

## CHAPTER ONE

### CORRELATION

#### 1.0 Introduction

The first chapter focuses on the nature of statistical data of correlation. The aim of the series of exercises is to ensure the students are able to use SPSS to explain the statistical theories and calculations. Meanwhile they are also competent in the analysis of data through manual calculation.

Correlation refers to a statistical measurement to measure and describe the relationship between two variables whereby changes in one variable will associated with be a concurrent change in the other variable.

According to Gravetter and Wallnau (2005), the two variables in correlation are observed as they naturally existed in the environment. In any of the correlation study, there shouldn't be any attempt or effort to manipulate the variables. For example, the relationship between number of hours of revision and anxiety level during exam could measure and record the number of hours spent by a group of students to do revision and then observe their anxiety levels in the exam hall, but the researcher is merely observing the occurrence naturally with no attempt to manipulate the number of hours spent and also their anxiety level in the exam hall.

#### 1.1 Scatter Plots

A **scatter plot** is an extremely useful tool when it comes to looking at the association between two variables (Caldwell, 2007). In short, a scatter plot allows simultaneously viewing the values of two variables on a case-by-case basis. A typical example used to illustrate the utility of a scatter plot involves the association between height and weight. Table 1.1 shows a hypothetical distribution of values of those variables (height and weight) for 20 cases.

**Table 1.1** Height/Weight Data for 20 Cases

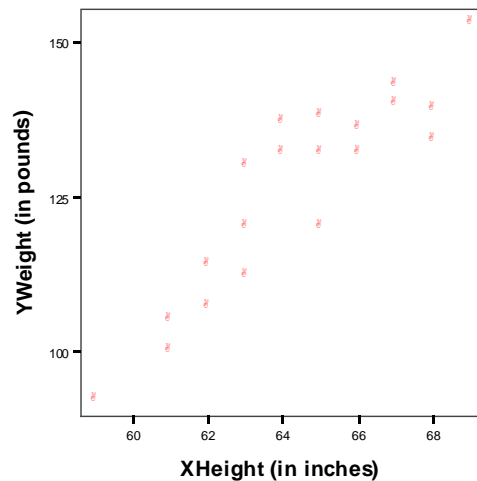
Case	Height (Inches)	Weight (pounds)
1	59	92
2	61	105
3	61	100
4	62	107
5	62	114
6	63	112
7	63	120
8	63	130
9	64	132
10	64	137
11	65	132
12	65	138
13	65	120
14	66	136
15	66	132
16	67	140
17	67	143
18	68	139
19	68	134
20	69	153

A visual representation of the same data in the form of a scatter plot is shown in Figure 1. Height measurements values are shown along the horizontal or *X* axis of the graph; weight measurement values are shown along the vertical or *Y* axis of the graph. Focusing on case number 1, shown in the lower left corner of the scatter plot, interpret the point as reflecting a person (case) with a height of 59 inches (or 4' 11") and a weight of 92 pounds.

Each of the 20 points can be interpreted in the same fashion—a reflection of the values of two variables (height and weight) for a given case. Note that the scales along the *X* and *Y* axes are different. The variable of height is expressed in inches, but the variable of weight is expressed in pounds.

## 1.2 Linear Associations: Direction and Strength

Two variables (Variable  $X$  and Variable  $Y$ ) can be associated in several ways. A scatter plot can provide a graphic and concise statement as to the general relationship or association between two variables. In short, a scatter plot tells something about the *direction* and *strength* of association.



**Figure 1.1** Height/Weight Data for 20 cases: Scatter Plot

To create a scatter plot, the score obtained from the observation will be recorded as  $X$  and  $Y$  in a table and a scatter plot will be used to represent the data. In scatter plot, the  $X$  values will be placed on the horizontal axis of a graph and the  $Y$  values are placed on the vertical axis of the graph. The pattern of the data will show the relationship between the  $X$  values and  $Y$  values.

To say that two variables are related or associated in a positive or direct association is to say that they track together; it means that high values on Variable  $X$  are generally associated with high values on Variable  $Y$ , and low values on Variable  $X$  are generally associated with low values of Variable  $Y$ . In a negative or inverse association, high values on Variable  $X$  are associated with low values on Variable  $Y$ , and low values on Variable  $X$  are associated with high values on Variable  $Y$ . In short, the variables track in opposite directions.

The idea of a perfect relationship is useful, because it helps to understand what is meant by strength of association. In many respects, the strength of an association is just an expression of how close one might be to being able to predict the value on one variable from knowledge of the value on another variable. Some associations are stronger than others in the sense that they come closer than others to the notion of perfect predictability.

### 1.3 Positive Correlation and Negative Correlation

A positive correlation occurs when one variable indicates a high score while the other also indicates a high score; or when one variable indicates a low score and the other also indicates a low score. Take for example a study to find out whether there is a relationship between going on a diet and becoming thin. If the results indicate that the less people eat, the thinner they become; then we can conclude that there is a relationship between these two variables, and in this case, it is a positive correlation. Take another example, a study to find out whether there is a relationship between those who eat lots of sweet things and getting diabetes. If the results indicate that the more people eat sweet things, the higher chances of them getting diabetes; then we can conclude that there is a relationship between these two variables, and in this case, it is also a positive correlation.

A negative correlation on the other hand occurs when one variable indicates a high score while the other indicates a low score. Take for example a study to find out whether there is a relationship between people who drink lots of milk and the occurrence of osteoporosis. If the results indicate that the more the people drink milk, the less likely they get osteoporosis; then we can conclude that there is a relationship between these two variables, and in this case, it is a negative correlation.

What is important to note in correlation is not whether it is a positive correlation or a negative correlation. What is important is the degree of relationship, also known as 'correlation coefficient' or simply ' $r$ '. The bigger the degree of the correlation, i.e. the higher the value of  $r$  the stronger the relationship is between the two variables.

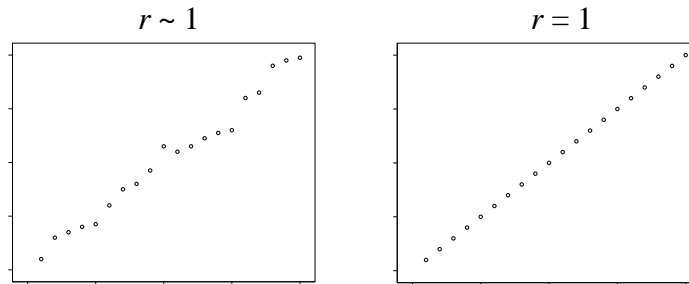
However, when the study indicates a correlation of 0 or almost 0, it means that there is no relationship between the two variables. This usually occurs when the two variables measured do not have any relevance to each other. Take for example, a study to find out whether there is any relationship between people who are intelligent and the ability to play badminton. If the results indicate a very scattered data and when calculated, it indicates a 0, we can conclude that there is no relationship between these two variables. This means that the ability to play badminton has nothing to do with the intelligence of that person.

The results can be observed either through a manual calculation process or by using the SPSS software. Firstly, the manual calculation method will be explained and then followed by the exploration of SPSS.

In general, there are 3 types of characteristics that correlation is measuring between variable  $X$  and variable  $Y$  as stated below:

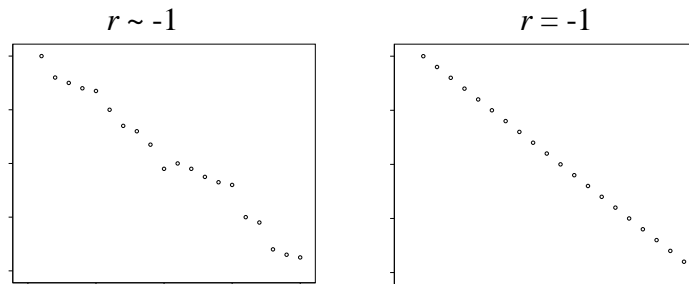
- Firstly is the direction of the relationship.

A positive correlation is a direct relationship where as the amount of one variable increases, the amount of a second variable also increases.



**Figure 1.2a:** Scatter plot of positive correlation

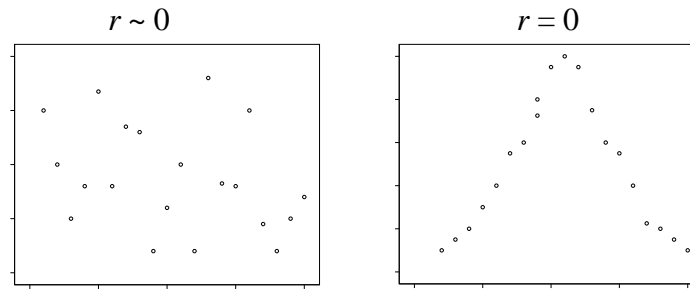
In a negative correlation, as the amount of one variable goes up, the levels of another variable go down.



**Figure 1.2b:** Scatter plot of negative correlation

In both types of correlation, there is no evidence or proof that changes in one variable cause changes in the other variable. A correlation simply indicates that there is a relationship between the two variables.

In zero correlation, there is no relationship between the variables.



**Figure 1.2c:** Scatter plot of zero correlation

- The Form of the Relationship
  - The commonly seen form of correlation is the linear form which the points in the scatter plot tend to form a straight line. Correlation is also commonly used to measure the straight-line relationships.
- The Degree of the Relationship
  - A perfect correlations is always identified by a correlation of +1.00 or -1.00 where the positive and negative sign does not reflects the face value of the data, it simply shows the direction of the data.
  - A zero correlation simply shows the data do not fit at all, it shows no relationship between the two measured variables.

#### 1.4 Two Variables: *X and Y*

When speaking in terms of *Variable X* and *Variable Y*, it is proposed that some logical connection between the two. For example, the *X* variable is commonly regarded as the **independent variable**, and the *Y* variable is commonly regarded as the **dependent variable**. In the language of research, an independent variable is a variable that is presumed to influence another variable. The dependent variable, in turn, is the variable that is presumed to be influenced by another variable.

For example, it is common to assert that there is a connection between a person's level of education and level of income. Educational level would be treated as the independent variable, and the level of income would be regarded as the dependent variable. In other words, education (independent) is thought to exert an influence on income (dependent).

## 1.5 The Logic of Simple Correlation

In truth, correlation analysis takes many forms (such as multiple correlation or partial correlation); the one being considered here is referred to as **simple correlation**. In other words, simple correlation analysis allows measuring the association between two interval/ratio level variables (assuming that the two variables, if associated, are associated in a linear fashion).

Z transformation is used to convert the scores on different scales to a single scale based on Z scores (or points along the baseline of the normal curve).

$$Z = \frac{\text{Raw score} - \text{Mean}}{\text{Standard Deviation}}$$

For example, look back at Figure 1. Note that the values along the horizontal and vertical axes are expressed in different scales or units of measurement; inches along the horizontal axis and pounds along the vertical axis. When considering the raw scores of the points represented in the scatter plot, then, deal with two different scales. The two sets of scores will be on the same scale, though, if they're transformed into Z scores. The same is true for any number of situations.

For example, student aptitude test scores (SAT scores) and grade point averages (GPAs). When expressed as raw scores, are based on very different underlying scales, but the raw scores can easily be transformed into Z scores to create a single scale of comparison. Data on education (expressed as the number of school years completed) and income (expressed in dollars) can share a common scale when transformed into Z scores. The list goes on. All it needs is the mean and standard deviation of each distribution. It is a simple transformation: Subtract the mean for each raw score in the distribution, and divide the difference by the end of standard deviation.

## 1.6 The Formula for Pearson's $r$

Because the computational formula  $r$  includes the steps necessary to convert raw scores to Z scores, it has a way of appearing extremely complex. Assume knowing the basis of Pearson's  $r$  (namely, the conversion raw scores into Z scores), though in a position to rely on a more *conceptual* formula. The heart of the more conceptual approach has to do with what is referred to as the cross products of the Z scores.

Table 1.2 shows pairs of values or scores associated with 10 cases. Columns 2 and 4 show the raw score distributions for the two variables,  $X$  and  $Y$ . The means and standard deviations of the raw score distributions are given at the bottom of the table. Columns 3 and 5 show the Z scores or transformations based on the associated raw scores. (Recall

that these are calculated by subtracting the mean of each raw score and dividing it by the standard deviation). Case number 1, for example, has a raw score  $X$  value of 20 (shown in Column 2) and a  $Z$  score ( $Z_X$ ) value of -1.49 (shown in Column 3). The raw score  $Y$  value for case number 1 is 105 (shown in Column 4), and the  $Z$  score ( $Z_Y$ ) value of -1.57 (shown in Column 5).

The cross products are obtained by multiplying each  $Z_X$  value (the entry in Column 3) by the associated  $Z_Y$  value (the entry in Column 5). The results of the cross product multiplication are shown in Column 6 ( $Z_X \cdot Z_Y$ ).

As in Table 1.2, the symbol  $Z_X$  denotes the  $Z$  scores for the  $X$  variable, and  $Z_Y$  denotes the  $Z$  scores for the  $Y$  variable. Sum the cross products and divide the sum by the number of paired cases minus 1. The result is the calculated  $r$ .

$$r = \frac{\sum(Z_X \cdot Z_Y)}{n - 1}$$

**Table 1.2** Cross Product Calculations for  $X$  and  $Y$  Variables (Positive Association)

(1) Case	(2) $X$	(3) $Z_X$	(4) $Y$	(5) $Z_Y$	(6) $Z_X \cdot Z_Y$
1	20	-1.49	105	-1.57	2.34
2	25	-1.16	126	-0.84	0.97
3	30	-0.83	122	-0.98	0.81
4	35	-0.50	130	-0.70	0.35
5	40	-0.17	155	0.17	-0.03
6	45	0.17	159	0.31	0.05
7	50	0.50	153	0.10	0.05
8	55	0.83	184	1.18	0.98
9	60	1.16	177	0.94	1.09
10	65	1.49	190	1.39	2.07
Sum of Cross Products = 8.68					
Mean of $X$ = 42.50					
Standard Deviation of $X$ = 15.14					
Mean of $Y$ = 150.10					
Standard Deviation of $Y$ = 28.65					

Note that using  $n-1$  in the denominator of the formula that some presentations of the formula rely on  $n$  alone. The difference in the two approaches traces back to the manner in which the standard deviation for each distribution was calculated (recall that the standard deviation is a necessary ingredient for the calculation of a  $Z$  score). The assumption in this text is that  $n - 1$  was used in the calculation of the standard deviations of Variable  $X$  and Variable  $Y$ .

The formula that follows, for example, is typical of how a computational; the formula for  $r$  might be presented:

$$r = \frac{\sum(Z_X \cdot Z_Y)}{n - 1}$$



Such a formula can be very handy if when using a calculator to compute the value of  $r$ . Given the increasing use of computers and statistical software, however, the real issue is likely to be whether or not a solid understanding of what lies behind a procedure and how to interpret the results. In the case of Pearson's  $r$ , the conceptual formula, based on the cross product calculations, gives one a better understanding of what is really involved in the calculation.

For the data presented in Table 1.2, the calculation is as follows:

$$r = \frac{\Sigma(Z_X \cdot Z_Y)}{n - 1}$$

$$r = \frac{8.68}{9}$$

$$r = +0.96$$

### Interpretation

The calculated  $r$  value is +0.96, but there is still the question of how one would interpret it. Statisticians actually use the information provided by the  $r$  value in two ways.

The value of  $r$  is referred to as the **correlation coefficient**. The sign (+ or -) in front of the  $r$  value indicates whether the association is positive (direct) or negative (inverse). The absolute value of  $r$  (the magnitude, without respect of the sign) is a measure of the strength of the relationship. The closer the value gets to 1.0 (either +1.0 or -1.0), the stronger the association.

### Considerations while interpreting correlations

- Correlation is merely describing a relationship between two variables. It does not prove and explain which variable causes the other variable to change. For example, the amount of time spent on reading does not necessary cause the increase of IQ level of a person. There is a relationship between these two variables but correlation is not trying to explain or prove the causal relationship.
- Healey (2007) stated that the value of correlation must come from a representative sample size. The range of scores represented in the data will greatly affect the value of correlation.
- The outlier or the extreme data points will also influence the value of a correlation greatly (Gravetter & Wallnau, 2005).
- Correlation must always be squared,  $r^2$  before the relationship is being judged. This value is known as Coefficient of Determination (Gravetter & Wallnau, 2005). For example, when a correlation,  $r = +.6$  is calculated, it does not mean it is a moderate degree being  $+.6$  is half way in between 0 and +1.00. Although +1.00 is equals to 100% perfectly predictable relationship, a correlation of  $.6$  does not equals to 60% accuracy. To describe the accuracy, one must square the correlation.

Thus, when  $r = .6$ , the accuracy of predicting the relationship is equals to  $r^2 = .6^2 = .36$ , or 36% accuracy.

### **Pearson Correlation (Pearson product-moment correlation)**

The Pearson correlation measures the degree and direction of the linear relationship between two variables. Below are the computational formulas involved in measuring the relationship between two variables.

$$\text{Calculated } r: r_{\text{cal}} = \frac{(n \cdot \sum XY) - (\sum X \cdot \sum Y)}{\sqrt{[(n \cdot \sum X^2) - (\sum X)^2] \times [(n \cdot \sum Y^2) - (\sum Y)^2]}}$$

Degree of freedom,  $df = n - 2$

One condition for correlation to exist is that, the results should indicate that the *computed* 'r' is higher than the *critical* 'r'. *Computed* 'r' refers to the value which is obtained either through manual calculation or through SPSS. *Critical* 'r' on the other hand, refers to the value which is obtained from the statistical table.

To get the critical value of  $r$  from the table, one must know the sample size ( $n$ ), the probability of making error (alpha level). When the  $r_{\text{cri}} > r_{\text{cal}}$ , it shows that there is no significant relationship between the 2 variables and when  $r_{\text{cri}} < r_{\text{cal}}$ , it shows that there is a significant relationship between the two variables.

When there is no significant relationship between the two variables, it means the researcher has to accept the null hypothesis whereas when there is a significant relationship between the two variables, the researcher has to reject the research hypothesis.

## **1.7 Correlation for SPSS**

Correlation analysis is used to describe the relationships and directions between two variables. There are different ways available from SPSS to measure correlation. In this chapter, Pearson product moment correlation coefficient is presented.

There are 2 types of correlation.

- Simple bivariate correlation: also known as zero-order correlation which means relationship between two variables.
- Partial correlation: Such correlation will allow you to explore the relationship between two variables, while at the same time controlling for another variable.

## **1.8 Pearson Correlation Coefficients ( $r$ )**

The range of  $r$  is from -1 to +1. Positive relationship indicates a positive relationship between two variables. This means when one variable increases, another variable will also increase. For example, increasing number of hours in study is associated with better performance in the examination. Whereas negative relationship indicates a negative

relationship between two variables. As one variable increases, the other decreases. For example, increasing hours of watching television are associated with lower performance in the examination.

The absolute value (ignoring the sign) indicates the strength of the relationships. For example:

- +1 or -1 means perfect correlation
- 0.9 means positive strong correlation
- 0.6 means positive average/moderate correlation
- 0.1 means positive weak correlation
- -0.9 means negative strong correlation
- -0.6 means negative average/moderate correlation
- -0.1 means negative weak correlation
- 0 means no relationship between the two variables

**Table 1.3a: Strength of Positive Correlation Coefficients**

Perfect												+1
Strong												+0.9
											+0.8	
										+0.7		
Moderate							+0.6					
						+0.5						
					+0.4							
Weak				+0.3								
			+0.2									
		+0.1										
Zero	0											

**Table 1.3b: Strength of Negative Correlation Coefficients**

Perfect	-1											
Strong		-0.9										
			-0.8									
				-0.7								
Moderate					-0.6							
						-0.5						
							-0.4					
Weak								-0.3				
									-0.2			
										-0.1		
Zero												0

## 1.9 Scatterplot

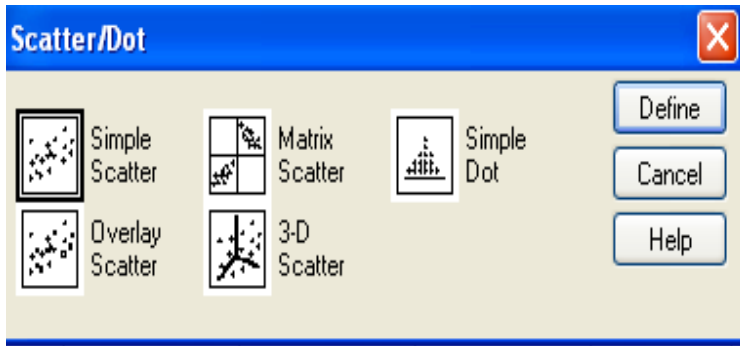
Before performing a correlation analysis, it is better to generate a scatterplot. This enables you to check for the assumption of linearity. In addition, it gives you better idea of the direction and relationship between the variables.

### Procedure for Generating a Scatterplot

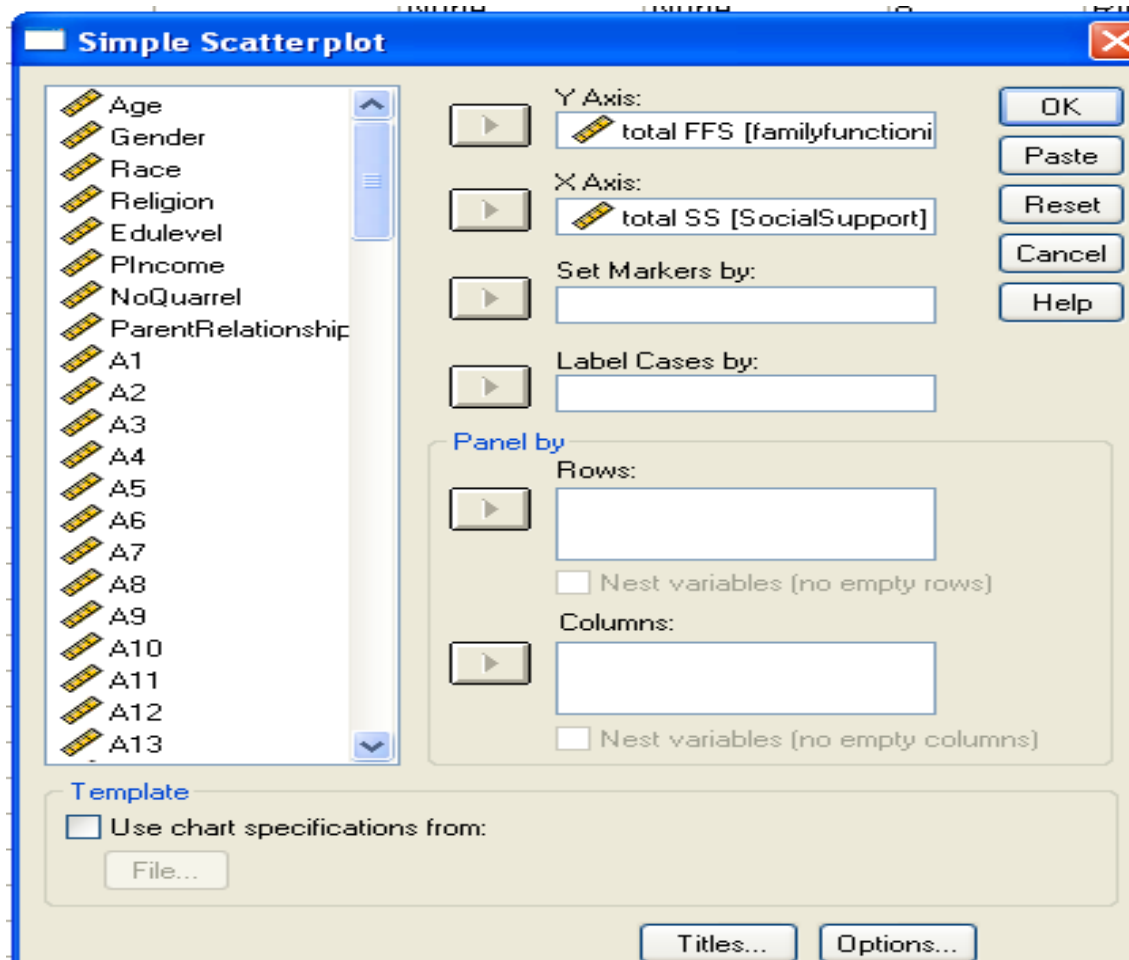
- Use Data Set1 Family Functioning
- Select **Graph** from the menu
- Click on **Scatter**



- Click on **Simple** and **define** button



- Move dependent variable to Y-axis
- Move independent variable to X-axis
- Click on continue and then **OK**



### Details of Example: Family Functioning, Social Support and Self-Esteem

The interrelationships among some of the variables included in the family functioning data set provided in the CD given can be used to demonstrate the use of correlation. The survey was designed to find out the relationship among family functioning, perceived

social support and self-esteem among college and university students. Refer Data Set1 Family Functioning.

In this survey, the aim is to examine relationships between variables. This data set contains information on:

- Age
- Gender
- Race
- Religion
- Educational Level
- Parents Income
- Number of Quarrels
- Parent Relationship
- Family Functioning
- Social Support
- Self Esteem

1.9.1 Use Pearson's  $r$  to show the relationship between Family Functioning and Social Support.

**Answer:**

Family Functioning	
	.377(**)
Social Support	

\*\* $p < .01$

The relationship between family functioning and social support was explored using Pearson's product moment correlation. Result revealed that there was a positive correlation ( $r=.377, p<.01$ ) between family functioning and social support suggesting that students with better family functioning have higher perceived social support. See Table 7.

Overall, social support contributed 14.21% ( $r = .377$ ) to family functioning.

Table 1.4b: Correlations with SPSS

		total FFS	total SS
total FFS	Pearson Correlation	1	.377(**)
	Sig. (2-tailed)		.000
	N	246	246
total SS	Pearson Correlation	.377(**)	1
	Sig. (2-tailed)	.000	
	N	246	246

\*\* Correlation is significant at the 0.01 level (2-tailed).

1.9.2 Use Pearson's  $r$  to show the relationship between Family Functioning and Self-Esteem.

Table 1.4c: Correlations with SPSS

		total FFS	Total SE
total FFS	Pearson Correlation	1	.117
	Sig. (2-tailed)		.066
	N	246	246
total SE	Pearson Correlation	.117	1
	Sig. (2-tailed)	.066	
	N	246	246

**Answer**

**There is no significant relationship between family functioning and self-esteem**  
 $r = .117, p > 0.05$

1.9.3 Let us proceed further and examine how family functioning and social support predicts student's self-esteem. Use Pearson correlation matrix in the analysis.

Table 1.4d: Correlations with SPSS

		total FFS	Total SE	total SS
total FFS	Pearson Correlation	1	.117	.377(**)
	Sig. (2-tailed)		.066	.000
	N	246	246	246
total SE	Pearson Correlation	.117	1	.439(**)
	Sig. (2-tailed)	.066		.000
	N	246	246	246
total SS	Pearson Correlation	.377(**)	.439(**)	1
	Sig. (2-tailed)	.000	.000	
	N	246	246	246

\*\* Correlation is significant at the 0.01 level (2-tailed).

**Answer**

**a) There is a significant relationship between family functioning social support,**  
 $r = .377, p < .01$ . When there is more social support, there is better family

- functioning.  $r^2 = .142$ . Social support contributes 14.2% towards family functioning.
- b) There is a significant relationship between social support and self esteem,  $r = .439$ ,  $p < .01$ . When there is more social support, the student's self esteem becomes higher.  $r^2 = .193$ . Social support contributes 19.3% towards self esteem.
  - c) There is no significant relationship between family functioning and self-esteem,  $r = .117$ ,  $p > .01$ .

1.9.4 Examine the following scatterplots. Try to predict:

- a) The strength /magnitude of the relationships (perfect, strong, moderate, weak or zero).
- b) The direction of the relationships (positive, negative or zero)

**Answer**

**Positive Weak Relationship between family functioning and social support,  $r = .377$ ,  $n = 246$**

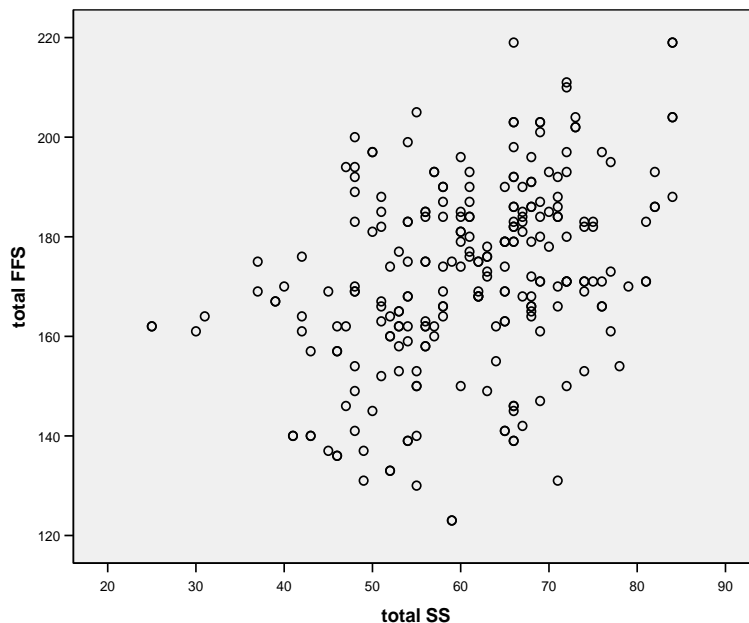


Figure 1.3a: Scatterplot of FFS and SS

**Answer**

**Positive Moderate Relationship between social support and self-esteem,  $r = .439$ ,  $n = 246$**



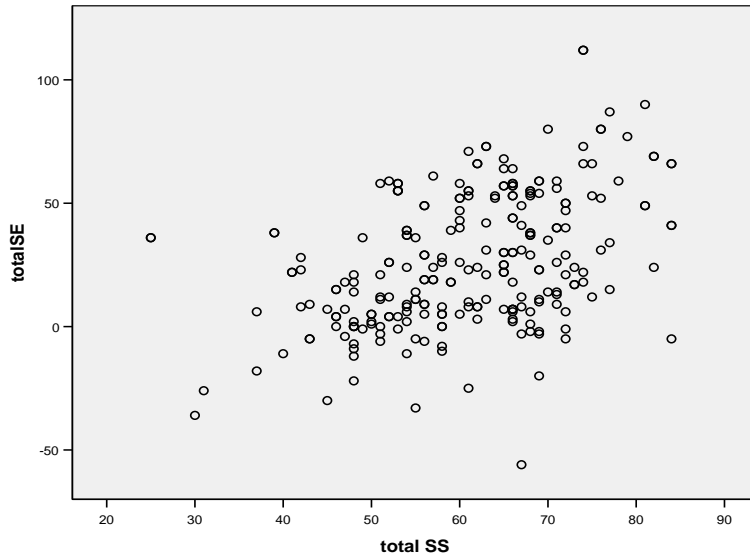


Figure 1.3b: Scatterplot of SE and SS

**Answer**

**Zero Relationship between family functioning and self-esteem,  $r = .117$ ,  $n = 246$**

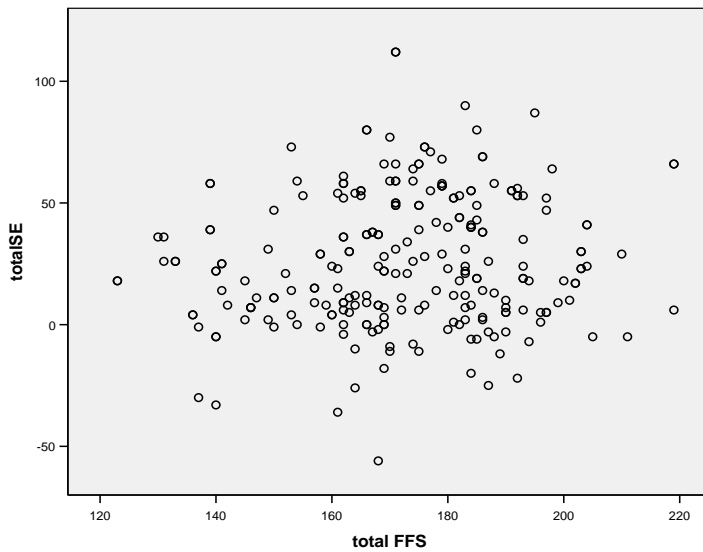


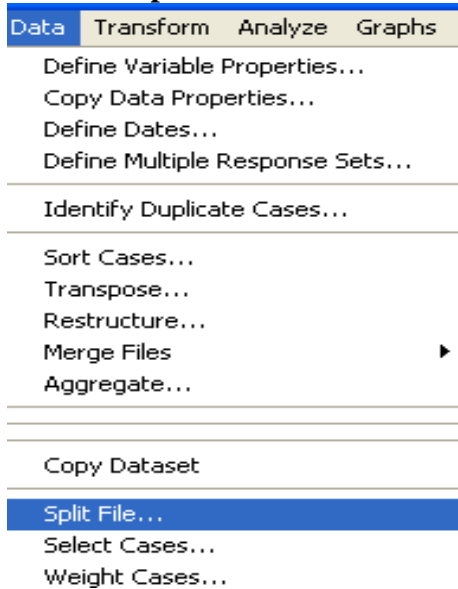
Figure 1.3c: Scatterplot of SE and FFS

### 1.10 Comparing the Correlation Coefficients for Two Groups

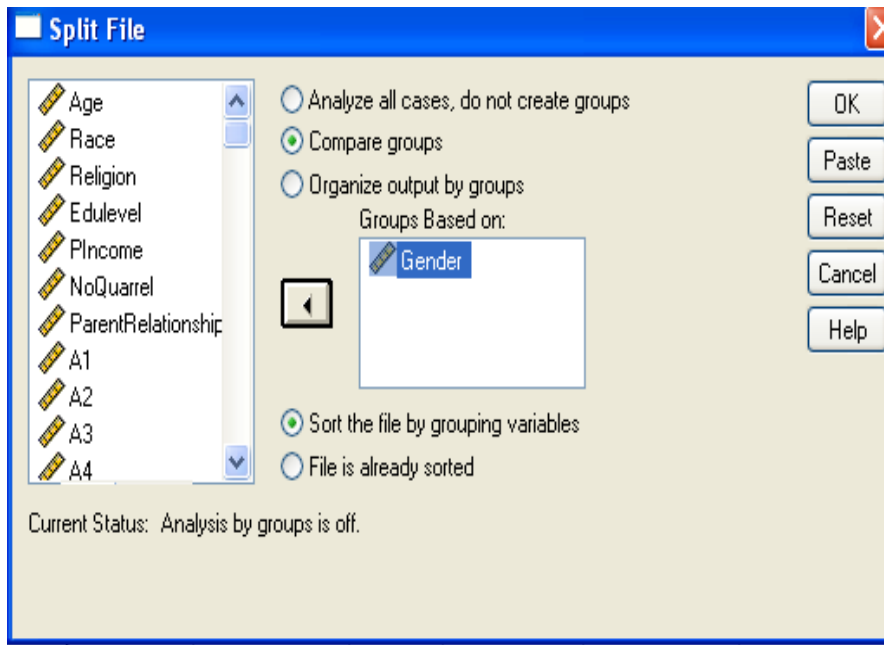
When doing correlational research, you may want to compare the strength of correlation coefficients for two separate groups. For example, you may want to look at the relationship between family functioning, social support and self-esteem for males and females separately. Below is the procedure for the comparing.

### Split the sample (Use Data Set1 Family Functioning)

- Select **Data** from the main menu.
- Click **Split File**



- Click on **Compare Groups**
- Move the grouping variable (e.g gender) into the box labeled **Groups based on**.
- Click on **OK**



This will split the sample by gender and analyse the two groups separately. When you have finished analyzing males and females separately, you have to turn off the **Split File**. Then click on the button **Analyse all cases, do not create groups** and click on **OK**.

The output generated from family functioning data set is shown:

Table 1.5: Correlations for Male and Female Groups with SPSS

Gender			total FFS	total SS
Male	total FFS	Pearson Correlation	1	.440(**)
		Sig. (2-tailed)		.000
		N	123	123
	total SS	Pearson Correlation	.440(**)	1
		Sig. (2-tailed)	.000	
		N	123	123
Female	total FFS	Pearson Correlation	1	.282(**)
		Sig. (2-tailed)		.002
		N	123	123
	total SS	Pearson Correlation	.282(**)	1
		Sig. (2-tailed)	.002	
		N	123	123

\*\* Correlation is significant at the 0.01 level (2-tailed).

### 1.11 Interpretation of Output from Correlation for Two Groups

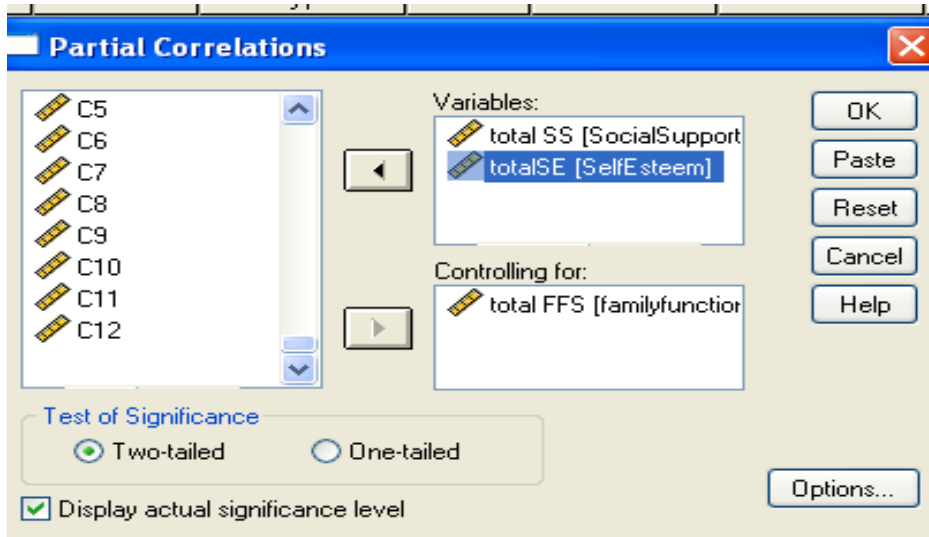
The correlation between family functioning and social support for male was .440, while for females it was slightly lower,  $r=.282$ . It is important to note that this process is different from testing the statistical significance of the correlation coefficients reported in the output table above. The significance levels reported for males: Sig. = .000; for females: Sig. = .002 provide a test of the null hypothesis that the correlation coefficient in the population is 0. However, assesses the probability that the difference in the correlations observed for the two groups (males and females) would occur as a function of a sampling error. In fact, there was no real difference in the strength of the relationship for males and females.

### 1.12 Partial Correlation

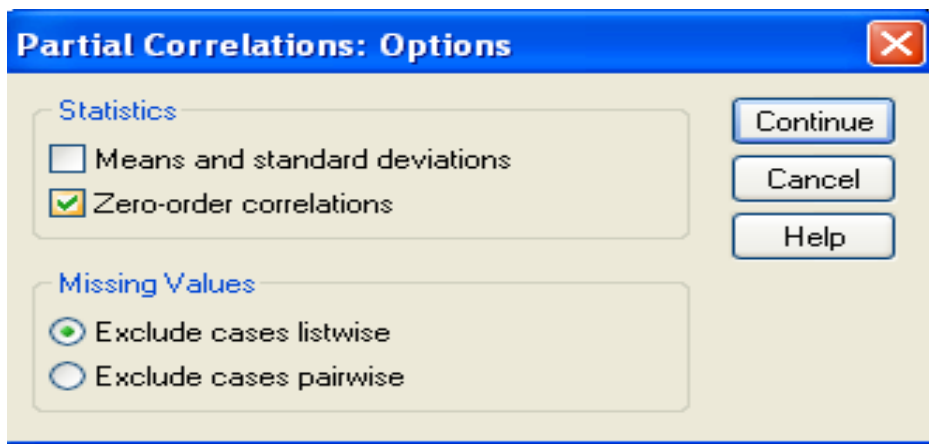
Partial correlation is similar to Pearson product-moment correlation. However, it allows you to control for an additional variable. This additional variable might be influencing your two variables by interest. By removing the confounding variable, you can get a more accurate indication of the relationship between your two variables. Use Data Set1 Family Functioning.

### Procedure for Partial Correlation

- Select **Analyze** the menu
- Click on **Correlate**, then on **Partial**
- Move two continuous variables (e.g Social support and Self-esteem) that you want to correlate into the **variables** box.
- Move the variable that you want to control into the **Controlling for** box (e.g Family functioning)
- Click on Options.



- In the **Missing values** section, click on Exclude cases pairwise
- In the **Statistics** section, click on **Zero Order Correlations**
- Click on **Continue** and then **OK**



## Example of Partial Correlation

Use family functioning data set and demonstrate the generated output.

Table 1.6: Partial Correlations with SPSS

Control Variables			total SS	totalSE	total FFS
-none-(a)	total SS	Correlation	1.000	.439	.377
		Significance (2-tailed)	.	.000	.000
		Df	0	244	244
	totalSE	Correlation	.439	1.000	.117
		Significance (2-tailed)	.000	.	.066
		Df	244	0	244
	total FFS	Correlation	.377	.117	1.000
		Significance (2-tailed)	.000	.066	.
		Df	244	244	0
total FFS	total SS	Correlation	1.000	.429	
		Significance (2-tailed)	.	.000	
		Df	0	243	
	totalSE	Correlation	.429	1.000	
		Significance (2-tailed)	.000	.	
		Df	243	0	

Cells contain zero-order (Pearson) correlations.

## Interpretation of Partial Correlation

In the top half of the table, the word “none” indicates that no control variable is in operation. In this case the  $r=.439$

The bottom half of the table repeats the same set of correlation analyses but controlling or taking out the effects of the control variable (e.g family functioning). The  $r=.429$ .

By comparing the two sets of correlation coefficients, you will be able to see whether controlling the additional variable had any impact on the relationship between the two variables.

In this case, there was only a small decrease in the strength of the correlation (from .439 to .429). This suggests that the observed relationship between social support and self-esteem is not due merely to the influence of family functioning.

## Presenting the Result

Partial Correlation was used to explore the relationship between social support and self-esteem while controlling for scores on the family functioning. There was a moderate, positive, partial correlation between social support and self-esteem ( $r=.429$ ,  $p < .01$ ). This indicated that high level of self-esteem was associated with an increase level of social support. An inspection of the zero order correlation ( $r=.439$ ) suggested that controlling

for family functioning had very little effect on the strength of the relationship between these two variables.