CHAPTER SIX
Methodology

6.1 Introduction

The aim of the study is to formulate and investigate the validity of a structure of work values during an early stage of career process by developing a Work Values Questionnaire. This structure was explored by administering a Work Value Questionnaire consisting of 93 items on an initial group of 3000 students. The 93-item questionnaire was generated in accordance with the structure and proposed scales set out in the previous chapter. A biographical questionnaire was attached and participants were requested to complete the biographical questionnaire as well as the questionnaire. The instructions for completing the questionnaire were printed on the first page of the questionnaire and were read to participants before they started to answer it.

The group of 3000 students were from 23 secondary schools and seven tertiary institutions that agreed to co-operate in the study. The tertiary institutions that participated were Rand Afrikaans University, University of Pretoria, and University of the Witwatersrand, Witwatersrand Technikon, Pretoria Technikon, Damelin and the Johannesburg Technical College. Third year and honours students from Rand Afrikaans University administered the questionnaires. Participation was voluntary. 1365 students completed questionnaires which could be considered for analysis. The rest of the responses were rejected due to incomplete data. A description of the participants follows in Table 6.1. to Table 6.8.

Table 6.1 Age categories of the participants

Age category	Frequency	Valid percent age	Cumulative percent age
15 years	47	3,5	3,5
16 years	42	3,1	6,6
17 years	88	6,5	13,1
18 years	81	6,0	19,1
19 years	78	5,8	24,8
20 years	146	10,8	35,6
21 years	161	11,9	47,5
22 years	108	8,0	55,5
23 years and older	602	44,5	100,0
Total	1356	100,0	

Table 6.2 Gender distribution of the participants

Gender	Frequency	Valid Percent	Cumulative Percent
Male	514	37,5	37,5
Female	842	62,5	100,0
Total	1356	100,0	

Table 6.3 Language distribution of the participants

Language	Frequency	Valid Percent	Cumulative percent
English	536	39,6	39,6
Afrikaans	627	46,4	86,0
African languages	193	14,0	100,0
Total	1356	100,0	

Table 6.4 Area in which participants grew up

Area	Frequency	Valid Percent	Cumulative Percent
City	630	46,6	46,6
Town	480	35,5	82,0
Township	138	10,2	92,2
Farm	64	4,7	97,0
Village	41	3,0	100,0
Total	1353	100,0	

Table 6.5 Highest academic qualification of participants

Academic Qualification	Frequency	Valid Percent	Cumulative Percent
Std. 6 or lower	36	2,7	2,7
Std. 7 or 8	129	9,7	12,4
Std.9 or 10	443	33,2	45,5
First year Technikon	31	2,3	47,8
Second year Technikon	34	2,5	50,4
Diploma	156	11,7	62,1
First year University	71	5,3	67,4
Second year University	199	14,9	82,3
Baccalaureus degree	136	10,2	92,4
Honours degree	99	7,4	99,9
Ph.D.	2	0,1	100,0
Total	1336	100,0	

Table 6.6 Career groups of participants' aspired occupation

Career group	Frequency	Valid Percent	Cumulative Percent
Professional	951	70,9	70,9
Administrative	144	10,7	81,6
Clerical	58	4,3	85,9
Sales	79	5,9	91,8
Trade	77	5,7	97,5
Farming, Forestry and Gardening	18	1,3	98,9
Domestic Worker	6	0,4	99,3
Unskilled Worker	3	0,2	99,6
Unemployed	6	0,4	100,0
Total	1342	100,0	

Table 6.7 Career group of participants' fathers

Career group	Frequency	Valid Percent	Cumulative Percent
Professional	530	40,3	40,3
Administrative	200	15,2	55,6
Clerical	80	6,1	61,6
Sales	149	11,3	73,0
Trade	221	16,8	89,8
Farming, Forestry and Gardening	59	4,5	94,3
Domestic Worker	19	1,4	95,7
Unskilled Worker	26	2,0	97,7
Unemployed	30	2,3	100,0
Total	1314	100,0	

Table 6.8 Career group of participants' mothers

Career group	Frequency	Valid Percent	Cumulative Percent
Professional	314	23,7	23,7
Administrative	293	22,1	45,8
Clerical	178	13,4	59,2
Sales	117	8,8	68,1
Trade	40	3,0	71,1
Farming, Forestry and Gardening	16	1,2	72,3
Domestic worker	84	6,3	78,6
Unskilled worker	17	2,0	80,7
Unemployed	256	19,3	100,0
Total	1352	100,0	

In the rest of this chapter, I describe and motivate the use of a particular research strategy. Mouton (1998) describes it as the legitimisation of the methodological dimension of research. The aim of this study is to formulate and investigate the validity of a structure of work values during an early stage of career process. This aim will be operationalised through the development of a Work Values Questionnaire. In light of this aim, the research strategy should sketch the logical steps and methods, as well as, possible difficulties that can be experienced as a result of the use of these methods and techniques (Mouton, 1998).

According to Layder (1993) it is necessary to propose a total research strategy that refers to a broader perspective rather than only the method used for resolving a specific problem statement. In this regard, three elements are discussed namely, the role of theory, social processes and social activities, as well as, time perspectives.

First, it is necessary to determine whether the research aims at the testing of a theory, the development of theory or a combination of both. According to Layder (1993), a theory encompasses more than the description of an empirically determined relationship between variables. It should rather be viewed as a network of concepts consisting of underlying assumptions. Theory exposes, on a philosophical level, the attitude of the researcher to social sciences. Layder (1993) uses a researcher's approach to causality as an example to illustrate this point. He shows that a researcher could take a positivist stance in search of a generalisation of causality or a realistic stance of identifying causal mechanisms. It seems that Layder differentiates between a stance of meta theory and temporal locality. Second, it is necessary to identify the levels on which the research functions. Third, the time frame within which the research is conducted is discussed. Layder (1993) explains that the history of an individual is positioned within the broader context of history.

In the rest of the chapter, I discuss the steps that are followed in the construction of the questionnaire. This construction process determines the accuracy, reliability and validity of the questionnaire. I follow the guidelines of Schepers (1992) in the construction of the Work Values Questionnaire. In the rest of the chapter, I refer to the theoretical background, format of the questionnaire as well as statistical procedures utilised in finalising the selection of items included in the final questionnaire. Exploratory and confirmatory factor analysis as statistical techniques are discussed.

6.2 Construction of the questionnaire

Smit (1991) identifies three categories of procedures that should be followed in the construction of a psychological test. The first category refers to the groundwork that the researcher needs to do. Aspects of relevance are the specification of an aim for the questionnaire and the transformation of this aim in operational terms. I discuss this aspect of the questionnaire development in section 6.3 of this chapter.

The second category consists of the writing, re-writing and administration of the questionnaire for the purposes of statistical analysis, item selection and organisation of the questionnaire in the final format. First, I discuss the proposed format for the questionnaire and more specifically the items that form part of the questionnaire. Second, I discuss the statistical techniques including exploratory and confirmatory factor analysis that are used for item selection and the organisation of the questionnaire.

The last category consists of standardising procedure, the technical evaluation and scoring of the questionnaire. As the aim of the study is to formulate and investigate the validity of a structure of work values, it is not anticipated that a full questionnaire, which can be standarised, will be derived from this research. This aspect falls outside the scope of the present study.

6.3 Theoretical background

The aim of the study is to formulate and investigate the validity of a structure of work values during an early stage of career process. A Work Values Questionnaire is developed to study such structure. The three theoretical aspects considered in the development process of this questionnaire are the cultural contextual space of South Africa, the constructs of values and work values.

First, the questionnaire has to incorporate a multi-cultural context. The impact of culture and its consequences is discussed in Chapter Four. The theoretical perspectives with regard to the construct of values are discussed in Chapter Two. The questionnaire should in a useful manner, operationalise the theoretical perspectives as discussed in Chapter Two. Third, work values as conceptualised in this study, are discussed in Chapters Three, Four and Five.

Items of the Work Values Questionnaire should be operationalised according to the theoretical perspectives in the above-mentioned chapters. On an operational level, the items of the Work Values Questionnaire give participants the opportunity to engage in evaluating each item. The value judgement that is made will be reflected on the answering sheet of the questionnaire. This value judgement reflects the abstract values of the participant. The abstract values in turn reflect the theoretical conceptualisation of the specific work value constructs. Each item reflects an aspect of value theory described in

Chapter Two in the stem and one aspect of work values as described in Chapter Five in the rest of the item.

6.4 Format of the questionnaire

This section deals with the importance of the use of a framework and the format of the items in the questionnaire.

6.4.1 The importance of the use of a framework

In Chapter Five, a proposal for a framework for the organisation of work values is made. The motivation for such an organisation refers to user aspects of the questionnaire and characteristics that are inherently associated with a framework.

The potential application value of this questionnaire lies in the field of career psychology. I view career psychology in the broadest possible sense. In other words, it is envisaged that this questionnaire could be used to add value to any decision making or meaning making process in the world of work. Behaviour can seldom be viewed as influenced by a singular value (Leidtka, 1989). Decision making and meaning making processes in the world of work cannot be excluded from this assumption. It can be expected that clusters of values, rather than individual values, will influence these processes. This is the first reason why I decided to investigate clusters or frameworks of work values.

Frameworks have inherently useful characteristics. According to Botha (1983), frameworks distinguish clearly between aspects that are included and excluded from the framework. This aspect plays a role in the legitimisation of the constructs that are included in the proposed questionnaire. In other words, I do not claim that the proposed questionnaire measures all values that are relevant within the working context, but identify which values are measured by this particular questionnaire. The proposed frameworks for measurement by this questionnaire are Collectivity, Power Distance, Uncertainty Avoidance, Individualism and Humanist Values.

Botha (1983) further states that each framework is organised in a particular manner and functions according to certain rules. In my opinion, this may imply that valuable information can be lost if one only measures individual values without considering the underlying relationships between such values. In other words, the relevance of a specific value can have one meaning when it is considered in isolation and a different meaning when it is considered in the context of a framework of values.

6.4.2 Format of the items

In this section, I discuss the format of the questionnaire and the instructions for answering the questionnaire. The final questionnaire should consist of the least possible number of items. Items should be presented in a mixed format as opposed to presentation according to frameworks, in an attempt to minimise the effects of possible transparency and prejudice.

Schepers' (1992) suggestions for the formulation of items are utilised in the writing of questionnaire items. Schepers (1992) proposes that items should be posed as questions. This format has the following benefits. If items are posed as a question, responses can be given on a continuum (for example, a five-point scale anchored on two points). Alternatively, responses to statements can be formulated in a dichotomous manner such as a Yes or No response. The latter poses problems for statistical analysis such as item analysis techniques. A further benefit of the items-as-questions-format is that it counters acquiescence bias (Schepers, 1992).

Each item in the Work Values Questionnaire will be posed as a question. An example of an item is: "To what extent do you view it as important to work in a friendly atmosphere?" Responses are given on a five-point scale, anchored on the two extreme responses.

Do not agree 1 2 3 4 5 Agree strongly

Although Schepers (1992) recommends the use of a seven-point scale when using factor analysis as a technique, I decided to use a five-point scale in light of the specific nature of the sample. The ages of participants in the study varied between fifteen and 23 years. The younger participants could find it difficult to deal with the complexity of a seven-point scale.

Instructions for answering the questionnaire are included in Addendum 1. Participants are requested to complete all items of the questionnaire. It is explained that items should be answered with the ideal job or ideal working circumstances in mind. The reason for this is that some participants in the study have yet to enter full time employment. The nature of the questionnaire is explained, referring to the fact that there are no correct or incorrect answers to this questionnaire and that we are interested in the honest personal opinion of the participant. An example of a question and answer is provided. The next section of this chapter will deal with the statistical analysis of the data.

6.5 Factor analysis

Galtung (1969) describes the rationale behind factor analysis in the following manner. It is a method that is used to divide variables for in-groups. According to Ferguson and Takane (1989), factor analysis is a method through which meaningful deductions about the inter-relatedness of different variables can be generated. Maxwell (1997) supports these views and explains that the factor model is suitable for the analysis of the corrective structure of variables measured indirectly. This can be achieved in two ways. First, the initial number of variables is reduced to a smaller number of variables, named factors. Second, specific meaning is ascribed to the factors according to the structural characteristic that can exist in each of the relationships (Ferguson & Takane, 1989: Kerlinger, 1985). In this study, the focus is on the inter-relatedness between the items and factors as well as between various factors.

6.5.1 Exploratory and / or confirmatory factor analysis

Loehlin (1998) distinguishes between the exploratory and confirmatory strands of factor analysis. Exploratory factor analysis is utilised to search for the latent structure underlying set of variables. This type of factor analysis does not require a specific apriori model framework. The goal is to find a reduced set of latent variables (factors) that can explain the correlations between the larger set of original variables.

Confirmatory factor analysis can only be used if clarity exists on the relations between all the various factors and the variables (Gorsuch, 1997). During this process specific hypotheses, meeting the expectations of the researcher, are tested (Hair, Anderson, Tatham & Black, 1995). In a confirmatory factor analysis the researcher typically formulates an explicit measurement model and then tests the validity of the model against empirical data.

The goal of this study is to formulate and investigate the validity of a structure of work values of South Africans during an early stage of career process. Both exploratory and confirmatory factor analyses are used in succession to study and validate this structure.

6.5.2 Component analysis versus common factor analysis

Within the broad spectrum of factor analysis, a distinction is drawn between principal component and common factor analysis. In this study, I have made use of common factor analysis. Various reasons exist for opting for this type of factor analysis.

Gorsuch (1997) argues that the nature of principal component analysis opens a greater risk for mistakes and erroneous judgement. Gorsuch (1997) further gives preference to common factor analysis, as it acknowledges that part of the variance of each variable is unique and not shared with any other variable. In other words, the sources of variance of a variable are twofold, namely, the latent variables or common factors and second the influences that are unaffected by any other measure. The unique variance can be divided into specific and error components. The specific variance refers to reliable variance that the variables share with no other variable (Gorsuch, 1997; Cliff, 1987).According to Hair et al. (1995) error variance can be attributed to unreliability in the data-gathering process, measurement error or the presence of a random component. Gorsuch (1997) explains that apart from the error component, the rest of the equation is the sum of proportional weights of the correlation of all factors or constructs with the specific item. The equation does not only represent the relation between the item and the principal factor loading, but also includes the relation between the item and the loading on all other factors, as well as, a residual component. The residual component or unique variance accounts for what is needed to complete the fit or total variance. This approach makes it possible to select items that are clearly related to one factor only and will improve the quality of the selection of items to scales (Gorsuch, 1997). According to Hair et al. (1995) common factor analysis is specifically useful if little information about unique and error variance is available and where the latent constructs still need to be identified, as in the case with the present study. Common factor analysis attempts to separate unique variance from the remaining variance (Cliff, 1987). From the above, it can be seen that the purpose of common factor analysis is to analyse and explain the common or shared variance between variables.

The rest of this chapter, I describe the steps followed in applying common factor analysis to the data obtained from 1354 participants. The suitability of an item for inclusion in the final structure will be determined by whether this particular item or variable is related to one specific factor or construct.

6.5.3 Steps in the factor analysis

The following steps are used to extract factors by means of the exploratory factor analysis. The sample of 1354 participants is divided in two groups. The data of Group One is used to perform an exploratory factor analysis. For this process, the number of factors to be extracted is determined by a Scree-test and then a principal axis factor analysis with iterative communalities is performed. The items that withstood the scrutiny of this process are subjected to a second and then third principal axis factor analysis wherein poor items are sequentially deleted or eliminated. The data of Group Two is then used to perform a fourth principal axis factor analysis and a confirmatory factor analysis in order to validate the structure obtained with Group One. The rest of this chapter deals with a description of the above methodology.

6.5.4 First principal axis factor analysis

6.5.4.1 Division of the sample

The SPSS-programme is used to divide the responses of 1354 participants randomly in two groups. The purpose of this division is that responses from Group One will be used to perform an exploratory factor analysis in order to find the best fitting model with the data. Secondly, Group Two will be used to validate the measurement model obtained with the data of Group One. Two groups are created as one cannot use the same data to suggest and test a model (Cliff, 1987).

The second step is to utilise the responses of Group One to determine the best fitting model possible with the empirical data. The first decision is to determine the number of factors that need to be extracted. An important guideline will be to extract only factors that are well defined and psychologically meaningful.

For exploratory work, a number of techniques exist by which the number of factors for extraction can be determined. Hair et al (1995) describes the latent root criteria as the most commonly used technique. With this technique all factors with an eigenvalue >1 are regarded as significant. An eigenvalue >1 will explain at least as much variance as is found in a single variable (Diekhoff, 1992). Diekhoff (1992) and Hair et al. (1995) are in agreement that this technique can be problematic when large numbers of variables are analysed, as too many factors can be extracted. The Percentage of Variance Criterion uses the cumulative percentages of variance extracted by successive factors a criterion. The extraction of factors is continued until a solution represents approximately 60 % or more of the total variance. However, this criteria does not guarantee that all the factors will be well defined or meaningful. The Scree-test is used to indicate the numbers of factors that contributes significantly to the variance in the variables at the point prior to unique variance dominating the common variance structure (Diekhoff, 1992)

The Scree-test plots the obtained eigenvalues against the number of factors. Each eigenvalue represents the percentage of variance represented by a particular factor. Diekhoff (1992) views the eigenvalues as reflecting the strength of the relationship between the factor and the original variables. The eigenvalues are plotted on the one axis of a graph. The number of factors in the order of extraction is plotted on the other axis of the graph. The variance that each successive factor contributes decreases to an extent where a flattening or straightening out of the Scree-plot is visible. At this point of the flattening the remaining factors explain approximately the same amount of variance. All factors above the flattening contribute significantly to the variance in the variables. This will be the maximum number of factors that can be extracted with the principal axis factor analysis. Factors below the flattening will contain too large a proportion of the unique variance to be acceptable for inclusion in the final solution (Hair et al., 1995). A further consideration is that only factors with three or more significant loadings will be retained, because factors containing less than three significant loadings cannot be scored as scales (Gorsuch, 1997).

6.5.4.2 Communalities

After the number of factors has been determined a principal axis factor analysis with iterated communalities will be performed on the responses of Group One. The estimation of the communalities is one aspect that distinguishes common factor analysis from component analysis (Cliff, 1987). The communalities reflect the proportion of variance of each variable explained by the extracted factors. A variable’s communality is calculated by adding the squared loadings for the specific variable across factors. High communalities indicate that the factors extracted are explaining a high proportion of the variance in the variables. Low communalities are indicative of the possible need for further extraction (Diekhoff, 1992). A principal axis factor analysis requires that the analysis should start with the communalities of the variables in the diagonal of the correlation matrix. However, these communalities are not available at the start of the study. In this study communalities will be estimated by means of the squared multiple correlation of each variable with all the other variables. The obtained communalities will be compared with the original estimates and if there is a large discrepancy between the two, the factor analysis will be repeated with the new communalities in the diagonal of the correlation matrix. This process will be iterated until the inserted and obtained communalities converge (Cliff, 1987). Once the number of factors has been determined and the communalities have converged the resulting factor matrix will be considered for interpretation or further rotation. If this unrotated matrix provides an interpretable result and meets the objective of data reduction, it can be accepted as the solution. This is rarely the case. In most cases, rotation is utilised to obtain a more interpretable, simpler and theoretically more meaningful solution (Hair et al., 1995).

6.5.4.3 Rotation

De Bruin (1998) refers to rotation as the transformation of the factor matrix to an equivalent mathematical solution that is psychologically more interpretable and meaningful. Diekhoff (1992) views one purpose of rotation as that of obtaining a “simple structure”.

Thurstone’s rules for the obtaining of simple structure are that in each row at least one loading close to zero should be found and in each column at least as many variables with zero or near-zero loadings as there are factors, should be found. For every factor or column there should be several variables with loadings on that factor or column but not in the other columns. When the number of factors are ≥ 4, a large proportion of the variables should have negligible (close to zero) loadings on any other columns of factors. There should only be a small number of variables with nonzero loadings in another column. (Kerlinger, 1985).

Kerlinger (1985) emphasises Thurstone's comment that original factor matrices are arbitrary and lack directive and specific reference frames (axes). The most meaningful context for interpretation can be created if the axes are rotated and one of the steps in factor analysis is to find a uniquely suitable position for the reference axes.

Rotations are guided by the rules of simple structure. Rotation of the axes can be oblique or orthogonal. An oblique rotation provides an opportunity to investigate the correlation between factors. This is not the position with an orthogonal rotation as the angles between the axes are fixed at 90°, which ensures that no correlation exists between the axes or factors. Orthogonal rotation is criticised to be unrealistic as factors usually show some form of correlation with one another (Kerlinger, 1985). On the other hand, oblique rotation is criticised for posing difficulty in interpretation especially when rotated factors are correlated. During rotation the total variance of the variables stays constant but is redistributed more equally between the factors (Diekhoff, 1992).

According to Hair et al. (1995) there is an absence of rules guiding selection of a specific orthogonal or oblique rotation technique. In light of the exploratory nature of this phase of the study, an oblique rotation will be used. More specifically Promax will be used as an oblique rotation technique. If the factors are found to be uncorrelated the solution will be equivalent to that obtained by an orthogonal Varimax rotation. Once the rotation is finished the rotated factor matrix must be interpreted. Through rotation, one aims to find variables that have a high loading on one factor only. The rotated factor matrix can be scrutinised for inclusion or exclusion of certain variables according to criteria set out (see the next two paragraphs).

6.5.4.4 Analysis of rotated loading for each item / variable

Hair et al. (1995) makes suggestions for interpreting the significance of factor loadings. In this regard the practical significance is regarded of greater importance than mathematical propositions or statistical significance. In the present study the variables are individual items. Items are unreliable. According to Gorsuch (1997) individual items can possibly measure unique characteristics that might be unrelated to a specific construct. The distribution of responses to an item impact on the correlation between items, which might not necessarily relate to a construct. In light of this unreliability it was decided to regard loadings ≥0,30 as significant as this would reduce the possibility of selecting items with high loadings by chance.

The first step in this phase is by means of inspection, identify all loadings ≥ 0,30 in the obtained rotated factor solution. Good and acceptable items will be present with a high loading on one factor only. In other words, loading in secondary factors should be significantly lower than the loading on the primary factor. Therefore, an acceptable item has to obtain a loading ≥ 0, 30 on a single factor and not obtained another loading ≥ 0,30 on any other factor.

6.5.4.5 Interpretation of factors

In this step, an analysis is made in order to decide which factors are suitable for inclusion and which are not. Only factors with more than three loadings ≥ 0,30 are retained. The reason for using 0,30 items is that items are not reliable. By using these criteria a strong possibility exists that loadings ≥ 0,30 cannot be attributed to chance and that these factors will be replicated in analysis of the data with a new group of respondents. Finch and West (1997) argues that a scale should not consist of less than three items.

6.5.5 Second principal axis factor analysis

The items that withstood the scrutiny of the previous two steps are used as variables for a second principal axis factor analysis. The number of factors is confirmed by the Scree-test, the factor analysis is performed and the Promax rotation is completed.

6.5.6 Third principal axis factor analysis

The same process of elimination of items as described in 6.5.4.4 is used. The items that withstood this scrutiny are used as variables for a third principal factor analysis.

The factor correlation matrix is inspected to ensure that the initial requirement that items are selected that is clearly related to one factor only, is met. This aim is achieved if the correlation between the factors is low.

6.5.7 Fourth principal axis factor analysis (Group Two)

The possibility exists that the factor structure as obtained for Group One will not be replicated for another group of respondents. This situation is tested by extracting five factors for Group Two by means of the same methodology used in 6.5.3. The results of this factor analysis are compared with the results obtained in the third principal factor analysis. From this comparison a measurement model is created. This model consists of a proposed matrix describing the specific items that will be highly correlated to a specific factor.

6.5.8 Confirmatory factor analysis

The final step is to use the responses of Group Two to perform a confirmatory factor analysis. A confirmatory factor analysis can only be used if clarity exists of the relations between all the various factors and the variables. Hypotheses about the relations between variables and factors are generated with an exploratory factor analysis (Gorsuch, 1997). The hypothesis of these relations is referred to as model specification (Finch & West, 1997). In this study, the model specification will be obtained from the combined outcome of the series of principal axis analyses performed on the responses of Group One. The factor pattern matrix or model to be tested will only be described in the next chapter, as this structure will only be available after the completion of the exploratory factor analysis with the data of Group One and Two.

The basic idea of confirmatory factor analysis is to specify a model of the relationships between factors (or constructs) and variables (in this case items) and to then assess the fit between the postulated model and empirical data. A good fit provides evidence in support of the construct validity of the measured model (Kerlinger, 1985). This will pave the way for accepting the model as the data does not contradict the model (Judd, Jessor & Donovan, 1986).

The aim is to find a fit where the discrepancies or residuals between the specified estimated matrix and the matrix containing the observed or measured covariance, will be small. The postulated model will require that every variable (or item) load on one factor (or construct) only. This loading will be estimated from the observed data. All other loadings will be constrained to equal zero. Such a measurement model fulfills Thurstone's (1947) criteria for simple structure. The covariances between the factors will also be freely estimated from the observed data and will be contained in the Φ -matrix (Comrey & Lee, 1992). The observed covariance matrix of measured variables for Group Two (S), the estimated factor pattern matrix (Λ) and the matrix of covariances among the factors (Φ) will be used to estimate the covariance matrix for the population (Σ). The parameters of the model will be estimated in such a way as to minimise the discrepancy between Σ and S (Finch & West, 1997). All parameters will be estimated with the maximum likelihood method.

The degree of the fit between the postulated model and the obtained data will be further evaluated by means of a number of fit indices that are referred to as Goodness of Fit Indices. The result of each index will indicate whether the model can be considered as adequate. Finch and West (1997) suggest that such a decision should be based on the interpretation of multiple indices. In the following section I will describe the relevance of each index as well as provide guidelines for interpretation of the indices.

6.5.8.1 The chi-square statistic

Ferguson and Takane (1989) describe the chi-square statistic as a mechanism to compare a theoretical model with actual empirical data. More specifically deviations between the covariance matrix of the common factor model and the obtained loadings and unique variance (Cliff, 1987). In the context of the chi-square statistic, a null hypothesis is postulated that no difference exists between a model and observed data. The value of chi-square will determine whether the null hypothesis will be rejected or fail to be rejected. A chi-square-value smaller than the critical value required for significance ($p < 0{,}05$) and degrees of freedom, will result in the null hypothesis being rejected. The degrees of freedom equal the difference between the number of observed variances and covariances and the number of parameters to be estimated (Judd, Jessor & Donovan, 1986). It is interesting to note that in confirmatory factor analysis, the researcher actually hopes that the null hypothesis will not be rejected. Failure to reject the null hypothesis, will mean that the differences between the estimated population covariance matrix and the observed covariance matrix is not statically significant. Stated differently, the postulated model shows a good fit with the observed data.

Criticism against the chi-square statistic is that it is heavily influenced by sample size (Ferguson & Takane, 1989; Cliff, 1987; Loehlin, 1998). Other criticisms against this specific index are that the null hypothesis poses an unrealistic test. In other words in practice it would be very rare to expect that no difference would exist between two matrices. This method does not indicate the measurement of discrepancy or degree of fit obtained between two matrices (Kim & Mueller, 1982).

Because of this criticism additional heuristic indices are utilised. Joreskog and Sorbom developed such two indices namely the Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI) (Comrey & Lee, 1992). These two indices and the Root Mean Square Error of Approximation Index (RMSEA) will be described in the following paragraphs.

6.5.8.2 The Goodness of Fit Index (GFI)

The GFI indicates the closeness of a perfect fit between a model and observed data. The index varies from zero to one, where a score of one indicates a perfect fit (Cliff, 1987; Comrey & Lee, 1992). A value $<$ 0,90 indicates that a change in the model should be considered to improve the fit with the observed data (Comrey & Lee, 1992).

6.5.8.3 The Adjusted Goodness of Fit Index (AGFI)

The AGFI is an adjusted version of the GFI that also accounts for the number of variables as well as the degrees of freedom (Comrey & Lee, 1992). In other words it accounts for the number of conditions that a covariance or correlation matrix needs to meet to fit the specified model (Kim & Mueller, 1978). This index also varies between zero to one, where a score of one indicates a perfect fit (Comrey & Lee, 1992). According Cole (1987) and Sharma (1996) values $\geq$ 0,80 are indicative of a satisfactory fit between model and data.

6.5.8.4 The Root Mean Square Error of Approximation Index (RMSEA)

The RMSEA measures the fit between the covariance matrices per degree of freedom between the model and observed data. Guidelines for interpretation of this index state that RMSEA values $\leq$ 0,05 are indicative of a close fit between the model and data. RMSEA values between 0,05 and 0,08 indicate a reasonable and acceptable fit between the model and data. Values $>$ 0,10 indicate room for improvement (Finch & West, 1997).

6.6 Conclusion

In this chapter, I described the methodology that is used in the construction of the Work Values Questionnaire. Specific emphasis is placed on the statistical analysis of the responses of the participants. Two statistical techniques form the basis for analysis and acceptance of the proposed questionnaire, namely exploratory and confirmatory factor analysis. In Chapter Seven, I report the results obtained by implementing this methodology.