Why and When Statistics is Required, and How to Simplify Choosing Appropriate Statistical Techniques During Ph.D. Program in India?

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ABSTRACT

Purpose: *The purpose of this article is to explain the key reasons for the existence of statistics in doctoral-level research, why and when statistical techniques are to be used, how to statistically describe the units of analysis/samples, how to statistically describe the data collected from units of analysis/samples; how to statistically discover the relationship between variables of the research question; a step-by-step process of statistical significance/hypothesis test, tricks for selecting an appropriate statistical significance test, and most importantly which is the most user-friendly and free software for carrying out statistical analyses. In turn, guiding Ph.D. scholars to choose appropriate statistical techniques across various stages of the doctoral-level research process to ensure a high-quality research output.*

Design/Methodology/Approach: *Postmodernism philosophical paradigm; Inductive research approach; Observation data collection method; Longitudinal data collection time frame; Qualitative data analysis.*

Findings/Result: *As long as the Ph.D. scholars can understand i) they need NOT be an expert in Mathematics/Statistics and it is easy to learn statistics during Ph.D.; ii) the difference between measures of central tendency and dispersion; iii) the difference between association, correlation, and causation; iv) difference between null and research/alternate hypotheses; v) difference between Type I and Type II errors; vi) key drivers for choosing a statistical significance test; vi) which is the best software for carrying out statistical analyses. Scholars will be able to (on their own) choose appropriate statistical techniques across various steps of the doctoral-level research process and comfortably claim their research findings.*

Originality/Value: *There is a vast literature about statistics, probability theory, measures of central tendency and dispersion, formulas for finding the relationship between variables, and statistical significance tests. However, only a few have explained them together comprehensively which is conceivable to Ph.D. scholars. In this article, we have attempted to explain the reasons for the existence, objectives, purposes, and essence of 'Statistics' briefly and comprehensively with simple examples and tricks that would eradicate fear among Ph.D. scholars about 'Statistics'.*

Paper Type: *Conceptual.*

Keywords: Research Methodology; Research Design; PhD; Ph.D.; Coursework; Doctoral Research; Statistics; Statistical Techniques; JASP; Measures of Central Tendency; Measures of Dispersion; Mean; Median; Mode; Skewness; Kurtosis; Range; Standard Deviation; Coefficient of Variation; Type 1 Error; Type 2 Error; Significance Level; Alpha; Beta; Null Hypothesis; Research Hypothesis; Alternate Hypothesis; Hypothesis Testing; Significance Testing; Statistical Significance; Descriptive Statistics; Inferential Statistics; Parametric Test; Non-parametric test; Normal Distribution; Bell Curve; Postmodernism

1. BACKGROUND :

A majority of stakeholders in the research education system have a lower level of clarity about the most important and indispensable steps of the doctoral-level research process i.e., i) statistically describing units of analysis/samples and data; ii) statistically discovering the relationship between variables of the research question; iii) testing the statistical significance of the relationship discovered. A majority of them guide the Ph.D. scholars to begin the journey without educating the scholars about the most important aspects/objectives/purposes of statistical techniques. They also mandate that scholars use certain statistical techniques that are commonly used in a discipline or the one with which they are comfortable. In addition, there is a humongous confusion about i) whether the scholar needs to be an expert in Mathematics/Statistics?; ii) the difference between measures of central tendency and dispersion; iii) the difference between association, correlation, and causation; iv) difference between null and research/alternate hypotheses; v) difference between Type I and Type II errors; vi) key drivers for choosing a statistical significance test. This lower level of clarity and the beginning of the Ph.D. journey without a clear understanding of the objectives/purposes of the statistical techniques is making it difficult for Ph.D. scholars to complete the journey successfully and most importantly if some scholars complete their Ph.D. journey successfully, their awareness about the 'Why' they used certain statistical techniques is very low. We believe that if the scholars can begin their Ph.D. journey by allocating a higher level of focus and time toward understanding key objectives/purposes of the existence of statistical techniques and their role in the doctoral-level research their journey will be with a very lower level of complications. But this reality is knowingly or unknowingly, intentionally, or unintentionally suppressed by a majority of stakeholders in the research education system in India. In other words, this *suppressed reality* has resulted in creating humungous confusion among Ph.D. scholars in India about the existence of statistics in doctoral-level research and created fear among scholars about 'Statistics'.

Furthermore, various research studies have identified factors affecting the Ph.D. success rate across the world. "To name a few a) scholar-supervisor/guide relationship; b) mentorship; c) dissertation process; d) role of the department; e) role of peer qualities; f) transformational learning experience provided; g) level of curiosity and interest in reviewing the existing literature; h) planning and time management skills; i) level of creative thinking and writing skills; j) amount of freedom in the research project; k) level of a supportive environment for Ph.D. scholars' well-being; l) higher-education practices; m) supervisors' research capabilities and gender; n) expectations set by the research environment; o) Ph.D. scholars' expectations; p) support network; q) level of Ph.D. scholars' socialization with the research community; r) Ph.D. scholars' navigation system; s) different terminologies for various components of doctoral-level research are given by different disciplines creating undue confusion in scholars' minds; t) data collection methods which just play the role of data collection and it is just one of the steps of the doctoral-level research process being portrayed as the research methodology/design; u) scholars' inability to identify their genuine interest in a fact/phenomenon/reality/truth/dependent variable, intensive review of existing literature, locating an important research gap, and finally formulating a research question; v) a lower level of clarity about the most important and indispensable step of the doctoral-level research process i.e., choosing an appropriate research philosophical paradigm that lays stepping stones toward answering the research question in a scientific and scholarly way; w) a lower level of clarity about the most important and indispensable step of the doctoral-level research process i.e., choosing an appropriate research approach/reasoning that paves path for decision concerning data collection and analysis; x) a humongous confusion among Ph.D. scholars in India about the difference between research methodology/design and research data collection methods; y) lower level of clarity and the beginning of the Ph.D. journey without a clear understanding of the essence of research data collection time frames; z) lower level of clarity about the right sample size and appropriate sampling techniques; aa) lower level of clarity about the difference between Mechanical/Electrical/Electronic instruments and Human instruments, the difference between 'Adopted', 'Adapted', and 'Developed' Human instruments, and difference between validity and reliability" [1-55].

One thing Ph.D. scholars must always remind themselves of throughout their Ph.D. journey is the fact that they will be awarded a Ph.D. degree for doing doctoral-level research. Doing doctoral-level research and generating research outputs such as research articles and a thesis determines the probability of success in getting a Ph.D. degree. The first step of the doctoral-level research process is identifying research gaps and formulating a research question, the second one is choosing an appropriate research philosophical paradigm, the third step is choosing an appropriate research approach/reasoning, the fourth step is choosing the appropriate research data collection method choice, the fifth step is choosing an appropriate data collection time frame, the sixth step is to derive the sample size, the seventh step is to choose samples from the research population, the eighth step is to select a data collection instrument, the ninth step is checking the calibration, validity, and reliability of the data collection instrument, the tenth step is collecting the data using the data collection instrument, the eleventh step is describing the samples/units of analysis and collected data, the twelfth step is discovering relationship between variables, and the thirteenth step is testing the statistical significance of the relationship discovered [48].

It is thus inevitable and imperative that Ph.D. scholars understand the essence of statistical techniques. The doctoral-level research which is the single most important requirement of the Ph.D. program is cognitively demanding and intends to create researchers who can create new knowledge or interpret existing knowledge about reality by using different perspectives, paradigms, and reasoning. Knowledge sharing requires autonomy, good quality time, a stress-free brain for deep thinking, and the freedom to look for more meaningful findings. This is the single most important reason for making doctoral-level research flexible wherein the scientific and scholarly world gives autonomy to Ph.D. scholars to formulate their question and answer it within 3-6 years using an appropriate research approach/reasoning. Nevertheless, only 50% of scholars admitted to Ph.D. in India completed, and that too in ten years whether or not they are aware of the importance of reasoning in doctoral-level research [46].

Choosing appropriate statistical techniques is one of the most important decisions scholars need to make during their Ph.D. journey and selection of appropriate statistical techniques depends upon i) the type of the research question (descriptive; relational; causal) [49]; ii) the research philosophical paradigm (positivism; interpretivism; critical realism; postmodernism; pragmatism) [50]; iii) the research approach/reasoning (deductive; inductive; abductive) [51]; iv) time available for scholars to collect data [46]; v) data collection method and method choice [52]; vi) resources that are available for scholars to collect data [46]; vii) data collection time frame choice [53]; vii) sample size and sampling technique chosen [54]; viii) data collection instrument [55].

2. OBJECTIVE :

There is a humongous confusion among Ph.D. scholars in India about i) whether the scholars need to be an expert in Mathematics/Statistics?; ii) the difference between measures of central tendency and dispersion; iii) the difference between association, correlation, and causation; iv) difference between null and research/alternate hypotheses; v) difference between Type I and Type II errors; vi) key drivers for choosing a statistical significance test; vi) which is the best software for carrying out statistical analyses. Furthermore, choosing appropriate statistical techniques before claiming the research findings is very important during doctoral-level research as this determines the quality of research and research output. *Owing to such confusion the key objective of this article is to explain the reasons for the existence of statistics in doctoral-level research, why and when statistical techniques are to be used, how to statistically describe the units of analysis/samples, how to statistically describe the data collected from units of analysis/samples; how to statistically discover the relationship between variables of the research question; step-by-step process of statistical significance test, tricks for selecting an appropriate statistical significance test, and most importantly which is the most user-friendly and free software for carrying out statistical analyses. In turn, guiding them to choose appropriate statistical techniques across various stages of the doctoral-level research process to ensure a high-quality research output. In addition, our key objective is to eradicate fear among Ph.D. scholars about 'Statistics' and impart knowledge about statistical techniques with the help of simple examples and tricks.*

3. WHY AND WHEN STATISTICS IS REQUIRED DURING PH.D.? :

Scholars might think about whether they are good at Mathematics/Statistics. However, they need to be cognizant of the fact that, Statistics is not Mathematics! and does not require talent or previous association with subjects concerning Mathematics/Statistics. It just requires hard work, and more than the hard work requires scholars to focus on the purpose of deriving sample size and the role of statistical techniques. Scholars need not be an expert in Mathematics or Statistics and most importantly they are not required to memorize the formulas. They just need to know why they have taken the help of a particular formula. Statistics also uses numbers, but numbers are not the primary focus. It is a form of inductive reasoning that uses mathematics as one of its tools to discover new knowledge. It is a thinking tool and science of learning from data [46] [58-62]. Scholars need the help of statistical techniques to i) describe samples/units of analysis and the data collected from them; ii) discover the relationship between variables of the research question; iii) test the significance of the relationship discovered.

4. DESCRIBING SAMPLES/UNITS OF ANALYSIS AND THE DATA COLLECTED FROM THEM :

Once scholars have completed the data collection using the data collection instruments chosen and they are checked for their calibration, validity, and reliability in the previous steps. Now in step eleven of the doctoral-level research process, they need to describe the data they have collected related to respondents/participants/subjects/groups/units of analysis/samples and other variables of their research question. Scholars must be aware that during their Ph.D., they are required to describe their samples/units of analysis and data only using statistical techniques commonly known as Measures of Central Tendency and Measures of Dispersion. Before we explain these measures we need to understand an important aspect of these measures that are popularly known as the Normal Distribution Curve/Bell Curve (The shape of a bell).

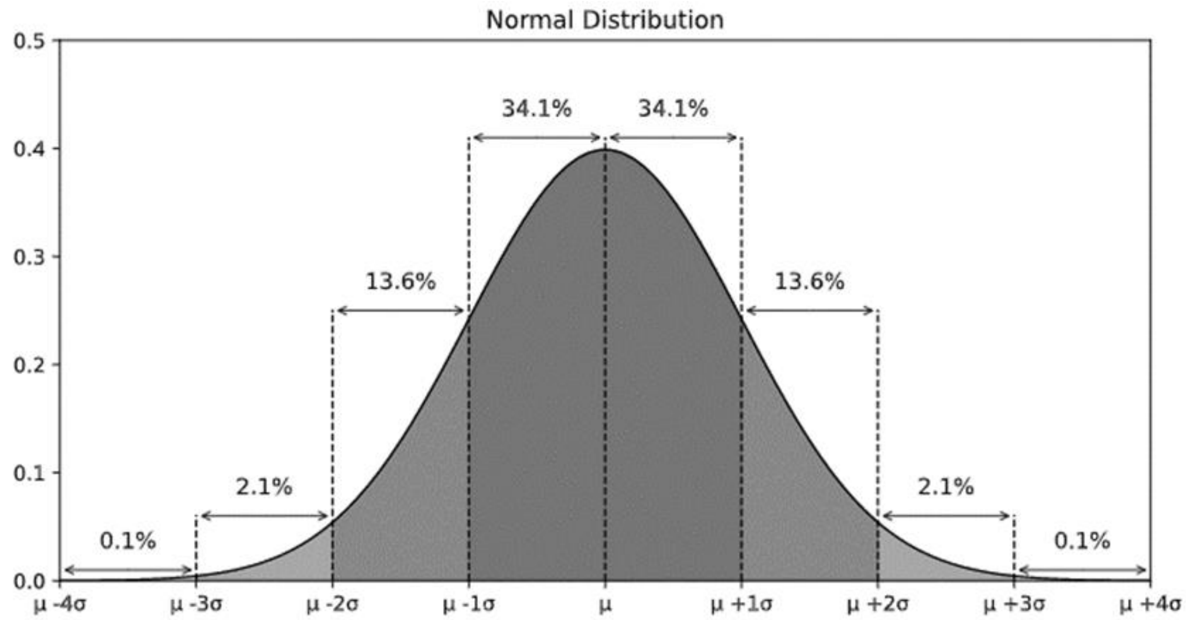

Fig. 1: Normal distribution/Bell curve [56]

The normal distribution is a continuous probability distribution wherein values lie symmetrically and are mostly situated around the mean (average). In a normal distribution, data is symmetrically distributed with no skew. When plotted on a graph, the data follows a bell shape, with most values clustering around a central region (mean) and tapering off as they go further away from the center (mean). All kinds of variables in Natural and Social sciences are normally or approximately normally distributed. Height, birth weight, reading ability, job satisfaction, or NET scores are just a few examples of such variables. Because normally distributed variables are so common, many statistical tests are designed for normally distributed populations. Understanding the properties of normal distributions means scholars can use inferential statistics to compare different groups and make estimates about populations using samples. Figure 1 illustrates the standard characteristics of a normal curve. The center point or the 'Peak' of the curve is the mean (average) of the data; the whole area to the left of the center point is the 'Left-side' of the normal curve; the whole area to the right of the center point is 'Right-side' of the normal curve. We can see that the Left and Right sides of the curve are symmetrical. The measures of central tendency focus on 'How close' each data point is to the peak/center/mean/average whereas the measures of dispersion focus on 'How far' each data point is from the peak/center/mean.

4.1. Describing Data Using Measures of Central Tendency :

As we are aware, scholars might be collecting a huge amount of data and it is impossible to describe the data of each respondent/participant/subject/group/unit of analysis/sample and each variable of the research. To describe the data collected in simple ways scholars must use the measures of central tendency. Simply, the measures of central tendency try condensing larger data into a single figure/number that is capable of conveying important information about the data, and instead of studying the entire data, it is sufficient to understand the single figure/number that gives a rough idea about the entire data scholars have collected [63-71]. Key measures of central tendency are Mean (arithmetic; geometric; harmonic); Median; Mode; Skewness; Kurtosis.

4.1.1. Mean :

Mean is the sum of a collection of numbers divided by the count of numbers in the collection. The collection is often a set of results of an experiment or an observational study, or frequently a set of results from a survey. The term arithmetic mean is preferred in some contexts in mathematics and statistics because it helps distinguish it from other means, such as the geometric mean and the harmonic mean. The arithmetic mean is appropriate if the values have the same units of measurement, whereas the geometric mean is appropriate if the values have different units of measurement. The harmonic mean is appropriate if the data values are ratios of two variables with different measures, called rates. Scholars can use the below formula (1) to calculate the Mean of their data set.

$$A = \frac{1}{n}\sum_{i=1}^{n} a_i$$

A = arithmetic mean
n = number of values
a_i = data set values

(1)

4.1.2. Median :

It is the value separating the higher half (50%) from the lower half (50%) of a data sample, a population, or a probability distribution. The median is that value in the distribution such that 50 percent of observations are below it and 50 percent are above it. For a data set, it may be thought of as the middle value. The median for ungrouped data is defined as the middle value when the data is arranged in ascending or descending order of magnitude. The basic feature of the median in describing data compared to the mean is that it is not skewed by a small proportion of extremely large or small values, and therefore provides a better representation of a 'typical' value. Scholars can use the below formula (2) to calculate the Median of their data set.

4.1.3. Mode :

It is the point of maximum frequency in a distribution around which other items of the set cluster densely. The mode should not be computed for ordinal or interval data unless these data have been grouped first. Scholars can use the below formula (3) to calculate the Mode of their data set.

$$\mathrm{Med}(X) = \begin{cases} X[\frac{n}{2}] & \text{if n is even} \\ \frac{(X[\frac{n-1}{2}] + X[\frac{n+1}{2}])}{2} & \text{if n is odd} \end{cases}$$

X = ordered list of values in data set
n = number of values in data set

(2)

$$\text{Mode} = l+[(f-f1)/(2f-f1-f2)]\times h$$

l=lower limit of median class

f=frequency of median class

f1=The frequency of the classes preceding the modal class

f2=The frequency of the classes following the modal class

h=size of interval of median class

(3)

4.1.4. Skewness :

It measures the lack of symmetry in the distribution, meaning whether the left and right sides of the distributed data are equal or not. In the case of symmetrical distribution Mean = Median = Mode, for a positively skewed distribution, Mean > Median > Mode, and in the case with a negatively skewed distribution where Mean < Median < Mode. Figure 2 illustrates these three possible Skewness. Skewness is measured by calculating the difference between mean and mode. The skewness number/figure also tells us about the direction of outliers. A skewness value greater than 1 or less than -1 indicates a highly skewed distribution. A value between 0.5 and 1 or -0.5 and -1 is moderately skewed. A value between -0.5 and 0.5 indicates that the distribution is fairly symmetrical. Scholars can use the below formula (4) to calculate the Skewness of their data set.

Skewness = Mean–Mode

(4)

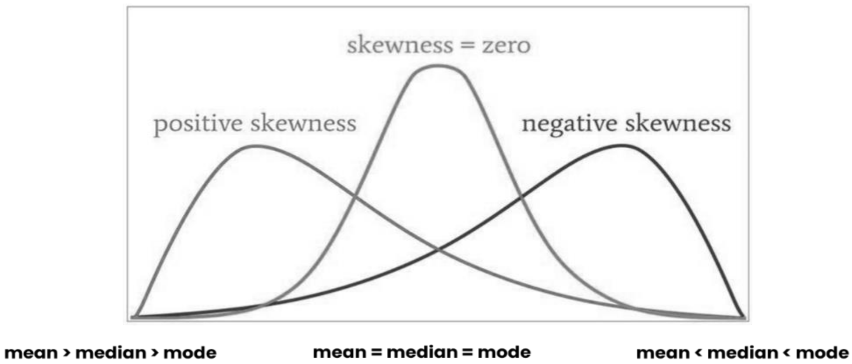

Fig. 2: Three possible Skewness in the distribution

4.1.5. Kurtosis :

In probability theory and statistics, Kurtosis is a measure of the 'tailedness' of the probability distribution of a real-valued random variable. For kurtosis, the general guideline is that if the number is greater than +1, the distribution is too peaked. Likewise, a kurtosis of less than –1 indicates a distribution that is too flat. Figure 3 illustrates these three types of possible Kurtosis.

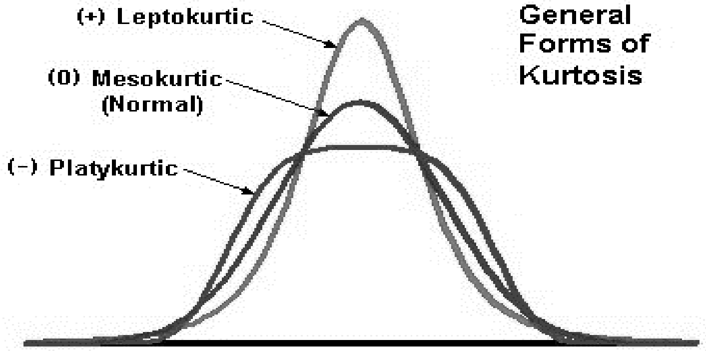

Fig. 3: Three possible Kurtosis in the distribution

4.2. Describing Data Using Measures of Dispersion :

Measures of central tendency locate the center of a distribution. However, they do not provide enough information to scholars to fully understand the distribution being examined. Measures of central tendency do not indicate how items are spread out on either side of the peak/center/mean of the distribution curve and this is the key reason for scholars to use the measures of dispersion to understand how far from the mean their data set is spread [72-81]. Key measures of dispersion are Range; Standard Deviation; Coefficient of Variation;

4.2.1. Range :

It is the difference between the highest (maximum) value and lowest (minimum) value in an ordered set of values. It is also the size of the smallest interval (statistics) which contains all the data and provides an indication of statistical dispersion. It is measured in the same units as the data. Since it only depends on two of the observations, it is most useful in representing the dispersion of small data sets. It is also a commonly used measure of the variability of the data which gives a rough idea of how widely spread out the most extreme observations are but gives no information as to where any of the other data points lie. Scholars need to be careful as the Range of their data set can be misleading when they have outliers in their data set. One extreme value in the data will give scholars a completely different range. Scholars can use the below formula (5) to calculate the Range of their data set.

$$\text{Range} = X_{\text{max}} - X_{\text{min}} \tag{5}$$

X_{max} = Highest value in the data set

X_{min} = Lowest value in the data set

4.2.2. Standard Deviation :

It is a measure of the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the mean of the data set, while a high standard deviation indicates that the values are spread out over a wider range. Is most commonly represented in mathematical texts and equations by the lower-case Greek letter sigma **σ**, for the population standard deviation, or the Latin letter **s**, for the sample standard deviation. It is expressed in the same unit as the data. Scholars can use the below formula (6) to calculate the Standard Deviation of their data set.

$$s = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \overline{x})^2}{N-1}} \tag{6}$$

s = sample standard deviation

N = the number of observations

x_i = the observed values of a sample item

$\overline{x}$ = the mean value of the observations

4.2.3. Coefficient of Variance :

When the units of measurement are different for different variables in the case of multiple distributions a relative measure of dispersion is used which is known as the coefficient of variance. This measure is independent of the unit of measurement. Also known as relative standard deviation. It is often expressed as a percentage (%). It shows the extent of variability with the mean. In most cases, a coefficient of variance is computed for a single independent variable with numerous, repeated measures of a dependent variable. Scholars can use the below formula (7) to calculate the Coefficient of Variance of their data set.

Coefficient of Variance = Standard Deviation ÷ Mean (7)

In addition to measures of central tendency and dispersion, scholars must also ensure they have described the data using Relative and Absolute frequencies. The absolute frequency describes the number of times a particular value for a variable has been observed to occur. A relative frequency describes the number of times a particular value for a variable has been observed to occur concerning the total number of values for that variable.

We have shown the difference among all the measures of central tendency and dispersion in table 1. For example, if scholars have a data set about the age of Seven Samples viz 23, 26, 26, 26, 28, 35, and 54 years, the Mean age is 31 years; Median of the age is 26 years; the Mode of age is 26 years; Skewness is 5; Range is 31 years; Standard Deviation is 11 years; Coefficient of Variance is 35.5%. This was a simple example. Imagine if we have 100/1000/10000 such data points and using the measures of central tendency scholars can calculate the Mean, Median, and Mode of these data points to describe their data in simple and understandable figures/numbers.

Table 1: An example of Measures of Central Tendency and Dispersion

Type	Description	Example	Result	UoM
Arithmetic Mean	Sum of Values of a Data Set Divided by Number of Values	(23+26+26+26+28+35+54) ÷ 7	**31**	Years
Median	Middle Value Separating the Greater and Lesser Halves of a Data Set	23, 26, 26, 26, 28, 35, 54	**26**	Years
Mode	Most Frequent Value in a Data Set	23, 26, 26, 26, 28, 35, 54	**26**	Years
Skewness	Measures LACK of Symmetry in the Distribution. Measured by the Difference Between Mean and Mode.	23, 26, 26, 26, 28, 35, 54	**5**	Nil
Range	Difference Between the Highest (Maximum) Value and Lowest (Minimum) Value in an Ordered Set of Values.	23, 26, 26, 26, 28, 35, 54	**31**	Years
Standard Deviation	A Measure of the Amount of Variation or Dispersion of a Set of Values.	23, 26, 26, 26, 28, 35, 54	**11**	Years
Coefficient of Variance	It Shows the Extent of Variability in Relation to the Mean	23, 26, 26, 26, 28, 35, 54	**35.48**	%

5. DISCOVERING THE RELATIONSHIP BETWEEN VARIABLES OF THE RESEARCH :

Once scholars have understood the entire data collected about respondents/participants/subjects/ groups/units of analysis/samples and variables of the research question with the help of Measures of Central Tendency and Measures of Dispersion they are now ready for discovering the relationship among variables of their research question which was the main goal of research during the Ph.D. program. In step twelve of the doctoral-level research process, scholars are now required to discover this relationship with the help of statistical techniques. Scholars must be aware that knowing the relationship between variables of their research question is the key objective. Only when we know the relationship we will be able to solve the research problem or answer the research question scientifically/scholarly. There are majorly three types of relationships scholars can discover between variables of their research question such as i) Association, ii) Correlation, and iii) Causation [82-88].

5.1. Association :

In the case of an association, we study the relationship between two attributes that are not measurable quantitatively (Nominal/Unordered data). Association is evaluated in the case of attributes. An attribute divides the whole group into two classes, one possessing the attribute and another not possessing the attribute (Dichotomous). The coefficient of association indicates an association between two attributes and also whether the association is positive or negative. With the help of the coefficient of association, we cannot find the expected change in 'A' (attribute 1) for a given change in 'B' (attribute 2) and vice-versa. Attributes 'A' and 'B' are associated only if they appear together in a greater number of cases than is to be expected if they are independent. The coefficient of association can be calculated using the formula (8). Scholars are required to be cautious before claiming any association between Variables and we strongly suggest scholars consider following the below two steps before claiming an association. Do note that the coefficient of association can only disclose the direction of the association (Negative/ Positive/Neutral) and not the magnitude of the association (Poor/Moderate/Strong).

$$\text{If } (AB) > (A)(B)/N = \text{Positively Associated/Related}$$

$$\text{If } (AB) < (A)(B)/N = \text{Negatively Associated/Related}$$

$$\text{If } (AB) = (A)(B)/N = \text{No Associated/Related (Independent)} \tag{8}$$

- **Step 1 – Initial Association** - First, find the initial association. For example, finding an association between 'Ph.D. Type' (Full-time/Part-time) and 'Scholars' Active Status' (Active/Inactive).
- **Step 2 – Final Association** - After finding the initial association now try to refine the initial association by introducing another attribute about the main Variables. For example, refining the initial association found between 'Ph.D. Type' (Full-time/Part-time) and 'Scholars' Active Status' (Active/Inactive) by introducing 'Gender' (Male/Female) of the scholar and confirm if the initial association found is true for both the Male and Female. This will help scholars check if the initial association was spurious or suppressed or correct. Scholars need to ensure like the 'Gender' Variable they have checked all the possible Variables before claiming an association.

5.2. Correlation :

In the case of correlation analysis, we will be able to understand the relationship between two variables, which we can measure quantitatively (Ordered/Discrete/Continuous). The relationship between two variables can be measured by a correlation coefficient, which not only gives the direction (Negative/Positive/Neutral) of the relationship but also provides the magnitude of the relationship (Poor/Moderate/Strong). The correlation coefficient is a measure of the degree or extent of a linear relationship between two Variables. It allows us to understand if two different variables are changing at the same time in the same direction, and to estimate the influence level they might have on each other. The correlation coefficient of +1 would be a perfect correlation; 0 will be no correlation; -1 is a negative correlation. Figure 4 illustrates three different directions of correlation.

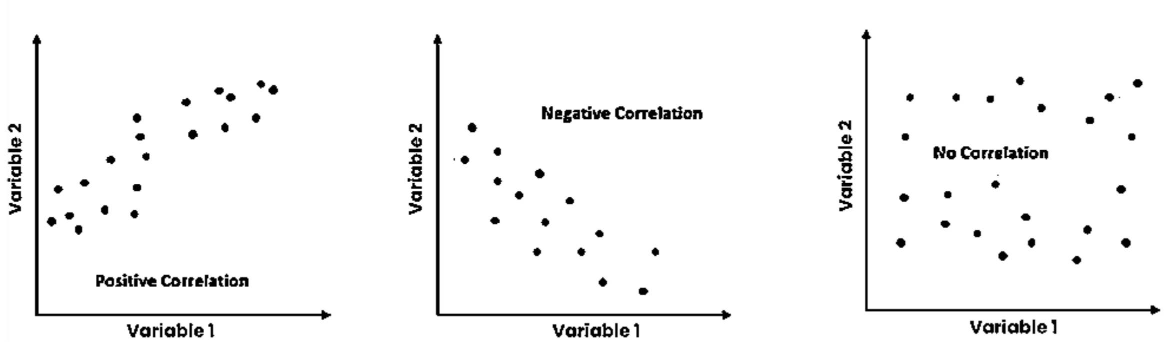

Fig. 4: Three possible correlations

Scholars can calculate the correlation using Pearson's correlation formula (9). A correlation coefficient between -0.30 to +0.30 is weak; -0.40 to +0.40 is moderate; -0.70 to +1.00 is strong.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (9)$$

r = correction coefficient

x_i = values of the x-variable in a sample

$\bar{x}$ = mean of the values of the x-variable

y_i = values of the y-variable in a sample

$\bar{y}$ = mean of the values of the y-variable

5.3. Causation :

A causal relationship exists when one Variable in a data set influences another Variable. Thus, one event triggers the occurrence of another event. A causal relationship is also referred to as a cause-and-effect relationship. Causality is the area of statistics that is commonly misunderstood and misused by researchers. In the mistaken belief that because the data shows a correlation it is mistaken as if there is an underlying causal relationship. The use of a controlled study is the most effective way of establishing causality between variables. Before claiming a causation relation between Variables ensure the following.

- Do a temporal sequencing: '**x**' (Independent Variable) must come before **'y'** (Dependent Variable)**.**
- Ensure a non-spurious relationship: The relationship between '**x**' and '**y**' cannot occur by chance alone.
- Eliminate alternate causes: Ensure there are no other intervening or unaccounted variable that is responsible for the relationship between '**x**' and '**y'.**

We recommend scholars understand the key differences between association, correlation, and causation. Association is used for variables that are not quantitatively measurable. The presence of a correlation is not sufficient to infer the presence of a causal relationship. While causation and correlation can exist at the same time, correlation does not imply causation. Correlation is always two ways, whereas a causal relationship, by definition, is one-way. For example, just because people in London tend to spend more in the shops when it is cold (Winter season) and less when it is hot (Summer season) does not mean cold weather causes high spending. A more plausible explanation would be that cold weather tends to coincide with Christmas Eve and the New Year Sales Promotions by the Retailers.

6. TESTING THE SIGNIFICANCE OF THE RELATIONSHIP BETWEEN VARIABLES OF THE RESEARCH QUESTION :

Scholars might think that what is left after all once they have discovered a relationship between variables of their research question. Hold on, the research is not yet complete. There are a few more steps that require the help of statistical techniques. If scholars had collected a census of the entire population (collecting data from each respondent/participant/subject/group/unit of analysis/sample of the research population), their job is done after discovering the relationship. However, scholars should be cognizant of the fact that they have collected data from a few select units of analysis/samples of the research population which means they cannot claim the relationship discovered in the units of analysis/samples to be existing in the research population also. In step thirteen of the doctoral-level research process, scholars need to now estimate the likelihood of the statistic they observed in the units of analysis/samples, being the same as the 'real' parameter in the research population. This step is commonly known as the Test of Significance/Hypothesis Testing/Inferential Statistics. Let us take a look at figure 5, where by doing the test of significance we will now be able to estimate the relationship between variables of our research question to the entire research population. The white patches we see in the research population are the units of analysis/samples that were chosen for collecting the research data.

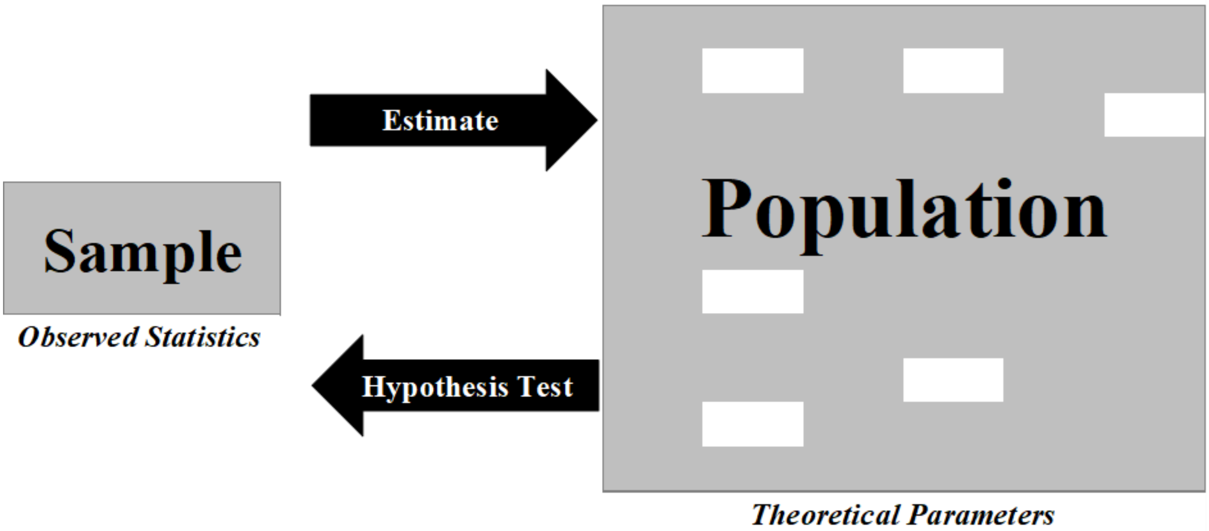

Fig. 5: Population and Sample [57]

The key goal is to use a small sample of data to infer about a larger population. The goal of statistical modeling itself is all about using a small amount of information to extrapolate and generalize information to a larger group (Population). Use estimated data that value in population and give a measure of uncertainty in our estimation. The accuracy of statistical inference depends heavily on the sampling technique, and do note that if the sample is not a good representative of the population, the generalization will be inaccurate. The idea of inferring about the research population at large with a smaller sample is quite intuitive, many statistics we see on social media and the internet are inferential, a prediction of an event based on a small sample. The basic goal of the statistical inference/Significance test is to draw certain inferences about the variables that characterize the distribution of an interesting variable in a particular population based on a random sample. Correct data analysis is crucial. Accurate data analysis is required to understand study findings and reach suitable conclusions. Inference serves as the foundation for significance/hypothesis testing in statistical analysis. Inference, and by extension inferential statistics, was the process of learning something about a population from a sample of that population. Given that it is typically not possible to have all the information about a target group, Consequently, we obtained information from a few samples of that population.

What is the likelihood that the association scholars found in the samples are also present in the population? What is the likelihood that the relationship scholars believe exists between the variables in their research topic is merely a coincidental occurrence? Would scholars still discover the same association between their variables in each sample if they took multiple samples from the same population? Would a population census reveal the existence of this link in the population from which the samples were taken? Or did scholars just happen to make their discovery or find it by chance? The significance test estimates the likelihood that the association we found in the samples we used was the result of pure random chance. There is never a 100% guarantee that two variables in the samples are related to one another. To be regulated, there are too many sources of mistakes, for instance, mistakes with sampling, bias in the researcher, issues with validity and dependability, etc. If we assume that our finding of a relationship is valid, we can estimate the likelihood of being incorrect using probability theory and the normal distribution curve. We refer to our observation, discovery, or finding of the link as a statistically significant finding if the likelihood that we are mistaken is low. According to statistical significance, there is a strong possibility that our conclusion that a relationship between the Variables exists is accurate. Sample Size and Sampling Technique have an immediate impact on it. Because practical significance which is independent of sample size must be considered when results are statistically significant. Any research discovery must always be evaluated for both statistical and practical significance, which is also known as effect size, especially if an experiment was used to gather the data. The test of significance or hypothesis test is a step-by-step process. There are four key steps for testing the statistical significance of the relationship discovered viz., i) Step 1 - stating the null hypothesis; ii) Step 2 - stating the research/alternate hypothesis; iii) Step 3 - selection of a probability of error level i.e., significance level; iv) Step 4 - selection of an appropriate significance test to compute the value of the test statistic, compare the test statistic with the standard critical value and make a final decision/conclusion/claim about the existence of relationship among variables in the research population.

6.1. Significance Test Step 1 - Stating the Null Hypothesis :

A null hypothesis usually states that there is no relationship between variables. Do note that stating a null hypothesis is mandatory. For example, i) there is no relationship between the length of the 'facing interviews' training program and the rate of campus placement; ii) longer 'facing interviews' training programs will place the same number or fewer students into jobs as shorter programs.

6.2. Significance Test Step 2 - Stating the Research/Alternate Hypothesis :

A research hypothesis states the expected relationship between/among variables of the research question. It is a supposition, proposed explanation, assumed theory, or logical imagination about the relationship between variables while formulating the research question in the first step of the doctoral-level research process. It may be stated in general terms, or it may include dimensions of direction and magnitude. For example, i) the length of the 'facing interviews' training program is related to the rate of campus placement (General hypothesis); ii) the longer the 'facing interviews' training program, the higher the rate of campus placements (Directional hypothesis); iii) longer 'facing interviews' training programs will place twice as many students into jobs compared to shorter programs (Magnitude hypothesis). Depending upon the type of research question formulated, scholars can state their research hypothesis in three ways as listed below.

Descriptive Hypothesis: Stating the existence, size, form, or distribution of some variable. for example, online retail stores (Unit of Analysis) are experiencing high customer traffic (Dependent Variable) due to lockdown (Independent Variable).

Relational Hypothesis: Stating the relationship between two variables concerning the unit of analysis/sample. For example, 'Made in India' (Independent Variable) products are perceived by Indian consumers (Units of Analysis) to be of better quality (Dependent Variable) than 'Made-in-China' products (Independent Variable). This is an example of an Association hypothesis (The data type of Dependent and Independent Variables is Nominal). However, when we state that the variables occur together in some specified manner without implying that one causes the other it is known as the Correlational hypothesis. For example, rural students (Independent Variable) score (Dependent Variable) is lesser in competitive exams than urban students (Independent Variable).

Causal Hypothesis: Stating that the existence/change in one variable causes/leads to a change in another Variable. For example, an increase in campus recruitments (Independent Variable) at the Institute of Management and Commerce of Srinivas University (SUIMC) increases admissions (Dependent Variable) to 'SUIMC' in the next admission cycle.

6.3. Significance Test Step 3 - Selecting a Probability of Error Level :

Even in the best research work, there is always a possibility that we will make a mistake regarding the relationship between variables. There are two possible mistakes or errors we might make while claiming a relationship. The First is called a 'Type I Error' that occurs when we assume that a relationship found in units of analysis/samples also exists in the population when in fact the evidence is that it does not. In a Type I Error, we should accept the null hypothesis and reject the research hypothesis, but the opposite occurs. The probability of committing a Type I Error is called 'alpha' (Significance Level). The Second is called a 'Type II Error' that occurs when we assume that a relationship that was found in units of analysis/samples does not exist when in fact the evidence is that it does exist in the population. In a Type II Error, we should reject the null hypothesis and accept the research hypothesis, but the opposite occurs. The probability of committing a Type II error is called 'beta'. Generally, reducing the possibility of committing a Type I Error increases the possibility of committing a Type II Error and vice versa, reducing the possibility of committing a Type II Error increases the possibility of committing a Type I Error. We should generally try to minimize Type I Errors. An example below might enable us to understand the practical impact of committing Type I and Type II Errors. In the example below let us decide, which type of error would we prefer to commit.

- **Research/Alternate Hypothesis:** Heavy rain has reduced crop yields in Raichur district, making farmers of Raichur district eligible for Government disaster relief fund.
- **Null Hypothesis:** Heavy rain has not reduced crop yields in the Raichur district, making farmers of Raichur districts ineligible for Government disaster relief funds.

If a Type I Error is committed by us, then farmers of the Raichur district are assumed to be eligible for the disaster relief fund, when it is not (the null hypothesis should be accepted, but it is rejected). The Government may be spending disaster relief funds when it should not, and taxes may be raised for everyone in the State of Karnataka to recover the relief fund expenses. And if a Type II Error is committed by us, then farmers of Raichur district are assumed to be not eligible for the disaster relief fund, when they are eligible (the null hypothesis should be rejected, but it is accepted). The Government may not spend disaster relief funds when it should, and this might increase the Suicidal rate of farmers in the Raichur district.

In doctoral-level research, scholars are generally required to specify the probability of committing a Type I Error that they are willing to accept, i.e., the value of alpha or significance level. If scholars belong to the Languages, Education, Social Sciences, Commerce, Management, Economics, or similar disciplines, we recommend selecting an alpha/significance level of 0.05 (5%) which means scholars want to be 95% confident about their claim (Confidence Level). This also means that scholars are willing to accept a probability of 5% of making a Type I Error (assuming a relationship between two variables exists when it does not). However, if scholars belong to disciplines or their research is involving Public Health, Basic/Natural Science, Engineering, Technology, or similar disciplines where a high level of precision is required we recommend setting an alpha/significance level of 0.01 (1%) which means 99% Confidence level. Do note that if the relationship between the variables is strong, and the level chosen for alpha is 0.05, then moderate or small sample sizes will detect it, and as the relationships get weaker, however, and/or as the level of alpha gets smaller, larger sample sizes will be needed for the research to reach statistical significance.

6.4. Significance Test Step 4 - Calculate Test Statistic :

It is mandatory for scholars to know the characteristics of the data collected by them as they determine what type of significance test among several available tests they can use to calculate the test statistic. There are two main characteristics of data as illustrated in figure 6. Scholars must check whether it is Categorical (Qualitative) such as Nominal Unordered (example: male/female; yes/no); Ordinal/Ordered/Scale (example: ratings; strongly disagree to strongly agree). Or is it Numerical (Quantitative) such as Discrete/Counts (example: number of male students; the number of stores; the number of Covid-19 positive cases); Continuous (example: height; weight; sales value)? Scholars must note that this is the origin of qualitative and quantitative research and they are nothing to do with research methodology/design. They just indicate the type of data used to describe, explain, or claim certain findings about reality/fact/phenomenon/dependent variable. Do note that once we calculate the test statistic for the data collected we are now left with only comparing the calculated test statistics with standard critical values to finalize the research finding/claim about the relationship. There are three main types of critical values such as i) Critical values of 'Chi-square' distribution; ii) Critical values for 't' distribution; iii) Critical values of 'f' distribution [89-107]. Scholars need not either calculate or worry about these standard critical values as these are standard and available openly accessible. The biggest question now in the scholars' mind is, if there are many types of tests of significance, how will I choose an appropriate one? We have come up with a simple technique for choosing an appropriate significance test. Do note that we might come across one or more of the thirteen scenarios when we enter the statistical significance test step of the doctoral-level research process. We recommend scholars choose a significance test according to the scenario they are into.

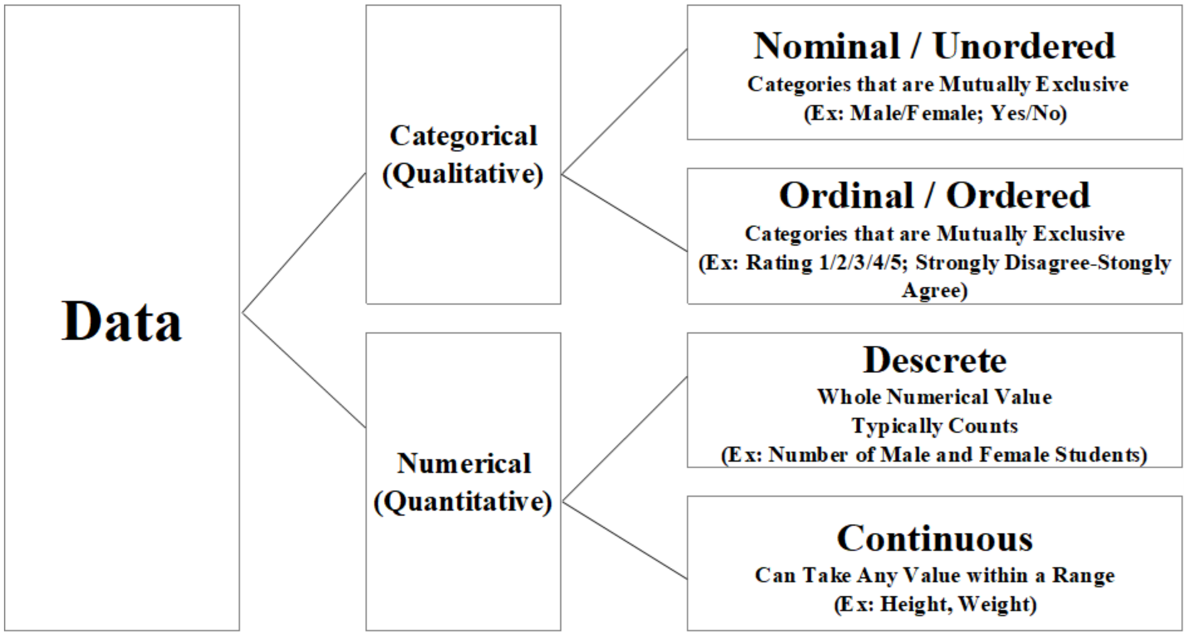

Fig. 6: Characteristics of data

6.4.1. Scenario 1 :

If the data type of the Independent and Dependent Variable is 'Categorical/Qualitative', and scholars are comparing 'Two Different Groups' as shown in figure 7 then scholars can choose either the Chi-square test of significance or Fisher's Exact test of significance or Mann-Whitney 'U' test of significance.

Chi-square Test of Significance: A Chi-square statistic is one method to show a relationship between two Categorical/Qualitative Variables. The Chi-square test for an association that is also called the Chi-square test for independence is used to find a relationship between two Categorical/Qualitative Variables. The Chi-square test can also be used to demonstrate non-association. A Chi-squared statistic is a single number that tells scholars how much difference exists between the observed counts and the counts scholars would expect if there were no relationship at all in the population. Scholars could also use a p-value to decide the inference. Do note that the Chi-square statistic can only be used on numbers and should not be used for percentages, proportions, means, or similar statistical values. For example, if scholars have 10% of 200 people, scholars will need to convert that to a number (i.e., 20) before scholars calculate the test statistic. The Chi-square test statistic can be calculated using the formula (10). The decision rule is IF calculated Chi-square is Lesser than the Critical Value then ACCEPT Null Hypothesis; IF calculated Chi-square is Greater than the Critical Value then ACCEPT Research/Alternate Hypothesis.

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \qquad (10)$$

χ^2 = chi squared
O_i = observed value
E_i = expected value

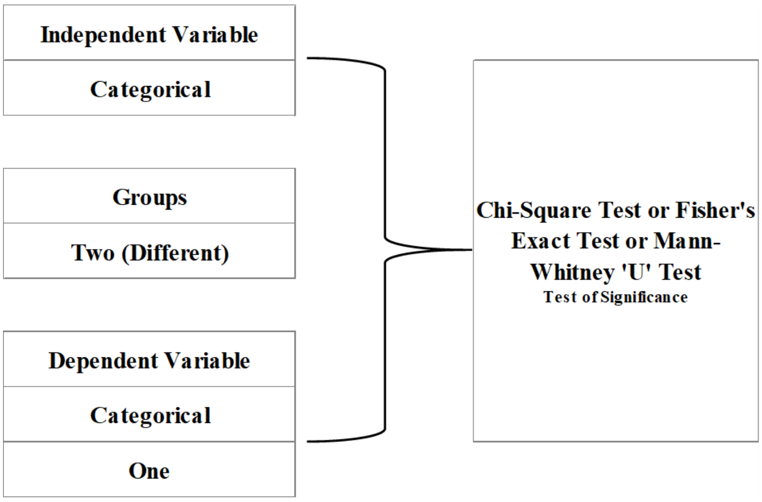

Fig. 7: Combination for Scenario 1

Fisher's Exact Test of Significance: Fisher's Exact test of independence is a statistical test used when scholars have two nominal Variables and would like to find out if proportions for one nominal Variable are different among values of the other nominal Variable. For experiments with small numbers of participants (usually under around 1,000), Fisher's Exact is more accurate than the Chi-square test. Fisher's Exact test is a statistical test used to determine if there are non-random associations between two Categorical/Qualitative Variables. It is a multivariate generalization of the hypergeometric probability function. Fisher's Exact test statistic can be calculated using the formula (11). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

$$p = \frac{(a+b)!(c+d)!(a+c)!(b+d)!}{a!b!c!d!n!} \qquad (11)$$

p = P-value
a, b, c, d = values in a contingency table
n = total frequency

Mann-Whitney 'U' Test of Significance Test: The Mann-Whitney 'U' test is the Non-parametric equivalent of the Two-sample t-test. While the t-test assumes the distribution of a population, the Mann-Whitney 'U' test makes no such assumption. The test compares two populations (Groups). The null hypothesis for the test is that the probability is 50% that a randomly drawn sample of the first population will exceed a sample of the second population. Another option for the null hypothesis is that the two samples come from the same population i.e., that they both have the same Median. Assumptions for the Mann-Whitney' U' test are i) the Dependent Variable should be measured on an ordinal scale or a continuous scale; ii) the Independent Variable should be two independent, Categorical/Qualitative groups; iii) observations should be independent, in other words, there should be no relationship between the two groups or within each group; iv) observations are not normally distributed. However, they should follow the same shape. Mann-Whitney test statistic can be calculated using the formula (12). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

$$Z = \frac{U_i - \frac{n_1 \times n_2}{2}}{SE}$$

Where,

$$U_i = R_i - \frac{n_i \times (n_i + 1)}{2}$$

$$SE = \sqrt{\frac{n_1 \times n_2}{N(N-1)} \times \left(\frac{N^3 - N}{12} - \sum_i T_i\right)} \qquad (12)$$

$$T = \sum T_i$$

'n_1' is the number of items in Group 1.
'n_2' is the number of items in Group 2.
'N' is the total number of items

6.4.2. Scenario 2 :

If the data type of the Independent and Dependent Variable is 'Categorical/Qualitative' and scholars are comparing 'Two Same Groups' as shown in figure 8 then scholars can choose either the Wilcoxon Signed Rank test of significance or McNemar's test of significance.

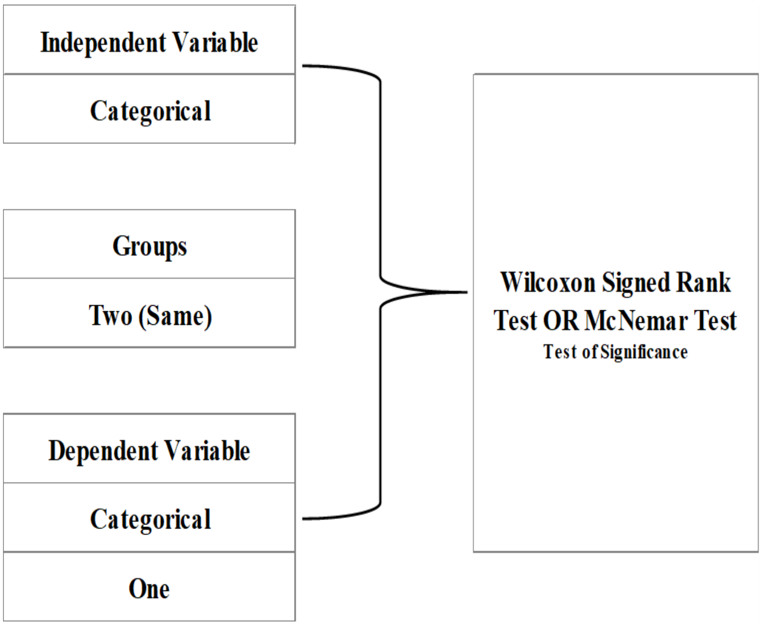

Fig. 8: Combination for Scenario 2

***Wilcoxon Signed Rank Significance Test*:** The Wilcoxon signed rank test also called the Wilcoxon signed rank sum test is a non-parametric test. When the word Non-parametric is used, it does not quite mean that scholars know nothing about the population. It usually means that scholars know the population data does not have a normal distribution. The Wilcoxon signed rank test should be used if the differences between pairs of data are non-normally distributed. The Wilcoxon signed rank test compares the sample median against a hypothetical median. The Wilcoxon matched-pairs signed rank test computes the difference between each set of matched pairs, then follows the same procedure as the signed-rank test to compare the sample against some median. Wilcoxon test statistic can be calculated using the formula (13)**.** The decision rule is IF the calculated Wilcoxon value is Lesser than the Critical Value then ACCEPT Null Hypothesis; IF the calculated Wilcoxon value is Greater than the Critical Value then ACCEPT Research/Alternate Hypothesis.

$$W = \sum_{i=1}^{N_r} [\text{sgn}(x_{2,i} - x_{1,i}) \cdot R_i]$$

W = test statistic
N_r = sample size, excluding pairs where x1 = x2
sgn = sign function
$x_{1,i}, x_{2,i}$ = corresponding ranked pairs from two distributions
R_i = rank i

(13)

McNemar's Test of Significance: McNemar's test is a Non-parametric test for paired nominal data. It is used when scholars are interested in finding a change in proportion for the paired data. For example, scholars could use this test to analyze Retrospective Case Studies, where each treatment is paired with a control. It could also be used to analyze an experiment where two treatments are given to matched pairs. This test is sometimes referred to as McNemar's Chi-square test because the test statistic has a Chi-square distribution. It is the same as Wilcoxon but provides information about any change in the distribution also. McNemar test statistic can be calculated using the formula (14)**.** The decision rule is IF calculated McNemar Chi-square is Lesser than Critical Value then ACCEPT Null Hypothesis; IF calculated McNemar Chi-square is Greater than Critical Value then ACCEPT Research/Alternate Hypothesis.

$$\chi^2 = \frac{(b-c)^2}{b+c}$$

'b' is the number of items positively changed.
'c' is the number of items negatively changed

(14)

6.4.3. Scenario 3 :

If the data type of the Independent and Dependent Variable is 'Categorical/Qualitative', and scholars are comparing 'More than Two Same Groups' as shown in figure 9 then scholars can choose the Cochran-Mantel-Haenszel (CMH) test of significance. The CMH test is a test of association for data from different groups or stratified data from one group. It is a generalization of the McNemar test, suitable for any Experimental design including Case-control studies and Prospective studies. While the McNemar can only handle pairs of data i.e., a 2 x 2 contingency table, the CMH test can handle the analysis of multiple 2 x 2 x k tables from stratified samples. The results from the tables are weighted i.e., given different levels of importance according to the size of the sample in each stratum. For pairs of data, the results from CMH and McNemar will be the same.

$$Q = k \times (k-1) \times \frac{\sum_{j=1}^{k} \left(C_j - \frac{N}{k}\right)^2}{\sum_{i=1}^{n_f} R_i \times (k - R_i)}$$

Where; 'k' is the number of variables; 'N' is the total number of successes; 'C' is the number of successes in each experiment/treatment; 'nf' is the total number of cases; 'R' is the number of successes for each case.

The CMH test statistic is particularly useful in clinical trials, where confounding variables cause extra connections between the Dependent Variable and Independent Variable. CMH test statistics can be calculated using the formula (15). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

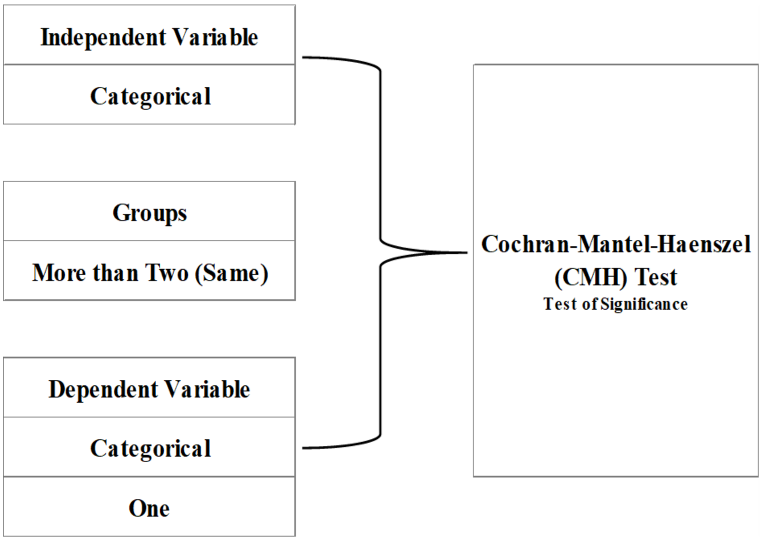

Fig. 9: Combination for Scenario 3

6.4.4. Scenario 4 :

If the data type of the Independent and Dependent Variable is 'Categorical/Qualitative', and scholars are comparing 'More than Two Different Groups' as shown in figure 10 then scholars can choose either The Kruskal-Wallis 'H' test of significance or Goodman and Kruskal's 'Gamma' Coefficient test of significance.

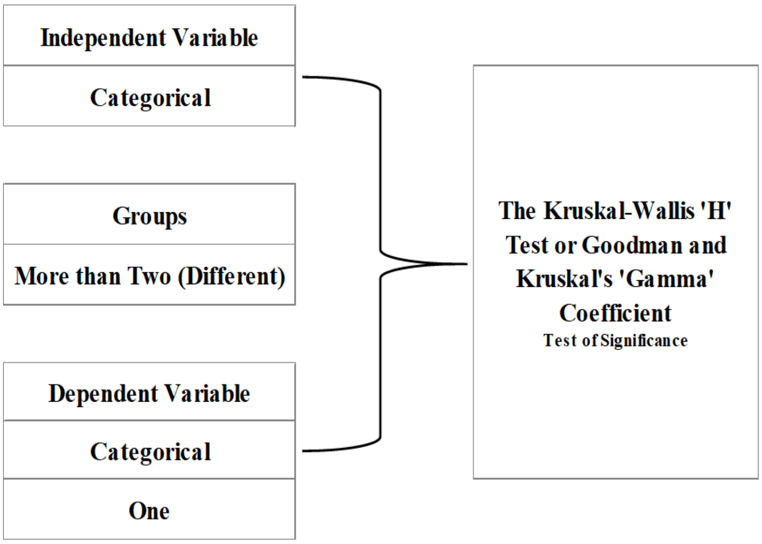

Fig. 10: Combination for Scenario 4

The Kruskal-Wallis 'H' Test of Significance: The Kruskal-Wallis test is the Non-parametric alternative to the One-way ANOVA. Non-parametric means that the test does not assume the data comes from a particular distribution. The Kruskal-Wallis 'H' test is used when the assumptions for ANOVA are not met like the assumption of normality. It is sometimes called the One-way ANOVA on ranks, as the ranks of the data values are used in the test rather than the actual data points. The test determines whether the Medians of two or more groups are different. The Kruskal-Wallis 'H' test will tell scholars if there is a significant difference between groups. However, it will not tell scholars which groups are different. For that, scholars will need to run the Post-hoc test. The Kruskal-Wallis test statistic can be calculated using the formula (16). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

$$H = \frac{12}{N(N+1)} \left[\sum_{i=1}^{k} \frac{R_i^2}{n_i} \right] - 3(N+1)$$

$$\begin{aligned} R_i &= \sum \text{ of ranks of group } i \\ n_i &= \text{size of sample } i \\ N &= \sum_{i=1}^{k} n_i \\ k &= \text{number of groups} \end{aligned} \quad (16)$$

Goodman and Kruskal's Gamma Coefficient Test of Significance: The Gamma coefficient also called the Gamma statistic, or Goodman and Kruskal's Gamma tells us how closely two pairs of data points match. Gamma tests for an association between points and also tells us the strength of the association. The goal of the test is to be able to predict where new values will rank. The Gamma coefficient ranges between -1 and 1. The closer scholars get to a 1 or -1, the stronger the relationship. For some disciplines, it may be the preferred method for all ordinal data arranged in a bivariate table. If scholars have two dichotomous variables, use Yule's 'Q' instead. The Kruskal Gamma Coefficient test statistic can be calculated using the formula (17). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

$$\gamma = \frac{N_c - N_d}{N_c + N_d}$$

N_c is the total number of pairs that rank the same (concordant pairs)

N_d is the number of pairs that don't rank the same (discordant pairs) (17)

Do note that all the Significance tests from Scenario 1 to 4 are also known as Non-parametric significance tests. If the distribution of the data does not follow a Normal Distribution Curve these tests are recommended.

6.4.5. Scenario 5 :

If the data type of the Independent Variable is 'Categorical/Qualitative', Dependent Variable is 'Quantitative', and scholars are comparing 'Two Same Groups' as shown in figure 11 then scholars can choose Paired t-test of significance. Also known as Student's t-tests is a parametric test based on the Student's or t-distribution. Student's distribution is named in honor of William Sealy Gosset (1876–1937), who first determined it in 1908. Paired t-test is used to determine whether the Mean difference between two sets of observations is zero. A Paired t-test is used when we are interested in the difference between two Variables for the same Unit of Analysis/Sample/subject/respondent. Often the two Variables are separated by time (Before and After; Pre and Post). The Paired t-test is also known as the Dependent Samples t-test, the Paired-difference t-test, the Matched Pairs t-test, and the Repeated-samples t-test. The paired t-test statistic can be calculated using the formula (18). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

$$t = \bar{x}_{diff} / (s_{diff}/\sqrt{n}) \tag{18}$$

$\bar{x}_{diff}$: sample mean of the differences

s: sample standard deviation of the differences

n: sample size (i.e. number of pairs)

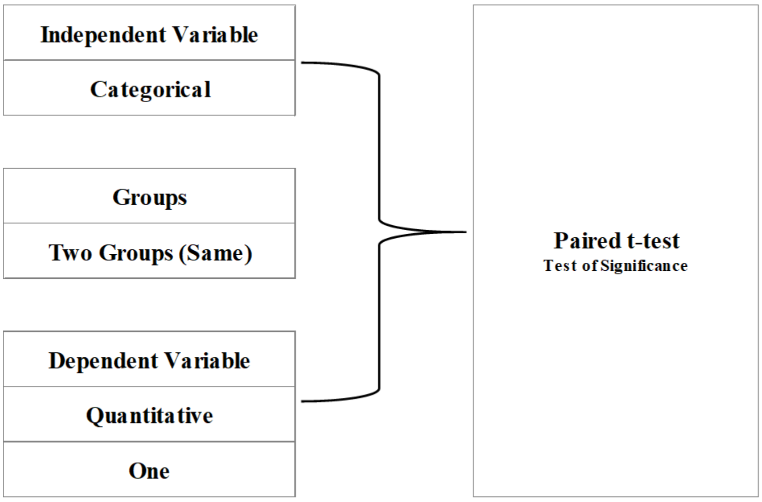

Fig. 11: Combination for Scenario 5

6.4.6. Scenario 6 :

If the data type of the Independent Variable is ‘Categorical/Qualitative’, Dependent Variable is ‘Quantitative’, and scholars are comparing ‘Two Different Groups’ as shown in figure 12 then scholars can choose the Unpaired t-test of significance. An Unpaired t-test compares the Means of two independent or unrelated groups to determine if there is a significant difference between the two. The unpaired t-test is also known as the Independent Samples t-test. The Unpaired t-test statistic can be calculated using the formula (19). The decision rule is IF the calculated p-value is Greater than the Significance level then ACCEPT Null Hypothesis; IF the calculated p-value is Lesser than the Significance level then ACCEPT Research/Alternate Hypothesis.

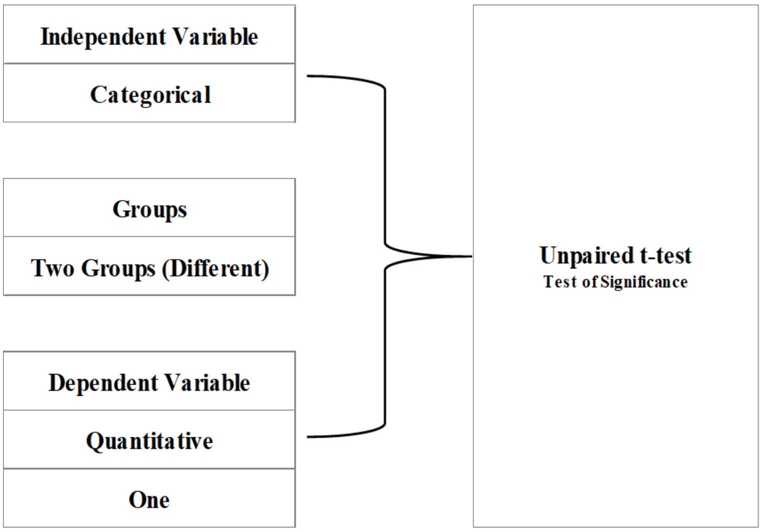

Fig. 12: Combination for Scenario 6

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Where,

x bar 1 and x bar 2 are the sample means
s^2 is the pooled sample variance
n_1 and n_2 are the sample sizes
$n_1 + n_2 - 2$ degrees of freedom

$$s^2 = \frac{\sum_{i=1}^{n_1}(x_i - \bar{x}_1)^2 + \sum_{j=1}^{n_2}(x_j - \bar{x}_2)^2}{n_1 + n_2 - 2} \qquad (19)$$

6.4.7. Scenario 7 :

If the data type of the Independent Variable is ‘Categorical/Qualitative’, Dependent Variable is ‘Quantitative’, and scholars are comparing ‘More than Two Different Groups’ as shown in figure 13 then scholars can choose a One-way ANOVA test of significance. ANOVA, which stands for analysis of variance. It is used to analyze the difference between the Means of more than two groups. A One-way ANOVA uses one Independent Variable, while a Two-way ANOVA uses two Independent Variables. ANOVA tells scholars if the Dependent Variable changes according to the level of the Independent Variable. ANOVA uses the f-test for statistical significance. This allows for the comparison of multiple means at once because the error is calculated for the whole set of comparisons rather than for each two-way comparison which would happen with a t-test. The decision rule is IF the f-critical > f ratio, then ACCEPT Null hypothesis, and there is no relation between the variables under observation. If the f-critical < f ratio, then ACCEPT Research/Alternate hypothesis, and in turn, supports the idea that the variables affect each other.

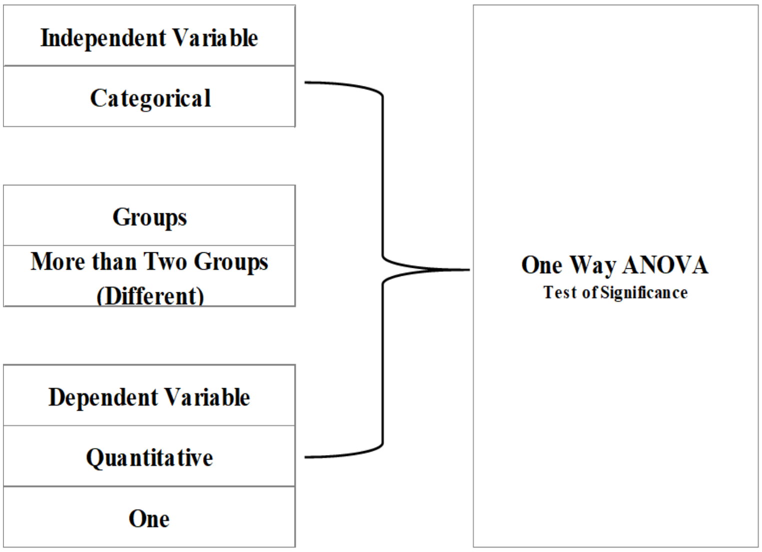

Fig. 13: Combination for Scenario 7

6.4.8. Scenario 8 :

If the data type of the Independent Variable is ‘Categorical/Qualitative’, Dependent Variable is ‘Quantitative’, and scholars are comparing ‘More than Two Same Groups’ as shown in **Figure 14** then scholars can choose Two-way ANOVA without Replication. When there is only a single observation for each combination of the nominal Variables, there are only two null hypotheses. That the Means of observations grouped by one factor are the same, and that the Means of observations grouped by the other factor are the same. It is not possible to test the null hypothesis of no interaction. Instead, scholars have to assume that there is no interaction to test the two main effects. When there is no replication, scholars calculate the Mean Square for each of the two main effects, and scholars also calculate a total Mean Square by considering all of the observations as a single group. The remainder-mean-square which is also called the discrepancy or Error Mean Square is found by subtracting the two main effect Mean Squares from the Total Mean Square. The f-statistic for the main effect is the main effect Mean Square divided by the remainder Mean Square. The decision rule is if the f-critical > f ratio, then ACCEPT Null hypothesis. If the f-critical < f ratio, then ACCEPT Research/Alternate hypothesis.

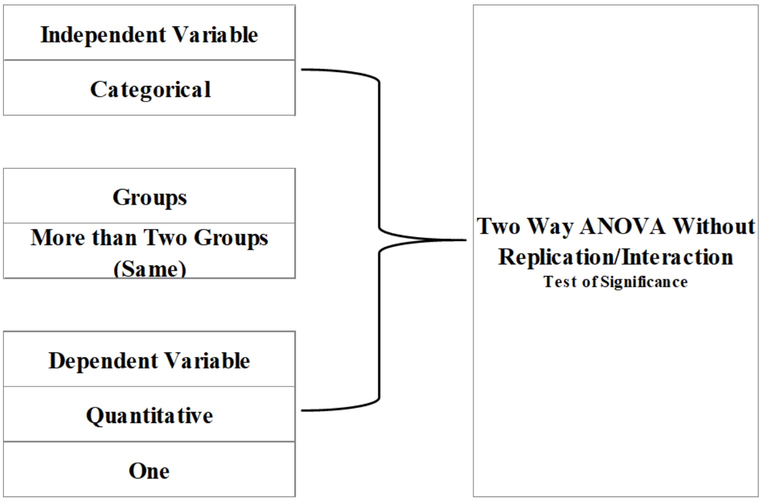

Fig. 14: Combination for Scenario 8

6.4.9. Scenario 9 :

If the data type of the Independent Variable is ‘Categorical/Qualitative’, Dependent Variable is ‘Quantitative’, and scholars are comparing ‘More than Two Different Groups’ as shown in figure 15 then scholars can choose Two-way ANOVA with Replication test of significance.

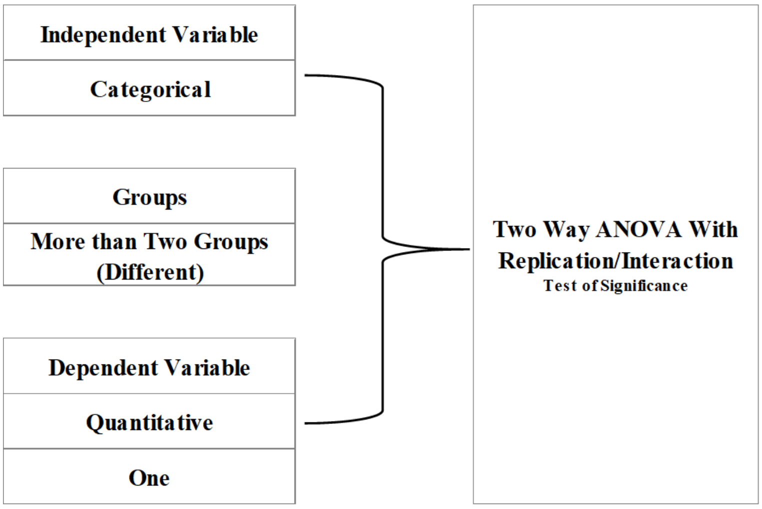

Fig. 15: Combination for Scenario 9

When scholars do a Two-way ANOVA without replication, scholars can still test the two main effects, but scholars cannot test the interaction. This means that the tests of the main effects have to assume that there is no interaction. If scholars find a significant difference in the Means for one of the main effects, scholars will not know whether that difference was consistent for different values of the other main effect. When the sample sizes in each subgroup are equal (a balanced design), scholars calculate the Mean Square for each of the two factors (the main effects), for the interaction, and for the variation within each combination of factors. Scholars then calculate each f-statistic by dividing a Mean Square by the within-subgroup Mean Square. When the sample sizes for the subgroups are not equal (an unbalanced design), the analysis is much more complicated, and there are several different techniques for testing the main and interaction effects. If scholars are doing a Two-way ANOVA, the statistical life will be a lot easier if scholars make it a balanced design. The decision rule is if the f-critical > f ratio, then ACCEPT Null hypothesis. If the f-critical < f ratio, then ACCEPT Research/Alternate hypothesis.

6.4.10. Scenario 10 :

If the data type of the Independent Variable is 'Categorical/Qualitative', scholars have 'More than One Quantitative Dependent Variables', and scholars are comparing 'More than Two Different Groups' as shown in figure 16 then scholars can choose the MANOVA test of significance. Multivariate Analysis of Variance (MANOVA) is an extension of the univariate analysis of variance (ANOVA). MANOVA is a procedure for comparing multivariate sample Means. As a multivariate procedure, it is used when there are two or more Dependent Variables and is often followed by significance tests involving individual Dependent Variables separately. The MANOVA will compare whether or not the newly created combination differs by the different groups, or levels, of the Independent Variable. In this way, the MANOVA essentially tests whether or not the independent grouping variable simultaneously explains a statistically significant amount of variance in the Dependent Variable. The calculated test statistic of MANOVA is known as Wilks Lambda which ranges from 0 to 1. The decision rule is, that the lower the Wilks Lambda, the larger the between-group dispersion. A small (close to 0) value of Wilks' Lambda means that the groups are well separated. a large (close to 1) value of Wilks' Lambda means that the groups are poorly separated.

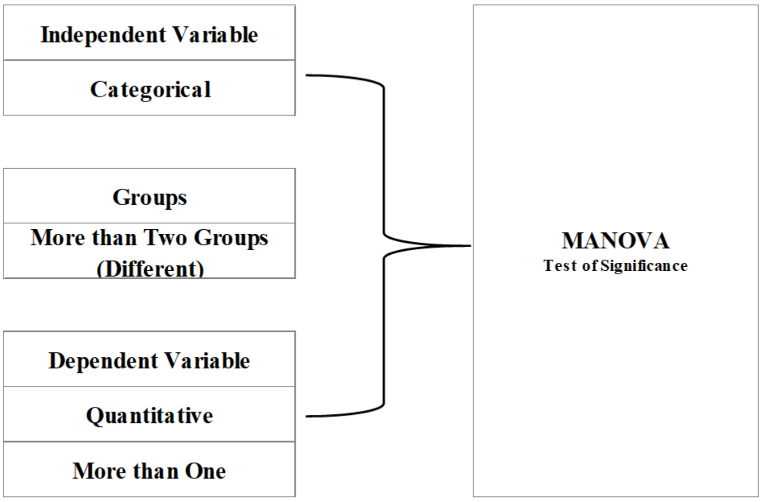

Fig. 16: Combination for Scenario 10

6.4.11. Scenario 11 :

If the data type of the Independent Variable is 'Quantitative' and scholars have 'One Independent Variable'; the data type of 'Dependent Variable' is 'Quantitative' and scholars have 'One Dependent Variable' as shown in figure 17 then scholars can choose Simple Regression test of significance. The correlation coefficient measures the strength of the linear relationship between two Variables on a continuous scale, whereas regression attempts to determine the strength and character of the relationship between one Dependent Variable (usually denoted by **'y'**) and one Independent Variable. It is used when scholars want to predict a continuous Dependent Variable from given values of an Independent Variable. Do note that with regression analysis, causal relationships among the variables cannot be determined. While the terminology is such that we say 'x' predicts 'y', we cannot state that 'x' causes 'y'. Scholars need to also look at the R-squared (the coefficient of determination) value that determines the proportion of variance in the Dependent Variable that can be explained by the Independent Variable. The R-squared value shows how well the data fit the regression model (the goodness of fit). It is always recommended to consider the 'Adjusted r-squared value' that takes into consideration the number of Independent Variables and Samples. This can take any value between 0 to 1. Values above 0.50 are acceptable. However, for Basic and Health Sciences it should be a minimum of 0.90. A higher adjusted r-squared indicates the forecast/prediction/relational model is a good fit. Be aware that just because scholars get a higher r-squared value causal relationships between the Variables cannot be determined.

In addition to testing the significance of the relationship, Simple Regression helps build predictive models.

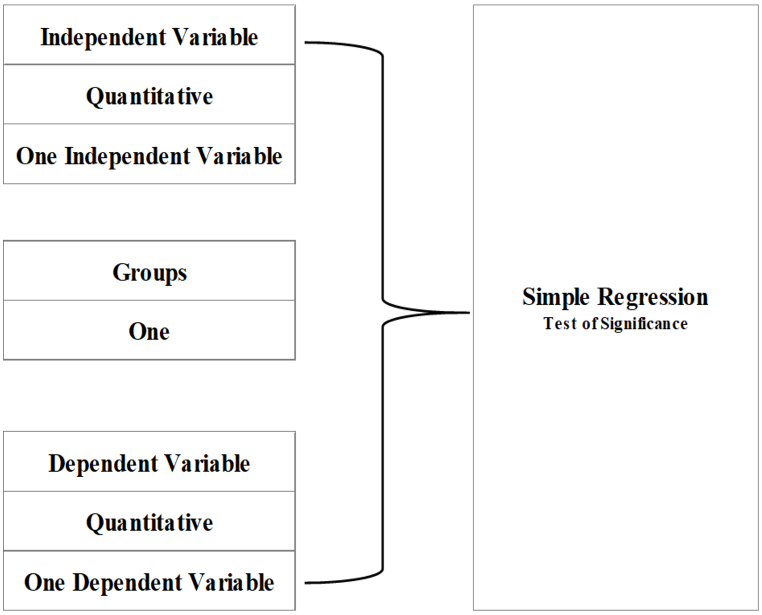

Fig. 17: Combination for Scenario 11

6.4.12. Scenario 12 :

If the data type of the Independent Variable is 'Quantitative' and scholars have 'More than One Independent Variable'; the data type of 'Dependent Variable' is 'Quantitative' and scholars have 'One Dependent Variable' as shown in figure 18 then scholars can choose Multiple Regression test of significance.

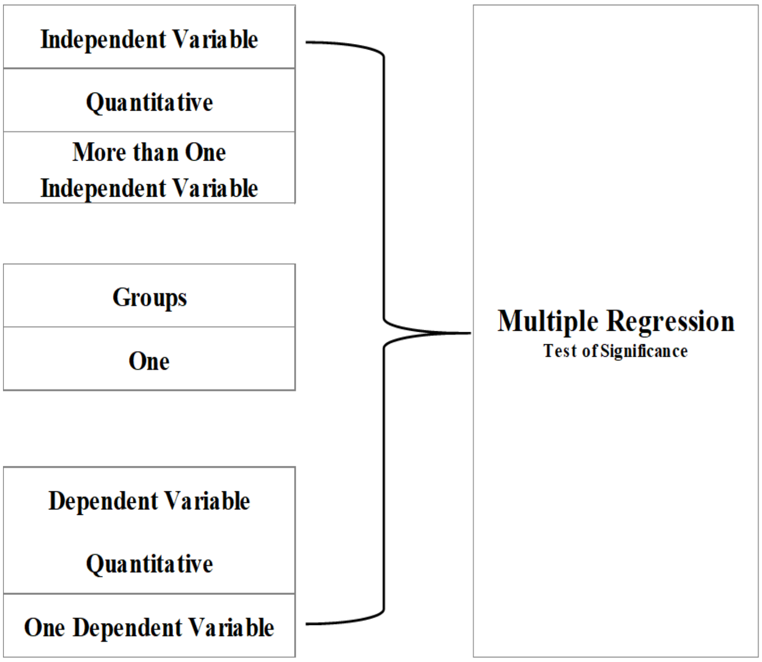

Fig. 18: Combination for Scenario 12

Multiple regression is used to analyze the relationship between a single Dependent Variable and several Independent Variables. This approach can be applied to analyze multivariate time series data when one of the Variables is dependent on a set of other Variables. Scholars can model the Dependent Variable 'y' on the set of Independent Variables. At any time, an instant when scholars are given the values of the Independent Variables ('x'), scholars can predict the value of 'y'. Scholars can use multiple linear regression when scholars want to know i) how strong the relationship is between two or more Independent Variables and one Dependent Variable. For example, how rainfall (Independent Variable 1), temperature (Independent Variable 2), and amount of fertilizer added (Independent Variable 3) have affected the crop growth (Dependent Variable 1); ii) the value of the Dependent Variable at a certain value of the Independent Variables the expected yield of a crop (Dependent Variable 1) at certain levels of rainfall (Independent Variable 1), temperature (Independent Variable 2), and fertilizer addition (Independent Variable 3).

6.4.13. Scenario 13 :

If the data type of the Independent Variable is 'Quantitative' and scholars have 'More than One Independent Variable'; the data type of 'Dependent Variable' is 'Categorical/Qualitative' and they have 'One Dependent Variable' as shown in figure 19 then scholars can choose Logistic Regression test of significance. The logistic model or logit model is used to model the probability of a certain class or event existing such as active/inactive; pass/fail; win/lose; yes/no; healthy/sick, etc. This can be extended to model several classes of events such as determining whether an image contains a Dog, Cat, Lion, etc. each event would be assigned a probability between 0 and 1, with a sum of one. Logistic regression was used in the Biological Sciences in the early twentieth century. Later it became famous in many Social Science, Management, and Economics Applications. Logistic regression is easier to implement and interpret, and very efficient to train. If the number of observations (Sample Size) is lesser than the number of features (Variables), logistic regression should not be used, otherwise, it may lead to overfitting.

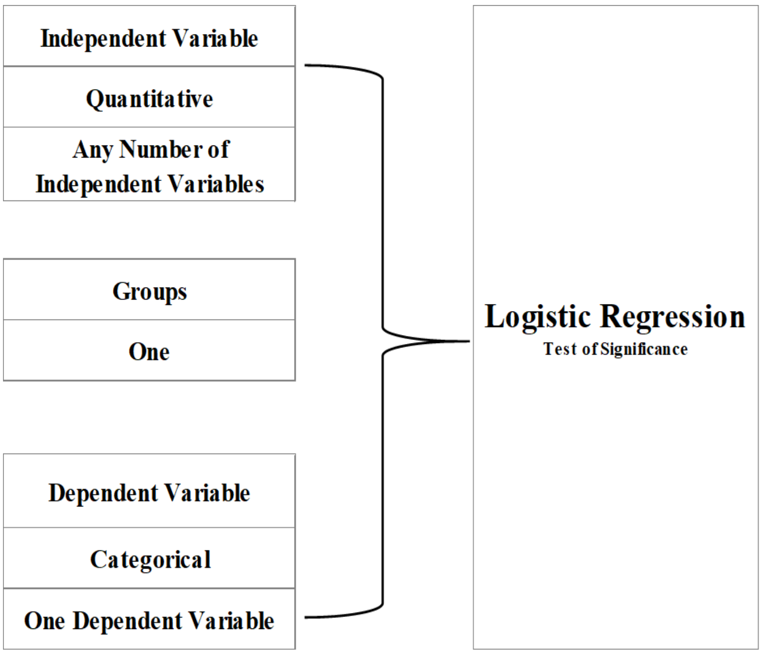

Fig. 19: Combination for Scenario 13

Do note that all the Significance tests from Scenario 5 to 13 are also known as Parametric significance tests. If the distribution of the data follows a Normal Distribution Curve these tests are recommended.

6.4.13. Summary of 13 Scenarios :

For a quick check, we have tabled all these thirteen scenarios in one summary table as shown in table 2. Before scholars chose a significance/hypothesis test scholars must ensure they have quickly glanced through this table and are clear about their decision about selecting a particular significance/hypothesis test. Most statistical software is programmed to understand the data type of variables and accordingly allows scholars to choose a particular significance/hypothesis test. However, it is the scholars' responsibility to understand why a particularly significant test is chosen. Furthermore, they can also choose the significance tests based on the normality of their data set.

Table 2: Summary table of possible Scenarios

Scenario	Independent Variable	Dependent Variable	How Many Number of Groups Being Compared	Recommended Statistical Significance Test
1	Categorical/Qualitative	Categorical/Qualitative	Two (Different)	Chi-Square Test
	Categorical/Qualitative	Categorical/Qualitative		Fisher's Exact Test
	Categorical/Qualitative	Categorical/Qualitative		Mann-Whitney 'U' Test
2	Categorical/Qualitative	Categorical/Qualitative	Two (Same)	Wilcoxon Signed Rank Test
	Categorical/Qualitative	Categorical/Qualitative		McNemar's Test
3	Categorical/Qualitative	Categorical/Qualitative	More than Two (Same)	Cochran-Mantel-Haenszel (CMH) Test
4	Categorical/Qualitative	Categorical/Qualitative	More than Two (Different)	The Kruskal-Wallis 'H' Test
	Categorical/Qualitative	Categorical/Qualitative		Goodman and Kruskal's 'Gamma' Coefficient
5	Categorical/Qualitative	Numerical/Quantitative	Two (Same)	Paired T-test
6	Categorical/Qualitative	Numerical/Quantitative	Two (Different)	Unpaired T-test
7	Categorical/Qualitative	Numerical/Quantitative	More than Two (Different)	One Way ANOVA
8	Categorical/Qualitative	Numerical/Quantitative	More than Two (Same)	Two Way ANOVA Without Replication/Interaction
9	Categorical/Qualitative	Numerical/Quantitative	More than Two (Different)	Two Way ANOVA With Replication/Interaction
10	Categorical/Qualitative	Numerical/Quantitative	More than Two (Different)	MANOVA
11	Numerical/Quantitative	Numerical/Quantitative	One	Simple Linear Regression
12	Numerical/Quantitative	Numerical/Quantitative	One	Multiple Linear Regression
13	Numerical/Quantitative	Categorical/Qualitative	One	Logistic Regression

We know that scholars might think about how they are going to calculate the test statistic even if they have chosen an appropriate test of significance. Scholars need not worry. They have a 'Facilitator' known as Statistical Software that will help them calculate test statistics for their data set in nearly no time. We have listed a few software that scholars can use for statistical analyses.

Paid Statistical Software: Microsoft XLSTAT; IBM SPSS; Tableau; Minitab; R; SAS; Amos; Smart-Pls.

Free Statistical Software: Microsoft Excel Data Analysis Tool and Solver; JASP (Jeffreys's Amazing Statistics Program [108]).

We recommend scholars use JASP which is a free and open-access statistical software. It is managed by the University of Amsterdam which is one of the Top 100 Universities in the World. Do note that there are plenty of YouTube videos that can demonstrate every aspect of JASP software in detail.

7. CONCLUSION :

Ph.D. scholars might think about whether they are good at Mathematics/Statistics. However, they need to be cognizant of the fact that, Statistics is not Mathematics! and does not require talent or previous association with subjects concerning Mathematics/Statistics. It just requires hard work, and more than the hard work requires scholars to focus on the purpose of deriving sample size and the role of statistical techniques. Scholars need not be an expert in Mathematics or Statistics and most importantly they are not required to memorize the formulas. They just need to know why they have taken the help of a particular formula. Statistics also uses numbers, but numbers are not the primary focus. It is a form of inductive reasoning that uses mathematics as one of its tools to discover new knowledge. It is a thinking tool and science of learning from data [46] [58-62]. Scholars need the help of statistical techniques to i) describe samples/units of analysis and the data collected from them; ii) discover the relationship between variables of the research question; iii) test the significance of the relationship discovered.

A majority of scholars avoid formulating 'Relational' and 'Causal' types of research questions as they need to be answered with the help of statistical techniques. 'Descriptive' type of research question is the most preferred research question formulated by scholars who are scared of 'Statistics'. Furthermore, a majority of Ph.D. scholars out of enthusiasm formulate a 'Relational' or 'Causal' type of research question and when they reach the steps that require them to use appropriate statistical techniques they become blank. This is merely happening because scholars are not imparted knowledge about the irreplaceable benefits of 'Statistics' in doctoral-level research. Ph.D. scholars must understand that statistical techniques are just a tiny part of the overall doctoral-level research and they exist only to help scholars come up with research findings/claims that are comfortably acceptable to the research community globally [47].

It is the responsibility of every stakeholder in the research environment and system to ensure that the scholars are made aware of every step involved in carrying out doctoral-level research in addition to the objectives, purpose, essence, and reasons for the existence of statistical techniques in the doctoral-level research which would enable them to choose appropriate statistical techniques to achieve their key research objective during the Ph.D. journey. Designing robust coursework that is intended to create awareness about statistics and statistical techniques is an appropriate way of fulfilling this responsibility. As long as the Ph.D. scholars can understand i) they need NOT be an expert in Mathematics/Statistics and it is easy to learn statistics during Ph.D.; ii) the difference between measures of central tendency and dispersion; iii) the difference between association, correlation, and causation; iv) difference between null and research/alternate hypotheses; v) difference between Type I and Type II errors; vi) key drivers for choosing a statistical significance test; vi) which is the best software for carrying out statistical analyses. Scholars will be able to (on their own) choose appropriate statistical techniques across various steps of the doctoral-level research process and comfortably claim their research findings.

REFERENCES :

[1] Titus, S. L., & Ballou, J. M. (2013). Faculty members' perceptions of advising versus mentoring: Does the name matter?. *Science and Engineering ethics*, *19*(3), 1267-1281. Google Scholar↗

[2] Ali, A., & Kohun, F. (2006). Dealing with isolation feelings in IS doctoral programs. *International Journal of Doctoral Studies*, *1*(1), 21-33. Google Scholar↗

[3] Ali, A., Kohun, F., & Levy, Y. (2007). Dealing with Social Isolation to Minimize Doctoral Attrition- A Four Stage Framework. *International Journal of Doctoral Studies*, *2*(1), 33-49. Google Scholar↗

[4] Spaulding, L. S., & Rockinson-Szapkiw, A. (2012). Hearing their voices: Factors doctoral candidates attribute to their persistence. *International Journal of Doctoral Studies*, *7*, 199. Google Scholar↗

[5] Golde, C. M., & Dore, T. M. (2001). At cross purposes: What the experiences of today's doctoral students reveal about doctoral education, *ERIC Processing and Reference Facility*, 1-62. Google Scholar↗

[6] Golde, C. M. (2005). The role of the department and discipline in doctoral student attrition: Lessons from four departments. *The Journal of Higher Education*, *76*(6), 669-700. Google Scholar↗

[7] Golde, C. M., & Walker, G. E. (Eds.). (2006). *Envisioning the future of doctoral education: Preparing stewards of the discipline-Carnegie essays on the doctorate* (Vol. 3). John Wiley & Sons. Google Scholar↗

[8] Gardner, S. K. (2009). Student and faculty attributions of attrition in high and low-completing doctoral programs in the United States. *Higher education*, *58*(1), 97-112. Google Scholar↗

[9] Gardner, S. K. (2010). Faculty perspectives on doctoral student socialization in five disciplines. *International Journal of Doctoral Studies*, *5*, 39. Google Scholar↗

[10] Solmon, M. A. (2009). How do doctoral candidates learn to be researchers? Developing research training programs in kinesiology departments. *Quest*, *61*(1), 74-83. Google Scholar↗

[11] Nogueira-Martins, L. A., Fagnani Neto, R., Macedo, P. C. M., Citero, V. D. A., & Mari, J. D. J. (2004). The mental health of graduate students at the Federal University of São Paulo: a

preliminary report. *Brazilian Journal of Medical and Biological Research*, *37*, 1519-1524. Google Scholar↗

[12] Knox, S., Schlosser, L. Z., Pruitt, N. T., & Hill, C. E. (2006). A qualitative examination of graduate advising relationships: The advisor perspective. *The Counseling Psychologist*, *34*(4), 489-518. Google Scholar↗

[13] Grady, R. K., La Touche, R., Oslawski-Lopez, J., Powers, A., & Simacek, K. (2014). Betwixt and between: The social position and stress experiences of graduate students. *Teaching Sociology*, *42*(1), 5-16. Google Scholar↗

[14] Russell, J., Gaudreault, K. L., & Richards, K. A. R. (2016). Doctoral student socialization: Educating stewards of the physical education profession. *Quest*, *68*(4), 439-456. Google Scholar↗

[15] Russell, J. A. (2015). Rolling with the punches: Examining the socialization experiences of kinesiology doctoral students. *Research quarterly for exercise and sport*, *86*(2), 140-151. Google Scholar↗

[16] Harding-DeKam, J. L., Hamilton, B., & Loyd, S. (2012). The hidden curriculum of doctoral advising. *NACADA Journal*, *32*(2), 5-16. Google Scholar↗

[17] Mansson, D. H., & Myers, S. A. (2012). Using mentoring enactment theory to explore the doctoral student–advisor mentoring relationship. *Communication Education*, *61*(4), 309-334. Google Scholar↗

[18] Robinson, E. M., & Tagher, C. G. (2017). The companion dissertation: Enriching the doctoral experience. *Journal of Nursing Education*, *56*(9), 564-566. Google Scholar↗

[19] Haynes, K. N. (2008). Reasons for doctoral attrition. *Health*, *8*, 17-4. Google Scholar↗

[20] Mazerolle, S. M., Bowman, T. G., & Klossner, J. C. (2015). An analysis of doctoral students' perceptions of mentorship during their doctoral studies. *Athletic Training Education Journal*, *10*(3), 227-235. Google Scholar↗

[21] Holsinger Jr, J. W. (2008). Situational leadership applied to the dissertation process. *Anatomical Sciences Education*, *1*(5), 194-198. Google Scholar↗

[22] McNamara, J. F., Lara-Alecio, R., Hoyle, J., & Irby, B. J. (2010). Doctoral program issues: Commentary on companion dissertations. *A Doctoral Issues Presentation at the National Council of Professors of Educational Administration* Lexington, KY, August 2, 2006. Google Scholar↗

[23] Carter-Veale, W. Y., Tull, R. G., Rutledge, J. C., & Joseph, L. N. (2016). The dissertation house model: Doctoral student experiences coping and writing in a shared knowledge community. *CBE—Life Sciences Education*, *15*(3), ar34. Google Scholar↗

[24] Devos, C., Boudrenghien, G., Van der Linden, N., Azzi, A., Frenay, M., Galand, B., & Klein, O. (2017). Doctoral students' experiences leading to completion or attrition: A matter of sense, progress and distress. *European journal of psychology of education*, *32*(1), 61-77. Google Scholar↗

[25] Beatty, S. E. (2001). The doctoral supervisor-student relationship: some American advice for success. *The Marketing Review*, *2*(2), 205-217. Google Scholar↗

[26] Carpenter, S., Makhadmeh, N., & Thornton, L. J. (2015). Mentorship on the doctoral level: An examination of communication faculty mentors' traits and functions. *Communication Education*, *64*(3), 366-384. Google Scholar↗

[27] Most, D. E. (2008). Patterns of doctoral student degree completion: A longitudinal analysis. *Journal of College Student Retention: Research, Theory & Practice*, *10*(2), 171-190. Google Scholar↗

[28] Stock, W. A., Siegfried, J. J., & Finegan, T. A. (2011). Completion rates and time-to-degree in economics PhD programs (with comments by David Colander, N. Gregory Mankiw, Melissa P.

McInerney, James M. Poterba). *American Economic Review*, *101*(3), 176-88. Google Scholar↗

[29] Wamala, R., Ocaya, B., & Oonyu, J. C. (2012). Extended Candidature and Non-Completion of a Ph. D. at Makerere University, Uganda. *Contemporary Issues in Education Research*, *5*(3), 175-184. Google Scholar↗

[30] https://academy.pubs.asha.org/2011/12/higher-education-practices-that-promote-phd-completion/. Retrieved in October 2022.

[31] Preston, J. P., Ogenchuk, M. J., & Nsiah, J. K. (2014). Peer mentorship and transformational learning: PhD student experiences. *Canadian Journal of Higher Education*, *44*(1), 52-68. Google Scholar↗

[32] Devine, K., & Hunter, K. H. (2017). PhD student emotional exhaustion: the role of supportive supervision and self-presentation behaviours. *Innovations in Education and Teaching International*, *54*(4), 335-344. Google Scholar↗

[33] Van Rooij, E., Fokkens-Bruinsma, M., & Jansen, E. (2021). Factors that influence PhD candidates' success: the importance of PhD project characteristics. *Studies in Continuing Education*, *43*(1), 48-67. Google Scholar↗

[34] Chenevix-Trench, G. (2006). What makes a good PhD student?. *Nature*, *441*(7090), 252-252. Google Scholar↗

[35] Dericks, G., Thompson, E., Roberts, M., & Phua, F. (2019). Determinants of PhD student satisfaction: the roles of supervisor, department, and peer qualities. *Assessment & evaluation in higher education volume 44*(7), 1053-1068. Google Scholar↗

[36] Corsini, A., Pezzoni, M., & Visentin, F. (2022). What makes a productive Ph. D. student?. *Research Policy 51*(10), 104561. Google Scholar↗

[37] Lindvig, K. (2018). The implied PhD student of interdisciplinary research projects within monodisciplinary structures. *Higher Education Research & Development*, *37*(6), 1171-1185. Google Scholar↗

[38] Holbrook, A., Shaw, K., Scevak, J., Bourke, S., Cantwell, R., & Budd, J. (2014). PhD candidate expectations: Exploring mismatch with experience. *International Journal of Doctoral Studies*, *9*, 329. Google Scholar↗

[39] Björkman, B. (2015). PhD supervisor-PhD student interactions in an English-medium Higher Education (HE) setting: Expressing disagreement. *European Journal of Applied Linguistics*, *3*(2), 205-229. Google Scholar↗

[40] Dimitrova, R. (2016). Ingredients of good PhD supervision-evidence from a student survey at Stockholm university. *Utbildning och Lärande/Education and Learning*, *10*(1), 40-52. Google Scholar↗

[41] Sullivan-Bolyai, S., & L'Esperance, S. (2022). Reflections on virtual research conferences and PhD student socialization: The missing link of in-person human connectedness. *Applied Nursing Research*, *64* (April 2022), 151553. Google Scholar↗

[42] Alpert, F., & Eyssell, T. H. (1995). Getting the most from your doctoral program: Advice for the Ph. D. student in finance. *Journal of Financial Education*, 12-20. Google Scholar↗

[43] Groen, J. (2020). *Perceptions of Transformation and Quality in Higher Education: A Case Study of PhD Student Experiences* (Doctoral dissertation, University of Ottawa). Google Scholar↗

[44] Helfer, F., & Drew, S. (2013). A small-scale investigation into Engineering PhD student satisfaction with supervision in an Australian university campus. In *24th Annual Conference of the Australasian Association for Engineering Education* (pp. 1-9). Google Scholar↗

[45] Cunningham-Williams, R. M., Wideman, E., & Fields, L. (2019). Ph. D. Student Development: A Conceptual Model for Research-Intensive Social Work PhD Programs. *Journal of Evidence-Based Social Work*, *16*(3), 278-293. Google Scholar↗

[46] H. R., Ganesha., & Aithal, P. S. (2022). *Doing Ph.D. in India. A Step-by-Step Guide.* First Edition. Notion Press. India & Singapore. ISBN: 9798887832005. Google Scholar↗

[47] Ganesha, H. R. & Aithal, P. S. (2022). The '8Fs' Concept for Simplifying the Complications of Ph.D. Journey in India. *International Journal of Case Studies in Business, IT, and Education (IJCSBE), 6*(2), 320-339. Google Scholar↗

[48] Ganesha, H. R. & Aithal, P. S. (2022). The DDLR Model of Research Process for Designing Robust and Realizable Research Methodology During Ph.D. Program in India. *International Journal of Management, Technology, and Social Sciences (IJMTS), 7*(2), 400-417. Google Scholar↗

[49] Ganesha, H. R. & Aithal, P. S. (2022). PHDRQ Model for Identifying Research Gaps and Formulating A Research Question During Ph.D. Program in India. *International Journal of Case Studies in Business, IT, and Education (IJCSBE), 6*(2). 408-421. Google Scholar↗

[50] Ganesha, H. R. & Aithal, P. S. (2022). Why is it Called Doctor of Philosophy and Why Choosing Appropriate Research Philosophical Paradigm is Indispensable During Ph.D. Program in India?. *International Journal of Philosophy and Languages (IJPL), 1*(1). 42-58. Google Scholar↗

[51] Ganesha, H. R. & Aithal, P. S. (2022). Approaching Research in Different Ways. How to Choose an Appropriate Research Approach/Reasoning During Ph.D. Program in India?. *International Journal of Philosophy and Languages (IJPL), 1*(1). 59-74. Google Scholar↗

[52] Ganesha, H. R. & Aithal, P. S. (2022). How to Choose an Appropriate Research Data Collection Method and Method Choice Among Various Research Data Collection Methods and Method Choices During Ph.D. Program in India?. *International Journal of Management, Technology, and Social Sciences (IJMTS), 7(*2), 455-489. Google Scholar↗

[53] Ganesha, H. R. & Aithal, P. S. (2022). When to Collect Data? Choosing an Appropriate Time Frame for Data Collection During Ph.D. Program in India?. *International Journal of Applied Engineering and Management Letters (IJAEML), 6*(2), 271-287. Google Scholar↗

[54] Ganesha, H. R. & Aithal, P. S. (2022). Deriving Right Sample Size and Choosing an Appropriate Sampling Technique to Select Samples from the Research Population During Ph.D. Program in India. *International Journal of Applied Engineering and Management Letters (IJAEML), 6(*2), 288-306. Google Scholar↗

[55] Ganesha, H. R. & Aithal, P. S. (2022). Choosing an Appropriate Data Collection Instrument and Checking for the Calibration, Validity, and Reliability of Data Collection Instrument Before Collecting the Data During Ph.D. Program in India. *International Journal of Management, Technology, and Social Sciences (IJMTS), 7*(2), 497-513. Google Scholar↗

[56] https://www.w3schools.com/statistics/statistics_standard_normal_distribution.php. Retrieved in November 2022.

[57] Lee, Nick., & Lings, Ian. (2008). *Doing business research: a guide to theory and practice*. 1st Edition, Sage Publications Ltd., Page 293. Google Scholar↗

[58] Ahmed, S. I., Khan, S. A., Yasin, M. F., Khurshid, S., Saleem, Z., & Shabbir, R. (2017). Statistics is Essential for all Fields of Scientific Researches. *International Journal of Scientific and Engineering Research, 8*(11), 745-753. Google Scholar↗

[59] TANI, H. (1988). A Fundamental Knowledge of Statistics for the Researches. *Journal of exercise physiology, 3*(3), 149-154. Google Scholar↗

[60] Singh, Y. K. (2006). *Fundamental of research methodology and statistics*. New Age International. Google Scholar↗

[61] Byshevets, N., Denysova, L., Shynkaruk, O., Serhiyenko, K., Usychenko, V., Stepanenko, O., & Syvash, I. R. Y. N. A. (2019). Using the methods of mathematical statistics in sports and

educational research. Google Scholar↗

[62] Yates, F. (1951). The influence of statistical methods for research workers on the development of the science of statistics. *Journal of the American Statistical Association*, *46*(253), 19-34. Google Scholar↗

[63] Manikandan, S. (2011). Measures of central tendency: The mean. *Journal of Pharmacology and Pharmacotherapeutics*, *2*(2), 140. Google Scholar↗

[64] Manikandan, S. (2011). Measures of central tendency: Median and mode. *Journal of pharmacology and pharmacotherapeutics*, *2*(3), 214. Google Scholar↗

[65] Chakrabarty, D. (2021). Measuremental Data: Seven Measures of Central Tendency. *International Journal of Electronics*, *8*(1). Google Scholar↗

[66] Chakrabarty, D. (2021). Model Describing Central Tendency of Data. *International Journal of Advanced Research in Science, Engineering and Technology*, 2350-0328. Google Scholar↗

[67] McCluskey, A., & Lalkhen, A. G. (2007). Statistics II: Central tendency and spread of data. *Continuing Education in Anaesthesia, Critical Care and Pain*, *7*(4), 127-130. Google Scholar↗

[68] Silver, G. L. (2007). Operational measures of central tendency. *Applied mathematics and computation*, *186*(2), 1379-1384. Google Scholar↗

[69] Gonzales, V. A., & Ottenbacher, K. J. (2001). Measures of central tendency in rehabilitation research: What do they mean?. *American journal of physical medicine & rehabilitation*, *80*(2), 141-146. Google Scholar↗

[70] Suco, E., Samere, M., & Hong, S. L. (2012). Enabling Students to Understand Measures of Central Tendency and Variation. *Mathematics Teaching*, *231*, 20-22. Google Scholar↗

[71] Williams, R. B. G. (1984). Measures of central tendency. In *Introduction to Statistics for Geographers and Earth Scientists* (pp. 51-60). Palgrave, London. Google Scholar↗

[72] Manikandan, S. (2011). Measures of dispersion. *Journal of Pharmacology and Pharmacotherapeutics*, *2*(4), 315. Google Scholar↗

[73] Kołacz, A., & Grzegorzewski, P. (2016). Measures of dispersion for multidimensional data. *European Journal of Operational Research*, *251*(3), 930-937. Google Scholar↗

[74] Bhardwaj, A. N. K. U. R. (2013). Comparative Study of Various Measures of Dispersion. *Journal of Advances in Mathematics*, *1*(1). Google Scholar↗

[75] Högel, J., Schmid, W., & Gaus, W. (1994). Robustness of the standard deviation and other measures of dispersion. *Biometrical journal*, *36*(4), 411-427. Google Scholar↗

[76] Hirschman, A. O. (1943). On Measures of Dispersion for a Finite Distribution. *Journal of the American Statistical Association*, *38*(223), 346-352. Google Scholar↗

[77] Sathe, Y. S., & Kamat, A. R. (1957). Approximations to the distributions of some measures of dispersion based on successive differences. *Biometrika*, *44*(3/4), 349-359. Google Scholar↗

[78] Grzegorzewski, P. (2018, September). Measures of dispersion for interval data. In *International Conference Series on Soft Methods in Probability and Statistics* (pp. 91-98). Springer, Cham. Google Scholar↗

[79] Th. Gries, S. (2021). Analyzing dispersion. In *A practical handbook of corpus linguistics* (pp. 99-118). Cham: Springer International Publishing. Google Scholar↗

[80] Yadav, S. K., Singh, S., & Gupta, R. (2019). Measures of Dispersion. In *Biomedical Statistics* (pp. 59-70). Springer, Singapore. Google Scholar↗

[81] Wooditch, A., Johnson, N. J., Solymosi, R., Medina Ariza, J., & Langton, S. (2021). Measures of Dispersion. In *A Beginner's Guide to Statistics for Criminology and Criminal Justice Using R* (pp. 77-88). Springer, Cham. Google Scholar↗

[82] Altman, N., & Krzywinski, M. (2015). Points of Significance: Association, correlation and causation. *Nature methods*, *12*(10). Google Scholar↗

[83] Rezaee, Z., Aliabadi, S., Dorestani, A., & Rezaee, N. J. (2020). Application of time series models in business research: correlation, association, causation. *Sustainability*, *12*(12), 4833. Google Scholar↗

[84] Rohrer, J. M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in methods and practices in psychological science*, *1*(1), 27-42. Google Scholar↗

[85] Georges, M. (2011). The long and winding road from correlation to causation. *Nature Genetics*, *43*(3), 180-181. Google Scholar↗

[86] Bleske-Rechek, A., Morrison, K. M., & Heidtke, L. D. (2015). Causal inference from descriptions of experimental and non-experimental research: Public understanding of correlation-versus-causation. *The Journal of general psychology*, *142*(1), 48-70. Google Scholar↗

[87] Simon, H. A. (1954). Spurious correlation: A causal interpretation. *Journal of the American statistical Association*, *49*(267), 467-479. Google Scholar↗

[88] Freedman, D. (1997). From association to causation via regression. *Advances in applied mathematics*, *18*(1), 59-110. Google Scholar↗

[89] Shaver, J. P. (1993). What statistical significance testing is, and what it is not. *The Journal of Experimental Education*, *61*(4), 293-316. Google Scholar↗

[90] Johnson, D. H. (1999). The insignificance of statistical significance testing. *The journal of wildlife management*, 763-772. Google Scholar↗

[91] Carver, R. (1978). The case against statistical significance testing. *Harvard Educational Review*, *48*(3), 378-399. Google Scholar↗

[92] Nickerson, R. S. (2000). Null hypothesis significance testing: a review of an old and continuing controversy. *Psychological methods*, *5*(2), 241. Google Scholar↗

[93] Sham, P. C., & Purcell, S. M. (2014). Statistical power and significance testing in large-scale genetic studies. *Nature Reviews Genetics*, *15*(5), 335-346. Google Scholar↗

[94] Kline, R. B. (2013). *Beyond significance testing: Statistics reform in the behavioral sciences*. American Psychological Association. Google Scholar↗

[95] Hochberg, Y., & Benjamini, Y. (1990). More powerful procedures for multiple significance testing. *Statistics in medicine*, *9*(7), 811-818. Google Scholar↗

[96] Mohr, L. B. (1990). *Understanding significance testing* (Vol. 73). Sage. Google Scholar↗

[97] Masson, M. E. (2011). A tutorial on a practical Bayesian alternative to null-hypothesis significance testing. *Behavior research methods*, *43*(3), 679-690. Google Scholar↗

[98] Efron, B. (2007). Correlation and large-scale simultaneous significance testing. *Journal of the American Statistical Association*, *102*(477), 93-103. Google Scholar↗

[99] Dempster, A. P. (1997). The direct use of likelihood for significance testing. *Statistics and Computing*, *7*(4), 247-252. Google Scholar↗

[100] Mulaik, S. A., Raju, N. S., & Harshman, R. A. (2016). There is a time and a place for significance testing. In *What if there were no significance tests?* (pp. 109-154). Routledge. Google Scholar↗

[101] Schmidt, F. L. (1996). Statistical significance testing and cumulative knowledge in psychology: Implications for training of researchers. *Psychological methods*, *1*(2), 115. Google Scholar↗

[102] Szucs, D., & Ioannidis, J. P. (2017). When null hypothesis significance testing is unsuitable for research: a reassessment. *Frontiers in human neuroscience*, *11*, 390. Google Scholar↗

[103] McLEAN, J. E., & Ernest, J. M. (1998). The role of statistical significance testing in educational

research. *Research in the Schools*, *5*(2). Google Scholar↗

[104] Brandstätter, E., & Kepler, J. (1999). Confidence intervals as an alternative to significance testing. *Methods of Psychological Research Online*, *4*(2), 33-46. Google Scholar↗

[105] https://online.stat.psu.edu/statprogram/. Retrieved in November 2022.

[106] https://www.scribbr.com/statistics/. Retrieved in November 2022.

[107] https://www.statisticshowto.com/. Retrieved in November 2022.

[108] https://jasp-stats.org/. Retrieved in November 2022.

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