CHAPTER VI

RESEARCH RESULTS AND FINDINGS II

This chapter discusses the findings from the standard statistical tests for logistic regression. Analysis of residuals to determine the influence of outliers and multicollinearity tests to determine the reliability of the logistic regression results was conducted. The overall goodness of fit of the model was analyzed using R^2, model χ^2 and Hosmer and Lemeshow goodness-of-fit test. Wald statistic was used to determine support for the research hypotheses. The logit coefficients were interpreted using change in log odds and percentage change in odds. The accurate prediction of group membership is assessed using classification tables and indices of predictive efficiency and their statistical significance are discussed.

6.1 Introduction

The binomial logistic regression technique was selected because the dependent variable is nonmetric and dichotomous and the independent variables are ordinal and interval. Binomial logistic regression is preferred over discriminant analysis in this study because it is a more robust technique and requires fewer assumptions. It does not have to strictly meet the assumptions of normally distributed variables, homoscedasticity and linearity of relationships between independents and the dependent (Hair et al., 1998).

The logistic regression model which is based on the conceptual model for EDI adoption is specified as follows:

$$\ln \frac{p}{1-p} = \begin{array}{l}\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \\ \beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_{11} + \beta_{12} X_{12}\end{array} \qquad (6.1)$$

where p = probability of adoption, 1 – p = probability of nonadoption

β_0 = constant and β_i = logistic regression coefficients for i = 1, … ,12

X_1 = Capital size

X_2 = Top Management Support

X_3 = Information Technology Capability

X_4 = Internal Championship

X_5 = External Pressure

X_6 = Interorganizational Trust

X_7 = Legal Framework

X_8 = Costs

X_9= Risks X_{10} = Security

X_{11} = Technological Complexity X_{12} = Benefits

The tests of the twelve research hypotheses is equivalent to testing whether the coefficients β_1 to β_{12} are significantly different from zero, i.e. $\beta_1 = \beta_2 = \ldots = \beta_{12} = 0$. Significant and positive coefficients imply adoption facilitators while significant and negative coefficients imply adoption inhibitors. The binomial logistic regression results are presented next.

Statistical tests for standard logistic regression as proposed by Tabachnick and Fidell (2001: 562) are reported in the following sections. The first four tests are necessary to ensure that the sample is adequate for logistic regression tests. The recommended tests are checks for (1) Adequacy of expected frequencies (if necessary). This test is omitted because the expected frequencies are adequate. (2) Outliers in the solution (if fit inadequate), (3) Multicollinearity, (4) Evaluation of overall fit. If overall fit is adequate then (a) Significance of tests for each predictor and (b) Parameter estimates, (5) Odds ratio, (6) Classification of prediction success table and (7) Interpretation in terms of means and /or percentages are performed.

6.2 Analysis of Residuals

Residuals analysis is used to identify cases for which the model works poorly or cases that exert more than their share of influence on the estimated parameters of the model (Menard, 2002). Studentized residual, the leverage and the dbeta are the diagnostics used.

Studentized residuals with values less than -3 and greater than +3 deserve closer attention; values less than -2 or greater than +2 may also be of some concern. The leverage of any case is $p = (k + 1)/n$ where k is the number of independents and n is the sample size. Leverage values several times the value of p deserve closer attention. A criterion for identifying cases which fit poorly is those with dbeta > 1.0.

Table 6.1 presents the results from analysis of residuals. All cases in the sample have positive and negative dbetas very close to 0.00. This result shows that the dbeta statistic did not identify any poor fitting cases. The leverage statistic p = (12 + 1)/284 has a value of 0.05 for the full model. Both the cases number 90 and 170 have a leverage of 0.17 and 0.08 respectively. These two values are between two to three times larger than the p value of 0.05 and need closer attention. Four cases with case number 17, 63, 178 and 264 have studentized residuals of 2.19, 2.06, 2.12 and 2.42 respectively and need closer attention. These four cases (outliers) were found to exert inordinate influence on the logistic regression model and were removed from sample. Logistic regression analysis was run without the outliers.

6.3 Assessing Multicollinearity

Multicollinearity results in larger portions of shared variance and lower levels of unique variance from which the effects of the individual independent variables can be determined. As multicollinearity increases, the total variance explained decreases and the amount of unique variance for the independent variables is reduced to levels that make estimation of their individual effects quite problematic (Hair et al., 1998).

The degree of multicollinearity and its effects on the logistic regression results are examined in the following sections. Remedies for collinearity are required if high levels of multicollinearity are identified.

Each of the 12 independent variable (taken as the dependent variable) was regressed once against the other 11 independent variables. The result is 12 regression models for each independent variable taken as the dependent variable. Table 6.2 summarizes the R^2 value, tolerance statistic and VIF values from these 12 regression models**.**

Tolerance as defined below is computed:

$$\text{Tolerance} = 1 - R_x^2 \qquad (6.2)$$

where R_x^2 is the variance in each independent variable x, explained by all of the other independent variables.

The VIF value, which is the inverse of tolerance, i.e. VIF = 1/tolerance is also computed. A very low tolerance and hence high VIF value denote high collinearity. A common cutoff threshold is a tolerance value of 0.10 which corresponds to a VIF value of above 10. This also corresponds to a multiple correlation of 0.95.

The R^2 and tolerance values in Table 6.2 do not show the presence of multicollinearity

Table 6.2: Multicollinearity Tests

Dependent Variable	R-Square	Tolerance*	VIF**
Capital Size	0.04	0.96	1.05
Top Management Support	0.58	0.42	2.40
Information Technology Capability	0.51	0.49	2.04
Internal Championship	0.49	0.51	1.96
External Pressure	0.55	0.45	2.21
Interorganizational Trust	0.73	0.27	3.76
Legal Famework	0.55	0.45	2.22
Costs	0.42	0.58	1.73
Risks	0.70	0.30	3.30
Security	0.70	0.30	3.30
Complexity	0.38	0.62	1.61
Benefits	0.38	0.62	1.62

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6.4 Test of Nonlinearity in the Logit

Box-Tidwell transformation (Hosmer and Lemeshow, 1989, 2000) was used to test for nonlinearity in the logit. The Box-Tidwell transformation involves adding a term of the form (X)(lnX) to the logistic regression equation. A statistically significant coefficient for this variable implies there is evidence of nonlinearity in the relationship between logit(Y) and X.

12 terms of the form (X)(lnX) were added, one term for each of the independent variables in the logistic regression model. A logistic regression run was performed.

Table 6.3 presents the results of the Box-Tidwell test for nonlinearity in the logit. All the 12 interaction terms were not found to be statistically significant at an alpha level of 0.05. The Box-Tidwell tests show that nonlinearity does not exist in the relationship between logit(Y) and the independent variables X.

Table 6.3: Test of Nonlinearity in the Logit

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
Capital Size	4.16	4.22	0.97	1.00	0.32	63.81
Top Management Support	4.04	3.94	1.05	1.00	0.31	57.10
Information Technology Capability	-0.85	4.57	0.03	1.00	0.85	0.43
Internal Championship	-1.60	2.05	0.61	1.00	0.44	0.20
External Pressure	3.37	3.42	0.97	1.00	0.32	28.94
Interorganizational Trust	9.32	5.51	2.86	1.00	0.09	11149.14
Legal Framework	-2.74	2.71	1.02	1.00	0.31	0.06
Cost	-2.30	4.14	0.31	1.00	0.58	0.10
Risks	-2.55	6.54	0.15	1.00	0.70	0.08
Security	6.56	6.30	1.08	1.00	0.30	703.55
Complexity	-0.39	2.43	0.03	1.00	0.87	0.68
Benefits	-2.60	5.30	0.24	1.00	0.62	0.07
LCapital Size	-1.94	2.27	0.73	1.00	0.39	0.14
LTop Management Support	-1.71	1.74	0.97	1.00	0.33	0.18
LInformation Technology Capability	0.45	1.99	0.05	1.00	0.82	1.56
LInternal Championship	0.85	0.95	0.80	1.00	0.37	2.34
LExternal Pressure	-1.31	1.53	0.73	1.00	0.39	0.27
LInterorganizational Trust	-3.76	2.40	2.46	1.00	0.12	0.02
LLegal Framework	0.93	1.20	0.60	1.00	0.44	2.54
LCost	0.60	1.77	0.12	1.00	0.73	1.83
LRIisks	1.27	2.80	0.21	1.00	0.65	3.56
LSecurity	-2.93	2.66	1.22	1.00	0.27	0.05
LComplexity	0.12	1.12	0.01	1.00	0.91	1.13
LBenefits	1.07	2.27	0.22	1.00	0.64	2.92
Constant	-22.38	14.31	2.44	1.00	0.12	0.00

6.5 Assessing the Goodness of Fit and Pseudo R^2

The likelihood ratio R^2 is defined as

$$R_L^2 = \frac{G_M}{D_O} = \frac{G_M}{(G_M + D_M)} \qquad (6.3)$$

where

G_M is the model χ^2,

D_M is -2LL statistic (or deviance) for the full model

D_O is -2LL statistic (or deviance/initial chi-square) for the null model

R_L^2 is a proportional reduction in -2LL or a proportional reduction in the absolute value of the log likelihood measure. R_L^2 shows the degree to which the independent variables in the model reduce the variation, as measured by D_O.

Nagelkerke R^2 is a modification of the Cox and Snell R^2 so that it can vary from 0 to 1. The contingent coefficient R_C^2 is a pseudo-R^2 measure proposed by Aldrich and Nelson. A limitation of the R_C^2 measure is it cannot attain a value of 1 even for a perfect model fit. Hagle and Mitchell (1992) proposed a correction for Aldrich and Nelson's pseudo-R^2 that allows it to vary from to 0 to 1. Since there is no consensus on the single best pseudo-variance measure, researchers should use these measures only as rough guides without attributing great importance to a precise figure (Pampel, 2000; pp. 50)

Table 6.4 shows the Cox and Snell R^2, Nagelkerke R^2, R_L^2 (likelihood ratio R^2), R_C^2 (Aldrich and Nelson R^2) and the R_c^2 adjusted (Hagle and Mitchell R^2) for the logistic regression model.

Table 6.4: Pseudo R square

Pseudo R square	Value
Cox and Snell R^2	0.15
Nagelkerke R^2	0.21
R_L^2	0.13
R_C^2	0.14
R_C^2 adjusted	0.25

The proportional reduction in error (PRE) for the model varies between 13.00% for R_L^2 and 25.00% for R_C^2 adjusted. R^2 values should be at least 0.25 for a reasonable model fit. The pseudo R^2 values in Table 6.4 show that in general, the model does not fit the data well. It should be noted that these pseudo R^2 values are to be used only as a rough guide (Pampel, 2000; pp. 50).

6.6 Assessing the Goodness of Fit: G_m (Model χ^2) -2 Log Likelihood

The log likelihood criterion is used to select variables in the logistic regression model. The maximum likelihood estimation (MLE) criterion is applied to obtain the lowest possible value of -2LL for the model.

Model χ^2, G_M is computed as -2LL for the null (initial) model minus -2LL for the researcher's model (i.e. $D_0 - D_M$). G_M provides a test for the null hypothesis that $\beta_1 = \beta_2 = \ldots = \beta_K = 0$ in the logistic regression model. G_M thus tests the null hypothesis that all population logistic regression coefficients except the constant are zero. When the significance of G_M <=

0.05, the null hypothesis that knowing the independents makes no difference in predicting the dependent in logistic regression is rejected. We conclude that information about the independent variables allows us to make a better prediction of P(Y=1). A model that fits the data well have p value (significance) of <=0.05.

Table 6.5 shows $G_{M,}$ its significance, improvement χ^2, D_M and initial χ^2 D_O for the model.

Table 6.5: Significance of Model Chi-Square, Initial Chi-Square and Improvement Chi-Square

GM*	Sig GM	DM**	D0***
44.84	0.00	293.79	338.63

GM* Model chi-square; DM ** chi square for final model; D0*** Initial chi-square

G_M is 44.84 and its significance is 0.00. We reject the null hypothesis that knowing the independents makes no difference in predicting the dependent. G_M shows good model fit for sample.

6.7 Wald Statistic and Hypothesis Results

The logistic regression model is

$$\ln\frac{p}{1-p} = -3.20 + 0.60 capsize + 0.20 tms + 0.14 itcap + 0.28 ichamp + 0.51 extpres + 0.78 itrust$$
$$- 0.66 lframe - 0.73 \cos t + 0.45 risks - 0.35 \sec uri - 0.08 complex - 0.14 benefit \quad (6.4)$$

The Wald statistic is used to test the significance of the logistic regression coefficients of each independent variable. The significance of the regression coefficients is used to determine support for the research hypotheses. The Wald statistic and the hypotheses testing results are discussed in the following sections.

Table 6.6 shows the logit coefficient (B), standard error, Wald statistic, degree of freedom and significance (p probability level).

Table 6.6: Logistic Regression

	B	S.E.	Wald	df	Sig.	Exp(B)
Capital Size	0.60	0.26	**5.39**	1	**0.02**	1.83
Top Management Support	0.20	0.26	0.58	1	0.45	1.22
Info Technology Capability	0.14	0.28	0.25	1	0.62	1.15
Internal Championship	0.28	0.21	1.79	1	0.18	1.32
External Pressure	0.51	0.24	**4.35**	1	**0.04**	1.67
Interorganizational Trust	0.78	0.36	**4.73**	1	**0.03**	2.17
E-commerce legal framework	-0.66	0.24	**7.28**	1	**0.01**	0.52
Cost	-0.73	0.27	**7.39**	1	**0.01**	0.48
Risks	0.45	0.36	1.51	1	0.22	1.56
Security	-0.35	0.33	1.15	1	0.28	0.70
Technological Compexity	-0.08	0.21	0.15	1	0.70	0.92
Benefit	-0.14	0.30	0.23	1	0.64	0.87
Constant	-3.20	1.31	5.95	1	0.01	0.04

Since there are no large logit coefficients in Table 6.6, the problem of inflated standard error and reduced Wald statistic does not arise.

Wald statistic values greater than 1 are considered significant. The Wald statistic for capital size, external pressure, interorganizational trust, legal framework and costs are 5.39, 4.35, 4.73, 7.28 and 7.39 respectively.

Equation 6.4 shows the coefficients of the seven variables (Top Management Support, IT Capability, Internal Championship, Total Risks, Total Security, Complexity and Total Benefits) were not significant. The coefficients of the five variables (Capsize, External Pressure, Interorganizational Trust, Legal Framework and Total Costs) were significantly different from zero ($p \le 0.05$).

Wald statistics provide support for four hypotheses, i.e., hypothesis H_2 (cost is negatively related to EDI adoption), hypothesis H_6 (size is positively related to EDI adoption), hypothesis H_{11} (external pressure is positively related to EDI adoption) and hypothesis H_{12} (interorganizational trust is positively related to EDI adoption).

The study's research findings may not be directly comparable with previous studies because of two main reasons. Firstly, many earlier studies focus on the adoption of other forms of interorganizational systems (IOS) or electronic commerce/business and not on electronic data interchange. EDI adoption is comparable to a certain extent with IOS adoption because both share many common characteristics. Secondly, the methodology employed e.g. regression analysis, discriminant analysis, structural equation modelling, etc. and the different mix of variables also do not allow for direct comparison.

Hypothesis H_1 postulates that the benefits of EDI will have a positive effect on a company's decision to adopt EDI. The study's insignificant finding differs from the previous findings where benefits is positively related to innovation adoption (Bradford and Florin, 2003; Crum et al., 1996; Zhu and Kraemer, 2005; Li and Mula, 2009). Even though adopters and non-adopters perceive benefits as fairly important, benefits by itself is no longer an influential factor in EDI adoption unlike earlier research results of Tornatzky and Klein (1982), Rogers (1983, 1995, 2003) and Scala and McGrath (1993).

The insignificant finding could be due to the following reasons. While EDI adopters and non-adopters perceive direct benefits and indirect benefits to be fairly important to EDI adoption, they also realize that the benefits such as cost savings, improved logistics and market share can be difficult to obtain and only over a long time. This argument is supported by Premkumar et al. (1994) and Johnston and Vitale (1988). In the absence of incentives from one's trading partners or the government, benefits itself are not a strong enough pull factor for EDI adoption. Premkumar et al. (1997) also concur with this reasoning.

Strong support ($p = 0.01$) was found for hypothesis H_2 which postulates that costs will be negatively related to EDI adoption. This finding concurs with prior innovation adoption research where costs is a negative factor in the adoption of interorganizational information systems (Chau and Tam, 2000; Soliman and Janz, 2004). This finding is also consistent with findings of EDI adoption in small business (Kuan and Chau, 2001) where there was very strong support ($p < 0.01$) that adopter firms perceive lower levels of financial costs than non-adopter firms. Further support is provided by Chau and Jim (2002) where there was support for the hypothesis that higher levels of perceived costs of adopting EDI will negatively affect the likelihood of EDI adoption in small business. Seyal and Rahim (2006) investigation of

EDI adoption in Bruneian small businesses also showed that perceived costs are negatively related to EDI adoption. Findings by Kuan and Chau (2001), Chau and Hui (2001), Chau and Jim (2002) and Seyal and Rahim (2006) showed that costs were negatively related to EDI adoption in the small business context. The finding of hypothesis H_2 is applicable to small, medium and large companies in the context of this study.

Costs being negatively related to EDI adoption could be due to the following reasons. The cost of technology is a reason not to adopt EDI because the recovery of costs through EDI benefits generally occurs over the long term. Premkumar et al. (1994) and Johnston and Vitale (1988) also support this point of view. Costs are still an important consideration when implementing traditional EDI (Philip and Pedersen, 1997). Costs is still an important barrier to EDI adoption even though costs are lower today with Internet EDI and cheaper hardware (Borden, 2004, Machiraju et al., 2004). Costs perception is also directly related to company size. Larger companies with more financial resources are less likely to perceive costs as negatively as smaller companies with less financial resources (O'Callaghan and Kaufmann, 1992).

Hypothesis H_3 postulates that EDI risks will have a negative effect on a company’s decision to adopt EDI. Ratnasingham and Swatman (1997) built on the list of EDI risks identified by Jamieson (1996). Lim and Jamieson (1995) ranks the importance of EDI risks but the scope of their study did not differentiate the importance of risks between adopters and non-adopters. This research takes a step further to determine the significance of risks to EDI adoption.

Risk was found to be insignificant on a company’s EDI adoption decision. The insignificant results are similar to Frambach et al. (2002) study which found that perceived risks play a minor role in the adoption process. The perceived risks level was also found to increase (non-significantly) from evaluation to the adoption stage.

A reason is EDI adopters would have found through usage that their implemented security measures are safe enough for them to continue their EDI transactions with their partners. Research findings by Copeland and Hwang (1997) and Johnston and Vitale (1988) also support this argument. They are therefore not too worried about the EDI risk. EDI non-adopters do not perceive risks to be significant because they do not run the risks of EDI operations.

Hypothesis H_4 postulates that EDI security will have a positive effect on a company's decision to adopt EDI. Prior research on security has identified problems with standards, networks, data security and controls (Banerjee and Golhar, 1993; Ratnasingham, 1998; Soliman and Janz, 2004). Studies have shown that the lack of standards is a significant barrier to EDI implementation (Banerjee and Golhar, 1993; Emmelhainz, 1998). Perceived importance of standard compliance, interoperability and interconnectivity and selection of EDI standards are significant factors in open systems adoption and EDI implementation (Angeles et al., 2001; Chau and Tam, 1997). Our findings show that EDI standards are fairly important to adopters and non-adopters but is not a significant factor to differentiate between them. Our findings differ from the earlier studies on EDI standards because it is more complete by including digital signature, password and data encryption security. Previous studies either use EDI standards or a combination of the above.

Security was found to be insignificant on a company's EDI adoption decision. A reason is that the EDI adopters have not faced much security issues during their EDI operations and therefore do not regard security as being important. One possible reason could be the encryption used in Internet EDI (using SSL protocol) has improved through the years. The strength of encryption has increased from 32 bits to 64 bits to 128 bits to 256 bits. This explains why prior studies showed security posed a problem because of weaker encryption.

Hains (1994a, 1994b) and Ratnasingham (1997) also provide a similar argument. EDI non-adopters also do not perceive security to be significant because they currently have no EDI systems to protect.

Hypothesis H_5 postulates that EDI technological complexity will have a negative effect on a company's decision to adopt EDI. Prior adoption research has shown that complexity is negatively related to EDI adoption (Bouchard, 1993, Jeyaraj et al., 2006; Rogers, 1983, 1998, 2003). Our findings did not concur with these earlier research. Technological complexity was found to be insignificant on a company's EDI adoption decision.

By carefully training its users, EDI adopters may find EDI is not that difficult to use. Angeles et al. (2001) and Jun and Cai (2003) similarly showed that training helps reduce the difficulty of using a system. The technical complexity is mostly shielded from the end user as translation of formats is handled by the software and is unseen by the end user (Machiraju et al., 2004). EDI non-adopters do not perceive technological complexity to be significant because having no experience with EDI systems they find it difficult to perceive whether it's complex or not.

Moderate support ($p = 0.02$) was found for hypothesis H_6 which postulates that size will be positively related to EDI adoption. Meta-analysis research on IOS adoption (Hausman and Oyedele, 2004; Jeyaraj et al., 2006) showed that size consistently has a positive influence on IOS adoption. Our research concur with the finding that the larger the company the more likely it will adopt EDI (Henriksen, 2002; Hwang, 1991; Gavidia, 2001). Grover (1993) found that size has strong discriminatory power in the adoption of customer-based interorganizational systems. Studies in information systems adoption (Bajwa et al., 2005; Thong, 1999) also concur with our results. Prior adoption studies in small business, EDI implementation (McGowan and Madey, 1998; Premkumar, 2003), electronic commerce (Zhu et al., 2003), enterprise resource planning (Buonanno et al., 2005; Laukkanen et al., 2007) and open systems (Chau and Tam, 2000) also showed size to be a positive factor in adoption.

The reasons that size has a positive effect on EDI adoption are as follows. A large company has more slack resources to facilitate adoption. Based on the argument by Slappendel (1996), a large company with increased problems of coordination and control may find the adoption of new technology which reduces coordination complexity and costs to be useful. Large companies which engage in a larger variety of production activities are more likely to find any given innovation applicable to their operations. Tornatzky and Fleischer (1990) also support this argument. Large companies with high EDI volumes and large number of business partners can easily achieve economies of scale. The above are strong reasons why a large company adopt disproportionately more innovations than a small company.

Hypothesis H_7 postulates that top management support will have a positive effect on a company's decision to adopt EDI. Prior adoption research has shown that top management support is positively related to EDI adoption (Hwang, 1991; Jeyaraj et al., 2006; Seyal and Rahim, 2006). Our findings did not concur with these earlier research. Top management support was found to be insignificant on a company's EDI adoption.

Top management support will have very little influence on EDI adoption if forced upon them by a more powerful trading partner and the company still wants to do business with the dominant partner (Chewlos et al., 2001; Hart and Saunders, 1997; Ratnasingham, 2000). Top management in a subsidiary also has little influence on EDI adoption if the decision to adopt EDI is already taken by its parent company.

Hypothesis H_8 postulates that information technology capability will have a positive effect on a company's decision to adopt EDI. Prior adoption research has shown that information technology capability is positively related to EDI adoption (Jeyaraj et al., 2006; Markus and Soh, 2002; Zhu et al., 2002). Our findings did not concur with these earlier research. Information technology capability was found to be insignificant on the EDI adoption decision.

The reason could be that most companies have already invested in a networked computerized system. These companies which do not lack the necessary IT infrastructure will not perceive IT capability as very important for EDI adoption. Companies have the option of outsourcing their application development or buying off-the-shelf applications and thus may not perceive support and knowledge of internal IT staff as important to EDI adoption. Rohde (2004) provides a similar argument.

Hypothesis H_9 postulates that internal championship will have a positive effect on a company's decision to adopt EDI. Prior adoption research has shown that internal championship is positively related to innovation adoption (Garfield, 2000; Premkumar and Ramamurthy, 1995; Volkoff et al., 1999). Our findings did not concur with these earlier research. Internal championship was found to be insignificant on the EDI adoption decision.

Internal championship is insignificant to EDI adoption because even a champion (enthusiastic and committed individual) can actually not do much to increase the chances of EDI adoption. Decision making on IT adoption in many companies today is the responsibility of an information systems steering committee which considers all projects based on merits (Boockholdt, 1999). The influence of a champion is therefore limited.

Moderate support ($p = 0.04$) was found for hypothesis H_{11} which postulates that external pressure will be positively related to EDI adoption.

Jeyaraj et al. (2006) review of IT innovation research showed that external pressure was the second best predictor of IT adoption. Our research finding is consistent with previous research that external pressure is positively related to EDI adoption in small businesses (Chau and Hui, 2001; Chen and Williams, 1998; Iacovou et al., 1995), EDI adoption (Chwelos et al., 2001) and EDI implementation (Banerjee and Golhar, 1993). Our finding concurs with Teo et al. (2003) study where all three institutional pressures (mimetic, coercive and normative pressure) have a significant positive influence on an organization's intention to adopt financial EDI. Firms facing higher levels of competitive pressure are more likely to adopt e-business (Zhu et al., 2003). Previous IOS adoption studies also support our finding that external pressure is positively related to adoption (Hausman and Oyedele, 2004; Premkumar, 1995; Premkumar and Ramamurthy, 1995, Soliman and Janz, 2004; Tornatzky and Fleischer, 1990).

The reasons for the research findings are given next. A company may be forced to adopt an IT innovation if its dominant trading partner is already using the IT innovation and it does not want to lose doing business with its dominant partner. Following from Hart and Saunders (1997) argument, external pressure from one's trading partners is a key factor for EDI adoption by smaller companies which do not have much choice. A company may also be pressured to adopt an IT innovation if its industry is mostly using the IT innovation, for example the automotive industry (Agi et al., 2005, Huang and Iravani, 2005; Tuunainen, 1998). It may find itself at a competitive disadvantage if it chooses not to adopt the IT innovation.

Moderate support ($p = 0.03$) was found for hypothesis H_{12} which postulates that interorganizational trust will be positively related to EDI adoption.

This finding is consistent with the assertions of authors such as Arrow (1973), Reeve and Stern (1986) and Felkner (1992) that trust relationships between partners is more likely to promote electronic linkages between them. Our finding also concurs with Chan and Lee (2002) case study findings on the roles of power, trust and value which provided evidence that trust on supplier and IT have a significant effect on SME's e-procurement adoption behavior. Prior studies in EDI adoption (Hart and Saunders, 1997, 1998) and IOS adoption (Hausman and Oyedele, 2004; Soliman and Janz, 2004) have shown that interorganizational trust is a significant determinant of EDI adoption Studies in organizational innovation adoption (Frambach and Schillawaert, 2002) and in e-commerce adoption (Ratnasingham, 1998) also concur with our finding that interorganizational trust is positive for adoption.

The reasons for the findings are as follows. Trust is a necessary component for an interorganizational information system (IOS) to function effectively between trading partners and the computer systems of trading partners. Based on Mishra (1995) argument, a trading partner has to rely on the competence, reliability and openness of its exchange partner's computer system and network. A trading partner also has to rely on the competence, reliability and openness of its exchange partner's ability to deliver and adhere to agreements. If the partner is negligent, then the threat of a security breach affecting the company (such as the spreading of malicious code or stealing of information) becomes a possibility. Furthermore, a trustful relationship with EDI partners will mitigate the uncertainties introduced by EDI information sharing. Hart and Saunders (1997) concurs with this reasoning. It follows that uncertainty reduction by forming a trustful relationship will have a positive influence on EDI adoption.

Hypothesis H_{14} postulates that Legal Framework is positively related to EDI adoption. Hypothesis H_{14} was not supported ($p = 0.01$) but was significant in the opposite direction to that hypothesized for the model.

EDI adopters perceive the existence of e-commerce legal framework to be marginally more important than the EDI non-adopters. The lack of a clear legal environment is a barrier to innovation adoption (Teo and Ranganathan, 2004). Adequate legal framework has consistently been shown to be positively related to innovation adoption (Markus and Soh, 2002; Tarafdar and Vaidya, 2004). The Malaysian e-commerce cyberlaws such as the Digital Signature Act, Computer Crimes Act, Electronic Commerce Act and the Personal Data Protection Bill have been enacted and should provide adequate protection to those parties engaged in electronic transactions.

The above findings could be explained as follows. EDI non-adopters may not fully understand that the existing e-commerce laws will provide them the necessary protection. Because of this, EDI non-adopters tend to perceive e-commerce legal framework as more negatively related to EDI adoption. EDI adopters usually have a better understanding of the existing e-commerce laws and perceive that protection by these laws is adequate. Because of this, EDI adopters tend to perceive e-commerce legal framework as less negatively related to EDI adoption.

Table 6.7 summarizes the findings of the 14 research hypotheses.

Table 6.7: Hypotheses Testing Results

	Hypotheses	Results
H_1	Benefits will be positively related to EDI adoption	NS
H_2	Costs will be negatively related to EDI adoption	Supported**
H_3	Risks will be negatively related to EDI adoption	NS
H_4	Security will be positively related to EDI adoption	NS
H_5	Technological complexity will be negatively related to EDI adoption	NS
H_6	Size will be positively related to EDI adoption	Supported**
H_7	Top management support will be positively related to EDI adoption	NS
H_8	IT capability will be positively related to EDI adoption	NS
H_9	Internal championship will be positively related to EDI adoption	NS
H_{10}	Organizational compatibility will be positively related to EDI adoption	Not tested
H_{11}	External pressure will be be positively related to EDI adoption	Supported**
H_{12}	Interorganizational trust will be positively related to EDI adoption	Supported*
H_{13}	Critical mass will be positively related to EDI adoption	Not tested
H_{14}	E-commerce legal framework will be positively related to EDI adoption	NS**

* indicates coefficient is significant at alpha <= 0.10 ** indicates coefficient is significant at alpha <= 0.05 NS: Not Supported

6.8 Hosmer and Lemeshow Goodness of Fit Test

If the significance of the Hosmer and Lemeshow (H-L) goodness-of-fit test statistic is <= 0.05, the null hypothesis that there is no difference between observed and model-predicted values of the dependent is rejected. If the H-L goodness-of-fit test statistic is > 0.05, we fail to reject the null hypothesis which implies “the model fits”.

Table 6.8 presents the Hosmer and Lemeshow χ^2 and significance level.

Table 6.8: Hosmer and Lemeshow Test

Chi-square	df	Sig
7.30	8	0.50

The Hosmer and Lemeshow test has a χ^2 of 7.30 and a significance of 0.50. Since the significance of the H-L goodness-of-fit test statistic is > 0.05, we fail to reject the null hypothesis which implies "the model fits". This indicates that there is no statistically significant difference between the observed and predicted classifications. This provides support for acceptance of the research model as a significant logistic regression model.

6.9 Interpreting Logits

Logit coefficients are unstandardized logistic regression coefficients which correspond to the b (unstandardized regression) coefficients in ordinary least squares regression. For a dichotomous dependent variable, if the logistic coefficient for an independent variable x_i is b_i, then a unit increase in the independent variable x_i is associated with a b_i change in the log odds of the dependent variable.

6.9.1 Interpreting the Logit Coefficient

The significant ($p < 0.05$) logistic regression coefficients b_1, b_5, b_6, b_7, b_8 of equation 6.4 in terms of change in log odds, percentage change in odds and change in predicted probability at the mean proportion adopter are discussed next.

6.9.1.1 Change in Log Odds

The log odds is the term $\ln\frac{p}{1-p}$ in equation (6.4). Table 6.9 shows the change in log odds.

Table 6.9: Change in Log Odds

Independent Variable	Change in Log Odds
Capital size	**0.60**
External pressure	**0.51**
Interorganizational trust	**0.78**
Legal Framework	**-0.66**
Cost	**-0.73**

A unit increase in capital size, external pressure, interorganizational trust, legal framework and costs is associated with a corresponding 0.60, 0.51, 0.78, -0.66 and a -0.73 change in the log odds of the dependent variable.

Analysis of change in log odds concurs with hypothesis H_2 (costs, -ve), H_6 (size, +ve), H_{11} (external pressure, +ve) and H_{12} (interorganizational trust, +ve). Interorganizational trust (0.78) has the largest positive effect on the log odds of adoption while cost (-0.73) has the largest negative effect on the log odds of adoption.

6.9.1.2 Percent Change in Odds

The odds is the term $\frac{p}{1-p}$ .Table 6.10 shows the percent change in odds of being an adopter.

Table 6.10: Percent Change in Odds

Independent Variable	BX	EXP(BX)	Odds DV=1 Change by a Factor of*	Percentage Change in Odds**
Capital Size	**0.60**	1.83	0.83	82.94
External Pressure	**0.51**	1.67	0.67	66.70
Interorganizational Trust	**0.78**	2.18	1.17	117.49
Legal Framework	**-0.66**	0.52	-0.48	-48.21
Cost	**-0.73**	0.48	-0.52	-51.81

The logistic coefficient b_i for capital size, external pressure and interorganizational trust is 0.60, 0.51 and 0.78 respectively. The odds ratio e^{b_1} for capital size, external pressure and interorganizational trust is 1.83, 1.67 and 2.18 respectively. When capital size, external pressure and interorganizational trust increases by one unit each, the odds that the dependent variable = 1 increase by a factor of 1.83, 1.67 and 2.18 respectively when the other independent variables are controlled. Each additional unit of capital size, external pressure and interorganizational trust increases the odds of being an adopter by 83%, 67% and 118% respectively controlling for other variables in the model.

The logistic coefficient b_i for legal framework and cost is -0.66 and -0.73 respectively. The odds ratio e^{b_1} for legal framework and cost is 0.52 and 0.48 respectively. When legal framework and cost increases by one unit each, the odds that the dependent variable = 1 decrease by a factor of 0.48 and 0.52 respectively when the other independent variables are controlled. Each additional unit legal framework and cost decreases the odds of being an adopter by 48% and 52% respectively controlling for other variables in the model.

Analysis of percentage change in odds concurs with hypothesis H_2 (costs, -ve), H_6 (size, +ve), H_{11} (external pressure, +ve) and H_{12} (interorganizational trust, +ve). Interorganizational trust increases the odds of being an adopter the most (118%) while costs decreases the odds of being an adopter the most (52%).

6.10 Analysis of Predictive Efficiency

This section discusses the accurate prediction of group membership using classification tables and the indices of predictive efficiency λ_p, τ_p and φ_p and the statistical significance of λ_p, τ_p using binomial d statistic.

Table 6.11 shows the classification table for EDI adopters and non-adopters.

Table 6.11 Classification Table

Observed	**Predicted**		
	USER		Percentage Correct
	Non-Adopters	Adopters	
Non-Adopters	184	14	92.90%
Adopters	55	27	32.90%
Overall			75.40%

The overall accuracy of the model is 75.40%. The sensitivity is 32.90% and the specificity is 92.90%. Positive predictive value (PPV) is 65.85% and negative predictive value (NPV) is 76.98%. The PPV gives a 65.85% confidence that a company is predicted to be an EDI adopter and a 76.98% confidence that a company is predicted to be an EDI non-adopter.

Table 6.12 shows the λ_p, τ_p and φ_p values and the binomial d statistic.

Table 6.12: Predictive Efficiency Indices and Binomial d statistic

Predictive Indices	**Value**
λ_p	0.16
τ_p	0.41
φ_p	0.30
d statistic	
*d** (lamda-p)*	1.71
*d*** (tau-p)*	5.70

** significant at $\alpha = 0.05$, *** significant at $\alpha = 0.01$

λ_p with a value of 0.16 means that the model will reduce the errors in classifying the dependent (adopter class) by 16% compared to classifying the dependent by always guessing a case based on the most frequent category of the dichotomous variable. τ_p with a value of 0.41 means that the model will reduce the errors of classification (adopter class) by 41%. φ_p with a value of 0.30 means that the model will reduce the error of classification (adopter class) by 30%. All three values of the indices of predictive efficiency (0.16 to 0.41) show that there is an improvement in error reduction in classification with the model than without the model.

Binomial d is a significance test for measures of association. The binomial d statistic for λ_p is 1.71 and significant at an alpha of 0.05. The binomial d statistic for τ_p is 5.70 and significant at an alpha of 0.01. This means that the proportion predicted incorrectly with the model differ significantly from the proportion predicted incorrectly without the model. This provides support for acceptance of the research model as a significant logistic regression model.

6.11 Statistical Significance of Classification Rate

The accuracy of the classification rate from binary logistic regression can be determined by evaluating the statistical significance of the overall classification rate and the classification rate for each group.

The test statistics z_g (Huberty, 1984) is to assess the statistical significance of the classification rate for any group. The test statistics z is to assess the statistical significance of the overall classification rate for the sample. Huberty's (1984) index *I* gives the percent reduction in error (PRE) over chance classification that would result if a given classification method is used.

6.11.1 Statistical Tests for Classification Rate

Table 6.13 shows the Z statistical tests and Huberty's index *I*.

Table 6.13: Statistical Tests for Classification Rate

Statistical Tests	Value
Z_1^*	6.87*
Z_2^*	0.72
Z^*	5.70*
Huberty's Index *I*	68.07

* significant at $\alpha = 0.10$, ** significant at $\alpha = 0.05$, *** significant at $\alpha = 0.01$

Both the Z_1^* statistic with a value of 6.87 and the Z^* statistic with a value of 5.70 are significant at an alpha of 0.05. The Z_1^* and Z^* statistics show that the logistic regression model performs very well in predicting correctly the membership of the EDI non-adopter group (group 1) and the membership of the sample (adopters and non-adopters). Huberty's Index *I* shows that the percentage reduction in error over chance classification is 68.07%.

The statistic Z_2^* with a value of 0.72 is insignificant at an alpha of 0.05. The Z_2^* statistic shows that the logistic regression model performs poorly in predicting correctly the membership of the EDI adopter group (group 2).