During the past year, 35 per cent of respondents had purchased something from a catalogue or brochure sent to them (Question 58), and 9 per cent had called a toll-free number to place an order (Question 60). A total of 14 per cent said that they had bought something through telemarketing (Question 59).

From the above descriptive statistics it is clear that: the majority of respondents did not exert protective behaviour toward their personal information (Questions 49-53); did not feel that their personal privacy had been invaded (Question 54); and did not have knowledge about how to protect their personal information (Question 55). This corresponds with the descriptive statistics of Questions 56 to 60, which indicated that a minority of the respondents is active in terms of transactions on the Internet or through direct marketing media, where individuals are more exposed to possible privacy invasions. One exception here was that a total of 51 per cent of the respondents had, occasionally, refused to provide information to a company because they contended that the information requested was not really needed or it was too personal.

The next section focuses on the purification of the information privacy scale.

7.4 SCALE PURIFICATION

As has been mentioned in previous chapters, there is an absence of validated measurements for empirical studies addressing individual perceptions on information privacy. Therefore, a measurement instrument was developed, but it had to be validated for use in future information privacy research. The scale purification process aimed to address the primary research objective, namely, to identify and explore the information privacy concerns of South African consumers. A prerequisite step in the creation of a validated measurement instrument was the consideration of the dimensionality of the relevant construct (Smith *et al.*, 1996:168). This led to a scale purification process consisting of three distinct phases:

- first, an assessment of the underlying dimensionality of privacy concerns using exploratory factor analysis (Section 7.3.1);

- second, an assessment of the internal consistency of the measurement instrument by calculating the item-to-total correlation as well as the Cronbach alpha coefficients (Section 7.3.1.1); and
- third, testing the validity of the factor model identified by the exploratory factor analysis using confirmatory factor analysis (Section 7.3.2).

It is important to note that a different set of data is required to test the validity of a factor model identified using exploratory factor analysis. Therefore the sample was randomly split in half (Hair *et al.*, 1998:114; Lattin, Carroll & Green, 2003:199). First, the one half of the data was used to determine the actual number of dimensions underlying the construct. The other half of the sample was used to validate the measure that resulted from the analysis.

The scale purification process will is now discussed in detail.

7.4.1 Exploratory factor analysis

The data were prepared for the factor analysis by handling the missing values by means of casewise deletion. Respondents who had marked the 'don't know' or 'refuse' options were discarded, since they did not indicate their degree of agreement or disagreement on the 5-point Likert scales and could not be included in the factor analysis. Although the casewise deletions reduced the dataset from 800 to 627 respondents, this did not present a problem, since this was still an adequate sample size. Variables 1 to 45 (Questions 1 to 45) were included in the factor analysis, as they all measured privacy concerns. No mean substitution was necessary since all the remaining respondents had indicated their concerns on the 5-point scales.

Program 4M of the BMDP statistical package (SAS Institute, 2000a) was used to factor analyse the data. The first step was to examine whether the data was suitable for factor analysis. The critical assumptions underlying factor analysis are more conceptual than statistical. From a statistical standpoint, the researcher must ensure that the data matrix has sufficient correlation to justify the application of factor analysis (Hair *et al.*, 1998:99). Visual inspection of the correlations revealed a substantial number of correlations greater than 0.30, indicating that factor analysis was appropriate. The correlations between variables were also analysed by computing the partial correlations between variables (the correlations between variables when the effects of other variables are taken into account). The small partial correlations indicated that 'true' factors existed in the data because the variables were explained by the factors (variates with loadings for each variable).

The next step in the scale purification process consisted of an exploratory factor analysis to assess whether the data contained different underlying dimensions of privacy concerns. For this purpose, a Maximum Likelihood Exploratory Factor Analysis (common factor analysis) was conducted to identify the latent dimensions or constructs represented in the original variables. When a large set of variables is factored, the method first extracts the combinations of variables explaining the greatest amount of variance and then proceeds to combinations that account for smaller amounts of variance (Hair *et al.*, 1998:103). To determine how many factors to extract, a combination of several criteria was used, namely, the latent root criterion, percentage of variance criterion and the scree test criterion (Cattell, 1966:245-276; Hair *et al.*, 1998:104).

- First, the latent root criterion was applied. The rationale for the latent root criterion is that each variable contributes a value of 1 to the total eigenvalue. Only latent roots (or eigenvalues) greater than 1 are considered significant, and all factors with latent roots less than 1 are considered insignificant and are discarded (Hair *et al.*, 1998:103). In this analysis (with all 45 of the privacy concerned items in the questionnaire), a number of 10 eigenvalues were greater than one, indicating a possibility of ten different factors for the data. Table 7.13 indicates the respective eigenvalues for the ten factors.

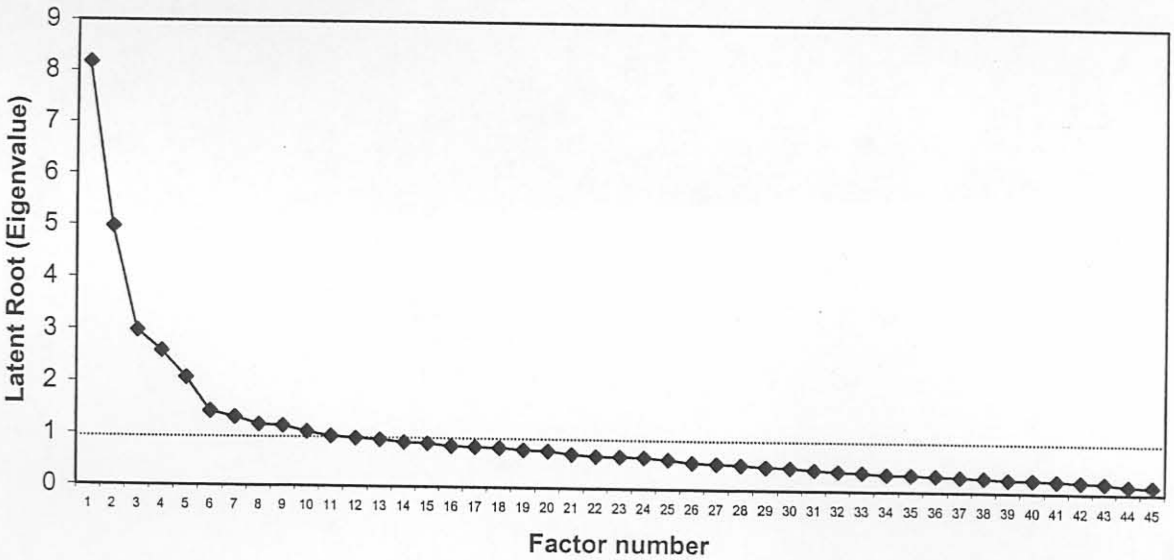
Table 7.13 Eigenvalues for identified factors

Factor	Eigenvalue	Cumulative proportion of variance explained
1	8.17	0.0776
2	4.97	0.1561
3	2.98	0.2520
4	2.59	0.3132
5	2.09	0.3640
6	1.42	0.4038
7	1.32	0.4425
8	1.19	0.4577
9	1.17	0.4758
10	1.05	0.4882

- Second, the percentage of variance criterion was considered. This is an approach based on achieving a specified cumulative percentage of total variance extracted by successive factors. Although no threshold has been adopted, a solution that accounts for 60 per cent of the total variance is regarded as satisfactory, but can even be less in instances where information is less precise (Hair *et al.*, 1998:104). As can be seen from Table 7.13 above, the first ten factors specified a cumulative percentage of 49 per cent of the total variance. It is, however, evident that the last three factors (Factors 8 to 10) each contributed less than two per cent to the cumulative percentage.

- Finally, the scree test was examined to establish the number of factors to be extracted. A scree test is used to identify the optimum number of factors that can be extracted before the degree of unique variance starts to dominate the common variance structure. A scree test is derived by plotting the latent roots against the number of factors in their order of extraction, and the shape of the resulting curve is used to evaluate the cut-off point. The point at which the curve begins to straighten out is considered to indicate the maximum number of factors to extract (Hair *et al.*, 1998:104). According to Kline (1999:75), there is agreement among most factor analysts of any repute that Cattell's scree test is close to the best solution of selecting the correct number of factors. From the scree plot of the unaltered correlation matrix (see Figure 7.2), it is evident that the cut-off point for the number of factors to be extracted in this study, was between five and six factors, after which the curve straightened out.

Figure 7.2 Eigenvalue plot for scree test criterion



The scree test suggested that a fewer number of factors (between five or six factors) had to be considered for extraction compared to the latent root and percentage of variance criteria (suggesting ten factors). However, when considering the small contribution of Factors 8 to 10 to the cumulative percentage of total variance extracted, it supported the scree test result of considering fewer factors for extraction. Based on the indications of the different criteria discussed above, it was decided to extract six factors during the first round of analysis.

Maximum Likelihood Exploratory Factor Analysis was conducted, specifying a Direct Quartimin oblique rotation of the original factor matrix. The oblique rotation technique was used because the theoretically underlying dimensions were assumed to be correlated with each other, and an oblique factor rotation allowed for intercorrelation between factors (Hair *et al.*, 1998:102). Items were considered for deletion depending on the item's factor loading. Factor loadings greater than 0.50 were considered to meet the minimum level and to have practical and statistical significance for all the factor solutions. The 0.50 criterion for the significance of the factor loadings was based on the sample size and the number of variables being analysed (Hair *et al.*, 1998:111-112). Items with loadings below 0.50 and items that did not load on any factor were identified for possible deletion. Items that loaded on more than one factor were considered for interpretation on the factor on which it had a significant loading, and, depending on their contribution to the research, were considered for possible deletion.

The factor loadings of the rotated six-factor matrix were examined, and that items did not meet the minimum criteria (as discussed above) were deleted. The six-factor solution did not yield satisfactory results, with only one item loading significantly on Factor 6 (refer to Appendix 3 for the rotated six-factor loading matrix for all the variables). It was decided not to pursue this solution any further, and to extract five factors during a second round of analysis. The same procedure was followed, namely factor rotation followed by a process to delete items that did not load significantly, did not load on any factors, or loaded on more than one factor. Again the factor solution did not perform very well. Only three items loaded significantly on Factor 5 (with one of the items being a double loading) (refer to Appendix 4 for the rotated five-factor loading matrix for all the variables). This was followed by a decision to consider a four-factor model for the third round of analysis.

The four-factor solution (containing all 45 items) had a total of 30 items loading greater than 0.50 on the four factors, with loadings varying between 0.50 and 0.77. The four-factor solution explained 36 per cent of the total variance. The ten items that loaded below 0.50 (Questions 1, 2, 8, 9, 10, 13, 16, 22, 23 and 42), the five items that did not load on any factors (Questions 3, 4, 5, 6 and 7), and the two items that loaded onto more than one factor (Questions 31 and 35) were discarded (refer to Appendix 5 for the initial four-factor loading matrix containing all 45 items). The four-factor model was respecified and the analysis was repeated on the remaining 28 items. The respecified four-factor solution indicated another two items that loaded below 0.50 and one item that loaded on more than one factor. These items were again deleted, the model respecified, and the analysis repeated. The next factor solution indicated that the remaining 25 items loaded greater than 0.50 on one of the four factors. When a factor solution had been obtained in which all variables had a significant loading on a factor, labels could be assigned to the different factors. Based on the interpretation of the items that loaded on these scales, they were labelled 'privacy protection', 'information misuse', 'solicitation' and 'government protection'.

Of the eight dimensions that were built into the measurement instrument (refer to Chapter 5, Section 5.3), two dimensions were represented by two factors each, two dimensions grouped together under one factor, and the remaining four dimensions grouped together in another factor. Detail on the items of each factor is provided below:

- **Factor 1:** The first factor contained nine items, with eight items stemming from two of the anticipated dimensions, namely privacy protection policies and behavioural intentions. The factors that loaded onto factor one represented four items pertaining to privacy protection policies, and four items to behavioural intentions. Only one item did not belong to either of the two dimensions and related to data disclosure. Since all the items referred to consumers' privacy protection in general, the factor was labelled 'privacy protection'.

- **Factor 2:** The items in the second factor belonged to three of the identified dimensions, namely data storage and security, data use, and data disclosure and dissemination. Although this factor did not relate to any of the eight dimensions, all the items in the factor related to information use or misuse by organisations. This factor identified a 'new' but significant concern and was labelled 'information misuse'.

- **Factor 3:** All six the items of the solicitation dimension loaded onto factor three. This indicated a strong concern that consumers have regarding a desire to be left alone. Since the third factor related directly to one of the anticipated dimensions, namely solicitation, it was therefore labelled 'solicitation'.

- **Factor 4:** After deleting the items that did not meet the minimum criteria, only three items relating to the dimension of legislation and government protection remained. All three of these items loaded onto factor four, and the factor was labelled 'government protection'.

Since the four-factor solution emerged as the most interpretable factor structure, the internal consistency of the different factors can be assessed.

7.4.1.1 Reliability assessment

The final 25 items derived from the factor analysis were tested for their reliability by submitting them to item analysis (calculation of corrected r_{it}-values[2] of the items) using item-to-total correlations. The items for each subscale were analysed separately (Steenkamp & Van Trijp, 1991:286). Rules of thumb suggest that the item-to-total correlations should exceed 0.50 (Hair *et al.*, 1998:118). The item analysis revealed no item-to-total values below 0.50 and no items were deleted. The item-to-total correlations can be viewed in Table 7.15. The final four-factor solution had a total of 25 items with loadings varying between 0.54 and 0.84, with the four factors explaining 49 per cent of the total variance. Eigenvalues between 6.3 and 0.18 were obtained, with five eigenvalues greater than 1. The final sorted rotated factor loading matrix is set out in Table 7.14.

[2] When an item is correlated with the total score of which it is part, the value of the r_{it} tends to be inflated and there is a need for correction (Guilford, 1954:439).

Table 7.14 Sorted four-factor loading matrix

Item	Factor 1 Privacy protection	Factor 2 Misuse	Factor 3 Solicitation	Factor 4 Government protection
Q39 (PP3)	**0.755**	-0.018	-0.130	0.020
Q32 (BI1)	**0.717**	0.018	-0.014	-0.050
Q45 (PP5)	**0.674**	-0.090	0.037	0.034
Q41 (BI4)	**0.641**	-0.072	0.009	0.114
Q44 (BI5)	**0.628**	0.053	-0.023	-0.097
Q36 (PP2)	**0.619**	-0.079	0.007	0.221
Q38 (BI3)	**0.611**	0.006	0.063	0.158
Q20 (DD2)	**0.602**	0.137	-0.035	-0.012
Q33 (PP1)	**0.541**	0.032	0.181	-0.048
Q19 (DD1)	0.026	**0.843**	-0.033	-0.091
Q17 (DU5)	-0.047	**0.788**	-0.007	0.029
Q15 (DU3)	-0.025	**0.728**	-0.009	0.007
Q18 (DU6)	0.124	**0.664**	-0.016	0.034
Q21 (DD3)	0.010	**0.606**	0.021	-0.030
Q12 (DS6)	-0.005	**0.576**	0.039	0.131
Q11 (DS5)	-0.060	**0.549**	0.053	0.025
Q26 (SOL2)	-0.017	0.067	**0.762**	0.160
Q30 (SOL6)	-0.103	-0.042	**0.644**	-0.023
Q25 (SOL1)	-0.004	0.101	**0.721**	0.153
Q29 (SOL5)	-0.012	-0.066	**0.607**	0.038
Q28 (SOL4)	0.083	0.030	**0.541**	-0.121
Q27 (SOL3)	0.106	0.091	**0.540**	-0.073
Q40 (LEG4)	0.072	0.048	0.016	**0.810**
Q37 (LEG3)	0.062	0.081	-0.030	**0.804**
Q34 (LEG2)	0.018	0.009	0.040	**0.786**

Finally, Cronbach's coefficient alpha was used to assess the internal consistency or reliability of the construct indicators. Values ranged between 0 and 1, with higher values indicating higher reliability among the indicators. A lower limit of 0.70 was set for Cronbach's alpha, as suggested by Nunnally (1978:103). The reliability results of the item analysis and Cronbach's alpha are summarised in Table 7.15.

Table 7.15 Summary of item analysis and Cronbach's alpha

Scale	Items	Item-to-total correlation	Cronbach's alpha after deletion	Reliability
Privacy protection	Q20	0.571	0.861	0.87
	Q32	0.664	0.855	
	Q33	0.510	0.867	
	Q36	0.631	0.855	
	Q38	0.624	0.856	
	Q39	0.679	0.852	
	Q41	0.604	0.857	
	Q44	0.548	0.864	
	Q55	0.600	0.857	
Information misuse	Q11	0.552	0.853	0.86
	Q12	0.614	0.845	
	Q15	0.652	0.838	
	Q17	0.703	0.831	
	Q18	0.623	0.842	
	Q19	0.728	0.827	
	Q21	0.530	0.855	
Solicitation	Q25	0.643	0.774	0.81
	Q26	0.667	0.768	
	Q27	0.538	0.797	
	Q28	0.531	0.798	
	Q29	0.516	0.802	
	Q30	0.586	0.787	
Government protection	Q34	0.729	0.837	0.87
	Q37	0.754	0.815	
	Q40	0.773	0.797	

From Table 7.15 it is evident that all the Cronbach's alpha coefficients of the underlying dimensions were above the recommended cut-off value of 0.70, with values ranging between 0.81 and 0.87, and it can therefore be concluded that the four derived scales are reliable.

The four factors are discussed individually below.

7.4.1.2 Factor 1: Privacy protection

Several items loaded on the first factor. All items (except for one relating to data disclosure) pertained to either the behavioural intentions of consumers to protect their privacy, or privacy policies of organisations regarding data collection, storage, use, disclosure and solicitation. Table 7.16 provides detail on the privacy protection factor.

Table 7.16 Items and loadings for Factor 1 (Privacy protection)

Item	Question	Factor loading
PP3	Companies should have privacy protection policies indicating the reasons for collecting personal information from consumers.	0.755
BI1	You would request a company to remove your personal information from their records if you suspected that they were misusing it.	0.717
PP5	Companies should have privacy protection policies indicating how they will protect the customer's information while it is in their possession.	0.674
BI4	You would support a company's efforts that will ensure that your personal information is safely kept.	0.641
BI5	You would refuse to provide your personal information to a company who cannot provide reasons why they want to collect your personal information.	0.628
PP2	Companies should have privacy protection policies indicating that no personal information will be provided to other companies without consent from their customers.	0.619
BI3	You would request having your personal information removed from any company's records if they sell the information to others.	0.611
DD2	You are uncomfortable when companies share your personal information with other companies without asking your permission first.	0.602
PP1	Companies must have privacy protection policies to make provision for customers who would not like to receive unrequested advertising material.	0.541

These privacy protection behaviour or policies covered general privacy issues ranging from concerns about the sharing of personal information with third parties, to the reasons for collecting information from consumers and the safekeeping of information by companies.

7.4.1.3 Factor 2: Information misuse

The second factor, labelled 'information misuse', included five items relating to how companies use or misuse personal information, as well as two safety concern items. Table 7.17 indicates the factor loadings of the seven items that constituted Factor 2.

Table 7.17 Items and loadings for Factor 2 (Information misuse)

Item	Question	Factor loading
DD1	Companies regularly share personal information with other companies without the permission of the individuals to whom the information belongs.	0.843
DU5	You believe that consumers' personal information is often misused by companies.	0.788
DU3	You believe that companies regularly use consumers' information for other purposes than that for which it was collected.	0.728
DU6	You are concerned about the possible misuse of your personal information by companies.	0.664
DD3	You believe that companies regularly share personal information of consumers with other companies, so that these other companies could offer products and services to consumers.	0.606
DS6	You fear that your personal information may not be safe while stored in a company's records.	0.576
DS5	Personal information is safe while stored in a company's records.	0.549

The two safety concern items (see DS6 and DS5 in Table 7.17) were seen as related to information misuse, because it can be argued that when a consumer's information is not safe while stored in a company's records, it opens up opportunities for misuse.

7.4.1.4 Factor 3: Solicitation

Privacy often relates to the right to be left alone, and to be free from intrusion or interruption. One of the privacy concerns of individuals seems to be media intrusiveness because consumers have little or no control over the prospecting efforts of organisations. Table 7.18 contains detail on the items that loaded on Factor 3.

Table 7.18 Items and loadings for factor 3 (Solicitation)

Item	Question	Factor loading
SOL2	It bothers you that you receive so much unrequested advertising material that is of no interest to you.	0.762
SOL1	Companies send consumers too much unrequested advertising material that is not of interest to them.	0.721
SOL6	You are pleased when you receive information about new products and services from companies with which you have not done business before.	0.644
SOL5	Consumers are not interested in getting information about new products and services from companies with which they have not done business before.	0.607
SOL4	You do not mind when you receive telephone calls at your home from companies wanting to sell products and services to you.	0.541
SOL3	Too many companies call consumers at their homes to sell products and services to them.	0.540

The sheer volume of direct mail, telemarketing and e-mails relates to the physical intrusion of marketing communications in the daily lives of consumers. The results indicate that South African consumers share solicitation concerns because the third factor contained all six items relating to solicitation.

7.4.1.5 Factor 4: Government protection

The last factor is labelled 'government protection', because only items relating to the role of government in protecting information privacy by means of legislation loaded significantly on this factor. Table 7.19 provides the factor loadings for the three items relating to government protection.

Table 7.19 Items and loadings for Factor 4 (Government protection)

Item	Question	Factor loading
LEG4	Government should limit companies' use of personal information to only that purpose for which it was collected.	0.810
LEG3	Government should do more to protect the safety of personal information.	0.804
LEG2	Government should restrict companies to collecting only the information needed for a specific transaction.	0.786

It is clear that the optimal solution, based both on interpretability and statistical measures, was formed by a four-factor model. As mentioned earlier, the exploratory factor analyses were conducted on one half of the sample. The next step is to use the remaining half of the sample to validate the four-factor model by using confirmatory factor analysis.

7.4.2 Confirmatory factor analysis

Confirmatory factor analysis (CFA) is the predominant method of analysis found in the literature concerning validation studies, particularly when validating the internal factor structure of a newly developed test instrument (Steenkamp & Van Trijp, 1991:283; Hair *et al.*, 1998:114, 247; Burgers *et al.*, 2000:154; Ferrara, 2000:102). Confirmatory factor analysis can be used to test the structure of a model that is identified using exploratory factor analysis. It is important to use a different set of data when testing the validity of the factor model identified by exploratory factor analysis (Hair *et al.*, 1998:114; Lattin *et al.*, 2003:199). Therefore, as mentioned earlier, the sample was split in half using the one half to derive a scale, and using the other half of the sample to confirm the earlier results.

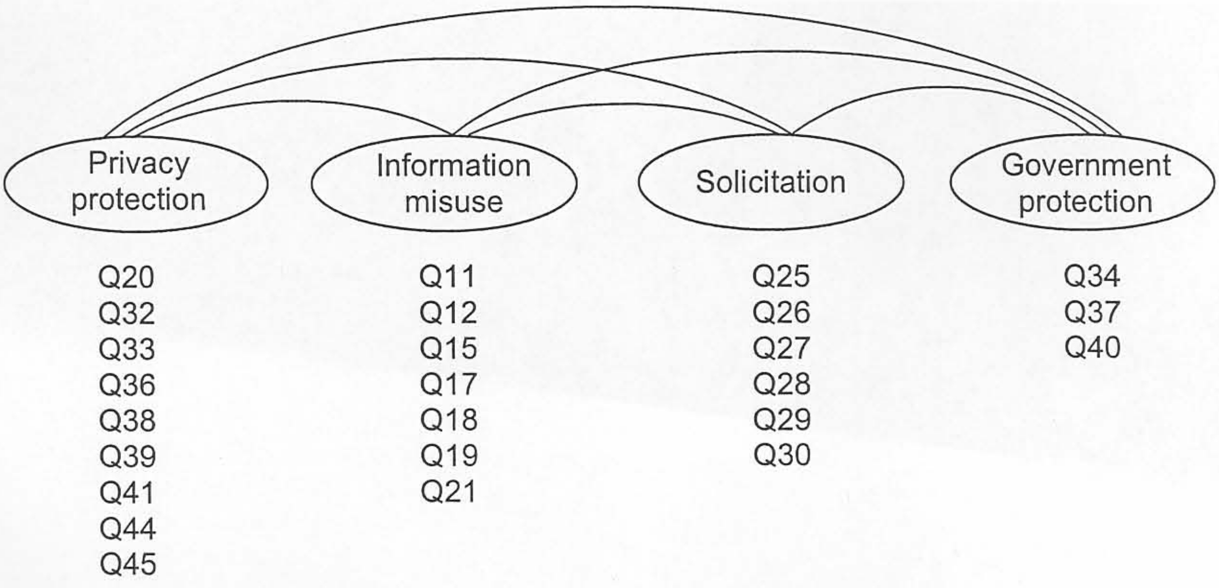
Two assumptions that underlie traditional Structural Equation Modeling programmes are (a) that the variables on which the matrix coefficients are based are intervally scaled, and (b) that the variables have a multivariate normal distribution. The first assumption, namely the scale requirement, was met since all items were measured using 5-point Likert scales. The second assumption, the normality requirement, is often difficult to comply with. The maximum likelihood estimation technique was therefore used for analysis because this technique is relatively robust with regard to violation of normality (Grimm & Yarnold, 2000:233). The data were also examined for any outliers before they were converted to matrix format, and no outliers were found in the dataset. Maximum likelihood estimation was used with the aid of the SAS Proc Calis programme (SAS Institute, 2000b) to execute the confirmatory factor analysis.

7.4.2.1 The theoretically based model converted into a path diagram for CFA

The previously discussed factor analysis indicated the existence of four factors (indicating four underlying dimensions). Therefore, the hypothesised model posited four factors (privacy protection, information misuse, solicitation and government protection), with each set of variables acting as indicators of the separate constructs (or factors).

The next stage was to portray the relationships in a path diagram. In this case, the four hypothesised factors were considered exogenous constructs. From here on forward, each 'factor' identified by the exploratory factor analysis is referred to as a 'construct'. The path diagram, including the variables measuring each construct, is shown in Figure 7.3. The correlations between the different concerns are represented by the curved lines connecting the four constructs.

Figure 7.3 Path diagram for CFA



All the constructs in the path diagram were exogenous, and therefore only the measurement model and the associated correlation matrices for exogenous constructs and indicators needed to be considered. Without a structural model, the measurement model constitutes the entire structural equation modeling effort (referred to as confirmatory factor analysis). To specify the measurement model, a transition was made from factor analysis, where there was no control over which variables described each factor, to confirmatory analysis, where the variables that define each factor can be defined (Hair *et al.*, 1998:598).

The objective of the CFA is an exploration of the pattern of interrelationships. The correlation matrix was therefore used as the input data type. No offending estimates were found for the measurement model and no corrections were needed before the model could be interpreted and the goodness-of-fit assessed.

7.4.2.2 Determining overall model fit

The first assessment of model fit must be done for the overall model (Hair *et al.*, 1998:621). With confirmatory factor analysis, overall model fit portrays the degree to which the specified indicators represent the hypothesised constructs. By applying numerous tests of fit, the proximity of fit between the data and the model can be assessed. Model fit determines the degree to which the structural equation model fits the sample data. Model fit criteria commonly used are chi-square (χ^2), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI) and root-mean-square residual (RMR) (Schumacker & Lomax, 1996:124). Because some of the fit indices evaluate different aspects of fit, it is important to evaluate fit based on multiple fit statistics so that judgments will not be an artifact of analytic choice. Assessment of model adequacy must be based on multiple criteria that take into account theoretical, statistical and practical considerations (Grimm & Yarnold, 2000:271). The fit indices that were used to assess the overall model fit for the present study are discussed below.

(a) Chi-square (χ^2)

The overall model fit provided by the χ^2 value is often used as the first step in evaluating model acceptance or rejection (Baumgartner & Homburg, 1996:152). The χ^2 statistic in isolation is not a meaningful statistic without taking into account the degrees of freedom (df) of a model (Baumgartner & Homburg, 1996:152). CFA researchers also advocate a χ^2/df ratio as an initial start to model acceptence (Schumacker & Lomax, 1996:125; Spangenberg & Theron, 2002:19). A significant χ^2 value relative to the degrees of freedom indicates that the observed and estimated matrices differ. Statistical significance indicates the probability that this difference is due to sampling variation. A non-significant χ^2 value indicates that the two matrices are not statistically different. In this study, a non-significant χ^2 value with associated degrees of freedom was sought. The χ^2 criterion is, however, sensitive to sample size. If the sample size increases (generally above 200), the χ^2 test has a tendency to indicate a significant probability level (Schumacker & Lomax, 1996:125). Because the chi-square test is sensitive to sample size (the sample size for the current study is 313) and can lead to a rejection of a model differing in a trivial way from the data for large sample sizes, it is prudent also to examine other measures of fit (Bagozzi & Heatherton, 1994:45; Baumgartner & Homburg, 1996:149; Ferrara, 2000:106). Thus, a comparison of the GFI, AGFI and RMR measures, which are independent of sample size, was performed to assess the model's fit (Smith *et al.*, 1996:177).

(b) Goodness-of-fit (GFI) and Adjusted Goodness-of-fit (AGFI)

The GFI is based on a ratio of the sum of the squared differences between the observed and reproduced matrices to the observed variances, thus allowing for scale (Schumacker & Lomax, 1996:126). The AGFI adjusts the GFI index for the degrees of freedom of a model relative to the number of variables. The advantage of GFI and AGFI is that they are scales between zero (poor fit) and 1 (perfect fit) and are not a function of sample size. One rule of thumb is that for a good fit, GFI should exceed 0.95 and for an acceptable fit, GFI should exceed 0.90. Similarly, a model with a good fit should have an AGFI value greater than 0.90, and a model with acceptable fit should have an AGFI greater than 0.80 (Lattin *et al.*, 2003:182). Most researchers expect values to be greater than 0.90 for correctly specified models (Hair *et al.*, 1998:657; Grimm & Yarnold, 2000:270).

(c) Root-mean-square residual (RMR)

The RMR index uses the square root of the mean of the squared residuals which is an average of the residuals between observed and estimated input matrices (Schumacker & Lomax, 1996:126). Ideally, RMR should be near zero for a good model fit (Ferrara, 2000:106). Values of 0.05 or less are regarded as indicative of a model that fits the data well (Grimm & Yarnold, 2000:270; Spangenberg & Theron, 2002:19).

(d) Root mean square error of approximation (RMSEA)

RMSEA is another measure that attempts to correct for the tendency of the chi-square statistic to reject any specified model with a sufficiently large sample (Hair *et al*., 1998:656). RMSEA expresses the difference between the observed and estimated covariance matrices in terms of the degrees of freedom of the model, and is a fit index that focuses on estimated population fit. An empirical examination of several measures has found that the RMSEA was best suited to use in a confirmatory strategy with larger samples (Hair *et al*., 1998:656). Although rarely encountered, RMSEA values below 0.01 would indicate a model that fits the data exceptionally well, since values approaching zero are desired. Different RMSEA cut-off values have been suggested: some consider values below 0.05 to indicate a very good fit (Spangenberg & Theron, 2002:19); others indicate that values between 0.05 and 0.08 are indicative of acceptable fit (Baumgartner & Homburg, 1996:152; Hair *et al*., 1998:656; Grimm & Yarnold, 2000:271). Hu and Bentler (1999:1) suggest a cut-off value close to 0.06 for RMSEA before one can conclude that there is a relatively good fit.

(e) Bentler & Bonnet's normed fit index (NFI) and the comparative fit index (CFI)

NFI compares model fit to that of a model for the same data presuming independence of the measured or observed variables. It is one of the more popular measures ranging from 0 (no fit at all) to 1 (perfect fit). There is no absolute value indicating an acceptable level of fit, but a commonly recommended value is 0.90 or greater (Hair *et al*., 1998:657; Maruyama, 1998:244; Grimm & Yarnold, 2000:270). NFI tends to underestimate when small samples are used and an adjustment was proposed to the NFI, namely the comparative fit index (CFI), which takes sample size into account. Some researchers have suggested that the CFI should be a fit statistic of choice in structural equation modeling research (Grimm & Yarnold, 2000:270). The proposed cut-off value for CFI is close to 0.95 (Hu & Bentler, 1999:1).

The different fit indices for this study's overall model fit are reported in Table 7.20.

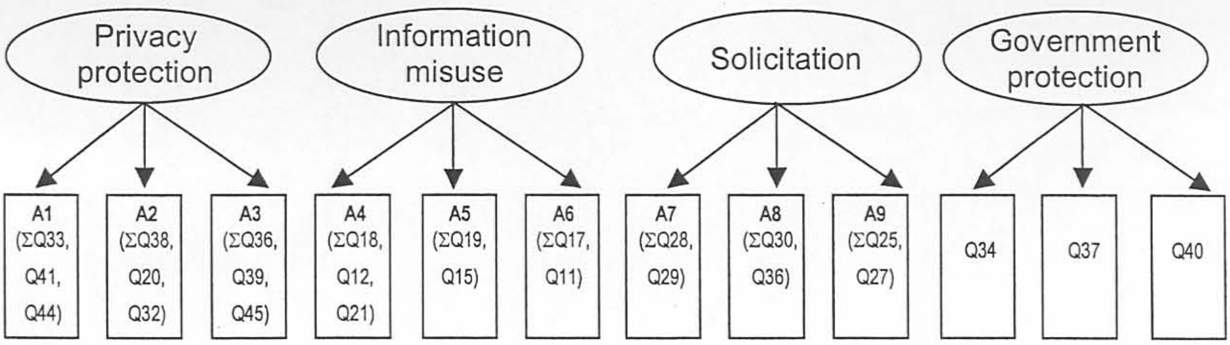
Table 7.20 Fit indices for the overall model fit

Chi-square/df	(789.9013/269) $p<0.0001$
Goodness of fit index (GFI)	0.83
Adjusted goodness of fit index (AGFI)	0.79
RMR	0.07
RMSEA	0.08
CFI	0.84
NFI	0.78

From Table 7.20 it is evident that several of the fit indices (χ^2, GFI, AGFI, RMR, CFI and NFI) were below the suggested cut-off values as suggested by various researchers (as discussed above). Bagozzi and Heatherton (1994:47) indicate that when more than five items per factor are treated as individual measures of factors in a multifactor CFA, it is difficult to achieve a satisfactorily fitting model and the indices obtained from confirmatory factor analysis could be an underestimate of the model fit values. Their view has been supported by several other researchers, such as Baumgarter and Homburg (1996:144), who believe that it is practically unavoidable that one has to combine items into composites if the number of indicators is even moderately larger, for example, ten items. Hair *et al.* (1998: 598) have confirmed that researchers are not likely to obtain good results from structural equation modeling (SEM) with models that have more than 20 measures.

As a solution to this problem, Bagozzi and Heatherton (1994:47) have proposed the calculation of item aggregates to obtain more accurate estimates of model fit indices. When the number of items per construct is relatively small (five to seven items), it seems prudent to form two composites for each construct in which each composite is a sum of items. When nine or more items exist per construct in a scale, it is feasible to form three or more composites as indicators for each construct. In the present study, the four-factor solution contained 25 items. It was decided to use item pairing to form composite variables for three of the four constructs to minimise the instability of the parameter estimates (Ferrara, 2000:105). Composites were achieved in this dataset by randomly selecting items within a specific factor to be paired with another item of the same factor, resulting in a total of nine composite variables or item pairs. Figure 7.4 illustrates the composites formed from the individual items for each of the constructs.

Figure 7.4 Item pairing to form composites



A minimum of three composites was formed for each construct. Several researchers recommend that each construct be assessed using a minimum of three indicators (or items) each (Baumgarter & Homburg, 1996:144; Hair *et al.*, 1998:598). Three of the four constructs were each represented by three item pairs (consisting of two or three items each). From Figure 7.4 it can be observed that A1 to A3 represented the three item pairs of general privacy; A4 to A6 item pairs represented misuse; and A7 to A9 represented solicitation. Because government protection consisted of only three indicators, there was no need to form item pairs for this construct as well.

The item pairing resulted in a reduction of the number of items from 25 to 12. After the composites had been formed, the overall model was assessed again and the fit indices are shown in Table 7.21 below.

Table 7.21 Fit indices for overall model fit (containing composites)

Chi-square/df	(104.2686/49) p=0.0000
Goodness of fit index (GFI)	0.95
Adjusted goodness of fit index (AGFI)	0.92
RMR	0.04
RMSEA	0.06
CFI	0.97
NFI	0.94

From Table 7.21 it is clear that these fit values differ from the values presented in Table 7.20 before composites were formed. The fit indices depicted in Table 7.21 indicate that all the values are within the accepted cut-off levels, demonstrating a very good fit for the overall four-factor model. The only value that did not show an acceptable fit was the chi-square value. The chi-square measure was highly significant [χ^2 (49) = 104.2686; p=0.0000] indicating a poor model fit. However, given the large sample size, the significant chi-square was probably an artifact of sample size (refer to Section 7.3.2.2) and should be interpreted as such.

7.4.2.3 Determining the measurement model fit

The different constructs can now be evaluated by assessing each construct's validity. Construct validity is the one type of validity that has received great attention over the years and is consequently the one with the best developed technology for assessment (Steenkamp & Van Trijp, 1991:287; Smith *et al*., 1996:178; Hair *et al*., 1998:118; Burgers *et al*., 2000:155). The following criteria were used to assess construct validity for this study: unidimensionality, reliability, convergent validity and discriminant validity.

(a) Unidimensionality

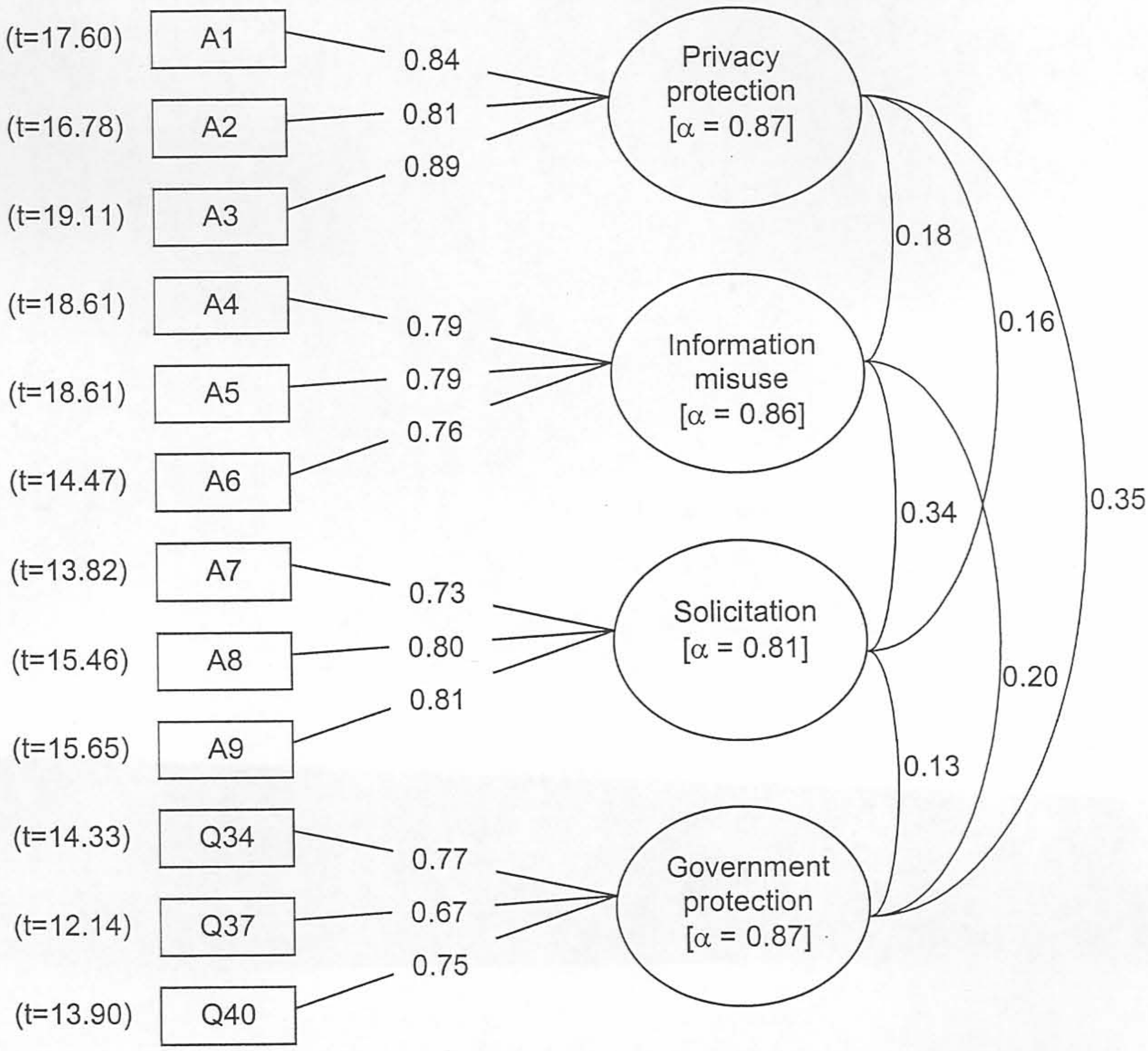
Unidimensionality can be defined as the existence of one construct underlying a set of items, and has been recognised as one of the critical and basic assumptions of measurement theory (Hattie, 1985:139). In this study, unidimensionality refers to each of the factors separately where each item is related to one factor. The overall fit of the model provides the necessary and sufficient information to determine whether a set of items is unidimensional (Kumar & Dillon, 1987:100). The good model fit (GFI=0.95, AGFI=0.92, CFI=0.97, and RMSEA=0.06) indicates that the scale is unidimensional. Other researchers believe that unidimensionality is obtained when an item loads on only one construct and when only high loading items are selected (Steenkamp & Van Trijp, 1991:286). In this survey, items that did not load on only one factor were deleted, and only items loading higher than 0.50 were selected, demonstrating unidimensionality of the construct.

(b) Convergent validity

Convergent validity is demonstrated when a measure has relatively high correlations with other measures of the same common factor. Thus, convergent validity assesses the degree to which two measures of the same concept are correlated. High correlations indicate that the scale is measuring its intended concept (Hair *et al.*, 1998:118). Convergence implies that all within-construct correlations are both high and of approximately the same magnitude (Steenkamp & Van Trijp, 1991:290). According to Anderson and Gerbing (1988:414), within-method convergent validity should be achieved before reliability is estimated.

There are several approaches to the assessment of convergent validity through CFA. The statistical significance of the regression coefficient, the correlation of the item with the construct, as well as the overall fit of the model are all indicators of within-method convergent validity (Hildebrandt, 1987:35; Steenkamp & Van Trijp, 1991:289; Smith *et al.*, 1996:181; Burgers *et al.*, 2000:155). Within-method convergent validity was first assessed by testing the significance and magnitude of each indicator's coefficient. Each variable's *t* value was investigated in terms of how its loading exceeded the critical values at the 0.05 significance level (critical value 1.96) as well as the 0.01 significance level (critical value 2.576). All the *t* values were well above 1.96 and 2.57 (see Figure 7.5). The magnitude of the items was then assessed. Hildebrandt (1987:35) suggests in respect of the latter criterion that the correlation between the item and the construct (or factor) should exceed 0.50. All items loaded significantly higher than 0.70 on their respective constructs, except for one item that loaded 0.67. Thus, all variables are significantly related to their specified constructs, verifying the posited relationships between indicators and constructs. The significance and magnitude of the items can be seen in Figure 7.5.

Figure 7.5 Significance and magnitude of items in the CFA model



The afore-mentioned conditions (statistical significance of the regression coefficient and the correlation of the item with the construct) should be evaluated, provided that a third requirement of convergent validity is met, namely that the overall fit of the model is acceptable (Steenkamp & Van Trijp, 1991:289). As reported earlier, a good overall model fit was obtained. All these findings support the convergent validity of the information privacy scale.

(c) Reliability

Another method to assess construct validity is to estimate the reliability (Steenkamp & Van Trijp, 1991:290; Burgers *et al.*, 2000:155) and variance-extracted measures (Hair *et al.*, 1998:611; Smith *et al.*, 1996:185) for each construct to assess whether the specified indicators are sufficient in their representation of the constructs. As mentioned previously, all four constructs exceeded the recommended reliability level of 0.70 (0.88, 0.82, 0.83 and 0.77), indicating an adequate reliability for the four scales (Hair *et al.*, 1998:623).

Another measure of reliability is the variance-extracted measure. The average variance extracted is the sum of the squared standardised loading divided by the sum of the squared standardised loadings plus the sum of the indicator measurement error. This measure reflects the overall amount of variance in the indicators accounted for by the latent construct. Higher variance extracted values occur when the indicators are truly representative of the latent construct. Guidelines suggest that the variance-extracted values should exceed 0.50 for a construct (Hair *et al.*, 1998:612). For the variance-extracted measures, all four constructs exceeded the recommended 50 per cent with values of 0.72, 0.61, 0.61 and 0.53. Thus, the explained variance by each factor is significantly higher than the variance due to measurement error, indicating adequate convergent validity for each factor (Fornell & Larcker, 1981:42). Table 7.22 depicts the values for Cronbach's alpha as well as the average variance extracted (AVE).

Table 7.22 Summary of reliability values

FACTORS	Cronbach's alpha	AVE*
General privacy	0.87	0.72
Misuse	0.87	0.61
Solicitation	0.86	0.61
Government protection	0.82	0.53

* Appendix 6 contains details on the calculation of the average variance extracted.

(d) Discriminant validity

Discriminant validity is determined by demonstrating that a measure does not correlate very highly with another measure from which it should differ (Peter, 1981:136), or must have lower correlations with measures of different factors (Zikmund, 2003:304; Hair *et al.*, 1998:118). If the correlations are too high, this suggests that the measure does not capture a distinct or isolated trait (Peter, 1981:137; Churchill & Iacobucci, 2002:413). Discriminant validity is evident in several ways (Cole, Cho & Martin, 2001:94). The first involves cross-loadings in the factor analysis. In none of these analyses was a measure allowed to load on any factor other than the one it was designed to represent. The model also provided a good fit to the data without allowing such cross-loadings. More rigorous evidence of discriminant validity is also evident by observing the average variance extracted by each factor relative to that factor's shared variance with other factors in the model (Fornell & Larcker, 1981:41). Table 7.23 provides the factor intercorrelations of the four-factor model.

Table 7.23 Factor intercorrelations of the four-factor model

FACTORS	General privacy	Misuse	Solicitation	Government protection	AVE
General privacy	1.00				0.88
Misuse [squared correlation]	0.188 [0.035]	1.00			0.82
Solicitation [squared correlation]	0.160 [.025]	0.338 [0.114]	1.00		0.83
Government protection [squared correlation]	0.351 [0.123]	0.201 [0.040]	0.131 [0.017]	1.00	0.77

In every case, the average variance extracted (AVE) associated with a factor is greater than the shared variance (squared correlation) between that factor and every other factor. It is clear from Table 7.23 that the AVE's are all greater than the squared correlations between a factor and every other factor. This is also indicative of the existence of discriminant validity.

The results from all the relevant analyses provided support for the validation of the proposed model. Confirmatory factor analysis were used to assess the unidimensionality, reliability, and validity of the scale (Steenkamp & Van Trijp, 1991:283). The overall model goodness-of-fit results and the measurement model assessments lent substantial support for confirmation of the proposed four-factor model.

7.5 HYPOTHESES TESTING

The process of hypotheses testing was conducted as follows: first, statistical hypotheses were determined by formulating null and alternative hypotheses (as set out in Chapter 5). The next step was to specify the circumstances under which H_0 would or could not be rejected, by choosing a level of significance. A significance level is a critical probability in choosing between the null hypothesis and the alternative hypothesis. A five per cent significance level (α=0.05) was set for all hypotheses. Thereafter an appropriate statistical technique with a corresponding test statistic was chosen. Finally, the values of the test statistics were calculated, the test results interpreted and a decision was made to reject or not reject the null hypotheses. All the significant results are indicated in bold print.

All the hypotheses that were tested with the same statistical technique are discussed in the same section. This means that the hypotheses do not necessarily follow a chronological order. The following section provides detailed results for the hypotheses testing based on the above-mentioned principles.

7.5.1 Testing hypotheses using chi-square tests

Hypotheses 2b, 3b, 3c and 6 were tested by means of chi-square (χ^2) tests. In H_{2b} and H_{3b}, two groups were compared on a variable measured on a nominal scale and were therefore tested with the two-sample chi-square test for independency (Sections 7.4.1.1 and 7.4.1.2). H_{3c} was tested with the k-sample chi-square test for independency (an extension of the two-sample chi-square test) because comparisons were made between