reading or spelling disability, Byring (1986) reported greater right-hemisphere, fronto-centro-temporal activation while the control group's activation was dominant in the left hemisphere during reading. Mattson, Sheer, and Fletcher, (1992) provided 40 Hz activity evidence for left hemispheric mediation of verbal information; the reading disability group had less 40 hz activity than the controls or the arithmetic disability group. Four cortical regions discriminated between participants with and without dyslexia: the medial frontal lobe or supplementary motor area, the left lateral frontal lobe, left midtemporal lobe or auditory associative area, and the left posterior quadrant, which included

Wernicke's area (Duffy, et al., 1980). These regions were associated with higher mean alpha frequency, during reading tasks and dependent upon state; paired associates and reading tasks activated the medial frontal region bilaterally while speech and baselines activated the left midtemporal region. Theta activity was not as prominently altered by state, but group differences were indicated in the left midtemporal, left medial frontal regions, and the right anterolateral frontal region, specifically, Broca's area, for reading state. Duffy and McAnulty (1990) had asserted that dyslexic subgroups had identifiable and differing topographic signatures. They reported that, among other results, boys with dyslexia exhibited more left hemispheric higher amplitude alpha especially in the frontal and temporal regions when compared to controls; they suggested that aberrant electrical activity was compensatory rather than pathological.

Not all studies have shown electrophysiological hemispheric asymmetry differences between participants with dyslexia and those with normal ability. Some research has demonstrated bilateral differences in spectral frequency bands, power, and amplitude during reading, word and phonological tasks (Ackerman, et al, 1998; Faber & Zelinkova, 1996; Flynn, Deering, Goldstein, & Rahban, 1992; Galin, et al., 1992; Rippon & Brunswick, 2000;). Faber and Zelinkova (1996) identified a differential delta pattern during a reading task; the dyslexia participants demonstrated a greater delta increase bilaterally in the central and parietal electrodes when compared to the control participants. Bilateral alpha reports have included children with dyslexia who demonstrated a relatively smaller phonological task-related parietal-occipital alpha suppression (Rippon & Brunswick, 2000); and lower amplitude alpha in the bilateral temporal-occipital areas and midline parietal areas when reading aloud (Flynn, et al.,

1992). Galin and colleagues (1992) reported smaller increases in theta power for boys with dyslexia as compared to normal readers. Data were collected when participants were switching from silent to oral reading tasks. Rippon and Brunswick (2000) reported increased frontal theta amplitude for children with dyslexia during a phonological task. Ackerman and colleagues (1998) noted a negative correlation between response times and delta/theta power ($r = -.349$, $p < .05$) for children with dyslexia during a continuous rapid naming task; slower namers had more overall delta/theta power. Rippon and Brunswick (2000) also reported that their participants with dyslexia produced greater bilateral parieto-occipital low beta during phonological tasks. Similarly, participants identified with dysphonetic dyslexia differed from non-LD by producing less relative beta amplitude in temporal-parietal-occipital locations while reading aloud (Flynn, et al., 1992). Bilateral mid temporal low-beta differed between silent and oral reading tasks for dyslexic boys and they produced a smaller task related increase in high and low beta than controls (Galin, et al., 1992). This direction in children's dyslexia research has demonstrated wide ranging bilateral EEG spectral results.

Few QEEG studies have been done with adult dyslexia samples. Rumsey, et al., (1989) used a word recognition task to assess adults; men with dyslexia demonstrated right greater than left hemisphere beta asymmetry compared to controls. This was significant because these participants had not demonstrated asymmetry during baseline. The authors suggested that these participants may have had a greater commitment of processing resources combined with reduced processing efficiency. The authors also thought that the evidence of severity of the dyslexia participants was greater than the EEG results reflected. No evidence was provided to suggest that these men with dyslexia

were differentially subtyped. These results my have represented a mixed clinical group; also, primary diagnosis was accomplished with a discrepancy regression technique that has been demonstrated to over identify people with LD. Given the limited sensitivity of EEG to subtle neuroanatomical differences, group heterogeneity would have confounded its ability to highlight true differences (Bigler, et al, 1998). Knight (2001) reported a reduced power trend for adults with dyslexia. High and low alpha was reduced for a Stroop task, however, the reported results did not meet statistical critierion ($p < .05$). The lack of statistical significance may have been an effect of sample size. The topographical maps of dyslexia participants demonstrated greater delta and 21-25 Hz beta when compared to controls. These results have implicated alpha and beta in cortical processing that supports reading skills.

Many issues have been raised about the use of QEEG as an investigative form for adult clinical group diagnosis. Baseline or resting measures have not always distinguished between dyslexic and control groups, supporting the theoretical notion that cognitive differences were more aptly revealed during processing activity (Duffy & McAnulty, 1990; Flynn, et al., 1992; Rippon & Brunswick, 2000). Observed differences often have been elicited during difficult tasks specific to the groups' deficits; however, the moderate differences identified may reflect poor stimulus subskill specificity or mixed clinical subtypes of dyslexia. The majority of QEEG research in dyslexia has been done with children calling into issue generalizability (Bigler, et al., 1998; Byring, 1986; Duffy, et al., 1980; Flynn, et al., 1992; Mattson, et al., 1992; Rippon & Brunswick, 2000). Children's studies used as models for adult dyslexia samples may be problematic. Waveforms have been shown to change with maturity; absolute and relative alpha power

has been shown to increase until about the age of 10 and then gradually reduce from the second decade of life into extreme old-age particularly in the parietotemporal areas (Niedermeyer, 1993); absolute and relative theta and delta decrease with age (Harmony, et al, 1995). In fact, the changing EEG spectrum attributable to maturation has been implicated in some forms of poor readers (Harmony, et al., 1995). Persistent LD from childhood into adulthood has suggested a stable neuroanatomic locus responsible for the deficit (Bigler, et al., 1998). With this in mind, children's studies may offer heuristic value to adult focused dyslexia research.

Cognitive Automatization

Automaticity

Automaticity has been conceptualized to reflect cognitive neural processes that are fast, efficient, and purposeful without requiring effort or volition (Brown, Joneleit, Robinson & Brown, 2002; Schneider & Chein, 2003). Explanations of the processes have depended to some degree on the theoretical perspective. For example, automaticity research has been performed with social psychology, information processing, cognitive neuropsychology, memory systems, attention networks, and computer models (Carr, 1992; Cohen, Servan-Schreiber, & McClelland, 1992; Bargh & Ferguson, 2000; Schneider & Chein, 2003; Treisman, Vieira, & Hayes, 1992). Common ground across models for acquired automaticity has included the requirement of consistent practice with the consequents of increased speed of processing and reduced need for attention. These models have also included the notion that automatic behavior is involuntary and unaffected by interference with competing processes (Anderson, 1992; Cohen, et al., 1992).

The definition of an automatized process in cognitive neuropsychology, such as that which supports attention or word recognition, has presumed modular neural substrates that function in parallel and become active during a particular configural input. Automaticity research has been undertaken with a variety of cognitive abilities including language, numerosity, and social behavior (Bargh & Ferguson, 2000; Brown, et al., 2002; Leverett, Lassiter, & Buchanan, 2002; Pansky & Algom, 2002). To focus on neuropsychological definition, automaticity may yet be useful in the evaluation of skilled performance and skill acquisition (Brown, et al., 2002).

Automatization of skills, processes, or acquisition of expertise, has been described in the two parts of the dual processing theory, *knowledge compilation* and *product tuning* (Nicolson & Fawcett, 1990). According to this model, compiling new knowledge has been thought to require a large cognitive load demand; many resources are engaged to accommodate new information, attention needs, and memory systems. Cognitive skills, comprised of an assembly of interacting task components have been subjected to automatization (Brown, et al., 2002). Declarative knowledge is accumulated and proceduralized, thus, transforming it into automated production rules. Tuning the information, or effects of practice, has been thought to optimize the instructions to specific tasks. Practice has been thought to automatize lower level task components, such as those required for linguistic processing, freeing attention for higher functionality (Cohen, et al., 1992).

Automatic processing has been described as being involuntary (Brown, et al., 2002; Cohen, et al., 1992). Due to the fast, effortless, parallel processing of well-learned information, volitional control is not engaged and automatic processing cannot be

interrupted. The involuntary quality of word recognition, for example, has suggested that no conscious volition is required for understanding the written word and, thus, has become automated due to practice with high-frequency words over many years of reading experience (Brown, et al., 2002). For well-learned words, attention may be released from lower level processing of orthographic and phonological input and may be freed to deal with novel lexical, syntactic and semantic information in each sentence. In addition, because these skills have been automated, they may be difficult to inhibit and may interfere with competing tasks (Anderson, 1992). This is consistent with Schneider and Chein's (2003) interpretation, but with one exception; a complex stimulus may contain differential priority codes, the highest priority coded stimuli would be preferentially attended and processed. In this interpretation, a given stimulus (e.g. Stroop stimuli) might be involuntarily processed in one arrangement yet require attention and resources for processing in another configuration.

Automatic processing has been described as being deterministic (Bargh & Ferguson, 2000). Consistent training, experience or exposure may have provided neural associations that, when activated, culminate in a predictable outcome. Skill acquisition research has established that conscious deliberation and choice have been excluded as a forces directing the outcomes. Bargh & Ferguson (2000) summarized this point of view with the following comments:

> Modern research on skill acquisition has affirmed that intentional processes (e.g. driving a car, reading, playing a violin, making a social judgment) become fast and effortless with practice. The hallmark of these automatic skills is that once they are put into operation by a conscious intention, they then operate

> autonomously in complex interaction with environmental events—once they are in operation, conscious choices and guidance to completion are no longer necessary. (p. 933).

Visual word recognition among other reading tasks has been shown to be dependent upon exposure to and consistent training with verbal stimuli to develop identification proficiency. This type of experience has been in keeping with automating brain functionality with a deterministic outcome, notably, the recognition of words without conscious activation of the process. Stroop tasks have been used to evaluate reading and language, presuming that their component skills (i.e. orthographic and semantic analysis) are subject to automatization (Brown, et al., 2002; Leverett, Lassiter, & Buchanan, 2002). Stroop stimuli were developed as manipulations of colors and color-words that have been thought to reflect cognitive processing interference (Atkinson, Drysdale, & Fulham, 2003; Mead et al., 2002). The incongruent form of Stroop stimuli was designed to display color-words which are presented in differing colors, i.e. the word 'RED' presented in blue color. Many have assumed that the colored format involves a functional conflict between the automatized word recognition and attention to the color. The automatization argument was debated by Carr (1992) who suggested that attention is a controlled element during such tasks and, therefore, is subject to volition. Since orthographic and semantic processing have been demonstrated to require neural activation of different attention-related neural structures (see Neurophysiology section), attention and automaticity, as they related to reading skills, can be viewed as existing in a partnership of varying complexity. The greater the automaticity provision of a skill, the less attention is required. Carr's (1992) point-of-view has provided the interpretation that attention,

rather than being part of a deterministic automated process, requires effort and, therefore, is not automatic, per se. Selective attention has been instrumental in the study of the Stroop effect; however, attention as a component skill may be only partially automatized. Some researchers have suggested that the Stroop effect may not be as clearly delineating of automatic semantic functionality as prevailing trends propose (Brown, et al., 2002; Besner, 2001; Besner & Stolz, 1999; Carr, 1992; Pansky & Algom, 2002). Indeed, many functions described as automatic may be susceptible to interference and attention influences (Cohen, et al., 1992; Pansky & Algom, 2002).

The acquisition and practice of language skills has been shown to develop cortical/neural efficiency or automaticity; in effect, practice makes perfect. The process of language acquisition and related skills is begun at birth with a combination of intrinsic and extrinsic variables; the child's genetic predisposition interacts with environmental influences. The nervous system has been shown to mature throughout childhood; myelination has continued, dendritic connections have increased, and unused neural materials have been discarded. The brain has been shown to be most sensitive to language in early childhood (Love & Webb, 2001). Neural resources have provided for language acquisition and other types of behaviors. Given the plastic nature of the developing brain, the majority of people have lateralized language function to the left hemisphere. Language lateralization has implied genetic and automatic programming, which has been a foundational argument by Nativists for the Language Acquisition Device (LAD) (Shaffer, 2002). The sounds, organization, meaning, and rules of language have been demonstrated to be acquired by environmental reinforcement and models that provide necessary stimulation for neural circuitry promoting the underlying

preparedness for academic potential (Shaffer, 2002). By the time a child has been admitted into first grade, he/she has acquired approximately 10,000 to 14,000-word receptive vocabulary. Sentence complexity has been shown to resemble adult speech with appropriate syntactic application and pragmatic usage (Matlin, 2003; Shaffer, 2002). Most children have acquired and automatized language usage in its most basic sense by school age. The primary medium for curriculum demand has been predominantly language focused, reinforcing the basics and adding new neural associations. New language functioning was accrued by effort, but established functionality was automatized and was made available for immediate, low-effort use.

With increased automatization, the cognitive load has been reduced, diminishing the need for attention and energy resources (Nicolson & Fawcett, 1990) with increased speed of processing as a by-product of greater automatization (Cohen, et al., 1992, Towler, Hutchens, & Lubar, 2004). Automatization of basic language skills has included phonetic, semantic, and visual decoding skills, which have been considered necessary for fluent reading ability. Fluency and sophistication in reading skills have demonstrated early automatization of decoding skills (Chall, 1983) and are thought to be the result of parallel processing (Posner and Raichle, 1997). Research has demonstrated a strong relationship between the failure to develop automatized language skill processes with reading problems (Felton, Wood, Brown, Campbell, & Harter, 1987; Hutchens, 1988; Wolf, 1986; Wolf, et al., 1986). The consequences of weak automatization of reading subskills have been shown to interfere cumulatively across the academic lifetime (Nicolson & Fawcett, 1990).

Tests of Automaticity

Automatization of reading related skills has been hypothesized to be constrained in dyslexics due to an unequal yoking of neural substraits that support underlying cognitive subskills (Berninger, 2001). The consistent practice of high frequency words has been shown to successfully integrate both phonological (sound) and orthographic (visual) stimulus coding subskills in expert readers. Automatic, effortless processes supporting visual word recognition has been shown to promote reading fluency. Readers with diagnosed LD have been shown to be unsuccessful at automatizing these cognitive subskills (Hutchens, 1988). As a result of the numbers of neural, cortical connections which may be dysfunctional, they have demonstrated a variety of weak reading behaviors including decreased processing speed, increased cognitive load, increased attention demands, reduced comprehension, reduced reading fluency and increased effort (Chall, 1983; D'Angiulli & Siegel, 2003; Hutchens, 1988; van der Leij & van Daal, 1999). Linguistic tasks that have been designed to measure automatized performance have been shown to discriminate good readers from poor readers (Wolf, et al., 1986). Instruments sensitive to neuropsychological processing or more subtle cognitive skills have discriminated children of normal achievement referred for learning difficulties from children with severe discrepancy achievement (Morgan, et al., 2000). Measures of reading related skill automaticity include the Color-Word Stroop, Rapid Automatized Naming (RAN), and Rapid Alternating Stimuli (RAS).

The Stroop Test. Stroop's (1935) tasks have been viewed as the preeminent demonstration of verbal automaticity ability (Besner, 2001; Mead, et al., 2002; Schneider & Chein, 2003). The Stroop tasks have been used to study attention and word

recognition, presuming that the component skills, such as orthographic and semantic analysis, are subject to automatization (Brown, et al., 2002; Leverett, et al., 2002). The three tasks representing the Stroop archetype, namely Word Reading, Color Naming and Color-Word Reading, have been manually administered to obtain response time (RT), latency (i.e. time to first response) and performance errors. Of the tasks, the Color-Word Reading task was designed for the examinee to verbalize the color and ignore the color word that has been presented simultaneously (e.g., the word 'blue' presented in red color); processing interference was the expected cognitive effect of the task. The incongruent stimuli consisted of the color-word, the word 'blue,' overlaid with a color, such as red, that creates a processing issue for the neural structures supporting visual, perceptual, attentional, and verbal functionality. The interference effect has been traditionally measured by subtracting the RT from the congruent word-color condition, that is the word 'red' overlaid with the color red, from the RT from the incongruent condition. Manual responses, which may include semantic-level processing (Brown & Besner, 2001), have been used successfully in research to create the Stroop-effect, though the effect may be moderate when compared to the verbal response-time format (Brown & Besner, 2001; Mead, et al., 2002). The majority of Stroop-related research has presumed that the automated functionality associated with word recognition is semantic but some research supports a phonological or articulatory-motor origin (Carr, 1992).

According to Schneider and Chein (2003), the processing issues that have been predominant in the Stroop effect can be explained by the dual processing theory: controlled or automatic processing. They associated the two processes with different phenomenon. Controlled-processing was described as slow and serial, easily established

across training formats, sensitive to context, easy to manipulate, necessary for learning, and limited in capacity. Controlled-processing also required considerable effort. Alternatively, automatic-processing was described as fast and parallel, established by consistent training, robust to stressors (e.g. fatigue and stress), difficult to manipulate, not used in learning, and sensitive to stimulus priority assignments. This process required much less effort than that of controlled processing.

Recent research has suggested that the Stroop effect reflects at least lexical/semantic level processing (Catena, Fuentes, & Tudela, 2002). The processing interference of the incongruent color-word task has been thought to reflect an automatic word recognition process involving verbal memory access. Measures of Stroop interference, however, may have reflected response competition phenomenon as opposed to strictly speed of processing issues (Atkinson, Drysdale, & Fulham, 2002; Mead, et al., 2002). Research has demonstrated that Stroop interference effects have discriminated between children/adults diagnosed with LD and children/adults of normal development (Everatt, 1997; Golden & Golden, 2002). The interference effect may not have been as pronounced in people diagnosed with LD because of their reduced automatized functionality supporting color-word reading (Cox, et al., 1997). In this study, parents of LD children were grouped and categorized by IQ and verbal automaticity scores. Poor readers, presumably with poorly automatized verbal skills, had similar Stroop interference scores to the better readers. Response time and brain imaging studies have been designed using both standard and non-standard Stroop stimuli to highlight attention issues in non-clinical and clinical groups (Knight, 2001; Towler, 2002). Also, researchers have investigated the automatic verbal aspect of the effect by manipulating the Stroop

stimuli on computerized administrations (Besner & Stolz, 1999; Besner, 2001). Few studies have been designed to focus upon the automatic dysfunction in adults with LD (Cox, et al. 1997).

Naming Tasks. The task demand for RAN and RAS has been continuous rapid naming and has been demonstrated to be sensitive to developmental automaticity deficits. These measures have been shown to reveal both phonological and speed of processing issues (Denkla, 1999; Meyer, et al., 1998; for a review see Wolf, Bowers & Biddle, 2000). RAN and RAS stimuli were constructed to test the automaticity deficit supposition. The stimuli were constructed of color squares, letters, numbers, and objects and have been modified for words (Hutchens, 1988; Towler, Hutchens, & Lubar, 2004). They are organized in blocks of 50 stimuli arranged in paragraph form; that is five lines of ten stimuli. The goal of the tasks was to name each consecutive item on the stimulus page as quickly as possible. The tasks reflected component elements of reading; phonological performance is demonstrated by naming, processing speed is revealed through total response time, and a reading analog is provided with sequential and contextual components. The RAN digits and letters subtests may have required visual recognition processing comparable to the Color-Word Stroop tasks (Wile & Borowsky, 2004). Hutchens (1988) explored Geschwind' (1965) assertion that the cognitive components, which are common between rapid naming stimuli and reading performance, are used to attach verbal labels to abstract, visual stimuli; Hutchens' data showed significant differences in adult groups, while Geschwind suggested RAN and RAS to be good early predictors of reading performance. Retrieval speed rather than naming accuracy has been shown to differentiate dyslexic readers from others for both children

and adults (Wolf, et al., 2000; Denkla, 1999). Morgan, et al. (2000) demonstrated that all but the Objects measure of RAN and RAS were useful in distinguishing children with severe achievement discrepancies from children with similar neuropsychological profiles but of normal achievement who were referred for learning difficulties. With a related set of stimuli, Zabell and Everatt (2002) demonstrated that college students in the control condition performed object and digit naming tasks more quickly than students with phonological deficits.

Automaticity and Neurophysiology

A theory of brain organization that has effectively explained language skill automatization would account for functional lateralization, parallel processing, hierarchical control and flexible attention. Schneider and Chein (2003) proposed neural structures that are present in cortical organization that are predictive of acquired, automatic behavioral phenomenon. Dual processing theory was used to describe the aspects of performance identified in their model: the control system, exerting hierarchical and attentional direction, and automatic processes, responsible for sub-skill aggregation. Control system processes, providing executive resources across all tasks, have been thought to be necessary components of automatization that would be active in a wide variety of novice task performances. These effort expending processes have been described as slow and serial, sensitive to context, easy to manipulate, and limited in capacity. Control processes have been thought to exert influence on automated processes in hierarchical and sequential fashion. Automatic and controlled processes have been thought to be based upon activity within the same neural substrates for a given task. Automatic processing has been described as comparatively effortless, fast and parallel,

established by consistent training, robust to stressors (e.g. fatigue and stress), and difficult to manipulate. Acquired automatized language processing would have occurred in areas of the cortex involved predominantly with stimulus coding and would be impacted by repetition. During learning and practice, neural substrates common between the two systems should have demonstrated increased activity early in the process and decreased activity as automaticity developed. Schneider and Chein's view was that while brain locus of activity does not change with experience, activity level does change.

Neural substrates indicative of control system processes and associated with paired associate learning have included the dorsolateral prefrontal, anterior cingulate, posterior parietal, occipital-temporal, and cerebellar areas (Schneider and Chein, 2003). The authors labeled each cortical area according to mission based upon their computer-based modeling: goal processor, activity monitor, attention controller, episodic store, respectively. The cerebellum, though not defined by Schneider and Chein (2003), also may play a role in the automatization of overlearned tasks, such as those skills required for reading (Ramus, et al., 2003). The thalamus was included as a gating and report relay structure that has interconnections with all of the stated structures. The authors reported that during the early phase of paired associate learning tasks, these areas were very active. The substrates exhibited substantial reductions in activation over time as learning occurred. In addition, the authors noted that a meta-analysis of neuroimaging literature demonstrated that these areas were consistently reported with reduced activity following practice-dependant change across skill domains. In keeping with predictions, these cortical areas were activated during a wide variety of learning domains and exhibited reduced activity over time with practice.

Brain imaging studies have supported the lower levels of brain activity associated with skill automatization (Smith, McEvoy, & Gevins, 1999; Posner & Raichle, 1997). Lower levels of brain activity have suggested greater processing efficiency especially for those who have developed automatized skills. For example, Posner and Raichle (1997) used PET to demonstrate that noun generation (i.e. reading nouns aloud from a list) activated the anterior cingulate, left frontal cortex (including Broca's area), left posterior temporal cortex (including Wernicke's area), and right cerebellum. Following 15 minutes of intense practice, the activation in all previously affected areas was reduced and was in keeping with Schneider and Chein's (2003) predictions for automated activity.

Posner and Raichle (1997) suggested that multiple pathways for language generation exist to allow smooth automatic access or detailed analysis. According to these researchers, noun generation practice affected automatic functioning by reducing activation in the primary pathway (as described previously) and shunting the task demand through the insular cortex, a more efficient circuit with reduced energy usage. Carr (1992) has suggested that a restructuring occurs in the development of automaticity, observed largely in PET studies in which activation disappears in cortical and cerebellar areas initially activated during novel verbal tasking after intense practice. While this evidence is contrary to Schneider and Chein's (2003) assertion that the locus of activity does not change, the results reported by Posner and Raichle (1997) lend it support.

Attention, subsumed by the control system, has been a very important aspect in the study of learning and automatization. Proposed neural substrates supporting the attention networks involve the anterior cingulate cortices, posterior lateral parietal cortices, and supplementary motor areas (Carr, 1992). These neural substrates have been

organized into two cooperative networks that interact in selective attention: the posterior attention system (PAS) for orthographic analysis and the anterior attention system (AAS) for semantic and memory processing (see Carr, 1992, for complete discussion). The PAS has been posited to be comprised of the posterior lateral parietal cortices and subcortical structures (e.g. pulvinar nucleus and superior colliculus) that act within the perceptual mechanism to allocate spatial attention and precipitate perceptual movement. A sequence of operations has been proposed whereby the PAS attends to a spatial stimulus, selectively engaging, and disengaging to move to feature and shape information that will be the focus of perceptual processes. In summary, PAS's function has been posited to select perceptual inputs from a spatial environment for the purpose of object or stimulus recognition. The AAS has been thought to be comprised of the anterior cingulate and the immediately superior supplementary motor areas perhaps including the supplementary speech areas. The role of the AAS has been thought to be related to executive functions that control access to working memory, long term memory, and the motor system. Carr (1992) reported research that demonstrated the AAS neural connectedness to the hippocampus, entorhinal temporal cortex, primary motor cortex and the basal ganglia. The AAS has been demonstrated to send projections to inferior prefrontal areas (e.g. computation of lexical semantics) and parietal areas (e.g. interacting with PAS). The AAS, according to Carr, was the preeminent position to provide executive functionality. In addition, AAS activity has been demonstrated to occur across perceptual and productive tasks, to increase with task demand, to decrease with increased practice, and during the Stroop conflict condition (Mead, et al., 2002).

Automaticity and QEEG

Acquired automaticity has been described in terms of dual processing theory that can be related to changes in cortical activation and mental effort applied throughout the acquisition process. Dual processing theory has provided definitions of controlled and automated processing to give context to the activation in neural substrates during novice and expert applications of cognitive skills (Schneider & Chein, 2003). Controlled processes related to the learning of a specific skill are described as being most active during knowledge compilation and requiring a large cognitive load for successful performance (Nicolson & Fawcett, 1990); learning new information has been shown to require greater allocation of attention and cortical resources resulting in slower processing speeds, increased mental effort, and greater focal, cortical activation (Bargh & Ferguson, 2000; Schneider & Chein, 2003). Automatized processes have been described as resulting from the fine tuning that has occurred during skills practice (Nicolson & Fawcett, 1990). Experts with well-learned skills have been thought to benefit from the resulting reduction in cortical activation associated with practice by increasing processing speed, requiring less mental effort, and reducing attention requirements for successful performance (Bargh & Ferguson, 2000; Schneider & Chein, 2003). Smith and colleagues (1999) have suggested that EEG would be sensitive to practice-related changes in cognitive resources, as such, brain activation in cortical locations specific to reading subskills may be susceptible to QEEG/EEG. The examination of brain activation and its relationship to the EEG spectrum and mental effort has provided insight into the use of EEG/QEEG in examining cortical activation changes related to differential skill automatization.

Schneider and Chein (2003) have stipulated that cortical activation associated with newly learned and expert ability represents activity in the same neural substraits; neural substrates involved in learning and practice should demonstrate increased activity early in the process and decreased activity as automaticity, or expertise, is developed. Segalowitz (2000) has suggested that brain activation is most variable while acquiring new skills, suggesting that the learning brain has differentially utilized resources, which are dependent on focal resources specific to task demand, and has not developed an efficient process. Cortical activation that supports reading subskills, word recognition and word naming has been shown in the left hemisphere (Dogil, et al., 2004; Mead, et al., 2002; Schack, Chen, & Witte, 1999;); general cortical locations have included lateral frontal and tempero-parietal cortices. Greater cortical activation in terms of EEG spectrum has been represented by relationships between theta, alpha and beta waveforms. Focal beta and theta activity has been shown to be greatest during early stages of learning while alpha has been shown to be relatively reduced (Gevins, et al., 1998; Klimesch, 1999). Fairclough, Venables, and Tattersall (2005) noted that global mean absolute alpha power decreased in central and parietal electrodes (i.e., CZ, PZ, P3 and P4) until midway through visual tracking tasks and then increased as participants learned the tasks. Global mean absolute beta increased across tasks, decreasing only during the last task session, which suggested that greater cortical activation occurred while learning task requirements. While this task has different requirements than strictly reading subskills, it has demonstrated the consistency of focal activation differences for learning across task domains which was another specific assumption made by Schneider and Chein (2003). For brain activation during novice task performances to be demonstrated for reading

subskills, i.e., word recognition and word naming, increased theta and beta activity should be present in the lateral frontal and temporo-partietal cortices while alpha activity is reduced.

Schneider and Chein (2003) have suggested that expert ability would be demonstrated by decreased focal cortical activation in the same cortical foci as was found for novice ability during cognitive tasks. The activity due to a general automatization of function has been associated with the parietal cortices without prefrontal activation (Segalowitz, 2000) which has suggested little attention and working memory input after development of expertise. Specificity of focal activation in EEG research has been demonstrated in learning tasks. EEG correlates of expertise have included focal increases of alpha (7.5 to 12 Hz) with training. Smith, McEvoy, and Gevins (1999) reported results indicating an increase in centrally distributed alpha activity as participants developed expertise with verbal/spatial working memory tasks. Between sessions alpha band activity increased with task practice; 10.5 Hz power, fast alpha, increased at both posterior temporal electrode locations across verbal task training blocks. During multiple blocks of verbal and spatial memory tasks, energy in the alpha band increased across the first learning session, slow alpha power (9 HZ activity) increased most distinctly at the fronto-central areas. Slow alpha has been associated with nonspecific attention and expectancy processes while fast alpha has been associated with focal task-specific demands (Smith, et al., 1999). Average frontal mid-line theta (6.5 HZ activity) increased across sessions as well and has been associated with the anterior attention network. Fairclough, et al., (2005) measured EEG activity at central and parietal electrodes across different difficulty levels of computerized visual-spatial tasks; they reported theta activity

at PZ and P4 as discriminating between high and low task demand; theta activity increased with task demand. In the context of expertly automatized function, low theta activity should be present because of the reduced task demand. Fairclough, el al., (2005) also noted that global mean absolute alpha power decreased until midway through visual tracking tasks and then increased as participants learned the tasks. Global mean absolute beta increased across tasks until decreasing with the final task. The change in bandpower spectral distribution between novice and expert applications has been demonstrated in theta, alpha, and beta bands.

Demonstration of mental effort has been characterized in terms of task demand, effortful expenditure, cognitive engagement, and cortical activation levels (Dogil, et al., 2004; Fairclough, et al., 2005; Gevins, et al., 1998; Klimesch, 1999). Mental effort during cognitive analysis of novel problems has been related to controlled processing (Fairclough, et al., 2005). Control circuits are tasked by the effort expended; the prefrontal cortex and the frontal-posterior reciprocal circuits are tasked differentially, in part due to attentional influences. EEG activity associated with increased task demand especially while activating working memory includes increased power in the beta band and suppression of alpha activity, as well as increased theta activity in the frontal locations (Gevins, et al., 1998; Klimesch, 1999). Effortful semantic processing has been associated with upper alpha band desynchronization (i.e. 10 to 12 hz) in the left prefrontal cortical areas roughly associated with Broca's area (Dogil, et al., 2004). During Raven's Progressive Matrices, a visuo-spatial closure task series, and reading tasks, Faber and Zelinkova (1996) demonstrated that both the dyslexia group and the control group bilaterally suppressed alpha during the tasks. The similarity of activity between groups

during the Raven's task is not unexpected as it is not associated with the neuroanatomical loop as that of reading tasks. Suppression of alpha during a task would be an expected response and indicative of cognitive engagement. Fairclough, et al., (2005) reported theta activity positively correlated to task demand while global mean absolute alpha decreased until the tasks had been learned. Global mean absolute beta power also increased with task demand. Greater task specific cognitive engagement related to mental effort has been shown to be related to focal increases in theta and beta while alpha activity decreases.

Statement of the Problem

The present study investigated components of automatized reading subskills as they were differentially distributed between adults diagnosed with Learning Disabilities and their normally achieving peers. At the heart of acquired automaticity is skilled performance or expertise (Brown, et al., 2002). Research has supported the view that neural organization associated with dyslexia is deficient at the level that supports basic sub-skill processing. This abnormality ultimately has impinged the neural network's ability to automatize the phonetic and orthographic components of reading skills. In essence, people with dyslexia have not effectively developed phonetic expertise and have utilized greater mental effort to accomplish reading tasks without benefiting from the streamlining, energy-saving processes inherent to brain development. The subsequent brain activation effects would be highlighted in the EEG spectra derived from cognitive performance during tests of automaticity when compared to true experts, people of normal neuro-developmental etiology.

The preceding discussion refers to the change in focal cortical activation from the introduction of a novel task to the completion of learning the new skill; activity thought to be accessible with EEG. Research focusing on EEG correlates of automaticity has suggested that group differences would be highlighted in the theta, high alpha and low beta bands. Since people diagnosed with dyslexia have not fully automatized reading subskills, requiring greater mental effort than non-clinical counterparts, then the EEG spectra should reflect the cognitive, mental effort which are exemplified by group differences.

Research Hypotheses

This project had four goals, three identified as hypotheses and the remaining goal was to operationalize dyslexia-group selection criteria by providing clear academic, psychometric, and neuropsychological evidence of dysfunction. This study was designed to utilize elements of the neuropsychological diagnostic model to provide a homogenous sample of phonetically impaired individuals with dyslexia. The lack of sample homogeneity has been a consistent criticism throughout LD literature, resulting in threat to internal validity and inconsistent data patterns. The rationalization for sample criterion discussed in the method section was that the selection of participants with a true dysphonetic deficit would permit the investigation of automated subskills thought to be specific to reading. The following hypotheses were thought to be more reliably tested by including only those adults with applicable dyslexia diagnoses in the research sample. Each hypothesis was stated in the null with the expected outcome explained in the accompanying discussion.

$H_0$1: Non-clinical and dyslexia participants do not differ in their response times for the RAN, RAS, and Color-Word Stroop.

A goal of this project was to examine automaticity in adults with dyslexia and non-clinical participants by comparing RAN, RAS and Color-Word Stroop performance response times, and the Color-Word Stroop interference effects between groups. Since RAN, RAS and Color-Word Stroop have successfully discriminated between students diagnosed with LD and those of normal development, concurrent administrations of these continuous neuropsychological tasks should reveal similar speed of processing related differences between groups. Participants with dyslexia will have slower rapid naming times and smaller Stroop interference effects than the non-clinical participants.

$H_0$2: Passive data collection following the performance of the active tasks for RAN, RAS, and Color-Word Stroop will not reveal spectral differences in the left inferior precentral region or the posterior superior temporal cortex.

$H_0$3: Data collected during active task recording of the Color-Word Stroop will not discriminate between groups by demonstrating similar spectral activity in the left inferior precentral region and the posterior, superior temporal cortex.

Finally, to extend the brain imaging literature of adult dyslexia with QEEG, the last two goals were accomplished by comparing EEG recordings passively collected after computerized administrations of both RAN, RAS and Color-Word Stroop stimuli and by studying waveform changes during an active task for both groups during a computerized administration of the Color-Word Stroop. RAN, RAS and Color-Word Stroop tasks have discriminated between participants with and without LD in response time studies,

suggesting that these tasks reveal a cortical processing deficit. Word reading and Stroop incongruent stimuli have demonstrated activity in the left inferior precentral gyrus with Fmri (Mead, et al., 2002; Turkeltaub, Eden, Jones, & Zeffiro, 2002). Phonological skills have been posited to modulate the posterior superior temporal cortex during the acquisition of reading skills (Turkeltaub, Gareau, Flowers, Zeffirio & Eden, 2003). These cortical locations have been hypothesized to demonstrate activation during the passive collection of remnant activity directly after administration of sequential stimuli; residual effects may be available without the interference of artifact, which has been identified as a limitation of the stimulus-type. In addition, since baseline measures have rarely discriminated between samples of LD and non-LD, EEG was recorded during the performance of the Color-Word Stroop. The sample of dyslexia participants was characterized as being unable to develop expertise with phonetic-orthographic subskills; therefore, group differences were predicted in alpha, theta and low beta. Participants with dyslexia diagnoses were expected to produce less relative high alpha power while increasing relative theta and relative low beta at the cortical locations of interest when compared to the control participants.

CHAPTER TWO

Methodology

This investigation was designed to augment the learning disabilities and quantitative electroencephalography (QEEG) literature. The study explored psychometric performances and concurrent electroencephalographic (EEG) recordings between adults with reading difficulties and adults of normal reading ability. Validating psychometrics were required for group membership, as well as measures of componential reading skills to ensure group homogeneity. The current methodology adapted existing neuropsychological tests of automaticity to EEG collection procedures for use both during and after performance tasks. The following sections are provided to describe participants, measures, methodology, and instrumentation utilized to meet the project objectives.

Participants

Recruitment

Non-clinical participants. Non-clinical participants were recruited via the Human Participation in Research online bulletin board as per the UT Department of Psychology's undergraduate research participation protocol. Volunteers expressed their interest in participation by registering on the bulletin board and providing contact information as part of the registration procedure. The primary investigator then contacted the volunteers to explain the study's requirements, to answer any questions, and to make data collection appointments for the research lab. Extra credit in designated coursework was offered in accordance with the standard procedure established by the Department of Psychology. A

copy of the participant's brain map was offered as an additional incentive for participation.

The following criteria was applied to both male and female volunteers for non-clinical (NC) group inclusion: age of at least 18 years, no personal history of learning disabilities, and intellectual ability which corresponded to the average range or greater. Inclusion criteria required no neurological or psychological health disturbances as reported by volunteer participants.

Learning disability participants. Identification of current and former college students diagnosed with learning disabilities occurred through the UT Office of Disability Services (ODS), The Assessment Center (TAC), and Tennessee Wesleyan's Academic Success Center (TNWASC). These agencies sent an invitational recruitment letter (see Appendix A) to potential volunteers with learning disabilities in reading via email or first class mail. Interested students initiated contact with the primary investigator, the Learning Disabilities Coordinator, or TAC Director in order to maintain confidentiality; the primary investigator received no student information prior to student-initiated contact. Incentives for participation included their contributing to learning disabilities research and receiving a copy of the participant's brain map.

Both male and female volunteers were required to meet the following criteria for learning disability (LD) group inclusion: age of at least 18 years, a learning disability diagnosis that represented a deficit in the academic domain of reading, and intellectual ability which corresponded to the average range or greater. Inclusion criteria also included no neurological or psychological health disturbances as reported by volunteer participants; diagnostic documentation was required for validation of historical variables.

Volunteer respondents provided personal contact information and individual permission to access their psychometric records (see Appendix B). The review of diagnostic psychometrics for LD group inclusion was conducted on the premises where assessment files were permanently stored, specifically, ODS, TAC or TNWASC. In order to ensure homogeneity of this sample, a defining characteristic of a phonetic subtype deficit was required for LD group inclusion.

Participation in this investigation was voluntary for all participants with a minimum of risk. Each volunteer made an appointment for research procedures located in the Brain Research and Neuropsychology Laboratory (BRNL). An email and a reminder phone call prior to participation verified the appointment and provided directions to the research lab. Data were coded by number and confidentiality was maintained throughout. Participants received clear communication that they were free to withdraw from the study at any time; however, extra course credit was contingent upon completion of the research protocol.

Procedures

This study was designed to contribute to the scientific automaticity and learning disabilities literature by utilizing procedures which discriminated component reading skills assessed in groups of students with learning disabilities from normally achieving peers. The group selection methodology contributed to the identification of a common subtype of dysphonetic reading skill in this group of participants with learning disabilities. Those participants with dyseidetic or semantic skills deficits in historical documentation were not included in order to minimize the confounds to group homogeneity in learning disabilities research. All group selection procedures were

gleaned from those tests that have been previously validated in distinguishing individuals with learning disabilities from their normal achieving peers.

Direct assessment procedures described in the following sections occurred in the BRNL. One 2 ½-hour session included all psychometric and EEG procedures. The primary investigator administered all psychometric instruments and recorded EEG. Participants read and signed appropriate informed consent (see Appendix C) prior to data collection.

Psychometric Measures

Psychometric measures were administered according to standard procedures established for each instrument. All participants completed the study psychometrics and a self-report form concerning personal, medical, neurological, and psychological history.

The Neuropsychological Assessment of Learning Disabilities checklist (NALD). Initial data collection for the LD group included the NALD checklist, a tool designed for the review of documentation provided by the LD group participants (see Appendix D). The NALD checklist was developed according to neuropsychological principles of differential diagnosis of learning disabilities. It was comprised of developmental conditions and events correlated with LD symptomology (Hutchens, 1988). The NALD checklist used during the review of historical documentation verified the participant's qualification for LD group inclusion.

The Profile of Mood States – Revised (POMS-R.) The POMS-R (McNair, Lorr, & Droppleman, 1992) verified mood state claims from self-reports (see Appendix E). The POMS-R has established college-aged norms used in the assessment of emotional valence in this population (McNair, Lorr, & Droppleman, 1992); this measure was used

to increase internal validity with regard to exclusionary criteria for group membership. It has also been utilized in QEEG research as a repeated measure of subjective mood (Caldwell, 2001). Using the average standard score (SS) of 50 (*SD* = 10), mood-state scores at or above 2*SD* of the mean (30 – 70) were used as exclusionary to eliminate potential confounds of emotionality.

DSM-IV ADHD Symptom checklist. The DSM-IV ADHD Symptom checklist (see Appendix F) was derived from criteria for diagnosis of attention deficits within the *Diagnostic and Statistical Manual of Mental Disorders (4th ed.-TR)* (American Psychiatric Association, 2000). It has been used in QEEG research methodology for differential identification of attention deficits in groups of college students (White, 2001), and was designed to represent two major aspects of attention deficits, inattentive and hyperactive-impulsive behaviors. Six or more 'yes' answers to either set of nine symptoms, representing inattentive or hyperactive-impulsive deficits, were predictive of potential deficits in attention skills. Previous research with clinical groups has revealed a potential confound in the inclusion of individuals with attention deficits. The differential exclusion of attention deficits for diagnosis was therefore optimal; however, the occurrence of attention concerns within the LD population has been confirmed. Due to the small sample size, the primary investigator acknowledged potential threats to internal validity for the current investigation; subsequent analyses will include the identification of subgroups within the LD group, both with and without positive reports of attention deficit symptomology.

Peabody Picture Vocabulary Test, third edition, (PPVT-III). PPVT-III has been used in many published studies to verify general intellectual functioning (e.g. Dunn &

Dunn, 1997) and was employed in the present study. The PPVT-III yielded a standard, IQ-related score, derived from an individual's performance on a receptive vocabulary task (Dunn, 1965). The standard score has been repeatedly validated as a viable estimate of general intellectual functioning (Bell, Lassiter, Matthews, & Hutchinson, 2001; Dunn, 1965; Dunn & Dunn, 1965; Dunn & Dunn, 1997; White, 2000). The average standardized score for PPVT-III is 100 with a standard deviation of 15. In a college sample, PPVT-III was shown to correlate with the WAIS-III Full-Scale Intelligence Quotient (FSIQ) in the Average to High Average ranges (r = 90 – 120) and to underestimate FSIQ at the Superior range by approximately 10% (Bell, et al., 2001). The pictorial administration of the PPVT-III was valuable to this study because of the reliance on visual and aural stimuli and a non-verbal response format reflecting receptive vocabulary.

Woodcock Johnson Psychoeducational Battery-Revised, Tests of Achievement (WJ-R-A). Word Attack, Letter-Word Identification, and Passage Comprehension were the subtests selected from the WJ-R-A to discriminate phonological deficits in LD group participants. The obtained scores from the WJ-R-A were standard scores with an average of 100 and a standard deviation of 15, and were derived from individual subtest performances requiring verbal responses. Each subtest assessed reading subskills for use in LD group participants' skills verification. Other studies, which used Word Attack and Letter-Word Identification subtests, identified student groups with phonetic deficits (Breier, et al., 2003; Howes, Bigler, Lawson, & Burlingame, 1999). The Word Attack standard scores are viewed as one discriminating measure in adults with dysphonia. Nonsense words, as per the format of the Word Attack subtest, have been shown to be related to phonemic discrimination and reflect dysphonetic difficulties (Tallal, 1980).

This contrasts with performance from the Passage Comprehension subtest. Tallal, Miller and Fitch (1993) described a dyslexia subtype that was characterized by primary weaknesses in associated meaning without the phonetic decoding skill dysfunction. Relatively lower scores in the Passage Comprehension subtest identified this semantic subtype. Identification of the dysphonetic subtype in reading permitted the homogeneity of the LD group and later examination of in-group differences for subtype analyses, as well as those between the learning disability and normally achieving groups.

Rapid Automatized Naming (RAN) and Rapid Alternating Stimuli (RAS). RAN and RAS (see Figure 1) are validated measures of automatized functioning. Response times have distinguished students with reading disabilities from students of normal reading achievement in previous research (e.g., Hutchens, 1988; Kinsbourne, et al. 1991;

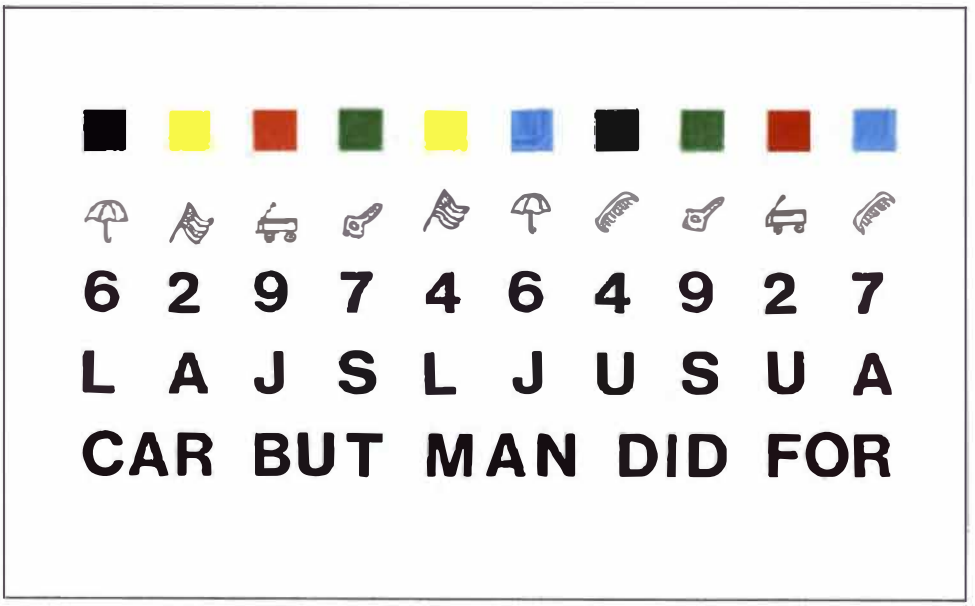

Figure 1. RAN and RAS Stimulus Elements: Colors, Objects, Numbers, Letters, and Words.

Wolf, 1986, 1991, etc.). Performance has been shown to tap basic automatized, integrated naming and orthographic functions related to reading behavior. RAN and RAS stimuli were placed in a task sequence in a Microsoft PowerPoint presentation. RAN stimuli consisted of five blocks of 50 stimuli each of Colors, Digits, Letters, Objects and Words; RAS stimuli consisted of five blocks of 50 stimuli each of Colors-Objects, Digits-Letters, Objects-Digits-Letters, and Colors-Objects-Digits-Letters, the order was fixed for increasing complexity. The tasks entailed rapidly naming each item in the respective stimulus blocks while latency and response time measures were recorded. The primary investigator recorded latency and response times with a stopwatch accurate to one-hundredth of a second and capable of capturing intermediate time points using the lap-split function. Timing began with the presentation of the stimulus block and an intermediate time was recorded for each participant when the first item was named; timing ceased when the last item was named. Latency was defined as elapsed time from presentation of the stimulus block to the intermediate time point. Response time was defined as elapsed time from presentation of the stimulus block to the last item named. The order of task administration was standard across participants.

The Color-Word Stroop (C-WS). The Stroop format for this study was modified from the Color-Word Reading subtest of the original, standard stimuli (see Figure 2). Congruent stimuli consisted of color-words, e.g. RED, GREEN, and BLUE, presented in their corresponding colors, e.g. the word RED presented in red. Incongruent stimuli were color-words presented in a color other than the corresponding color, e.g., the word RED presented in the color blue or green. Two types of modifications to the C-WS stimuli were created to meet the stimulus requirements for both passive and active task EEG

RED RED

Figure 2. Traditional Stroop Stimuli: Congruent and Incongruent, respectively.

recordings utilized in data collection.

The modified design for passive EEG recordings consisted of Congruent and Incongruent stimuli placed into stimulus blocks in the presentation style of RAN and RAS (see Figure 3). The stimuli consisted of two blocks of 50 Stroop stimuli; one block each for Congruent and Incongruent subtests. As with RAN and RAS, this task entailed rapidly naming each item in the stimulus block. Latency and response times were recorded; the definitions were consistent with those described for RAN and RAS procedures. The Stroop effect performance score was obtained by subtracting the Congruent-Block response times from the Incongruent-Block response times. The order for Stroop tasks was Congruent-Block followed by Incongruent-Block and was standard Across study participants because of the increased task demand for the latter.

The subsequent C-WS stimuli, for active EEG recording, consisted of two sets of 200 stimuli. The two stimulus sets were constructed in ratios; the Congruent-Task consisted of 80% congruent and 20% incongruent stimuli and the Incongruent-Task consisted of 80% incongruent and 20% congruent stimuli. The composition of stimuli was designed to limit habituation and encourage cognitive engagement. Stimulus presentation consisted of a single word presented at the center of a computer screen. Participants responded by naming the color of the stimulus word silently followed by pressing a stationary key to advance to the next stimulus slide. No latency or response

A.

RED	GREEN	BLUE	RED	GREEN	BLUE	RED	BLUE	GREEN	RED
BLUE	GREEN	RED	GREEN	BLUE	RED	GREEN	BLUE	RED	GREEN
RED	BLUE	GREEN	BLUE	RED	GREEN	BLUE	RED	BLUE	RED
GREEN	RED	BLUE	GREEN	BLUE	RED	BLUE	RED	GREEN	BLUE
GREEN	BLUE	RED	GREEN	BLUE	GREEN	RED	BLUE	RED	GREEN

B.

RED	GREEN	BLUE	BLUE	GREEN	RED	RED	GREEN	BLUE	GREEN
BLUE	GREEN	RED	RED	BLUE	GREEN	GREEN	RED	BLUE	BLUE
GREEN	RED	GREEN	GREEN	BLUE	RED	BLUE	BLUE	GREEN	BLUE
RED	BLUE	GREEN	RED	BLUE	GREEN	GREEN	RED	RED	GREEN
RED	BLUE	BLUE	GREEN	RED	GREEN	BLUE	RED	GREEN	RED

Figure 3. The Stroop Stimuli Organized into Block Format for Naming Tasks.

A. Congruent-Block stimulus. B. Incongruent-Block stimulus.

times were recorded for this procedure. See the following EEG procedures section for definitions of passive and active task recordings.

EEG Recording

Equipment. The primary investigator recorded the EEG protocol with the Truscan 32 EEG software (Deymed Diagnostic, 2003). Participants were fitted with a 19-channel electrode cap by Electro-Cap International (n.d.) with linked-ears referencing using the International 10/20 System of electrode placement (Andreassi, 1995; Jasper, 1958). A mild, hypoallergenic electrode gel provided a measure of conductance between each electrode and the scalp. Electrode impedance, a measure of signal interference, was determined and required to be below 10 kilo-Ohms for all participants for recording to begin. EEG activity was recorded at 128 samples-per-second. A 2-Hertz high-pass filter excluded data below 1.5 Hz, as these frequencies are susceptible to contamination by the largest forms of muscle artifact. Excluding this frequency band allowed the retention of data important to hypothesis testing.

Instruction. Each participant received orientation instruction for the EEG protocol prior to the beginning of the record. The primary investigator instructed participants about muscle artifacts; participants practiced blinking and sitting quietly both with their eyes opened and eyes closed. They practiced grouping eye-blinks in order to limit eye-blink artifact distribution during data collection for maximum integrity of the record. Practice included alternating the behavioral sequences of holding eyes opened for 10 seconds, blinking several times followed by holding eyes opened again. Participants were instructed to follow this eye-blink method for all eyes-opened recording conditions

and to limit eye movements while remaining still and comfortably seated during eyes-closed recording conditions.

Baselines. The first EEG recordings included resting, 3-minute, eyes-opened (EO) and 3-minute, eyes-closed (EC) baselines to document resting cortical activation levels for each group. In the EO condition, the participants focused their eyes upon a spot on the computer screen for 3-minutes. Participants were encouraged to blink using the practiced blinking technique. In the EC condition, participants closed their eyes and focused them forward. They were given the instruction to hold gaze, "...as if looking straight forward, with eyes in parallel to the nose."

Passive recording tasks. The RAN, RAS and C-WS block stimuli provided the stimulus conditions for the passive recording tasks. The active naming tasks entailed rapidly naming each item in the stimulus block with recording subsequent to the movement required in naming; participants sat quietly with eyes closed while EEG was recorded for 75-seconds. EEG recordings began immediately upon the completion of each naming task subtest; the passive recordings occurred after each of the five RAN subtest blocks, four RAS subtest blocks, and two C-WS blocks. Recordings occurred in a fixed sequence beginning with RAN subtests, RAS subtests and ending with the Stroop Congruent and Incongruent-Block tasks.

Active recording tasks. The C-WS Congruent and Incongruent-Task stimulus sets provided the conditions for active task recordings. This procedure entailed participants silently naming the color of each presented stimulus, using "inner speech", and advancing the stimulus manually while the EEG was being recorded. Inner speech in this context was defined as subvocalization. Participants were told to silently name the color of the

stimulus and then advance the stimulus slide by pressing a computer key with a finger of the right hand. Instructions included, "Use the voice inside your head to speak the name of the color of the word. Do not read the word; name only the ink color. First name the color with your inside voice, then advance the slide by pressing the button with your finger." EEG was recorded during the entire manual performance. Manual response strategies have been hypothesized to include semantic-level processing (Brown & Besner, 2001), thus tapping the skills strength of the designated clinical LD group. Response time was not recorded during the manual response format since the verbal behaviors that validate response time performances create artifact in the EEG record. The order of active task recording was fixed to accommodate the increasing complexity of each subsequent task with the Congruent-Task followed by the Incongruent-Task.

EEG data preparation. EEG data preparation included data aggregation, artifact rejection and spectral organization. RAN and RAS tasks were comprised of multiple subtests from which the EEG data were collected with the passive collection technique. Data were aggregated across RAN and RAS subtests, respectively, and prepped for data analyses.

Artifacts in the EEG record represented background noise and included but were not limited to eye rolls, lateral eye movements, eye-blinks, teeth grinding, muscle tension, and head movement. Spectral artifacts were rejected by visual examination of digitized EEG trace.

Spectral filtering for data was accomplished with *Eureka!* free academic software (Congedo & Sherlin, 2005). The following waveform-bands formed the basis for the relative power spectral data organization strategy for EC baseline, EO baseline, passive

and active task data: delta (2-3.5 Hz), theta (4-7.5 Hz), low alpha (8-9.5 Hz), high alpha; (10-12.5 Hz), low beta (13-20.5 Hz), and high beta (21-31 Hz). Delta, low alpha, and high beta bands were not included in hypothesis testing for the present investigation.

CHAPTER THREE

Results

The following discussion was designed to describe and analyze group differences in acquired automaticity and brain activation. The data description order was: psychometrics, automaticity measures and electroencephalographic (EEG) results, which were further described by task.

Twenty-three participants were screened using the previously identified criteria. Each participant completed the self-report forms of the DSM-IV ADHD Symptom checklist and the Profile of Mood States – Revised (POMS-R) to verify self-reported attention and emotional states. The principle investigator administered the Peabody Picture Vocabulary Test, third edition, (PPVT-III) and the selected subtests of the Woodcock Johnson Psychoeducational Battery-Revised, Tests of Achievement (WJ-R-A), Letter-Word Identification, Word Attack, and Passage Comprehension. These instruments provided data for inclusion in the reading disability and normally achieving adult groups.

Psychometric performance distributions have been shown to be non-normal in the learning disabilities population (Breier, et al., 2003). The variability of academic skills within this population has influenced ability and achievement results that have contributed to the non-normal distribution of scores. The literature has reflected that non-parametric statistics have been standard practice in learning disabilities research (Breier, et al., 2003); therefore, a non-parametric test of the results was chosen for study analyses. The Kruskal Wallis two-sample, non-parametric test was used to evaluate between group

differences for psychometrics, latency measures, and response times. The statistical criterion for group differences was .05-level for all result comparisions.

Participants

Non-Clinical Sample

The non-clinical (NC) group (n = 11) consisted of five male and six female adult college students with a mean age of 20.41 years (SD = 1.31, range = 18.67 - 22.42 years). Nine participants were Caucasian; two participants were of Indian and African American minority groups. All spoke English as their language of origin.

Group inclusion criteria included measures of average or better intellectual ability and no evidence of neurological or psychological disturbances. Participants met group inclusionary criteria with an aggregated estimate of intelligence from the PPVT-III in the average range or higher (M=106.82, SD = 8.68, Range = 96 – 127). Other inclusion criteria were met by self-reported developmental history with no indicated neurological or psychological health disturbances. DSM-IV Checklist identified two participants whose self-reported attention was inconsistent with results. Two participants scored 6-points or greater on one measure of DSM-IV Checklist; one each of inattentive and hyperactive-impulsive symptoms, but did not have a history of attention diagnoses. No participant's standard score on POMS-R met exclusionary criteria of greater than 2SD above/below the mean, which verified self-reported emotional states. No participant data was excluded based on emotional disturbance measures (see Table 1).

Learning Disability Sample

Participants with Learning Disabilities (LD) were twelve adults either currently in college or having completed a baccalaureate degree; seven LD participants were seven

Table 1

Profile of Mood States (POMS): Group Comparisons of Subscale Scores

	Standard Scores		Group Differences	
POMS subtests	Range	*M*(*SD*)	X^2	*p*
Tension-Anxiety				
LD [a]	33 – 65	43.08(9.81)	.12	.734
NC [b]	34 – 59	43.73(8.31)		
Depression – Dejection				
LD	34 – 66	44.42(9.13)	.42	.515
NC	37 – 54	41.64(6.38)		
Anger – Hostility				
LD	33 – 60	46.83(8.35)	.08	.781
NC	39 – 58	45.09(6.55)		
Vigor – Activity				
LD	46 – 68	56.00(6.62)	.05	.828
NC	41 – 63	54.45(7.27)		
Fatigue – Inertia				
LD	35 – 66	48.17(9.46)	.75	.387
NC	37 – 55	44.82(6.16)		
Confusion – Bewilderment				
LD	32 – 66	43.42(9.41)	.19	.665
NC	32 – 66	42.27(9.67)		

[a] $n = 12$. [b] $n = 11$.

males and five females with a group mean age of 29.47 years (*SD* = 11.97, Range = 18.67 – 49.42 years). Eleven of the participants were Caucasian and one was African American. All spoke English as their language of origin.

The specific criteria for group membership was evidence of a phonetic deficit; the review of historical diagnostic documentation with the NALD demonstrated the requisite evidence. Eleven participants were Caucasian and one was African American. As with the NC group, inclusion criteria included measures of average or better intellectual ability and no evidence of neurological or psychological disturbances. The participants met group inclusion criteria by yielding an average estimated intelligence in the average range or higher (*M* = 106.83, *SD* = 9.91, Range = 87-122) as measured by the PPVT-III. Self-reported developmental histories indicated no neurological condition or psychological health disturbances with the exception of one participant who was taking neuroleptic medication for pain control associated with severely degenerating vertebral discs. Review of historical diagnostic documentation revealed three participants with prior diagnoses of attention deficits. Three participants scored 6-points or higher on both attention measures of the DSM-IV ADHD checklist, one participant scored 6-points on the inattentive measure. No participant's standard score on POMS-R met exclusionary criteria of greater than 2*SD* above/below the mean, which verified self-reported emotional states. No data was excluded based on emotional disturbance measures (see Table 1).

Age. Kruskal Wallis test revealed statistically significant age differences between groups $X^2(1, N = 23) = 5.48$, $p = .019$. On average, the LD group was older than the NC group, 29.47 (*SD* = 11.97) and 20.41 (*SD* = 1.31) years, respectively (see Table 2). This

Table 2

Mean Age Comparison

	Years		Group Differences	
Group	Range	*M*(*SD*)	X^2	*p*
Learning Disability (LD)[a]				
	18.67 – 49.42	29.47(11.97)		
Non-clinical (NC)[b]				
	18.17 – 22.41	20.41(1.31)	5.48*	.019

[a]$n = 12$. [b] $n = 11$.

* $p < .05$

difference has significance for this study's results as age may influence psychometric performances (Kaufman & Lichtenberger, 1999). See the additional analyses after the response time data for examined results correlated with age.

Data Analysis

Psychometric Measurement

The following psychometric measures were evaluated for validating group inclusion criteria. ThePOMS-R examined self reported mood states, which was potentially exclusionary. The PPVT-III provided evidence of average or above receptive vocabulary and was included to verify general intellectual functioning. WJ-R-A provided the means to verify group phonetic and semantic comprehension abilities. Each examination was performed according to publisher's standard administration procedures.

POMS-R. The groups did not differ in emotional valence as defined by the POMS-R (see Table 1). None of the six measures, e.g., Tension-Anxiety, Depression-Dejection, Anger-Hostility, Vigor-Activity, Fatigue-Inertia, and Confusion-Bewilderment, met statistical criterion for group differences.

PPVT-III. Comparison of all participant data revealed group mean PPVT-III scores that were nearly identical (see Table 3). The range of scores for NC and LD groups were 31 and 35 standard points, respectively. Groups did not differ in estimated IQ, suggesting that the groups operated at similar levels of intellectual functioning.

WJ-R-A. Selected subtests of the WJ-RA, Word-Attack, Letter-Word Identification, and Passage Comprehension, were used to evaluate the phonological

Table 3

Psychometrics: Group Mean Scores Comparisons

	Standard Scores		Group Differences	
Test	Range	*M*(*SD*)	X^2	*p*
Peabody Picture Vocabulary Test Third Edition				
PPVT-III				
LD	87 – 122	106.83(9.91)	.12	.735
NC	96 – 127	106.82(8.68)		
Woodcock-Johnson Psychoeducational Battery Revised: Tests of Achievement subtests				
Letter-Word Identification				
LD	80 – 133	101.92(14.70)	3.89*	.049
NC	97 – 140	111.82(12.83)		
Passage Comprehension				
LD	82 – 115	101.50(10.28)	.00	.951
NC	88 – 128	102.64(11.61)		
Word Attack				
LD	65 – 124	97.33(15.18)	10.28*	.001
NC	109 – 149	119.73(13.32)		

* $p < .05$

deficit skills of each group. The NC group had higher mean SS for both, Word-Attack and Letter-Word Identification (see Table 3). The lower LD group mean performance for Word-Attack reflected the phonemic deficit compared to the NC group. The lower mean standard scores (SS) from the LD group's performances satisfied criterion of reduced phonetic ability. LD and NC group's standard scores for Passage Comprehension were not statistically different at the .05-level.

Exploratory Analyses

The LD sample was not divided by dyslexic subtype, however, it contained two potential learning disability subgroups. Those participants selected for inclusion in the data set who obtained the lowest SS with the Word Attack subtest of the WJ-R-A were exemplars of the dysphonetic deficit ($n = 6$). Those whose Passage Comprehension SS were lowest were compared for semantic deficits ($n = 6$). The subgroups did not differ in intellectual ability as measured by PPVT-III. The subgroups had statistically different mean standard scores for two of three WJ-R-A subtests; Word Attack and Letter-Word Identification (see Table 4). Psychometric comparisons showed that the two subtype groups differed in phonetic ability. No semantic deficit was identified; thus, the second group was not identified with semantic dysfunction.

Automaticity Measures

The response time data related in this section evaluated the first hypothesis. The first null hypothesis was that no group differences would be present for response time or Stroop effect measures of automaticity tasks. The first automaticity comparisons consisted of response time measures for subtests of Rapid Automatized Naming (RAN), Rapid Alternating Stimuli (RAS) and Color-Word Stroop (C-WS), both Congruent and

Table 4

Psychometrics: Subtyped LD Group Mean Scores Comparisons

	Standard Scores		Group Differences	
Test	Range	*M*(*SD*)	X^2	*p*
Peabody Picture Vocabulary Test Third Edition				
PPVT-III				
Dysphonetic [a]	96 – 117	109.33(7.50)	.64	.423
Semantic [b]	87 – 122	104.33(12.03)		
Woodcock-Johnson Psychoeducational Battery Revised: Tests of Achievement subtests				
Letter-Word Identification				
Dysphonetic	80 -101	92.50(7.06)	4.69*	.030
Semantic	94 – 133	111.33(14.58)		
Passage Comprehension				
Dysphonetic	91 – 115	105.17(9.48)	1.09	.297
Semantic	82 – 112	97.83(10.52)		
Word Attack				
Dysphonetic	65 – 104	88.17(13.01)	5.04*	.025
Semantic	93 – 124	106.50(11.66)		

[a] $n = 6$. [b] $n = 6$.

* $p < .05$

Incongruent subtests.

Each RAN, RAS, and C-WS subtest consisted of a block of 50 stimuli that were named sequentially aloud. Timing began with the presentation of the stimulus block. Timing ceased when the last item was named. Response time was defined as elapsed time from presentation of the stimulus block to the last item named. Subtest performance times were measured in seconds.

All data were group aggregated for mean comparisons. Large numbers of analyses have been shown to influence family-wise error. Parametric methods such as MANOVA have been used in typical strategies to reduce the number of analyses; however, the psychometric and response time data distributions for this study have been assumed to be non-normal as has been standard practice in Learning Disabilities literature (Breier, et al., 2003). To evaluate the response time data, within subject data were aggregated across subtests for RAN and RAS. C-WS response time data were not aggregated between subtests because the relative differences were evaluated by Stroop effect data. These aggregate data distributions resulted in two omnibus response time analyses evaluated with the Kruskal Wallis test. If the result of the analyses met the statistical criterion for group differences, further group analyses for each subtest would be conducted.

Rapid Automatized Naming. The NC and LD groups differed significantly on RAN, $X^2(1, N = 23) = 6.37, p = .012$ (see Table 5). Follow-up tests revealed statistically significant group differences for mean response times with four of five RAN subtests, Colors, Objects, Letters, and Words (see Table 6). In each performance, the NC group's average subtest performance was faster than the average LD group's performance.

Table 5

Omnibus Tests for Response Time Data by Task

	Seconds		Group Differences	
Task	Range	*M*(*SD*)	X^2	*p*
Rapid Automatized Naming (RAN)				
Response Time				
LD[a]	118.51-190.01	150.70(26.31)	6.37*	.012
NC[b]	99.33-145.06	123.77(14.07)		
Rapid Alternating Stimuli (RAS)				
Response Time				
LD	95.05-173.24	131.65(25.37)	7.67*	.006
NC	83.12-133.89	104.19(13.83)		

* $p < .05$

Table 6

Rapid Automatized Naming (RAN): Group Mean Response-Time Comparisons

	Seconds		Group Differences	
RAN Subtests	Range	*M*(*SD*)	X^2	*p*
Colors				
LD [a]	24.84 – 46.96	35.41(7.77)	5.19*	.024
NC [b]	22.80 – 32.89	28.43(10.09)		
Objects				
LD	31.08 – 47.22	38.00(6.07)	4.13*	.042
NC	26.76 – 41.89	32.42(5.46)		
Digits				
LD	18.61 – 32.65	24.37(4.79)	2.97	.085
NC	15.36 – 25.40	20.54(2.70)		
Letters				
LD	19.30 – 35.52	26.14(5.30)	6.06*	.014
NC	14.19 – 26.31	20.94(2.99)		
Words				
LD	20.39 – 37.29	26.78(5.05)	7.34*	.007*
NC	16.27 – 26.02	21.43(2.90)		

[a] $n = 12$. [b] $n = 11$.

* $p < .05$

Average group response times for Digits subtest were not statistically different.

Rapid Alternating Stimuli. The NC and LD groups differed significantly on RAN, $X^2(1, N = 23) = 7.67, p = .006$ (see Table 5). Follow-up tests indicated statistically significant group differences in mean response times for three of four RAS subtests, including Colors-Objects, Digits-Letters, and Colors-Objects-Digits-Letters (see Table 7). In each case, the NC group's average response time on the tasks was faster than the LD group's average response time. The NC and LD groups were not statistically different for the Objects-Digits-Letters subtest.

Color-Word Stroop. The NC and LD mean response times were statistically different for the C-WS Incongruent subtest, $X^2(1, N = 23) = 5.17$, p = .023; mean response times were 47.43(9.64) and 56.92(10.21), respectively. NC participants performed the task, on average, more quickly than the LD participants. The mean response times for the Congruent subtest were not statistically different between groups (see Table 8).

The Stroop effect was measured by subtracting timed performances for Congruent subtest from Incongruent subtest for each individual. Then the effects were averaged for each group. The group mean differences were not statistically significant (see Table 8).

Overall, the response time data utilized to test the first hypothesis indicated that the LD and NC groups performed differently in eight of eleven subtests. This largely refuted the null hypothesis that indicated no group response time differences would be present. The LD group required more time to complete the eight subtests when compared to the NC group. The Stroop effect data did not differ between groups, which supported the null, suggesting that the group performances were similar.

Table 7

Rapid Alternating Stimuli (RAS): Group Mean Response-Time Comparisons

	Seconds		Group Differences	
RAS Subtests	Range	*M*(*SD*)	X^2	*p*
Colors-Objects				
LD [a]	28.55-51.01	39.69(6.47)	8.02*	.005
NC [b]	24.96-46.64	31.22(6.39)		
Digits-Letters				
LD	20.79-42.86	28.68(7.49)	5.62*	.018
NC	17.04-25.05	22.44(2.15)		
Objects-Digits-Letters				
LD	21.41-40.26	30.27(6.17)	3.64	.056
NC	18.79-35.71	25.14(4.53)		
Colors-Objects-Digits-Letters				
LD	24.12-46.69	33.02(7.12)	6.68*	.010
NC	21.03-30.15	25.38(3.43)		

[a] $n = 12$. [b] $n = 11$.

* $p < .05$

Table 8

Color-Word Stroop: Group Mean Comparisons

	Seconds		Group Differences	
Measure	Range	*M*(*SD*)	X^2	*p*
		Response Time		
Congruent subtest				
LD [a]	23.29-44.27	34.42(7.04)	3.19	.074
NC [b]	21.69-34.35	28.78(4.13)		
Incongruent subtest				
LD	39.33-74.39	56.92(10.21)	5.19*	.023
NC	32.86-69.50	47.43(9.64)		
		Stroop Effect		
LD	4.85-41.01	22.49(11.35)	.85	.356
NC	5.84-36.87	18.65(8.98)		

[a] $n = 12$. [b] $n = 11$. * $p < .05$

Additional Analyses

Age correlations. For this small sample ($n = 23$), groups were collapsed to compare age across psychometric distributions. The small sample size limited investigation of effects to correlations; four participants were above age 35-years and the rest clustered between 18 and 26-years. The correlation was chosen to evaluate the impact of age on response time variables. Age was positively correlated across groups for RAN subtests of Colors, Objects and Digits (see Table 9). The Incongruent subtest of the C-WS also met the statistical criterion for positive correlation to age. No other response time results correlated significantly with age.

Age has been shown to differ between groups and to be highly correlated to the RAN and C-WS response time data. Though the size of the groups was small, an exploratory Multivariate Analysis of Covariance (MANCOVA) was performed to evaluate the effect of age on identified group differences for RAN and C-WS subtests. Age was covaried across subtests for the automaticity tasks which were statistically significant for positive correlation to age, i.e., the RAN-Colors, RAN-Digits, RAN-Letters and Incongruent-Task. MANCOVA results indicated that group differences identified in previous analyses disappeared for the RAN-Colors, RAN-Letters and Incongruent-Task., Wilks lambda = .79, $F(4.17) = 1.15$. $p = .336$. The RAN-Digits subtest results remained statistically non-significant for group differences. In this limited sample, age was overly influential on three of eleven response time data results.

In light of the evidence of the influence of age on two of the RAN and one C-WS subtests which had evidenced statistical support for group differences, the support for the null hypothesis, i.e. no group differences, has increased. Only five of the eleven

Table 9

Response Times Correlations with Age:

Rapid Automatized Naming and Color-Word Stroop Subtests

				N = 23				
Subtest	AGE	Colors	Objects	Digits	Letters	Words	Congruent	Incongruent
AGE	—	.43*	.60**	.55**	.41	.34	.41	.44*
Colors		—	.74***	.77***	.88***	.88***	.67***	.46*
Objects			—	.67***	.69***	.59**	.44*	.62**
Digits				—	.89***	.86***	.62**	.17
Letters					—	.96***	.60**	.28
Words						—	.60**	.19
Congruent							—	.39
Incongruent								—

*$p < .05$. **$p < .01$. ***$p < .001$.

automaticity tasks have remained to support group response time group differences.

EEG Recording

Baseline data. Baseline data were included to provide group comparisons of pre-task cortical activations. Relative power was chosen to evaluate the task driven physiological data of this study to provide a measure of relationship between waveforms attributable to resting versus task activity. Relative power refers to the relative relationship between the waveform bands to the entire EEG spectrum and has been presented in the metric of micro-volts (uV). The baseline was designed to evaluate group cortical activation prior to the study tasks. The baseline data analyses were evaluated and presented in terms of relative power or uV.

EEG scalp electrode data have been shown to demonstrate a high degree of correlation between electrodes. This multicollinearity between variables has been shown to be a problem when attempting to identify marginal or small effects (Cohen & Cohen, West, & Aiken, 2003). The high degree of correlation between variables in a multivariate format has been shown to increase the probability that an effect will not be found. In this data, the multivariate analyses were chosen to reduce the familywise error. Familywise error has been defined as the increasing probability that an effect will be found as the number of analyses is increased. The subtest electrode data was placed in a repeated measures format. The assumption was that electrophysiological data would be expected to be correlated across tasks for the same electrode for each individual. The omnibus test for the passive and active tasks was designed to see if groups differed across tasks for each electrode, much in the same way as multiple measures of intelligence scores, which would be highly correlated for an individual, could be tested for group

differences. The omnibus test for the baseline data assumed that the two electrodes were correlated and were place in a repeated measures format. Two electrodes were measured for each individual and, thus, two similar measures for each individual. In the same fashion, the omnibus test was designed to evaluate the groups for the total effect. In so grouping the data, the probability has been expanded; however, it has provided a balance to the family wise increase expected with multiple analyses.

Omnibus tests were performed for each baseline by waveform, i.e., relative theta, high alpha, and low beta, and across electrodes, i.e., F7 and T5; thus, three omnibus tests were performed per baseline. Multivariate analysis of variance (MANOVA) in a repeated measures format was used to identify group differences for each electrode by waveform. The electrode was the within subjects factor and group was the between subjects factor. Results that met statistical criterion for a between subjects effect were to be further analyzed with by ANOVA for specific tests of the second hypotheses.

The baseline data were provided to compare group cortical activation prior to study participation; however, this data was not included in hypothesis testing. In the event that passive and active task data indicated group effects, specific data comparisons between baselines and tasks would be prepared. These comparisons were deemed necessary for hypothesis testing in the event of statistical evidence of group cortical activation differences attributable to study tasks.

The Eyes-Opened (EO) baseline data was analyzed by waveform. The data demonstrated no statistically different group effects for relative theta, high alpha, or low beta at electrodes F7 and T5, which were specific locations of study hypotheses for task data (see Table 10). The descriptive data were presented in Table G-1. These results

Table 10

Multivariate Analysis of Variance (MANOVA): Tests for Baseline Group Effects at Electrodes F7 and T5 by Waveform

Waveform	Wilks' Lambda	*F*	*df*	*p*
		Eyes-Opened Baseline		
Relative Theta (4-7.5 Hz)				
	.99	.12	1,21	.729
Relative High Alpha (10-12.5 Hz)				
	.94	1.43	1,21	.246
Relative Low Beta (13-20.5 Hz)				
	.88	2.75	1,21	.112
		Eyes-Closed Baseline		
Relative Theta (4-7.5 Hz)				
	.97	.68	1,21	.421
Relative High Alpha (10-12.5 Hz)				
	.96	.93	1,21	.346
Relative Low Beta (13-20.5 Hz)				
	.96	.88	1,21	.358

suggested that for the targeted cortical locations, both groups utilized similar cortical activation levels during a closed eyes resting state.

The Eyes-Closed (EC) baseline analyses yielded no statistically significant group effects at electrodes F7 and T5 for relative theta, high alpha or low beta (see Table 10). The descriptive data were presented in Table G-1. These results suggested that for the targeted cortical locations, both groups utilized similar cortical activation levels during an opened eyes resting state. Data from both the EO and EC baselines suggested that cortical activation at F7 and T5 were similar between groups prior to initiation of study tasks.

Passive task data. The following results reflected analyses of the second hypothesis. The second hypothesis investigated electrophysiological data passively collected after the active task. The null hypothesis stated that no group differences would be present at electrodes F7 or T5 for the relative theta, high alpha or low beta waveform bands. Electrodes F7 and T5 were specific focuses of the second hypothesis as they overlay cortical substraits which were hypothesized to be sensitive to the phonemic subskills.

The passive data collection technique required participants to name items on the RAN, RAS, C-WS block stimuli, i.e., the Congruent-Block and Incongruent-Block subtests, and then sit quietly with eyes closed for EEG recording. Data was analyzed by electrode, i.e., F7 and T5, across tasks for each waveform, i.e., theta, high alpha, and low beta, to reduce family-wise error. For example, the passively collected data was examined for relative theta by evaluating F7 data across tasks between groups, then data from T5 was evaluated across tasks between groups. Multivariate analysis of variance (MANOVA) for repeated measures was used to evaluate groups by task for each electrode. The task was

the within subjects factor and group was the between subjects factor. Results that met statistical criterion for a between subjects effect were to be further analyzed with ANOVA for specific tests of the second hypotheses.

Omnibus tests for passive data collected after RAN, RAS, Congruent-Block, and Incongruent-Block tasks revealed no significant effect of group for theta, high alpha, or low beta for either of the F7 or T5 electrodes (see Table 11). See Tables H-1 and H-2 for descriptive data by task. The data collected from the passive recording of tasks did not demonstrate any significant differences for the hypothesized locations of the left hemisphere. Thus, the data reflected that the NC and LD groups utilized resources similarly during physiological recordings made after active tasks and supported the null hypothesis.

Active task data. The following results reflected analyses of the third hypothesis. The third hypothesis investigated electrophysiological data collected during the active tasks. The null hypothesis stated that no group differences would be present at electrodes F7 or T5 for the relative theta, high alpha or low beta waveform bands.

The Stroop Congruent-Task and Incongruent-Task were active EEG recording tasks compared to the four previous tasks that relied upon passive data collection procedures. Data from one participant in the NC group (n = 10) was missing in both active tasks; 22 participants contributed to the active task data. As before with the passive data collection, group data were analyzed across tasks by electrode and waveform for omnibus testing; thus, six omnibus tests were performed. MANOVA was used to evaluate groups by task for each electrode per waveband. The task was the within subjects factor and group was the between subjects factor. Results that met the

Table 11

Multivariate Analysis of Variance (MANOVA): Tests of Group Effects by Task for Passively Collected Data

Waveform	Wilks' Lambda	*F*	*df*	*p*
Relative Theta (4-7.5 Hz)				
F7	1.00	.01	3/19	.998
T5	.98	.11	3/19	.952
Relative High Alpha (10-12.5 Hz)				
F7	.97	.20	3/19	.895
T5	.87	.92	3/19	.450
Relative Low Beta (13-20.5 Hz)				
F7	1.00	.01	3/19	.998
T5	.89	.77	3/19	.523

.05 statistical criterion for a between subjects effect were to be further analyzed with ANOVA for specific tests of the second hypotheses.

MANOVA tests for data collected during both Congruent-Task and Incongruent-Task revealed no significant effect of group by task for relative theta, high alpha, or low beta for either the F7 or T5 electrodes (see Table 12). These results suggested that during active recording tasks, both groups evidenced similar cortical activation levels at the targeted locations. Descriptive data by task was placed in Table I-1.

These data suggested that the NC and LD groups utilized their left inferior frontal and left posterior parietal cortical resources similarly during the active tasks. The data supported the null hypothesis of similar group left hemisphere cortical activation levels during reading related tasks.

Summary. Both the passively and actively collected EEG data analyses were not statistically significant for group differences in the evaluation of hypotheses involving F7 and T5. Baseline data analyses were outside the scope of hypothesis testing but were available for meaningful analysis in the presence of group differences. Since no data met statistical criterion, baseline data comparisons to task data were not performed.

Additional comments. Age was demonstrated to be overly influential on three of response time data analyses. Though no statistically significant electrophysiological results were found, a look at the correlational relationships between all waveform data, i.e., relative theta, high alpha, and low beta, at each electrode, i.e., F7 and T5, was reviewed for each baseline and task. No correlational data met the .05 statistical criterion.

Table 12

Multivariate Analysis of Variance (MANOVA): Tests of Group Effects by Task for Active Tasks

Waveform	Wilks' Lambda	*F*	*df*	*p*
Relative Theta (4-7.5 Hz)				
F7	.94	1.25	1/20	.277
T5	.94	1.22	1/20	.283
Relative High Alpha (10-12.5 Hz)				
F7	1.00	.00	1/20	.994
T5	.91	1.96	1/20	.177
Relative Low Beta (13-20.5 Hz)				
F7	.83	4.19	1/20	.054
T5	.99	.13	1/20	.724

CHAPTER FOUR

Discussion

This chapter was constructed to discuss the psychometric performance differences for group inclusion and validation, followed by response time and electrophysiological group differences. This discussion was organized by hypotheses integrating each task specific to the evaluation of group performance. The first research hypothesis was tested by response time data. The second and third hypotheses were addressed by electroencephalography data collected by passive and active data collection techniques, respectively. An evaluation of each null hypothesis was provided for the conclusion of each section. Finally, characteristics that limited data generalization have been presented along with promising directions for application and future research.

Overview

The present investigation examined the topic of reading subskill automaticity through performance measures in response times and electroencephalography (EEG). Participants in the learning disability sample (LD) had documented diagnoses representing reading skills deficits which were validated for their inclusion in the study. The comparative non-clinical sample (NC) had no history of learning disability and provided evidence of normal reading achievement. Group inclusion requirements included psychometric measurement of general intellectual functioning (PPVT-III) and discrimination of group phonetic reading skills differences by selected subtests of the Woodcock Johnson Psychoeducational Battery-Revised, Tests of Achievement (WJ-R-A); specifically the Word Attack subtest verified group phonetic skills differences. Group comparisons of psychometric automaticity measures for hypothesis testing

included Rapid Automatized Naming (RAN), Rapid Alternating Stimuli (RAS), and the Color-Word Stroop (C-WS). Electrophysiological (EEG) activity generated during automaticity tasks was used as a primary comparison of participants' aggregated cortical activity for each measure. Electrophysiological measures included a passive data collection technique utilized after administration of RAN, RAS and C-WS tasks, and an active data collection technique used during a computerized administration of the C-WS Incongruent and Congruent tasks. Analyses were specific to apriori hypotheses and all were evaluated by a criterion of significance at $p \leq .05$.

Group Criteria Comparisons

The goal of participant selection and psychometric measurement was to identify group similarities and planned differences providing for the enhancement of the internal validity of the data. One notable group demographic difference was mean age. The NC and LD group participants differed statistically in mean age, (M_{NC} = 20.41 years, M_{LD} = 29.47 years, p = .019). Age has implications for response time and electrophysiological data. This topic has been discussed further in the data limitations at the conclusion of the chapter.

The groups did not statistically differ in emotional valence as measured by the Profile of Mood States, Revised (POMS-R). The POMS-R was used to assess depression, anxiety and other emotional qualities that have been identified as potential confounds not addressed in earlier studies. Mood state data were demonstrated not only to be at similar levels, but also to be within the acceptable clinical standard of 2 *SD* within each group. Exclusion of significant variance in emotionality provided for the

interpretation of standard psychometric measures in accordance with standard clinical procedures. These data also contributed to the internal validity of the subject samples.

The PPVT-III standard scores (SS) verified participants' intellectual qualifications for study participation. The average group scores (M_{NC} = 106.8, M_{LD} = 106.8) were not significantly different, which demonstrated equivalence in estimated intellectual level between groups and further contributed to internal validity of the clinical (LD) and comparison (NC) groups. The distribution of individual scores across groups revealed one score from the LD group which was a non-significant outlier that corresponded to the Low Average range according to publishers' classification criteria (Dunn & Dunn, 1997). All other scores from both the LD and NC groups spanned the Average to Superior ranges. Both groups' SS distributions corresponded to the range of scores that may be most valid for the PPVT-III in estimating cognitive ability (Bell, et al., 2001). The average group scores and the standard score distributions evidenced no significant differences, thus equivalence between groups in intelligence as defined by semantic abilities and receptive vocabulary.

The WJ-R-A Passage Comprehension subtest yielded individual standard scores which verified semantic ability equivalence in the comparison between LD and NC groups; semantic reading skills were not significantly different. NC and LD mean group performances corresponded to the average for their age (M_{NC} = 102.6, M_{LD} = 101.5). The range of obtained scores, standardized as per publisher's scoring procedures, for the NC group was slightly broader. The highest individual SS for the NC group was 128 compared to LD group's highest individual SS of 115 (see Table 3). The absence of

group differences suggested comparable application of verbal semantic skills in this reading task.

The WJ-R-A subtests, Word Attack and Letter-Word Identification, were included to verify the phonetic verbal subskill component that was part of the LD group selection criteria; these criteria were used to define the LD dysphonetic subtype and further circumscribed the clinical sample for internal validity of cognitive processes. The difference of 22.4 standard points between averaged group scores for the Word Attack subtest ($M_{NC} = 119.7$, $M_{LD} = 97.3$; $p = .001$) highlighted the substantial phonetic deficit, or difference in phonetic expertise, in the LD group and supported the phonetic deficit criterion for group membership. The between group difference of 9.9 standard points for the Letter-Word Identification subtest, was not as robust a difference as evidenced for the Word-Attack subtest, and met the relative difference criterion identified in earlier research; this pattern provided converging evidence of the LD group's difficulty with application of phoneme-grapheme association skills.

The identification of a phonetic deficit was central to the selection of reading disability participants; the Neuropsychological Assessment of Learning Disabilities checklist (NALD) was created to assist in recording this information from the supporting diagnostic information. Those participants who had previously identified dysphonetic deficits were included in the study; usually, the individual's file reported Word Attack subtest SS that were lower than Passage Comprehension SS. After the WJ-R-A subtests were administered to the LD participants during study procedures, six participants' Passage Comprehension scores were below their Word Attack scores.

An identified subtype of dyslexia has demonstrated comprehension difficulties without the same degree of dysphonetic component (Tallal, et al., 1993). The psychometric comparison of the semantic subtype would be comparable to non-clinical performance in that the WJ-R-A Word-Attack and PPVT-III receptive vocabulary performances would be similar. Alternately, one difference between semantic and dysphonetic subtypes would be seen in subtests loaded on semantic components. To test whether the LD group contained a semantic subtype, the PPVT-III and WJ-R-A subtest scores were evaluated between the groups with lowest Word Attack scores, indicative of dysphonia ($n = 6$), and Passage Comprehension scores, pertaining to semantic comprehension deficits ($n = 6$). This additional examination was to compare the constituent skills between these subgroups relating to the LD subtypes, i.e., dysphonetic and semantic dyslexia (see Table 4). The PPVT-III subgroup averages were not statistically different ($M_D = 109.3$, $M_S = 104.3$), thus they had comparable receptive vocabulary skills. The aggregated Word Attack ($M_D = 88.2$, $M_S = 106.6$; $p = .025$) and Letter-Word Identification ($M_D = 92.5$, $M_S = 111.3$; $p = .030$) SS were statistically different between the two groups, but the Passage Comprehension scores were not ($M_D = 105.2$, $M_S = 97.8$). The phonetic skills were different between the two groups; however, the constituent semantic skill was not different between the subgroups, thus application of the description of semantic dyslexia would be inappropriate. For the present discussion, since the LD group aggregate ($n = 12$) did differ from the NC group in average phonetic ability, then it was interpreted under the dysphonetic construct.

Automaticity

Psychometric Measures

The overarching topic of this investigation was automaticity of language subskills. Consistent practice with paired phoneme-grapheme subskill components during reading has been thought to produce acquired automatization resulting in increased speed of processing and reduced need for attention; the consequences have included reduced cognitive engagement related to mental effort and reduced performance times. The most skilled readers, those with the greatest expertise with combining the phoneme-grapheme components have been shown to perform neuropsychological tasks that tap these subskills with a minimum of time and effort, reflecting that automaticity. Readers with poorly automatized reading subskill components, specifically those with learning disabilities, theoretically have been thought to require more time and expend greater effort to accomplish the same neuropsychological tasks.

This investigation explored the speed of processing component of automaticity via response time data recorded during neuropsychological automaticity tasks. Group selection criteria based on phoneme skill differential allowed the examination of automaticity differences specific to differing levels of phonetic expertise consistent with phoneme/grapheme paring. Group comparisons consisted of response times obtained from performances during neuropsychological tasks designed to replicate tasks of reading with orthographic components that tap speed of processing, i.e. RAN and RAS (e.g., Denkla, 1999; Wolf, Bowers & Biddle, 2000). The C-WS provided an additional comparator, the Stroop effect, which has been posited to reflect lexical/semantic level processing (Catena, Fuentes, & Tudela, 2002; Leverett, et al., 2002).

The First Hypothesis

The first null hypothesis with the psychometric scope was based upon two components, response times during automaticity tasks and Stroop effects. The first null hypothesis based on response time data posited that the NC and LD groups would not differ in response times; however, the LD group, because of the less well developed automatization of the phoneme-grapheme subskill components, was expected to require more time to complete each task.

The second part of the first null hypothesis stated that the Stroop effects, based on the response time relationships between the Congruent-Block and Incongruent-Block subtests of the C-WS, would not be different between the NC and LD groups. Stroop effects literature has suggested that the Stroop taps semantic/lexical processing (Catena, et al., 2002). The clinical group was selected based on phonetic as opposed to semantic deficits. If, as Cox, et al. (1999) has conjectured, the word recognition skills have been poorly automatized in the LD group, then the Stroop effects should be different between groups. The LD group's Congruent-Block and Incongruent Block performances would be more similar, producing smaller Stroop effect scores when compared to the NC group's scores.

Response Times

RAN and RAS. The obtained results from the response times of the RAN and RAS subtests were like those of other studies involving college students with Learning Disability diagnosis (e.g., Hutchens, 1988; Zabell & Everatt, 2002). Seven of the nine timed performance tasks yielded significant differences in times taken to complete the naming task, thus, discriminating between the LD and NC groups (see Tables 6 and 7).

The LD group performed significantly more slowly in all but two of the RAN and RAS subtests; RAN-Digits ($p = .085$) and RAS-Objects-Digits-Letters ($p = .056$) subtest response times did not statistically differ between groups in this college sample, but were very close to meeting the statistical criterion. This lack of statistical significance may be an effect of sample size. Overall, the LD group participants required more time to complete the majority of tasks.

The response time differences between the NC and LD groups for RAN and RAS were consistent with the body of literature that discriminated between both children and adults diagnosed with learning disabilities and non-clinical controls (Denkla, 1999; Hutchens, 1988; Morgan, et al., 2000; Wolf, et al., 2000; Zabell & Everatt, 2002). Contrarily, in this sample age was shown to be a mitigating factor for two group response time performances of the RAN subtests and for the Incongruent C-WS subtest. Response time measures have been shown to be related to speed of processing, which through association with such performance measurements, has been shown to decline with age and has been thought to tap the fluid domain in tests of intelligence (Kaufman and Lichentenberger, 1999). Clearly age provided an alternative explanation for some group response time differences in this investigation.

The remaining response time data, which were three of the four RAS subtests, and two of the RAN subtests, occurred in context with the LD and NC groups' phonemic skills differences revealed by the WJ-R-A; the semantic applications were similar between groups, as seen in the WJ-R-A Passage Comprehension. The RAN subtests were the more basic of the two naming tasks reflecting the visual presentation of sequential, contextual, orthographic, executive, and phonetic elements of reading (Denkla

1999; Wolf, et al., 2000). The RAS subtests were the most complex tasks challenging executive functions, such as cognitive set switching, while the participants named the mixed stimuli. All of these stimulus components have been hypothesized to add incremental processing speed requirements to rapid naming tasks and have been shown to be challenging for children and adults with dysphonia (Denkla 1999; Wolf, et al., 2000). Since other sources of dysfunction were eliminated during participant selection and validated by psychometric testing during study procedures, e.g., emotional content, basic perceptual and semantic processing deficits were excluded, the disruption of the phonetic component has provided a persuasive argument for influencing the response time data; however, as Wolf, Bowers and Biddle (2000) have demonstrated, phonological awareness, representation, and access are only a few of the components of the integrative processes that support the rapid automatized naming of reading related stimuli. The clearest statement to be made from the data was that the LD participants required more time to complete five of the naming tasks and this phenomenon was in the presence of remarkable group phonetic differences.

Color-Word Stroop. The C-WS congruent and incongruent stimuli were converted into block stimuli in order to present the tasks in a manner similar to RAN and RAS; time taken to complete these naming tasks was measured and compared by group. The Congruent-Block average response times were not different between groups (M_{NC} = 28.78 s, M_{LD} = 34.42 s; p = .074). The Congruent-Block was an analog for the RAN Color naming task. Both tasks shared the same stimulus requirements; the sequential, contextual, orthographic, executive, and phonetic elements of reading were present. Sample size may have also contributed to the lack of statistical effects.

The LD group performance time was slower for the Incongruent-Block subtest (M_{NC} = 47.43 s, M_{LD} = 56.92 s; p = .023) when compared to the NC group. This was consistent with response time differences for RAS subtests; however, when the affect of age was held constant, group differences disappeared. Like the RAS stimuli when compared to the RAN, the Incongruent-Block was the more complex of the C-WS stimulus blocks and required effective cognitive set-switching skills, such as search/retrieval processes from multiple phoneme/grapheme interrelated modules, which in addition to attention skills have been allocated within executive functions (Denkla, 1999). However, the speed of processing element underlying executive functions has been shown to be sensitive to effects of age (Kaufman and Lichentenberger, 1999) to which study data has provided support.

Stroop effect. The Stroop effect was calculated by subtracting the Congruent-Block from the Incongruent-Block response times for group participants and then creating a mean effect for each group. The resulting effect time has been thought to represent cognitive interference; a representation of executive function differences between the two types of stimuli. The standard derived Stroop effect has been considered a robust clinical measure of cognitive interference with clinical applications and has demonstrated efficacy for Learning Disabilities (Cox, et al., 1997; Golden & Golden, 2002).

The group Stroop effects for this study did not meet statistical criteria for group differences. A trend was evident such that LD group participants had a broader range of effect scores (see Table 8) and experienced greater interference (M_{NC} = 18.65 s, M_{LD} = 22.49 s). An absence of statistical group differences was contrary to the literature in

which the Stroop effect was different between samples of people with reading difficulties and normal reading achievement (e.g., Everatt, 1997; Golden & Golden, 2002). The Stroop stimuli have been hypothesized to access semantic/lexical processing (Catena, et al., 2002). In clinical research conducted by Cox, et al. (1997), lack of statistical group differences between reading impaired and normal adult reader's Stroop effect scores were theorized to be related to poorly automatized semantic components. The Stroop effect would not be present in adults with reading disability because they do not have the same quality of semantic processing as normal readers.

The interpretation for the present study posited that for Cox et al.'s (1997) argument to be supported, the LD group's Congruent-Block and Incongruent-Block subtest scores would be more alike than different when compared to the NC group's performances. If poorly automatized semantic processing inhibited the cognitive interference effect, then the congruent and incongruent Stroop stimuli would pose similar perceptual challenges; thus, a smaller Stroop effect would have been present for the LD group. This was obviously not the case for study participants with Reading Disability characterized by dysphonia. Data from this study demonstrated the robust group equivalence in semantic processing with Passage Comprehension subtest results. The NC and LD groups demonstrated equivalent semantic ability and similar Stroop effect scores despite the large group differences in phonetic ability; therefore, the Stroop effect data could be interpreted in light of semantic processing requirements, but not from Cox et al.'s point-of-view. Alternately, the response time data for the Incongruent Stroop subtest were highly correlated with age. The interpretation of the impact of age on the Stroop effect was not clear for this data. As it stands, the LD participants' relative

response times for the two subtests suggested that the combined tasks contained common stimulus elements that presented similar perceptual challenges for both the LD and NC participants.

Evaluation of First Hypothesis

The first hypothesis as stated in the null was that the NC and LD group participants would not differ in their response times for the RAN, RAS, and C-WS tasks. The hypothesis was tested in two ways, first, by comparing the group response time data and, second, by comparing group Stroop effects.

The first hypothesis was evaluated by comparing average response times between groups. For the RAN and RAS subtests, all but the RAN Digits and RAS Objects-Digits-Letters subtests met statistical criteria for group differences, but age mitigated the group effects for the RAN Colors and Objects subtests. As the C-WS stimuli were modified to be comparable to RAN and RAS in response time data, the group performances to the individual subtests were included in the evaluation of the first hypothesis. Only the Incongruent-Block met statistical criteria for group differences which were also mitigated by age. The LD group's longer response times in the remaining five subtests reflected slower processing speed for meeting the stimulus processing demands. Five of eleven subtests for RAN, RAS and C-WS clearly demonstrated longer average response times for the LD group; since less than half of the automaticity subtests reliably met the statistical criteria for group differences for this part of the hypothesis, the null was retained.

An additional evaluation of the first hypothesis included comparisons of the average group Stroop interference effects. The Stroop effect results were not statistically

different between groups. As the LD groups' Stroop effects were not smaller than the NC group's, and in the context of equivalent group semantic skills, research suggesting semantic processing differences was not supported. The LD group's Stroop effect was similar to the NC group's effect; therefore, the null was retained.

Phonemic Ability and Automaticity. The LD group's level of phonemic subskill processing, theoretically less well developed than that of the NC group, was consistent with other studies as a result of inclusion criteria targeting the dysphonetic subtype of the reading disability. Previous studies have suggested relationships between phoneme-grapheme subskills and processing speed differences between the groups of differential phoneme processes ability which was moderately supported by data from this investigation. The LD group performance on the Word Attack subtest revealed phonemic processing to be at a level below that of the NC group while semantic skills were shown to be equivalent. Group response time differences in the RAN and RAS neuropsychological data may have reflected the relative phonemic neurocortical processing elements that are componential to processing speed; however, the support was weak. The inference of slower speed of processing in the LD student having been reflected in previous research was the impetus for the application of EEG methodology, posited to capture group cortical activation differences in this investigation.

Electrophysiological Measures

The second part of the examination of automaticity was designed to evaluate an aspect of mental effort by addressing relative cortical activation. Data from electrophysiological activity (EEG) was generated after and during completion of the neuropsychological automaticity tasks. Automaticity related EEG activity in the

literature has been studied in relation to cortical activation changes that occur as a result of practice. Cortical activation has been shown to change predictably between the acts of learning new information and the expert application after practice, as well as in relation to increased task demand (Fairclough, et al., 2005; Gevins, et al., 1998; Klimesch, 1999; Smith, McEvoy, & Gevins, 1999). Increased cortical activation, related to recruitment of cortical resources and mental effort, has been associated with learning new information; reduced cortical activation or mental effort has been associated with the ease of processing automatized or over-learned material. Research has shown participants exert higher cortical activation levels when learning new information and, alternately, to require less activation and effort with fluent, well learned material (Fairclough, et al., 2005; Smith, et al, 1999).

Both NC and LD group participants have had formal experience with the phonetic and orthographic subskills associated with reading. The NC group participants, however, applied these subskills more effectively as reflected by their relatively superior performance in Word Attack skills in this investigation. Their faster response times for the three RAS, subtests also hinted at greater fluency in the reading related subskills associated with these neuropsychological tasks when compared to the LD group's performance. Cortical activity associated with fluent ability has been depicted as reflecting less mental effort and faster performance times. Since the two groups were characterized as differing in phonetic ability, the more expert participants should produce less activation in cortical regions that have been recruited for task demand when compared to participants of lesser ability. The EEG record has been posited to reflect this

differential mental effort as cortical activation differences expended during the completion of the neuropsychological tasks.

QEEG Baselines

Baselines have been common procedures in the brain imaging literature for distinguishing between resting and task dependant cortical activity (e.g. Angelakis & Lubar, 2002; Towler, 2002). For this investigation, both resting eyes-opened (EO) and eyes-closed (EC) baselines were included to evaluate group comparisons during resting conditions at locations targeted for but not included in hypothesis testing.

Eyes-opened baseline. The resting EO baseline showed no cortical activation differences between groups. This data established that prior to the study tasks, both groups were producing similar levels of relative theta (4-7.5 Hz), high alpha (10-12.5 Hz) or low beta (13-20.5 Hz) activity around the left inferior precentral (F7) and the posterior, superiortemporal (T5) regions. These results were consistent with the eyes-opened resting task condition without influence of age effects.

Eyes-closed baseline. The EC baseline also demonstrated group equivalences in cortical activation levels for relative theta, high alpha and low beta activity around the left inferior precentral (F7) and the posterior, superior temporal (T5) regions. These results were consistent with the closed eyes resting state and demonstrated that both of the LD and NC groups were

Baseline summary. Data from both baselines provided evidence of group similarities of cortical activation during resting states for the targeted locations of the left hemisphere. No activation differences had been anticipated as resting baseline data rarely has discriminated between LD and NC samples especially with such small cortical

area data sampling. Most QEEG studies have focused on global measures because of the limited resolution of the method. The goal of this project, however, was to demonstrate stringent group selection criteria in the identification of the phonetic skills differences and to yoke that criterion into QEEG methodology to investigate the automaticity deficit in terms of effortful processing at specifically targeted locations of interest. The similarity of group cortical activation demonstrated in the F7 and T5 electrodes suggested that at rest, these two groups were not different in the distribution of cortical activation.

The Second Hypothesis

The second hypothesis, as stated in the null, was that passive data collection of EEG following the performance of the active automaticity tasks RAN, RAS, and C-WS would reveal no waveband activation differences in the left inferior precentral region, electrode F7, or the left posterior superior temporal cortex, electrode T5. The analyses that were used to evaluate this hypothesis were two specific electrodes that were positioned over to the cortical locations of interest, i.e., F7 and T5. Should the LD group, recruiting more cortical resources to accomplish the tasks, produce greater cortical activation in the left inferior precentral region or the left posterior superior temporal cortex, then the EEG data would show significant cortical activation differences at F7 and T5, respectively, when compared to the NC group data.

The cortical locations that were most likely to be activated by the selected automaticity tasks included the left inferior precentral gyrus and the posterior superior temporal cortex. These locations have been demonstrated to involve cortico-cortical processing and, therefore, accessible to EEG. Word reading and Stroop incongruent stimuli have demonstrated activity in the left inferior precentral gyrus with fMRI (Mead,

et al., 2002; Turkeltaub, Eden, Jones, & Zeffiro, 2002). Activity from this region has been shown to be accessible via the left frontal electrode (F7). Phonological skills have been posited to modulate the posterior superior temporal cortex during the acquisition of reading skills (Turkeltaub, et al, 2003). Activity from this region has been shown to be accessible through the left posterior temporal electrode (T5). Residual activation effects were hypothesized to be available directly after administration of sequential stimuli, especially in the absence of vocal artifacts.

Passive Recordings

A special recording technique was devised to capture cortical activation attributable to the neuropsychological tasks used in this investigation. The passive data collection technique was applied in an attempt to identify differential cortical activation during the performance of neuropsychological tasks. This technique was designed to avoid vocal artifact as it has been problematic to EEG recordings during tasks requiring vocal responses. EEG data were collected immediately after each of the RAN, RAS, and C-WS subtests that were presented for naming and response times were recorded for automaticity investigation; each participant had been trained for an immediate transition from task performance to eyes-closed repose during these recordings. Data collected after each subtest were aggregated and processed according to uniform procedures (see Chapter 2). The goal of the passive recording technique was to avoid vocally produced artifacts in the EEG record and to collect remnant cortical activity attributable to the performances of the same neuropsychological tasks used to examine the speed of processing component of automaticity.

Rapid Automatized Naming (RAN). Passive recording after administration of RAN subtests revealed group similarities in both cortical areas and degree of activation. No differential group cortical activation effects were present in the specifically tested electrodes of F7 and T5 for the theta, high alpha or low beta relative wavebands. The data showed that the between group remnant activity collected after RAN subtests was not different. All non-significant results were considered areas of commonality between the groups.

Both LD and NC groups produced similar remnant activity across the targeted cortical locations for the RAN. The RAN automaticity task required many types of subskills for successful completion, for example phoneme-grapheme pairing, visual-spatial organization, sequential-contextual pattern recognition and articulatory responses. The group remnant activation levels suggested that both groups allocated and utilized cortical resources for this performance in a similar manner.

Rapid Alternating Stimuli (RAS). Passive recording after administration of RAS subtests revealed group similarities in both cortical areas and activation. No differential group effects were present for any relative waveband, specifically, theta, high alpha, and low beta, in the electrodes F7 and T5. As with the RAN data, all non-significant results were areas of commonality between the groups.

The cortical activation results from the passive recordings of RAS were similar to that seen in RAN data. The results pointed to group activation similarities rather than differences. The remnant activity data suggested that cortical activation in the left inferior precentral region and the left posterior superior temporal cortex for the automaticity tasks was similar between groups.

Congruent-Block. The congruent stimuli were color-words that were displayed in the same color, e.g., the word "red" displayed in the color red. Standard Stroop stimuli were modified into block form for this task; in essence a reading analog was created with sequential and contextual components similar to reading task demands and to RAN and RAS stimuli. The naming task was to name the color while not reading the color-word. Data collection was such that task results could be compared between groups in the manner of the RAN and RAS data.

No processing differences were revealed in the theta, high alpha or low beta relative wavebands for the electrodes F7 and T5. Largely, cortical resources were distributed similarly in the inferior precentral region and the left posterior superior temporal cortex during the passive data collection after task performance.

The passive data collection technique once again produced results that revealed more about group similarities of cortical activation than differences for the Congruent-Block. The congruent stimulus has not been shown to precipitate cognitive interference as its partnered subtest, the Incongruent-Block; therefore, focal cortical activation differences may not have been a reasonable expectation. The similarity of group response time performances for the Congruent-Block in this study concurred with these results. Thus, the LD and NC participants utilized similar cortical resources for comparable response time performances.

Incongruent-Block. The standard incongruent Stroop stimuli were also modified into block form for this task consistent with the Congruent-Block; results were, therefore, comparable between groups across automaticity tasks throughout the investigation. The incongruent stimuli were color-words that were displayed in another color, e.g., the word

"red" displayed in the color blue. The naming task was to name the color without reading the color-word. No passively collected group cortical activation differences were found in relative theta, low alpha, high alpha, and low beta were found for F7 and T5 electrodes in this passively collected data.

No result was significant between groups for the Incongruent-Block subtest, which suggested cortical resources were utilized similarly for both groups. The lack of group differences could be explained by the groups' use of similar cortical resource strategies for accomplishing the task; cortical resources may have been utilized similarly between the two electrodes for both groups. Visual processing was only part of the tasking as participants struggled to name the color of a word without reading it. The Stroop stimuli's loading on semantic and executive functioning have been the focus of research studies involving clinical samples (e.g., Bush, et al., 1999; Towler, 2002). Magnetic resonance imagining (MRI) has utilized Stroop stimuli to investigate attention, an executive ability, as it relates to the anterior cingulate (AC) and the dorsolateral prefrontal circuit (DLPC) that are located in the frontal lobes (Bush, et al., 1998; Bush et al., 1999). These previous studies confirmed strong activation of AC and DLPC with additional activation at the posterior cingulate for the control samples. The groups in this investigation have demonstrated similar semantic applications; therefore, semantic processing and executive processing, may be the mitigating factors in both groups for cortical processing with this task. Given previous research results, the lack of cortical activation differences from the passively collected data, and the similar group semantic abilities, these results suggested that for this sample semantic abilities and executive functions attributable to the left frontal cortices may not explain response time

differences described earlier. Processing requirements for this task appear to have been similarly allocated between the two groups for the Incongruent-Block performance.

Evaluation of Second Hypothesis

The null hypothesis was that passive EEG data collection following the performance of the active tasks for RAN, RAS, and C-WS subtests would not reveal waveband activation differences in the left inferior precentral region (F7) or the posterior superior temporal cortex (T5). The second hypothesis was evaluated by comparing passively collected EEG data for RAN, RAS, Congruent-Block and Incongruent-Block subtests between groups. Group differences in relative high alpha, theta and low beta were expected as they represent differential application of mental effort. The more experienced performers, in this case the NC participants, would produce greater alpha since they have theoretically better automatized phonetic subskill functioning. The less experienced reading subskill performers or the LD participants would increase theta and low beta activity during performances as they have theoretically reduced phonetic subskill automatization. Specifically, the LD group in contrast to the NC group was expected to produce less relative high alpha while increasing relative theta and low beta at electrodes F7 and T5. The LD group's predominant phonetic weakness was expected to especially be evident in cortical activation of the posterior left hemisphere, but frontal lobe affects were possible due to phonetic articulation, semantic coding and executive function task requirements. The poorly automatized subskills of the LD group were thought to require greater mental effort and, thus, would modify cortical activation accordingly.

A summary of the data that was used to test the second hypothesis revealed no group differences for the targeted relative wavebands or cortical locations. Remnant activation differences in the left hemisphere and at the electrodes, F7 and T5, specific to the hypothesis were not reflected in this data. These locations were predicted to show cortical activation differences reflecting differential effortful processing between participants with dysphonia and those with strong phonetic skills. As no data supported the premise, the null was retained.

Concluding comments. The similarity of relative activation levels between groups during all of the passively recorded task conditions may have reflected a limitation of task demand. The stimulus blocks contained 50 items and required only 25 to 40 seconds for task execution. The block naming tasks may not have sufficiently activated the cortical locations in proximity to the electrodes requisite to the EEG threshold sensitivity. The response time data collected prior to the RAN and C-WS tasks was not significant between groups when covaried with age, though the corresponding electrophysiological data was not correlated to age and suggested that group performance and cortical activation was similar. Alternately, what activation that remained after task completion may have been insufficient to be captured by the electrodes. QEEG used in the passive collection of data may not be sufficiently sensitive to such transient activation especially in a clinical sample hypothesized to have subtle neocortical structural defects. Tasks requiring greater cognitive load, such as rapidly naming blocks of 150 or more items, may be necessary for a passively collected activation effect to be revealed.

The Third Hypothesis

Active Recordings

In the null, the third hypothesis stated that for the active data collection condition, the EEG waveband activation data would not discriminate between groups in the left inferior precentral region (F7) or the posterior superior temporal cortex (T5). Whereas the passive EEG recording technique occurred after the automaticity task performances, the active data collection occurred during the performance of the Stroop tasks. The incongruent and congruent Stroop stimuli were modified to test the third hypothesis. The computerized presentation of 200 stimulus words for the Congruent-Task consisted of 80% congruent stimulus words and 20% incongruent stimulus words. The Incongruent-Task stimuli ratios were 80% incongruent and 20% congruent stimulus words. EEG was recorded while participants actively viewed and manually advanced the single word stimuli on a computer screen while using internal, subvocal responses to minimize vocal artifact. As with the passive data tasks the participants named the color while avoiding reading. The data that were used to evaluate this hypothesis were from two electrodes that were positioned over the cortical locations of interest, i.e., F7 and T5. Data derived from the EEG recorded during the active tasks were posited to provide evidence of group differences revealing differential effortful processing.

Congruent-Task. Electrodes F7 and T5 were not statistically significant for any of the relative power bands. The relative theta, high alpha, and low beta data were not statistically different between the NC and LD groups. These results suggested that both groups experienced similar cortical activation in left frontal and posterior parietal cortical locations while accomplishing the active task.

Incongruent-Task. No significant activation differences were present in the F7 or T5 electrodes. The relative theta, high alpha, and low beta data were not statistically different between the NC and LD groups. These results reflected the similarity of cortical activity produced during the task; effortful cortical activation was largely similar between groups.

Evaluation of the Third Hypothesis

The third hypothesis, as stated in the null, was that data collected during the active task recording of the C-WS would demonstrate similar cortical activation in the left inferior precentral region (F7) and the posterior, superior temporal cortex (T5) for both groups. As per the second hypothesis, the LD group cortical activity focus was in electrodes F7 and T5. If the mental effort was different between the two groups, which differed in phonetic expertise, the LD group would have produced less relative high alpha power while increasing relative theta and relative low beta, thus, suggesting that their cortical processing was more effortful.

Both the Congruent-Task and Incongruent-Task produced no statistically significant results for the actively collected EEG data. Neither F7 nor T5 data demonstrated group differences that were interpretable in terms of mental effort. Since no group relative cortical activation differences were present at targeted electrodes, the null was retained.

Semantic Ability and Stroop.

Previous research and Stroop effect data from this study has suggested that Stroop stimuli require semantic processing (Catena, et al., 2002). Task demand for the active tasks should have been sufficient to reflect group cortical activation differences. In

contrast to the passive data collection tasks which were short on stimulus-perceptual processing time, these two tasks were designed to provide sufficient time for perceptual processes to be engaged during task performance. The Stroop stimuli, presented as a single stimulus with manual advancement, may have elicited similar cortical processing effects between the two groups. Manual Stroop tasks have been shown to produce effects in fMRI, which has been shown to be very sensitive to vocal artifact (Mead, et al., 2002; Bush, et al, 1999). Other explanations such as age effects and intellectual ability were eliminated; however, data interpretation was limited due to no direct performance evidence as did the cited studies. Yet a cogent explanation of similar group electrophysiological effects would be that given the phonetic group differences and the semantic group equivalences, non-significant electrophysiological data at F7 may have reflected similar group levels of semantic processing in the inferior precentral cortices.

Study Limitations and Future Directions

Limitations of the Present Investigation

The inferential nature of the data obtained from the automaticity tasks and EEG methodology has limited generalization of results to other adults with reading disabilities. No measurement instrument produced data that directly measured the study constructs. Automaticity tasks produced response time measures that were interpreted in the context of processing speed; they have been shown to tap task specific cognitive processing speeds, but not to be direct measures of it (Wolf, et al., 2000). Brain activation as measured by EEG was interpreted based upon previous research findings. It has been shown to be an imaging mechanism with good temporal resolution; however, the scalp based electrodes and diffuse spatial resolution have made localizing waveform sources

imprecise (Coleman, 1995; Sarter, Berntson, & Cacioppo, 1996). Behavioral interpretations related to specific brain states and neural substrates have been considered inferential in this brain imaging technique.

The small sample size may have implications for data distributions produced by psychometric, response time and QEEG methodologies. Inferential statistics, which are robust methods of identifying group differences, have been based on assumptions of normality (Cohen, et al., 2003). Small sample sizes have tended to produce data distributions which violate those assumptions. Nonparametric statistics were used to analyze the psychometric data in this study; however, small sample sizes have been shown to affect the power of these tests to identify real differences. The statistical power for finding group differences, also known as Type 2 error, was reduced in this investigation especially in light of the group response time data trends in which the LD group performances were longer when compared to the NC group but statistical significance was lacking. Several data from the passive and active EEG recording methodologies also narrowly missed statistical criterion. Increasing the sample sizes would benefit statistical power and permit a more valid test of the effects.

Age was a group characteristic from this project which limited data generalization. Groups statistically differed in average age. The LD group had one participant at age 35-years and three participants above the age of 45-years whereas the oldest member of the NC group was 22-years. Mean ages for the LD and NC groups were 29.5 and 20.3-years, respectively. Similarity in average group performance of the PPVT-III suggested comparable intellectual functioning; however, speed of processing was a component of this study and has been shown to be age sensitive. According to Kaufman

and Lichtenberger (1999), intelligence measures have been conceptualized in fluid and crystallized components. The fluid component has been thought to correspond to reasoning ability and novel problem solving, while the crystallized component has been thought to correspond to school-acquired knowledge and acculturation. Verbal skills have been considered subsumed by the crystallized domain. Kaufman and Lichentenberger (1999) contended that verbal intelligence is maintained across the majority of the lifespan and can be increased with use even through the decade of the 60's. Speed of processing, through its association with measurement of performance, which has been thought to tap the fluid domain in tests of intelligence, has been shown to decline with age. In this investigation six response time measures were shown to be affected by age, therefore, confounding the interpretive quality of the results.

A large body of EEG research has provided evidence that EEG changes with age (Duffy, Albert, McAnulty, & Garvey, 1984; Hartikainen, Soininen, Partanen, Helkalal, & Reikkinen, 1992; Koyama, Hirasawa, Okubo, & Karasawa, 1997). Most EEG research reports age-related changes in resting baselines. In particular, beta desychronization has been positively correlated with age (Duffy, et al., 1984). No electrophysiological data for baseline in this study met statistical criteria for group differences in relative theta, high alpha and low beta for baseline, passive tasks or active tasks. Overall, these results have been interpreted in terms of similar group activations.

A group characteristic that could affect data interpretation was the failure to isolate attention as a potential mediating variable in all participants. Attention deficits have been shown to affect psychometric performance (Kaufman & Lichtenberger, 1999) and waveforms produced during cognitive tasking (Lubar & Lubar, 1999). As other

researchers have noted, attention deficits are often comorbidly diagnosed in adults diagnosed with learning disabilities (Marks, Newcorn, & Halperin, 2001). Attentional measures were not used as criteria for participation in the present study. Of the total sample (n = 23), two participants in the NC group and one in the LD group self-reported concerns with "paying attention," while three LD participants had prior attention deficits diagnoses. The addition of the data from these six participants was in the interest of maintaining a minimum number for the total sample membership. Present focus on attention and distractibility in school performance has contributed to a heightened awareness of the potential influence of attention in academic performance. As such, all subjects were included in analyses.

Implications for Clinical Applications

The Neuropsychological Assessment of Learning Disabilities checklist (NALD) was developed as a tool to focus the search of historical diagnostic data for clinical group criteria selection. The content of NALD checklist has been shown to represent developmental conditions and events relevant to LD symptomology (Hutchens, 1988). Investigations based upon historical data that represent LD diagnoses can include tedious and time consuming hunts for relevant details through reams of paper. LD diagnosis methodology has been shown to be variable between agencies (Peterson & Shinn, 2002) and students with history of early diagnosis often carry years of historical documentation to colleges. In both cases, finding relevant details in thick files can be challenging. The NALD was created to make the process more manageable.

The identification of LD subtypes has been shown to be an important element of differential diagnosis for individualizing programs for skill remediation (Fletcher, et al.,

1998). Skill acquisition strategies for semantic and phonetic subskills require different remediation methods for learning disabilities due to differential cortical processing. The differential diagnoses of subskills relevant to academic deficits have been shown to reflect true skills deficits (Allen, 2002; Berninger, 2001; Gaddes & Edgell, 1994); the phonetic and semantic skills validations from this study permitted the selection of a group of LD participants with reading disability with relatively poor phonetic skills, but whose semantic skills were equivalent to the readers of normal ability. The use of the WJ-A-R subtests, RAN, RAS, and the modified C-WS stimuli, provided converging evidence of the phonetic and semantic skills of the groups and can be applied to individual diagnostics.

Implications for Future Research

Elements of this study have provided direction for future research. LD sub-typing, attention, and age have been suggested as confounding issues that would be clarified in the development of discrete research samples. The formation of LD sub-typed groups would be most worthwhile to evaluate group differences. A principle argument for this study was that research has largely ignored subtyping dyslexias resulting in the mixed body of results. The semantic subtype was initially investigated as an acquired form of paralexia in which an adult with acquired reading skills suffered trauma to the language dominant hemisphere (Gaddes & Edgell, 1994). Today, an identified subtype of dyslexia has demonstrated comprehension difficulties without the same degree of dysphonetic component (Tallal, et al., 1993). The phonetic dysfunction has been thought to be related to surface level cortical processing and was thought to be most easy to image with EEG. The psychometric comparison of the semantic subtype would be

comparable to non-clinical performance in that the WJ-A Word-Attack and receptive vocabulary performances would be similar; however, the Passage Comprehension SS would be statistically lower than both the non-clinical and dysphonetic based comparators. Creating sub-typed samples would be useful for characterizing the two groups psychometrically and psychophysiologically.

Creating comorbid attention and age-based groups would also be an important research direction. In the current study, three of the LD participants were previously diagnosed with attention deficits and four were above the age of 35-years. In both cases, creating groupings of participants would have allowed for a better characterization of the effects. An LD group with comorbid presence of attention deficits compared to the neuropsychologically validated clinical group without attention deficits would have been useful in identifying differences attributable to attention in psychometric performance and cortical activation. The age-based groupings would have allowed the robust covariance of age to results derived from investigation, thereby eliminating age as a confound.

Finally, study results that were non-significant have provided direction for future investigation. Data excluded from this study by hypothesis testing could be used to direct future investigations. During the Incongruent-Task, the data at the right parietal (P4) electrode for relative high alpha and low beta implicated a differential group effect for relative high alpha and low beta wavebands. Because of the hypothesized relationship to the PAS in the posterior parietal cortices, an ANOVA was performed comparing the LD and NC group data at P3, PZ, and P4 (see Table 13). The statistically significant data was found in relative high alpha and low beta which is reflected in Table 13.

Table 13

Future Research with the Incongruent-Task:

The Posterior Attention System (PAS) and the Posterior Parietal Electrodes

		In microVolts		Group Differences	
Bandwidth		Range	*M*(*SD*)	*F*(1,20)	*p*
High Alpha					
P3	LD[a]	.894 – 2.94	1.79(.765)	1.187	.289
	NC[b]	.860 – 3.44	2.17(.850)		
PZ	LD	.944 – 3.37	1.79(.770)	3.447	.078
	NC	.901 – 4.72	2.57(1.19)		
P4	LD	1.01 – 3.05	1.76(.625)	5.097*	.035
	NC	1.31 – 4.00	2.48(.866)		
Low Beta					
P3	LD	.295 - .959	.588(.208)	4.312	.051
	NC	.250 - .626	.430(.132)		
PZ	LD	.251 – 1.01	.559(.230)	4.982*	.037
	NC	.242 - .642	.377(.126)		
P4	LD	.258 - .916	.580(.222)	5.551*	.029
	NC	.231 - .533	.399(.108)		

[a] $n = 10$. [b] $n = 12$.

*$p < .05$

The data of importance to the discussion was place in context on Figure 4. The data has demonstrated that relative high alpha and low beta represent group differential activation for the task demands of the incongruent stimulus-type. The NC group produced greater high alpha not only at P4, but also at PZ, though the latter was not a statistically significant effect. The LD group produced greater low beta at all three electrodes, though the P3 result was not statistically significant. The band of electrodes across the posterior parietal cortices may form the basis of a hypothesis. These limited data have tentatively implicated the posterior attention system (PAS) (Carr, 1992) and have highlighted the importance of the visual modality related to graphemic perception as an input modality important to reading. The neural circuitry of the PAS has been thought to be located in the posterior and lateral parietal lobes (Carr, 1992) and fMRI evidence has suggested that participants with attention deficits activate lateral anterior to posterior cortical circuits during Stroop variants (Bush, et al., 1999). The LD group may have relied upon the visual-spatial qualities of the stimuli to complete task requirements. The PAS, previously shown to receive visual-spatial input from the posterior association cortices, may be the primary processing medium for this sample. The LD participants' cortical activation may have emphasized visual processing during the task when compared to the NC participants. Groups that have been differentially diagnosed to control attention, phonetic, semantic and non-clinical variables, warrant investigation of these electrodes.

Concluding Comments

This study provided the opportunity to construct methodology that selected participants with learning disabilities in the reading domain, i.e., the NALD, and verified group phonetic differences and semantic equivalences through the psychometric

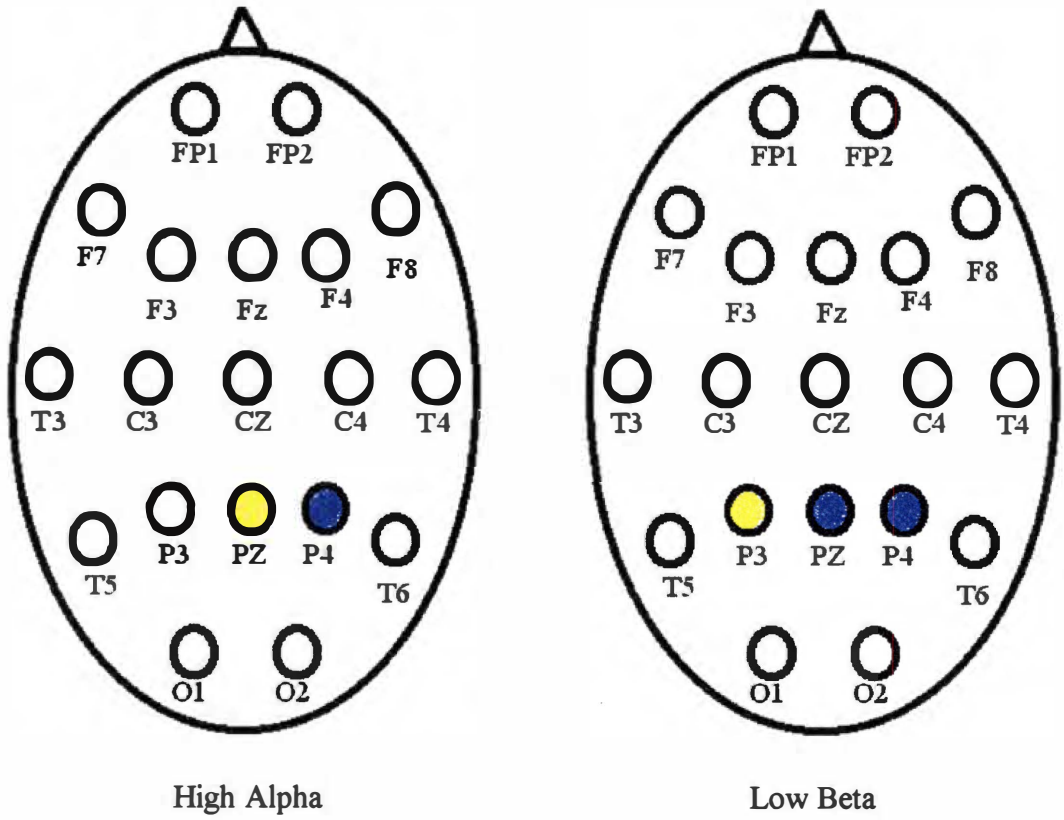

Figure 4. Future Research with the Incongruent-Task. Blue: electrodes that met .05 criterion for significance with ANOVA. Yellow: statistically non-significant electrodes. Data from these posterior cortical locations have provided a research hypothesis. The posterior attention system (PAS), which has neural circuits in the posterior parietal lobes (Carr, 1992), has been implicated in the active recording of the Incongruent-Task. In relative high alpha, the NC group produced more than the LD group. For relative low beta, the LD group produced more than the NC group. The PZ and P3 non-significant electrodes missed statistical critierion, but were close with $p < .078$ and $p < .051$, respectively.

elements. Group characteristics in Learning Disability research have been shown to be problematic in published research in which data validity hinges upon group homogeneity. The group selection methodology from this investigation represented the application of theoretically sound criteria to increase the internal validity of the data.

This study provided some evidence of group response time differences, related to speed of processing, which supported the concept of automaticity deficits in participants with dyslexia. Automaticity deficits in this Learning Disability sample were characterized by slower response times; the LD group required more performance time when compared to the NC group to complete the RAS tasks. Overall data interpretation was limited by group attention and age differences as potential confounds. Electrophysiological data, reflecting cortical activation and mental effort, did not illuminate left hemisphere group differences attributable to automaticity performances; however, the lack of significant Stroop effect and physiological data in the context of group phonetic differences and semantic equivalences, showed some support for the semantic processing requirement of the Stroop stimuli.

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APPENDICES

APPENDIX A

Dear Student:

You have received this email from UT Office of Disability Services because you have been diagnosed with reading disability. I would like to extend to you a unique opportunity to participate in brain imaging research! You are invited to participate in research that focuses on information processing in students with Learning Disabilities (LD). Having had a psychological evaluation, in your file you already have the measures of ability that can be correlated with brain imaging data, such as EEG (Electroencephalography). This research is being done to integrate data into a holistic assessment model, a promising direction for research and practice. The only way that we can do this research is if people like you volunteer to participate; adult students with a history of LD diagnosis are **greatly needed and are key to the project's success**. This project will require a little of your time and access to the documentation for your diagnosis.

The project is doctoral research being conducted by Kerry Towler, M.A.. Teresa Hutchens, Ph.D. and Joel Lubar, Ph.D. who are both licensed psychologists from the UT Department of Psychology are supervising. Here are the project particulars:

- ✓ The purpose is to investigate brain activation differences both during cognitive tasks and between LD and non-LD individuals.
- ✓ Participation time will only require about 2 ½ hours to do all the tasks and your EEG recording in the Brain Research and Neuropsychology Lab located in Walter's Life Sciences building, room A-305.
- ✓ EEG's will be recorded during rest and brief simple tasks (naming, reading, etc.).
- ✓ Participants will also be asked to sign a release for me to get your test scores and developmental information from Disability Services, which will be **coded anonymously, preserving confidentiality**.
- ✓ It's a great place to get your extra credit for research participation if you are taking a Psychology course that provides it.

The University's Office of Research Compliances (Institutional Review Board) and the Office of Disability Services have reviewed this research project and given permission to invite you to volunteer for this unique research opportunity. There is no harm or risk associated with participation; in fact, you are free to discontinue your participation at any point during the project. All personal information will be safeguarded in confidence in the materials room (410-A) on the fourth floor of Austin Peay Building.

If you are willing to be a participant, please contact me either by email or by phone listed below:

Kerry Towler, M.A.
ktowler@utk.edu
Lab) 865-974-3222

I will return your call or email to make an appointment with you. At that time, details of the study will be presented and you can ask any questions you may have.

Thank you for your consideration of this important research project.

Sincerely,

APPENDIX B

Subject number_____

Authorization for Release of Information

I hereby grant permission for UT Office of Disability Services to release educational, psychological, and developmental records on file to

Kerry Towler, M. A. from the Brain Research and Neuropsychology Laboratory, UT Department of Psychology.

The following individuals are specifically granted permission to obtain and review these documents:

Kerry Towler, M.A., a student researcher
Teresa A. Hutchens, Ph. D., a supervising, licensed Psychologist.

I understand that this information is to be used to support doctoral research being conducted by Kerry Towler, M.A. approved by University's Office of Research Compliances (Institutional Review Board) and the Office of Disability Services. In addition, to preserve confidentiality, this information will be coded and stored in a locked room, Austin Peay Suite 410, for three years after the completion of the project.

Signature:

_____ _____

Client Date

APPENDIX C

Informed Consent

Title of Project: *Neuropsychological Selection of Phonological Dyslexics and the Electrophysiological Examination of Automaticity Deficits.*

Principal Investigators: Kerry Towler, M.A., Teresa Hutchens, Ph.D., Joel Lubar, Ph.D.
Objective of Project: The purpose of this project is to investigate brain electrical activity during specified tasks correlating that data with cognitive ability measures. The data collected will help us to determine if brain electrical activity changes between tasks.

Project Summary: You will participate in an electroencephalographic (EEG) recording session and in some tasks that assess cognitive abilities. You will be asked to accomplish several cognitive tasks while the EEG is being recorded. Some cognitive abilities will be assessed before the EEG as a validity check for the information gathered during the EEG recording.

Your EEG will be recorded in one session. Several active tasks and two baselines will be recorded prior to the active tasks; a three-minute eyes-opened and a three-minute eyes-closed baseline. To record your EEG, an electrode cap with 19 sensors will be placed on your head. Electrode gel is applied to each sensor by a small tube inserted through the sensor. The gel forms a conductive pathway between the sensor and the scalp. There is no significant discomfort with this procedure either in the preparation or the wearing of the cap during the testing. An earclip electrode will be placed on each earlobe after a light cleaning with Omniprep solution, which removes skin oil and allows for good sensor contact. All creams and gels used during this evaluation are hypo-allergenic, with no risk of irritation. Since muscle movements produce electrical activity that can contaminate the EEG, you will be asked to sit still, with eyes closed, in a relaxed posture.

You will participate in an assessment of intellectual ability in which the Peabody Picture Vocabulary Test- Third Edition (PPVT-3), three Reading subtests of the Woodcock Johnson Psychoeducational Battery-Revised, Tests of Achievement (WJA-R), test of Rapid Automatized Naming (RAN), test of Rapid Alternating Stimuli (RAS), and the Color-Word Stroop will be administered. These tests have been established as good and valid measures of cognitive functioning. In addition, you will listen to some music. There are no negative effects associated with these tasks.

You will be receiving extra-credit or a Brain Map for participating in this study.

Amount of time required: There will be one 2 ½ hour session during regular University of Tennessee hours for both psychometrics and EEG.

Confidentiality: Only persons listed as Principal Investigators will have access to material that identifies you as a participant in this study. The data from this experiment will potentially be shared professionally, but your name will be coded to prevent identification. These records will be stored in a locked file cabinet in the Brain Research and Neuropsychology Laboratory, A305 Walters Life Sciences, for at least three years past the duration of the study.

If you have any questions about this study, please feel free to ask them. Any future questions may be addressed to

Kerry Towler, M.A.
Department of Psychology
University of Tennessee, Knoxville
(423) 974-3222

Dr. Teresa Hutchens, Ph.D.
Department of Psychology
University of Tennessee, Knoxville,
(423) 974-4183

Dr. Joel Lubar, Ph.D.
Department of Psychology
University of Tennessee, Knoxville
(423) 974-3222 or 974-3360

Statement of Consent: I certify that I have read and fully understand the procedures contained within this form and agree to participate as a subject in the research described therein. My participation is given voluntarily and without coercion or undue influence. I understand that I may discontinue participation at any time. However, I understand that students participating for extra credit will only receive credit after completion of participation in the study.

Signature of Participant	Name of Participant	Date
Signature of Witness	Name of Witness	Date

APPENDIX D

Neuropsychological Assessment for Learning Disabilities Checklist(NALD)

What was the referral question?

_____
_____
_____
_____

DOB:_____ **Age at last evaluation:**_____

Gender:_____ **Race:**_____

Historical failure to achieve pattern present? Y or N

Comments:_____
_____

Psychoeducational Assessment: Chronic Discrepancy met? Y or N

Methodology: Simple Discrepancy Regression
Neuropsych

IQ Global scores: WAIS-R WAIS-III WISC
Other

FSIQ_____VIQ_____PIQ_____

Subtest scores:

Vocabulary:_____ Pict Completion:_____

Similarities:_____ DS Coding:_____

Arithmetic:_____ Block Design:_____

Digit Span:_____ Matrix Reasoning:_____

Information:_____ Pict Arrangement:_____

Comprehension:_____ Symbol Search:_____

Letter-Number Sequencing Object Assembly:_____

Achievement scores:

Oral Expression:_____ Reading Comp:_____

Listening Comp:_____ Math Calculation:_____

Written Expression:_____ Math Reasoning:_____

Basic Reading:_____
_____

Reported Discrepancy:_____

Evaluation of Non-Related Subject Achievement:_____

Ecological Validation:

Behavioral Assessment (when in file, profile attached):

_____(Child Behavior checklist: parent/teacher)

Neuropsychological Assessment (when in file, profile attached):

_____Halstead-Reitan or_____Luria-Nebraska Batteries

_____Pattern of sensory-perceptual motor/cognitive dysfunction

_____Cerebral dysfunction present?

Risk Factors (Check all that are indicated):

Maternal Pregnancy Conditions:

_____HBp

_____Diabetes

_____Toxemias

_____Bleeding during

_____Alcoholism

_____Drug Abuse

_____Viral Exposure:_____

_____Illness:_____

_____Medications:_____

_____Other:_____

Prenatal, Perinatal, Postnatal Conditions:

_____Premature Delivery

_____Delivery Abnormal

_____Forceps Delivery

_____Anesthesia Delivery

_____Prolonged Labor

_____Complicated Labor

_____Low birth weight (<1500 grams)

_____Fetal Distress

_____Anoxia

_____PKU (phenylketonuria)

_____Hyerilirubinemia

_____Surgery

_____Extended Hospital stay

Infancy and Childhood Conditions:

Ingestion/exposure:

_____Lead

_____Poison

_____Alcohol

_____Drug OD

Adverse rxn:

_____Medications

_____Allergens

Illness:

_____Life-threatening

_____High fever (>104F)

_____Encephalitis

_____Meningitis

Other:_____

Sensory impact:

_____Chronic ear infections

_____Tubes in ears

_____Amblyopia

Chronic Conditions:

_____Seizure disorders

_____Asthma

_____Diabetes

_____Sickle-cell

___Malnutrition

Orthopedic Conditions:

_____Restorative Surgery_____

_____Movement restriction_____

Conditions at Diagnosis:

_____Malnourished
_____Obese
_____Recent prolonged illness
_____Chronic health condition
_____Diabetes
_____Metabolic disorder
_____Recent prolonged meds
_____Psychostimulants
_____Anti-convulsives
_____Alcohol
_____Drug use habit
_____Emotional Eval
_____Attention Eval

Environmental conditions:
_____Meal habits
_____Sleep pattern

Social Interactions:
_____Peer concerns
_____Teacher concerns
_____Authority concerns

Parental Climate:
_____Relationship
_____Divorce
_____Death of immediate family
_____Recent family addition
_____Family Relocation

Educational Experience:

Absence of Instructional opportunity:_____

Truancy:_____

Grades skipped or failed:_____

Frequent School changes:_____

Alternative placement made:_____

Hemispheric Dominance:

Handedness:_____Evidence:_____

Familial Handedness History:_____

Change in handedness:_____ Footedness:_____

Evidence of mirror writing:_____

Language dominance indicator:_____(Dichotic Listening Test)

Developmental Delay:

Motor:

Bladder/Bowel control:

Self-care: Dressing Eating Cleanliness

Family History:

First degree relative LD:

Other relative LD:

Any familial handicap/abnormality:

Maternal illness affect on subsequent children:

Evaluation of Exclusionary Criteria:

Sensory deficits: Y or N, If Y, what deficit?_____

Mental retardation: Y or N

Emotional Disturbance: Y or N, If Y, what diagnosis?_____

Resource Restriction: Environment, Culture, Economic,
Other_____

Principle Diagnosis:

Secondary Diagnosis (if applicable):

APPENDIX E

NAME _____ DATE _____

SEX: Male (M) Female (F)

IDENTIFICATION

Below is a list of words that describe feelings people have. Please read each one carefully. Then fill in ONE circle under the answer to the right which best describes HOW YOU HAVE BEEN FEELING DURING THE PAST WEEK INCLUDING TODAY.

The numbers refer to these phrases.

0 = Not at all
1 = A little
2 = Moderately
3 = Quite a bit
4 = Extremely

Col (C) O.P. (O)

	NOT AT ALL	A LITTLE	MODERATELY	QUITE A BIT	EXTREMELY
1. Friendly	0	1	2	3	4
2. Tense	0	1	2	3	4
3. Angry	0	1	2	3	4
4. Worn out	0	1	2	3	4
5. Unhappy	0	1	2	3	4
6. Clear-headed	0	1	2	3	4
7. Lively	0	1	2	3	4
8. Confused	0	1	2	3	4
9. Sorry for things done	0	1	2	3	4
10. Shaky	0	1	2	3	4
11. Listless	0	1	2	3	4
12. Peeved	0	1	2	3	4
13. Considerate	0	1	2	3	4
14. Sad	0	1	2	3	4
15. Active	0	1	2	3	4
16. On edge	0	1	2	3	4
17. Grouchy	0	1	2	3	4
18. Blue	0	1	2	3	4
19. Energetic	0	1	2	3	4
20. Panicky	0	1	2	3	4
21. Hopeless	0	1	2	3	4
22. Relaxed	0	1	2	3	4
23. Unworthy	0	1	2	3	4
24. Spiteful	0	1	2	3	4
25. Sympathetic	0	1	2	3	4
26. Uneasy	0	1	2	3	4
27. Restless	0	1	2	3	4
28. Unable to concentrate	0	1	2	3	4
29. Fatigued	0	1	2	3	4
30. Helpful	0	1	2	3	4
31. Annoyed	0	1	2	3	4
32. Discouraged	0	1	2	3	4
33. Resentful	0	1	2	3	4
34. Nervous	0	1	2	3	4
35. Lonely	0	1	2	3	4
36. Miserable	0	1	2	3	4
37. Muddled	0	1	2	3	4
38. Cheerful	0	1	2	3	4
39. Bitter	0	1	2	3	4
40. Exhausted	0	1	2	3	4
41. Anxious	0	1	2	3	4
42. Ready to fight	0	1	2	3	4
43. Good natured	0	1	2	3	4
44. Gloomy	0	1	2	3	4
45. Desperate	0	1	2	3	4
46. Sluggish	0	1	2	3	4
47. Rebellious	0	1	2	3	4
48. Helpless	0	1	2	3	4
49. Weary	0	1	2	3	4
50. Bewildered	0	1	2	3	4
51. Alert	0	1	2	3	4
52. Deceived	0	1	2	3	4
53. Furious	0	1	2	3	4
54. Efficient	0	1	2	3	4
55. Trusting	0	1	2	3	4
56. Full of pep	0	1	2	3	4
57. Bad-tempered	0	1	2	3	4
58. Worthless	0	1	2	3	4
59. Forgetful	0	1	2	3	4
60. Carefree	0	1	2	3	4
61. Terrified	0	1	2	3	4
62. Guilty	0	1	2	3	4
63. Vigorous	0	1	2	3	4
64. Uncertain about things	0	1	2	3	4
65. Bushed	0	1	2	3	4

MAKE SURE YOU HAVE ANSWERED EVERY ITEM.

POM 021

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APPENDIX F

DSM-IV ADHD Symptom Checklist

Subject Number: _____ Date: _____

DO YOU OFTEN:

1. Y N fail to give close attention to details or make careless mistakes in schoolwork, work, or other activities

2. Y N have difficulty sustaining attention in tasks or play activities

3. Y N not seem to listen when spoken to directly

4. Y N not follow through on instructions and fail to finish schoolwork, chores, or duties in the workplace

5. Y N have difficulty organizing tasks and activities

6. Y N avoid, dislike, or are reluctant to engage in tasks that require sustained mental effort (such as school work or homework)

7. Y N lose things necessary for tasks or activities (e.g. school assignments, pencils, books, tools, etc.)

8. Y N get easily distracted by extraneous stimuli

9. Y N become forgetful during daily activities

10. Y N fidget with your hands or feet or squirm when seated

11. Y N leave your seat in classroom or other situations in which remaining seated is expected

12. Y N have feelings of restlessness

13. Y N have difficulty playing or engaging in leisure activities quietly

14. Y N feel as if always "on the go" or act as if "driven by a motor"

15. Y N talk excessively

16. Y N blurt out answers before questions have been completed

17. Y N have difficulty waiting your turn

18. Y N interrupt or intrude on others (e.g., butt into conversations)

source: Diagnostic and Statistical Manual of Mental Disorders (4th ed.) (DSM-IV)

APPENDIX G

Table G-1

Baselines: Descriptive Statistics of Group Data

	LD[a] Group		NC[b] Group	
	Range	*M*(*SD*)	*Range*	*M*(*SD*)
Bandwidth	In microVolts		In microVolts	
		Eyes-Opened (EO)		
Theta				
F7	.39 – 3.97	2.18(.95)	1.47 – 3.13	2.23(.57)
T5	.91 – 3.34	1.73(.71)	.59 – 2.59	1.71(.60)
High Alpha				
F7	.72 – 2.59	1.26(.52)	.62 – 2.76	1.52(.69)
T5	.91 – 3.58	2.02(.77)	1.15 – 4.49	2.49(1.05)
Low Beta				
F7	.29 - .85	.59(.17)	.26 - .75	.49(.17)
T5	.33 – 1.26	.68(.31)	.23 - .70	.46(.16)
		Eyes-Closed (EC)		
Theta				
F7	.56 – 4.13	2.10(.91)	1.04 – 3.63	2.30(1.11)
T5	.70 – 4.43	1.50(1.03)	.29 – 2.88	1.51(.99)
High Alpha				
F7	.02 -2.49	1.42(.68)	.59 – 3.31	1.67(.98)
T5	.16 – 3.70	2.50(1.15)	1.08 – 6.99	3.07(1.75)
Low Beta				
F7	.24 – .72	.47(.17)	.15 - .58	.36(.12)
T5	.16 – 1.09	.48(.29)	.18 - .52	.29(.12)

[a] $n = 12$. [b] $n = 11$.

APPENDIX H

Table H-1

Passive Tasks: Descriptive Statistics of Group Data

	LD[a] Group		NC[b] Group	
	Range	*M*(*SD*)	*Range*	*M*(*SD*)
Bandwidth	In microVolts		In microVolts	
	Rapid Automatized Naming (RAN)			
Theta				
F7	.50 - 3.88	1.99(.84)	.91 - 3.59	2.08(.98)
T5	.62 - 4.36	1.38(1.03)	24 - 2.60	1.33(.88)
High Alpha				
F7	.71 - 2.83	1.69(.59)	607 - 3.76	2.00(1.11)
T5	.50 - 4.93	2.91(1.12)	1.03 - 7.61	3.51(1.94)
Low Beta				
F7	.27 - .85	.47(.19)	.18 - .58	.37(.11)
T5	.17 - 1.26	.51(.37)	.17 - .50	.29(.10)
	Rapid Alternating Stimuli (RAS)			
Theta				
F7	.41 - 3.77	2.02(.86)	1.00 - 3.99	2.15(1.10)
T5	.57 - 4.18	1.45(1.02)	.27 - 3.28	1.37(.970)
High Alpha				
F7	.69 - 2.75	1.70(.61)	.65 - 3.35	2.01(1.07)
T5	.50 - 4.21	2.86(1.04)	1.16 - 7.53	3.60(1.98)
Low Beta				
F7	.28 - .79	.46(.16)	.14 - .59	.36(.13)
T5	.17 - 1.38	.52(.37)	.16 - .53	.29(.10)

[a] $n = 12$. [b] $n = 11$.

Table H-2

Passive Tasks: Descriptive Statistics of Color-Word Stroop Subtest Data

	LD[a] Group		NC[b] Group	
Bandwidth	Range In microVolts	*M*(*SD*)	*Range* In microVolts	*M*(*SD*)
		Congruent-Block		
Theta				
F7	.47 - 4.08	2.01(.917)	.86 - 3.60	1.99(.98)
T5	.72 - 4.57	1.33(1.05)	.23 - 2.87	1.33(.88)
High Alpha				
F7	.76 - 2.96	1.79(.641)	.74 - 4.02	2.03(1.18)
T5	.40 - 5.46	3.10(1.34)	1.11 - 7.97	3.33(2.08)
Low Beta				
F7	.26 - .804	.46(.18)	.18 - .50	.36(.09)
T5	.15 - 1.20	.48(.34)	.18 - .52	.28(.10)
		Incongruent-Block		
Theta				
F7	.47 - 4.08	2.01(.92)	1.05 - 3.74	2.10(1.03)
T5	.64 - 4.44	1.39(1.01)	.25 - 3.03	1.38(.92)
High Alpha				
F7	.65 - 3.02	1.74(.66)	.64 - 3.57	1.93(1.13)
T5	.41 - 4.64	2.92(1.10)	1.14 - 7.72	3.27(2.07)
Low Beta				
F7	.27 - .79	.45(.18)	.16 - .52	.35(.12)
T5	.16 - 1.29	.50(.38)	.16 - .48	.28(.10)

[a] $n = 12$. [b] $n = 11$.

APPENDIX I

Table I-1

Active Tasks: Descriptive Statistics of Group Data

	LD[a] Group		NC[b] Group	
	Range	*M*(*SD*)	*Range*	*M*(*SD*)
Bandwidth	In microVolts		In microVolts	
		Congruent-Task		
Theta				
F7	.45 - 3.36	2.17(.77)	1.93 - 4.09	2.52(.73)
T5	1.09 - 3.44	1.81(.68)	1.46 - 3.34	2.03(.58)
High Alpha				
F7	.61 - 1.61	1.09(.34)	.67 - 1.81	1.14(.41)
T5	1.06 - 3.14	1.90(.70)	1.70 - 2.27	1.65(.38)
Low Beta				
F7	.35 - .86	.58(.16)	.24 - .64	.49 (.15)
T5	.34 - 1.25	.69(.26)	.26 - .81	.56(.17)
		Incongruent-Task		
Theta				
F7	.47 - 3.53	2.22(.85)	1.84 - 3.56	2.48(.60)
T5	.89 - 3.24	1.88(.64)	.96 - 3.40	1.98(.68)
High Alpha				
F7	.61 - 1.66	1.08(.38)	.64 - 1.81	1.13(.36)
T5	.91 - 3.13	1.72(.73)	.96 - 3.38	1.73(.68)
Low Beta				
F7	.31 - .88	.56(.17)	.23 - .65	.51(.15)
T5	.35 - 1.07	.66(.22)	.25 - .73	.54(.16)

[a] $n = 12$. [b] $n = 10$.

VITA

Kerry Towler was born in Fayetteville, Arkansas, on April 25th, 1962. She completed high school in 1980 while attending Southside High School in Fort Smith, Arkansas. She attended several undergraduate institutions while moving her family for her husband's military service. She obtained her B. S. in psychology in 1998 from the University of Central Arkansas in Conway. The M. A. in psychology was completed in 2002 at the University of Tennessee, Knoxville. Her emphasis of graduate study was experimental electroencephalography with an interest in brain and behavior relationships. She completed her doctorate at the University of Tennessee in 2006.

Kerry is currently an Assistant Professor at Tennessee Wesleyan College, a small private college in Athens, Tennessee,

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