# What Junior Researchers Must Know Before and After Data Collection: Difference between Parametric and Nonparametric Statistics

**Joanita Kataike[1,3], Jowel Kulaba[2], Xavier Gellynck[1]**

[1]Department of Agricultural Economics, Ghent University Coupure Links 653, 9000 Ghent, Belgium

[2]Bishop Stuart University, P.O. Box 9 Mbarara Uganda

[3]School of Business and Management Studies, Mountains of the Moon University, P.O. Box Fort-Portal, Uganda

**Abstract:** ***Often junior researchers face the challenge of inadequate knowledge and skills in statistical techniques because not all academic disciplines teach statistics. Although these researchers are supposed to conduct research as part of their academic award fulfilment, one wonders how to solve a given research problem statistically without introductory classes in the past. Thus, this article attempts to explain the primary scales of measurement for survey data. Furthermore, the paper differentiates between parametric and non-parametric test statistics by explaining distinctive statistical tests required for each type of measurement scale. A cross reference was used to synthesize relevant answers for the research question. As a topic of interest, frequently Journal reviewers and editors comment on the robustness of results based on the choice of measurement scale and the test statistics used. Therefore, the authors are motivated essentially to provide a comprehensive point of reference for researchers interested in quality statistical research methods.***

**Keywords:** Parametric, Nonparametric, Data collection, Permissible statistics

## 1. Introduction

The selection of statistical tests appropriate for each research question is the most challenging feature in statistics but also the most necessary in order to eliminate measurement errors. Understanding the level of measurement is one of the initial steps of data analysis and the key to researchers regardless of the diversity and complexity in statistics. During data analysis, the choice of an appropriate statistical method is of paramount importance so as to ensure that the results communicated can be interpreted in a meaningful way [1]. Consequently, the type of data required to answer a research question should correspond with measurement scales used to collect that data. In a broader context, each scale of measurement is associated with different types of data. For instance, continuous data can take any value depending on the precision of measurement that is within a range take an example of age or height [2]. Similarly, discrete data takes a specific whole number for example number of children [3]. The above two types of data described are quantitative in nature and their associated measurement scales are interval and ratio[3, 4].

Besides, there is also data which can be grouped as a categorical which less qualitative in nature. The associated scales of measurement are nominal scale if categories have no nature order for example gender or ordinal scale if categories are organized in a certain order for instance income or level of education (low, moderate, high) but the distances between categories might not be the same [5-7]. Unless data collected is appropriate, one cannot easily choose a suitable statistical test. Therefore, the statistical test selected to analyse the data should be in accordance with the type of data collected considering the scale of measurement. However, this has been problematic to many jounior researchers. Therefore this article articulates permisseable statistical test in accordance to the data collection scales of measurement.

Notably, there are four types of measurement scales these are nominal, ordinal, interval, and ratio [8]. Nominal scale uses numbers which serve only as labels for identifying and categorizing objects [8-10]. It is mostly used in the first part of the survey questionnaire to capture data on sample characteristics however, exploratory research designs can also use a yes or no scale of measurement that is nominal in nature [7]. Nominal scale is used to measure whether individual items belong to a certain distinct category. Subcategories of nominal scale with only two categories (e.g. gender- male/female) is called dichotomous; whereas a scale with three or more categories, for instance, marital status (single, unmarried, married, divorced or widower) are known as dummy variables. Nominal data has no order because the assignment of numbers to the categorical variables is purely random [11].

Next, ordinal scale, this is a ranking scale in which numbers are assigned to objects to indicate the relative extent to which the objects possess some characteristics [8, 12]. With ordinal scales, it is the order of the values which is important and significant, but the difference between each one is not really known. For instance, unhappy or very Happy [13].

The third measurement scale is an interval scale that numerically represent equal distances on the scale of equal values for the characteristics being measured [8, 14, 15]. Interval itself means space in between, an interval scale describes a certain type of continuous data. These are numbers which are equidistant but even though they are as such, the difference between two measures does not have the same meaning. In simple terms, there is no true Zero and this is the most important thing to remember. Interval scales not only tell us about the order but also the value of each item. The commonly used interval scale is a 5 or 7-point Likert scale [15]. Take an example of temperature; a temperature of 30$^0$C is not thrice as hot as 10$^0$C. And if it is 0$^0$C, you cannot say that there is no temperature.

Finally, ratio scale is the highest scale, it allows the researcher to identify, classify or rank objects and compare intervals or difference [8]. This scale possesses all the properties of nominal, ordinal, interval and an absolute zero point [16]. The variables can be meaningfully added, subtracted, multiplied or divided ratio [13]. The central tendency can be measured by mode, median, or mean; measures of dispersion, such as standard deviation and coefficient of variation can also be calculated from ratio scales [17]. Besides tha four levels of measurement scales discussed above there are several other scales of measurement therefore, readers are refered to [8, 13] for further measurement scales such as comparative scales, non-comparative, itemised rating scales. Table I summarises the key levels of measurement and the appropriate permissible statistics.

**Table I:** Primary measurement scales

| Scale | Basic characteristics | Common examples | Marketing example | Permissible statistics | |
|---|---|---|---|---|---|
| | | | | Descriptive | Inferential |
| Nominal | Numbers identify and classify objects Yes/No | Student registration numbers, Country of origin | Classification, bank types Gender | Percentages Mode | Chi-square Binomial test |
| Ordinal | Numbers indicate the relative position of objects but not the magnitude of difference between them | Rankings of the top four teams in the football World cup | Ranking of service quality delivered by a number of hotels /banks. Rank order of the top best 100 universities | Percentile, Median | Rank order correlation Friedman ANOVA |
| Interval | Difference between objects can be compared; zero point is arbitrary | Temperatures | Attitudes, opinions, index numbers, consumer behaviour | Range, Mean Standard deviation | Product moment correlations, *t*-tests, ANOVA Regression Factor analysis |
| Ratio | Zero point is fixed ratios of scale values can be computed | Length, weight | Age income cost sales, market share | Geometric mean (centre number) Harmonic mean | Coefficient of variation |

***Source:*** [8]

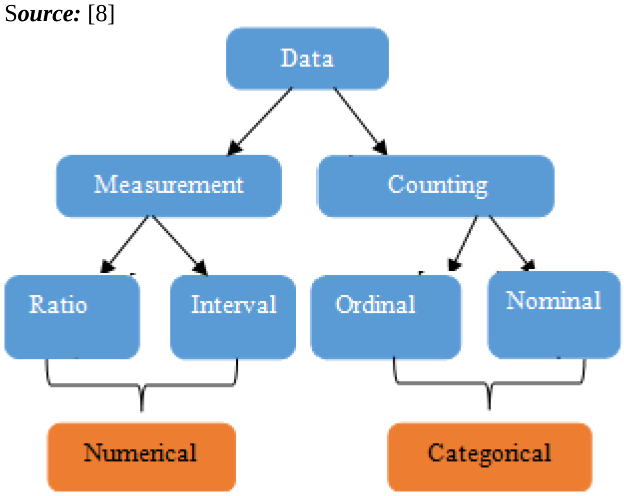


**Figure I:** Classifying levels of measurement scale
***Source:*** Author's compilation based on Norman [18] and Fellows and Liu [19]

## 2. Differences between Parametric and Nonparametric Statisitical Tests

### Parametric statistics

Parametric tests are hypothesis testing procedures which assume that the variables of interest are measured on an interval or ratio scale and observations must be drawn from the normally distributed population [8, 13, 20]. There are several examples of parametric tests in empirical context [21-28]. These studies clearly exemplify several parametric tests and their appropriateness. The appropriate use of such tests requires one to check whether the data fulfil certain assumptions or conditions.

According to [29] and [30] da[29]ta has to fillfull certain assumptions in order to run parametric tests. First, they suggest that observations should be independent i.e. when the occurrence of A does not affect the probability of B. Second, data should follow a normal distribution with mean zero and a given variance. Statistical tests such as Kolmogorov-Smirnov, Shapiro-Wilk and D'Agostino-Pearson are used under the null hypothesis to test that the sample data fits a standard normal distribution". See [31] for details on how to compute these three normality tests and explanations.

Finally, heteroscedasticity though it is a hard word to pronounce it is not difficult to understand. Heteroscedasticity refers to the circumstance in which the variability of a variable is unequal across the range of values of a second variable that predicts it [29]. It can be tested mathematically using the Levene's test or graphically by a scatterplot. For instance, the level of education can be a heteroscedastic variable when predicted by age. If your sample data fulfils the three major assumptions of parametric tests, then the researcher is free to choose from the list of parametric statistical methods relevant to a given research question. If these assumptions are not fulfilled(most especially normality), results obtained will not be reliable because data symmetry is key to conducting parametric tests.

The most popular parametric test statistics include; *t* test or student *t* test, Pearson product correlation coefficient, the z-test, and ANOVA. First, the *t*-test which is the most widely used parametric test [8]. The t- test compares the mean of two groups to see if any differences between them are statistically significant. If the p-value associated with t is low (<0.05) then there is evidence to reject the null hypothesis [32]. This implies that the two groups are statically different. It is important that the t-test can be used even when the distribution is not perfectly normal and it can be a one or two sample *t*-test.

The one sample *t*-test used to compare differences in mean scores of interval or ratio scales for normally distributed data [33]. One sample test does compare the mean of a single. So if only a single mean is calculated from the sample, one might ask himself what does the one sample t-test compare the mean with?, The one sample t-test compares the mean score found in an observed sample to the hypothetically assumed value. Typically, the hypothetically assumed value is the sample mean or some other theoretically derived value. In simple terms the null hypothesis that can be tested using a one sample t-test whereby the researcher is interested in testing whether the sample mean conforms to a given null hypothesis ($H_0$).

Unlike the two sample *t*-test which deals with samples that could be independent or paired. A two-sample *t*-test is a univariate hypothesis test using the *t* distribution which is used when the standard deviation is unknown. Therefore, the mean, standard deviation and number of samples is used to calculate the test statistic [8, 25, 33]. In a dataset with a large number of samples, the critical value for the *t*-test of 1.96 for an alpha of 0.05, obtained from a *t*-test tabular [34].

The *z*-test, it is also a univariate parametric test that uses standard normal distribution similar to *t*-test. All statistical tests are best on the area of acceptance and an area of rejection, for what is termed as one tailed test the rejection area is either the upper or lower tail of the distribution. The acceptable threshold for significant critical *z*-values of a one-tailed test is 1.96 and a significant level of 0.05. A one tailed test is used when the hypothesis is directional meaning that the predicted outcome is at either the upper or lower end of the distribution. Note that if the population standard deviation was assumed to be known rather than estimated from the sample, a *z*-test would be appropriate. However, with the *z*-test the variance of the standard population is used to obtain the *z*-test statistics rather than the standard deviation of the study groups [13]. Furthermore, the z-chart can generate the percentage of the standard population outside the mean of the sample population and if the test is greater than 95% of the standard population on one-tailed mean, the p-value is less than 0.05 then the statistical significance is achieved [33]. The counterpart (two-tailed test)

Pearson product correlation coefficient (often referred to as Pearson's r) is a measure of the linear correlation between two variables X and Y [13]. The correlation coefficient (r) or Pearson's r is a value which explains how well two continuous variables from the same sample correlate with each other. It is just an association not a causal relationship. The value for r is between 1.0 (strong positive relationship) and -1.0 (strong negative relationship). It is important to note that during construct conceptualization the researcher should have two types of constructs that are; independent and dependent in nature so as to predict the correlation using Pearson's r parametric test.

Finally, ANOVA (Analysis of Variance) is a statistical technique for examining the difference among means of two or more groups [8]. The null hypothesis is stated while performing ANOVA to test whether the means and variances are the same across the groups. The statistics of ANOVA is called the F-ratio/value [32]. As with the t and z statistics, the f statistic is compared with an F distribution table to determine whether it is greater the given critical values. Besides, ANOVA may be performed in various forms, for instance, MANOVA; a two-way multivariate analysis of variance, a researcher may have several independent and dependent variables and wish to test for differences in two or more vector means. Other statistical tests such as covariance analysis or ANCOVA also are part of ANOVA in multivariate perspective.

## 3. Non-Parametric Statistics

When data fails to fulfil the assumptions of a parametric test, researchers opt for non-parametric tests given the fact that they are less restrictive. The test can also be used for small sample size of <30. Therefore, non-parametric tests are used when the variables are non-metric. Although non-parametric tests do not require restrictive statistical assumptions, it is recommendable that the sample obtains a criteria that is; computing the same aggregates for instance, mode, median, range [35]. Furthermore, non-parametric tests also assume that the variables are measured on a nominal or ordinal scale [8]. The tests can further be categorised depending on whether one or two samples are involved (*see Figure 2 for various tests).* The widely used non-parametric tests are discussed below.

First will briefly look at the Chi-square. In order to conduct this test, there must be two types of random variables with one being numerical and the other categorical of dichotomous. The chi-square ($x^2$) test is used to determine whether the distribution of categorical variables differ from one another. For instance, gauging consumer perception of a given product in comparison to men and women. The test also helps to investigate whether a frequency distribution observed could real or have resulted by chance. If the difference observed between the variables is small, then probably chance is the only factor to consider. On the contrary, if the difference is large something else causing it (intervening variables). More so, in advanced statistics chi-square determines the goodness of fit as one of the model fit indices [36, 37].

Secondly, Spearman rank coefficient has two rank data points and the test statistic values range from 1.0 to -1.0 for positive and negative coefficients respectively. Similar to Pearson product correlation coefficients, the test is conducted to predict how well two individual variables X and Y predict each other. However, it is important to note that data obtained need not to be linear. Several empirical and conceptual studies have been conducted to elaborate this test, for instance, [38] provides an in-depth analysis on when and how Spearman rank coefficient should be used. [39] explored consumer preferred food attributes in India using the same test. Many business research have used Spearman rank coefficient test for instance [40-43].

Thirdly, Mann-Whitney U test is a non-parametric test measured on an ordinal scale. Alternatively, the test is known as Wilcoxon rank test because it was initially developed by Wilcoxon in 1945 for two samples of the same size. Further developed by Mann and Whitney in 1947 to incorporate different sample sizes. Therefore, Mann-Whitney U test is used to compare the median of different two independent groups when the dependent variable is either ordinal or continuous. Most statistical software will give you a p-value to judge whether a significant difference exist. The recent practical examples [44-47] explicitly demonstrate Mann-Whitney U test. The test is also mathematically similar to conducting an independent sample t-test with ranked values and is the mathematical basis for the H-test known as Kruskal Wallis H which is basically a series of pairwise Mann-Whitney U test.

Finally, the Kruskal-Wallis test known as one-way ANOVA on ranks, uses ranks of ordinal data to perform an analysis to determine if there is statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable [48]. Similar to Mann-Whitney U test, Kruskal Wallis test ranks grouped data into rank order and individual sums of the different groups to compute the H values of the test statistic. The degrees of freedom used to find the critical values is the number of group minus 1 [33]. Empirical examples which give a detailed elaboration on Kruskal Wallis test are [49-52].

**Table II:** Narrative difference between parametric and nonparametric tests

| Parametric | Nonparametric |
|---|---|
| Null hypothesis is made on the parameter of the population distribution | The null hypothesis is free from parameters |
| The population must have the same variances | Variable under study has underlying continuity |
| Information about the population is completely known | No information about the population is known |
| A parametric test focuses on the mean | Nonparametric focuses on order or ranking |
| Parametric statistical procedures rely on assumptions about the shape of the distribution | Less or no assumptions made |

***Source:*** Own compilation

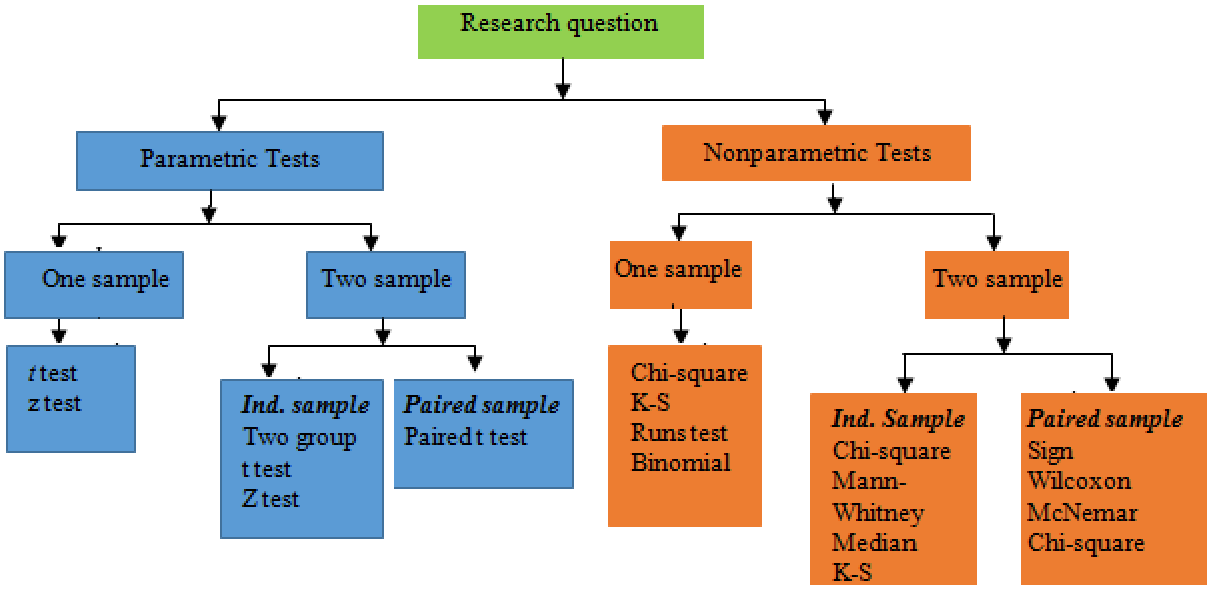


**Figure II:** Classification of a one and two sample tests
***Sources:*** adapted from [8, 13]

## 4. Conclusion

The distinction between the two statistical techniques i.e. parametric and nonparametric is very important for quality empirical research as aforementioned, therefore, Figure II illustrates the two tests based on two sample types for independent and paired samples. As Table II narratives the main differences between these two tests. In the context of our research question that is; what a junior researcher must know before and after data collection in educational research is the difference between parametric and nonparametric tests. Usually parametric tests are conducted in relation to alternative hypothesis of group differences. Whereas nonparametric tests are null hypothesis testing.

In the case of parametric, the t-test is used to examine hypothesis related to the population mean. It is important to note that in the family of t tests different tests are suitable for testing hypotheses based on the sample type as illustrated in Figure II, one sample, independent sample or paired sample. In regard to parametric test assumptions, the test for normality is usually troublesome for small sample size less than 30, in such instances nonparametric tests are the best option. However, parametric tests have robust statistical power compared to nonparametric. In other words, the power efficiency of parametric tests is stronger than nonparametric.

In conclusion, reviewers and statisticians often criticise the choice of statistical method given the level of measurement scale. Thus, researchers have to be aware of what test statistic is suitable for their research question before data collection in order to mitigate the causes of measurement error. Like any other study, our study also has certain limitations. First, although we have differentiated between the parametric and nonparametric tests and the explained the primary measurement scales, there is need for further differentiation of these statistical tests in the perspective of advanced statistical techniques such as regression analysis, structural equation modeling and multilevel analyses. Second, the debate of power efficiency between parametric and nonparametric tests is still unsolved, therefore an integrative empirical study comparing the two statistical tests would harmonise this debate.

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## Author Profile

**Joanita Kataike** is a Ph.D. researcher at the Department of Agricultural Economics, Faculty of Bioscience Engineering, Ghent University. Analysing the impact of chain governance structures and performance measurement: A case of triad agrifood sector. Lecturing at Mountains of the Moon University, in field of Quantitative Research methods, Applied Statistics and Marketing Research. Joanita Kataike is the corresponding author, can be contacted at; Joanita.Kataike@UGent.be or joanitakat@gmailcom

**Jowel Kulaba,** is an enthusiastic researcher and his research interests are in Public Health, Medical Laboratory, Epidemiology & Biostatistics. Jowel is completing his bachelors' degree in Public Health at Bishop Stuart University, Mbarara Uganda. He can be contacted at; joel.kulaj@gmail.com

**Xavier Gellynck** is a professor at the Department of Agricultural Economics, Faculty of Bioscience Engineering Ghent University. As head of the division of Agri-food Marketing and Chain Management he is involved in several research projects related to topics on chain and network management, innovation and relationship performance, and b-2-b marketing in the Agri-food sector. He can be contacted at Xavier.Gellynck@UGent.be