

Quantitative analysis

This chapter

- focuses on the nature and idiosyncrasies of quantitative analysis
- demonstrates how grouped quantitative data are presented
- presents descriptive and correlational analysis
- introduces tests of significance
- demonstrates how to employ statistical tests without mathematics.

Key headings

Introduction

- 1 Steps of data analysis
 - 2 Presentation of grouped data
 - 3 Statistical processing
 - 4 Associations
 - 5 Tests of significance
- Main points
Where to from here?
Further reading

Introduction

Quantitative analysis is a diverse and complex process. In the first instance, it entails a primary analysis (dealing with raw data freshly produced by a study), a secondary analysis (involving previously analysed data), or a meta-analysis. Apart from this, it contains statistical techniques of a varying degree. Statistical processing can be conducted manually or electronically (Rassenberger, 1989; Reid, 1987). Easy access to computers and the many advantages of electronic processing have made this a standard procedure of quantitative analysis. Examples of such advantages are

- fast data processing and analysis of huge amounts of data
- relatively inexpensive data processing and analysis
- high reliability

- accuracy of computations
- accessibility of sophisticated statistical tests to non-statisticians.

The diverse and complex nature of quantitative analysis will be addressed in this chapter in a manner that not only simplifies its diversity without neglecting its quality but also avoids entanglement in the problems of its mathematical nature. In essence, this chapter will introduce statistics, in a student-friendly manner, where no mathematics, no formulae, no manual computations and no old-fashioned statistical methods will be employed (see Sarantakos, 2002). The focus of data analysis will be mainly on what quantitative analysis entails; when, and under what conditions statistical procedures are used; how computers are instructed to conduct the tests for you, and how the test results are interpreted within the study. For this a computer and the IBM SPSS Statistics software ('SPSS') (version 19, 18, 17, 16 or 15) are required.

1

Steps of data analysis

Data analysis begins where data collection ends; and this is when the instruments of data collection that contain the data (e.g. questionnaires) are completed. From this point on, the researcher will follow a systematic process that entails the following steps: (a) data preparation for computer entry, (b) entering the data in the computer, (c) processing and analysing the data, (d) data presentation, (e) interpreting the findings and (f) drawing conclusions (see Box 16.1). In the following sections we shall address these steps in detail.

Box 16.1

Tasks of quantitative analysis

- 1 *Data preparation.* Checking, editing and coding.
- 2 *Data entry.* Entering the data in the computer.
- 3 *Graphic presentation.* For example, presenting the findings in the form of graphs or tables.
- 4 *Data processing and analysis.* Conducting statistical analysis.
- 5 *Interpretation of the findings.* Explaining the meaning of data individually.
- 6 *Conclusions.* Proposing direct answers to the research question.

1.1 Data preparation

Data preparation first involves checking, editing and coding. Hence information gathered through the study should be checked and edited so that it is clear, legible, relevant and appropriate. Editing is done where necessary; if answers are missing and/or illegible, the researcher will decide whether to accept or to reject them.

Coding is the process of converting verbal responses to numerical codes. For instance, 'Male' may be given the code 1, and 'Female' code 2. Coding can be performed before data collection (pre-coding) or after it (post-coding). The numbers expressing the codes (e.g. 1 and 2) are called *values*, and the concepts they represent (e.g. 'Male' and 'Female') the *value labels*.

In quantitative analysis, coding can also be employed when open-ended questions are employed. This involves first the development of categories, and second the assignment of the corresponding value label and the value to each question. For instance, when the open-ended question deals with the question of how power issues are handled in families, the categories may be 'patriarchal', 'democratic' and 'matriarchal', and the values 1, 2 and 3 respectively. This is followed by a careful reading of the answer, identification of the appropriate category, and entering the corresponding number in the designated place next to the answer. Value labels will be used when entering the data in the computer. Usually, category construction is conducted before the commencement of the study, and the relevant codes are presented in the code book, which is generally made available to coders.

Missing answers to questions, or inaccurate responses (e.g. when the tick indicating the gender has been placed ambiguously between 'Male' and 'Female') must also be recorded. They are called missing values and are represented by '9', '99' or '999', depending on whether the expected value has one, two or three figures.

Finally, investigators are expected to monitor coding in order to prevent errors or bias. Coder reliability is significant and is usually checked in two contexts, the reliability of the coder (i.e. that the coder maintains a stable and uniform pattern of coding, and that variability in coding is avoided) and inter-coder reliability (checked by testing how uniform the pattern of coding is when performed by several coders).

1.2 Data entry in the computer

When data preparation is completed, the analyst moves to data entry. This obviously requires access to a computer and to relevant software, as noted above. The software employed in this chapter is SPSS and comes in various versions, which although in essence employ the same computation procedures, often employ different paths to address these tasks. In our analysis, we employ the versions 19, 18, 17, 16 and 15. Any of these versions will be appropriate and compatible with your computer, particularly versions 15–19.

The procedure within SPSS takes place in the 'Data Editor' which appears in two formats: 'Data View', and 'Variable View'. The results of the analysis are shown in the 'Viewer'. Data entry entails two steps: (a) defining the variables and (b) entering the data. During the former, the name and attributes of each variable are defined and mounted in the 'Variable View'. During the latter, the data related to each variable will be added to 'Data View'. This way, the software can identify and access variables and their contents, and subject them to statistical analysis. Both steps will be described next.

1.2.1 Defining the variables

The procedure of defining the variables is like building 'boxes' inside the computer, adequately labelled and prepared, to accommodate the data that belong to that variable. You will tell the computer, for instance, to construct a box, to call it, say, 'Gender', to divide it into two parts, labelled 'Male' and 'Female', and to assign them the values 1 and 2 respectively. This is where the answers will be placed when the actual data are entered. You repeat this process for each variable.

Box 16.2

Perception of marriage questionnaire (extract)

Please tick the option that reflects fully your views on the issues listed below

Office
use only

1 What is your gender?	Male (✓) 1	__1__
	Female () 2	
2 What is your age?	Below 25 () 1	__2__
	26 – 50 (✓) 2	
	50 – 75 () 3	
3 Would you consider yourself...	Very religious () 1	__3__
	Religious () 2	
	Not religious (✓) 3	
	Anti-religious () 4	
4 Are you currently...	Single (✓) 1	__1__
	Married () 2	
	Cohabiting () 3	
	Divorced/separated () 4	
	Widowed () 5	
5 Are you in favour de-institutionalizing marriage?	Strongly in favour () 1	__5__
	In favour () 2	
	No opinion () 3	
	Against () 4	
	Strongly against (✓) 5	
6 Are you in favour of polygamy?	Yes () 1	__2__
	No (✓) 2	
	I don't know () 3	
7 Should the state take over the responsibility for children?	I think so () 1	__3__
	I don't think so () 2	
	I don't know (✓) 3	
8 Overall, are families as happy as they used to be?	I think so () 1	__2__
	I don't think so (✓) 2	
	I don't know () 3	
9 Are you in favour of prohibiting abortion	Yes (✓) 1	__1__
	No () 2	
	I don't know () 3	

To demonstrate how variables are defined, we shall use the variable GENDER, and show how this is done. All other variables are defined in the same way. To define the variable *Gender*, we follow the following steps.

1. Go to SPSS Data Editor and Click on **Variable View** (at the bottom of the screen). The Variable View window appears.
2. Type **Gender** under **Name** (first column, first line of the screen).
3. Click below **Type**, and on the shaded box and choose **numeric**.
4. Click below **Width**, and set it at 8.
5. Click below **Decimals** and set it at 0. Decimals are not required.
6. Click below **Label** and type in the full name of the variable, e.g. 'Gender'. (You can use up to 60 characters.)
7. Click below **Values** and then on the shaded box. A new window appears.
 - Type 1 in the first box and 'Male' in the second. Click **Add**.
 - Type 2 in the first box and 'Female' in the second; then click **Add**.
 - Click **OK**. This brings us back to Variable View.
8. Click below **Missing** and on the shaded box. In the new window activate **Discrete missing values**, and in the box below type 9. Click **OK**. This brings us back to Variable View. Number 9 has been added to the box.
9. Click below **Columns**, and set the width to 8.
10. Click below **Align** and set it to 'Right'.
11. Click below **Scale** and given that gender is a nominal variable, set it to 'nominal'.
12. Click below **Role** and on the shaded box and choose **Input**.

The same procedure will be employed to define the remaining variables. When all variables have been defined this step of data entry is completed. Their list will appear in the Variable View window (see Figure 16.1) and will be accessible for adjustments, corrections or deletions. Apart from this, a column has been assigned to each variable in the Data View window carrying their name at the top of the column (see Figure 16.2).

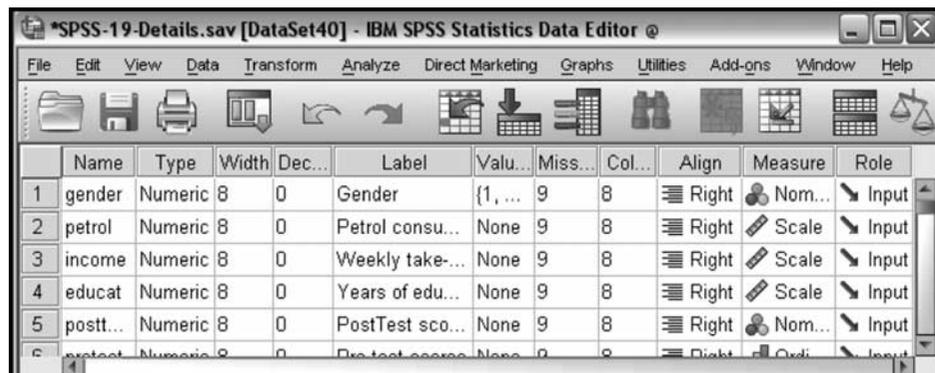


Figure 16.1 Data Editor: Variable View.

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	gender	petrol	income	educat	posttest	pretest	drugshot	capital	gaymar	status
1	1	16	530	10	13	17	1	1	5	1
2	2	12	490	12	1	3	2	2	2	3
3	2	11	560	14	10	12	3	4	4	3

Figure 16.2 Data Editor: Data View.

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(SPSS was acquired by IBM in October, 2009.)

1.2.2 Entering the data

Data entry is a simple procedure during which numbers are transferred from the paper to the computer. If the data collection instrument was a questionnaire, data entry is the transfer of the code of each answer to the column assigned to that variable. Remember that, in simple terms, in the Data View window:

- *a row is a 'case' and a case is a questionnaire* (or any other instrument of data collection) containing the answers of one respondent, as recorded and coded by the researcher. If the study contains 500 respondents, the window will contain 500 rows.
- *a column is a variable*, a part of that questionnaire, an answer to a question, or a code.

Hence, data entry means (a) opening the **first questionnaire** (or any other data collection instrument) and transferring the answers (e.g. codes) to the corresponding variable box of the **first line** of the Data View window. For instance, in Figure 16.2, the results of the first questionnaire (1, 16, 530, 10, 13, 17, 1, 1, 5, 1) were inserted in the *first line* and under the corresponding variables 'gender', 'petrol', 'income' etc. (b) Data entry also means opening the **second** questionnaire and transferring the results to the corresponding variable box of the **second line** of the Data View window. As shown in Figure 16.2, the results of the second questionnaire (2, 12, 490, 12, 1, 3, 2, 2, 2, 3) were inserted in the *second line* and under the corresponding variables 'gender', 'petrol', 'income' etc. The same procedure is repeated for each of the remaining questionnaires or other data sources.

Variable definition and data entry have enriched the system of the computer by installing the necessary parameters required to receive and store data, as well as by providing the data needed to complete statistical operations. What is required for the completion of the project is to instruct the computer, using the language of SPSS, on how to complete the specific tasks associated with the detailed research questions. These instructions will be introduced next when the various statistical methods are presented.

2 Presentation of grouped data

Fully entered data provide the source of information that allows researchers to gain information about the nature and structure of the data, before progressing to more detailed explorations. Two examples of such presentations of grouped data are *tables* and *graphs*, as we shall see next.

2.1 Tables

The most common types of tables are *univariate tables* (frequency tables), containing one variable, such as the number of children per family; *bivariate tables* (crosstabs), containing two variables, such as the number of children of British and Irish families; and *multivariate tables* (containing more than two variables, such as the number of children by nationality, maternal age, maternal education and maternal ethnic background). Tables contain certain elements which distinguish them from each other. The most common elements are shown in Box 16.3.

Box 16.3

The main elements of tables

- The *class interval* is the part of the range ordered into a group; for example, in the age distribution is 1–5, 6–10, 11–15 and 16–20 years, the four subdivisions (1–5, 6–10 etc.) are the class intervals.
- The *class width* is the difference between the lower and the upper interval level.
- *Class limits* are the numbers that define the boundaries of a class interval. For example, in the class interval 1–5, 1 is the lower and 5 the upper class limits.
- *The midpoint* is the value that lies between the upper and the lower limits of a class interval. For instance the midpoint in the class interval 1–5 is 3.
- *Frequency* is the number of observations in each item, category or class interval.
- An *open-ended class* is a class that has only one limit. The classes 'under 5 years', 'under \$2.00', '65 years and over' are open-ended classes.

2.1.1 Rules of presentation

Data presentation is based on a set of rules. The rules most frequently listed by a number of writers (see Becker, 1989; and Mahr, 1995) are shown in Box 16.4.

Box 16.4

Rules of data presentation

- *Clarity*. Information should be presented clearly, and without ambiguity or confusion.
- *Simplicity*. Information should be easily readable.
- *Economy of space*. Neither excessive spacing nor undue crowding should occur in data presentation.
- *Order of variables*. Independent and dependent variables should be presented in their correct places.
- *Appearance*. Tables and graphs should have a pleasant appearance. ▶

- *Accuracy.* Marginals should accurately correspond with cell values, and footnotes with relevant references.
- *Objectivity.* Figures contained in tables or graphs should not be misleading and should not encourage erroneous conclusions.

2.1.2 Table construction using SPSS

Frequency tables

To obtain frequency tables through SPSS you can use any of the versions referred to earlier in this chapter, i.e. 19, 18, 17, 16 and 15. The steps followed to construct a frequency table are shown below.

1. Select **Analyse / Descriptive Statistics / Frequencies.**
2. Transfer the variable 'Political system' to the Variable(s) box.
3. Activate Display frequency tables, and click **OK.**

Table 16.1 Political System

	Frequency	Percent	Valid %	Cumulative %
Democracy	426	85.0	85.0	85.0
Socialism	40	8.0	8.0	93.0
Communism	25	5.0	5.0	98.0
Monarchy	9	2.0	2.0	100.0
Total	500	100.0	100.0	

The Viewer presents a table showing the political preferences of 500 students, expressed in their number and percentage per political system.

2.1.3 Crosstabs

To obtain bivariate crosstabs – e.g. the number of students smoking, by gender (Male–female) – we proceed as follows:

1. Go to **Analyse / Descriptive Statistics** and click **Crosstabs.**
2. Set 'Gender' in the Rows box, and 'Smoking' in the Columns box.
3. Click **OK.**

Detailed answers to the question how many students smoke 'never', 'often', 'very often' for male and female students separately is shown in Table 16.2.

It is worth noting that when you instruct the computer to produce bivariate tables, you need to specify whether you require percentages, and if so, whether you need them in the rows, the columns or in both. You have to respond accordingly.

Table 16.2 Smoking by gender

		Never	Often	Very often	Total
Gender	Male	30	20	0	50
	Female	10	30	10	50
Total		40	50	10	100

2.2 Graphs

Graphs are figures that offer a visual presentation of the results. Some consist of a skeleton and a body. While the skeleton in such graphs is the same, the shape of the body usually varies from one type to the other. Other graphs use circles, bars, columns, maps, pictures or other figures to display relevant information.

Box 16.5

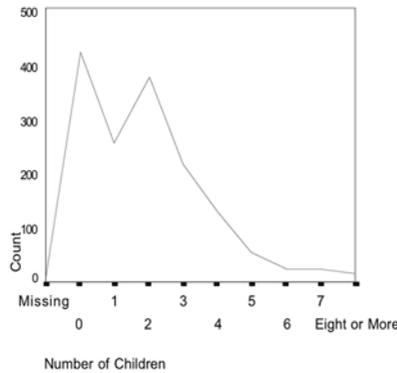
Points to remember

- The two lines placed at right angles to each other intersecting at the lower left-hand part of a figure are the *coordinate axes*.
- The point of intersection of the coordinate axes is called the *origin*, and serves as the zero point.
- The zero is placed close to the right of the intersection of the axes.
- Values above the origin are positive; values beneath the origin are negative.
- The horizontal line of the coordinate axes is called the *X-axis* or *abscissa*.
- The vertical line of the coordinate axes is called the *Y-axis* or *ordinate*.
- The values of the independent variable are scaled along the abscissa.
- The values of the dependent variable are marked off along the vertical axis, that is, along the ordinate.
- In ordinal scales the lowest values are placed on the left-hand end and the highest values on the right-hand end of the line.
- The values of a nominal scale can be placed in any order.

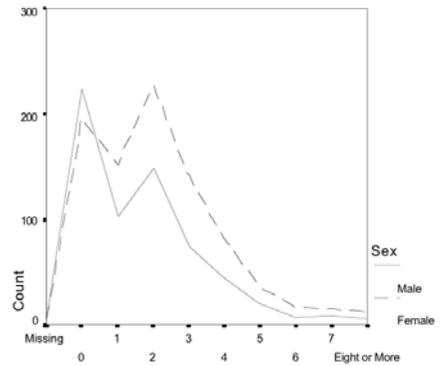
2.2.1 Line graphs

There are many types of graphs employed by researchers to display their findings visually. This section will introduce some of the most common graphs, and explain their structure and purpose. Those are line graphs, histograms, bar graphs (clustered and stacked), scattergrams and pie charts.

Line graphs (or line charts) contain a number of dots joined with straight lines. Line charts can be simple, or multiple. Each line represents one variable. To present the number of children per family we only need one line showing how many families have one, two, three, four etc. children. More lines are used if more variables are to be presented in the graph.



Simple line graph

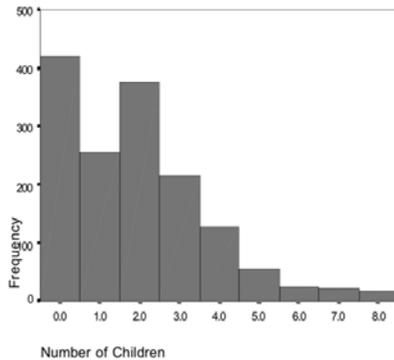


Multiple line graph

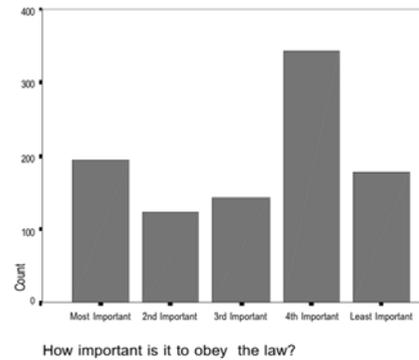
Figure 16.3 Line graphs.

2.2.2 Histograms and bar graphs

A *histogram* is a graph plotted on the coordinates and shows the form, breadth, centre and height of the distribution. Histograms display continuous scale values; hence, bars are set adjacent to each other, without space between them.



The histogram

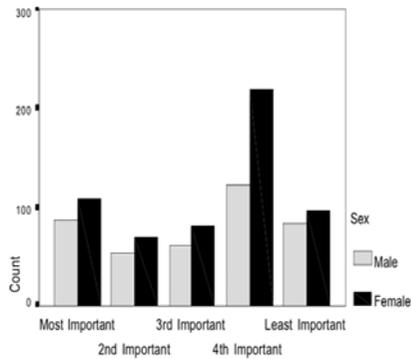


Vertical bar graph

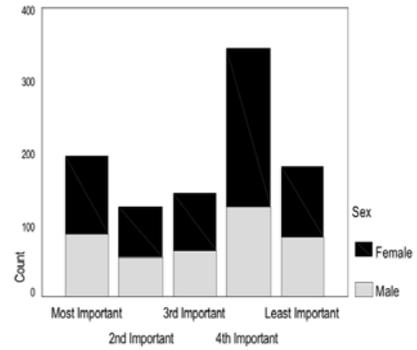
Figure 16.4 Histogram and vertical bar graph.

Bar graphs are similar to histograms in that they consist of bars that indicate the magnitude of the values of the variable in question; however, the bars are not joined together but set apart from each other. They are employed to present nominally scaled variables including values with discrete intervals. They can be vertical (bars running vertically) or horizontal (bars running horizontally).

There are *simple* bar graphs (presenting single values), *clustered* bar graphs (presenting sets of bars side-by-side), and *stacked* bar graphs (presenting bars stacked on top of each other), as shown in Figure 16.5.



Clustered bar graph

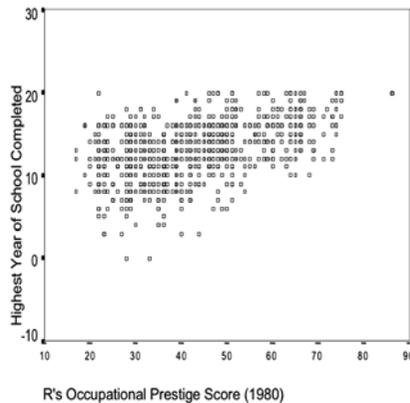


Stacked bar graph

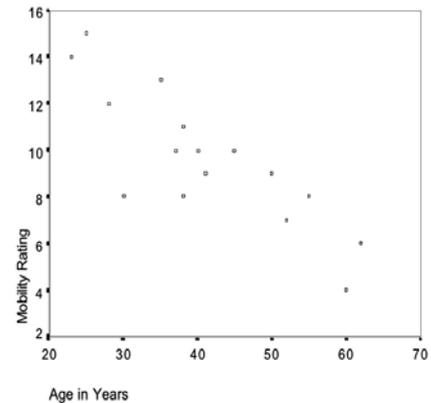
Figure 16.5 Clustered bar graph and stacked bar graph.

2.2.3 Scattergrams

A scattergram is a graph employed when correlations are computed, and describes the relationship between two variables. This relationship is expressed in the shape of the dots it contains. Scattergrams indicate whether there is a relationship between the two variables, and if so, whether the relationship is positive, negative, strong or weak. (a) The closer the dots are to a straight line, the stronger the relationship. (b) Dots gathered around a line starting from the origin and cutting the angle of the two axes in the middle indicate a positive correlation. (c) Dots like those in Scattergram B indicate a negative correlation. Scattergram A shows no correlation between the variables.



Scattergram A



Scattergram B

Figure 16.6 Scattergrams.

2.2.4 Pie charts

Pie charts present variables in the form of a circle (pie) with each of their parts occupying a segment of the pie that is proportional to its real size and are used to describe one categorical variable. Pie charts are an easy way of displaying relationships between the whole sample and its parts as well as comparisons between the parts of the sample. For instance, in Figure 16.7, pie charts offer a clear picture of the extent of drinking habits of the population, and allows comparisons with other populations. It shows also two versions of pie charts, the *simple chart* and one with an *'exploded slice'*.

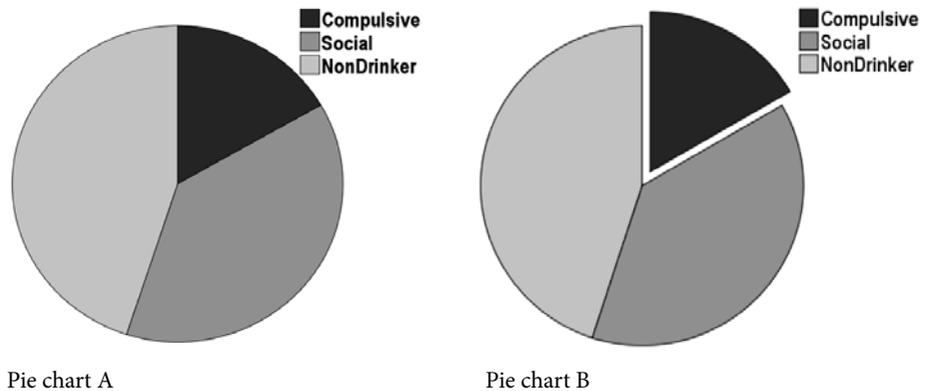


Figure 16.7 Drinking habits.

2.2.5 Chart construction using SPSS

Provided that the computer has access to files with relevant data, SPSS can instantly construct one or more charts at wish. One way of constructing charts begins with Analyse, / Descriptive Statistics / Frequencies offers three options and employs an easy procedure. Another begins with Graphs / Legacy dialogs, offering 15 options and employs a relatively complex procedure. A third option is Graphs / Graph builder which for some students was found to be unnecessarily demanding.

The first option seems to have the advantage that it follows the path employed in many other tests, and requires no reorientation. The steps employed in this option are shown below.

1. Analyse / Descriptive Statistics / Frequencies
2. Transfer the variable to the Variable(s) box and click **Charts**
3. Activate Bar, Pie chart or Histogram
4. Continue / click **OK**

This procedure shows that regardless of which chart you wish to employ, the path is the same. You only select the chart you wish to construct and this is the only difference between them. The choice 'Bar' includes three types, *simple bar*, *clustered bar* and *stacked*

bar. Using the second option has the advantage that it offers a choice of 15 types of charts, although most of them are outside the parameters of this chapter. Be that as it may, a summary of the procedures employ in this case is presented below.

Box 16.6

How to obtain charts

1 How to obtain bars

Simple bars

- Go to Graphs / Legacy dialogs / Bar / Simple
- Activate Summaries for groups of cases / Define
- Transfer variable to Category axis box and click **OK**

Clustered bars

- Go to Graphs / Legacy dialogs / Bar / Clustered
- Activate Summaries for groups of cases / Define
- Transfer Gender to the Define clusters by box and click **OK**

Stacked bars

- Go to Graphs / Legacy dialogs / Bar / Stacked
- Activate Summaries for groups of cases
- Click **Define / Activate N of Cases**
- Transfer variable to Category axis box
- Transfer Gender to the Define clusters by box / Click **OK**

2 How to obtain pie charts

- Go to Graphs / Legacy dialogs / Pie
- Activate Summaries for groups of cases
- **Click Define / Activate N of Cases**
- Transfer variable to Define slices by box / click **OK**

How to explode a slice:

- While in the Viewer, double-click on the pie chart
- Click the pie / a slice / elements / explode slice
- Click **File / Close**

3 How to obtain histograms

- Go to Graphs / Legacy dialogs / Histograms
- Transfer Age to the variable box
- Activate Display normal curve / click **OK**

4 How to obtain scattergrams

- Go to Graphs / Legacy dialogs / Scatter/Dot / Simple / Define
- Transfer the one variable to Y-Axis box and the other to X-Axis box
- Click **OK**

Most students opt for the former which is sufficient and adequate at this stage of our level of analysis, and is also employed in all other methods of analysis discussed in this chapter.

Box 16.7

Relational measures and their function

Measures	Description and examples
Rate	The rate compares the computed frequency of a variable with the possible frequency. It is obtained by dividing the former by the latter.
Ratio	Ratio describes the relationship between two parts of a group or a variable, such as gender where males and females are its parts. To compute the ratio of males to females we divide the number of males by the number of females. If their numbers are 26 and 37 respectively, the ratio of males to females will be $(26/37 = 0.7)$, namely 7 males for every 10 females.
Percentage	Percentage describes the relationship between a subgroup (n) to the total group (N) and is obtained by using the formula $n/N \times 100$. In the example above, the percentage of males is 41.27% $(26/63 \times 100 = 41.27)$, and of females 58.73% $(37/63 \times 100 = 58.73)$.

3

Statistical processing

Statistical processing includes techniques that allow a detailed analysis of the data. One such technique will offer general descriptions of the data, and is known as *descriptive analysis* (descriptive statistics). Another technique focuses on relationships between variables, looking for associations (correlations), and is known as *relational analysis* (relational statistics). The third form of statistical processing is *significance testing*, which informs about the extent to which our findings reflect the criteria of the (target) population, and whether the study allows generalization of the findings.

We begin our exploration with some elementary techniques of descriptive statistics.

3.1 Relational measures

Numerical figures alone have little informative power in qualitative research. They become informative and significant when they are interrelated. For instance, 500 respondents thinking in a particular way is a large number if it is a part of a sample of 600, but relatively small if it comes from a sample of 10,000 respondents. Relational measures serve to relate figures to each other or to the whole. The measures considered here are rate, ratio and percentage; the latter in particular is extensively used not only in research but in everyday life. These measures are briefly described in Box 16.8.

Box 16.8**Measures of central tendency**

Measure	Description and examples
Mean	Is the average of all observations. It is obtained by adding up all scores and dividing the sum by the number of scores. → IS USED in interval and ratio data
Median	Is the point on a (rank-ordered) distribution that divides the observations (not their values) into two equal parts. In the distribution 36, 33, 30, 28, 26, 23, 18, 12, 11, 8, 4, the median is 23 (there are five observations on each side of 23). → IS USED in ordinal, interval and ratio data
Mode	Is the category with the largest number of observations. If in a test 6 students received an A, 9 a B, 16 a C and 7 a P, the mode is C. → IS USED in nominal, ordinal, interval and ratio data.

3.2 Measures of central tendency

The measures of central tendency are used to compute the average, the most common or the typical value in a distribution. The most useful measures that compute such values are the *mean*, the *mode* and the *median*. Their application depends on the nature of the data they describe. Their features are shown in Box 16.9.

Box 16.9**When to use the mean, the mode and the median**

- *The mode* is used if the variable is nominally scaled, although it can be used for all types of data.
- *The mean* is chosen if the variable is ordinal, interval or ratio.
- If the distribution shows a central tendency, the mean or median is a better measure; if there is no central tendency the mode is preferable.
- If the distribution is skewed, the median is a better measure. This is particularly so for distributions of interval data. When the skew is extreme, and if the distribution contains ordinal data, the mode may be a better choice.
- If a quick but rough measure is acceptable, the mode can be helpful.
- If information about the central trend is wanted, the mean is the best choice.
- If information is needed about the location of cases in the two halves of the distribution, the median is a better measure.

All measures have certain attributes, and are therefore equally useful. Their suitability depends very much on the nature of distribution they measure and other factors, as shown in Box 16.10 (Foddy, 1988; Pfeifer, 2000):

Of these measures, the mean has many important mathematical properties and is a stable measure, which is not easily affected by shifts of a few data. It is therefore the most commonly used measure of central tendency.

3.3 Measures of dispersion

These measures are employed when we need to know how far the scores are spread around the mean, and about the average deviation of the scores from the mean. The measures of dispersion considered in this discussion are the *variance*, *standard deviation* and *range*. Their main features are briefly described in Box 16.10.

Box 16.10

Variance, standard deviation and range

Measure	Description and examples
Variance	the average of the distances of the individual scores from the mean, OR the mean of the squared deviations of the observations from the mean.
Standard deviation	the square root of variance. E.g. in a class of students with a mean IQ of 120, a standard deviation (SD) of 5 means that the average deviation of these students from the mean IQ is 5 points, i.e. most students have an IQ between 115 and 125.
Range	the distance between the highest and the lowest score of a distribution. E.g. if the lowest maths score is 45 and the highest 90, the range is $(90 - 45 = 45)$ 45.

The computation of the measures of dispersion follows the steps shown below. Note that, since variance and standard deviation serve the same purpose, only standard deviation will be considered in this section. Note also that these measures can be computed together with the measures of central tendency. Following the steps given below, the screen displays the mean, mode, median, variance, standard deviation and range.

1. Click **Analyse / Descriptive statistics / Frequencies**.
2. Transfer the variable of your choice to the Variable(s) box.
3. Activate Display frequency tables.
4. Click **Statistics** / activate Mean, Mode, Median, variance, standard deviation and range.
5. Click **Continue / OK**.

All 6 scores listed in line 4 above are presented together in the table shown in the Viewer.

3.4 Comparing scores: z-scores

Assume two students took a test in social research, one in a psychology class and the other in a sociology class. Student A obtained 65/100 and Student B 70/100. The question here is: Can we conclude that on the basis of these scores Student B performed better in the test than Student A? The z-score answers this question. The procedure employed here compares the two scores in conjunction with the means of their distribution. For instance, if the score 65 comes from a distribution with a mean of 60 and the score 70 from a distribution with a mean of 70, it is logical to assume that 65 is above average and 70 is just an average score, and hence, student A performed better than Student B.

In statistical terms, z-scores transform raw scores into scores measured in a distribution where the mean is 0 and the SD is 1, and where the scores are measured in SD units. Hence, in such a computation a z-score of +1.5 means that the raw score that corresponds to this z score is one-and-a-half times higher than the standard deviation; in other words, it is a relatively good score. Likewise, a z-score of -1 means that the corresponding raw score is one SD below the mean.

To compute the z-scores for a set of data, using SPSS, we proceed as shown below. It must be noted that all scores of the variable will be converted to z-scores.

1. Click **Analyse / Descriptive statistics / Descriptives**.
2. Transfer the variable to be converted to the Variable(s) box.
3. Activate 'Save standardized values as variable'.
4. Click **OK**.

Following these steps, the computer will display a new variable next to the one you wanted to convert, including the corresponding z-scores. These scores can be accessed statistically like any other set of data. To compare two scores, both distributions must be converted to z-scores.

4 Associations

4.1 Nature of association measures

A correlation is a method that examines the relationship between two variables. More specifically, correlations examine three major aspects of relationships. These are:

- the presence or absence of a correlation, that is, whether or not there is a correlation between the variables in question
- the direction of correlation, that is, whether an existing correlation is positive or negative
- the strength of a correlation, that is, whether an existing correlation is strong or weak.

The presence, direction and strength of correlation are demonstrated in the coefficient of correlation. In general, the coefficient ranges from -1 to $+1$. A zero correlation indicates that there is no correlation between the variables. The closer the coefficient is to 1 ($+1$ or -1), the stronger the correlation; and the closer it is to 0, the weaker the correlation.

The direction of correlation is indicated by the sign that stands in front of the coefficient. When it is positive (+) it means that variables change in the same direction (positive correlation); in other words, when one variable is high (e.g. income) the other (e.g. quality of life) is also high. A negative ($-$) sign indicates that the variables move in opposite directions (negative correlation): when one (e.g. income) decreases, the other (e.g. criminality) increases. It must be stressed that correlation does not imply causation.

Box 16.11**Measuring correlations**

A correlation is:

- very low if the coefficient has a value under 0.20
- low if the coefficient has a value between 0.21 and 0.40
- moderate if the coefficient has a value between 0.41 and 0.70
- high if the coefficient has a value between 0.71 and 0.91
- very high if the coefficient is over 0.91.

(Pfeifer, 2000)

4.2 Available options

There are three different types of correlation tests (nominal, ordinal and interval-ratio), each using a number of specific tests. The choice of the type of test depends on the type of distribution (whether continuous or discrete), the structure and characteristics of the distribution, and the level of measurement. Table 16.3 displays a few popular measures, grouped according to level of measurement.

Table 16.3 Association tests by level of measurement

Level	Association tests
Nominal	ϕ coefficient, Cramer's V, Contingency coefficient (C), Tschurprow's T, Yules Q, and Lambda test
Ordinal	Spearman's rank correlation; Tau-a, Gamma coefficient, Sommer's d, and Tau-b
Interval-ratio	Pearson's product-moment correlation

In this section only one measure for each level of measurement will be introduced. These are ϕ coefficient and Cramer's V, Spearman's rho and Pearson's r.

4.3 Nominal measures of association

Nominal measures are employed when they test nominal variables. It is important to remember that coefficients here range from 0 to 1, with 0 being the lowest level of their value; negative values have no meaning here. Phi (ϕ) coefficient and Cramer's V (computed together) is a nominal measure and will be introduced below.

Box 16.12**Testing nominal association: an example**

A survey shows that 70 of the 100 male students and 55 of the 100 female students are against examinations. Can we argue that the differences between these two groups are large enough to allow the conclusion that gender is associated with their position to examinations? Knowing the student's gender, can we predict their attitude to examinations?

4.3.1 Phi ϕ coefficient and Cramer's V

Phi is employed with 2 × 2 tables, while Cramer's V can be used also for larger tables. In SPSS, both are computed together and also produce similar results. Still, when used in larger tables, phi values can exceed 1; in such cases we use Cramer's V. To compute phi and Cramer's V we proceed as shown below:

1. Select **Analyse / Descriptive statistics / Crosstabs**.
2. Transfer one variable to Row(s) box, and the other to Column(s) box.
3. Click **Statistics** and then activate 'Phi and Cramer's V'.
4. Click **Continue**, and then click **OK**.

After completion of this procedure, the computer will display the table shown below. Here we look for (a) the 'value' and (b) the 'Approx. Sig'.

Table 16.4 Symmetric measures: Phi & Cramer's V

	Measures	Value	Approx. Sig
Nominal by Nominal	Phi	.145	.041
	Cramer's V	.145	.041
N of Valid Cases		200	

The value of ϕ is .145, and the approximate significance level is .041. What does this mean? This means that the association between the two variables is 'very low' (below 0.20), almost negligible, and that this is statistically 'very significant' (.041 is below the set limit of .05); hence we conclude that there is no association between 'gender' and 'attitude to examinations'.

4.4 Ordinal measures of association

Ordinal measures are employed when ordinal data are tested, that is, with ranking pairs. Of the various measures employed in ordinal data, Spearman's rho is the most common measure, and will be introduced next.

Box 16.13

Testing ordinal association: an example

The 15 students of a tutorial class were ranked twice, once according to their participation in sport (RANK 1) and once according to their academic performance (RANK 2). Using these rankings, can we say that there is a correlation between participation in sport and academic performance?

4.4.1 Spearman's rank-order correlation coefficient

This is a product-moment, non-parametric correlation coefficient which deals with ranks (not magnitudes), and measures the strength of the linear association between variables.

Unlike other ordinal measures, rho is a correlation-based measure. Using the example above (Box 16.13), we instruct the computer as follows:

1. Select Analyse / Correlate and click on **Bivariate**.
2. Transfer the two variables to be correlated to the Variable(s) box.
3. Activate Spearman by clicking on the square box in front of it.
4. Activate One-tailed or Two-tailed as required.*
5. Activate Flag significant correlations, and then click **OK**.

The Viewer shows a set of tables, of which the following is the most relevant.

Table 16.5 Spearman's correlation

			Academic ranking	Sport ranking
Spearman's rho	Academic ranking	Correlation Coefficient	1.000	.952**
		Sig. (2-tailed)	—.	.000
		N	15	15
	Sport ranking	Correlation Coefficient	.952**	1.000
		Sig. (2-tailed)	.000	—.
		N	15	15

* Choose 'One-tailed' if the direction of the correlation is known; if not, choose 'Two-tailed'.

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

What are we looking for here? The points that contain the answer to our question are: (a) correlation coefficient (which is .952) and (b) the significance level (Sig. (2-tailed)) which is .000. This means that there is a very high and dependable association between the two variables (.952), and that the correlation is very significant. Simply stated, students ranked highly in one area (sport) are highly ranked also in the other academic performance.

Box 16.14

Testing interval/ratio association: An example

A journalist interviewed 500 public servants employed in the same department (Criminal Justice) and of the same educational background. The question was whether there was a correlation between length of service and yearly income. Can one say that the longer the service, the higher the income?

4.5 Interval/ratio measures of association

4.5.1 Pearson's product-moment correlation coefficient, r

This is the most common measure of association of variables scaled on an interval level. It is a symmetric test that deals with pairs of scores and with magnitudes of observa-

tions; it tests whether there is a linear correlation between the variables and if so whether the correlation is positive, negative, strong or weak. Pearson's r is computed as follows:

1. Choose Analyse / Correlate and click **Bivariate**.
2. Transfer the variables Years and Income to Variable(s) box.
3. Activate Pearson by clicking on the square box in front of it.
4. Activate One-tailed or Two-tailed.
5. Activate Flag significant correlations, and then click **OK**.

Using the data of the survey described above, the Viewer shows the following display.

Table 16.6 Pearson correlation

		Years of service	Level of income
Years of service	Pearson Correlation	1	.883**
	Sig. (2-tailed)	—	.001
	N	500	10
Level of income	Pearson Correlation	.883**	1
	Sig. (2-tailed)	.001	—
	N	500	10

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

What are we looking for here? The focal points here are (a) the correlation coefficient (.883) and (b) the Sig. (2-tailed) which is .001. This means that there is (i) a positive correlation (.883 has no negative sign); (ii) a strong correlation (.883); and (iii) a very significant correlation (shown in .001 and **). (Note that two stars next to .883 indicate a *very significant* correlation.) Hence we can conclude that there is a very strong association between years of service and level of income.

4.5.2 Coefficient of determination

The coefficient of determination describes the common variance, that is, the degree of variability shared by the two variables. It is the square of the coefficient of correlation (r^2), and offers an index of predictability: it allows the researcher to make predictions about one variable if the degree of determination is known. For example, an r of .7, which in most cases is as high as one is expected to obtain in real situations, can only explain 49 per cent of the changes that can be explained by the independent variable.

Box 16.15**Coefficient of determination****What is a coefficient of determination?**

The coefficient of determination describes the common variance, that is, the degree of variability shared by the two variables. It is the square of the coefficient of correlation (r^2), and offers an index of predictability: it allows the researcher to make predictions about one variable if the degree of determination is known. For example, an r of .7, which in most cases is as high as one is expected to obtain in real situations, can only explain 49 per cent of the changes that can be explained by the independent variable.

5**Tests of significance****5.1 Introduction**

Tests of significance are employed when we want to know about the significance of our findings, that is, about the extent to which the findings of the study reflect or are consistent with what happens in the target population. For example: Are our findings a truthful reflection of what happens in the population or the result of methodological or of other problems? Or better: Can our findings be generalized? (See Box 16.16.)

Box 16.16**What is significance level?**

Level of significance is a measure which indicates the extent to which the findings of a study are significant. This level is provided by the computer when relevant tests are conducted. The level of significance ranges from 0 to 1. A significance level of 0 means that there is a very high probability that our results reflect those of the target population. The risk of making a mistake in this conclusion is 0 in 100. The exact opposite means a significance level of 1. Here the chance of making a mistaken conclusion is 100 in 100. In the statistical jargon, a significance level indicates the risk of rejecting the null hypothesis (H_0) when it should have been accepted, which we are prepared to take. This is referred to as alpha (α).

The α values most commonly accepted by social researchers are 0.05 and .001. In these cases, we accept that there is a 5 per cent (for .05 level) or 1 per cent (for .001 level) probability of rejecting a true H_0 . In other words, if we were to randomly take a number of samples from the same population, a difference as great as that given in the findings at the 0.05 level would occur by chance only five times in 100 samples; the remaining 95 times the differences will reflect differences in the target population. The study is obviously more precise if the differences are significant at the 0.01 level, where the chance of rejecting a true H_0 is 1 in 100. Briefly, what we have to remember is that coefficients are significant if their level is between .05 and 0.000.

What are we talking about here? Assume that a study of 200 students found that female students cheat in the examinations to a higher degree than male students do. The question that concerns the researcher is: Is this result a true reflection of what happens in the target

population? Do female students in general cheat more than male students? H_0 (null hypothesis) proposes that there is no difference in examination cheating of male and female students. Significance tests will show whether H_0 is correct.

Table 16.7 Overview of significance tests

Number and type of samples	Non-parametric tests		Parametric tests
	Nominal level	Ordinal level	Interval/ratio level
One	χ^2 -test (Goodness-of-fit test)	Kolmogorov–Smirnov test	t -test
Two independent	χ^2 -test of independence Fisher's exact test z -test for proportions	Mann–Whitney U-test Wald–Wolfowitz runs test	t -test
Two dependent	McNemar test	Sign test Wilcoxon test	t -test
More than two independent	χ^2 -test	Kruskal–Wallis H-test	ANOVA
More than two dependent	Cochran Q-test	Friedman test	ANOVA

Sources: S. Siegel (1956). *Non-parametric Statistics for Behavioral Sciences*, London: McGraw-Hill; and R.G. Knapp (1985). *Basic Statistics for Nurses*, New York: Wiley and Sons.

There are several types of test of significance, depending on three factors:

- whether the distributions are scaled on a nominal, ordinal or interval/ratio level
- whether the study includes one or more samples (one-sample tests, two-sample tests, k-sample tests)
- whether the samples are related (matched) or independent.

The main types of significance test are shown in Table 16.7. These tests follow a strict procedure, beginning with setting a research hypothesis, formulating the null hypothesis (H_0) and the alternative hypothesis, computing test statistics and then checking whether the null hypothesis can be accepted or rejected. In the discussion that follows we shall consider only a few tests, introducing their purpose and relevance, showing briefly how their values are derived and interpreted. Hence, the main points that will be covered when discussing these tests will be:

- when and under what conditions specific tests are employed
- how they are computed (using SPSS), and
- how their values are interpreted.

More information on these tests can be found in the workbook accompanying this text, and in relevant literature.

Table 16.8 Some nominal-level tests of significance

Number of samples	Type of samples	Significance test
One sample	N/A	χ^2 goodness of fit z-test for proportions
Two samples	Independent	χ^2 test of independence Fisher exact test
	Dependent	McNemar test
k-samples	Independent	χ^2 test
	Dependent	Cochran Q test

5.2 Nominal-level tests: chi-square tests

Researchers employ a number of nominal-level tests. The choice of a particular test depends on a number of factors, such as type of samples and degree of dependence between them. Examples of such tests are listed in Table 16.8. In the following discussion we shall introduce chi-square (χ^2) only.

Box 16.17

A chi-square test is:

A nominal-level test of significance applied to ascertain the degree to which findings produced by a sample-based study can be generalized. For instance, if a study of 500 (of the 5,000) first-year students of the local university found that 95 per cent of the respondents are against examinations, chi-square tests can tell us whether or not this is a true reflection of what the majority of the 5,000 first year students prefer.

Chi-square (χ^2) tests (pronounced *kya square*) are the most popular and most frequently used tests of significance in the social sciences; they provide information about whether the collected data are close to the value considered to be typical and generally expected, and whether two variables are related to each other. There are two types of chi-square tests, namely the goodness-of-fit test and the test of independence.

5.2.1 Goodness-of-fit test: One variable

This test is employed when the study includes one variable only. Consider the example shown in Box 16.18.

Box 16.18

One-variable goodness-of-fit test: An example

Of 300 female nurses surveyed, 100 were found to support fully the administration of their hospital, 150 to tolerate it, and 50 to be openly against it. Are the numerical differences here significant enough to justify the conclusion that, overall, female nurses in the target population think likewise?

We begin the computation by assuming that in general the views of the nurses are equally divided among the three options, and proceed as shown below:

1. Select Analyse / Non-parametric tests and click **Legacy dialogs**.
2. Click **Chi-square** and transfer variable to the Test variable list box.
3. Activate Get from data and All categories equal.
4. Click **Options** and activate Descriptive.
5. Click **Continue / OK**.

Following this, the computer displays the table shown below which contains the value of chi-square, the degrees of freedom, and the significance level. The figure that is most relevant to us is the significance level, which is .000. The meaning of this finding was explained earlier in Box 16.16.

Table 16.9 Test Statistics: Chi-square goodness-of-fit test

	Attitudes
Chi-square	50.000
df	2
Asymp. Sig.	.000

Simply, this indicates a very high level of significance, the highest one can obtain. Hence we reject H_0 , and conclude that the differences between the three groups of nurses identified in the study reflect differences in the population and are not caused by other factors.

Let us now repeat the computation, this time taking the option that the expected frequencies are not equal, but that, say, 50 per cent are expected to be in favour, 30 per cent tolerant and 20 per cent against:

1. Select Analyse / Non-parametric tests and click **Legacy dialogs**.
2. Click **Chi-square** and transfer variable to the Test variable list box.
3. Activate Values then enter 50 and click **Add**.
4. Enter 30 and click **Add**; then enter 20 and click **Add**.
5. Click **Options** and activate Descriptive.
6. Click **Continue / OK**.

Table 16.10 Test Statistics: Chi-square goodness-of-fit test

	Attitudes
Chi-square	58.333
df	2
Asymp. Sig.	.000

The computer shows that the chi-square value is 58.333, and that with 2 degrees of freedom $p = .000$. Interpretation of the figures is the same as that of the previous case, namely that the differences between the three groups of nurses identified in the study reflect differences in the population and are not caused by other factors.

5.2.2 Chi-square test of independence: Two variables

This test is employed when two nominal-level variables are being studied. The main question regarding this test is not about the ‘fit’ of the observed values of one variable in the theoretical model, but whether the two variables are independent from or related to each other. H_0 states that the variables are independent.

Box 16.19

Chi-square test of independence: two variables: an example

The results of a survey on attitudes to abortion, including 100 males and 100 females found that many more men than women were against abortion. Can we say that they are sufficiently different to reject the zero association between them, and the assumed independence of the variables? Are attitudes to abortion independent from gender?

To compute the chi-square test of independence we proceed as follows:

1. Select Analyse / Descriptive statistics / Crosstabs.
2. Transfer abort to the Row(s) box and gender to the Column(s) box.
3. Click **Statistics** and activate Chi-square.
4. Click **Continue / OK**.

When this procedure is completed, the Viewer shows the Chi-Square Tests table. The relevant point for us here is the level of significance, noted in the table as ‘Asymp. Sig. (2-sided)’.

Table 16.11 Chi-Square Tests

	Value	Df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	10.666 ^a	1	.001		
Continuity Correction ^b	9.759	1	.002		
Likelihood Ratio	10.767	1	.001		
Fisher’s Exact Test				.002	.001
Linear-by-Linear Association	10.613	1	.001		
N of Valid Cases	200				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 45.50.

b. Computed only for a 2x2 table

What are we looking for here? Given the high significance level [Asymp. Sig (2-sided)= 0.002], we reject the H_0 , and with it the assumption that the variables (attitudes to abortion and gender) are independent. Thus it is reasonable to conclude that the variables are dependent; consequently, men and women have different attitudes to abortion.

5.3 Ordinal-level tests

Ordinal-level tests deal with ordinal data, and serve the same purpose that nominal-level tests serve in their context. There are many such tests; a list of some popular ordinal-level tests is given in Table 16.12.

In the social sciences, ordinal-level tests are not used as frequently as nominal and interval/ratio tests. For this reason, in this section only a brief description of these tests will be given. In the following we shall describe the main characteristics of the tests, where and how they are employed and how to interpret their findings. Their computation is simple, particularly when using SPSS, as we shall see next.

SPSS assembles these tests under the general name of *non-parametric tests*. Consequently the path you need to follow to find these measures is Analyse > Non-parametric tests. This leads you to a list of measures containing the following: chi-square, binomial, runs, one-sample K-S, 2 independent variables, k independent variables, 2 related samples and k related samples. Each of these items contains one or more of the tests introduced in this section. A list of these tests per list item is given below:

Table 16.12 Ordinal level tests

Number of samples	Type of samples	Significance test
One sample	N/A	Kolmogorov–Smirnov test
Two samples	Independent	Wald–Wolfowitz runs test Mann–Whitney <i>U</i> -test
	Dependent (related)	Sign test Wilcoxon test
<i>k</i> -samples	Independent	Kruskal–Wallis <i>H</i> -test
	Dependent (related)	Friedman test

In SPSS, these tests can be approached through the following path:

1. Go to Analyse / Non-parametric tests.
2. Click **One sample, or** Independent samples, **or** related samples ('Related' stands for dependent).
3. Click **Settings**.

After activating 'Settings' a number of tests related to the option in line 2, will appear on the screen. There is a great variety of tests to cover all types of samples employed by researchers conducting data analysis. From there, you only need to follow the program instructions.

5.4 Interval/ratio-level tests: t-tests

This section addresses two of the most common interval/ratio-level tests. They are also called *parametric tests of significance*, as they are based on the assumption that the population is normally distributed, adhering to the principles of normal curve. Table 16.13 displays the interval/ratio significance tests that will be presented or referred to below, arranged according to the number of types of samples tested.

Table 16.13 Interval/ratio-level significance tests

Number of samples	Type of samples	Significance tests
One sample	N/A	t-test
Two samples	Independent or dependent	t-test
<i>k</i> -samples	Independent	Simple ANOVA
	Dependent	Multiple ANOVA

5.4.1 *T*-tests

The t-test is used predominantly for small samples, although it is also taken to be appropriate for large samples (Argyrous, 1996: 223). There are two types of t-tests; the one-sample test, and the two-sample test.

Box 16.20

What is a t-test?

A t-test is an interval/ratio test of significance which has the purpose of ascertaining whether or not the findings of a sample-based study are significant, that is, also valid for the target population. It checks the degree of generalizability of the findings of this study. The t-test serves the same purpose as chi-square tests, except that it is suitable for interval/ratio variables

5.4.2 *One-sample t*-tests

A single-sample t-test compares the sample mean with the population mean, and tests whether there is a significant difference between them. Consider the following example.

Box 16.21

One-sample t-test: An example

A lecturer has grounds to believe that female nurses at her institution are more conservative than female nurses at other institutions. To test this assumption she ascertains the scores of 26 female nurses using a conservatism scale, and computes the mean (5.715) and standard deviation (1.384). Given that the average conservatism score of female nurses is known to be 4.4, can she argue that the differences are significant?

The lecturer employs the one-sample t-test to test her hypothesis. The steps to follow are shown below (the variable name is 'conserv'):

1. Select Analyse / Compare means / One-sample T Test.
2. Transfer 'conserv' to the Test variable(s) box.

3. Type 4.4 in the Test value box.
4. Click **Options** and set Confidence interval to 95 per cent.
5. Activate Exclude cases analysis by analysis (in Missing values sector).
6. Click **Continue / OK**.

The computer displays the following table:

Table 16.14 One-sample test

	Test Value = 4.4					
	t	df	Sig. (2-tailed)	Mean 95% Difference	Confidence Interval of the Difference	
					Lower	Upper
Conservatism	4.846	25	.000	1.315	.76	1.87

What are we looking for here? The decisive figure is the significance level (Sig.), which is very high (.000). On the basis of this we can reject the null hypothesis. This means that the differences between the means are due to differences in the target population. Hence, the conservatism score of the female nurses in question is significantly different from that of their counterparts in the target population.

5.4.3 Two-sample t-test for dependent (paired) samples

Two-sample tests are used to check the differences between the means of two samples. These samples can be dependent or independent; hence there is a test for independent samples, and one for dependent samples. In this discussion we focus on the dependent samples test. The t-test is employed here to test the differences between each pair of data.

Box 16.22

Two-sample t-test: An example

A journalist interviews ten respondents twice, first at an initial meeting, and then after they have attended a symposium on homosexuality. The point of investigation was to ascertain whether the views of the subjects on this matter changed significantly after the symposium. The scores of the two surveys were entered in the computer. The null hypothesis states that there are no differences between the scores. Is this correct?

Let us consider the example shown in Box 16.22, and see what the results of the t-test suggest. We begin with the computation, which proceeds as follows:

1. Choose Analyse / Compare means and click **Paired-samples T test**.
2. Highlight and transfer both variables to the Paired variables box.
3. Click **Options** and set Confidence interval to 95%.

4. Activate Missing values as required.
5. Click **Continue**, and click **OK**.

The Viewer displays the table 'Paired samples test' containing the test results, which contains relevant information, especially the value of t, and the level of significance.

Table 16.15 Paired samples test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std.Dev	Std.Error of the Mean	95% Conf Interval of the Difference				
					Lower	Upper			
Pair 1	Pre-test / post-test scores	1.80	1.033	.327	1.06	2.54	5.511	9	.000

Where to from here? Given the very high significance level (.000), the H_0 that the means are equal is rejected. Hence the mean obtained after the symposium is significantly different from the first mean. Consequently, the differences between the means are significant. It is therefore reasonable to assume that the symposium and the contact the respondents had with delegates had an impact on their views on homosexuality.

5.4.4 Two-sample t-test for unrelated (independent) samples

The purpose of this test is to assess whether the mean scores of two unrelated samples are different and if so to what extent. For instance, is the average time spent by women and men in sport activities different, and if so is the difference statistically significant? The unrelated samples are 'Men' and 'Women'; and the means to be compared are the average time spent by women and men in sport. To address this question, we collect relevant data, enter them in the SPSS and follow the procedure described below.

1. GO TO Analyse / Compare Means / Independent samples T test.
2. Transfer categorical variable to Grouping Variable box.
3. Click **Define Groups** and insert 1 in the top box and 2 in the other box.
4. Click **Continue / Options** and Set Confidence interval to 95%.
5. Activate Exclude cases analysis by analysis and click **Continue**.
6. Transfer the other variable to Test Variable(s) box, and click **OK**.

The results of this procedure are presented in the Viewer and shown in table below. We focus on t-test results that are below the 't-test for equality of the means' title and particularly on the significance level (Sig (2-tailed)). The rule is that if Sig level is significant, (i.e. the difference between the means is significant), it is assumed that men and women are not equally involved in sport. If Sig score is not significant, then it is assumed that

men and women are equally involved in sport. Given that the significance level is .429, i.e. far above .05 and hence not significant, we can conclude that on the basis of our t-test results, women's involvement in sport is not different from that of men.

Table 16.16 Independent samples test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Sport involvement	Equal variances assumed	.135	.716	.799	38	.429	.700	.876	-1.073	2.473
	Equal variances not assumed			.799	37.79	.429	.700	.876	-1.073	2.473

It must be noted that the procedure described above was for cases where the significance level (.429) is the same for both. If the significance level varies we need to consult 'Levene's test for Equality of Variances' included in the table. If Levene's significance level (Sig.) is .05 or lower, we use the results set given in the line 'Equal variances assumed'. If Levene's significance level (Sig.) is higher than .05, we use the results set given in the line 'Equal variances not assumed'.

5.5 Analysis of variance (ANOVA)

This is one of the most powerful and most common statistical tests employed in the social sciences, and is suitable for interval/ratio-level distributions. It is known either as *analysis of variance* or as the *F-test* and is used as a simple factorial, general factorial or multivariate factorial test; these tests are also known as single or one-way (when one criterion is used), as two-way (when two criteria are used), or as N-way (factorial) analysis (when more criteria are used). It is called the F-test after its creator, Sir R. D. Fisher.

Box 16.23

Analysis of variance is:

An interval-ratio test of significance, suitable for comparing two or more samples. It appears in a variety of models and operates in the same way and has the same purpose as t-tests, except that the latter are suitable for comparisons of two samples. ANOVA is considered to be more powerful than t-tests.

ANOVA is employed if certain conditions are met. The following are the most important:

- *Random sampling.* The sample is taken randomly.
- *Independence.* Scores are independent from each other.
- *Normality.* Scores are normally distributed.
- *Homogeneity.* Variances are equal.

The two most common tests are one-way and two-way ANOVA. One-way analysis of variance is employed when there is one factor (acting like an independent variable) and one dependent variable. The factor is a nominal variable (males, females; ethnic groups, marital status etc.); the dependent variable is a quantitative variable. Although there are two variables being tested, one-way ANOVA looks at whether the sample groups vary systematically in one way, or with regard to one aspect only.

A two-way analysis of variance includes two criteria of classification as well as two independent variables and one dependent variable. For instance, if we ask about the effects of social class on overall happiness we employ a one-way analysis of variance; but if we relate social class and marital status to overall happiness we employ a two-way analysis. In the first example there is one factor: social class. In the second there are two factors: social class and marital status.

5.5.1 Computing ANOVA

As stated above, a one-way analysis of variance is employed when there are two variables, one factor and a one-way classification. To explain the way in which ANOVA tests are conducted we use the example in Box 16.24.

Box 16.24

One-way ANOVA: An example

A group of students from five countries were surveyed to establish their attitudes to the family. Questionnaires were completed and accurate figures were gathered for each country. The question here is whether there are significant differences in the family attitudes of students of these countries. ANOVA will assist us to answer this question.

After the data are entered in the computer, we proceed as follows:

1. Select **Analyse / Compare means / One-Way ANOVA.**
2. Transfer **Familism** to **Dependent List** box.
3. Transfer **Country** to **Factor** box.
4. Click **Options / Descriptive** and **Continue.**
5. Click **Post Hoc** / activate **Tukey** / Click **Continue / OK.**

When the computation is completed, the Viewer displays the ANOVA table (also known as F-Table), and the 'Descriptives' table. Our focus is on the former (see below) and on the significance level, which is .000. A significance value of .000 suggests that the null hypothesis of equality of the means is rejected. In simple terms this means that the various groups studied have different attitudes to families, or, more precisely, that it is reasonable to assume that *at least one group differs* from the others.

Table 16.17 ANOVA-familism scores

	Sum of squares	df	Mean squares	F	Sig.
Between groups	60.983	3	20.328	57.300	.000
Within groups	19.867	56	.355		
Total	80.850	59			

5.5.2 Post hoc comparisons

Although this finding is exactly what one would expect from the results of ANOVA, for a researcher interested in more detail, such as the number and identity of groups that differ from each other and the extent of difference, to mention two, the results are not sufficient to answer the research question. The additional information can be provided by using post hoc comparisons. This is the reason for including this option in the analytic procedure of ANOVA, and for obtaining the 'Multiple Comparisons' table together with the F-table. Simply, while ANOVA answers the question whether there is a significant difference between all groups studied, post hoc looks at the individual groups and at the differences between them.

Table 16.18 Multiple comparisons – familism scores

(I) Country of birth	(J) Country of birth	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Australia	Austria	-.533	.217	.079	-1.11	.04
	Greece	-2.067*	.217	.000	-2.64	-1.49
	USA	.667	.217	.017	.09	1.24
Austria	Australia	.533	.217	.079	-.04	1.11
	Greece	-1.533*	.217	.000	-2.11	-.96
	USA	1.200*	.217	.000	.62	1.78
Greece	Australia	2.067*	.217	.000	1.49	2.64
	Austria	1.533*	.217	.000	.96	2.11
	USA	2.733*	.217	.000	2.16	3.31
USA	Australia	-.667	.217	.017	-1.24	-.09
	Austria	-1.200*	.217	.000	-1.78	-.62
	Greece	-2.733*	.217	.000	-3.31	-2.16

* The mean difference is significant at the 0.05 level.

What are we looking for? The parts of the table that contain the answer to our question are the columns (I) Country of birth, (J) Country of birth, and Sig. The first contains the

country that is compared to all others. The second contains the countries that are being compared to the single country shown in the first column. The third contains the significance level. For instance, the second row of the table compares Australia to Austria, Greece and USA and the significance levels are .079, .000 and .017 respectively. The same information is provided in the rest of the table for Austria, Greece and USA. The task of the researcher is to examine the comparisons of the countries one-by-one and identify which countries differ and to what extent.

For instance, while the differences between Greece and all other countries of the sample are highly significant (reflecting the results of ANOVA), the difference between Austria and Australia are not significant although they are significant for Greece and USA. This shows that using post hoc comparisons refines and strengthens the findings of ANOVA, and therefore researchers tend to use it as a part of the procedure of ANOVA.



Main points

- Quantitative and qualitative research employ different types of data analysis.
- Quantitative analysis employs advanced statistics to process quantitative data.
- Most quantitative researchers conduct statistical analysis using computers.
- Quantitative researchers present summaries of their findings in tables and graphs.
- The rate, the ratio and the percentage are relational measures. They relate parts of a group to each other or to the group.
- The mean, the mode and the median are measures of central tendency.
- The variance, the standard deviation and the range are measures of dispersion.
- The most common correlation measures are Pearson's r and Spearman's ρ .
- Tests of significance relate statistics to parameters; they ask: Does the sample reflect accurately the target population?
- The most common tests of significance are chi-square, t-tests and ANOVA.



Where to from here?

Before you leave this chapter, visit the companion website for the fourth edition of *Social Research* at <http://www.palgrave.com/sociology/sarantakos4e> to review the main concepts introduced in this chapter and to test yourself on the major issues discussed.



Further reading

- Betts, K., Hayward, D. and Garnham, N. (2001) *Quantitative Analyses in the Social Sciences: An Introduction*. Croydon, Victoria: Tertiary.
- Crombie, I. K. and Davies, H. T. O. (2009) *What is Meta-analysis?* London: Hayward Medical Communications.

- Dargatz, D. A. and Hill, G. W. (2007) 'Analysis of Survey Data', in S. Sarantakos, (ed.), *Data Analysis*, Vol. II, pp. 317–32. London: Sage.
- Faber, J. and Sheper, W. J. (2007) 'Social Scientific Explanations? On Quine's Legacy and Contextual Fallacies', in S. Sarantakos, (ed.), *Data Analysis*, Vol. IV, pp. 249–65. London: Sage.
- Hannan, M. T. and Tuma, N. B. (2007) 'Methods for Temporal Analysis', in S. Sarantakos, (ed.), *Data Analysis*, Vol. III, pp. 49–76. London: Sage.
- Lucas, J. W. (2007) 'Theory-Testing, Generalization and the Problem of External Validity', in S. Sarantakos, (ed.) *Data Analysis*, Vol. IV, pp. 225–48. London: Sage.
- McCullough, B. D. (2007) 'Assessing the reliability of statistical software: Part II. In S. Sarantakos, (ed.), *Data Analysis*, Volume IV, pp. 378–397. London: Sage.
- Sarantakos, S. (2000) *Basic Stats Without Maths*. Sydney: Harvard Press.
- Sarantakos, S. (2007a) *A Toolkit for Quantitative Data Analysis Using SPSS*, London: Palgrave Macmillan.
- Sarantakos, S. (ed.) (2007b) *Data Analysis*, (SAGE Benchmarks in Social Research Methods series). London: Sage.