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MA Summer School
Learning to Love Quantitative Methods of Inquiry
SPSS Laboratory Manual

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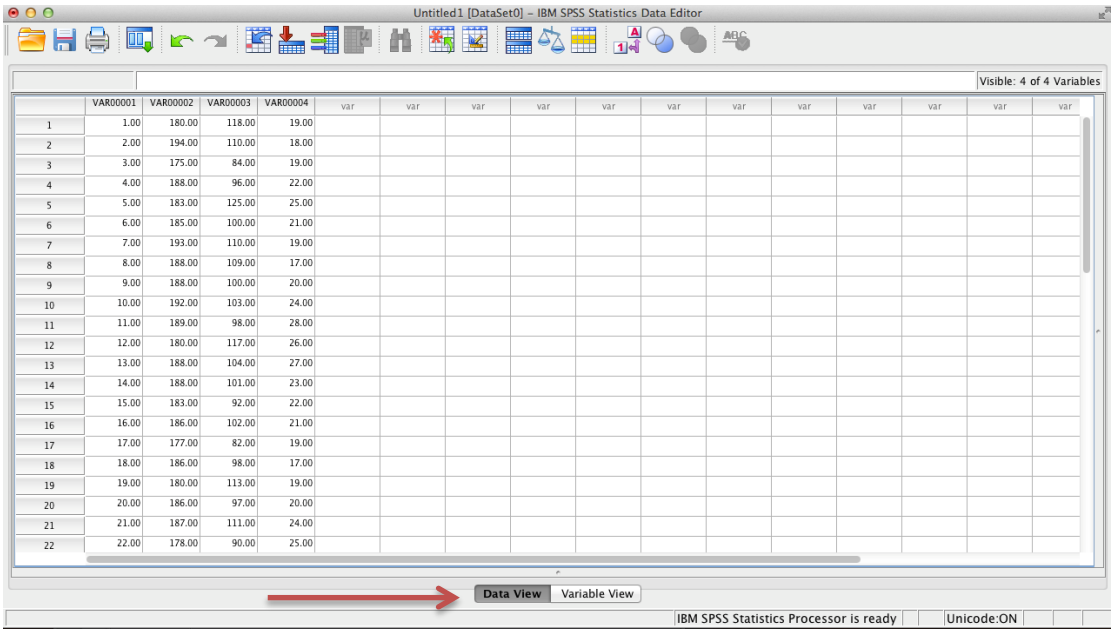
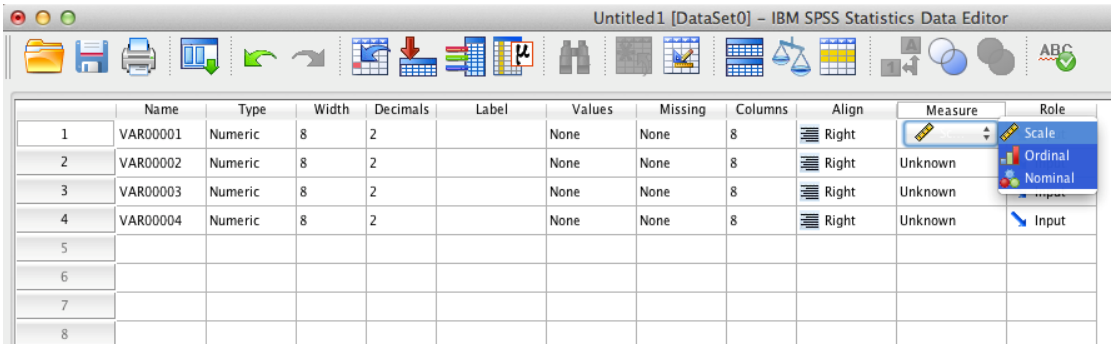
1.0 SPSS Getting Started

SPSS has two 'views' in which you will work, these are:
Data View and Variable View:

Data View:



Variable View:



This is where you will define your variables — essentially label the data you are working with. The first row is used to create an ID number for each individual participant (omit real names for anonymity and ethical reasons). Each row thereafter is one of your sets of data. Label these as Height, Weight and Age.

Defining variables:

Referring to the image above, you need to define information about each variable, the main ones you will need to define are summarised in the following table:

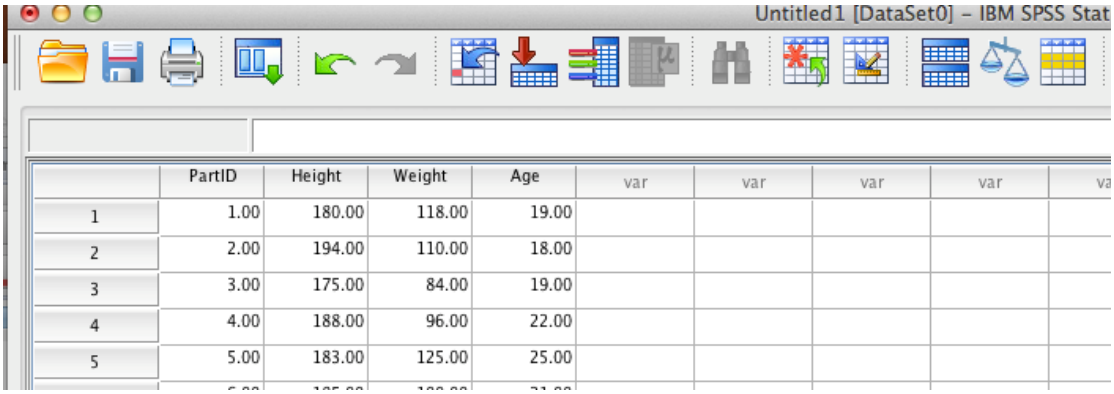
Variable.	Some notes
Name	Up to 8 characters, no spaces Could relate to the question number (e.g. Q1) or be descriptive (e.g. Height)
Type	e.g. numeric, date, string (alphanumeric or letters)
Width	The number of characters that can be entered
Decimals	Identify the number of decimal places you want to work with- Relate this to the actual measure, can you have 0.3 of a heart beat?
Label	Description of the variable (i.e. a longer description of the variable name)
Values	This is often set in survey/questionnaire data Labels that explain the values - Numeric values are preferable It is common to define 99 as a missing value (i.e. if a respondent failed to answer a question) Be consistent e.g. always 1 = no, 2 = yes
Missing	Optional: if you declare that a value is "missing", SPSS will omit the values from analysis
Columns	Defines the width of the column in *data view*
Align	Left, right or centre alignment of data in cells
Measure	**Nominal, ordinal or scale (interval/ratio)**

Measure in SPSS:

The last column needing to be defined is 'Measure'. Here you must decide if a variable is Nominal, Ordinal or Scale.

- A **Nominal** (sometimes also called categorical) variable is one whose values vary in categories. It is not possible to rank the categories created.
  e.g. Gender varies in that an individual is either categorised as "male" or "female".
- An **Ordinal** variable is one where it is possible to rank the categories or put them in an order. The intervals between the categories used are not defined. e.g. likert scale from a questionnaire.
- **Scale** variables:
  An **Interval** variable is one where the measurement scale uses the same interval between one measurement and the next (but the zero point is arbitrary).
  e.g. Temperature is measured so that the interval between 19 degrees and 20 degrees is the same as the interval between 20 degrees and 21 degrees. The zero point on the Centigrade scale of measurement is arbitrarily set (freezing point of water) and does not mean there is "no temperature".
  *A **Ratio** variable is the same as an interval variable but there is a true zero point. For example, height is a ratio variable, as a value of zero centimeters means there really is "no height". **Interval and ratio are often treated as one – Scale***

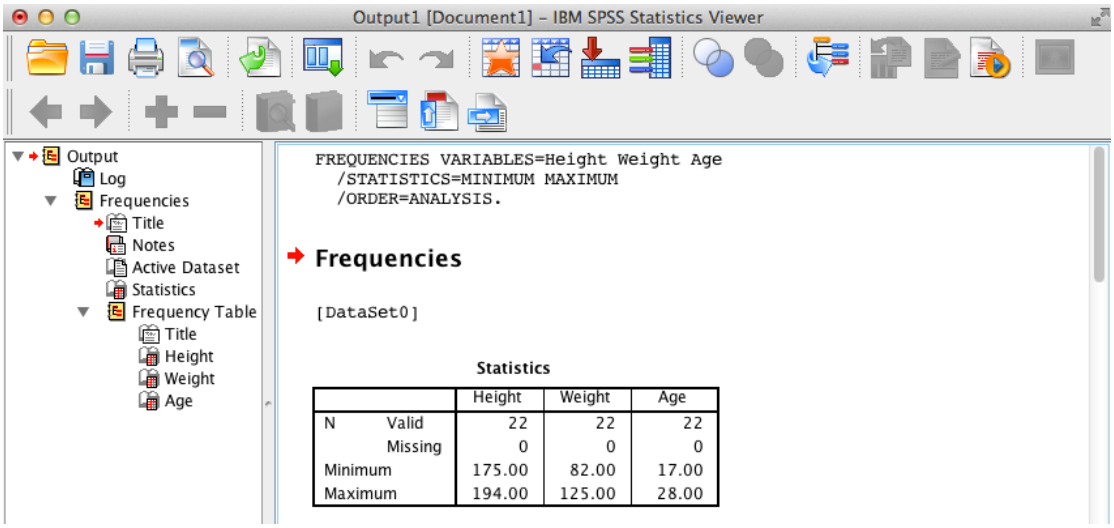
Once you have set your variable view your screen should now look like this:



Where you have a number of variables and data points it may be worth checking for errors. To do this:

1. From the main menu, click on: **ANALYSE**, then **DESCRIPTIVE STATISTICS**, then **FREQUENCIES**.
2. Choose the variables you wish to select (e.g. height, weight)
3. Click on the arrow button to move these in to the variable box
4. Click on **STATISTICS**, tick **MINIMUM** and **MAXIMUM** in the **DISPERSION** section
5. Click **CONTINUE**, the **OK**.

You should then see an output screen that looks like this:



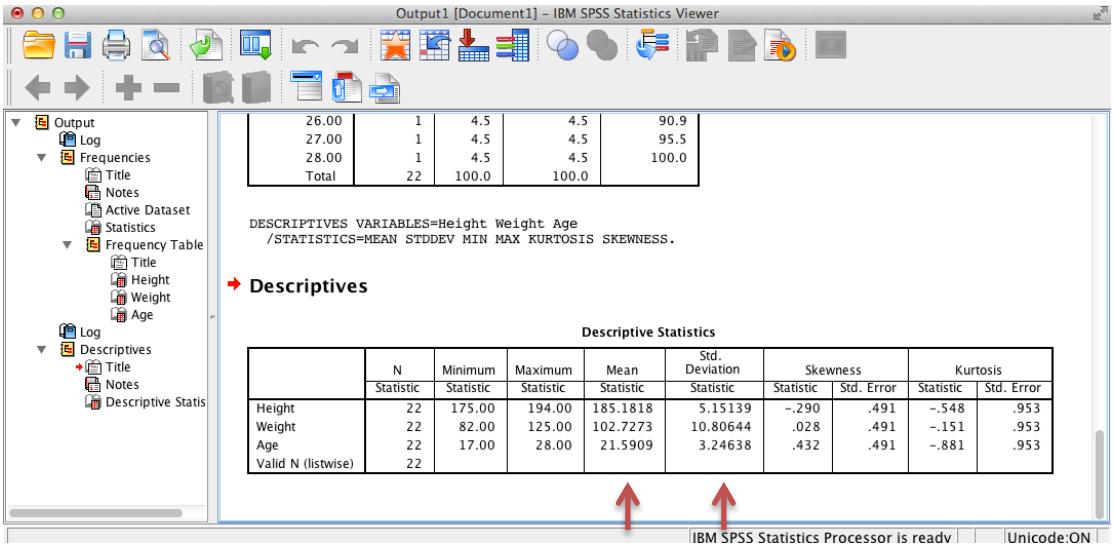
You should check that you have the correct number of valid entries **(N=22),** that you have zero missing entries and that the maximum and minimum values for each variable look correct and make sense (i.e. the maximum and minimum age look correct).

If these are correct, then you can progress on to descriptive statistics. These are a set of summary statistics that include mean, median and standard deviation.
Mean: average
Median: middle value of the data set
Standard Deviation: amount of variation of the data away from the mean.

To find your descriptive statistics:

1. Click on **ANALYSE,** then **DESCRIPTIVE STATISTICS**, then **DESCRIPTIVES**
2. Click on all the variables you would like analysed and click the arrow button to move them in to the **VARIABLES** box.
3. Click on **OPTIONS**, and click **MEAN, STANDARD DEVIATION, MINIMUM, MAXIMUM, SKEWNESS** and **KURTOSIS.**
4. Click on **CONTINUE** and **OK**.

You should see the following output generated:



Skewness and Kurtosis tell us about the symmetry and the 'peakedness' of the distribution of the data. If the distribution was perfectly normal, you would expect to see a value of 0 for skewness and kurtosis – though this is uncommon in social sciences! A positive score for skewness indicates a positive skew- the scores are clustered to the left and vice versa. Positive kurtosis indicates that the data is peaked (clustered in the centre) and has long thin tails. A negative kurtosis indicates that the curve is relatively flat, and you probably have too many cases in the extremes.

Assessing Normality:

Many of the **parametric tests** we wish to apply assume that the distribution of the data of the dependent variable is 'normal'. By 'normal' we mean that the data is symmetrical, with a bell shaped curve that shows the greatest frequency of scores in the middle, and smaller frequencies towards the extremes.

Let's look at the 'normality' of the participants' weight.

1. Click on **ANALYSE**, then **DESCRIPTIVE STATISTICS,** then **EXPLORE**
2. Click on the 'weight' variable, and move this across to the Dependent List box.
3. In the **DISPLAY** section, make sure that **BOTH** is selected.
4. Click **PLOTS**. Under **DESCRIPTIVE,** click on **HISTOGRAM** and **NORMALITY PLOTS WITH TESTS**.
5. Click on **CONTINUE**
6. Click on **OPTIONS,** under **MISSING VALUES**, click on **EXCLUDE CASES PAIRWISE**
7. Click **CONTINUE** and then **OK.**

The output generated for this procedure is shown below:

Explore

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Weight	22	100.0%	0	0.0%	22	100.0%

Descriptives

			Statistic	Std. Error
Weight	Mean		102.7273	2.30394
	95% Confidence Interval for Mean	Lower Bound	97.9360	
		Upper Bound	107.5186	
	5% Trimmed Mean		102.6667	
	Median		101.5000	
	Variance		116.779	
	Std. Deviation		10.80644	
	Minimum		82.00	
	Maximum		125.00	
	Range		43.00	
	Interquartile Range		13.50	
	Skewness		.028	.491
	Kurtosis		-.151	.953

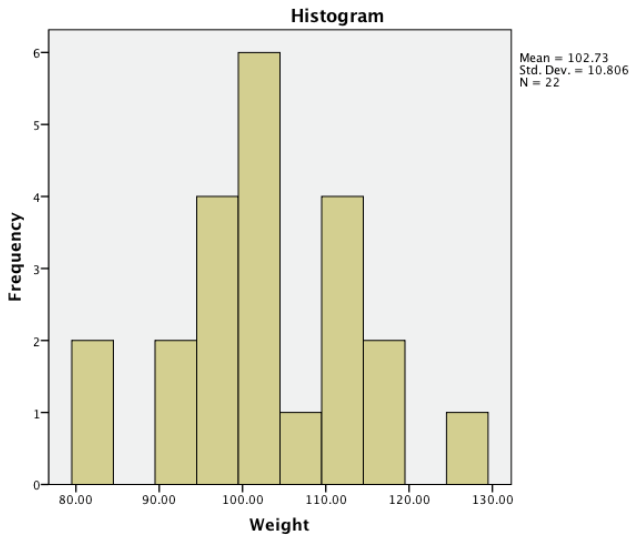
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Weight	.089	22	.200*	.984	22	.967

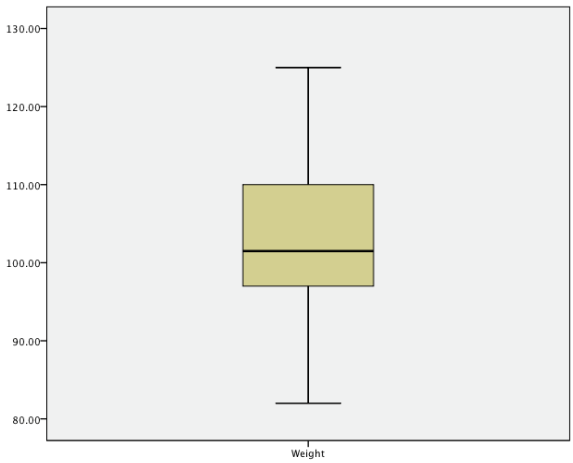
*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Weight



Boxplot:



Interpreting your Normality Tests:

This output will give you descriptive statistics, skewness and kurtosis.
In the table labeled **'TEST FOR NORMALITY'**, you are given the results of the **KOLMOGOROV-SMIRNOV** statistic. This assesses the normality of the distribution of the scores.

- A non-significant result here is value of MORE THAN 0.05 and this indicates normality.
- Our score here is **0.200**, which is greater than 0.05 and so our weight data is normally distributed; therefore **parametric statistics** can be used.

The actual shape of the distribution can be seen in the **HISTOGRAMS** presented in the output. You will also have on your screen a normal probability plot (NORMAL Q-Q PLOT). These plot the observed score against an expected value from the normal distribution – a reasonably straight line suggests a normal distribution here too.

The final plot that is provided in the output is a **BOXPLOT**. The rectangle represents 50 per cent of the data/scores provided. The horizontal line inside the box represents the median. The whiskers that come out of the box stop at the smallest and largest values. If you have small circles outside of this range, these are classed as **outliers** – individual data sets that are abnormally large or small. It is worth checking that these data points are correct and that you have not made an inputting error. If it is correct – you need to decide what to do with it. Some authors recommend removing this participant/data set from the data file. You should discuss these extreme values with your supervisor.

NOTE:

Parametric and Non-Parametric statistics are very different. Typically where the numbers collected are interval or ratio (a scale of some sort) the preferred statistic will be parametric. In psychology other social sciences, the 'data' generated is not usually an objective or fixed number – it is a subjective and often self-reported element, e.g. motivation or confidence. In these situations 'pure' science advocates state that the data should be analysed using NON-PARAMETRIC tests, however social scientists will frequently use PARAMETRIC tests to analyse their findings. Please discuss this with your tutor PRIOR to any data collection.

BASIS FOR COMPARISON	PARAMETRIC TEST	NON-PARAMETRIC TEST
Meaning	A statistical test, in which specific assumptions are made about the population parameter.	A statistical test used in the case of non-metric independent variables, is called non-parametric test.
Basis of test statistic	Distribution (if distribution is NORMAL we can use a parametric test)	Arbitrary (if distribution is not normal or unknown then we need to use the non-parametric equivalent test)
Measurement level	Interval or ratio	Nominal or ordinal
Measure of central tendency	Mean	Median
Information about population	Completely known	Unavailable

2.0 Calculating Cor*relation*

Correlation analysis is used to describe the **strength** and **direction** of the linear relationship between two variables. SPSS gives you a number of different tests for correlation depending upon your level of data.

Data	Test	Name
Interval or Ratio	Parametric	Pearson Product-Moment coefficient
Ordinal	Non-Parametric	Spearman Rank Order test

Example research question: Is there a relationship between X and Y?

We will try to establish if there is a relationship between Cervical Spine FLEXION and EXTENSION strength.

Before we start the analysis, let's go through the checking process described in section 1.0

1. Does my descriptive data look correct?

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
FLXN	42	15.30	30.60	21.9500	3.85545	.342	.365	-.249	.717
EXTN	42	15.60	30.00	22.2667	3.58722	.113	.365	-.268	.717
Valid N (listwise)	42								

2. Is my data normally distributed?

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
FLXN	.090	42	.200*	.968	42	.274
EXTN	.082	42	.200*	.975	42	.488

*. This is a lower bound of the true significance.

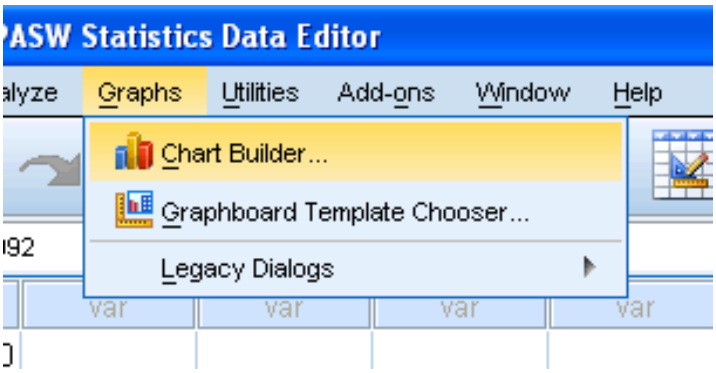
a. Lilliefors Significance Correction

Our significant on the Kolmogorov-Smirnov test is greater than 0.5 – meaning our data is normally distributed and therefore we can use parametric statistics.

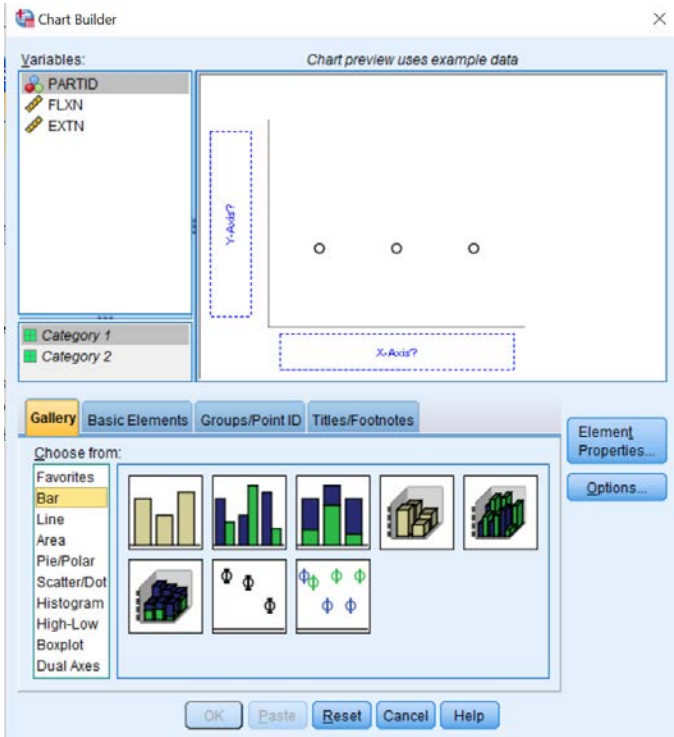
Before you complete a correlation analysis, it is useful to generate a scatterplot so that you can visualise any relationship that may be present.

To generate a scatterplot:

1. Click Graphs > Chart Builder... on the top menu as shown below:

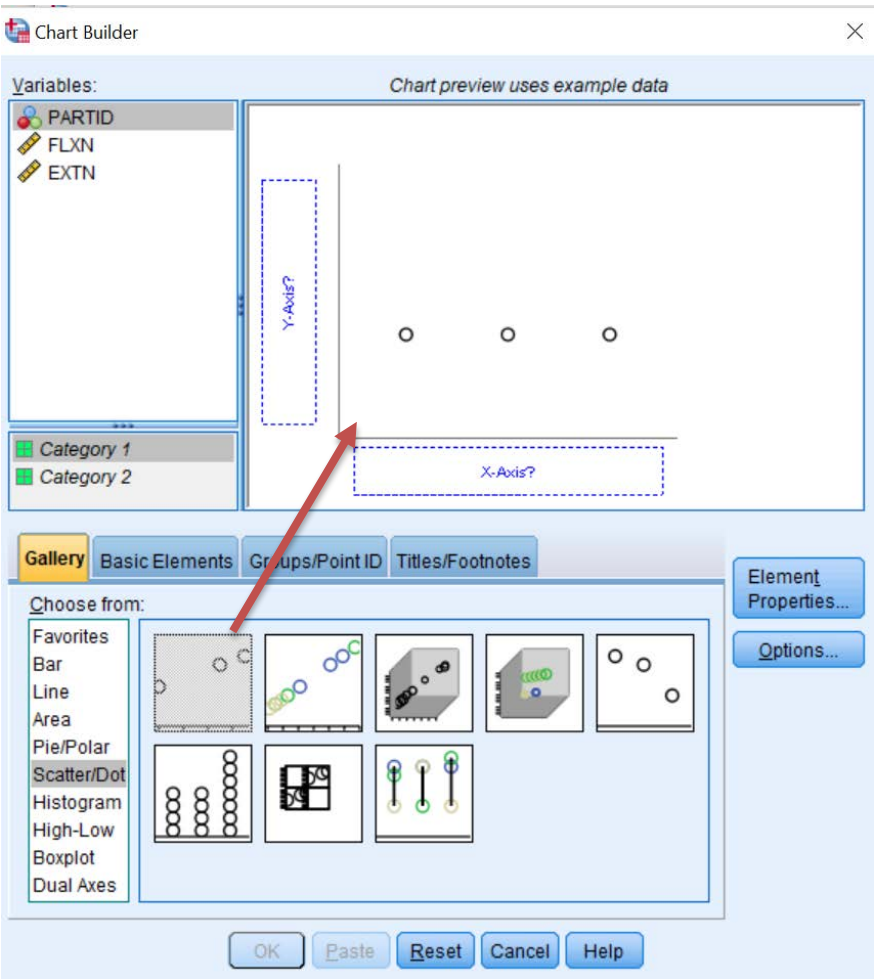


2. You will be presented with the following screen:

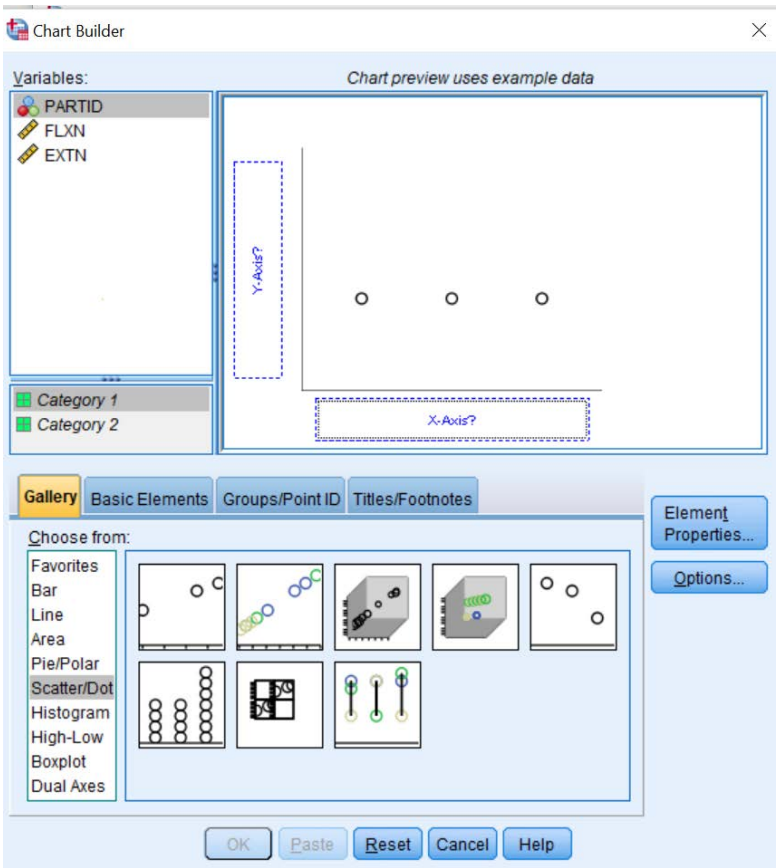


3. Under the Gallery Tab (

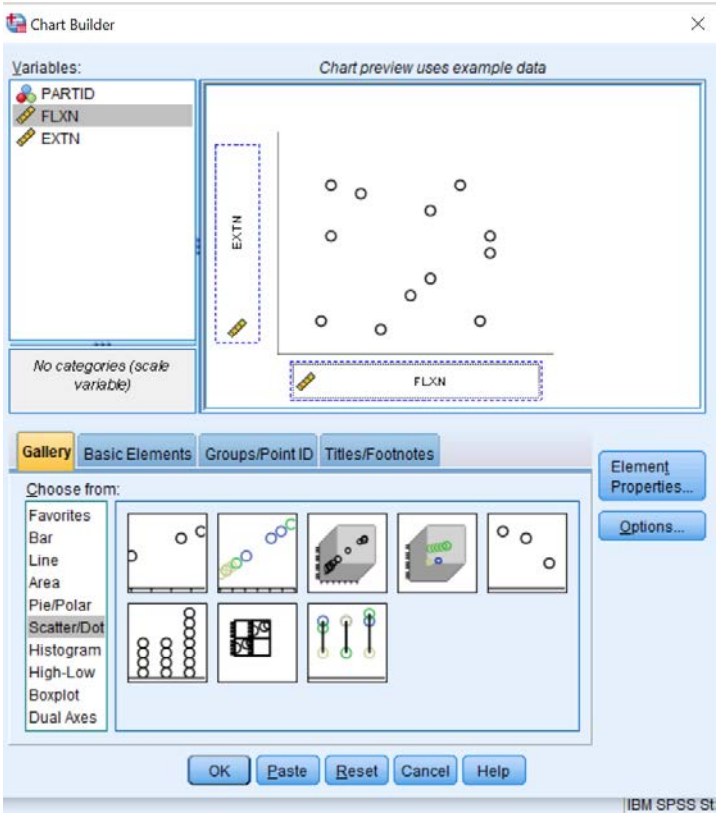
), select the Scatter/Dot option and the simple scatterplot icon (top-left icon). Drag-and-drop this icon into the Chart Preview Area (as shown by the in the diagram below).



4. You will be presented with the following dialog boxes: Chart Builder and Element Properties. As you can see, the Chart Preview Area has been populated with a template of a simple scatterplot.



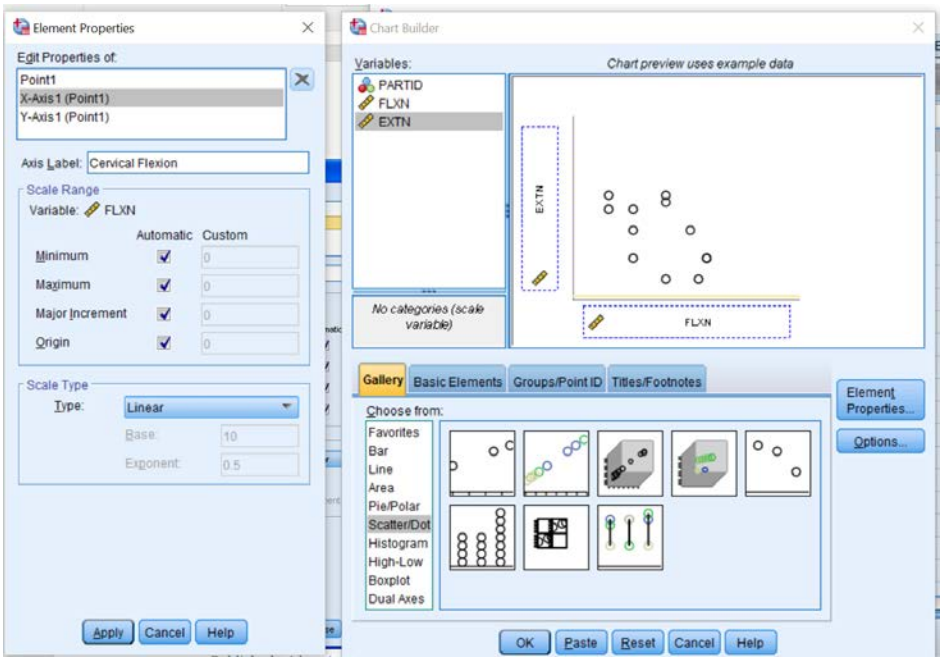
5. Usually, the dependent variable sits in the Y-AXIS and the Independent variable sits in the X-AXIS. For the purposes of the above example, we have dragged **FLEXION** in to the "X-Axis?" box, and **EXTENSION**, into the "Y-Axis?" box within the Preview Chart Area by drag-and-dropping the variables from the Variables: box.



6. If you wish to change the axis labels, select "X-Axis1 (Point1)" and/or "Y-Axis1 (Point1)" in the Element Properties dialog box and type in the new axis title. Below we demonstrate changing the X-Axis label from "FLXN" to "Cervical Flexion". Remember to click the

button after each label change. Repeat with the Y-Axis by changing the label from "EXTN" to "Cervical Extension", and again, click the

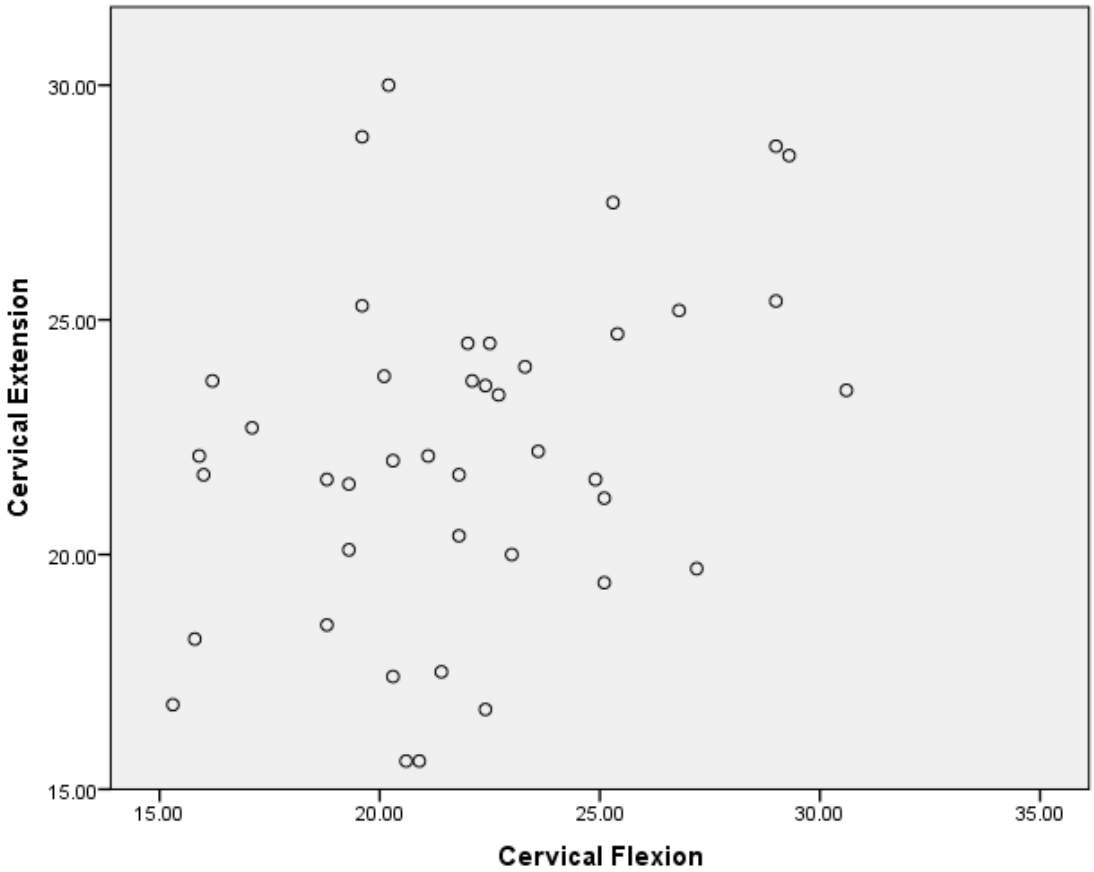
button.
7.



8. Click the

button.

Try to generate a scatterplot of Flexion and Extension from workbook two on your excel spreadsheet.



Looking at the scatterplot, we can check for outliers – any data points that sit out on their own. We look at the spread of the data – if they are dispersed this can indicate a low correlation. If the data looks as though it would sit on a curved line then Pearson's correlation should not be used as it assumes a linear relationship.

Calculating Pearson Product-Moment Correlation:

1. Click on **ANALYSE**, then **CORRELATE**, then on **BIVARATE**
2. Select **FLEXION** and **EXTENSION** from the variables list and move then across to the box marked **VARIABLES**
3. Check that the **PEARSON** box and the **TWO TAIL** box is checked – for non-parametric statistics select **SPEARMAN** test
4. Click on OPTIONS, make sure that the **EXCLUDE CASES PAIRWISE** option is checked. Under **OPTIONS** you can also select to include means and standard deviations.
5. Click **CONTINUE**, and **OK.**

The output generated is shown below:

Correlations

Correlations

		FLEXION	EXTENSION
FLEXION	Pearson Correlation	1	.357*
	Sig. (2-tailed)		.020
	N	42	42
EXTENSION	Pearson Correlation	.357*	1
	Sig. (2-tailed)	.020	
	N	42	42

*. Correlation is significant at the 0.05 level (2-tailed).

Sig. (2-tailed) is our level of significance.

- It needs to be **BELOW 0.05** for the result to be significant.

At 0.020 this value indicates a significant relationship between neck flexion strength and neck extension strength.

To determine the **direction** of the relationship, we must look at the Pearson Correlation (r). This number can be either positive or negative.

- If the value is negative, then there is a negative correlation between the two variables (i.e. high score on one variable and low score on the other).

To determine the **strength** of the relationship, we must gain look at the Pearson Correlation (r) statistic.
This can range from -1.00 to +1.00.

- A **r** of 0 indicates no relationship at all and a correlation on +1.00 indicates a perfect positive correlation.

Cohen has given us the following guidelines for interpreting the strength of a correlation:

Positive r	Negative r	Interpretation
r= 0.10 to 0.29	r = -0.10 to -0.29	Small
r = 0.30 to 0.49	r = -0.30 to -0.49	Medium
r = 0.50 to 1.0	r = -0.50 to -1.0	Large

Therefore, our result is as follows:

A significant, moderate, positive relationship exists between neck flexion strength and neck extension strength in professional rugby union players (r=0.36, n=42, P<0.05).

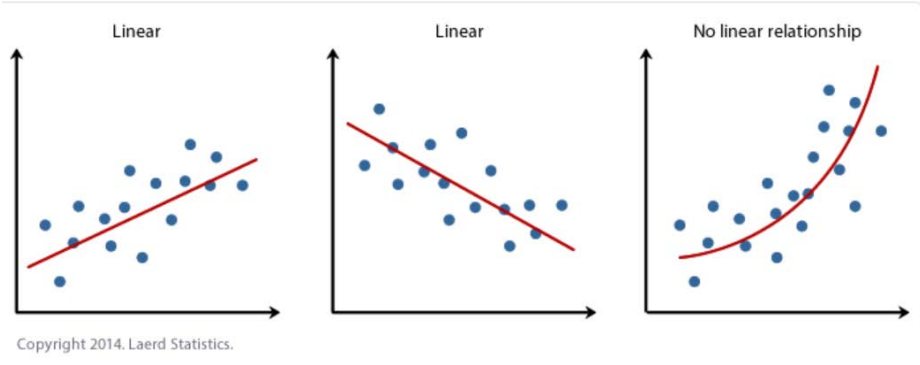
2.1 Linear Regression Analysis

Linear regression is the next step up after correlation. It is used when we want to predict the value of a variable based on the value of another variable. The variable we want to predict is called the dependent variable (or sometimes, the outcome variable). The variable we are using to predict the other variable's value is called the independent variable (or sometimes, the predictor variable).

Based upon our correlation of neck flexion and extension, let's see if we can predict neck flexion (dependent variable) from neck extension values (independent variable).

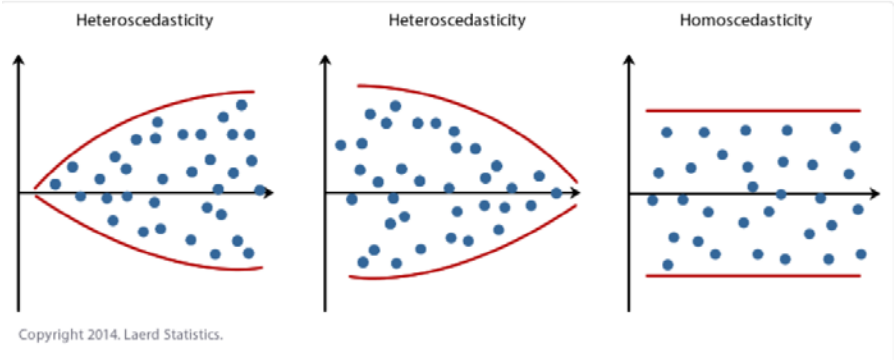
Before we do this, we must check a few assumptions of the test are fully met.

1. We are dealing with interval or ratio data
2. We have a linear relationship…



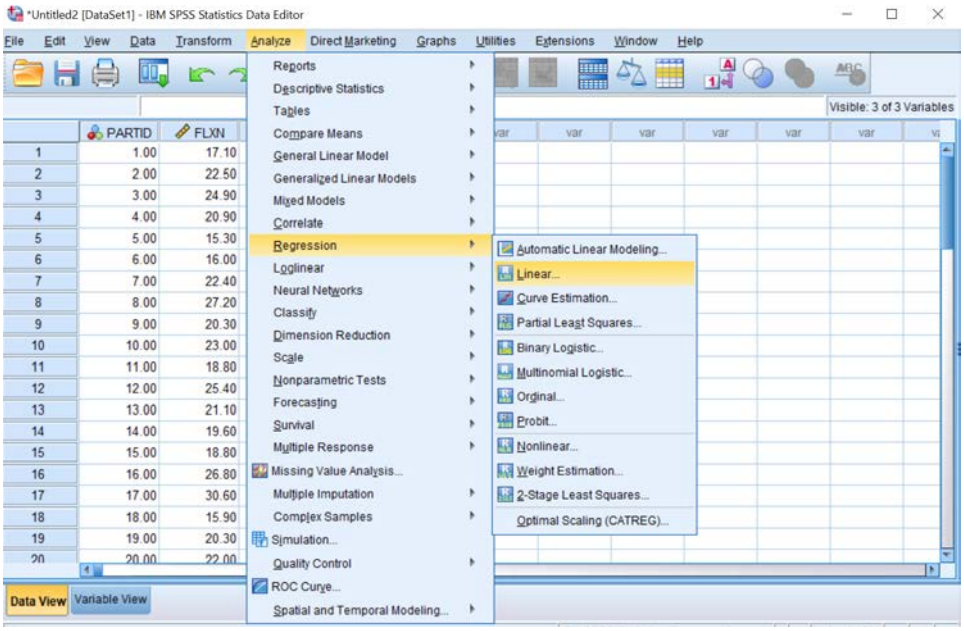
3. We have no significant outliers (from boxplots or scatterplot)

4. Our data shows homoscedasticity

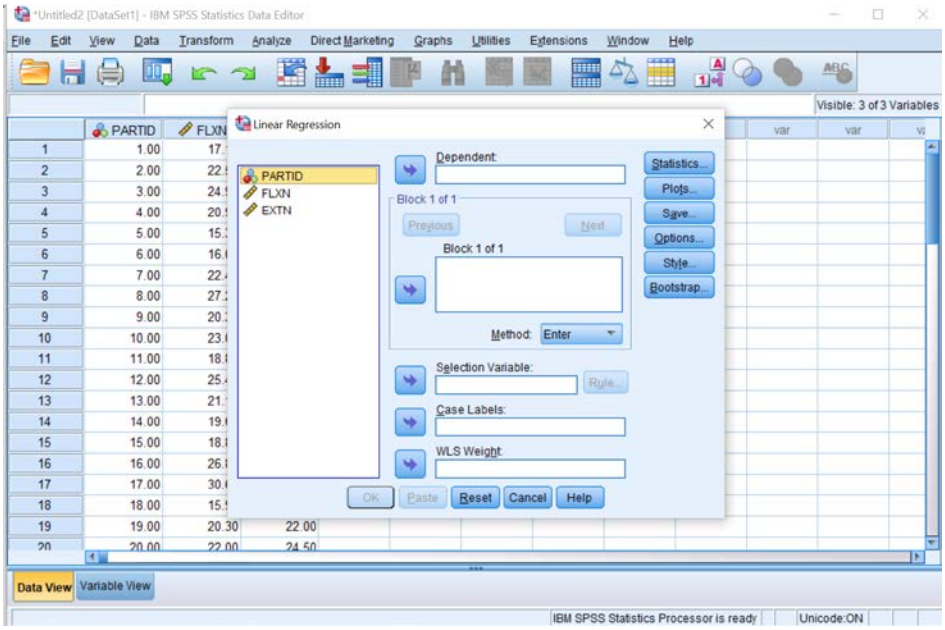


To perform a Linear Regression…..

1. CLICK on **ANALYSE**, then **REGRESSION**, the **LINEAR**



2. This will open the Linear Regression Box:



3. Select your **Dependent Variable (FLXN)**
4. Select your **Independent Variable (EXTN)**
5. Click **OK**

The output generated is shown below:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.357[a]	.127	.105	3.64662	1.669

a. Predictors: (Constant), EXTN

b. Dependent Variable: FLXN

In the model summary we see two statistics; R and R^2.

- R is a simple correlation. It is identical to the Pearson Correlation value of 0.357 completed earlier
- R^2 is the interesting statistic. Its value explains how much of the total variance in the dependent variable (FLXN) can be explained by the independent variable (EXTN). In this case, only 12.7% of the variance in FLXN can be explained by EXTN.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	77.531	1	77.531	5.830	.020[b]
	Residual	531.914	40	13.298		
	Total	609.445	41			

a. Dependent Variable: FLXN

b. Predictors: (Constant), EXTN

The next table is the **ANOVA** table, which reports how well the regression equation fits the data (i.e., predicts the dependent variable).

This table indicates that the regression model predicts the dependent variable significantly well.
Look at the "**Regression**" row and go to the "**Sig.**" column. This indicates the statistical significance of the regression model that was run.

- Here, *p = 0.020*, which is less than 0.05, and indicates that, overall, the regression model statistically significantly predicts the outcome variable (i.e., it is a good fit for the data).

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	13.414	3.580		3.747	.001
	EXTN	.383	.159	.357	2.415	.020

a. Dependent Variable: FLXN

The **Coefficients** table provides us with the necessary information to predict FLEXION from EXTENSION. We can use the values in the "**B**" column under the "**Unstandardized Coefficients**" column to present the regression equation as:-

FLXN = 13.414 + 0.383(EXTN)

For example, a player with an EXTN strength score of 20.5Kg will have a predicted FLXN score of:

FLXN = 13.414. + 0.383(20.5)
FLXN = 21.27Kg

3.0 Comparing Groups to Find a Difference

Before we start to use these statistical tests, let's refresh our understanding of the terms used:

T-Tests	Used to establish a difference between two groups (e.g. males/females)
ANOVA	Analysis of Variance techniques are used for two or more groups
Paired Samples	Sometimes called repeated measures because they analyse the data between the same group of people tested on more than one occasion (matched pairs)
Between Groups	Sometimes called an independent samples test are used when the subjects in each group are different people (or independent)
One-Way	e.g. analysis of variance is used when you only have one independent variable
Two-Way	E.g. analysis of variance is used when you have two independent variables
Multivariate analysis of variance	Used when you have more than one dependent variable

These types of analysis assume that the dependent variable is measured at the interval or ratio level. It also assumes that data is collected from a random sample from a population. Another assumption is that all measurements are independent of each other and that the data is normally distributed. A final assumption is that the samples are drawn from populations of equal variances; that the variability of scores for each of the groups is similar. This assumption can be tested using the Levene test for equality of variance. This will be reported in the t-test and ANOVA output sheets.

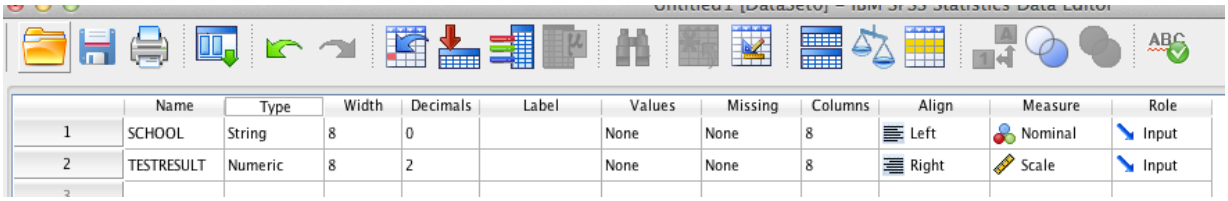
Independent Samples T-Test

An independent T-Test is used when you want to compare the mean score on some continuous variable, for two different groups of subjects. On your excel sheet, under the tab 'Independent T-Test' you will see data from two sets of students from two separate schools on a standardised test (e.g. balance, % body fat, self esteem). The type of research question we might be answering here is:- Is there a significant difference between school A and school B on the standardised test?

If your data does not meet the assumptions of this test (i.e. data is not normally distributed) you should use the Mann-Whitney Test.

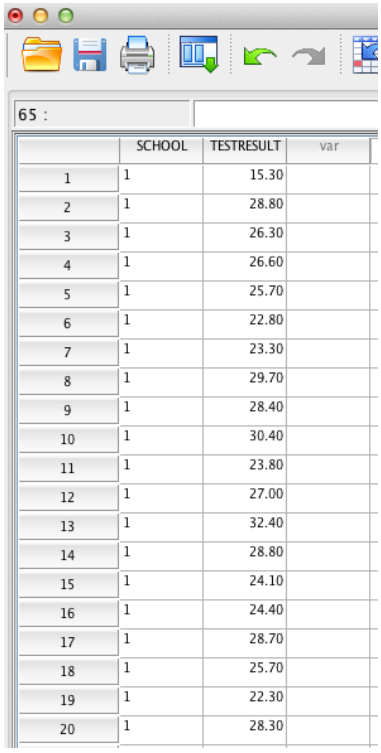
Calculating the Independent Samples T-Test:

Before we run the test, we will need to enter the data in to SPSS in a specific way. In the variable view, you need to allocate a column for school – using Nominal (non-numeric data) and a column for the test result (scale/ratio data).



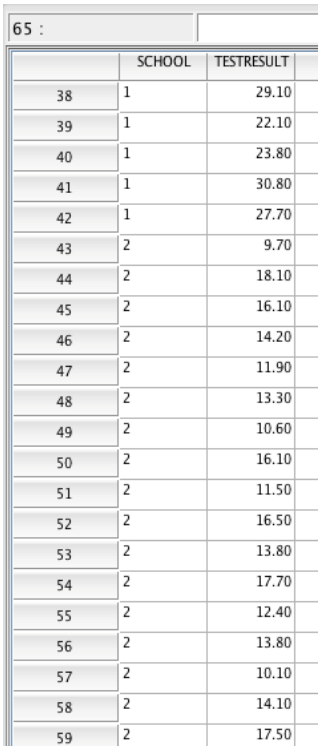
	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	SCHOOL	String	8	0		None	None	8	Left	Nominal	Input
2	TESTRESULT	Numeric	8	2		None	None	8	Right	Scale	Input

You will need to code your schools as 1 and 2.
E.g. Cut and paste School A's results in from the excel sheet in to column two labeled TESTRESULT and code this as (1) in the SCHOOL column. Directly underneath School A's test results you will cut and paste in School B's results and code these as (2) in the SCHOOL COLUMN.



65 :

	SCHOOL	TESTRESULT	var
1	1	15.30	
2	1	28.80	
3	1	26.30	
4	1	26.60	
5	1	25.70	
6	1	22.80	
7	1	23.30	
8	1	29.70	
9	1	28.40	
10	1	30.40	
11	1	23.80	
12	1	27.00	
13	1	32.40	
14	1	28.80	
15	1	24.10	
16	1	24.40	
17	1	28.70	
18	1	25.70	
19	1	22.30	
20	1	28.30	



65 :

	SCHOOL	TESTRESULT
38	1	29.10
39	1	22.10
40	1	23.80
41	1	30.80
42	1	27.70
43	2	9.70
44	2	18.10
45	2	16.10
46	2	14.20
47	2	11.90
48	2	13.30
49	2	10.60
50	2	16.10
51	2	11.50
52	2	16.50
53	2	13.80
54	2	17.70
55	2	12.40
56	2	13.80
57	2	10.10
58	2	14.10
59	2	17.50

Once we have the data entered correctly we can complete the Independent T-Test.

1. Click **ANALYSE,** then click on **COMPARE MEANS**, then click on **INDEPENDENT SAMPLES T-TEST**
2. Move the dependent variable **(TESTRESULT)** in to the area labelled **TEST VARIABLE**
3. Move the independent variable **(SCHOOL)** in to the section labelled **GROUPING VARIABLE**
4. Click on **DEFINE GROUPS** and type in the numbers used in the data set to code each group. In the current data file School A is 1, School B is 2, therefore type 1 in **GROUP BOX 1**, and 2 in **GROUP BOX 2**
5. Click **CONTINUE,** then **OK**

The output generated from SPSS is shown below:

T-Test

Group Statistics

	SCHOOL	N	Mean	Std. Deviation	Std. Error Mean
TESTRESULT	1	42	25.8095	3.42208	.52804
	2	42	13.2690	2.85602	.44069

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
TESTRESULT	Equal variances assumed	.503	.480	18.233	82	.000	12.54048	.68778	11.17227	13.90868
	Equal variances not assumed			18.233	79.458	.000	12.54048	.68778	11.17162	13.90934

The group statistics box will give you the mean and standard deviation for each of your groups and number of participants. Check these against your records- if these are incorrect you may have coded your groups incorrectly.

You should then check the assumptions of the test have been met – check the Levene's test for equality of variances.

- If the significance value is larger than 0.05 you should use the first line in the table (Equal variances assumed).

In this case Levene's test gives us a significance of 0.480, which is greater than 0.05 so we can assume equal variance.

To find out if the difference between the two groups is significant, you should refer to the column labelled 'SIG. (2-TAILED)". Make sure you use the correct line (in our case, equal variances assumed) and note the number given. If the value is equal or less than 0.05 then there is a significant difference in the mean score of your groups. Our result is P= 0.000, which is less than 0.05. Therefore we can state that there is a significant difference between school A and school B on the

test result.

We now know there is a difference, but what we don't know is how big the difference is.
The magnitude of the difference is calculated by the **Effect Size** statistic.

Effect Size

Effect size is most commonly represented by eta squared. Eta squared can range from 0 to 1 and represents the proportion of variance in the dependent sample that is explained by the independent variable.

SPSS does not calculate effect size for independent samples t-test, but this can easily be done by hand using the following equation:

$$\text{Eta Squared} = \frac{t^2}{t^2 + (N1 + N2 - 2)} = \frac{(18.233)^2}{(18.233)2 + (42+42-2)}.$$

Where:

- t is taken from the SPSS output (18.233)
- N1 is the number of participants in School A
- N2 is the number of participants in School B

In this example the Eta squared value is 0.80

- According to Cohen (1988),

Effect size	*r*
Small	0.10
Medium	0.30
Large	0.50

To write a statement of these results you could state the following:

An independent samples T-test was conducted to compare the test results of School A and School B. A significant difference in test results was observed between School A [*M*= 25.8, *SD*= 3.4) and School B (*M*=13.3, *SD* = 2.85; *t* = 18.233, *P*=0.000]. The magnitude of the differences in the means was very large (eta squared = 0.80).

Paired Samples T-Test

A paired samples T-Test (also known as a repeated measures T-Test) is used when you only have one group of participants and you collect data form them on two separate occasions or under two different conditions. This is the test of choice for pretest/posttest experimental designs. In this design, you test your participants before and after some experimental intervention.

The type of research question you are looking to answer here is 'Is there a significant difference in participants test scores following an intervention'. If your data does not meet the assumptions of parametric testing, you can consider using the Wilcoxon Signed Rank Test as a non-parametric alternative.

To perform the paired samples T-Test:

1. Click **ANALYSE**, then **COMPARE MEANS**, then **PAIRED SAMPLES T-TEST**.
2. Click on **PRETEST** and move this across to the **PAIRED VARIABLES** box
3. Click on **POSTEST** and move this across to the **PAIRED VARIABLES** box
4. Click **OK**

The output generated by SPSS is shown below:

T-Test

[DataSet0]

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	PRETEST	244.1250	40	49.11900	7.76640
	POSTEST	236.2500	40	47.24120	7.46949

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	PRETEST & POSTEST	40	.682	.000

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 1	PRETEST - POSTEST	7.87500	38.47889	6.08405	-4.43115	20.18115	1.294	39	.203

To interpret the results you should firstly, determine the overall significance. Look at the final column labelled Sig. (2-tailed). This is your probability value. As per usual;

- If this value is below 0.05 then you can conclude there is a significant difference between your two scores.

In the example given to you, significance is 0.203 which is greater than 0.05, and therefore non-significant. You should also take note of your t-value (1.294) and the degrees of freedom (df= 39) as you will need these when reporting your results.

You should then compare the mean values of your two groups. In the first output box, the paired samples statistics are given. Examine the mean scores for each test. These will tell us if there was a (significant) increase or decrease in the test as a result of the intervention.

Effect Size

Again we will need to calculate effect size by hand IF the results are SIGNIFICANT:

$$\text{Eta Squared} = \frac{t^2}{t^2 + N - 1} \qquad \text{E.g.} = \frac{1.294^2}{1.294^2 + 40 - 1}$$

Within our example our Eta squared is 0.04.
According to Cohen (1988) and Sawilowsky (2009);

Effect size	*d*	Reference
Very small	0.01	Sawilowsky, 2009
Small	0.20	Cohen, 1988
Medium	0.50	Cohen, 1988
Large	0.80	Cohen, 1988
Very large	1.20	Sawilowsky, 2009
Huge	2.0	Sawilowsky, 2009

a small effect = 0.01; a moderate effect = 0.06; and a large effect is 0.14. If our results were significant, then we could state that we observed a small effect size.

To write a statement of our pretest/posttest results we could state:

A paired-samples T-Test was conducted to evaluate the impact of the (intervention) on (test scores). There was no statistically significant difference observed between pretest (*M*=244, *SD*=49) and posttest [*M*=236, *SD*=47, *t*(39)=1.294, *P*>0.05].

Where significance is found, you can also include a statement of the effect size.

One-Way Analysis of Variance

In research, we are often interested in comparing the mean scores of more than two groups. In these cases we need to use Analysis of Variance (ANOVA). One-way ANOVA involves one independent variable (referred to as a factor), which has a number of different levels. We calculate the F ratio, which represents the variance between groups. A significant F test indicates that we can reject the null hypothesis. It tells that a difference exists however it does not tell us where any difference may lie. To find the location of the difference we need to conduct post-hoc tests.

One – Way Between Groups ANOVA with post-hoc tests

The one-way between groups ANOVA is used when you have one independent variable with three or more levels and one dependent continuous variable. E.g. we would have one measure taken from 3 different populations.

The type of research question we are looking to answer here is:
Is there a significant difference between (group 1), (2) and (3) on (Test X)? If your data does not meet the assumptions of a parametric test, then the non-parametric equivalent test should be used, in this case the Kruskal-Wallis test.

To perform the one-way between groups ANOVA with post-hoc tests:-

1. Click on **ANALYSE**, then **COMPARE MEANS**, then **ONE-WAY ANOVA**.
2. Click on your dependent variable (Test Score). Move this to the **DEPENDENT LIST** box.
3. Click on your independent variable (Group). Move this to the box labelled FACTOR.
4. Click **OPTIONS** and select **DESCRIPTIVE, HOMOGENEITY OF VARIANCE TEST, BROWN-FORSYTHE, WELCH** and **MEANS PLOT**.
5. For **MISSING VALUES**, select **EXCLUDE CASES ANALYSIS BY ANALYSIS**
6. Click **CONTINUE**
7. Click on the button labelled **POST-HOC** and select **TUKEY**.
8. Click **CONTINUE**, and then **OK.**

The output generated is shown below:

Oneway

Descriptives

TESTSCORE

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	40	35.6025	3.13561	.49578	34.5997	36.6053	30.10	43.20
2.00	23	33.1304	6.71501	1.40018	30.2266	36.0342	14.50	43.20
3.00	18	26.3278	3.11029	.73310	24.7811	27.8745	21.60	31.00
Total	81	32.8395	5.71235	.63471	31.5764	34.1026	14.50	43.20

Test of Homogeneity of Variances

TESTSCORE

Levene Statistic	df1	df2	Sig.
9.019	2	78	.000

ANOVA

TESTSCORE

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1070.559	2	535.280	27.113	.000
Within Groups	1539.915	78	19.742		
Total	2610.474	80			

Robust Tests of Equality of Means

TESTSCORE

	Statistic[a]	df1	df2	Sig.
Welch	53.990	2	37.164	.000
Brown-Forsythe	23.903	2	39.065	.000

a. Asymptotically F distributed.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: TESTSCORE

Tukey HSD

(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	2.47207	1.16273	.091	-.3060	5.2501
	3.00	9.27472*	1.26110	.000	6.2616	12.2878
2.00	1.00	-2.47207	1.16273	.091	-5.2501	.3060
	3.00	6.80266*	1.39828	.000	3.4618	10.1435
3.00	1.00	-9.27472*	1.26110	.000	-12.2878	-6.2616
	2.00	-6.80266*	1.39828	.000	-10.1435	-3.4618

*. The mean difference is significant at the 0.05 level.

Homogeneous Subsets

Double-click to activate

TESTSCORE

Tukey HSD[a,b]

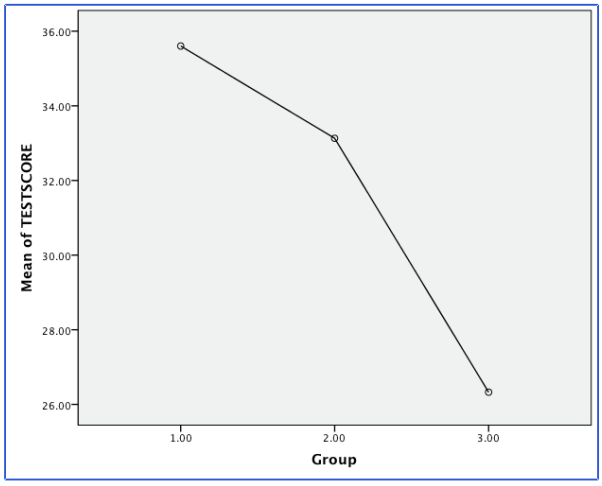
Group	N	Subset for alpha = 0.05	
		1	2
3.00	18	26.3278	
2.00	23		33.1304
1.00	40		35.6025
Sig.		1.000	.136

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 24.187.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots



Interpretation of the SPSS one-way between-groups ANOVA with post hoc tests

1. Descriptive Statistics. This table gives your standard descriptive information. Make sure this looks correct – do you have the correct number (N) in each group?

2. Test of Homogeneity of Variances. This uses Levene's test – which determines if the variance in scores is the same for each of the three groups. Check the significance value for this test (Sig.).

- If it is GREATER than 0.05 then your data has NOT violated the assumption of homogeneity of variance.
  In our example, our significance is 0.000, which is smaller than

0.05. We have violated the assumptions and therefore we need to look at the table headed ROBUST TESTS of EQUALITY OF MEANS. The two tests shown here are WELCH & BROWN-FORSYTHE. These tests are preferable when the homogeneity of variance is violated. Instead of looking at the ANOVA table, use the WELCH results. For the purposes of teaching here, we will assume that the homogeneity of variance assumption has not been violated, and we are able to use the ANOVA statistic.

3. ANOVA. Within the ANOVA table, the most important column is marked Sig. If the Sig. value is less than or equal to 0.05, then there is a significant difference somewhere among the mean scores. In our example the significance is 0.000, and therefore significant. Even if we acknowledge the homogeneity of variance violation, our Welch tests' significance result in also 0.000.

4. Post-Hoc Tests. Post-hoc test results are presented in the table labelled 'Multiple Comparisons'. You only need this section if you level of significance is less than or equal to 0.05. Remember these tests will only show you where any significant differences occur. Look down the column labelled 'Mean Differences'. Look for any asterisks (*) next to the values listed. If you find an asterisk, this means that the two groups being compared are significantly different from one another at the $P<0.05$ level. The exact significance value is given in the column labelled Sig. From our results, significant differences exist between group 3 and group 1; and group 3 and group 2. No significant difference exists between group 1 and group 2.

Effect Size

Again, SPSS will not calculate the effect size for this analysis, but it can be determined using the following equation:

$$\text{Eta squared} = \frac{\text{Sum of squares between groups}}{\text{Total sum of squares}}$$

The Eta squared value for our example is 0.4, which in Cohen's (1988) terms would be a large effect size.

Cohen's classifies 0.01 as a small effect, 0.06 as a medium effect and 0.14 as a large effect.

To present the results from your one-way between-groups ANOVA with post-hoc tests, consider the following statement:

A one-way between-groups analysis of variance was conducted to explore the impact of sport on hamstring strength scores (Group 1: rugby union, Group 2: football, Group 3: ice hockey). There was a statistically significant difference at the P<0.05 level [*F* = 27.113, *P*=0.000). The magnitude of the difference was large. Eta squared was calculated as 0.4. Post hoc comparisons using Tukey's test indicates that the mean score of hamstring strength scores for ice hockey (*M*= 26.3, *SD* = 3.1) was significantly different from rugby union (*M*= 35.6, *SD*= 3.1), and football (*M*= 33.1, *SD* = 6.7).

One-Way Repeated Measures ANOVA

In a one-way repeated measures design each participant is exposed to two or more different conditions, or measured on more than three occasions.
In our example, a group of children have been scored on a test on three separate occasions. Pre-test data was collected in July, they were then subjected to an intervention aimed at improving their score on the test and were reassessed in September. Finally they were tested again in December as a follow up.

An example research question suitable for this type of analysis is: 'Is there a change in test scores over time'. You must have one independent variable and one dependent variable. In addition to considering the effect of an intervention over time, it can also be used in a research design where each participant is assessed in three different areas (e.g. speed, agility, strength). One-way repeated measures ANOVA will tell you if there is a significant difference somewhere among the three sets of scores.

If your data fails to meet the assumptions of parametric testing, the non-parametric alternative is the Friedman Test.

To perform the one-way repeated measures **ANOVA**:

1. Click on **ANALYSE**, then click on **GENERAL LINEAR MODEL**, then on **REPEATED MEASURES**.
2. In the **WITHIN SUBJECT FACTOR NAME** box, type in the name that represents your independent variable (e.g. Time).
3. In the **NUMBER OF LEVELS** box, type the number of levels or time periods involved (in this example we have 3 time points).
4. Click **ADD**
5. Click on the **DEFINE** button
6. Select the three variables that represent your repeated measures variable **(PRETEST, POSTTEST, RETENTION)**. Click the arrow button to move them to the **WITHIN SUBJECTS VARIABLES** box.
7. Click on **OPTIONS**
8. Select **DESCRIPTIVE STATISTICS, ESTIMATES OF EFFECT SIZE**
9. Click **CONTINUE,** then **OK**.

The output generated is shown below:

General Linear Model

Within-Subjects Factors

Measure: MEASURE_1

time	Dependent Variable
1	PRETEST
2	POSTTEST
3	RETENTION

Descriptive Statistics

	Mean	Std. Deviation	N
PRETEST	394.7423	89.92499	26
POSTTEST	446.5000	75.84835	26
RETENTION	438.7538	72.51256	26

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
time	Pillai's Trace	.537	13.891[b]	2.000	24.000	.000	.537
	Wilks' Lambda	.463	13.891[b]	2.000	24.000	.000	.537
	Hotelling's Trace	1.158	13.891[b]	2.000	24.000	.000	.537
	Roy's Largest Root	1.158	13.891[b]	2.000	24.000	.000	.537

a. Design: Intercept
Within Subjects Design: time

b. Exact statistic

Your SPSS output will have a number of additional boxes underneath the one presented above. This technique generates a lot of complicated looking output. These are not necessarily required for this type of test but are provided for all multivariate statistics on SPSS.

Interpretation of the SPSS one-way repeated measures ANOVA test

1. Descriptive Statistics: This table gives your standard descriptive information. Make sure this looks correct – do you have the correct number (N) in each group?

2. Multivariate Tests: In this table you are interested in the **Wilks' Lambda** value and the corresponding probability value given in the column labelled **Sig.** This is the most commonly reported statistic for the one way repeated measures ANOVA. In our example, the Wilks' Lamba value is 0.463 with a probability value of 0.000. The P-value is less than 0.05, therefore we can conclude that there is a statistically significant effect for time. This suggests there was a change in test scores across the three different time periods.

3. Effect Size: Although we have a significant difference, we should also consider the effect size of this result. The value to consider is the Partial Eta squared value presented in the Multivariate Tests output box. In our example the value is 0.537. Using Cohen's (1988) guidelines (of 0.01 = small, 0.06 = moderate, 0.14 = large effect), this result suggests a very large effect. Ideally you would now perform a Post Hoc test to identify where the differences lie in your data, however post hoc testing for this type of analysis is complicated.

Students are directed to Stevens, J. (1996). *Applied multivariate statistics for the social sciences.* Malway NJ: Lawrence Erlbaum (chapter 13) for more information.

To present your results, follow the example below:

A one-way repeated measures ANOVA was conducted to compare (test scores) at time 1 (pre intervention), time 2 (post intervention) and time 3 (3 month follow up). The means and standard deviations are presented in Table XX. There was a significant effect for time [Wilks' Lambda = 0.000, *F*(2, 24) = 13.981, *P*=0.000, multivariate partial eta squared = 0.537].

Table 1.0 Descriptive Statistics for Test Scores Pre and Post Intervention and 3 Month Retention.

	Mean	Std. Deviation	N
Pre Test	394.7423	89.92499	26
Post Test	446.5000	75.84835	26
Retention	438.7538	72.51256	26

4. Two-Way Between-Groups Analysis of Variance

The two-way between-groups ANOVA is a useful statistic to apply when you have two independent variables and your comparison is between groups i.e. there are different people in each group.

Remember your typical research question:

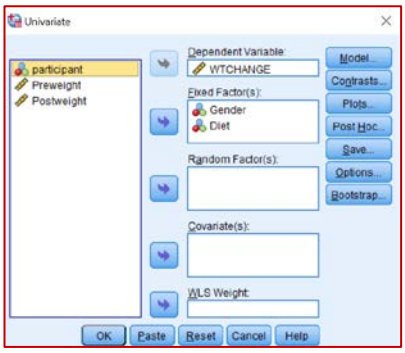
"The effect of independent variable on dependent variable"

Let's add two independent variables in to this question:-
"The effect of DIET and GENDER on WEIGHT LOSS"

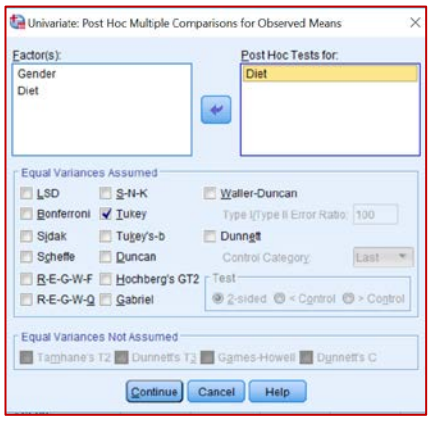
The advantage of this approach is that we can examine the main effect for each independent variable AND also explore any interaction effect that may also be present. We might find that different diets are more effect for weight loss for different genders.

To perform a two-way between-groups ANOVA:

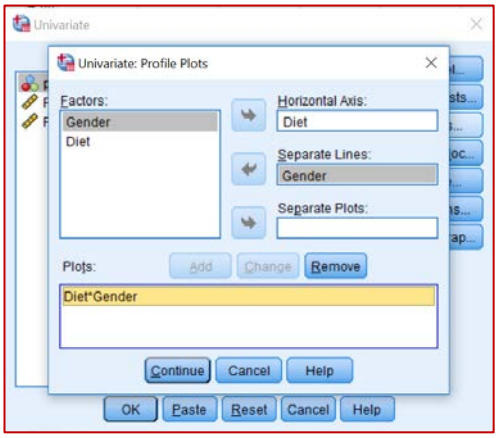
1. Click on **ANALYSE**, then **GENERAL LINEAR MODEL** and then **UNIVARIATE**
2. Click on your dependent, continuous variable **(WTCHANGE)** and move it in to the box labelled **DEPENDENT VARIABLE**
3. Click on your two independent, categorical variables **(DIET, GENDER)** and move them in to the box labelled **FIXED FACTORS**



4. Click on **OPTIONS**
   a. Select **DESCRIPTIVE STATISTICS, ESTIMATES OF EFFECT SIZE** and **HOMOGENEITY TESTS**
   b. Click **CONTINUE**
5. Click on the **POST HOC** button
   a. From the **FACTORS** list choose the **INDEPENDENT VARIABLE** with more than 3 levels or groups **(DIET)**
   b. Use the arrow to move this in to the **POST HOC TESTS FOR** section
   c. Choose **TUKEY'S** test
   d. Click on **CONTINUE**



6. Click on the **PLOTS** button
    a. In the **HORIZONTAL** box put the independent variable with the most groups **(DIET)**
    b. In the box labelled **SEPARATE LINES** out the other independent variable **(GENDER)**
    c. Click **ADD**
    d. You should see the two variables listed in the section labelled **PLOTS (DIET*GENDER)**



7. Click on **CONTINUE** and then **OK**

Interpretation of the SPSS two-way between-groups ANOVA test

1. Descriptive Statistics: As always, this table gives your standard descriptive information. Make sure this looks correct – do you have the correct number (N) in each group?

Descriptive Statistics

Dependent Variable: WTCHANGE

Gender	Diet	Mean	Std. Deviation	N
1.00	1.00	-16.3750	4.17261	8
	2.00	-3.2857	1.11270	7
	3.00	-5.6667	3.14113	6
	Total	-8.9524	6.74148	21
2.00	1.00	-4.1667	.75277	6
	2.00	-9.0000	3.03315	6
	3.00	-4.0000	.57735	7
	Total	-5.6316	2.89080	19
Total	1.00	-11.1429	6.99293	14
	2.00	-5.9231	3.63917	13
	3.00	-4.7692	2.24179	13
	Total	-7.3750	5.47576	40

2. Levene's Test of Equality of Variance:

Levene's Test of Equality of Error Variances[a]

Dependent Variable: WTCHANGE

F	df1	df2	Sig.
3.105	5	34	.021

Again, we use this test as it is one of the assumptions underlying the ANOVA. We need the significance to be greater than 0.05 and therefore not significant. Unfortunately our significance is 0.021. This means that our variance of the dependent variable (change in weight) across the groups (diet, gender) is not equal. To remedy this, we will need to set a more stringent level of significance (P< 0.01 rather than 0.05).

3. Test of Between-Subjects Effects

Tests of Between-Subjects Effects

Dependent Variable: WTCHANGE

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	939.905[a]	5	187.981	27.853	.000	.804
Intercept	1982.778	1	1982.778	293.783	.000	.896
Gender	73.126	1	73.126	10.835	**.002**	**.242**
Diet	216.037	2	108.018	16.005	**.000**	**.485**
Gender * Diet	541.724	2	270.862	40.133	**.000**	**.702**
Error	229.470	34	6.749			
Total	3345.000	40				
Corrected Total	1169.375	39				

a. R Squared = .804 (Adjusted R Squared = .775)

The main output from the two-way ANOVA is a table labelled Tests of Between-Subject Effects.

a. Interaction effects

The first thing we will check for is the possibility of an interaction effect (e.g. that the influence of diet on weight loss depends on whether you are male or female). If you do find an interaction effect you cannot easily interpret the main effect. In the SPSS output we need to look at the interaction of Gender*Diet and we need to consider the significance. If the value is less than 0.05 (or in our case 0.01 as our Levene's test was significant) then there is a significant interaction. Our sig. value here is 0.000 meaning we have a significant interaction between diet and gender and weight loss. What we don't know where the interactions effect are…

b. Main Effects

We can now look at the specific independent variables to see if they have a significant effect on change in weight. Gender has a significance of 0.002 and Diet has a significance of 0.000. This means that males and females differ in terms of their weight change AND there is also a significant difference in weight change based upon diet.

4. Effect Size

You will remember that Cohen's (1988) criterion from earlier sections. The effect size for Diet is 0.485 (small to medium), Gender is 0.242 (small) and Diet*Gender is 0.702 (medium to large).

Effect size	*d*	Reference
Very small	0.01	Sawilowsky, 2009
Small	0.20	Cohen, 1988
Medium	0.50	Cohen, 1988
Large	0.80	Cohen, 1988
Very large	1.20	Sawilowsky, 2009
Huge	2.0	Sawilowsky, 2009

The difference between diet groups and gender appears to be of moderate to large practical significance.

5. Post Hoc Tests

Although we know that there is a significant difference in weight loss based upon the type of Diet the participant was on, we do not know where these differences occur e.g. is diet 1 significantly better for weight loss than diet 2 or 3?

Gender isn't considered here as we don't really need a post hoc test to tell us where the difference lay - the descriptive statistics tell us that males lost an average of 8.9Kg ± 6.74 and females lost an average of 5.6Kg ± 2.89Kg. This is significant based upon our ANOVA (P=0.002) and so we can easily state that males lost significantly more weight than females.

Diet type has more than 2 levels (3 different diets) and so we need to use a post hoc test (Tukey's) to identify where the significant differences are to be found.

Multiple Comparisons

Dependent Variable: WTCHANGE

Tukey HSD

(I) Diet	(J) Diet	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	**2.00**	**-5.2198***	1.00062	**.000**	-7.6717	-2.7678
	3.00	**-6.3736***	1.00062	**.000**	-8.8256	-3.9217
2.00	**1.00**	**5.2198***	1.00062	**.000**	2.7678	7.6717
	3.00	-1.1538	1.01898	.501	-3.6508	1.3431
3.00	**1.00**	**6.3736***	1.00062	**.000**	3.9217	8.8256
	2.00	1.1538	1.01898	.501	-1.3431	3.6508

Based on observed means.

The error term is Mean Square(Error) = 6.749.

*. The mean difference is significant at the .05 level.

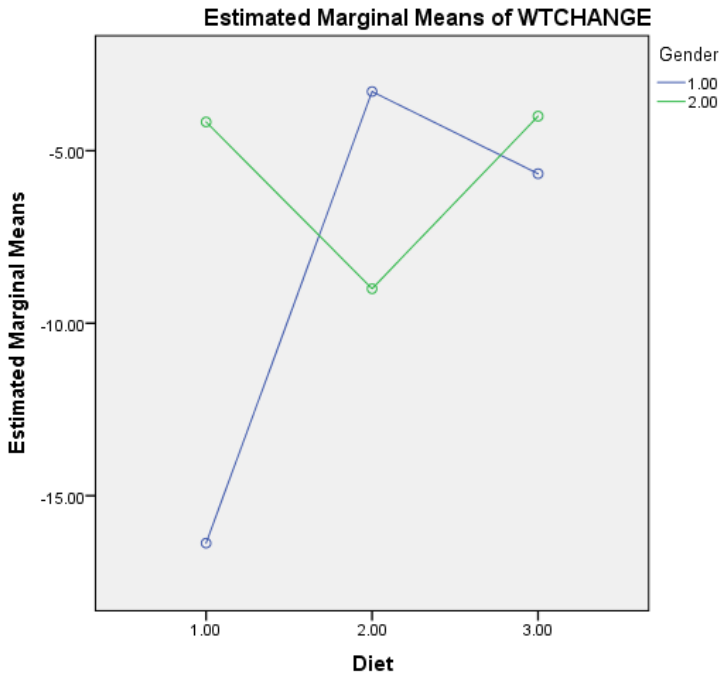
Anything value in the Mean Difference column with a * next to it is statistically significant. Let's work through this table.

Diet 1 = low carb/high fat and protein
Diet 2 = intermittent fasting (5:2)
Diet 3 = calorie restricted

There is a significant difference in weight loss comparing Diet 1 to Diet 2 (P=0.000) and Diet 1 to Diet 3 (P=0.000). There is no significant difference in weight loss when comparing Diet 2 and Diet 3 (P=0.501).

6. Plots

Lastly, the SPSS output will provide a plot of your data. This is a great way to visualise the results of your study. Here we can easily see that Males lost the most weight on diet 1, and females lost the most weight on diet 2.



Presenting the results from the Two-Way Between-Groups ANOVA:

A two-way between-groups analysis of variance was conducted to explore the effect of gender and diet on weight loss. Subjects were randomly allocated to one of three diet conditions for a period of 6 weeks and weight was measured pre and post diet period. The main effect for gender [F(1, 34) = 10.84 , p = 0.002] and the interaction effect of gender and diet were significant [F(2, 34) = 40.13, p = 0.000]. There was a statistically significant interaction effect for diet (F= 16.005, P= 0.000) with a moderate effect size (partial eta squared = 0.485). Post hoc comparisons using Tukey's HSD test indicate that the mean weight loss for diet 1 (M= -11.14, SD = 6.99) was significantly different from diet 2 (M= -5.92, SD = 3.64) and diet 3 (M= -4.74, SD= 2.24). There was no significant difference in weight loss between diet 2 and diet 3 (p=0.501).

5. Mixed Between-Within Analysis of Variance

Up to this point we have examined the differences between:

a. Two groups assessed once (e.g. school 1 vs school 2 on a test result) using an independent samples T-Test
b. One group over two time points (e.g. pretest vs post test) using a paired t-test
c. More than two groups assessed once (e.g. ice hockey vs soccer vs rugby players) using a one-way between groups ANOVA
d. One group over more than two time points (e.g. pretest vs post test vs retention, OR speed vs agility vs strength) using a one-way repeated measures ANOVA

We have either assessed between-subjects design or within-subjects/repeated measures design separately. However, your research may have both elements: you have two or more groups (e.g. male/female or class 1/class 2), assessed on two or more time points or tests (e.g. pretest/post test or exam grade/ confidence). SPSS allows you to combine between-subjects and within-subjects variables in the same analysis. This test is referred to as 'Mixed between-within subjects ANOVA' (Tabachnick and Fidell, 2001).

In our example we are considering the following design:

	Preseason (June 2017)	Mid Season (February 2018)	Start of Preseason (July 2018)
Team 1			
Team 2			

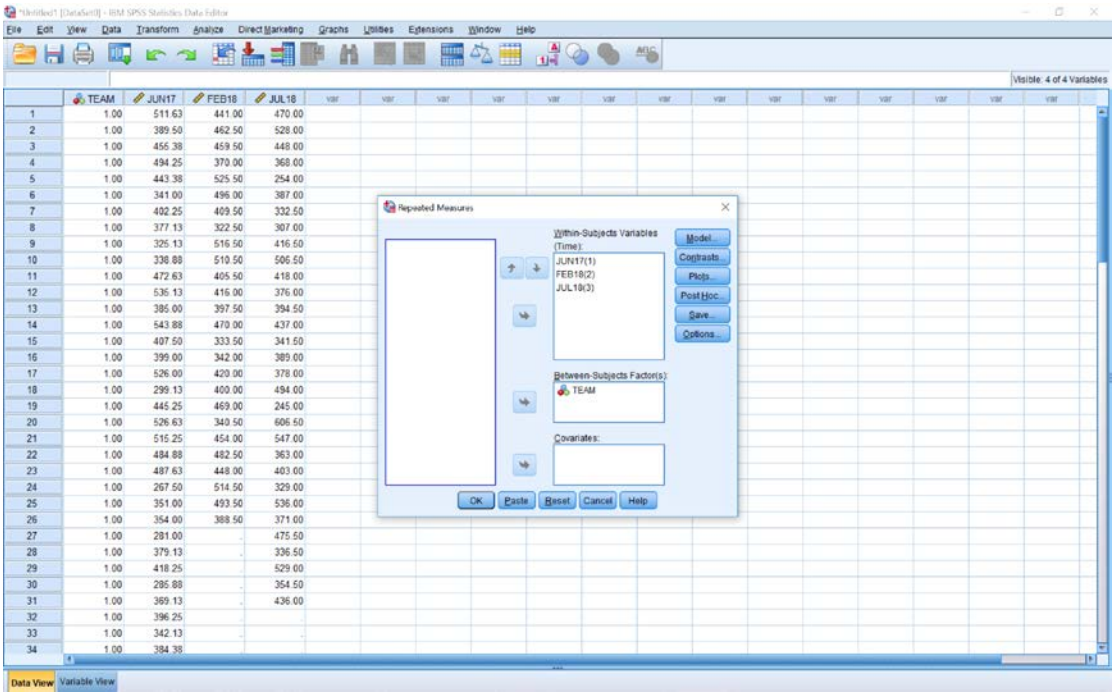
We have two professional rugby union teams, and we have measured their hamstring strength over the course of a rugby season. We would like to know:-

1. If there is a difference across the season in hamstring strength
2. If there is a difference between the two teams across the season

To perform the mixed between-within ANOVA:-

1. Click on **ANALYSE**, then click on **GENERAL LINEAR MODEL**, then on **REPEATED MEASURES**
2. In the box labelled **WITHIN-SUBJECTS FACTOR NAME** type a name that describes the within subjects factor e.g. time.

3. In the **NUMBER OF LEVELS** box type in the number of levels that this factor has (in this instance we have 3 time points, JUNE, FEB, JULY)
4. Click on the **ADD** button then click on **DEFINE**
5. Click on the variables that represent the within-subjects factor
6. Click on the arrow to move these in to the **WITHIN-SUBJECTS VARIABLES** box
7. Click on the **BETWEEN-SUBJECTS VARIABLE** and use the arrow to move it across to the **BETWEEN-SUBJECTS FACTOR** box



8. Click on **OPTIONS**
    a. Under **DISPLAY** select **DESCRIPTIVE STATISTICS, ESTIMATES OF EFFECT SIZE, HOMOGENEITY TESTS**
    b. Click on **CONTINUE**
9. Click on **PLOTS**
    a. Click on the within-groups factor (e.g. Time) and move it to the box labelled **HORIZONTAL AXIS**
    b. In the **SEPARATE LINES** box click on the **BETWEEN GROUPS VARIABLE** (e.g. Team)
10. Click on **ADD**. In the box your variables listed (time*team)
11. Click **CONTINUE**, then **OK**

Interpretation of the SPSS mixed between-within ANOVA test

Descriptive statistics

Descriptive Statistics				
	TEAM	Mean	Std. Deviation	N
JUN17	1.00	426.1106	80.22808	26
	2.00	429.2460	104.39133	31
	Total	427.8158	93.34835	57
FEB18	1.00	434.1731	60.72923	26
	2.00	472.4677	85.79860	31
	Total	455.0000	77.20329	57
JUL18	1.00	409.4615	88.94582	26
	2.00	250.3790	56.82326	31
	Total	322.9430	107.94375	57

Use this section to check your results – does everything look correct? Have you got the correct numbers in each team? Do the values make sense based upon the scale used? You can get a general feel for the data here:- team 2 appear much stronger in February but much weaker in July, but what we don't know is if these differences are statistically significant.

Homogeneity of Intercorrelations

Box's Test of Equality of Covariance Matrices[a]	
Box's M	11.609
F	1.819
df1	6
df2	20110.932
Sig.	.091

This is an assumption of the type of ANOVA we have used. The assumption states that the pattern of inter-correlations among the various levels of repeated measure factor(s) should be consistent from level to level of the Between-subject Factor(s). This test is very sensitive, and so we set our Alpha level as 0.001 rather than 0.05. We are hoping for a NON-SIGNIFICANT value here! Our significance value is greater than 0.001 (0.91) and so our findings are NON-SIGNIFICANT and we meet the assumptions of the test.

Interaction Effect

Before we can look at the main effect, we need to look at the interaction effect: is there the same change in hamstring strength over time for the two teams?

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Time	Pillai's Trace	.627	45.360[b]	2.000	54.000	.000	.627
	Wilks' Lambda	**.373**	45.360[b]	2.000	54.000	**.000**	**.627**
	Hotelling's Trace	1.680	45.360[b]	2.000	54.000	.000	.627
	Roy's Largest Root	1.680	45.360[b]	2.000	54.000	.000	.627
Time * TEAM	Pillai's Trace	.524	29.670[b]	2.000	54.000	.000	.524
	Wilks' Lambda	.476	29.670[b]	2.000	54.000	**.000**	.524
	Hotelling's Trace	1.099	29.670[b]	2.000	54.000	.000	.524
	Roy's Largest Root	1.099	29.670[b]	2.000	54.000	.000	.524

This is indicated by the second set of rows in the MULTIVARIATE TESTS table **(Time*TEAM)**. Look at the Wilks' Lambda row, and the probability given in the column labelled Sig. In this case the Wilks' Lambda test shows a statistically significant interaction effect (p=0.000).

Main Effects

We can now move on and assess the main effects for our independent variables (e.g. Team)

Within-subjects Effect

We need to look firstly at the Wilks Lambda statistics for TIME (highlighted in **BLUE** in the table above).

Our statistic for time is 0.373 and we have a significance value of 0.000. We can use this statistic to report a *statistically significant* effect for time. The Partial Eta Squared column will tell us about the magnitude of the difference. In this case the Partial Eta Squared statistic is 0.627. You'll remember from Cohen (1988) that anything greater than 0.14 is considered to have a large effect, so we can state we have a VERY LARGE effect size for hamstring strength over time.

Between-subjects Effect

Now that we have established a within-subjects effect (over time) we now need to establish the main effect of our between-subjects variable (Team 1 vs Team 2).

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	27645795.190	1	27645795.190	3972.620	.000	.986
TEAM	**65244.046**	**1**	**65244.046**	**9.375**	**.003**	**.146**
Error	382749.588	55	6959.083			

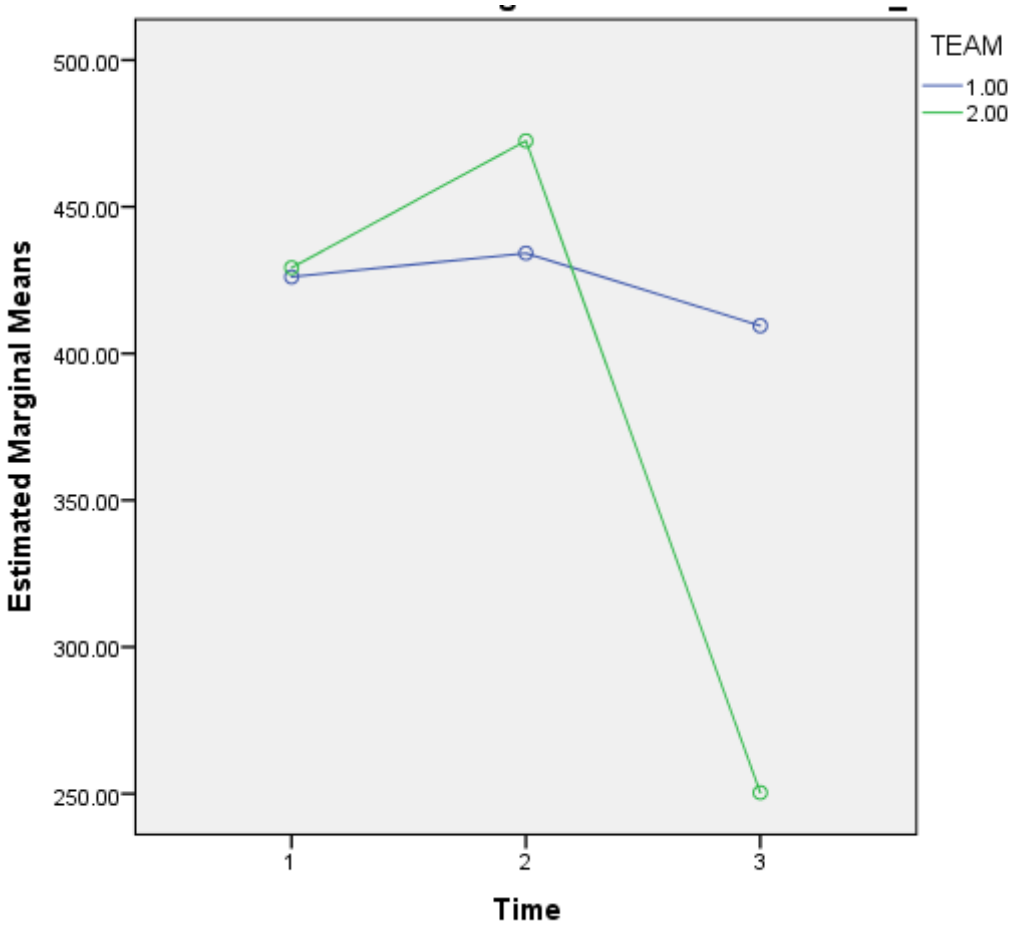
We need to look at the table labelled 'Tests of Between-Subjects Effects' (see above). Read across the variable named TEAM. The Significance value here is 0.003, and is less than our alpha level of 0.05 therefore our between-subjects difference is significant. The effect size is also given as Partial Eta Squared. This is listed as 0.146, and is therefore considered to be a large effect.

To report the statistics you simply need to use the templates for the between-groups and repeated measures ANOVA listed earlier:-

A one-way repeated measures ANOVA was conducted to compare hamstring strength scores at 3 time points (preseason, midseason and end of season). The means and standard deviations are presented in Table XX. There was a significant effect for time [Wilks' Lambda = 0.000, *F*(2, 45.36) = 0.373, *P*=0.000, multivariate partial eta squared = 0.627]

A one-way between-groups analysis of variance was conducted to the difference in hamstring strength between two rugby union teams across a season. There was a statistically significant difference at the P<0.05 level [*F* = 9.375, *P*=0.003). The magnitude of the difference was large. Eta squared was calculated as 0.146.

Finally, the graph presented in the SPSS output can be used to visually represent the results:



Analysing Data from Questionnaires

This is challenging – by definition, questionnaire data often handles NOMINAL data (e.g Gender) and ORDINAL data (e.g. Likert scales). This is often viewed poorly within quantitative analysis, however some disciplines will still use parametric statistics to analyse results. Before commencing any data capture, it is important you discuss and confirm your data analysis method with your supervisor.

Example questionnaire 1:

First Name & Last Initial	**Group Membership OR Specify connection to you** *Circle one OR Report other*	**On a scale of 1 to 10, how much does this person influence your participation in sports?** *1=Not at all 10=Greatly Influences*	**Compared to your physical activity/exercise level this person is…?** *Circle one*
EXAMPLE Jane S.	Family College Friend (Significant Other) Other: Trainer (specify)	2	(Better) Worse you Same as
1.	Family College Friend Significant Other Other:_____(specify)	_____	Better Worse you Same as
2.	Family College Friend Significant Other Other:_____(specify)	_____	Better Worse you Same as
3.	Family College Friend Significant Other Other:_____(specify)	_____	Better Worse you Same as

Here we have NOMINAL DATA in column 2 (group membership) and ORDINAL DATA in column 3 (likert scale).

Analysing this data:-

It is suggested you CODE the data first, especially for the NOMINAL DATA:

e.g. column 2
1 = Family
2 = College friend
3 = Significant other

Column 4
1 = better
2 = same
3 = worse than you

You can then input this in to Excel and/or SPSS:

PARTICIPANT	Q1	Q2	Q3
1	1	5	2
2	3	8	3
3	2	3	2
4	3	10	2
5	1	8	3
6	3	5	3
7	2	7	1
8	3	3	3
9	1	8	2
10	1	9	3

Questions that can be answered by Statistics:-

1. Correlations between:-
    a. Group membership and influence
    b. Group membership and exercise level
    c. Influence and exercise level
2. Differences between (paired t-test) :-
    a. Group membership and influence
    b. Group membership and exercise level
    c. Influence and exercise level
3. Differences between (Repeated measures ANOVA):-
    a. Group membership and influence and exercise level

Example questionnaire 2:-

Some questionnaires have a total score awarded, or a score awarded for some elements or sections of the questionnaire. The Competitive State Anxiety Invesntory-2 (CSAI-2) is one such example (Martens, Burton, Vealey, Bump and Smith, 1990). The questionnaire measures State Anxiety – how anxious you are in specific environmental states such as sports competition. It measures cognitive anxiety, somatic (physical) anxiety and self-confidence and is found below:

"The following are several statements that athletes use to describe their feelings before competition. Read each statement and circle the appropriate number to indicate how you feel right now, at this moment. There are no right or wrong answers. Do not spend too much time on any one statement"

	Not at all	**Somewhat**	**Moderately so**	**Very much so**
1. I am concerned about this competition.	1	2	3	4
2. I feel nervous.	1	2	3	4
3. I feel at ease.	1	2	3	4
4. I have self-doubts.	1	2	3	4
5. I feel jittery.	1	2	3	4
6. I feel comfortable.	1	2	3	4
7. I am concerned I may not do as well in this competition as I could.	1	2	3	4
8. My body feels tense.	1	2	3	4
9. I feel self-confident.	1	2	3	4
10. I am concerned about losing.	1	2	3	4
11. I feel tense in my stomach.	1	2	3	4
12. I feel secure.	1	2	3	4
13. I am concerned about losing.	1	2	3	4
14. My body feels relaxed.	1	2	3	4
15. I'm confident I can meet the challenge.	1	2	3	4
16. I'm concerned about performing poorly.	1	2	3	4
17. My heart is racing.	1	2	3	4
18. I'm confident about performing well.	1	2	3	4
19. I'm worried about reaching my goal.	1	2	3	4
20. I feel my stomach sinking.	1	2	3	4
21. I feel mentally relaxed.	1	2	3	4
22. I'm concerned that others will be disappointed with my performance.	1	2	3	4
23. My hands are clammy.	1	2	3	4
24. I'm confident because I mentally picture myself reaching my goal.	1	2	3	4
25. I'm concerned I won't be able to concentrate.	1	2	3	4
26. My body feels tight.	1	2	3	4
27. I'm confident of coming through under pressure.	1	2	3	4

Item 14 is a reverse question, for example, if you circled 3, count that as 2 points (1 = 4; 2 = 3; 3 = 2; 4 = 1).

To calculate your scores simply add up the values given to the following questions:
Cognitive state anxiety: Sum items 1, 4, 7, 10, 13, 16, 19, 22, and 25.
Somatic state anxiety: Sum items 2, 5, 8, 11, **14**, 17, 20, 23, 26.
Self-confidence: Sum items 3, 6, 9, 12, 15, 18, 21, 24, and 27.

Your scores for each will range from 9 to 36, with 9 indicating low anxiety (confidence) and 36 indicating high anxiety confidence.

Questions that can be answered by statistics:

1. Correlations between:
    a. Cognitive anxiety and self-confidence
    b. Cognitive anxiety and somatic anxiety
    c. Somatic anxiety and self confidence
    d. Cognitive anxiety OR somatic anxiety OR self-confidence AND performance (e.g. race time, or judges scores or error count/deductions)
2. Differences between (paired t-test):
    a. Cognitive anxiety and self-confidence
    b. Cognitive anxiety and somatic anxiety
    c. Somatic anxiety and self confidence
    d. Cognitive anxiety OR somatic anxiety OR self-confidence AND performance (e.g. race time, or judges scores or error count/deductions)
3. Difference between (repeated measures ANOVA)
    a. Cognitive anxiety & somatic anxiety & self-confidence
    b. Change in cognitive anxiety/somatic anxiety/self-confidence over time (leading up to competition)
4. Difference between (one way between groups ANOVA)
    a. Males vs Females
    b. Team sports vs Individual Sports
    c. Elite athletes vs Non-elite athletes
    d. Previously injured vs non-previously injured athletes.

MA Summer School

Learning to Love Quantitative Methods of Inquiry

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