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Inferential Statistics for Social and Behavioural Research

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Abstract: This paper provided an insight to the effective use of inferential statistics for social and behavioural research. As a theoretical paper, it explored the importance of tests of significance emphasizing the need to use the appropriate test for a particular research. It showed that a parametric test is one that involves the estimation of the value of at list one population parameter and the fact that the population is normally distributed. It has also presented the nonparametric tests as distribution-free tests used when the nature of the population distribution from which samples are drawn is assumed not to be normal. It then gave examples of parametric tests a including the t-test, One way analysis of variance and the Pearson r Product Moment Correlation coefficient and the non-parametric tests as including the Chi-square test among others. The writer then gave the advantages and disadvantages of using these tests indicating the implications for future research. It was concluded that the use of appropriate statistical techniques is critical requirement for effective conduct of social and behavioural research.

Key words: Inferential statistic anaylsis, behavioural research, social research, education, chi-square test and t-test

INTRODUCTION

Inferential statistics involve the use of statistical techniques in the testing of the hypotheses and drawing inferences from the findings of a study (Baddie and Halley, 1995; Kolawole, 2001). These statistical techniques are of two major types. These are the non-parametric tests and the parametric test. The non-parametric tests include the chi-square test and the kolmogorov-Sminov test while the parametric tests include the t-test, analysis of variance and Pearson Product Moment Correlation Coefficient (Adeyemi, 2002). For the purpose of this study; the inferential statistics to be examined in this study include the chi –square test, t-test, analysis of variance and Pearson Correlation Coefficient.

Various tests of significance are usually selected by researchers for analyzing data in social and behavioural research (Cohen and Manion, 1989; Oppenhelm, 1992). The tests are those appropriate for different sets of data. The choice of a test of significance depends on what the researcher is investigating. In choosing such a test, the following should be noted.

- Tests of significance usually assist the researcher to decide whether he or she should reject a null hypothesis and infer whether the difference between two means is significant.
- The test of significance is made at a selected probability level. This means that in social or behavioural research, only 5 times out of every 100 studies (0.05), the null hypothesis is probably false and must be rejected.
- There are different tests of significance that could be applied in research. Each of these tests must be appropriate in a given situation. The factors that determine which test of significance to be selected for a given study include scale of measurement represented by the data, method of subjects' selection, number of groups and the number of independent variables. Researchers need to select an appropriate test suited for a particular set of data or study. In doing this, the first step is to decide whether a parametric test or a nonparametric test would be suitable for such a study.

Parametric tests: The word 'parametric' implies some characteristics, quality or value of the population data. A parametric test involves the estimation of the value of at list one population parameter. For example, the within-group variance calculated in F-test is an estimate of the corresponding within-population variance. It assumes that the population is normally distributed. Thus, parametric tests are generally powerful in the sense that they are more likely to lead the researcher to rejecting a null hypothesis that is false. The researcher therefore, is less likely to commit a Type 2 Error that occurs by failing to reject a false null hypothesis (Welkowitz, *et al.*, 1976). Parametric tests require certain assumptions to be met before it can be meaningfully used in social and behavioural research.

Assumptions of Parametric Tests:

- The variable being measured should be normally distributed in the population. Since most variables examined in social and behavioural research are normally distributed (Best, 1981), this assumption is always met.

- The data must be at the interval or ratio level of measurement. Since most measures used in social and behavioural research are at the interval level, the assumption is also always met.
- Subjects should be selected independently for the study. This means that the selection of one subject should in no way affect the selection of other subjects (Babbie, 1975). The selection should also be by random sampling in order to allow chance to play its part in the selection.
- The variances of the population must be equal noting the fact that the variance of a group of scores is the square of the standard deviation.

In order to identify which test to apply in a given situation, we have to note the following steps:

(i) Postulate the null-hypothesis
(ii) Postulate the alternative hypothesis
(iii) Set the level of significance (alpha) and the sample size (N)
(iv) Select the appropriate table value in the region of rejection (R)
(v) Collect the data
(vii) Analyze the data with the appropriate identified statistic.
(viii) If the computed result falls within the rejection region, that is, if $p < 0.05$, reject the null hypothesis (Ho)..
(ix) If the computed value falls outside the rejection region,

that is, if $p > 0.05$, then, accept the null hypothesis (Ho). Examples of parametric tests are the z -test, t – test and the analysis of variance (ANOVA).

Nonparametric Tests: Nonparametric tests are distribution-free tests used when the nature of the population distribution from which samples are drawn is assumed not to be normal (Champion, 1970). They also used when data are in the nominal level of measurement. They are always in groups or categories and represented by frequency counts. They are equally used when data are expressed in ordinal form and ranked in the order of 1st, 2nd, 3rd or 4th and so on. They are also used when the nature of the distribution is not known or when largely violated (Siegel, 1988).. Since they are based on counted or ranked data rather than on measured values, nonparametric tests are less precise. Hence, they could only be used when parametric assumptions could not be met. They however have the merit of having their validity not being based on assumptions about the nature of the population distribution.

Nonparametric tests are tests that do not require any estimation. They are used when scores are not normally distributed but largely skewed. This is because they do not make any assumption about the shape of the distribution. A typical example is the Chi-square test which is distribution-free as it tests the equality of the entire distribution of frequencies. The Chi-square test uses nominal data or scale and does not assume anything about the population. It is applicable to the entire population even if the data do not fix in into a normal distribution. Other examples of nonparametric tests include the Kolmogorov – Smirnov test, Mann-Whitney U test, Sign test, Wilcoxon matched-Pairs Signed–ranks test and the Lambda symmetrical/ asymmetrical test (Berenison, & Levine, 1979).

THE CHI - SQUARE TEST

The chi-square test is a nominal level non-parametric test of significance that could be used to test the differences or relationship between two variables. It applies only to discrete data that are counted rather than data with measured values (Kinnear, & Gray, (1994). As a nonparametric test useful when data are in the form of frequency counts, the chi-square occurs in two or more mutually exclusive categories and it is denoted by the following formula:

$$\chi^2 = \Sigma\left[\frac{(O-E)^2}{E}\right]$$

Where χ^2 = Chi – square; O = Observed frequency; E = Expected Frequency.

Uses of the Chi-Square: The Chi-square test is useful when the data collected represent a nominal scale and categories are true categories such as male and female or artificial categories such as tall and short. It compares proportions that were observed in a study with proportions expected if the groups were equal. In computing chi-square, therefore, the differences between the observed frequency and expected frequency are squared and divided by the expected number on each occasion. The sum of these quotients is the Chi-square value. The significance of a Chi-square value is determined by consulting a Chi-square table using the appropriate degree of freedom and level of significance (Moore, 1994). It should be noted however, that the Chi-square value increases as the difference between observed and expected frequencies increases.

Chi-square Goodness of Fit Test: Also known as goodness of fit, in the sense that it is a test of last result, the Chi-square statistic helps in determining whether observations differ from what is expected by chance. It is also referred to as a goodness of fit statistic because it is a statistical evaluation of the difference between sample observations and observations provided by a hypothesized model (Champion, 1970). In analyzing data with the Chi-square goodness of fit, variables could be discrete while data should be at the nominal level of measurement for an appropriate analysis.

One-Dimensional Chi Square: This is a type of Chi-square test presented in a 1 x 2 or 1 x 3 or more, that is, one row, two columns or one row, three columns or one row, more than three columns contingency table.

Example: The expected frequencies (E) in cell 1 = 60; expected frequencies (E) in cell 2 = 60; Observed frequencies (O) in cell 1 = 75; observed frequencies (O) in cell 2 = 4 (Table 1). Having determined the expected and observed values, then apply the Chi square formula

$$\chi^2 = \left[\frac{(O-E)^2}{E}\right]$$

Two-dimensional Chi- Square: The Chi square might also be used when frequencies are categorized along more than one dimension. This is a kind of a factorial Chi-square. Although 2 x 2 tables are common, contingency tables might be for any number of categories, such as 2 x 3, 2 x 4 or 3 x 3 tables.

Example: To compute the expected frequencies for each cell, multiply the total of each row by the total of the corresponding column and divide by the overall total (Table 2).

∴For Row 1, column 1:

$$Expected\ Frequency = \frac{Total\ Row\ 1 \times Total\ column\ 1}{Overall\ Total}$$

Chi square Test for Two Independent Samples: The Chi-square test for independent samples is a useful statistical technique for determining whether two nominal or higher level measures are related. It is used when dealing with more than one sample. If one of the variables is an independent variable and the other is a dependent variable, the test may be used to analyze data from a simple randomized design, which may be either experimental or ex-post-facto design. There is no restriction whatsoever in respect of the categories either in the roll or column variables.

After determining the expected and observed values in the appropriate contingency tables, then apply the Chi-Square formula

$$\chi^2 = \Sigma\left[\frac{(O-E)^2}{E}\right]$$

Testing For Significant Relationship: In order to test whether there is any relationship in the pattern of responses, the Crammer's r Contingency Coefficient and Index Relationship (Cr) is determined. The Crammer's r (Cr) is to test how strong or loose the relationship is. It is represented by the following formula.

$$Cr = \sqrt{\left(\frac{k}{K-1}\right)\left(\frac{\chi^2}{N-\chi^2}\right)}$$

Assumptions for the Chi-square Test:

- There are some restrictions with respect to the sample size. No cell should have an expected frequency of less than 5 (Champion, 1970). If however, cell frequencies are less than 5, the resulting Chi-square value would be grossly inflated and would not reveal a true picture of the ways the variables are distributed. However, categories might be collapsed in order to raise the expected frequencies above 5.
- It is also assumed that the researcher must obtain a sample of independent observations.

Advantages of the Chi- square test:

- The Chi-square test is the most flexible statistical technique for determining whether one's observations differ from what is expected by chance.
- Tables are usually provided which allow the researcher to determine the significance of any given Chi-square value with the appropriate number of degrees of freedom.
- Because few assumptions exist with Chi –square, it is possible to apply the Chi- square to virtually every analysis where data are in categories.

Disadvantages:

- One major disadvantage for using the Chi square test is with small N.
- When N is less than 5, the Chi- square test should not be applied.

THE t- TEST

The t- test is a parametric test used to test the significant difference between two means. It is a statistical test of significance suitable for interval or ratio data (Norusis/ SPSS, 1993). It is also used to test the trend and the significance of correlation. It could be computed as a t-test of difference between two means or a t-test of related samples. Related samples are those that have

Table1: Contingency table for One Dimensional Chi square (1 x 2)

Individually	In Groups
E = 60	E = 60
O =75	O = 45

Table 2: Contingency table for Two Dimensional Chi square (2 x 2)

	Males	Females	Total
Individual	E	E	
	O	O	
Group	E	E	
	O	O	
Total			120

something other than the tested characteristic in common. The independent samples should be selected in such a way as to assume that they are unrelated to one another. The examples of t-test include the following.

Student t- test: The student t-test is a technique by which we can determine the significance of the difference between the means of two groups of scores. It provides an index ' t ' which is the ratio of the difference between the means of the two groups. It is given by the formula:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{\sigma_1}{N_1} + \frac{\sigma_2}{N_2}}}$$

Where $\bar{x}_1$ = Mean for group 1 and $\bar{x}_2$ = Mean for group 2 σ_1 =Standard Deviation for group 1; σ_2 =Standard Deviation for group 2; N_1 = Number of cases in the series for group 1; N_2 = Number of cases in the series for group 2.

Example: Assuming the following data was derived from an investigation

Data $\bar{x}_1$: = 170; σ_1 = 60; n_1 = 18

Data $\bar{x}_2$: = 200; σ_2 = 62; n_2 = 10

Now apply the t-test formula

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{\sigma_1}{n_1} + \frac{\sigma_2}{n_2}}}$$

$$\therefore t = \frac{170 - 200}{\sqrt{\frac{60^2}{18} + \frac{62^2}{10}}}$$

$$t = \frac{30}{\sqrt{\frac{3600}{18} + \frac{3844}{10}}}$$

$$t = \frac{30}{\sqrt{200 + 384.4}}$$

$$t = \frac{30}{\sqrt{584.4}}$$

$$t = \frac{30}{24.17}$$

$\therefore$ Computed t = 1.24

The Student t- test could also be used to determine the significance of correlation by using the following formula.

$$t = \frac{r}{\sqrt{1 - r^2}} \sqrt{n - 2}$$

Where r = Correlation Coefficient and n = Sample Size

The t- test of difference between two Independent Means For Equal Standard Deviations: The commonest use of the t-test is to determine whether the difference between two groups is significant. In experimental situations, One group is manipulated and the effects of the manipulation are analyzed by comparing the performance of the two groups using the formula:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{\left((\Sigma x_1)^2 - \frac{\Sigma x_1^2}{N_1} + (\Sigma x_2)^2 - \frac{\Sigma x_2^2}{N_2}\right)\left(\frac{1}{N_1} + \frac{1}{N_2}\right)}{(N_1 + N_2) - 2}}}$$

t– test for Non- Independent or Related Samples: Another use of the t - test is to determine the significance of a difference between two related means. It is most commonly used when two scores are recorded for the same individual. Both experimental groups have the same number of measures since they represent two measures of the same subject or matched pairs of subjects. The t-test formula to be applied is as follows:

$$t = \frac{\overline{D}}{\sqrt{\frac{\Sigma D^2 - \frac{(\Sigma D)^2}{N}}{N(N-1)}}}$$

where: D = Difference between the matched pairs and N = Total Number in the sample

Assumptions of the t- test:

- Data should be at interval level of measurement.
- The population should be normally distributed

Advantages of the t - test:

- When the N is less then 30, the t- test is appropriate.
- The t-test is a realistic test as it assumes that the standard deviation is unknown.

Disadvantages of t- test: For single sample test, as the N increases, the sampling distribution tends to approach a normal distribution and the Z test would be an appropriate tool to apply.

ONE- WAY ANALYSIS OF VARIANCE (ANOVA)

The one- way analysis of variance is an interval level test of significance used to compute the differences in the means of more than two groups of data (Kim, & Kohout, 1970). In computing the one-way analysis of variance, there must be at least three groups.

Computational Procedures:

- Let SSb represent the Sum of Squares between groups.

$$SSb = \frac{\Sigma T^2 j}{nj} - \frac{T^2}{N}$$

In evaluating this term,
(i) Sum the scores in each group.
(ii) Square the total for each group.
(iii) Divide these squares by the number of subjects in the each group.
(iv) Sum for all groups.

- Let SSw represent the Sum of Squares within groups.

$$SSW = \Sigma\Sigma x_i^2 - \frac{\Sigma T^2}{nj}$$

In evaluating the term,
(i) Sum all scores in each group.
(ii) Square the sum for each group.
(iii) Square the entire total for all groups
(iv) Divide these squares by the number of subjects in each group.
(v) Do the summation for all the groups.

- Let SSt represent the total Sum of Squares of K samples. It is the sum of squared deviation from the mean for all subjects in all samples. Thus,

$$SSt = \frac{\Sigma\Sigma X_{ij}^2}{j=1} - \frac{T^2}{N}$$

To evaluate the term, $\Sigma\Sigma X_1 j^2$
(i) Square each score in the entire collection,
(ii) Sum all of these squares

To evaluate the term $\frac{T^2}{N}$
(i) Sum all the scores in the entire collection.
(ii) Divide by N.

$$\therefore SSt = SSw + SSb$$

Degrees of Freedom (df) df = $K - 1, N - K$ where df for SSb = $K - 1$, df for SSw = $N - k$; df for SSt = $N - 1$; df for SSt = $k - 1 + N - k$

MSb: The Sum of Squares between groups (SSb) should be divided by its degree of freedom to obtain the Mean of Squares between the groups

$$\therefore MSb = \frac{SSb}{k-1}$$

MSw: The Sum of Squares within the groups should also be divided by its degree of freedom to obtain the Mean of Squares within the groups

$$\therefore MSw = \frac{SSw}{N-k}$$

To Compute the F ratio:

$$\therefore F = \frac{MSb}{MSw}$$

To determine the critical or table F value: At a specified level of significance, say 0.05 level, check the F tables for the point where the degree of freedom intersects the 0.05 level of significance. The value at the point of intersection is the critical or table F value.

Interpretation: If the calculated or computed F is greater than the table or critical F, reject the null hypothesis. But if the calculated or computed F is less than the critical F, then accept the null hypothesis.
Advantages of the Analysis of variance

- The analysis of variance has one major advantage over the t test. It could be used with more than two groups or samples.
- With more than 2 samples, the difference between the mean scores of all the samples examined say 3 or 4 or 5 could be determined in a single test. This procedure is more convenient than conducting separate t test for each pair of samples.

Disadvantages: One disadvantage of the analysis of variance is that it cannot identify where a difference lies between the means being examined.

POSTERIORI COMPARISON OR POST HOC TESTS

Since one major disadvantage of the analysis of variance is that it cannot identify where a difference lies between the means of the different groups being examined, a posteriori or post hoc test needs to be conducted to determine where the significant difference is allocated among the groups. A Posteriori comparison refers to a situation when the researcher is unwilling to limit the number of the comparisons in advance of the data collection. The Scheffé test fall under Posteriori comparison or post hoc tests.

THE SCHEFFÉ TEST

Suppose we found from the One- way analysis of variance that there was a difference among the means of the various groups but we have not been able to locate where the difference was within the groups, we need to apply the Scheffé test. The Scheffé test is a test of significance that computes an F ratio for each mean being compared In applying the Scheffé test formula,

- Compare the mean of group 1 with the mean of Group 2 ($\bar{x}_1$ and $\bar{x}_2$)
- Compare the mean of Group 1 with the mean of Group 3 ($\bar{x}_1$ and $\bar{x}_3$)
- Compare the mean of Group 2 with the mean of Group 3 ($\bar{x}_2$ and $\bar{x}_3$)

Step 1: Compare the mean of group 1 with the mean of group 2 ($\bar{x}_1$ and $\bar{x}_2$)

$$F = \frac{\left(\overline{X}_1 - \overline{X}_2\right)^2}{MSw\left(\frac{1}{n_1} + \frac{1}{n_2}\right)(K-1)}$$

Step 2: Compare the mean of group 1 with the mean of group 3 ($\bar{x}_1$ and $\bar{x}_3$)

$$F = \frac{\left(\overline{X}_1 - \overline{X}_2\right)^2}{MSw\left(\frac{1}{n_1} + \frac{1}{n_3}\right)(K-1)}$$

Step 3: Then, compare the mean of group 2 with the mean group 3 ($\bar{x}_2$ and $\bar{x}_3$)

$$F = \frac{\left(\overline{X}_1 - \overline{X}_2\right)^2}{MSw\left(\frac{1}{n_2} + \frac{1}{n_3}\right)(K-1)}$$

where: MSw = mean of square within group; $\bar{x}_1$ = mean; N = Number in the series.

Interpretation: If the computed F value is greater than the critical F value, the researcher has to conclude that there is a significant difference between the mean of one group and the mean of the other. But if the computed F value is less than the critical F, the researcher would conclude that there is no significant difference between the mean of one group and the mean of the other group..

CORRELATION COEFFICIENT

The term ‘correlation’ is the degree of relationship between two variables while a correlation coefficient is an index of relationship between the two variables. It is a numerical statement that draws inference concerning the relationship between two variables Thus, a measure of association shows that two variables might co-vary in a pattern. When one is high, the other is systematically higher or lower. If the coefficient is high, it is considered to reflect a close relationship. Therefore, correlation enables a researcher to identify with some degree of accuracy how the values of one variable are co-related to the values of another variable (Gay, 1996).

The Pearson r Product-Moment Correlation Coefficient: The Pearson r Product-Moment Correlation Coefficient is one of the most popular interval level parametric measures of association used to determine the relationship between two variables (Best, 1981). Apart from having interval level data, the researcher must satisfy certain assumptions before he or she could use and interpret the Pearson r. Thus, suppose a researcher wishes to examine the relationship between years of students’ education and their levels of income. He has to draw a table with six columns for the data collected. Column one would contain the number of individuals, that is, the N. Column two would contain the values of X, that is, number of years of students’ education. Column three would contain the values of Y, that is, the levels of income. Column four would contain the square of X, that is, X^2. Column five would contain the square of Y, that is, Y^2 while the sixth column is the product of both X and Y, that is, XY. After computing the data, apply the formula.

$$r = \frac{N\Sigma XY - (\Sigma X)(\Sigma Y)}{\sqrt{\left(N\Sigma X^2 - (\Sigma X)^2\right)\left(N\Sigma Y^2 - (\Sigma Y)^2\right)}}$$

Or

$$r = \frac{\Sigma XY - \frac{(\Sigma X)(\Sigma Y)}{N}}{\sqrt{\left(\Sigma X^2 - \frac{(\Sigma X)^2}{N}\right)\left(\Sigma Y^2 - \frac{(\Sigma Y)^2}{N}\right)}}$$

Positive Correlation: Variables are positively correlated if an increase in one variable is accompanied with a corresponding increase in the other variable. This is positive correlation (+1). If one value decreases with the other value at the same time, the correlation is also positive. Suppose an achievement test is administered to a group of students at the beginning and at the end of a school year, a correlation between the two tests can be found. Generally, there will be a tendency for a student who scored above the group average at the beginning of a school year to have scored above the group average at the end of the school year. The two scores are said to be positively correlated.

Negative Correlation: When two variables are perfectly negatively correlated, an inverse relationship exists such that a high score on one variable is associated with a lower score on the other variable. The two variables are said to be negatively correlated. If the value of one variable increases while the value of the other variable decreases then, the correlation would be tending towards –1. If the level of education increases and the chances of promotion decreases, this shows a negative correlation between the two variables.

Zero Correlation: This occurs when there is no correlation or relationship between two variables. For instance, if there is no relationship at all between a man's low education and his standard of living, the correlation would be zero. When there is no tendency for a higher score in one variable to be associated with either a higher or lower score in the other variable, the variables are said to be un-correlated and the coefficient is zero.

Assumptions for using the Pearson r:

- In order to meaningfully use the r, the data must be at the interval level of measurement.
- The association between the two variables should be linear.

Advantages of Pearson r:

- If the assumptions for using the r are met, Pearson r is probably the best coefficient of correlation to apply in educational research.
- Statisticians and researchers are very conversant with the r and as such, much has been done to develop its interpretation than for other measures of association.

Disadvantages of Pearson r:

- A major disadvantage of the r is in the stringent assumptions.
- The assumptions are sometimes very complex in their application.

Implications for future research: A good knowledge of the various statistical techniques by researchers implies a successful completion of research findings. It also implies that the researcher would be able to make an effective utilization of the appropriate inferential statistics in any given situation in research studies. However when researchers are unable to identify the appropriate statistical technique to be used in analysing data, it becomes difficult to derive actual findings and make inferences from research findings. Therefore, a good mastery of the inferential statistics would be helpful to researchers in their bid to finding solution to research problems.

CONCLUSION

This paper has opened up the mind of young researchers into the use of statistical techniques in social and behavioural research. The write-up has led the researcher to conclude that an effective use of inferential statistics could be made if a good mastery of the techniques is borne in mind by researchers. It was also concluded that the use of appropriate statistical techniques is a critical requirement for effective conduct of social and behavioural research.

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