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Applying Major Parametric Tests Using SPSS in Research

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Abstract

This article provides a comprehensive overview of the most commonly used parametric tests, such as one sample t-test, dependent samples t-test, independent samples t-test, analysis of variance, and analysis of covariance. A parametric test is a statistical test that assumes the data being analyzed follows a certain probability distribution, typically a normal distribution. A statistical test is a procedure used in statistical analysis to make inferences about a population based on a sample of data. It covers the basics of statistical analysis, including the assumptions of parametric tests and how to check for these assumptions. It includes the access to use SPSS (Statistical Package for the Social Sciences) software to perform the tests, with detailed demonstration of outcomes and the ways of reporting them briefly. It is prepared on the basis of the secondary qualitative data garnered from journal articles, books, and web site materials. It is a valuable resource for researchers, students, and professionals who want to improve their statistical analysis skills and gain proficiency in executing analyses by using SPSS in their research in the social sciences, psychology, and other related fields.

Keywords: Analysis of covariance, analysis of variance, parametric tests, t-tests

1. Introduction

Research is an investigative process that involves collecting, analyzing, and interpreting data or information from a variety of sources. It is an intellectual and creative activity (Best & Kahn, 2010), and a search of knowledge (Kothari & Garg, 2014). A researcher draws the conclusion from the outcomes of the research based on data. Data refers to facts or information, especially when scrutinized and used to find out things or to make decisions (Hornby, 2010). It can be defined as collected measure of independent and dependent variables that can be applied for numerical calculations (Wrench, Thomas-Maddox, Richmond, & McCroskey, 2009). It can be qualitative and quantitative, and the quantitative data are statistically analyzed. Quantitative research employs the data in the form of numbers. A collection of information shown in numbers is statistics (Hornby, 2010).It is a tool for creating innovative understanding from a set of numbers (Pandey, 2022). Statistics are a set of numerical data (Croxton & Cowden, 1939). Similarly, only numerical data constitute statistics (Gupta, 2018). Such statistical tests can be used only with numerical data. Statistical tests are based on certain assumptions (Cohen, Manion, & Morrison, 2011).Statistical analysis is an essential part of research, and parametric tests are some of the most commonly used statistical methods. Moreover, the statistical tests to be used depend on the scales of data being treated (Cohen, Manion, & Morrison, 2011). These tests are based on the assumptions of normality, independence, equal variances, and interval or ratio scale data, and they provide a way to test hypotheses, make inferences about populations, and estimate the uncertainty of results. Research examines the relationship and correlation between variables. A variable is an image, insight or concept that is capable of measurement (Kumar, 2011). Variables can exhibit dissimilarities in values, usually in magnitude, or strength, or in direction (Zikmund, Babin, Carr, Adhikari, & Griffin, 2016).

One of the key aspects of this article is that it emphasizes the importance of checking assumptions, interpreting results, and reporting findings in a clear and concise manner. It also provides tips and best practices for data preparation, interpretation, and reporting to help readers to avoid common mistakes and to improve the quality of their research. It underlines the assumptions of parametric tests and how to check for these assumptions. The most critical assumption regarding parametric tests is that the population from which a random sample is selected should retain a normal distribution(Cunningham & Aldrich, 2012).This is an important step in the analysis process, as it helps researchers to determine whether the assumptions are met, and whether the test is appropriate for the data. The decision for a statistical test is based on the scientific question to be answered, the data structure, and the study design (Prel, Röhrig, Hommel, & Blettner, 2010). If the assumptions are not met, the non-parametric tests are to be applied, or to it is necessary to transform the data to meet the assumptions.

Applying parametric tests is essential for researchers who intend to analyze data and make inferences about populations. Although parametric tests can be done by using statistical formulae, calculations are tough and tedious. SPSS (Statistical Package for the Social Sciences) is a software package that is used for statistical analysis in social sciences, health sciences, marketing, education, and other fields. It provides a wide range of tools for data analysis, including descriptive statistics, inferential statistics, and data visualization. The software allows users to perform complex data manipulations, analyze data, and create charts and tables for presentations and reports. SPSS offers two types of statistical hypothesis tests: parametric and non-parametric (Cunningham & Aldrich, 2012). There are only two types of hypotheses that can be statistically tested in research. They are either a hypothesis of difference or a hypothesis of association (Gunawardena, 2011). A hypothesis is a conjectural statement of the relation between two or more variables (Kerlinger, 2011). It should be clear and precise (Kothari & Garg, 2014).

Any researcher who is a complete novice at the analyses of the parametric tests will undoubtedly be benefitted from this article as it provides measurement scales, the name of the tests, assumptions to be followed to use particular tests, demonstration of outcomes and their analyses.

2. Literature Review

Literature review embraces the following aspects:

2.1 Scales of Measurement

A measurement scale is a system of assigning numbers or categories to data in order to describe and analyze it. Scales refer to a device providing a range of values that correspond to different values in a concept being measured (Zikmund, Babin, Carr, Adhikari, & Griffin, 2016).

The four main types of measurement scales are nominal, ordinal, interval, and ratio.

Nominal scale: It is used to classify or categorize data. It has no numerical order and the data can only be put into categories.

Ordinal scale: It is used to order data. It has a numerical order, but the differences between the numbers are not equal.
Interval scale: It is used to measure data that has equal intervals between numbers. It has a numerical order, and the differences between the numbers are equal. It does not have a true zero point.
Ratio scale: is used to measure data that has a true zero point. It has a numerical order, equal intervals between numbers, and a true zero point.
It can be vividly seen that each type of scale has specific characteristics. Examples of each scale are presented in the following table.

Table 1: *Scales of measurement*

Scales of measurement	
1. Nominal or Categorical	**2. Ordinal**
I. Constant Variable: Having only one level : Sun, Moon, Nepal, Earth, Sky etc. **II: Dichotomous Variable** :Having two levels: **Yes-no question**: Yes/ No, **Coin**: head/ tail **True-false Item:** True / False **Gender**: Male /Female **III. Polytomous Variable:** Having more than two levels: **Religion:** Hindu, Buddhist, Christian… **Party:** Congress, Communist, Liberal, Labour Blood group: A, B, O, AB **Subject:** English, Maths, Science, Nepali **Colour**: Red/ Blue / Green/ Yellow/ Brown …	**Income:** Above Average, Average, Below Average **Socioeconomic Status:** Upper, Middle, Low **Attitude**: Strongly Agee, Agree, Undecided, Disagree, Strongly Disagree **Condition:** Strongly Favorable , Favorable, Uncertain, Unfavorable, Strongly Unfavorable **Satisfaction**: Strongly Satisfied, Satisfied, Uncertain, Dissatisfied, Strongly Dissatisfied **Class Position of Students**: Good, Average, Bad **Age**: Child, Young, Old **Income**: High , Middle, Low **Temperature:** Hot, Cold, Moderate **Weight:** Very Heavy, Heavy, Light **Mark Score**: Very High, High, Average, Low **Ordinal Number**: First, Second, Third, Fourth.. **Height:** Very High, High, Average, Below Average **Distance:** Extremely Far, Far, Not so Far, Near
3. Interval	**4. Ratio**
Range: 10-19, 20-29, 30-39 etc. **Centigrade** : Starting point 0 to the boiling point 100 (100 equally spaced intervals) **Fahrenheit** : Starting point 32 to the boiling point 212 (180 equally spaced intervals)	**Age:** 25 years, 5 Months, 3 weeks **Income**: Rs. 50,000, $ 500, £ 525.. (Per Month, Week, Year) **Expenditure:** Rs. 40,000, $ 200, £ 325.(Per Month, Week, Year) **Weight:** 40 kgs, 500 grams, **Mark Score:** 40, 50, 35, 20 **Height:** 4 feet, 5 feet, 7 feet **Distance:** 5kms, 7 kms, 10 ms, 4.5 miles. **Cardinal Number**: One, Two, Three, Four…

A researcher can employ particular statistical tools with the certain scales of measurement. It is to keep in mind that SPSS takes interval and ratio data as a scale.

Table 2: *Statistical tools and scales of measurement*

Statistical tools	Nominal	Ordinal	Interval	Ratio
Mode	Yes	Yes	Yes	Yes
Frequency Distribution	Yes	Yes	Yes	Yes
Median	No	Yes	Yes	Yes
Mean	No	No	Yes	Yes
Range	No	No	Yes	Yes
Standard deviation	No	No	Yes	Yes
Addition & subtraction	No	No	Yes	Yes
Multiplication & division	No	No	No	Yes

Table 2 signifies that the ratio scale of measurement is the most versatile scale that can be used in multifarious statistical tools in quantitative research studies. Parametric test can be used to both interval and ratio scale if the data are normally distributed. These tests are applied to both interval and ratio scaled data (Best & Kahn, 2006). It is strongly advised not to calculate the mean and standard deviation for data measured at the nominal or ordinal levels though the computer and SPSS can calculate them (Cunningham& Aldrich, 2012).

2.2 Parametric Tests

A parametric test is a statistical test that assumes that the data being analyzed follows a certain probability distribution, typically a normal distribution. These tests make assumptions about the population parameters, such as the mean and standard deviation, and use that information to make inferences about the population. Parametric tests assume that the sample data are normally distributed and have the same characteristics as the population, whereas nonparametric tests make no such assumptions. Parametric tests are more powerful and have a greater ability to pick up differences between groups (where they exist); in contrast, nonparametric tests are less efficient at identifying significant differences (Ranganathan, 2021). The goal of inferential statistics may be to assess differences between groups (comparison), establish an association between two variables (correlation), predict one variable from another (regression), or look for agreement between measurements (agreement). Studies may also look at time to a particular event, analyzed using survival analysis (Ranganathan, 2021). The choice of statistical test used to analyze research data depends on the study hypothesis, the type of data, the number of measurements, and whether the data are paired or unpaired (Ranganathan, 2021). Data refer to facts or recorded measures of certain phenomena (Zikmund, Babin, Carr, Adhikari, & Griffin, 2016). A non-parametric test is a statistical test that does not make assumptions about the probability distribution of the data being analyzed. These tests are also known as distribution-free tests or distribution-free methods. Sample size in the parametric depends on population, confidence level and margin of error. A sample is a subset of a larger population (Zikmund, Babin, Carr, Adhikari, & Griffin, 2016). The sample size refers to the number of observations or individuals that are selected from a populationto be studied in a research. Population is a group of individuals who comprise the same characteristics (Creswell, 2012).Confidence level is the range of values for some estimate that accounts for a specific percentage of possibility (Zikmund, Babin, Carr, Adhikari, & Griffin, 2016). The margin of error is a measure of the degreeof uncertainty associated with a sample estimate.

2.3 Assumptions of Parametric Tests

Assumptions, which are the things taken to be true, refer to beliefs, hypotheses, or suppositions that are used as the basis for further reasoning or analysis. Although the assumptions of parametric tests vary depending on the specific test being used, some common assumptions include:

Normality: The data being analyzed follows a normal distribution, or at least approximately so.

Independence: The observations in the sample are independent of one another.

Equal variances: The variances of the populations being compared are equal.

Interval or ratio scale: The data is measured on an interval or ratio scale, which allows for meaningful comparisons of the values.

Linearity: The relationship between the independent and dependent variable is linear.

It is important to check the assumptions of the specific test. If these assumptions are not met, it is better to use a non-parametric test. Failure to meet these assumptions and using a parametric test may lead to inaccurate results and invalid conclusions. Normality of data is an important condition for parametric test. There are several ways to check the normality of data:

Visual inspection: One of the most common ways to check for normality is to create a histogram,a Q-Q plotor a box plot of the data. The following figures depict the normality of data distribution.

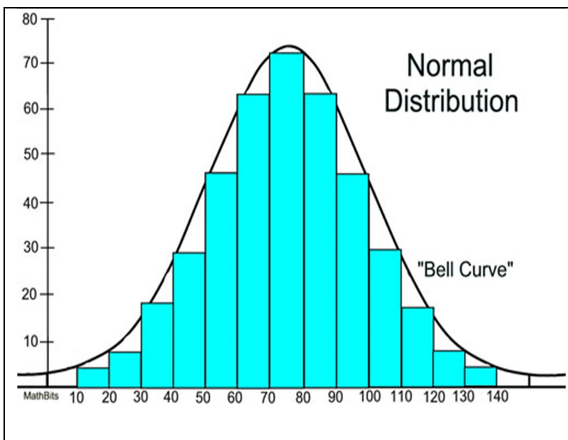

Figure 1: *Histogram*

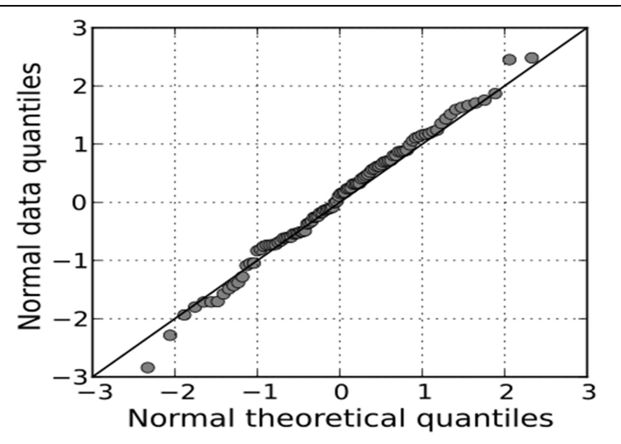

Figure 2: *Q-Q plot*

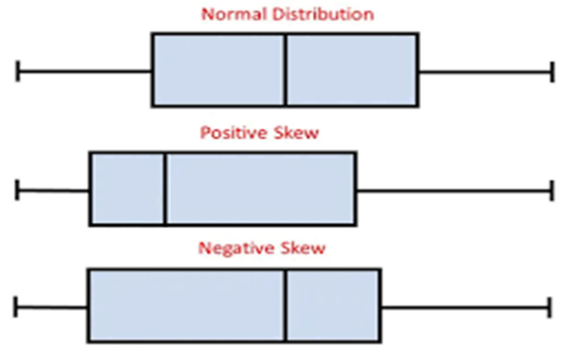

Figure 3: *Box plot*

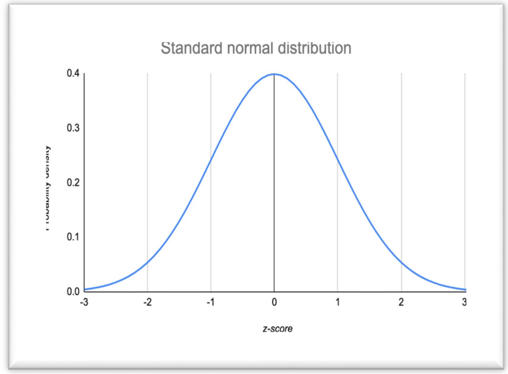

Figure 4: *Bell shape*

Statistical tests: There are several statistical tests that can be used to check for normality, including the Shapiro-Wilk test, the Lilliefors test, and the Anderson-Darling test. These tests provide a p-value. The p-value above 0.05 indicates that the data are normally distributed.
We can compute the normality by using SPSS.
SPSS: Analyze → Descriptive Statistics → Explore
Shapiro-Wilk's test ($P > 0.05$)]
Measures of skewness and kurtosis: Skewness and kurtosis are measures of the shape of the distribution. A normal distribution has a skewness of 0 and a kurtosis of 3. If the data deviates from these values, it may not be normally distributed.

2.4 Some Major Parametric Tests

There are several parametric tests, but some major parametric tests are:

2.4.1 One-sample t-test

The one-sample t-test is a statistical test used to determine whether a sample of data comes from a population with a specific mean. It compares the mean of the sample to a known or hypothesized population mean. The test is used when the sample size is small or when the population standard deviation is unknown.
The test is conducted by comparing the sample mean to the hypothesized population mean using a t-statistic.
SPSS: **Analyze → Compares Means → One-sample T Test**
<u>**Steps** of using One-sample T Test in SPSS</u>

- Open SPSS and enter the data into the program.
- Click on "Analyze" and select "Compare Means" and then "One-Sample T-Test."
- Select the variable to be tested and enter the value you want to compare it to in the "Test Value" field.
- Click on "Options" to set any additional parameters, such as the level of significance.
- Click on "OK" to run the test and view the results, which will include the test statistic, p-value, and whether or not the null hypothesis is rejected.
- Interpret the results to determine whether there is a significant difference between the sample mean and the test value or not.

Executing the one sample t-test from the mark scores in English of 30 students
11, 6, 4, 10, 9, 10, 15, 12, 14, 7, 12, 17, 8, 21, 24, 8, 11, 12, 11, 5, 13, 12, 19, 4, 12, 7, 15, 12, 17 & 6.
We need to assume a test value here. Suppose it is 10.

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Null Hypothesis: There is no significant difference between the test value and the mean score of the students.

Outcome Demonstration in SPSS

Table 1. One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Test Score	30	11.13	4.297	.785

Table 2. One-Sample Test

	Test Value = 10					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Test Score	1.445	29	.159	1.133	-.47	2.74

Reporting of the outcomes

Table 1 exhibits that the mean score obtained by the students was slightly more than the test value. Table 2 shows that the observed t- value (1.445) was less than the critical t-value (2.045) and $p > .05$ while considering a test value 10. It indicates the acceptance of the null hypothesis and shows that there was no significant difference between the test value and the mean score of the students.

It is to keep in mind that if the observed t-value was greater than 2.045 and p was less than .05, we would reject the null hypothesis. It means there was a significant difference between the test value and the mean score of the students.

2.4.2 Dependent samples t-test

The dependent samples t-test, also known as a paired samples t-test, is a statistical test used to determine if there is a significant difference between two related or dependent samples. It is used when the same individuals are measured twice, or when the two samples are matched in some way. The test is conducted by comparing the means of the two related samples using a t-statistic.

SPSS: **Analyze → Compares Means → Paired Samples T Test**

<u>**Steps of using dependent samples T Test in SPSS**</u>

- Open SPSS and enter the data into the program.
- Click on "Analyze" and select "Compare Means" and then "Related-Samples T-Test."
- Select the two related variables to be compared in the "Test Variable(s)" field.
- In the "Paired Variable" field, select the variable that links the two test variables together.
- Click on "Options" to set any additional parameters, such as the level of significance.
- Click on "OK" to run the test and view the results, which will include the test statistic, p-value, and whether or not the null hypothesis is rejected.
- Interpret the results to determine whether there is a significant difference between the two related sample means or not.

Executing the dependent samples t-test by using the following marks scores of 30 students

Test_1	11,6,,4,10,9,10,15,12,14,7,12,17,8,21,14,8,11,12,11,5,13,12,19,4,12,7,15,12,17 & 6
Test_2	13,8,6,12,11,12,14,14,16,9,14,19,10,14,14,10,11,12,11,12,11,12,19,4,12,7,15,12,17&6

Null Hypothesis: There is no statistically significant difference between the pretest mean score and the posttest mean score of the students.

Outcome Demonstration in SPSS

Table 1. Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair	Test_1	11.90	30	3.556	.649
	Test_2	11.13	30	4.297	.785

Table 2. Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair	Test_1 - Test_2	.767	2.176	.397	-.046	1.579	1.929	29	.064

Reporting of the outcomes

Table 1 shows that there was a little difference between the mean scores of Test_1 and Test 2. Similarly, Table 2 exhibits that the probability figure marked as Sig (two-tailed) in the table was bigger than 0.05. The observed value of t was smaller than the table value of t (2.045) at 0.05 significance level of the test, and $p > 0.05$. It implies that there was no statistically significant difference between the mean scores secured by students in the two tests. It refers to the acceptance of the null hypothesis.

It is to note that if the observed t-value was greater than 2.045 and p was less than .05, we would reject the null hypothesis. It means there was a statistically significant difference between the mean scores secured by students in the two tests.

2.4.3 Independent samples t-test

The independent samples t-test, also known as the two-sample t-test, is a statistical test used to determine if there is a significant difference between the means of two independent samples. It is used when the two samples are not related and come from different populations.

The test is conducted by comparing the means of the two independent samples using a t-statistic.

SPSS: Analyze → Compares means → Independent Samples T Test

Steps of using independent samples T Test in SPSS

- Open SPSS and enter the data into the program.
- Click on "Analyze" and select "Compare Means" and then "Independent-Samples T-Test."
- Select the two independent variables to be compared in the "Test Variable(s)" field.
- In the "Grouping Variable" field, select the variable that separates the two independent groups of data.
- Click on "Options" to set any additional parameters, such as the level of significance.
- Click on "OK" to run the test and view the results, which will include the test statistic, p-value, and whether the null hypothesis is rejected or not.
- Interpret the results to determine whether there is a significant difference between the two independent sample means or not.

Executing the independent samples t-test by using the mark scores of the students of the two groups

Control Group	7,8,9,7,8,6,10,6,8,9,12,8,8,9 & 12
Experimental Group	6,13,6,14,9,9,8,10,7,11,13,8,5,9 &17

Null Hypothesis: There is no statistically significant difference between the pretest mean scores secured by students of the Experimental and Control Groups.

Outcome Demonstration in SPSS

Table 1. Group Statistics

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Pretest	Con Grp	15	8.47	1.807	.467
	Exp Grp	15	9.67	3.374	.871

Table 2. Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Pretest Score	Equal variances assumed	5.075	.032	-1.214	28	.235	-1.200	.988	-3.224	.824
	Equal variances not assumed			-1.214	21.425	.238	-1.200	.988	-3.253	.853

Reporting of the outcomes

Table 1 shows that there was a little difference between the pretest mean scores of the control group and the experimental group. Similarly, Table 2 exhibits the probability figure marked as Sig (two-tailed) in the table was bigger than 0.05. The observed value of t was smaller than the table value of t (2.048) at 0.05 significance level of the test, and $p > 0.05$. It implies that there was no statistically significant difference between the pretest mean scores secured by students of the Experimental Group and the Control Group. Therefore, the null hypothesis was accepted.

It is to regard that if the observed t-value was greater than 2.045 and p was less than .05, we would reject the null hypothesis. It means there was a statistically significant difference between the pretest mean scores secured by students of the Experimental Group and the Control Group.

2.4.4 Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) is a statistical method used to test whether there is a significant difference between the means of more than two groups. It is used to determine if there is a significant difference in the mean of a dependent variable between more levels of an independent variable.

There are different types of ANOVA such as One-way ANOVA, Two-way ANOVA, and Repeated Measures ANOVA. One –way ANOVA is very common. It is used when we have one independent variable and one dependent variable, and we want to test whether the means of more groups are different.

SPSS: Analyze → Compare Means → One-way ANOVA

<u>**Steps of using one-way ANOVA in SPSS**</u>

- Open SPSS and enter the data into the program.

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- Click on "Analyze" and select "General Linear Model" and then "One-Way ANOVA." Or
- Click on "Analyze" and select "Compare Means" and then "One-Way ANOVA
- Select the dependent variable in the "Dependent Variable" field and the independent variable (also known as the "factor" or "grouping variable") in the "Factor" field.
- Click on "Options" to set any additional parameters, such as the level of significance.
- Click on "OK" to run the test and view the results, which will include the test statistic, p-value, and whether or not the null hypothesis is rejected.
- To check the difference between the group means. Post Hoc test like Tukey, LSD, and Bonferroni can be used
- Interpret the results to determine whether there is a significant difference between the means of the groups defined by the independent variable or not.

Executing one-way ANOVA from the following the mark scores secured by the three groups

Group A	7,8,9,7,8,6,10,6,8 & 9
Group B	12,8,8,9,12,6,13,6,14& 9
Group C	9,8,10,7,11,13,8,5,9& 17

Null Hypothesis: There is no significant difference in the mean scores of the three groups.

Outcome Demonstration in SPSS

Table 1. One-way ANOVA

Test Score	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	24.067	2	12.033	1.694	.203
Within Groups	191.800	27	7.104		
Total	215.867	29			

Reporting of the outcomes

The table shows that there was no statistically significantly difference among groups as determined by one-way ANOVA that F (2, 27) = 1.694, which was smaller than the table value (3.354) and p > .05. This shows that three groups were similar in their test scores. The result accepts the null hypothesis.

It is to notice that if the observed f-value was greater than 3.354 and p was less than .05, we would reject the null hypothesis. It means there was a statistically significant difference in the mean scores secured by students of three groups..

2.4.5 Analysis of Covariance (ANCOVA)

Analysis of Covariance (ANCOVA) is a statistical method that is used to test the equality of means of two or more groups while controlling for the effects of one or more continuous variables called covariates. ANCOVA is an extension of ANOVA and is used when there are both categorical (independent) variables and continuous (covariate) variables in the data.

The test statistic is usually an F-statistic and the null hypothesis is that the regression coefficients associated with the categorical independent variable are equal to zero.

ANCOVA is useful when the goal is to control for the effects of one or more continuous variables on the dependent variable, and to see whether the categorical independent variable still has a significant effect on the dependent variable after accounting for the covariates.

SPSS: Analyze → General Linear Model → Univariate

Steps of using ANCOVA in SPSS

- Open SPSS and enter the data into the program.
- Click on "Analyze" and select "General Linear Model" and then "ANCOVA."
- Select the dependent variable in the "Dependent Variable" field, the independent variable (also known as the "factor" or "grouping variable") in the "Factor" field and covariate in the "Covariate" field.
- Click on "Options" to set any additional parameters, such as the level of significance.
- Click on "OK" to run the test and view the results, which will include the test statistic, p-value, and whether or not the null hypothesis is rejected.
- To check the difference between the group means, Post Hoc test like Tukey, LSD, Bonferroni, etc can be used.
- Interpret the results to determine whether there is a significant difference between the means of the groups defined by the independent variable, after accounting for the effects of the covariate or not.

Executing one-way ANCOVA from the test scores secured by two groups

Group	Pretest Scores	Posttest Scores
Control Group	7,8,9,7,8,6,10,6,8,9,12,8,8,9& 12	11,6,4,10,9,10,15,12,14,7,12,17,8,21&14
Experiment Group	6,13,6,14,9,9,8,10,7,11,13,8,5,9& 17	8,11,12,11,5,13,12,19,4,12,7,15,12,17 & 6

Null Hypothesis: There is no statistically significant difference between the control group and the experimental group on the posttest score after controlling the effects of the pretest score on them

Outcome Demonstration in SPSS

Table 1. Between-Subjects Factors

		Value Label	N
Group	1.00	Con Grp	15
	2.00	Exp Grp	15

Table 2. Tests of Between-Subjects Effects

Dependent Variable: Test_2

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.982[a]	2	.991	.050	.951
Intercept	314.912	1	314.912	15.938	.000
Test_1	.782	1	.782	.040	.844
Group	.757	1	.757	.038	.846
Error	533.484	27	19.759		
Total	4254.000	30			
Corrected Total	535.467	29			

a. R Squared = .004 (Adjusted R Squared = -.070)

Reporting of the outcomes

Table 2 which employs the posttest score as the dependent variable , group as Fixed factor and the pretest score as Covariate shows that there was no statistically significant difference between the control group and the experimental group on the posttest score after controlling the effects of the pretest score on them . F (1, 27) = .038, which was much lower than the table value (4.210). Sig. was .846. The Adjusted R Squared (-.070) indicates that the model was not a fit. The result accepted the null hypothesis.

It is to underline that if the observed f-value was greater than 4.210 and p was less than .05, we would reject the null hypothesis. It means there was a statistically significant difference between the control group and the experimental group on the posttest score after controlling the effects of the pretest score on them.

2.5 Significance of Statistical Tools

Statistics is a body of mathematical techniques or processes for gathering, organizing, analyzing, and interpreting numerical data (Best & Kahn, 2006).Statistical tools are an essential part of research as they allow researchers to analyze data and make inferences about populations. They provide a way to test hypotheses and make decisions about whether the results of a study are meaningful or simply due to chance. They also allow researchers to estimate the uncertainty of their results and to make predictions about future outcomes. They are used in many areas of research including social science, medicine, psychology, economics, and natural sciences. They can be used to evaluate the effectiveness of a treatment, to identify relationships between variables, to test the validity of a survey, or to make predictions about future events.

One of the most important contributions of statistical tools is to help researchers control for the effects of chance. Without the use of statistical tools, it would be difficult to distinguish between meaningful results and those that occurred by chance. They provide researchers with a way to estimate the uncertainty of their results and to make predictions about future outcomes. In addition, they also enable researchers to make inferences about populations from samples. This is particularly important in fields such as medicine where it is not always feasible or ethical to study entire populations. They play a crucial role in research by providing a way to analyze data, test hypotheses, and make inferences about populations. They help researchers to determine the reliability and validity of their findings, and to identify patterns or trends in their data. Statistical significance is that it is the function of not only the magnitude of the result but also the size of the sample investigated (Dornyei, 2007). In brief, statistical tools are an essential part of research, providing a means to analyze data, test hypotheses, and make inferences about populations. They help researchers to control for the effects of chance, to estimate the uncertainty of results, and to make predictions about future outcomes. The use of these tools is critical in ensuring that the results of research studies are valid and reliable.

3. Method and Materials

The research design for this study was qualitative. The data were collected from various sources, such as books, journal articles, and websites. The materials involved in this study were different types of parametric tests.

4. Conclusion

Parametric tests are powerful tools for researchers to analyze data and make inferences about populations. They are based on the assumptions of normality, independence, equal variances, and interval or ratio scale data. These assumptions make it possible to use the normal distribution and the properties of the normal distribution to test hypotheses. The most common parametric tests include t-tests, analysis of variance, and analysis of covariance. These tests have different assumptions and are used in different situations. For

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example, the one-sample t-test is used to test the mean of a sample against a known population mean, dependent samples t-test is employed to examine the mean values of two tests of a group, while the independent samples t-test is used to compare the means of two independent samples. Analysis of variance is used to test for differences in means among more than two groups, while analysis of covariance is used to test for differences in mean scores while controlling for the effects of one or more continuous variables.

It's worth noting that it's important to check the assumptions of these tests before conducting them and to use non-parametric tests if assumptions are not met. These tests are widely used in research to make inferences about populations, but it's important to use them appropriately to draw valid conclusions. This comprehensive overview of the major five parametric tests with outcome demonstration in SPSS and the reporting of the outcomes presented as specimens will be indubitably advantageous to research scholars for making the analyses of these tests.

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