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DETERMINATION OF APPROPRIATE STATISTICAL PROCEDURES FOR QUANTITATIVE DATA ANALYSIS IN MATHEMATICAL SCIENCESAND EDUCATIONAL RESEARCH

+Wonu, N.
Department of Mathematics/Statistics, Ignatius Ajuru University of Education,
P.M.B 5047 Port Harcourt, NIGERIA

Ndimele, S.C.
Department of Educational Psychology, Guidance and Counselling, Ignatius Ajuru University of Education,
P.M.B 5047 Port Harcourt, NIGERIA

+Corresponding author (email): wonu.nduka@iaue.edu.ng

Abstract
This study is a peer review into the determination of the appropriate statistical procedures for quantitative data analysis in mathematical sciences and educational research. Diverse statistical formulas were discussed. Appropriate parametric and non-parametric statistics for data analysis were identified. Data and its types, underlying assumptions and rationale regarding the utilization of any statistic, as well as the process of determining the appropriate statistical technique for any data analysis were also explained. Implications for improvement in research data analysis and results reporting were also drawn. The study recommended among others that: researchers should endeavour to understand the basic assumptions and the rationale underlying the use of any quantitative statistical technique before utilizing it for data analysis to ensure the reliability of their research findings, and researchers should do well to compute nonparametric tests using appropriate statistical procedures or transform those data which could not meet the parametric assumptions before computing the proposed parametric test appropriately.

Keywords: Statistical Procedures, Quantitative, Data Analysis, Research, Science, Education

Introduction

Research reports have over the years greatly influenced policymaking and brought about changes in the trend of events in society. Research is a well-articulated and coordinated effort of people (concerned professionals) which involves the collection of data, analysis and interpretation of the collected data and reporting of the results or findings with a view of proffering solution to the problem identified in any area of human endeavour. A research venture cannot be accomplished or meaningful without the collection and analysis of data. Data is factual information, often in the form of facts or figures obtained from experiments or surveys used as a basis for making calculations or drawing conclusions or information for computer processing which could be numbers, text, images, and sounds, in a form that is suitable for storage in or processing by a computer (Ecartar, 2008). Ogundipe et al., (2006) simply described data as building blocks of information. This implies that through data, vital information can be derived to solve a problem. Preceding the input phase of data analysis is the data organization, which entails the arrangement of the data for proper input into the computer system. No matter the type of programme or computer to be used, if the data collected are not properly organized, the researcher or data analyst will find it difficult to analyze their meaning before doing the real analysis using an appropriate statistic. Thus, data collected in the research process can only be said to be useful when such data are properly organized, analyzed and interpreted, else such data remains meaningless.

Data can generally be classified into qualitative and quantitative. Qualitative data are not represented in numerical magnitude and are measured on the nominal and ordinal scales of measurement. Qualitative data are inherently discrete. Examples of qualitative data are sex (male, female), position (cleaner, cook, driver), colour (red, blue, white). On the other hand, quantitative data are data that can be represented in numerical magnitude. Quantitative data are normally measured on interval and ratio scales. However, quantitative data contain all the features of nominal and ordinal scales plus those of interval and ratio scales; hence they are both discrete and continuous. Although, this study focused on quantitative data, however, it should be noted that the choice of statistical techniques for data analysis is highly dependent on the nature of data involved, research questions and hypotheses and design of the study among others.

Measurement in mathematical sciences and educational research is concerned with assigning numerical values to observations based on some specific rules. Measurement metamorphoses certain attributes of our perception into familiar numbers. The various ways in which measurement can be established are known as scales of measuring instruments. There are four scales of measurement which includes: nominal, ordinal, interval and ratio scales. Data obtained on these scales are described as nominal, ordinal, interval and ratio data respectively. The type of scale determines the level of refinement of the data obtained and the appropriate statistical analysis to which the data can be subjected.

Problem specification

Experience shows that many researchers find it difficult to determine and utilize the appropriate statistical procedures for the analysis of their research data. Inappropriate knowledge of research statistics has forced some researchers to utilize any statistic they are conversant with not minding its suitability in the study. This action would not only lead to wrong results and findings but wrong conclusions and recommendations, hence there is a need for a paper of this kind. In line with the foregoing, this study provided a guide to researchers for easy identification of appropriate statistics to be utilized for data analysis based on some factors such as available data, sample size and number of groups among others.

Purpose of the study

The main purpose of this study was to determine the appropriate statistical procedures for data analysis in any study. Specifically, the objectives of the study were to:

1. determine the suitable statistic for answering a research question.
2. determine the appropriate statistic for testing a hypothesis.

Review of Related Literature

Types of Data (based on the scale of measurement)

a. Nominal Data: These are data obtained from a discrete scale. This simply involves assignments to classes or categories. It involves the use of numbers to identify objects or individuals. No category is less or greater than the other. It is a form of labelling for identification purposes. It does not bear any magnitude or relationship to another one. Examples:

i. Location: Urban, Semi-urban, Rural
ii. Sex: Male, Female
iii. Response: Yes, No

Labelling enables us to distinguish a category from another. The attributes lack any special order or magnitude.

b. Ordinal data: These are data obtained from an ordinal scale that has magnitude and order. It is possible to categorize members of a group as well as compare any two such members in terms of relative magnitude or size: ‘greater than’ or ‘equal to’ or ‘less than. Examples:

i. Grades in an examination: A, A+, A-, B+, B-, C, D
ii. Examination position in a class: 1^{st}, 2^{nd}, 3^{rd}etc
iii. Sizes of shoes: 10,9, 8, 7,6,

Consider the example of the sizes of shoes of individuals. The common difference between each of the shoe sizes above is 1. In ordinal data, it is worthy of note that equal intervals do not suggest equal quantities (Nworgu, 1991).

c. Interval data: These are obtained from an interval scale**.** Interval scale has the property of the order, equal intervals and connotes equal quantities of the measured attributes, but has no absolute zero. Example:

i. Performance test scores: The interval between scores of 50 and 54 on one hand and scores of 55 and 59, on the other hand, are equal. A score of zero on the test does not suggest a total lack of knowledge on what is measured; hence there is no absolute zero.
ii. Celcius scale: 0^oC, 1^o C, 2^oC, etc.
iii. Calendar (days): 1, 2,3,4,5, etc.

The fact that a zero on this scale is not absolute since it does not mean the complete lack of the attribute measured can be observed in the zero (0^oC) of the temperature scale does not connote a total absence of heat.

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d. **Ratio data** are obtained from a superior scale that has the attribute of magnitude, equal interval and absolute zero. Example:
i. Measuring height (cm): 50, 40, 30, etc.
ii. Weights of Objects (kg): 60, 50,40, etc.
iii. Absolute Temperature Scale: 0^oK, 120^oK, 130^oK, etc.

A real or absolute zero is present in the ratio data. The rule has a zero (0.00 cm) which connotes the absence of height, 0.00 kg also represent the absence of weight and the 0^oK connotes a complete lack of heat in the Kelvin temperature scale. This kind of data is of limited use in education. Its example in education includes: deviation score, age and gain scores. The ratio data is more regular in the physical sciences because their measuring scale or instrument is more refined than those in education.

Descriptive and Inferential Statistics

Descriptive statistics is concerned with the methods of collecting, summarizing and description of data. As crucial as descriptive statistics are, it is important to point out that the ultimate in any research work is inferential statistics. This is because inferential statistics go beyond the level of drawing inferences (generalizations) about the characteristics of a population based on data collected from a random sample of that population. Inferential statistical analysis is a mathematical method that allows a researcher to generalize to a large group of people based on data collected from a small number of participants in a study (a randomly selected sample).Parametric and non-parametric statistics are the two types of inferential statistics and they are discussed below.

Parametric Statistics

Parametric statistics are statistical tools that employ the mean and variance of the sample data. Parametric tests are tests with fundamental assumptions based on the structure of the population distribution and the type of scale used to characterize the observations. Some parametric tests are fairly robust and can be used even if certain assumptions are not met.

Assumptions for the use of Parametric Tests for Data Analysis

The following are some of the assumptions necessary for the use of most parametric tests for data analysis:
1. Independence of samples; however, there are specific parametric tests for non-independent observations.
2. Homogeneity of variance, specifically for a small sample.
3. Normality of the population distribution.
4. Linearity of the data (expressed in interval or ratio scales only).

The t-test and F-test (ANOVA, including ANOVA, ANCOVA& MANOVA) as well as Pearson's Product Moment Correlation (PPMC), are examples of parametric inferential statistics. When the data (dependent variable) is in interval or ratio form, parametric tests are utilized. The t-test compares the actual mean difference observed to the difference that would be anticipated by chance. The t-test is commonly used to find out if there is a statistically significant difference between the two sample means. T-statistic, F test and Chi-square can be used to show whether there is an association or no relationship between two variables, but they cannot tell the degree or direction of the relationship, which is their limitation in assessing relationships. There exist three types of t-statistics and this includes t-test for small sample size (N<30), t-test for large sample size ($N \geq 30$) and t-test for pared sample or correlated groups.

t-test for an independent large sample ($N \geq 30$)

The independent-samples t-statistic system compares means for two groups of cases. For the application of the t-test, **some fundamental requirements or assumptions are necessary:**
1. the subjects should be randomly assigned to two groups so that any difference in response is due to the treatment (or lack of treatment) and not to other factors,
2. The population standard deviation is unknown.
3. The population has a normal distribution.

The formula of t-statistic for computing two means of independent samples is given below.

$$t = z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1 - 1} + \frac{S_1^2}{n_2 - 1}}} \quad (1)$$

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or

$$t = z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_1^2}{n_2}}} \quad (2)$$

where

$\bar{X}_1$ and $\bar{X}_2$ = mean of the 1st and 2nd group respectively.
S_1 and S_2 = Standard deviation of the 1st and 2nd group respectively
$n_1$and n_2 = number of the of respondents in the 1st and 2nd group respectively

However, Best and Kahn (2007) proved that the formula (3) below which is meant for a small sample could also be applicable for the large sample.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{(N_1 - 1)S_1^2 + (N_2 - 1)S_2^2}{N_1 + N_2 - 2}\left(\frac{1}{N_1} + \frac{1}{N_2}\right)}} \quad (3)$$

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1 - 1} + \frac{S_1^2}{n_2 - 1}}} \quad (4)$$

t-test for independent small sample ($N < 30$ **)**

The method of pooled variances provides an appropriate test of the significance of the difference between two independent means when the sample sizes are modest and their variances are equal. The formula below is more accurate than any other for determining the significance of the difference between two independent means. The adjustment in the formula is for the fact that the distribution of scores for small samples becomes increasingly different from the normal distribution as sample sizes become increasingly smaller.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{(N_1 - 1)S_1^2 + (N_2 - 1)S_2^2}{N_1 + N_2 - 2}\left(\frac{1}{N_1} + \frac{1}{N_2}\right)}}$$

or

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{(N_1 - 1)S_1^2 + (N_2 - 1)S_2^2}{N_1 + N_2 - 2}\left(\frac{N_1 + N_2}{N_1 - N_2}\right)}} \quad (5)$$

also

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\Sigma d_1^2 + \Sigma d_2^2}{N_1 + N_2 - 2}\left(\frac{N_1 + N_2}{(N_1)(N_2)}\right)}} \quad (6)$$

Formula (6) has been tested and found to be most appropriate only when the $N_1 = N_2$. Wali (2002) used it to test the significance of the difference between the mean performance of samples of male and female students in Mathematics, and it gave accurate results. Then using the t-distribution**,** the suitable t-critical value for rejection of the null hypothesis would be determined from $N_1 + N_2 - 2$ degrees of freedom (df).

Nworgu (1991:161) proved that the formula (7) below could be used even when the sample size is small.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_1^2}{n_2}}} \qquad (7)$$

The author indicated that z-test is usually adopted in testing hypothesis about the difference between two population means when the sample size is large, thus, the **t** in the formula (7) above should be replaced by a **z**; the reason being that if the sample size becomes sufficiently large, the t-distribution coincides with the z-distribution.

t-test for two correlated or matched groups (dependent samples)
The two previous t-statistics considered for testing the significance of the difference between two independent means (cases when $N \geq 30$ and $N < 30$) are based on the **assumption that the individuals were randomly assigned to two groups.** Nonetheless, there are circumstances in which it is appropriate to determine the significance of the difference between means of groups that are not randomly assigned. The formula of t-statistic for comparing two means of dependent or correlated samples is given below.

t-test: The direct difference score method

$$t = \frac{\bar{D}}{\sqrt{\frac{N\Sigma D^2 - (\Sigma D)^2}{N - 1}}} \qquad (8)$$

Where
N= the number of pairs.
D= the difference between each paired score.
$\bar{D}$ = the mean of the sum of the difference between each paired score.
Since the groups are dependent samples, it is necessary to compute the coefficient (r) of correlation between the two sets of scores of the subjects or the scores of the matched pairs in the case of the experiment.

When the coefficient of correlation is used, the suitable t-test formula is given as:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2} - 2r\left(\frac{S_1}{\sqrt{N_1}}\right)\left(\frac{S_2}{\sqrt{N_2}}\right)}} \qquad (9)$$

The number of degrees of freedom (df) is a subtraction of 1 from the number of pairs, ie. N-1

Analysis of Variance
The Analysis of Variance (ANOVA) is a type of parametric (inferential) statistic that is used to test the significance of two or more means obtained from a variable's measurement. It's used to test a hypothesis regarding how two or more means differ. The ANOVA is a useful tool for determining whether the means of more than two samples differ too much to be attributed to sampling error. Only differences between the two means can be tested using the t-test based on the standard error of the difference between the two means. When there are more than two means, the t-test can be used to compare one to the other. Multiple t-tests, on the other hand, can cause the Type I error rate to surge. The analysis of variance can be used to examine the significance of differences between various means without increasing the Type I error rate.

Underling Parametric Tests Assumptions for the use of Analysis of Variance (ANOVA) in Data Analysis
To adopt the Analysis of Variance for data analysis in research, the following parametric tests assumptions must be obeyed:

a. The samples are either unrelated or related. Each group is made up of a random sample of subjects from a normal population.
b. The variances of the samples are approximately equal or equal, especially for a small sample. The groupings should be made of a population with equivalent variances.

c. The data are interval or ratio data, and the variable being measured is also normally distributed in the population. The values of the factor variables should be integers.

To test these assumptions, Levene's homogeneity-of-variance test is applicable. One-way Analysis of Variance (ANOVA), Factorial Design Analysis of Variance (Two-way or n-way), Analysis of Covariance (ANCOVA), and Multiple Analysis of Variance are the variations of ANOVA. We'll go over the One-way Analysis of Variance. For a more in-depth study of the mathematical formulas underpinning each kind, the authors recommend consulting more advanced statistics works. The mathematical processes and steps required in computing analysis of variance (e.g. ANCOVA) are quite technical and time-consuming, but with the use of a standard computer application software package, data analysis of a complex study can be completed swiftly and with minimal or no errors.

One-Way Analysis of Variance (ANOVA)

This is an analysis of variance with a single categorization. It tests the association between one independent variable and one dependent variable. It's used to compare the means of two or more groups with the same or different numbers of subjects. The One-Way ANOVA procedure generates a one-way analysis of variance for a quantitative dependent variable by a single factor (independent) variable. The hypothesis that numerous means are equal is tested using an analysis of variance. The procedure for computation of one-way ANOVA is summarized in Table 1 below:

Table 1: Summary of the one-way ANOVA computation procedures

Source of variation	Sum of squares (SS)	Degree of freedom(df)	Mean Square (MS)	F
Between group (B)	$SSB = \frac{(\sum X_1)^2}{n_1} + \frac{(\sum X_2)^2}{n_2} + \frac{(\sum X_3)^2}{n_3} - \frac{(\sum\sum X)^2}{N}$	$df_B = K - 1$	$MSB = \frac{SSB}{df_B}$	$F = \frac{MSB}{MSW}$
Within group (W)	$SSW = SST - SSB$	$df_W = N - K$	$MSW = \frac{SSW}{df_W}$	
Total	$SST = \sum\sum X^2 - \frac{(\sum\sum X)^2}{N}$	$df_T = N - 1$		

You may wish to know which means differ in addition to determining that there are differences among the means. A priori contrasts and post hoc tests are the two types of tests used to compare means. A priori contrasts are tests that are put up before the experiment is undertaken, whereas post hoc contrasts are tests that are run after the experiment has been completed. Trends between categories can also be tested. The following types of statistics are obtained for each group: Mean, standard deviation, standard error of the mean, minimum, maximum, and 95% confidence interval for the mean are all examples. Multiple comparisons: Bonferroni, Sidak, Tukey's honestly significant difference, Hochberg's GT2, Gabriel, Dunnett, Ryan-Einot-Gabriel-Welsch F test (R-E-G-W F), etc. Levene's test for homogeneity of variance, analysis-of-variance table and robust tests of the equality of means for each dependent variable, user-specified a priori contrasts, and post hoc range tests, and user. They are simple to carry out with the help of SPSS.

The Pearson Product Moment Correlation (r)

This is the most commonly used type of correlation for the measurement of the relationship between two or more variables in which the two variables are usually denoted as X and Y.

The data for measurement using Pearson's correlation must be in at least interval scales. When we are interested in determining the relationship between two variables (one independent and one dependent), we conduct a simple correlation, while for a study involving more than two variables (three or more independent variables and one dependent variable), we conduct multiple correlation analysis. Most often, the raw score method for Pearson's correlation (r) is used to compute Pearson's correlation coefficient using the formula below:

$$r = \frac{N\sum XY - (\sum X)(\sum Y)}{\sqrt{N\sum X^2 - (\sum X)^2}.\sqrt{N\sum Y^2 - (\sum Y)^2}} \qquad (10)$$

Where

r =Pearson's correlation coefficient

$\sum X$ = sum of X scores

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$\sum X^2$ = sum of squared X scores

$\sum Y$ = sum of Y scores

$\sum Y^2$ = sum of squared Y scores

$\sum XY$ = sum of the products of paired X and Y scores,

N =Number of paired scores.

However, the formula below can be used to compute the multiple correlation coefficients for two independent variables (X_1 and X_2) and one dependent variable (Y):

$$R = \sqrt{\frac{r^2YX_1 + r^2YX_2 - 2rYX_1rYX_2rX_1X_2}{1 - r^2X_1X_2}} \quad (11)$$

Where

X_1 and $X_2$are total scores for the two independent variables

R is the multiple correlation coefficients.

Conditions Necessary for Appropriate use of the Pearson's Correlation for Data Analysis

i. Subjects (respondents) should be selected at random.
ii. The measurement scale should be interval or ratio in nature.
iii. Data should be normally distributed.
iv. How a hypothesis is stated should be such that can be tested.
v. Homoscedasticity- there should be homogeneity or equal variances between groups, etc.

Regression Analysis

Regression analysis is used mainly to: (a) determine the magnitude and direction of the relationship between the independent and dependent variable. (b) establish prediction (including forecasting of time-series data), inference, hypotheses testing and modelling of a causal relationship (Adesoji & Babetunde, 2009). For the linear regression analysis, the regression model is obtained manually with the formula below:

$$Y= \beta_0 + \beta_1 X+\mu \quad (12)$$

Where Y =dependent (response) variable

X = independent (factor) variable

β_0= constant or intercept term (unknown population parameter)

β_1= coefficient or slop parameter (unknown population parameter)

μ= error term (unobserved random variable)

For the multiple regression analysis, the regression model is obtained manually with the formula:

$$Y=\beta_0+ \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + --- + \beta_nX_n+\mu \quad (13)$$

Where $\beta_1, \beta_2, \beta_3$ ---β_n are coefficient parameters

X_1, X_2, X_3 --- X_n are independent variables

β_0 and μremains as defined above.

Assumptions Underlying the use of Regression Analysis

i. Independent variable (s) is/are error-free.
ii. The dependent variable is subject to error which is assumed to be a random variable.
iii. The sample must be representative of the population.
iv. Predictors must be linearly independent.
v. The variance of the error must be homoscedasticity (constants).

Non-parametric Statistics

In the late 1960s and early 1970s, Non-Parametric Analysis (NPA) was introduced as an alternative (Johnson & Wichern, 2007). During this time, the NPA technique, like other data analysis methods, began to gain popularity in statistical software packages devoted to statistical procedures, primarily NPA and parametric tests (Creswell, 2008). Non-parametric tests do not take into account the shape of the distribution of the variable in the population. Non-parametric tests are tests that are not based on a distribution. A non-parametric test is "less powerful" than a

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parametric test in that it is less likely to reject a null hypothesis at a given level of significance when it is untrue, and it usually requires a larger sample size to achieve the same level of significance.

Conditions Necessary for the use of Non-Parametric Tests

The non-parametric tests are suitable and appropriate for data analysis when the following conditions are satisfied:
1. When the normality of the population distribution from which the samples are collected is unknown.
2. When a parametric assumption has been significantly violated during the research process.
3. When the variables (data) are represented on an ordinal (ranking) or nominal scale (frequency count and percentages).

Chi-Square (χ^2), Man-Whitney (Test U), Kruskal-Wallis (Test H), Median(X2), and other non-parametric inferential statistics are examples. Because statisticians have not reached a consensus on which of the statistics (parametric and non-parametric tests) is preferable, we recommend that researchers employ any of the statistical tests they are comfortable with, taking into account the underlying assumptions. The next sections go over the various non-parametric inferential statistics.

Mann-Whitney U-test

Using randomly selected samples from the same population, this test is used to determine the significance of a difference between two populations. It's used to figure out if two samples taken at random came from the same population. It's a non-parametric test that is comparable to a parametric t-test. When the observations are written as ordinal data and the t-test assumptions are not met, the Mann-Whitney test can be used. U_1 is the most important calculation.

The Mann-Whitney's U critical values can be used to determine the significance of an observed U in a small sample experiment. If any of the groups has a size greater than 20 (Statisticians disagree on this number), the sampling distribution of U approximates the normal distribution, and the null hypothesis can be tested using the normal probability table's z-critical values. The Mann-Whitney U-test is a rank-sum test in which the combined samples N1 and N2 are ranked from lowest to highest, without regard for groups, and then the ranks of each sample are added together and indicated as R1 and R2.

To test the difference between the rank sums, use the formulas

$$U_1 = N_1 N_2 + \frac{N_1(N_1+1)}{2} - R_1 \qquad (14)$$

$$U_2 = N_1 N_2 + \frac{N_2(N_2+1)}{2} - R_2 \qquad (15)$$

Where N_1 and N_2 are sample sizes in group 1 and group 2 respectively, while R_1 and R_2 are the sums of ranks in group 1 and group 2 respectively.

We need to calculate only one of the U, for the other can simply be computed by the formula:

$$U_1 = N_1 N_2 - U_2 \qquad (16)$$

The z-value can be determined by the statistic

$$Z = \frac{U - \frac{N_1 N_2}{2}}{\sqrt{\frac{N_1 N_2 (N_1 + N_2 + 1)}{12}}} \qquad (17)$$

In using this formula, it does not matter whether the larger or smaller U value obtained from the formula is used in the computation of z. The sign of z will depend on which is used; the value of z will be numerically equal. The authors of this paper readers to the works of Spiegel and Stephens (1999) and Best and Khan (2007) for a detailed understanding of the use of the formulas in the computation of the Mann-Whitney U-test manually.

The Kruskal-Walis H-test

The U-test is a nonparametric test that is used to determine whether two samples are from the same population. To generalize this for K samples, the H-test is utilized. It is used to test the null hypothesis that K random samples from different samples come originated from identical populations. The one-way ANOVA would have been utilised since the K samples are independent, but when the assumptions of the one-way ANOVA are not met, the H-test is utilized.

All data are ranked as if they were in one sample from lowest to highest such as we did in the U-test previously. Suppose that we have k samples of sizes n_1, n_2, …n_k, with the sum of the sample sizes given by $N=n_1+n_2+….+n_k$ and R_1, R_2…, R_k are the sums of each sample, given the formula as;

$$H = \frac{12}{N(N+1)}\left(\frac{R^1}{n_1} + \frac{R^2}{n_2} + ...\frac{R_k^2}{n_k}\right) - 3(n+1) \quad (18)$$

If n1, n2,...nk are all at least 5, the sampling distribution of H is roughly a Chi-square with k-1 degrees of freedom. The X2 approximation cannot be utilized in any sample with fewer than 5 elements, hence the test must be based on a particular table. The value of H produced by the formula above will be smaller than it should be if there are too many ties among the observations in the sample data. The correction factor gives the corrected value of H, which is denoted as (Hc).

$$Hc = 1 - \frac{\Sigma(T^3 - T)}{N^3 - N} \quad (19)$$

where T is the number of ties corresponding to each observation and the sample is taken over all the observations. If there are no ties, T =0 and no correction is needed. However, the use of correction is not imperative (i.e the presence of ties is not enough to permit a change in the decision).Kindly go through the works of Spiegel and Stephens (1999) and Best and Khan (2007) for a detailed understanding of the use of the formulas in the computation of the H-test manually.

Spearman's Rank Correlation

This is a non-parametric test that is used to measure the relationship between two variables. The Spearman's rank correlation coefficient is a measure of the association based on the ordinal feature of data. It is a form of the Pearson Product Moment Correlation (PPMC) that can be used with ordinal data or when the assumptions of PPMC are violated. If variables X and Y may be ranked from 1 to the highest (n), in order of size, importance etc. the coefficient of correlation varies from -1 to 1. The Spearman's formula for rank correlation is given by the statistic:

$$r_s = 1 - \frac{6\Sigma D^2}{N(N^2 - 1)} \quad (20)$$

Where

D=the difference between the ranks of corresponding values of X and Y

N=number of pairs of values (X,Y) in the data.

The stand error of the rank correlation coefficient is given by the formula:

$$z = r_2\sqrt{n-1} \quad (21)$$

In SPSS for windows, H-test for Spearman's Rank Correlation is obtained through the Bivariate Correlations procedure which computes Pearson's correlation coefficient, Spearman's rho, and Kendall's tau-b with their significance levels. Correlations measure how variables or rank orders are related.

Chi-Square (χ^2)

Chi-square(χ^2) testis a non-parametric test. It is used to determine if the proportions of two or more categories differ from the expected proportion. It is applied when data (dependent and independent variables) is nominal. If there are 1-k samples the use the Chi-square (χ^2) test. The most important point to note is that the two variables to be related using Chi-square (χ^2) test must be nominal and but data must not be dichotomous. The Chi-square test is given by the formula:

$$\chi^2 = \frac{(O-E)^2}{E} \quad (22)$$

Where E=Expected frequency and O=Observed frequency

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The classification of data is vital in research because it points to the mathematical operations and suitable statistical techniques to be adopted for the analysis of such data.

Determination of the Appropriate Statistical Technique for Data Analysis Based on Data Type

As discussed earlier, we have four scales of measurement to which data can belong, viz: Nominal, Ordinal, Interval and Ratio. The first two are for non-parametric statistics and the last two are for parametric tests. There are two major types of tests used in statistical analysis in the mathematical sciences, the test of a relationship and the test of difference based on questions. When the parametric assumptions of the independent unbiased sample, normality of the distribution of the data and equality of variance are satisfied the parametric tests are carried out else, the non-parametric tests are adopted. Table 2 shows how appropriate statistical tools for data analysis can be determined based on the data type.

Table 2: Determination of the Statistical Tools-Based on Data Type

Scale of Data	**One sample**	**Two Samples**		**More than two samples**	
		Independent	Related	Independent	Related
Nominal	Binomial	Fisher exact test	McNemar Test	Chi-square (x^2) k-samples test	Cochran Q
	Chi-square (x^2) One-sample test	Chi-square (x^2) Two-sample test			
Ordinal	Kolmogorov-Smirnov One-sample test	Mann-Whitney U-test	Wilcoxon matched pairs test	Kruskal-Wallis test	Freidman Two-way ANOVA rank test
		Kolmogorov-Smirnov test Wald-Wolfowitz	Sign test	Ordinal regression analysis	
		Spearman rho			
		Ordinal regression analysis			
Interval and ratio	t-test	t-test	t-test for paired samples	One-way ANOVA	Repeated measures ANOVA
		Pearson product Moment correlation		Two-way ANOVA	
				Turkey hsd test	
				Scheffe'test	

Adopted from Cohen et al. (2007)

The flowchart (Figure 1) below provided series of questions to be answered by a researcher before choosing a particular statistic for data analysis. The first question is: Is the assumption of normality reasonable? If yes, is the assumption of equal variances reasonable? If yes, the researchers should use ANOVA or t-test. If the assumption of equal variances is not reasonable, and transformation does not help, then the researcher should use Welch's ANOVA or Welch's t-test, but if transformation is helpful, the use ANOVA or t-test. On the other hand, if the assumption of normality is not reasonable, and transformation does not help, then a non-parametric test should be used.

The flowchart below also demonstrated how appropriate statistical tools can be selected for the analysis of continuous data.

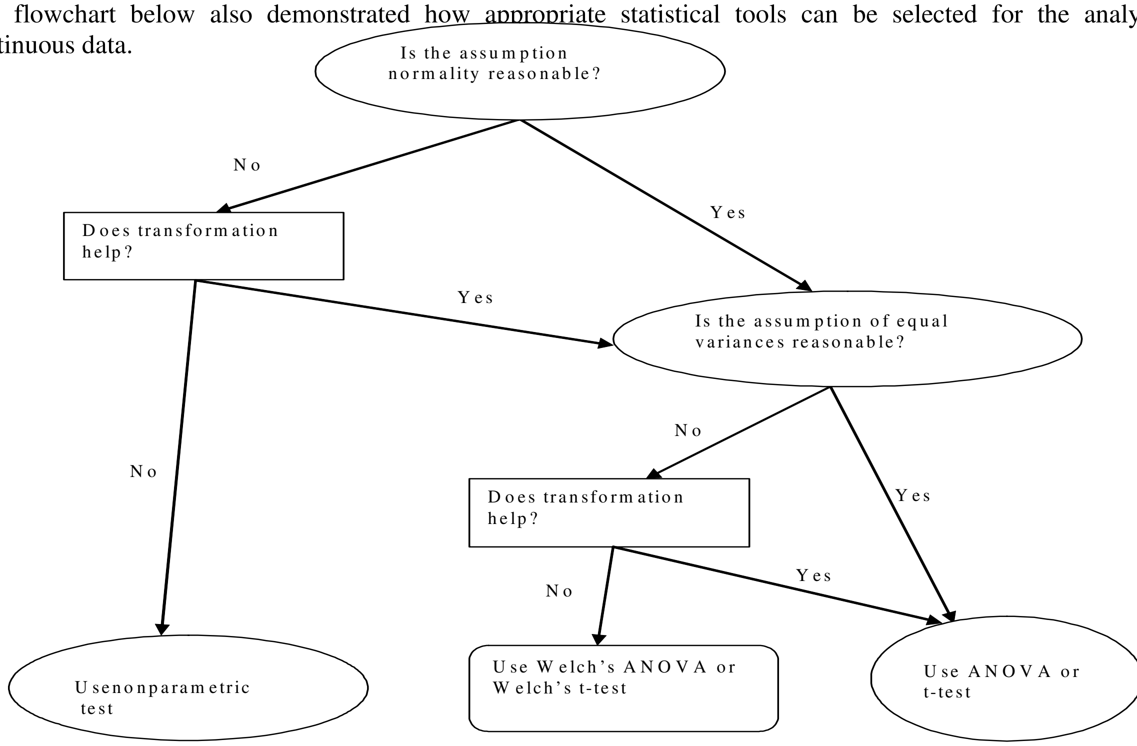

Fig. 1: Flowchart demonstrating a selection of statistical tests for continuous data, adopted from Morgan (2017).

Further Illustrations on how to determine the Appropriate Statistical Technique to be adopted for Data Analysis

Case 1: Statistic involving nominal data: Suppose the data obtained is discrete/categorical or nominal, that is, the independent variable and the dependent variables are measured in nominal form. Suppose there is only one sample the binomial or Chi-square test can be performed. Also, if two samples are involved, Fisher exact test and Chi-square test (for independent samples) and McNemar test for related samples could be carried out. Suppose there are more than two groups of samples, the Chi-square test (for independent samples) and Cochran Q test (for related samples) could be carried out (Cohen, et al., 2007).

Case 2: **Statistic involving ordinal data:** When ordinal data is involved, non-parametric tests are appropriate for data analysis. Suppose one sample is involved, the Kolmogorov-Smirnov test can be executed. If two samples are involved, the Mann-Whitney U-test, Kolmogorov-Smirnov test, Wald-Wolfowitz, Spearman rho and ordinal regression analysis should be carried out for independent samples, whereas Wilcoxon Matched pairs test and Sign test should beconducted for related samples. Suppose the samples are more than two, the Kruskal-Wallis test and Ordinal regression analysis are to be carried out for the independent sample, whereas the Freidman Two-way ANOVA rank test is to be done for more than two related samples (Cohen, et al., 2007).

Case 3: Statistic involving interval and ratio data: Suppose interval or ratio data are involved, for one sample, the t-test is to be carried out whereas an independent sample t-test and Pearson Product Moment Correlation are to be carried out for independent samples. If the samples are related, the t-test for paired samples could be computed. When two independent samples are involved, the one-way ANOVA, Two-way ANOVA, Turkey test and Scheffe's

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test is computed; and repeated measures of ANOVA for more than two related samples (Cohen, et al., 2007) could be conducted.

Case 4: Statistic involving different data types

Research involving the relationship between variables: The two variables are required to compute the correlation coefficient. Data collected from each of the variables will fall into one of the measurement scales or data. If one variable is nominal and the second is also nominal, then compute the Phi Coefficient, ϕ (two levels each). If one is nominal and the other is ordinal, then compute Rank-Biserial. If one is nominal and the other is interval or ratio data, use Point-biserial. If both of them are ordinal, then use Spearman Rho. If one is ordinal and the second is interval or ratio, convert the interval or ratio to ordinal and use Spearman Rho. If both data are interval or ratio, then use Pearson's correlation (where there are no dependent and independent variables). However, if there exist dependent and independent variables, then compute the regression analysis. It is worthy of note that Pearson Product Moment Correlation and Linear regression analysis are most appropriate when the sample size is greater than or equal to 30 subjects.

Suppose a research question seeks to find out the relationship between two variables measured using interval or ratio scale, the mean and standard deviation might be inappropriate in answering the research question. For example, **"**what is the relationship between student attitude towards Mathematics and mathematical problem-solving task performance?" …The mean and standard deviation cannot be used to answer the above research questions. It is possible to use the Pearson Product Moment Correlation (PPMC) to answer the research question. This will enable the researcher to determine the strength and direction of the relationship between the two variables through the value of the computed Pearson's computed r. If the corresponding hypothesis is a direct transformation of the research question, then the p-value associated with the computed r-value using a software package could be used to test the hypothesis. It is wrong to use the mean and standard deviation to answer the research question and then use PPMC or linear regression to test the corresponding hypothesis if the tested hypothesis is a direct transformation of the research question.

Research involving the difference between group means or median: Suppose the dependent variable is continuous, when computing differences between a single mean and a hypothetical one, the one-sample t-test is computed. Suppose multiple means are involved regarding the difference on a single dependent variable and the parametric assumptions are satisfied, compute independent sample t-test for two groups, else compute the Mann-Whitney U test or Wilcoxen Rank sum test. It is possible to transform data if the parametric assumptions are not satisfied. If more than two groups are involved, still check the parametric assumptions. When the assumptions are satisfied, compute One-way ANOVA (compare means) as well as the post hoc tests for significant differences. However, if the assumptions are not satisfied, compute the Kruskal-Wallis test (compare medians) or transform data and still compute the One-way ANOVA.

Research involving large or small sample: The independent sample t-test could be used to test for the significance of the difference between mean scores obtained from two independent groups. Equation (1) and equation (2) could be used to compute the t-value when the sample size is greater than or equal to 30. Best and Kahn (2007) proved that formula (3) could also be used for the large sample. The equations (5-7) are used when the sample size is less than 30.

Conclusion

The present study elucidated the meaning and types of data utilized in quantitative data analysis in the mathematical sciences and educational research. The underlying assumptions and the rationale for the use of each statistic were considered. The tests of differences and relationships were distinguished. The parametric tests were also distinguished from the non-parametric tests. The use of appropriate statistical tool (s) for data analysis in mathematical sciences and research enterprise generally by researchers or investigators based on the underlying assumptions/rationale for the use of each statistical tool, as well as the nature of the data involved is germane for unbiased data analysis and research reports. It could also be deduced that with the application of appropriate statistical tool(s) in data analysis, research findings and conclusions drawn would be meaningful enough for solving research problems (i.e. problems of humanity).

Based on the review of literature, underlying assumptions and rationale for the appropriate use of statistical tools for data analysis in research, the following implications for improvement in research data analysis and results reporting were drawn:

a. With this study, researchers would always keep in mind the basic assumptions, and rules of thumb (especially for small samples) that must be justified for a statistical tool to be used for analysis to minimize the error level in the data analysis, presentation, interpretation and reporting.
b. This study, when duly digested and put into practice, could help researchers or investigators to enhance the quality and reality of their research findings and thus enable the sensitivity of the findings to be assessed.
c. In addition, it is possible that with the use of appropriate statistical tool (s) for data analysis, researchers would be able to draw meaningful conclusions and inferences in their studies which could, in turn, increase the public trust and usability of research reports.
d. Researchers would find this article as a practical guide to quantitative data analysis and research reporting.

Recommendations

1. Researchers should endeavour to consider the basic assumptions and the rationale underlying the use of any quantitative statistical technique before utilizing it for data analysis to ensure reliability in their research findings.
2. Researchers should always consider the type of data and the number of groups involved when deciding on the statistical test to carry out in any study because convenience in the use of specific statistics cannot be a yardstick for its utilization in all cases.
3. Data analysts and statisticians should do well to transform those data which could not meet the parametric assumptions before carrying out the analysis to enable them to compute the proposed parametric test appropriately; else a suitable non-parametric alternative test could be carried out where necessary.
4. For data transformation, logarithm, the square root and reciprocal are good choices for carrying out data transformation.

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