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EEG DISCRIMINANT ANALYSES OF CHILDREN WITH LEARNING DISABILITIES:

CORRELATIONS TO SCHOOL ACHIEVMENT AND NEUROPSYCHOLOGICAL PERFORMANCE

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ABSTRACT

Objectives: 1- to evaluate the ability of the power spectrum of brain electrical activity to discriminate between age matched normal children and children diagnosed as learning disabled (LD) and, 2- to correlate brain electrical activity with intelligence, school achievement and neuropsychological performance test scores.

Methods: Electrical potentials (EEG) were recorded from 19 channels in a resting eyes closed state for 1 to 10 minutes in two groups of children (normal, N= 277 & LD, N = 58). The learning disabled group of children were randomly divided into two sub-groups: a test group (N = 29) and a replication group (N = 29). Age matched normal control children were also randomly selected to be members of a test group (N = 146) or a replication group (N = 131). Electrophysiological spectral measurements were compared between the test LD and test normal control groups by t-tests and then variables with $P < .05$ were factor analyzed. A total of 10 variables were selected and entered into a stepwise discriminant analysis based on being the two highest loading variables on each of five factors with eigenvalues > 1. Cross-validation of the 10 variables and the discriminant functions was analyzed by independent classification using the replication LD and normal groups and correlations were performed between behavioral variables such as the Wide range Achievement Test and WISC-R sub-tests and electrophysiology.

Results: The test discriminant was 96.xx sensitive and 9xx% specific and the strongest effect size was in the anatomical power differences, especially in frontal and temporal regions. The replication discriminant or independent cross-validation was 94.59%, specificity 99.3%, ppv 94.59%, and npv 98.62. The multiple regression between electrophysiology and neuropsychological and school performance was typically in the range of $r = 0.5$ and $r = 0.75$ ($P < .000001$)..

Conclusions: Dorsal frontal electrical power greater than parietal electrical power and dorsal frontal electrical power greater than anterior temporal electrical power was correlated with lower school achievement. When the ratio of electrical power = 0, then I.Q, = approximately 100 and neuropsychological test performance and school achievement were approximately average. Higher I.Q. was correlated with a reversal of the direction of the electrical power differences between frontal and parietal and frontal and temporal

Key Words: qEEG, Attention Deficit Disorder, Discriminant Analyses.

1.0- Introduction

The estimated incidence of learning disorders ranges from 3% to 6% of the school age population (American Academy of Pediatrics, 2000; Barkley, 1998; Pelham et al, 1992). Specific learning disorders (SLD) are defined as deficits in one area of academic competence whereas generalized learning disorders (LD) are defined as deficits in two or more academic areas (e.g., reading and/or spelling and/or arithmetic). Often children with learning disorders also exhibit comorbidity of attention deficits (ADD) and/or hyperactivity (ADHD) in varying degrees. While there are many possible causes and comorbidities associated with learning disorders, a common factor in all of the suspected sub-categories of LD is that there is a failure in school achievement and/or social problems interacting with others (Barkley, 1997; 1998).

An important practical issue in the evaluation of a child with learning disabilities is to determine to what extent the child's problems in school are due to an organic or neurological problem versus the extent that they are due to emotional problems such as in families in divorce or in dysfunctional family and social environments. The detection of an organic basis for a child's learning disorder is aided in part by the analysis of the quantitative EEG or qEEG (Chabo et al, 1996; 2001; Clarke et al, 2001; Hughes and John, 1999; John et al, 1977; Lubar et al, 1985; 1999).

The purpose of the present study is to explore the ability of the qEEG to discriminate between normal children performing at grade level from a group of age matched general learning disabled children (LD) and specific learning disabled children (SLD) and to explore the ability of the EEG to detect the severity of problems in school, as validated by correlations to school achievement and neuropsychological test scores.

2.0 Methods

2.1 Learning Disabled Children

A total of 58 children were selected for the general and specific learning disabilities (LD and SLD) group, the selection criteria were: 1- performing two grade levels below average on one or more sub-tests of the Wide range Achievement Test (reading, spelling, arithmetic), 2- met two or more of the DSM-III criteria for learning disabilities and, 3- Full-Scale I.Q. ≥ 70. The children in this group had a mean age of 12.07, sd 2.69 and ranged in age from 6.01 years to 17.18 years (male = 46 or 79.3%). All of the learning disordered children met at least two of the DSM-II criteria for attention deficit disorder (ADD), however, none of the children met all six DSM-III criteria for ADD. Ten out of the 58 children, in addition to meeting two or more of the DSM-III criteria for LD also met two or more of the DSM-III criteria for attention deficit with hyperactivity (ADHD). Thus, the population in this study were all below normal school achievement with possible ADD and/or ADHD co-morbidities, however, these co-morbidities were not strong enough to fully match the DSM-III criteria for ADD and/or ADHD.

The children were all students in the public school systems of rural and urban Maryland. All of the children were recruited in cooperation with the public schools and through newspaper advertisements. The criteria for inclusion as learning disabilities (LDs) was based on clinical interviews with the child and parents, school classifications and performance on the Wide Range Achievement Test (WRAT) in spelling, reading and arithmetic.

None of the children had a history of traumatic brain injury or neurological disorders such as seizure activity. None of the LD children had not been medicated for at least 24 hours prior to testing in this study.

2.2 Age Matched Normal Control Children

A total 277 age matched normal children with a mean age of 11.09 years , s.d., 2.99 and ranged in age from 6.0 to 18.37 years (male = 213 or 77%) were recruited from the same public schools and using the same advertisements as were the LD children. The parents and children in the normal control group were given the same clinical interview and parent questionnaires as were the LD children and the time of day for EEG recording was random and the same as the LD group. None of the normal control children were reported by the school system as having academic difficulties or behavior-based problems. All of the normal control children were within the normal range of intelligence (Full Scale I.Q. $\geq$ 70) and were performing at grade level in reading, spelling and arithmetic as measured by the WRAT and none were classified as learning disabled nor were the normal control children in special education classes. Children with a history of neurological disorders were excluded from the study and none of the normal control children had taken medication of any medication at least 24 hours before testing in this study.

2.3 Neuropsychological and School Achievement Testing

Neuropsychological and school achievement tests were administered on the same day that the EEG was recorded for both the LD and the normal control children. There were no differences in the number of tests or in the sequencing between the EEG and neuropsychological tests for the two groups of children in this study. The neuropsychological tests included block design, digit span, picture completion, vocabulary, coding and mazes in the WISC-R. The nationally normalized Wide Range Achievement Test (WRAT) was used to evaluate the level of school achievement or competence in reading, spelling and arithmetic. The majority of the children in both the ADD and normal control groups were right handed (88.4% and 84.2% respectively). None of the children in the study had a history of neurological disorders and all were members of the public school system. Full scale I.Q. scores for the normals ranged from 84 to 154 (mean = 109.95, sd = 13.43) and for the LD children the range was from 70 to 130 (mean = 85.02, sd = 11.18).

2.3 EEG Recording

Power spectral analyses were performed on 2 to 5 minute segments of EEG recorded during an eyes closed and an eyes open condition. The EEG was recorded from 19 scalp locations based on the International 10/20 system of electrode placement, using linked ears as a reference. EKG and eye movement electrodes were applied to monitor artifact and all EEG records were visually edited to remove any visible artifact. Each EEG record was plotted and visually examined and then edited to remove artifact using the Neuroguide software program (NeuroGuide, 2002). Split-half reliability tests were conducted on the edited EEG segments and only records with > 90% reliability were entered into the spectral analyses. The amplifier bandwidths were nominally 0.5 to 30 Hz, the outputs being 3 db down at these frequencies. The EEG was digitized at 100 Hz and then spectral analyzed using a complex demodulation procedure (Otnes and Enochson, 1977). Absolute and relative power were computed from the 19 scalp locations in the delta (0.5 to 3.5 Hz), theta (3.5 to 7 Hz), alpha (7.5 to 13 Hz), and beta (13 to 22 Hz) frequency bands. The frequency bands, including the center frequencies (f_c) and one-half power values (B) were delta (0.5 to 3.5 Hz; f_c = 2.0 Hz; and B = 1.0), theta (3.5 to 7.0 Hz; f_c = 4.25 Hz; and B = 3.5 Hz), alpha (7.0 to 13.0 Hz; f_c = 9.0 Hz; and B = 6.0 Hz), beta (13 to 25 Hz; f_c = 19 Hz; and B = 14.0 Hz). EEG amplitude was computed as the square root of power. Relative power was the ratio of power in a given band/sum of all bands (i.e., total power) x 100.

Relative power ratios of the different frequency bands of EEG from a specific electrode were computed for theta/beta, theta/alpha, alpha/beta, delta/theta, delta/alpha and delta/beta.

EEG anatomical power differences were computed as a ratio of differences in absolute power between two scalp locations or (A – B / A + B) x 200 where A and B are the absolute power recorded from two different electrode locations. When A = B , then amplitude asymmetry = 0. Interhemispheric comparisons are (left – right/left + right) and intrahemispheric comparisons are posterior derivation – anterior derivation/posterior derivation + anterior derivation (Thatcher et al, 1983).

EEG coherence and phase were computed for all intrahemispheric and interhemispheric pair wise combinations of electrodes (Thatcher et al, 1983). Coherence is defined as:

$\Gamma^2{}_{xy}(f) = \frac{(G_{xy}(f))^2}{(G_{xx}(f)G_{yy}(f))}$, where $G_{xy}(f)$ is the cross-power spectral density and $G_{xx}(f)$ and $G_{yy}(f)$ are the respective autopower spectral densities. Coherence was computed for all pairwise combinations of the 19 channels for each of the 4 frequency bands. The computational procedure to obtain coherence involved first computing the power spectra for x and y and then computing the normalized cross-spectra. Since complex analyses are involved this produced the cospectrum ('r' for real) and quadspectrum ('q' for imaginary). Then coherence was computed as: $\Gamma^2_{xy} = \frac{r^2_{xy} + q^2_{xy}}{G_{xx} G_{yy}}$.

The total number of QEEG variables (N = 896) as well as the number of QEEG variables in different categories of the analyses are given in Table I.

Insert Table I

2.4 - Statistical Analyses

Condescriptive analyses were conducted in which the sampling distribution of each EEG variables was evaluated. Estimates of Gaussianity were computed for each variable using measures of skewness, kurtosis and normal probability plots. Only the EEG phase variables and the power ratios were not normally distributed and, therefore, a logarithmic transform was used so that the distribution of the variables was approximately normal.

The LD children were randomly divided into two groups N = 29 Group I and N = 29 Group II) and the Normal Controls were randomly divided into two groups (N = 146 Group I and N = 131 Group II). Group I normal controls and Group I LD children were members of the training set used in the initial discriminant analyses. Group II normal controls and LD children were members of the test set used to independently cross-validate the training set discriminant analyses based on Group I subjects. Univariate t-tests and factor analyses were used to identify which EEG variables were significantly different between the LD and normal control children in Group I as described in section 3.1.

For the training set, Linear step-wise discriminant analyses were computed using SPSS (1994). A Bayesian procedure was used in order to adjust for differences in sample size between the LD and normal control groups in both the training set and cross-validation procedures. ROC (Receiver Operating Characteristics) curves were calculated using MedCalc (Schoonjans, 2000) and sensitivity, specificity, positive predicted values (PPV) and negative predicted values (NPV) were defined according to the equations of Swets (1988) and MedCalc (Schoonjans, 2000) as: Sensitivity = True positives (TP)/(TP + False Negatives (FN)). Specificity was defined as: True Negatives (TN)/(TN + False Positives (FP)). PPV = TP/(TP + FP) and NPV = TN/(FN + TN).

3.0 Results

3.1 - Training Set EEG Variable Selection

A two-stage process was used to reduce the total universe of possible EEG variables for the training-set discriminant analyses and to maximize the subject to variable ratio. The first step involved univariate t-tests using the 29 LD subjects and the 146 normal control subjects in Group I with the QEEG measures in Table I as the independent variables. As shown in Table I, the EEG variables were grouped into five categories: 1- relative power, 2- power ratios, 3- coherence, 4- phase and 5- anatomical power differences . All EEG variables that had a probability value $< .01$ were identified and selected for entry into the second step which was factor analyses. Variables with $p > .01$ were discarded. The results of the t-test analysis, after adjusting for the number expected by chance alone, revealed no statistically significant differences between groups in absolute power. However, relative power, ratios of power, coherence, phase and anatomical power ratios yielded many statistically significant differences between groups.

Independent varimax factor analyses were performed on each of the five groups of EEG variables (relative power, power ratios, coherence, phase and anatomical power ratios). A criteria for selection of individual EEG variables to be entered into the discriminant function was a loading $> .8$ on a given factor. Using this criteria then a total of 32 summary EEG variables were selected for entry into the training set discriminant analysis.

3.2 – Training Set Discriminant Analysis

A two group discriminant analysis was conducted in which the previously selected 32 EEG variables (section 3.1) were the predictor variables and the two groups were the random selection of 29 LD children and the random selection of 146 age matched normal control children (Group I subjects).

The step-wise training set discriminant analysis resulted in the entry of ten (10) variables from the initial list of 32. The 12 step-wise selected variables in the training set discriminant analysis is shown in Table II. It can be seen that variables selected in the step-wise procedure were five left hemisphere and five right hemisphere variables.

TABLE II

List of EEG power spectral variables entered into the training-set discriminant function and the t-test results with probability significance levels between normal and LD children.

Variables	Probability
Theta/Beta frequencies relative power ratio F3	0.0000
Theta/Beta frequencies relative power ratio T3	0.0002
Theta frequency amplitude asymmetry between C3 and T3	0.0000
Theta frequency amplitude asymmetry between O2 and T6	0.0000
Theta frequency amplitude asymmetry between F4 and F8	0.0000
Alpha frequency amplitude asymmetry between F3 and T5	0.0115
Beta frequency amplitude asymmetry between F3 and P3	0.0072
Beta frequency amplitude asymmetry between C4 and T4	0.0000
Beta frequency amplitude asymmetry between C3 and C4	0.0003
Theta frequency coherence between FP2 and O2	0.0062

Table III shows the classification accuracies of the training set discriminant analyses. The linear discriminant analysis classified 91.9% of the LD children as members of the LD group and 98.6% of the normal controls were accurately classified as normal yielding an overall classification accuracy of 97.19%. Sensitivity = 91.89%, specificity = 98.58%, PPV = 94.4% and NPV = 97.88%.

TABLE III

Computer classification of normal and LD children in the training-set discriminant analysis.

Actual group	N	Classification percent as Normal	LD
Normal	146	100 (N = 146)	0.0 (N = 0)
LD/SLD	29	3.4 (N = 1)	96.6 (N = 28)

Overall classification accuracy =99.43%.

Figure 1 (A) shows the distribution of the discriminant scores in the 2 groups of training set subjects (open columns = LD & SLD group, closed columns = normal group) and figure 1B shows the ROC curve (Receiver Operating Characteristic). Figure 1 (C) are head diagrams of the EEG variables entered into the step-wise discriminant function. In Figure 1A the scales of the axes are the same for the 2 distributions so that the relative proportion of discriminant scores can be compared. The discriminant scores ranged from approximately +3.63 (normal control extreme) to –5.47 (LD extreme).

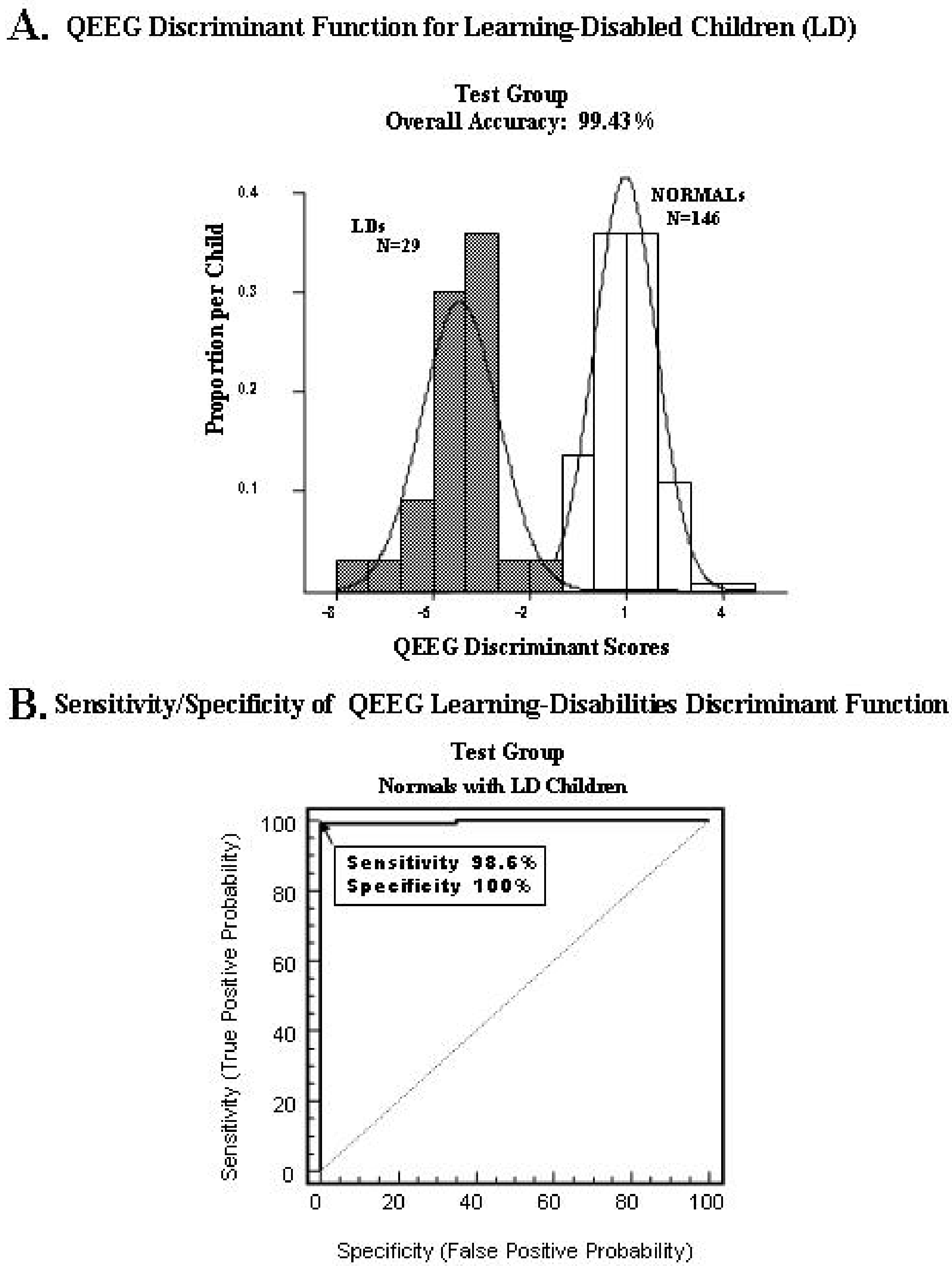


Figure One: Top (A) shows the distribution of the discriminant scores in the training set discriminant function for the two groups of subjects (open columns = Normal control subjects, N = 146; closed columns = LD & SLD subjects, N = 29). The scale of the y-axis is the same for the 2 distributions so that the relative proportion of discriminant scores can be compared. The discriminant scores on the x-axis ranged from -5.47 to + 3.63. (B) is a head diagram of the scalp locations of the EEG summary variables entered into the discriminant function in A. Bottom (C) is the Receiver Operating Characteristic (ROC) curve of the training set discriminant function in (A).

The criteria discriminant score where normal children were classified as members of the LD group was ≤ -1.5176.

3.3 - Cross Validation of the Discriminant Function

Independent cross-validation of the discriminant analysis was computed by determining the ability of the training set discriminant function in section 3.2 to accurately classify a different LD & SLD and normal control groups of children. Table IIIA shows the classification accuracy of the linear discriminant function in the cross-validation of the independent group of 29 LD and 131 normal children with 94.6% of the LD & SLD children classified as members of the LD & SLD population and 99.3% of the normal controls classified as normals which yielded an overall cross-validation classification accuracy of 96.95%.

TABLE III

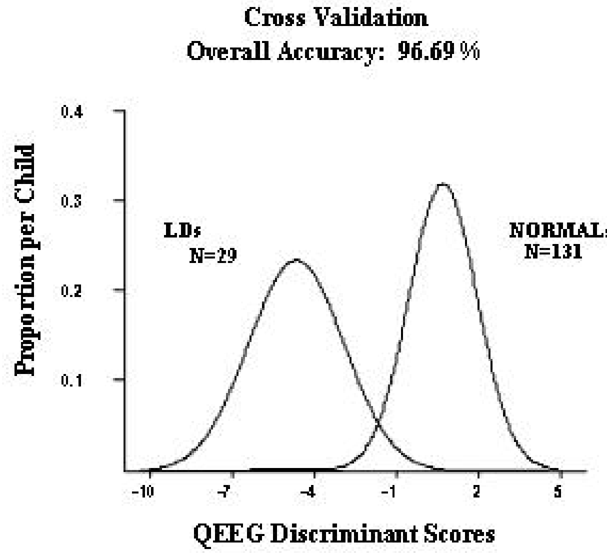
Computer classification of normal and LD children in the training-set discriminant analysis.

Actual group	N	Classification percent as Normal	LD
Normal	146	100 (N = 146)	0.0 (N = 0)
LD/SLD	29	3.4 (N = 1)	96.6 (N = 28)

Overall classification accuracy =99.43%.

Figure 2A shows the distribution of the linear discriminant scores in the cross-validation discriminant function and figure 2B shows the ROC curve (Receiver Operating Characteristic). The sensitivity of the cross-validation discriminant was 94.59%, specificity = 99.3%, PPV = 94.59% and NPV = 98.62%.

A. Cross-Validation Discriminant Function for Learning-Disabled Children



B. Sensitivity/Specificity of Learning-Disabled Discriminant Function

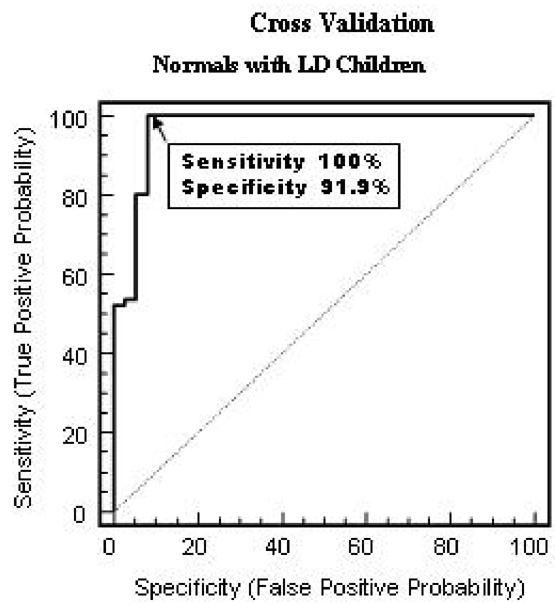


Figure Two: Top (A) shows the distribution of the cross-validation discriminant scores for two groups of additional subjects not entered into the training set discriminant function in figure 1. The left distribution are from the LD & SLD subjects, N = 29 and the right distribution are from the normal control subjects, N = 131. The scales of the y-axis is the same for the 2 distributions so that the relative proportion of discriminant scores can be compared. The discriminant scores on the x-axis ranged from -6.79 to + 4.06. Figure 1 (B) is the Receiver Operating Characteristic (ROC) curve of the cross-validation discriminant function in (A).

3.4 –Validation of EEG Discriminant Scores based on Correlations with Neuropsychological Test and School Achievement Scores

Neuropsychological validation of the EEG discriminant scores was accomplished by Pearson correlation analyses between the EEG discriminant scores and the various neuropsychological and school achievement scores from the same subjects. Table IV shows the results of these analyses in which statistically significant correlations were noted between various neuropyshological and school achievement scores and the EEG discriminant scores obtained from the same subjects as in the training set discriminant function (N = 175). The direction of the correlation between the EEG discriminant scores and neuropsychological and achievement scores showed that the more negative the

TABLE IV

Computer classification of normal and LD children in the cross validation discriminant analysis.

Cross Validat group	N	Classification percent as Normal	ADD/ADHD
Normal	131	97.7 (N = 128)	2.3 (N = 3)
LD/SLD	29	6.9 (N = 2)	93.1 (N = 27)
Cross Validation classification accuracy = 96.69%.			

discriminant score then the poorer the neuropsychological performance. In other words, the more severe the classification of the child as indicated by the EEG discriminant function then the worse the neuropsychological and school achievement scores. WRAT Reading achievement scores had the highest correlations with the EEG discriminant function (Table IV). The individual EEG variables were also significantly correlated with the neuropsychological scores and the school achievement scores, however, individual EEG variables did not correlate as highly with neuropsychological tests or school achievement as did the discriminant score. That is, the linear multivariate vector of the discriminant function exhibited higher correlations to neuropsychological performance and school achievement than any single EEG variable alone.

3.5 –EEG Severity Index of LD and Learning Disabilities

The use of a discriminant function as a linear predictor requires that the severity scores from mildly disabled LD children lie intermediate to the discriminant scores for normal controls and general learning disabled LD children and thus represent a continuum of discriminant scores. The distribution between specific LD (SLD) and general LD could be a step function or some non-linear shape and the discriminant function would not be capable of predicting a continuum of severity. A simple test of the linearity of a severity function is to determine if the mean of a group of specific LD children discriminant scores are intermediate between normal and general LD. In order to cross-validate the initial discriminant function and to test the linearity hypothesis a discriminant analysis was conducted between the 141 training set normal control children and a sub-set of the LD children defined as general LD by being two grade levels below normal on two or more sub-tests of the WRAT. Once the normal vs. severe discriminant function was computed, then this same function was used to classify mild LD children as being members of the normal group or the severe LD group. The mild LD test group (N = 32) was defined as LD but only two grade levels below normal on one of the sub-tests of the WRAT using the previously computed normal vs. severe LD discriminant function.

The prediction of the linearity hypothesis of severity of LD is that the mild LD children are expected to exhibit EEG discriminant scores that are intermediate between normal and severe.

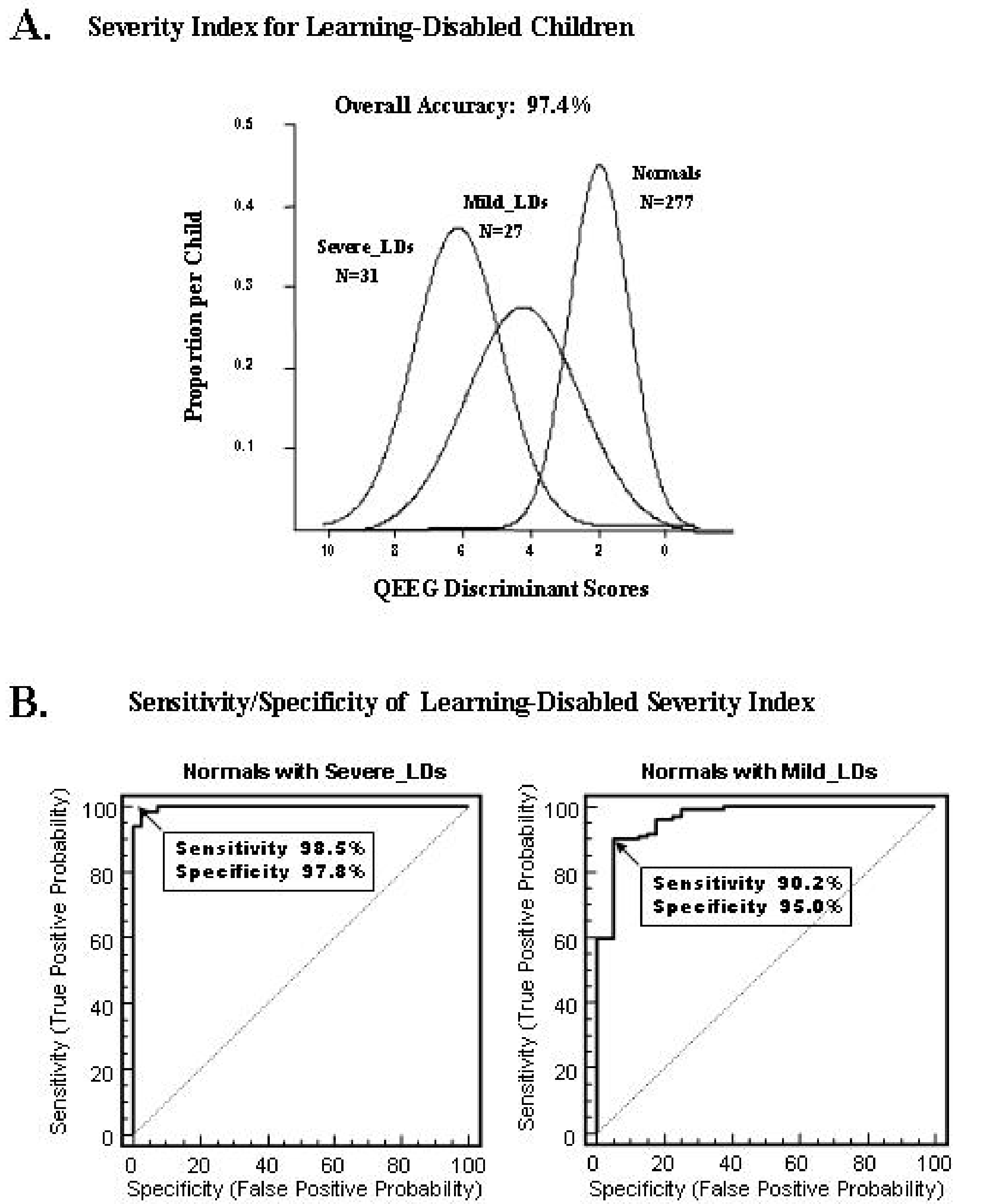


Figure Three: (A) are the distributions of the discriminant scores between a group of age general learning disabled children (N = 31) (the distribution on the left) and age matched normal control subjects (N = 2777) (the distribution on the right). The intermediate distribution is the cross-validation discriminant scores from the group of specific learning disabled children (SLD) (N = 27) but who were not part of the normal vs. general learning disability discriminant function. The scales of the y-axis is the same for the 3 distributions so that the relative proportion of discriminant scores can be compared. In order to display the discriminant scores as a measure of severity value of 6 was subtracted from each discriminant score. In this way the discriminant scores ranged from approximately 0 to 10 and provided a normalized range of values from normal to high severity. (B) are the Receiver Operating Characteristic (ROC) curves of the left and middle discriminant distributions with respect to the normal controls in (A).

Figure 3A shows distribution of discriminant scores for the three groups of children. It can be seen that the mean of the discriminant scores for the mild LD children tended to fall between the mean of the discriminant scores of the normal and severe groups. ROC curves for the EEG severity index are shown in figure 3B.

A second test of linearity of a qEEG severity index was to examine the scatter plots of the correlations between the qEEG discriminant scores and the school achievement and neuropsychological performance in the same children. The hypothesis for a linear severity index of LD would be a relatively straight line regression relationship between EEG and cognitive function and school achievement. Figure 4 is a representative example of the linear regression scatter plots that were observed in the analyses in Table IV.

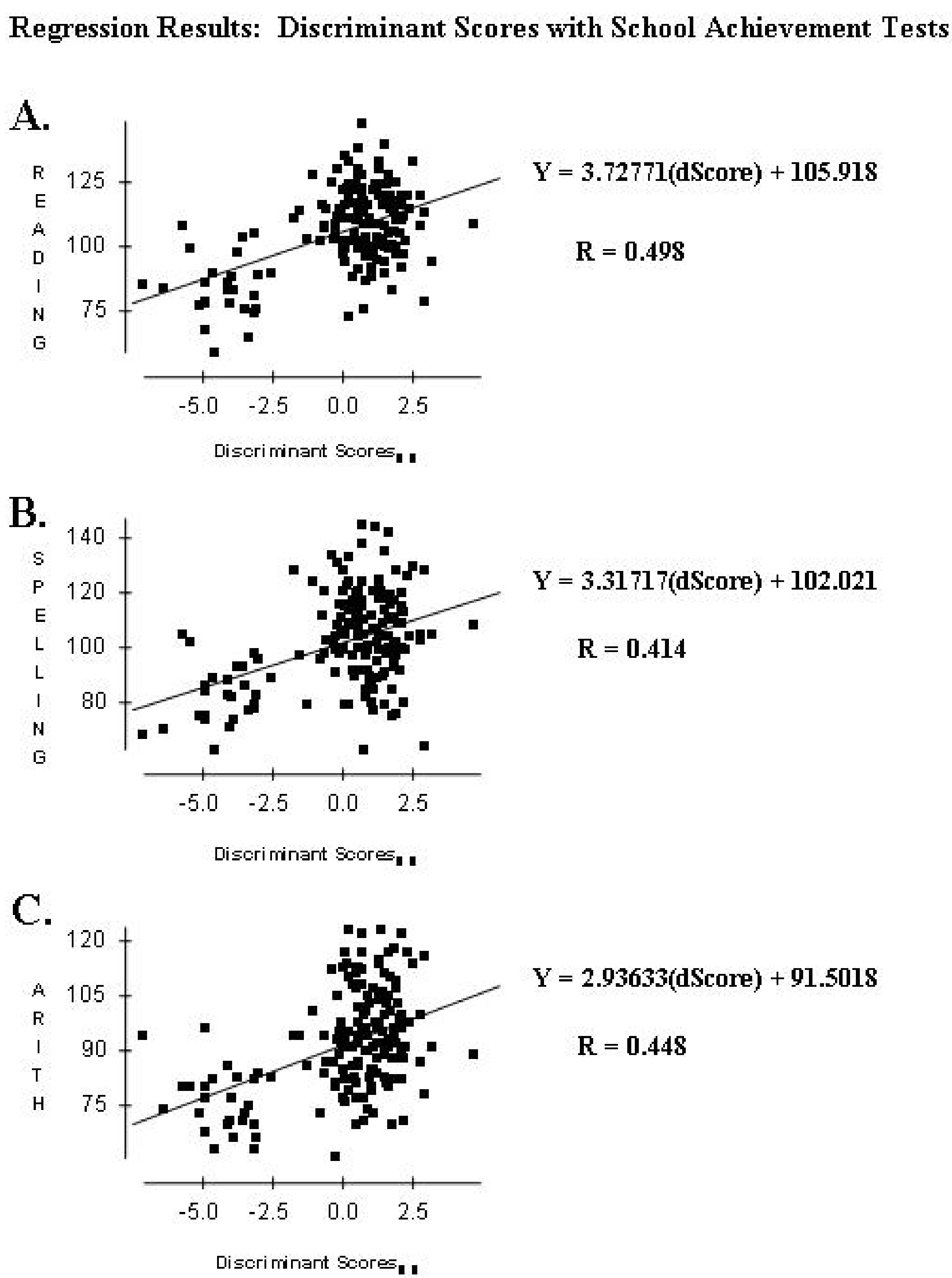


Figure Four: Scattergrams showing a linear relationship between the Wide Range Achievement scores (WRAT) in reading, spelling and arithmetic (y-axis) and EEG discriminant scores from the severity index discriminant function (fig. 3) on the x-axis (N = 231). Regression equations are shown on the right. Correlation results are shown in

Table V. All of the correlations were significant at P < .00001.

It can be seen that a relatively straight or linear function exists between the qEEG dsicriminant scores and school achievement, thus, further supporting the validity of a qEEG severity index of LD.

3.5 – EEG Anatomical power differences and Cognitive Function

Examination of Table IV reveals a pattern of correlation between anatomical power differences and school achievement and neuropsychological test scores in which the signs of the anatomical power differences were reversed for lateral frontal-temporal and medial frontal-parietal regions. In general the lateral-medial anatomical power differences values tended to be positively correlated where as the anterior-posterior anatomical power differences tended to be negative correlated.

In order to explore this aspect of the study correlations between school achievement and neuropsychological test scores were evaluated for delta, theta, alpha and beta frequencies in the frontal-temporal (F4-T4) vs. the frontal-parietal (F4–P4) electrode combinations using all of the LD children and the normal controls (N = 359). Table V shows that opposite signs of correlation to school achievement and neuropsychological test performance were present in all frequency bands. Table V also shows a consistent

TABLE IV

Computer classification of normal and LD children
in the cross validation discriminant analysis.

Cross Validat group	N	Classification percent as Normal	ADD/ADHD
Normal	131	97.7 (N = 128)	2.3 (N = 3)
LD/SLD	29	6.9 (N = 2)	93.1 (N = 27)
Cross Validation classification accuracy = 96.69%.			

and statistically significant positive correlation between F4-T4 and F4-P4 which shows that there is a strong covariance or coupling between these two anatomical systems. Figure 5 shows the scattergrams of the individual normal and LD children in which the Wide Range Achievement scores in reading are on the y-axis and anatomical power differences between frontal – temporal and frontal-parietal are on the x-axis.

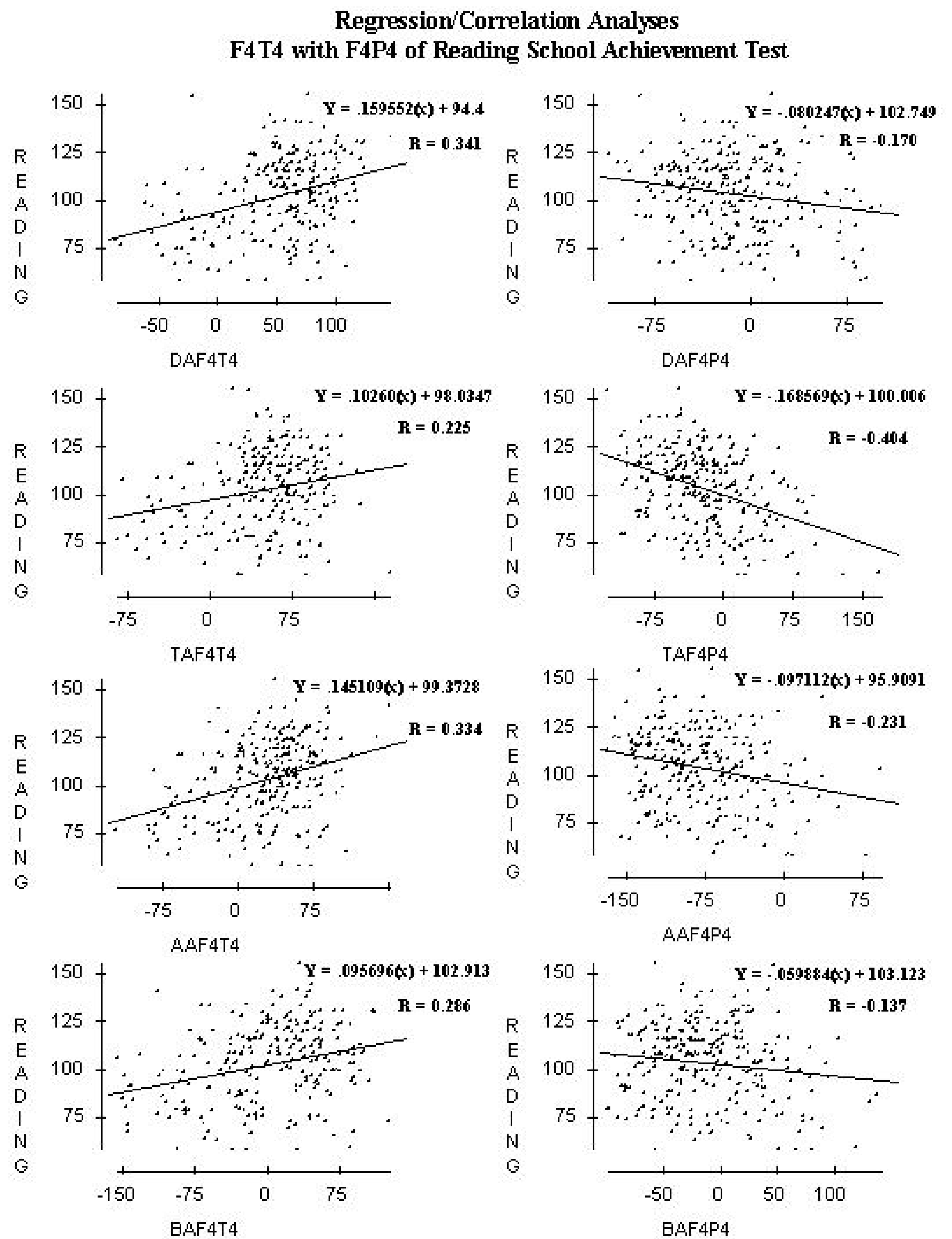


Figure Five: Scattergrams (N = 281) showing a linear relationship between the Wide Range Achievement (WRAT) reading scores (y-axis) and EEG amplitude asymmetry between F4-T4 (left column) and EEG amplitude asymmetry between F4-P4 (right column) across four frequency bands (Delta, Theta, Alpha & Beta as Rows). The direction of correlation was the same independent of frequency. The complete correlation matrix between WRAT and WISC-R test scores and all of the EEG amplitude asymmetry variables entered into the discriminant function is shown in Tables V and VI. The regressions in this figure ranged in statistical significance from $P < .05$ to $P < .0001$.

Although the beta frequency was weakest, nonetheless the overall direction of correlation was independent of EEG frequency with inverse intercorrelations that were independent of EEG frequency band. In other words, the correlation between school achievement and EEG amplitude ratio between two scalp locations was independent of frequency (delta, theta, alpha & beta frequency bands, Figure 5).

Figure 5 are scatter grams of the correlations between F4-T4 and F4-P4 anatomical power differences and WRAT reading scores in different frequency bands. The left column shows that when medial frontal power (F4) is less than lateral temporal power (T4) that school achievement is low and that as medial frontal power (F4) exceeds lateral temporal power (T4) then reading scores are higher. The right column shows the opposite direction of correlation to the F4-T4 anatomical power differences in the left column. In the right column when medial frontal power (F4) is greater than medial parietal (P4) power then school achievement is low and when power in F4 > P4 power then school achievement scores are higher. The F4-T4 and F4-P4 amplitude ratios are positively correlated (Table V), thus two oppositely interrelated conditions appear to be coupled and predictive of cognitive function and school achievement in this study.

4.0 - Discussion

The results of this study are consistent with the results of previous qEEG studies in which an age matched normal control group is compared to children with specific learning disabilities (LD) with or without attention deficit disorder (ADD) or hyperactivity (ADHD) (Chabot et al, 1996; 2001; Chabot and Serfontein, 1996; Lubar et al, 1985; 1999; Monastra et al, 1999; Thatcher et al, 1983; Thatcher and Lester, 1985). Although no distinction between the class of attention deficit children with/or without hyperactivity and children with general learning disabilities was conducted in this study, previous qEEG studies have reported that different EEG patterns can discriminate between different sub-groups of learning disabled children with attention deficit disorders (Chabot et al, 1996; 2001; Clarke et al, 1998; 2001).

In the present study, seven of the ten variables in the discriminant equation were anatomical power differences (or amplitude asymmetries) . Anatomical power differences were simply a stronger class of "summary" variables than any other class of summary variables, including EEG coherence and EEG phase. While not as strong as anatomical asymmetries, the EEG power ratios of theta/beta and alpha/beta were more significantly related to the discriminant function and the neuropsychological tests than was coherence and phase. The finding of a greater discriminatory strength of power ratios in comparison to EEG coherence and phase is consistent with studies by Lubar et al, 1999 and Chabot et al, 1996.

4.1 - Sensitivity and Specificity of the Discriminant Analyses.

Previous qEEG studies of samples of children with generalized learning disabilities (LD) defined by being two grade levels below normal in one area of school achievement and severe learning disorders (SLD) defined as being two grade levels below normal on two or more measures of school achievement were discriminated from an age matched normal control group at approximately 80% accuracy (John et al, 1983; 1989). In the John et al (1983; 1989) studies attention deficit disorder (ADD) or hyperactivity attention deficit disorder (ADHD) were not specifically studied. Studies by Chabot and Serfontein (1996) and Chabot et al (1996) discriminated LD children from age matched normal controls at approximately 94% accuracy. In the Chabot et al (1996) study LD children were discriminated from attention deficit disorders or ADD at 91.4% accuracy. In the same study 86.6% of the ADD children were classified as LD and 96.6% of the low IQ LD children were classified as LD.

In the present study correlation analyses demonstrated a continuum of EEG deviation related to school achievement and neuropsychological test performance (Tables IV, V & VI). These findings indicate that, while sub-types of learning disabilities and attention deficit disorders may be distinguished using qEEG based on other studies (Cabot et al; 1996; Clarke et al, 2001), it is also possible to demonstrate a common set of qEEG variables which discrimininate LD from age matched normal controls and that reflect a continuum of deviation from normal as validated by correlations to school achievement and neuropsychological test scores.

4.2 – Meaning of EEG Anatomical Power Differences and Learning Disabilities

EEG anatomical power differences in this study were defined as: A-B/A+B, where A and B are the spectral power at two different scalp locations (section 2.3). For example, if EEG power in the alpha frequency band is the same for the left and right hemisphere at locations C3 and C4, then amplitude asymmetry = zero because 0/(C3+C4) = 0. The more different the EEG amplitude at the two scalp locations the larger is the ratio and the sign of the ratio is the direction of the difference (e.g., L > R or L < R). Intrahemispheric anatomical power differences are amplitude differences between two scalp locations within a hemisphere at a given frequency, e.g., left frontal-parietal F3-P3 at alpha and interhemispheric anatomical power differences are differences between homologous left and right hemisphere scalp locations.

The anatomical power ratios in this study not only discriminated between the LD and age matched normal controls but these variables were also linearly related to school performance and cognitive function (Table IV, V & VI & Figs. 4 and 5). Examination of Table VI shows that the sign of the correlation between anatomical power differences and cognition is positive in the anterior - posterior direction (e.g., frontal-parietal, parietal-occipital) while the sign of the correlation is negative in the lateral-medial direction, e.g., temporal-frontal). In other words, the more different the amplitude between temporal and frontal then the better was school performance, and conjointly, the less the difference in the anterior-posterior direction then the better was school performance.

Figure 6 is an illustration that emphasizes the differential amplitude relationship between temporal and frontal (laterial - medial) on the one hand and frontal and posterior (anterior - posterior) regions on the other in LD children in this study. The y-axis is the estimated range of cognitive function as measured by school achievement and/or neuropsychological test scores as shown in Tables IV, V and VI and Figs. 4 and 5. The x-axis is the range of EEG amplitude asymmetry independent of frequency. The top row illustrates that poor school achievement is correlated with medial frontal amplitudes less

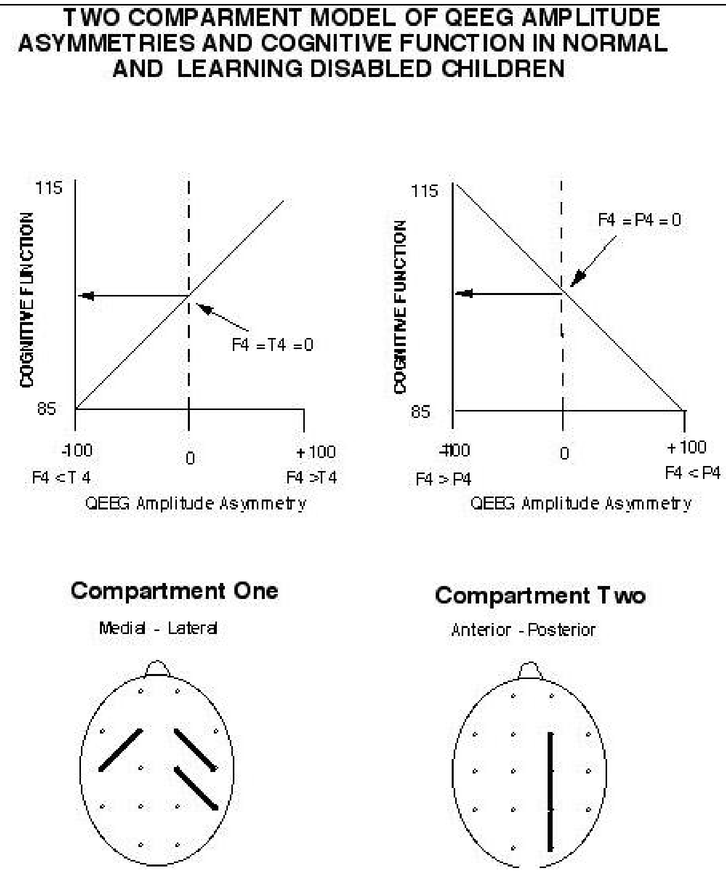


Figure Six: Top row are diagrams to illustrate the observed relationships between EEG amplitude asymmetry and cognitive function as measured on a standardized test such as the WRAT or WISC-R. The zero point projection is based on the findings in figure 5 and Tables V & VI which points to approximately mid-range of the estimate of cognitive functioning in the correlations in this study. Bottom row is a head diagram of the locations of the anatomical power differences in the top row and in Tables V & VI in which there is a different direction of correlation between the laterial - medial electrode sites (e.g., T3/4-F3/4) in comparison to the anterior - posterior electrode sites (.g., F4-P4, P4-O2) as well as negative correlations between them. (Table VI).

than lateral temporal amplitudes (F4 < T4). The zero point or where F4 = T4 projects to approximately the mid range grade level of school achievement and cognitive functioning in general. As frontal amplitudes exceed temporal amplitudes (i.e., F4 > T4) than better than average performance was predicted. Conjointly, the frontal-parietal relationship illustrates that poor school achievement is correlated with frontal amplitudes less than parietal amplitudes (F4 < P4). The zero point or where F4 = P4 projects to approximately the mid range grade level of school achievement and cognitive functioning in general. As medial frontal amplitudes exceed parietal amplitudes (i.e., F4 > P4) than better than average performance was predicted.

4.3 - Sub-Cortical vs. Neocortical Hypotheses

There was a widespread occurrence of anatomical power differences measures in the discriminant function and amplitude asymmetry correlations were widely distributed. Different neurochemical regimes in the frontal-temporal as opposed to the dorsal frontal-parietal regions are one hypothesis to explain the results, another hypothesis is that a single sub-cortical control process is reflected in the neocortical EEG amplitude differences observed in this study. The fact that qEEG coherence and qEEG phase were not as significantly related to cognitive function as was the ratios of the power measures indicates that cortico-cortical network properties are less important than the energy ratios of the qEEG spectrum itself. This supports anatomically deeper sources, such as subcortical thalamic, hippocampal, basal ganglia and reticular formation which may be involved in distinguishing LD from normals more than the neocortex itself.

The results of the study also indicate the operation of two different neocortical spatial gradients: 1- a lateral-medial and, 2- an anterior-posterior spatial gradient operating in both LD and normal children. Increased difference in amplitude between lateral temporal to medial frontal exhibited positive correlations to school performance and neuropsychological test performance, while increased difference between pre-frontal to posterior cortex exhibited a negative relationship (fig. 5). The hypothesis of a single and unifying sub-cortical origin of the anatomical relationship between scalp voltages observed in this study is not inconsistent with a sub-cortical dynamic of an unknown type.

4.5 – Clinical Utility of an EEG Discriminant Function and Severity Index of Learning Disabilities

A continuum of relationships between qEEG and cognitive function was demonstrated by intermediate discriminant scores for mild LD children, the relative high accuracy and sensitivity of the discriminant function and the relative high linear correlations with school performance and neuropsychological scores. These associated findings support the clinical application of the qEEG discriminant functions for the purposes of estimating false negatives and false positives for an organic basis of attention deficit disorders and low school achievement. In figure 4 and Tables IV, V & VI a given child's discriminant score reflects the severity of LD within a 95% confidence band. Examination of the relative contribution of different EEG dimensions of the severity index, such as seen in figure 1B, may facilitate the neurophysiological evaluation of LD and it may be useful in the evaluation of LD and learning disabilities in general. The EEG discrimiant function may also be of value in estimating the probability that there is a neurological basis for a child's complaints or problems in school as opposed to family divorce or environmental factors.

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