CHAPTER 4: DATA ANALYSIS AND RESULTS

This chapter aimed to present the process of data analysis such as descriptive statistics and data preparation for multivariate analysis to test the influence of the socio-technical factors on information security in order to develop information security culture framework for securing e-government services. This chapter describes the analysis of the survey profiles and responses, descriptive statistics for the variables of the socio-technical factors influencing information security. It also provides an interpretation of the mean values obtained for each construct and each measured variable.

As a part of data analysis, the collected data were analyzed using SPSS version 23.0. The data preparation process ensured that the data set met the following criteria which are presented in Figure 4.1.

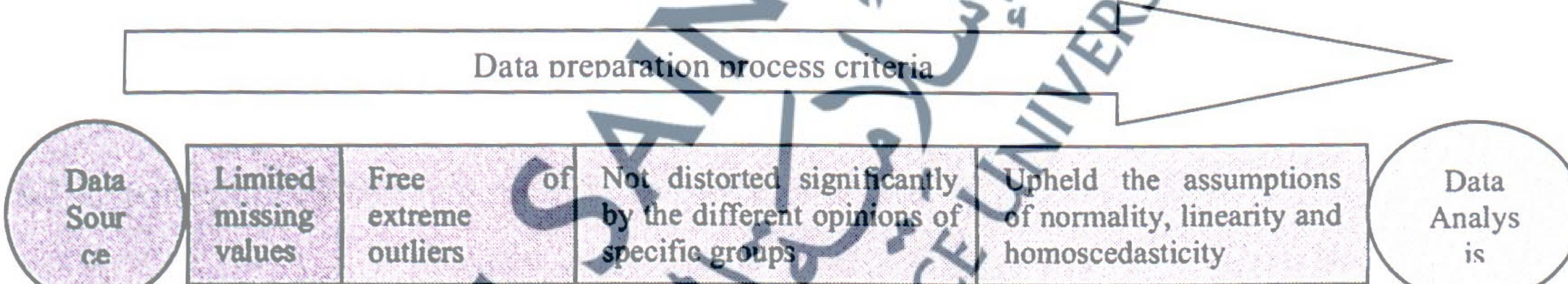

Figure 4.1: Data preparation process criteria

These were the conditions required by subsequent multivariate analyses (EFA, CFA and SEM analyses). It is also necessary to validate the developed security culture framework. Furthermore reliability test was applied in order to assess the validity and reliability of the employed instruments. Additionally, factor analyses were performed to uncover and confirm factor structures that represent the framework construct. Figure 4.2 shows data analysis process. Following sections presents the analysis of scale reliability.

The Exploratory Factor Analysis (EFA) was conducted to uncover the appropriate factor structures of the framework construct. Confirmatory Factor Analysis (CFA) was employed to confirm and refine the identified structure of each framework construct to ensure its reliability and validity. Finally it summarizes and concludes the chapter.

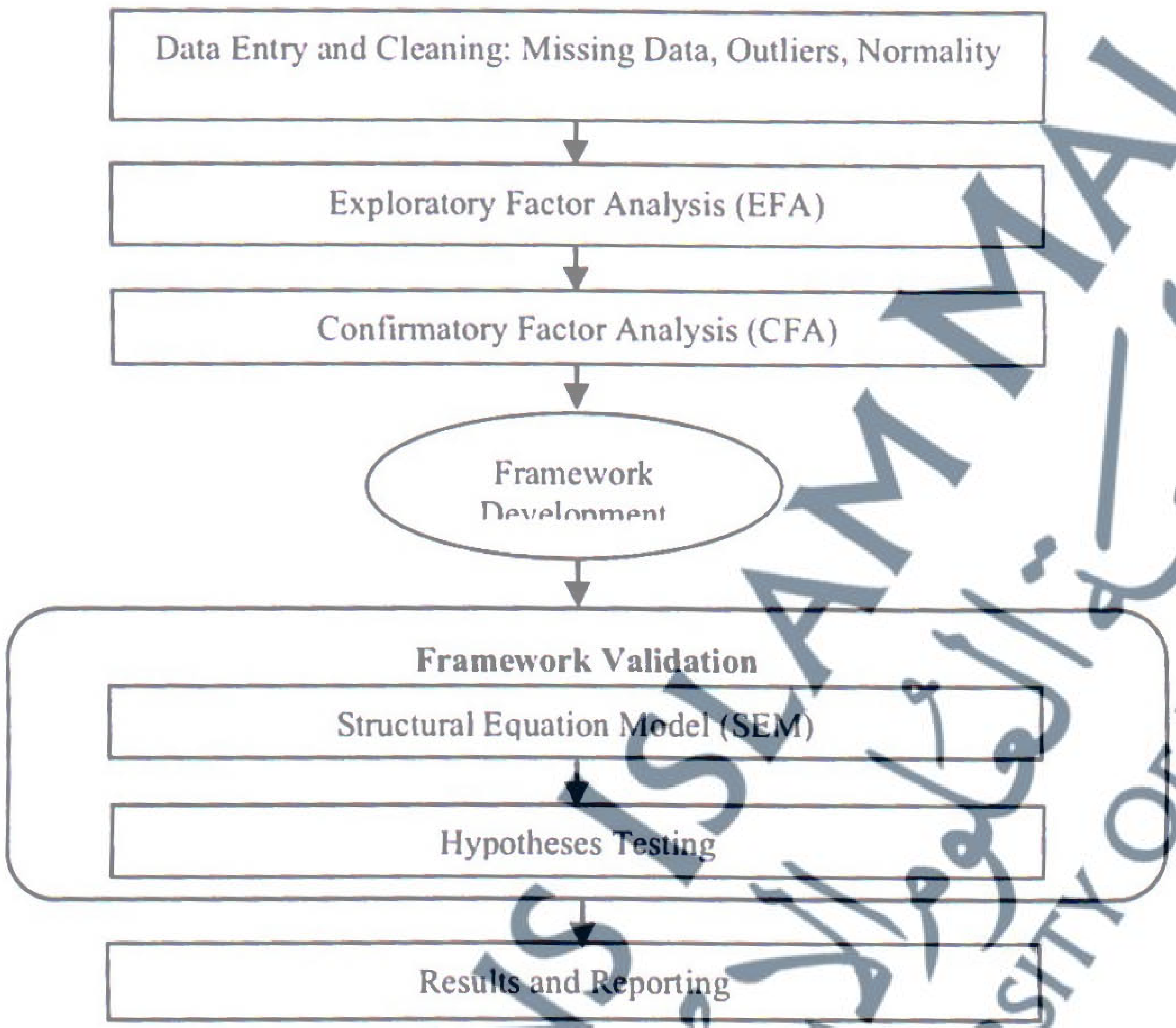

Figure 4.2: Data Analysis Process

4.1 Questionnaire Survey And Respondent Profiles

4.1.1 Questionnaire Survey

An online questionnaire survey was conducted in Malaysia from June 2015 to October 2015. The survey packages (a cover letter explaining the purposes and benefits of the survey, and a set of questions) were e-mailed to 600 participants from JPA. 346 were collected online. 34 of the returned questionnaires were excluded from the analysis, due to significant incompletion. As a result, total of 312 valid questionnaires were collected. The questionnaire response rate of 50% is considered adequate for most surveys (Creswell, 2013). 30% response rate is considered acceptable (Sekaran & Bougie, 2010). In this study, questionnaire response rate was 52 per cent which is satisfactory for research conducted in information security field. The following section details the profiles of the survey sample respondents.

4.1.2 Respondent Profiles

The purpose of examining the respondent profiles is to determine whether the sample could adequately represent the survey population. Generally speaking, respondents were classified based on the following categories:

- Respondent's job title.
- Respondent's education.
- Years of experience.

However, in this study the effects of demographic information are removed from the regression analysis because these variables may undesirably impact on the core relationship examination. Therefore, data on these variables was collected and analyzed only for descriptive purposes.

The demographic information about the respondents is summarized in Table 4.1.

Table 4.1: Frequencies of Demographic Variable

	Frequency	Percentage
***Job task**		
Security staff	46	14.75
IT staff	127	40.70
Users	139	44.55
Respondent education background		
Bachelor	189	60.5
Master	101	32.4
Ph. D	22	7.1
Years of Experience		
Less than 5	74	23.72
5 to 10	149	47.76
Above 10	89	28.52

*** Job task was grouped into three categories (Security staff for anyone dedicated to information security only such as Chief Information Security Officer, security director, security consultant, Information Security Analyst, information security managers and officers etc.; IT staff for Chief information officers, IT managers and IT staff; and Users for department managers, operation staff and technical staff (not IT related).**

The demographic information about the respondents in Table 4.1indicated that, the job title breakdown for the respondents was 44.55% for Users, 40.70% for IT and 14.75% for Security staffs. The respondents' education, 60.5% of the respondents had a bachelor's degree, 32.4% had Master's degree and 7.1% had PhD's degree. The respondents' experience in their job, 47.76% had between 5 to 10 years, 28.52% more than 10 years and 23.72% less than 5 years.

Though testing may not establish a causal relationship between demographics and the studied variables, the information may provide background data, as well as will give an additional perspective on the organization and the respondents. The qualification level, job titles and years of experience were included in order to investigate any bias in the sample. These questions helped ensure that the respondents represented diverse organization. The data measured confirmed the eligibility of the employees to participate in the study and the sample could adequately represent the survey population.

4.2 Data Screening

Data screening is critical to prepare data for multiple regression analysis (Kline, 2015). Data screening through exploratory data analysis includes looking for missing data, influential outliers and distributional characteristics. Significant missing data results in convergent failures, biased parameter estimates and inflated fit indices (Hair et al., 2010; Shah & Goldstein, 2006). Influential outliers are linked to normality and skewness issues with observed variables. Assessing data normality (along with skewness and kurtosis) is important because framework estimation methods are based on assumptions of normality (Tabachnick & Fidell, 2013). Non-normal data may result in inflated goodness of fit statistics and underestimated standard errors (Dimitrov, 2014; Mindrila, 2010). The following section details the survey data screening procedures undertaken to ensure the data's suitability for subsequent statistical analyses.

4.2.1 Missing Data Analysis

One of the most pervasive problems in data analysis is missing values, since incomplete questionnaires could bias the results. However, it is quite common that data sets have missing observations (Allison, 2012). Missing data are the result of two main causes: one is attributable to the respondent and the other external to the respondent (Hair et al., 2010). In some circumstances, a respondent might refuse to answer some of the questionnaire items due to organization policy or perceptions regarding the sensitive nature of the questions. Causes external to the respondent could simply be a data entry error. As a result, 34 cases were removed as significant data was missing (e.g., due to significant incompletion), and the final sample retained for analysis was 312 respondents.

4.2.2 Assessment of Normality

Normality is the most important fundamental assumption in multivariate analysis. Normality refers to the shape of the data distribution for a variable and its correspondence to the normal distribution (Ghasemi & Zahediasl, 2012). There are two types of normality- univariate and multivariate (Stevens, 2012). 'Univariate normality' refers to the degree to which the data distribution of a specific variable corresponds to a normal distribution, whilst 'multivariate normality' refers to a normal joint distribution of more than one variable (Hair et al., 2010). This section presents an examination of univariate normality to enable a preliminary assessment and demonstration of the data distribution for each variable, in order to justify the use of specific statistical analysis procedures.

Multivariate normality is addressed in the framework assessment using the Structural Equation Modeling (SEM) technique. In general, the assessment of normality can be carried out visually or statistically (G. Garson, 2012). A visual inspection allows researchers to observe and judge how well a variable's data histogram corresponds to a bell-shaped curve. However, researchers commonly adhere to 'skewness' and 'kurtosis', which are considered to be two important components of normality.

Table 4.2: Assessment of normality

Variable	Skew	Kurtosis
EC1	-.719	-.474
EC2	-.727	-.472
EC3	-.621	-.622
L1	-.692	-.694
L2	-.652	-.609
L3	-.736	-.453
L4	-.729	-.517
IC1	-.411	-.667
IC2	-.470	-.639
IC3	-.457	-.692
TM1	-.571	-.491
TM2	-.510	-.605
TM3	-.487	-.504
TM4	-.599	-.488
IP1	-.663	-.240
IP2	-.605	-.295
IP3	-.480	-.557
T1	-.503	-.934
T2	-.594	-.850
T3	-.554	-.932
AW1	-1.159	.154
AW2	-.871	-.503
AW3	-.857	-.521
AW4	-.855	-.536
ISS1	-.916	.004
ISS2	-.897	.025
ISS3	-.870	-.183
SC1	-.896	.179
SC2	-.836	.182
SC3	-.790	.219
SC4	-.738	-.029
EF1	-.694	.062
EF2	-.771	.147
EF3	-.897	.381
EF4	-.791	.118
Multivariate		56.835

Skewness provides an indication of the symmetry of the distribution; a skewed variable is a variable whose mean is not in the centre of the distribution (Seltman, 2012). Kurtosis however provides information about the 'peakedness' or 'flatness' of a distribution compared with the normal distribution (Hair et al., 2010). Theoretically, the value of both skewness and kurtosis in a perfect distribution is zero (however, this is an uncommon occurrence in social research). To have a normal distribution, both skewness and kurtosis of the distribution should fall between -2.00 and +2.00 (G. Garson, 2012). The results of normal distribution tests indicated that the absolute values of skewness and kurtosis of all variables ranged from -1.159 to -0.411 and from -0.932 to 0.381 respectively, which fall within the aforementioned recommended ranges of -2.00 to +2.00 (as shown in Table 4.2). These results provide support and justification for the normality of the data set.

4.2.3 Assessment of Standard Deviations and Standard Errors of the Mean

Standard deviation (SD) is a measure of how well the mean represents the observed data; whereas standard errors of the mean (SE) is an indication of how well a particular sample represents the population (Field, 2009). A large standard deviation indicates that the scores cluster more widely around the mean, showing the mean is not a good representation of the data. A small standard deviation, on the other hand, indicates fewer dispersed data about the mean, showing the mean adequately represents the data.

Standard Error (SE) represents the variability of the sample mean. A large SE indicates that there is a lot of variation between the means of the different samples, which suggests that the sample is a poor representation of the population. On the other hand, a small SE indicates that most sample means are similar to the population mean and therefore the sample is an accurate reflection of the population. The values of SD and SE of all variables in this study were relatively small when compared to the means (Table 4.3). Therefore, it can be reasonably concluded that the mean value can be used as a representative score for each variable in the data set. In addition, the small values of the SE suggest that the sample used was sufficiently representative of the population.

Table 4.3: Descriptive Statistics

	N	Mean		Std. Deviation
	Statistic	Statistic	Std. Error	Statistic
EC1	312	3.63	.072	1.276
EC2	312	3.67	.072	1.280
EC3	312	3.55	.073	1.292
L1	312	3.49	.077	1.361
L2	312	3.50	.075	1.323
L3	312	3.53	.074	1.312
L4	312	3.55	.075	1.317
IC1	312	3.35	.070	1.244
IC2	312	3.39	.070	1.238
IC3	312	3.35	.071	1.262
TM1	312	3.51	.067	1.184
TM2	312	3.50	.068	1.195
TM3	312	3.49	.068	1.208
TM4	312	3.57	.070	1.233
IP1	312	3.52	.066	1.167
IP2	312	3.52	.065	1.140
IP3	312	3.46	.067	1.189
T1	312	3.30	.078	1.386
T2	312	3.32	.077	1.364
T3	312	3.33	.079	1.397
AW1	312	3.91	.075	1.331
AW2	312	3.70	.079	1.393
AW3	312	3.70	.079	1.396
AW4	312	3.72	.079	1.401
ISS1	312	3.72	.070	1.235
ISS2	312	3.68	.068	1.209
ISS3	312	3.73	.071	1.258
SC1	312	3.60	.065	1.147
SC2	312	3.63	.064	1.132
SC3	312	3.63	.060	1.064
SC4	312	3.59	.065	1.147
EF1	312	3.57	.062	1.103
EF2	312	3.62	.061	1.085
EF3	312	3.63	.062	1.089
EF4	312	3.61	.064	1.126

4.2.4 Preliminary Findings

As described in the previous sections, the standard deviations of all 38 variables were not large. As a result, the mean values were determined to adequately represent the overall response for each variable. A descriptive data analysis was done to provide an understanding of the characteristics of the data collected from the questionnaire survey of Malaysian organizations. At the beginning of the chapter, an examination of the profiles of the 312 respondents revealed that the opinions given by these respondents provided reliable information according to their current positions, qualifications and experiences in which they were employed. The data screen showed an acceptable normal distribution without extreme outliers and upheld the assumptions of normality, linearity and homoscedasticity. In addition, the standard deviation and standard error of the mean indicated that a mean value could be used as a representative score for each variable and that the sample used in the study sufficiently represented the population. As a result of the above, the data is considered suitable input for the subsequent analysis, such as multivariate analysis (EFA, CFA and SEM analyses), which are presented in the next sections.

4.3 Scale Reliability

Reliability is defined as "the degree to which an instrument measures the same way each time it is used under the same conditions with the same subject" (Adams et al., 2014). For a scale to be valid and possess practical utility, it must be reliable (Tavakol & Dennick, 2011). In this study, to ensure that such a set of measurement scales consistently and accurately captured the meaning of the constructs, an analysis of scale reliability was performed through an assessment of internal consistency and inter-total correlations. The assessment procedures and associated results are presented in following sections.

4.3.1 Internal Consistency

Kline (2015) refers "internal consistency" to the degree to which responses are consistent across the items as. Cronbach's alpha coefficient is the most common measurement for internal consistency which calculates the estimated correlation of a set of items and true scores. A low Cronbach's alpha coefficient indicates that variables may be so heterogeneous that they perform poorly in representing the measure (i.e. the construct). Cronbach's Alpha, above 0.70, is considered as an acceptable indicator of internal consistency and the values of 0.60 to 0.70 are at the lower limit of acceptability, as suggested in the literature (Creswell, 2013). Table 4.4 presents the Cronbach's alpha for each construct. However, Cronbach's alpha is not a statistical test. It is a coefficient of reliability (or consistency) (Leow, 2015). Therefore, it has been suggested that analysis of the inter-total correlations for the items should be considered (Kumar, 2015; Pallant, 2007). The values of the alpha coefficient of all the construct scales ranged from 0.895 to 0.958, suggesting good internal consistency and reliability for the scales with this sample. Therefore, the measurement scales appear to be composed of a set of consistent variables for capturing the meaning of the framework constructs

Table 4.4: Cronbach's Alphas of Measurement Scales for Each Construct

NO	Construct Measurement Scales	Number of Items	Cronbach's Alpha
1	Ethical Conduct (EC)	3	0.944
3	Legal & law (L)	4	0.954
4	Compliance (IC)	3	0.907
5	Top Management Support (TM)	4	0.940
6	Information Security Policy (IP)	3	0.934
7	Information Security Training (T)	3	0.958
8	Security Awareness (AW)	4	0.895
9	IS structure (ISS)	3	0.942
10	Security culture (SC)	4	0.910
11	Security Effectiveness (EF)	4	0.939
12	All Construct Measurement Scales	38	

4.3.2 Item-Total Correlations

Item-total correlation refers to the correlation of a variable, with the composite score of all variables forming the measure of the construct (Lu et al., 2007). In SPSS, the value of the item-total correlation is corrected. The corrected item-total correlation excludes the score of a variable of interest when calculating the composite score (Koufteros, 1999). A value of the corrected item-total correlation of less than 0.30 indicates that the variable is measuring something different from the construct as a whole (Field, 2013). Thus the results of item-total correlations presented in Tables 4.5 show that all of the variables within each construct measure the actual construct, as their corrected item-total correlations were greater than 0.30.

Table 4.5: Item-Total Correlations Of Each Construct

Variables description	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Item-Total Correlations of Ethical Conduct		
In the course of my professional activities, I shall conduct myself in accordance with the highest standards of moral, ethical and legal behavior.	.887	.915
I always Identify, define and address ethical, cultural, and legal issues related to work projects.	.881	.919
I will appropriately report any use of property of a client or employer in ways which are unauthorized, and without the clients or employer's knowledge and consent.	.880	.920
Item-Total Correlations of legal and law		
The legislations for e-government are in place.	.862	.948
Policy is updated when legal & regulatory changes require it.	.902	.935
Information security policies are written with the proper understanding of legal requirements.	.912	.933
The policy covers the legal aspects of security	.877	.943
Item-Total Correlations of information security compliance		
I always adhere to the information security policy	.755	.899
Information security measures comply with international standards	.855	.833
There is a regular check on technical compliance	.815	.867
Item-Total Correlations of Top management support		
Top management takes security issues into account when planning corporate strategies.	.845	.926
Senior leadership's words and actions demonstrate that security is a priority.	.874	.917
Visible support for security goals by senior management is obvious.	.875	.916
Senior management gives strong and consistent support to the security program.	.837	.929
Item-Total Correlations of information security policy		
Policy clearly defines information security objectives.	.865	.902
The information security policy clearly defines roles and responsibilities of employees.	.881	.890
The information security policy is reviewed regularly (or when the environment changes).	.844	.919
Item-Total Correlations of security training		
Users receive adequate security refresher training appropriate for their job function	.909	.941
I am always educated or trained about new security policies	.916	.935
Education and learning are encouraged and supported.	.909	.941
Item-Total Correlations of security awareness		
An effective security awareness program exists.	.590	.925
Information security awareness is communicated well.	.791	.855
The e-government awareness policies are regularly used.	.858	.829
I am aware of any information security policy in my organizations	.838	.836

Item-Total Correlations of IS structure		
IT infrastructure is ready for the e-government initiatives.	.875	.918
IT infrastructures accommodate integration with e-government.	.890	.907
The IT infrastructure is continuously improved.	.872	.921
Item-Total Correlations of security culture		
A culture exists that promotes good security practices.	.723	.909
Security has traditionally been considered an important organizational value.	.855	.862
Practicing good security is the accepted way of doing business.	.821	.876
Information security is a key norm shared by organizational members.	.790	.886
Item-Total Correlations of security effectiveness		
The information security program achieves most of its goals.	.855	.921
The information security program has kept risks to a minimum.	.844	.924
Current information security measures provide effective protection for electronic data.	.862	.918
Overall, the information security program is effective.	.860	.919

From the results as shown on Table 4.5, there is one item which is AW1 (An effective security awareness program exists) caused a substantial decrease in alpha. Therefore this item was deleted.

4.4 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) was employed to reduce the large number of variables to a smaller, more manageable set (Strang, 2015). EFA is particularly useful as a preliminary analysis in the absence of a sufficiently detailed theory about the relations of the variables to the underlying constructs (Anderson & Gerbing, 1988; Tabachnick & Fidell, 2013). Although all measured variables in the constructs were derived from previous research (an extensive literature review), the EFA was deemed necessary since these variables had not been operationalized extensively within the Malaysian context. The following sections provide the details of the analysis.

4.4.1 Factorability of Data

The factorability refers to the suitability of the data to be factorized in terms of the inter-correlation between variables (Pallant, 2013; Tabachnick & Fidell, 2013). As the variables included in the analysis were deemed to measure the same underlying construct, a correlation matrix that was factorable needed to include sizable values for the correlation (Field, 2013). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity are generally applied to determine the factorability of such a matrix (Pallant, 2013). The strength of the inter-correlations among the variables within each construct was supported by the inspection of the correlation matrix with evidence of coefficients greater than 0.30. As presented in Table 4.6, the values of Kaiser-Meyer- Olkin (KMO) of constructs was 0.873 making them well above the minimum acceptable level of 0.60 (Tabachnick & Fidell, 2013). In addition, the 312 cases in this study satisfied the minimum acceptable sample size of 200 and exceeded the minimum requirement of five times as many cases as the variable to be analyzed in each construct (Hair et al., 2010) . Finally, Bartlett's test of sphericity for each construct was highly significant at $p < 0.001$ level, indicating that there were adequate relationships between the variables included in the analysis(Field, 2013). These results confirmed the factorability of the EFA conducted for each construct.

Table 4.6: KMO and Bartlett's Test of Sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.873
Bartlett's Test of Sphericity	Approx. Chi-Square	10094.255
	df	561
	Sig.	.000

4.4.2 Factor Extraction and Rotation

EFA needs to follow two essential steps to produce an appropriate solution that explains an adequate number of factors representing a construct: (1) factor extraction, and (2) factor rotation and interpretation (Pallant, 2013). Factor extraction aims to uncover factors based on a particular method and criteria to determine the adequacy of the number of factors, whereas factor rotation and interpretation aims at improving the interpretation of a given factor solution (Tabachnick & Fidell, 2013).

In the current study, factor extraction was performed using principal components analysis (PCA) to achieve an empirical summary of the data set. PCA is an extraction method used widely for defining the factors needed to represent the structure of the variables. Several criteria were used to achieve the number of factors that best describe the underlying relationship among variables, namely: (1) latent root criterion, (2) Catell's scree test, (3) a priori criterion, and (4) percentage of variance criterion (Pallant, 2013) . The Latent root criterion suggests that factors having an Eigen value greater than 1 are significant, and that those with less than 1 should be disregarded (Yong & Pearce, 2013) . The Catell's scree test employs a graphical plot of Eigen values against a number of factors in their order of extraction. The point where there is a sudden change of slope in the curve indicates the maximum number of factors to be extracted (GORSUCH, 2014). The a priori criterion is a simple criterion where the number of factors is known prior to undertaking the factor analysis. This approach is considered particularly useful when testing a theory or hypothesis about the number of factors to be extracted. It is also an appropriate criterion in attempting to replicate another researcher's work and extracting the same number of factors that were previously found (Hair et al., 2010). The percentage of variance criterion ensures practical significance for the derived factors by confirming that they explain at least a specified amount of variance (Tabachnick & Fidell, 2013).

The Varimax orthogonal rotation was the preferred method, since it was the simplest and most commonly used rotation (Hartas, 2015). According to Malhotra (2010), it is quite common to consider a solution that accounts for 60 per cent (or less) of the total variance in social science research, since the information in this area, by nature, is often less precise. The majority suggest that 75 – 90% of the variance should be accounted for (G. D. Garson, 2013), (Pett et al., 2003). However, some indicate as little as 50% of the variance explained is acceptable (Beavers et al., 2013)

Factor loadings will determine the degree to which the variables load into these factors once the factors have been extracted (Field, 2013). In most circumstances, the initial factor solution does not provide an adequate interpretation, since most variables will have high loadings on the most important factor and small loadings on the other factors, regardless of the extraction method employed (Tabachnick & Fidell, 2013). As a result, factor rotation was employed to achieve simpler and more meaningful solutions. A specific criterion was employed to justify the significance of the factor loadings after the factor had been rotated. A factor loading of 0.50 and above was considered significant at the 0.05 level (Awang, 2015; Kline, 2015).

4.4.3 Exploratory Factor Analysis Results

Based on the above techniques and criteria, the EFA was performed using the SPSS 23.0 program. The scree test identified ten factors which accounted for 86.934 percent of the total variance, as represented in Figure 4.3.

As represented, Table 4.7 indicates that all variables were significant (factor loadings greater 0.647). However, Simple structure is achieved when each factor is represented by several items that each load strongly on that factor only, all items measuring construct loaded lower on the other constructs and loaded highly on that (Pett et al., 2003). An item is considered to be a good identifier of the factor if the loading is 0.5 or higher and with Eigen values of greater than 1 (Field, 2013); and cross-loading on another factor greater than .40 (Beavers et al., 2013). Table 4.7 depicts the results of the analysis after suppressing loadings of less than 0.4.

The Results of Exploratory Factor indicates that these factors solutions were supported by the cumulative percentage of the variance extracted, around 86.934%, and were considered satisfactory solutions in the social sciences field. The Cronbach's alpha coefficients of all scales were very high and well above the 0.70 threshold level, ranging from 0.907 to 0.958, thus demonstrating internal consistency. Furthermore the factor loadings was greater than 0.5. All items measuring construct were loaded lower on the other constructs and loaded highly on that particular construct. This confirmed the construct validity.

Table 4.7: Rotated Factor Loadings of the Research framework Constructs

	Component									
	1	2	3	4	5	6	7	8	9	10
L3	.939									
L2	.939									
L1	.916									
L4	.913									
TM2		.891								
TM3		.890								
TM1		.872								
TM4		.849								
EF3			.840							
EF4			.834							
EF1			.827							
EF2			.819							
T2				.951						
T1				.948						
T3				.938						
ISS1					.923					
ISS2					.920					
ISS3					.907					
EC3						.928				
EC1						.928				
EC2						.923				
IP2							.914			
IP1							.899			
IP3							.896			
AW3								.928		
AW4								.910		
AW2								.906		
IC2									.921	
IC3									.874	
IC1									.866	
SC3										.752
SC2										.745
SC1										.740
SC4										.647

These results therefore confirmed that the developed scales comprised reliable and valid items, which adequately captured the meaning of the framework constructs and their related factors.

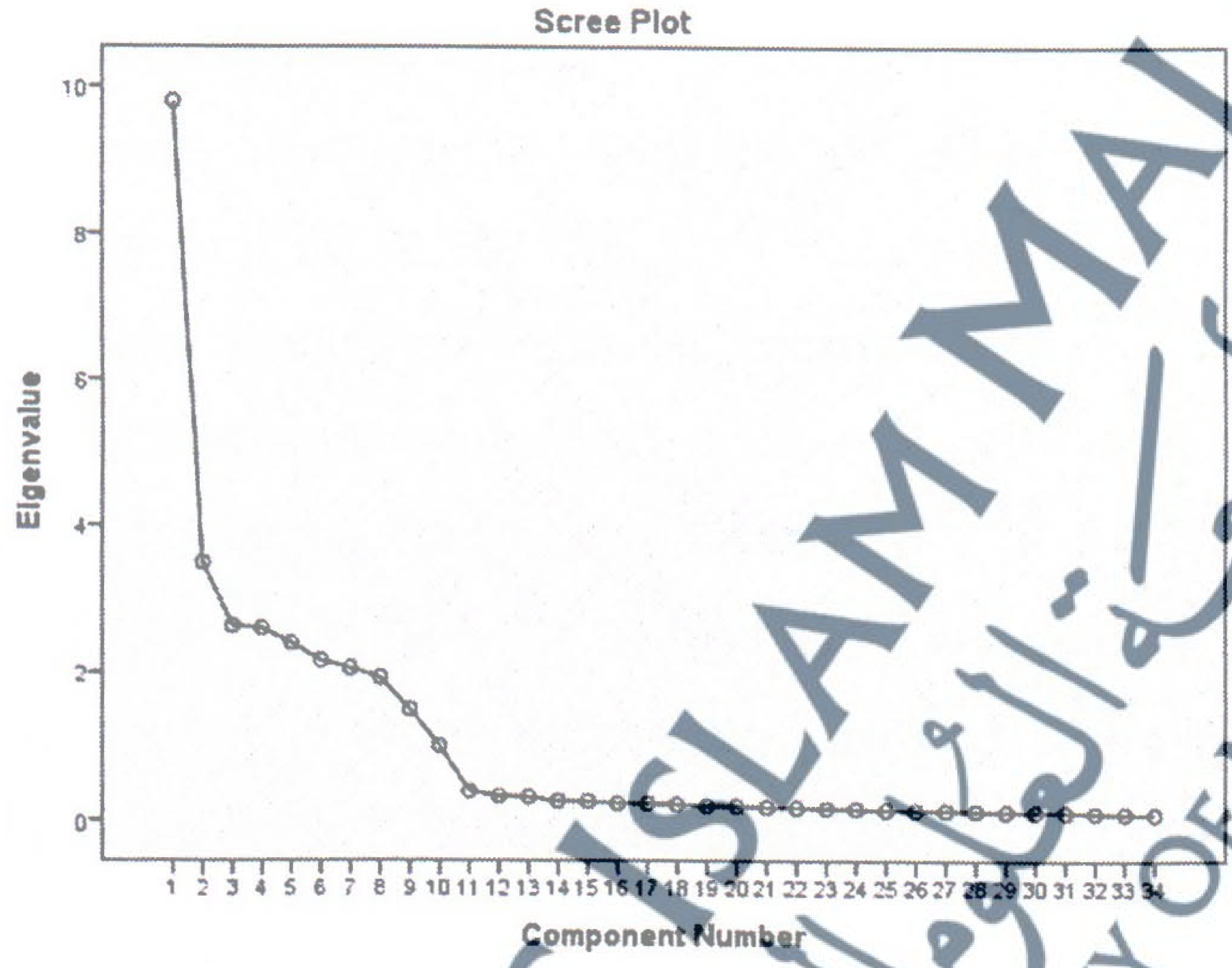

Figure 4.3: Scree Plot

4.5 Confirmatory Factor Analysis

Reliability is necessary but not a sufficient condition of validity of the measurement scales (Zikmund et al., 2012). It is important to confirm whether the collected data are appropriate (fit) for the hypothesized framework (proposed measurement) before conducting statistical analysis techniques such as multiple regression analysis and correlation matrix analysis. The assessment of construct validity is a critical element in measurement theory (Tojib & Sugianto, 2011). Construct validity is "the extent to which the constructs or a set of measured items actually reflects the theoretical latent construct those items are designed to measure" (Hair et al., 2010). To assess 'construct validity' adequately, a contemporary analytical method, namely the Confirmatory Factor Analysis (CFA), which is a subset of the structural equation modeling technique, was employed. CFA provides a stricter interpretation than those methods employed in the exploratory analysis (i.e., item-total correlation, EFA) (Anderson & Gerbing, 1988; Brown, 2015).

CFA in general is a way of testing how well the a priori factor structure and its respective pattern of loadings match the actual data. CFA can also be used to refine an existing theoretical perspective, support an existing structure and test a known dimensional structure in an additional population (Castro-Costa et al., 2014; DiStefano & Hess, 2005). EFA, however, provided a preliminary factor structure for each construct, based on the factors extracted and the pattern of loadings. To strengthen the EFA results, CFA was employed to further refine and support the identified factor structures. This process involved assessing how well the factor structure of each construct fitted the data and examining the framework parameters to assess construct validity. These factors were treated as a CFA model so that they could portray a set of relationships showing how the measured variables represented a latent factor (Hair et al., 2010). The main difference between CFA and EFA is that in CFA the number of factors, and the relations between the variables and factors, had to be known and specified prior to the analysis (Moutinho & Hutcheson, 2011; Suhr & Shay, 2009). The next sections will provide details of the analysis.

4.5.1 Assessment of Model Fit and Estimation Methods

The most important feature of CFA is its ability to determine how well the specified factor framework represents the data, which can be done by examining the model fit indices. If the fit indices prove to be good, the framework is invariably accepted. Rather than being rejected, a framework with unsatisfactory fit indices is re-specified to improve the model fit. Fit indices are also commonly classified as either absolute or incremental, as described below:

1. Absolute fit indices are direct measure of how well the specified model reproduces the observed data. Absolute fit indices provide the most basic assessment of how well the theory fits the sample data (Hair et al., 2010). The most fundamental absolute fit index is a Chi-square (X^2) statistic, which generally includes the value of X^2, degree of the freedom (df) and significance level (p-value). By convention, the non-significant X^2 indicates that the model fits the data. Thus the model is accepted. On the other hand, a significant X^2 ($p < 0.05$) suggests that the framework does not fit the data and should be rejected. However, absolute indices may be adversely affected by sample size(Kline, 2015). The significantX^2 ($p < 0.05$) is not applicable for large sample size more than 200 (Awang, 2015). As a result, numerous alternative indices have been developed to quantify the degree of model fit, including goodness-of-fit index (GFI), adjusted-goodness-of-fit index (AGFI), standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA) and the root mean square residual (RMR).

2. **Incremental fit indices** are concerned with the degree to which the model of interest is superior to the following alternative baseline models (Savalei & Bentler, 2010). The most common baseline model is referred to as a null model, which assumes all observed variables are uncorrelated. Some of the most popular incremental fit indices are: normed-fit-index (NFI), comparative-fit-index (CFI), Tucker-Lewis index (TLI) and incremental-fit-index (IFI).

3. **Estimation Method** requires accurately calculating the model parameters and fitting indices, and an appropriate estimation method. There are a variety of estimation methods available, including maximum likelihood (ML), generalized least square (GLS), weighted least square (WLS), asymptotically distribution free (ADF) and ordinary least square (OLS). The choice of the estimation method generally depends upon the distributional property of the data, model complexity and sample size (Grace et al., 2012). Each estimation method has computational advantages and disadvantages. ML assumes data are univariate and multivariate normal, but it is relatively unbiased under moderate violation of normality (G. Garson, 2012). WLS and ADF do not require an assumption of normal distribution, but they demand a very large sample size for accurate estimates. OLS is considered the most robust method and requires no distributional assumption, but it is scale invariant and does not provide fit indices or standard errors for estimates (Shah & Goldstein, 2006).

Since this study sample is 312, which is relatively good for CFA, ML was considered as the most appropriate method. Although ML requiring data distribution is multivariate normal, it was still found robust under the condition of moderate non-normality. In addition, these data characteristics also justified the use of the following model fit indices: X^2/df, TLI, NFI, CFI, IFI, and RMSEA. According to Rick H Hoyle (2012), these fit indices were not found to be substantially biased under the condition of non-normality when using the ML estimation method. For the framework to be considered as having an acceptable fit, all six indices were measured against the following criteria:

- $X^2/df < 3.0$ (Awang, 2015; Kline, 2015).
- TLI, NFI, GFI, CFI and IFI > 0.90 (Awang, 2015; Schumacker & Lomax, 2016).
- RMSEA < 0.08 (Awang, 2015; Rick H.. Hoyle, 2011).

4.5.2 Assessment of Construct Validity

Assessing construct validity using the CFA involved an examination of convergent validity and discriminant validity. The convergent validity refers to the extent to which the measured variables of a specific construct share a high proportion of variance in common. The discriminant validity refers to the extent to which a construct is truly distinct from other constructs (Hair et al., 2010). The assessment of convergent validity focuses on the magnitude of the standardized factor loadings and their significance level.

As a guideline, Khine (2013), suggested that factor loadings should be greater than 0.50. In addition, variables should also have adequate reliability, which can be determined by inspecting the R^2 (or squared multiple correlation, SMC) values. A variable should have an R^2 value greater than 0.50 in order to demonstrate an acceptable reliability (Byrne, 2013). However, discriminant validity provides evidence that a construct is unique and captures some phenomena other measures do not (Kline, 2015). Discriminant validity can be assessed by an inspection of the correlation coefficient between each pair of factors. The value of the correlation coefficient should be less than 0.850 (Hair et al., 2010).

4.5.3 Confirmatory Factor Analysis Results

The CFA was performed on each construct using the AMOS (version 23.0) program, which is an extension program to SPSS. The results of each construct are presented in

Tables 4.8. The factor loading, critical value and significance level of each variable shown in the tables provided a measure for the convergent validity. The value of R^2 provided a measure with which to assess the reliability of the variables, and the value of the correlation between the factors provided an indication of the discriminant validity, the correlation value between the factors less than 0.850 Table 4.9.

Table 4.8: The factor loading and R^2 result

Construct	Item	Factor loading	R^2
Ethical Conduct	EC1	.928	.860
	EC2	.920	.847
	EC3	.916	.840
Legal & law	L1	.883	.779
	L2	.927	.860
	L3	.946	.895
	L4	.909	.826
Compliance	IC1	.821	.675
	IC2	.923	.852
	IC3	.884	.782
Top Management Support	TM1	.879	.773
	TM2	.913	.834
	TM3	.912	.831
	TM4	.871	.758
Information Security Policy	IP1	.913	.833
	IP2	.932	.868
	IP3	.880	.775
Information Security Training,	T1	.936	.877
	T2	.947	.896
	T3	.939	.881
Security Awareness,	AW2	.857	.785
	AW3	.947	.896
	AW4	.886	.866
IS structure	ISS1	.911	.831
	ISS2	.935	.875
	ISS3	.910	.827
Security culture	SC1	.763	.583
	SC2	.906	.822
	SC3	.870	.757
	SC4	.856	.733
Security Effectiveness	EF1	.890	.791
	EF2	.880	.775
	EF3	.897	.805
	EF4	.898	.807

Table 4.9: The Discriminant Validity Index Summary

	T	EF	SC	IP	ISS	AW	TM	IC	L	EC
T	1									
EF	0.259	1								
SC	0.326	0.706	1							
IP	0.114	0.39	0.461	1						
ISS	0.146	0.329	0.381	0.135	1					
AW	0.093	0.265	0.302	0.06	0.208	1				
TM	0.174	0.459	0.535	0.321	0.202	0.191	1			
IC	0.062	0.378	0.42	0.137	0.189	0.145	0.246	1		
L	0.082	0.224	0.289	0.076	0.213	0.12	0.14	0.029	1	
EC	0.085	0.282	0.331	0.191	0.077	0.178	0.248	0.192	0.028	1

The CFA results of the Socio-technical factors that influence the security effectiveness construct are presented in Table 4.8-4.9. The framework (Figure 4.4) appears to have an adequate fit: (X^2 = 587.194; df = 482; X^2/df = 1.218; GFI= 0.900, NFI = 0.944, TLI = 0.988, CFI = 0.989; IFI = 0.990; and RMSEA = 0.026). All the factor loadings, ranging from 0.928 to 0.947, were greater than the threshold level of 0.50 and were all significant at $p < 0.001$ level, suggesting convergent validity. All the R^2 values were either greater than, or close to, 0.50, indicating the reliability of the variables. All the correlation coefficients between each pair of factors were less than 0.850, thus supporting the discriminant validity of the construct.

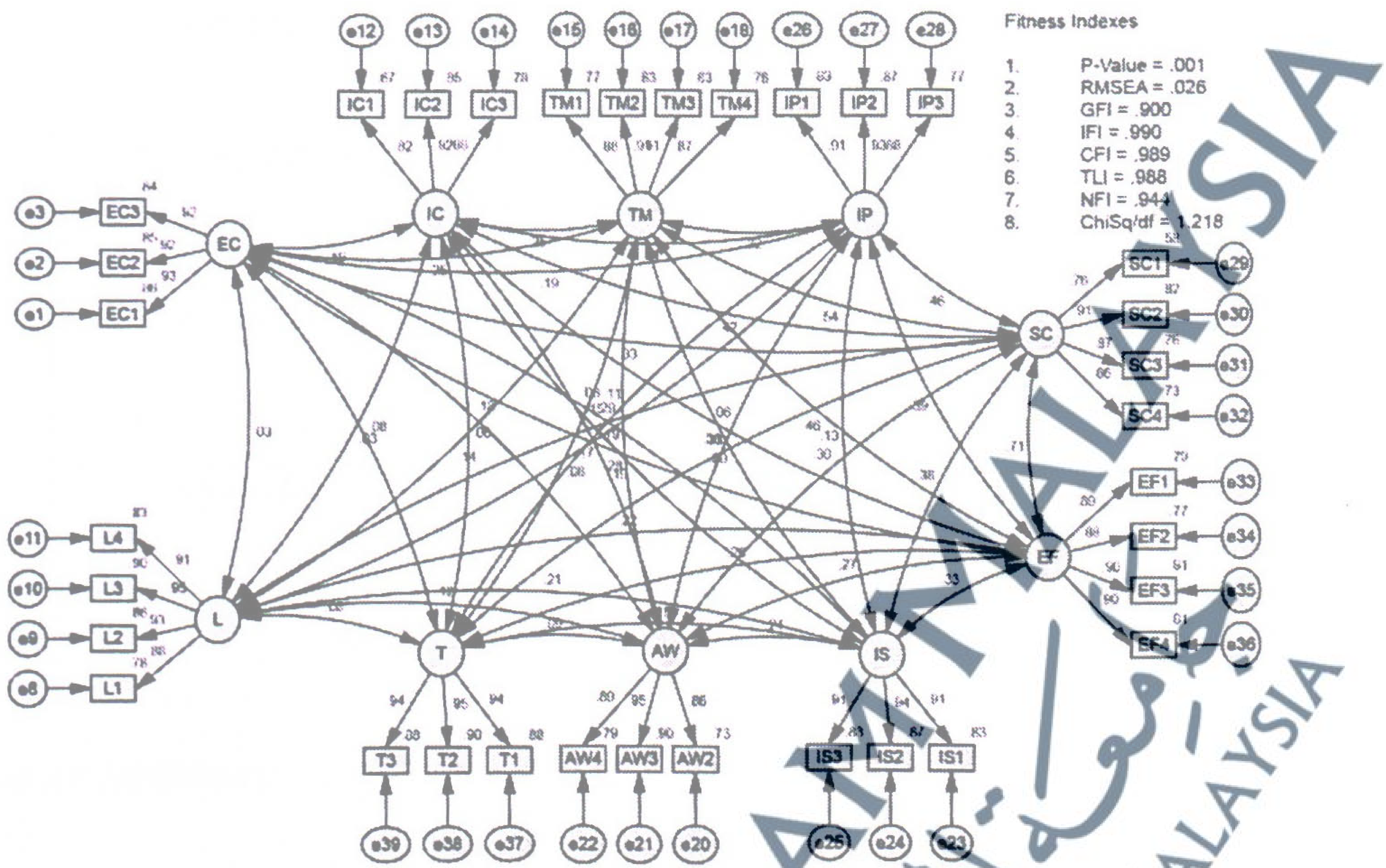

Figure 4.4: CFA Framework For Socio-Technical Factors That Influence The Security

Table 4.10 Confirmatory Factor Results Summaries

Construct	Item	Factor loading	R^2	Alpha
Ethical Conduct	EC1	.928	.860	0.944
	EC2	.920	.847	
	EC3	.916	.840	
Legal & law	L1	.883	.779	0.954
	L2	.927	.860	
	L3	.946	. 895	
	L4	.909	. 826	
Compliance	IC1	.821	.675	0.907
	IC2	.923	.852	
	IC3	.884	.782	
Top Management Support	TM1	.879	. 773	0.940
	TM2	.913	.834	
	TM3	.912	.831	
	TM4	.871	.758	
Information Security Policy	IP1	.913	. 833	0.934
	IP2	.932	.868	
	IP3	.880	.775	
Information Security Training,	T1	.936	.877	0.958
	T2	.947	.896	
	T3	.939	. 881	
Security Awareness,	AW2	.857	. 785	0.895
	AW3	.947	. 896	
	AW4	.886	.866	

IS structure	ISS1	.911	.831	0.942
	ISS2	.935	.875	
	ISS3	.910	. 827	
Security culture	SC1	.763	. 583	0.910
	SC2	.906	. 822	
	SC3	.870	. 757	
	SC4	.856	.733	
Security Effectiveness	EF1	.890	. 791	0.939
	EF2	.880	. 775	
	EF3	.897	.805	
	EF4	.898	.807	
Model fit	X^2 = 587.194; df = 482; X^2/df = 1.218; GFI= 0.900, NFI = 0.944, TLI = 0.988, CFI = 0.989; IFI = 0.990; and RMSEA = 0.026			

4.6 Chapter Summary

An examination of the respondents' profiles revealed that the opinions given by these respondents provided reliable information according to their current positions, qualifications and experiences in which they were employed. The data screen showed an acceptable normal distribution without extreme outliers and upheld the assumptions of normality, linearity and homoscedasticity.

The constructs of factors were based on the Eigen value. The scree test and the *a priori* criterion summarized these factor solutions where they were supported by the cumulative percentage of the variance extracted, around 86.934%, and were considered satisfactory solutions in the social sciences field. One variable were removed in the awareness constructs due to improve Cronbach's alpha coefficients for awareness constructs. Finally, the Cronbach's alpha coefficients of all scales were very high and well above the 0.70 threshold level, ranging from 0.895 to 0.958.

These results therefore confirmed that the developed scales comprised reliable and valid items, which adequately captured the meaning of the model constructs and their related factors.

In addition, the summary of the CFA results confirmed the factor structures derived from the EFA of the factors that influence information security culture. However, the CFA restructured the research framework constructs. Construct validity was obtained within each construct because all variables significantly and substantially loaded onto their respective factors with an acceptable level of reliability. In summary, the results from the rigorous CFA procedures yielded the final factor structures with adequate reliability and validity for each of the model constructs Table 4.10.

In conclusion, the EFA and CFA developed and confirmed good measurement scales for the constructs, with very good reliability, validity and conceptual definitions. These results form the basis for creating the factors that are used in the subsequent framework development and assessment, which is presented in chapters 5 and 6.