CHAPTER IX
RESEARCH DESIGN

9.1 INTRODUCTION

What social researchers find most interesting about studying social organizations is not how well they operate, but which characteristics do not seem to further their goals - in other words, which activities are dysfunctional (Baker, 1988:9).

In this chapter the research design, the population and sample determination, the collection and interpretation of data, and the relevant statistical methods are discussed.

9.2 THE RESEARCH DESIGN

According to Leedy (1993:139) the nature of the data and the problem for research dictate the research methodology. "All data, all factual information, all human knowledge must ultimately reach the researcher either as words or numbers. If the data is verbal, the methodology is qualitative; if it is numerical, the methodology is quantitative". Leedy (1993:243) describes quantitative methods as valuable to express and describe information that is more difficult by using words only. According to Dooley (1990:276) qualitative research refers to social research based on non-quantitative observations made in the field and analyzed in non-statistical ways. Dooley (1990:277) explains that non-quantitative observation is less structured than quantitative research, being flexible, spontaneous, and open-ended. A qualitative observer who looks, listens, and flows with the social currents of the setting can be expected to acquire perceptions from different points of view. Comparing and contrasting different interviews and perceptions of the same subject or behaviour are likely to produce a more detailed and less distorted understanding of the real issues at hand.

Thus, even though the quantitative criteria of reliability and validity cannot be applied to qualitative data, such data have an intuitive appeal as accurate and unbiased (Dooley, 1990:277). The most obvious difference between quantitative and qualitative research can be seen in the notational system used to report the findings. Numbers, figures, and inferential statistics appear in the result sections of quantitative studies. In contrast, qualitative research typically reads like a story written in everyday language (Dooley, 1990:279). In this study a qualitative and quantitative research strategy were utilized to investigate the factors that influenced the effectiveness or ineffectiveness of the transformation process. Quantitative techniques were used to assess attitudes of the factors that influenced transformation, to investigate work-related needs, work motivation, and locus of control variables. A qualitative strategy was used to gather information about the need for change in this organization, the diagnosis of the current organization, planning of change strategies, implementation of change interventions, and management of the transformation process within the organization. The researcher's role was established as an objective observer of each and every aspect of the transformation process that entailed data collection, evaluation and feedback to the external consultants. The data for the quantitative research is highlighted in terms of age, home language, religion, qualifications, income, job grades, geographical area employed, and occupational levels as independent variables. The survey method (questionnaires) was selected as the most appropriate method to gather data from the employees.

9.2.1 SURVEY RESEARCH

Dane (1990:338) defines survey research as a method of "obtaining information directly from a group of individuals". Chadwick, Bahr and Albrecht (1984:442) view it as "a research technique that puts questions to a sample of respondents by means of a questionnaire or an interview". Self-administered questionnaires, interview surveys, and telephone surveys are three main methods of survey research (Baker, 1988:168; Babbie, 1989:238).

Theron (1992:337) notes that the survey research process starts with the selection of valid measurement(s)/questionnaire(s) that contain the questions that measure the intended concept(s). Therefore the questions need to be worded carefully and unambiguously, must be acceptable to the respondents, not give offence, and be easily understood by everyone (Theron, 1992:337). Once the questionnaire has been selected or developed, the respondents need to be selected. The relevant criterion in selecting respondents is that the questions should apply to the population from which the respondents have been selected (Theron, 1992:337). The next step was to administer the questionnaires. The questionnaires were distributed by the researcher to all employees in the organization with instructions on how they had to be completed, and when they had to be returned.

9.2.2 THE SURVEY RESEARCH PROCESS

Baker (1988:174-175) discusses four types of questions that may form part of a questionnaire, viz. closed-ended questions, open-ended questions, contingency questions, and matrix questions. Examples of a matrix questionnaire are the response categories of a Likert scale. The respondents select a response from a set of five or seven response categories, as used in the Motivation, Locus of Control, and Transformation Questionnaire. Open-ended questions were also used near the end of the Transformation Questionnaire for more detailed and personalized answers to sensitive questions. Open-ended questions should be worded in such a way that they are understandable. The set of questions should also be designed in such a way that they effectively assess the attitudes towards, and measure the topic concerned (Baker, 1988:168).

9.2.3 ADMINISTERING THE QUESTIONNAIRES

Chadwick et al.(1984:147) suggest two strategies for collecting data by self-administered questionnaires, namely hand-delivered to individual respondents and collected after a few days, or administered to groups. According to Chadwick et al.(1984:147) the second strategy is more efficient. It enables the instructor to explain the purpose of the questionnaire, as well as the instructions for completion and to handle individual enquiries. The strategy also ensures a common understanding and motivation of the group, which saves time and still allow respondents time to complete the questionnaire privately.

The Motivation and Locus of Control Questionnaire was administered after the first five months of transformation, to groups of voluntary employees in Head Office and all the Branches of the organization. The researcher administered the questionnaires to all the groups, explaining the purpose and aim of the study, as well as the instructions for completion. On completion the questionnaires were handed to the instructor.

The Transformation Questionnaire was administered after the first eleven months of transformation, to groups of voluntary employees in Head Office only. The researcher administered the questionnaires to all the groups, explaining the purpose and aim of the study, as well as the instructions for completion. On completion the questionnaires were handed to the instructor.

9.3 POPULATION AND SAMPLE DETERMINATION

Baker (1988:144) argues that the quality of a sample, however careful the selection, can be no better than the sampling frame from which it is drawn. If the sampling frame is not truly representative of the population, it supposedly enumerates, then the sample cannot be representative of the population. Steyn, Smit and Du Toit (1987:12) define the population as the total group of people or the comprehensive collection of items that are relevant to the study. Supporting that definition, De la Rey (1978:16) argues that a population should be seen as a whole, while the sample can be viewed as a part of the whole. Baker (1988:144) defines a sample as a selected set of elements or units drawn from a larger whole of all the elements, the population. The population, in this case, is the total work force of a large agricultural financier, which amounts to 1 022 employees. Table 9.1 presents the population of the organization.

From Table 9.1 it is evident that the majority of the population is 40 years and younger. The majority is male and married. From the population 17,8% have tertiary qualifications. The largest group of the population have more than 21 years of service and the second largest group have 16-20 years of service.

TABLE 9.1: BIOGRAPHICAL DATA OF THE POPULATION.

	Frequency	Percentage	Cumulative percentage
Age			
18 - 20 years	14	1,4	1,4
21 - 25 years	184	18,0	19,4
26 - 30 years	213	20,8	40,2
31 - 40 years	337	33,0	73,2
41 - 50 years	196	19,2	92,4
Over 51 years	78	7,6	100,0
Total	1 022	100,0	-
Gender			
Male	581	56,8	56,8
Female	441	43,2	100,0
Total	1 022	100,0	-
Marital status			
Married	630	61,6	61,6
Unmarried	336	32,9	94,5
Divorced	56	5,5	100,0
Total	1 022	100,0	-
Educational qualifications			
Matric	840	82,2	82,2
Diploma	93	9,1	91,3
Degree	70	6,8	98,1
Post-graduate degree	19	1,9	100,0
Total	1 022	100,0	-
Years of service			
Less than a year	51	5,0	5,0
1 - 2 years	131	12,8	17,8
3 - 5 years	112	10,9	28,7
6 - 10 years	152	14,9	43,6
11 - 15 years	148	14,5	58,1
16 - 20 years	183	17,9	76,0
More than 21 years	245	24,0	100,0
Total	1 022	100,0	-

9.4 STATISTICAL METHODS

Data will be extensively analyzed according to criteria developed and expressed by Ferguson (1981), Tabachnick and Fidell (1983 and 1989), Ott and Mendenhall (1990), Shavelson (1981) and Harris (1975). The major tools of analysis may be descriptive statistics, correlational statistics, analysis of variance, Student's t test, Kruskal-Wallis non-parametric one-way analysis of variance, Hotelling's T^2 test, discriminant analysis and the Mann-Whitney test. The researcher hopes to ascertain the influence of independent or moderator variables such as age, gender, language, marital status, religion, educational qualifications, income, years of service, geographical area employed, and job grade on transformation factors.

The applicable statistical methods available on the computer programmes Statistical Packages for the Social Sciences (SPSS[R]), and Statistical Analysis Systems (SAS) - will be utilized to analyze the work-related needs or motivation factors, the locus of control factors, and the attitudes related to transformation factors.

9.4.1 ANALYSIS OF VARIANCE

Bohrnstedt and Knoke (1988:219) define analysis of variance (Anova) as "a statistical test of the difference of means of two or more groups". Ferguson (1981:234) defines Anova as "a method for dividing the variation observed in experimental data into different parts, each part assignable to a known source, cause or factor". Anova is thus a method to statistically ascertain whether or not differences between two or more groups exist (Theron, 1992:343). The variance is partitioned into variance between groups:

$$\sigma^2 = \frac{n\,\Sigma d^2}{r - 1} \qquad \text{.....A}$$

and variance within groups:

$$\sigma^2 = \frac{\Sigma\Sigma x_i^2}{r\,(n - 1)} \qquad \text{.....B}$$

and is expressed as the ratio $\frac{A}{B}$, called the F ratio (Du Toit, 1963:108). Theron (1992:343) notes that besides the fact that groups can be compared to establish reliable differences between them, the extent to which the dependent variables differ as a function of group membership can be determined, as well as the strength between independent and dependent variables. According to Theron (1992:343) the logic behind an analysis of variance may be explained as follows: "The Anova model tests the null hypothesis (H_o) that all sample means are drawn from the same population and therefore are equal. The H_o may be presented as H_o: $\mu_1 = \mu_2 \ldots = \mu_j$. This implies that the group means will be equal to the grand mean. The Anova model revolves around the question of how much of the total variation in the dependent variable (DV) can be explained by the independent variable (IV) (treatment variable) and how much is left unexplained" (Theron, 1992:344). The general Anova model with one IV may be presented as:

$$Y_{ij} = \mu + a_j + e_{ij} \quad \text{where}$$

e_{ij} = error term. (Error term is the difference between the observed score and the score predicted by the model).

This formula, according to Bohrnstedt et al.(1988:222), indicates that the score of observation I, which is also a member of group j (hence Y_{ij}), is a function of a group effect, a_j, plus the population mean and random error, e_{ij}. The numerator of the sample variance is then partitioned into two independent additive components to enable the researcher to estimate the proportion of variance in Y_{ij}. The formula:

$$\sum_{i=1}^{n} (Yi - \bar{Y})^2$$ is applied to divide the numerator into two

components.

$$\sum_{i=1}^{N} (Yi - \bar{Y})^2 = \sum_{j=1}^{J} \sum_{i=1}^{nj} (Y_{ij} - \bar{Y})^2$$ as the sum of the

observations across the J subgroups or treatments equal the total sample size N. The term:

$$\sum_{j=1}^{J} \sum_{i=1}^{nj} (Y_{ij} - \bar{Y})^2$$ is called the sum total

of the squares (SS_{total}) and is partitioned into a between sum of squares ($SS_{between}$) and a within sum of squares (SS_{within}). Variance is thus expressed as the F ratio:

$$\frac{MS_{between}}{MS_{within}}$$ (Theron, 1992:345).

The total sum of squares refers to a number obtained by subtracting the scores of a distribution from their mean, squaring and summing these values. Between sum of squares is a value obtained by subtracting the grand mean from each group mean, squaring these differences for all individuals and summing them. Within sum of squares refers to the value obtained by subtracting each subgroup mean from each observed score, squaring and summing them (Bohrnstedt et al., 1988:219-224; Ott et al., 1990:527-540). Dividing the $SS_{between}$ and SS_{within} by their respective degrees of freedom, provide the $SS_{between}$ and the SS_{within} with which the F ratios may be calculated.

The different techniques of analysis of variance are one-way analysis of variance, factorial Anova, one-way Manova and factorial Manova. A one-way classification of variance enables the researcher to measure the effect of an independent variable on (a) dependent variable (s) (Ferguson, 1981:235). In factorial Anova two independent variables or experimental variables are simultaneously investigated. It involves two bases of classification. These classification variables in analysis of variance are called factors. Because there are two factors, the design is termed a "two-way design" (There might be three or more factors but the larger the design the more difficult the interpretation of results). The two-way design contains an effect term for each factor and a term for the interaction effect produced by both factors operating simultaneously. Each score is considered to be influenced by its row, column and cell. Effects due to either column or row are called main effects while the effects due to column and row in combination are called interaction effects (Mason et al., 1989:231). Main effects are thus due to a single factor while interaction effects refer to influences of two or more factors in combination.

In a two-way factorial Anova the total sum of squares is partitioned into three parts, viz. a between-rows sum of squares, a between-columns sum of squares and an interaction sum of squares. The total sum of squares of all observations about the grand mean is:

$$\sum_{r=1}^{R} \sum_{c=1}^{c} \sum_{i=1}^{n} (X_{rci} - X_{\ldots})^2$$ (Ferguson, 1981:253).

However, with more than one measurement for the treatment combinations (experimental conditions), the total sum of squares may be divided into four additive components, viz. a between-rows sum of squares, a between-columns sum of squares, an interaction sum of squares and a within-cells sum of squares. The variance is expressed as the ratio of the interaction effects (S_{rc}^2) to the within cells effect (S_w^2):

$$F_{rc} = \frac{S_{rc}^2}{S_w^2}$$

(Ferguson, 1981:252-266; Theron, 1992:347).

Multivariate analysis of variance (one-way Manova) is "a generalization of analysis of variance to a situation in which there are several dependent variables" (Tabachnick et al., 1989:371). For example, a researcher would like to measure the effect of different types of treatment on three types of anxiety (test anxiety, anxiety related to life stresses, and so-called free-floating anxiety). The independent variable is the different types of treatment offered (desensitization, relaxation treatment, and a control group with no treatment). Subjects are then randomly subjected to the treatment, and are measured on the three types of anxiety. The dependent variables are the scores on all three measures for each subject. Manova is used to assess whether a combination of the three anxiety measures varies as a function of the treatment (Tabachnick et al., 1989:371). Factorial Manova implies the extension of Manova to research comprising more than one independent variable (Tabachnick et al., 1983:58). Manova has the advantage that the measuring of several dependent variables may improve the chance of discovering changes produced by different treatments and interactions. Manova may also reveal differences not shown in separate Anovas. However, the analysis is quite complex. In factorial Manova, a " best linear combination' of dependent variables is formed for each main effect and interaction. The combination of dependent variables that best separates the groups of the first main effect may be different from the combination that best separates the groups of the second main effect or the cells from an interaction" (Tabachnick et al., 1989:371).

Manova is also subjected to the limitations of unequal sample sizes, multivariate normality, outliers, linearity, multi-collinearity and singularity and homogeneity of variance-covariance (Tabachnick et al., 1983:226-227). These limitations are discussed in detail under the heading "Discriminant analysis" in paragraph 9.4.3.

Manova revolves around research questions such as: Is change in behaviour associated with different levels of an independent variable due to something other than random fluctuations or individual differences occurring by chance (main effects of independent variables) and do independent variables interact in their effect on behaviour (interactions among independent variables)(Tabachnick et al., 1983:226-227)? According to Tabachnick et al. (1983:235-238) an appropriate data set for Manova should contain one or more independent variable(s) (classification variables) and two or more dependent variables (measures) on each subject or sampling unit within each combination of independent variables. Each independent variable may have two or more levels. The Manova equation for equal n can be developed through extension from Anova. Anova involves the partitioning of the total variance into two independent additive components, viz. sum of squares. For factorial designs the variance between groups can be further partitioned into variance associated with the first independent variable, variance and variance associated with the interaction between the two independent variables. Each n is the number of scores composing the relevant marginal or cell mean or $SS_{bg} = SS_D + SS_T = SS_{DT}$ (Tabachnick et al., 1983:238; Theron, 1992:348).

Analysis of variance may also be used to conduct a profile analysis as Anova is analogous to the parallelism test, levels test and flatness test (discussed under Hotelling's T^2 test). Treatments correspond to rows, the dependent variables to columns and the interaction between columns and rows is also assessed (Harris, 1975:81).

Multiple comparison techniques (mean separation tests) allow the researcher to investigate post hoc hypotheses involving the means of individual groups or sets of groups. Examples of multiple comparison techniques are the Duncan test, the T test, Tukey's test, the Bonferroni test, and the Scheffé test. According to the SAS /STAT Users' Guide (1990) there is a serious lack of standardized terminology in the literature on multiple comparisons. Failure to reject a hypothesis that two or more means are equal should not lead to the conclusion that the population means are equal. "Failure to reject the null hypothesis implies only that the difference in population means, if any, is not large enough to be detected with the given sample size" (SAS /STAT Users' Guide, 1990:941). The Scheffé test is the most popular and is a relatively conservative multiple comparison technique (Shavelson, 1981:470; Howell, 1989:240). This test is done on all pairs of means - the T option in the means statement. However, it is difficult to calculate the exact probability, but a pessimistic approximation can be derived by "assuming the comparisons are independent, giving an upper bound to the probability of making at least one type of error" (SAS /STAT Users' Guide, 1990:941). Two other methods, the Bonferroni (Bon) additive inequality, and the Sidak multiplicative inequality, can be utilized for control of the maximum experiment wise error rate (MEER) under a set of contrasts, or other hypothesis tests. According to the SAS /STAT Users' Guide (1990:943) the Bonferroni inequality can provide simultaneous inferences if more than one hypothesis has to be tested. Any statistical application can be utilized in these comparisons. Tukey, as quoted by the SAS Users' Guide, proposed a test specifically for pair wise comparisons based on the studentized range. This test is also called the " honest significant difference test " that controls the MEER when sample sizes are equal (SAS /STAT Users' Guide, op.cit.).

Tukey (1953) and Kramer (1956) independently proposed a modification for unequal cell sizes, and the Tukey-Kramer method was developed. This method is less powerful than the Bon, Sidak, and Scheffé methods, and also more conservative (SAS /STAT Users Guide, 1990:944). However, the Scheffé test is compatible with the overall ANOVA F, in that this method never declares a contrast significant before the overall F is significant. The Scheffé method is less powerful than the Bon and Sidak methods if the number of comparisons is largely relative to the number of means. Multiple comparisons by means of the Scheffé test may be conducted regardless of whether the overall F is significant. Howell (1989:235) presented the formula:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{MS_{error}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

with degrees of freedom (df) equal to the number of groups –1 and $N_1 + N_2 - 2$ in order to perform the Scheffé test. The specific approach used for the calculation of the post hoc Scheffé test, describing the data, is that of Horvath (1985:226). It is similar to the method described by Howell (1989:236-240) but differs in terms of the formula by which the critical values in the F tables are determined. Horvath (op. cit.) uses the normal critical F values while Howell's approach is similar, except that the obtained F ratio is multiplied by a factor of (k – 1) where k is equal to the number of groups or subgroups (i.e. the row-effect).

9.4.2 HOTELLING'S T^2 TEST

Hotelling's T^2 test enables the researcher to compare two groups on several variables simultaneously (De la Rey, 1978:71). Student's t test and Hotelling's T^2 test can both be employed to test a single group or two independent groups (Harris, 1975:67). According to Tabachnick et al.(1983:56) Hotelling's T^2 test is a special case of multivariate analysis of variance (as the t test is a special case of univariate analysis of variance) in which two groups compromise the independent variable. Hotelling's T^2 test is applied to determine whether the groups differ on a set of dependent variables (Theron, 1992:347). Hotelling's T^2 test determines whether the centroids (combined averages on the dependent variables) differ for the two groups. Harris (1975:78) offers the following formula to compute Hotelling's T^2 test:

$$T^2 = [N_1N_2 / (N_1 + N_2)]\,(\bar{X}_1 - \bar{X}_2)^1 S_C^{-1}\,(X_1 - X_2)$$

There is no evidence relating to the robustness of T^2 except that large sample sizes are needed. The test, therefore, is N sensitive. So a large and representative sample of determined size is needed for reliable and valid results. When the dependent measures originated from a normal distribution, the computed T^2 values conform to the F distribution (Harris, 1975:87).

Certain assumptions, however, have to be met before a T^2 analysis of data may be conducted (Harris, 1975:85-88). The averaging together of the covariance matrices for two groups (the independent variable) before conducting a T^2 analysis of the differences between two groups, involves the implicit assumption that the differences between S_1 and S_2 simply represent random fluctuations about a common population covariance matrix Σ. The null hypothesis (H_o) includes both the hypotheses that $\mu_1 = \mu_2$ and that $\Sigma_1 = \Sigma_2$. However, the second hypothesis is only an assumption on which the correctness of the validity of the first one depends. Rejection of the H_o thus could be due to the fact that $\Sigma_1 \neq \Sigma_2$ rather than to non-null differences between μ_1 and μ_2. Hotelling's T^2 test is more sensitive to difference in means than to differences in variances and covariances, and the true significance level of T^2 is unaffected by discrepancies between Σ_1 and Σ_2, as long as the sample sizes are fairly large and $N_1 = N_2$ (Harris, 1975:85). The symbol Σ refers to the common population covariance matrix.

In some situations the entries in the population variance-covariance matrix are a priori specified (preplanned). The observed variances could be uniformly larger than the hypothesized values suggest. The individual differences in choice probability are inflating the response variabilities. The researcher should therefore be careful to apply formulas for the mean and variance of a multinominal distribution to situations where the assumption that all S_S have the same generating probability (ties) is unlikely to be met. According to Harris (1975:86) the formula for T^2 is easily corrected to known covariance formulas simply by substituting Σ for S or S_c. The significance of the resulting T^2 is then obtained from the chi-square table with p degrees of freedom. Another assumption on which Hotelling's T^2 test is based is that the vectors of outcomes of variables are sampled from a multivariate normal distribution. As already stated, little is known about the robustness of T^2. For fairly large samples however, computed T^2 values conform to the F distribution, no matter what shape the parent population takes (Theron, 1992:352).

Besides Hotelling's T^2 test, other methods to determine profile similarities are the method of Du Mas, the method of Du Toit, the method of Osgood and Suci, and Cattell's method (Smit, 1991:97-104). However, because these methods are not going to be used in the case in hand, they will not be discussed in detail. Hotelling's T^2 test is a suitable test to apply in profile analysis as the overall T^2 test for two samples "lumps together two sources of differences between the two groups' response vectors (profiles): a difference in the level of the two curves and differences in the shapes of the two curves" (Harris, 1975:80). Methods that analyze these two sources of difference, viz. level and shape, separately and in addition, provide a simple test of the flatness of the combined or pooled profile for the two groups are known as profile analysis. Three methods are available in profile analysis to test the response vectors, viz. a parallelism test, the levels test, and the flatness test (Harris, 1975:80-81). The parallelism approach tests the hypothesis that the profiles of the two groups have the same shape, that is:

$$\mu_{\text{slope 1}} = \mu_{\text{slope 2}} = 0.$$

In this instance the slope of each line segment making up that profile will be the same for each group. The levels approach tests the hypothesis that the profiles for the two groups are at the same mean level, that is $\mu_{w1} - \mu_{w2} = 0$. This implies that the aggregali mean of the means of the separate variables is identical for the two groups, which means that the difference between two group means on any variable is zero. The flatness test tests the hypothesis that the pooled profile for the two groups combined is perfectly flat. The combined means are all equal to the same value. The flatness test takes advantage of the fact that a flat profile implies that all line-segment slopes are truly zero (Harris, 1975:81; Theron, 1992:352).

These three tests are analogous to a two-way univariate analysis of variance in which treatments correspond to rows and response measures (dependent variables) correspond to columns. Harris (1975:81) puts it quite aptly: "The levels test corresponds to a test of the row main effect; the flatness test to a test of the column main effect; and the parallelism test to a test of the interaction between rows and columns. Thus in profile analysis, as in two-way analysis of variance, the interaction test takes precedence with significant departure from parallelism implying that (a) the two groups must be compared separately on each outcome measure and non-significant departures from the equal levels test hypothesis and or the flatness test hypothesis are essentially non-interpretable since the significant interaction between groups and measures implies that both are significant sources of variation". Greater attention is paid to the concept "Profile analysis" in the next section.

9.4.3 DISCRIMINANT ANALYSIS

Measures of profile analysis such as measures of profile similarity which entail clustering of variables with factor analysis, measuring the relationship with Bravais-Pearson product-moment correlation, and Osgood and Suci's (1952) distance measure D will not be discussed in detail here as the researcher plans to utilize either Hotelling's T^2 test or Discriminant analysis for profile analysis. Discriminant analysis can be employed as a measure for profile analysis. Nunnally (1967:372) views profile analysis as "a generic term for all methods concerning groupings of persons". Nunnally proceeds by advancing two major classes of problems in profile analysis, viz. that in which the group composition or group membership is known in advance of the analysis and those problems where group membership is not known in advance. The purpose of the analysis in the first instance is to distinguish groups from one another on the basis of scores in a data matrix or scores obtained on a battery of tests. In the second instance the basis of the analysis is to assign individuals to group in terms of their profile scores (Nunnally, 1967:372).

In the case in hand group membership is known in advance and the purpose of the analysis (discriminant) is to distinguish the groups on the basis of scores in the data matrix. The major purpose of discriminant analysis is to predict group membership from a set of predictors (Tabachnick et al., 1989:505). The predictors are a set of psychological test scores such as individual-centred leadership, coaching for development, job satisfaction, team spirit, social and esteem needs, combined motivation needs, and locus of control orientation. Discriminant analysis is Manova turned around. Manova can be used to determine whether group membership produces reliable differences on a combination of dependent variables. If this is the case then the combination of variables can be used to predict group membership - the Discrim procedure. In the Discrim procedure the independent variables are the predictors and the dependent variables are the groups (Tabachnick et al., 1989:506). Classification is a major extension of Discrim over Manova. Each group must be a sample from a multivariate normal population and the population covariance matrices must all be equal. Linear combinations of the independent variables (or predictors) are formed to serve as the basis for classifying cases into one of the groups (Norusis, 1990:137).

According to Nunnally (op.cit., 1967:373-374) profiles have three characteristics, viz. level, dispersion and shape. The level of the profile is defined by the mean score of the person over the variables in the profile. The dispersion refers to the extent or degree of divergence from the average. The standard deviation of scores for each person may be seen as a measure of the dispersion. The shape refers to the curve and its high and low points. The method used for clustering profiles in the case in hand is discriminant function analysis. Discriminant function analysis is employed when groups are defined a priori and the purpose of the analysis is to distinguish the groups from one another on the basis of scores obtained in a battery of tests or scores in a data matrix (Nunnally, 1967:388).

According to Theron (1992:355) discriminant function analysis is extremely sensitive to multivariable outliers. Outliers are cases with extreme values on a variable or combination of variables that unduly influences the average and variability of scores and invalidates the generalizability of the solution to the population. Therefore outliers have to be eliminated or transformed before discriminant analysis can be performed. The discriminant model also assumes a linear relationship among all predictor variables within each group. Violation of this assumption, however, simply leads to reduced power rather than to an increase in Type I error (a statistical decision error that occurs when a true null hypothesis is rejected; its probability is $1 - \alpha$). The discriminant model is also based on the assumption of homogeneity of variance-covariance. If classification is the goal of the analysis this assumption has to be met. If the sample sizes are quite large, discriminant function analysis displays robustness in respect of violation of the assumption of equal variance-covariance matrices. With unequal and/or small sample sizes, homogeneity of variance-covariance should be assessed (Theron, 1992:355).

Scatterplots of the scores on the first two canonical discriminant functions can also be assessed for each group separately. Scatterplots roughly equal in size give evidence of homogeneity of variance-covariance matrices. The discriminant model also assumes that two variables in a matrix should not be perfectly or almost perfectly correlated (multicollinearity). Neither should one score be a linear or nearly linear combination of others (singularity). Multicollinearity and singularity make the inversion of matrices unreliable (Tabachnick et al., 1983:300-301). The discriminant function minimally or maximally separates two groups and the second discriminant function, which operates orthogonally to the first, then separates the remaining groups on the basis of information not accounted for by the first discriminant function (Tabachnick et al., 1983:295). According to Tabachnick et al.(1983:295) the total number of possible discriminant functions is either one fewer than the number of groups or equal to the number of predictor variables. However, the authors are adamant that only the first two discriminant functions discriminate significantly and reliably among groups.

The significance of a set of discriminant functions is established by partitioning the variance in the set of predictors into two sources, viz. variance that is attributable to differences between groups and variance attributable to differences within groups (Tabachnick et al., 1983:302). Tabachnick et al. advance as a fundamental formula for testing the significance, the equation:

$$\sum_{ij}\sum (Y_{1j} - GM)^2 = n\sum_{j} (\overline{Y}_j - GM)^2 + \sum_{ij}\sum (Y_{1j} - \overline{Y}_j)^2$$

and use this procedure to form cross-products matrices in the following way:

$$S_{total} = S_{bg} + S_{wg}$$ (Tabachnick et al., 1983:237,302).

The total of cross-products matrices is partitioned into cross-products matrices with differences between the two groups (S_{bg}) and differences associated with subjects within groups (S_{wg}). A classification equation is developed for each group to classify cases into groups. According to Tabachnick et al.(1983:306) each case has a classification score for each group. A case is assigned to the group for which it has the highest classification score. Tabachnick et al.(1983:306) advance a classification equation:

$$C_j = c_{jo} + c_{j1}Y_1 + c_{j2}Y_2 + \ldots + c_{jp}Y_p.$$

A score on classification function for group $j(C_j)$ is determined by multiplying the raw score on each predictor variable (Y) by its associated classification function coefficient cj. Then these products are summed over all predictor variables and are added to a constant c_{jo} (Tabachnick et al., 1983:306).

There are three types of discriminant function analysis, viz. direct discriminant function analysis, hierarchical discriminant function analysis and stepwise discriminant function analysis. The direct discriminant function solves equations simultaneously on the basis of all predictor variables. All the predictor variables enter the equations at once and the dependent variables are considered simultaneously. The hierarchical mode evaluates contributions to group discrimination by predictor variables as they enter the equations in some priority order that is determined by the researcher. This enables the researcher to assess the predictive power of each variable. The researcher may thus determine if the classification of cases to groups improves by adding a specific variable (or a set of variables). When prior variables are viewed as co-variates and the added variable as a dependent variable, this can be seen as an analysis of the covariance. Stepwise discriminant function analysis refers to the determination of the order of entry of variables into the discriminating equation by means of available statistical criteria. The researcher has no a priori reason for ordering entry of variables (Tabachnick et al., 1983:309-313). Stepwise analysis is used for the case in hand. As the researcher does not have a priori reasons for ordering the entry of variables into the discriminant equations, statistical criteria, which are available with the Stepwise function, have to be applied to determine the order of entry.

The maximum number of discriminant functions extracted within a single discriminant analysis is the lesser of either the number of groups minus one, or equal to the number of predictor variables. However, not all the functions may carry important information. It happens quite frequently that the first few discriminant functions account for the major share of discriminating power with no additional information forthcoming from the remaining functions (Tabachnick et al., 1983:318).

Discriminant function plots may be used to interpret the discriminant functions. The discriminant functions are presented by way of pairwise plots of group centroids on all significant discriminant functions. These centroids are the means of obtaining the discriminant scores for each group on each dimension. A discriminant function plot is simply a plot of the canonical discriminant functions evaluated at group means (Tabachnick et al., 1983:313,319).

Discriminant functions may also be interpreted by examining the loadings of predictor variables on them. Loading matrices are basically factor-loading matrices. These factor-loading matrices comprise correlations between predictor variables and each of the discriminant functions (also called canonical variables) that enable the researcher to name and interpret the functions. Mathematically, the loading matrix "is the pooled within group correlation matrix multiplied by the matrix of standardized discriminant function coefficients" (Tabachnick et al., 1983:320).

9.4.4 STUDENT'S T TEST

Like Hotelling's T^2 test, Student's t test is also an inferential statistic to test for significant differences between two groups. The two groups may be dependent or independent. Student's t test enables the researcher to decide whether observed differences between two sample means are caused by chance or represent a true difference between populations (Shavelson, 1981:419). De la Rey (1978:71) states the following assumptions that have to be met before the t test can be used:

- The scores in the respective populations must be normally distributed;
- As the t test is based on sample means, the two samples must be big and of equal or almost equal size;
- The measurements must be on interval or ratio level; and
- The scores in the groups must be randomly sampled from their respective populations.

The use of the t test also imposes a number of requirements on the collection of data:

- There is one independent variable with two levels (i.e. groups);
- A subject appears in one and only one of the groups; and
- The level of the independent variable may differ from one another either qualitatively or quantitatively (Shavelson, 1981:421).

Applied to test hypotheses, the purpose of the t test is to decide whether or not to reject the null hypothesis which is a probabilistic decision as it cannot be made with complete certainty. To determine the probability of observing the difference between the sample means of the two groups under the assumption that the null hypothesis (Ho) (Ho = no difference between the means of two groups) is true, a significance test to decide whether the observed sample difference in means has a low probability of occurring in the populations, has to be performed. Bohrnstedt et al.(1988:204-205) advance the formula for doing this:

$$S^2 = \frac{(N_1 - 1)S_1^2 + (N_2 - 1)S_2^2}{N_1 + N_2 - 2}$$

where

$N_1 + N_2 - 2$ are the degrees of freedom which are associated with S^2. The value of t is calculated by applying the formula:

$$t(N_1 + N_2 - 2) = \frac{(\bar{Y}_2 - \bar{Y}_1) - (\mu_2 - \mu_1)}{S(\bar{Y}_2 - \bar{Y}_1)}$$

$$= \frac{\bar{Y}_2 - \bar{Y}_1}{\sqrt{\frac{S_2}{N_1} + \frac{S_2}{N_2}}}$$

Student's t test assumes that the distribution of variables in the populations, from which the samples are drawn, is normal. But it also assumes that the variances in the populations from which the samples are drawn are equal ($\sigma_1^2 = \sigma_2^2$). This is known as homogeneity of variance (Ferguson, 1981:179, 245). According to Ferguson (1981:245), moderate departures from homogeneity should not have a serious effect on the inferences drawn from the data. Gross departures from homogeneity, however, may lead to serious errors in the results. Ferguson (1981:245) recommends that under circumstances of gross departures from homogeneity, a transformation of the variable that may lead to greater uniformity of variance be used or a nonparametric procedure be applied. Ferguson (1981:182) also advances a formula when testing the difference between means for independent samples, assuming homogeneity of variance. A single estimate S^2 is used in calculating the t value:

$$t = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\frac{S^2}{N_1} + \frac{S^2}{N_2}}}$$

However, should the two population variances be different ($\sigma_1^2 \neq \sigma_2^2$), two variance estimates are obtained, viz. S_1^2 and S_2^2 which are estimates of σ_1^2 and σ_2^2. The difference is divided by the standard error of the difference and t is computed simply by using the separate variance estimate. The resulting ratio is:

$$t' = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}}}$$

This ratio (t') is neither normal nor does it approach a t-distribution.

9.4.5 NON-PARAMETRIC STATISTICS

Two non-parametric statistics are considered, viz. the Kruskal-Wallis one-way analysis of variance and the Mann-Whitney U test. Applying non-parametric statistics one or more of certain assumptions have to be met (De la Rey, 1978:113):

- The distribution of scores has to be skewed;
- Measurement must be on nominal or ordinal level;
- The sample size must be small ($N \leq 30$);
- Situations where it is impossible to make certain assumptions in regard to the sample; and
- Situations where it is impossible to realize certain research aims because appropriate parametric statistics are not available.

9.4.5.1 KRUSKAL-WALLIS ONE-WAY ANALYSIS OF VARIANCE

The Kruskal-Wallis one-way analysis of variance is applied to help to decide if k independent samples from different populations differ significantly. There should be more than two independent samples. The decision is also probabilistic as the problem according to Siegel (1956:84) is to determine whether differences among samples represent merely chance variations or signify genuine population differences. Siegel (1956:184) observes that the Kruskal-Wallis statistic tests the H_0 that the k samples come from the same population or from identical populations with respect to averages.

In the computation of the Kruskal-Wallis test the observations or scores are all ranked in a single series. Siegel (1956:185) supplies the following formula to calculate the Kruskal-Wallis statistic (H) and observes that if the null-hypothesis (H_o) is true, then H is distributed as chi-square with degrees of freedom = k – 1, provided that the sizes of the various k-samples are not too small:

$$H = \frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j 2}{n_j} - 3(N+1)$$

where k = number of samples

n_j = number of cases in j th sample

N = Σnj, the number of cases in all samples combined

R_j = sum of ranks in the j th sample

$\sum_{j=1}^{k}$ = directs one sum over the k samples.

9.4.5.2 **MANN-WHITNEY U TEST**

The Mann-Whitney U test is a well-known distribution-free test for two independent samples. Although it is a non-parametric test for comparing the central tendency of two independent samples, it may also be applied to normally distributed populations. Instead of computing means as the sample statistic, however, the Mann-Whitney U test is based on the ranking of sample scores. Ranking is a sophisticated mathematical operation and can be performed at ordinal level data. The Mann-Whitney U test tests the H_o that the two samples were randomly drawn from identical populations. This test is especially sensitive to population differences in central tendency (Theron, 1992:365).

This H_o is broader than the H_o tested by the corresponding t test that deals with means of the two samples. The H_o tested by the Mann-Whitney U test is based on the assumption that the two populations have the same shape and dispersion (Theron, 1992:365).

According to Theron (1992:365) the logic of the Mann-Whitney U test is quite easy to understand. To compute U, the scores from both samples are pooled and ranked from highest to lowest. Tied observations are then assigned to the mean of the rank position they would have occupied had there been no ties. The ranks of observations from group 1 are then summed. Thereupon the ranks for the two samples are totalled and compared. The statistic used in this test, viz. the U value is then given by the number of times a score in one group (with n_2 cases) precedes a score in the other group (with n_1 cases) in the ranking. If the two samples represent populations not significantly different from each other, then the total ranks should be similar in value. Tied scores are assigned to the average of the ranks they would have had if they had not been tied. The formula to compute U is:

$$U = N_1 N_2 + \frac{N_1 (N_1 + 1)}{2} - \Sigma R_1$$

where ΣR_1 = the sum of ranks for sample 1 (Siegel, 1956:120).

On determining the value of U, the test of significance has to be conducted. A z-score is obtained with the aid of the formula:

$$Z \text{ (obtained)} = \frac{U - \mu_u}{\sigma_u}$$

where U = the sample statistic

μ_u = the mean of the sampling distribution of sample U's

σ_u = the standard deviation of the sampling distribution of sample U's (Siegel, 1956:121), to find the critical region as marked by Z (critical). Based on Z (critical) the researcher makes a decision to reject or to accept the H_o of no difference (Healy, 1990:193-197; Howell, 1989:300-305).

9.4.6 CORRELATIONAL STATISTICS

Ott et al.(1990:417) define correlation as a "measure of the strength of the relationship between two variables x and y". The value so obtained is called the coefficient of linear correlation, or simply the correlation coefficient. The stronger the correlation, the better x predicts y. The population correlation coefficient r (rho) is computed as:

$$r = \frac{S_{xy}}{\sqrt{S_{xx} \cdot S_{yy}}}$$

This is called the Bravais-Pearson product-moment correlation coefficient. Bohrnstedt et al. (1988:271) present the formula as:

$$r_{xy} = \sqrt{R_{y \cdot x}^{2}}$$

The Bravais-Pearson product-moment correlation may have a positive or negative sign attached to it to indicate the direction of the correlation. The value of r can range between –1,00 for a perfect inverse association to +1,00 for a perfect positive correlation with zero (r = o) indicating no relationship at all. Bohrnstedt et al.(1988:271) see the usefulness of the correlation coefficient in its communication of directionality and magnitude of the association. Ott et al.(1990:420-422) note several interpretations of the coefficient of correlation:

- A correlation coefficient equal to 0,5 does not mean that the strength of the relationship between two variables (x and y) is halfway between no correlation and perfect correlation. The more closely x and y are linearly related, the more the variability in the y-values can be explained by variability in the x-values and the closer r^2 will be to 1. If $r = 0,50$ the independent variable x is accounting for 25% ($r^2 = 0,25$) of the total variation in the y-values. r^2 is called the coefficient of determination. The coefficient of determination is a proportional reduction in error statistic (a characteristic of some measures of association which allows the calculation of reduction in errors predicting the dependent variable) for linear regression that expresses the amount of variation in the dependent variable explained or accounted for by the independent variable (Bohrnstedt et al., 1988:269).
- X and y could be perfectly related in some way or other than in a linear manner when $r = 0$ or a very small value.
- Correlations are difficult to add up. The sum of coefficients of correlation does not account for the variability of the y-values about their sample mean.

According to Theron (1992:368-369) Spearman's correlation coefficient for ranked data (r_s) may also be calculated. This coefficient of correlation is based on ranked data. Ranking details separate ranking of a number of items on two dimensions. Based on this ranking, the correlation between the two sets of ranks is determined. (Ranked data are data for which the observations have been replaced by their numerical ranks from lowest to highest, and Spearman's correlation (r_s) is a correlation coefficient based on ranked data). Howell (1989:110) presents the formula for the calculation of Spearman's rho (r_s) as:

$$r_s = 1 - \frac{6\Sigma D^2}{N(N^2 - 1)}$$

9.4.7 **DESCRIPTIVE STATISTICS**

Mason et al.(1989:428) define descriptive statistics as statistics used to summarize data. Bohrnstedt et al.(1988:66-81) divide descriptive statistics into measures of central tendency and measures of variation (or dispersion).

9.4.7.1 **MEASURES OF CENTRAL TENDENCY**

The mode, the median and the mean are measures of central tendency. The mode is the value or category in a frequency distribution that has the largest number, or percentage of cases. The median refers to the value or score that exactly divides an ordered frequency distribution into equal halves, viz. the outcome is associated with the 50 th percentile. The most frequently used measure of central tendency is the mean that is commonly called the average. The mean is the sum of all scores in a distribution divided by the number of scores, viz. the mean is the arithmetic average. In this research the mean is the measure of central tendency that may be applied to interpret the result of t-scores, discriminant analysis and one-way and other approaches to analysis of variance.

9.4.7.2 **MEASURES OF VARIATION, SKEWNESS, AND KURTOSIS**

Besides the skewness, and kurtosis, the measures of distribution variation that would be calculated and presented, are the variance, standard error of the mean, and the standard deviation.

Skewness indicates the dispersion of a distribution "based on the observation that when a distribution is symmetrical the sum of cubes of deviations above the mean, will balance the sum of cubes of deviations below the mean"(Ferguson, 1981:69). A value of 0 for skewness indicates a normal distribution (Norusis, 1984:40). If the distribution is skewed to the right (longer tail to the right), the sum of cubes of the deviations above the mean will be greater than the corresponding sum of cubes of the deviations below the mean (Ferguson, 1981:69). If the distribution is skewed to the left (longer tail to the left), the sum of cubes of the deviations below the mean will be greater than the corresponding sum of cubes of the deviations above the mean (Ferguson, 1981:69).

Kurtosis gives an indication of the peak of a distribution. A kurtosis value of 0,263 indicates a normal distribution. When the distribution is flatter than a normal distribution, the kurtosis value is less than 0,263 (the distribution is platikurtic). When the distribution is more peaked than a normal distribution, the kurtosis value is more than 0,263 (the distribution is leptokurtic) (Steyn et al., 1987:79).

The variance is a measure of dispersion for continuous variables of scores about the mean and the standard deviation is the square root of the variance and is also used to describe a dispersion of a distribution. The usual way of assigning meaning to the standard deviation is in terms of how many scores fall no more than a standard deviation above or below the mean. For a normal distribution exactly two-thirds of observations lie within one standard deviation of the mean. The standard deviation is basically a measure of the average of the deviation of each score from the mean (Shavelson, 1981:305).

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The standard error of the mean refers to the standard deviation of sample means in a sampling distribution. It provides information about the amount of error likely to be made by inferring the value of the population mean from the sample means. The greater the variability among sample means, the greater the chance that inferences about the population mean from a single sample mean will be in error (Shavelson, 1981:305).

9.4.7.3 FREQUENCY TABLES

Frequency tables comprise of information about the frequencies across values for the biographical variables, work-related motivational needs, locus of control factors, and work-related attitudes during transformation. The percentage and cumulative percentage will be used to describe and summarize the data.

9.4.7.4 CROSS-TABULATION

A frequency distribution is a useful display of the quantitative attributes of continuous variables or the qualitative attributes of discrete variables. But a cross-tabulation (joint contingency table) is "a tabular display of the joint frequency distribution of two discrete variables which has r rows and c columns" (Bohrnstedt et al., 1988:101). Thus a cross-tabulation indicates the joint outcomes of two variables. The cells that comprise the body of any table show these joint outcomes of two variables. Bohrnstedt et al.(1988:103) view a cell as "an intersection of a row and a column in a cross-tabulation of two or more variables". Marginal distributions consisting of row marginals and column marginals are frequency distributions of each of two cross-tabulated variables. Row marginals are the row totals and column marginals are the column totals. Cross-tabulations will be used to display the demographic variables in relation to the work-related motivational needs, or locus of control factors, or the work-related attitudes during transformation.

9.5 CONCLUSIONS

In this chapter the research design was discussed. The research strategy consisting of both a qualitative approach and quantitative research included, were explained. The process of survey research was discussed in detail and was related to the aim of this study. The population was demarcated, the method and procedures for administering the questionnaires, and the data-collection were discussed. The relevant statistical methods including descriptive and inferential methods were explained. The various statistical methods were discussed, namely descriptive statistics, different approaches to the analysis of variance, profile analysis (discriminant analysis), the Student's t test, Hotelling's T^2 test, non-parametric inferential statistics, and correlation statistics.

In the next three chapters the information gathered for the qualitative strategy regarding the need for change in this organization, the diagnoses of the current organization, planning of change strategies, implementation of change interventions, and management of the transformation process within the organization are discussed.