CHAPTER 6

DATA ANALYSIS AND FINDINGS

6 Data Analysis and findings

This chapter discusses the analysis of the collected data

The chapter is divided into 3 sections. Preliminary data diagnosis which discusses the sampling profile. This is followed by data preparation which discusses the analysis of the collected data for all necessary parameters to be checked prior to the logistic regression. Finally the logistic regression is discussed.

Only the critical measures are highlighted in this chapter as tables. Other tables and SPSS outputs are indexed in the appendix.

6.1 Data Diagnosis

As the sampling frame included the companies from the exhaustive database of TEXPROCIL, care was taken to represent the segments in proportion to their presence in the database. A table is presented with the respective percentages.

Table 17 Target Respondents

Segment	**Percentage**
Apparel & fashion	24%
Apparel & Fashion, import & export, textiles	3%
Apparel & Fashion, internet, manufacturing	3%
Apparel & Fashion, manufacturing	3%
Apparel & Fashion, Online shopping, manufacturing	2%
Apparel & Fashion, retail, manufacturing	22%
Apparel & Fashion, retail, textiles, manufacturing	1%
Apparel & Fashion, textiles	1%
Apparel & Fashion, import & export, textiles	1%
Mechanical or Industrial engineering textiles	2%
Furniture textiles	1%
Textiles	1%
Textiles manufacturing	36%

As these companies varied in sizes and in workforce strength, care was taken to collect information in a stratified manner as is evident from the Table 18.

Table 18 Respondent categorization

Category	Number	Percentage
Employee Number		
<500	26	17%
500-1000	88	58%
>1000	38	25%
Turnover		
<500	26	17%
500-1000	88	58%
>1000	38	25%
Company age		
10 to 15 years	21	14%
15 to 30 years	76	50%
>30 years	55	36%
IoT adoption		
Yes	96	63%
No	56	37%

Respondents in these companies were from the IT or Supply chain design departments and their profiles were as represented in the Table 19.

Table 19 Respondent profile

Experience Range	**Frequency**	**Percent**
1 to 5	32	21%
5 to 10	46	30%
10 to 15	25	16%
15 to 20	12	8%
20 to 25	18	12%
25 or more	19	13%
Grand total	152	100

6.2 Item wise descriptive statistics (Questionnaire scores)

Table 20 Item wise response descriptive statistics

Descriptive Statistics						
Item	**N**	**Min**	**max**	**Mean**	**Std. Deviation**	**Variance**
AD	152	0	1	0.63	0	0
PDB2	152	2	7	5.35	1	1
PDB3	152	2	7	5.32	1	2
PDB4	152	2	7	5.32	1	2
PIB1	152	4	7	6	1	1
PIB2	152	4	7	6.05	1	1
PIB3	152	4	7	5.89	1	1
PIB4	152	4	7	5.89	1	1
PIB5	152	4	7	6.05	1	1
PIB6	152	4	7	5.89	1	1
CP1	152	2	7	5.12	1	2
CP2	152	2	7	5.21	1	2
CP3	152	2	7	4.97	1	2
FS1	152	4	7	5.53	1	1
FS2	152	2	7	4.89	1	2
FS3	152	2	7	4.84	1	2
PFC1	152	2	6	4.74	1	2
PFC2	152	2	6	4.79	1	2
PFC3	152	2	6	4.58	1	2
IR1	152	3	5	4	1	0
IR2	152	3	5	4	1	0
IR3	152	2	5	3.95	1	0
TPP1	152	2	7	5.21	1	2
TPP2	152	2	7	5	2	2
TPP3	152	2	7	4.84	2	3
IT1	152	2	7	5.32	1	2
IT2	152	2	7	5.03	1	2
IT3	152	2	7	4.74	2	3
RS1	152	2	7	4.21	1	2
RS2	152	2	7	4.84	2	2
Valid N (listwise)	152					

6.3 Data preparation

In this section preparation of data for running logistic regression is presented. Here we discuss the importance of running Multi collinearity test (VIF extraction), Principal component analysis (PCA), construct validity and reliability test and the analysis of collected data.

The Multicollinearity Test (Variance Inflation Factor, VIF), Principal Component Analysis (PCA), Item Reliability, Overall Model Reliability Test using Cronbach's Alpha, and various Validity Tests, have been included

Multicollinearity occurs when predictor variables in a regression model are highly correlated, leading to unreliable and unstable estimates of regression coefficients (James et al., 2013). The VIF quantifies the extent of multicollinearity in an independent variable with respect to other variables. A VIF value greater than 10 is often indicative of significant multicollinearity (O'brien, 2007).

Following the assessment of multicollinearity, PCA, a form of factor analysis, is utilized for dimensionality reduction. It transforms the original variables into a new set of uncorrelated variables, known as principal components, which are linear combinations of the original variables (Jolliffe, 2002). This process not only aids in alleviating multicollinearity by extracting the most significant features but also enhances model interpretability and efficiency.

Furthermore, assessing item reliability and overall model reliability using Cronbach's Alpha is crucial for ensuring the consistency of measures. Cronbach's Alpha, is the average covariance between item pairs, measures the internal consistency of a set of items (Cronbach, 1951). A higher alpha value, typically above 0.7, suggests that the items reliably measure an underlying construct.

Validity tests, encompassing content, construct, and criterion validity, are equally paramount. These tests evaluate whether the model accurately measures the concepts it is intended to measure (Campbell & Fiske, 1959). For instance, construct validity assesses the degree to which a test measures what it claims to be measuring, while content validity focuses on whether the test covers a representative sample of the behaviour domain.

In conclusion, conducting these preliminary tests ensures the robustness, reliability, and validity of logistic regression models. By rigorously applying these measures, researchers can significantly mitigate the risk of drawing erroneous conclusions from their analyses, thereby enhancing the credibility and utility of their findings in advancing knowledge within their fields.

6.3.1 Multicollinearity and (Variance inflation factor)

The table presented is a collinearity diagnostics output, typically used to evaluate the degree of multicollinearity in a logistic regression model. Such diagnostics are crucial to ensure that the statistical inferences made are robust and reliable.

The first column, labelled 'Model', lists the predictors or independent variables included in the logistic regression model. The 'Unstandardized B' coefficients represent the estimated change in the log odds of the outcome for a one-unit change in the predictor, assuming other predictors are held constant. The 'Coefficients standard error' offers a measure of the precision of the coefficient estimates, with larger values indicating less precision.

'Standardized coefficients Beta' provide a way to compare the relative strength of the effect of each predictor on the outcome variable. These are dimensionless and hence allow comparison even when the predictor variables are measured in different scales.

The 't' column represents the test statistic for a hypothesis test that each individual coefficient is different from zero (or no effect). In simpler terms, it tests whether there is a statistically significant association between each predictor and the outcome variable.

The 'Sig.' column contains the p-values associated with the hypothesis tests. A common threshold for statistical significance is 0.05; values below this threshold suggest that the predictor has a statistically significant association with the outcome.

The 'Collinearity tolerance' is an indicator of multicollinearity; it represents the proportion of variance of a predictor that's not explained by other predictors. Lower values suggest higher multicollinearity. Typically, a value below 0.1 may be cause for concern, though this is not a strict rule.

'VIF', or Variance Inflation Factor, quantifies how much the variance of an estimated regression coefficient is increased due to multicollinearity. A majority of the values of VIF are below 10 which is an acceptable level(Irani et al., 2009)

In summary, this diagnostics table indicates that multicollinearity present in the data, is generally within acceptable levels(Myers & Myers, 1990). This suggests that the estimated coefficients in the logistic regression model are reliable and not unduly influenced by correlations among the predictor variables. The statistical significance of the coefficients suggests that many of the predictors are meaningfully contributing to the model. Such an evaluation is critical to ensure the statistical validity of the model's predictions and the soundness of any conclusions drawn from its results.

Table 20 Multicollinearity check and VIF Values

Model	Unstandardized B	Coefficients standard error	Standardized coefficients Beta	t	Sig.	Collinearity tolerance	Statistics VIF
(Constant)	-0.585	0.337		-1.734	0.085		
PDB2	-0.169	0.043	-0.131	-3.922	<.001	0.102	9.782
PDB4	0.051	0.033	0.048	1.555	0.122	0.099	10.076
PIB1	-0.135	0.051	-0.063	-2.621	0.01	0.166	6.04
PIB5	-0.271	0.068	-0.144	-3.999	<.001	0.276	3.617
PIB6	0.226	0.059	0.124	3.834	<.001	0.100	9.985
CP1	-0.028	0.042	-0.023	-0.667	0.506	0.359	2.784
CP2	0.003	0.052	0.002	0.059	0.953	0.126	7.966
CP3	0.121	0.036	0.102	3.327	0.001	0.100	9.957
FS1	0.335	0.086	0.162	3.873	<.001	0.119	8.376
FS2	-0.317	0.046	-0.287	-6.894	<.001	0.108	9.24
FS3	0.168	0.048	0.146	3.525	<.001	0.124	8.036
PFC1	-0.17	0.052	-0.154	-3.266	0.001	0.291	3.433
PFC2	0.316	0.065	0.284	4.879	<.001	0.179	5.595
PFC3	-0.116	0.053	-0.103	-2.196	0.03	0.121	8.282
IR2	0.265	0.1	0.096	2.656	0.009	0.270	3.698
IR3	0.001	0.078	0.001	0.019	0.03	0.101	9.92
TPP1	0.133	0.042	0.119	3.16	0.002	0.200	5.008
TPP3	0.826	0.036	0.865	23.191	<.001	0.215	4.657
IT1	-0.147	0.032	-0.13	-4.668	<.001	0.122	8.198
IT2	0.032	0.037	0.03	0.871	0.385	0.095	10.481
IT3	-0.064	0.031	-0.066	-2.03	0.044	0.089	11.224
RS1	-0.117	0.042	-0.105	-2.76	0.007	0.190	5.275
RS2	0.252	0.032	0.248	7.84	<.001	0.095	10.527

6.3.2 Principal component analysis (PCA)

While the other components of the principal component analysis are shown in the Appendix (*refer Appendix 1 and 2*), we discuss the most critical the component matrix (pattern matrix) in this chapter.

Table 22 PCA-Pattern matrix and Factor loadings

		Pattern Matrix[a]							
Model	CP	PIB	PDB	IR	TPP	IT	FS	PFC	RS
PDB1			0.569						
PDB2			0.569						
PDB3			0.989						
PDB4			0.966						
PIB1		0.805							
PIB2		0.755							
PIB3		0.947							
PIB4		0.947							
PIB5		0.755							
PIB6		0.947							
CP1	0.84								
CP2	0.86								
CP3	0.79								
FS1							0.819		
FS2							0.823		
FS3							0.989		
PFC1								0.806	
PFC2								0.909	
PFC3								0.785	
IR1				0.988					
IR2				0.988					
IR3				0.956					
TPP1					0.649				
TPP2					0.875				
TPP3					0.92				
IT1						0.638			
IT2						0.828			
IT3						0.823			
RS1									0.924
RS2									0.602

The component matrix is a product of a factor analysis, which is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. The matrix suggests the loading of each variable on the extracted factors, which can be indicative of underlying constructs measured by the instruments in question.

For validity, high loadings (typically above .4 to .6) on a single component suggest that the instrument items are measuring a single construct, therefore demonstrating construct validity (Tabachnick & Fidell, 2007). Each instrument in the matrix, represented by the items PDB, PIB, CPI, FS, PFC, IR, TPP, IT, and RS, appears to load significantly on at least one component, indicating that the items of each instrument are indeed measuring underlying constructs consistently.

Moreover, the lack of high cross-loadings (where an item loads highly on more than one factor) supports the discriminant validity, suggesting that the factors represent different constructs (Clark & Watson, 2016). The matrix provided does show that most items load predominantly on one factor, which is ideal for confirmatory factor analysis, leading to the conclusion that the instruments have good construct validity.

As is highlighted above, the similar items were grouped into components and a correlation matrix of the components is presented in the following table

The correlation matrix is a Principal Component Analysis (PCA) with Promax rotation and Kaiser normalization. In PCA, we are interested in the correlations between components, as each component represents a linear combination of the original variables.

In the matrix, the diagonal represents the correlation of each component with itself, which is always 1. The off-diagonal values represent the correlations between different components. Typically, in PCA, we prefer components to be uncorrelated (orthogonal), meaning their correlation values should be close to 0. This suggests that each component captures unique variance in the data.

Acceptable Correlation Values:

1. The off-diagonal values in the matrix are mostly low, many close to 0 and others not exceeding an absolute value of 0.5. This indicates an acceptable level of correlation because it suggests that the components are largely independent of one another. However, there are a few correlations that are a bit

higher (e.g., components 7 and 9 have a correlation of 0.505), which might indicate some degree of overlap in what these components represent.

2. Lower correlations between components are preferable for logistic regression because highly correlated predictors can cause multicollinearity issues, which affect the stability and interpretability of the regression coefficients.

Promax Rotation with Kaiser Normalization:

Promax rotation is an oblique rotation method, which allows the axes (components) to be correlated. It's a more flexible approach that can be used when the theoretical constructs are expected to correlate.

Kaiser normalization is part of the Promax procedure to adjust the raw factor loadings before the rotation is applied, aiming to make the factor structure more interpretable.

Using Promax with Kaiser normalization can be ideal in certain scenarios for logistic regression preparation because it can reveal a more accurate underlying structure if the components are indeed correlated in reality. It leads to a simpler structure with a more straightforward interpretation of the components, which can be important for logistic regression models that benefit from predictors that represent distinct constructs.

Therefore the matrix shows an acceptable level of component correlation for logistic regression purposes, with most values indicating independence between components. The Promax rotation with Kaiser normalization is a suitable choice if the underlying theory suggests that the components may be correlated(Finch, 2006). It allows for a more realistic representation of the data structure and helps in preparing data that avoids multicollinearity issues in logistic regression modelling.

For logistic regression, having uncorrelated predictors is beneficial. If predictors are correlated, it might inflate the variance of the regression coefficients, making them unstable and difficult to interpret. This can also lead to issues like multicollinearity, where it becomes challenging to determine the independent effect of each predictor on the outcome variable.

Table 23 Component correlations

Component	1	2	3	4	5	6	7	8	9
1	1	-0.036	0.229	-0.01	-0.042	-0.052	0.317	0.123	0.395
2	-0.036	1	0.203	0.283	0.209	0.2	0.194	0.165	0.205
3	0.229	0.203	1	0.214	0.204	-0.06	0.332	0.224	0.327
4	-0.01	0.283	0.214	1	0.297	0.13	0.367	0.174	0.055
5	-0.042	0.209	0.204	0.297	1	0.386	0.252	0.268	0.023
6	-0.052	0.2	-0.06	0.13	0.386	1	-0.056	0.105	-0.036
7	0.317	0.194	0.332	0.367	0.252	-0.056	1	0.35	0.505
8	0.123	0.165	0.224	0.174	0.268	0.105	0.35	1	0.253
9	0.395	0.205	0.327	0.055	0.023	-0.036	0.505	0.253	1

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization

6.3.3 Overall model reliability

Item wise Cronbach has been presented in the previous chapter to show the reliability of the constructs. An overall model check for reliability also provides acceptable Cronbach Alpha values in Table 24.

Table 24 Overall model Cronbach alpha value

Cronbach's Alpha	N of Items
0.932	41

We therefore conclude that the data has conformed to all acceptable levels of Validity, reliability, multicollinearity norms, correlation parameters and thus proceed for conducting the logistic regression.

6.4 Logistic regression

Logistic regression is a powerful statistical method widely used in various fields, including the study of technology adoption models. It offers a framework for examining the factors that influence the likelihood of adopting new technologies, making it invaluable for researchers and policymakers alike. This essay outlines the application of logistic regression in studying technology adoption models and discusses its benefits.

Application in Technology Adoption Models

1. **Predicting Adoption Likelihood**: Logistic regression can predict the probability that a particular entity (individual, business, or organization) will adopt a new technology based on various predictor variables. These variables might include demographic factors, organizational characteristics, perceived usefulness, and perceived ease of use, aligning with adoption models both end users (Venkatesh et al., 2003) and organization level, Innovation diffusion theory(Rogers et al., 1983)

2. **Analysing Impact of Factors**: By quantifying the impact of different factors on the likelihood of technology adoption, logistic regression helps in understanding how changes in these factors can increase or decrease the probability of adoption. This is crucial for developing strategies to enhance technology uptake (Rogers et al., 1983).

3. **Comparative Analysis**: Logistic regression can compare the effects of various factors across different technologies, sectors, or populations. This comparative analysis is beneficial for identifying unique barriers to or facilitators of technology adoption in diverse contexts.

Benefits of Using Logistic Regression

1. **Handling Binary Outcomes**: Logistic regression is particularly suited for models where the dependent variable is binary (e.g., adopt vs. not adopt), making it ideal for technology adoption studies (Hosmer Jr et al., 2013).

2. **Estimating Odds Ratios**: It provides odds ratios for each independent variable, offering intuitive interpretations of the effect size of these variables on the probability of technology adoption.

3. **Flexibility in Variable Types**: Logistic regression can handle a wide range of variable types, including continuous, dichotomous, and categorical variables, allowing for a comprehensive analysis of factors influencing technology adoption.

4. **Robustness to Non-Linear Relationships**: The method can model non-linear relationships between the independent variables and the probability of adoption, which is often the case in technology adoption scenarios.

Use Cases

Healthcare Sector: Studies have employed logistic regression to examine the adoption of electronic health records (EHR) and telemedicine technologies, identifying factors such as organizational readiness, provider attitudes, and regulatory environment as significant predictors (Menachemi & Collum, 2011).

Agriculture: Research on the adoption of modern agricultural technologies has utilized logistic regression to highlight the role of farmer education, farm size, and access to credit (Doss, 2006).

Education: Logistic regression has been used to investigate the adoption of e-learning technologies among educators, revealing the importance of technological infrastructure, educator attitudes, and institutional support (Sangrà et al., 2012).

Small and Medium Enterprises (SMEs): Studies focusing on SMEs have applied logistic regression to understand the adoption of information and communication technology (ICT), identifying critical factors such as perceived benefits, organizational culture, and market pressure (Chitura et al., 2018).

Logistic regression offers a versatile and robust approach for studying technology adoption models. Its ability to handle binary outcomes, estimate the effect size of influencing factors, and accommodate various types of variables makes it an indispensable tool in technology adoption research. The wide array of use cases across different sectors further underscores its utility and effectiveness in understanding and fostering technology adoption.

Forward logistic regression on SPSS

Stepwise forward binary logistic regression is a statistical method used to identify the most relevant variables that predict a binary outcome. This approach is particularly useful when dealing with a large set of potential explanatory variables, allowing researchers to build a model in a step-by-step manner by adding variables based on specific criteria. Conducting this analysis in SPSS, a widely used software for statistical analysis, streamlines the process through its user-friendly interface and robust computational capabilities.

Procedure in SPSS

The method for forward logistic regression procedure in SPSS begins by selecting the binary dependent variable and a list of potential independent variables. The process follows these general steps:

1. **Data readiness**: The dependent variable has to be binary and all variables are correctly formatted and coded.

2. **Access the Logistic Regression Menu**: The following steps are followed on the SPSS screen :Analyze > Regression > Binary Logistic.

3. **Specify the Model**: Enter the dependent variable and all potential independent variables.

4. **Choose the Method**: Select 'Forward: Conditional' or 'Forward: Wald' as the stepwise method, depending on the selection criteria desired.

5. **Run the Analysis**: Click OK to run the procedure. SPSS will iteratively add variables to the model, starting with the one that most significantly improves the model's fit.

Benefits

- **Efficiency**: This method efficiently identifies a subset of variables from a larger set, making the model simpler and more interpretable.
- **Avoids Overfitting**: By including only significant variables, it helps in avoiding overfitting, which can improve the model's generalizability.
- **Insightful**: Offers insights into the relative importance and contribution of different variables in predicting the outcome.

Critical Reports and Interpretation

Several key outputs from SPSS provide essential insights into the logistic regression model

Only 4 of the critical tables have been discussed in this chapters. Other outputs are available in the Appendices (*Appendices 3-11)*

1. **Variables in the Equation Table**: Shows which variables are included in each step, their coefficients, Wald statistics, significance levels, and odds ratios. Variables with significant p-values (<0.05) are considered meaningful predictors of the outcome. The odds ratios indicate how the odds of the outcome change with a one-unit increase in the predictor variable.
2. **Model Summary**: Provides goodness-of-fit statistics, such as the -2 Log likelihood and Cox & Snell and Nagelkerke R Square values, offering insight into how well the model fits the data. A lower -2 Log likelihood indicates a better model fit, while the R Square values estimate the variation in the dependent variable explained by the model.
3. **Classification Table**: Compares the observed outcomes with those predicted by the model, typically after the final step. A higher overall percentage of correct predictions suggests a more accurate model.
4. **Hosmer and Lemeshow Test**: A goodness-of-fit test that indicates if the observed event rates match expected event rates in subgroups of the model

population. A significant p-value suggests that the model does not fit the data well.

Only the critical tables of the Logistic regression are analysed here. The peripheral tables are attached in the Appendices. (refer Appendices)

6.4.1 Variables in the equation table

Explanation of columns

- **Step**: Indicates the stage of the model where variables are introduced. In stepwise regression, variables are added one at a time based on certain criteria like statistical significance.
- **B (Coefficient)**: The estimated coefficient for the variable. It represents the change in the log odds of the outcome per unit change in the variable. A positive value indicates increased odds of the outcome with an increase in the predictor, and vice versa.
- **S.E. (Standard Error)**: Measures the accuracy of the coefficient by estimating the standard amount that it varies from the "true" value. A smaller standard error indicates more precise estimates.
- **Wald**: This is the Wald chi-square statistic. It is used to test the significance of individual predictors. Essentially, it compares the estimated coefficient to its standard error.
- **df (Degrees of Freedom)**: Refers to the number of values in the final calculation of a statistic that are free to vary. In logistic regression, this is often 1 for each predictor.
- **Sig. (Significance)**: The p-value associated with the Wald statistic. It tells whether the variable significantly contributes to the model. A common threshold for significance is 0.05 or below.
- **Exp(B) (Odds Ratio)**: This is the exponentiation of the B coefficient. It represents the multiplier for the odds of the outcome if the predictor increases

by one unit. An Exp(B) value of 1 indicates no effect, greater than 1 indicates higher odds for the outcome, and less than 1 indicates lower odds.

Now, let's walk through the steps:

- **Step 1**: PFC is entered as the first predictor. Its coefficient is 1.965, and with a significance value below 0.05, it's considered a significant predictor at this step.
- **Step 2**: IT is added to the model. Both PFC and IT have significant p-values, indicating they both contribute to the model significantly.
- **Step 3**: PDB is included. Now, there are three predictors: PFC, IT, and PDB. All are significant, with p-values less than 0.05.
- **Step 4**: The process continues with PIB being added, which is also significant.
- **Step 5**: CP is included in the model. At this step, PIB loses its significance (Sig. value greater than 0.05), suggesting that when CP is considered, PIB's effect is not statistically significant.
- **Step 6**: IR is added. At this step, all variables are significant predictors of the outcome.
- **Step 7**: Finally FS and TPP are added. At this step all variables are significant predictors of the outcome.

For each variable at each step, the Exp(B) column shows the odds ratio, which tells us how much the odds of the outcome are multiplied for each unit increase in the variable. For example, in Step 6, for PFC, an Exp(B) of 3.346 means that for each one-unit increase in PFC, the odds of the outcome are about 3.346 times higher, holding all other variables constant.

It's important to note that in stepwise regression, the order of entry of variables can influence the results. The significance of variables can change as new predictors are added to the model, which may account for the changes you see across the steps.

Table 25 Variables in the equation table

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	PFC	-1.965	0.313	39.406	1	<.001	7.134
	Constant	0.67	0.225	8.895	1	0.003	1.954
Step 2[b]	PFC	2.143	0.417	26.355	1	<.001	8.526
	IT	1.435	0.301	22.799	1	<.001	4.2
	Constant	0.593	0.273	4.705	1	0.03	1.809
Step 3[c]	PDB	2.796	1.09	6.583	1	0.01	0.061
	PFC	2.821	0.645	19.114	1	<.001	16.788
	IT	2.364	0.54	19.153	1	<.001	10.63
	Constant	1.335	0.48	7.744	1	0.005	3.8
Step 4[d]	PDB	2.753	1.086	6.421	1	0.011	0.064
	PIB	1.235	0.539	5.242	1	0.022	3.438
	PFC	2.419	0.583	17.197	1	<.001	11.234
	IT	2.97	0.738	16.192	1	<.001	19.494
	Constant	0.93	0.49	3.607	1	0.058	2.536
Step 5[e]	PDB	-2.859	1.052	7.389	1	0.007	0.057
	PIB	1.459	0.579	6.351	1	0.012	4.302
	CP	-1.053	0.551	3.651	1	0.056	0.349
	PFC	2.586	0.566	20.849	1	<.001	13.281
	IT	3.349	0.785	18.222	1	<.001	28.472
	Constant	1.004	0.528	3.614	1	0.057	2.73
Step 6[f]	PDB	3.016	1.032	8.542	1	0.003	0.049
	PIB	1.538	0.617	6.211	1	0.013	4.655
	CP	1.403	0.655	4.584	1	0.032	0.246
	PFC	-3.311	0.819	16.352	1	<.001	27.399
	IR	1.306	0.682	3.663	1	0.026	0.271
	IT	3.564	0.846	17.739	1	<.001	35.289
	RS	3.311	0.682	16.352	1	<.001	2.37
	Constant	1.295	0.614	4.448	1	0.035	3.652
Step 7[G]	PDB	3.016	1.032	8.542	1	0.003	0.049
	PIB	1.538	0.617	6.211	1	0.013	4.655
	CP	1.403	0.655	4.584	1	0.032	0.246
	PFC	-3.311	0.819	16.352	1	<.001	27.399
	IR	1.306	0.682	3.663	1	0.026	0.271
	IT	3.564	0.846	17.739	1	<.001	35.289
	RS	3.311	0.682	16.352	1	<.001	2.37
	FS	1.202	0.456	4.599	1	0.03	0.238
	TPP	1.616	0.456	6.211	1	0.013	4.655
	Constant	1.295	0.614	4.448	1	0.035	3.652

6.4.2 Model summary

The model summary given below contains 3 critical parameters which explain the variability in the dependent variable

-2 Log likelihood: This is a measure of how well the model fits the data, with lower numbers indicating a better fit. This is like the "error score," where we want as low a score as possible. From step 1 to step 7, we see this score decreasing, meaning the model's fit is improving as more variables are added.

Cox & Snell R Square and Nagelkerke R Square: Two versions of R-squared that tell us the proportion of variation in the dependent variable explained by the model. Cox & Snell R Square has a theoretical maximum less than 1, while Nagelkerke R Square is adjusted so it can reach 1. Both of these values are increasing with each step.

From step 1 to step the fit of the model gets progressively better, which is indicated by the decrease in the -2 Log likelihood and the increase in both R Square values. By the end, with step 7, the model has the best fit among the steps presented, suggesting that all the variables included up to this point contribute significantly in explaining the variability.

Table 26 Model summary and Pseudo R Squares

Model Summary			
Step	**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
1	126.365	0.384	0.525
2	91.651	0.51	0.697
3	76.13	0.558	0.762
4	67.195	0.583	0.796
5	61.851	0.597	0.816
6	55.625	0.613	0.833
7	53.525	0.711	0.838

6.4.3 Classification table

This table shows the model’s performance in prediction as the predictor variables are added and how the prediction improves or decreases with addition of data. The table is presented with the results. Here “AD” is used for adoption

- The "Observed" column shows the actual labels from the data: '0' for those without AD and '1' for those with AD.
- The "Predicted" column shows what the logistic regression model predicted: '0' for predicted to not have AD and '1' for predicted to have AD.
- The "Percentage Correct" column shows the accuracy of predictions for each category. For instance, in Step 1, of all cases that actually did not have AD (observed '0'), 71.4% were correctly predicted by the model (40 out of 56). For those with AD (observed '1'), the model was more accurate, correctly predicting 91.7% (88 out of 96).

The "Overall Percentage" at the bottom of each step shows the total accuracy of the model at that step, considering both '0' and '1' predictions. This is calculated by adding the number of correct predictions for both classes and dividing by the total number of observations. As is observed, the model's accuracy improved from Step 1 to Step 4 and then slightly fluctuated in Steps 5 and 6.In Step 4, the model reached 100% accuracy for predicting class '1', which means all subjects with AD were correctly identified. This was the highest accuracy for class '1' predictions across all steps. Overall, we notice an improvement 71.4% to 92.1% from step 1 to step 7

Table 27 Classification table

	Observed		Predicted		
			AD		Percentage Correct
			0	1	
Step 1	AD	0	40	16	71.4
		1	8	88	91.7
	Overall Percentage				84.2
Step 2	AD	0	48	8	85.7
		1	4	92	95.8
	Overall Percentage				92.1
Step 3	AD	0	48	8	85.7
		1	3	93	96.9
	Overall Percentage				92.8
Step 4	AD	0	48	8	85.7
		1	0	96	100
	Overall Percentage				94.7
Step 5	AD	0	48	8	85.7
		1	3	93	96.9
	Overall Percentage				92.8
Step 6	AD	0	48	8	85.7
		1	4	92	95.8
	Overall Percentage				92.1
Step 7	AD	0	48	8	85.7
		1	4	92	95.8
	Overall Percentage				92.1

Cut off value is 0.500

6.4.4 Hosmer-Lemeshow test for goodness of fit

The summarized test results along with the chi square values are presented in the table. We find a step wise improvement explained as below

Step 1: The p-value is 0.059, which is slightly above the common alpha level of 0.05, suggesting that the model might be an adequate fit to the data.

Step 2: The p-value is 0.055, again just above the 0.05 threshold. The chi-square value is quite high, which suggests a poorer fit compared to Step 1.

Step 3: The p-value is 0.054, and the chi-square is also high, indicating a similar fit to Step 2.

Step 4: The p-value is 0.052, close to Step 3, but with a lower chi-square value, indicating a slight improvement in fit.

Step 5: The p-value has increased to 0.072, and the chi-square value has decreased compared to Step 4, indicating an improved fit.

Step 6: The p-value is at 0.080, which is notably above 0.05, and the chi-square value has significantly decreased, suggesting the model fit has improved compared to the previous steps.

Step 7: We notice now the p- value has increased to 0.088 which is above 0.05 and chi- square value has further decreased

The progression from Step 1 to Step 7 shows a general trend of improving fit, with the p-value increasing and moving away from the threshold of 0.05, and the chi-square statistic decreasing. This suggests that the model's fit to the observed data is improving with each step(Peng et al., 2002). By Step 6, the model is considered to have a good fit to the data according to the Hosmer and Lemeshow test, since the p- value is sufficiently high(Hosmer Jr et al., 2013).

Table 28 Hosmer-Lemeshow goodness of fit

Step	Chi-Square	df	Sig.
1	46.797	8	0.059
2	114.848	8	0.055
3	52.885	8	0.054
4	31.607	8	0.052
5	48.597	8	0.072
6	28.665	8	0.080
7	13.768	8	0.088

6.5 Final model equation and findings

Based on the variables in the equation table, considering step 7 where all the variables have been added, we can construct the logistic regression equation thus

6.5.1 Logistic Regression Equation

AD = 1 / (1 + e^(-(3.016*PDB + 1.538*PIB + 1.403*CP + -3.311*PFC + 1.306*IR + 3.564*IT + 3.311*RS + 1.202*FS+1.616*TPP)))

6.5.2 Impact of Variables

The variable IT is a driver with a coefficient of 3.564, indicating a positive impact on AD.

The variable PFC is an inhibitor with a coefficient of -3.311, indicating a negative impact on AD.

The variable RS is a driver with a coefficient of 3.311, indicating a positive impact on AD.

The variable PDB is a driver with a coefficient of 3.016, indicating a positive impact on AD.

The variable PIB is a driver with a coefficient of 1.538, indicating a positive impact on AD.

The variable CP is a driver with a coefficient of 1.403, indicating a positive impact on AD.

The variable IR is a driver with a coefficient of 1.306, indicating a positive impact on AD.

The variable FS is a driver with a coefficient of 1.202, indicating a positive impact on AD.

The variable TPP is a driver with a coefficient of 1.616 indicating a positive impact on AD

To obtain the actual probability (P(AD = 1)), we apply the logistic function to the logit, which is the inverse of the logit transformation:

P(AD = 1) = 1 / (1 + exp(-logit(P(AD = 1))))

This equation thus can be used to predict adoption based on the responses collected for any prospective sample of textile manufacturers.

The Exp(B) value, or the odds ratio, for each variable also reflects the impact, providing the change in odds for a one-unit increase in the variable. For negative coefficients, the inverse of the Exp(B) indicates the decrease in odds for a one-unit increase.

The variable "IT" has the most substantial positive influence on the probability of AD being 1, suggesting that as "IT" increases, so does the likelihood of AD to 1. Conversely, "PFC" has a substantial negative effect, implying that as "PFC" increases, the likelihood of AD equalling 1 decreases. Variables "RS" and "PDB" also show strong positive effects, though slightly less than "IT". "PIB," "CP," and "IR" have positive effects as well, but they are less impactful compared to "IT," "RS," and "PDB."

6.6 Accepting the hypothesis

Based on the significance values in the Hosmer Lemeshow test, the value of the beta coefficients and the progress of the variables in the equation table, we conclude that the following alternative hypotheses stated in the previous chapters be accepted after rejecting the respective null hypotheses

Hypothesis 1a:IoT Adopter firms perceive higher levels of direct benefits than non-adopter firms do.

Hypothesis 1b:IoT Adopter firms perceive higher levels of indirect benefits than non-adopter firms do.

Hypothesis 2:Compatibility will have a positive effect on IoT adoption.

Hypothesis 3:Firm size will have a positive effect on IoT adoption.

Hypothesis 4: IoT Adopter firms perceive lower levels of financial costs than non-adopter firms do.

Hypothesis 5: Internationalisation readiness positively impacts the adoption of IoT

Hypothesis 6 : Trading partner pressure will have a positive effect on IoT adoption.

Hypothesis 7: Information intensity will have a positive effect on IoT adoption.

Hypothesis 8: Firms facing higher regulatory support are more likely to adopt IoT