INTRODUCTION

Statistics is a branch of science that deals with the collection, organisation, analysis of data and drawing of inferences from the samples to the whole population. This requires a proper design of the study, an appropriate selection of the study sample and choice of a suitable statistical test. An adequate knowledge of statistics is necessary for proper designing of an epidemiological study or a clinical trial. Improper statistical methods may result in erroneous conclusions which may lead to unethical practice.

VARIABLES

Variable is a characteristic that varies from one individual member of population to another individual. Variables such as height and weight are measured by some type of scale, convey quantitative information and are called as quantitative variables. Sex and eye colour give qualitative information and are called as qualitative variables [Figure 1].

Quantitative variables

Quantitative or numerical data are subdivided into discrete and continuous measurements. Discrete numerical data are recorded as a whole number such as 0, 1, 2, 3… (integer), whereas continuous data can assume any value. Observations that can be counted constitute the discrete data and observations that can be measured constitute the continuous data. Examples of discrete data are number of episodes of respiratory arrests or the number of re-intubations in an intensive care unit. Similarly, examples of continuous data are the serial serum glucose levels, partial pressure of oxygen in arterial blood and the oesophageal temperature.

A hierarchical scale of increasing precision can be used for observing and recording the data which is based on categorical, ordinal, interval and ratio scales [Figure 1].

ABSTRACT

Statistical methods involved in carrying out a study include planning, designing, collecting data, analysing, drawing meaningful interpretation and reporting of the research findings. The statistical analysis gives meaning to the meaningless numbers, thereby breathing life into a lifeless data. The results and inferences are precise only if proper statistical tests are used. This article will try to acquaint the reader with the basic research tools that are utilised while conducting various studies. The article covers a brief outline of the variables, an understanding of quantitative and qualitative variables and the measures of central tendency. An idea of the sample size estimation, power analysis and the statistical errors is given. Finally, there is a summary of parametric and non-parametric tests used for data analysis.

Key words: Basic statistical tools, degree of dispersion, measures of central tendency, parametric tests and non-parametric tests, variables, variance
Categorical or nominal variables are unordered. The data are merely classified into categories and cannot be arranged in any particular order. If only two categories exist (as in gender male and female), it is called as a dichotomous (or binary) data. The various causes of re-intubation in an intensive care unit due to upper airway obstruction, impaired clearance of secretions, hypoxemia, hypercapnia, pulmonary oedema and neurological impairment are examples of categorical variables.

Ordinal variables have a clear ordering between the variables. However, the ordered data may not have equal intervals. Examples are the American Society of Anesthesiologists status or Richmond agitation-sedation scale.

Interval variables are similar to an ordinal variable, except that the intervals between the values of the interval variable are equally spaced. A good example of an interval scale is the Fahrenheit degree scale used to measure temperature. With the Fahrenheit scale, the difference between 70° and 75° is equal to the difference between 80° and 85°: The units of measurement are equal throughout the full range of the scale.

Ratio scales are similar to interval scales, in that equal differences between scale values have equal quantitative meaning. However, ratio scales also have a true zero point, which gives them an additional property. For example, the system of centimetres is an example of a ratio scale. There is a true zero point and the value of 0 cm means a complete absence of length. The thyromental distance of 6 cm in an adult may be twice that of a child in whom it may be 3 cm.

STATISTICS: DESCRIPTIVE AND INFERENTIAL STATISTICS

Descriptive statistics on categorical variables are unordered. The data are merely classified into categories and cannot be arranged in any particular order. Ordinal variables have a clear ordering between the variables. However, the ordered data may not have equal intervals. Interval variables are similar to ordinal variables, except that the intervals between the values of the interval variable are equally spaced. Ratio scales are similar to interval scales, in that equal differences between scale values have equal quantitative meaning. However, ratio scales also have a true zero point, which gives them an additional property. For example, the system of centimetres is an example of a ratio scale. There is a true zero point and the value of 0 cm means a complete absence of length. The thyromental distance of 6 cm in an adult may be twice that of a child in whom it may be 3 cm.

Descriptive statistics on interval variables try to describe the relationship between variables in a sample or population. Descriptive statistics provide a summary of data in the form of mean, median and mode. Inferential statistics use a random sample of data taken from a population to describe and make inferences about the whole population. It is valuable when it is not possible to examine each member of an entire population. The examples if descriptive and inferential statistics are illustrated in Table 1.

Descriptive statistics
The extent to which the observations cluster around a central location is described by the central tendency and the spread towards the extremes is described by the degree of dispersion.

Measures of central tendency
The measures of central tendency are mean, median and mode. Mean (or the arithmetic average) is the sum of all the scores divided by the number of scores. Mean may be influenced profoundly by the extreme variables. For example, the average stay of organophosphorus poisoning patients in ICU may be influenced by a single patient who stays in ICU for around 5 months because of septicaemia. The extreme values are called outliers. The formula for the mean is:

\[
\text{Mean} = \frac{\sum x}{n}
\]

Where \(x\) is the score of each individual and \(n\) is the number of scores.

Table 1: Example of descriptive and inferential statistics

| Descriptive statistics |
|------------------------|
| The intracranial pressures (mmHg) of 10 patients admitted with severe head injury in Intensive Care Unit are 13, 32, 35, 42, 30, 19, 32, 27, 36 and 31. These data can be summarised to best represent the observations. We can rank the observations from lowest to highest: 13,19,27,30,31,32,32, 35, 36 and 42. We get now a clearer idea of the intracranial pressures in severe head injury. The idea about the commonly observed values 9 (the smaller and larger values less represent our sample) |
| The sample mode (most commonly observed value) is 32 |
| Mean value is 29.7 mmHg |

| Inferential statistics |
|------------------------|
| If one plans to study the association of learning disabilities after exposure to anaesthesia before the age of 4 years, it will be feasible to compare the learning disabilities between children who have received anaesthesia and those who have not received anaesthesia |
| It is impossible to measure the learning disability in all children of an entire population. However, it is possible to measure the learning disability in a representative random sample in different schools and draw inferences that could be applicable to the whole population |
Mean, \( \bar{x} = \frac{\sum x}{n} \) where \( x \) = each observation and \( n \) = number of observations.

Median \( [6] \) is defined as the middle of a distribution in a ranked data (with half of the variables in the sample above and half below the median value) while mode is the most frequently occurring variable in a distribution. Range defines the spread, or variability, of a sample.

It is described by the minimum and maximum values of the variables. If we rank the data and after ranking, group the observations into percentiles, we can get better information of the pattern of spread of the variables. In percentiles, we rank the observations into 100 equal parts. We can then describe 25%, 50%, 75% or any other percentile amount. The median is the 50\( ^{th} \) percentile. The interquartile range will be the observations in the middle 50% of the observations about the median (25\( ^{th} \)–75\( ^{th} \) percentile).

Variance \( [7] \) is a measure of how spread out is the distribution. It gives an indication of how close an individual observation clusters about the mean value. The variance of a population is defined by the following formula:

\[
\sigma^2 = \frac{\sum (X_i - \mu)^2}{N}
\]

where \( \sigma \) is the population variance, \( X_i \) is the population mean, \( X_i \) is the \( i \)th element from the population and \( N \) is the number of elements in the population. The variance of a sample is defined by slightly different formula:

\[
s^2 = \frac{\sum (x_i - \overline{x})^2}{n-1}
\]

where \( s \) is the sample variance, \( x \) is the sample mean, \( x_i \) is the \( i \)th element from the sample and \( n \) is the number of elements in the sample. The formula for the variance of a population has the value '1' as the denominator. The expression '1' is known as the degrees of freedom and is one less than the number of parameters. Each observation is free to vary, except the last one which must be a defined value. The variance is measured in squared units.

The square root of the variance is the standard deviation (SD). The SD of a population is defined by the following formula:

\[
\sigma = \sqrt{\frac{\sum (X_i - \mu)^2}{N}}
\]

where, \( \mu \) is the population mean, \( X_i \) is the population mean, \( X_i \) is the \( i \)th element from the population and \( N \) is the number of elements in the population. The SD of a sample is defined by slightly different formula:

\[
s = \sqrt{\frac{\sum (x_i - \overline{x})^2}{n-1}}
\]

where \( s \) is the sample SD, \( x \) is the sample mean, \( x_i \) is the \( i \)th element from the sample and \( n \) is the number of elements in the sample. An example for calculation of variation and SD is illustrated in Table 2.

### Table 2: Example of mean, variance, standard deviation

| Observation | 90 | 90 | 70 | 70 | 80 |
|-------------|----|----|----|----|----|
| Mean        | 80 |
| Variance    | 100 |
| SD          | 10 |

Normal distribution of a population is defined by the following formula: where \( \mu \) is the mean of the population and \( N \) is the number of observations in the population.

\[
\frac{N}{\sum (X_i - \mu)^2} = \sigma
\]

Variance of a sample is defined by slightly different formula:

\[
\frac{n-1}{\sum (x_i - \overline{x})^2} = s
\]

Normal distribution of a sample is illustrated in Table 2. Variance and SD is discussed in Table 2.

#### Inferential statistics

The following reading is a longer version of the reading on inferential statistics.

The normal distribution is considered to be a bell-shaped curve with the mean, median, and mode all being equal. It is symmetrical about the mean and is characterized by two parameters: the mean (\( \mu \)) and the standard deviation (\( \sigma \)). A normal distribution is completely determined by these two parameters. The mean represents the center of the distribution, while the standard deviation measures the spread or variability of the data around the mean.

The mean (\( \mu \)) is the average of the data points and is calculated as:

\[
\mu = \frac{\sum x_i}{n}
\]

where \( x_i \) represents each observation and \( n \) is the total number of observations.

The standard deviation (\( \sigma \)) measures the dispersion of the data points around the mean. It is calculated as:

\[
\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{n}}
\]

where \( x_i \) represents each observation, \( \mu \) is the mean, and \( n \) is the total number of observations.

In a normal distribution, approximately 68% of the data points fall within one standard deviation of the mean, 95% fall within two standard deviations, and 99.7% fall within three standard deviations. This is known as the empirical rule or the 68-95-99.7 rule.

The normal distribution is a continuous probability distribution that is symmetrical about the mean and is used to model many natural phenomena, such as the distribution of heights, weights, and IQ scores.

### Skewed distribution

Skewed distributions are characterized by a longer tail in one direction compared to the other. Two types of skewness are positive skew and negative skew.

- **Positive skew** (right-skewed): The longer tail is on the right side, indicating that the distribution has a few high values.
- **Negative skew** (left-skewed): The longer tail is on the left side, indicating that the distribution has a few low values.

### Inferential statistics

In inferential statistics, we make inferences about a population based on a sample. This involves estimating population parameters and testing hypotheses. The sample mean is used to estimate the population mean, and the sample variance is used to estimate the population variance.

#### Example

An example for calculating the mean, variance, and standard deviation of a sample is shown in Table 2.

| Observation | 90 | 90 | 70 | 70 | 80 |
|-------------|----|----|----|----|----|
| Mean        | 80 |
| Variance    | 100 |
| SD          | 10 |

### Normal distribution

The normal distribution is described by two parameters: the mean (\( \mu \)) and the standard deviation (\( \sigma \)). The probability density function (PDF) of a normal distribution is given by:

\[
f(x) = \frac{1}{\sqrt{2\pi \sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}
\]

where \( f(x) \) is the probability density at \( x \) and \( \pi \) is the mathematical constant approximately equal to 3.14159.

The cumulative distribution function (CDF) of a normal distribution is defined by the integral of the PDF from negative infinity to \( x \):

\[
F(x) = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{x-\mu}{\sigma \sqrt{2}} \right) \right]
\]

where \( \text{erf} \) is the error function and approximately equals the integral of \( e^{-t^2} \) from \(-\infty\) to \( t \). This function gives the probability that a normally distributed random variable is less than or equal to \( x \).
the population. The purpose is to answer or test the hypotheses. A hypothesis (plural hypotheses) is a proposed explanation for a phenomenon. Hypothesis tests are thus procedures for making rational decisions about the reality of observed effects.

Probability is the measure of the likelihood that an event will occur. Probability is quantified as a number between 0 and 1 (where 0 indicates impossibility and 1 indicates certainty).

In inferential statistics, the term ‘null hypothesis’ 
\( (H_0 \text{ ‘H-naught,’ ‘H-null’}) \) denotes that there is no relationship (difference) between the population variables in question.\[9\]

Alternative hypothesis (\( H_1 \) and \( H_a \)) denotes that a statement between the variables is expected to be true.\[9\]

The \( P \) value (or the calculated probability) is the probability of the event occurring by chance if the null hypothesis is true. The \( P \) value is a numerical between 0 and 1 and is interpreted by researchers in deciding whether to reject or retain the null hypothesis [Table 3].

If \( P \) value is less than the arbitrarily chosen value (known as \( \alpha \) or the significance level), the null hypothesis (\( H_0 \)) is rejected [Table 4]. However, if null hypotheses (\( H_0 \)) is incorrectly rejected, this is known as a Type I error. Further details regarding alpha error, beta error and sample size calculation and factors influencing them are dealt with in another section of this issue by Das S et al.\[12\]

**PARAMETRIC AND NON-PARAMETRIC TESTS**

Numerical data (quantitative variables) that are normally distributed are analysed with parametric tests.\[13\]

Two most basic prerequisites for parametric statistical analysis are:
- The assumption of normality which specifies that the means of the sample group are normally distributed
- The assumption of equal variance which specifies that the variances of the samples and their corresponding population are equal.

However, if the distribution of the sample is skewed towards one side or the distribution is unknown due to the small sample size, non-parametric statistical techniques are used. Non-parametric tests are used to analyse ordinal and categorical data.

**Parametric tests**

The parametric tests assume that the data are on a quantitative (numerical) scale, with a normal
### Table 4: Illustration for null hypothesis

A study was planned to evaluate if the use of intravenous dexmedetomidine attenuated the haemodynamic and neuroendocrine responses to fixation of skull pin head holder in patients undergoing craniotomy. Sixty patients were randomly assigned, half in each group, to receive a single bolus dose of dexmedetomidine (1 µg/kg) intravenously over 10 min before induction of anaesthesia or normal saline (placebo) in the control group.

It is possible for this study to be framed in a particular way that indicates competing beliefs about the drug to be studied in the patient population.

First, we assume that dexmedetomidine makes no difference - has no effect. This is called the null hypothesis - the no change hypothesis. The symbol used is H0 – ‘H’ for hypothesis and ‘0’ for zero change (the word ‘null’ is another way of saying ‘zero’).

Second, we set up an alternate hypothesis H1, which takes the opposite point of view - namely use of dexmedetomidine does make a difference (blunts the haemodynamic response).

The data are used to produce a test value - a test statistic - in this case, it measures the heart rate, arterial blood pressure and serial levels of cortisol, prolactin, insulin and blood glucose in each group (dexmedetomidine group and control group).

Then, the process evaluates whether the difference in these parameters between the two groups is significantly large.

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3. To test if the population means estimated by two dependent samples differ significantly (the paired t-test). A usual setting for paired t-test is when measurements are made on the same subjects before and after a treatment.

The formula for paired t-test is:

\[ t = \frac{d}{SE_d} \]

where \( d \) is the mean difference and \( SE \) denotes the standard error of this difference.

The group variances can be compared using the F-test. The F-test is the ratio of variances (var l/var 2). If F differs significantly from 1.0, then it is concluded that the group variances differ significantly.

### Analysis of variance

The Student’s t-test cannot be used for comparison of three or more groups. The purpose of ANOVA is to test if there is any significant difference between the means of two or more groups.

In ANOVA, we study two variances – (a) between-group variability and (b) within-group variability. The within-group variability (error variance) is the variation that cannot be accounted for in the study design. It is based on random differences present in our samples.

However, the between-group (or effect variance) is the result of our treatment. These two estimates of variances are compared using the F-test.

A simplified formula for the F statistic is:

\[ F = \frac{MS_b}{MS_w} \]

where \( MS_b \) is the mean squares between the groups and \( MS_w \) is the mean squares within groups.

### Repeated measures analysis of variance

As with ANOVA, repeated measures ANOVA analyses the equality of means of three or more groups. However, a repeated measure ANOVA is used when all variables of a sample are measured under different conditions or at different points in time.

As the variables are measured from a sample at different points of time, the measurement of the dependent...
variable is repeated. Using a standard ANOVA in this case is not appropriate because it fails to model the correlation between the repeated measures: The data violate the ANOVA assumption of independence. Hence, in the measurement of repeated dependent variables, repeated measures ANOVA should be used.

**Non-parametric tests**

When the assumptions of normality are not met, and the sample means are not normally distributed, parametric tests can lead to erroneous results. Non-parametric tests (distribution-free test) are used in such situation as they do not require the normality assumption. Non-parametric tests may fail to detect a significant difference when compared with a parametric test. That is, they usually have less power.

As is done for the parametric tests, the test statistic is compared with known values for the sampling distribution of that statistic and the null hypothesis is accepted or rejected. The types of non-parametric analysis techniques and the corresponding parametric analysis techniques are delineated in Table 5.

Median test for one sample: The sign test and Wilcoxon’s signed rank test

The sign test and Wilcoxon’s signed rank test are used for median tests of one sample. These tests examine whether one instance of sample data is greater or smaller than the median reference value.

**Sign test**

This test examines the hypothesis about the median \( \theta_0 \) of a population. It tests the null hypothesis \( H_0 = \theta_0 \). When the observed value \( (X_i) \) is greater than the reference value \( (\theta_0) \), it is marked as +. If the observed value is smaller than the reference value, it is marked as − sign. If the observed value is equal to the reference value \( (\theta_0) \), it is eliminated from the sample.

If the null hypothesis is true, there will be an equal number of + signs and − signs.

The sign test ignores the actual values of the data and only uses + or − signs. Therefore, it is useful when it is difficult to measure the values.

**Wilcoxon’s signed rank test**

There is a major limitation of sign test as we lose the quantitative information of the given data and merely use the + or − signs. Wilcoxon’s signed rank test not only examines the observed values in comparison with \( \theta_0 \) but also takes into consideration the relative sizes, adding more statistical power to the test. As in the sign test, if there is an observed value that is equal to the reference value \( \theta_0 \), this observed value is eliminated from the sample.

Wilcoxon’s rank sum test ranks all data points in order, calculates the rank sum of each sample and compares the difference in the rank sums.

**Mann–Whitney test**

It is used to test the null hypothesis that two samples have the same median or, alternatively, whether observations in one sample tend to be larger than observations in the other.

Mann–Whitney test compares all data \((x_i)\) belonging to the X group and all data \((y_i)\) belonging to the Y group and calculates the probability of \(x_i\) being greater than \(y_i\): \(P(x_i > y_i)\). The null hypothesis states that \(P(x_i > y_i) = P(x_i < y_i) = 1/2\) while the alternative hypothesis states that \(P(x_i > y_i) \neq 1/2\).

**Kolmogorov-Smirnov test**

The two-sample Kolmogorov-Smirnov (KS) test was designed as a generic method to test whether two random samples are drawn from the same distribution. The null hypothesis of the KS test is that both distributions are identical. The statistic of the KS test is a distance between the two empirical distributions, computed as the maximum absolute difference between their cumulative curves.

**Kruskal–Wallis test**

The Kruskal–Wallis test is a non-parametric test to analyse the variance. It analyses if there is any difference in the median values of three or more...
independent samples. The data values are ranked in an increasing order, and the rank sums calculated followed by calculation of the test statistic.

Jonckheere test
In contrast to Kruskal–Wallis test, in Jonckheere test, there is an a priori ordering that gives it a more statistical power than the Kruskal–Wallis test.[14]

Friedman test
The Friedman test is a non-parametric test for testing the difference between several related samples. The Friedman test is an alternative for repeated measures ANOVAs which is used when the same parameter has been measured under different conditions on the same subjects.[13]

Tests to analyse the categorical data
Chi-square test, Fischer’s exact test and McNemar’s test are used to analyse the categorical or nominal variables. The Chi-square test compares the frequencies and tests whether the observed data differ significantly from that of the expected data if there were no differences between groups (i.e., the null hypothesis). It is calculated by the sum of the squared difference between observed \(O\) and the expected \(E\) data (or the deviation, \(d\)) divided by the expected data by the following formula:

\[
\chi^2 = \sum \frac{(O - E)^2}{O}
\]

A Yates correction factor is used when the sample size is small. Fischer’s exact test is used to determine if there are non-random associations between two categorical variables. It does not assume random sampling, and instead of referring a calculated statistic to a sampling distribution, it calculates an exact probability. McNemar’s test is used for paired nominal data. It is applied to \(2 \times 2\) table with paired-dependent samples. It is used to determine whether the row and column frequencies are equal (that is, whether there is ‘marginal homogeneity’). The null hypothesis is that the paired proportions are equal. The Mantel-Haenszel Chi-square test is a multivariate test as it analyses multiple grouping variables. It stratifies according to the nominated confounding variables and identifies any that affects the primary outcome variable. If the outcome variable is dichotomous, then logistic regression is used.

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**SOFTWARES AVAILABLE FOR STATISTICS, SAMPLE SIZE CALCULATION AND POWER ANALYSIS**

Numerous statistical software systems are available currently. The commonly used software systems are Statistical Package for the Social Sciences (SPSS - manufactured by IBM corporation), Statistical Analysis System ((SAS - developed by SAS Institute North Carolina, United States of America), R (designed by Ross Ihaka and Robert Gentleman from R core team), Minitab (developed by Minitab Inc), Stata (developed by StataCorp) and the MS Excel (developed by Microsoft).

There are a number of web resources which are related to statistical power analyses. A few are:

- StatPages.net - provides links to a number of online power calculators
- G-Power - provides a downloadable power analysis program that runs under DOS
- Power analysis for ANOVA designs an interactive site that calculates power or sample size needed to attain a given power for one effect in a factorial ANOVA design
- SPSS makes a program called SamplePower. It gives an output of a complete report on the computer screen which can be cut and paste into another document.

**SUMMARY**

It is important that a researcher knows the concepts of the basic statistical methods used for conduct of a research study. This will help to conduct an appropriately well-designed study leading to valid and reliable results. Inappropriate use of statistical techniques may lead to faulty conclusions, inducing errors and undermining the significance of the article. Bad statistics may lead to bad research, and bad research may lead to unethical practice. Hence, an adequate knowledge of statistics and the appropriate use of statistical tests are important. An appropriate knowledge about the basic statistical methods will go a long way in improving the research designs and producing quality medical research which can be utilised for formulating the evidence-based guidelines.

**Financial support and sponsorship**
Nil.

**Conflicts of interest**
There are no conflicts of interest.
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