APPLICATION OF STATISTICAL TOOLS IN SOCIAL SCIENCE RESEARCH – A COMPARATIVE STUDY BETWEEN PARAMETRIC TEST AND NON-PARAMETRIC TEST

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ABSTRACT

Statistics is a wide subject useful in almost all disciplines especially in Research studies. Each and every researcher should have some knowledge in Statistics and must use statistical tools in his or her research, one should know about the importance of statistical tools and how to use them in their research or survey. The comparison of parametric and nonparametric is essential while choosing the statistical tools. Hence in this paper, I have made an attempt to give a brief report or comparative study of parametric and nonparametric test used in research studies.

Keywords:- *Statistical Tools, Research, Analysis etc,.*

INTRODUCTION

The subject Statistics is widely used in almost all fields like Biology, Botany, Commerce, Medicine, Education, Physics, Chemistry, Bio-Technology, Psychology, Zoology etc.. While doing research in the above fields, the researchers should have some awareness in using the statistical tools which helps them in drawing rigorous and good conclusions. The most well known Statistical tools are the mean, the arithmetical average of numbers, median and mode, Range, dispersion, standard deviation, inter quartile range, coefficient of variation, etc. There are also software packages like SAS and SPSS which are useful in interpreting the results for large sample size.

The Statistical analysis depends on the objective of the study. The objective of a survey is to obtain information about the situation of the population study. The first Statistical task is therefore is to do a descriptive analysis of variables. In this analysis it is necessary to present results obtained for each type of variable. For qualitative and dichotomous variables, results must be presented as frequencies and percentages. For quantitative variables, the presentation is as means and deviations. After this analysis, you can access the association between variables and predictive analysis based on multiple regression models. You can also use software packages like SPSS, EP Info, STATA, Minitab, Open Epi, Graph pad and many others depending on your usage and familiarity with the software. You should also start looking at the distributions of age, gender, race and any measures of socio-economic status that you have (income, education level, and access to medical care). These distributions will help to inform your analysis in terms of possible age- adjustment, weighting and another analytical tool available to address issues of bias and non representative samples.

HISTORY OF STATISTICS

The word ‘statistics’ derives from the modern Latin term statisticum collegium (council of state) and the Italian word statista (statesman or politician). ‘Statistics’ was used in 1584 for a person skilled in state affairs, having political knowledge, power or influence by Sir William Petty, a seventeenth-century polymath and statesman, used the phrase ′political arithmetic′ for ‘statistics’. (A book entitled Sir William Petty, 1623–1687, written by Lord Edmond Fitzmaurice, and published in London in 1895, quotes Petty as saying that ‘By political arithmetic, we mean the art of reasoning by figures upon things relating to government’.) By 1787, ‘statistic’ (in the singular), meant the science relating to the branch of political science dealing with the collection, classification and discussion of facts bearing on the condition of a state or a community.

'Statists' were specialists in those aspects of running a state which were particularly related to numbers. This encompassed the tax liabilities of the citizens as well as the state's potential for raising armies. The word 'statistics' is possibly the descendant of the word 'statist'.

By 1837, statistics had moved into many areas beyond government. Statistics, used in the plural, were (and are) defined as numerical facts (data) collected and classified in systematic ways. In current use, statistics is the area of study that aims to collect and arrange numerical data, whether relating to human affairs or to natural phenomena.

STATISTICS

Statistics is a range of procedures for gathering, organising, analysing and presenting quantitative data. 'Data' is the term for facts that have been obtained and subsequently recorded, and, for statisticians, 'data' usually refers to quantitative data that are numbers. Essentially therefore, statistics is a scientific approach to analysing numerical data in order to enable us to maximise our interpretation, understanding and use. This means that statistics helps us turn data into information; that is, data that have been interpreted, understood and are useful to the recipient. Put formally, for your project, statistics is the systematic collection and analysis of numerical data, in order to investigate or discover relationships among phenomena so as to explain predict and control their occurrence. The possibility of confusion comes from the fact that not only is statistics the techniques used on quantitative data, but the same word is also used to refer to the numerical results from statistical analysis. In very broad terms, statistics can be divided into two branches – descriptive and inferential statistics.

1. Descriptive statistics is concerned with quantitative data and the methods for describing them. ('Data' (facts) is the plural of 'datum' (a fact), and therefore always needs a plural verb.) This branch of statistics is the one that you will already be familiar with because descriptive statistics are used in everyday life in areas such as government, healthcare, business, and sport.

2. Inferential (analytical) statistics makes inferences about populations (entire groups of people or firms) by analysing data gathered from samples (smaller subsets of the entire group), and deals with methods that enable a conclusion to be drawn from these data. (An inference is an assumption, supposition, deduction or possibility.) Inferential statistics starts with a hypothesis (a statement of, or a conjecture about, the relationship between two or more variables that you intend to study), and investigates whether the data are consistent with that hypothesis. Because statistical processing requires mathematics, it is an area that is often approached with discomfort and anxiety, if not actual fear. Which is why this book tells you which statistics to use, why those statistics, and when to use them, and ignores the explanations (which are often expressed mathematically) of the formulae in which they tend to be articulated, though it does give advice on what you should bear in mind when planning your data collection.

One of the major problems any researcher faces is reducing complex situations or things to manageable formats in order to describe, explain or model them. This is where statistics comes in. Using appropriate statistics, you will be able to make sense of the large amount of data you have collected so that you can tell your research story coherently and with justification. Put concisely, statistics fills the crucial gap between information and knowledge.

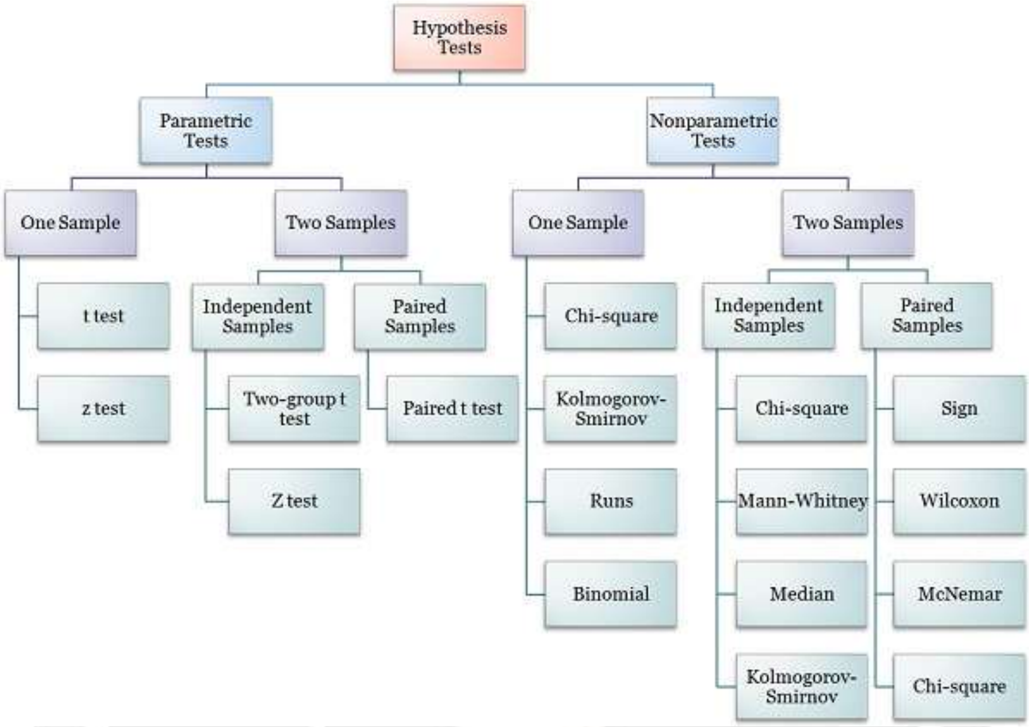
ROLE OF STATISTICS IN RESEARCH

In research, use of statistics is of direct importance to you while collecting and analyzing data. The results and findings will be more accurate, more believable and, consequently, more useful. Some of the reasons using statistics to analyze data are the same reasons why you are doing the research. Ignoring the possibility that you are researching because the project or dissertation element is compulsory, rather than because the researcher very much want to find something out, researcher are likely to be researching the followings:

- Measure things;
- Examine relationships;
- Make predictions;
- Test hypotheses;
- Construct concepts and develop theories;
- Explore issues;
- Explain activities or attitudes;
- Describe what is happening;
- Present information;
- Make comparisons to find similarities and differences;
- Draw conclusions about populations based only on sample results.

These results are outcome of analyzing the data from parametric and nonparametric test. The use of parametric and nonparametric test to exhibit the outcome in which the researcher expects.

HYPOTHESIS TESTS HIERARCHY



COMPARISON CHART

BASIS FOR COMPARISON	PARAMETRIC TEST	NONPARAMETRIC TEST
Meaning	A statistical test, in which specific assumptions are made about the population parameter, is known as parametric test.	A statistical test used in the case of non-metric independent variables, is called non-parametric test.
Basis of test statistic	Distribution	Arbitrary
Measurement level	Interval or ratio	Nominal or ordinal
Measure of central tendency	Mean	Median
Information about population	Completely known	Unavailable
Applicability	Variables	Variables and Attributes
Correlation test	Pearson	Spearman

PARAMETRIC TESTS Vs NON-PARAMETRIC TESTS

The researcher has the plenty of opportunity to choose the statistical tools on the basis of their data. The comparison of parametric and non-parametric test is given below:

I. TESTS OF CENTRAL TENDENCY

A. One sample

Parametric Tests

1. Single Sample z Test

a. What it tests: Whether a sample of subjects or objects comes from a population – does the sample mean equal the population mean?

b. Limitations: You must know the standard deviation and mean of the population.

c. Assumptions: The sample represents the population. The sample was randomly selected. The population is normally distributed.

2. Single-Sample t Test

a. What it tests: Whether a sample of subjects or objects comes from a population – does the sample mean equal the population mean?

b. Limitations: You must know the mean of the population

c. Assumptions: The sample represents the population. The sample was randomly selected. The population is normally distributed.

Non-parametric Tests

1. Wilcoxon Signed-Ranks Test

a. What it tests: Whether a sample of subjects or objects comes from a population – does the sample median equal the population median?

b. Limitations: You must know the median of the population.

c. Assumptions: The sample is representative of the population. The sample was randomly selected. The population distribution is symmetrical.

B. Two or more independent samples

Parametric Tests

1. *t Test for Two Independent Samples*

a. What it tests: Do two independent samples represent two different populations with different mean values

b. Limitations: You can only compare two samples, no more

c. Assumptions: The samples are representative of the populations. The samples were randomly selected. The samples are independent. Both populations are normally distributed. The variances of the two populations are equal.

2. *Single Factor Between-Subjects or One Way Analysis of Variance (ANOVA)*

a. What it tests: In a group of any number of samples (three, five, ten), do at least two of the samples represent populations with different mean values?

b. Additional procedures: This test does not tell you which of the means differed – just that there was a difference between some of them. For planned comparisons you may use multiple t tests to determine which means differ. For unplanned tests you may use Fisher's LSD test to determine which means differ.

c. Limitations: Only one independent variable d. Assumptions: Samples are representative of the populations. The samples were selected randomly. The samples are independent. All of the populations are normally distributed. The variances of all of the populations are equal.

3. Single Factor Between-Subjects Analysis of Covariance (ANCOVA)

a. What it tests: It is a form of ANOVA. It allows you to use data about an extraneous (non-experimental) variable that has a linear correlation with the dependent variable to (1) remove variability in the dependent variable and/or (2) adjust the mean scores of the different groups for any pre-existing differences in the dependent variable that were present prior to the administration of the experimental treatments. The most commonly used co-variate (the extraneous or non-experimental variable) is a pretest score for the dependent variable.

b. Limitations: Only one extraneous variable. Single factor ANCOVA is sometimes used for a design in which subjects are not randomly assigned to groups (quasi-experimental designs). This use is problematic! This includes in some cases using single factor ANCOVA for inferential designs (ex post facto studies where the group are based on something like sex, income or race). This is even more problematic!

c. Assumptions: Samples are representative of the populations. All of the populations are normally distributed. The variances of all of the populations are equal.

Non-parametric Tests

1. Mann-Whitney U Test

a. What it tests: Do two independent samples represent two populations with different median values?

b. Limitations: You can only compare two samples, no more. Do not use this test for proportions (percentages).

c. Assumptions: The samples are representative of the populations. The samples were randomly selected. The samples are independent. The original variable that was measured was a continuous random variable. The distributions of the populations are identical in shape.

C. Two or More Dependent Samples

Parametric Tests

1. t Test for Two Dependent Samples

a. What it tests: Do two dependent samples represent populations with different mean values?

b. Limitations: Only two samples (groups, populations)

c. Samples are representative of the populations. Samples were randomly selected. Both populations are normally distributed. The variances of the two populations are equal.

2. Single Factor Within-Subjects ANOVA

a. What it tests: In a group of any number of dependent samples (three, five, ten), do at least two of the samples represent populations with different mean values?

b. Additional procedures: This test does not tell you which of the means differed – just that there was a difference between some of them. For planned comparisons you may use multiple t tests to determine which means differ. For unplanned tests you may use Fisher's LSD test to determine which means differ.

c. Limitations: Only one independent variable

d. Assumptions: Samples are representative of the populations. Samples were randomly selected. All of the populations are normally distributed. The variances of all of the populations are equal.

Non-parametric Tests

1. Wilcoxon Matched Pairs Signed Ranks Test

a. What it tests: Do two dependent samples represent two different populations?

b. Limitations: Only two samples, no more. You must have two scores to compare for this test because it is based on the difference between the two. These can be two scores for the same subject (first as a control and then as a treatment) or two scores for matched pairs of subjects (one in the control group and one in the treatment group).

c. Assumptions: Samples are randomly selected. Samples are representative of the populations. The distribution of the difference scores in the populations is symmetric around the median of the population of difference scores.

2. Binomial Sign Test for Two Dependent Samples

a. What it tests: Do two dependent samples represent two different populations?

b. Limitations: Only two samples. You need two scores. This test is based on whether the subject's (or matched pairs of subjects) score increases or decreases – by the sign (positive or negative). You can use this test with the assumption of symmetric distribution for the Wilcoxon Matched Paris Test is violated.

c. Assumptions: Samples are randomly selected. Samples are representative of the populations.

3. Friedman Two-Way Analysis of Variance by Ranks

a. What it tests: In a group of any number of dependent samples (three, five, ten), do at least two of the samples represent populations with different median values?

b. Additional procedures: Like the parametric ANOVA, the Kruskal-Wallace test does not tell you which of the means differed. You must perform pairwise comparisons to determine where the differences lie. See a good statistics book to learn how to do this. You can use the Wilcoxon matched pairs signed ranks test or the binomial sign test for two dependent samples.

c. Assumptions: Samples are randomly selected. Samples are representative of the populations. The original variable that was measured was a continuous random variable (this assumption is often violated – no idea if that's OK or not, but Sheskin does not seem to think it is a big deal).

II. TESTS OF DISPERSION

A. Single sample

Parametric Tests

1. Single Sample Chi-Square Test for Population Variance

a. What it tests: Does a sample come from a population in which the variance equals a known value?

b. Limitations: You must know the variance of the population.

c. Assumptions: The sample was selected randomly. The sample is representative of the population. The population is normally distributed.

Non-parametric Tests

1. NONE

B. Two or more independent samples

Parametric Tests

1. Hartley's F (max) Test for Homogeneity of Variance

a. What it tests: Are the variances of two or more populations equal?

b. Assumptions: The samples were selected randomly. The samples are representative of the populations. The populations are normally distributed. Sample sizes should be equal or approximately equal.

Non-parametric Tests

1. The Siegel-Tukey Test for Equal Variability

a. What it tests: Do two independent samples represent two populations with different variances?

b. Limitations: You must know or be willing to make some assumptions about the medians of the two populations (see assumption 3 below).

c. Assumptions: The samples were randomly selected. They are representative of the populations and they are independent. The samples represent populations with equal medians. If you know the medians of the populations and they are not equal, you can perform some adjustments and still use this test. If you do not know the medians and you are unwilling to assume they are equal (probably normally the case), do not use this test.

2. Moses Test for Equal Variability

a. What it tests: Do two independent samples represent two populations with different variances?

b. Limitations: The data for the dependent variable must have been interval or ratio data originally that were later transformed to ordinal data and the dependent variable must have been a continuous variable (not discrete).

c. Assumptions: The samples were randomly selected. The samples are independent and representative of the populations. The original data for the dependent variable were interval or ratio data (they were transformed to ordinal data later). The original data for the dependent variable were continuous (could assume any value). The distribution of two or more populations must have the same general shape (although it need not be normal).

III. TESTS OF DISTRIBUTION

A. One Sample

Parametric Tests

1. Single Sample Test for Evaluating Population Skewness

a. What it tests: Does the sample come from a population distribution that is symmetrical (not skewed)?

b. Limitations: None c. Assumptions: The sample is representative of the population. The sample was randomly selected.

2. Single Sample Test for Evaluating Population Kurtosis

a. What it tests: Does the sample come from a population distribution that is mesokurtic (not peaked)?

b. Limitations: None c. Assumptions: The sample is representative of the population. The sample was randomly selected.

3. D'Agostino-Pearson Test of Normality

a. What it tests: Does the sample come from a population that is normally distributed? b. Limitations: None c. The sample is representative of the population. The sample was randomly selected.

Non-parametric Tests

1. Kolmogorov-Smirnov Goodness-of-Fit Test for a Single Sample

a. What it tests: Does the distribution of scores in a sample conform to a specific theoretical or empirical (known) population distribution?

b. Limitations: You must know the distribution of the population. This can be a theoretical distribution (such as the normal distribution) or an empirical (real) distribution. The dependent variable must be continuous (not discrete). This tests takes continuous the continuous variable and converts the data into a cumulative frequency (hence it becomes nonparametric data) – but you must start with a continuous variable.

c. Assumptions: The samples were randomly selected. The samples are independent and representative of the populations. The original data for the dependent variable were continuous (could assume any value).

2. Lillefor's Test for Normality

a. What it tests: Does the distribution of scores in a sample conform to a population distribution for which either the mean or the standard deviation (or both) must be estimated (an unknown distribution)?

b. Limitations: The dependent variable must be continuous (not discrete). This tests takes continuous the continuous variable and converts the data into a cumulative frequency (hence it becomes nonparametric data) – but you must start with a continuous variable.

c. Assumptions: The samples were randomly selected. The samples are independent and representative of the populations. The original data for the dependent variable were continuous (could assume any value).

IV. MEASURES OF ASSOCIATION

A. Bivariate Measures

Parametric Tests

1. Pearson Product-Moment Correlation Coefficient

a. What it tests: Is there a significant linear relationship between two variables (X or predictor and Y or criterion or predicted) in a given population?

b. Other calculations needed: The “size” of the Pearson correlation coefficient (r) in and of itself may or may not indicate a statistically significant relationship between predictor variables and the criterion variable. At a minimum, you should use a Table of Critical Values for Pearson r and report this value when you use this statistic. The values vary for one-tailed and two-tailed hypotheses. Large r values can be meaningless. Alternatively, small values can be meaningful! You may also need to conduct one or more other tests for evaluating the value of the coefficients. Failure to take this step is common and makes many presentations of measures of association fairly useless. The “r” value alone is not enough!

c. Limitations: This is a bivariate measure – only two variables

d. Assumptions: The sample was randomly selected and represents the population. The two variables have a bivariate normal distribution – each of the two variables and the linear combination of the two variables are normally distributed. The relationship between the predictor (X) and criterion (Y or predicted) variables is of equal strength across the whole range of both variables (homoscedasticity). There is no autocorrelation between the two variables.

Non-parametric Tests

1. Spearman’s Rank-Order Correlation Coefficient

a. What it tests: In a sample from a population is there a correlation (relationship) Information about Statistical Tests - 11 between subjects’ scores on two different variables? Put another way, does a test subject’s score for Variable 1 (X) predict his/her score for Variable 2 (Y)?

b. Other calculations needed: The “size” of the Spearman’s rank-order correlation coefficient (rs) or Spearman’s Rho in and of itself may or may not indicate a statistically significant relationship between the two variables. You use a Table of Critical Values for Spearman’s Rho to determine significance. There are equations you can use, too, one of which gives a t value and one of which gives a z value. The values vary for one-tailed and two-tailed hypotheses. Large rs values can be meaningless. Alternatively, small values can be meaningful! You may also need to conduct one or more other tests for evaluating the value of the coefficients. Failure to take this step is common and makes many presentations of measures of association fairly useless. The “rs” value alone is not enough!

c. Limitations: Only two variables

d. Assumptions: The sample was randomly selected and represents the population. The relationship between the predictor (X) and criterion (Y or predicted) variables is of equal strength across the whole range of both variables (homoscedasticity).

B. Multivariate Measures

Parametric Tests

1. Multiple Correlation Co-efficient

a. What it tests: Is there a significant linear relationship between two or more predictor (X) variables and a criterion (Y or predicted) variable in a given population? b. Other calculations needed: The “size” of the multiple correlation coefficient (R) in and of itself may or may not indicate a statistically significant relationship between predictor variables and the criterion variable. At a minimum, you should compute the R2 statistic – the coefficient of multiple determination. Then compute the F statistic for R2. Use a Table of the F Distribution to determine significance. Large R values can be meaningless. Alternatively, small values can be meaningful! You may also need to conduct one or more other tests for evaluating the value of the coefficient. Failure to take this step is common and makes many presentations of measures of association fairly useless. The “R” or “R2” value alone is not enough!

c. Limitations: Although you can use a large number of predictor variables, the additional predictive power gained from adding more variables to the model decreases greatly after a few “good” predictors have been identified.

d. Assumptions: The sample was randomly selected and represents the population. The variables have a bivariate normal distribution – each of the variables and the linear combination of the variables are normally distributed. The relationship between the predictor (X) and criterion (Y or predicted) variables is of equal strength across the whole range of both variables (homoscedasticity). There is no multicollinearity between the predictor variables – they are not strongly correlated to each other.

2. Partial Correlation Coefficient

a. What it tests: What is the strength of the relationship between one predictor variable of several and the criterion variable? Put another way, you hold the values for all other predictor variables constant and then measure the strength of the one variable that interests you. It is sort of the reverse of multiple correlation.

b. Other calculations needed: The “size” of the partial correlation coefficient (r) in an of itself may or may not indicate a statistically significant relationship between the predictor variable and the criterion variable. At a minimum, you should compute the value for t and then use a Table of Student’s t Distribution to determine significance. The values vary for one-tailed and two-tailed hypotheses. Large r values can be meaningless. Alternatively, small values can be meaningful! You may also need to conduct one or more other tests for evaluating the value of the coefficients. Failure to take this step is common and makes many presentations of measures of association fairly useless. The “r” value alone is not enough!

c. Assumptions: The sample was randomly selected and represents the population. The variables have a bivariate normal distribution – each of the variables and the linear combination of the variables are normally distributed. The relationship between the predictor (X) and criterion (Y or predicted) variables is of equal strength across the whole range of both variables (homoscedasticity).

Non-parametric Tests

1. Kendall’s Coefficient of Concordance

a. What it tests: In a sample from a population is there a correlation (relationship) between subjects’ scores on three or more different variables? Put another way, does a test subject’s score for Variables 1, 2, 3 ... (X1, X2, X3...) predict his/her score for Variable 2 (Y)?

b. Other calculations needed: The “size” of the Kendall’s coefficient of concordance (W) in and of itself may or may not indicate a statistically significant relationship between the two variables. You use a Table of Critical Values for Kendall’s Coefficient of Concordance to determine significance. You can also computer the significance using the Chi-square statistic and a Table of the Chi-Square Distrition. The values vary for one-tailed and two-tailed hypotheses. Large W values can be meaningless. Alternatively, small values can be meaningful! You may also need to conduct one or more other tests for evaluating the value of the coefficients. Failure to take this step is common and makes many presentations of measures of association fairly useless. The “W” value alone is not enough!

c. Assumptions: The sample was randomly selected and represents the population. The relationship between the predictor (X) and criterion (Y or predicted) variables is of equal strength across the whole range of both variables (homoscedasticity).

RESULT AND DISCUSSION

The fundamental differences between parametric and nonparametric test are discussed in the following points:

1. A statistical test, in which specific assumptions are made about the population parameter, is known as the parametric test. A statistical test used in the case of non-metric independent variables is called nonparametric test.
2. In the parametric test, the test statistic is based on distribution. On the other hand, the test statistic is arbitrary in the case of the nonparametric test.
3. In the parametric test, it is assumed that the measurement of variables of interest is done on interval or ratio level. As opposed to the nonparametric test, wherein the variable of interest are measured on nominal or ordinal scale.
4. In general, the measure of central tendency in the parametric test is mean, while in the case of the nonparametric test is median.
5. In the parametric test, there is complete information about the population. Conversely, in the nonparametric test, there is no information about the population.
6. The applicability of parametric test is for variables only, whereas nonparametric test applies to both variables and attributes.
7. For measuring the degree of association between two quantitative variables, Pearson’s coefficient of correlation is used in the parametric test, while spearman’s rank correlation is used in the nonparametric test.

CONCLUSION

To make a choice between parametric and the nonparametric test is not easy for a researcher conducting statistical analysis. For performing hypothesis, if the information about the population is completely known, by way of parameters, then the test is said to be parametric test whereas, if there is no knowledge about population and it is needed to test the hypothesis on population, then the test conducted is considered as the nonparametric test.

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