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EEG and intelligence: Relations between EEG coherence, EEG phase delay and power

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See Editorial, pages 1999–2000

Abstract

Objective: There are two inter-related categories of EEG measurement: 1, EEG currents or power and; 2, EEG network properties such as coherence and phase delays. The purpose of this study was to compare the ability of these two different categories of EEG measurement to predict performance on the Weschler Intelligence test (WISC-R).
Methods: Resting eyes closed EEG was recorded from 19 scalp locations with a linked ears reference from 442 subjects aged 5–52 years. The Weschler Intelligence test was administered to the same subjects but not while the EEG was recorded. Subjects were divided into high IQ (≥ 120) and low IQ (≤ 90) groups. EEG variables at $P < .05$ were entered into a factor analysis and then the single highest loading variable on each factor was entered into a discriminant analysis where groups were high IQ vs. low.Q.
Results: Discriminant analysis of high vs. low IQ was 92.81–97.14% accurate. Discriminant scores of intermediate IQ subjects (i.e. $90 < \mathrm{IQ} < 120$) were intermediate between the high and low IQ groups. Linear regression predictions of IQ significantly correlated with the discriminant scores ($r = 0.818$–0.825, $P < 10^{-6}$). The ranking of effect size was EEG phase > EEG coherence > EEG amplitude asymmetry > absolute power > relative power and power ratios. The strongest correlations to IQ were short EEG phase delays in the frontal lobes and long phase delays in the posterior cortical regions, reduced coherence and increased absolute power.
Conclusions: The findings are consistent with increased neural efficiency and increased brain complexity as positively related to intelligence, and with frontal lobe synchronization of neural resources as a significant contributing factor to EEG and intelligence correlations.
Significance: Quantitative EEG predictions of intelligence provide medium to strong effect size estimates of cognitive functioning while simultaneously revealing a deeper understanding of the neurophysiological substrates of intelligence.

Keywords: qEEG; Coherence; Phase delays; Intelligence; IQ

1. Introduction

Correlations between intelligence and EEG measures have been reported in numerous studies (Giannitrapani, 1985). In general, two categories of EEG variables are correlated with IQ and neuropsychological test performance: 1, power or amplitude measures and; 2, network connection measures such as coherence and phase delays and non-linear dynamical models of network complexity. The EEG amplitude or power studies generally report a positive correlation between absolute power and IQ (Marosi et al., 1999; Schmid et al., 2002). Jausovec and Jausovec (2001) using LORETA imaging methods reported increased 3-dimensional current source density in the alpha and beta band as being positively related to IQ, which was consistent with the surface EEG measures of increased power. Decreased power in lower frequencies (delta and theta) is also reported as being positively correlated with IQ in learning disabled children (Marosi et al., 1999) but not in normal subjects

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(Martin-Loeches et al., 2001). Studies by Jausovec and Jausovec (2000a,b) indicate that increased power in the high alpha band (10–12 Hz) was more significantly correlated with IQ than increased power in the lower alpha frequency band (e.g. 8–9 Hz). However, genetic studies of the correlation between increased alpha power and increased alpha frequencies have failed to confirm these findings (Giannitrapani, 1985; Posthuma et al., 2001; Schmid et al., 2002).

The network measures of EEG typically report a positive correlation between neural complexity and intelligence. For example, negative correlations between EEG coherence and IQ especially in the frontal lobes have been reported (Barry et al., 2002; Marosi et al., 1999; Martin-Loeches et al., 2001; Silberstein et al., 2003; Thatcher et al., 1983) and increased dimensionality of the EEG is reported as being positively correlated with IQ in the eyes closed resting condition (Anokhin et al., 1999). Several EEG network studies have argued that increased complexity and increased neural efficiency are positively related to intelligence (Anokhin et al., 1999; Jausovec and Jausovec, 2003; Lutzenberger et al., 1992; Neubauer et al., 2004).

Coherence is a measure of phase angle consistency or phase 'variability' but is independent of the mean phase angle or mean phase shift between two time series (Bendat and Piersol, 1980; Otnes and Enochson, 1972). The correlation between the mean EEG phase shift and intelligence has not been studied as much as other EEG measures. Thatcher et al. (1983) showed both positive and negative correlations between brain maturation and phase delays depend on the topography of the electrodes. Some studies of EEG complexity and dimensionality and intelligence have included measures of phase delays but these studies have not analyzed or correlated phase delay with intelligence per se (Anokhin et al., 1999).

The purpose of the present study is to investigate the correlations between EEG and the WISC-R intelligence test using power measures (absolute power, relative power and power ratios) and EEG network measures (coherence and phase delay). Multivariate analyses will be used to compare low and high IQ subjects as a first step toward examining the relations between EEG and neuropsychological test performance.

2. Methods

2.1. Subjects

The study included a total of 442 subjects ranging in age from 5 to 52.75 years (males = 260). The age distribution was weighted toward younger subjects with $N = 398$ in the age range 5–15, $N = 40$ in the age range of 16–25 and $N = 4$ in the age range of 26–55. However, age was not a confounding variable because there were no statistically significant differences in age between different IQ groups. Subjects with a history of neurological disorders were excluded from the study and none of the subjects in the study had taken medication less than 24 h before testing in this study. The full scale IQ and age means, ranges and standard deviations of the subjects are shown in Table 1.

2.2. Neuropsychological measures

Neuropsychological and school achievement tests were administered on the same day that the EEG was recorded. The order of EEG and neuropsychological testing was randomized and counter-balanced so that EEG was measured before neuropsychological tests in one half of the subjects and neuropsychological tests were administered before the EEG in the other half of the subjects. All tests were performed on the same day. The Wechler Intelligence Scale for Children revised (WISC-R) was administered for individuals between 5 years of age and 16 years and the Weschler Adult Intelligence Scale revised (WAIS-R) was administered to subjects older than 16 years. The neuropsychological sub-tests for estimating full scale IQ were the same for the WISC-R and the WAIS and included information, mathematics, vocabulary, block design, digit span, picture completion, coding and mazes. The neuropsychological tests included block design, digit span, picture completion, vocabulary, coding and mazes in the WISC-R.

2.3. EEG recording

The EEG was recorded from 19 scalp locations based on the International 10/20 system of electrode placement, using linked ears as a reference. University of Maryland built EEG amplifiers were used to acquire EEG from 380 of the subjects at 100 Hz sample rate and Lexicor-NRS 24 EEG amplifiers at 128 Hz sample rate were used to acquire EEG from 62 of the subjects. There were no significant differences in the distribution of IQ scores or in the age range of subjects acquired by the two amplifier systems. Both amplifier systems were 3 db down at 0.5 and 30 Hz and the Lexicor NRS-24 Amplifiers and the University of Maryland amplifiers were calibrated and equated using sine wave calibration signals and standardized procedures. Two to 5 min segments of EEG were recorded during an eyes closed resting condition for all subjects. Each EEG record

Table 1
Age and full scale IQ means, ranges and standard deviations of the three groups of subjects

IQ groups	N	Mean age	SD age	Age range	Mean full IQ	SD full IQ	Full IQ range
Low IQ	74	11.76	5.71	5.00–52	83.05	6.11	70–90
Middle IQ	270	11.05	3.74	5.00–39	105.39	7.62	91–119
High IQ	98	10.44	4.64	5.17–37	128.33	7.47	120–154

was visually examined and then edited to remove artifact using the Neuroguide software program. Split-half reliability tests and test re-test reliability tests were conducted on the edited EEG segments and only records with >90% reliability were entered into the spectral analyses.

2.4. Power spectral analyses

Interpolation of the 100 Hz sampled EEG to 128 Hz was used in order to equate the sample rates for all subjects (Press et al., 1994). A Fast Fourier transform (FFT) auto-spectral and cross-spectral analysis was computed on 2 s epochs thus yielding a 0.5 Hz frequency resolution over the frequency range from 0 to 30 Hz for each epoch. A ratio of the microvolt sine wave calibration signals from 0 to 30 Hz that were used to calibrate the University of Maryland amplifier frequency characteristics and the Lexicor NRS-24 amplifier characteristics was computed and then used as equilibration ratios in the FFT to exactly equate the two amplifier systems. The 75% sliding window method of Kaiser and Sterman (2001) was used to compute the FFT in which successive 2 s epochs (i.e. 256 points) were overlapped by 500 ms steps (64 points) in order to minimize the effects of the FFT windowing procedure. Absolute and relative power were computed from the 19 scalp locations in the delta (1.0–3.5 Hz), theta (4.0–7.5 Hz), alpha (8–12 Hz), beta (12.5–25 Hz) and high beta (25.5–30 Hz) frequency bands. EEG amplitude was computed as the square root of power. Relative power was the ratio of power in a given band/sum of power from 1 to 30 Hz (i.e. total power)×100. Relative power ratios of the different frequency bands of EEG from a specific electrode were computed for theta/beta, theta/alpha, alpha/beta and delta/theta. The frequency ratios were limited to the 4 most commonly studied frequency ratios.

EEG amplitude asymmetry differences were computed as a ratio of differences in absolute power between two scalp locations or $(A-B/A+B)\times 200$ 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 171 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 5 frequency bands (delta, theta, alpha, beta and high-beta). 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 phase angle Θ_{xy} between two channels is the ratio of the quadspectrum to the cospectrum or $\Theta_{xy}=\arctan q_{xy}/r_{xy}$ which was computed in radians and transformed to degrees (Bendat and Piersol, 1980; Otnes and Enochson, 1972). The absolute phase delay in degrees was computed by squaring and then taking the square root of the phase angle or $\sqrt{\Theta^2_{xy}}$.

The total number of QEEG variables as well as the number of QEEG variables in different categories of the analyses are given in Table 2.

2.5. Selection of variables for discriminant analyses between high and low IQ groups

The subjects were separated into a high full scale IQ group (IQ≥120) and a low full scale IQ group (≤90 IQ) for purposes of the full scale IQ analyses. A similar separation into high (i.e. ≥120) and low IQ (≤90) groups was also made based on performance IQ and verbal IQ for separate discriminant analyses. Thus, 3 separate discriminant analyses were conducted (full scale IQ, performance IQ and verbal IQ). The procedures for variable selection and reduction were the same for all 3 analyses. In order to assess possible confounding by age, t-tests were conducted of differences between age in different IQ groupings (low IQ vs. middle IQ, low IQ vs. high IQ and middle IQ vs. high IQ). The results of the analysis showed that there were no statistically significant differences in age between any of the IQ groupings.

T-tests were conducted on all 2831 EEG measures and variables that were statistically significant at $P<.05$ were identified. EEG variables that were statistically significant at $P<.05$, were then entered into a varimax factor analysis to further reduce the measure sets. No correction for multiple comparisons was used because the goal of this step was data reduction to separate the most significant variables from the less significant variables rather than drawing an inferential conclusion. Separate varimax factor analyses were performed on each category of the spectral analysis variables and the highest loading variable on each factor was then identified for entry into the discriminant analysis. This resulted in the selection of 63 variables for the full scale IQ discriminant analysis, 79 variables for the verbal IQ discriminant analysis and 85 variables for the performance IQ analyses. Table 3 shows that this two-step process

Table 2
The total number and categories of qEEG variables

qEEG Measures:	TOTAL
Absolute Power_5 frequencies @ 19 channels	95
Relative Power_5 frequencies @ 19 channels	95
RP_Ratios_4 sets (T:B, T:A, A:B, D:T) @ 19 channels	76
Amplitude Asymmetry_5 frequencies @ 171 variable	855
Coherence_5 frequencies @ 171 variables	855
Absolute Phase_5 frequencies @ 171 variables	855
TOTAL VARIABLEs	2831

Neuropsychological Tests:		
	FULL SCALE IQ	
VERBAL IQ		PERFORMANCE IQ
Information Mathematics Vocabulary Digit Span	SUBTESTs	Picture Completion Block Design Coding Mazes

resulted in a 93.2–96.8% reduction in the total variable space (e.g. 63/2831) and a subject to variable ratio of 2.25–2.65.

Linear discriminant analyses were computed using SPSS (1994). A Bayesian procedure was used in order to adjust for differences in sample size between the high IQ and low IQ groups. Sensitivity, specificity, positive predicted values (PPV) and negative predicted values (NPV) were defined 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).

2.6. Validation by multiple regression analyses

Multiple regression analyses (SPSS, 1994) were conducted to independently validate the discriminant analyses and to compare to the discriminant analyses. The dependent variables were an IQ score (full scale IQ or verbal IQ or performance IQ in separate tests) and the independent variables were the EEG variables entered into the discriminant analyses described in Section 2.4.

3. Results

3.1. Discriminant analysis of high IQ vs. low IQ groups

Table 3 shows the number of EEG variables that were selected for entry into the discriminant analysis of the high IQ (IQ > 120) vs. low IQ (IQ < 90) subjects. The greatest number of variables in the 3 different discriminant analyses were: EEG phase, then amplitude asymmetry, then coherence, then relative and absolute power and then ratios of power. Although some of the EEG variables were used in all 3 analyses, most of the variables were unique to each analysis in terms of frequency and location.

Table 4 is a listing of the EEG variables that were selected for the discriminant analyses.

Fig. 1 shows the results of the 3 different discriminant analyses where the *y*-axes are the measured IQ scores and the *x*-axes the discriminant scores. Fig. 1 (Top) is the result of the full scale IQ analysis, bottom left are the results of the verbal IQ analysis and bottom right are the results of the performance IQ analysis. It can be seen that the high IQ vs. low IQ groups were separated in all 3 analyses.

Table 3
Data reduction by t-tests and factor analysis

IQ scores ≥ 120 vs. IQ scores ≤ 90	Total no. of *T*-test VARs		
	Full IQ	Verbal IQ	Performance IQ
Absolute power	23	19	51
Relative power	5	5	4
RP-ratios	3	1	4
Amplitude asymmetry	187	229	109
Coherence	170	181	222
Absolute phase	111	96	175
Factor analyses results	Total no. of final selected VARs		
	Full IQ	Verbal IQ	Performance IQ
Absolute power	4	4	6
Relative power	5	5	4
RP-ratios	3	1	4
Amplitude asymmetry	16	18	16
Coherence	15	24	14
Absolute phase	20	27	41
Total variables	63	79	85

Data reduction process: *T*-tests and factor analyses. *T*-Tests: significance at $P < .05$.

Table 4
List of the EEG variables that were selected for the discriminant analyses

Final selection of qEEE variables: full scale IQ

Absolute power	Amplitude asymmetry		Coherence	Absolute phase	
Delta-Cz	*Delta*	*Alpha*	*Delta*	*Delta*	*Alpha*
Alpha-O1	CzT4	CzO2	T6O1	FP1Fz	T5Pz
Beta-P3	FzF4	F3P3	CzPz	CzO1	F4T4
Beta-T4	C3Cz	F3T3	FzCz	T3Cz	F3O2
	Theta	FP2C4	F7F4	T4O1	T6O2
Relative power	F4O2	CzP4	T3O1	FzC4	*Beta*sd
Delta-FP1	FP1C3	F3T6	*Theta*	T3O2	P3O1
Delta-F7	FzC3	*Beta*	T3Cz	PzT6	CzT5
Beta-O1	F3Cz	F3P3	C3O1	*Theta*	P4T6
Beta-O2		*HI-Beta*	P4T6	CzT6	*HI-Beta*
HI-Beta-O1		F8C3	T5P3	FzT5	CzP3
		CzC4	*Alpha*	T5Pz	PzP4
Relative power ratios			FP2F7		FzF8
Alpha/Beta-O1			P4O1		
Alpha/Beta-O2			FP1Pz		
Delta/Theta-FP1			P3O1		
			Beta		
			T5O2		
			HI-Beta		
			T5P4		

Final selection of qEEG variables: verbal IQ

Absolute power	Amplitude asymmetry	Coherence		Absolute phase	
Delta-T3					
Theta-O1	*Delta*	*Delta*	*Alpha*	*Delta*	*Beta*
Alpha-O1	PzO2	C4O2	F3F8	FP1Fz	F4C3
Beta-T4	*Theta*	F7F4	P3O2	T3Cz	F8Cz
	FzPz	CzPz	F3T6	T3O2	*HI-Beta*
Relative power	C3T4	F8C4	T5P3	FP1Pz	PzP4
Delta-FP1	FP1Cz	T3O1	F7T5	T4O1	F4O2
Alpha-FP1	F3Cz	FP1F4	*Beta*	*Theta*	FzF8
Beta-O1	FzF4	C3C4	C3O1	FP2F4	CzP3
Beta-O2	*Alpha*	FP2F8	*HI-Beta*	T6O1	FP1FP2
HI-Beta-O1	F4Pz	F7P4	CzT5	*Alpha*	C3T5
	CzO2	*Theta*		F8P4	C4T6
Relative power ratios	FzT3	T3C4		FzF4	FP2O1
Alpha/Beta-O2	FzC4	F4Cz		F7T3	
	F4T6	C3O2		P4O1	
	O1O2	FzO2		T3P4	
	FP1F7	T6O2		FP2F8	
	Beta	P4O2		CzT4	
	F3P3	FP1F7		C3O2	
	F3Cz	T5O1		P3T6	
	F4T4			T4T5	
	P3P4				
	HI-Beta				
	FzF8				

Final selection of qEEG variables: performance IQ

Absolute power	Amplitude asymmetry	Coherence		Absolute phase	
Delta-Pz					
Alpha-Cz	*Delta*	*Delta*	*Delta*	*Alpha*	*HI-Beta*
Alpha-T3	C3O2	C3O2	FP1FP2	FP2Fz	CzP3
Beta-Fz	C3T4	PzP4	T3C4	T5Pz	F4T5
Beta-T4	T3C3	F7F4	C4T5	FP2F3	FzT4
HI-Beta-Cz	FzP3	*Theta*	CzT4	FP2O2	FzT3
	Theta	T3Cz	PzO1	P3T6	T5P3
Relative power	FP1Cz	P4T6	C4T6	P4O2	F4F8
Delta-Pz	FzPz	T5T6	T4T5	F3Cz	
Beta-O2	FP2F8	F8T5	F7O2	F7O1	
HI-Beta-O1	FP1F7	*Alpha*	FzCz	*Beta*	

(*continued on next page*)

Table 4 (*continued*)

HI-Beta-O2	O1O2	F3Fz	C3O2	C3T5
	Alpha	FP2P4	*Theta*	F3Cz
Relative power ratios	FP1C3	PzO2	C4T6	CzO1
Alpha/Beta-O2	FP1F4	FP1Pz	F4T5	P4T6
Delta/Theta-Cz	T5O2	*Beta*	T3T5	CzT6
Delta/Theta-C4	*Beta*	T6O1	FP2F7	FzT3
Delta/Theta-C3	PzO1	*HI-Beta*	T5T6	PzO2
	FzP3	C4O1	T4T5	T5O2
	HI-Beta	T3P3	F8T5	T3O2
	F4F8		F4T3	
	FzCz			

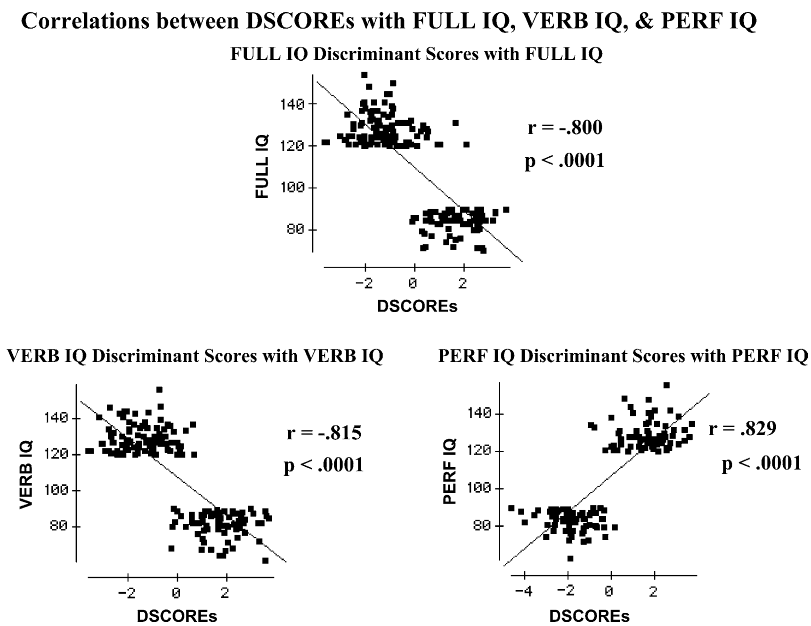

Fig. 1. Top middle shows the distribution of the discriminant scores on the *x*-axis and full scale IQ scores on the *y*-axis for the high IQ (>120) and low IQ (<90) groups of subjects. Bottom left shows the distribution of the discriminant scores on the *x*-axis and Verbal IQ scores on the *y*-axis for the high IQ (>120) and low IQ (<90) groups of subjects. Bottom right shows the distribution of the discriminant scores on the *x*-axis and performance IQ scores on the *y*-axis for the high IQ (>120) and low IQ (<90) groups of subjects.

Table 5 shows the results of the discriminant analysis of high IQ vs. low IQ groups. Overall classification ranged in accuracy from 97.14% for performance IQ to 94.77% for verbal IQ to 92.81% for full scale IQ Sensitivity ranged from 96.84% for verbal IQ to 95.98% for performance IQ to 91.75% for verbal IQ Specificity ranged from 98.5% for performance IQ to 94.29% for full scale IQ to 92.2% for verbal IQ

Table 5
Results of the discriminant analyses

Results		Classification	
		IQ≥120	IQ ≤90
Discriminant analysis: full scale IQ (total selected variables=63), classification accuracy=92.81%			
Full IQ ≥120	*n*=97	(89) 91.8%	(8) 8.2%
Full IQ ≤90	*n*=70	(4) 5.7%	(66) 94.3%
90<full IQ<120	*n*=267	(153) 57.3%	(114) 42.7%
Discriminant analysis: verbal IQ (total selected variables=79), classification accuracy=94.77%			
Verb IQ ≥120	*n*=95	(92) 96.8%	(3) 3.2%
Verb IQ ≤90	*n*=77	(6) 7.8%	(71) 92.2%
90<verb IQ<120	*n*=270	(147) 54.4%	(123) 45.6%
Discriminant analysis: performance IQ (total selected variables=85), classification accuracy=97.14%			
Perf IQ≥120	*n*=73	(70) 95.9%	(3) 4.1%
Perf IQ≤90	*n*=67	(1) 1.5%	(66) 98.5%
90<perf IQ<120	*n*=302	(151) 50.0%	(151) 50.0%

EMG artifact rejection resulted in missing data in one or more channels and the SPSS list wise case option deleted 8 subjects, leaving $N=434$ for the full-scale IQ analysis. As seen in Table 5, there were slight differences in sample size between the 3 IQ groups that were entered into the discriminant analyses because of differences in categorization based on the verbal or performance IQ subtests. For example, subjects with a performance IQ that places them in the middle IQ group may have a lower verbal IQ that places them in the low IQ group, etc. These differences were relatively small and had no significant effect on the overall accuracy of the full scale, verbal and performance IQ discriminant analyses.

In order to further determine that age was not a confounding variable, the full scale IQ discriminant analysis was re-computed after deletion of subjects greater than 16 years of age. The results of this analysis showed that age is not a confounding variable and that stable, accurate and reproducible discrimination between high and low IQ groups is independent of age.

3.2. Cross-validation of mid range IQ subjects

The EEG discriminant function is a linear regression equation that returns a single value for each subject based on the EEG variables and a unique set of regression coefficients (Norusis, 1994). Discriminant functions are not just classifiers of the probability of membership of a group, but may also be a linear estimate of values intermediate to the extreme values contained in the original groups that were discriminated (Thatcher et al., 2001). A simple test of the linearity of a discriminant function is to determine if the discriminant scores for subjects within the intermediate range of IQ, i.e. $90<\mathrm{IQ}<120$ are intermediate to the discriminant scores for the two extreme groups of subjects (i.e. <90 and >120). *T*-tests between the mean ages of the intermediate IQ vs. the low IQ and high IQ groups were not significant. The bottom row of each section of Table 4 shows the classification accuracy of the subjects that were intermediate in $90<\mathrm{IQ}<120$. It can be seen in Table 5 that the intermediate IQ subjects were approximately evenly split between the high and low IQ groups which is expected if the discriminant function is a linear predictor of IQ

Fig. 2 shows the distribution of discriminant scores for the two extreme IQ groups as well as the intermediate IQ subjects. It can be seen that the discriminant function does behave as a linear estimator of IQ because the intermediate IQ subjects produced intermediate discriminant scores.

3.3. Cross-validation using multivariate regression analyses

The finding that intermediate value IQ subjects produce intermediate value discriminant scores indicates that multivariate regression analysis should yield similar

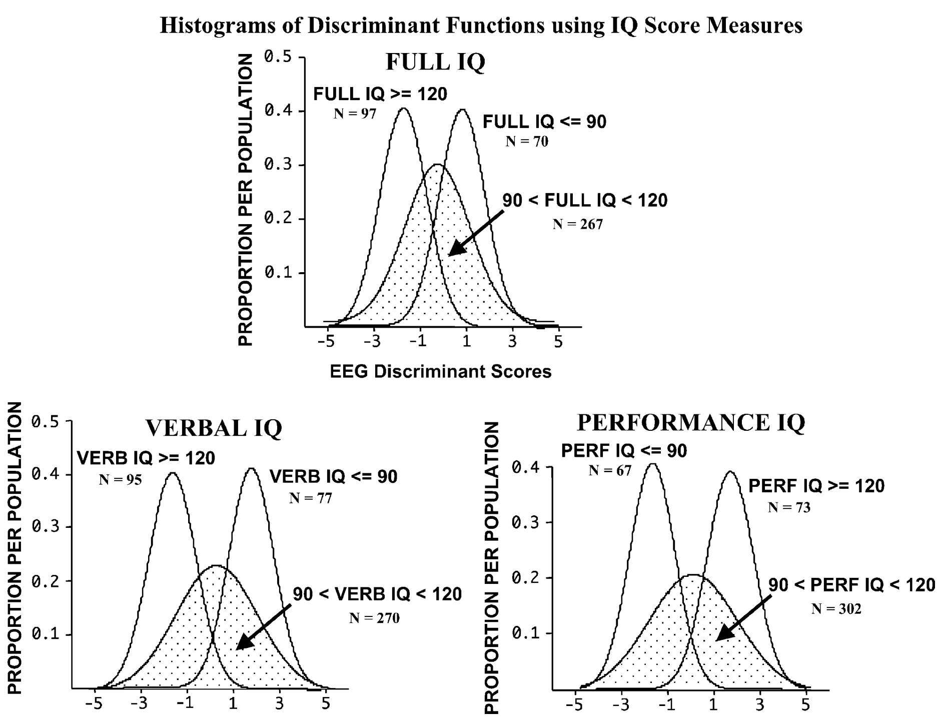

Fig. 2. Top middle shows the distribution of the discriminant scores on the *x*-axis for the full scale IQ analyses for the 3 groups of subjects. The distribution to the left is the high IQ group (>120 IQ), the distribution on the right is for the low IQ group (<90) and the middle distribution scores are from subjects with IQ scores intermediate between the high and low IQ groups (i.e. >90 and <120). Bottom left is the corresponding data for the verbal IQ scores. Bottom right is the same as the top middle but for the performance IQ scores.

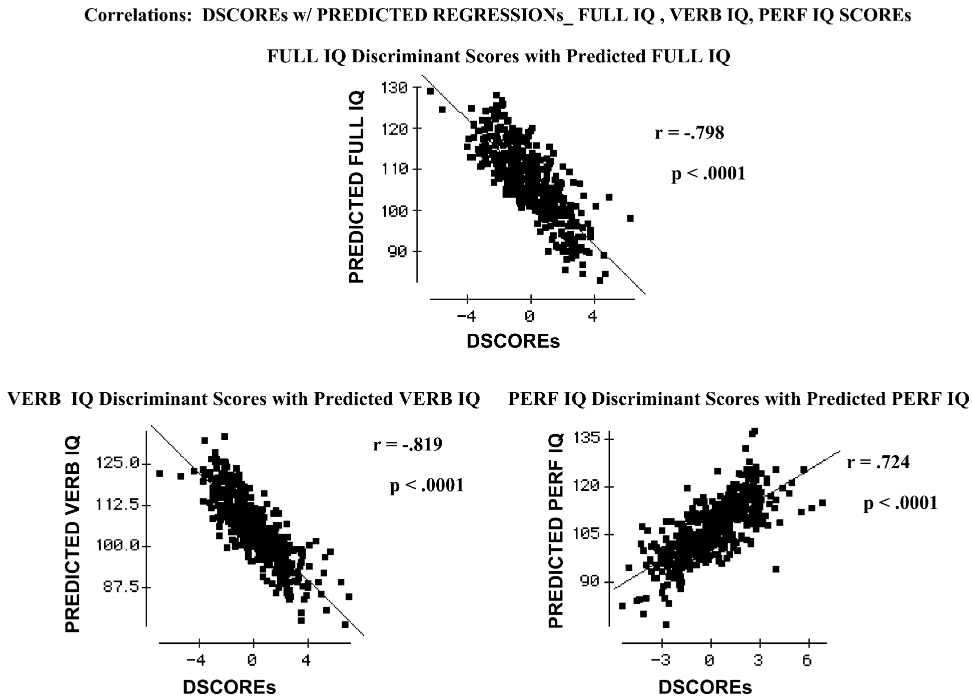

Fig. 3. Top middle shows the prediction of Full Scale IQ for all subjects ($N=422$) based on the multivariate regression analysis on the y-axis and the discriminant scores on the x-axis. Bottom left is the corresponding data for the Verbal IQ scores. Bottom right is the same as the top middle but for the Performance IQ scores.

results to the discriminant analysis. The advantage of multivariate regression analyses is that there is no dependence upon discriminating between two groups of subjects such as low and high IQ groups and a continuum of IQ predictions are possible. Correlation analyses were conducted between the discriminant scores using the discriminant analysis and predicted IQ scores using the multivariate regression analysis. Validation of both analyses is related to the extent that these two separate analyses are correlated. Fig. 3 shows the results of

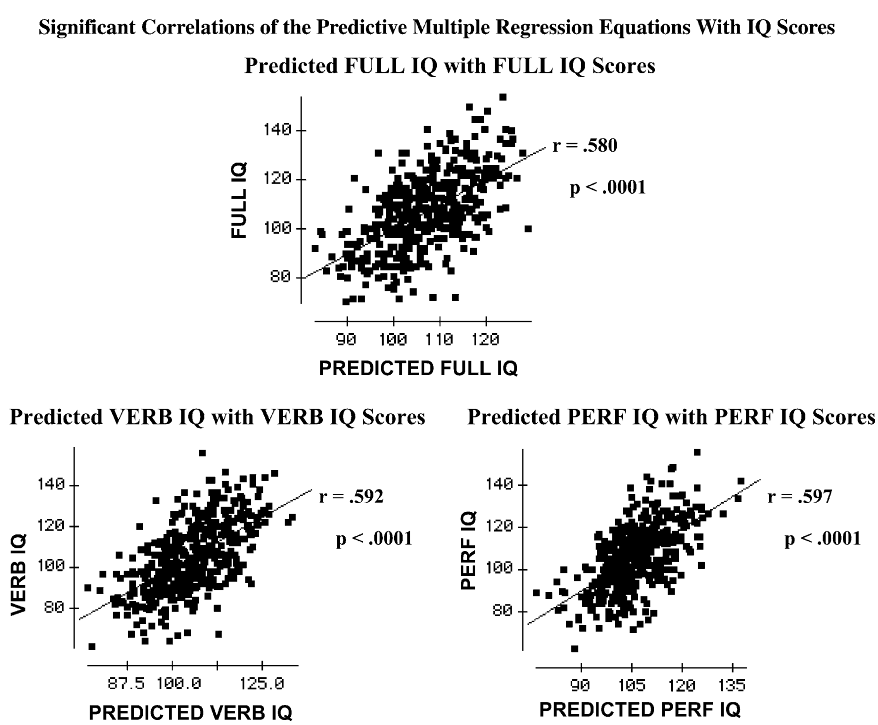

Fig. 4. Top middle shows the measured Full Scale IQ scores for all subjects ($N=422$) on the y-axis and the multivariate regression prediction of IQ scores on the x-axis. Bottom left is the corresponding data for the verbal IQ scores. Bottom right is the corresponding data for the performance IQ scores.

Table 6
Multivariate correlation results of the regression analyses to predict IQ

		Multiple regression analyses		
		FULL IQ_63	VERB IQ_79	PERF IQ_85
NeuroP-sychs	FULL IQ	0.57	0.57	0.59
	VERB IQ	0.55	0.59	0.56
	PERF IQ	0.54	0.50	0.60
VERB IQ Subtests	INFOR	0.56	0.58	0.56
	MATH	0.48	0.54	0.51
	VOCAB	0.55	0.57	0.55
	DIGSP	0.44	0.50	0.47
PERF IQ Subtests	PICTCOM	0.50	0.47	0.53
	BLOCK	0.51	0.52	0.56
	CODING	0.47	0.44	0.53
	MAZES	0.51	0.49	0.56

the correlation between the discriminant scores and the predicted IQ using multivariate regression analyses in the total population as well as independently for the different sub-groups of subjects shown in Table 1. Fig. 3 shows that there are statistically significant correlations between the multiple regression prediction of full scale IQ scores and the discriminant scores in all combinations of subjects in this study.

As another test of EEG predictions of IQ, multiple regression analyses were conducted to evaluate the linearity and predictive accuracy of the EEG variables used in the discriminant analysis. In these analyses, the IQ scores were the dependent variables (y-axis) and the EEG measures were the independent variables (x-axis). Fig. 4 shows a scattergram plot and correlation between the measured IQ scores and the predicted IQ in 3 separate multivariate regression analyses. The multiple regressions ranged in value from 0.580 for full scale IQ to 0.597 for performance IQ

Table 6 summarizes the results of the 3 multiple regression analyses including the ability of the EEG variables in Table 4 to predict performance on the individual neuropsychological subtests of the WISC-R.

3.4. Short frontal phase delays, long posterior phase delays, lower coherence and higher power are positively related to higher IQ scores

Correlation analyses were conducted to determine the direction of association between the EEG measures that had statistically significant high and low IQ EEG differences using the t-test. In order to interpret the direction or sign of the correlation, non-parametric sign tests were conducted. The direction of correlation in the ratio EEG variables such as relative power or power ratios or amplitude asymmetry is difficult to interpret and, therefore, the sign of the correlations was not analyzed. Table 7 summarizes the results of the correlations analyses for absolute power, coherence and absolute phase delays for the full scale IQ, verbal IQ and performance IQ discriminant variables. It can be seen in Table 7 that absolute power was consistently positively correlated with IQ and that coherence was consistently negatively correlated with IQ

In contrast, absolute phase delays were a mixture of positive and negative correlation in which overall

Table 7
Summary of the sign of the correlation coefficients between IQ and EEG

	Absolute power		Coherence		Absolute phase	
	POS+	NEG-	POS+	NEG-	POS+	NEG-
DQFULL frequency						
DELTA	8	0	1	58	20	10
THETA	1	0	1	39	13	3
ALPHA	6	0	2	24	13	2
BETA	7	0	0	14	13	6
HI-BETA	0	0	0	30	5	9
TOTAL	22	0	4	165	64	30
DQVERB frequency						
DELTA	6	0	0	49	11	13
THETA	3	0	0	37	0	6
ALPHA	4	0	0	42	3	16
BETA	2	0	0	10	1	7
HI-BETA	0	0	0	6	1	13
TOTAL	15	0	0	144	16	55
DQPERF frequency						
DELTA	10	0	1	74	36	4
THETA	3	0	2	40	28	3
ALPHA	16	0	18	9	16	0
BETA	11	0	0	25	19	1
HI-BETA	2	0	0	53	7	1
TOTAL	42	0	21	201	106	9

Correlations at $P < .05$ of significant T-test variables with IQ scores.

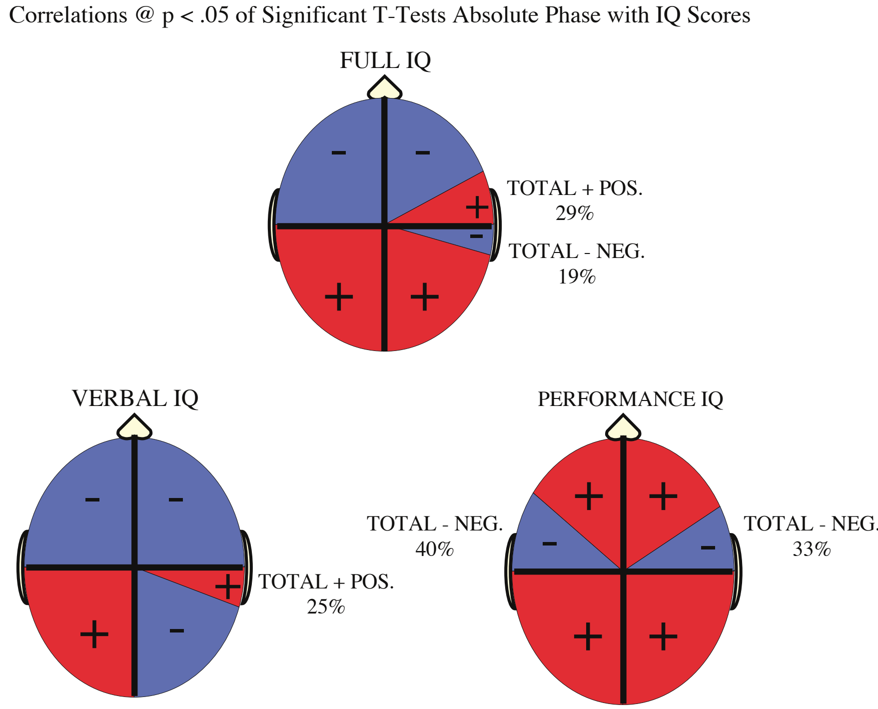

Fig. 5. Head diagrams of the distribution of statistically significant correlations between EEG phase variables and intelligence. Top middle is Full Scale IQ correlations, bottom left are the distributions of verbal IQ correlations and bottom right are the distributions of performance IQ correlations. Positive correlations are marked by '+' and negative correlations are marked by '−'. Only short distance interelectrode correlations are included in this figure. The total number of positive and negative correlations for all statistically significant correlations is in Table 7.

approximately 1/3 of the EEG phase variables were negatively correlated with IQ

Fig. 5 summarizes the locations of the positive vs. negative correlations between short distance EEG phase and IQ in 4 quadrants of the scalp (i.e. adjacent interelectrode distances approx. 6–7 cm). It can be seen that negative correlations primarily occurred in the frontal regions and that there were different locations of positively and

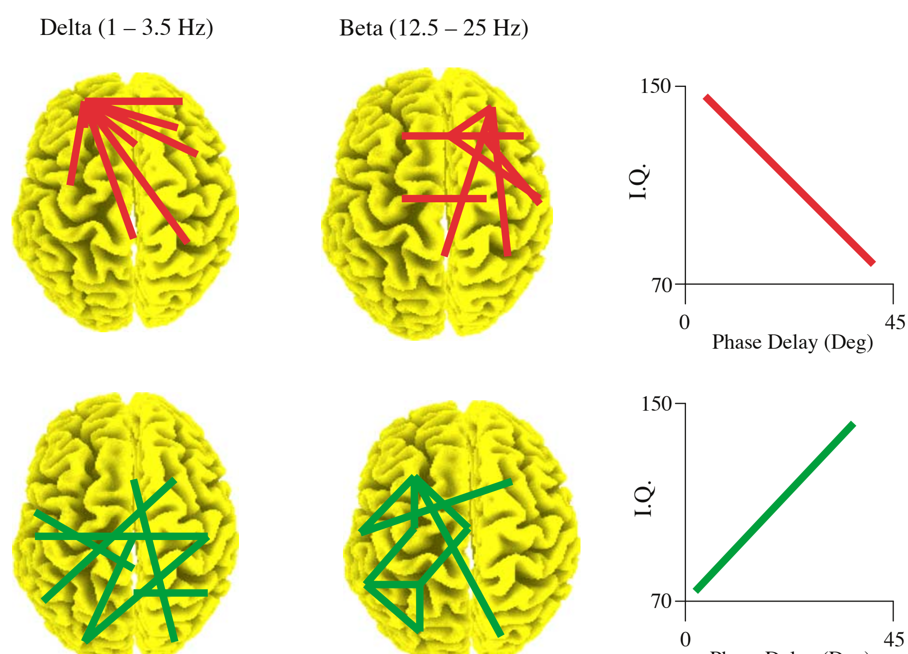

Fig. 6. Diagrammatic illustration of some of the significant between full scale IQ and phase delays summarized in Table 7 and Fig. 5. Left column is the delta frequency band (1–3 Hz) and the right column is the beta frequency band (13–25 Hz). Top row (red color) are negative correlations (i.e. the shorter the phase delays the higher is IQ) and the bottom row (green color) are positive correlations (i.e. the longer the phase delays then the higher is IQ).

negatively correlated EEG phase variables between verbal IQ and performance IQ. In the case of phase, a negative correlation is where the shorter the phase delay the higher the IQ and a positive correlation is where the longer the phase delay the higher the IQ

Differences in the direction or sign of significant correlations and EEG frequency bands in the correlations to verbal IQ and performance IQ are shown in Table 7. In summary, EEG coherence was more positively correlated with performance IQ in the alpha frequency band than was verbal IQ and there were relatively fewer negative phase delay correlations for performance IQ than for verbal IQ.

4. Discussion

A continuum of relationships between EEG and cognitive function was demonstrated by the intermediate discriminant scores of $90<\mathrm{IQ}<20$ as well as by the correlations between multiple regression predictions of IQ and the IQ discriminant function (see Fig. 3). Similar effect sizes or strengths of correlation between the EEG and IQ have been reported in other studies, for example, Schmid et al. (2002) reported similar positive correlations between EEG power and IQ. Posthuma et al. (2001) reported EEG and IQ heritability correlations in the 66–83% range. Anokhin et al. (1999) reported EEG coherence and IQ correlations in the $r=0.6$ range. Similar to the studies cited above, the findings in this study showed significant correlations between EEG and intelligence and thus demonstrated predictive validity between EEG and neuropsychological performance. There were no statistically significant differences in mean age between the different IQ groups and removal of adult subjects did not significantly alter the discriminant analyses. Therefore, age difference or age distributions cannot account for the findings in this study. In the present study, increased power, decreased coherence and shorter frontal lobe phase delays were positively correlated with intelligence, independent of age, and these measures likely reflect fundamental factors that underlay efficient cognitive functioning.

4.1. EEG amplitude and intelligence

Absolute power was positively correlated with full scale, verbal and performance IQ (see Table 7). This means that, on an average, the higher the absolute amplitude or power of the EEG then the higher the IQ. This finding is consistent with studies by Jausovec and Jausovec, 2001 and Martin-Loeches et al., 2001 and others (Giannitrapani, 1985). Energy and intelligence are necessarily linked and increased electrical currents are expected to be positively correlated with intelligence. However, a 2–5% synchrony of synaptic generators can produce 90% of the signal recorded at the scalp surface (Nunez, 1994). Therefore, the positive correlation between amplitude and intelligence is not simple because it is a mixture of phase synchrony and total numbers of synaptic generators.

4.2. EEG frequency and intelligence

There were too few power variables that survived the multivariate data analysis to provide detailed frequency analyses. However, it is not inconsistent to expect correlations to alpha resonance and other rhythmic resonances related to network complexity and arousal. The network measures such as EEG coherence and phase delays were generally independent of frequency and all 5 frequency bands contributed almost equally to the multivariate regression analyses whether for phase delays or coherence or amplitude asymmetry (see Table 4). The experimental design in the present study did not involve a task instead EEG was recorded in a resting condition and not during the neuropsychological tests themselves. This difference in experimental design may in part account for the relative strength of correlations in the present study. It is important to recognize that the term EEG 'resting state' is a state where a high level of neural network dynamics are continuously ongoing in which the readiness or 'potential' to allocate neural resource is continuously present. Studies designed to investigate EEG power in 3-dimensional source space in low vs. high IQ populations may help to further illuminate this dynamic.

4.3. EEG coherence and intelligence

Coherence is a statistical measure of phase consistency between two time series. Amplitude-independent measures such as coherence were more strongly correlated with IQ in this multivariate analysis than were the power measures of the EEG. This indicates that the network properties of shared information and coupling as reflected by EEG coherence are the most predictive of IQ. Similar findings have been reported by Gasser et al. (2003), Mizuhara et al. (2004) and Silberstein et al. (2003). Also similar to studies by Silberstein et al. (2004) the results of the present study found that decreased coherence was positively correlated with IQ. This is consistent with a model that relates decreased coherence to increased spatial differentiation as well as increased complexity of the brain and thereby increased speed and efficiency of information processing (Silberstein et al., 2004; Thatcher et al., 1983, 1986).

4.4. EEG phase 'delay' and intelligence

Phase angle is the lead or lag delay between two time series. EEG spectral time delay equals zero when volume conduction is involved. However, volume conduction cannot account for the findings in this study because the phase delays varied as a function of electrode distance and with different directions of correlation to IQ as a function of anatomy. EEG time delays significantly greater than zero between any two scalp electrodes are mediated by long distance axons and short distance axons as well as the rise times of summated synaptic potentials in the vicinity of the electrode (Nunez, 1981). Nunez (1981, 1994) has estimated that approximately 10% of the EEG electrical potential recorded from any scalp electrode is from the radial dipoles directly underneath the electrode. Approximately 80% of the recorded electrical potential sources are located in a field about 3 cm in diameter and 95% in a 6 cm radial field (Nunez, 1994). However, these measures of EEG amplitude are irrelevant to phase delays because phase delay is independent of the amplitude of the two EEG time series. Therefore, the number of connections or strength of connections may have less relevance than the ability to synchronize distributed generators.

The results of this study showed that the shorter the phase delay the higher the IQ. The limit of shorter phase is equal to 0. Near-zero phase delay not due to volume conduction is often measured in spatially distributed EEG scalp regions during cognitive tasks (Klimesch et al., 2000, 2004). The results of this study are consistent with a near-zero phase delay model of frontal lobe coupling to the extent that the direction of change is the same as in many of the zero phase delay neural models of cognition (Eckhorn et al., 1988; John, 1963, 2002).

4.5. Frontal lobe vs. posterior cortex and intelligence

There was a significant anatomical difference between the frontal lobes and posterior cortical regions. For example, the frontal short distance electrode phase delays were negatively correlated with IQ while the phase delays in posterior short distance electrodes were positively correlated with IQ. A general model to explain the data is to postulate two systems: 1, a frontal command system and; 2, a posterior sensory integration system. In system 1, the shorter phase delays reflect speedier frontal command and more efficient control of the posterior cortical resources. In system 2, it is postulated that the longer phase delays reflect increased local processing time and increased information load, which are positively correlated with IQ. Fig. 6 is a diagrammatic illustration of the general differences in frontal vs. posterior phase delays to illustrate the differences in direction of the correlation with IQ.

5. Summary

Full scale IQ, performance IQ and verbal IQ correlations involved slightly different combinations of EEG measures, nevertheless, coherence and phase dominated all 3 discriminant analyses. This indicates that the EEG correlations in this paper primarily concern a ‘general property’ of intelligence referred to as the ‘G factor’ of the Weschler intelligence test which is a measure of a general or integrative property of human intelligence independent of the verbal and performance subtests. To integrate the findings in this study, it is hypothesized that general intelligence is positively correlated with faster processing times in frontal connections as reflected by shorter phase delays. Simultaneously, intelligence is positively related to increased differentiation in widespread local networks or local assemblies of cells as reflected by reduced EEG coherence and longer EEG phase delays, especially in local posterior and temporal lobe relations. The findings are consistent with a ‘network binding’ model in which intelligence is a function of the efficiency by which the frontal lobes orchestrate posterior and temporal neural resources. It is hypothesized that the best fitting components of a model that link EEG and IQ are: 1, efficient resource allocation through frontal lobe near-zero phase lags; 2, high organizational complexity and; 3, optimal levels of arousal.

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