CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

This chapter presents the research methodology of this study in order to achieve the objective of the study. The organization of the chapter is as follows. Section 4.2 explains the process of research approach before the design of the research is formulated in Section 4.3. Then, Section 4.4 elaborates the data collection process by explaining the collection of financial statement data, the selection of *sukuk* default firms and non-default firms, and the sampling frame of the study. Section 4.5 discusses the sampling frame of *sukuk* default and non-default firms while Section 4.6 discusses the framework of estimating the predictability of *sukuk* default. Section 4.7 describes variables measurement on predictability of *sukuk* default, liquidity risk, solvency ratio and corporate governance. Section 4.8 discusses methodology on logistic regression along with the assumptions undertaken and reconfirms with decision tree analysis, J48 for model building. Finally, Section 4.9 summarizes the chapter.

4.2 Research Approach

This study applies research approach as it is important in order to explain further about the research design, such as the technique for data collection and type of analysis, hence helping the researcher in deciding upon the study's research strategies (Easterby-Smith et al., 2002). Many already know that there are two types of the research approaches, which are deductive and inductive (Saunders et al., 2009). The deductive approach is a process of testing the theory. It refers to the process of theory development and hypothesis testing. Within this approach, the researcher draws a conclusion through logical deduction and reasoning. Hypotheses from existing knowledge are tested and decided whether to be accepted or otherwise. This approach is often used in quantitative research (Ghauri & Gronhaug, 2002, Saunders et al., 2009). According to Bryman and Bell (2003), deduction involves viewing the relationship between theory and research.

The inductive approach is the process in which the researcher gathers the data and develops the theory. In other words, the theory is the outcome of the research (Saunders et al., 2009). The inductive researcher typically uses a grounded theory to analyse data for theory development. Based on the points provided, the deductive approach is applied in this study due to the study's interest in determining the relationship between the independent and dependent variables by using the existing theory as well as testing the hypothesis. Therefore, the deductive approach is relevant for this study.

In relation to that, this study uses financial ratios for measurement of the *sukuk* defaulted firms. The reason why financial ratios are used in this study is because financial ratios are useful indicators of a firm's performance and financial situation. In addition, financial ratios can be classified according to the information provided. Apart from that, the suitability of using ratios in this study as another way of avoiding the problems involved in comparing firms of different sizes. Such ratios are ways of comparing and investigating the relationship between different pieces of financial information. Using ratios eliminate the size problem because the size effectively divides out and left with percentages, multiples, or time periods.

Subsequent approach was based on the previous study study (Easterby-Smith et al., 2002; Saunders et al., 2009), the researchers selected 'the paired-sample' designed to assist in providing a 'control' over factors that otherwise could be unclear about the relationship between failures and ratios. In this case, this study uses the similar approach. In fact, from the literature review, it is stated that as early as 1923, the ratio suggested that there must be incorporation of industry factors in any complete ratio analysis (Keige, 1991).

In terms of the methodology used in this research, the researcher opined that the classification of the default firms according to the industry is an essential pre-requisite to the selection of the non-default firms. The selection process is based on a paired-sample designed that for each defaulted firm in the sample, a non-defaulted firm of the same industry is selected. Previously, the names of the non-defaulted firms are obtained from a massive list of almost 1,000 firms accessible via Bloomberg. The list composed convenient feature of which the firms are segmented into industries and sectors. The non-defaulted firms selected are based on the following procedures; (i) turned to that portion of the list where firms of that industry number were found; (ii) took the industry number of a defaulted firm; (iii) if the firm did not fulfill these conditions, returned to the list and tentatively selected the firm which was next closest (Euclidean) to industry and sector; (iv) if that firm was in Bloomberg's and was non-defaulted, then accepted it as one of the firms to be studied; (vi) repeat this procedure for each of the defaulted firms in the sample; and (v) repeat this procedure until an acceptable firm was found.

4.3 Research Design

Upon conducting the research approach, the design of this research has come into form as well "to provide frameworks that lay down the methods and procedures for collecting and analysing data" (Zikmund, 2003). Besides, it is a general plan in what way a researcher should answer research questions (Saunders et al., 2009). A research can be classified as either exploratory or descriptive according to the purpose of the research study (Sekaran, 2003).

In literature, exploratory research refers to the study in which little information is known about the subject matter, or there are no earlier related studies that can be referred to (Collis & Hussey, 2003). The findings of type of studies are useful to understand the problems identified. Meanwhile, a descriptive study describes the exceptional or characteristic features of something as it exists, and is useful to summarise the information (Sekaran, 2003). This type of study is structured with a clearly stated hypothesis and investigative questions (Cooper et al., 2002). Hypothesis testing in this type of study usually explains the relationship among variables (Sekaran, 2003). These types of study require clear specification of what, where, when, why and how. As mentioned earlier, the purpose of this study is to determine the factors that influence the predictability of *sukuk* defaulted firms based on liquidity risk, solvency ratio indicator and corporate governance characteristics. Thus, based on the types of research design, it appears that the descriptive research design is appropriate with this study.

The research design for this study is summarised in Figure 4.1. The first step was an extensive literature review of the research area followed by an identification of the research framework on the predictability of *sukuk* defaulted firms, while developing the hypotheses employed in this study. Secondly, data gathering, data processing and preliminary data testing were conducted. This is followed by analysing the dataset using two softwares, SPSS and WEKA. Next, the discussions on factors associated with predictability of *sukuk* defaulted firms in Malaysia and finally conclusion and recommendations. Details are discussed in the following sections.

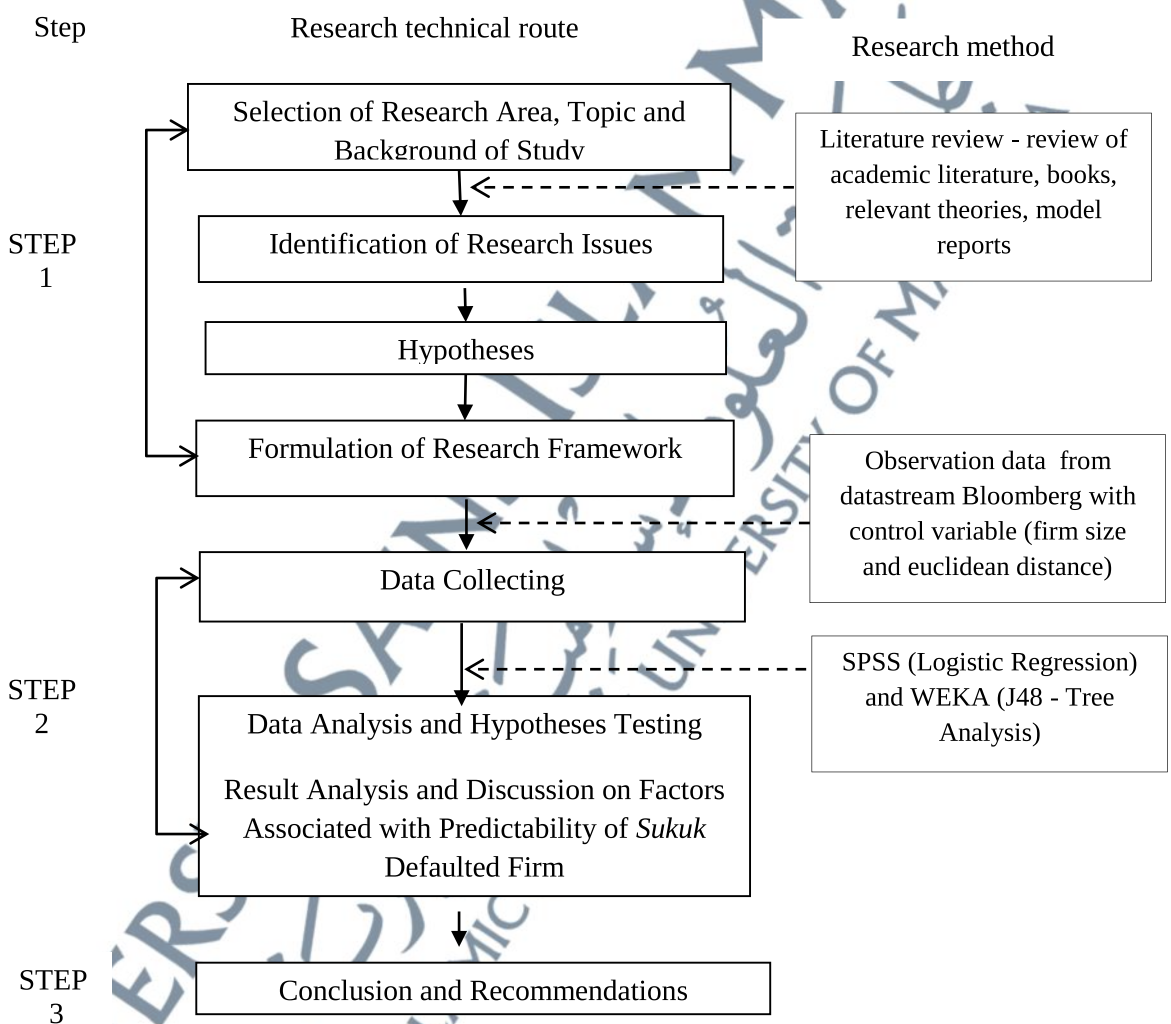

Figure 4. 1: Research Design

4.4 Data Collection

There are two methods applied in this study for data collection. First method is the library research via university online and offline subscription as well as other resources like news, magazine, bulletin, reports (Accounting and Auditing Organization for Islamic Financial Institutions (AAOIFI) and International Islamic Financial Market (IIMF), Islamic Finance News, seminal papers, forum's papers (World International Economic Forum (WIEF), International Islamic Capital Market Forum (IICMF), reviews, newspaper, proceedings and other related documents on accounting, economics and governance.

Second, from compilation hundreds of annual reports. This research is the first of its kind written. The methods used while implementing this research are based on researcher's own tacit knowledge combined with research methodology books. At the initial stage of this study, processes involved are as follows:

i. Researcher collected annual reports of the firms under study;
ii. Researcher then segregated the balance sheets, profit and loss accounts, cash flows from the annual reports;
iii. Then, every transaction from the balance sheets, profit loss accounts and cashflows were manually written in researcher's sheet. This stage had to repeat three times for the whole screening process due to the development of the research process. Initially, this research was to explore the liquidity risk contributed to *sukuk* default firms. The financial ratios used were based on literature of liquidity ratios;
iv. Upon the development of the research process, the research diagram expended to other two variables which are financial crisis and corporate governance

characteristics. When this research started end of 2012, the global financial crisis of 2007 to 2008 had just receeded but the impact still exists. In 2014, *sukuk* default was last recorded. However, financial crisis was dropped and replaced with solvency ratio;

v. The manual data were then keyed in in excel and converted into SPSS as the preparation of analysis. WEKA was the last method used in this study to conform to the data analysis and robustness of the results; and

vi. Final data that used for this study were defined, concluded and analysed.

This research has to be repeated again when new variables are used in this study. This research uses both deduction and induction approaches. There were approximately 300 annual reports screened out of total population of 35 *sukuk* defaulted firms in between 2002 to 2011. Later, the research were expanded to 2014. The research was conducted until 2014 to ensure that the total population of *sukuk* defaulted firms were covered during those stipulated years in Malaysia.

The softcopy of annual reports were obtained from Rating Agency Malaysia Berhad (RAM) and Malaysian Rating Corporation Berhad (MARC). Next, another compilation of all balance sheets, income statements, profit and loss accounts and cash flows accounts from the firms' annual reports were analysed by the researcher in order to get the dataset in terms of accounting figure before the figures were formulated to financial ratios.

The accounting dataset taken from the *sukuk* defaulted firms' annual reports were arranged from year one to the fifth year prior to the failure based on the annual report of each firm. In this study, the 'first year prior to failure' is termed as (i) the year that is included in the most current financial statements, classified as before the date of which the firm was registered default by the rating agencies; (ii) the financial statements could not be more than six months old during the date of failure. Whereas for the second year is termed as, the ‘second year after the first year prior to failure’. While the third, fourth, as well as the fifth year are similarly defined.

Conversely, the financial statements of the *sukuk* non-defaulted firms were taken from the same years as those of the sukuk defaulted firms. The accounting dataset were also based on year one to the fifth year prior to the failure. Practically, if two (2) firms were defaulted in 2006 and 2011, data were taken from the most current financial statements of the firms which were December 31, 2005 and 2010, respectively. The first year prior to failure would include the 2005 statements of the former and the 2010 statements of the latter. This is due to the fact that financial statements data were not available for every single year prior to failure, thus decreasing the number of observations at the time before failure. Meanwhile, in the first year prior to failure, the sample size was at the highest. Additionally, there was no availability of data over other period as a condition for inclusion in the sample, due to the fact that a possible bias might be introduced in the current study. Afterward, the research continued to the process of formulation for financial ratios of liquidity risk, solvency ratios and corporate governance characteristics.

4.5 Sampling Frame of *Sukuk* Default and Non-Default Firms

This section discussed the sampling frame of this research. Following are the sampling frame gathered for dataset between years 2006 to 2011 which were displayed according to year as shown in Table 4.1.

Table 4.1: Sampling Frame of *Sukuk* Default and Non-Default Firms, 2006-2011

Year of Default	Frequency	%
1. 2006	8	13.33
2. 2007	17	28.33
3. 2008	6	10.00
4. 2009	19	31.67
5. 2010	8	13.33
6. 2011	2	3.33
TOTAL	60	100

Source: Researcher's Analysis (2019)

From the table, it shows that the highest frequency of the sampling is in 2009 which was nineteen (about 31.67 per cent), followed by 17 frequency in 2007 which was about 28.33 per cent. In years 2006 and 200, the number of the frequencies were 8 each and registering 13.33 per cent each of the total defaulted. Therefore, the highest frequency based on year of default was in 2007 and 2009. The data is used as the basis for this study. Apparently, the year of default coincided with the year of global financial crisis in 2007-2008.

The dataset that consists of 60 *sukuk* defaulted and non-defaulted firms were then classified according to industries. The industries composition was heterogeneous. The 16-different types of industries were discussed earlier in Chapter 2. The following were the list of 60 *sukuk* defaulted and non-defaulted firms used in this study; viz, Europlus Corporation Sdn. Bhd., Maxisegar Sdn. Bhd., Perspektif Perkasa Sdn. Bhd., Ambang Sentosa Sdn. Bhd., Peremba Jaya Holdings Sdn. Bhd., Memory Tech Sdn. Bhd., The Royal Mint of Malaysia Sdn. Bhd., Paradym Resources Industries Sdn. Bhd., Sistem-Lingkaran Lebuhraya Kajang Sdn. Bhd., ACE Polymers (M) Sdn. Bhd., Stenta Films (M) Sdn. Bhd., Jana Niaga Sdn. Bhd., Intelbest Corporation Sdn. Bhd., BSA International Bhd., Evermaster Bhd. 50, Tracoma Holdings Bhd., Englotech Holding Bhd., Oxbridge Height Sdn. Bhd., M-Trex Corporation Sdn. Bhd., Ingress

Sukuk Bhd., Oilcorp Bhd., Malaysian International Tuna Port Sdn. Bhd., Straight A's Portfolio Sdn. Bhd., PSSB Ship Management Sdn. Bhd., Malaysian Merchant Marine Bhd., Nam Fatt Corporation Bhd., Vastalux Capital Sdn. Bhd., and Dawama Sdn. Bhd. The total samples were 30 firms.

The non-defaulted *sukuk* firms viz Zaki, Century, Damansara, Dutaland, Adventa, ALAM, Atlan, BURSA, Chemical, Degem, DRB-HICOM, EP, Hong Leong, Hubline, Lafarge, Leader Steel, MMarine, MSteel, Mupha, NaimH, PPetroleum, Petronas GAS, Sime Darby, Symphony, Tomei, Top Glove, UMW and Utusan Melayu. The total samples were 30 firms.

From the compilation, it is discovered that most of the frequently represented industries are sectors in investment holdings, property developments and constructions, industrial products and consumer products in which there were five firms respectively as stated in Table 2.4 in Chapter 2. Further discussion is done in Chapter 5. In terms of value, *sukuk* denominated values were between RM40 millions to RM300 millions, and the mean value of *sukuk* was approximately RM6millions. Meanwhile, the types of *sukuk* that were frequently represented were *Bai'Bithaman Ajil* Islamic Debt Securities (BaIDS) and *Musyarakah* as stated in Table 5.6 in Chapter 5.

4.6 Framework of Estimating the Predictability of *Sukuk* Default

This model framework is adapted from Failure Prediction Model by Beaver (1966), explained in Chapter 3. This thesis explores the causes of default on the *sukuk* issuing firms (Y). Before factor analysis of variables that used in this study, the applicability test is needed, whose basic idea is to test the correlations of the original variables. If the correlation between the variables is low, it is not suitable for factor analysis. Kaiser-Meyer-Olkin (KMO) test (Kaiser,1970) and Bartlett's test of sphericity (Tobias & Carlson, 1969) are commonly used to accomplish the examination. Normally, if the value of KMO is greater than 0.5 and the p-value of Bartlett's test is less than 0.05, factor analysis is suitable (Dziuban & Shirkey, 1974). The results of KMO test and Bartlett's test are listed in Table 4.2.

Table 4.2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.531
Bartlett's Test of Sphericity	Approx. Chi-Square	111.156
	df	15
	Sig.	0.000

Table 4.2 shows that the KMO value is 0.531, greater than 0.5, and the p-value of Bartlett's test is 0.000, indicating that there exits strong correlation between variables and it is suitable to use factor analysis to extract the principal components.

Main Component Extraction

Table 4.3 is the common factor variance table of the factor analysis, showing the degree of commonality of all variables, a common indicator to measure the effect of principal component analysis. The higher the degree of commonality is, the better the result of analysis will be (Dziuban & Shirkey, 1974).

Table 4.3: Common Factor Variance

	Initial	Extraction
QR	1,000	0.145
CR	1,000	0.718
DTER	1,000	0.620
ICR	1,000	0.175
ID	1,000	0.859
AC	1,000	0.885

As shown in Table 4.3, the degrees of commonality of most variables are more than 0.5, revealing that the extracted principal components contained relatively complete original information of the variables, and therefore have better explanatory power. The principal component analysis method is used to extract the common factors, taking the cumulative variance contribution rate as a reference value and the eigenvalue as an auxiliary criterion (Moore, 1981). In general, if the eigenvalue is greater than or equal to 1 and the cumulative variance contribution is greater than or equal to 0.5, the extracted common factors are considered to reflect the information of the original variables well.

As shown in Table 4.4, there are 2 principal components of which the eigenvalues are greater than 1, and the cumulative variance contribution rate of the first six principle components has reached over 56.706 per cent. Thus, it can be considered that the extracted principal components can reflect the the original variable information.

Table 4.4: Variance Contributions of All Components

Comp	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Var	Cum %	Total	% of Var	Cum %	Total	% of Var	Cum%
1	2.144	35.725	35.725	2.144	35.725	35.725	2.055	34.250	34.250
2	1.259	20.980	56.706	1.259	20.980	56.706	1.347	22.455	56,.706
3	1.000	16.659	73.365						
4	0.889	14.817	88.182						
5	0.615	10.257	98.439						
6	0.094	1.561	100.000						

The screen plots can visually reflect the cumulative effect of the principal factors and the original variables, helping to determine the number of principal factors to be extracted. As shown in Figure 4.1, the changes in eigenvalue start to decrease from the two principal component, which shows that it is reasonable to select 2 principal factors. In summary, through the analysis of the cumulative variance contribution rate, degree of commonality of variables and gravel map, it can be verified that extracting 2 principal components is reasonable and scientific

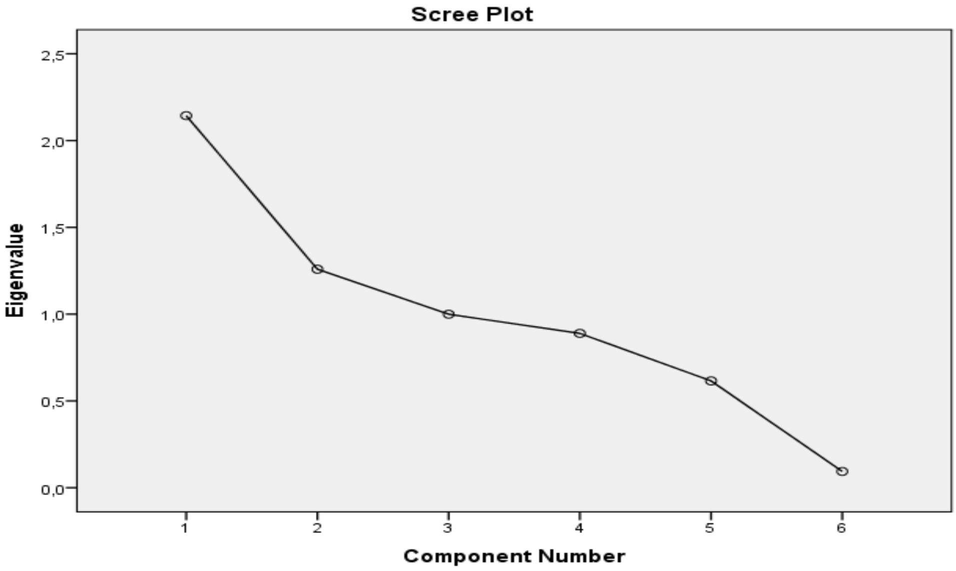

Figure 4.1 Screen Plot of Eigenvalues

Principal Component Extraction and Interpretation

As mentioned before, extracting 2 principal components can take into account the vast majority of the original variable information and eliminate the correlation between original variables. However, it is difficult to name the foremost factors through the initial component matrix. Therefore, the maximum variance method was employed to perform orthogonal rotation of the initial component matrix to make the meaning of each principal factor clearer. The greater the factor loading value of variable on the principle component, the closer the relationship between the variable and the principal component (Moore, 1981).

Table 4.5: Rotated Component Matrix

Variables	Components	
	F_1	F_2
QR	0.381*	0.020

CR	0.186	0.826*
DTER	-0.210	0.759*
ICR	0.393*	0.143
ID	0.918*	-0.126
AC	0.913*	-0.229

Note:*denotes the close relationship between variables and principal components

As can be seen from Table 4.5, (1) principal component 1 is more ideal in reflecting the original information of the four variables; Quick Ratio (QR), Interest Coverage Ratio (ICR), Independent Director (ID), and Audit Committee (AC) with the degree of 38.1 per cent, 39.3 per cent, 91.8 per cent, and 91.3 per cent. These indicators reflect the profitability of the enterprise, so the principal component 1 can be named as liquidity and governance factor (F1). (2) principal component 2 is more ideal in reflecting the original information of the two variables; Cash to Asset Ratio (CR), and Debt to Equity Ratio with the degree of 82.61 per cent, and 75.9 per cent. Thus, the principal component 2 can be named as asset and interest factor (F2).

According to the variable factor score coefficient matrix given in Table 5, the expression of the six principal components can be written as:

Table 4.6: Component Coefficient Matrix

Variables	Components	
	F1	F2
QR	0.192	0.053
CR	0.174	0.648

DTER	-0.030	0.557
ICR	0.210	0.147
ID	0.446	-0.005
AC	0.433	-0.084

F1 = 0.192 QR + 0.174 CR -0.030 DTER + 0.210 ICR + 0.446 ID + 0.433 AC

F1 = 0.053QR + 0.648 CR + 0.557 DTER + 0.147 ICR -0.005 ID -0.084 AC

Based on the factor of analysis above and literature, the causes of *sukuk* default are categorized into three indicators, which are; liquidity risk indicator, solvency ratio indicators and corporate governance characteristics. It can be expressed as follows:

$$Y = a + bx_1 + cx_2 + dx_3 + e$$

Where : a, b, c, d = coefficient

x_1 = liquidity risk

x_2 = solvency ratio

x_3 = corporate governance

e = error

The liquidity risk (a) refers to the quick ratio (QR) and cash ratio (CR). For the default and non-default firms under study, the liquidity ratios that are below the threshold of 1 is assumed contributed to the default.

Meanwhile, the solvency ratio (b) refers to two components which are debt to equity ratio (DtER) and interest coverage ratio (ICR). Those indicators were choosen based on literature written by Enekwe et al.(2014). It is assumed that the value below the optimum level contributes to the default.

The corporate governance (CG) consists of independent director (ID), and existence of audit committee (AC). It is assumed that firms which are non-compliance with the MCCG (2000-2007) and MCCG (2007-2011) as well as the *Shariah* committee (2004) and SGF (2011) required criteria, which may have contributed to default.

Based on the discussion above, this present study developes the predictability of *sukuk* defaulted model based on general concepts of bond and defaulted bond. By using financial ratios, this study implies both concepts of *sukuk* defaulted firms and non-defaulted firms; and bond defaulted and non-defaulted firms (Ardiansyah & Qoyum, 2010; 2011; 2013). The detail of the method will be explained in the following sections.

4.7 Research Measurement

The measurement for variables used in the study is also in accordance with the theoretical framework. Below are the descriptions of the measurements employed.

4.7.1 Predictability of *Sukuk* Defaulted Firm

The measurement of the variables employed in this study is based on the Research Framework as proposed in Chapter 3. Based on the Framework, this study determines to predict *sukuk* default as the dependent variable (dv). Since this study is conducted on the default case, a dummy variable is used to measure the dependent variable. The default cases are used as a baseline in predicting *sukuk* default firms. Based on the literature in Chapter 3, the previous study conducted on default *sukuk* used paired-samples which are a default and non-default. The default and non-default *sukuk* firms used in this study are determined either by RAM or MARC. The default *sukuk* has to be registered as default every time. Therefore, the list of defaulted firms are taken from RAM or MARC. Meanwhile, the list of non defaulted firms are taken from Bloomberg in between 2006 until 2011. Data collecting was done from year of default (t), t+1, and t+2.

This study carried out ratios such as quick ratio, cash ratio, debt to equity ratio and interest coverage ratio to determine liquidity risk and solvency. It is due to the different sizes of each firm in comparing firms. Ratios are ways of comparing and investigating the relationship between different sets of financial information. Ratios are used in this study as follows:

IV	**Used ratio**
Liquidity risk	QR- Quick Ratio CshR- Cash Ratio
Solvency ratio	DtER-Debt to Equity Ratio ICR-Interest Coverage Ratio
Corporate Governance	ID-Independence Director AC-Audit Committee

As discovered in the available literature, as early as 1930's, there had been attempts to research predictive power of ratios, where control groups were employed. Paul J. Fitzpatrick (1930) employed the use of a case by case method of analysis, and studied before three to five year trends of thirteen kinds of ratios for twenty firms, which had failed during the period of 1920-1929. Consequently, his research was followed by a comparative analysis of a matched sample of nineteen successful firms, and it was concluded that there was some degree of failures in all the ratios predicted, although the net worth of debt, net profit to net worth, as well as net worth to fixed assets ratios were generally seen as the best indicators. Nevertheless, Fitzpatrick's study had some disadvantages, like the fact that the samples were too small as well as too selective. In general, the shortcomings of the study at that time were outweighed by the essential cruciality of their contribution. The is due to the fact that the said study represented an extremely significant event in the development of ratio analysis as they were the first who carefully developed attempts to employ the scientific approach to determine the utility of ratios (Rehman, 2013).

Conversely, previous study carried out by Kamstra and Kennedy (1998) titled Combining Bond Rating Forecast Using Logit, imitated the Kamstra-Kennedy variables; i) debt ratio, ii) interest coverage, iii) return on assets, iv) subordination status (dummy) as well as v) total firm assets. Furthermore, it was discovered in a data set of 265 observations, an ordered logit forecast combination of bond yields as statistically significant as well as quantitatively increasing the result in forecasting the rating prediction over the traditional one.

4.7.2 Liquidity Risk Variable Measurement

Contrary to credit risks and market, the liquidity risk has been mostly unexplored (Zhang, 2005). Researchers have different views on liquidity risk measures. Zhang (2005) believed that there is no commonly agreed definition for liquidity measure yet. In the conventional financial system, different tools, methods, variables and measures of computations are used in hypothesizing the existence of liquidity risk in certain types of investment securities. Castagna and Fede (2013) opined that by using different forms of variables, researchers derived multiple conclusions in their research and was later classified into different schools of thought.

Researchers used different types of measurements such as trade size, bid spread, frequency for direct steps. Others use indirect measurements such as listed, lost price, amount of withdrawn, age, coupons, number of contributors, fluctuation in price, and dissemination of revenue. Ericsson and Renault (2001) used the binomial model for non-liquid bonds and provides several qualitative properties of liquidity revenue spreads, including domination over the spread of credit yield on short matured bonds and declining sloping-term structures. Meanwhile, Zhang (2005) used the bid-ask spread to measure liquidity.

In addition, a group of researchers, Holmes and Sugden (1992), Moyer et al., (1992), Price, Haddock & Brock (1993) stated that studies on liquidity risk were usually based on financial ratios as financial ratios were useful indicators of a firm and financial performance. In order to determine the liquidity of the firm, it is conducted by examining the relationship between the firm’s current assets and approaching obligations (Weston & Brigham,1993). Financial ratios consist of liquidity ratios in which the quick measures of a firm’s ability can give enough cash to conduct business over the next few months (Moyer et al., 1992).

A firm that proposes to remain an active business aggregation must have sufficient cash at hand to pay its bills when they are due. Hence, the firms must keep liquid. A liquid asset is one that can be easily transformed to cash at a fair market value. The reason is that a common precursor to financial distress or bankruptcy is low or declining liquidity, therefore liquidity ratios are good leading indicators of cash flow problems. Hence, liquidity ratios that are used in this study are quick ratio (QR) and cash ratio (CR). Both ratios are standard financial ratios that most business firms use to measure liquidity ratios.

Quick Ratio Measurement

As for quick ratio measurement, some authors, Virtanen (2010) and Adalessossi (2015), used the same ratio to asses the risk of default or bankruptcy (default) in some public firms predicted. It was due to the fact that quick ratio is a more reliable measure of liquidity for manufacturing firms and construction firms that have relatively high levels of inventory, work in progress and receivables. The quick ratio is similar to the current ratio except that it excludes inventories, which is usually the least-liquid current asset. From the accounting perspective, the generally low liquidity of inventory results from two factors which are:

i. Many types of inventory cannot be easily sold because they are partially completed items, special-purpose items, and the like; and
ii. Inventory is typically sold on credit, therefore, becomes account receivables before being converted into cash.

The formula of the QR is as below:

$$\text{Quick Ratio} = \frac{\text{Current Asset - Inventory}}{\text{Current Liabilities}}$$

Based on the formula, quick ratio indicates the level of cash and other current assets that can be readily converted into cash in comparison to the short term obligations of a firm. For instance, a quick ratio of 0.5 is an indication that a firm would be able to settle half of its current liabilities instantaneously. This type of ratio is an indicator of the solvency of an entity, thus requires analysis over a certain period of time in the context of the industry the firm is operating.

Thus, there is a need for firms to maintain a quick ratio that gives sufficient leverage against liquidity risk and providing certain level of volatility and predictability in a specific business sector among other considerations. Also, the more uncertain the business environment, there is likelihood that firms should maintain higher quick ratios. Conversely, where cash flows are predictable and stable, firms prefer to keep the quick ratio at relatively lower levels. However, it is necessary for firms to achieve the right balance between liquidity risk that is rising from a low quick ratio and the risk of loss, as a result of a high quick ratio.

Sometimes, a higher quick ratio than the industry average may depict that the firm invested in many resources is much considered the working capital of the business that may be of more use and profitable elsewhere. Although, if there is more than enough cash at the disposal of a firm, there might be consideration of investing the surplus funds in new ventures, should the firm be out of investment options, it may be prudent to return the excess funds to shareholders in the form of increased dividend payments. Conversely, a quick ratio that is lower than the industry average, indicates that the firm is taking too much risk of not maintaining an appropriate amount of liquid resources, on one hand.

On the other hand, a firm may have a better way to obtain better credit terms with the suppliers on their competitors. When analysing a quick ratio over a number of periods, there is a need to consider seasonal variations in several industries that can cause the ratio to be traditionally higher or lower at a certain time of year. As a seasonal business experience breaking activity that leads to various stages of assets and liabilities over time, there are also requirements for quick ratios to be evaluated in the firm's specialized industry context. Traditionally, certain business sectors have a quick ratio, such as the retail sector. Thus, firms that lead the retail sector can negotiate with an excellent credit terms with the suppliers because of their dominance in the market, resulting in relatively high current liabilities compared to their liquid assets. Additionally, the business environment is relatively stable in the retail sector and the expansion of operations is incremental, thereby allowing such firms to maintain lower quick ratio without taking too much risk.

Cash Ratio Measurement

Based on literatures, the cash ratio is a liquidity ratio that measures the ability of a firm to pay its present liability with only cash and cash equivalents. The cash ratio is more stringent than the current ratio or a quick ratio as no other current assets can be used to pay off current debt in cash. Thus, cash ratio is also taken consideration in predicted default firm as well as conducted by Khlifa (2017). In fact, cash ratio has become an important determinant of the failure. Altman (2011) convinced that examining cash ratio as an issue is important to predict corporate failure. In addition, Sharma and Iselin (2003) stated that because accruals system provides management with the opportunity to 'window-dress' their account and cash ratio information regarded as a source of alternative as it provides a little opportunities to manipulation.

Subsequently, Fawzi et al., (2015) in their study analyzed problematic data 52-52 and distressed Malaysian companies for three years before year 2009 until 2012. The results found that cash ratio from operating activities total liabilities, cash flows from operating activities to long term liabilities, cash flows from operating activities to total revenue, cash flows from operating activities and interest expense in interest and cash flow expenses from activities to total liabilities are significant predictors of financial difficulties.

The findings from the literatures indicate several reasons that many creditors prefer the cash ratio. Therefore, firms have to maintain adequate cash balances to pay off the current debts. Creditors also like the fact that inventories and accounts receivables are left out of the equation because both of these accounts are not guaranteed to be available for debt servicing. Inventories could take months or years to sell and receivables could take weeks to collect. Cash is guaranteed to be available for creditors.

The formula for CR as below:

$$\text{Cash Ratio} = \frac{\text{Cash + Cash Equivalents}}{\text{Total Current Liabilities}}$$

From the equation above, the cash ratio depicts how well a firm can pay off its current liabilities with only cash in addition with cash equivalents. This ratio depicts cash as well as equivalents as a percentage of current liabilities. A ratio of 1 provides that the firm has a similar amount of cash as well as equivalents to its current debt. To put this differently, in order to clear its current debt, the firm would have to employ all of its cash as well as its equivalents. A ratio above 1 depicts that all the current liabilities can be set off with cash and equivalents as well. Conversely, a ratio below 1 provides that the firm requires more than just its cash reserves to clear off its current debt.

As similar in most liquidity ratios, a higher cash coverage ratio refers that the company is more liquid and can more easily pay its debt. Creditors are more particularly interested in this ratio as they need to be sure that their loans will be repaid. While on the other hand, any ratio above 1 means a good liquidity measure.

4.7.3 Solvency Ratio Variable Measurement

The solvency ratio is measured by debt to equity ratio (DtER) and interest coverage ratio (ICR). These types of variables are measured using data from firms' annual reports and database. Lakshan and Wijekoon (2013) stated the accuracy of the model prediction comprises the financial ratio of 77.86 per cent per annum before failure. In addition, the accuracy of the model prediction in the three years before failure is more than 72 per cent. Therefore, this model is robust in obtaining accurate results up to three years before failure. The details on the measurement of the variables is explained as follows.

Debt to Equity Ratio (DtER) Measurement

Meanwhile, Trujillo-Ponce et al., (2014) introduced debt to equity ratio as the influence factors of credit risk in Europe market over the years from 2002 to 2009. The debt ratio to equity is a financial ratio that compares the amount owed by the firm to a total equity. The debt to the equity ratio represents the company's financing percentage which comes from creditors and investors. Higher debt to the equity ratio indicates that more payables (bank borrowings) are used from investor financing (shareholders).

The formula of DtER is as below:

$$\text{Debt to Equity Ratio} = \frac{\text{Total Libilities}}{\text{Total Equity}}$$

In addition, each industry has a different debt to equity benchmarks, as some industries tend to use more debt funding than others. The debt ratio 0.5 means that there are half of the liability of any equity. The firm’s assets are financed 2:1 by investors to the creditor. This means that investors have 66.6 cents per dollar assets of the company while the creditor only owns 33.3 sen on the dollar.

Further, debt to equity ratio of 1 means that investors and creditors have the same interest in business assets. Lower debt to the equity ratio usually shows a more financially stable business. Firms with higher debt to equity ratios are treated as risks to creditors and investors from companies with lower ratios. Unlike equity financing, the debt must be paid to the lender. As debt financing also requires the debt service or fixed interest payment, the debt can be a much more expensive financing than the equity financing. Companies leveraging on large amounts of debt may not be able to make payments.

Debt to equity ratio is taken into consideration as variable in this study has been conducted by Brîndescu-Olariu (2016). He conducted a study on predicting bankruptcy which has similiar case with default non default firm. Risk assessment of default risk in general and in particular always regard as bankrupt analysis financial ratios. Financial ratio analysis has been used since the second half of the 19th century, which was initially intended as an instrument for evaluating the ability of payment from companies that apply for bank loans.

Creditors see higher debt to equity ratios as risky as it suggests that investors do not finance the operations of any creditors. In other words, investors do not have as many skin in the game as creditors do. This could mean that investors do not want to finance business operations because the firm does not perform well.

Interest Coverage Ratio (ICR) Measurement

The interest coverage ratio is referred to as a solvency ratio which aimed to measure a firm's ability in making interest payments over its debt in a way that is timely. Dissimilar with the debt service coverage ratio, being able to make principal payments on the debt itself is not the problem of this liquidity ratio. Its main focus is to calculate the firm's ability to afford the interest on the debt as conducted by Purheidari and Alfatuni (2007) in predicting bankruptcy.

Therefore, investors as well as creditors employ this computation to determine the risk and profitability of a firm. Taking as an example, the main concern of an investor is about seeing his investment in the firm to grow higher in value. A large part of this appreciation is based on operational efficiencies and profits. Thus, investors are more interested to know that their firm can afford to pay its bills in a timely manner without having to sacrifice its profits and operations.

Consequently, creditor also employs the interest coverage ratio to determine whether a firm is able to support additional debt. Thus, if a firm cannot afford to pay the interest on its debt, it certainly would not be able to clear off the principal payments. Hence, creditors employ the use of these formulae to calculate the risk associated with lending, on one hand.

The formula of ICR is as below:

$$\text{Interest Coverage Ratio} = \frac{\text{Earnings Before Interest and Taxes (EBIT)}}{\text{Interest Expenses}}$$

On the other hand, more enfaces are placed mostly on how much risk an investor or creditor is willing to take when carrying out analyses on a coverage ratio. However, depending on the desired risk limits, bank might be more comfortable with a number than another. But in the event that the computation is less than 1, it invariably implies that the firm is not making enough money to set off its interest payments. Thereby, the firm forgets paying back the principal payments on the debt. On the contrary, a firm with a calculation that is less than 1 would not be able to pay the interest on its debt. This category of the firm is beyond risky and probably would never receive any bank financing.

Furthermore, in a situation where the coverage equation equals to 1, its means is that the firm makes adequate money to set off its interest. This scenario is not much better than the last one due to the fact that the company is still not able to afford to settle off the principle payments. Thus, it can only cover the interest on the current debt.

Again, in the case where coverage measurements are higher than 1, it reflects that the firm makes higher than sufficient money required to pay its interest obligation with some additional income left to make the principal payment. However, majority of creditors seek at least 1.5 protection before any loan request. In other words, the bank wishes to ensure that the company can make at least 1.5 times of their total interest payout.

4.7.4 Corporate Governance Variable Measurement

In term of corporate governance, the corporate governance consists of a set of relationships between the shareholders, managers and auditors in a firm as well as a control system to protect shareholders' rights. The control system which based on accountability and social responsibility. Therefore, the firm has to perform a set of duties and responsibilities that lead to accountability and transparency. In the past, corporate governance focused on the leadership of the firm rather than control. Now its includes control.

A firm has to evolve with the changing world and competitiveness in the market conditions. The external factors like monetary policy, the financial developments in the market, the dominance of the competitive situations, the unpredictable of financial crisis could lead to many firms default. Mokarami and Motefares (2013) indicated that there is a significant relationship between corporate governance and default firm. Another author, Marzuki (2005) has also determined the relationship between corporate governance and default firm in Malaysia. His study used a combination of units of measurements as such the board, the structure of ownership and leadership. The study compared between healthy and unhealthy firms by using binary logistic regression. The study found that insignificant relationship between characteristics of the corporate governance and default however both profitability and liquidity ratios has effects to the healthy and unhealthy firms.

From the previous researches, thus, this study used corporate governance as variable. The corporate governance characteristic are formed by two units of measurements which are Independent Director (ID) and Audit Committee (AC) and the data from the firms’ annual reports and Bloomberg database as in Appendix 6.

The formula of ID and AC are as follows:

Composition of Independence Directors:

One-third of the Board's membership = 1;

Not One-third of the Board's membership = 0

Existence of Audit comittee: Yes = 1; No = 0

This study also referred to MCCG 2000-2007, *Shariah* Committee 2004 and *Shariah* Governance Framework 2011. This is because these years fell within the period of 2006-2011. The Independent Director (ID) and Audit Committee (AC) are also used to measure corporate governance characteristics based on the panel logit model. In overall, the summary on the variables and unit of measurements involved in this study which based on Objective 2: To Investigate Impact of Liquidity Risk, Solvency Ratio and Corporate Governance to the Defaulted *Sukuk* is explained in Table 4.2.

Table 4.8: List of Variables and Unit of Measurements

Variable 1: Liquidity Risk

Variables	Symbol	Description	Frequency	Source
Dependent Variables: Predictability of *sukuk* default				
Independent Variables:				
Quick ratio	QR	Resulting from current asset minus inventory and divided by current liabilities	Yearly	Annual report
Cash ratio	CR	It is proxied by the ratio cash and current liabilities	Yearly	Annual report

Variable 2: Solvency Ratio

Variables	Symbol	Description	Frequency	Source
Dependent Variables: Predictability of *sukuk* default				
Independent Variables:				
Debt to equity ratio	DtER	It is proxied by the yield of total liabilities divided by total equity	Yearly	Annual report/Bloomberg
Interest coverage ratio	ICR	It is generated by earning before interest and taxes divided with interest expenses	Yearly	Annual report/ Bloomberg

Variable 3: Corporate Governance

Variables	Symbol	Description	Frequency	Source
Dependent Variables: Predictability of *sukuk* default				
Independent Variables:				
Independent director	ID		Yearly	Annual report/Bloomberg
Audit committee	AC		Yearly	Annual report/Bloomberg

However, with regard to this study, *sukuk* firm's predictability of default is conceptualised into three dimensions; (i) the indicators of liquidity risk, (ii) indicators of solvency ratio, and (iii) corporate governance characteristics. Two intangible methods were conducted; (a) preliminary analysis to create profiles, and (b) logistic regression and decision tree analysis to establish the factors associated with each of these predictable measurements.

4.8 Research Methodology

This study employs both statistical and data mining methods to predict *sukuk* default determinants. There are number of different models available to estimate default non default such as Black-Scholes Model, Merton Model, Altman z-score Model, logistics regression and decision tree. Altman z-score has some weaknesses such as the possibility that the firm's accounting people have manipulated the input data and the financial reports does not represent the actual state of the firm. This would obviously take away the truthfulness of the model. The accuracy of the default predicting models should (theoretically) not be depended on time or sample used in the model.

The Merton model's major weakness is the set of assumptions that may not represent reality. For example is the assumption that stock returns are normally distributed, something that is not always reflected in the real world. (Assumptions explained in detail below). Previous comparing research has had contradicting result and a final decision on which model is superior has not been able to have been taken. For example did Campbell et al (2006) find that the Merton model was not accurate enough to predict default.

Thus, this study uses binary logistics regression and decision tree to create a model of predictability of *sukuk* default from several theoretical variables from firm's financial ratios, market variables and specific *sukuk* characteristics. Statistical techniques require the assumption of a certain functional form for relating dependent variables to independent variables. When the assumed functional form is not correct, the statistical techniques merely confirm that but do not predict the right functional form (Dutta & Shekhar, 1988). According to Intrator and Intrator (2001) logistic regression model is interpretable but often does not provide adequate prediction, thus it makes their interpretation questionable. Therefore, in this case, the selection of significant variables is applied using the stepwise method for binary logistic model and classification of decision tree.

4.8.1 Logistic Regression Model in Predicting *Sukuk* Defaulted Firm

As mentioned in the previous chapter, the main purpose of this study is to investigate default and non-default indicators of *sukuk* firms in Malaysia. As such, it is based on a predictive model that would possibly explain the default and non-default of *sukuk* firms. The model would also be used as the basis for testing the hypotheses posited in this study by looking at the directions of the explanatory variables compared to the dependent variables.

Generally, the study adopts the hypothetical-deductive approach, underpinned by model and theories, namely Failure Predictive Model, Agency Theory and Stakeholder Theory. Meanwhile, the use of descriptive and statistical test analysis are employed to analyse the data of this study. As such, multivariate regression through logistic regression techniques is employed to generate the models (model of the liquidity risk indicators, model of the solvency ratio indicators, model of the corporate governance characteristics, and model of the predictability of *sukuk* defaulted firms). The following section highlights the methods of analysis employed in this study.

Based on previous studies, logistic regression is beneficial when the forecast is based on the values of the independent variable. The logistic regression is linear-regression fixed for dichotomous dependent variables and is set to determine the odds ratio for each explanatory variables used in the model. This helps form the regression multivariate regression between the independent and dependent variables (Lee et al., 2007). As a result of this regression, determining the likelihood of two answers (0 and 1) or (Yes or No) depends on the definition of the value of the two response variables (Tabachnick & Fidell, 2001). Binary Logistic (or binomial) is a form of regression used when dependent variable is dichotomy and independent variable are of any kind. In addition, logistic regression can be conducted to predict the variables depending on continuous basis and/or the free category and to determine the percentage of independent variables; to assess the relative interest free; to assess the impact of interactions; and to understand the impact of the variables in control (Grason, 2009). The effects of an unexplained variable are usually described in terms of possible ratios.

Another authors Dutta et al., (2015) explained that logistic regression used to predict results that permit accuracy, such as group membership of variables that can be dichotomous, continuous or discrete, or a mixture of all of these. Typically, a categorical response variables are as presence/absence or failure/success. In the case where the variables are categorical, combined explanation categorical and continuous logistic regression are popular.

In this study, predictability of *sukuk* default as a dependent variable is conceptualised as default firm and non-default firm. The default firm measure is in a qualitative form and categorised as '1' for default and '0' for non-default. In order to enable these qualitative measures to be regressed in multivariate regression technique, logistic regression methods were used.

Logit is a possible log that events occur. The coefficient in the logistic (β1, β2, etc) model will inform Logit's changes based on the predictor value. Hair (2006) as well as Hosmer and Lemeshow (2000) explained the assumption of the logistic model. They noted that logistic regression are popular partly because it allows researchers to cope with many stringent assumptions of the regression of the OLS as such:

1. Logistic regression does not take a linear relationship between independent and dependent variable. It can handle non-linear effects even though exponential and polinomial terms are not explicitly added as extra free because of the functionality of link logit on the left side of the logistic regression is not linear. However, it is also possible and allowed to add clear interactions and power terms as variables on the right of the logistics, such as in an unforgettable regression.
2. The dependent variables must be normally distributed (but does not assume the distribution as in the range of exponential distribution families, as usual, (Poisson, Binomial, Gamma). The solution may be more stable if the predictors have normal distribution of multivariate.
3. Logistic regression does not require that the independents be interval.
4. The dependent variable need not be homoscedastic for each level of the independents; that is, there is no homogeneity of variance assumption; variances need not be the same within categories.
5. Logistic regression does not require that the independents be unbounded multinomial.
6. Normally distributed error terms are not assumed.

There are two types of measurement scales for the category variables as variables depend on the model (Agresti, 1996). First, it's a category scale that has natural orders, for example the time correlation of research and results (low, medium, high), opinions of certain ideas (neutral, agreeing, disagree), etc. Secondly, the category variable has an unordered scale called a nominal variable. Examples are religious relations (Islam, Catholic, Hindu, Budha), and transport mode (bicycle, train, walking). For a nominal variable, a configuration of the listing category is irrelevant, and statistical analysis should not depend on the order.

In the ordered model, the individual unit's responses are limited to one of the M values ordered. Cummulative Logit Model assumes that the ordinal nature of the response was attributed to the limit of methodological in collecting data that resulted in the same value as the same as the reverse response variable (McKelvey & Zavoina, 1975). However, when the model violates one of the basic assumptions of the model ordered, which is a parallel assumption test, it is recommended to continue the method for multinomial logistics to capture the difference coefficient among equation. Moreover, the method designed for nominal variables such as multinomial logistics can be used by both nominal and ordinal variables, as they only require a scale of categories.

The multinomial logistic strategy usually involves allowing one category to assume a specific values, say Y = h0, where h0 = 1. This category is then used as the reference category for the rest of the other categories. Based on that, the group members can be classified by computing the probability of that member being in that specific group as compared to being a member of the reference group which is the odd ratio. This method is also known as the base-line category type (Arnesti, 1996). The following example taken from Touray (2004) and Menard (1995) shows how this model is derived. Consider the dependent variable with several categories = M, then M-1 equations are needed; one for each category contrast to the base-line category.

The change in predictor variables can be related to the dependent categories as given in the general form of the equation.

Pseudo R-Square Test

Cox and Snell, Nagelkerke, and the analogies McFadden-R2 statistical measures that can be used for R-Square, but do not have a percentage of variance that explains interpretations and cannot be reported in such conditions (Tabachnick & Fidell, 2001). On the other hand, all should be taken as an additional step of the size of the model effect, the higher the better. Cox and Snell R-Square is an attempt to replicate the interpretation of a range of R-Square based on the odds, but the maximum can (and usually) be less than 1.0, making it difficult to interpret. A R-Square Nagelkerke is a further modification of the Cox and Snell coefficient to ensure that it can vary from 0 to 1. Thus, R-Square Nagelkerke will usually be higher than Cox and Snell measurements but will tend to run lower than the same R-Square. R-Square McFadden is a theoretical measure of information interpreted as a reduction in entropy that the researcher model achieves as compared to the model of bypassing-only (Magidson, 1981).

Model Fitting Information

The likelihood ratio also used in model fitting information in order to test the overall model (Hosmer & Lemeshow, 2000). This test is also known as model chi-square test. There are two models that are referenced in the model fitting information. The first one is "Intercept Only" model that refers to the null model, while the second one is "Final" model which is also called as the fitted model. The logistic equation is the linear combination of predictor variables which maximizes the log likelihood that the dependent variable equals the predicted value/class. The difference in the -2 log likelihood measures how much the final model improves over the null model.

The appropriate model is noticeable at the level 05 or better. Finding interest (P < =. 05 is the usual cutoff) leading to an invalid hypothesis rejection that all of the predictions are zero. When the test is likely to be important, at least one of the predictors is noticeable in connection with the dependent variable. Putting another way out, a possible ratio of an invalid hypothesis test that all of the population of the regression logistic coefficient unless the constant is zero. And put it in a final way, the possible ratio of tests shows the difference between an error not knowing free (early Chi-Square) and the error when free is included in the model (deviance). When the probability (Chi-Square model) < =. 05, pushing an invalid hypothesis that knows free does not make a difference in predicting depending on logistic regression.

The likelihood ratio test looks at the Chi-Square model (Chi-square divergence) by pushing the deviance (-2LL) for the final model (full) of deviance for the model intercept only. The degree of freedom in this test is the same as the number of terms in the model minus 1 (for constant). This is just like a difference in the number of terms between the two models, because an invalid model only has a term. Chi-Square Model is a suitable improvement that is an explanation variable compared to an invalid model.

Assumptions

The analytical logistic methods of analysis allow the use of several continuous and category variables to explain the results or variables depending on. The scenario is that, when variables are categorized, the use of handy logistic regression to detect explanation between the variables is practised (Stearns et al., 1995). The main objective of the logistic regression is to achieve the highest possible prediction of forecast with a predictor (Hair, 1995). The regression principle of logistics is to state the similarities of various linear regression in terms of logarithmic and thus, overcoming the problem of violating assumptions from liability. Parameter values are estimated using the maximum method-probability, a technique in which the coefficient that makes the value observed most likely has occurred then selected.

Model Specification

The logistic regression defines the log odds of the event (defaulting of the firm) occurring. The general equation for the logistic regression may be written as follows:

$$\ln (Odds) = \beta o + \beta X + \beta 2\ X2 + \ldots . \beta nXn + \varepsilon \qquad (4.1)$$

where: βo, β,$\beta 2$, βn = coefficient of variable; X, X2, Xn = Independent variable

ln (Odds) is the natural log of the odds, and its quantity is called a logit. On the right-hand side of the equation (4.1) are the standard linear regression terms of the independent variables and the intercept.

4.8.2 Decision Tree Model in Predicting *Sukuk* Defaulted Firm

Decision tree approach is used in this study in order to have a better result. In financial and economic studies, many researchers use decision tree model in predicting worst payment status between non-financial business (Gstat & Priestley, 2017), as well as predicting personal bankruptcy (Livshits et al., 2010; Sharifah

Heryati et al., 2019), predicting financial distress (Gepp & Kumar, 2015; Irimia-Dieguez & Blanco-Oliver, 2015).

Gstat and Priestley (2017) described how to use the decision trees to create regression models stratified by selecting different slices of the population data for regression modelling in-depth. They conducted the study on predicting the worst payment status between non-financial business, and assessed the performance of the model tree results against traditional logistic regression model for this task. The process from the study are described as follows. Techniques such as machine learning, support Vector Machines and Neural Networks were used to improve the modeling predictions, where the model does not yield easily explainable, and therefore, difficult to apply in the financial regulations regulations (Irimia-Dieguez & Blanco-Oliver, 2015). Furthermore, the decision trees are easy to explain, and provide easy-to-interpret of the visualization model decision. It aims dataset for analysis provided by Equifax and has more than 300 potential predictors from 11 million unique businesses. After the discovery phase of data, including the imputation, cleaning and transforming potential, cognitive and decision tree models-logistic regression model was constructed in the same dataset that concluded the analysis. Evaluating model based on Index ROC and Kolmogorov-Smirnov Statistics, decision trees model and logistic regression are performed. Findings showed that decision trees has better accuracy and explainable in predicting worst payment status. As mentioned in Sharifah Heryati et al., (2019)'s study, decision trees provide good results in identifying appropriate strata regression.

Followings are the discussions on decision tree. Decision trees are a variety of form analysis variables (or double effect). All forms of multiple variable analysis enable to predict, clarify, explain, or classify the result (or target). Example of analysis of multiple variables is the probability of being sold or the possibility to respond to marketing campaigns due to the effect of the combination of several input variables, factors or dimensions. Changing the analysis capabilities of various decision trees enables the firm to go beyond the relationship of one reason, a simple effect to know and explain things in the context of a variety of influences. Some analysis of this variable is very important to resolve the problem as almost all critical revenue that determines success is based on various factors. In addition, it became clear that although it is easy to set up a reason, per-effect relationship in the form of tables or graphs, this approach can lead to costly and confusing results.

Further elaboration on decision tree is as follow. The decision trees lies in the relative power, ease of use, robustness with a wealth of data and level of measurement and facilitating the interpretability. Decision tree was developed and delivered in stages; therefore, set the combination of various influences (which is necessary to explain the relationship benefits completely) in a group of relationships present one reason, a recursive tree effects in the form of decisions. This means that decisions dealing with short term memory limit is human effective enough and easier to understand than more complex various techniques. Decision tree makes raw data, increases knowledge and awareness of the business, engineering, and scientific issues, where they allow the use of knowledge in a set of simple rules which are easy to read with robust result.

Thus, this study chooses decision tree as analysis method. It is a decision support system that utilizes a tree-graph decision and the possible classification, including chance event problem or classification problem. A decision tree, or a classification tree, is used to study classification function which concludes the value of dependent attribute (variable) given the values of independent attributes (input variables). This verifies a problem known as supervised classification because the information on dependent variable and the targeted classes are given (Korting, 2013; Bhargava et al., 2013). Rokach & Maimon (2008) as well as Novotna (2012) stated that a decision tree is a predictive model that can be used for both decision and clasification problems. Classification tree can be used to classify an object of an instance, such as companies, to a predefined set of classes or rating groups. The companies are firstly classified according to most relevant variable, subsequently divided into subgroup according to other variables until they are classified into several classes or groups (Witzany, 2010; Novotna, 2012).

To construct a classification tree requires several phases. First is the selection of attributes to place the root node. This root node means a directed tree which has no incoming edges but has external edges. The branch nodes have exactly one incoming edge and the leaves or decision nodes are the nodes without external nodes.

In the decision tree, each internal node splits up the input set into several subsets, one for every value of the attribute (Witten, Frank & Hall, 2011). Now the process can be repeated recursively for each branch. At the end, the last leaves nodes are assigned to one class representing the most appropriate target value. The samples (instances) are classified by navigating them from the root of the tree down to a leaf, according to the outcome of the test along the path.

Information Gain

For classification tree J48, the best splitting attributes is usually counted using information gain. The information gain is an impurity-based criterion that uses entropy measurement (origin from information theory) as the impurity measure (Quinlan, 1986; Witten et al., 2011). Entropy is a measurement of disorder data that are calculated in bits, nats or bans (Bhargava et al., 2013).

In order to get a small and efficient tree, the splitting criteria should be based on the highest gain. In this research, there are 60 in a class instance. These instances are divided further into two different groups on the bases of their calculated entropy and information gain. Entropy will select the best attribute (variable) as root nodes and based on that the samples are divided from 60 samples into two classes. Subsequently, this information gain is also used for splitting criteria along the branch.

Pruning Methods

Overfitting-avoidance is an important technique to be applied in the classification tree creation because of outliers. To address overfitting problem, pruning method is introduced to classify the data correctly and reduce unnecessary nodes. There are two classifications of pruning; the post-pruning and pre-pruning (Witten et al., 2011; Bhargava et al., 2013; Moertini, 2013).

The post-pruning or known as backward pruning is performed after the creation of classification tree, whereas the pre-pruning or forward pruning is performed during the creation of classification tree. In other words, pre-pruning allows the nodes to be selected first in order to avoid unnecessary nodes incorporated in the model. Apart from that, post-pruning method also gives an advantage. For example, situations occur in which two attributes are individually seemed to have nothing to contribute but are powerful predictors when combined with a sort of combination lock effect in which the correct combination of the two attribute values is very informative but the attributes taken individually are not.

Table 4.8 highlights summary of literature on methodology referred in this study.

Table 4.8: Table of Summary of Literature on Methodology

No.	**Method**	**Literature**
1.	Logistic regression	Arundina (2015) Neophytou et. al., (2000)
2.	Decision tree	Arundina (2015) Gstat & Priestley (2017)

4.9 Summary

This chapter deliberates on the meticulous process involved in modelling the *sukuk* defaulted firms. It involves in inspecting the data so as to get the possible and the most appropriate method to be used. Subsequently, the variable rationale and hypothesis are presented in order to justify the variable used to build *sukuk* defaulted firms characteristics and prediction model. Therefore, the main contribution of this research is to suggest a new characteristics of *sukuk* defaulted firm and model based on liquidity risk, solvency ratio and corporate governance characteristics.