# CHAPTER 3

# RESEARCH METHODOLOGY

## 3.1 Introduction

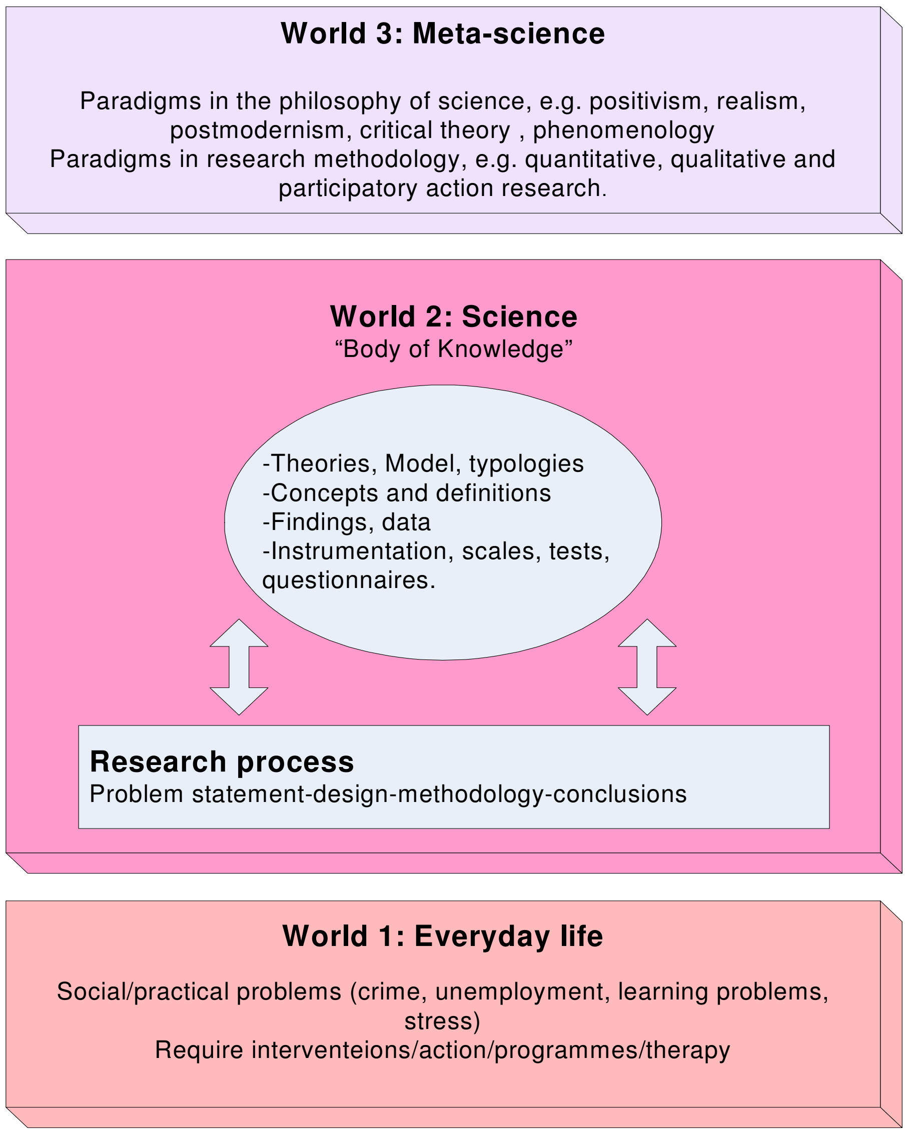
In ordinary life, man works and lives in a world where he continuously is confronted with problems, which are usually solved through problem solving thought processes. Behaviour is adapted or new behaviour patterns are learned and adopted in order to live a normal life.

Mouton (2001) refers to this as the world of everyday life and lay knowledge. However, there is another world, the second world according to Mouton, where man takes phenomena from everyday life and systematically finds the truth about it through processes of science and scientific research and develops the truth into theories. Theories are developed for others to build on and to be proven as correct or to be rejected on the grounds of empirical evidence (Lutz, 1983; Mouton, 2001).

Mouton (2001) lastly refers to a third world, namely a world of metascience. The third world goes beyond the scientific truth where new paradigms and philosophies are developed and confirmed. These paradigms and philosophies guide scientific research processes and form the basis of all new knowledge formation (Mouton, 2001). Refer to Figure 3.1 for Mouton's summary of this in a basic framework.

Lutz (1983) briefly refers to the stages of development in the Western world's research philosophy. First the church was displaced as the source of secular truth. Then, developing from philosophy, the natural sciences could stand on their own research feet with their traditional research model (or the scientific research model) with phases of theory evaluation, hypothesis, measurement, data collection, analysis, and hypothesis testing and theory formation. The social sciences developed from the natural sciences and started to provide independent scientific knowledge.

**Figure 3.1: The Basic Science Framework**




Adapted from: Mouton (2001).

The development of the independent social sciences meant that empirical data was made available to serve as evidence when the validity of social problems or social research results was determined (Lutz, 1983). On grounds of empirical data, research results could be verified independently. The fact that the social sciences under certain circumstances adhere to the research methods of the natural sciences is referred to as a form of positivism (Bailey, 1982). This, however, is an ongoing debate. Early views on this issue were that of Emile Durkheim, who believed that social phenomena are orderly and could therefore be generalized. According to Mouton (1993), Durkheim believed that social facts, which refer to all social phenomena that exist independently of the individual's influence sphere, are equal to that of the facts of the natural sciences in as far as they exert external influence on the individual (Mouton, 1993). Hughes (1990) interprets Durkheim's social facts construct as criteria to use when objectively investigating social phenomena as if they were physical facts. Especially the scientific method of experimentation could be used to explain social observable facts, according to Durkheim. This view is in sharp contrast to the view of Dilthey, who believes that human behaviour is unpredictable and nothing could be generalized about it (Bailey, 1982).

According to Bailey (1982), Max Weber suggested an intermediate approach. Weber believed that the scientific research method had a role to play in social research, but that it was insufficient. Bailey (1982) further reflected the views of Weber as that the social sciences also needed a research method that could facilitate direct understanding (Verstehen) and which again could not be used in the natural sciences because of a different relationship between researcher and research data.

Modern-day social scientists believe that social phenomena are indeed orderly enough to be able to predict. To do this, social sciences should try to find actual causes for the researched phenomena, which is unrealistic. Ultimately, casual explanation would be the best alternative for the natural sciences' actual cause research goal (Bailey, 1982).

The above-mentioned views are not to express the positivism debate in its fullest consequences. It merely serves to introduce the argument that the social sciences work hard to prove that their own research philosophy and research method can deliver empirical results that are based on direct experience and that can be independently verified (Lutz, 1992), and with which social phenomena can be investigated, described and solved to add value to man's everyday life.

## 3.2 The Research Approach

### *3.2.1 Qualitative or quantitative approach?*

Robert Burns emphasizes that the core difference between qualitative and quantitative is their "disagreement about the simplification of reality" (Burns, 2000:12). The following table depicts the difference between the two approaches according to Eisner (Burns, 2000):

**Table 3.1: Eisner's critical difference between qualitative and quantitative approaches**

| Drive | Qualitative | Quantitative |
|---|---|---|
| *Concerned with* | Processes | Consequences |
| Work with | Organic wholeness | Independent variables |
| Interest | Meanings derived from direct | Behavioural statistics |

| | | |
|---|---|---|
| | experience | |
| Expected outcome | Context-bound conclusions based on perceptions and interpretations | Scientific generalisations. |

Adapted from: Burns (2000)

Burns (2000) views the strengths and limitations of the two different approaches as follows:

*Strength of the quantitative approach*

This approach uses reliable measurements, control of which is achieved through sampling and design. In the natural sciences this method is used to determine causation of phenomena, which can be proven through testing of hypotheses. This testing is done through the deductive process, which produces data that can be statistically analysed.

*Limitations of the quantitative approach*

When this approach is used in social science research, the focus on human behaviour complicates the hypothetical predictions that are set. Social behaviour cannot be investigated in a controlled experimental environment. Because this approach therefore cannot be totally objective, its generalizations cannot always be made true for all people (Burns, 2000).

*Strengths of the qualitative approach*

The results of the investigation are often unexpected, because the researcher is much more personally involved in the process and has an insider view of the field. It is usually possible to suggest different relationships from the results. The research report is narrative as opposed to the statistical nature of the quantitative approach (Burns, 2000).

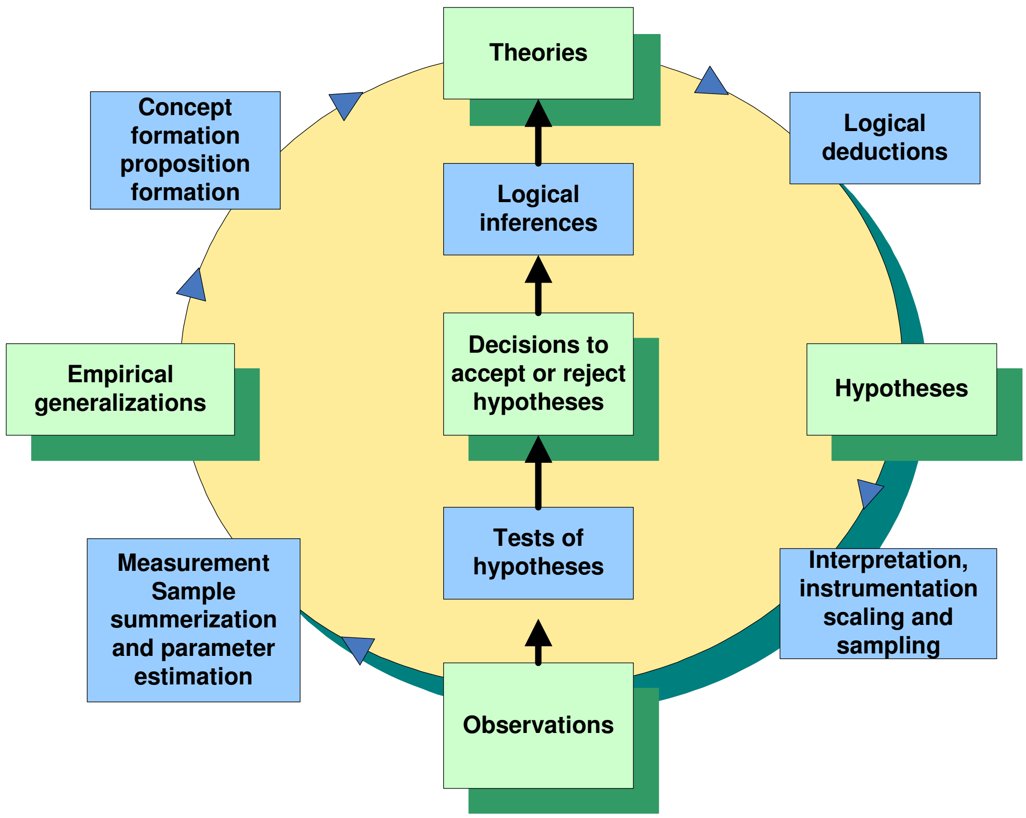
*Limitations of the qualitative approach*

The qualitative approach is criticized by followers of the quantitative method for inadequate validity and reliability of its measuring methods. Because of the inadequate measurements, it is difficult to apply conventional standards (Burns, 2000). The context in which the data is gathered cannot be replicated, nor can the results be generalized. The approach has a strong subjective nature and has the potential to be biased. It usually takes time for the researcher to establish a relationship of trust with the respondents and it is difficult to guarantee the anonymity of those participating in the research (Burns, 2000).

*The Scientific Model*

Based on the qualitative process, the scientific model of Wallace has been widely used and referred to (Baker, 1994). The process model is depicted figure 3.2:

**Figure 3.2: Wallace's Model of Science**




Adapted from: Burns (2000).

The deductive part of the process starts with theories on top of the model. Wallace (Baker, 1994) suggested first to scrutinize the theory to establish its suitability to deliver the envisaged results. Thereafter the deductive process may begin. Then hypotheses as a form of prediction are set (Baker, 1994). These predictions are used to determine and confirm the actual observations that will be made rather "than for predicting the actual outcome of such observations" (Baker, 1994: 57). Again the importance of the hypotheses that are set lies in the specification of the measurements that will be used to test the theory. Then the sample is chosen so that it will represent the population the best. The final step in the process is to decide whether to accept or reject the hypotheses. If the results confirm what was expected from the hypotheses, it is accepted and rejected if the results cannot support the hypotheses. The process may be repeated if the results stimulate the creation of new hypotheses that were not anticipated in the beginning (Baker, 1994).

The inductive part of the model will not be used and will therefore not be discussed.

### *3.2.3 Research Paradigm*

According to Bailey (1982), researchers have certain values or a prior logical-rational model (Baker, 1994) that predisposes them to a particular paradigm. As an example, Bailey lists some of the social paradigms as follows:

**Table 3.2: Some Common Social Research Paradigms**

| **Paradigm** | Unit of analysis | Data-collection method used | Data-analysis technique |
|---|---|---|---|
| " Scientific" or statistical | Usually micro, but may be macro | Survey | Statistics |
| Social psychology and small-group research | Micro | Usually laboratory experiment or observation | Statistical |
| Ethnography | From micro to macro (e.g. collective behaviour) | Observation and field notes | Verbal or qualitative analysis of field notes |
| Ethno-methodology | Micro | Observation and tape recording | Verbal analysis of field tapes and notes |

Adapted from: Bailey (1982)

The current research will follow the quantitative approach. It was decided to make use of a survey to collect the data, and the data will be analysed statistically. As indicated by Bailey in the table above, the strength of this process lies in the reliability of the measurements. In this case, four existing developed measurements are used. The formulated research questions that will guide the research will be tested through a deductive process, meaning that the hypotheses are deduced from generalized theory (Burns, 1983). This approach will allow statistical analysis and the following techniques will be used:

Factor analysis using the Oblique procedure and then evaluated by means of a confirmatory factor analysis;
Intercorrelation to determine relationships;
A multiple-regression analysis, and
A structural equations model to confirm the theoretical model.

## 3.3 The Design

The research was designed with the conceptualized model in mind (refer to Figure 1.1: The team evaluative and interaction influencing process model). The research design started with a review of the existing literature of team climate, emotional intelligence, team member exchange and goal orientation.

As reflected by the conceptual model, the study is in essence a correlation study. According to Stern (1979), a correlation study is one that “measures two or more variables and attempts to assess the relationship between them, without manipulating any variable” (Stern, 1997:34). The focus of the research is to establish whether any of or all the variables are related and if related, to what degree?

One important strong point of this method is that it can determine a relationship between variables. However, the condition is that each of the variables is measured in each of the individuals being studied (Stern, 1979). A limitation is that a correlation study cannot give conclusive information about the causes of the relationship, just that the variables are related or not (Stern, 1979). Also refer to the different research questions formulated in Chapter 1 to confirm the study as a correlation study.

## 3.4 The Questionnaire

Questionnaires deliver optimal results when used in natural environments like work teams in organization (Rosenthal & Rosnow, 1984). The authors believe that a questionnaire is especially useful in situations where the proposed sample have the language skills and experience to express their own feelings and behaviour patterns adequately (Rosenthal & Rosnow, 1984).

The questionnaire is a popular and versatile mode to gather data (Rosenthal & Rosnow, 1984; Wagenaar & Babbie, 2004). It is usually mailed to the selected sample with a stamped return envelope, or can also be delivered and collected after completion (Bailey, 1982; Rosenthal & Rosnow, 1984). Controlling the data gathering is important, as follow-up letters and reminders to return the completed questionnaires before the due date has proven to increase the response rate drastically (Rosenthal & Rosnow, 1984). May (2001) describes the questionnaire as a data gathering method to have similarities to the research methodologies of the natural sciences, because all surveys are either based on some theoretical assumption or tries to construct a new theory. Questionnaires measure behaviour, attitudes and facts. The questions in the survey should be constructed so that the respondents are able to answer each with confidence (May, 2001; Wagenaar & Babbie, 2004).

Because questionnaires are completed individually by the respondents and without the assistance of the researcher, the respondents should be capable and willing to answer the questions. This differs from a structured interview where the researcher may be able to confirm understanding of the notion in question with the respondent (Bailey 1982).

For this research a questionnaire was compiled consisting of four previously developed instruments, viz measuring the concepts of emotional intelligence, team member exchange, goal orientation and team climate, respectively. These four measurements where chosen because they had been used in previous research and were available for use in this research effort.

All four instruments were developed outside South Africa. The factor structure of all four instruments that were used in the South African context, were compared with the original structure reported by their respective developers in order to confirm the intercultural transferability of the construct. Culture groups differ in their behaviour patterns because their perception of their social reality is different. This confirms Anastasi's (1988) view that a culture-free test is a fallacy, because heredity and environmental factors influence behaviour. As a psychological test reflects behaviour, it will be highly unlikely to develop a scale that is culture-free and universally applicable owing to each culture group's unique perception of their own social environment (Anastasi, 1988; Samuda, 1998).

Refer to Annexure A for a copy of the questionnaire used in this research. The following instruments were included in this survey, with an indication of the behavioural domain measured by each instrument:

Emotional Intelligence Scale, measuring appraisal and expression of emotion, regulation of emotion and utilization of emotion, (Schutte, Malouff, Hall, Haggert, Cooper, Golden, & Dornheim, 1998).

Team Member Exchange Quality, measuring quality of working relationships within a team, effectiveness of team meetings and team cohesiveness. (Seers, 1998).

Goal Orientation Scale, measuring a learning goal orientation and a performance goal orientation (Button, Mathieu & Zajac, 1996)

Team Climate Inventory, measuring vision as team goal, participative safety, task orientation and support for innovation (Anderson & West: 1998).

## 3.5 Emotional Intelligence Scale

This 33-item scale was developed by Schutte *et al.* (1998) to measure the ability to adaptively recognize, express, regulate and harness emotions of the self and of others. It is intended to assess emotional intelligence as conceptualized by Salovey & Mayer (1990). They designed a 5-point Likert-type scale on which “1” represents “strongly disagree” and “5" represents “strongly agree” to answer each item. Items 5, 28 and 33 are reverse scored. An orthogonal-rotation factor analysis was conducted on 62 items and resulted in four factors with loadings of 0,40 and above (Schutte et al., 1998). Of the four factors, one strong factor with 33 items and an Eigenvalue of 10,79 loaded at 0.40 and higher. The set of 33 items represented the different categories of the original Salovey and Mayer-model (1990) proportionately the best and it was decided that this one strong factor constituted the scale (Schutte *et al.*, 1998). An internal consistency showed a Cronbach’s alpha of 0.90 for the 33-item scale (Schutte *et al.*, 1998).

### *3.5.1 Team Member Exchange Quality*

Seers (1998) developed the Team Member Exchange Quality Scale by adapting the initial instrument used by Seers and Graen (1984). Extensive research was previously done on the exchange relationship between team leader and team members. Seers saw the need to research the relationship and exchange between members in a team (Seers 1998). Team Member Exchange Quality Scale measures the employee’s evaluation of the quality of work relationships with other team members. The scale consists of 18 Likert-type items on a seven-point scale ranging from “1” as “totally disagree” to “7” as “totally agree”.

Seers (1989) subjected the 34 team related items to a principal axis factor analysis with varimax rotation to identify the items that represent the theory in a reliable scale. Three strong factors were identified: the first to reflect the team’s meeting effectiveness, the second to represent the team members’ cohesiveness and the third factor to reflect the quality of the working relationship among the team members (Seers, 1998).

The factor loading of the different variables can be depicted as follows:

**Table 3.3: Team member Exchange Quality Scale**

| Item number | Factor One | Factor Two | Factor Three |
|---|---|---|---|
| | Meeting effectiveness | Team member cohesiveness | Quality of working relationship |
| 1 | .80 | | |

| Item number | Factor One<br>Meeting effectiveness | Factor Two<br>Team member cohesiveness | Factor Three<br>Quality of working relationship |
|---|---|---|---|
| 2 | .78 | | |
| 3 | .64 | | |
| 4 | .60 | | |
| 5 | | -.66 | |
| 6 | | .62 | |
| 7 | | .59 | |
| 8 | | -.74 | |
| 9 | | | .55 |
| 10 | | | .48 |
| 11 | | | .48 |
| 12 | | | .46 |
| 13 | | | .46 |
| 14 | | | .62 |
| 15 | | | .58 |
| 16 | | | .73 |
| 17 | | | .65 |
| 18 | | | .54 |

Adapted from: Seers (1998)
Items 5 and 8 are reverse scored.

The developed measurement was performed at the organization in two follow-up sessions, 12 months apart. Owing to changes in the organization, only 123 of the original 154 employee respondents completing the questionnaire in the first session could be used again in the follow-up session a year later (Seers, 1989). The scale characteristics can be depicted as follows:

**Table 3.4: TMX Scale characteristics**

| Factor | Number of Items | Mean | | Standard Deviation | | Alpha-coefficient | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 1 | 2 | 1 | 2 |
| 1 | 4 (Meeting) | 3.43 | 3.31 | .90 | .88 | .83 | .84 |
| 2 | 4 (Cohesion) | 2.86 | 3.02 | .89 | .82 | .80 | .75 |
| 3 | 10 (Quality of work role) | 2.78 | 2.69 | .55 | .55 | .85 | .82 |

Adapted from: Seers (1998)

### *3.5.2 Goal Orientation Scale*

Button, Mathieu and Zajac (1996) used the theoretical and empirical work of Dweck's motivational theory (1989) to generate a pool of performance and learning goal orientation items. The items were further formulated so that the content was not specific to a particular setting or a particular type of achievement activity (Button, Mathieu & Zajac, 1996). A scale with 20 items (10 items each for performance and learning goal orientation) was tested in four different studies.

Ten items were generated to reflect that performance goal orientation conceptually. Accordingly, the concept implied that an individual strives to gain favourable judgement on his performance or that the individual would avoid challenging tasks in order to evade negative judgement on his competence. The other 10 items were selected to reflect a learning goal orientation, which proposes that an individual always tries to understand something new or strives to increase his level of competence in a particular task. An individual with a learning orientation will not turn down a challenging task and will rather try to improve on previous standards (Button, Mathieu & Zajac, 1996).

The questionnaire of 20 items was taken put to an undergraduate psychology class (N=374). The Cronbach Alpha for the 10 performance goal orientation questions was .76 and .79 for the l0 learning goal questions. Two confirmatory factor analyses were done on the data. The first was done to confirm that performance and learning orientations are indeed two different dimensions. The second analysis was done to determine the relation between the two dimensions and other demographic and motivational variables (Button, Mathieu & Zajac, 1996). Also tested was the goodness of fit for a two-factor solution or a single factor solution. The latter resulted in a poor fit to the data. The two-factor model fitted the data slightly better. In comparison the analysis results were as follows:

**Table 3.5: Goodness of fit results**

| One-factor Model | Two-factor Model |
|---|---|
| $X^2$(170, N=374)=1035.76, p<.001 | $X^2$(169, N=374)=427.88, p<.001 |
| RMSAE= .12 | RMSAE= .06 |
| GFI= .68 | GFI= .68 |
| NNFI= .33 | NNFI= .80 |
| CFI= .40 | CFI= .82 |

Adapted from: Button, Mathieu & Zajac (1996).

The factor loadings for each variable were statistically significant ($p<.05$) and were greater than .41 in the two-factor model (Button, Mathieu & Zajac, 1996). Two items were dropped from each factor and these 16 items were further analysed.

Button, Mathieu & Zajac, (1996), also completed a study in order to establish whether the dispositional measures of performance and learning goal orientation could be distinguished from the situational measures of the same two constructs. The study resulted in two models that were fitted to the data. The first was a four-factor model placing performance goal orientation, learning goal orientation, situational performance goal and situational learning goal orientation each in separate latent factors (Button, Mathieu & Zajac, 1996). The second model placed the performance goal (both dispositional and situational) and the learning goals (again both dispositional and situational) in two separate factors (Button, Mathieu & Zajac, 1996). The goodness of fit results indicated that the four-factor model had a significantly better fit to the data. This meant that dispositional and situational aspects of goal orientation are distinguishable (Button, Mathieu & Zajac, 1996). In reality, this result can be interpreted as "*while dispositional goal orientations predispose individuals to adopt particular response patterns across situations, situational characteristics may cause them to adopt a different or less acute response pattern for a specific situation*" (Button, Mathieu & Zajac, 1996:40).

The results therefore indicated convincingly that goal orientation is best represented by two distinguishable and uncorrelated dimensions, viz performance goal orientation and learning goal orientation, as reflected in the questionnaire (Button, Mathieu & Zajac, 1996).

### *3.5.3 Team Climate Inventory*

Anderson and West (1998) developed the Team Climate Inventory to measure the climate for work group innovation specifically. It consists of 38 Likert-type questions on a seven-point scale. These items range from "1" as "totally disagree" to "7" as "totally agree".

From 61 items that were factor analyzed, 38 items indicated 5 different factors with an alpha reliability of 0,5 or above. The factors are as follows:

Vision, with 11 items and a coefficient alpha of 0,94;
Participative safety, with 8 items and a coefficient alpha of 0,89;
Support for innovation, with 8 items and a coefficient alpha of 0,92;
Task orientation, with 7 items and a coefficient alpha of 0,92; and
Frequency of interaction, with 4 items and a coefficient alpha of 0,84.

The instrument was used to measure the level of team climate for innovation under senior management teams in 27 hospitals in the UK (Kivimaki *et al.,* 1997). The instrument was also adapted for use in Sweden under production teams (Kivimaki *et al.,* 1997).

Exploratory factor analysis indicated the original four factors (vision, participatory safety, task orientation and support for innovation). However, on a British sample, factor analysis resulted in the identification of a fifth factor, called interaction frequency (Kivimaki *et al*., 1997).

Kivimaki *et al* (1997) replicated previous research by investigating the psychometric properties of a Finnish version of the TCI. They specifically tested the internal homogeneity, underlying factor structure, construct validity and factor replicability across samples of high and low job complexity (Kivimaki *et al*., 1997). A large Finnish sample (N=2 265) was used and some of the factor analysis results of the Finnish research can be summarized as follows:

The five-factor solution had a slightly better explanation of the total variance than the four-factor solution (63.9% and 64.7% over the slightly weaker 61.1% and 61.8%) (Kivimaki *et al*., 1997);

After varimax rotation, the five-factor solution showed considerably fewer items cross-loaded than the four-factor solution and thus indicated a better fit to the data (Kivimaki et al., 1997).

The results of the five-factor solution corresponded with the original formulation of the TCI, which was confirmed by confirmatory factor analysis (Kivimaki *et al.,* 1997).

### *3.5.4 The Sample*

Gaining access to different organizations in order to ask approval to participate in the survey, proved more difficult than initially planned.

It was decided to use a convenience sampling method, so called because the sample includes anybody who appears to be able to answer the questions or who shows interest in the survey (Bailey, 1982; Baker, 1994). De Vos (1998) refers to this sampling method as accidental sampling, because it usually includes those who are nearest and most available in the sample. Babbie (2007) warns against the danger of over generalizing results from such a sample. Babbie (2007) points out that this method is frequently used but he considers it risky

Baker (1994), however, believes that careful planning can soften this risk. If the probability is considered that the selected respondents are likely to comply with the research request and are able to answer the questions, a degree of control is restored.

### *3.5.5 Sample selection*

Eight organizations were selected across the country based on the convenience of access to them. Each organization was contacted personally and was asked to indicate how many employees who would be able and willing to complete the questionnaires. It was suggested that the profile of the ideal respondent would be someone who works in a team environment and who would understand questions on normal day-to-day behaviour in organizational context. The requirement was set that the participants should work in a team environment irrespective of the team structure (hierarchical or work team, virtual team, matrix team, self-management team or project team). An indication of the respondent's team structure was requested as a separate question in the biographical section of the questionnaire.

Thereafter each contact was supplied with an official letter addressed to their Human Resources Manager or individual they identified as coordinator of the data collection action, requesting access to employees in order to complete the questionnaires. A copy of the individual letters is attached as Annexure B. After approval that the respective organizations may be included in the study, the questionnaires were distributed to the organizations.

### *3.5.6 Data Collection*

Three hundred and seventy-five hard copies of the questionnaire were distributed to the different contact persons at the identified companies. The questionnaires were delivered either in person to those in Pretoria and Johannesburg or by courier for those in Nelspruit, Bloemfontein and Cape Town. The anonymously completed responses were collected in the same manner after the contact persons notified the researcher that the completed questionnaires were ready to collect.

Each organization reacted differently to the request. Some responded within two weeks (like the Hospital Emergency Team and the Local Government division in Pretoria). Others needed a reminder. Contact persons were phoned and requested to send the completed questionnaires through. The IT Project Management Group in Johannesburg was reminded four times before any response was provided. As indicated in the feedback summary depicted in Table 3.3, this company had a 54% return rate of 150 distributed questionnaires. The transport company in Bloemfontein in the end decided not to partake in the research. Their management group decided that certain development interventions in their company had the same research results in mind and therefore supported their own initiatives. This announcement came at a very late stage, which left this researcher without an option to replace this company in the identified population. The results registered in Table 3.6 were finalized after four follow-up communications, either by e-mail or by phone.

This method resulted in drawing the following sample:

**Table 3.6: Details of research sample**

| Type of Organisation | Questionnaires Distributed | Questionnaires Received | % Re-sponse |
|---|---|---|---|
| Large Life Insurance Co. IT team | 30 | 17 | 56.6% |
| Local Government Project Team | 30 | 13 | 43.3% |
| Local Government Town Planning | 40 | 32 | 80% |
| Hospital Emergency Room Team | 20 | 19 | 95% |
| Public Transport Company | 35 | 0 | 0% |
| IT Project Management Group | 150 | 81 | 54% |
| HR Department Tertiary Institution | 50 | 12 | 24% |
| Academic Admin Tertiary Institution | 20 | 16 | 80% |
| Total | 375 | N=190 | 50.6% |

There is no consensus on how to determine the correct sample size. There is, however, common agreement that a sample should reflect all the elements of the bigger population. How the population is defined will therefore influence the character of the sample. The larger the population, the smaller the percentage of that population that should be represented in the sample (Bless et al., 2006; Brynard & Hanekom, 2006; De Vos *et al.,* 2005.).

It is also acknowledged that larger samples will produce statistically more significant results. The homogeneity or heterogeneity of the population will also influence the size of the sample (De Vos *et al.*, 2005). According to De Vos *et al.* (2005), high heterogeneity will require a larger sample in order to reflect the diverse character of the population. Bless *et al.* (2006) summarize the decision requirements on sample size as follows:

The degree of accuracy required;
The degree of variability or diversity in the population, and
The number of different variables examined simultaneously in data analysis. (Bless, Higson-Smith, & Kagee, 2006:108).

Table 3.6 above depicts the sample drawn for the current study. The sample is highly heterogeneous, represents 50% of the population and falls inside the acknowledged limits of traditional methods to determine sample sizes (Bless *et al.*, 2006).

Hair *et al.* (1998) described another method to determine a sample size. They believe that in order to do effective factor analysis, the sample size should be five times the number of variables being analyzed. The longest scale has 38 items, and with the total number of 112 items, the current sample size is deemed acceptable.

Wagenaar & Babbie (2004) argue that there are no strict standards to determine the most correct sample size. They believe that proof of a lack of response bias is more important than the response size itself. They argue that a 70% response rate is very good and a 50% return can be considered as adequate.

Field (2005) agrees that there are no hard or fast rules concerning sample size for factor analysis. He believes that a sample of 300 is good and a sample of 100 poor. However, Field (2005) argues that factor loading is perhaps a better method to determine factor reliability than only sample size. A combination of the two methods would be the ultimate. According to Field (2005), factors with ten or more loadings of .40 and above, within a sample of 150 or more, should be sufficient.

## 3.6 Respondents

The sample (N=190) had an average age of 39.12 (SD=9.54), and 72% were in the age group 30-49. Only 6% of the respondents were older than 55, the oldest two in the group being 65-69. Kreitner and Kinicki (2001) refer to extensive research on age stereotypes and the results that age was positively linked to performance and specifically within the age group 25-30. From 30 onwards the profile flattened out. However, the results emphatically indicated that older age is not necessarily linked to non-performance (Kreitner & Kinicki, 2001).

**Table 3.7: Age distribution**

| Demographic information of the sample | | |
|---|---|---|
| Demographic Characteristics | Sample | |
| | Frequency | % |
| Age | | |
| <29 | 27 | 14 |
| 30-39 | 72 | 38 |
| 40-49 | 64 | 34 |
| 50-59 | 23 | 12 |
| 60-69 | 3 | 2 |
| Total | 189* | 100 |

The gender distribution was 39% male and 61% female.

**Table 3.8: Gender distribution**

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| Gender | | |
| Male | 74 | 39 |
| Female | 116 | 61 |
| Total | 190* | 100 |

Of the 190 respondents, 23% had a secondary education. The graph illustrates that 58% of the respondents either have a post-school diploma, a national diploma or a Bachelor's degree. It further illustrates that 19% of the sample has a postgraduate qualification. This means that the sample represents an educated part of the population as 77% of the respondents have a post-school qualification.

**Table 3. 9: Qualification distribution**

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| Qualification | | |
| Secondary | 4 | 2 |
| Gr. 12 | 39 | 21 |
| Post-school cert. | 28 | 15 |
| Nat. Diploma | 41 | 22 |
| Bachelor's degree | 42 | 22 |
| Honours degree | 19 | 10 |
| Master's degree | 16 | 8 |
| Doctoral degree | 1 | 1 |
| Total | 190* | 100 |

The question on the number of individuals per work team (mean was 9.4 with a SD=12.84) resulted in a large number of different team sizes. This may be attributed to respondents probably identifying their work group as a team. A team can be defined as a small group of people with a common commitment. The ideal team size is 8 but can be any size between 4 and 10 (Kreitner & Kinicki, 2001). The majority (55%) of the respondents worked in teams of between 4 and 8 members per team. The graph below depicts the difference in team size as reported by the respondents:

**Figure 3.3: Team size**

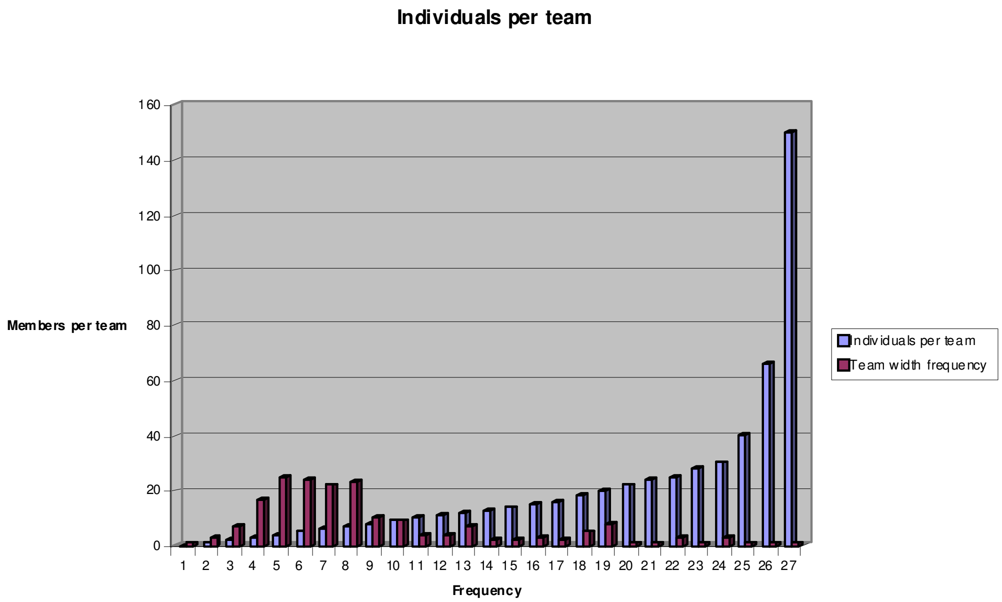



**Table 3.10: Members per team**

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| Number of individuals in work team | | |
| 0 | 1 | 1 |
| 1 | 3 | 2 |
| 2 | 7 | 4 |
| 3 | 17 | 9 |
| 4 | 25 | 13 |
| 5 | 24 | 13 |
| 6 | 22 | 12 |
| 7 | 23 | 12 |
| 8 | 10 | 5 |
| 9 | 9 | 5 |
| 10 | 4 | 2 |
| 11 | 4 | 2 |
| 12 | 7 | 4 |
| 13 | 2 | 1 |
| 14 | 2 | 1 |
| 15 | 3 | 2 |
| 16 | 2 | 1 |

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| 18 | 5 | 3 |
| 20 | 8 | 4 |
| 22 | 1 | 1 |
| 24 | 1 | 1 |
| 25 | 3 | 2 |
| 28 | 1 | 1 |
| 30 | 3 | 2 |
| 40 | 1 | 1 |
| 66 | 1 | 1 |
| 150 | 1 | 1 |
| Total | 190* | 100 |

Respondents were required to indicate their typical team structure out of five possibilities, namely a matrix team, a virtual team, a project team, a self-management team and a work team. The responses indicated that 70% belonged to a typical hierarchical structure as depicted by the work team model structure in the questionnaire. Another 7% or 13 responses belonged to a matrix type team. Six or 3% worked in a virtual team environment, 18 could identify their team as a project team and two belonged to a self-managed team.

**Table 3.11: Team structure**

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| Team Structure | | |
| Matrix | 13 | 7 |
| Virtual | 6 | 3 |
| Project | 18 | 9 |
| Self-management | 2 | 1 |
| Work team | 151 | 79 |
| Total | 190* | 100 |

It is probably difficult to categorize job types in only 3 categories. The respondents, however, indicated their different work role or job types as 22% technical, 32% managerial and 46% administrative.

**Table 3.12: Work role**

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| Work Role | | |
| Technical | 41 | 22 |
| Managerial | 61 | 32 |
| Administrative | 88 | 46 |
| Total | 190* | 100 |

Of the 189 respondents who completed this question, 26% were in team leader positions, with 74% working as team members.

**Table 3.13: Team role**

| Demographic Characteristics | Sample | |
|---|---|---|
| | Frequency | % |
| Team Role | | |
| Team leader | 49 | 26 |
| Team member | 140 | 74 |
| Total | 189* | 100 |

(*Totals may differ owing to missing data.)

## 3.7 Techniques and Procedures

The data will be measured and analysed using the BMDP Statistical Software (1993) for the factor analysis and the Prelis 2.80 of Jőreskog and Sőrbom (2006) for the Confirmatory Factor Analysis.

All the psychometric instruments will be factor-analyzed by using the Oblique procedure and then evaluated by means of a Confirmatory Factor Analysis. A Structural Equations Model will be built to confirm the theoretical model and will be subjected to a Confirmatory Factor Analysis.

# CHAPTER 4

# RESULTS

## 4.1 Factor Analysis

As discussed in the previous chapter, the questionnaire used in the current study consists of four previously developed measures. It was necessary to submit these measures to a factor analysis for two main reasons. Firstly, the main goal of factor analysis is to "summarize patterns of correlation among observed variables" (Tabachnick & Fidell, 2001:582). Factor analysis reduces numerous variables to a few factors and help to describe these factor groupings. There are two types of factor analysis. Exploratory Factor Analysis is done early in the research to help order data patterns. Confirmatory Factor Analysis is more complex and is usually used in testing a hypothesis about latent processes in the data (Tabachnick & Fidell, 2001). In essence, factor analysis is done to confirm the number of factors per measure, but also to confirm which variables load on to which factor (Hatcher, 1994). Hair et al (1998) state that it is possible for a researcher to have a preconceived structure per measure in mind and the researcher would then need to confirm whether the data fits the expected structure by using a Confirmatory Factor Analysis. This was the case with the questionnaires used in the current study, as the number of factors was known through the available statistics when the measures were developed. The number and nature of the factors needed to be confirmed as they are used in a new context.

The second reason to submit the data to a Confirmatory Factor Analysis is because all four measures were developed in the United States. Culture groups differ in their behaviour patterns because their perception of their social environment is different. To use a scale which was developed in another social context and expect it to measure the same dimensions, is risky. Such scales should therefore be independently validated (Van Wyk *et al.*, 1999) to ensure that the same variables load on the same number of factors as far as possible.

## 4.2 Analytical procedure

The analysis was planned by this researcher with support from the study leader and statistically analysed by the Department of Statistics of the University of Pretoria. The analysis was done on BMDP Statistical Software, Release 7.1 package. To ensure that the internal reliability and their factor structures compared favourably with the original questionnaire, the instruments used were revalidated by means of factor analysis. First order Exploratory Factor Analysis was carried out using principal axis factoring with Direct Quatirmin rotations according to the number of expected factors. The following rules were used to evaluate the results:

Eigenvalues > 1.00 were identified. Clear breaks on a scree plot were marked and all numbers above the break indicated the potential number of factors.

Based on this number of factors identified, an Exploratory Factor Analysis was done.

The results of the Exploratory Factor Analysis were evaluated by accepting all items loading value at ≥ 0.25 on a factor. Items loading on more than one factor and those loading ≤ 0.25 were left out of the next analysis round.

This process was repeated until the above rules were satisfied.

Garson (2008:28) believes that the decision of what the minimum value for a factor loading should be is purely arbitrary. However he acknowledges the social sciences practice of .3 or .35 as cut-off minimum. Garson (2008:28) is of the opinion that lower loadings may be included if the researcher believes it is of value to include such a loading.

With reference to the above-mentioned decision-making rules, Tabachnick & Fidell, (2001) believe that the factor loading value with an orthogonal rotation (when the factors are not correlated) should usually be 0.32 or larger. Under this rotation, the loading value refers to the correlation strength between variable and factor. As soon as it can be established that the factors are indeed correlated (which is usually the case), an oblique rotation is required (Tabachnick & Fidell, 2001). The loading value is then an indication of the measure of the unique relationship between factor and variable (Tabachnick & Fidell, 2001). It was decided to set the factor loading limit at ≥ 0.25. Tabachnick & Fidell, (2001) refer to suggestions that loadings in excess of 0.71 is excellent, 0.63 is very good, 0.55 could be considered as good, 0.45 as fair and anything less than 0.32 as poor. "The size of loading is influenced by the homogeneity of scores in the sample. If homogeneity is suspect, interpretation of lower loadings is warranted" (Tabachnick & Fidell, 2001: 625). Yet the researcher should take the decision whether the consideration of lower loadings is justified. The character of the factor and whether the inclusion of a variable in the factor grouping will add value to the description of the specific factor, will be of importance, even if the variable loads as low as 0.25. (Hatcher, 1994; Tabachnick & Fidell, 2001). Some of the factor analysis results necessitated the inclusion of factor loadings as low as ≥.25 and it was therefore decided to set the bottom range as such.

The results of the study, based on the guiding rules described above, were then submitted to a Confirmatory Factor Analysis to determine which model best fits the data. These results indicate whether the validity of the original measure used on the South African data is satisfactory (Van Wyk *et al.,* 1999).

### 4.3 Confirmatory Factor Analysis

Confirmatory factor analysis confirms the existence of a predicted number of latent factors as well as the variables loading onto the factor that they characterize. This model is then tested within a population of choice with the idea that the model will reflect certain phenomena of reality (Hatcher, 1994). If the data succeeds in reflecting the measured characteristics of the population, the model is considered to fit the model (Hatcher, 1994).

The aim when evaluating a model for a good fit to the data is to have a non-significant Chi-square (Tabachnick & Fidell, 2001). Chi-square is used to test for the significance of the difference in fit between the observed model and the implied model (Hatcher, 1994; Tabachnick & Fidell, 2001).

Chi-square ($X^2$) is, however, sensitive to sample size and the model fit of a large sample is often difficult to determine (Hardy & Bryman, 2004). With a good fit scenario, $X^2$ will be relatively small and the corresponding p-value will be large (above 0.05 and closer to 1.00) and will usually result in the p-value being reported as significant (Hatcher, 1994). The Chi-square ($X^2$) is usually the first step in model evaluation. Because $X^2$ is statistically sensitive to sample size, other indices, less sensitive, were developed to support the model-fit evaluation process (Hardy & Bryman, 2004).

A low and insignificant value of $X^2$ is what is desired (Kline, 1998), meaning that the difference between the observed and the implied model is insignificant. Kline (1998) refers to a practice where $X^2$ value is divided by the degree of freedom in order to lessen the effect of sample size. This practice is also called the practical chi-square fit index (Tabachnick & Fidell, 2001), where a p-value of .0001 is highly significant and technically means that the model does not fit. If $X^2$/df results in the ratio to be less than 2, as a rule of thumb, the model may be accepted (Hatcher, 1994). Yet there are other fit indices designed to measure the fit and which are much less sensitive to the sample size (Kline, 1998).

The statistical software used in this study, Lisrel 8.80, supplied 35 different goodness of fit indices. The question is whether all indices should be used in the evaluation of the model fit? According to Hatcher (1994), it is good to start the model fit assessment process reviewing some overall goodness of fit indices like the chi-square test, the Bentler Comparative Fit Index (CFI), and the Bentler-Bonnet Non-normed Fit Index (NNFI). Kline (1998) adds an index based on the standardized residuals to Hatcher's list. Vermeulen and Mitchell (2007: 211) decided to use only six goodness of fit indices in their study out of a possible 11 produced indices. These were Model chi-square, the Root Mean Squared Error of Approximation (RMSEA), the 90% confidence interval of the RMSEA, the Bentler Bonnet Non-normed FIT Index (NNFI), the Comparative Fit Index (CFI) and lastly the Bollen Incremental Fit Index (IFI).

The Bentler Comparative Fit Index (CFI) as well as the Normed Fit Index (NFI) indicates the proportion in improvement of the overall fit of the observed model relative to the implied model. The CFI, if compared to the NFI, is less influenced by sample size and is therefore more popular to use (Kline, 1998). Much the same is the Non-normed Fit Index (NNFI), but it includes a model-complexity correction (Kline, 1998). Small sample sizes may cause the NNFI value to be lower than other fit indices (Kline, 1998). The RMSEA estimates "the lack of fit in a model compared to a perfect (saturated) model" (Tabachnick & Fidell, 2001:699). An RMSEA value of 0.06 or less is considered a good fit and any value larger than .10 indicates a poor fit (Hardy & Bryman, 2004; Tabachnick & Fidell, 2001).

As a guide to decide on the values of an ideal fit for the measurement model, Hatcher (1994) suggests the following values:

The *p*-value of chi-square should be non-significant and should be larger than .05 and closer to 1.00. Owing to its sensitivity to sample size, this index will rarely be non-significant.
Chi-square should be less than 2.
The comparative fit indices CFI and NNFI should both exceed .9.

## 4.4 Factor Structure for Emotional Intelligence Scale

The decision guiding rules as described above were followed when the results from the factor analysis of the Emotional Intelligence Scale were analysed. The eigenvalues of the unaltered correlation matrix resulted in 10 factors ≥ 1. The eigenvalues were 7.58, 2.22, 2.08, 1.82, 1.51, 1.42, 1.26, 1.16, 1.11 and 1.05, respectively.

Because the first eigenvalue was significantly stronger than the rest it was decided to run the first factor analysis with only one factor. Setting the variable loading limit on ≥ .25, the result was that all the variables loaded on to one factor. Refer to Table 4.1 below. If the loading limit was lifted to 0.55, as suggested by Tabachnick & Fidell, (2001), the results changed to very poor as only 8 items out of 33 loaded ≥ 0.55.

**Table 4.1: Rotated Factor Loading 1 for EI Scale**

| Item | Factor 1 |
|---|---|
| A1 | 0.4868 |
| A2 | 0.4561 |

| Item | Factor 1 |
|---|---|
| A3 | 0.5819 |
| A4 | 0.3520 |
| A6 | 0.3025 |
| A7 | 0.5179 |
| A8 | 0.5557 |
| A9 | 0.5452 |
| A10 | 0.3921 |
| A11 | 0.3685 |
| A12 | 0.5474 |
| A13 | 0.3592 |
| A14 | 0.4484 |
| A15 | 0.3231 |
| A16 | 0.5255 |
| A17 | 0.4808 |
| A18 | 0.6137 |
| A19 | 0.4802 |
| A20 | 0.5145 |
| A21 | 0.4978 |
| A22 | 0.9801 |
| A23 | 0.4658 |
| A24 | 0.6116 |
| A25 | 0.3930 |
| A26 | 0.4264 |
| A27 | 0.6842 |
| A29 | 0.5114 |
| A30 | 0.4960 |
| A31 | 0.4238 |
| A32 | 0.6222 |
| A5* | 0.7720 |
| A28* | 0.3597 |
| A33* | 0.3683 |

(* Scores are reverse scored)

The one strong factor result is in total congruence with the original developed scale of Schutte *et al*. (1998). However, this fact was criticised by Austin *et al.* (2004) when they commented on the lack of reverse-keyed items in the scale and reported that two other studies found four sub factors in a re-development effort of the Emotional Intelligence Scale of Schutte *et al.* (1998). These comments motivated the decision to try and use the opportunity to see if more than one factor can be extracted from the data. The results was however not satisfactory and it was decided to remain with the the one factor result which supported the theory.

The loadings were re-evaluated and it was decided to do a final analysis with the loading limit at 0.25. Problem items 5, 6, 7, 8, and 33 were removed. Items 9 and 11 were retained because of their considered value to the factor, although both had loadings on two factors (refer to Table 4.2). This analysis had the following result:

**Table 4. 2: Factor loadings with deleted variables for Emotional Intelligence Scale**

| Item | Factor Loadings |
|---|---|
| A1 | 0.266 |
| A2 | 0.377 |
| A3 | 0.508 |
| A4 | 0.383 |
| A9 | 0.409 |
| A10 | 0.443 |
| A11 | 0.447 |
| A12 | 0.686 |
| A13 | 0.503 |
| A14 | 0.536 |
| A15 | 0.407 |
| A16 | 0.639 |
| A17 | 0.313 |
| A18 | 0.454 |
| A19 | 0.617 |
| A20 | 0.496 |
| A21 | 0.621 |
| A22 | 0.555 |
| A23 | 0.624 |
| A24 | 0.478 |
| A25 | 0.415 |
| A26 | 0.448 |
| A27 | 0.497 |
| A29 | 0.402 |
| A30 | 0.613 |
| A31 | 0.556 |
| A32 | 0.467 |
| AA28* | 0.237 |

| Item | Factor Loadings |
|---|---|
| Cronbach Alpha | 0.888 |
| % Variance | 24.10 |
| Squared Multiple Correlation (SMC) | 0.906 |

(*reverse scored)

The one-factor result confirms the result of the original instrument by Schutte *et al*. (1998).

A Confirmatory Factor Analysis was carried out on the one-factor solution and yielded the following indices:

**Table 4.3: Results of Confirmatory Factor Analysis of the Emotional Intelligence Scale on the one-factor model (N=190)**

| Indices | Value |
|---|---|
| Degrees of freedom | 350 |
| Satorra-Bentler Scaled Chi-square | 620.577 (P=0.0) |
| Root Mean Square Error of Approximation (RMSEA) | 0.0640 |
| 90 percent Confidence Interval for RMSAE | (0.0557; 0.0721) |
| Bentler & Bonner's Non-normed Fit Index (NNFI) | 0.959 |
| Comparative Fit Index (CFI) | 0.962 |
| Bollen Incremental Fit Index (IFI) | 0.962 |

The indices shown in Table 4.3 indicate an acceptable fit to the data. The practical Chi-square ($X^2$/df) is 1.77, which is acceptable. A RMSEA score of <06 is good. The score of 0.064 is therefore acceptable (Tabachnick & Fidell, 2001). The comparative fit indices are all larger than 0.9 and are therefore acceptable (Hatcher, 1994).

## 4.5 Factor Structure of Team Member Exchange Quality

An Exploratory Factor Analysis with a Direct Quartimin rotation was carried out on the responses of the 18 Team Member Exchange Quality items. It generated five eigenvalues ≥ 1, with 4.2, 2.23, 1.67, 1.45, and 1.20 as a result. Five factors were extracted in the first analysis. The decision-making rules described previously were used. It yielded a poor factor structure. The process was repeated until three factors were identified, which was in agreement with the factors identified by the developers of the original measure. The results were as follows:

**Table 4.4: Rotated Factor Loadings for Team Member Exchange Quality**

| Item | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|
| B1 | 0.748 | 0.028 | 0.045 |
| B2 | 1.012 | -0.120 | -0.004 |
| B3 | 0.821 | -0.092 | 0.071 |
| B4 | 0.611 | 0.242 | -0.040 |
| B6 | 0.132 | 0.816 | -0.089 |
| B7 | -0.005 | 0.910 | -0.119 |
| B9 | 0.046 | -0.055 | 0.536 |
| B10 | 0.008 | 0.315 | 0.310 |
| B11 | -0.054 | 0.034 | 0.461 |
| B12 | 0.104 | 0.186 | 0.584 |
| B13 | -0.014 | 0.450 | 0.359 |
| B14 | 0.079 | -0.138 | 0.474 |
| B15 | 0.108 | 0.067 | 0.288 |
| B16 | -0.065 | 0.114 | 0.613 |
| B17 | -0.033 | -0.082 | 0.423 |
| BB5 | 0.100* | 0.293* | 0.086* |
| BB8 | 0.403* | 0.280* | -0.061* |

(*items are reverse scored)

A final Exploratory Factor Analysis, followed by a Direct Quartimin rotation, was done after removing items 10, 13 and BB8 from the results depicted in Table 4.4 above. The results were very much in line with the original instrument. Although the second factor only consists of three items (B6, B7 and BB5), they represent the dimension of Team Cohesiveness well if compared to the original instrument.

The results of the final analysis are as follows:

**Table 4.5: Final Rotated Factor Loadings for Team Member Exchange Quality**

| Item | Factor 1 (Meetings) | Factor 2 (Exchange) | Factor 3 (Cohesiveness) |
|---|---|---|---|
| B1 | 0.734 | | |
| B2 | 1.005 | | |
| B3 | 0.818 | | |
| B4 | 0.581 | | |

| | | | |
|---|---|---|---|
| B6 | | | 0.830 |
| B7 | | | 0.931 |
| B9 | | 0.525 | |
| B11 | | 0.445 | |
| B12 | | 0.566 | |
| B14 | | 0.486 | |
| B15 | | 0.294 | |
| B16 | | 0.620 | |
| B17 | | 0.447 | |
| BB5* | | | 0.297 |
| Cronbach Alpha | 0.8795 | 0.7097 | 0.6802 |
| % Variance | 24.41 | 9.37 | 11.6 |
| Sq. Multiple Correlation | 0.951 | 0.772 | 0.887 |

(*item reverse scored)

Table 4.6 below indicates the inter-correlation of the Team Member Exchange Quality.

**Table 4.6: Intercorrelation of the Team Member Exchange three-factor solution**

| | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|
| Factor 1 | 1.00 | | |
| Factor 2 | 0.301 | 1.00 | |
| Factor 3 | 0.414 | 0.155 | 1.00 |

A Confirmatory Factor Analysis was carried out on the final three-factor results to establish how well the model fitted the data. The results are as follows:

**Table 4.7: Confirmatory Factor Analysis of Team Member Exchange Quality**

| Indices | Value |
|---|---|
| Degrees of freedom | 74 |
| Satorra-Bentler Scaled Chi-square | 139.448 (P=0.00) |
| Root Mean Square Error of Approximation (RMSAE) | 0.0684 |
| 90 percent Confidence Interval for RMSAE | (0.543; 0.0857) |
| Bentler & Bonner's Non-normed Fit Index (NNFI) | 0.946 |
| Comparative Fit Index (CFI) | 0.956 |
| Bollen Incremental Fit Index (IFI) | 0.956 |

According to the rationale to decide on the goodness of fit described above, this model fit is not good but can be accepted.

## 4.6 Factor Structure of Goal Orientation

The Exploratory Factor Analysis followed by a Direct Quartimin rotation, carried out on the responses of Goal Orientation, produced three eigenvalues of 6.54, 2.94, and 1.15, respectively. The original instrument had two factors of 8 items each. Goal Orientation is distinctively based on two dimensions, Performance Goal Orientation and Learning Goal Orientation. It was therefore not feasible to try and analyse a third factor, as it would be contradictory to the theory. A two-factor factor analysis was carried out and the results were a very good match to the original instrument:

**Table 4.8: Final rotated Factor Analysis of Goal Orientation**

| Item | Factor 1 (Learning) | Factor 2 (Performance) |
|---|---|---|
| C1 | -0.062 | 0.552 |
| C2 | -0.123 | 0.788 |
| C3 | -0.074 | 0.776 |
| C4 | 0.119 | 0.644 |
| C5 | 0.224 | 0.656 |
| C6 | 0.141 | 0.553 |
| C7 | -0.053 | 0.725 |
| C8 | 0.093 | 0.535 |
| C9 | 0.830 | 0.016 |
| C10 | 0.663 | 0.136 |
| C11 | 0.896 | -0.106 |
| C12 | 0.872 | -0.100 |
| C13 | 0.641 | 0.107 |
| C14 | 0.751 | 0.074 |
| C15 | 0.862 | -0.050 |
| C16 | 0.651 | 0.027 |
| Cronbach Alpha | 0.9238 | 0.8634 |
| % Variance | 37.50 | 16.31 |
| Sq. Multiple Correlation | 0.937 | 0.881 |

The inter-correlation between the two factors was:

**Table 4.9: Inter-correlation of the two-factor Goal Orientation Scale**

| | Factor 1 | Factor 2 |
|---|---|---|
| Factor 1 | 1.00 | |
| Factor 2 | 0.363 | 1.00 |

The Confirmatory Factor Analysis carried out on the two-factor solution (N=190) of Goal Orientation was as follows:

**Table 4.10: Confirmatory Factor Analysis of the two-factor solution of Goal Orientation**

| Indices | Values |
|---|---|
| Degrees of freedom | 103 |
| Satorra-Bentler Scaled Chi-square | 180.302 (P=0.0) |
| Root Mean Square Error of Approximation (RMSEA) | 0.0630 |
| 90 percent Confidence Interval for RMSEA | (0.0475; 0.0781) |
| Bentler & Bonner's Non-normed Fit Index (NNFI) | 0.982 |
| Comparative Fit Index (CFI) | 0.984 |
| Bollen Incremental Fit Index (IFI) | 0.984 |

Again the fit is not exceptionally good, but can be accepted. The practical Chi-square is 1.75, RMSEA is just over 0.06 and the comparative indices are all stronger than 0.9.

## 4.7 Factor Structure of Team Climate Inventory (TCI)

The responses (N=190) on Team Climate Inventory were subjected to an Exploratory Factor Analysis, followed by a Direct Quartimin rotation, and yielded five eigenvalues. These values were 20.49, 3.33, 1.72, 1.44 and 1.13, respectively. The decision-making rules justified the extraction of five factors during the factor analysis. However, the original instrument only produced four factors. A Finnish version of the instrument produced a five-factor solution, which guided the current study to first try the five-factor solution as also suggested by the eigenvalue result.

**Table 4.11: Principal Factor Analysis for a 5-factor solution for Team Climate Inventory (TCI)**

| Item | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
|---|---|---|---|---|---|
| D1 | 0.043 | -0.019 | -0.052 | 0.857 | 0.131 |

| Item | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
|---|---|---|---|---|---|
| D2 | -0.011 | 0.059 | 0.098 | 0.880 | 0.033 |
| D3 | -0.038 | 0.047 | 0.289 | 0.696 | 0.001 |
| D4 | 0.015 | 0.075 | 0.420 | 0.488 | -0.001 |
| D5 | 0.128 | 0.238 | 0.086 | 0.154 | -0.255 |
| D6 | 0.066 | -0.029 | 0.712 | 0.189 | -0.024 |
| D7 | 0.135 | -0.045 | 0.659 | 0.282 | -0.005 |
| D8 | 0.072 | -0.105 | 0.794 | 0.231 | -0.066 |
| D9 | -0.053 | 0.132 | 0.788 | -0.087 | -0.010 |
| D10 | 0.033 | -0.004 | 0.771 | 0.039 | 0.090 |
| D11 | 0.107 | 0.137 | 0.500 | 0.161 | 0.187 |
| D12 | 0.320 | 0.163 | 0.048 | 0.047 | 0.437 |
| D13 | 0.205 | 0.134 | 0.023 | 0.013 | 0.424 |
| D14 | 0.000 | 0.137 | -0.037 | 0.116 | 0.745 |
| D15 | 0.135 | 0.041 | 0.067 | 0.142 | 0.685 |
| D16 | 0.128 | 0.141 | 0.037 | 0.107 | 0.686 |
| D17 | 0.015 | 0.177 | 0.220 | 0.078 | 0.451 |
| D18 | -0.008 | 0.368 | 0.243 | 0.206 | 0.257 |
| D19 | 0.091 | 0.379 | 0.349 | 0.045 | 0.189 |
| D20 | 0.187 | 0.377 | 0.082 | 0.178 | 0.136 |
| D21 | 0.290 | 0.318 | 0.268 | -0.072 | 0.113 |
| D22 | 0.140 | 0.628 | -0.039 | 0.010 | 0.152 |
| D23 | -0.073 | 0.879 | 0.049 | 0.008 | -0.022 |
| D24 | 0.066 | 0.793 | -0.016 | 0.054 | 0.144 |
| D25 | 0.091 | 0.756 | 0.106 | -0.050 | 0.118 |
| D26 | 0.028 | 0.841 | -0.032 | 0.125 | 0.042 |
| D27 | 0.273 | 0.497 | 0.057 | 0.039 | 0.091 |
| D28 | 0.459 | 0.285 | 0.106 | -0.016 | 0.167 |
| D29 | 0.554 | -0.102 | 0.037 | 0.023 | 0.152 |
| D30 | 0.649 | 0.104 | 0.032 | -0.026 | 0.208 |
| D31 | 0.579 | 0.093 | 0.093 | 0.047 | 0.127 |
| D32 | 0.557 | 0.012 | 0.240 | -0.110 | 0.176 |
| D33 | 0.578 | 0.139 | 0.231 | 0.042 | -0.010 |
| D34 | 0.629 | 0.187 | 0.148 | 0.029 | -0.072 |
| D35 | 0.983 | 0.017 | -0.154 | 0.054 | -0.025 |
| D36 | 0.952 | -0.041 | -0.058 | 0.042 | -0.056 |
| D37 | 0.830 | 0.076 | 0.063 | 0.038 | -0.083 |
| D38 | 0.497 | 0.328 | 0.051 | 0.034 | -0.021 |

Referring to the results in Table 4.11, nine items either loaded on two or three factors simultaneously or had a low factor loading. It was then decided to try to extract only four factors based on the example of the original instrument. A second four-factor extraction had to be made after the items that were again loading on more than one factor, as well as those with low loadings, were removed. The results were as follows:

**Table 4.12: Principal Factor Analysis rotated for a 4-factor solution for Team Climate Inventory (TCI)**

| Item | Factor 1 (Vision) | Factor 2 (Part Safety) | Factor 3 (Supp for Innovation) | Factor 4 (Task Orient) |
|---|---|---|---|---|
| D1 | 0.748 | 0.000 | -0.136 | 0.212 |
| D2 | 0.897 | -0.030 | -0.041 | 0.092 |
| D3 | 0.936 | -0.070 | -0.021 | 0.042 |
| D4 | 0.864 | -0.002 | 0.033 | 0.013 |
| D6 | 0.818 | 0.052 | 0.044 | -0.072 |
| D7 | 0.863 | 0.123 | -0.008 | -0.036 |
| D8 | 0.916 | 0.074 | -0.028 | -0.120 |
| D9 | 0.600 | -0.028 | 0.240 | -0.089 |
| D10 | 0.697 | 0.032 | 0.092 | 0.039 |
| D11 | 0.577 | 0.085 | 0.168 | 0.179 |
| D12 | 0.030 | 0.283 | 0.150 | 0.490 |
| D13 | -0.032 | 0.177 | 0.127 | 0.480 |
| D14 | -0.008 | -0.063 | 0.085 | 0.844 |
| D15 | 0.120 | 0.088 | 0.006 | 0.738 |
| D16 | 0.061 | 0.092 | 0.100 | 0.731 |
| D17 | 0.223 | 0.014 | 0.143 | 0.472 |
| D20 | 0.221 | 0.194 | 0.340 | 0.150 |
| D21 | 0.153 | 0.289 | 0.352 | 0.094 |
| D22 | -0.061 | 0.142 | 0.624 | 0.163 |
| D23 | 0.036 | -0.052 | 0.889 | -0.039 |
| D24 | 0.008 | 0.059 | 0.791 | 0.157 |
| D25 | 0.021 | 0.093 | 0.776 | 0.112 |
| D26 | 0.088 | 0.044 | 0.791 | 0.057 |
| D29 | 0.027 | 0.538 | -0.089 | 0.152 |
| D30 | -0.035 | 0.369 | 0.111 | 0.221 |
| D31 | 0.110 | 0.561 | 0.106 | 0.132 |
| D32 | 0.090 | 0.541 | 0.052 | 0.168 |

| Item | Factor 1 (Vision) | Factor 2 (Part Safety) | Factor 3 (Supp for Innovation) | Factor 4 (Task Orient) |
|---|---|---|---|---|
| D33 | 0.236 | 0.584 | 0.167 | -0.031 |
| D34 | 0.154 | 0.648 | 0.210 | -0.107 |
| D35 | -0.098 | 0.970 | 0.009 | -0.001 |
| D36 | -0.028 | 0.962 | -0.045 | -0.048 |
| D37 | 0.090 | 0.841 | 0.088 | -0.101 |
| Cronbach Alpha | 0.958 | 0.943 | 0.941 | 0.904 |
| % Variance | 52.9 | 9.1 | 3.9 | 3.47 |
| Sq Multiple Correlation | 0.967 | 0.958 | 0.948 | 0.910 |

The intercorrelation between the four factors was:

**Table 4. 13: Intercorrelation of the four-factor Team Climate Inventory**

| | Factor 1 | Factor 2 | Factor 3 | Factor 4 |
|---|---|---|---|---|
| Factor 1 | 1.000 | | | |
| Factor 2 | 0.519 | 1.000 | | |
| Factor 3 | 0.572 | 0.656 | 1.000 | |
| Factor 4 | 0.419 | 0.568 | 0.548 | 1.000 |

A Confirmatory Factor Analysis carried out the four-factor solution (N=190) of Team Climate Inventory was as follows:

**Table 4. 14 Confirmatory Factor Analysis on the four-factor solution of Team Climate Inventory**

| Indices | Values |
|---|---|
| Degrees of freedom | 458 |
| Satorra-Bentler Scaled Chi-square | 801.379 (P=0.0) |
| Root Mean Square Error of Approximation (RMSAE) | 0.0630 |
| 90 percent Confidence Interval for RMSAE | (0.0557; 0.0702) |
| Bentler & Bonner's Non-normed Fit Index (NNFI) | 0.988 |
| Comparative Fit Index (CFI) | 0.989 |
| Bollen Incremental Fit Index (IFI) | 0.989 |

The model fit indices indicate an acceptable fit.

## 4.8 Correlations

Pearsons Product Moment Correlation Coefficient is an indication of association and measures the degree to which two variables are linearly related (Easton & McColl: 2007, 2). A positive correlation refers to the notion that a change in one variable will concomitantly cause the covariant to change. A negative correlation refers to an inverse correlation between two variables. A value of 0.00 indicates no linear relationship, while a value closer to +1 is considered a positive correlation and a correlation closer to –1 is an indication of a negative or no relationship. A correlation close to 0 further means that the two variables vary separately. Zero indicates a complete independence between the two variables and contrary to that, a correlation of either 1.00 or –1.00 would indicate a complete dependence, positive or negative (Bailey, 1982; Healy, 1990; Rummel, 1976).

It was important to have an illustration of the correlations to see if the resulting relationships correspond with the conceptual research model posed in Chapter 1 as a guide to the study. This study tries to establish whether there are relationships between the independent variables, Emotional Intelligence, Goal Orientation and Team Member Exchange, and the dependent variable, Team Climate for Innovation. The table below illustrates the most important correlations with $r \geq 0.25$ and significant levels of $\leq 0.05$ from the Pearson's Correlation Coefficients analysis.

**Table 4. 15: Correlation relationships of independent with dependent variables**

| Variable | Variable name | Team Climate for Innovation | Correlation value | Level of Significants | $100^*r^2$ |
|---|---|---|---|---|---|
| fa1 | EI | fd1 | .235 | .0011 | 5.52% |
| | EI | fd2 | .1065 | .1434 | 1.13% |
| | EI | fd3 | .2037 | .0048 | 5.62% |
| | EI | fd4 | .24192 | .0008 | 5.85% |
| fb1 | TMX meetings | fd1 | .5399 | <.0001 | 29.15% |
| | TMX meetings | fd2 | .50397 | <.0001 | 25.40% |
| | TMX meetings | fd3 | .53625 | <.0001 | 28.76% |
| | TMX meetings | fd4 | .44568 | <.0001 | 19.86% |
| fb2 | TMX exchange | fd1 | .42621 | <.0001 | 18.17% |
| | TMX exchange | fd2 | .52597 | <.0001 | 27.66% |
| | TMX exchange | fd3 | .50229 | <.0001 | 25.23% |
| | TMX exchange | fd4 | .44235 | <.0001 | 19.57% |
| fb3 | TMX Cohesive | fd1 | .23144 | .0013 | 5.36% |

| Variable | Variable name | Team Climate for Innovation | Correlation value | Level of Significants | 100*r² |
|---|---|---|---|---|---|
| | TMX Cohesive | fd2 | .25439 | .0004 | 6.47% |
| | TMX Cohesive | fd3 | .26070 | .0003 | 6.80% |
| | TMX Cohesive | fd4 | .31560 | <.0001 | 9.96% |
| fc1 | Learning | fd1 | .15736 | .0301 | 2.48% |
| | Learning | fd2 | .06085 | .4043 | .37% |
| | Learning | fd3 | .0648 | .3744 | .42% |
| | Learning | fd4 | .10212 | .1609 | 1.04% |
| fc2 | Performance | fd1 | .13566 | .0620 | 1.84% |
| | Performance | fd2 | .02335 | .7491 | .05% |
| | Performance | fd3 | .08903 | .2219 | .79% |
| | Performance | fd4 | .08238 | .2585 | .68% |

The correlation matrix is reflected below as Table 4.16

**Table 4. 16: Pearsons Correlation Coefficients, N=190**

| | | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 | F10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | fa1 | fb1 | fb2 | fb3 | fc1 | fc2 | fd1 | fd2 | fd3 | fd4 |
| F1 | r | 1.000 | | | | | | | | | |
| | p | | | | | | | | | | |
| F2 | r | .0625 | 1.000 | | | | | | | | |
| | p | .3912 | | | | | | | | | |
| F3 | r | .1444 | .4125 | 1.000 | | | | | | | |
| | p | .0468 | <.0001 | | | | | | | | |
| F4 | r | .3039 | .2690 | .1735 | 1.000 | | | | | | |
| | p | <.0001 | .0002 | .0166 | | | | | | | |
| F5 | r | .2015 | .1122 | -.0677 | .3259 | 1.000 | | | | | |
| | p | .0053 | .1231 | .3529 | <.0001 | | | | | | |
| F6 | r | .1552 | .1754 | -.0153 | .1304 | .3678 | 1.000 | | | | |
| | p | .0324 | .0155 | .8339 | .0729 | <.0001 | | | | | |
| F7 | r | .2350 | .5399 | .4262 | .2314 | .1573 | .1356 | 1.000 | | | |
| | p | .0011 | <.0001 | <.0001 | .0013 | .0301 | .0620 | | | | |
| F8 | r | .1065 | .5039 | .5259 | .2543 | .0608 | .0233 | .6113 | 1.000 | | |
| | p | .1434 | <.0001 | <.0001 | .0004 | .4043 | .7491 | <.0001 | | | |
| F9 | r | .2037 | .5362 | .5022 | .2607 | .0648 | .0890 | .65331 | .7663 | 1.000 | |
| | p | .0048 | <.0001 | <.0001 | .0003 | .3744 | .2219 | <.0001 | <.0001 | | |
| F10 | r | .2419 | .4456 | .4423 | .3156 | .1021 | .0823 | .5685 | .7019 | .7346 | 1.000 |
| | p | .0008 | <.0001 | <.0001 | <.0001 | .1609 | .2585 | <.0001 | <.0001 | <.0001 | |

Healy (1990) emphasizes that the correlation coefficient answers only the following three questions: Is there a relationship? How strong is the relationship and what is the direction thereof?

The last column of Table 4.14 indicates $r^2$ as a percentage of variance explained by the correlation and is once again a confirmation of the results discussed above.

## 4.9 Path analysis

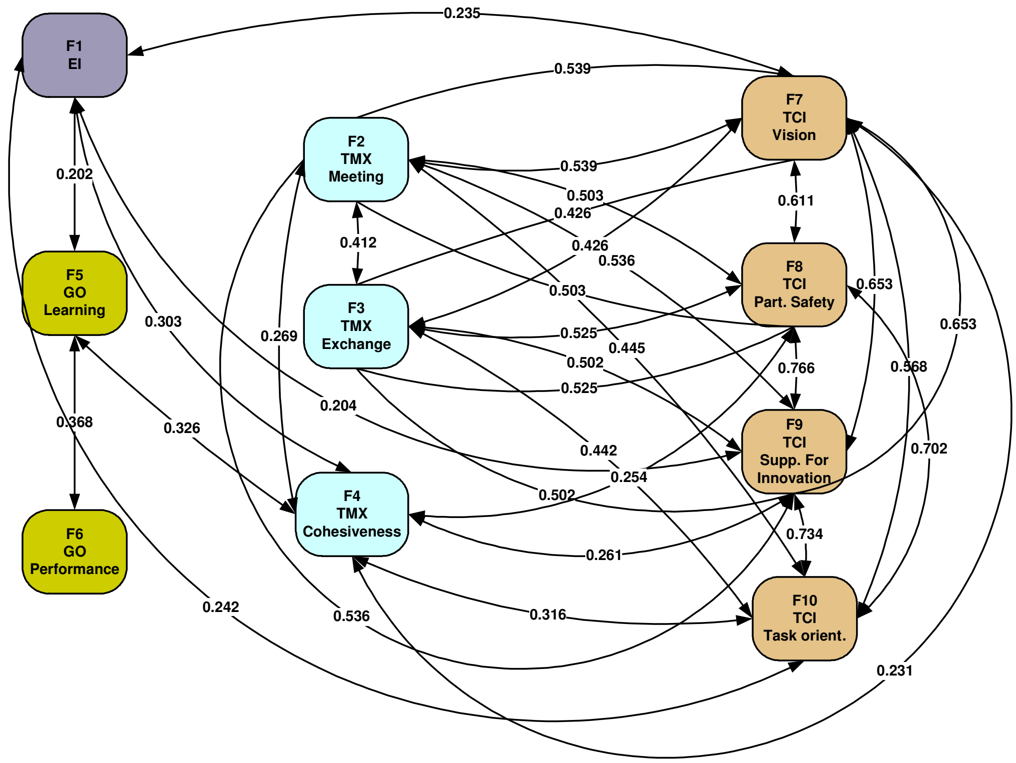
The SAS statistical package, specifically the Proc Calis procedure, was used to do this analysis (SAS Institute Inc. 1999). The aim of this analysis was to answer the second research question, “What is the predictability of emotional intelligence, team member exchange and goal orientation on a team climate for innovation?” as outcome variable. The analysis was also done to eventually build a structural equation model to predict a team climate of innovation, as final answer to research question five.

As suggested by Hatcher (1994), Proc Calis is run to perform a confirmatory factor analysis in order to confirm the factor structure of a data set. A measurement model is then built and validated from this analysis. This is done to reflect the causal relationship of the latent variables within the model. Latent variables emerge from the findings as a combination of different variables in a factor cluster to form a conceptual construct. A Structural Equation Modelling (SEM) procedure or path analysis maps the interaction between these latent variables to a specific outcome (Hatcher, 1994; Kline, 1998).

One of the outcomes in this study is to build this structural model as confirmation of the initial conceptual model set as guideline to the study in Chapter 1. A confirmatory factor analysis was done on each of the four different instruments, with the results reflected in Table 4.3 for Emotional Intelligence (EI), Table 4.7 for Team Member Exchange (TMX), Table 4.10 for Goal Orientation (GO) and Table 4.14 for Team Climate (TCI). However, the data is non-normal and the sample size (N=190) was unfortunately too small to accommodate all of the latent variables in one model. It is common practice that if the measurement model cannot be verified, the researcher will not proceed to develop the structural model that specifies causal relationships between the latent variables (Garson, 2007; Hatcher, 1994; Kline, 1998). It was decided not to proceed with the SEM procedure but to follow another route

As far as could be determined, the postulated combined relationship between emotional intelligence, goal orientation, team member exchange and team climate had never been studied previously. The research conceptual model as combination is also not based on empirical theory but was develop out of four different existing instruments, each based on its own theoretical structure. It was then decided to develop a model based on the correlation matrix in order to reflect the relevant relationships between the different variables. The connections as illustrated in Figure 4.1 only reflect a relationship between two variables and do not indicate any causality.

**Figure 4. 1: Correlation model >.25**




Furthermore, it can be deduced from the correlation results (Table 4.16) that not all the reflected relationships are statistically significant. As was previously reported, only the relationship between team member exchange and team climate for innovation is of any significance. Referring to the correlation matrix in Table 4.16 as well as the correlation model in Figure 4.1, it appears that a weak relation exists between emotional intelligence (F1-fa1) and one factor of team climate for innovation (F4-fb3-Cohesiveness), and another between emotional intelligence (F1-fa1) and team climate for innovation (F10-fd4-Task orientation). This result supports the decision to reject the research conceptual model.

It was decided to do a path analysis by estimating the parameters with diagonally weighted least squares estimation (Garson, 2007). This estimation is a distribution-free method and the normal distributed data assumption is therefore not needed (Garson, 2007; Hatcher, 1994).

A model was developed based on the existing theories as conceptualized in the research model, but with only the strongest correlation relationship links between the factors. This model is reflected in Figure 4.2. The intent was to determine the causal relationships between the independent variables (EI, TMX and GO), and the dependent variable team climate for innovation (TCI). Two more models were developed, each time adding more of the weaker correlations in order to establish a more comprehensive and better fitting model. The three models are represented in Figures 4.2, 4.3, and 4.4, respectively. These models were subjected to the path analysis, and a summary of their different goodness of fit indices follows thereafter in Table 4.17.

Garson (2007) warns against overestimating goodness of fit for models with a small sample (<200), because the model is not necessarily strong when the fit indication is high. According to Garson (2007), GFI should at least be greater than .95, but owing to problems associated with the measure, it is no longer considered the preferred measure of goodness of fit. Garson suggests that an adjusted GFI be used. An adjusted GFI (AGFI) measure of >1.0 is considered a very good fit, whilst a value of <0 is associated with a poor fit. Again a cut-off score of .95 should be considered as the minimum (Garson, 2007).

Root mean square residual (RMR) is according to Garson difficult to interpret. However, a value of closer to 0 is preferred.  Standardized RMR is considered a better measure, but unfortunately this was not provided by the analysis (Garson, 2007; Kline, 1998).

Parsimonious GFI is a variant of GFI and was developed to penalize models for the lack of parsimony (Garson, 2007). Under normal circumstances complex models will provide a better fit than less complex models. When models are compared, the rule of thumb is that the higher parsimony measure represents the better fit to the data.

**Figure 4. 2: Path Analysis Model 1**

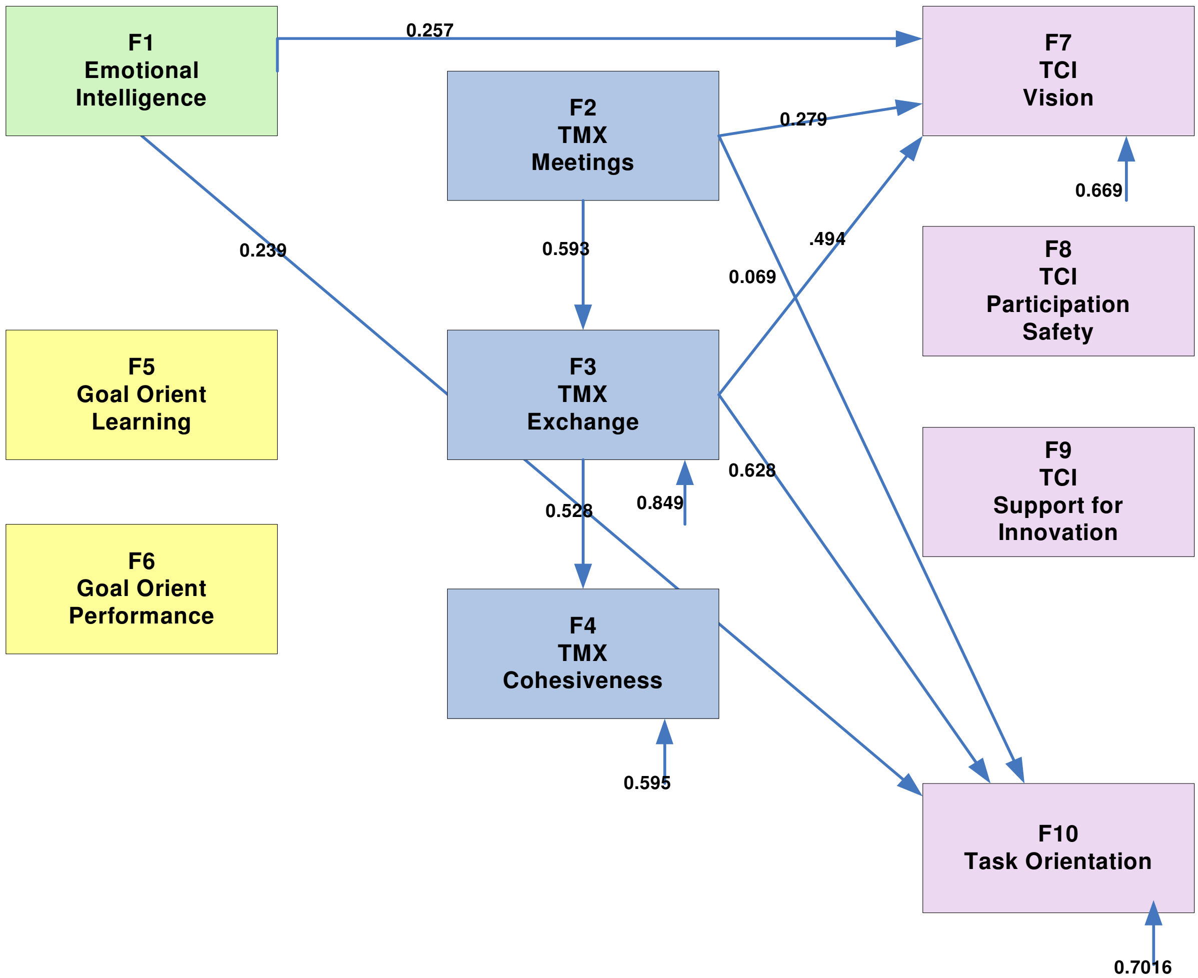


**Figure 4. 3: Path Analysis Model 2**

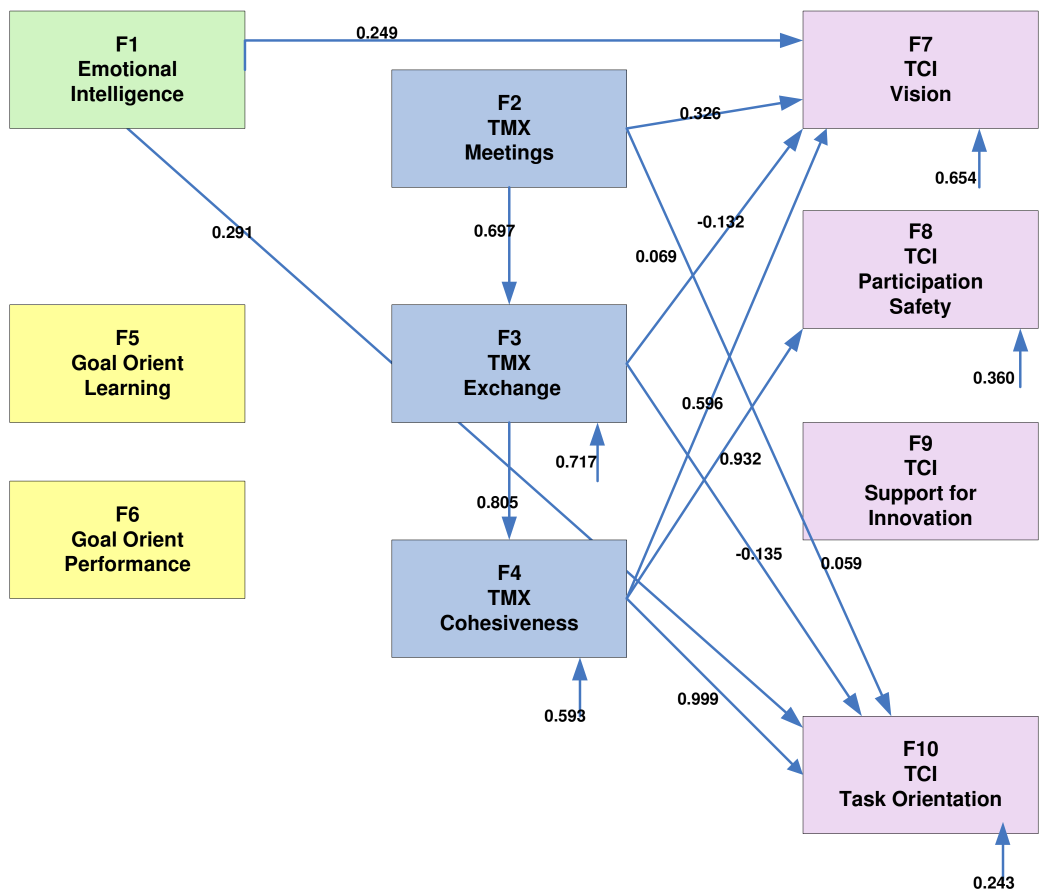


**Figure 4. 4: Path analysis Model 3**

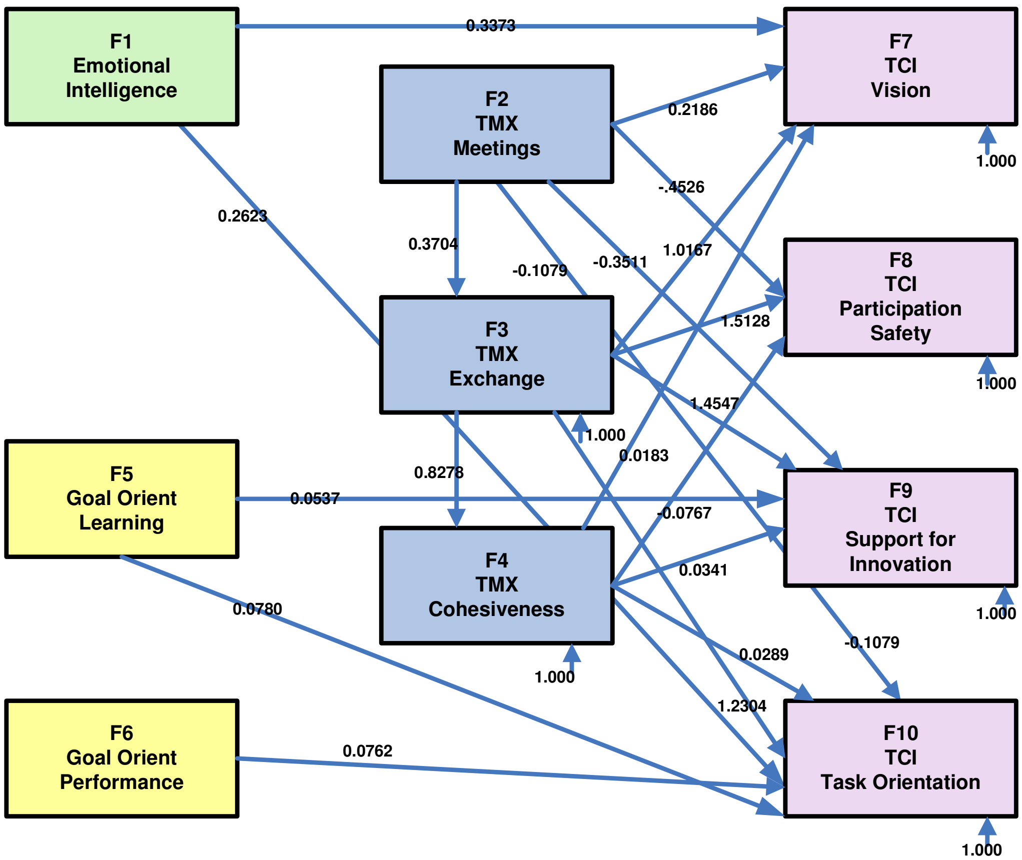



**Table 4.17: Goodness of fit indices summary**

| Indices | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Fit function | 132.8451 | 100.7546 | 41.9322 |
| GFI | 0.9859 | 0.9870 | 0.9955 |
| AGFI | 0.9852 | 0.9863 | 0.9953 |
| RMR | 0.1679 | 0.1705 | 0.0993 |
| P.GFI | 0.9639 | 0.9596 | 0.9717 |

From the available goodness of fit indices, it is clear that the models fit the data adequately to well. The root mean square residuals are smaller than the recommended <.10 (<.04 for a well fitting model) which is considered a good fit. Although the GFI, AGFI and RMR values of all three models indicate a good fit, the PGFI indicate an adequate fit of the models with the data. Comparing the three models, it was decided to accept model 3 as the best fitting model.

In order to answer research question four, a model was developed to reflect the causal relationship between team member exchange and team climate of innovation only. The degree to which TMX predict TCI is depicted in Figure 4.5 below.

**Figure 4. 5: Path analyses TMX and TCI**

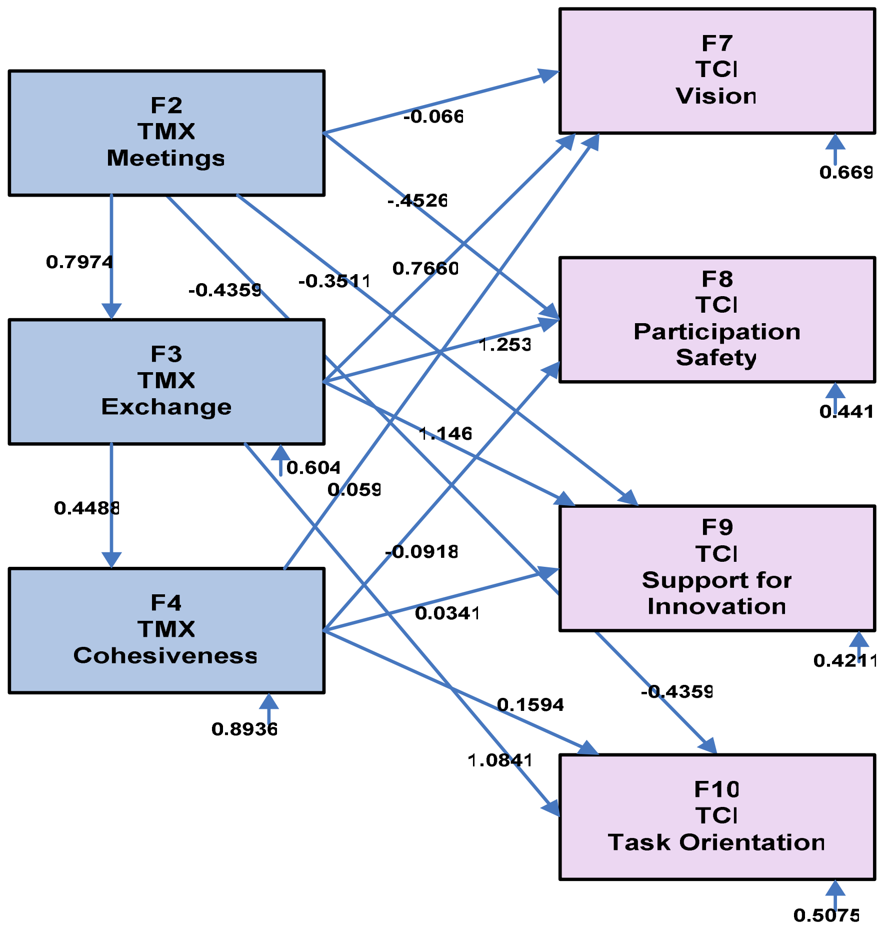



**Table 4. 18: Goodness of fit: Model 4-TMX in relation to TCI**

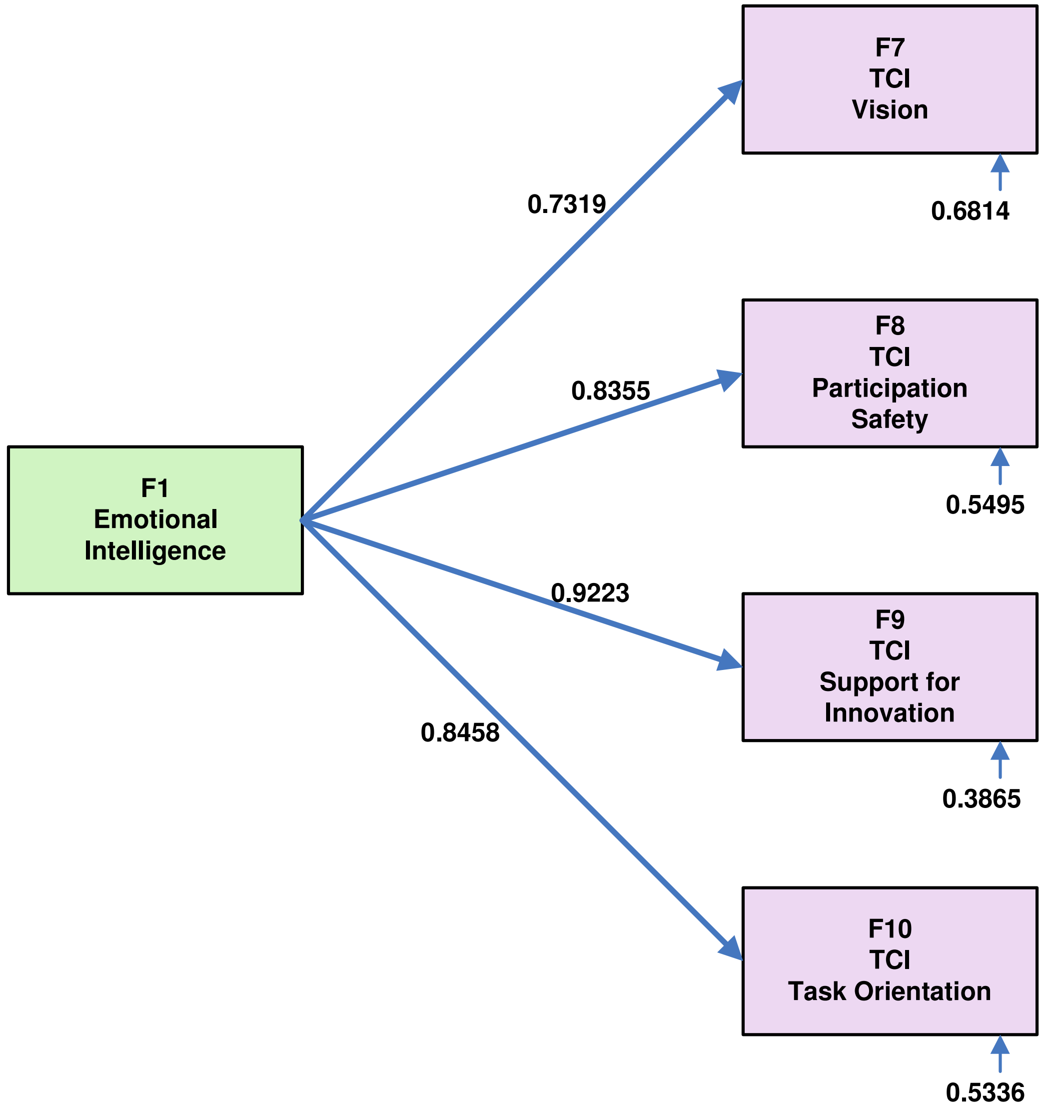
| Indices | Value |
|---|---|
| Fit Function | 5.2319 |
| Goodness of Fit Index | 0.9989 |
| GFI Adjusted for Degrees of Freedom | 0.9988 |
| Root mean Square Residual (RMR) | 0.0625 |
| Parsimonious GFI (Mulaik, 1989) | 0.9410 |

Based on the initial research conceptual model, it was argued that emotional intelligence should have a strong causal relationship with team climate. This argument stems from emotional intelligence theory and proposes that individuals with strong emotional intelligence abilities should be able to understand their own emotions as well as the emotions of others and also be in control of their own emotions and be able to influence emotions and therefore also perceptions of other individuals. The correlation results indicated very weak correlations and the emotional intelligence and team climate relation was therefore not included in the bigger model. In the light of the strong theoretical link between emotional intelligence and team climate, it was decided to run a path analysis for these two variables only. As was expected on theoretical grounds, a strong causal relationship between emotional intelligence and team climate was achieved. The goodness of fit indices and the path analysis are depicted below.

**Table 4.19: Goodness of fit: Emotional Intelligence in relation to TCI**

| Indices | Value |
|---|---|
| Fit Function | 25.3171 |
| Goodness of Fit Index | 0.9960 |
| GFI Adjusted for Degrees of Freedom | 0.9957 |
| Root mean Square Residual (RMR) | 0.1194 |
| Parsomonious GFI (Mulaik:1989) | 0.9600 |

**Figure 4.6: Path analyses Emotional Intelligence and Team Climate**




No clear previous research results were available to motivate the inclusion of goal orientation as variable in the research conceptual model. It was argued that based on available theory it will probably be easier to convince individuals with a learning goal orientation to meet higher team goals and to look for more innovative solutions to difficult problems, than it would be to influence individuals with a performance goal orientation to do the same. Again the correlation results indicated very weak relationships and again this was the reason why this variable was not included in the bigger model analysis. Based on the positive results that were achieved when the emotional intelligence and team climate model was developed, it was decided to analyse the goal orientation and team climate relationship as a separate model. As can be seen, in Table 4.20 the goodness of fit results are actually good except for the RMR that should be closer to 0 and is therefore weak. However, the path analysis based on the diagonally weighted least square estimates showed surprising results. No causal relationship exists between a learning goal orientation and team climate, but a very strong relationship is indicated between performance goal orientation and team climate. This was surprising as the theoretical profile suggested the opposite. Possible reasons for this will be discussed in the next chapter. The goodness of fit and path analysis is depicted below:

**Table 4.20: Goodness of fit: Goal Orientation in relation to TCI**

| Indices | Value |
|---|---|
| Fit Function | 15.5337 |
| Goodness of Fit Index | 0.9970 |
| GFI Adjusted for Degrees of Freedom | 0.9967 |
| Root mean Square Residual (RMR) | 0.1049 |
| Parsomonious GFI (Mulaik:1989) | 0.9475 |

**Figure 4.7: Path analyses Goal Orientation and Team Climate**