CHAPTER 2

History of the scientific standards of QEEG normative databases

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I. INTRODUCTION

Normative reference databases serve a vital and important function in modern clinical science and patient evaluation. There are numerous clinical normative databases that aid in the evaluation of a wide range of clinical disorders; for example, blood constituent normative databases; MRI, fMRI and Positron Emission Tomography (PET) normative databases; ocular and retinal normative databases; blood pressure normative databases; nerve conduction velocity normative databases; postural databases; bone density normative databases; ultra sound normative databases; genetic normative databases; and motor development databases, to name a few. A comprehensive survey of existing clinical normative databases can be obtained by searching the National Library of Medicine's database using the search terms "Normative Databases" at http://www.ncbi.nlm.nih.gov/sites/entrez.

All clinically applied normative databases share a common set of statistical and scientific standards that have evolved over the years. The standards include peer reviewed publications, disclosure of the inclusion/exclusion criteria, tests of statistical validity, tests of reliability, cross-validation tests, adequate sample sizes for different age groups, etc. Normative databases are distinct from non-clinical control groups in their scope, and their sampling restriction to clinically normal or otherwise healthy individuals for the purpose of comparison. Another distinguishing characteristic of normative databases is the ability to compare a single individual to a population of "normal" individuals in order to identify the measures that are deviant from normal, and the magnitude of deviation. Normative databases themselves do not diagnose a patient's clinical problem. Rather, a trained professional first evaluates the patient's clinical history, and clinical symptoms and complaints, and then uses the results of normative database comparisons in order to aid in the development of an accurate clinical diagnosis.

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As mentioned previously, the age range, the number of samples per age group, the mixture of gender and socio-economic status, geographical distribution and thus a "representative" population are also distinguishing characteristics of a "normative" database because an individual is compared to a group of subjects comprising a reference normative database. In the case of QEEG, matching of amplifier frequency characteristics when a patient's EEG was acquired by a different amplifier than the database amplifier is also critical for normative databases but rarely important for standard "control group" studies. Cultural and ethnic factors and day-to-day variance and random environmental factors are typically factored into "normative" databases as "random control" factors; in contrast, a more limited sampling process is often used in non-clinical "control groups."

The adequacy of the sample size of any database is related to the "effect size" and the statistical power, and thus sample size, varies depending on these factors (Cohen, 1977). In general, sample size is less important than careful calibration, elimination of artifact, accepted standards during the collection of data and accepted standards for the analysis of data and approximation to a Gaussian distribution. Peer reviewed publications are essential for all databases because high standards are required by anonymous reviewers and scientifically sub-standard databases will either not be published or if they are then the limitations are made public. To not publish a normative database in a peer reviewed journal is unacceptable and is a non-starter when a clinician considers the database that they are going to use to evaluate a patient. State licensing agencies and other authorities should be notified when sub-standard databases are used to evaluate a clinical patient, and, certainly, signed informed consent informing the patient that they are being evaluated using an unpublished and/or sub-standard database is necessary to protect the public.

II. DEFINITIONS OF DIGITAL EEG AND QUANTITATIVE EEG (QEEG)

Nuwer (1997) defined digital EEG as ". . . the paperless acquisition and recording of the EEG via computer-based instrumentation, with waveform storage in a digital format on electronic media, and waveform display on an electronic monitor or other computer output device." The primary purposes of digital EEG is for efficiency of storage, the saving of paper, and for the purposes of visual examination of the EEG tracings. An attempt was made to distinguish digital EEG from quantitative EEG by defining quantitative EEG (QEEG or qEEG) as "the mathematical processing of digitally recorded EEG in order to highlight specific waveform components, transform the EEG into a format or domain that elucidates relevant information, or associate numerical results with the EEG data for subsequent review or comparison." (Nuwer, 1997, p. 278).

The reality is that there is no clear distinction between digital EEG and quantitative EEG because both involve mathematical transformations. For example, the

process of analog-to-digital conversion involves transforms by analog and digital filtering as well as amplification, sample and hold of the electrical scalp potentials, remontaging and reformatting the EEG. Clearly, digital EEG involves mathematical and transformational processing using a computer, and therefore the distinction between quantitative EEG and digital EEG is weak and artificial.

III. SIMULTANEOUS DIGITAL EEG TRACINGS AND QUANTITATIVE EEG

Figure 2.1 illustrates a common modern quantitative EEG analysis where EEG traces are viewed and examined at the same time that quantitative analyses are displayed, so as to facilitate and extend analytical power. Common sense dictates that the digital EEG and QEEG, when simultaneously available, facilitate rapid, accurate and reliable evaluation of the electroencephalograpm. Since 1929, when the human EEG was first measured (Berger, 1929), modern science has learned an enormous amount about the current sources of the EEG, and the manner in

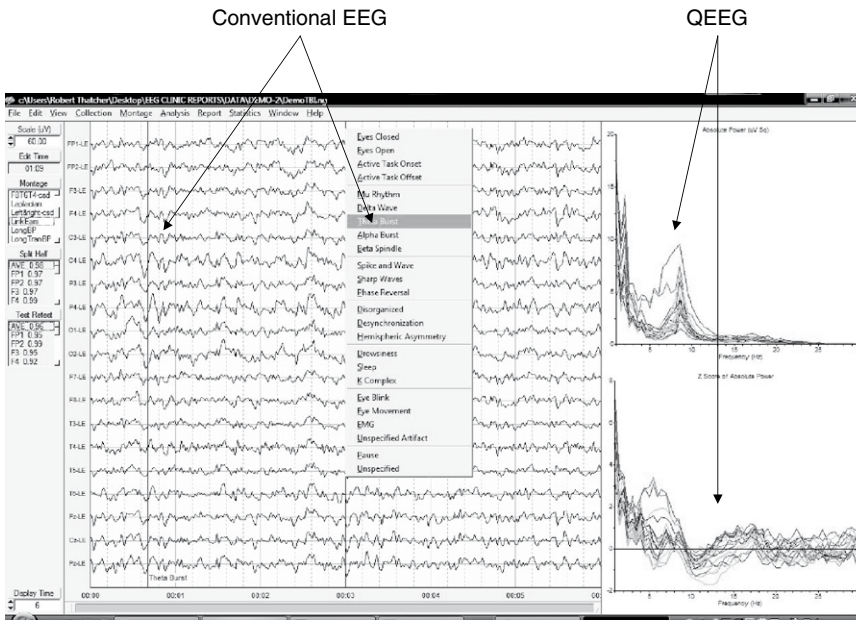

FIGURE 2.1 Example of conventional digital EEG (left) and QEEG (right) on the same screen at the same time. The conventional EEG includes examination and marking of EEG traces and events. The QEEG (right) includes the Fast Fourier Transform (top right) and normative database Z-scores (bottom right).

which ensembles of synaptic generators are synchronously organized. It is known that short distance local generators are connected by white matter axons to other local generators that can be many centimeters distant. The interplay and coordination of short distance local generators with the longer distant white matter connections has been mathematically modeled, and shown to be essential for our understanding of the genesis of the EEG (Nunez, 1981, 1995; Thatcher and John, 1977; Thatcher *et al.*, 1986).

The first QEEG study was by Hans Berger (1932, 1934) when he used the Fourier transform to spectrally analyze the EEG, as he recognized the importance of quantification and objectivity in the evaluation of the electroencephalogram (EEG). The relevance of quantitative EEG (QEEG) to the diagnosis and prognosis of brain dysfunction stems directly from the quantitative EEG's ability to reliably and objectively evaluate the distribution of brain electrical energies, and to compare different EEG measures to a normative database.

IV. TEST–RETEST RELIABILITY OF QEEG

The clinical sensitivity and specificity of QEEG is directly related to the stability and reliability of QEEG upon repeat testing. The scientific literature shows that QEEG is highly reliable and reproducible (Hughes and John, 1999; Aruda *et al.*, 1996; Burgess and Gruzelier, 1993; Corsi-Cabera *et al.*, 1997; Gasser *et al.*, 1988a, 1988b; Hamilton-Bruce *et al.*, 1991; Harmony *et al.*, 1993; Lund *et al.*, 1995; Duffy *et al.*, 1994; Salinsky *et al.*, 1991; Pollock *et al.*, 1991).

The inherent stability and reliability of QEEG can even be demonstrated with quite small sample sizes. For example, Salinsky *et al.* (1991) reported that repeated 20-second samples of EEG were about 82% reliable, at 40 seconds the samples were about 90% reliable and at 60 seconds they were approximately 92% reliable. Gasser *et al.* (1985) concluded that: "20 sec. of activity are sufficient to reduce adequately the variability inherent in the EEG" and Hamilton-Bruce *et al.*, (1991) found statistically high reliability when the same EEG was independently analyzed by three different individuals. Although the QEEG is highly reliable even with relatively short sample sizes, it is the recommendation of most QEEG experts that larger samples sizes be used; for example, at least 60 seconds of artifact-free EEG, and preferably for 2–5 minutes, should be used in a clinical evaluation (Duffy *et al.*, 1994; Hughes and John, 1999).

Although there are common purposes and applications of normative databases in clinical science, nonetheless, each type of normative database poses its own special requirements and details. In the sections to follow we focus exclusively on quantitative electroencephalographic (QEEG) normative databases. The goal of this chapter is to present the history of the application of scientific standards as they apply to QEEG, and to provide a practical guide for the understanding and evaluation of QEEG normative databases.

V. HISTORY OF STANDARDS OF QEEG NORMATIVE DATABASES

The earliest quantitative EEG (QEEG) reference normative database was developed in the 1950s at UCLA as part of the NASA study and selection of astronaughts for purposes of space travel (Adey *et al.*, 1961, 1964a and 1964b). The UCLA database involved several hundred carefully selected subjects who were candidates for the burgeoning NASA space exploration program, as well as UCLA faculty and students. Careful clinical inclusion and exclusion criteria were not used because there was no intended clinical application of this early QEEG reference normative database. Instead, the essential quantitative foundations of QEEG normative databases were tested such as the calculation of means and standard deviations, and measures of Gaussianity, complex demodulation, Fourier spectral analysis and basic statistical parameters necessary for any reference normative database.

Predictive accuracy and error rates depend on the data that make up a given EEG database as well as the statistical methods used to produce and compare QEEG normative databases. Historically, many of the statistical standards of normative databases were first applied by two Swedish Neurologists—Dr. Milos Matousek and Dr. Ingemar Petersen—in 1973 in the first peer reviewed publication of a normative database (Matousek and Petersen, 1973a; 1973b). Matousek and Petersen set the standards of peer reviewed publications, clinical inclusion/exclusion criteria, and parametric statistical standards for future QEEG normative databases. The cultural validity and reliability of the Matousek and Petersen 1973 database were established by E. Roy John and colleagues in 1975 when they successfully replicated, by independent cross-validation, the Matousek and Petersen Swedish database after collecting EEG from carefully screened 9- to 11-year-old Harlem black children who were performing at grade level and had no history of neurological disorders (John, 1977; John *et al.*, 1977, 1987).

VI. HISTORY OF INCLUSION/EXCLUSION CRITERIA AND "REPRESENTATIVE SAMPLES"

Matousek and Petersen (Matousek and Petersen, 1973a, 1973b) measured QEEG in 401 subjects (218 females) ranging in age from 2 months to 22 years and living in Stockholm, Sweden—all without any negative clinical histories and performing at grade level. The sample sizes varied from 18 to 49 per one-year age groupings. Similar inclusion/exclusion criteria were later used in the construction of the NYU normative database (John, 1977; John *et al.*, 1977, 1987), the University of Maryland (UM) database (Thatcher, 1988; Thatcher *et al.*, 1983, 1986, 1987, 2003, 2005a, 2005b) and Gordon and colleagues (2005) in the development of independent QEEG normative databases. Careful screening of the subjects that comprise a normative database is critical so that representative samples of healthy

and otherwise normally functioning individuals are selected, and individuals with a history of neurological problems, psychiatric problems, school failure and other deviant behaviors are excluded.

Representative sampling means a demographically balanced sample of different genders, different ethnic backgrounds, different socio-economic status, and different ages. This is important in evaluating a QEEG normative database because the database is a "reference" in which many demographic factors must be included in order to minimize sampling bias.

VII. HISTORY OF ARTIFACT-FREE DATA AND RELIABILITY MEASURES

Sample adequacy in a QEEG normative database requires strict removal of artifact and measures of high test–retest reliability. Historically, multiple trained individuals visually examined the EEG samples from each and every subject that was to be included in the database. Removal of artifact by visual examination is necessary regardless of any digital signal processing methods that may be used to remove artifact. Split-half reliability and test–retest reliability measures with values >0.9 are also important in order to provide a quantitative measure of the internal consistency and reliability of the normative database (John, 1977; John *et al.*, 1987; Thatcher, 1998; Thatcher *et al.*, 2003; Duffy *et al.*, 1994).

Caution should be exercised when using reconstruction methods such as Independent Components Analysis (ICA) or Principal Component Analysis (PCA) to compute a QEEG normative database. In general, these methods should be avoided because they will invalidate the computation of coherence and phase differences because the regression and reconstruction affect the raw digital samples themselves and distort coherence and phase. The best method of eliminating artifact is by making sure that high standards of recording are met, and that the patient's EEG is monitored during recording so that artifact can be minimized. Elimination of artifact after recording should involve the deletion of the artifact from the analysis and not by regression and/or reconstruction using methods such as ICA or PCA.

VIII. HISTORY OF SAMPLE SIZE PER AGE GROUP

There is no absolute sample size that is best for a QEEG database because, statistically, sample size is related to the "effect size" and "power" (Hayes, 1973; Winer, 1971). The smaller the effect size the larger the sample size necessary to detect that effect. The power of a statistical measure varies as a function of sample size and the effect size (Cohen, 1977). Another issue related to sample size is the degree to which a sample approximates a Gaussian distribution. As explained in the section below, increased sample size is often necessary in order to achieve closer approximations

to Gaussian, which in turn is related to the accuracy of cross-validation. Thus, the sample size is one of several inter-related issues in all normative databases, and the sample size should not be singled out as being the most important factor in a QEEG normative database. It is best to refer to "adequate" sample size as measured by the extent to which the samples are Gaussian, and the degree of cross-validation accuracy (John *et al.*, 1987; Thatcher *et al.*, 2003). The term *adequate* is related to the effect size, which in the case of human development is critical because different rates of maturation occur at different ages.

As mentioned previously, the Matousek and Petersen (1973a, 1973b) normative QEEG database had a total sample size of 401 in children ranging in age from 1 month to 22 years. It was known that there are rapid changes in EEG measures during early childhood, and for this reason Matousek and Petersen (1973a) and Hagne *et al.* (1973) emphasized using relatively large sample sizes during the period of time when the brain is changing most rapidly. For example, Hagne *et al.* (1973) used a sample size of N = 29 for infants from three weeks of age to 1 year of age. In step with this fact were the subsequent QEEG normative databases at NYU (John *et al.*, 1977, 1987) and UM (Thatcher, 1998; Thatcher *et al.*, 1987, 2003) in which the preferential increase in sample size during early childhood was emphasized as well as during old age when potential rapid declines in neural function may occur.

IX. HISTORY OF AGE STRATIFICATION VS. AGE REGRESSION

There are two general approaches that deal with the issue of sample size per age group:

- age stratification, and
- age regression.

Age stratification involves computing means and standard deviations of age groupings of the subjects (Matousek and Petersen, 1973a; John, 1977; Thatcher *et al.*, 1987, 2003). The grouping of subjects, and thus the number of subjects per age group, depends on the age of the sample and the relative rate of maturation. Matousek and Petersen (1973a, 1973b) used one-year age groupings, Thatcher *et al.* (1987) (University of Maryland database) used one-year age groupings as well as two- and five-year age groupings (Thatcher *et al.*, 2003, 2005a, 2005b). A simple method to increase stability and sample size is to use "sliding" averages for the age stratification. For example, Thatcher *et al.* (2003) used one-year age groups with 0.75 year overlapping to produce a series of sliding averages, and more recently used two-year age groupings with 0.75-year overlapping. Which method is chosen depends on the accuracy of cross-validation and age resolution, with careful examination of validation at different ages of the subjects.

The second method called *age regression* was first used by John *et al.* (1977, 1980) in which a least squares regression was used to fit a straight line to the EEG data

samples over the entire age range of the subjects. Once the intercepts and coefficients are computed then one simply evaluates the polynomial equation using the age of the subject in order to produce the expected mean and standard deviation for that particular subject. A Z-score is then computed by the standard method $Z = X - x/sd$. An important consideration when using an age regression method is the order of the polynomial, and the amount of variance accounted for by a polynomial. If there are rapid maturational changes in the brain, thus producing a "growth spurt", then a simple linear regression is likely to miss the growth spurt. A quadratic or cubic polynomial which will account for more of the variance over age will likely detect growth spurts better than a simple linear regression.

X. HISTORY OF GAUSSIAN DISTRIBUTION APPROXIMATION AND CROSS-VALIDATION

The statistics of replication and independent cross-validation of normative QEEG databases was first applied by E. Roy John and collaborators in 1974 to 1977 (John, 1977; John *et al.*, 1977, 1987). As mentioned previously, the first independent cross-validation of a normative QEEG database was by John and colleagues in which the EEG from a sample of New York Harlem black children were compared to the Matousek and Petersen (5, 6) norms with correlations >0.8 in many instances and statistically significant correlations for the majority of the measures (John, 1977).

The importance of approximation to a Gaussian distribution was emphasized by both Dr. E. Roy John and Dr. Frank Duffy, a Harvard Neurologist, in the 1970s and 1980s. In 1994 the American EEG Association produced a position paper in which the statistical standards of replication, cross-validation, reliability and Gaussian approximation were iterated as acceptable basic standards to be met by any normative QEEG database (Duffy *et al.*, 1994). The American EEG Society included the same standards. From 1980 into the 1990s Dr. John and colleagues continued to evaluate and analyze the statistical properties of normative QEEG databases, including EEG samples obtained from different laboratories in non USA locations in the world. Gaussian approximations and reliability, and cross-validation statistical standards for QEEG databases were applied to all of these databases by John and Colleagues (John *et al.*, 1987, 1980; Prichep, 2005) and as well as by other QEEG normative databases, for example, Gasser *et al.* (1988a, 1988b) and Thatcher and colleagues (1983, 1986, 1987, 2003, 2005a, 2005b).

Figure 2.2 shows examples of approximate Gaussian distributions and the sensitivity as calculated in Fig. 2.3. Table 2.1 is an example of a standard table of sensitivities for different age groups in the University of Maryland QEEG normative database (Thatcher *et al.*, 2003).

Figure 2.3 shows an example of Gaussian approximation and cross-validation of a QEEG normative database. It shows an illustrative bell-shaped curve showing the ideal Gaussian and the average cross-validation values of the database by which estimates of

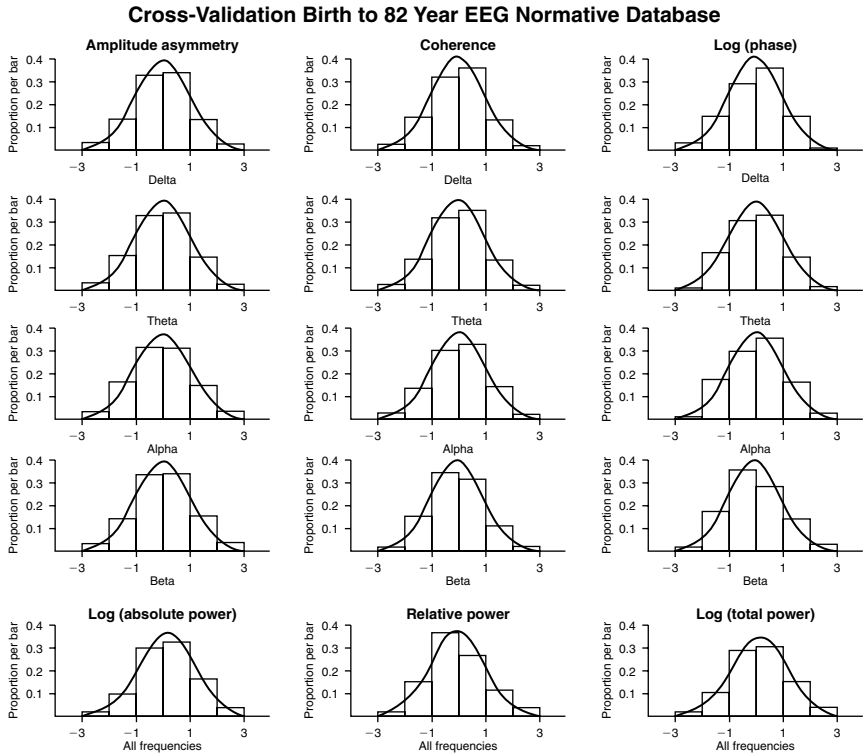

FIGURE 2.2 Histograms of the Z-Score Gaussian distributions and cross-validation for all ages (adapted from Thatcher *et al.*, 2003).

statistical sensitivity can be derived. True positives equal the percentage of Z-scores that lay within the tails of the Gaussian distribution. False negatives (FN) equal the percentage of Z-scores that fall outside of the tails of the Gaussian distribution. The error rates or the statistical sensitivity of a quantitative electroencephalogram (QEEG) normative database are directly related to the deviation from a Gaussian distribution. Fig. 2.3 depicts a mathematical method of estimating the statistical sensitivity of a normative EEG database in terms of the deviation from Gaussian.

XI. HISTORY OF THE USE OF THE Z-SCORE AND QEEG NORMATIVE DATABASES

Matousek and Petersen (1973a, 1973b) computed means and standard deviations in one-year age groups, and were the first to use T-tests and Z-scores to compare an individual to the normative database means and standard deviations. The T-test is defined as the ratio of the difference between values divided by the standard deviation. The Z statistic is defined as the difference between the value from an

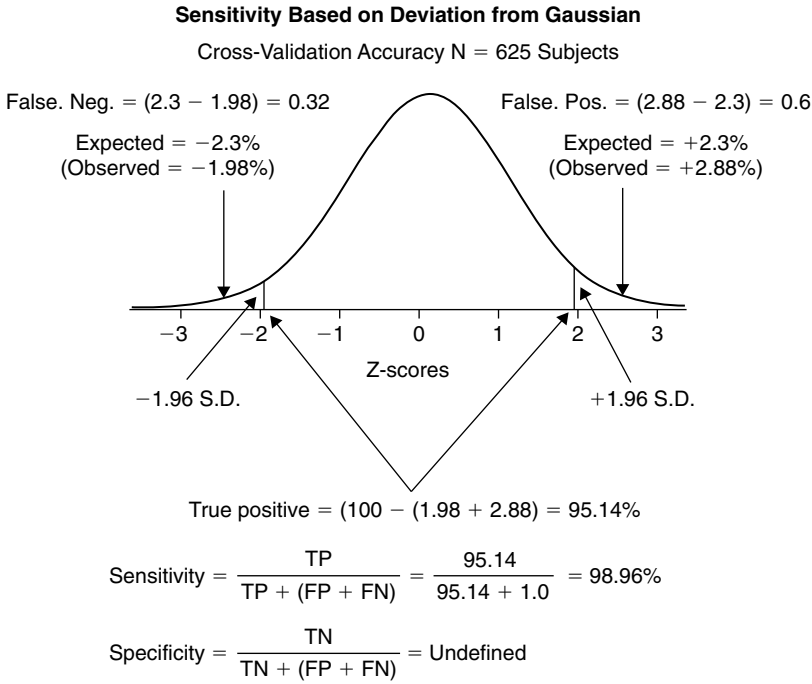

FIGURE 2.3 An example of a normal or Gaussian curve showing values of Z (±1.96) that includes the proportion which is 0.95 of the total area. The left and right tails of the distribution show probability values of 0.025 (one-tailed). The classification accuracy of any sample of subjects is based on the assumption that a normal distribution can be compared. The probability of finding an observed EEG value in a given range of any population can be determined, and then the sensitivity of the sample can be tested by cross-validation (adapted from Thatcher *et al.*, 2003).

individual and the mean of the population divided by the standard deviation of the population or

$$Z = \frac{x_i - \overline{X}}{SD}.$$

John and colleagues (John, 1977; John *et al.*, 1977, 1987) expanded on the use of the Z-score for clinical evaluation including the use of multivariate measures such as the Mahalanobis distance metric (Cooley and Lohnes, 1971; John *et al.*, 1987; John *et al.*, 1988). A direct normalization of the Gaussian distribution using Z-scores is useful in comparing individuals to a QEEG normative database (Thatcher, 1998; Thatcher *et al.*, 2003). That is, the standard score form of the Gaussian is where the mean = 0 and standard deviation = 1 or, by substitution into the Gaussian equation for a bell shaped curve, then

$$Y = \frac{1}{\sqrt{2\pi}} e^{-z2/2}$$

TABLE 2.1 Example of cross-validation and sensitivity tests of a normative database using the procedures described in Figure 2. (Adapted from Thatcher *et al.*, 2003.)

FFT Normative Database Sensitivities				
2 STDEVs AGES	CALC SENSITIVITY: FP = TP/(TP + FP) or FN = TP/(TP + FN)			
	(+/−2 SD)	(>=2 SD)	(<=−2 SD)	
0–5.99	0.95448265	0.9771774	0.97730526	
6–9.99	0.95440363	0.9772031	0.97720054	+/−**2 Std. Dev.**
10–12.99	0.9543997	0.97724346	0.97715624	
13–15.99	0.95440512	0.97723601	0.97716911	
16-ADULT	0.9543945	0.97718143	0.97721307	
ALL	0.95442375	0.97720714	0.97721661	
3 STDEVs AGES	CALC SENSITIVITY: FP = TP/(TP + FP) or FN = TP/(TP + FN)			
	(+/−3 SD)	(>=3 SD)	(<=−3 SD)	
0–5.99	0.99743898	0.99871123	0.99872774	
6–9.99	0.99744112	0.99871611	0.99872501	+/−**3 Std. Dev.**
10–12.99	0.99744688	0.99873171	0.99871518	
13–15.99	0.99743186	0.99871951	0.99871234	
16-ADULT	0.99743835	0.99870216	0.99873619	
ALL	0.99744002	0.99871716	0.99872286	

where Y = Gaussian distribution and the Z-score is a deviation in standard deviation units measured along the baseline of the Gaussian curve from a mean of 0, and a standard deviation = 1 with deviations to the right of the mean being positive and those to the left negative. By substituting different values of Z then different values of Y can be calculated. For example, when $Z = 0, Y = 0.3989$ or, in other words, the height of the curve at the mean of the normal distribution in standard-score form is given by the number 0.3989. For purposes of assessing deviation from normal, the values of Z above and below the mean, which include 95% of the area of the Gaussian are often used as a level of confidence necessary to minimize Type I and Type II errors (Hayes, 1973). The standard-score equation is also used to cross-validate a normative database, which again emphasizes the importance of approximation to a Gaussian for any normative QEEG database.

XII. CROSS-VALIDATIONS OF NORMATIVE DATABASES: NEW YORK UNIVERSITY AND UNIVERSITY OF MARYLAND

As described previously, cross-validation is critical in determining the sensitivity and false positives and false negatives of a normative database. Due to the expense to acquire independent data, most cross-validations are computed using a leave-one-out cross-validation procedure (John *et al.*, 1977, 1987; Thatcher *et al.*, 2003, 2005a, 2005b). A completely independent cross-validation using different subjects is

TABLE 2.2 Correlation coefficients from an independent cross-validation of NYU vs. UM normative EEG databases (reprinted by permission of CNS Response, Inc.)

	Absolute power	Absolute power	Relative power	Relative power	Coherence	Coherence	Amp. asym	Amp. asym
	Anterior	Posterior	Anterior	Posterior	Anterior	Posterior	Anterior	Posterior
Delta	0.815	0.880	0.854	0.925	0.804	0.935	0.854	0.820
Theta	0.926	0.940	0.877	0.895	0.853	0.914	0.902	0.816
Alpha	0.951	0.958	0.901	0.887	0.873	0.946	0.899	0.979
Beta	0.820	0.882	0.757	0.784	0.848	0.900	0.846	0.876

the best method of cross-validation although it is, as previously stated, more expensive and difficult and, accordingly, no independent cross-validations of two different normative databases have been conducted in the last 30 years, until recently.

In 2007 an independent cross-validation of the New York University and the University of Maryland databases was conducted. The study was conducted because a company had collected raw digital EEG from several hundred clinical patients, and had computed Z-scores using the New York University (NYU) normative database (John, 1977; John *et al.*, 1977, 1987, 1988). The question was: does the University of Maryland (UM) normative database produce similar Z-scores as the NYU database using the same exact raw digital data? The correlation coefficients from the independent cross-validation between the NYU and UM normative databases are shown in Table 2.2. The analysis included 332 psychiatric patients and an age range from 6.2 years to 84.9 years. Anterior includes electrodes Fp1/2, Fz, F3/4, F7/8, T3/4, C3/4 and Cz. Posterior includes electrodes O1/2, P3/4, T5/6 and Pz. The correlations ranged from 0.757 to 0.979. The high degree of cross-validation accuracy in this study is emphasized by the fact that at 331 degrees of freedom a correlation of 0.142 is significant at $P < 0.01$.

Figure 2.4 shows bar graphs of the correlation coefficients from the independent cross-validation comparison between the NYU and the UM Z-scores. This study is important because it demonstrates a high degree of cross-correlation and cross-validation between two independent QEEG normative databases. Both the NYU and UM databases were constructed in medical centers with government grants and oversight, and both have been clinically validated in peer reviewed publications (John *et al.*, 1977, 1987, 1988; Thatcher *et al.*, 1986, 1987, 2003, 2005b) as well has having FDA registration.

XIII. HISTORY OF AMPLIFIER MATCHING AND QEEG NORMATIVE DATABASES

Surprisingly, this particular standard was largely neglected during much of the history of QEEG normative databases. E. Roy John and colleagues (from 1982 to 1988)

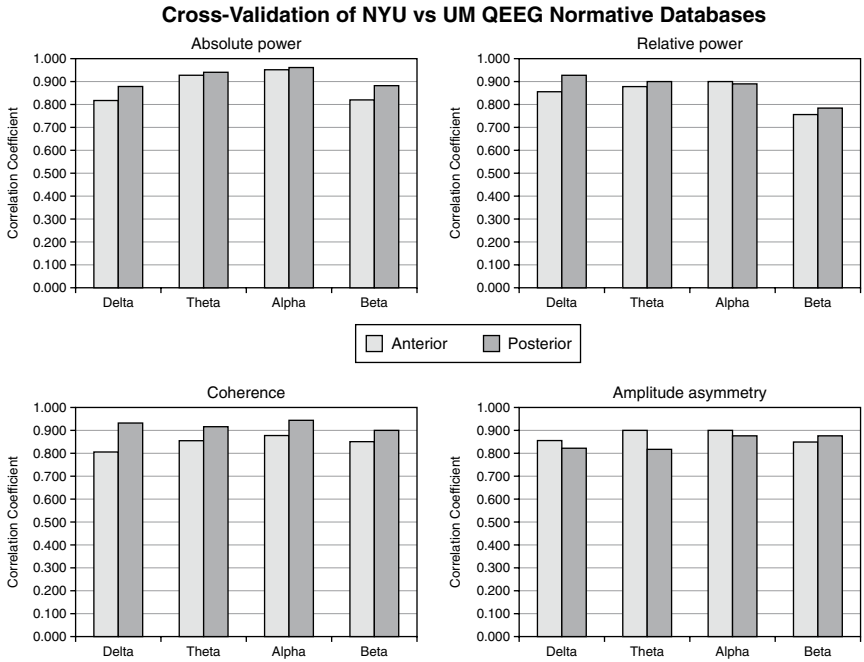

FIGURE 2.4 Results of an independent cross-validation comparison of Z-scores from 332 psychiatric patients ranging in age from 6.2 years to 84.9 years using the New York University (NYU) and University of Maryland (UM) normative databases. Anterior and posterior refer to the anterior and posterior location of electrodes. Highly significant independent cross-validation was observed, which shows the high degree of consistency between two peer reviewed and clinically validated QEEG normative databases. (Reprinted with permission from CNS Response, Inc.)

formed a consortium of universities and medical schools that were using QEEG. The consortium met several times over a few years and was one of the supporters of the edited volume by John titled *Machinery of the Mind* (John, 1990).

One of the important issues consistently raised at the consortium meetings was the need for "standardization." In the 1980s it was technically difficult to match different EEG systems because of the infantile development of analysis software. This history forced most QEEG users to use relative power because absolute power was not comparable between different EEG machines. There was no frequency response standardization between different EEG machines, and thus there was no cross-platform standardization of QEEG. It was not until the mid 1990s that computer speed and software development made amplifier matching and normative database amplifier equilibration a possibility.

The first use of standardized matching of amplifiers was to the University of Maryland (UM) database. The procedure involved injecting microvolt calibration sine waves into the input of amplifiers of different EEG machines, and then

injecting the same microvolt signals into the normative database amplifiers thus obtaining two frequency response curves (Thatcher *et al.*, 2003). Equilibration of a normative QEEG database to different EEG machines is the ratio of the frequency response curves of the two amplifiers that are then used as amplitude scaling coefficients in the power spectral analysis. This was an important step because suddenly absolute power Z-scores and normative database comparisons became possible.

Relative power is a last resort type of measure to be used when there is no equilibration of absolute amplitude because relative power always distorts the spectrum, and relative power depends on absolute power in order to interpret relative power. This is because relative power is a percentage of the whole, and thus an increase in mid "beta," e.g., 14–18 Hz will be seen as a decrease in "theta," e.g., 4–7 Hz when in fact there is no change in theta and vice versa. The frequencies in absolute power are independent of each other and are not distorted. It is always best to use absolute values whenever possible, and not relative values or even ratios. A ratio can change due to the denominator or the numerator, and one cannot determine which has changed without evaluating the absolute values used to compute the ratios.

As illustrated in Fig. 2.5, a simple method of amplifier equilibration to exactly match the frequency characteristics of different amplifiers is to calibrate the amplifiers using microvolt sine waves at discrete frequencies from 1–30 Hz and injecting the sine waves into the inputs of the EEG amplifiers. Then take the ratio of the microvolt values at each frequency and use the ratios to exactly equate the spectral output values to the normative database amplifiers. This method creates a universal equilibration process so that microvolts in a given amplifier are equal to

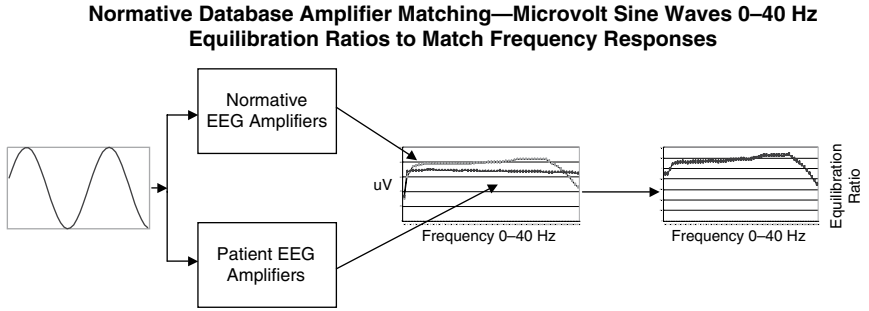

FIGURE 2.5 Flow chart of the amplifier standardization procedure. Micro-volt (uV) sine waves are injected into the input of amplifiers, and the frequency responses are calculated. The frequency response of the normative database amplifiers and the frequency response of the Deymed amplifier are in the middle graph. As shown in the right graph, EEG amplifier systems are then equated as the ratio of the two amplifier frequency response curves and the spectral analysis is adjusted based on the equilibration ratios so that there is a standardized import and matching of amplifier systems, with the common unit being microvolts (uV).

microvolts in all other amplifiers including the normative database amplifiers. By equilibrating amplifiers, then direct comparisons between a given patient's EEG and the normative database means and standard deviations are valid and meaningful. If amplifier matching is not accomplished, all normative database comparisons are potentially invalid and caution should be exercised not to use a normative database when amplifiers have not been equilibrated.

We have found that amplifiers differ primarily from 0–2 Hz, and in order to accurately match to the normative database amplifiers one can filter at 1 Hz, thus avoiding mismatches at less than 1 Hz. There is a wide variety of different frequency response curves for different amplifiers and there is no one "gold standard" for EEG amplifiers. For older amplifiers that have a more limited frequency response, e.g., the NYU and University of Maryland amplifiers and Biologic, then the match of frequencies is limited to the frequency range that is common between the two amplifier systems. For example, Deymed has a nearly flat response from 0.5 Hz to 70 Hz, and thus the match to the NYU and UM amplifiers is only from 0.5 Hz to 30 Hz because the latter amplifiers used cut-off filters at approximately 30 Hz. Many amplifiers currently in use also have cut-off frequencies of around 30 Hz but there is still a lot of information in the EEG from 0.5 Hz to 30 Hz, and equilibration is necessary to optimally use these amplifiers in a normative database comparison.

XIV. CONTENT VALIDITY OF QEEG NORMATIVE DATABASES

A. Neuropsychological correlations

Content validity is defined by the extent to which an empirical measurement reflects a specific domain of content (Nunnally, 1978). For example, a test in arithmetic operations would not be content valid if the test problems focused only on addition, thus neglecting subtraction, multiplication and division. By the same token, a content-valid measure of cognitive decline following a stroke should include measures of memory capacity, attention and executive function, etc.

There are many examples of the clinical content validity of QEEG and normative databases in ADD, ADHD, schizophrenia, compulsive disorders, depression, epilepsy, TBI (Thatcher *et al.*, 1998a, 1998b) and a wide number of clinical groupings of patients as reviewed by Hughes and John (1999). There are over 250 citations in the review by Hughes and John, and there are approximately 23 citations to peer reviewed journal articles in which a normal reference database was used. Another recent review of QEEG normative databases and the clinical application of QEEG to psychiatric disorders cited 169 publications (Coburn *et al.*, 2006). An Internet search of the National Library of Medicine will give citations to more QEEG and content-validity peer-reviewed studies using a reference normal group

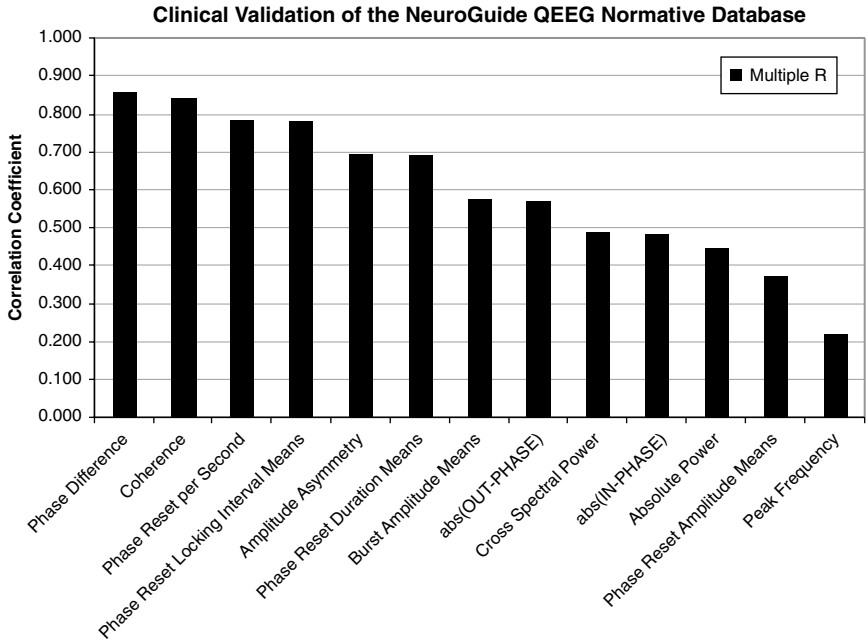

FIGURE 2.6 Correlations between QEEG measures and full-scale I.Q. (WISC-R). N = 332 subjects from the University of Maryland QEEG normative database (see Table 1.3). The highest correlations between QEEG and I.Q. are phase differences and coherence (47). The x-axis shows different QEEG measures, and the y-axis the correlation coefficient in a multivariate regression analysis with full-scale I.Q. as the dependent variable. Phase Reset and Burst Metrics are new measures which also exhibit high clinical correlations and clinical validation.

than were included in the Hughes and John review or the Coburn *et al.* (2006) review. Finally, for a recent review that emphasizes clinical correlations and clinical validation of a normative database see Gordon *et al.* (2005).

Figure 2.6 and Table 2.3 show an example of the range of clinical correlations to full-scale I.Q. in 373 normal individuals from 5 to 55 years of age.

It can be seen in Figure 2.6 that relative high correlations with I.Q. (0.859) are achievable when using a normative database and multiple regression of different variable types, and that different QEEG measures exhibit different magnitudes of correlation. The multiple regression prediction of I.Q. is not intended to replace neuropsychological tests. However, an advantage of a QEEG normative database prediction of I.Q. is that it can be repeated without confounding by learning, and it can be given to untestable patients such as stroke, paralysis and uncooperative individuals. Also, QEEG predictions of intelligence provide an insight into which aspects of neural functioning, such as location and connectivity, contribute to the prediction of intelligence, thus providing a deeper understanding of intelligence in an individual subject.

TABLE 2.3 List of correlations between full-scale I.Q. and QEEG measures from 373 normal subjects aged 5–55 years (47)

QEEG measure	Correlation coefficient—QEEG and full-scale I.Q. (Wisc-R)
Phase Difference	0.859
Coherence	0.842
Phase Reset per Second	0.785
Phase Reset Locking Interval Means	0.780
Amplitude Asymmetry	0.691
Phase Reset Duration Means	0.688
Burst Amplitude Means	0.574
Out-of-Phase Cross-Spectral Power	0.570
Cross Spectral Power	0.485
In-Phase Cross-Spectral Power	0.481
Absolute Power	0.443
Phase Reset Amplitude Means	0.372
Peak Frequency	0.218

B. Example for traumatic brain injury

There are numerous peer reviewed journal articles showing high correlations between Z-scores involving the UM and NYU and other normative databases over the last 20 years (see review by Hughes and John, 1999). It is beyond the scope of this chapter to attempt to review all of these studies. Instead, we will focus on one of the many clinical correlation sub-groups, namely, traumatic brain injury.

The National Library of Medicine lists 1,672 peer reviewed journal articles on the subject of EEG and traumatic brain injury. The vast majority of these studies involved quantitative analyses and, in general, the scientific literature presents a consistent and common quantitative EEG pattern correlated with TBI. Namely, reduced amplitude of the alpha and beta and gamma frequency bands of EEG (8–12 Hz, 13–25 Hz and 30–40 Hz) (Mas *et al.*, 1993; von Bierbrauer *et al.*, 1993; Ruijs *et al.*, 1994; Korn *et al.*, 2005; Hellstrom-Westas and Rosen, 2005; Thompson *et al.*, 2005; Tebano *et al.*, 1988; Thatcher *et al.*, 1998a, 2001a; Roche *et al.*, 2004; Slewa-Younan, 2002; Slobounov *et al.*, 2002) and changes in EEG coherence and phase delays in frontal and temporal relations (Thatcher *et al.*, 1989, 1991, 1998b, 2001a, 2001b; Hoffman *et al.*, 1995,1996; Trudeau *et al.*, 1998). The reduced amplitude of EEG is believed to be due to a reduced number of synaptic generators and/or reduced integrity of the protein/lipid membranes of neurons (Thatcher *et al.*, 1997, 1998a, 2001b).

EEG coherence is a measure of the amount of shared electrical activity at a particular frequency, and is analogous to a cross-correlation coefficient. EEG coherence is amplitude independent and reflects the amount of functional connectivity between distant EEG generators (Nunez, 1981, 1994; Thatcher *et al.*, 1986). EEG phase delays between distant regions of the cortex are mediated

in part by the conduction velocity of the cerebral white matter, which is a likely reason that EEG phase delays are often distorted following a traumatic brain injury (Thatcher *et al.*, 1989, 2001a). In general, the more severe the traumatic brain injury, the more deviant the QEEG measures (Thatcher *et al.*, 2001a, 2001b).

Quantitative EEG studies of the diagnosis of TBI typically show quite high sensitivity and specificity, even for mild head injuries. For example, a study of 608 mild TBI patients and 103 age matched control subjects demonstrated discriminant sensitivity = 96.59%; Specificity = 89.15%, Positive Predictive Value (PPV) = 93.6% (Average of Tables 2.2, 2.3, 2.5) and Negative Predictive Value (NPV) = 97.4% (Average of Tables 2.3, 2.4, 2.5) in four independent cross-validations. A similar sensitivity and specificity for QEEG diagnosis of TBI was published by Trudeau *et al.* (1998) and Thatcher *et al.* (2001a). All of these studies met most of the American Academy of Neurology's criteria for diagnostic medical tests of:

1. The "criteria for test abnormality was defined explicitly and clearly"
2. Control groups were "different from those originally used to derive the test's normal limits"
3. "test–retest reliability was high"
4. The test was more sensitive than "routine EEG" or "neuroimaging tests", and
5. The study occurred in an essentially "blinded" design (i.e., objectively and without ability to influence or bias the results).

XV. HISTORY OF THREE-DIMENSIONAL CURRENT SOURCE NORMATIVE DATABASES

Parametric statistics that rely upon a Gaussian distribution have been successfully used in studies of Low Resolution Electromagnetic Tomography or LORETA (Thatcher *et al.*, 2005a, 2005b; Huizenga *et al.*, 2002; Hori and He, 2001; Waldorp *et al.*, 2001; Bosch-Bayard *et al.*, 2001; Machado *et al.*, 2004). Bosch-Bayard *et al.* (2001) created a Z-score normative database that exhibited high sensitivity and specificity using a variation of LORETA called VARETA.

A subsequent study by Machado *et al.* (2004) extended these analyses again using VARETA. Thatcher *et al.* (2005a) also showed that LORETA current values in wide frequency bands approximate a normal distribution after transforms with reasonable sensitivity. This same paper compared Z-scores to non-parametric statistical procedures, and showed that Z-scores were more accurate than non-parametric statistics (2005a). Lubar *et al.* (2003) used non-parametric statistics in an experimental control study with similar levels of significance as reported by Thatcher *et al.* (2005a). Fig. 2.7 shows an example of how a log transform can move a non-gaussian distribution toward a better approximation of a Gaussian when using LORETA (Thatcher *et al.*, 2005a, 2005b).

LORETA three-dimensional current source normative databases have also been cross-validated, and the sensitivity computed using the same methods as for the surface EEG (Thatcher *et al.*, 2005b). Figure 2.8 shows an example of localization accuracy of a LORETA normative database in the evaluation of confirmed neural pathologies.

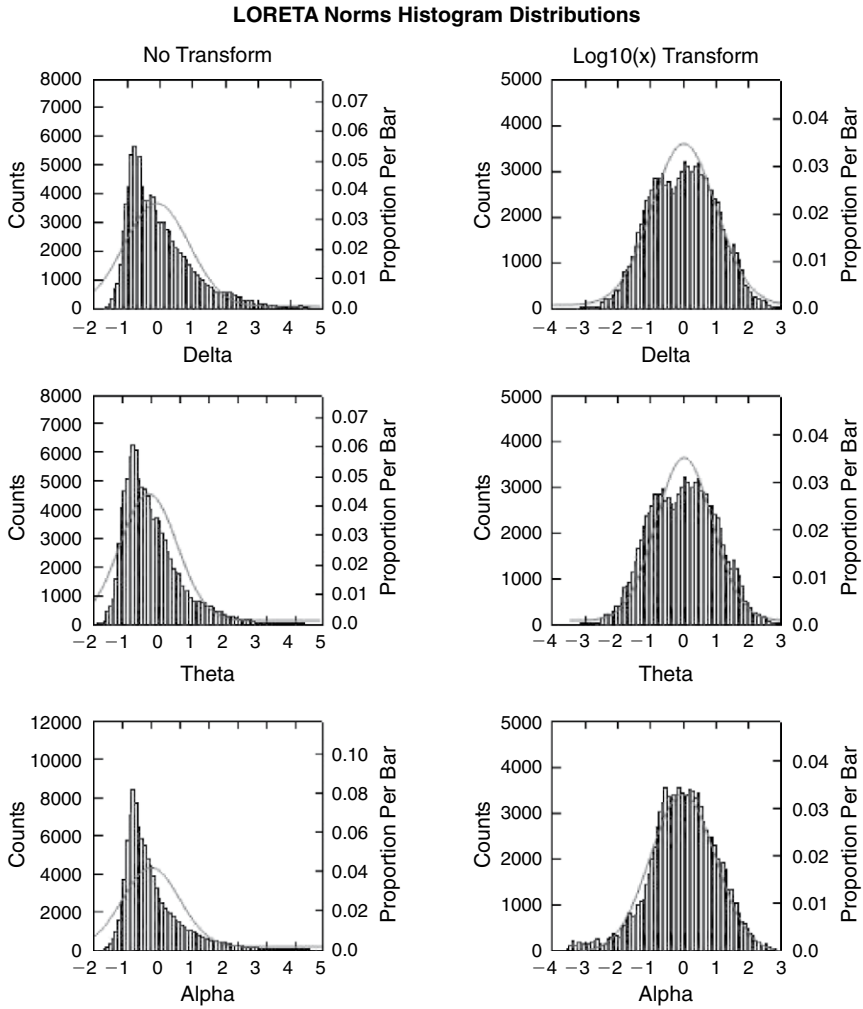

FIGURE 2.7 Shows the distribution of current source densities before (left) and after (right) $\log_{10}$ transform for the delta, theta and alpha frequencies. It can be seen that reasonable approximation to Gaussian was achieved by the $\log_{10}$ transform. (From Thatcher *et al.*, 2005a.)

All of these studies demonstrated that when proper statistical standards are applied to EEG measures, whether they are surface EEG or three-dimensional source localization, then high cross-validation accuracy can be achieved. Recently, Hoffman (2006) confirmed that high accuracy can be achieved using a LORETA Z-score normative database to evaluate patients with confirmed pathologies (e.g., left temporal lobe epilepsy and focal brain damage) using the University of Maryland normative database (Thatcher *et al.*, 2003) and the University of Tennessee normative database (Lubar *et al.*, 2003).

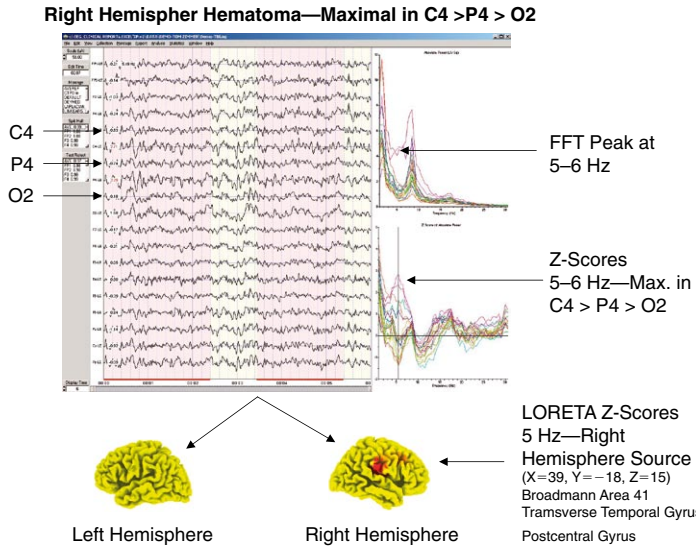

FIGURE 2.8 The EEG from a patient with a right hemisphere hematoma where the maximum shows waves are present in C4, P4 and O2 (Top). The FFT power spectrum from 1–30 Hz and the corresponding Z-scores of the surface EEG are shown in the right side of the EEG display. Left and right hemisphere displays of the maximal Z-scores using LORETA (Bottom). It can be seen that only the right hemisphere has statistically significant Z values. Planned comparisons and hypothesis testing based on the frequency and location of maximal deviation from normal on the surface EEG are confirmed by the LORETA Z-score normative analysis. (From Thatcher *et al.*, 2005b.) (see color plate.)

XVI. HISTORY OF THREE-DIMENSIONAL SOURCE CORRELATION NORMATIVE DATABASES

Thatcher *et al.* (1994), Thatcher (1995) and Hoechstetter *et al.* (2004) used a multiple dipole source solution for scalp EEG electrical potentials. They then used coherence to compute the correlation between the three-dimensional current sources, and demonstrated changes in the correlation between current sources related to different tasks. Pascual-Marqui *et al.* (2001) used low resolution electromagnetic tomography (LORETA) to compute current sources, and then used a Pearson Product correlation coefficient to explore differences in source correlations between a normal control group and a group of schizophrenic patients. Recently, high statistical standards were applied to LORETA three-dimenional source correlations in a QEEG normative database (Thatcher *et al.*, 2007a). All of these studies revealed interesting and reproducible relations between current sources and network connectivity that provide a deeper understanding of the surface EEG dynamics.

The same statistical standards as enumerated previously were applied to the LORETA source correlation normative database, i.e., peer reviewed publication, gaussian approximation, removal of artifact, high reliability and cross-validation. The LORETA normative database studies prove that nearly any measure can be used in a normative database as long as the appropriate statistical and scientific standards are met.

XVII. HISTORY OF REAL-TIME Z-SCORE NORMATIVE DATABASES

As mentioned above, many different normative databases can be constructed and validated as long as the basic scientific standards of gaussianity, cross-validation, amplifier matching and peer reviewed publications are met. A recent example of a new application of a normative database is the use of complex demodulation as a joint-time-frequency-analysis (JTFA) for the purposes of real-time biofeedback (Thatcher, 1998, 2000a, 2000b; Thatcher *et al.*, 1987, 2003). This method has recently been implemented in EEG biofeedback systems and used to compute statistical Z-scores in real-time. Complex demodulation is an analytic technique that multiplies a time series by a sine wave and a cosine wave, and then applies a low pass filter (Granger *et al.*, 1964; Otnes and Enochson, 1977; Thatcher *et al.*, 2007b). This results in mapping of the time series to the unit circle or "complex plane" whereby instantaneous power and instantaneous phase differences and coherence are computed.

Unlike the Fourier transform which depends on windowing and integration over an interval of time, complex demodulation computes the instantaneous power and phase at each time point, and thus an instantaneous Z-score necessarily includes the within subject variance of instantaneous electrical activity as well as the between subject variance for subjects of a given age. The summation of instantaneous Z-scores is Gaussian distributed and has high cross-validation (Thatcher *et al.*, 2003), however the individual time point by time point Z-score is always smaller than the summation due to within subject variance. The use of within subject variance results in a more "conservative" estimate of deviation from normal, solely for the purposes of instantaneous biofeedback methods. A standard FFT normative database analysis should first be computed in order to identify the electrode locations and EEG features that are most deviant from normal which can be linked to the patient's symptoms and complaints.

Linking a subject's symptoms and complaints, e.g., PTSD, Depression, Schizophrenia, TBI, etc. to functional localization of the brain is an important objective of those who use a normative database. Similar to a blood bank analysis, the list of deviant or normal measures is given to the clinician as one test among many that are used to help render a diagnosis. It is important that linking deregulation of neural activity in localized regions of the brain to known

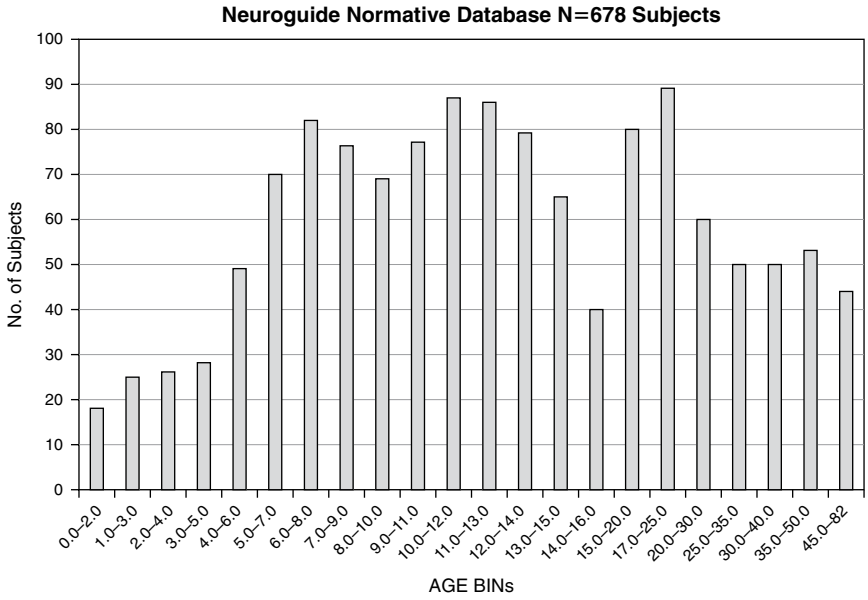

FIGURE 2.9 The number of subjects per age group in the Z-score Lifespan EEG reference normative database. The database is a "lifespan" database with 2 months of age being the youngest subject and 82.3 years of age being the oldest subject. Two-year means were computed using a sliding average with 6-month overlap of subjects. This produced a more stable and higher age resolution normative database, and a total of 21 different age groups. The 21 age groups and age ranges, and number of subjects per age group, are shown in the bar graph. (Adapted from Thatcher *et al.*, 2003.)

functional localization, for example left parietal lobe and dyslexia, right frontal and depression, cingulate gyrus and attention deficit, occipital lobes and vision problems, etc. is done by a trained clinician. Textbooks on functional localization in neurology and psychiatry are available to aid the clinician in learning about the link between a patient's symptoms and different brain regions (Heilman and Valenstein, 1993; Brazis *et al.*, 2007). A link of the anatomical locations and patterns of a patient's deviant Z-scores is important in order to derive clinical meaning from the QEEG.

Once a QEEG normative database analysis is completed, then one can use a Z-score biofeedback program to train patients to move their instantaneous Z-scores toward zero or the norm. The absolute value and range of the instantaneous Z-scores, while smaller than those obtained using the offline QEEG normative database, are nonetheless valid and capable of being minimized toward zero. An advantage of a Z-score biofeedback program is simplification by reducing diverse measures to a single metric, i.e., the metric of a Z-score. Thus, there is greater standardization and less guesswork about whether to reinforce or suppress

coherence or phase differences or power, etc. at a particular location and particular frequency band.

Figure 2.9 shows the number of subjects per year in the normative EEG lifespan database, N = 625, that spans an age range from 2 months to 82 years of age. It can be seen that the largest number of subjects is in the younger ages (e.g., 1 to 14 years, N = 470) when the EEG is changing most rapidly. A proportionately smaller number of subjects represents the adult age range from 14–82 years (N = 155). In order to increase the time resolution of age, sliding averages were used for age stratification of the instantaneous Z-scores for purposes of EEG biofeedback. Two-year means were computed using a sliding average with 6-month overlap of subjects. This produced a more stable and higher age resolution normative database and a total of 21 different age groups. The 21 age groups and age ranges, and number of subjects per age group, are shown in the bar graph in Figure 2.9.

XVIII. ACTIVE TASKS VS. EYES CLOSED AND EYES OPEN QEEG DATABASES

An active task refers to the recording of EEG and/or evoked potentials (EPs) while a subject performs some kind of perceptual or cognitive task. Many EEG, EP and event-related potential (ERP) studies have reported reproducible changes in brain dynamics which are task dependent. Such studies are important for understanding normal and pathological brain processes responsible for perceptual and cognitive function. In contrast, an eyes closed or eyes open EEG state involves an alert subject simply sitting quietly and not moving. The eyes closed and/or eyes open conditions are commonly used as reference normative EEG databases because of the simplicity and relative uniformity of EEG recording conditions. Such databases can be compared across laboratories and populations with relatively high reliability. Active tasks, on the other hand, are dependent on the intensity of stimuli, the background noise of the room, the distance between the subject and the stimuli, the subject's understanding of the task instructions, the subject's motivation, etc. These are very difficult to control across experimenters or across clinics for the purposes of constructing a "reference" normative EEG database.

One of the most carefully constructed active task normative database is by Brain Resources, Inc. in Australia (Gordon *et al.*, 2005). The BRC database does require replication of specific task conditions using a Neuroscan, Inc. EEG amplifier system. The relative sensitivity and specificity of resting eyes open and eyes closed EEG versus an active task normative database has not been published to our knowledge. Another well constructed and tested active task normative database is the go no-go task developed by Russian scientists (Kropotov *et al.*, 2005) with medium to high sensitivity and accuracy in the evaluation of attention deficits and other disorders. We were unable to find any peer reviewed journal articles of EEG databases produced by Dr. Kropotov and therefore there is no

information on the sensitivity, cross-validation, amplifier matching and other standards for EEG databases.

It should be kept in mind that the alert eyes closed EEG state is very much an active state, e.g., there is still about 20% glucose metabolism of the whole body occurring in the brain of an eyes closed subject (Herscovitch, 1994; Raichle, 2002). During the eyes closed state, there is dynamic circulation of neural activity in connected cortical, reticular and thalamo-cortical loops (Thatcher and John, 1977; Nunez, 1995). The allocation of neural resource is simply different from when the subject is directing his or her attention to an experimentally controlled situation. Active tasks are very important because they reflect the switching and dynamic allocation of neural resource, which also has clinical importance. However, a scientifically sound and stable resting EEG normative database can enhance and also facilitate the understanding of the underlying neural dynamics and clinical condition of a patient during an active task. For example, comparison to a resting baseline normative database during different active task conditions may help reveal anatomical localization of neural processes and network dynamics without the need for a comparison to an exactly matching active task.

XIX. SUMMARY OF NORMATIVE DATABASE VALIDATION AND SENSITIVITY TESTS

Figure 2.10 is an illustration of a step-by-step procedure by which any normative EEG database can be validated and sensitivities calculated. The left side of the figure is the edited and artifact clean and reliable digital EEG time series, which may be re-referenced or re-montaged, that is then analyzed in either the time domain or the frequency domain.

The selected normal subjects are grouped by age with a sufficiently large sample size. The means and standard deviations of the EEG time series and/or frequency domain analyses are computed for each age group. Transforms are applied to approximate a Gaussian distribution of the EEG measures that comprise the means. Once approximation to Gaussian is completed, Z-scores are computed for each subject in the database and leave one out Gaussian cross-validation is computed in order to arrive at optimum Gaussian cross-validation sensitivity. Finally, the Gaussian validated norms are subjected to content and predictive validation procedures such as correlation with neuropsychological test scores and intelligence, etc. and also discriminant analyses and neural networks and outcome statistics, etc. The content validations are with respect to clinical measures such as intelligence, neuropsychological test scores, school achievement and other clinical measures. The predictive validations are with respect to the discriminative, statistical or neural network clinical classification accuracy. Both parametric and nonparametric statistics are used to determine the content and predictive validity of a normative EEG database.

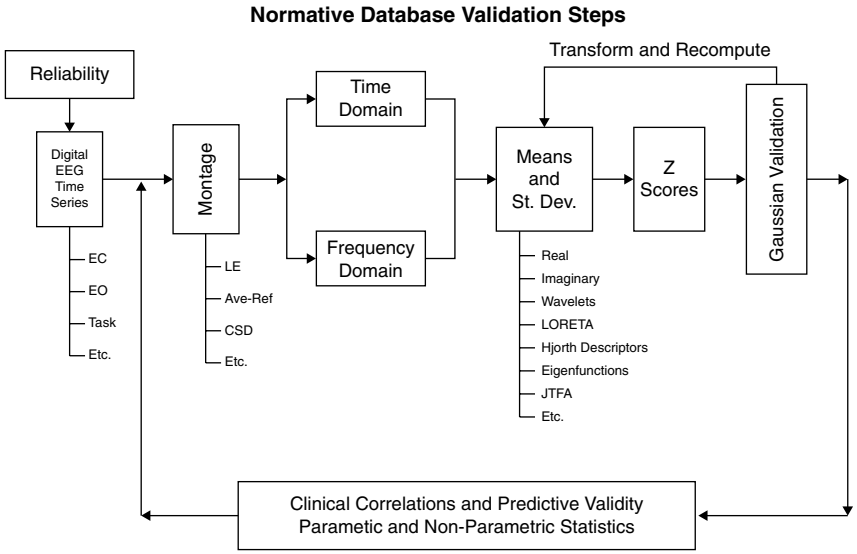

FIGURE 2.10 Illustration of the steps involved in developing a normative QEEG database. The left is the start of the process with data acquisition, amplifier matching, artifact rejection and quality control. Approximation to a Gaussian is followed by cross-validation, and then finally clinical correlations. (From 11.)

XX. GOLD STANDARD CHECK LIST FOR A NORMATIVE QEEG DATABASE

Table 2.4 is a "Gold Standard" check list which summarizes the minimal standards of QEEG normative databases that were discussed previously. Those clinicians interested in using a QEEG normative database are encouraged to enter a check for each of the standards that a given database has met. The more standards that are met the better.

XXI. PROBLEMS IN COMBINING SUB-STANDARD QEEG DATABASES WITH SCIENTIFICALLY ACCEPTABLE DATABASES

Often an EEG data sample from a patient is sent to a laboratory or QEEG service, and the data is compared to multiple databases including sub-standard databases. As expected, the results are often conflicting, contradictory and confusing. There is an assumption that somehow multiple comparisons to multiple databases is better than comparing a patient's EEG to a single well-published database that has met high statistical and scientific standards. This assumption is wrong and potentially

TABLE 2.4 List of "gold standards" by which to judge QEEG normative databases

	Standards	Yes	No
1	Amplifier matching		
2	Peer reviewed publications		
3	Artifact rejection		
4	Test–retest reliability		
5	Inclusion/exclusion criteria		
6	Adequate sample size per age group		
7	Approximation to a Gaussian		
8	Cross-validation		
9	Clinical correlation		
10	FDA registered		

dangerous to unsuspecting patients and clinicians who are provided with multiple comparisons. If a patient or a clinician receives multiple database comparisons involving unmatched amplifier characteristics then they should ask the provider of the normative database for the methods of amplifier equilibration, and for a list of the scientific standards of the normative databases.

It is the responsibility of users of normative databases to know the scientific standards of the database that they are comparing their patients to, and to provide informed consent to patients in situations where the patient's EEG samples are compared to a non peer-reviewed database, and/or unknown number of subjects per year database, and/or unknown inclusion/exclusion criteria database, and/or no statistical validation test database, and/or a non-FDA registered database, etc. State law and the FDA and IRBs require wording in an informed consent form that is clear and unambiguous in which the patient is informed that their EEG data will be compared to an unpublished or otherwise unknown QEEG normative database. Hopefully the "Gold Standards" check list in Table 2.4 will help in this process.

XXII. FUTURE STANDARDIZATION OF QEEG NORMATIVE DATABASES

The post-Newtonian period of European history (1685–1850s) is marked by an emphasis on standards and rules as an outgrowth of Newtonian mathematics in the 1600s. It was recognized that standards were a prerequisite for the future industrial revolution involving mass production and efficient engineering and growth of new knowledge. A similar need for standardization of QEEG normative databases is present today. Amplifier equilibration and standardization has long been an elusive goal as mentioned previously. However, new technologies are

available that provide for simple and inexpensive standardization of EEG amplifiers for purposes of comparison.

In the future the essential standard will be to equate the microvolt measurement of the electrical energies of the human brain recorded at different frequencies from different amplifiers using accepted statistical tests and standards of validation and verification as listed in rows 2 to 10 in Table 2.4.

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