CHAPTER 6:
METHODOLOGY AND ANALYSIS RESULTS

6.1 Introduction

Having outlined the research philosophy for this study and the way to achieve the objectives, this chapter reports on the results of the quantitative research. To recap, there are two major research questions in this study. One is to investigate the drivers which lead organisations to adopt CRM, the other one is to explore the impact of CRM on organisational performance. In this chapter, the antecedents and consequences of CRM adoption are analysed empirically among organisations in the services sector of Hong Kong, thus addressing the proposed hypothesised relationships developed in chapter 4. At the same time, the mediating effect of information utilisation and the effect of CRM adoption were also modelled. Different sophisticated approaches techniques have been used to assess the proposed relationships.

First, the response rate of the survey is discussed. Second, the analysis strategy is described. Multiple regression and logistic regression were initially used to test the significance of determinants for CRM adoption. Due to the weakness of regression models, SEM was finally used to determine the drivers of CRM adoption as well as to find out the relationship between CRM adoption, information utilisation and organisational performance. A full explanation of the analysis procedure is presented in section 6.10. Reliability and validity of items created in chapter 5 were examined during the estimation of measurement model.

The analysis will relate back to literature and the qualitative study in previous chapters. In this case, the results can be compared with both current understanding in this area and the results from the qualitative phase of the research. Finally, at the end of the chapter, there will be short summary of the results.

6.2 Survey responses

In this section, information about response rate, non response error and respondents' position will be discussed.

6.2.1 Response rate

The data collection period was between May and June 2006. At the end of the data collection period, there were a total of 215 fully completed questionnaires that were valid for analysis out of 4,000 mailings. A range of methods were used to improve the response during the data collection.

With the aim of improving the response rate of the survey, the questionnaires were sent in May to avoid major holidays in Hong Kong. Moreover, a freepost reply envelope was used to encourage return. Monetary incentives had been considered before the fieldwork as it has been shown to increase response rate (Jobber and O'Reilly, 1998). However, even the smallest monetary incentive would be expensive and it might also cause response bias (the opinions of respondents who are not attracted by incentives cannot be collected). Moreover, monetary incentive is less effective for business samples. In addition, the anonymity followed by university sponsorship (which appeared through the text and logos in the covering letter and questionnaire) could increase the response rate.

Evidence suggests that a follow-up should take place after the main mailing to improve response rate (Greer *et al.*, 2000; Jobber and O' Reilly, 1998). Follow-ups may raise the respondents' view of the importance of the survey and may also arrive at a more convenient time. Methods include: sending a new covering letter, questionnaire and return envelop to all respondents, sending a reminder letter, telephone reminders and combinations of these and choosing a smaller sub-sample to follow-up. As mail follow-up options were too expensive, telephone follow-up was chosen. Telephone calls were made to all companies which had not responded. After the telephone follow-up, the response was faster and more returns were received.

Letters with wrong addresses or wrong contact persons were returned; there were 152 respondents in this category at the end. Hence, 215 completed questionnaires resulted in a response rate of around 6%. The total number of eligible respondents is calculated from the sample size minus the non-eligible. This is close to the figure that we expected. After checking the questionnaires, the questions were well answered apart from some refusals, i.e. some of the respondents had refused to answer the amount of investment in CRM adoption because of confidentiality concerns. During the telephone follow-up, some respondents refused to participate into the survey over the phone. The reasons for non responses are stated in the following table.

Table 6.1 – Reasons for non response

Reasons	%
Insufficient time to complete questionnaire	25
Policy against taking part in surveys	14
Cannot find the questionnaire	21
Information confidential	19
Questionnaire too long	18
Did not use CRM thus considered questionnaire was not appropriate	3
Total	100

Regarding the response rate, although the response rate appears not very high, it is in line with my expectation during the evaluation of different data collection methods. Mail survey would have lower response rate in general compared to telephone interviews or face–to-face interviews because no interviewers are involved to persuade the respondents to participate. However, as mentioned in chapter 5, mail survey is said to offer many advantages to market research, including wider distribution, less distribution bias, better likelihood of thoughtful reply, no interview bias and cost savings (Cavusgil and Elvey-Kirk, 1998). In addition, recent surveys with similar populations and method of administration indicate that the response of this survey is acceptable in Hong Kong. The response rate in this research is a bit lower than the normal response rate of industrial mail surveys, 10%, as quoted by Hart (1987) but is close to the response rate, 7.8%, of previous mail surveys, from Chinese small businesses (Siu and Kirby, 1998). It is well recognised within the market research industry that response rates are declining (Shaw *et al*., 2005). The situation is especially serious[1] because there are many surveys for different purposes in different modes that have appeared in recent years.

6.2.2 Non response error

Non response error arises when some of the respondents included in the sample do not respond. The primary causes of non response error are refusals. Non response will cause the net or resulting sample to be different in size or composition from the original sample. Non response error is defined as the variation between the true mean value of the variable in the original sample and the true mean value in the net sample (Malhotra, 2004). For example, companies did not respond to this study because they were finalising some plans for CRM systems. In this case, non response error might affect the ability to generalize results of the research study, because we do not know how the non respondents view the research issues and there is chance that their opinions are different from those who responded.

Hence, analysis was performed to examine if there is any difference between early and late respondents using a t-test for independent samples on key metric variables and Chi-square on nominal variables. The analysis is based upon the principle that late respondents are similar to early respondents within demographic variables (Armstrong and Overton (1977). The following tables show the results of testing. Early respondents means the usable responses arrived within the first two weeks after posting (N=59) and late responses means the usable responses arrived after the telephone follow-up

[1] As a statistician working in a university in Hong Kong, with almost ten years' experience, the author found that the response rate of surveys conducted in Hong Kong is relatively lower than in other developed countries, except those imposed by the Census Department of Government.

started (N=31).

Table 6.2 – t-test for non response bias

Variables	Early respondents (responses arrived within the first 2 weeks) (N=59)	Late respondents (responses arrived after the telephone follow-up started) (N=31)	P value	t statistic
Average number of employees	204	368	0.543	-0.61
Average years of establishment	24	18	0.376	0.89

Table 6.3 – Chi-square for non response bias

Variables	P value	Pearson Chi-square
Adoption of CRM	0.297	1.089
International company	0.662	0.191

The two groups were compared on: firm size, the years of company established, adoption of CRM (binary variable on CRM adoption) and whether it is an international company. The results showed that no significant differences were observed at the 5% significance level across these key variables.

In addition, the results of attitudinal measures towards major construct variables are also compared between early and late respondents. These independent variables were tested because they are important in determining the levels of engagement with CRM representing CRM adoption.

Table 6.4 – t-test for non response bias – attitudinal measures

Variables	Early respondents (responses arrived within the first 2 weeks) (N=59)	Late respondents (responses arrived after the telephone follow-up started) (N=31)	P value	t statistic
	Mean	Mean		
Scale on levels of engagement with CRM	65	67	0.400	-0.85
Rogers' attributes of innovation adoption	48	48	0.806	0.257
Perceived accessibility of IT solutions	15	16	0.378	-0.89
Competition intensity	21	23	0.026	-2.73
Desire of customer intimacy	13	12	0.183	1.34
Attitude towards change	19	19	0.982	-0.02
Market orientation	43	45	0.209	-1.27
Innovation orientation	10	11	0.548	-0.60
Group culture	18	19	0.628	-0.49
Information utilisation	24	24	0.883	0.15
Customer satisfaction	11	12	0.153	-1.44
Performance	14	14	0.672	-0.43
Employee satisfaction	17	18	0.597	-0.53

There are no significant differences between the early and late respondents for almost all constructs except competition intensity. In fact, competition is a component within Rogers' attributes of innovation adoption and the results indicated that there is no significant difference between the early and late respondents for that construct. Therefore, the difference found for the construct – competition intensity may only due to random error; hence, it confirms that non response error should not be a major problem within this study. Also, the non response error should not be an issue if enough responses are gained and the samples are randomly selected.

6.2.3 Respondents' position

In this survey, the letters were addressed to *the Marketing manager*, *Customer Relationship manager*, *Sales manager and Director* as they were viewed as being the most knowledgeable about the adoption of CRM situation in their organisation or able to identify who would be the most appropriate person to complete the questionnaire. Addresses were collected from the websites and the trading development council directory as mentioned. The addresses cover the services sector including retail, wholesale and retail trade, import/export trade, restaurants and hotels, transport and storage, communications, financing and insurance and business services in Hong Kong. Analysis showed that 21% were Directors or Vice Presidents, 30% were Marketing managers, 25% were Sales or Account managers and 24% were Customer Relationship or Communication managers. More than 60% of the interviewees had worked in their companies for over 5 years. Hence, the information obtained should be very relevant to the objectives of this research.

6.3 Respondent's profile

In order to examine whether the information collected is representative in this study, the general characteristics of the responded companies including company size, company age, industry, management style and situation in adopting CRM were inspected in this section.

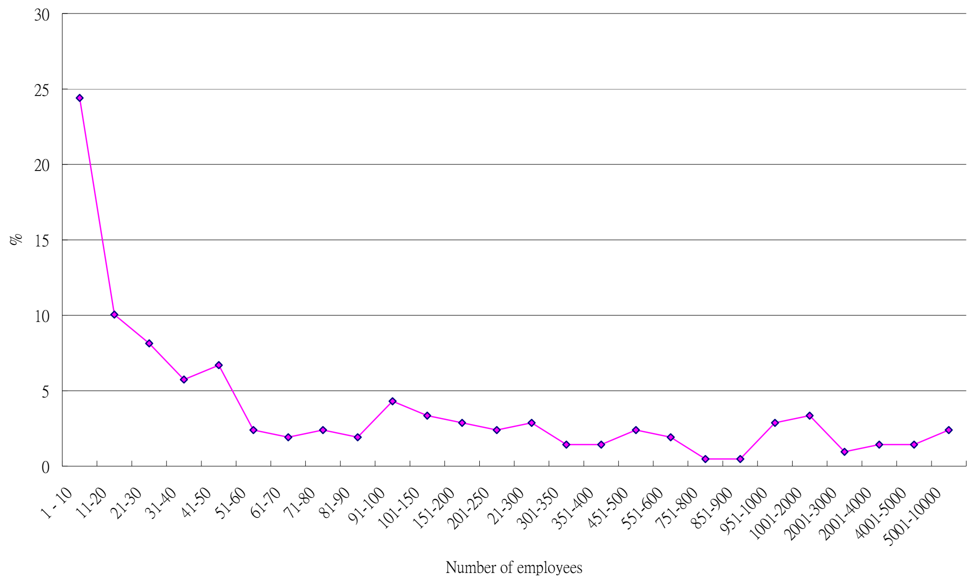
i. Company size

The number of employees in the company is used to assess the size of the respondent companies. It was found that companies of different size were included in the sample. The smallest business has a total of 2 employees and the largest business has a total of 10,000 employees. Figure 6.1 showed the distribution of the company size of the respondent companies.

Table 6.5 – Number of employees

	Sample size	Minimum	Maximum	Mean	Std. Deviation
Number of Employees	215	2	10000	522.76	1521.099

Figure 6.1 – Distribution of company size

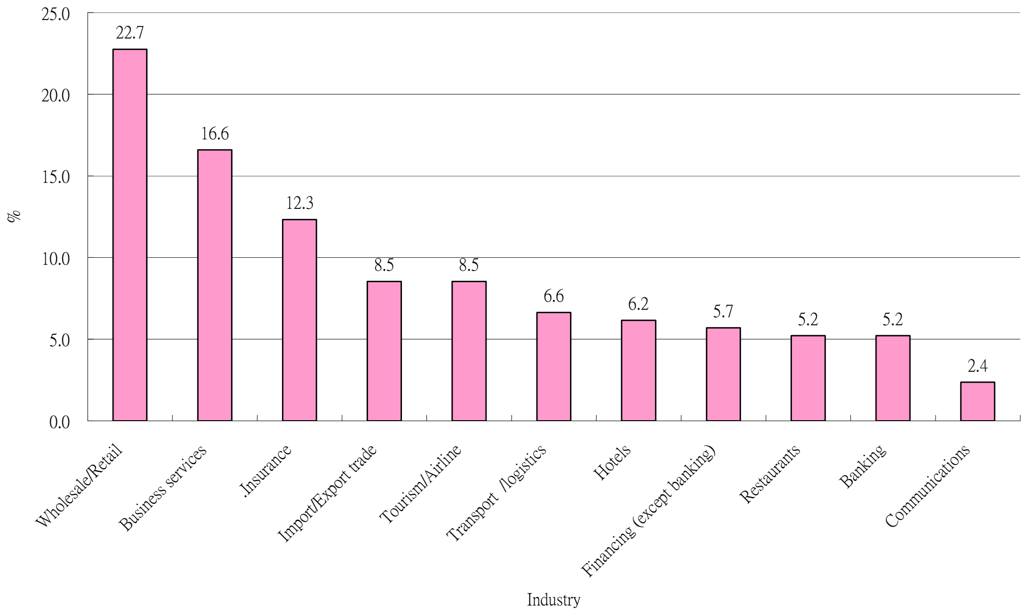


The average age of the respondent companies was 26 years. Very few of them were over 100 years old. This was quite unexpected as very few organisations have been set up for many years in Hong Kong. Due to the variation in the company size in the samples, it is believed that the sample includes different scales of companies in Hong Kong. Hence, the samples are considered to be representative for investigating the CRM adoption issues in this research.

ii. Industry

Most of the respondent companies were in the wholesale and retail industry (22.7%) and business services (16.6%). More than 10% of the respondents were in the hotel and banking industries. When comparing to the original mailing, the largest percentage of the letters were sent to the establishments from Import/Export trade (25.9%), Financing (except banking) (15.4%) and Communications (Communications). Although the distribution is not the same, different areas in the services sector (Figure 6.2) have participated in this survey, which suggests that the results should be representative because all these areas are the major industries of the services sector in Hong Kong.

Figure 6.2 – Industry



iii. Management style

Only 36.7% of the respondent companies were international companies. Decision making for 77% of those international companies was driven by Hong Kong management. Thus, the survey information should be able to reflect the situation in Hong Kong.

In addition, 49% of the respondents answered the questionnaire based on business customers and 51% of the respondents answered the questionnaire based on the retail market situation.

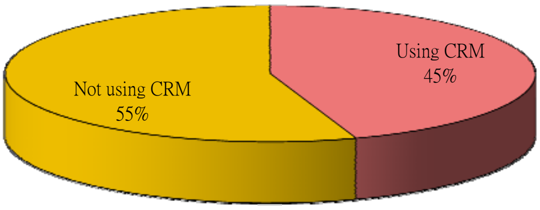
iv. Situation in adopting CRM

As explained in chapter 5, companies in the services sector in Hong Kong may not want to admit that they did not use CRM and some of them may not even understand the definition of CRM well, therefore, it makes me conceptualize CRM adoption in terms of levels of engagement with CRM and hence both direct question and agreement to a series of statements were used to assess whether the respondent companies adopted CRM to avoid reporting error. Answers to the direct question on CRM usage and answers to the series of statements related to levels of engagement with CRM will be assessed in this section in order to determine which scale is better to be used as a dependent variable for further analysis.

Direct question

With respect to the direct question, 45% of the respondents reported that their organisations are using CRM and 55% reported that their organisations are not using CRM. The difference in percentage is not too high, hence the sample size of adopters and non adopters is similar in comparing the situation of CRM adoption when this question is used for classification. Nevertheless, this is a slightly surprising outcome given the difficulties that were encountered in identifying non adopters during the qualitative phase. The implication is that the inability to identify non-adopters may have been driven by respondents' reluctance to admit in an interview that their company was a non adopter.

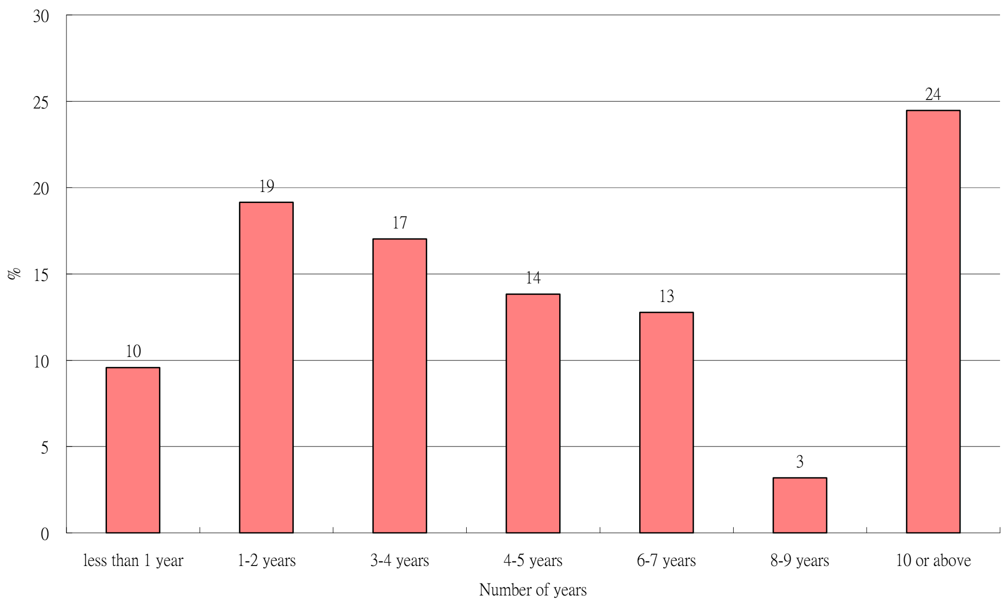
Figure 6.3 – CRM adoption



Respondents who reported themselves as adopters of CRM were asked about the 1) number of years that they have been using CRM and 2) the amount of investment in CRM adoption. More ideas on these two aspects could be gathered from the answers.

The number of years that respondent companies have been using CRM is shown in figure 6.4. 24% of the companies have been using CRM for 10 years or above. On the other hand, 19.5% of the CRM *non adopters* reported that they may use CRM in the next 12 months.

Figure 6.4 – Years that companies have been using CRM



Furthermore, the average spending of CRM adopters on CRM activities was around HK$ 3,400,000.

Table 6.6 shows how the respondents answered the series of questions that were measuring the levels of engagement with CRM according to the self-reported classification on CRM adoption. It was surprising that only a few differences were found between CRM adopters and non CRM adopters. The significant results were shown by t tests.

The absence of differences between self reported adopters and non adopters may reflect that fact that some of the items in the measurement scale relate to broad management practices and philosophies whereas respondents may tend to be thinking of CRM in terms of specific systems.

Table 6.6 – Answers to CRM adoption questions

	Using CRM N=97	Not using CRM N=118	t statistic	p value
Through ongoing dialogue, we work with individual key customers to customise our offerings.	3.80	3.74	0.520	0.603
My organisation provides customised services and products to our key customers.	3.90	3.90	-0.011	0.991
My organisation makes an effort to find out what our key customer needs.	4.13	3.97	1.550	0.123
When my organisation finds that customers would like to modify a product/service, the departments involved make coordinated efforts to do this.	3.94	4.02	-0.629	0.511
My organisation has the sales and marketing expertise and resources to succeed in CRM.	3.57	3.05	3.837	0.000**
Our employee training programmes are designed to develop the skills required for acquiring and deepening customer relationships.	3.54	3.15	2.809	0.005**
My organisation has established clear business goals related to customer acquisition, development, retention and reactivation.	3.69	3.51	1.410	0.160
Employee performance is measured and rewarded based on meeting customer needs and on successfully serving the customers.	3.53	3.51	0.105	0.917
Our organisational structure is meticulously designed around our customers.	3.30	3.19	0.859	0.391
My organisation's employees are willing to help customers in a responsive manner.	4.03	3.99	0.353	0.724
My organisation fully understands the needs of our key customers via knowledge leaning.	3.72	3.54	1.487	0.138
My organisation provides channels to enable ongoing, two-way communication with our key customers and us.	3.81	3.61	1.563	0.138
Customers can expect prompt service from employees of my organisation.	4.05	4.04	0.088	0.930

	Using CRM N=97	**Not using CRM N=118**	**t statistic**	**p value**
My organisation has the right technical personnel to provide technical support for utilisation of computer technology in building customer relationships.	3.53	3.27	1.883	0.061
My organisation has the right software to serve our customers.	3.52	3.22	2.114	0.036*
My organisation has the right hardware to serve our customers.	3.36	3.44	-0.567	0.571
Individual customer information is available at every point of contact.	3.57	3.28	2.220	0.028*
My organisation maintains a comprehensive database of our customers.	3.83	3.39	3.501	0.001**

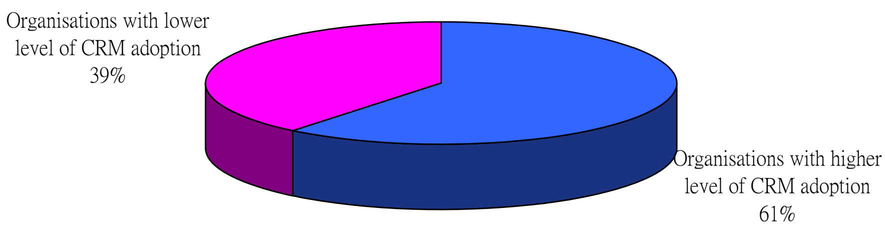
- *Statistically significant at less than 0.05 level
- **Statistically significant at less than 0.01 level

Series of statements on levels of engagement with CRM

Answers to the questions outlined in table 6.6 above give a profile of respondents use of CRM broadly defined. This data can be used in a number of ways. One simple approach is to use this as a basis for classifying respondents into basic and complex adopters. This will produce a binary categorisation which will be different from but may overlap with the simple self reported classification. By applying cluster analysis, cases are grouped in a systematic way, rather than self reported answers. Two segments (high engagement and low engagement adopters) were finally concluded as the sample size in each group for more than two clusters will not be enough for performing further model estimation. The idea of cluster analysis for creating two groups should be more objective and meaningful.

The cluster analysis results indicated that the percentage of organisations with a higher levels of engagement with CRM is 61% and a lower levels of engagement with CRM is 39% as a result of the cluster analysis.

Figure 6.5 – CRM adoption (cluster results)



The results of t tests provide evidence on the significant differences of answers to the statements between the two groups identified by cluster analysis, although it should be noted that since cluster analysis seeks to create differences between groups, the observation of significant t-statistic is unsurprising. It was also seen that the answers to the set of questions related to CRM adoption based on the multi-dimensional scale tended to be *more positive* for organisations which were classified as *high engagement adopters*. Table 6.7 shows the answers to the questions on CRM adoption.

Table 6.7 – Answers to CRM adoption questions (cluster results)

	High engagement adopters N=131	Low engagement adopters N=84	t statistics	p value
Through ongoing dialogue, we work with individual key customers to customise our offerings.	3.99	3.42	4.449	0.000**
My organisation provides customised services and products to our key customers.	4.19	3.44	6.088	0.000**
My organisation makes an effort to find out what our key customer needs.	4.25	3.71	5.128	0.000**
When my organisation finds that customers would like to modify a product/service, the departments involved make coordinated efforts to do.	4.24	3.57	5.962	0.000**
My organisation has the sales and marketing expertise and resources to succeed in CRM.	3.69	2.64	8.450	0.000**
Our employee training programmes are designed to develop the skills required for acquiring and deepening customer relationships.	3.65	2.81	6.436	0.000**
My organisation has established clear business goals related to customer acquisition, development, retention and reactivation.	4.07	2.83	12.237	0.000**
Employee performance is measured and rewarded based on meeting customer needs and on successfully serving the customers.	3.84	3.02	7.046	0.000**
Our organisational structure is meticulously designed around our customers.	3.65	2.61	9.671	0.000**
My organisation's employees are willing to help customers in a responsive manner.	4.34	3.50	8.469	0.000**
My organisation fully understands the needs of our key customers via knowledge leaning.	4.03	2.99	10.448	0.000**
My organisation provides channels to enable ongoing, two-way communication with our key customers and us.	4.13	3.04	9.826	0.000**
Customers can expect prompt service from employees of my organisation.	4.39	3.51	7.842	0.000**

	High engagement adopters N=131	Low engagement adopters N=84	t statistics	p value
My organisation has the right technical personnel to provide technical support for utilisation of computer technology in building customer relationships.	3.85	2.67	9.928	0.00**
My organisation has the right software to serve our customers.	3.77	2.70	8.386	0.00**
My organisation has the right hardware to serve our customers.	3.75	2.86	7.746	0.00**
Individual customer information is available at every point of contact.	3.77	2.85	8.091	0.00**
My organisation maintains a comprehensive database of our customers.	3.99	2.95	9.351	0.00**

- **Statistically significant at less than 0.01 level

According to the results in table 6.6 and 6.7, it is very clear that the direct question and the series of questions give different measures on the CRM adoption construct. Simple self-reported question depended on what individuals understand CRM to be. On the other hand, the metric scale system is richer and also less dependent on respondents own individual definitions.

The differences between self-reported answers and clustered results on CRM adoption situation can be seen from table 6.8. Only 48.3% of non CRM adopters classified in the self-reported approach are also classified as simple/non adopters in the cluster analysis approach. It is not surprising though the classification on CRM adoption is so different. As discussed many times throughout the thesis, participants may not be able to classify themselves as CRM adopters correctly due to lack of workable definition of CRM so far. Moreover, some of them may even be unwilling to admit that they are non CRM adopters. Hence, opinions given to the series of statements on the levels of engagement with CRM would give a more objective picture on the CRM adoption situation of the participated companies. In other words, the results of clustering solution based on the answers to the series of statements on CRM adoption tend to offer a more objective classification on CRM adoption.

Table 6.8 – Differences between self-reported and cluster results on CRM adoption situation

			Self-reported CRM adoption		
			No	**Yes**	**Total**
Cluster results on CRM adoption	**Low engagement adopters**	**Count (Percentage)**	57 (48.3%)	27 (28.7%)	84 (39.6%)
	High engagement adopters	**Count (Percentage)**	61 (51.7%)	67 (71.3%)	128 (60.4%)
		Count (Percentage)	118 (100.0%)	94 (100.0%)	212 (100.0%)

In order to have objective results when comparing the opinions of CRM adopters and non CRM adopters, therefore, the author decides to use both the classification from both the self reported categorisation and the results of clustering in the further analysis in this chapter.

Before presenting the analysis results, the strategy of analysis is now discussed in section 6.4.

6.4 Analysis strategy

As mentioned earlier, it was found in the exploratory interviews that companies in the services sector in Hong Kong may not want to admit that they did not use CRM and some of them may not even understand the definition of CRM well. Accordingly, it was decided to conceptualize CRM adoption in terms of levels of engagement with CRM in the analysis rather than just a simple binary adopt/not adopt. For measurement purposes, two basic approaches were adopted. The first approach used a simple self declaration question (using CRM or not using CRM) to produce the traditional binary categorisation, although the qualitative work had raised concerns about the extent to which respondents would be prepared to categorise themselves as non adopters. The second approach used a measure of the levels of engagement with CRM questions proposed by Sin *et al*. in 2005 (which is a metric scale). As the first way of measuring CRM adoption is quite simplistic and dependent on respondents understanding of CRM, therefore, the metric scale was also used in order to classify the respondents into ‚CRM adopters and non CRM adopters in a more objective way by cluster analysis. The results in the previous section show that the two classification methods were worth further investigation. As a result, analysis of the determinants of CRM adoption was undertaken using both measures – the binary classification (self reported classification as well as clustered classification) and the metric scale.

Regression models were first used in order to investigate which drivers affect the adoption of CRM. Multiple regression was performed when CRM adoption was treated as a metric scale and logistic regression was performed when CRM adoption was treated as a binary variable. Regression analysis estimates relationships between one or more response variables (also called dependent variables, explained variables or predicted variables) and the predictors (also called independent variables, explanatory variables or control variables). Logistic regression is a form of regression which is used when the dependent is a dichotomy and the independents are of any type. Therefore, CRM adoption will be the dependent variable and drivers will be the independent variables.

Prior to estimating the measurement model, Exploratory Factor Analysis (EFA) was first undertaken to find out if the items can be grouped under the factors proposed as the conceptual theory. Then, Confirmatory Factor Analysis (CFA) was performed in order to assess the fit of the indicator variables in relation to the latent variable.

EFA seeks to uncover the underlying structure of a relatively large set of variables. The researcher's assumption is that any indicator may be associated with any factor. This is the most common form of factor analysis. There is no prior theory and factor loadings are used to obtain an impression of the factor structure of the data. There are different methods of extracting the factors from a set of data. The method chosen will matter more, to the extent that the sample is small, the variables are few, and/or the communality estimates of the variables differ. By far the most common form of factor analysis is Principal Components Analysis (PCA). PCA seeks a linear combination of variables such that the maximum variance is extracted from the variables. It then removes this variance and seeks a second linear combination which explains the maximum proportion of the remaining variance, and so on. This is called the principal axis method and results in orthogonal (uncorrelated) factors. PCA analyses total (common and unique) variance. Rotation serves to make the output more understandable and is usually necessary to facilitate the interpretation of factors. The sum of eigenvalues is not affected by rotation, but rotation will alter the eigenvalues (and percent of variance explained) of particular factors and will change the factor loadings. The most common rotation method is Varimax rotation. It is an orthogonal rotation of the factor axes to maximise the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix, which has the effect of differentiating the original variables by extracted factor. Each factor will tend to have either large or small loadings of any particular variable. A varimax solution yields results which make it as easy as possible to identify each variable with a single factor. This is the most common rotation option.

CFA seeks to determine if the number of factors and the loadings of measured (indicator) variables on them conform to what is expected on the basis of pre-established theory. Indicator variables are selected on the basis of prior theory and factor analysis is used to see if they load as predicted on the expected number of factors. The researcher's assumption is that each factor is associated with a specified subset of indicator variables. A minimum requirement of confirmatory factor analysis is that one hypothesises beforehand the number of factors in the model, but usually also the researcher will posit expectations about which variables will load on which factors (Kim and Mueller, 1978). The researcher seeks to determine, for instance, if measures created to represent a latent variable really belong together. There are two approaches to confirmatory factor analysis:

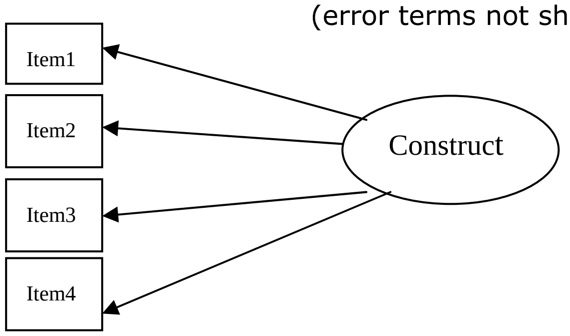
The Traditional Method: Confirmatory factor analysis can be accomplished through any general-purpose statistical package which supports factor analysis. Note that for SEM, CFA uses principal axis factoring (PAF) rather than principal components analysis (PCA) as the type of factoring. This method allows the researcher to examine factor loadings of indicator variables to determine if they load on latent variables (factors) as predicted by the researcher's model. This can provide a more detailed insight into the measurement model than can the use of single-coefficient goodness of fit measures used in the SEM approach. As such the traditional method is a useful analytic supplement to the SEM CFA approach when the measurement model merits closer examination.

The SEM Approach: Confirmatory factor analysis means the analysis of alternative measurement (factor) models using a structural equation modelling package such as AMOS or LISREL. While SEM is typically used to model causal relationships among latent variables (factors), it is equally possible to use SEM to explore CFA measurement models. Conceptually, a structural equation model implies a structure of the covariance matrix of the measures (hence an alternative name for this field, "analysis of covariance structures"). Once the model's parameters have been estimated, the resulting model-implied covariance matrix can then be compared to an empirical or data-based covariance matrix. If the two matrices are consistent with one another, then the structural equation model can be considered a plausible explanation for relations between the measures. The researcher is more likely to use SEM to determine whether a certain model is valid, rather than using SEM to find a suitable model.

Compared to EFA, CFA requires the specification of an *a priori* model, the number of factors, which items load on each factor, a model supported by theory or previous research and error explicitly. These items were loaded on the proposed construct when performing the analysis in order to find out whether the goodness-of-fit of the structure is acceptable or good.

Figure 6.6 – Example diagram of CFA

(error terms not shown on diagram)



As the SEM approach was used, there are some important measures to determine the goodness of fit of the analysis. Kline (1998) recommended at least four tests, such as chi-square; GFI, NFI, or CFI and NNFI. Other tests include AGFI, TLI, and RMSEA. These tests will be explained later in this section.

Finally, a Structural Equation Model (SEM) was used to investigate the proposed hypotheses in this research. "SEM is a methodology for specifying, estimating, and testing hypothesized interrelationships among a set of substantively meaningful values" (Bentler, 1996, p.9). It is a multivariate technique "combining aspects of multiple regression and factor analysis to estimate a series of interrelated dependence relationships simultaneously (Hair *et al*, 1998, p.583) It is a method similar to multiple regression, but in a more powerful way which takes into account the modelling of interactions, nonlinearities, correlated independents, measurement error, correlated error terms, multiple latent independents each measured by multiple indicators, and one or more latent dependents also each with multiple indicators. SEM may be used as a more powerful alternative to multiple regression, path analysis, factor analysis and analysis of covariance. That is, these procedures may be seen as special cases of SEM, or, put another way, SEM is an extension of the general linear model (GLM) of which multiple regression is a part.

Advantages of SEM compared to multiple regression include more flexible assumptions (particularly allowing interpretation even in the face of multicollinearity), use of confirmatory factor analysis to reduce measurement error by having multiple indicators per latent variable, the attraction of SEM's graphical modelling interface, the desirability of testing models overall rather than coefficients individually, the ability to test models with multiple dependents, the ability to model mediating variables, the ability to model error terms, the ability to test coefficients across multiple between-subjects groups, and the ability to handle difficult data (time series with autocorrelated error, non-normal data, incomplete data).

In 2003, Wisner pointed out that structural equation modelling is a confirmatory approach to data analysis requiring the prior assignment of inter-variable relationships. It tests a hypothesised model statistically to determine the extent to which the proposed model is consistent with the sample data. Structural equation modelling incorporates observed (indicator) and unobserved (latent) variables, which are separated into measurement models and a structural equation model. Observed variables are those that can be measured, while unobserved variables cannot be directly measured and must be inferred or hypothesised from the observed variables. The measurement models specify how the latent variables are measured in terms of the indicator variables as well as addressing the reliability and validity of the indicator variables in measuring the latent variables, and describe the amount of explained and unexplained variance in the model (Byrne, 1998; Schumacker and Lomax, 1996).

In structural equation modelling, there is no single test of significance that can absolutely identify a correct model given the sample data (Schumaker and Lomax, 1996). Many goodness-of-fit criteria have been established to assess an acceptable model fit (Bentler, 1992). The author will focus on reporting some common measures such as chi-square; GFI, NFI, CFI, NNFI, AGFI, TLI, and RMSEA.

Model chi-square, also called discrepancy or the discrepancy function, is the most common fit test, printed by all computer programs. AMOS outputs it as CMIN. The chi-square value should not be significant if there is a good model fit, while a significant chi-square indicates lack of satisfactory model fit. This measure is sensitive to the sample size of the data. The larger the sample size, the more likely the rejection of the model and the more likely a

Type II error (rejecting something true). In very large samples, even tiny differences between the observed model and the perfect-fit model may be found significant.

The chi-square fit index divided by degrees of freedom (relative chi-square) is a measure in an attempt to make it less dependent on sample size. AMOS lists relative chi-square as CMIN/DF.

Goodness-of-fit index, GFI is the fit function when all model parameters are zero. GFI varies from 0 to 1, but theoretically can yield meaningless negative values. A large sample size pushes GFI up. By convention, GFI should be equal to or greater than .90 to accept the model. LISREL and AMOS both compute GFI.

Root mean square error of approximation, RMSEA, is also called RMS or RMSE or discrepancy per degree of freedom. By convention, there is a good model fit if RMSEA is less than or equal to .05.

The comparative fit index, CFI, is also known as the Bentler Comparative Fit Index. CFI compares the existing model fit with a null model which assumes the latent variables in the model are uncorrelated (the "independence model"). CFI varies from 0 to 1. CFI close to 1 indicates a very good fit.

Tucker-Lewis index, TLI is computed as (chisqn/dfn - chisq/df)/(chisqn/dfn - 1), where chisq and chisqn are model chi-squares for the given and null models, and df and dfn are the associated degrees of freedom. TLI close to 1 indicates a good fit and tends to run lower than GFI.

Adjusted goodness-of-fit index, AGFI is a variant of GFI which adjusts GFI for degrees of freedom. AGFI should also be at least .90. Like GFI, AGFI is also biased downward when degrees of freedom are large relative to sample size, except when the number of parameters is very large.

By using SEM to analyse, not only the relationship between the determinants and CRM adoption can be examined, but also the relationship between CRM adoption, mediator and the effect on organisational performance can be investigated at the same time. In addition, the model can contribute to the literature because very little research to date has used a structural equation model for investigating CRM issues.

The SEM analysis was conducted based on the two-step approach proposed by Anderson and Gerbing (1988). It was adopted with measurements and structural models being estimated separately. The *measurement model* is the submodel in SEM that (1) "specifies the indicators for each construct and (2) ..assesses the reliability of each construct for estimating causal relationships"..The *structural model* "is the set of one or more dependence relationships linking the hypothesised model's constructs" (Hair *et al*. 1998, p.581, 583). The first step involved a confirmatory factor analysis to develop an acceptable measurement model. The measurement model defined the observed variables in terms of "true" latent variables (endogenous or exogenous) and a measurement error term. At this stage, each latent variable was allowed to correlate freely with every other latent variable. In step two, the measurement model has been accepted and is taken as fixed with attention then focused on estimating the postulated causal model framework. This theoretical model was then tested and a statistically acceptable model was found. The two-step approach has a number of comparative strengths that allow meaningful influences to be made. First, it allows tests of significance for all pattern coefficients. Second, the two-step approach allows an assessment of whether any structural model would give an acceptable fit. Third, an asymptotically independent test of the substantive or theoretical model of interest can be made. Finally, the two-step approach provides a particularly useful framework for formal comparisons of the substantive model of interest with the next most likely theoretical alternatives.

The total disaggregated model was used in this research as individual item serves as an indicator for a construct (Bagozzi and Edawards, 1998). The total disaggregated model provides the most “fine-grained” analyses” of a construct because psychometric properties are evaluated for each individual item. Marsh, Hau and Grayson (1998) found that disaggregated solutions performed better than parceled ones. Furthermore, when the structural model was estimated, competing models, i.e. comparing the models with mediator and without mediator, was also adopted.

In general, SEM is referred to as a *covariance-based* technique, as implemented in popular softwares such as LISREL and AMOS (Bollen, 1989; Jöreskog, 1973; Rigdon, 1998), to assess if and to what degree a sample covariance (or correlation) matrix is consistent with a covariance matrix implied by the model specified by the user under the assumptions of multivariate normal distribution and independence of observations. However, a *variance-based* method known as *partial least squares* (PLS) (Chin, 1998; Fornell and Cha, 1994; Wold, 1982) that is documented in the PLS-Graph package, although less popular, is also available for SEM estimation.

In fact, the general applicability of the covariance structure models has long been questioned by some researchers because sample distributions are often either unknown or far from normal in practice. To deal with the violations of distributional assumptions as well as to avoid problems of improper solutions and factor indeterminacy associated with the covariance-based approach, PLS was formally introduced as an alternative approach to SEM. PLS estimates the case values of latent variables (LVs) as the weighted sum of their measurement variables (MVs) and, therefore, the problem of factor indeterminacy is eliminated. In addition, the least squares estimation method used by PLS eliminates the problem of improper solutions.

Major problems with the covariance-based approach (LISREL or AMOS)

First, there is an inherent *indeterminacy* problem in the covariance-based approach, i.e., case values for the latent variables (LVs) are never appropriately obtained in the approach. Thus, the ability to estimate scores of the LVs and, in turn, to predict the measurement variables (MVs) is not provided.

Second, the covariance-based approach requires a large sample size and a multivariate normal distribution for the MVs, which is always difficult to meet in practice, especially in survey research. When these requirements are not met, i.e., when sample size is small (in relation to the total number of parameters to be estimated) and the MVs' distribution is not normal (e.g., skew as in many surveys), improper solutions such as negative variance estimates can often be produced.

Third, all MVs must be treated in a *reflective* manner, i.e., they must be causally influenced by the respective LVs under the covariance-based approach. However, sometimes some MVs may be *formative* in nature, i.e., they influence the respective LVs. In this situation the covariance-based approach is unable to explain the MVs' covariances. According to Diamantopoulos and Winklhofer (2001), this is not always true. The choice between a formative and a reflective specification should primarily be based on theoretical considerations regarding the causal priority between the indicators and the latent variable involved. If the objective is explanation of abstract, formative indicators would give greater explanatory power.

Summary features of PLS

The PLS method emerged to resolve the above problems commonly associated with the covariance-based approach. The key idea of PLS is to help the researcher obtain determinant values of the LVs for predictive purposes. If the LVs' values are determined, then each equation in the SEM is a simple linear regression equation and can be estimated using the traditional *ordinary least squares* (OLS) method. Thus, parameter estimates are obtained in the PLS approach by minimising each residual variance to better predict the corresponding dependent variable rather than minimising the difference between the sample and model-implied covariance matrices to explain the covariations of all MVs, as in the covariance-based approach.

PLS is an iterative procedure, providing a way to directly estimate the LV scores. The procedure is *partial* in the *least squares* sense because each step of the procedure minimises *one* residual variance in *one* regression equation to estimate the relevant parameters involved in that specific equation, given proxies or fixed estimates for the other parameters –– hence PLS only needs a sufficiently small sample size which can be determined by the largest single regression equation in the SEM. Since PLS is to minimise the *variance* of the residual or to account for as much *variance* as possible of the dependent variable (either LV or MV) in each of the model's regression equations, it is also *variance-based* or *prediction-oriented*. Since LV scores are determinant, PLS can also model *formative* MVs (i.e., the MVs cause or form the LV or, graphically, the arrows are directed towards the LV from the MVs) by regressing the MVs on the LV (i.e., the LV is optimally predicted by its MVs), in addition to modelling *reflective* MVs (i.e., the MVs are causally influenced by the LV or, graphically, the arrows are directed towards the MVs from the LV) as in the covariance-based approach by regressing the LV on each MV (i.e., each MV is optimally predicted by the LV). PLS's determinant nature also avoids identification problems that can occur in the covariance-based approach.

Table 6.9 provides a detailed account of the main features of the PLS approach in comparison with the covariance-based approach.

Table 6.9 – Main Features of the PLS and the Covariance-Based Approaches

The PLS Approach	The Covariance-Based Approach (LISREL or AMOS)
Variance structure analysis	Covariance structure analysis
No specific requirements	Multivariate normal distribution, independent observations, & large sample size
Prediction-oriented	Parameter-oriented
Consistency at large	Consistency
Optimal prediction accuracy	Optimal parameter accuracy
Case values of LVs are estimated	Factor indeterminacy
Both reflective and formative MVs	Reflective MVs only

The sample size for AMOS relates to the total number of parameters to be estimated, including path coefficients, variances of variables (including MVs, LVs and error terms), and covariances among variables. So a simple rule is that the sample size required by AMOS should be greater than 5 times the number of parameters. Sample size for PLS is determined by the largest single regression equation of the SEM, i.e., it relates to the number of MVs of that LV which has the maximum number of MVs.

After evaluating the advantages and disadvantages, it was found that the nature of the data allowed me to use AMOS to estimate the SEM model. PLS was only applied to work out the useful indicator of model validity - Average Variance Extracted (AVE). AVE is the variance in indicator items captured by a construct as a proportion of captured plus error variance. It is calculated as the sum of the squared standardized indicator item loadings on the factor representing the construct, divided by this sum plus the sum of indicator item error. If S1 = the sum of squared principal components analysis factor loadings of the indicator variables on the factor representing their construct and S2 = the quantity (1 - the squared loading) summed for all indicators. Then AVE = (S1)/(S1 + S2). PLS can compute this indicator in the most user-accessible way and calculation errors can be avoided.

During the establishment of the measurement model, the reliability and validity of the model were also estimated.

After discussing the analysis strategy, analysis will start to be carried out. First, the results using exploratory factor analysis will be presented.

6.5 Exploratory factor analysis (EFA)

EFA was used to find out whether the underlying factors of the items are those suggested in the conceptual model. In addition, as there are newly developed items in the survey, EFA can help to explore if the items are grouped naturally to the same extent as what have been proposed in the model for this thesis. Tables 6.10 to 6.14 show the results of factor analysis of the constructs in the model.

The SPSS software package computed Bartlett's test of sphericity (Bartlett 1950) and the Kaiser-Meyer-Olkin measure of sampling adequacy (Kaiser 1970) in order to assist users to assess the adequacy of their correlation matrices for factor analysis. With respect to the Bartlett's test, very small values of significance (below 0.05) indicate a high probability that there are significant relationships between the variables, whereas higher values (0.1 or above) indicate the data is inappropriate for factor analysis.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy provides an index (between 0 and 1) of the proportion of variance among the variables that might be common variance (i.e., that might be indicative of underlying or latent common factors). The SPSS software package suggests that a KMO near 1.0 supports a factor analysis and that anything less than 0.5 is probably not amenable to useful factor

Table 6.10 – Results from factor analysis of items on Rogers' attributes of innovation

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
6. Customers' satisfaction is believed to be increased after the adoption of CRM.	0.590				
7. Adoption of CRM can increase customers' repeat purchases	0.757				
8. Adoption of CRM can increase average customers' life time value	0.702				
9. Adoption of CRM can increase the return on investment (ROI)	0.785				
10. CRM adoption can increase the profitability of our business	0.845				
11. CRM fits our need in keeping relationship with customers.		0.704			
12. The philosophy of CRM is consistent with our company value.		0.803			
13. The practice of CRM is consistent with our usual practice.		0.781			
14. The concept of CRM is easy to understand.			0.523		
15. We find that it is difficult to put CRM into practice.			0.873		
16. The CRM related IT support tools are difficult to use.			0.867		
17. CRM can be tried with the available system in the market.				0.640	
18. The practice of CRM is easy to be tested out.				0.821	
19. I have seen other companies benefit from CRM.					0.633
% variance explained	14.6	22.6	11.6	14.0	12.7
Eigenvalues	2.1	3.2	1.6	2.0	1.8
KMO = 0.9 Bartlett's test = 1528.06 (0.000)					

( ) denotes the significant values

The items can be grouped into 5 factors which are broadly in line with what was expected:

Factor 1: Relative advantage
Factor 2: Compatibility
Factor 3: Complexity
Factor 4: Trialability
Factor 5: Competition

Table 6.11 – Results from factor analysis of items on external factors

	Factor 1	Factor 2	Factor 3
20. The newly developed data mining tool or program helps to handle the customers' information more efficiently.	0.791		
21. Data warehousing provides an opportunity for our company to search for important historical customers' information.	0.824		
22. Advance in computer information systems can help to turn data of customers into information for strategic business purposes.	0.790		
23. The development of communication systems (e.g. email, fax, mobile SMS and website) helps our organisation communicate better across different departments and with customers.	0.696		
24. In our industry, it is essential to keep a good relationship with customers in order to be competitive.		0.588	
25. Most of our competitors have adopted customer relationship management strategy and this makes us have no choice but to choose it.		*0.397*	
26. Competition in our industry is cut-throat.		0.731	
27. There are many "promotion wars" in our industry.		0.844	
28. Anything that one competitor can offer, others can match readily.		0.762	
29. Our competitors are relatively weak.		*-0.272*	
30. Our organisation wants to build close relationships with customers.			0.634
31. Customers value a company with the strategy to enhance intimacy with them.			0.833
32. More customers want personalised services in our industry.			0.728
% variance explained	21.3	20.1	15.1
Eigenvalues	2.8	2.6	2.0
KMO = 0.7 Bartlett's test = 1135.9 (0.000)			

( ) denotes the significant values

The items can be grouped into 5 factors and they are again, broadly in line with what was expected:

Factor 1: Perceived accessibility of IT solutions

Factor 2: Competition intensity

Factor 3: Desire of customer intimacy

Since the magnitude of the loadings on questions 25 and 29 is a bit low (below 0.4) this indicates that these two questions cannot explain the underlying factor. Question 25 is a newly developed item and the results suggest that it cannot help to explain competition intensity. On the other hand, question 29 is an existing developed scale and there is the possibility that this statement is not applicable in the Hong Kong situation for explaining competition intensity. As the number of items is enough to measure that construct, as a consequence, a decision was made not to include them in the further analysis.

Table 6.12 – Results from factor analysis of items on factors within organization

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
33. Reform is beneficial to everyone in society.	0.799					
34. Changes will bring vitality to our company.	0.759					
35. The top management has full confidence in the change.	0.585					
36. Top management has full support for a practicing strategy in keep good relationship with customers.	0.674					
37. In order to change for the better, senior management believes that good customer relationship is a necessity.	0.759					
38. We constantly monitor our level of commitment and orientation to serving customers' needs.		0.506				
39. Our business objectives are driven primarily by customer satisfaction.		0.715				
40. Our strategy for competitive advantage is based on our understanding of customer needs.		0.671				
41. Our business strategies are driven by our beliefs about how we can create greater value for customers.		0.739				
42. We measure customer satisfaction systematically? and frequently.		0.660				

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
43. We give close attention to after-sales service.		0.531				
44. We rapidly respond to competitive actions that threaten us.			0.545			
45. Our salespeople regularly share information within our organisation concerning competitors' strategies.			0.633			
46. Top management regularly discusses competitors' strengths and strategies.			0.739			
47. We target customers where we have an opportunity for competitive advantage.			0.738			
48. All of our business functions (e.g. marketing/sales, manufacturing, research and development) are integrated into serving the needs of our target markets.				0.663		
49. All of our business functions and departments are responsive to each other's needs and requests.				0.448		
50. Our top managers from every function regularly visit our current and prospective customers.				0.731		
51. We freely communicate information about our successful and unsuccessful customer experiences across all business functions.				0.699		
52. Our company pays close attention to innovation.					0.527	
53. Our company emphasises the need for innovation for development.					0.515	
54. Our company promotes the need for development and utilisation of new resources.					0.642	
55. Our company tries to help employees understand what is happening in the company.						0.575
56. Our company gives employees opportunities to be involved in the decision-making process.						0.783
57. Our company promotes unity and cooperation.						0.666
58. Our company tries to help employees understand the dynamics of the market situation.						0.692
59. The organisational group culture towards keeping good customer relationship is strong.						0.613

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
% variance explained	10.7	13.2	14.5	8.1	9.0	15.5
Eigenvalues	2.9	3.6	3.9	2.2	2.4	4.2
KMO = 0.9	Bartlett's test = 3841.1 (0.000)					

( ) denotes the significant values

The items can be grouped into 6 factors and these were broadly in line with what was expected:

Factor 1: Attitude towards change
Factor 2: Customer orientation
Factor 3: Competitor orientation
Factor 4: Interventional coordination
Factor 5: Innovation orientation
Factor 6: Group culture

Table 6.13 – Results from factor analysis of items on information utilization

	Factor
60. We use customer information to develop customer profiles.	0.886
61. We use customer information to segment markets.	0.871
62. We use customer information to assess customer retention behaviour.	0.864
63. We use customer information to identify appropriate channels to research customers.	0.847
64. We use customer information to customise our offers.	0.837
65. We use customer information to identify our best customers.	0.810
66. We use customer information to assess the lifetime value of our customers.	0.786

The items are converged into one factor naturally.

Table 6.14 – Results from factor analysis of items on performance

	Factor 1	Factor 2	Factor 3
67. Customer satisfaction towards your organisation	0.769		
68. Customers' repeat purchases	0.802		
69. Word of mouth of customers	0.782		
70. Market share		0.857	
71. Average customers' life time value		0.646	
72. Return on investment		0.785	
73. Overall performance of the business		0.729	
74. Employees feel as though their future is intimately linked to that of this organisation.			0.902
75. The bonds between this organisation and its employees become stronger.			0.849
76. Employees are proud to work for this business unit			0.848
77. Our people have stronger commitment to this business unit.			0.845
78. Employees are fond of this business unit.			0.806
% variance explained	19.7	21.6	33.5
Eigenvalues	2.4	2.6	4.0
KMO = 0.9 Bartlett's test =1678.0 (0.000)			

( ) denotes the significant values

The items were grouped into 3 factors and the loadings are quite high, the corresponding factors are:

Factor 1: Customer satisfaction

Factor 2: Business performance

Factor 3: Employee satisfaction

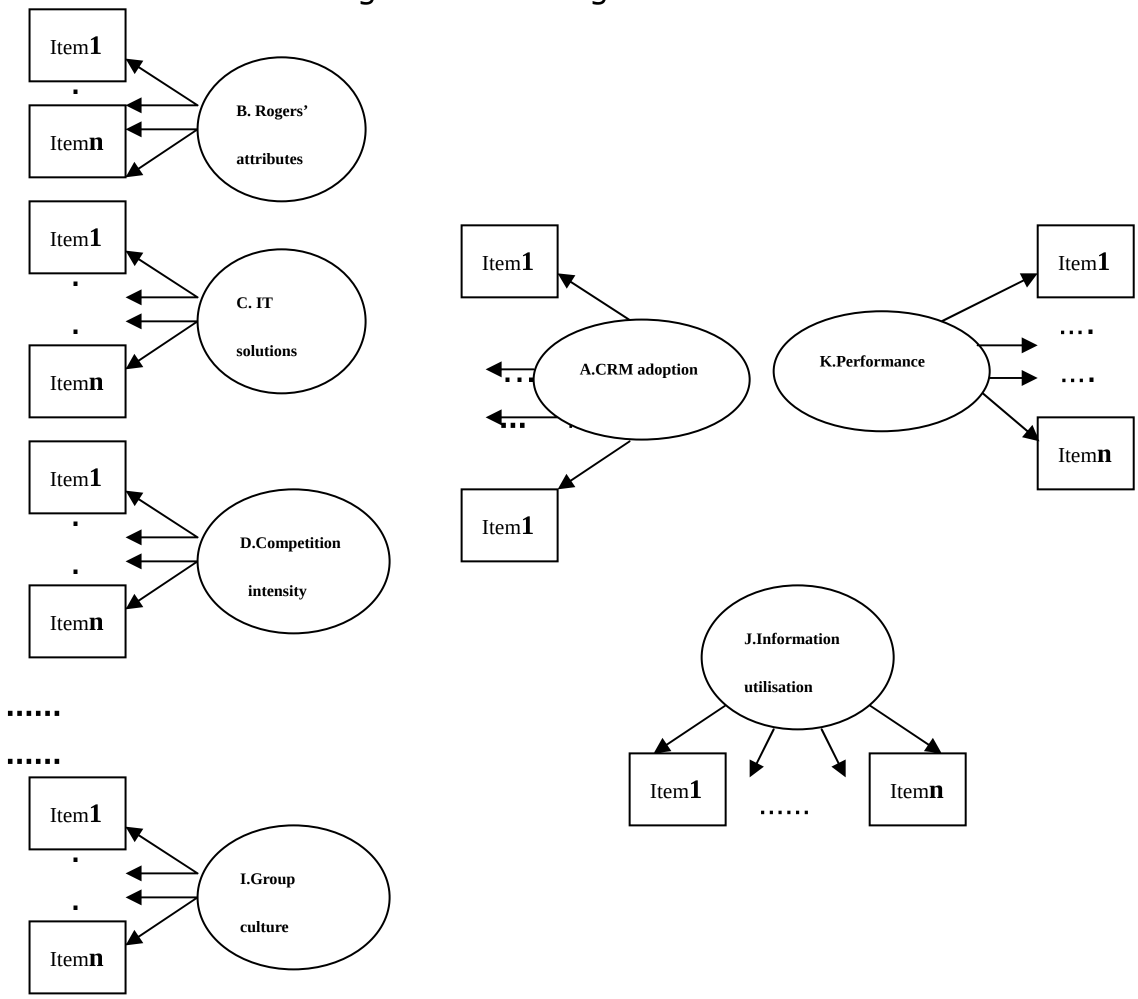
Overall, the results of EFA are very close to the proposed constructs described in theory or previous research. However, items with a loading of less than 0.4 will be deleted from the next part of analysis as they are not valid items of the particular construct. Although loadings of 0.5 to 0.6 are not high, they will be kept since they are able to fall into the presumed construct reasonably.

After exploring if the items could be grouped under the proposed construct, confirmatory factor analysis will be done. It is presented in the next section.

6.6 Confirmatory factor analysis (CFA)

After conducting EFA, the underlying structure of the large set of variables in this research was uncovered. In this section, the items grouped under the underlying constructs will be put together for performing the CFA using SEM approach. Corresponding items will be loaded on the proposed construct when conducting the analysis in order to find out whether the goodness-of-fit of the measurement model is acceptable. For example, items about the levels of engagement with CRM were linked to the latent variable "CRM adoption", items about Rogers' attributes of innovation were linked to the latent variable "Rogers' attributes of innovation" and so on. Each construct was estimated individually and all constructs were also put together for estimating simultaneously. The following diagram highlights the situation of estimation.

Figure 6.7 – Diagram of CFA



Note: Since there are a number of items grouped under each construct, therefore, the items are represented by item1 to itemn.

As discussed in the analysis strategy section, GFI, CFA, AGFI, TLI and RMSEA are some of the important measures to determine the goodness-of-fit. They are summarised in the table 6.15.

Table 6.15 – Goodness-of-fit measures

Model for Construct	χ^2	***p***	**Df**	χ^2 **/df**	**GFI**	**RMSEA**	**CFI**	**TLI**	**AGFI**
A. Scale on levels of engagement with CRM	205.75	0.000	127	1.620	0.904	0.054	0.957	0.949	0.870
B. Rogers' attributes of innovation	103.78	0.002	66	1.572	0.937	0.052	0.974	0.965	0.899
C. Perceived accessibility of IT solutions	16.00	0.003	4	4.001	0.964	0.118	0.960	0.941	0.909
D.Competition intensity	3.25	0.197	2	1.627	0.992	0.0584	0.982	0.947	0.962
E.Customer intimacy	11.54	0.001	1	*11.541*	0.966	*0.222*	0.902	0.707	0.797
F.Attitude towards change	29.58	0.000	6	*4.930*	0.947	*0.136*	0.949	0.916	0.867
G.Market orientation	144.01	0.000	72	2.000	0.912	0.068	0.912	0.936	0.871
H.Innovation orientation	18.05	0.000	1	18.049	0.933	*0.222*	0.968	0.904	0.693
I.Group culture	6.37	0.271	5	1.275	0.988	0.036	0.998	0.995	0.965
J.Information utilisation	50.66	0.000	15	*3.377*	0.936	*0.105*	0.968	0.955	0.881
K.Performance	128.70	0.000	51	2.524	0.955	0.084	0.955	0.942	0.864
Overall measurement	7291.67	0.000	3597	2.027	0.853	0.069	0.905	0.793	0.824

A few measures in table 6.15 (highlighted in italics) seem problematic. In particular some values for AGFI fall below the 0.9 threshold and some values of RMSEA are above the normal 0.05 cut-off. The constructs that appear to be particularly problematic are Customer Intimacy and Innovation orientation. However, the other measures such as CFI for those constructs show acceptable results. For the overall measurement model, the fit statistics are a little disappointing with both GFI and AGFI being a bit low and RMSEA being a little high. The CFI value was acceptable as was χ^2 **/df.** While recognising that there are some limitations to the measurement model as reported here, the combination of some good results from the EFA which acceptable results from the CFA was deemed to be a satisfactory basis on which to proceed.

The subsequent testing and model estimations were based on these confirmed structures. Section 6.7 will first discuss the reliability and validity of the measurement.

6.7 Reliability and validity of the model

Before estimating with regression analysis and SEM, reliability and validity of the measurements were inspected. According to Fornell (1992) and Fornell and Larcker (1981), a construct's AVE should be, at least, higher than 0.5 to guarantee a more valid variance is explained than error in its measurement. The AVEs of the constructs in the model are listed in table 6.16.

Table 6.16 – AVE of constructs in the model

Constructs	***AVE***
Relative advantage	0.67
Compatibility	0.78
Complexity	0.59
Trialability	0.70
Attitude towards change	0.62
Perceived accessibility of IT solutions	0.65
Market orientation	0.56
Innovation orientation	0.86
Group culture	0.70
CRM adoption	0.51
Information utilisation	0.71
Competition intensity	0.51
Customer satisfaction	0.74
Employee satisfaction	0.80

It was shown that all AVEs were higher than 50%. In other words, the relationships between the construct and its indicators were high.

Apart from the above-mentioned convergent validity, the constructs should also have high discriminant validity. According to Fornell and Cha (1994) and Fornell and Larcker (1981), the AVE should be higher than the correlations between all latent variables in the model. The correlations are shown in table 6.17.

Table 6.17 – Output of correlations of latent variables in the model

OR .. Correlations of latent variables

	Relative	Compatib	Complexi	Trialabi	Competit	Attitude	Market o
Relative	1.000						
Compatib	0.773	1.000					
Complexi	0.508	0.547	1.000				
Trialabi	0.488	0.473	0.448	1.000			
Competit	0.540	0.481	0.488	0.553	1.000		
Attitude	0.602	0.544	0.418	0.405	0.338	1.000	
Market o	0.534	0.584	0.401	0.525	0.472	0.687	1.000
Innovati	0.457	0.490	0.374	0.368	0.404	0.615	0.715
Group cu	0.426	0.418	0.322	0.414	0.291	0.628	0.744
Perceive	0.621	0.562	0.393	0.503	0.480	0.514	0.464
Competit	0.402	0.464	0.349	0.265	0.247	0.525	0.484
CRM adop	0.444	0.513	0.356	0.455	0.344	0.522	0.738
Informat	0.508	0.457	0.263	0.431	0.337	0.510	0.657
Customer	0.169	0.230	0.084	0.250	0.125	0.314	0.409
Business	0.178	0.269	0.091	0.349	0.261	0.180	0.414
Employee	0.278	0.300	0.211	0.355	0.245	0.381	0.550
Intimacy	0.460	0.491	0.394	0.341	0.349	0.602	0.582

OR .. Correlations of latent variables

	Innovati	Group cu	Perceive	Competit	CRM adop	Informat	Customer
Innovati	1.000						
Group cu	0.679	1.000					
Perceive	0.391	0.392	1.000				
Competit	0.435	0.451	0.493	1.000			
CRM adop	0.551	0.635	0.371	0.430	1.000		
Informat	0.593	0.566	0.458	0.301	0.523	1.000	
Customer	0.210	0.387	0.203	0.211	0.352	0.215	1.000
Business	0.323	0.291	0.154	0.072	0.337	0.356	0.574
Employee	0.384	0.550	0.191	0.211	0.510	0.352	0.524
Intimacy	0.429	0.507	0.430	0.538	0.479	0.385	0.276

OR .. Correlations of latent variables

	Business	Employee	Intimacy
Business	1.000		
Employee	0.511	1.000	
Intimacy	0.242	0.197	1.000

The results demonstrated satisfactory discriminant validity as the AVEs of all latent variables were greater than the correlations with other latent variables in general.

In addition, the analysis results showed that the reliability of the scale was good. Most of the Cronbach alpha values were between 0.8 and 0.9. Detailed figures for each question are shown in the Table 6.18 and Appendix 6.2.

Table 6.18 – Reliability analysis

Construct variable	***No. of items***	***Alpha***
Scale on levels of engagement with CRM	18	0.934
Rogers' attributes of innovation adoption	14	0.868
Perceived accessibility of IT solutions	4	0.821
Competition intensity	6	0.612
Desire of customer intimacy	3	0.674
Attitude towards change	5	0.845
Market orientation	14	0.914
Innovation orientation	3	0.920
Group culture	5	0.891
Information utilisation	7	0.931
Customer satisfaction	3	0.825
Performance	4	0.836
Employee satisfaction	5	0.938

Furthermore, the analysis results which emerged from factor analysis confirmed the validity of the scale. Factor analysis could be a way to provide evidence on construct validity. It could provide a measure of unidimensionality and hence validity. Loadings of items underlying a construct >0.7 support good validity. The details are shown in Appendix 6.3.

In addition, correlation analysis was performed in order to obtain more idea of convergent and discriminant validity. The results showed that the items under particular factor have correlations of 0.6 or above; however, the correlations of items between different underlying factors are only around 0.3. This demonstrated that the items are probably related to a same construct and the constructs are discriminated from each other.

Building in the discussion on reliability and validity checking, the chapter now moves on testing whether there are any differences in the responses in relation to the constructs between CRM adopters and non CRM adopters and estimating with regression analysis and SEM.

6.8 Preliminary testing (t test)

Prior to performing model estimations in relation to the propositions stated in the conceptual framework, t tests were performed in order to assess whether there are any differences in the responses in relation to the constructs between CRM adopters and non CRM adopters. In this case, more insights can be found from the collected information. The value of each underlying factor was represented by adding up its corresponding items since the EFA and CFA showed good and reasonable results *with GFI and CFI values close to or greater than 0.9* on the items' composition. As mentioned before, the self-reported CRM adoption (binary variable on adoption of CRM) and the status concluded from a cluster analysis (multi dimensional scale on levels of engagement with CRM) were also used in the testing. To recap, cluster analysis has been used to find out two segments on the levels of engagement with CRM. 39% of the respondents were regarded as high engagement adopters and 61% of the respondents were regarded as low engagement adopters.

Table 6.19 – t-statistics for the variables (self-reported CRM status)

Variables	N	Mean	Standard deviation	t-statistic
CRM adoption				
CRM adopters	97	3.7	0.639	1.923
Non CRM adopters	118	3.5	0.548	(0.056)
Relative advantage				
CRM adopters	97	4.0	0.614	4.460
Non CRM adopters	118	3.6	0.651	(0.000)**
Compatibility				
CRM adopters	97	3.9	0.666	4.064
Non CRM adopters	118	3.5	0.733	(0.000)**
Complexity				
CRM adopters	97	3.08	0.519	0.147
Non CRM adopters	118	3.07	0.573	(0.883)
Trialabilty				
CRM adopters	97	3.24	0.650	1.424
Non CRM adopters	118	3.12	0.605	(0.156)
Perceived accessibility of IT solutions				
CRM adopters	97	3.95	0.613	1.711
Non CRM adopters	118	3.79	0.732	(0.089)
Competition intensity				
CRM adopters	97	4.14	1.480	1.974
Non CRM adopters	118	3.84	0.692	(0.050)*
Desire of customer				
intimacy	97	4.18	0.530	2.955
CRM adopters	118	3.94	0.641	(0.003)**
Non CRM adopters				
Attitude towards change				
CRM adopters	97	3.89	0.602	1.143
Non CRM adopters	118	3.78	0.687	(0.254)
Customer orientation				
CRM adopters	97	3.85	0.624	2.367
Non CRM adopters	118	3.64	0.686	(0.019)

Variables	**N**	**Mean**	**Standard deviation**	**t-statistic**
Competition orientation				
CRM adopters	97	3.75	0.637	3.440
Non CRM adopters	118	3.42	0.724	(0.001)**
Interfunctional				
coordination	97	3.50	0.706	1.300
CRM adopters	118	3.37	0.743	(0.195)
Non CRM adopters				
Innovation orientation				
CRM adopters	97	3.69	0.776	2.643
Non CRM adopters	118	3.38	0.886	(0.009)**
Group culture				
CRM adopters	97	3.71	0.739	0.892
Non CRM adopters	118	3.62	0.720	(0.374)
Information utilisation				
CRM adopters	97	3.70	0.709	3.546
Non CRM adopters	118	3.33	0.803	(0.000)**
Customer satisfaction				
CRM adopters	97	3.78	0.640	0.011
Non CRM adopters	118	3.78	0.607	(0.991)
Business performance				
CRM adopters	97	3.63	0.581	3.711
Non CRM adopters	118	3.31	0.658	(0.000)**
Employee satisfaction				
CRM adopters	97	3.47	0.830	0.594
Non CRM adopters	118	3.41	0.684	(0.553)

- ( ) represents the p-value of the mean
- * Statistically significant at less than 0.05 level
- **Statistically significant at less than 0.01 level

Table 6.20 – t-statistics for the variables (from results of cluster)

Variables	N	Mean	Standard deviation	t-statistic
CRM adoption				
High engagement adopters	131	3.97	0.347	16.880
Low engagement adopters	84	3.06	0.445	(0.000)**
Relative advantage				
High engagement adopters	131	3.89	0.649	4.356
Low engagement adopters	84	3.51	0.608	(0.000)**
Compatibility				
High engagement adopters	131	3.92	0.673	5.386
Low engagement adopters	84	3.41	0.703	(0.000)**
Complexity				
High engagement adopters	131	3.13	0.582	1.855
Low engagement adopters	84	2.99	0.484	(0.065)
Trialabilty				
High engagement adopters	131	3.33	0.649	4.430
Low engagement adopters	84	2.95	0.519	(0.000)**
Perceived accessibility of IT solutions				
High engagement adopters	131	3.99	0.610	3.445
Low engagement adopters	84	3.67	0.741	(0.001)**
Competition intensity				
High engagement adopters	131	4.09	1.280	2.046
Low engagement adopters	84	3.78	0.752	(0.042)*
Desire of customer intimacy				
High engagement adopters	131	4.20	0.560	5.024
Low engagement adopters	84	3.80	0.593	(0.000)**
Attitude towards change				
High engagement adopters	131	3.98	0.580	4.345
Low engagement adopters	84	3.60	0.682	(0.000)**
Customer orientation				
High engagement adopters	131	4.03	0.547	9.572
Low engagement adopters	84	3.29	0.573	(0.000)**

Variables	**N**	**Mean**	**Standard deviation**	**t-statistic**
Competition orientation				
High engagement adopters	131	3.80	0.634	6.701
Low engagement adopters	84	3.20	0.648	(0.001)**
Interfunctional coordination				
High engagement adopters	131	3.70	0.659	7.500
Low engagement adopters	84	3.02	0.627	(0.000)**
Innovation orientation				
High engagement adopters	131	3.75	0.748	5.449
Low engagement adopters	84	3.15	0.863	(0.000)**
Group culture				
High engagement adopters	131	3.92	0.574	6.960
Low engagement adopters	84	3.28	0.768	(0.000)**
Information utilisation				
High engagement adopters	131	3.78	0.691	7.262
Low engagement adopters	84	3.07	0.710	(0.000)**
Customer satisfaction				
High engagement adopters	131	3.94	0.548	5.084
Low engagement adopters	84	3.52	0.637	(0.000)*
Business performance				
High engagement adopters	131	3.62	0.579	4.883
Low engagement adopters	84	3.20	0.654	(0.000)**
Employee satisfaction				
High engagement adopters	131	3.69	0.662	6.676
Low engagement adopters	84	3.05	0.718	(0.000)**

- ( ) represents the p-value of the mean
- * Statistically significant at less than 0.05 level
- **Statistically significant at less than 0.01 level

Results showed that the perception of CRM adopters and non CRM adopters on many of the constructs were different. As expected, the difference is more significant for the clustering groupings as cluster analysis helped to segment two distinct groups with considerable difference on each item. In particular, high engagement adopters got higher average score in all variables. Statistical models are then run for further testing.

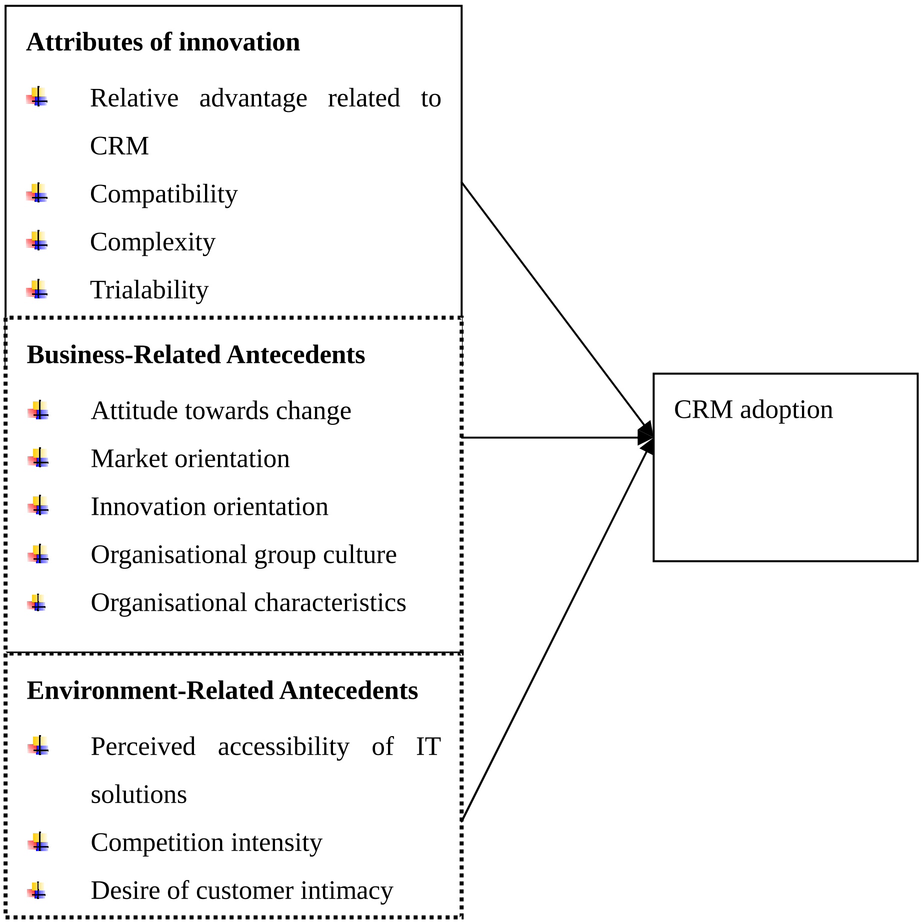
According to the analysis strategy before, regression models will first be performed. The detail is now shown in section 6.9.

6.9 Regression model

One of the objectives in this research is to explore the factors affecting CRM adoption. Figure 6.8 illustrates this part of the concept proposed in the conceptual framework. There are different measures to determine the adoption of CRM. One is using a metric scale and the other one is by using a binary variable.

Figure 6.8 – Conceptual Model (Factors of CRM adoption)

Factors Dependent variable



First, multiple regression was chosen as the method to estimate a model of the factors thought to influence the CRM adoption within service sectors. The metric scale on the levels of engagement with CRM representing CRM adoption in the questionnaire was put as the dependent variable in the model. Items of each construct were added together to form drivers in the model. Second, logistic regression was performed since the dependent variable in the model-CRM adoption can be viewed as a binary variable (both the self reported answer and the clustering solutions) as mentioned in the earlier section. The process of model estimation is now described.

6.9.1 Assumption for regression model

Diagnostic analysis was done prior to the examination of the stepwise models to assure the data were suitable for analysis. This study followed a diagnostic process described by Hair *et al*. (1998) to check for violations of regression assumptions, multicollinearity, and the presence of influential observations. First, the assumption of homoscedasticity is examined. A plot of residuals versus predicted values was done (Appendix 6.1). The results showed that the residuals variance is around zero and it implies that the assumption of homoscedasticity is not violated.

Second, regression model requires independence of error terms. Again, a residual plot shown in Appendix 6.1 can be used to check this assumption. The random and patternless residuals imply independent errors. Third, it is important to note that for regression the normality test should be applied to the residuals rather than raw scores. There is not a general agreement of the best way to test normality. By using normal probability plot, the normal distribution is represented by a straight line angled at 45 degrees. The standard residuals are compared against the diagonal line to show the departure. The plot in Appendix 6.1 shows that most of the residuals are very close to the straight line, hence, the departure from normality is slight.

Linearity is another assumption for multiple regression model. To examine the assumption of linearity, a scatterplot showing each independent variable against the dependent variable would help. I have done the plots and they showed a line trend. As a result, the assumption of linearity seems to be not violated.

Finally, the absence of multicollinearity in the regression model is important. A best approach to identify this problem is by using the Variance Inflation Factor (VIF). The details and figures were shown in section 6.9.2.

Hence, the analysis showed that the data should be appropriate for further analysis. The results of multiple regression are now going to be discussed.

6.9.2 Multiple regression

As described before, multiple regression was used because the metric scale measuring the levels of engagement with CRM in the questionnaire was put as the dependent variable in the model. Answer to each statement related to the levels of engagement with CRM was summed up to a form a dependent variable with continuous scale. At the same time, items of each construct were added together to form drivers in the regression model. The results illustrate how the twelve independent variables affect the levels of engagement with CRM.

Table 6.21 – Significant values of the Multiple regression model

	Model	B	Std. Error	t	P value	VIF
1	(Constant)	.694	.256	2.706	.007*	
	Relative advantage	-.027	.076	-.353	.725	3.032
	Compatibility	.143	.067	2.140	.034*	2.854
	Complexity	.026	.054	.479	.632	1.101
	Trialability	.066	.062	1.064	.289	1.958
	Observability	-.008	.039	-.194	.846	1.853
	Perceived accessibility of IT solutions	-.006	.058	-.098	.922	1.962
	Competitive intensity	.003	.027	.101	.919	1.199
	Attitude towards change	-.042	.069	-.601	.549	2.552
	Market orientation	.493	.089	5.552	.000**	3.778
	Innovation orientation	-.004	.053	-.068	.946	2.597
	Group culture	.150	.063	2.374	.019*	2.762
	Customer intimacy	.031	.063	.490	.625	1.893
	Number of employees	3.98E-006	.000	.180	.857	1.129
	Years of establishment	-.002	.001	-1.558	.121	1.074

a Dependent Variable: CRM adoption (summation of items for levels of engagement with CRM)

R^2 = 76.5%

* Significant at p<0.05

**Significant at p<0.01

F statistic is 18.0 with p<0.01 for the regression analysis. As can be seen from the t-test, *Compatibility* and *Group Culture* were significant at the 5% level; *Market Orientation* was significant at 1%. The results indicate that compatibility, group culture and market orientation are the drivers affecting the levels of engagement with CRM. Drivers with p-value higher than 0.05 were regarded as insignificant. The results are a bit surprising as quite a number of them are not significant drivers in affecting the levels of engagement with CRM.

When examining the regression model, it is important to examine the goodness of fit for the model. The coefficient of determination R^2 of 76.5% was calculated, indicating that the model is fairly fitted, despite the fact that relatively few of the explanatory variables appear to be significant. In addition, multiple regression assumes that there is no multicollinearity amongst the independent variables. In order to test for this, tolerance levels and associated variation inflation factors were examined. The lowest tolerance was 0.33 and the highest VIF was 3.03. Tolerance close to 0 or with a high VIF indicates high multicollinearity. Hence, the results showed that multicollinearity seems not to be a problem and the regression model is stable.

6.9.3 Logistic regression

Again, as explained earlier, logistic regression was performed when the dependent variable in the model-CRM adoption can be viewed as a binary variable (both the self-reported answer and the clustering solutions). Logistic regression was then generated using the twelve independent variables and the binary classification on CRM adoption as dependent variable. Table 6.22 to 6.25 offer a detailed description of the output of the analysis.

Self-reported CRM adoption

Table 6.22 – Significant values of the Logistics regression model

	B	S.E.	Wald	Sig.	Exp(B)
Relative advantage	1.292	.448	8.304	.004**	3.639
Compatibility	.319	.400	.637	.425	1.376
Complexity	-.430	.314	1.883	.170	.650
Trialability	-.063	.358	.030	.862	.939
Observability	.092	.225	.168	.682	1.096
Perceived accessibility of IT solutions	-.549	.336	2.674	.102	.577
Competitive intensity	.383	.304	1.586	.208	1.466
Attitude towards change	-1.035	.419	6.110	.013**	.355
Market orientation	.410	.531	.594	.441	1.506
Innovation orientation	.374	.321	1.355	.244	1.453
Group culture	-.670	.370	3.279	.070*	.512
Customer intimacy	.680	.372	3.353	.067*	1.974
Number of employees	.000	.000	2.761	.097*	1.000
Years of establishment	.009	.006	2.106	.147	1.009
Constant	-3.946	1.538	6.579	.010	.019

a Variable(s) entered on step 1: RA, Compat, Complex, Trial, q19, IT, compte, change, MO, IO, GC, intimacy, q82, q83.

* Significant at $p<0.1$

**Significant at $p<0.05$

Table 6.23 – Classification table

Classification Table[a]

Observed		Predicted: Is your company using CRM? no	Predicted: Is your company using CRM? yes	Percentage Correct
Is your company using CRM?	no	91	23	79.8
	yes	32	57	64.0
	Overall Percentage			72.9

a. The cut value is .500

It was shown that *Relative Advantage* and *Attitude towards change* were significant at the 5% level; three variables were significant at the 10% level namely: *Customer intimacy*, *Group culture* and *Number of employees*. The results indicated that relative advantage of CRM adoption, attitude towards change of top management, desire of customer intimacy, organisational group culture and size of company are drivers of CRM adoption. Overall, 72.9% of the cases were correctly classified.

Clustering solutions on CRM adoption based on the scale of levels of engagement with CRM

Table 6.24 – Significant values of the Logistics regression model

	B	S.E.	Wald	Sig.	Exp(B)
Relative advantage	-.035	.506	.005	.945	.966
Compatibility	.563	.448	1.582	.208	1.757
Complexity	.292	.395	.547	.460	1.339
Trialability	.097	.427	.052	.820	1.102
Observability	-.011	.253	.002	.966	.989
Perceived accessibility of IT solutions	.187	.377	.245	.620	1.206
Competitive intensity	-.131	.158	.685	.408	.877
Attitude towards change	-.803	.458	3.070	.080*	.448
Market orientation	3.363	.674	24.915	.000**	28.883
Innovation orientation	-.365	.339	1.159	.282	.694
Group culture	.588	.399	2.171	.141	1.800
Customer intimacy	-.033	.414	.007	.936	.967
Number of employees	.000	.000	.153	.695	1.000
Years of establishment	-.005	.007	.425	.515	.996
Constant	-12.245	2.373	26.618	.000	.000

a Variable(s) entered on step 1: RA, Compat, Complex, Trial, q19, IT, compte, change, MO, IO, GC, intimacy, q82, q83.

* Significant at p<0.1

**Significant at p<0.01

Table 6.25 – Classification table

Classification Table[a]

Observed		Predicted: Cluster Number of Case: CRM non adopter	Predicted: Cluster Number of Case: CRM adopter	Predicted: Percentage Correct
Cluster Number of Case	CRM non adopter	58	23	71.6
	CRM adopter	14	110	88.7
	Overall Percentage			82.0

a. The cut value is .500

It was shown that *Market Orientation* was significant at the 1% level. *Attitude towards change* was significant at the 10% level. The outcome pointed out that market orientation of a firm and attitude towards change of top management are drivers of levels of engagement with CRM. Overall, 82% of the cases were correctly classified.

As with multiple regression, it is important to examine the goodness of fit for the logistic regression model. A measure of model fit is in the Hosmer and Lemeshow value, which measures the correspondence of the actual and predicted values of dependent variables. Smaller difference in the observed and predicted classification indicate a better model fit, hence a good model fit is indicated by a non-significant chi-square value (Hair *et al*. 1998). Non-significant Hosmer and Lemeshow chi-square values were observed for the models with self reported CRM adoption (4.172) and clustered results on CRM adoption (7.693). This provides more evidence that the fitting models were stable.

In addition, the "pseudo R^2" measure examined the improvement in the 2LL value from the base model to the final model, and is similar to the R^2 used within multiple regression (Hair *et al.*, 1998). The -2LL measure compares the model to a "perfect model" in which all cases would be correctly classified (Pampel, 2000). Since the -2LL value has no insightful meaning, as it depends on the sample size, number of parameters and goodness of fit, it should be compared to the base model value which assumes that all coefficients are zero and only the constant term is included in the model (Pampel, 2000). For the self-reported CRM model, a "pseudo R^2" of 28.3% was calculated, indicating that the model provides an improvement of 28.3% above the base model. For the cluster results CRM model, a "pseudo R^2" of 48.9% was calculated, indicating that the model provides an improvement of 48.9% above the base model.

As reported in the earlier section, results on the direct question for CRM usage and results to the series of questions on the CRM adoption based on the scale on the levels of engagement with CRM will be used in the further analysis so as to have an objective analysis for CRM situation in this research. As a result, multiple regression is used when the answers to the series of statement related to the levels of engagement with CRM were added together to form a dependent variable in a continuous scale. Logistic regression is used when binary scale (self -reported categorization and clustering solutions) was used as dependent variable.

By comparing the results obtained from the two different types of regression models, it can be seen that measurement can impact on the results. The significant factors were found not to be the same under different methods of regression estimation. Only Market Orientation and Group Culture were found to be the common significant factors influencing CRM adoption. In other words, when the CRM adoption was measured by metric scale or binary variable, both Market Orientation and Group Culture were found to be the significant drivers for CRM adoption. This suggests that we may be relatively confident about their relevance to the CRM adoption as they are consistently significant under different types of regression estimation.

Among the logistic regression models with different categorisations on CRM adoption (self-reported and clustered results based on metric scale), only the Attitude Towards Change was found to be the common significant factor in affecting CRM adoption. The difference in results between the two models should be mainly due to the nature of the dependent variable. The self-reported CRM adoption situation may not be consistent with the answers to the metric scale on CRM adoption, hence, different significant factors were found. In addition, although the clustered categorisation on CRM adoption was based on the metric scale measuring the levels of engagement with CRM, the information has been grouped and summed. As a result, different factors were found significant.

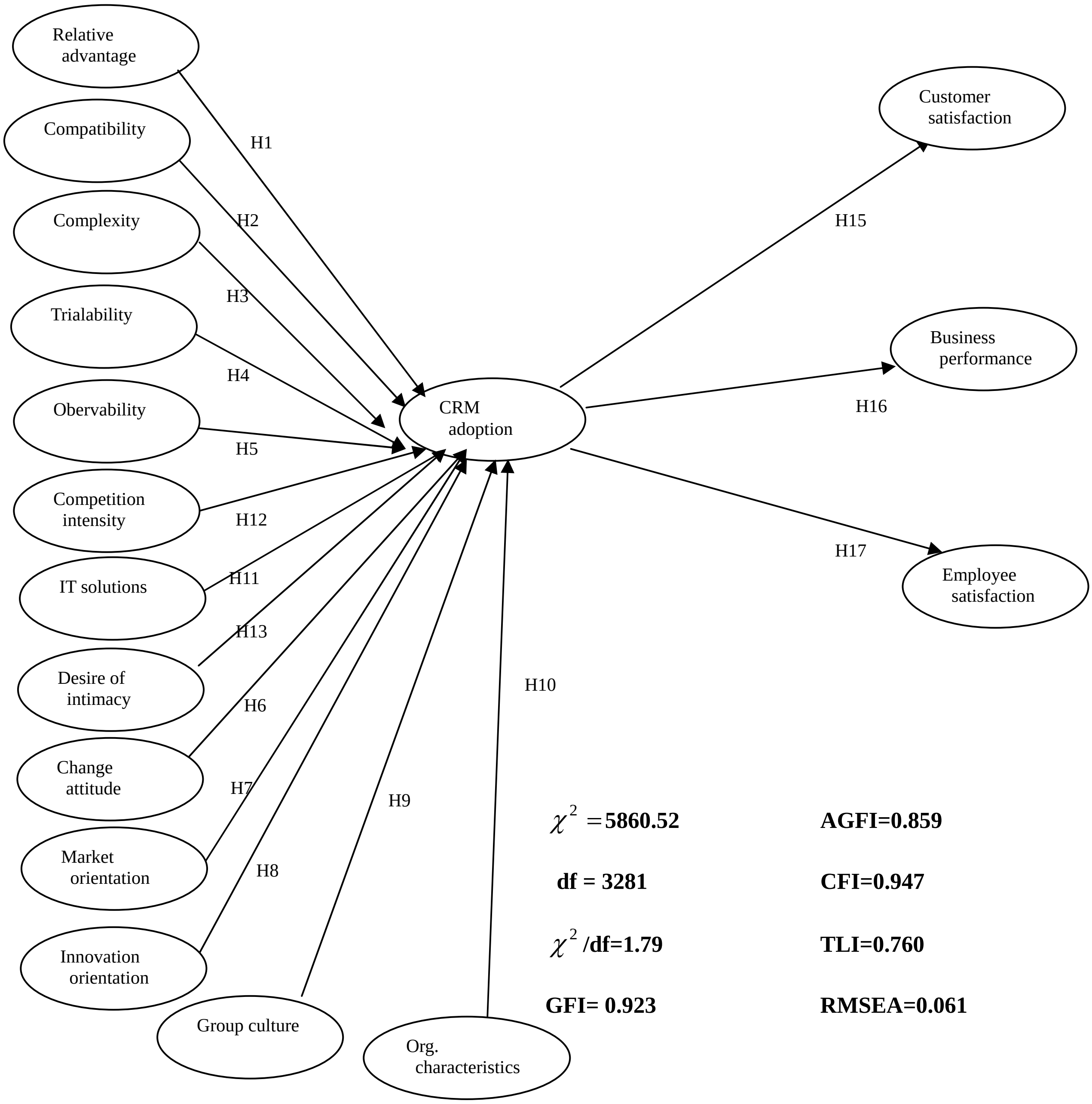
Due to the inconsistent outcomes derived from the regression models and only a few factors were found to be significant using regression models, therefore, SEM was finally employed as it was felt to be a better technique in order to examine the objectives of this research. Also, it should be better to measure the CRM adoption as a continuous variable. Section 6.10 will present the results of SEM.

6.10 Structural Equation Model (SEM)

SEM was run with the hypothesised relationships proposed in chapter 4. That means the impact of CRM adoption and the mediating effect between drivers and impact can be investigated as a whole. Unlike regression models, individual items for measuring the levels of engagement with CRM rather the sum of the items can be used in the SEM model. The model structures were shown in figures 6.9 and 6.10. A two-step approach proposed by Anderson and Gerbing (1988) was employed. The first step entails confirmatory factor analysis, applied to all the eighteen measurement models simultaneously. The rationale for this first step is to avoid unknown "interaction effects" of the measurement and structural models. In fact, the assessment of that should have already been reflected in the previous section about reliability and validity of the measurement model. The second-step required testing of the hypothesized dependence relationships between the proposed structural model's constructs. The objective was to "show that the operationalisation of the theory being examined was corroborated and not disconfirmed by the data" (Gefen *et al*., 2000, p.24-25).

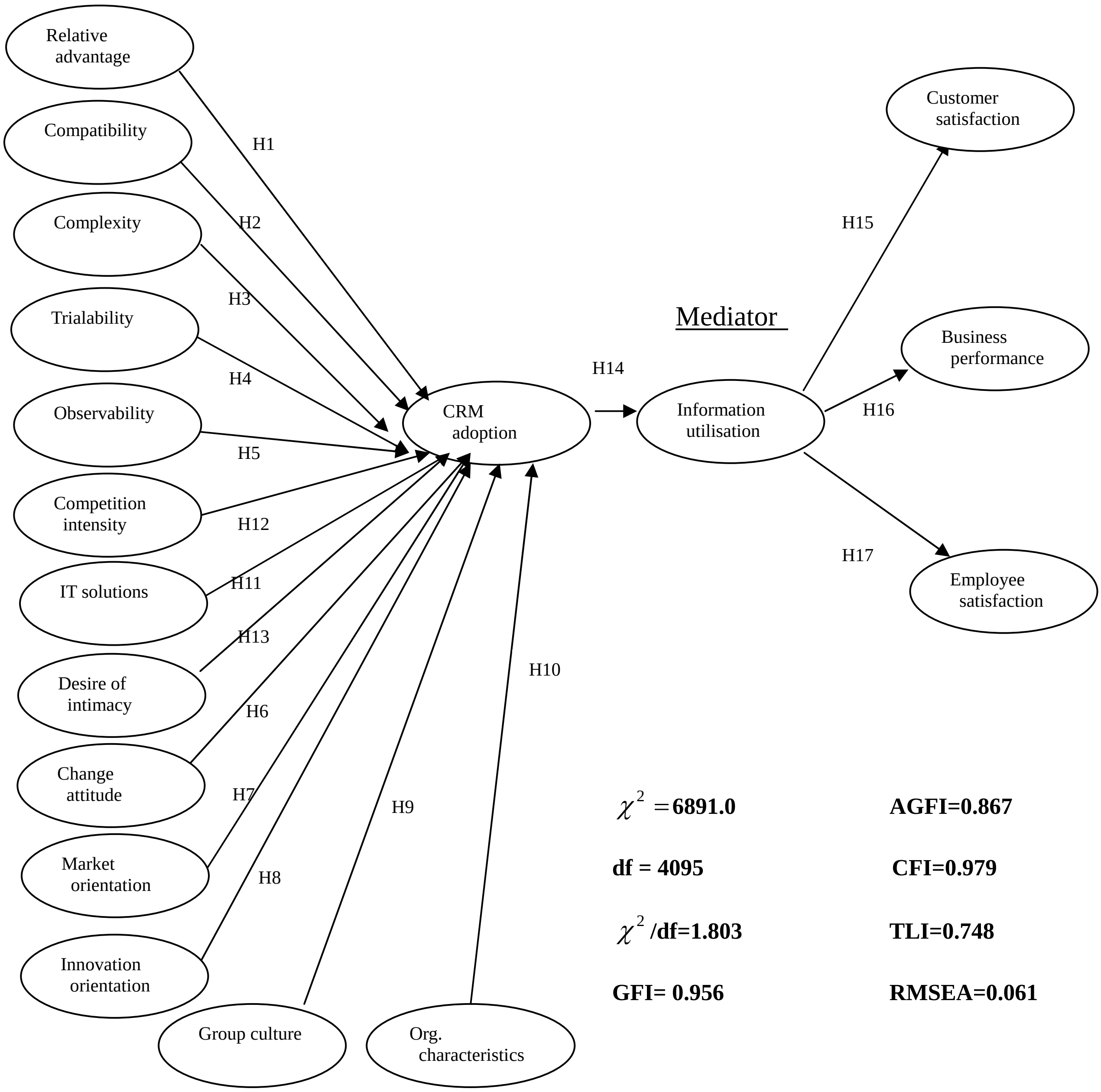
Firstly, the hypothesised model without mediator was depicted (model 1). CRM adoption is depicted as a composite construct arising from the proposed drivers (H1 – H13), then CRM adoption is expected to influence the organisational performance including customer satisfaction, business performance and employee satisfaction (H15-H17). The composite construct, CRM adoption , was formed by linking the 18 items representing four major dimensions of levels of engagement with CRM: key customer focus, CRM organisation, knowledge management and technology (see chapter 5) together (i.e. a single variable with 18 indicators). The hypothesised relationships were examined during the second-step of SEM estimation procedure. All cases were used in the analysis and a metric scale of CRM adoption (items were aggregated) was used in the model. After running an SEM analysis, goodness of fit tests were examined in order to determine if the model should be accepted or rejected. The common tests include *Chi-square*, *GFI*, *CFI*, *TLI*, *AGFI*, *and RMSEA*. These indicators were incorporated into the model as fully disaggregated and their meanings have already been explained in the earlier section in this chapter. At the same time, modification indices (MI) were examined in order to find out if there is potential weakness in the proposed model or there are some other ways to improve the model. For each fixed parameter specified, AMOS provides an MI - the value of which represents the expected drop in overall chi-square value if the parameter were to be freely estimated in a subsequent run. All freely estimated parameters automatically have MI values equal to zero. No large MI was suggested between two constructs; hence, no significant improvements were likely. Finally, the data in this study exhibit an acceptable level of fit without the mediator (χ^2 /df=1.79, p=0.000; GFI=0.923; RMSEA=0.061; CFI=0.947; TLI=0.760 and AGFI=0.859). The relatively low value for the AGFI reflects the relatively large number of paths in the model, but given that other measures of goodness of fit were better, this was not seen as a basis for rejecting the model.

Figure 6.9 CRM adoption model without mediator (Model 1)



Secondly, it is to adopt a competing model of the similar relationship as model 1 (H1-H13) (model 2) by adding information utilisation as mediator (H14) because information utilisation was believed to have a mediating effect between CRM adoption and organisational performance (H15 – H17). The results are as follows.

Figure 6.10 CRM adoption model with mediator (Model 2)



Same as model 1, MIs were used as a clue for suggesting any path to improve the specification of the structural model in order to decrease the chi-square value. As no large MI was found between two constructs, no new path was added to the model. Finally, the estimation results indicate that the model also provides acceptable level of fit (χ^2 /df=1.803, p=0.000; GFI=0.956; RMSEA=0.061; CFI=0.979; TLI=0.748 and AGFI=0.867). Hence, it offers support for the hypothesised model relationship.

Although the *p* values of the models are significant, Hair *et al*. (1998) suggest that the chi square statistic is sensitive to sample sizes and is more appropriate for sample sizes between 100 and 200, with the significance test becoming less reliable with sample size outside this range. Therefore, other absolute and incremental fit measures are more suitable for assessing fit.

The results demonstrated that there are significant relationships between most of the antecedents and CRM adoption as well as between CRM adoption and consequences. Two hypotheses were not fully supported in each model in the analysis. The summary of the standardised parameters is presented in table 6.26.

Table 6.26 – Summary of parameter estimates

Hypothesis	***Path***	***Standardised path estimate (Model 1)***	***Standardised path estimate (Model 2)***
H1	Relative advantage → CRM adoption	0.12**	0.45**
H2	Compatibility →CRM adoption	0.27**	0.55**
H3	Complexity → CRM adoption	-0.75*	-0.98*
H4	Trialability → CRM adoption	0.82**	0.52**
H5	Observability →CRM adoption	0.35**	0.66**
H6	Attitude towards change → CRM adoption	0.13*	0.11*
H7	Market orientation → CRM adoption	0.87**	0.10**
H8	Innovation orientation → CRM adoption	0.46**	0.43**
H9	Group culture →CRM adoption	0.12(p>0.10)	0.42(p>0.10)
H10a	Size of organisation →CRM adoption	0.30 (p>0.10)	0.44(p>0.10)
H10b	Year of establishment →CRM adoption	0.70 (p>0.10)	0.41(p>0.10)
H11	IT solutions →CRM adoption	0.85**	0.18**
H12	Competitive environment →CRM adoption	0.12**	0.12**
H13	Customer intimacy → CRM adoption	0.65**	0.18**
H14	CRM →Information utilization	-	0.58*

Hypothesis	***Path***	***Standardised path estimate (Model 1)***	***Standardised path estimate (Model 2)***
H15	CRM/information utilization → customer satisfaction	0.35**	0.54**
H16	CRM/information utilization → employees' satisfaction	0.59**	0.61**
H17	CRM/information utilization→ business performance	0.27**	0.36**

**Significant at p<0.01
* Significant at p<0.05

I would prefer model 2 rather than model 1 because it shows good fit as model 1. Although the significant factors are similar in both models, the construct - information utilisation fits well as a mediator in model 2. It seems that my conceptual framework applies in the services sector of Hong Kong based on the result of this research.

The results in model 2 revealed 1) no coefficients with signs contrary to what theory would suggest and 2) nearly all standard errors seem small as indicated by large t-ratios. Hence, it indicates a quite good fit of internal structure of the model with most items of significant coefficients according to the criterion proposed by Bagozzi and Yi (1988). Finally, there were no negative variance estimates in the latent variable and the error covariance matrices. These results revealed that no obvious mis-specifications and supported that most of the hypothesized questions was satisfactory.

In addition, size of the coefficients in the measurement model would indicate the degree of effect of the independent variables on the dependent variable. It was found that the five attributes of innovation proposed by Rogers' got the relative higher coefficients. These results are consistent with my expectation as those attributes are well known factors for innovation adoption. Besides, the coefficient of innovation orientation is also high. This construct was not specially mentioned by the respondents in the interviews. However, here shows that organizations really consider about innovation orientation when they adopt CRM.

Continuing the description of the analysis results, the next section will summarise the findings in relation to the hypotheses.

6.11 Interpretations of the results in relation to hypotheses

In addition to the specific findings associated with the hypotheses, two broad additional sets of observations emerge. The first relates to the issue of SEM versus regression and the impact of different forms of estimation on the results obtained. The second relates to different approaches to measurement and the way in which this might impact, particularly in relation to the concept of CRM adoption, which might appear to be straightforward but in practice may be interpreted quite differently, particularly so when measured by a direct question. The following table summarise which variables are significant for which type of estimation and which type of measurement.

Table 6.27 – Summary table on different types of estimation

✓ means significant × means insignificant **Factors/impacts**	**Multiple regression** CRM adoption as metric scale (average of a series of statements on levels of engagement with CRM)	**Logistic Regression** CRM adoption as binary variable (Self - reported)	**Logistic Regression** CRM adoption as binary variable (Cluster solutions based on the series of statements on levels of engagement with CRM)	**SEM** CRM adoption was a scale taking into account each item on levels of engagement with CRM **without mediator*	**SEM** CRM adoption was a scale taking into account each item on levels of engagement with CRM **with mediator*
Relative advantage	×	✓	×	✓	✓
Compatibility	✓	×	×	✓	✓
Complexity	×	×	×	✓	✓
Trialability	×	×	×	✓	✓
Observability	×	×	×	✓	✓
Perceived accessibility of IT solutions	×	×	×	✓	✓
Competitive intensity	×	×	×	✓	✓
Attitude towards change	×	✓	✓	✓	✓
Market orientation	✓	×	✓	✓	✓
Innovation orientation	×	×	×	✓	✓
Group culture	✓	✓	×	×	×
Customer intimacy	×	✓	×	✓	✓
Number of employees	×	✓	×	×	×
Years of establishment	×	×	×	×	×
Information utlilisation	NA	NA	NA	NA	✓
Customer satisfaction	NA	NA	NA	✓	✓
Employee satisfaction	NA	NA	NA	✓	✓
Business performance	NA	NA	NA	✓	✓

It can be seen that there are some inconsistencies between the results of SEM and the solutions of the multiple regression and logistic regression models. It is not surprising to see such differences because SEM is a more powerful tool to validate the measurement instruments as well as to test the hypothesised relationship in a model and even propose new relationships between constructs based on the modification indices for taking into account the measurement errors.

In this research, it was found that some results of SEM overlapped with results of the regression analysis (*Market Orientation* and *Attitude Towards Change*). To recap, the scores given by the respondents to the individual items representing the dependent variable (CRM adoption) were directly used in SEM for estimation. In multiple regression, the scores given to items for the levels of engagement with CRM were added together to form one variable as the dependent variable for estimation. In logistic regression, a binary variable was used as the dependent variable by using the self-reported answers on CRM adoption or the cluster grouping based on the scores given to the items of levels of engagement with CRM. Although the way in defining the dependent variable is varied, the consistency of the results across different forms of estimation on the dependent variable suggested that the overlapped independent variables are relevant irrespective of how CRM adoption is measured.

Building on the results found by regression model, SEM even suggested more significant drivers. Therefore, the results of SEM are concluded to be the final result. In other words, by treating the CRM adoption as continuous dependent variable with different items rather than using combined items or binary variable gives more significant relationships between the drivers and the CRM adoption. The results of SEM also suggest that there is a mediator between SEM and organisational performance and a significant effect of CRM on organisational performance. During the analysis of SEM, the model with mediator (model 2) showed as good fit as the model without mediator (model 1). When examining the coefficients of the estimated models, it was also found that the estimated path coefficients in model 2 were significant in the predicted directions except group culture and organisational characteristics. Hence, the final results are concluded from the analysis outcome of the hypothesised model 2. The results according to each proposition will further be explained below.

i. Hypotheses 1 to 5: Rogers' (1962) attributes of innovation

Rogers' attributes of innovation include relative advantage, compatibility, complexity, trialability and competition. The results indicated that all attributes of innovation were found to be positively related to the levels of engagement with CRM with large coefficient score except complexity. The negative relationship between complexity and the levels of engagement with CRM was demonstrated by the negative parameter estimate of complexity (-0.98). The findings are consistent with the literature review due to the innovation characteristics in the definition of CRM adoption and support the views given by the practitioners during the qualitative interviews.

ii. Hypothesis 6: Attitude towards change

The path between attitude towards change and levels of engagement with CRM was statistically significant and supports hypothesis 6 with a significant path estimate of 0.11. This finding suggests that the use of CRM is more sophisticated when the attitude towards change of top management is more positive.

iii. Hypothesis 7: Market orientation

Research question 7 hypothesised that market orientation is related positively to the levels of engagement with CRM. This hypothesis was supported by the estimated path parameter (0.10, $p<0.01$) indicating that the higher the market orientation, the more sophisticated the use of CRM. The results confirmed the findings obtained from the qualitative interview.

iv. Hypothesis 8: Innovation orientation

The hypothesised relationship between innovation orientation and the levels of engagement with CRM was found to be statistically significant with an estimate of 0.43. This finding supports hypothesis 7 and suggests that the higher the innovation orientation, the more sophisticated the use of CRM. The results provide quantitative support to the relationship as this construct was not explicitly mentioned during the qualitative interviews with the practitioners.

v. Hypothesis 9: Group culture

Although a positive relation between group culture and CRM adoption was expected from the literature review chapter and qualitative interviews findings, the path was insignificant. By focusing the results from SEM estimation, this finding appears to suggest that when companies decide to adopt CRM, group culture may not be an important factor for consideration. Although insignificant, the results indicated a positive path (+) for the relationship with the levels of engagement with CRM . During the interviews, participants indicated that the company values and staff's thinking would have influence on the adoption of CRM decisions.

vi. Hypothesis 11: Perceived accessibility of IT solutions

Similarly, support was found for hypothesis 11 that the higher the perceived accessibility of CRM related IT solutions, the higher the levels of engagement wirh CRM. It was indicated by the path estimate of 0.18 ($p<0.01$). The result is consistent with the literature in that the availability of IT solutions in the market allows organisations to implement CRM easier.

vii. Hypothesis 12: Competitive environment

The significant relationship between competition intensity and the levels of engagement with CRM indicates support for hypothesis 12 with a significant path coefficient of 0.12, suggesting a competitive environment makes organisations adopt CRM.

viii. Hypothesis 13: Desire of customer intimacy

Findings support the positive relationship (0.18, $p<0.01$) between desire of customer intimacy and levels of engagement with CRM. The results confirmed the findings from the qualitative interviews though not many papers explicitly investigated the driver role of the wish in creating customer intimacy to CRM adoption.

ix. Hypothesis 14: Information utilisation

In order to test the mediation effect of information utilisation, two models were developed using AMOS. The first model was tested without the mediator and the second one with the mediator. Both models fit the data appropriately (as shown in figures 8 and 9). In fact, as the differences between the two models were small for some criteria, the fully mediated model is reasonable and a more useful representation of the relationships among the constructs. Therefore, hypothesis 14 is accepted. A significant parameter of 0.58 ($p<0.05$) was calculated.

x. Hypotheses 15 to 17: Consequences

The analysis results also indicate that a higher levels of engagement with CRM leads to higher customer satisfaction, business performance and employees' job satisfaction through the mediator effect of information utilisation. They are demonstrated by the path parameter estimates (0.54, $p<0.01$; 0.61, $p<0.01$; 0.36, $p<0.01$) respectively.

xi. Hypothesis 10: Organisational characteristics

Organisational characteristics including size of organisation and year of establishment were put into the SEM model for testing. The results showed that both dimensions did not affect the levels of engagement with CRM which was demonstrated from the insignificant path parameter estimates (0.44, $p>0.1$; 0.41, $p>0.1$) respectively.

Table 6.27 summarises the support from the analysis.

Table 6.27 – Support for propositions from the analysis

Number	***Hypotheses***	***Support***
H1	*The greater the level of relative advantage associated with CRM, the higher the levels of engagement with CRM.*	Supported
H2	*The greater the compatibility associated with CRM, the the higher the levels of engagement with CRM.*	Supported
H3	*The lower the complexity associated with CRM, the higher the levels of engagement with CRM.*	Supported
H4	*The easier trialability associated with CRM, the higher the levels of engagement with CRM.*	Supported
H5	*The greater observability associated with CRM, the the higher the levels of engagement with CRM.*	Supported
H6	*The levels of engagement with CRM is higher if the managers' attitude towards change is more positive.*	Supported
H7	*The levels of engagement with CRM is higher if the market orientation of the organisation is higher.*	Supported
H8	*The levels of engagement with CRM is higher if the innovation orientation of the organisation is higher.*	Supported
H9	*The levels of engagement with CRM is higher if the group culture of the organisation is stronger*.	Not Supported
H10	*The adapters' characteristics (company size and year of establishment) affect the levels of engagement with CRM.*	Not Supported
H11	*The perceived accessibility of CRM related IT solutions, the higher the level of engagement with CRM.*	Supported

Number	***Hypotheses***	**Support**
H12	*The more intense the firm's competitive environment, the the higher the level of engagement with CRM.*	Supported
H13	*The level of engagement with CRM is higher if companies desire to create stronger customer intimacy.*	Supported
H14	*The better the information utilisation, the stronger the effects of CRM adoption on customer satisfaction, customer retention, employees' job satisfaction, organisational commitment and business performance.*	Supported
H15	*The levels of engagement with CRM lead to an increase in customer satisfaction and customer retention.*	Supported
H16	*The levels of engagement with CRM leads to stronger employees' job satisfaction and organisational commitment.*	Supported
H17	*The levels of engagement with CRM leads to better business performance.*	Supported

6.12 Conclusions

Seventeen hypotheses developed in the conceptual model in the previous chapter were tested in this chapter. The respondents' profile was examined and believed to be representative in reflecting the opinions of practitioners in Hong Kong about the CRM adoption decisions. Sophisticated analysis methods were employed to investigate which factors were likely to influence the CRM adoption in organisations in the services sector in Hong Kong.

Regression model was first used to test the significance of the proposed drivers to CRM adoption since the regression model was a common method to find a relationship between factors and dependent variables. Then, SEM was developed and used to conclude the final results because SEM is a more powerful analysis method to test the relationship pattern between constructs due to less limitations and assumptions. Construct validity and reliability values supported the model's reliability and satisfied the benchmark levels. Discriminant validity of the model was clearly established.

Once the measurement model was accepted, the structural relationships among the latent variables were tested. These relationships were justified in the literature review and subsequently continued throughout the exploratory interview of the research. The structural relationships outlined in the model also reflected the two key research objectives. 17 hypotheses were developed from these and presented with appropriately justified structural paths.

Measures of fit were developed for the structural model and all structural path estimates were calculated and presented. The results of SEM were encouraging with an acceptable model fit, supporting nearly all hypotheses proposed in the conceptual framework except relationship between group culture, organisational characteristics and CRM adoption. Competing models (with and without mediator) analysis was also performed. Results showed that the mediating effect of information utilisation was significant.

During the analysis, problem arises because of not large sample size collected from the survey. Due to the sample size limitation, only two clusters of the levels of engagement with CRM could be used for further analysis. In addition, the goodness of fit in the SEM estimation would be better if the sample size is larger as there are quite a number of variables in estimating the model. These related issues expanded upon in the final chapter.

Having now completed the analysis phase of the research, the next and final chapter will detail the analysis results regarding the research objectives. Also, it will discuss the implications of this research in the context of academic understanding and practitioner activity. Finally, the limitations of this study will be examined together with further research directions.