APPLICABLE STATISTICS IN BEHAVIOURAL RESEARCH

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IN HONOUR

OF

PROF. CHIKE OBI

PRESENTED AT THE FOUNDER'S DAY INAUGURATION OF PROF. CHIKE OBI MEMORIAL LECTURE
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Prof. Chike Obi got his B.Sc., M.Sc as a private student. He stunned the world with bewildering incredulity. The white man could not believe that a black man who had never travelled outside Nigeria could solve what puzzled the Europeans. He did. He went further to bag the PhD of Cambridge University.

He returned to Nigeria to train many generations of Mathematicians. Every Nigerian Mathematician alive in Nigeria today must be a son, grandson, a great grandson or great great grandson of Prof. Chike Obi, the African Mathematical genius.

Many of us grew up to be infected by the virus that made some of us believe that everything is quantifiable. We have successfully applied quantification in the social sciences. It has come to stay. However, many scholars without Mathematical background have tried to be scientific and quantitative. They have created monumental errors because they violate the mathematical and statistical assumptions underlying such applications. In this contribution I have touched on the errors which arise from the wrong attempts to be quantitative

In an earlier work (Ijomah 1970), it was pointed out that statistics and mathematics can never be substituted for judgment. But they assist us in making scientific decisions when facts have been collected through scientific or objective research operations. Once our data are faulty, the application of statistical and mathematical techniques as purifying tools is merely being quantophrenic (Ijomah 1970). Even when data have been carefully assembled, very often researchers, for the mere love of quantification, use the wrong techniques and wrong statistics in the analysis of data. As a result, wrong interpretations of data and wrong decisions are fed to students. Errors of judgment often referred to as type I and II errors have gone through research literature undetected, and false hypotheses have been erroneously accepted as true, and true ones rejected.

Statistics, adjudged suitable for ordinal data have been used for nominal data and we have cases where the dependent and independent variables are ordinal or interval, but statistics appropriate for nominal data have been used. For instance, why should a researcher use Jaspen's coefficient of multiserial correlation or point biseral for data with nominal classification and for which an ordinary x^2(Chi-square) would be adequate. Many of these errors have gone undetected because many users of statistics have not gone beyond the elementary exposure to statistical techniques.

In many institutions where a course in statistics has been allowed in the curriculum for any of the departments in the social and behavioural sciences, lecturers do not cover beyond measures of association. Many of the users of statistics have no mathematical background, and therefore are understandably incapable of appreciating the mathematical prescriptions for the use of any statistics.

A common test carried out by any user of statistics is that of association. Some call it correlation, and some refer to it as test of dependence or contingent relationship between X and Y which are classified as nominal variables. One is interested in knowing when the existence of Y – the dependent variable is, predicated upon the prior existence of X, the independent variable.

In empirical situations, could one say that the voting behaviour of the Nigerian electorate (Y) is dependent on ethnicity (X)? A measure of Association such as x^2 could point to the fact that there exists an association between ethnicity and voting behaviour. Usually, inexperienced researchers leap sky-high when a calculated x^2 rejects a hypothesis of no-association.

Many writers were quick to note the sacredness attached to .05 level of significance at which many researches make their decisions, and have given an early note of warning.

Some researchers fail to realize that measures of association are ordinary measures of proportional reduction in error of guessing. The measures only tell us that by knowing the independent variables, we reduce the error we would have committed if we had guessed the dependent variables without knowledge of the independent variable.

Consider the following guess work: John voted for a political party. If there is an association between ethnicity and voting behaviour, knowing John's ethnicity would reduce the error in predicting his voting behaviour. Thus, if John is a Yoruba man, the probability would be high that he voted for Chief Awolowo's party.

But this is only a guess work which could be wrong because the establishment of association at, for instance .05 level of significance could not be as rigorous as that established at .001 level. Besides, x^2does not tell the strength of the detected association. Predictions based on x^2 whose strength has not been given, are very often wrong.

Critics of quantification are themselves ignorant of requirements for effective quantification. Statistics must be seen as tools used in the social and behavioural sciences for analyzing facts with intent to finding meanings hidden beneath the facts; **they are never substitutes for the facts**.

**Read Sanford Labvitz, "Criteria for selecting a significance level: A Note on the sacredness of .05"; James Skipper et al, "The Sacredness of .05: A Note concerning the uses of statistical levels of significance in social research.*

They must be used with due respect for the conditions set out as prerequisites for their use. Henry Scheffe (1959:331-369) has discussed at length, the effects on research results of the statistician's depature from the underlying assumptions in analysis of variance. William Hays (1963), and Walker and Lev (1953) also examined the various sources of statistical errors.

Many critics of quantitative sociology may be justified because those who profess to be quantitative are actually "quantophrenic." In order to highlight the sources of errors which lead soft or qualitative sociologists to the view that the sociological phenomena are not easily amenable to quantification, the two broad classifications of statistics are discussed:

1) The Parametric and
2) The Non-Parametric.

In each classification, the various levels of measurement are discussed, and statistics appropriate for each level are discussed. Due to space limitation, all the statistics will not be discussed. Fuller discussions are contained in any good statistics text book.

But enough guideline will be given here for the benefit of students and researchers who intend to use statistics most profitably.

I. **Parametric Statistics**: A parametric statistic is one that makes certain assumptions about the nature of the population from which data have been collected. Most social researches are survey researches. But experience has shown that where parametric statistics have been used, the researcher has not taken the trouble to see whether he has met the assumptions required for the use of a parametric test. The theoretical justification for the use of parametric tests are provided by the assumptions.

The most powerful parametric statistics are the F-test and t-test. There are other summarizing statistics which are treated generally as measures of dispersion. Since the population of interest is usually too large for a total coverage, researchers are satisfied with inference from the sample to the population on the theoretical assumption that:

(a)The population is normally distributed, and therefore the sample would not be an biased sample, but a true reflection of the population. If the population is normally distributed, the sample statistic would be unbiased estimator of the population parameter, such that$\sum(\bar{x} - \mu) = 0$

(b) The observation must be made independently. The selection of any element of the population must not influence the selection or non-selection of another element.

These assumptions are theoretical. They are not easily met. **But Hays (1963:378) advises that the assumption of normal distribution of population may be violated if and only if the sample size is large.** As the sample size increases, so does the sample statistic approximate the population parameter. There is however the question of how large a sample should be in order to qualify as "large". This has remained a mute question. But the pioneering works of Fisher, Yates, Pearson and Hartley on the x^2 seem to have provided the answer. In the calculation of the x^2, it was observed that if N is less than 100, the value of x^2would be too large, and would lead to false rejection of a true NuII hypothesis. But if N is greater than 100, x^2 would be underestimated, and the NuII hypothesis would be accepted more often than not. Fisher and Yates'x^2earlier tables were tabulated up to 30 degrees of freedom. But Pearson and Hartley later brought it up to more than 30df. Nevertheless, Fisher and Yates argue that for n-degrees of freedom where $n > 30,$ the expression $\sqrt{2x^2}$ is approximately normally distributed with mean of$\sqrt{2n - 1}$, and standard deviation of 1.

Consequently, when we wish to test the significance of a x^2 based on more than 30 degrees of freedom, the expression $\sqrt{2x^2} - \sqrt{2n - 1}$, can be calculated and treated as a normal deviate with mean of zero and standard deviation of 1. Thus when the sample size is 30 or more, normality of distribution may be expected.

(c)the error variance σ_e^2 must be the same for each treatment group.

Hays also argues that the assumption of homogeneous variance may be violated provided the number of cases in each sample is the same. When the variances are not homogenous and the number of cases in the samples differ, **final inferences on the basis of the research findings cannot be valid.**

(d) the error associated with the observations must be independent. This assumption is most important for F-test, and its violation is very serious particularly in psychological research.

It is difficult to know from mere inspection of a research report whether these assumptions are met. We can only hope that where they are not met, researchers should be honour-bound to use less rigorous statistical measures such as the non-parametric statistics. Sidney Siegal (1956) discusses a number of non-parametric tests and their power-efficiency.

In general, parametric tests are interested in differences between means, in the expectation that if the sample is unbiased, its mean would be an adequate estimate of the population mean, and $\sum(\bar{x} - \mu = 0)$, and if two samples are taken from the same population, $\bar{x}_1 = \bar{x}_2 = \mu$. Even in the simplest summarizing statistics, many people do not know when to use the different measures of central tendency. Table I is therefore given as a guide in the use of measures of central tendency and dispersion. Table II discusses measures of Association. Readers should note that emphasis is placed on the choice of appropriate statistics for any given level of measurement.

Perhaps, it is pertinent at this point to caution that measures of association merely indicate the existence of an association between the dependent and independent variables. Some call this association correlation. **But regardless of what name we call it, the main task of survey research is to examine all the variables that account for the observed relationship**. These variables are broadly subsumed under the independent and dependent variable classification. Walter Wallace (1971:45) terms them the explicans and the explicandum. That is, the explanatory variable and that variable which is required to be explained. Leslie Kish (1959:329) calls them the predictor and the predictand. These are the main variables. All other variables which he groups into three are merely extraneous variables.

Research interest is to minimize the effects of these extraneous variables on the research data. If the data are carefully and honestly collected, the first class of the extraneous variables may be controlled. The control may be exercised in either both the selection and the estimation procedures. (Leslie Kish).

The second class of extraneous variables are confounded with the class of explanatory variables. During research design, the actual experiment and survey, the aim is to control as many of these extraneous variables as possible. During randomization we sift out the extraneous variables which are confounded with the explanatory variables.

The third class of the extraneous variables are uncontrolled variables which are treated as randomized errors. Ideally, they should be randomized. **But in actual practice, I am yet to read any research report which shows that this class of extraneous variables are actually randomized.**

When we apply controls such as repeated cross tabulations, regressions, standardization, matching of units, we seek to expunge the uncontrolled variables from the explanatory variables.

When we use statistics to test significance, we are in fact testing for the effects of the random uncontrolled variables upon the explanatory variables which have been confounded with the extraneous uncontrolled variables.

Therefore it is imperative that all uncontrolled variables be randomized. The main argument against the use of statistical measures hinges on the belief that the sociologists and behavioural scientists are unable to randomize their data. Randomization ensures that correlated biases are avoided, that the sample is not biased with respect to certain variables. The criticism leveled by Leslie Kish and others would appear to have been taken care of, if and only if researchers would work with the optimum sample size for any particular research. This ensures that the characteristics found in the sample reflect the population parameter, and that the sample is not biased.

Besides, the researcher, by using the optimum sample size has set in advance, the level of rigour which should guide his research. He thus escapes the criticism which Skipper *et al* leveled against the sacredness of .05 level of significance. For researchers who chose the level of significance post factum, the criticism is valid. But it is my contention that for those who use the level of significance to determine sufficient sample size, for the research, the attack is uncalled for. I have therefore show in this paper how to get the correct sample size.

If the alpha criterion for choosing the sample size is = .01, that is 99% confidence, it follows that the level of significance for the test should be .01, and preferably, a two – tailed test.

The only valid basis for applying Leslie Kish criticism is the fact that most research data in Africa are incomplete, unreliable, politically biased, or deliberately distorted by scholars anxious to rewrite the history of their people's past.

It is at this point that we call on African scholars and governments to appreciate the tragedy which befalls a scholar trying to understand his country. It is necessary that deliberate effort should be made to gather and compile accurate information so that there is a basis for comparing information gathered in survey research.

In survey research which is the field of sociologists, we can never observe the entire population. But on the assumption that the population is normally distributed, and that other conditions for parametric statistics are met, we calculate what, with some luck, we would regard as the unbiased estimate of the population parameter.

In advanced countries where the census is given some academic importance, population parameters may be obtained from census surveys. The researcher must bear the following in mind, when estimating the population parameter from the sample statistics:

Sample	Population
1. Frequency distribution is thought of in terms of relative frequency $\frac{fi}{n}$	Probabilities = p (x)
2. $\bar{x}$ = means	μ = mean
3. Standard deviation S	σ
4. Variance S^2	σ^2
5. The statistics is random variable	fixed parameters,
6. Estimators	targets

Since many factors intruding on survey research make it improbable that the estimator is equal to the target, it becomes fashionable to think in terms of the distribution of the sample statistics about the mean. Thus, $\mu = \bar{x} \pm \varepsilon$ where ε is the error as a result of intruding factors. We therefore look for a given probability that the sample statistic falls within a given confidence interval about the population parameter. If we want 95% confidence interval, it follows that

$$\Pr(\bar{x} - 1.96\frac{\sigma}{\sqrt{n}} \ z < \mu < \bar{x} + 1.96\frac{\sigma}{\sqrt{n}}) = 95\%$$

With this relationship, researchers can always calculate the appropriate sample size n, large enough to give adequate estimators of the target. The central limit theorem states that as the sample size increases, the distribution of the sample means would approach normality.

Any statistics text book shows how to calculate the sample size. For instance, we may be interested in a given population, and we want 99% confidence that the sample mean lies.1σ of the true population mean. From the table of normal distribution, we know that 99% confidence interval has a z = 2.58. Thus the deviation between the $\bar{x}\sigma$ and μ is (2.58) $\bar{x}$

since $\sigma\bar{x} = \frac{\sigma}{\sqrt{n}}$,

$(2.58)\ \sigma\bar{x} = (2.58)\frac{\sigma}{\sqrt{n}}$,

Since we want $\bar{x}$ to lie within .1σ from μ, and this must give us 99% confidence interval if the sampling is accurate, the sufficient sample size is calculated from the equation:

$$.1\sigma = 2.58\frac{\sigma}{\sqrt{n}}$$

$$\sqrt{n}\,(.1\sigma) = 2.58\,\sigma$$

$$\sqrt{n}\frac{\sigma}{10} = 2.58\,\sigma$$

$$\sqrt{n} = 2.58\,\sigma \times \frac{10}{\sigma}$$

$$\sqrt{n} = 25.8$$

$$n = (25.8)^2 = 665.64$$

Consequently, if we observed a sample of 666 cases, we would expect that our estimator could be wrong by more than .1σ only 1 out of 100 chances.

If we want 95% C.I. then the following equation would give us the correct sample size:

$$.1\sigma = 1.96\frac{\sigma}{\sqrt{n}}$$

One common error in research is the use of z when testing hypothesis about the mean. By using z, we assume that we know the population. But in practice, this is hardly known. Since our best estimates of the population come from samples, it is advisable to use the statistic which has an estimator we can calculate from the sample. The student's t uses $S\bar{x}$ as an estimate of $\sigma\bar{x}$,

whereas $z = \frac{\bar{x} - \mu}{\sigma\bar{x}}$, $t = \frac{\bar{x} - \mu}{\frac{S}{\sqrt{n}}}$,

Note that $S\bar{x}$ is an estimate of $\sigma\,\bar{x}$,

and $S\bar{x} = \frac{S}{\sqrt{n}}$

but $\sigma\bar{x} = \frac{\sigma}{\sqrt{n}}$,

In parametric statistics, our discussions centre around inferences about the means and variances of samples in their relationship with the population parameters.

In using x^2as an approximate of parametric statistic, we bear in mind that as the degree of freedom increases towards infinity, x^2 approximates a normal distribution. Thus, it is possible to convert x^2 to z, to t and even to F.

Note the following relations:

$$x^2_{(N-1)} = \frac{(N-1)s^2}{\sigma^2}$$

$$z^2 = \frac{(\times - \mu)^2}{\sigma^2} \qquad \frac{\Sigma(x - \mu)^2}{\sigma^2}$$

Both x and z range over the entire distribution. But x^2 is nonnegative entity and goes only from o to ∞.

x^2 (1) i.e. with 1 degree of freedom = z^2

But the conversions must be based on population parameters σ^2 and μ

But if we use unbiased estimate, we must subtract 1 df from N

hence $x^2_{(N-1)} = \frac{(N-1)\hat{S}^2}{\sigma}$

Otherwise, $x^2_{(N-1)} = \frac{NS^2}{\sigma^2}$ if the simple size is large.

Hays (1963:677) shows that an F ratio is the ratio of two independent x^2 each divided by its degree of freedom.

$$\text{Thus} \left(\frac{\frac{x^2_{(N-1)}\sigma_1^2}{N_1-1}}{\frac{x^2_{(N-1)}\sigma_2^2}{N_2-1}} \right) = \frac{\hat{S}_1^2}{\hat{S}_2^2} = F$$

For some distributions, x^2 is closely related to F and for others to t.

$$t = \frac{z}{\sqrt{\frac{x^2}{N-1}}} \quad \text{and} \quad t^2 = \frac{z^2}{\frac{x^2}{N-1}}$$

Note also that when scores are correlated, F cannot test the hypothesis of no difference in the variances. For instance, when we administer a test to a group at two time periods to see if there is a significant change at the end of the period,

$$F = \frac{\hat{S}_1^2}{\hat{S}_2^2} \quad \text{cannot test}$$

H$_{0:}$ $\sigma_1^2 = \sigma_2^2 = \sigma^2$ since s^2, and s_2^2 are based on correlated scores.

If σ_1^2 is the variance after the first test, and σ_2^2 the variance after the second test and if P_{12} is the correlation between the scores at the two tests, for the population we represent the sample statistics as $s^2$and s_2^2, and the correlation as γ_{12}

To test the Ho: $\sigma_1^2 = \sigma_2^2$

t should be used and not F; and t = $\frac{S_2^2 - S_1^2\sqrt{N-2}}{2s_1 s_2 \sqrt{1-\gamma_{12}^2}}$

There are other applicable tests for homogeneity of variances. There are Hartley's test which is simply the ratio of maximum S^2 over the minimum variance. But its disadvantage is that if the maximum ratio is not significantly large, none will be. (See Edwards, 1966:125-130)

There is also the Bartlet's test which has not been used by any Nigerian sociologist because of the complex mathematical computation. But it is equally reliable.

2. <u>NON-PARAMETRIC/DISTRIBUTION-FREE STATISTICS</u>

Fortunately, however, we are saved a lot of problems by the availability of new non-parametric or distribution–free techniques which make no assumption about the distribution of population parameters.

James Bradley (1968:45) contends that distribution-free test give sample-related information which are characteristics of variates drawn from population. Consequently, from mathematical point of view, the tests are related to the sample, but tend to be related to the population only “indirectly and logically” or by inference. The hypotheses they test are sample-related hypotheses which by inference are population-related hypotheses. Those who use these statistics will be spared the condemnation of soft or qualitative sociologists.

Requirements: The only requirement of distribution-free or non-parametric tests is that the observation be drawn randomly, and independently of the outcome of previous draw.

Table II lists applicable non-parametric statistics and specifies the levels of measurements. Along with non-parametric statistics for samples drawn from population, are also given some non-parametric measures of association, and tests for statistical inference.

Table I

Level of Measurement	Mathematical Postulates	Appropriate Summarizing Statistics
Nominal	Equivalence: If X = Y then Y = X; If X = Y and Y = z, then X = z	(1) The mode (2) Index of relative variation (3) Proportions (4) Variation ratio (5) H uncertainty measure
Ordinal	(1) Equivalence (2) Inequality: If a > b then b < a; if a > b and b >c then a > c	The Median, Range, percentage, quartiles, semi-interquartile.
Interval	(1) Equivalence (2) Inequality (3) Known ratio of any two intervals (4) Additive if a = g and b > g, then a + b > g and a + b = b +a	The Mean-Arithmetic Mean, The Harmonic Mean, Standard deviation, quadratic mean, variances
Ratio	(1) Equivalence (2) Inequality (3) Known ratio of any two intervals (4) Known ratio of any two scales.	The Geometric Mean Coefficient of Variation

Note: In listing appropriate summarizing statistics, we have dealt with only two measures –

(1) Measures of Central Tendency such as the Mode, the Median and the Mean.

(2) Measures of Dispersion such as the Standard deviation σ, the variance σ^2 .

TABLE II (a)

Levels of Measurement	Measures of Association	Significance Tests Statistical Inference	Non-Parametric statistics Most Commonly Used				
			One sample	Two Samples		More than two samples	
				Related samples	Independent samples	Related	Independent
Nominal	1. Phi = $\emptyset$, 2. Yule's Q 3. Tschuprow's t 4. Tetrachoric Correlation 5. Goodman Kruskal's x^2 Tau = x^2 6. Crammer's V 7. Dependency ratio 8. The Chi-Square 9. Lambda	1. Test of difference between proportions coefficient of Contingency C;	1.Binomial test 2.The hyper geometric distribution 3.Fisher's Exact Test 4.$x^2 -$ One sample test	1. McNemar's test for significance of change.	Fisher's Exact Probability test. x^2 Test for two independent samples.	Cochran Q test	Chi-Square x^2 for more than independent samples
Ordinal	1. Spearman's γ_s 2. Kendall's γ and W 3. Gamma γ 4. Somner's dyx 5. Flanagans Coefficient of Correlation	Goodman Kruskal's coefficient of rank association converted to z; for Spearman's γ, and Kendall's x^1 use t-test	Kolmogoro-v-Smirnov. One sample runs test	1. Sign test 2. Wilcoxon Matched Pairs 3. Signed Rank	1.Van der Waerden test 2.Klotz test 3.Median test 4.Mann-Whitney U test 5.Kolmogorov-Smirnov two sample test 6.Wald-Wolf-owitz runs test 7.Moses test of extreme reaction. 8.Savag test		

TABLE II (b)

Levels of Measurement	Measures of Association	Significance Tests Statistical Inference	Non-Parametric statistics Most Commonly Used				
			One sample	Two Samples		More than two samples	
				Related samples	Independent samples	Related	Independent
Interval	1.Pearson's γ, 2.Multiple Correlation; Ratio 3.Coefficient of Curvilinear correlation	For γ, use t, z transformation; Multiple R, use F –test Test for homogeneity of (1) Means (2) Variance		Walsh test; Randomization for marched pairs	Randomization test for two independent samples		
Nominal/ Ordinal	1.Use γ if order can be ignored in the ordinal scale; 2.Use θ = theta						
Nominal/ Interval	1. η = eta 2.γ and θ under certain conditions 3. Biserial correlation	Fisher's Analysis of variance General analysis of variance t-test					
Ordinal/ Interval	1. M = Jaspens coeffienct of Multiserial 2. Point biserial	t – test					

In general, measures of association are measures of proportional reduction in error of guessing. If for instance, there is an association between statistics and sociological research methods, one would expect that a student who does well in statistics should also do well in methods. If therefore we have a knowledge of a student's performance in statistics, we may risk a guess as to his performance in methods. Two kinds of guess work would be necessary here:

(1) If we had no knowledge of his performance in statistics, we could guess his performance in research methods with some errors. Call this error "$\mathcal{E}$"

(2) If we knew his performance in statistics, we could guess his performance in methods with a reduction in the error of guessing. That is, $\mathcal{E}$ would be reduced by 'e'

The measure we are interested in is the ratio of the reduced error $\mathcal{E} - $ e to the original error which is $\frac{\varepsilon - e}{\varepsilon}$

This ratio often referred to as the coefficient, ranges from o to +1, and for some measures it ranges from -1 to +1.

Let us examine one or two measures:

1. **YULE'S**

In 1912, Yule proposed a measure of association for a four-fold or 2 x 2 contingency table. He called this measures Yule's Q in honour of Quetlet. Yule's Q can only be used when the following conditions exist:

1) Data are in nominal scales

2) The table is a 2 x 2 contingency table. Consider the following:

Table III (a)

The association between Sex and Voting Behaviour-Voting for the Presidential Candidate, Mr. P in a given Polling Station

		Voting		
		Yes	No	Total
Sex	Male	800	500	1,300
	Female	400	400	800
	Total	1,200	900	2,100

Note that both variables are nominal:

Sex is nominal – either male or female

Voting is nominal – yes or no.

Note also that the table is a 2 x 2 table i.e. 2 columns and 2 rows.

If we substituted symbols for figures, we would have:

Table III (b)

		Voting		
		Yes	No	Total
Sex	Male	a	b	a + b
	Female	c	d	c + d
	Total	a + c + b + d		

Q is given by the formula:

$$Q = \frac{ad-bc}{ad+bc}$$

Since sex is prior to the act of voting, sex becomes the independent variable. In the hypothetical example given in Table III Q = .231

Q is a measure of one way prediction and only tells us that by knowing the independent variable we reduce our error in predicting the voting behaviour – the dependent variable. Inexperienced researchers have used Q for data that call for two way or mutual predictability. In the above example, Q does not help in predicting sex.

Advantages: The Q is a PRE (Proportional reduction in error) measure. In the above example, Q has enabled us to reduce 23% of the original error.

Disadvantages: One principal disadvantage is its limitation to a 2 x 2 table. When the researcher has data in 3 x 3 or K x K contingency table, Q cannot be used unless the researcher is able to collapse the tables to a 2 x 2 contingency table. The researcher should know however that when a table is collapsed, important information may be lost. If the researcher is very desirous to use a Q – related statistics, when his table is more than 2 x 2, the (Y) gamma may be used, because the Q is a special case of gamma even though the gamma is appropriate for ordinal data.

2. The (∅) Phi is another measure of association appropriate for nominal data. From table III(b), ∅ is given by the formula:

$$\emptyset = \frac{ad - bc}{\sqrt{(a + b)\,(c + d)\,(a + c)\,(b + d)}}$$

This Phi is limited to a 2 x 2 contingency table, and is a PRE measure. The numerator is the same as for the Q, but its denominator is based on the square –root of the products of the marginal distribution.

If we removed the square – root requirement in the denominator and squared the numerator, and multiplied the numerator by N, we would have a statistics which has a x^2 distribution for a 2 x 2 table only.

Consider the association between marriage and drinking habit.

Table IV

Association between Marriage and Drinking Habit.

		Drinking Habit		
		Never Drinks	Drinks Always	
Marriage Relations	Stable	a 60	c 15	a + c = 75
	Unstable	b 10	d 50	b + d = 60
	Total	a + c = 70	c + d = 65	N = 135

$\emptyset = .63$

The researcher can infer a positive association between drinking and marital relations. The association however is not complete, since ∅ may attain unity.

In order to use ∅ as a PRE measure it must be squared. Thus $\emptyset^2$ = $(.63)^2$ = .3969. This means that knowing drinking habit has reduced 39.69% of the original error in guessing the type of marital relations. Unlike the Q, the ∅ is a measure of two way prediction. That is to say, that by knowing any of the variables, the drinking habit or marriage relations, we reduce the error in guessing the second variable by 39.695% and vice versa. By squaring ∅ we bring the statistics closer to the x^2 . $\emptyset = \frac{x^2}{\mu}$ and $\emptyset = \sqrt{\frac{x^2}{\mu}}$

$$\mu\emptyset^2 = x^2$$

<u>Conclusion</u>

I have touched on Yule's Q and the Phi (∅) by way of illustration. It is as easy to demolish the use of statistical techniques in social research as it is to demolish the unempirical works of soft or qualitative researchers. The controversy is a testimony to the youth of the disciplines in the social and behavioural sciences. But perhaps, applicable statistics will remain applicable if we realize that there is no qualitative research that does not use elements of quantitative research. If research in the social sciences wishes to assume the posture of scientific research, it cannot escape from counting, enumeration, measurement and testing of hypotheses.

These cannot be achieved without quantification.

References

R. L. Anderson and T. A. Bancroft, Statistical Theory in Research, New York: McGraw –Hill Book Company, 1952

James V. Bradley, Distribution – Free Statistical Test, Englewood Cliffs, New Jersey: Prentice Hall, Inc, 1968

David Gold, "Statistical Test and Substance significance" in The American Sociologist, February 1969, Vol. 4, number 1. Pp. 42-46.

William Hays, Statistics for Psychologists New York: Holt Rinehart and Winston Inc. 1963

B.I.C Ijomah, "Problems of Quantitative Research in Africa", presented at the African Studies Conference in Boston, 1970. Published in the Conch Journal Vol. 3 No. 1 1971, Reprinted in William O'Barr et al. (eds). Survey Research in Africa, Evanston: Northwestern University Press, 1973.

Leslie Kish, "Statistical Problems in Research Design" in ASR, Vol. 24 No. 3, June 1959.

Sanford Labovitz, "Criteria for selecting a significance Level: A note on the Sacredness of 0.5: in The American Sociologist August 1968, Vol. 3, No. 3

Denton Morrison and Ramon E. Henkel, "Significance Tests Reconsidered" in The American Sociologist May 1969, Vol. 4 No. 2. Pp. 131-140

Hays, L.H., Statistics for the Social Science, Second Edition, Chicago: Holt Rineharts and Winston, Inc. 1972

Henry Scheffe, Analysis of Variance New York: John Wiley and Sons Inc. 1959.

Sydney Siegel, Non-Parametric Statistics New York: McGrawHill Book Company Inc. 1956.

James Skipper et al., "The Sacredness of .05: A Note concerning the uses of statistical levels of significances in Social Research." in The American Sociologist, February 1967 Vol. 2 No. 1 pp. 16 – 18

Helen Walker, and Joseph Lev, Statistical Inference, New York: Holt, Rinehart and Winston, Inc. 1953

Walter Wallace (ed.) Sociological Theory Chicago; Aldine Publishing Company, 1969

Mosteller F., Rourke, R.E.K., and Thomas, G.B. Probability with Statistical Applications. Reading, Mass.: Addison –Wesley, 1961.

Alexander, H.W., Elements of Mathematical Statistics. New York: Wiley, 1961.

Anderson, R.L., and Bancroft, T.A Statistical Analysis in Chemistry and The Chemical Industry. New York: Wiley, 1954

Cramer, H., Mathematical Methods of Statistics. Princeton, N.J.: Princeton University Press, 1946

Dixon, W., and Massey, F. Introduction to statistical analysis (ed.2). New York: McGraw-Hill, 1957

Freund, J.E., Mathematical Statistics. Englewood Cliffs, N.J.: Prentice-Hall, 1962

Grant D.A, Testing the null Hypothesis and the Strategy and Tactics of Investigating Theoretical Models. *Psych. Rev. 69, 1962, 54- 61*

Hoel, P.G. Introduction to Mathematical Statistics (ed.3). New York: Wiley

Kendall, M.G., and Stuart, A. The Advanced Theory of Statistics, 3 Vols. London: Griffin, 1961 – 1966

Lehmann, E.L Testing Statistical Hypotheses. New York: Wiley, 1959

Lewis, D. Quantitative Methods in Psychology. New York: McGraw-Hill, 1960

McNemar, Q. Psychological Statistics (ed. 4). New York: Wiley 1968