Chapter Five- Driving Innovation Factors by Using Factor Analysis

5.1 Introduction

In the previous chapter, the results of preliminary stages of analysis including normality, reliability, and demographic characteristics were presented and discussed. Also, the statistical procedures required to answer the research question of this study were touched upon. In this chapter, the goal is to drive the innovation factors by using Factor Analysis (FA). This method is widely used in the empirical studies with quantitative data to obtain similar groups of variables.

As previously mentioned in Chapter Two and Three, the foundation of this study, i.e. its theoretical framework, measurement instrument, and the type of analysis, is mainly based on the two related studies conducted by Lawson and Samson (2001), as well as Terziovski and Samson (2007). For example, Terziovski and Samson (2007) assigned the variables to twelve constructs and subjected them to Confirmatory Factor Analysis to ensure that they were reliable indicators of those constructs.

In this study, Factor Analysis is the major statistical analysis. The main goal of applying FA in this study is to discover which variables in the measurement instrument form coherent subsets that are relatively independent of one another (see Tabachnick & Fidell, 2007). Thus, the variables that are correlated with one another but largely independent of other subsets of variables are combined into factors. These factors are thought to reflect underlying processes that have created correlations among the variables (Tabachnick & Fidell, 2007, p. 607). Moreover, due to large number of variables on the ICS, FA is required as it offers the utility to reduce numerous variables down to a few factors (Tabachnick & Fidell, 2007). Consequently, these factors would be the drivers of innovation in Malaysia.

Nevertheless, it is noteworthy to mention that along the research road, due to contextual differences and the nature of data obtained; it was necessary to make modifications to the original theoretical framework[1], measurement instrument and analysis strategy whereby making this study unique on its own terms.

This chapter consists of nine main sections including this introduction and proceeds as follows. In Section 5.2 Factor Analysis is explained. In Section 5.3 the theoretical assumptions of FA are discussed. Section 5.4 presents the empirical results of FA assumption testing. Section 5.5 presents the process of driving the factors. In Section 5.6 derived factors are interpreted, and in Section 5.7 the results of Orthogonal Varimax Rotation are presented and discussed. Later, Section 5.8 presents the process of naming the factors. Section 5.9 shows the results of factor combinations, and finally Section 5.10 presents the conclusion.

5.2 Factor Analysis

Factor analysis is a statistic procedure or analysis which allows the researcher to condense a large set of variables or scale items down to a smaller, more manageable number of dimensions or factors. It does this by summarizing the underlying patterns of correlation and looking for groups of closely related items.

[1] The theoretical framework (TF) used by Terziovski and Samson (2007) had one extra construct labeled as Enablers. This construct comprised variables measuring New Product Development, E-Commerce, and Sustainable Development Orientation. As the target respondents of the present study are top management level, it could not be feasible to administer a questionnaire with 146 items, excluding basic company data items. Therefore, Enablers were removed from the TF of this study therefore making the questionnaire shorter and possibly enhancing the response rate.

In this study, 'exploratory' factor analysis using principal components analysis (PCA) has been employed. In PCA, the original variables are transformed into a smaller set of linear combinations, with all of the variance in the variables being used. Stevens (1996, pp. 362-363) admits a preference for PCA and gives a number of reasons for this. He recommends that it is psychometrically sound, simpler mathematically and it avoids some of the potential problems with 'factor indeterminacy' associated with factor analysis (Stevens, 1996, p. 363). Too, if you want an empirical summary of the data set, PCA is the better choice (Tabachnick & Fidell, 1996, p. 664).

5.3 FA Theoretical Assumptions[2]

There are several assumptions and practical considerations underlying the application of PCA. These are Sample Size, Factorability of the Correlation Matrix, Multicollinearity, and Outliers among Cases.

Sample size or *sample adequacy* is one of the most important criteria. As far as the theory and rule of thumbs are concerned, Coakes and Steed (2007, p. 123) assert that a minimum of five subjects per variable is required for factor analysis. A sample of 100 subjects is accepted but sample sizes of 200+ are preferable. "Comery and Lee (1992) gives as a guide sample sizes of 50 as very poor, 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 as excellent (as cited in Tabachnick & Fidell, 2007, p. 613)." However,

[2] Having entered all the independent variables (items on the measurement instrument= 104) into FA Procedure, it was recognized that the SPSS 17 (and later SPSS 16) was not able to produce KMO and Bartlett's test as well as Anti-Image Matrices. Therefore, attempts were made to reduce the number of items one by one to find out the cut-off point (a limitation of SPSS) for the maximum number of variables allowed to be entered. Therefore, as a result of this trial and error, 84 variables entered this analysis. The selection of the items to remove was based on the professional judgement of the researcher. The criterion was that items which are repeated in different form under the same construct and has lowest Cronbach's alpha have priority for elimination. Therefore, the analysis was started with 84 variables.

as a general rule of thumb, as recommended by Tabachnick and Fidell, it is comforting to have at least 300 cases for factor analysis (2007, p. 613). Moreover, some other rules of thumb consider $N \geq 50+8m$ (where m is the number of IVs) for testing multiple correlation (Tabachnick & Fidell, 2007, p. 123).

As far as the tests for measuring sample adequacy is concerned, first, it is necessary to calculate the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (Kaiser, 1970, 1974) and Barlett's Test of Sphericity (Bartlett, 1954). The KMO index ranges from 0 to 1, with 0.6 suggested as the minimum value for a good factor analysis (Tabachnick & Fidell, 1996). The Bartlett's Test of Sphericity (BTS) should be significant ($p<0.05$) for the factor analysis to be considered appropriate (Pallant, 2001, p. 153).

Factorability of the Correlation Matrix is another assumption. To be considered suitable for factor analysis the correlation matrix should show at least some correlations of r = 0.3 or greater. The Bartlett's test of sphericity should be statistically significant at $p<.05$ and the Kaiser-Meyer-Olkin value should be 0.6 or above.

Multicollinearity is another important assumption which should be examined by looking at correlation matrix and anti-image matrices. This can be identified if any of the squared multiple correlations are near or equal to 1. If this is the case, the inclusion of the offending variables needs to be considered (Coakes & Steed, 2007, p. 123). This issue has also been addressed in Pallant's (2001) as concerns for the strength of the inter-correlations among the items. According to Tabachnick and Fidell (1996) an inspection of the correlation matrix for evidence of coefficients greater than 0.3 is recommended (as cited in pallant, 2001).

The last assumption to be considered is *Outliers among Cases*. Factor analysis can be sensitive to outliers, so as part of the initial data screening process, these outliers should be checked for. Upon detecting outliers, these should either be removed or recoded to a less extreme value.

5.4 Assumption Testing

Considering the sample size required for this study, theoretically, 114 responses are required, i.e. $N \geq 50+8*8 \rightarrow N=114$ is needed. The actual sample size of this study amounts to 85, which means this assumption is not perfectly met. Notwithstanding the small sample size, there are *reasons* to consider and *techniques* to implement to overcome this deficiency.

As far as the reasons or justifications are concerned, it should be mentioned that first and foremost, the target respondents of this study are solely from top management level. This brings the feasibility of collecting the minimum required amount under question. Secondly, within the time frame (approximately four months) allocated to conduct the whole research project and lack of budget, it was not possible to reach the desired figure as of now. However, the data collection of this study is still in process for another four months to meet the requirements and prepare the results rich enough for ISI-level journal publication. Yet, this inadequacy can be considered as a shortcoming or limitation for this study. Lastly, the past research conducted in the same field in the context of Malaysia revealed a very low response rate. As an illustration, for NSI-4 conducted over the period of two years 2004-2006 or [even more] covering 2002-2004, the Malaysian government research body was able to collect only 486 responses from 4000 firms in the population representing the response rate of only 12.5 per cent. Therefore, consideration of the peculiarities of the geography under investigation explains a lot about the low response rate obtained for this study.

As far as the techniques for improving sample inadequacy is concerned, first, it is necessary to calculate the Kaiser-Meyer-Olkin (KMO) and Barlett's Test of Sphericity(Bartlett, 1954). Table 5.1 shows the initial result of KMO and Bartlett's Test.

Table 5.1: KMO and Bartlett's Test

Item		**Value**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.170
Bartlett's Test of Sphericity	Approx. Chi-Square	8477.469
Degree of Freedom (df)		3486
Significance (sig.)		.000

As the above Table 5.1 shows, KMO value is 0.170 which is not equal or above 0.6. However, the Barlett's Test of Sphericity value is significant p=.000. Therefore, even if Bartlett's Test result is healthy, the factor analysis is not appropriate yet. Before making a decision at this point, it is necessary to look at *Factorability of the correlation matrix* as another important assumption and examine the *Anti-Image Matrices* as another important measure to be considered and the one which is related to KMO value as well.

According to the correlation matrix[3] generated by SPSS, there are several correlations in excess of .3, however, the variables (items) are not highly correlated with one another. Therefore, the correlation matrix is appropriate for factoring. In fact, there is no sign of multicollinearity among the independent variables[4].

[3] Due to economy of space and lack of clarity, this matrix is available upon request and is not presented in A4 size in the Appendix.
[4] However, this is not the final table to look at, as there is going to be a lot of changes in this matrix.

The next step to assess the overall significance of the correlation matrix by examining the results of Bartlett's Test. Table 5.1 shows that Barlett's Test of Sphericity value is significant at p=.000 which is well below .05 revealing that no multicollinearity is presence. However, this does not reveal anything about the pattern of any correlations; therefore, at this point it is necessary to investigate the overall statistic to measure sampling adequacy (MSA) by consulting *Anti-Image Matrices.* If the value of a variable on the diagonal falls below 0.5 it should be omitted in an attempt to obtain a set of variables that can exceed the minimum acceptable MSA. In this study, the variables which had the value below the cut-off point of 0.5 were identified and removed one at a time starting from the lowest. This procedure was repeated twelve (12) times until all values on the diagonal were (well) above 0.5. Therefore, overall eleven (11) variables were removed. As a result of this, the KMO value improved from 0. 170 (initial) to 0.738 (final) while the Barlett's Test of Sphericity value remained constant (unchanged) and significant at p=.000. Table 5.2 shows the detailed results of KMO and Bartlett's Test evolution.

Removing the variables with value below cut-off point caused a reduction in the set of variables. As a result (see Table 5.2), for the reduced set of variables the Bartlett's test shows that non-zero correlations exist at the 0.01 per cent level of significance, therefore, the reduced set of variables collectively meets the necessary threshold of sampling adequacy with a value of 0.738. The MSA of each of the variables also exceeds the threshold value indicating that the reduced set of variables meets the fundamental requirements for factor analysis.

Table 5.2: Detailed Results on KMO and Bartlett's Test

No.	Variable Removed	Diagonal Value	Original Independent Construct	Resulting KMO	Bartlett's Test of Sphericity Approx. X^2	df	Sig.
0	START	-----	------------	.170	8477.469	3486	.000
1	We rely on 'off-the-shelf' technology for our competitive needs	.039[a]	Management of Technology	.346	8079.639	3403	.000
2	We rely principally on experience-based intuition when making major operating and strategic decisions	.077[a]	Culture and Climate	.517	7827.435	3321	.000
3	Social networks exist in our organization	.234[a]	Organizational Structure	.540	7646.272	3240	.000
4	Patent Disclosures	.282[a]	Info. and Org. Intelligence	.576	7430.328	3160	.000
5	Licensing Technologies	.289[a]	Info. and Org. Intelligence	.607	7229.622	3081	.000
6	The word 'innovation' appears in our mission statement	.366[a]	Leadership and Strategy	.600	7045.954	3003	.000
7	Offer workers legal rights in intellectual property, IP, they create	.314[a]	Creativity and Idea management	.628	6860.412	2926	.000
8	Publications	.351[a]	Info. and Org. Intelligence	.708	6713.153	2850	.000
9	Our culture sees 'failure' as an opportunity to learn	.438[a]	Culture and Climate	.715	6582.913	2775	.000
10	We have flat organizational structure	.458[a]	Organizational Structure	.724	6487.572	2701	.000
11	Consultants	.459[a]	Info. and Org. Intelligence	**.738**	6312.086	2628	.000
12	END	-----	-------------	**-----**	----------	------	----

5.5 Driving the Factors

The most frequently used methods for factor extraction are principal components (PC) and principal axis factoring (PAF), however, there is much debate in the literature over which method is the most appropriate (Coakes & Steed, 2007, p. 122). In this study, PC has been chosen.

The first step to take in the selection process is to choose the number of factors to be retained for further analysis. Table 5.3[5] , based on the SPSS output, contains information regarding 73 possible factors and their relative explanatory power expressed as *eigenvalues*. To determine how many factors (components) to 'extract', it is recommended to look for the components that have an eigenvalues of 1 or more only (Tabachnick & Fidell, 1996, 2007). Therefore, applying the latent root criterion (eigenvalues >1), 15 factors are retained. Cattell (1966) proposed a second method which is known as the graphical scree test. Accordingly, the factors to be retained are those which lie before the point at which the eigenvalues seem to level off (Cattell, 1966). In this study, this occurs after the first 15 factors. Figure 5.1 shows the result of scree test.

[5] Due to the economy of space the whole table which contains 73 factors is not presented in the text. See Appendix 2 for the complete Table

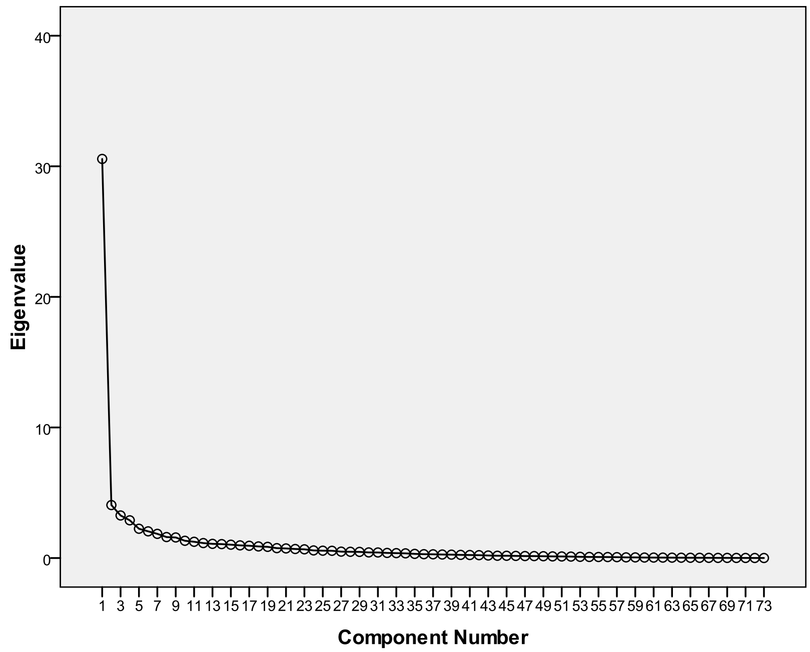
Table 5.3: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	30.564	41.869	41.869	30.564	41.869	41.869
2	4.057	5.557	47.426	4.057	5.557	47.426
3	3.260	4.466	51.892	3.260	4.466	51.892
4	2.889	3.957	55.849	2.889	3.957	55.849
5	2.243	3.073	58.922	2.243	3.073	58.922
6	2.044	2.801	61.723	2.044	2.801	61.723
7	1.852	2.537	64.260	1.852	2.537	64.260
8	1.606	2.200	66.460	1.606	2.200	66.460
9	1.576	2.158	68.618	1.576	2.158	68.618
10	1.323	1.812	70.430	1.323	1.812	70.430
11	1.245	1.705	72.135	1.245	1.705	72.135
12	1.146	1.569	73.704	1.146	1.569	73.704
13	1.087	1.489	75.193	1.087	1.489	75.193
14	1.066	1.461	76.654	1.066	1.461	76.654
15	**1.023**	1.401	78.054	1.023	1.401	**78.054**
16	.971	1.329	79.384			
17	.941	1.289	80.672			
18	.889	1.217	81.890			
…						
…						
72	.004	.006	99.996			
73	.003	.004	100.000			

Note: Extraction Method: Principal Component Analysis.

According to Table 5.3, the 15 factors retained represent 78.054 per cent of the variance of the 73 variables.

Figure 5.1: Scree Plot



5.6 Interpreting the Factors

In order to interpret these factors, it is necessary to examine two tables produced as SPSS output with the headings: Component Matrix[a] and Communalities (see Appendix 2). In 'Component Matrix' the relationship between each item or variable and a factor (component) is expressed as a correlation or loading. The items have been listed in terms of the size of their loadings on the factor to which they are most closely related. For example, majority of the items load most highly on the first, second, third, and fourth factors out of fifteen. Only very few items load on the remaining factors. Examination of the factor loading patterns indicates that the first factor which account for the largest amount of variance (41.869) is a general factor with every variable having a high loading on it. The loadings on the second factor and third factor show that a few variables have also high loadings on them; yet, not as high as their loadings on the first factor.

Examination of the Communalities (see Appendix 2) provides a summary statistics detailing how well each variable is explained by the 15 factors. The column headed "Extraction" on Communalities table show the amount of variance in a variable that is accounted for by the 15 factors taken altogether. According to this Table, the minimum variance is 0.658 which belongs to the variable: "We have suggestion/idea scheme in place" and the maximum variance is 0.879 which belongs to the variable: "Senior managers implement a culture of innovation". These large communalities indicate that a large amount of variance in a variable has been extracted by the factor solution.

Overall, as the interpretation of the results at this stage is extremely difficult and theoretically meaningless, the factor matrix must be rotated to redistribute the variance from the earliest factors to the later factors. Therefore, it is expected that this rotation results in a simpler and theoretically more meaningful factor pattern.

5.7 Applying an Orthogonal (Varimax) Rotation

In order to increase the interpretability of the extracted factors, rotation is necessary to maximize the loadings of some of the items. Later, these items can be used to identify the meaning of a factor. It is noteworthy to mention that rotation does not change the underlying solution, rather, it presents the pattern of loadings in a manner that is easier to interpret (Coakes & Steed, 2007, p. 185). Therefore, Varimax rotation is used.

As shown in Table 5.4, total amount of variance extracted is 76.654 which is not exactly the same in the rotated solution as was in the un-rotated one, 78.054. This is mainly due to the fact that SPSS was not able to generate Rotated Component Matrix table with maximum 25 iterations for convergence. Therefore, the Varimax rotation was done for 14 factors only.

Table 5.4: Total Variance Explained

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	13.402	18.358	18.358
2	7.485	10.254	28.612
3	5.168	7.079	35.691
4	4.617	6.325	42.017
5	4.600	6.301	48.318
6	3.011	4.125	52.442
7	2.670	3.657	56.099
8	2.651	3.632	59.731
9	2.497	3.420	63.152
10	2.317	3.174	66.326
11	2.221	3.042	69.368
12	2.081	2.850	72.218
13	1.704	2.335	74.553
14	1.534	2.101	76.654

Note: Extraction Method: Principal Component Analysis.

However, two differences are apparent from the examination of Tables 5.4, and 5.5. Firstly, the first factor now accounts for 18.35 per cent of the variance compared to 41.86 per cent for the un-rotated solution; the second factor now accounts for 10.25 percent of the variance compared to 5.55 per cent for the un-rotated solution, and this goes on. This observation leads to the conclusion that the explanatory power of factors has shifted slightly to a more even distribution because of the rotation.

Secondly, the interpretation of the factor matrix has been simplified. Whereas in the un-rotated solution where almost all variables loaded significantly on the first factor, in the rotated solution, the variables load significantly on other factors as well. Table 5.5 clearly demonstrates the significant loadings of variables onto 14 factors. Only heaviest loadings have been displayed in the Table.

As illustrated in Table 5.5, no variable loads significantly on more than one factor, therefore, at this stage interpretation of the factors has been simplified by rotating the factor matrix. In the next section factors will be named.

Table 5.5: Rotated Component Matrix[a]

# X	Variables/Items	Factors													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Rewards employees based on how well they perform their job	0.82													
2	Rewards employees based on how well their work group or team performs	0.8													
3	Promotes employees based on merit	0.79													
4	Uses hiring procedures that focus on who will best ‘fit in’ with the organization’s culture	0.75													
5	Our organization applies high standards of integrity	0.72													
6	We reward our employees to adopt a continuous improvement philosophy	0.7													
7	All employees strive to enhance customer value creation	0.69													
8	Provide training for professional development	0.67													
9	Our organization has aligned employee behaviours with stated organizational values	0.67													
10	The ‘learning organization’ concept is practiced in our organization.	0.63													
11	Champion (s) of change are effectively used at this site	0.58													
12	Our marketing and operations units work closely	0.56													
13	Our strategic decisions are based on quantitative analysis of data	0.56													
14	All employees are involved in learning programs	0.56													
15	Total Quality Management is embedded in our culture	0.54													
16	Respond quickly to customer needs	0.54													
17	The concept of the “internal customer” i.e. the next process down the line is well understood	0.53													
18	Send them to workshops and conferences	0.53													
19	We have an organization-wide people development process	0.51													
20	Develop ‘best in industry’ products/services	0.51													
21	Our major operating decisions are detailed in formal written reports	0.5													
22	Increase operating efficiencies	0.5													
23	Within our organization, individuals and work teams are assigned responsibility for knowledge management	0.47													
24	We have established collaborative partnerships	0.46													
25	We use re-engineering to achieve radical innovation in our processes	0.46													
26	Our operations strategy is aligned with our innovation strategy		0.76												
27	Senior managers implement a culture of innovation		0.73												
28	Senior managers actively encourage change		0.72												
29	Employee satisfaction is measured regularly		0.71												
30	Senior managers show a sense of urgency relating to opportunities for innovation		0.66												
31	Multi-tasking is actively used to build innovation capability		0.58												
32	There is a high degree of unity of purpose throughout our organization		0.57												
33	Our human resource plan is clearly focused on the recruitment of creative people		0.55												
34	We adopt an emergent (bottom up) strategy		0.53												
35	We have suggestion/idea scheme in place		0.5												
36	Knowledge is freely shared in our organization		0.5												
37	We have effective “top down”& “bottom up” communication processes		0.47												
38	Technology is a key part of innovation capability		0.789												

		Factors													
#X	Variables/Items	1	2	3	4	5	6	7	8	9	10	11	12	13	14
39	We develop our core technology strategy based on ‘competitive benchmarking’ information			0.77											
40	Our technology is efficiently aligned with the central business mission			0.66											
41	We develop our technology in collaboration with leading organizations in the field			0.65											
42	Informal networks with other organizations				0.85										
43	Networks with other organizations				0.85										
44	Board Members				0.56										
45	Trade magazines, government publications				0.51										
46	Market research studies				0.39										
47	We are normally the first organization to introduce new products/services in the market					0.83									
48	Is ‘first to market’ with new products/services					0.79									
49	Develop new process innovations					0.57									
50	Produce a continuous stream of state-of-the-art products/services					0.48									
51	Responds to early market signals concerning areas of opportunity					0.48									
52	Gathering of information through Strategic Intelligence					0.39									
53	Ensure that they develop their skills						0.7								
54	Ensure that they have interesting work						0.68								
55	Explicit tracking of competitor tactics							0.76							
56	We continuously obtain up-to-date market knowledge							0.5							
57	Customize products /services to fit customers’ needs								0.52						
58	Forecasting sales, customer preferences								0.52						
59	Develop customer loyalty								0.5						
60	Lead customers								0.49						
61	We place a strong emphasis on the marketing of tried products and/ or services								0.43						
62	Suppliers									0.69					
63	Gathering of information from suppliers									0.67					
64	Produces products/services at a cost level lower than that of our competitors									0.44					
65	We have eliminated barriers between departments										0.49				
66	Hired skilled employees										0.47				
67	Routine gathering of opinions from clients										0.35				
68	Restructuring is part of our innovation philosophy											0.51			
69	Entrepreneurship is widely supported at middle management level											0.49			
70	Independent R&D (in house or external)												0.72		
71	Reverse engineering												0.56		
72	Regularly conducts formal performance appraisal of employees													0.67	
73	Our major operating and strategic decisions are much more affected by industry experience														0.63

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 19 iterations.

5.8 Naming the Factors

Having derived a satisfactory factor solution such as the one presented in Table 5.5 (Rotated Component Matrix), it is time to assign meaning to each of the 14 rotated factors. This involves the interpretation of their loadings including their signs. The minimum acceptable level of significance for factor lodgings in this study is 0.4, i.e. variables which have loadings below this cut-off point will not affect the naming process. On the other hand, variables with higher or heavier loadings influence the name to a greater extent and practically represent a factor. Table 5.6 demonstrates the factor naming results.

Table 5.6: Factors' Names

Factor	Variables	Name	Composite Reliability	Mean	SD
1	X_1, X_2, X_3,...X_{25}	Strategic HRM	0.966	92.0824	18.80490
2	X_{26}, X_{27}, ...X_{37}	Leadership and Strategy	0.935	43.2353	8.99027
3	X_{38}, X_{39},X_{40}, X_{41}	Technology Management	0.855	10.9294	2.55319
4	X_{42}, X_{43}, ..., X_{46}	External Networking	0.845	17.6941	4.15768
5	X_{47}, X_{48}, ..., X_{52},	First-Mover Advantage	0.852	21.3176	4.62450
6	X_{53}, X_{54}	Work Place Learning	0.821	7.5412	1.47643
7	X_{55}, X_{56}	Competitor Analysis	0.641	7.7529	1.63958
8	X_{57}, X_{58}, ..., X_{61}	Customer Focus	0.859	19.40	3.60951
9	X_{62}, X_{63}, X_{64}	Supplier Intelligence	0.721	10.4471	2.61181
10	X_{65}, X_{67}, X_{68}	Internal Networking	0.718	10.8471	2.22810
11	X_{68}, X_{69}	Business Reengineering	0.592	7.1529	1.57741
12	X_{70}, X_{71}	Research and Development	0.730	6.4588	2.10754
13	X_{72}	Employee Performance Appraisal	-----*	-----	--------
14	X_{73}	Industry Experience	-----*	-----	--------

Note*: SPSS does not generate Cronbach's Alpha for one item only.

As Table 5.6 above shows, 14 factors which underlie 73 variables are named as follows: *Strategic Human Resource Management*, *Leadership and Strategy*, *Technology Management*, *External Networking*, *First-Mover Advantage*, *Work Place Leaning*, *Competitor Analysis*, *Customer Focus*, *Supplier Intelligence*, *Internal Networking*, *Business*

Reengineering, *Research and Development*, *Employee Performance Appraisal*, and *Industry Experience*.

5.9 Factor Combinations

Having named the factors, it is now proper to present factor combinations in a formulaic form.

$F = AX$

Where A represents the factor loadings, and X represents the variables. Therefore, the assumptions are as follows:

$F_1 = a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n$

$F_2 = a_{21}x_{21} + a_{22}x_{22} + a_{23}x_{23} + \ldots + a_{2n}x_{2n}$

....

....

$F_n = a_{i1}x_{i1} + a_{i2}x_{i2} + a_{i3}x_{i3} + \ldots + a_{ij}x_{ij}$

where *F* is the extracted factor, *a* is the factor loading, and *x* is the variable, *i* notation refers to the *i*th case in the *n* sample of observations and *j* notation refers to the *j*th case in the *n* sample of observations. Accordingly, based on Table 5.5, the equations can be written as follows:

$$F_1 = .82x_1 + .8x_2 + .79x_3 + .75x_4 + .72x_5 + .7x_6 + .69x_7 + .67x_8 + .67x_9 + .63x_{10} + .58x_{11} + .56x_{12} + .56x_{13} + .56x_{14} + .54x_{15} + .54x_{16} + .53x_{17} + .53x_{18} + .51x_{19} + .51x_{20} + .5x_{21} + .5x_{22} + .47x_{23} + .46x_{24} + .46x_{25}$$

F_2= .76x_{26}+ .73x_{27}+ .72x_{28}+ .71x_{29}+ .66x_{30}+ .58x_{31}+ .57x_{32}+ .55x_{33}+ 53x_{34}+ .5x_{35}+ .5x_{36}+ .47x_{37}+ .78x_{38}

F_3= .77x_{39}+ .66x_{40} + .65x_{41}

F_4= .85x_{42}+ .85x_{43}+ .56x_{44}+ .51x_{45}+ .39x_{46}

F_5= .83x_{47}+ .79x_{48}+ .57x_{49}+ .48x_{50}+ .48x_{51}+ .39x_{52}

F_6= .7x_{53}+ .68x_{54}

F_7= .76x_{55}+ .5x_{56}

F_8= .52x_{57}+ .52x_{58}+ .5x_{59}+ .49x_{60}+ .43x_{61}

F_9= .69x_{62}+ .67x_{63}+ .44x_{64}

F_{10}= .49x_{65}+ .47x_{66}+ .35x_{67}

F_{11}= .51x_{68}+ .49x_{69}

F_{12}= .72x_{70}+ .56x_{71}

F_{13}= .67x_{72}

F_{14}= .63x_{73}

These 14 factors are the input for Multiple Regression Model which will be discussed, presented and evaluated in the following chapter.

5.10 Conclusion

This chapter aimed at extracting a number of independent factors (IF) which underlie or cause the independent variables on the measurement instrument, ICS. As a matter of fact, these factors belong to innovation capability and they have the potential to drive a firm's innovation performance. Based on the relevant literature on innovation capability, the method used to achieve this aim was Exploratory FA. As a result, all assumptions were tested. As the sample size of this study at the point of analysis was rather small (N=85), it was necessary to use statistical techniques to obviate this technical problem. Therefore, measure of sampling adequacy (MSA) was examined. Those variables which had MSA values less than 0.5 were removed one at a time and therefore, KMO value improved to the very acceptable value of 0.738. As a result of this, eleven (11) variables were removed from the set of variable.

Having met the fundamental requirements for FA, this method was applied. From 73 variables on the ICS, fourteen (14) factors were derived. These factors were rotated, and later named, mainly based on the variables with heavier loadings. Finally, these fourteen (14) factors formed factor combinations which will be used in the Multiple Regression Model in the next chapter.