CHAPTER 6

RESEARCH METHODOLOGY RELATED TO THE STUDY UNDER INVESTIGATION

6.1 INTRODUCTION

The aim of this chapter, is to provide a better and adequate insight and understanding of the basic methodological techniques and methods used during the study, how it was applied and what purpose it played, in order to obtain the relevant data. Various aspects relating to the particular research methods and techniques will be investigated so as to determine whether it would be adequate and sufficient enough within the broad framework of this research study. The chapter will also provide a better understanding of what the empirical part of the study entails.

Aspects and concepts such as pollution size, sample frame, sample size, methods of data collection, as well as the validity and reliability of the research study, will be investigated. Attention will also be given to questionnaire design, data processing, analysis and the evaluation of results.

First, the term "methodology" needs clarification. Wellman and Kruger state as follows: "The application of various methods, techniques and principles in order to create scientifically obtained knowledge by means of objective methods and procedures within a particular discipline" (Wellman & Kruger, 2000:2). Research methodology can also be evaluated and interpreted according to the nature, scope and volume of particular research methods applied, which in turn form part of the logic behind the methods that are applied within the research methodological field of study.

The study of methodology is concerned with the acquisition of knowledge and is also very practical in nature and, therefore, is focused on specific ways and methods that can be applied to better understand the field and scope of study, which in the case of this particular study, refers to the various methods and principles used within the general research process. Another aspect closely related to methodology is research itself: "Research gives the history of a particular study, including what the researcher wanted to find out, why that seemed worth discovering, how the information was gathered and what he or she thought it all meant" (Locke, Silverman & Spirduso, 1998:23).

6.2 DEFINITION OF THE RESEARCH PROBLEM AND OBJECTIVES

6.2.1 Problem definition

According to Wellman & Kruger (2000:11), a research problem refers to some difficulty which the researcher experiences in the context of either a theoretical or a practical situation and to which he or she wants to obtain a solution. The definition on the research problem is, however, one of the most important steps and is the first stage in any research process.

The nature and problem of this particular study, are clearly stated and defined in Chapter 1. It is clear that there is an ever-increasing need for organisations to become more actively involved in the management of HIV/AIDS in the workplace. Especially from management's perspective, the issue can not be ignored any longer. It has become a priority for organisations to implement sufficiently structured policies, action programmes and strategies to effectively manage and minimise the impact of HIV/AIDS in the workplace. There is an ever-present need to actually investigate this aspect by means of applied research in the industry, in order to determine if management is committed or simply reluctant in respect of the whole issue of HIV/AIDS within the workplace (Wellman & Kruger, 2000:22). The purpose of the study is, therefore, to evaluate and investigate whether suitable and effective policies, action programmes and strategies are in place to manage and minimise the impacts of the HIV/AIDS epidemic within the working environment of organisations, and also to determine what the actual needs are of organisations with respect to the management and control of the disease.

As already mentioned, the method of applied research within the industry is a suitable method of research for this particular study, in that it has the following outcomes for the organisations under investigation.

- Firstly, the need for research in industry develops because of organisational problems. Problems arise, for example, with excessive absenteeism, staff turnover and job dissatisfaction, and this could be the beginning of a research study that is designed specifically to reduce the seriousness of the problems.
- Secondly, the goal of research in industry, is to improve the effectiveness of an organisation.
- Thirdly, the participants in research within industry, are typically employees or job applicants.
- Fourthly, if the results of research in industry are positive and usable, the research unit of the organisation where the research is done, will attempt to have the conclusions of the study accepted and implemented by the rest of the organisation (Wellman & Kruger, 2000:22).

6.2.2 Objectives of the research study

Primary objective

To investigate and analyse structures (strategies), action programmes and policies for the effective management and control of HIV/AIDS within the workplace.

Secondary objectives

The following secondary objectives support the primary objective.

- (1) To measure the impact of HIV/AIDS in the workplace.
- (2) To measure the effective management of the HIV/AIDS epidemic in the business environment.
- (3) To measure the role of management in combating the disease.

- (4) To measure existing action programmes, policies and strategies for the successful implementation of measures within the workplace.
- (5) To measure the success rate of these action programmes, policies and strategies for the organisation (if possible).

6.3 UNIVERSUM AND SAMPLING TYPES

6.3.1 Universum

The first step in the sampling process is to define the universum or population. According to Blakenship & Breen (1993:36) population refers to the total group under investigation, while Wellman and Kruger (2000:18) defy it as the study object, which may be individuals, groups, organisations, human products and events or the conditions to which they are exposed. The size of a particular population or universum is indicated by N and IF, for example, the size of the universum is 256; it wil be indicated as N=256 (Wellman & Kruger, 2000:47).

Another important aspect to be taken into account when defying the universum is to define the universum (population) units. Bennett (1997:31) also states, that an important point of departure is to define the unit analysis, which refers to the major entity that one is analysing within a particular study. According to this viewpoint, the analysis being done, is to determine what the unit is and not the sample that is being drawn.

Units of analysis typically refer to:

- humans;
- groups (for example, couples married in a particular year; households in a particular geographic region; homosexual clubs; gangs; criminal syndicates; etc.);
- organisations or institutions (for example, schools; classes; congregations; hospitals; political parties; companies; etc.);

- human products or outputs (for example, houses; paintings; articles published in a particular journal in a particular period; dramas; etc.); or
- events, for example, elections; riots; court cases; etc. (Wellman & Kruger, 2000:50).

In the case of this particular study, the universum is comprised individuals (HR Officials, Medical Officers, Occupational Health Nurses and EAP Advisors), while the unit analyse is the specific organisations that are being investigated within the area of study (Sudman & Blair, 1998:334). The next stage, is to determine the universum boundaries of units, which in the case of this research study, will be medium to large industrial organisations with a minimum of 500 or more employees (according to the American definition on organisational size).

6.3.2 The sample frame

Cooper and Schindler (1995:204) identify a sample frame as the listing of elements or units from which the actual sample will be drawn. Another descriptive definition of a sampling frame, is a complete list on which each unit of analysis is listed only once. The sample, however, should be representative of the sample frame, which ideally is the same as the universum, but which often differs, due to practical problems relating to the availability of information (Wellman & Kruger, 2000:49).

The availability of a sampling frame is one of the most important aspects in determining a suitable sampling design. The sample frame that was used in this particular study was organisations operating within the Vaal Triangle area; especially in the main industrial areas within the Greater Lekoa Vaal Metropolitan area.

Sudman & Blair (1998:338) identify the following ways in which the sample frame may differ from that of the universum.

- The frame may contain duplicate listings.
- The frame may contain ineligibles that are not part of the universum (population).

- People daily relocate from one population group to the other, or die.
- A frame may contain lists, which do not contain all relevant units of analysis, and if the missing units differ in a systematic manner from those on the list, incorrect conclusions will be the result.
- The frame may omit specific units of the universum.

It is also possible that biases could exist between the various viewpoints and opinions of the members within the universum under investigation. However, it is assumed that the viewpoints and information obtained from the sample frame, represents informed viewpoints of the universum units within the boundaries of this specific research study. The sample frame that was used in the study consists of all major industrial orientated organisations within the Greater Lekoa Vaal Metropolitan area.

6.3.3 Sample size, methods and response rate

6.3.3.1 Sample size

According to Lockhart & Russo (1994:144), a sample size refers to the number (n) of items to be selected from the universum of the population to make up a specific sample. Principles and considerations to be taken into consideration when determining the desirable sample size are identified by Cooper & Schindler (1998:25) and will hence be briefly discussed.

- Firstly when we determine the size of the sample (n), we should bear in mind the size of the population (N). In general, it holds that the smaller the total population, the relatively larger the sample should be in order to ensure satisfactory results.
- Secondly, the desired sample size does not depend on the size of the population only, but also on the variable. As a general rule, the larger the variance of the variable, the larger the sample required.
- Thirdly, if each stratum of a highly heterogeneous population is relatively homogeneous, a relatively smaller stratified sample than that required for a random sample may be sufficient. If the strata differ in size and heterogeneity,

the next step will be to adjust the size if the respective samples are taken from them accordingly. The smaller the stratum and/or the more heterogeneous it is, the relatively larger the sample should be, that is drawn from it.

- Fourthly, in determining sample size, it is important to bear in mind that the number of units of analysis from which usable data might be obtained must be smaller than the number, which have originally been drawn. It may not be possible to trace some individuals, others may refuse to participate in the research, while still more may not provide all the necessary information or may not complete their questionnaires, so that their information has to be discarded. Therefore, it is usually advisable to draw a larger sample than the one for which complete data are eventually desired.

As a general rule, no sample with fewer than 15 units of analysis should be used, but preferably one with more than 25 units of analysis (Huysamen, 1991:56). If the population size is 500, then the sample size should be 200. It is not necessary to use a sample size bigger than 500 units of analysis, no matter what the size of the population may be.

6.3.3.2 Sampling Methods

Due to the nature and scope of this particular study, it was decided that a questionnaire be sent out to various respondents and that personal interviews be conducted on a random scale. In this case, conceptually random sampling was the most attractive type of probability sampling used (Wellman & Kruger, 2000:52). However, it is also believed that personal interviews can be a very effective sampling tool for the purpose of gathering information, although it could be very costly. The greatest value, however, lies in terms of the depth of information and detail that can come from it (Cooper & Schindler, 1998:291).

Research questionnaires were sent out to all industrialised organisations having a minimum of 500 employees and more (refer Appendix F). Over a period of two months, 80 organisations were targeted, with a response rate of 53 completed questionnaires, which accounts for a 66,25 per cent overall success rate. With regard to personal interviews, a total of 21 interviews out of a possible 35 were conducted, which related to an overall 60 per cent response.

Mail surveys were not conducted because of the typical low response rates that are synonymous with the application of this type of survey method. Another important factor is that the so-called non-respondents to mail surveys could feel that they do not know enough about the topic of survey being conducted. (Leedy, 1997:32)

The most suitable alternative, was to design a research questionnaire that was aimed at a specific group of respondents that have significant information and know-how on the topic being investigated, supported by the interviews conducted.

6.3.3.3 Response Rate

The response rate for this study was 66,25 per cent (53 responses from a total of 80 were received).

The response rate refers to the number who is measured, observed or who respond to a survey (numerator), divided by the number of eligible respondents (denominator). All studies aim at a high response rate; however, no standard exists to assist the literature reviewer in deciding whether the aim has been achieved and, if not, the effect on the particular study's outcomes (Fink, 1998:87).

The response rate can be calculated by applying the following formula:

$$\text{Response rate} = \frac{\text{Number who respond}}{\text{Number eligible to respond}}$$

6.4 DATA COLLECTING METHODS

For the purpose of this study, it was decided to develop a well-structured questionnaire as an instrument for collecting data, which the respondents in question would complete. According to Blankenship & Breen (1993:122), there are certain fixed guidelines, as to which methods a researcher should use for collecting primary data, but that the researcher must collect data as accurately and as ambiguously as possible.

6.4.1 Questionnaire design

The first step in the design of the questionnaire was to draw up a preliminary questionnaire where all the questions asked were open-ended and unstructured. The purpose for this was to assure that the research problem really existed and the study was going to be of value to the subject discipline of business management. The preliminary questionnaires were distributed to eight respondents and randomly selected. The main purpose for this was to evaluate it against the objectives that were set out for this particular study.

The next step involved the listing of aspects of the relevant data obtained from the preliminary questionnaire, as well as from the actual problem definition and objectives. This was done in order to develop and finalise the final research questionnaire.

Parasuraman (1991:363) defines a questionnaire as a set of questions designed to generate the data necessary for accomplishing a research project's objectives. Equally important, is to evaluate the questions being asked. This can be achieved by asking the following questions, as described by Orna & Stevens (1995:21).

- Are the questions really necessary in view of the objectives for the particular research study?
- Will the respondents be willing and able to provide adequate information on the subject?
- Do the questions cover the content area for which it was designed?
- What does the research questionnaire seek to find out?
- What limits must be set to the breadth and depth of the particular questions asked?

- What are the potentially useful ways in applying the research questionnaire (methodological options)?

Once these questions have been addressed, the researcher must try and ascertain the type of questions he or she will be using within the limits of the actual research questionnaire. To achieve this aim the following type of questions could be useful, according to Bennett (1997:42).

- Open-ended questions, which require the respondents to provide their own personal opinions and answers to the questions.
- Multiple choice questions, which require the respondent to choose an answer or alternative answer from a list provided within the questionnaire.
- Dichotomous questions which are the opposite from multiple choice questions and which allows the respondent only one or two responses such as "Yes" or "No".
- A standard five-point Likert-scale, which are used in most questions in order to ensure consistency and which is also easy to complete by the relevant respondent.
- A nominal scale, which is used for questions relating to demographics that, can be completed by the respondent by means of a multiple-choice form.

6.4.2 Measuring instruments

In measurement, a clear distinction is made between different levels of measurement on the basis of the following four features of the numbers assigned within the research process.

- Distinguishability (the number 2 is different from the number 1).
- Order of rank (2 has a higher rank than 1).
- Equal intervals between successively higher numbers.
- Absolute size.

According to Wellman & Kruger (2000:133) a different level of measuring may be assigned corresponding to each of these four characteristics. Zikmund (2000:276) clearly describes these four categories of measurement scales.

- **Nominal scale**

  A scale in which the numbers or letters assigned to objects, serve as labels for identification or classification; a measurement scale of the simplest type.

- **Ordinal scale**

  A scale that arranges objects or alternatives according to their magnitudes.

- **Interval scale**

  A scale that not only arranges objects according to their magnitudes but also distinguishes this ordered arrangement in units of equal intervals.

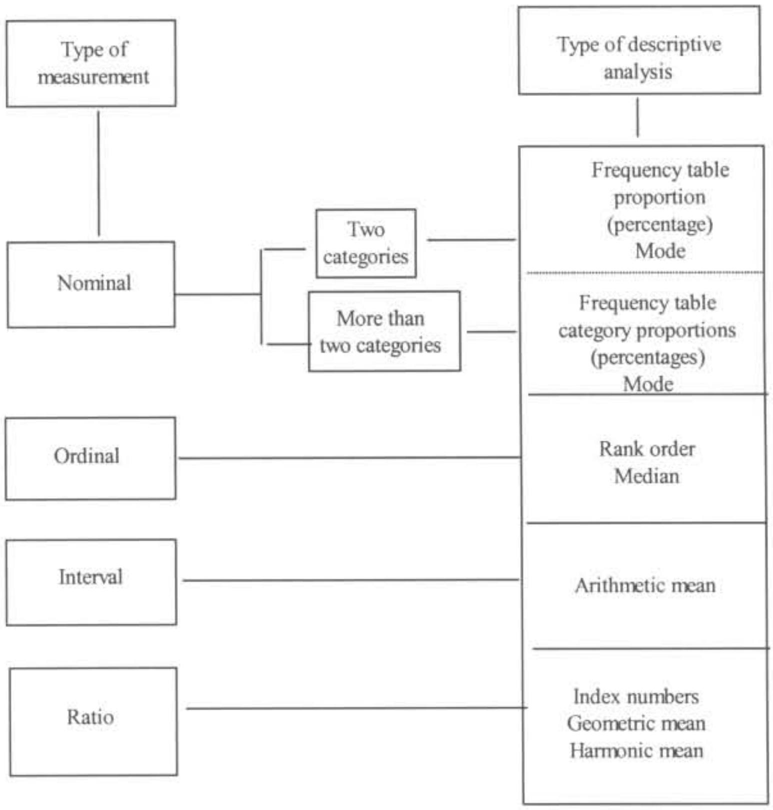
- **Ratio scale**

  A scale having absolute rather than relative quantities and possessing absolutes zero, where there is an absence of a given attribute.

The following tables clearly illustrate the various scale types used during the application of descriptive statistics.

Tables 6.1 and 6.2 to follow on p.152.

Table 6.1: Descriptive statistics permissible with different types of measurements



Source: Zikmund, 2000:437

Table 6.2: Scale types

Type of Scale	Numerical Operation	Descriptive Statistics
Nominal	Counting	Frequency in each category Percentage in each category Mode
Ordinal	Rank ordering	Median Range Percentile ranking
Interval	Arithmetic operations on intervals between numbers	Mean Standard deviation Variance
Ratio	Arithmetic operations on actual quantities	Geometric mean Coefficient of variation

Note: All statistics that are appropriate for lower-order scales (nominal is the lowest), are appropriate for higher-order scales (ratio is the highest).

Source: Zikmund, 2000:278

6.4.3 Questionnaire testing

The questionnaire was tested by distributing a copy to respondents in different fields in various organisations during a pilot study. Interviews were conducted and respondents were asked to comment on the clarity of the particular questions asked. The result was that the questionnaire was adapted and vague or unclear questions were being excluded from the final questionnaire.

It is, however, important to notice that there is always a chance that some questions could cause problems and as such, questionnaires need to be tested in order to identify and eliminate problems that might occur (Sudman & Blair, 1998:300).

6.4.4 Data processing and analysis

The Department of Statistics directly captured the various responses from the relevant research questionnaire at the University of Pretoria. Calculations were made in order for the researcher to check the reliability of data analysed.

After the researcher is sure that the relevant data has been correctly coded and entered, as described by Bennett (1997:44) he/she must then decide on an appropriate computer programme in order to analyse the data obtained. The following programmes can be considered.

- Quattro or Lotus that is particularly useful for specific data analysis programmes such as SAS and BMDP.
- The statistical program for the social sciences or SPSS package.

Finally the primary data were assimilated by means of a statistical software package where the final analysis and cross-tabulations were done.

6.4.5 Editing of data and code frame

The final responsibility of the researcher is to edit his/her own work and check for completeness and accuracy (Orna & Stevens, 1995:177). Although it is legitimate for an editor to complete a missing answer, the researcher must be aware of the fact that such an action could bias the responses of a particular research study.

In the case of this particular study, the editor did not complete incomplete answers, as it could bias the responses of the study. In some cases questionnaires were discarded as unreliable, due to a less than 70 per cent completeness, and were consequently totally ignored.

A code frame was drawn up, where every answer was given a code, in order to simplify the relevant data obtained. Coding refers to the assignment of numbers to answers, so that responses can be grouped into a limited number of classes or categories. In order to simplify the capturing of data every answer was coded (Cooper & Schindler, 1998:381). According to Bennett (1997:43), the following four aspects are important at this stage.

- The editing and encoding process has to be planned properly.
- A preliminary check should be run before data are subjected to final editing and encoding.
- Incorrect answers should be detected, especially if the answers to two or more questions are inconsistent.
- Where possible incomplete answers should be completed.

6.4.6 Data cleaning and transformation

The first step was to calculate out-of-range values for every variable, followed by wild-code checks in order to calculate the minimum and maximum values for each of the research questions. Any particular wild codes were then changed, according to the original response on the questionnaire. Averages for all the questions within the research questionnaire, were calculated with the aim of highlighting out-of-range values attached to each specific variable (Sudman & Blair, 1998:429).

Once the data have been captured the next step is to transform the raw data into usable variables in the process of analysing information. The process whereby data is transformed into a "List of required information", forms the essence of the searching and transformation that occur within the research process (Orna & Stevens, 1995:17).

The following transformations were part of this study.

- In order to get all scores for scale items to be in the same direction, particular ratings were reversed for those specific items.
- All scale totals were then transformed to a standardised 100-index (per cent).

6.5 DATA: ANALYSIS AND INTERPRETATION

Once the appropriate research design and suitable means of measuring the relevant variables have been done, the next step was to choose an appropriate statistical procedure to analyse and interpret the data that have been captured. The relevant data must be interpreted, so that results can be obtained against the formulated research problem (hypothesis). The analysis of data is done mainly by means of reliable statistical techniques and methods aimed at investigating variables and their effect, relationships and patterns of intent, within the particular area of study (Wellman & Kruger, 2000:201). For this particular study, data analysis was done through the SAS and SPSS software programmes to produce outputs respectively.

6.5.1 Tabulated data

Data tabulation is the process whereby data are converted into the "List of required information" required by a prior step in the research process. At this stage, the researcher has ample data, but very little information. (Information is "Meaningless" data that have been converted into useful units). The researcher may have many completed questionnaires, but until they are tabulated and analysed it will remain useless (Bennett, 1997:43).

The particular data for this research study was first analysed by means of tabular format. A standard set of tables were produced which included an average response rate for each of the items expressed in terms of a standardised 100-index (per cent). The average response, however, refer to the particular score of each item as expressed in terms of the standardised index.

According to Boyd (1981:407-415), a tabulation plan specifying the precise counts must be obtained and prepared so as to eliminate errors in the raw data. This means, that the researcher must choose between uni-variate and multi-variate tabulations in counting the particular data. The former is a tabulation of a set of responses to one question at a time, and the latter to the tabulation of responses of two or more questions simultaneously (Drew & Hardman, 1998:236-245). In some instances the deviation in the scores of items must be calculated in order to measure certain variations in responses.

Before discussing a few of the statistical methods, it is necessary to distinguish between categorical and continuous variables. Categorical variables are ones that cannot be quantified, or that can be measured only in terms of classes or categories, or that are more conveniently measured in categories than on a continuum (Bennett, 1997:46).

A second form of categorical data can be obtained by employing an ordinal scale. The data obtained are referred to as ordinal-scale responses. Although responses are categorised, the numbers possess the power of rank order. Two summary statistics, the mode and the median, can be used to good effect in interpreting ordinal scale responses (Zikmund, 2000:284).

Continuous variables, on the other hand, are ones that can be quantified or measured on a continuum rather than in a class or category. A respondent's age, height and number of children are examples here. Two types of response categories fall into this group, namely interval-scaled responses and ratio-scaled responses. All summary statistics, namely the mode, median and mean and the standard deviation, can be used to good effect in the case of interval-scaled responses.

The difference between interval-scaled responses and ratio responses, lie in the fact that, despite the fact that the values or units of measurement in the interval scale remain constant throughout, its starting point or zero point, is arbitrary. An interval scale, therefore, may start with zero (0) or one (1), with the result that different interval-scale responses cannot be meaningfully compared or interpreted. The ratio-scaled response, however, has an inherent, unambiguous starting point. The starting point of such scales will always be equal to absolute zero.

The above-mentioned classification should be kept in mind when selecting statistical procedures to analyse data, since some methods can be used only when the data is categorical, whilst in other cases the data has to be of a continuous nature (Parasuraman, 1991:407-447).

6.5.2 Chi-square analysis and analysis of variance

Data that are tabulated in column or row forms and that are representative of different categories, can significantly differ from one another. Differences attributed to sampling variations can make use of the following two techniques.

6.5.2.1 Chi-square analysis

The object of Chi-square analysis is to determine whether the differences observed between two sets of data are attributable to sampling variation or not. In order to employ this method, the following four conditions must be met.

- There must be two observed (collected) sets of sample data or one set of observed sample data and one hypothetical set of data. Typically, these data are arranged in columns and rows, or in frequency distribution form.
- The two sets of data must be based on the same sample size.
- Each cell in the data must contain an observed or hypothetical count (not percentage) of five or larger (refer Chapter 7).

- The different cells in a row or column may represent either categorical variable or continuous variable data that have been put into classes or categories (Boyd, et al, 1981:432).

Applying this method, involves the following.

- Calculating a statistic (called the Chi-square statistic) that summarises the difference between the two sets of data.
- Determining the degrees of freedom associated with the data set.
- Using these two values and a table of the Chi-square distribution so as to determine whether the calculated Chi-square statistic falls within the range which may easily have occurred by chance, as a result of sampling variation (Boyd, Westfall & Stasch, 1981:432-438).

The logic inherent in the χ^2 test allows us to compare the observed frequencies (O_i) with the expected frequencies (E_i) based on the theoretical ideas about the population distribution or the presupposed proportions. In other words, the technique tests whether or not the data come from a certain probability distribution. It tests the "goodness of fit" of the observed distribution with the expected distribution.

Calculation of the chi-square statistic allows us to determine if the difference between the observed frequency distribution and the expected frequency distribution can be attributed to sampling variation. The steps in the process are the following

- Formulate the null hypothesis and determine the expected frequency of each answer.
- Determine the appropriate significance level.
- Calculate the χ^2 value, using the observed frequencies from the sample and expected frequencies.
- Make the statistical decision by comparing the calculated χ^2 value with the critical χ^2 value.

After the chi-square test has been determined appropriately at the ,05 level of significance (or some other probability level), the chi-square statistic may be calculated (Zikmund, 2000:471).

To calculate the chi-square statistic, the following formula is used:

$$\chi^2 = \Sigma \frac{(O_i - E_i)^2}{E_i}$$

where

χ^2 = chi-square statistic
O_i = observed frequency in the ith cell
E_i = expected frequency I the ith cell

The sum-squared differences are, therefore:

$$\chi^2 = \frac{(O_1 - E_1)^2}{E_1} \qquad \frac{(O_2 - E_2)^2}{E_2}$$

Like many other probability distributions, the χ^2 distribution is not a single probability curve but a family of curves. These curves, although similar, vary according to the number of degrees of freedom ($k - 1$). Thus we must calculate the number of degrees of freedom.

6.5.2.2 Analysis of Variance

The major difference between Chi-square analysis and Analysis of Variance is that the latter is used to establish the significance of differences within a single set of data, rather than between two sets of data. This technique is most commonly employed with a set of categorical data collected in an experimental setting (Boyd, Westfall & Stasch, 1981:440-450).

6.5.3 Cross-tabulation, correlation and regression

The statistical procedures already discussed above, determine whether observed differences are significant, but they do not explain why these differences occur. To establish this cross-tabulation, correlation and regression were applied within the boundaries of this study. The use methods assume three things, according to Bennett (1997:48).

- The data to be analysed, are obtained from descriptive studies.
- The data are from representative samples.
- The data include measures on a number of variables for each respondent.

6.5.3.1 Cross-tabulation

Cross-tabulation is a method, which can be used when both the dependent and the independent variables are categorical. The following serves as an example.

Whenever a researcher wants to determine why respondents exhibit different behaviour from other, a number of independent variables could be selected that could influence the behaviour of respondents, and then these are cross-tabulated with the dependent variables (for example average consumption of a product). From this, the researcher would be able to establish whether the independent variable has an effect on the dependent variable (Parasuraman, 1991:407-447).

One of the major drawbacks of cross-tabulation, is that the results must be evaluated subjectively by the researcher. Some researchers employ correlation and regression analysis in order to overcome this problem, provided they have ordinal data at their disposal (Boyd, et al., 1981:456-462).

6.5.3.2 Correlation and regression

Correlation and regression analyses were also used during this study and typically refers to:

- data recorded as continuous variables (ordinal data),
- more than one variable being measured for each respondent, and
- the number of respondents being greater than the number of variables.

Example

When the researcher has two or more sets of variables and he or she wants to determine whether there is a relationship between, for example, income and wine consumption, he could use correlation analysis. It is accepted that there is a positive relationship between the variables of higher levels of wine consumption as associated with higher income. (In other words, the more money people earn, the more wine they drink).

When correlation analysis fails to describe the relationship between two variables, clearly the researcher may resort to regression analysis. Correlation analysis may point to a positive relationship between two sets of data, but it does not describe the effect changing the independent variable will have on the dependent variable (Boyd, et al., 1981:468-482).

6.5.4 Interdependencies: cluster analysis, factor analysis and Alpha factor analysis

One major difference between the methods discussed up to now and that of both cluster analysis and factor analysis is that the latter methods do not treat some of the variables as being independent and others as being dependent. Instead, they attempt to identify interdependencies among a number of variables without treating any of them as being dependent or independent.

In contrast with the previous mentioned methods, alpha factor analyses are used for both binary-type and large-scale data. Cronbach's Alpha coefficient is, therefore, a measure of correlation between observed scores and true scores to allow researchers to determine whether variables derived from test instruments, are reliable or not.

6.5.4.1 Cluster analysis

Cluster analysis is primarily used in market segmentation studies. This method identifies different groups (or clusters) of respondents. Respondents in any one cluster would thus be similar, while those who fell in different clusters, would be different from that of another cluster. This analysis searches through all the data and identifies respondents who have given identical or very similar answers to a certain combination of questions (Bennett, 1997:52).

Cluster analysis is normally used on data, which have been recorded on scales, such as a 5-point or 7-point scale, although it could also be used on continuous variable data and categorical variable data.

As part of the most important research techniques applied within this particular study, extensive attention will now be given to factor analysis, as well as to Cronbach's Alpha coefficient as part of a diverse number of techniques used to discern the underlying dimensions of regularity in phenomena.

6.5.4.2 Factor analysis

The general purpose of factor analysis, is to summarise the information contained in a large number of variables into a smaller number of factors.

If a researcher has a set of variables and suspects that these variables are interrelated in a complex fashion, then factor analysis may be used to untangle the linear relationships into separate patterns. The statistical purpose of factor analysis is to determine linear combinations of variables that aid in investigating the interrelationships. The researcher, however, may want to reduce the large number of variables to certain underlying constructs or dimensions that will summarise the important information contained in the variables. The purpose is thus, to discover the basic structure of a domain and to add substantive interpretation to the underlying dimensions. Factor analysis could accomplish this by combining these questions in order to create new, more abstract variables called factors. In general, the goal of factor analysis is to reduce a large number of variables to as few dimensions or constructs as possible (Zikmund, 2000:544).

Factor analysis, therefore, examines the relationship of exact or large series of variables with every other one so as to determine which are highly correlated with other ones. The process ends with a reduced number of alternative variables. Factor analysis thus calculates a series of factors that are a confirmation of the alternative variables being analysed. Factor analysis can also be used to reduce a large number of variables to a few interpretable dimensions (Blankenship & Breen, 1993:226).

The next step is to analyse the various factor loadings; a factor loading refers to the set of the correlation of the original variable with the factor. Each factor loading is, therefore, a measure of importance of a variable in measuring a particular factor, a means of interpreting and labelling each factor (Zikmund, 2000:545).

In addition to factor loading, the total variance of variables (factors) must be explained. Severe factor loading can be very helpful in this regard and indicate what percentage of the variance in an original variable is explained by a factor (Sudman & Blair, 1998:547).

The result is, therefore, that factor analysis procedures also apply factor scores that represent each observation's calculated value or score on each of the factors. The factor score will represent an individual's combined response to the several variables representing the factor. The factor scores may be used in subsequent analyses. When the factors are to represent a new set of variables that may predict or will be dependent on some phenomenon, the new input may be factor scores.

In addition to reducing a large number of variables to a manageable number of co-linearity dimensions, factor analysis may also reduce the problem of multi-co-linearity in multiple regression. If several independent variables are highly correlated, a factor analysis as a preliminary step prior to regression analysis and the use of factor scores, may reduce the problem of having several inter-correlated independent variables, as already mentioned. Thus factor analysis may be utilised to meet the statistical assumptions of various models (Zikmund, 2000:346).

By applying factor analysis, the researcher may also wish to know how much a variable has in common with all other factors. Communality is a measure of the percentage of variable's variation that is explained by the factors. A relatively high communality indicates, that a variable has much in common with the other variables taken as a group (Zikmund, 2000:547).

The question now arises, "How many factors will be in the problem's solution?" This question requires a complex answer. It is complex, because there can be more than one possible solution to any factor analysis problem, depending on factor rotation. The term rotation is important in factor analysis and it should receive some attention. Solutions to factor analysis problems may be portrayed by geometrically plotting the values of each variable for all respondents or observations made. Geometric axes may be drawn to represent each fact. New solutions are represented geometrically, by rotation of these axes. For example, in a scatter plot, the regression line is represented as the original X-axis rotated, so that it approximates the regression line. This type of rotation is known as variance (variability) of the new factor (variable). Therefore, a new solution with fewer or more factors is called a rotation (Cooley & Lohnes, 2001:3).

Other terminology closely inter-linked with factor analysis is a number of universal terms, such as the following.

- ***Eigen values***

  These equal the sum total of the squares loading for the variables on a factor, provided that a measure of the percentage of variance is contributing variables that are explained by the factor.

  Eigen values can be found for square symmetric matrices. There are as many Eigen values as there are rows (or columns) in the matrix. A realistic description of an Eigen value demands a sound knowledge of linear algebra. However, conceptually they can be considered to measure the strength (relative length) of an axis (derived from the square symmetric matrix). Eigen values are also known as Latent Variables (Zikmund, 2000:347).

- ***Rotated matrix***

This matrix represents the relationship between the original *p*-variables and the *k*-orthogonal linear combinations of these variables, the canonical variates or factors. The latter are only unique up to a rotation in the *k*-dimensional space they define. A rotation can then be found that simplifies the structure of the matrix of loadings, and hence the relationship between the original and the derived variables. That is, the elements, λ^*_{ij}, of the rotated matrix, ^*, are either relatively large or small. The rotations may be found by minimising the criterion:

$$V = \sum_{j=1}^{k}\sum_{i=1}^{p} (\lambda^*_{ij})^4 - \frac{\gamma}{p} \sum_{j=1}^{k}\left[\sum_{i=1}^{p}(\lambda^*_{ij})^2\right]^2$$

where the constant γ gives a family of rotations with $\gamma = 1$ giving varimax rotations and $\gamma = 0$ giving quartimax rotations.

It is generally advised that factor loadings should be standardised, so that the sum of squared elements for each row is one, before computing the rotations.

The matrix of rotations, *R*, such that ^* = ^*R*, is computed by using first an algorithm, which involves the pairwise rotation of the factors. Then using a similar method makes a final refinement, but instead of the Eigen value decomposition, the algorithm has been adapted to incorporate singular value decomposition (Sudman & Blair, 1998:548).

- ***Orthogonal matrix***

A square matrix **A** (of real elements) is said to be orthogonal if and only if

$$\mathbf{A}^{-1} = \mathbf{A}'.$$

From this definition, it follows that an orthogonal matrix has the property **A'A** = **I** and that the determinant of an orthogonal matrix is plus or minus one. Also, the inverse (as well as the transpose) of an orthogonal matrix is itself an orthogonal matrix (Bennett, 1997:54).

The researcher, however, must be aware of blindly using statistical procedures before understanding the full implications of the various options and the assumptions they are based on. The desire is to attempt to fit the technique to the problem and not the other way around.

Factor analysis, therefore, calculates a series of factors that are a weighed combination of the variables being analysed. These combinations can be expressed by applying the following formula -

$$F = w_1 x x_1 + w_2 x_2 \ldots + w_k x_k$$

where F is the factor x_1 through x_k are the variables being analysed, and w_1 through w_k weights applied to those variables: the weights for each factor and the various contributing variables, subject to a constraint that each factor is uncorrelated to al preceding factors (Zikmund, 2000:538).

The purpose of factor analytic techniques is firstly to reduce the number of variables and secondly, to detect structure in the relationship between variables. Therefore, factor analysis is applied as a data reduction or structure detection method (Zikmund, 2000:544).

6.5.4.3 Alpha Factor Analysis (Cronbach's Alpha)

The point of departure for the method of Alpha Factor analysis, as stated by its developers (Kaiser & Caffrey, 1965), ("... is that common factors (in a sample of tests) are to be determined which have maximum correlation with corresponding universe common factors". A set of factors satisfies this principle if each of them has maximum generalisability. The concept of generaliability has been studied by many researchers and can be traced back to Kuder-Richardson or the KR-20 formula of reliability for sum scales. In either case, the purpose is to check for the internal consistency within a single test (Cooley & Lohnes, 2001:23).

What is Cronbach Alpha? The Cronbach Alpha coefficient is a measure of squared correlation between observed scores and true scores. Put another way, reliability is measured in terms of the ratio of true score variance to observe score variance. The theory behind it, is that the observed score is equal to the true score, plus the measurement error (Y = T + E). For example, if I know 80 per cent of the materials but the score is 85 per cent because of lucky guessing, then the observed score is 85 while the true score is 80. The additional 5 points are due to the measurement error. A reliable test should minimise the measurement error so that the error is not highly correlated with the true score. On the other hand, the relationship between true score and observed score should be strong. Therefore, the reliability comes to the forefront when variables developed from summated scales are used as predictor components in objective models. Since summated scales are an assembly of interrelated items designed to measure underlying constructs, it is very important to know whether the same set of items would elicit the same responses if the same questions are recast and re-administered to the same respondents. Variables derived from test instruments are declared to be reliable only when they provide stable and reliable responses over a repeated administration of the test (http://www.joe.org/joe 1999 April/tt3.html).

Computation of Alpha is based on the reliability of a test relative to other tests with the same number of items, and therefore measuring the same construct of interest (Cooley & Lohnes, 2001:3).

For the purpose of this research study, either SAS or SPSS can perform this analysis effectively. SAS is a better choice due to its better detail. The SAS syntax to run Cronbach Alpha is as follows.

```
Data one;
        Input post_em1_post_em5;
Cards;
1 1 1 0 0 1
1 0 1 1 1 0
1 1 1 1 1 1
0 0 0 1 1 1
0 1 0 0 1 0
        proc corr alpha nocorr nomiss; var post_em1_post_em5; run;
```

In this example, the "nocorr" option suppresses the item correlation information. Although the correlation matrix can be used to examine whether particular items are negatively correlated with others, a more efficient way, is to check the table entitled "if items are deleted¡K". This table tells you whether particular items are negatively correlated with the total and thus it is recommended to suppress the correlation matrix from the output (http://www.ats.ulca.edu/stat/spss/faq/alpha.html).

It is important to include the "nomiss" option in the procedure statement. If the tester has not answered several questions, Cronbach Alpha will not be computed. In surveys, it is not unusual for respondents to skip questions that they don't want to answer. Also, if you use a scanning device to record responses, the scanner may not detect slight pencil marks. In both cases, you will have "holes" in your data set and the Cronbach Alpha procedure will be halted. To prevent this problem from happening, the "nomiss" option tells SAS to ignore cases that have missing values.

However, in the preceding approach, even if the tester skips one question, his entire test will be ignored by SAS. In a speeded test where testers may not be able to complete all items, the use of "nomiss" will lead to some loss of information. One way to overcome this problem, is to set a criterion for a valid test response. It is assumed, that 80 per cent of test items must be answered in order to be included into the analysis. The following SAS code should be implemented:

```
Data one; infile "c:\data";
        Input x1-x5;
        If nomiss (of x1-x5) > 1 then delete;
        Array x{I} x1-x5;
                Do I=1 to 5;
                If X(I) =. Then X (I) – 0;
        Proc corr alpha nomiss; var x1-=x5; run;
```

In this preceding SAS code, if a record has more than one unanswered question (80 per cent), the record will be deleted. In the remaining records, the missing values will be replaced by a zero and thus these records will be counted into the analysis (http://www.joe.org/joe 1999 April/tt3.html).

It is acceptable to count missing responses of a test as wrong answers and assign a value of "zero" to them. It is not appropriate to do so if the instrument is a survey such as an attitude scale. One of the popular approaches for dealing with missing data in surveys, is the Mean Replacement Method (Afifi * mp; Elashoff, 1966), in which means are used to replace missing data. The SAS source code for the replacement is the same as the preceding one, except for the following line.

```
If X (I) =. Then X (I) = mean (of x1-x5);
```

Cronbach Alpha can also be used with both binary-type and large-scale data. On the other hand, KR can be applied to dichotomously scored data only. For example, if your test questions are multiple choices or true/false, the responses must be binary in nature (either right or wrong). If your test is composed of essay-type questions and each question is worth 10 points, then the scale is ranged from 0 to 10.

To interpret the SAS output, the mean output as shown, tells the tester how difficult the items are. In this case the answer is either right (1) or wrong (0). The mean ranging from 0 to 1. 0.9, indicates that the question is fairly easy and thus 90 per cent of the testers have scored it. It is a common mistake that people look at each item individually and throw out the item that appears to be too difficult or too easy. Actually the entire test should be taken into consideration.

The Cronbach Alpha procedure involves two coefficients.

- ***Raw***

  It is based upon item correlation. The stronger the items are interrelated, the more likely it is the test is consistent.

- ***Standardised***

  It is based upon item co-variance. Variance is a measure of how a distribution of a single variable (item) spreads out. Co-variance is a measure of the distributions of two variables. The higher the correlation coefficient is the higher the co-variance.

Some researchers mistakenly believe that the standardised Alpha is superior to the raw Alpha because they assume that standardisation normalises skewed data. Actually standardisation is a linear transformation, and thus it never normalises data. Standardised Alpha is not superior to its raw counterpart. It is used when scales are comparable, because as mentioned before, variance and co-variance are taken into account for computation (http://www.joe.org/joe 1999 April/tt3.html).

In order to determine whether the entire test is consistent, Cronbach Alpha computation examines the co-variance matrix – all possible pairs, to draw a conclusion. Not all the information is usable. Users of Cronbach's Alpha have often wondered whether the liability that they obtained, is both good and representative.

However, the higher the Alpha is, the more reliable the test is. There isn't a generally agreed cut-off. Usually 0.7 and above is acceptable (Nunnally, 1978). It is a common misconception that if the Alpha is low, it must be a bad test. The test may measure several attributes/dimensions rather than one and thus the Cronbach Alpha is deflated. For example, it is expected that the scores of GRE-Verbal, GRE-Quantitative, and GRE-Analytical may not be highly correlated because they evaluate different types of knowledge.

If the test is not internally consistent, the researcher may want to perform factor analysis to combine items into a few factors, as already discussed.

The formula for calculating Cronbach's Alpha (α) is,

$\alpha = (k / k - 1)*[1-\Sigma (S_i^2)S^2{}_{sum}]$

where:

S_i^2 = the variance for the k individual items; and

$S^2{}_{sum}$ = the variance for the sum of all items.

If there is no true score but only error in the items (which is esoteric and unique, and therefore, uncorrelated across subjects), then the variance of the sum will be the same as the sum of variance of the individual items (http://www.statsoft.com/textbook/stathome.html).

Therefore, coefficient Alpha will be equal to zero. If all items are perfectly reliable and measure the same thing (true score), then coefficient Alpha is equal to (1), as already mentioned. (Specifically, $1-\Sigma (S_i^2)S^2{}_{sum}$ will be equal to (k-1)/k; if multiplied this by k/(k-1) the answer = 1).

6.6 VALIDITY AND RELIABILITY

Researchers often neglect to refer to any possible shortcomings and negative aspects related to the research results in question. Reliability and validity are major contributing factors for any research data especially in the case of this study for it to be useful and is, therefore, a necessity to prove the reliability and validity of the particular study in question. It is also important that any given measuring instrument must measure the following components.

- The construct intended.
- Irrelevant construct.
- Random measurement errors (Fink, 1998:110).

6.6.1 Validity of measures used

According to Cooper & Schindler (1998:148), validity addresses the problem of whether a measure (for example, an attitude measure) measures what it is supposed to measure. Validity therefore, refers to the measuring instruments applied, and that these measuring instruments are valid only to the extent that it measures what it is intended to measure.

The following types of validity can be identified, according to Locke, Silverman & Spirduso (1998:117):

- ***Internal validity***

  It is concerned with whether the research has been designed so that it truly deals with what is being examined. For example, can the data collected, actually be used to answer the questions being asked?

- ***External validity***

  This issue is concerned with the external question of whether or not the results will remain truthful when subsequently applied to people, situations or objects outside the scope of the original investigation.

For the purpose of this study, attention will now be given to the nature of both the important aspects relating to the concept validity.

6.6.2 Internal – versus external validity

The most common circumstance, in which external validity becomes an issue, occurs when one group of people is examined in a particular study, but the results and conclusions are applied to another group. What is true for the particular sample of people in the study, simply may not be valid for (may not tell the truth about) another group of people – particularly if that group differ in some substantial way.

Medical research commonly presents such problems of external validity. Because studies of this kind are so expensive and consume so much precious time, it can be tempting to extend hard-won knowledge about medicines or medical procedure to people not included in the samples of earlier investigations. It also can be unfair, misleading, wasteful, or dangerous (Locke, Silverman & Sipuro, 1998:117-121).

In contrast, internal validity is not concerned with generalisability as already mentioned, but with the integrity of the study itself. These issues range from simple and perfectly obvious to arcane and exceedingly obscure, but in the end, they all have to do with whether the study has been designed to yield truthful results.

According to Campbell and Stanley (1983) "instrumentation" of a study, presents some of the most common problems of internal validity. Data collection takes a variety of forms, including machines that use computer programmes to direct the monitoring of biological processes, survey forms filled out by door-to-door interviewers, psychological tests completed by subjects, field notes from investigators watching children on a playground, and systematic examination of cultural phenomena through the recording of words used in books, television, or movies: all very different methodologies, but all subject to the same question, "Do these data provide a truthful reflection of what the study is intended to examine?"

Nevertheless, the problems of internal and external validity are ubiquitous and must be confronted by researchers in study formats as disparate as questionnaire surveys and field ethnographies (Locke, Silverman & Spirduso, 1998:117-121).

6.6.2.1 *Other forms of validity applicable*

According to Zikmund (2000:282), validity can also include the following types of validity.

- ***Construct validity***

  Construct validity is established by the degree to which the measure confirms a network of related hypotheses generated from a theory based on the concepts. Establishing construct validity occurs during the statistical analysis of the data. In construct validity, the empirical evidence is consistent with the theoretical logic about the concepts. In its simplest form, if the measure behaves the way it is supposed to, in a pattern of inter-correlation with a variety of other variables, there is evidence for construct validity. To achieve construct validity, the researcher must have already determined the meaning of the measure by establishing what basic researchers call "convergent validity" and "discriminant validity".

- ***Criterion-related validity***

  With criterion validity, the criterion may be a construct that one would logically expect to be associated with the new measure. Thus, to establish validity, the new measure should "converge" with other similar measures. A measure of a theoretical concept has convergent validity when it is highly correlated with different measures of similar constructs.

- ***Discriminant validity***

  A measure has discriminant validity when it has a low correlation with measures of dissimilar concepts. This is a complex method of establishing validity and of less concern to the applied researcher than to the basic researcher.

- ***Concurrent validity***

Concurrent validity refers to a classification of criterion validity, whereby a new measure correlates with a criterion measure taken at the same time.

- ***Predictive validity***

Predictive validity refers to a classification of criterion validity whereby a new measure predicts a future event or correlates with a criterion measure administered at a later time.

- ***Content validity***

Content validity refers to the subjective agreement among professionals that a scale logically appears to reflect accurately what it purports to measure. The content of the scale appears to be adequate. When it appears evident to experts that the measure provides adequate coverage of the concept, a measure has face validity.

- ***Face validity***

Face validity refers to professional agreement that a scale logically appears to be accurately reflecting what was intended to be measured.

6.6.3 Reliability of measures used

Trochim (1997:2) defines reliability as the extent to which the measurement process is free from random error and that it is concerned with consistency, accuracy and predictability of the actual research findings. It is also important to distinguish between (at least) three irrelevant sources of systematic variations with the context of measurement, namely:

- measurement occasion
- measurement form, and
- measurement user.

Wellman & Kruger (2000:142:145), distinguish between the following types of reliability used within the research process.

- ***Test-retest reliability***

  Test-retest reliability refers to the degree to which a measurement/test is immune to a particular measurement/test occasion on which it is administered, so that scores obtained on one occasion, may be generalised to those which could potentially have been obtained on other comparable occasions. It also refers to the consistency of repeated measures of the same theoretical concept over a period of time and the correlation between those measures.

- ***Internal consistency***

  Internal consistency implies a high degree of generalisability across the item within the measurement/test. It also refers to two or more measures of the same theoretical concept obtained at the same point in time and the agreement between the measures ascertained.

- ***Parallel-form reliability***

  Parallel-form reliability of a measurement/test is determined by the interchangeable versions of a particular measurement/test, which have been compiled to measure the same construct and quality well, but by means of different content. This could also be measured by administering both forms that are measured and getting the desired correlation between the two forms.

- ***Interrater or inter-coder reliability***

Interrater or inter-coder reliability refers to the unreliability due to accidental, inconsistent behaviour on the part of the individual administering or scoring the measurement/test. In such cases, the frequency is found that a particular tester consistently marks either too strictly or too leantly. Interrater reliability is, however, appropriate when the measure is a continuous one in which case the correlation can be calculated between various ratings of the two concepts observed.

6.6.4 The importance of validity and reliability for research

It is clear, that the researcher must establish ways of collecting data that are both valid and reliable (Martins, Loubser & Van Wyk, 1996:104).

In many cases, instruments for collecting data can be checked for validity and reliability before they are actually put to use in a study. This is true, for example, of written tests, electronic and mechanical hardware, and rating scales. Often, reports contain descriptions of such verification, including figures that display precisely how close the research tools come to theoretically perfect validity and reliability.

However, validity and reliability remain elusive qualities, and few studies are designed in ways that resolve all possible threats to consistent truth. The reader of a research report has the right to expect that researchers have shown awareness of such issues, report what they have done to control the problems, and their success in doing so (Orna & Stevens, 1995:174).

The researcher must however, remember that standards for validity and reliability cannot be applied as simple absolutes. Given the complex nature of many research questions, reviewers often must ask, "How much lack of confidence in the consistent truthfulness of this study is tolerable?" The answer will be determined by many factors, but everyone – reviewers, editors, researchers, and readers – knows what is ideal. The research should come as close to producing reliably valid results as human skill and effort can devise (Orna & Stevens, 1995:176).

6.7 CONCLUSION

In this chapter only a few methods and techniques have been discussed in order to create scientifically obtained knowledge by using objective methods and procedures. However, research involves different methods for different studies because they have different aims. In this particular study, relevant and applicable methods and research techniques were used in order to investigate and test the research problem and objectives by means of tough methodological investigation techniques.

The universum was identified, from which a suitable sample frame was derived. The next step was to draw up a preliminary questionnaire in order to finalise the research questionnaire. The relevant data were captured by means of statistical programmes, edited, coded and finally analysed. The various methods, techniques and steps used, were clearly discussed within the scope of this particular chapter. Various tests were also applied in order to determine the viability and reliability of the research questionnaire and final results of the study.

During the research study, both a preliminary and a final questionnaire were drawn up, tested and distributed to approximately 80 respondents, of which 53 respondents successfully replied. This means, that a 66,25 per cent success rate was achieved. The relevant data were then captured on computer, edited, coded and finally analysed and interpreted.

In the next chapter the empirical findings of this particular research study will be discussed in detail.