Risk Management in SMEs using Data Mining Methods with Financial and Non-financial Indicators

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Abstract

As the economy develops, the importance of risk management increases significantly. Newly-developed data mining techniques have also provided an extended range of information for decision-makers and scholars about the Risk Management (RM) process. This study thus assessed the use of financial and non-financial indicators in the RM process based on a Business Intelligence (BI) approach and using data mining (DM) methodology. Its assessment focused on the selection of Key Risk Indicators (KRIs) among the various risk indicators for performance measurement and risk control. This study used a sample of 853 Chinese SMEs listed on the Shenzhen Stock Exchange. After comparison of LR, GA, NN, and CHAID, CHAID was found to be the most suitable mode, as it incorporates both financial and non-financial indicators and is also able to provide roadmaps to improve RM performance. This study also used a BI approach to quantify and standardise information from government reports and firms' annual reports to better generalise the available information for non-financial indicators. Four different types of risks were considered, following the enterprise risk management (ERM) framework, and using CHAID as the underlying method, the threshold values and roadmaps of the KRIs were thus identified. This study thus provides an integrated method for the risk management process in SMEs by using both financial and non-financial information generalised using a BI approach with the DM process. The critical contribution of this study is its combination of the DM process and RM process, which also allowed examination of the usefulness of non-financial indicators in the RM process with the ERM framework. Additionally, it provides practical guidance for using a BI approach for capturing information and transferring data.

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CONTENT

Abbreviations

AUC	Area Under Curve
BI	Business Intelligence
BPNN	Back Propagation Neural Network
CART	Classification and Regression Trees
CAS	Casualty Actuarial Society
CHAID	Chi-square Automatic Interaction Detector
COSO	Committee of Sponsoring Organisations of the Treadway Commission
DLI	Development and Life Index
DM	Data Mining
EWS	Early Warning System
ERM	Enterprise Risk Management
F and NF	Financial and Non-Financial
GAs	Genetic Algorithms
ISO	International Organization for Standardization
KDD	Knowledge Discovery in Databases
KRI	Key Risk Indicator
KPI	Key Performance Indicator
LR	Logit Regression
MDA	Multiple Discriminant Analysis
NSBC	National Statistical Bureau of China
NN	Neural Network
ST	Special Treatment
SMEs	Small and Medium sized Enterprises
RM	Risk Management
RMSE	Root Mean Square Error
ROC	Receiver Operation Characteristic

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1. Introduction

1.1 Background

Risk management (RM) has become an increasingly important issue for small and medium enterprises in recent years (Verbano and Venturini, 2011, 2013). The study of risk management began in the mid-twentieth century, and one of the first definitions of risk is attributed to Bernoulli, who proposed measuring risk as a geometric mean and minimising it by spreading it across a set of independent events (Bernoulli, 1954). Accordingly, using the traditional definition, risk is measured by combining two variables: a) frequency of occurrence (probability) of the "risky" event, also defined as the number of times the event under investigation would be expected to be repeated in a predetermined period, and b) the extent of the consequences (magnitude) of the event, which includes all of the results of its occurrence. However, there is no unified definition of risk concepts applied in the business literature (Wolke, 2017). Following Chapman and Cooper (1983), the risk is more clearly defined as the possibility of suffering economic and financial losses or physical material damage as a result of an inherent uncertainty associated with an action taken. In a later definition developed within the management literature, the concept of risk includes both the positive and negative consequences of an event wherever these may affect the achievement of the strategic, operational, and financial objectives of a company (BBA et al., 1999).

Given the complexity and magnitude of the risks that companies now face, scholars also recognise a macro classification of risks into two main categories (Mowbray et al., 1979). The first is the pure or static risk; this is the risk that only causes damage, and which offers no opportunity of benefit from its occurrence. It is characteristically unexpected because it is determined only by chance events. This risk falls entirely under the concept of the insurance policy (Ekwere, 2016). The second type is the speculative or dynamic risk; this is the sort of risk that can both cause damage and create opportunities (Ekwere, 2016). These are often thought of as typical entrepreneurial risks, with negative consequences only in some instances, for example, where investment does not generate a profit. Risks are generally related to planning and managing the different businesses and functions of an enterprise, such as production, product, marketing, and sales. Risky events can be triggered by external factors (economic, environmental, social, political, and technological aspects) or internal factors (infrastructure, human resources, processes, and technology as used by a company) (COSO, 2004).

Risk management is defined as the process of attempting to safeguard the assets of the company against the losses that it may incur in the exercise of its activities through the use of instruments of various kinds, including prevention, retention, and insurance, under best cost conditions (Urciuoli and Crenca, 1989). A related definition of risk management (RM) refers to the process of planning, organising, directing, and controlling resources to achieve given objectives when unpredictable good or bad events are nevertheless possible (Head, 2009). The International Organization for Standardization (ISO 31000, 2009) identifies the following principles of RM: it should create value; be an integral part of the organizational processes; be a part of decision making that explicitly addresses uncertainty; be systematic and structured; be based on the best available information; be tailored; take into account human factors; be transparent and inclusive; be dynamic, iterative, and responsive to change; and be capable of continual improvement and enhancement. The adoption of a risk management methodology can help firms to reduce uncertainty in enterprise management, ensure continuity in production and trading in the market, decrease the risk of failure, and promote the enterprise's external and internal image. In this way, risk management can create business value and maximise business profits by minimising costs (Urciuoli and Crenca, 1989).

Wolke (2017) stated that the risk management is considered as a process in most literature, which is as a sequence of events in time. More specifically, risk management follows a stage-gate process (Henschel, 2009; ISO 31000, 2009; Urciuoli and Crenca, 1989), and a critical preparatory step requires defining the risk management plan in a way that is consistent with strategic business objectives, as well as conducting context analysis. This initial stage aims to identify all the risks to which the enterprise is exposed. The second stage is risk assessment and analysis, which aims to determine the probability and expected magnitude associated with any such occurrence of damage. A threshold of acceptability must be defined in order to move to the next stage, which reflects the risk appetite of top management and the resources available for risk management. The third stage is the treatment of unacceptable risks, which identifies the most appropriate actions that can be taken to reduce either the probability or effect of the risk (Verbano and Venturini, 2013). The final process is supervision. In the literature, the first two phases (identification and evaluation and analysis) are often called risk assessment.

The implementation of a risk management system is a long-term, dynamic, and interactive process that must be continuously improved, and which should be integrated into the organisation's strategic planning (Di Serio et al., 2011). Compared with their larger counterparts, however, small- and medium-sized enterprises (SMEs) may not have sufficient capital and human resource to achieve this, which makes SMEs less competitive than other companies (Kim and Vonotas, 2014; Ekwere, 2016). Street and Cameron (2007) noted that newer and smaller enterprises are much more vulnerable to all types of risks, and thus, according to Organization for Economic Cooperation and Development (2001), smaller and newer companies are more likely to exit than their larger counterparts. Although SMEs are often more flexible regarding their ability to change their strategies and structures, they are also more likely to fail during economic crises due to their lack of capital and reliance on offering a smaller range of products and services. It is thus essential to identify and manage the risks faced by all SMEs to help them avoid such crises and to promote growth.

Proper risk management procedures can help companies to create value (Nocco and Stulz, 2006). Traditional risk management has adopted several different techniques, many of which began in the 1980s for dealing with crises in the insurance market. Lam (2004) stated that traditional risk management transferred the risks to third parties using insurance coverage. In the 1990s, the economic-financial context of firms pushed risk management towards managing the volatility of businesses and financial results (Lam, 2004). Here again, traditional risk management mainly focused on the financial aspects of companies.

Verbano and Venturini (2013) noted that risk management changed after the year 2000. The new methods take more holistic, integrated, future-focused, and process-oriented approaches, which aim to help companies to manage their critical business risks and maximise shareholder value. Verbano and Venturini (2013) also pointed out that, in recent decades, the types of risks, definitions, methods, techniques, and approaches that risk management is concerned with have changed significantly. Alquier and Tignol (2006) similarly stated that the SMEs are now more sensitive to business risk and competition, pointing out that a specific risk management method can be applied to SMEs that differs from the methods used for larger companies. Thus, the risk management procedures most suitable for SMEs are not same as those used in larger companies, making it necessary to determine suitable methods that consider the features, advantages, weaknesses, and unique requirements of SMEs.

The RM for SMEs and for large companies is different. Falkner (2015) stated that the

SMEs cannot profit as much as large companies from economics of scale. Meanwhile, most of SMEs have limited access to resources (Falkner, 2015). Altman et al (2010) also pointed out that the SMEs are more vulnerable to external environment than large companies. Brustbauer (2014) stated that the RM can help SMEs to identify and treat significant risks. However, the misjudging and failing to recognise risks can finally cause bankruptcy (Falkner, 2015). Marcelino-Sadaba, Pérez-Ezcurdia, Echeverría Lazcano and Villanueva (2014) stated that many SMEs cannot apply adequate RM due to the constrains of their limited resources and capital. As a result, the RM process designed for SMEs should consider different aspects than large companies. Specifically, the efficiency and accuracy are more important. Brustbauer (2014) stated that the RM in SMEs is usually lack of resources and reliable mechanisms. Brustbauer (2014) then emphasised that ERM framework can help the RM process in SMEs. However, many of SMEs do not have enough knowledge and awareness of RM process (Brustbauer, 2014). Therefore, the RM process for SMEs should be customised, which should also be easy to apply and provide reliable strategies.

The risk management methods that are suitable for SMEs are not the same as the risk management methods used successfully by larger companies (Verbano and Venturini, 2013; Ekwere, 2016). Carrier (1994) stated that the large firms and SMEs are different in structure and decision-making, where large firms are formalised, and SMEs are dynamic and adaptable. Rivaud-Danset, Dubocage and Salais (2001) found that the financial structure of SMEs and large firms are also different, where SMEs are more flexible in financial structure, rely more on short-term debts, and more highly leveraged. It therefore indicated that the SMEs are not stable as large firms, since the large firms have more constant financial structure. Alquier and Tignol (2006) stated that the SMEs are more sensitive to risks and competition. They pointed out that a specific risk management method is needed for SMEs, which differs from the methods used for larger companies. The RM for SMEs should consider the financial structure, the overall process and the focuses. Meanwhile, the significant indicators in larger companies may be also different, since many indicators and ratios in SMEs are different from larger companies. The RM process for SMEs is also different. According to Brustbauer (2014), the management should pay more attention on the resources and mechanisms for RM process in SMEs. The SMEs usually have less capital, knowledge and resources to conduct RM process, which means it is difficult for them to achieve the goals of RM process. The RM process for SMEs should consider the costs, the efficiency and the accuracy, where the larger companies can hedge and insure their risks with their abundant resources (Nocco and Stulz, 2006). In addition, the indicators of performance measurement for SMEs may be different as well. These significant indicators in RM for large companies may be not significant in SMEs. Brustbauer (2014) stated that the risk identification step are more important in RM process, which means the steps of RM process for SMEs will differ from large firms. Ekwere (2016) supported this point by stating that the methods of risk management required adoptions while applied in SMEs. However, as risk management practice by SMEs is a recent development, most of the existing research has focused on project management, research and development, accounting, finance, and insurance (Verbano and Venturini, 2013). The lack of research into appropriate risk management for SMEs is particularly apparent about the empirical evidence on risk management methods and process in SMEs (Kim and Vonortas, 2014). A focus on the study of risk management in SMEs is thus required to help improve the knowledge and performance of SMEs.

However, as risk management practice by SMEs is a recent development, most of the existing research has focused on project management, research and development, accounting, finance, and insurance. The lack of research into appropriate risk management for SMEs is particularly apparent about the absence of systematic empirical evidence on the nature, extent, and antecedents of risk management in small firms (Kim and Vonortas, 2014). A focus on the study of risk management in SMEs is thus required to help improve the knowledge and performance of SMEs. Previous research on risk management has mainly focused on large companies (Verbano and Venturini, 2011) or, at best, how risk changes with time (Barrieu and Karoui, 2004). However, SMEs are the predominant type of business throughout all Organization for Economic Cooperation and Development (OECD) economies and typically account for two-thirds of all employment (Altman et al, 2010), to the extent that these small and medium-sized enterprises represent over 90 percent of all firms in OECD member countries (OECD, 2011). SMEs are thus an important force for both domestic and international economic development (Liu, Li and Zhang, 2012). The number of SMEs is also increasing rather than decreasing, a development anticipated by economists (Liu et al., 2012). Their contribution to economic development is thus also significantly increased. In Italy, Japan, and France, SMEs account for 99 per cent of all enterprises, while in the United States, there are more than 2,000 million SMEs, representing 98 per cent of total companies. Small companies generate about 33 per cent of total industrial employment and output in Europe overall (Smit and Watkins, 2012). In Germany, SMEs contribute more than 60 per cent of the export value for the country (Liu et al., 2012), and in China, according to recent statistics, SMEs represent 99.3 per cent of the total number of enterprises.

Liu et al. (2012) took China's most economically developed city, Shanghai, as an example to prove the contributions made by SMEs to Chinese financial development. They stated that 98.7 per cent of total companies in that area is SMEs and that these contribute 30 per cent of the total output of the whole economy. In developing countries, SMEs play vital roles in the overall economy. For example, in China, SMEs generate 70 per cent of local employment, 60 per cent of industrial output, and 40 per cent of profits and taxes (Liu et al., 2012). Smit and Watkins (2012) further noted that the SMEs in the developing countries could contribute far more to the promotion of economic growth, job creation, and poverty mitigation than larger organisations.

Nevertheless, the risks faced by SMEs are very different from those risks faced by large enterprises. Corazza, Funari and Gusso (2016) stated: “the SMEs typically over-react to the phase of growth and decrease of economic cycle”. In defiance of their contributions to the economy, SMEs, therefore, find it much more difficult to obtain external financing from formal financial institutions (Shen, Shen, Xu and Bai, 2009).

More than large companies, SMEs required the adoption of risk management strategy and methodology, because the capital and resources cannot support them promptly respond to the changes in the internal and external environment (Ekwere, 2016). In the past decades, most managers of large corporations have focused on the purchase of insurance to manage risk (Nocco and Stulz, 2006). However, in recent decades, risk management as a process has expanded to much more than using insurance and hedging to limit financial exposure (Nocco and Stulz, 2006). New developments in risk management theory have driven these changes, and Nocco and Stulz (2006) pointed out that companies can now manage one risk at a time or manage all risks together by using an integrated framework. It should be clear that the latter method is more useful for small and medium companies in many ways because their structures are more flexible (Kim and Vonortas, 2014). As a result, the risk management process developed for SMEs becomes increasingly essential.

The variables used to analyse the success of larger companies and SMEs are also not the same; Altman et al. (2010) noted, for example, that non-financial variables play significant roles in financial analysis in the latter situation. However, few researchers have focused on applying non-financial variables when making predictions for companies. Fantazzni and Figini (2008) created a non-parametric model and compared the result with a standard logit model, while Gurent, Norden and Weber (2004) attempted to include non-financial variables such as age, type of business, and industrial sector alongside financial ratios in their models. However, these studies still did not focus on SMEs and only included limited amounts of non-financial information. As risk management frameworks have been developed and updated in recent years (Kim and Vonortas, 2014), it is, however, important to consider non-financial indicators in their role key indicators in the analysis of SMEs' issues.

Traditional risk management mainly focused on the financial risks faced by firms (Hull, 2000). However, as Keith (2014) stated, organisations almost invariably misestimate their readiness to assess potential risks and efficiently apply this knowledge to solve risk management problems. The risks management applications have been classified into nine different frameworks, where the enterprise risk management is one of them (Verbano and Venturuni, 2011, 2013). The risk frameworks decide the risk types and process (CAS, 2003). De Loach (2000) recommended integrated risk management (also called enterprise risk management or holistic risk management), which is a structured and disciplined approach to manage threats and opportunities, and Verbano and Venturini (2011) agreed that enterprise risk management could help firms manage all key business risks and opportunities as a whole, thus maximising shareholder value. The types of risks, definitions, methods, techniques, and approaches utilised are often based on cultural context, which differs between cases, making it difficult to construct a model that covers all aspects. Nevertheless, enterprise risk management is a step forward from basic financial risk management frameworks, as it deliberately includes non-financial circumstances (Verbano and Venturini, 2011). Thus, enterprise risk management can take into consideration all the aspects of a firm's management, including strategies, market, process, financial resources, human resources, and technologies (O’Donnell, 2005).

Nocco and Stulz (2006) stated that the ERM provides a long-run competitive advantage by optimising the trade-off between risk and return; however, the application of ERM in SMEs remains understudied (Verbano and Venturini, 2013). Each firm faces different risks based on its external and internal environment (COSO, 2004), and regarding capturing all aspects of this risk, the use of quantising and standardising the information in the form of indicators by using a business intelligence approach is also still understudied. The results of using non-financial indicators to examine enterprise risk management s thus remain unclear, and the effectiveness of different data mining methods for risk management in SMEs has also yet to be investigated and evaluated thoroughly. There are total nine risk frameworks in risk management applications (Verbano and Venturini, 2013), which includes financial risk management, enterprise risk management, etc. The ERM framework is to consider all the risks faced by firms in an integrated model. Although FRM and ERM are the most studied frameworks (Verbano and Venturini, 2013), the full steps of ERM framework are still understudied. In an attempt to provide possible solutions to these issues, this research aims to investigate the enterprise risk management framework for risk management in SMEs; to use non-financial indicators within the enterprise risk management framework; to compare different methods of selection of KRIs amongst risk indicators; and to provide roadmaps and to order risks within the enterprise risk management framework as part of the risk management process.

There are other studies attempted to integrate risk management process with other systems. Samani, Ismail, Leman and Zulkifli (2017) stated that they integrated quality management system with the RM process. Seghezzi, Schweikardt and Shiha (2001) combined business model with the quality system. Samani et al. (2017) also pointed out that there is a clause called ‘Integration into organisational processes’ in the ISO 31000: 2009 standard. According to this clause, RM should be effectively and efficiently embedded across all organisational practices and processes. If the risk management process was implied in a particular target, it is necessary to integrate the

RM process with other systems in order to achieve better performance. Under the ISO 31000 standard, there are three steps to risk assessment: risk identification, risk analysis, and risk evaluation (ISO 31000, 2009). The data mining has been used by some scholars (Koyuncugil and Ozgulbas, 2012) to detect the risks faced by firms. The data mining also followed a process that can discover patterns and rules from a large amount of data (Han, Kamber and Pei, 2012). Also, the data mining process can be embedded with other components to make it more specific for the research targets. As a result, the details in the integration of risk management process and data mining process will be developed in this study.

1.2 Existing Studies in Risk Management for SMEs

The study of risk management in small and medium-sized enterprises has become increasingly important in recent years. Altman et al. (2010) stated that, in the past few years, many scholars had done considerable research on the reasons for and rates of SME risk management, including Phillips and Kirchhoff (1989), Waston and Everett (1993) and Headd (2003). According to Verbano and Venturini (2011), however, much risk management is still performed based on only limited knowledge of the problems, strategies, and tools involved. A lack of sufficient capital and the absence of clear plans are significant problems in risk management for most SMEs. Chen, Wang and Wu (2010) similarly pointed out funding shortages are significant problems for most SMEs, and that they may thus not have sufficient capital and human resources to protect them from the economic recession. Although SMEs are often more flexible regarding adapting their strategies and structures, their particular characteristics make them less able to raise capital from outside (Chen et al., 2010). Thus, it is important to identify and manage the risks faced by all SMEs to help them avoid damage caused by funding shortages.

Hubbard (2009) stated that risk management is the "identification, assessment, and prioritisation of risks followed by coordinated and economical application of resources to minimise, monitor, and control the probability and impact of unfortunate events or to maximise the realisation of opportunities". Risk management, therefore, aims to predict and control risks that include issues caused by poor management skills, insufficient marketing, lack of ability to compete with other similar businesses, and the domino effect of business failures on the part of related organisations (Wu, 2010).

Dedicated study of risk management in SMEs is a recent development (Verbano and Venturini, 2013), it is important to work out what distinguishes SMEs from other companies. It is also necessary to make sure that any study adequately captures the problems faced by SMEs. Unfortunately, there is no universal definition for SMEs across all countries (Altman et al., 2009). Koyuncugil and Ozgulbas (2012) defined SMEs in the EU as enterprises in the non-financial business economy which employ less than 250 people, and which make less than 50 million euros per year in sales. This definition was commonly accepted in 1996, and it was updated in 2003 (Altman et al., 2009). In the US, the definition of SMEs is different, however. In general, SMEs in the US are considered to be those organisations employing fewer than 500 employees with annual receipts of fewer than 28.5 million dollars. Definitions of SMEs do not carry between different areas; this makes it necessary to specify the definition of SMEs in the target area in order to identify the study objects for any investigation in this field.

Although SMEs are a significant element in the global economy, the study of risk management for SMEs has not been a focus for most scholars. In contrast, the study of risk management in large companies began as early as 1970, and many scholars have developed sophisticated methods to manage the risks faced by large companies. During the past two decades, several models focused on large enterprises have been developed to detect different risks, including scorecard models, regression models, and financial ratio analysis (Altman and Sabato, 2007, Hill and Wilson, 2007, Lussier, 1995, Becchetti and Sierra, 2002). These models, which allow large enterprises to manage risks, are thus relatively mature. Additionally, based on previous studies, large companies frequently cover risks using insurance and hedge funds (Wu and Olson, 2009). SMEs do not have sufficient capital to allocate to risks in this, and compared with large companies, the failure rate of SMEs is exceptionally high, running at a high as 80 per cent in South Africa (Waston, 2004). The situation makes it essential to develop a model to allow SMEs to predict and control risks. All SMEs are tied to local economic conditions, and thus, if there is an economic recession, SMEs may suffer due to the unfavourable external environment and thus encounter financial difficulty (Smit and Watkins, 2012). Alongside these external factors, however, there are also internal factors that may affect the performances of SMEs. Smit and Watkins (2012) pointed out that human resource issues are important to SMEs' success, and managerial skills and training can also dramatically affect the success of SMEs. To understand the problems faced by SMEs, it is thus helpful to focus at least in part on human resource and management skills related problems.

Despite the paucity of general research in the field, several scholars have constructed models of risk management in SMEs (Altman and Sabato, 2007, Hill and Wilson, 2007, Lussier, 1995, Becchetti and Sierra, 2002). Bajo et al. (2012) applied an innovative tool, based on experts' knowledge and opinions (qualitative data) about firms in order to detect potential risks, while Chen et al. (2010), Wu (2010), and Ravisankar et al. (2011) applied data mining methods based on financial ratio (quantitative data) analysis. Those models attempted to ascertain risks via changes in key financial ratios (quantitative data). However, where such studies focused on financial ratio analysis, few of the scholars included non-financial indicators (qualitative variables) in their models. Although many scholars have suggested the study of a combination of non-financial indicators and financial indicators, no reliable model has yet been produced to predict risks using both kinds of data.

Enterprise risk management (ERM) was developed quickly since 2000 (Keith, 2014). In recent years, the enterprise risk management has offered a more holistic and integrated framework that makes it possible to integrate all risks into a single system in order to assess, monitor, and control them simultaneously (Verbano and Venturini, 2013). To achieve the goal of managing all risks in one model, it is, however, necessary to construct models based on ERM framework. Verbano and Venturini (2013) stated that the ERM is the most studied framework.

Casualty Actuarial Society (2003) defined ERM as a discipline can be used in any industries to increase the value of stakeholders. The purpose of using the ERM framework is to maximise the firm's value (Lam, 2000). The conceptual framework of ERM includes ERM risk types and the ERM process (CAS, 2003). As a result, the ERM framework can provide directions in indicators selection, process optimisation and risk identification, which can support the integration of RM process with another process, such as data mining process, quality management process, etc. The ERM framework was developed by CAS (2001), which was further studied by COSO (2003).

The ERM framework provided more specific explanations about the definition, scope, risk appetite, assessment and process of RM framework than ISO 31000 standard (Gjerdrum and Peter, 2011). In the different RM frameworks, the risk types and steps of the RM process are also different. Verbano and Venturini (2013) stated that there are total of nine different RM frameworks (i.e. Financial RM framework). In the studies of the ERM framework, the most studied risk type is operational risk, which takes ten out of sixteen studies (Verbano and Venturini, 2013). However, the ERM framework is a holistic risk management framework, which can consider all the risks in one model. CAS (2003) emphasised that the ERM provided a comprehensive view of risk management, which includes four risk types (Hazard risks, Financial risks, Operational risks and Strategic risks). Also, there are only five out of fourteen studies of ERM framework considered the total process rather than a part of the total process (i.e. Identification, evaluation, etc.). Since the ERM framework can be applied in any industries or organisations (CAS, 2003), the SMEs can use ERM framework to improve risk management process, which is also understudied (Verbano and Venturini, 2013). It thus emerges the need for studying the whole process with all risk types in the ERM framework. In this study, the ERM framework will consider the total process and all risk types by empirical methods.

The data mining process brought improvements to modern business operations (Choi, Chan and Yue, 2017). Johnson (2010) stated that the data mining techniques include association, classification, clustering and time-series analysis. In the risk management process by ISO 31000 standard, the association, classification and clustering will be mainly applied. The association techniques can discover the relationships between indicators (Johnson, 2010). The risk identification step in RM process can use association rules to find out potential rules and patterns. Risk assessment step can also apply data mining techniques, where the clustering can group similar data in the same groups. The features of groups can be obtained and then analysed. Johnson (2010) stated that, in data mining, classification techniques scored the risks and predicted future performance. Johnson (2010) also pointed out that the learning algorithm applied in the data mining methods can identify the relationships between indicators. The risk treatment step required to take steps to reduce the negative impact caused by risks.

Business Intelligence was used by firms to improve decision-making in the 1970s (Choi et al., 2017). The combination of BI systems and the data mining process has been developed to identify patterns, behaviours and specific relationships, which was first discussed in the 1950s (Choi et al., 2017). Waston and Wixom (2007) defined BI as a system that can get data in and out. Choi et al. (2017) pointed out that data mining is not easy for some databased, such as governmental big data, private firms. The BI system can provide support to the data mining process in data collection, data transferring steps. It concluded that data mining is still the "core engine" of BI system (Choi et al. (2017).

Business intelligence is defined as the systems that collect, transform, and present structured data from multiple sources for organisational use (Negash, 2004). It can reduce the time needed to obtain relevant business information and enable efficient use of such data in the management decision-making process (Den Hamer, 2004). A business intelligence system can also allow dynamic enterprise data searches, retrieval, analysis, and explanation, based on the needs of managerial decisions (Nofal and Yusof, 2013). Pirttimäki (2007) described Business Intelligence as a process that includes a series of systematic activities, which is driven by the specific information needs of decision-makers and has the objective of achieving a competitive advantage. According to Tyson (1986), business intelligence focuses on collecting, processing, and presenting data concerning customers, competitors, the markets, technology, products, and the environment. With BI approach, the data collection, data clean-up and data input will be more efficient, which can help the whole data mining process.

Research in this field is made more efficient by using the BI approach to analyse the target SMEs and to identify the risks. Thus, the first task for the current researcher was to become familiar with the needs of decision makers and how the BI approach is embedded in the risk management system. It was facilitated by the exploration of the BI literature to develop knowledge about BI and its relation to decision making, in order to identify whether the decision makers prefer specific technologies, tools, or applications, as well as to define the process of accessing, retrieving, and analysing data. However, when referring to the use of BI in their decision-making practices, it became clear that, for the subject group, BI used in organisational decision making was seen as neither a process nor a technology. Instead, the output of the BI processes and technologies was used as a key element in decision-making, created using analysis of data collected from different information systems within the organisation. It was thus natural for decision-makers to talk about how this BI output or analysis was created; however, they found it difficult to provide details, when they were asked to elaborate on the use of this output in their decision-making processes.

The idea of BI was first introduced in 1958 in the IBM Journal (Tutunea and Rus, 2012). Business intelligence systems are data-driven decision support systems, and the primary objective of BI is to provide timely and high-quality information for the decision-making process by allowing the analysis of large amounts of data about companies and their activities (Tutunea and Rus, 2012). BI can convert data into useful information, which helps transfer the data into knowledge using human analysis (Negash, 2004). Business intelligence systems can thus help decision makers to make decisions by facilitating access to structured and unstructured data, which helps to turn information into decisions. A risk management process involving data mining process can thus be represented as follows: in the “establish context” step, the purposes and objectives are confirmed; in the “risk assessment” step, the risk types and risk indicators are identified first, prior to the data being analysed using BI approach and input variables obtained; finally, the results are explained and checked. In the “risk treatment step”, the rules and pattern generated from the previous step will be applied to support decision making. Therefore, the BI approach can be used in the whole risk management process, while the detailed steps of integration were needed.

Contrary to conventional views of BI as a process or a set of technologies, there are no standard templates, procedures, or manuals that define how to use BI output in risk management procedures. Also, an initial exploration of the BI literature and its relationship to decision-making reveals that few studies have addressed how the output of BI can be used in decision-making processes (Shollo, 2013). Most previous work has concentrated on the methods and technologies used to collect, store, and analyse the data (Arnot and Pervan, 2008). Thus, the literature viewed BI as a processor technology, with little research on how BI outputs or products are used in risk management processes. Further, there is no accepted definition of what BI output is. The BI literature is characterised by normative ideas of what should happen when BI is used in decision-making and how it can enable people to make better decisions (Shollo, 2013). It also assumes an entirely rational approach to decision-making in which data is used to inform decisions by reducing uncertainty, ambiguity, or complexity (Shollo and Kautz, 2010). The underlying basis for the informative nature of BI output in decision-making is the assumption that there is a two-stage transformation process from data to information and from information to the knowledge that ultimately leads to making proper decisions (Shollo and Kautz, 2010).

The early warning system (EWS) can be used to improve the risk management process as well. Koyuncugil and Ozgulbas (2012) stated that the EWS is a monitoring and reporting system, which provides alerts for the potential problems and risks become harmful to firms. In the risk management process, "the risk treatment" step is going to use the results to support decision-making. The EWS can find out the specific indicators that result in crises of the organisations (Koyuncugil and Ozgulbas, 2012). Also, "the risk treatment" step can interact with the previous two steps of the risk management process (Samani et al., 2017). Koyuncugil and Ozgulbas (2012) stated: "the BI approach data mining accelerated the accuracy" of the EWS. However, the EWS should be designed upon the needs of specific situations. The risk factors in each EWS are not the same, where the EWS used in this study are required to be developed individually. Meanwhile, Koyuncugil and Ozgulbas (2012) pointed out the definitions of EWS and data mining are similar. The data mining process can discover the hidden rules and patterns of the database, which can be used in the EWS in order to generate warning signals. Therefore, the use of EWS will explain the results of the data mining process in a more specific aspect.

As mentioned above, the RM in SMEs is different from the RM in large firms. The difference in financial structure, sensitivity to the environment, focuses and resources make the RM process for SMEs more complicated, where the accuracy and efficiency should be considered ahead to other requirements. It is necessary to design the RM process for SMEs. The data mining process can improve the efficiency of the RM process, where the result of the DM process can provide more detailed and accurate views for the management. The ERM framework can help risk identification by using KPI and KRIs, which increases the efficiency of the RM process. The BI approach can standardise and visualise the full dataset, which can help the management to identify and focus on the main problems and improve the efficiency and accuracy of the DM process. The EWS provides more comprehensive views for risk treatment, where the threshold values and significance of KRIs can be found out. The effectiveness of the RM process will be improved by using EWS. The adoption of the DM process, ERM framework, BI approach and EWS can improve the performance of the RM process, which will simultaneously work with the existing problems in the RM process for SMEs. As a result, how the DM process, BI approach, ERM framework and EWS work in RM process for SMEs should be evaluated.

1.3 Research Aims

This study aimed to integrate data mining process to the risk management process with enterprise risk management framework to analyse both financial and non-financial indicators to improve the performance of SMEs by using BI approach. The research was based on the need to improve the accuracy of firm performance predictions and to control all the risks in an integrated model. Furthermore, the BI approach provided support regarding using non-financial indicators by quantising and standardising the information involved. It could thus provide a more comprehensive result than seen in other studies by including non-financial indicators in the proposed model. Thus, the aim of this research is:

To investigate how financial and non-financial indicators can be used in risk management procedures with the data mining process based on ERM by applying a BI approach for SMEs.

1.4 Research Objectives

In order to achieve the research aim, the primary research objective is to develop an approach to investigate the particular risks applicable to SMEs and model those risks. The research thus strives to find a model based on both financial and non-financial indicators using data mining methods. The financial variables are analysed to uncover which key indicators best predict business failure. Also, the non-financial indicators are included in the model by using the BI approach to quantise and standardise the indicators that can be used in the data mining process. This research thus focuses not on one risk at a time, as discussed by previous scholars such as Altman (2008) and Chen et al. (2010), but rather on a range of risks such as technology risk, operating risk, and market risk, as suggested by Kim and Vonortas (2014); indeed, it strives to take into account all risks in the enterprise risk management framework suggested by Verbano and Venturini (2013). This research is conducted using the listed companies' published data. As listed companies publish their statements every year, the data for these companies are generally reliable, and the data can be collected efficiently. Also, the use of secondary data can provide a more objective view, where the rules and patterns are generated by the data mining process.

Based on this, the underlying research objectives are

1. To integrate the risk management process data mining process.
2. To measure risks with both financial and non-financial information by using a business intelligence approach.
3. To comprehensively consider all the risk types within the enterprise risk management framework and integrate the use of KPIs and KRIs in the risk management process.
4. To find out the threshold value and importance of KRIs for SMEs based on the idea of the early warning system.
5. To evaluate the usefulness of financial indicators and non-financial indicators in the risk management process.
6. To examine the performance of different data mining methods in the risk management process in SMEs.

1.5 Research Questions

Achieving the objective noted above should make it possible to address the following questions:

1. Is it possible to integrate the data mining process with the risk management process and increase the effectiveness and efficiency of the risk management process?
2. How could the business intelligence approach increase the explanatory and provide a more comprehensive view of risk management process with financial and non-financial indicators for SMEs?
3. Can the risk types, KRIs and KPIs in the enterprise risk management framework improve the performance of the risk management process?
4. How can early warning system increase the explanatory and efficiency of the risk management process?

5. Are financial and non-financial indicators helpful regarding creating a model to measure firm performance, and if so, to what extent?
6. Which data mining method has the best performance in the risk management process for SMEs?

The first research question aims to find out the possibility of integration RM process and DM process. Then, the second one attempted to find out the usefulness of BI approach in data visualisation and data standardisation. The third question tried to find out the effectiveness of the ERM framework. There are two components of ERM framework were included, which are four risk types and KPI, KRIs. It is important to examine whether the two components are effective or not in the RM process for SMEs. The fourth question is going to explore how the EWS generate the rules and patterns from the DM process. The EWS can explain the results by identifying the threshold values and the importance of the indicators. It can then help the SMEs focus on significant indicators rather than all indicators, which increases the efficiency of the RM process. The fifth question attempted to find out the value of non-financial indicators, which is rarely tested in other studies. The value of non-financial indicators will be found out by comparing the performance of different groups of indicators (FIs and Non-FIs, FIs and Non-FIs). The last question examined four different DM methods, where the methods with the best performance will be suggested to apply in the RM process for SMEs. The prediction accuracy, the function and the explanatory of all DM methods will be compared, which aimed to provide more detailed results to improve the understanding of existing studies.

1.6 Research Contributions

The main contributions resulted from the aim and objectives of this research are summarised as:

1. This research is a valuable contribution to the existing RM process with ERM concepts and frameworks. It is achieved from a review of the current risk management process and researchers' views of the ERM framework. The importance of ERM framework is recognised, which covers the most comprehensive risk types in total of nine frameworks of risk management.
2. This research also contributes to the literature in the development of the risk management process and data mining process with the ERM framework. The data mining process found the potential rules and patterns from the database, where the idea was used in the risk management process with ERM frameworks in order to provide comprehensive solutions to reduce the risks faced by firms. Furthermore, the research selected SMEs as a research target, which tried to cover the understudied area mentioned by Verbano and Venturini (2013). In this research, the data mining process provides the analysis and evaluation of risk indicators, which could be applied for making decisions and reducing risks.
3. This research also contributes to a better understanding of the value of non-financial indicators with different data mining methods. This research examined the usefulness and meaningfulness of non-financial indicators in the risk management process based on ERM framework. Furthermore, the application of non-financial indicators could help to address the total four risks under the risk catalogues in the ERM framework. Meanwhile, the application of BI approach helps to collect non-financial indicators from annual reports and other materials, which solved the problem that the non-financial indicators were always ignored (Geng et al., 2015).
4. In the practical aspects, the process of constructing the model provides guidance about the combination of the data mining process and risk management process. The process includes the data collection, goal development, KPIs and KRIs selection, methods comparison and result evaluation. Each step will be detailed and discussed in order to provide an in-depth view of the entire framework. The

results obtained from this research could help decision-makers and scholars to focus on KRIs rather than all the indicators, which provide a more effective solution. Additionally, the combination of the data mining process and risk management process could be developed in other research areas, as long as the research topic could be in sync with the data mining process. The embedded BI approach and EWS provide support to the data mining process and risk management in many steps. The useful information can be transferred into indicators by using BI approach, which provided a broader view of risk catalogues. The EWS can efficiently use the rules and patterns generated in the data mining process to achieve the goals in the risk management process by providing warning signals and desire trends. As a result, this research could provide several practical guidelines for the whole risk management process, since the integrated framework is proposed to be developed.

1.7 Thesis Structure

This study is structured into seven chapters, including the current introductory chapter. The thesis is thus presented in two parts, which focus on theoretical and practical research, respectively.

The Outlines of this thesis are described as follow. Chapter 1 provides a brief overview of the research background, existing studies, research aims, research objectives, and research questions. It ends with a summary of the research structure and introduces an overview of each chapter.

Chapter 2 then reviews the existing literature on risk management frameworks and risk management in small and medium-sized enterprises. In that chapter, a review of the latest studies of risks faced by SMEs is also provided, as these are different from many past studies of risk management. Furthermore, this chapter provides the conceptual framework for the work and introduces several essential concepts.

Chapter 3 introduces a theoretical framework for risk management in SMEs. In particular, this chapter reviews the existing frameworks and theories, and based on an in-depth discussion of these frameworks, provides the focus of this study and emphasises its differences from existing studies. This chapter also introduces the data mining process and risk management process, linked by the BI approach. This chapter thus provides detailed information about the creation of the theoretical framework of this research. Then, Chapter 4 explains the methods used in this study in detail. A summary of the primary research paradigms and approaches is provided, and the reasons for choosing a positivist approach with a quantitative methodology are explained. Then, the proposed methods are explained in more depth based on an initial analysis of the collected data.

Chapter 5 includes an examination of clustering models and other feature clustering methods (CHAID, Logistic regression, genetic algorithms, and neural networks). The results for each method are introduced and discussed before Chapter 6 examines the results of the data analysis and compares the results with those from other studies in order to verify the effectiveness of the research. Finally, Chapter 7 summarises the research, discussing its achievements, limitations, and contributions and providing recommendations for further research

1.8 Summary

This research supports a new integration of risk management process with the data mining process. It also utilised the enterprise risk management framework for the risk management process, which aims to manage all risks simultaneously in an attempt to obtain more accurate and comprehensive predictions. After initial review, enterprise risk management framework was deemed to be a suitable approach for this research due to this propensity for increased accuracy. Based on the development path of the enterprise risk management framework, it is possible to include all risks in a model by developing an in-depth understanding of the risk management process.

The main difference between the current research and previous work is thus that this research aims to integrate all risks factors together before predicting risk within a single model. As mentioned by Verbano and Venturini (2013), there are fewer studies considered all risks in one model. The enterprise risk management framework supports this more holistic approach to analysing and monitoring all risks, while more traditional researches provide the experience of how to analyse risk, which has supported the development of risk management. Traditional risk management methods have, in particular, deeply analysed a wide range of financial factors and financial-related risks. A lack of full considerations for all types of risks in these financial results, however, leads this research to include non-financial factors in order to achieve more accurate predictions. The application of EWS and BI approach in data mining process provided more specific functional support, which helps the data mining process to be embedded into the risk management process.

2. Literature Review

2.1 The Development of Risk Management

Risk management was first developed in the USA between 1955 and 1960 (Mehr and Hedges, 1963), and it was initially used to reduce insurance costs. Verbano and Venturini (2011) stated that the traditional risk management function arose as part of insurance management; thus, the only risks identified and assessed were pure risks such as fires or storms. At that stage, financial or strategic risks were not considered. Mehr and Hedges (1963) suggested that scholars began to outline the complete process of risk management in the 1960s and that this included identifying, evaluating, and dealing with many more forms of risk. In the 1980s, insurance coverage thus became one of the methods used to deal with risks, in the form of transferring risks to third parties (Verbano and Venturini, 2011). Lam (2004) defined this stage of development in risk management as "traditional risk management". Later, in the 1990s, the evolution of the economic-financial context of firms pushed risk management towards managing the volatility of the business and financial results in an attempt to optimise firm performance (Lam, 2004; Doherty, 2000; Verbano and Venturini, 2011). In 2000, De Loach claimed that integrated risk management (enterprise risk management or holistic risk management) offered a structured and disciplined approach which could create value by evaluating and managing threats and opportunities

Hubbard (2009) similarly stated that risk management is the “identification, assessment, and prioritisation of risks followed by coordinated and economical application of resources to minimise, monitor, and control the probability and impact of unfortunate events or to maximise the realisation of opportunities”. Risk management thus aims to predict and control the risks caused by poor management skills, insufficient marketing, lack of ability to compete with other similar businesses, and any domino effect from business failures in related organisations (Wu, 2010).

Kloman (1990) noted that risk management is a discipline for living with the possibility that future events may have adverse effects. Sweeting (2011) further argued that risk management could reduce volatility in a firm’s return, helping to increase the value of the firm and reducing the probability of insolvency. However, risks do not solely mean the possibility of losses, and firms should aim to adopt a reasonable level of risk to ensure capital is used effectively. Risk management thus does not aim to reduce the risk level to zero. On the contrary, risk management aims to achieve the optimum level of risk to achieve higher profits. For example, where a new project is a high risk, and high return, a firm that has just experienced financial problems may not be able to launch it; however, the same project may be more acceptable to another firm with more available capital.

When deciding whether to take on a project or not, it is thus essential to apply risk management systems as part of the operating procedures of a firm. Sweeting (2011) pointed out that improved risk management can also allow the development of more profit for a given risk level. Firms can thus choose the most profitable projects with proper risk levels to maximise their returns. Such risk management procedures are not one-step actions, and the on-going process can help firms consistently choose the risk levels that match their risk appetites (Sweeting, 2011). In this way, firms can use a risk management system to allocate their capital wisely. When firms are considering developing strategies for development, it is essential for them to consider the risks that may be harmful to their objectives. Thus, firms should manage risks not only in their strategy but also among their operational activities, as well as taking account of the risks introduced by their counterparties and their internal departments. It is vital for firms to measure the whole range of risks they may face adequately to avoid a higher probability of bankruptcy.

According to Nocco and Stulz (2006), in the last decade, risk management has been developed beyond the simple use of insurances and hedges, and as such, risk management procedures need to take into account a wide variety of other kinds of risks. However, as there can be many different meanings of the term risk, it is essential to use an unambiguous definition (Sweeting, 2011). The risk is, in essence, uncertainty within a range of possible outcomes. There are two main possibilities for each event based on this concept, making it essential to distinguish between the upside and downside results of risk. When using the word risk, most people are referring to the downside effects. Based on this, risk refers to problems and missed opportunities that lead to the expected outcomes not being achieved. Sweeting (2010) stated that risks could be divided into risks dependant on uncertainty in the future and those that are the consequences of past events. The institution must have a clearly defined set of risk policies and the ability to measure that risk in order to manage the risks. Regarding the financial aspects, the risk is thus any event or action that may negatively affect the firm’s ability to achieve its objectives and execute its strategies, or the quantifiable likelihood of loss or lower than expected returns. This definition of risk makes it clear that the function of risk management is to find the balance between maximising profit and minimising loss.

According to Verbano and Venturini (2011), risk management was developed from 1963; however, it did not reach what is now known as the traditional risk management stage until the 1980s, where it was mainly used to transfer risks to third parties using hedging and insurance. Over the subsequent decade, risk management developed as an evolution of the economic-financial context of firms, as the focus point moved towards optimising firm performance (Lam, 2004). In 2000, a new concept named integrated risk management (enterprise risk management or holistic risk management), emerged, aligning human resource, strategy, technology, finance, and operating risks faced by firms. Verbano and Venturini (2011) argued that this enterprise risk management approach indicates that the risk management system can neglect traditional functional, divisional, departmental, or cultural barriers, thus managing all business risks and opportunities for a given firm as an integrated whole.

2.2 The ISO 31000 Framework

In recent years, scholars working on risk management topics have tended to have very similar goals, centred around identifying a sound basis for defining acceptable risks and obtaining reliable information to analyse those risks. However, when processing the information available, the same basic information has been examined using different processes with different assumptions; indeed, often, scholars have used the same word, but the meanings have been different. Against this slightly chaotic background, as ISO framework was thus developed to regulate the applicable forms and standards. Under this ISO framework, several standards are implemented to ensure the consistency and reliability of risk management systems (ISO 31000, 2009). The ISO framework creates rules whereby all firms should use a single set of vocabulary to enable the consistent use of definitions; firms should also use a pre-identified set of performance criteria and a common overarching process for identifying, analysing, evaluating, and treating risks; finally, all of these processes should be integrated into the decision-making steps for the organisation. The ISO framework was created by many specialist organisations guiding the development of the standards and based on input from hundreds of risk management specialists and their customers all over the world, ISO 31000:2009 and Guide 73 were created. This standard thus represents the experience of hundreds of experts in all aspects of the risk management area.

The first thing the standards do is to give a universal and acceptable definition of risk.

The definition of risk indicates what risk is and how it occurs, and the working group considered hundreds of candidate definitions. Eventually, the ISO standard definition was set in this way: “risk is the effect of uncertainty on objectives”. Based on this, the risk could be caused by internal or external factors where the consequence of any effect cannot be completely controlled, making it possible that organisations may fail to achieve objectives or suffer delay. The risk here is not defined as positive or negative; as a result, this definition of risk emphasises the process of optimising the likelihood of achieving the firm's objectives. The concept of risk control here is thus the aim of modifying the effects of risk. Previous definitions of risk have tended to describe only the negative aspects of risk, and thus the recognised ways to manage risk were to avoid risk or transfer it to others. However, as risk can bring both negative and positive effects, any responses should recognise the positive effect that also comes with risk, which can also be called an opportunity. Where it becomes possible to detect and understand risk, it is similarly possible to make use of the associated positive effects to achieve objectives. Risks can also be created or shifted when making decisions, and it could thus be argued that decisions made at different points in time could become either risks or opportunities. It should be clear from this that the risk management process is a natural part of the decision-making process, and should thus be considered in a much more comprehensive way. Risk management must also respond to the internal and external environment and be synchronised with other aspects of the decision-making process.

There are two components to the ISO 31000 standard for risk management. The first is the definitions of all terms used in risk management, to ensure consistency and to help people understand the guidance. The ISO has combined the creation of the standard with existing ISO and IEC vocabulary, as seen in Guide 73 published in 2002. The second component is the performance criteria. There are several requirements to ensure the effectiveness of the risk management process. In general, risk management under ISO 31000 standards should create and protect value; be part of decision making; be systematic, structured, and timely; be based on best available information; take into account human and cultural factors; be transparent and inclusive; be tailored; be dynamic, iterative, and responsive to change; and facilitate continual improvement of the organization (ISO 31000:2009). Also, further characteristics of risk management performance are provided in the annexe to the standard. The annexe describes the key outcomes, reflecting the results of risk management. If an organisation compares these objectives with its target, it can quickly determine whether its objective has been achieved or not. The annexe thus includes the following essential characteristics: setting performance goals and measurements by means of risk management; clearly defined and fully accepted accountability for risks, controls, and risk treatment tasks; explicit consideration of risks and the application of risk management in all decision making; keeping lines of communication with internal and external stakeholders open and reporting on risk management performance frequently and comprehensively; considering risk management to be central to the organisation's management progress.

The risk management process that has mainly been adopted is the same as AS/NZS 4360:2004. The process iterates in a continuous cycle of communication and consultation, monitoring and review. There are two parts to the process, one of which should be considered as a continuous activity. There are also two elements to this activity. The first is communication and consultation with internal and external stakeholders, as it is vital that the stakeholders’ objectives be fully understood and implemented when setting risk criteria. The monitoring and review of this should also be treated as a continuous process, as risks may occur or change at any time and the external and internal environment could also change, making it important to monitor such changes. Firms’ managers should thus monitor environmental factors, assure controls, take new information into account, and adjust their controls based on current success and failure markers.

Alongside the two continuous processes of risk management, there are five other procedures which could be considered one-step procedures. The first is to establish context, which is the most critical step in the whole risk management process. This step starts with defining objectives to achieve and listing potential external and internal factors before starting the risk assessment procedure. Under the ISO 31000 standard, there are three steps to risk assessment: risk identification, risk analysis, and risk evaluation. In the risk identification step, the risk is thoroughly investigated regarding what, how, when, and why the risk may happen. Risk analysis is the most complicated step in a risk assessment. The risks analysis step should provide an understanding of each risk, the consequences of the risk and the likelihood of those consequences are occurring. The results of the risk analysis may be qualitative, semi-quantitative, or quantitative, but based on those results, the effect of current controls should be analysed in order to determine any gaps in existing control methods.

In the ISO 31000 standard, there are no rules about the format of the approach used for analysis, which may thus be either qualitative or quantitative. However, any results should consider both the consequences and likelihood of a given event to determine the level and type of risk. Also, all available information and the risk assessment output should be used appropriately. All of these factors should also be held consistent with the risk criteria chosen. Another critical factor in risk analysis is the analytic method chosen. The confidence level and the sensitivity to assumptions should be considered throughout the analysis, which should be accomplished based on the requirements of the decision makers and shareholders. Risk analysis can use a variety of different variables depending on the type of the risk, the purpose of the analysis, and the dataset available. As mentioned, that data could be quantitative, semi-quantitative, or qualitative, again depending on the circumstances and the available dataset. Finally, the risk evaluation step brings together the decision-making process and the action taking process based on the results of the contextual step.

After the risk assessment process, existing control methods should be used to treat the risks. However, as the external and internal environment changes over time, such treatment should also follow these changes. Risk treatment thus also includes improving the existing control methods and developing new controls. It should also include an evaluation of different treatment methods, including a thorough analysis of the costs and benefits of the assessment of new risks and the prioritising and planning of the selected risk treatment options. Overall, the process is a complicated combination of different steps, and each step should be tested until the best option, with the most benefit and least cost, is found.

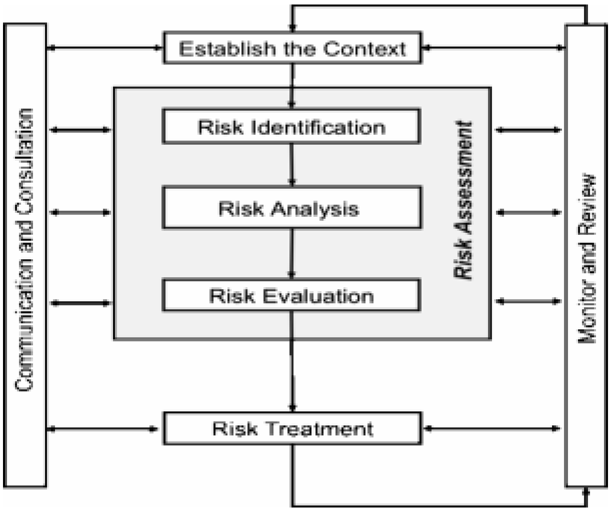


Figure 2.2 ISO standard risk management process (ISO 31000, 2009)

Figure 2.2 shows the process of RM by the ISO 31000 standard (2009). ISO 31000 requires the risk management process to be integrated into the decision-making process of a firm. However, due to the number of applicable standards, it is difficult to achieve them all in practice. The risk management framework not only describes the required elements but also describes the creation, implementation, sustaining and improving all elements. It is a complicated process which requires firms to design and revise their risk management system continuously over time. Additionally, the implementation of a plan may take longer than expected and change the culture of a company, and indeed, hierarchies of risk management plans may be required by large and complex companies to complement an overall plan which reflects the strategies of the board. The ISO 31000 standards could also be applied in project management; while it is true that risk management processes in various projects and companies are naturally different, applying the standards could ensure that more projects achieve their targets and that any changes are made based on an assessment of potential risks.

2.3 The COSO Enterprise Risk Management Framework

The Committee of Sponsoring Organizations (COSO) was established in the mid-1980s; initially, it was intended to sponsor research into the causes of fraudulent financial reporting (ACCA, 2017). Recently, the mission of COSO has become to "provide thought leadership through the development of comprehensive frameworks and guidance on enterprise risk management, internal control and fraud deterrence designed to improve organisational performance and governance and to reduce the extent of fraud in organisations" (COSO, 2017).

Although COSO's guidance is non-mandatory, it is influential because it provides frameworks against which risk management and internal control systems can be assessed and improved (ACCA, 2017). Many cases involving corporate scandals and deficient internal controls still arise, and COSO is a voluntary private sector initiative dedicated to improving organisational performance and governance by encouraging effective internal control, enterprise risk management, and fraud deterrence. The sponsoring organisations are five non-profits: the AAA (American Accounting Association), AICPA (American Institute of Certified Public Accountants), FEI (Financial Executives International), IIA (Institute of Internal Auditors), and IMA® (Institute of Management Accountants). On May 14th, 2013, COSO released an updated version of its Internal Control—Integrated Framework (COSO, 2017).

COSO’s new Framework is the result of a significant multiyear project that included two rounds of public review, intended to refresh and modernise the original Framework, ensuring it remains relevant. Business models have changed significantly over the organisation's period of existence, including the more excellent use of shared services and outsourced service providers (COSO, 2003; Stephen, 2013). The complexity and pace of change regarding rules, regulations, and standards have also intensified demands on companies, as have evolving technology, and improvements to business performance, business processes, and decision making. The regulators and other stakeholders thus have higher expectations regarding governance oversight, risk management, and the detection and prevention of fraud. Since 1992, many such changes have significantly increased business risk, resulting in a much higher need for competence and accountability. Also, collectively, many lessons have been learned from applying the 1992 Framework.

The original Framework included lengthy discussions of internal control concepts that are now institutional knowledge. Further, although the concept of internal control principles may have been embedded in the original Framework, the principles themselves were “hidden” within the details. Practitioners have previously used the framework primarily for internal control over external financial reporting, yet the framework encompasses three significant categories of objectives, operations, overall reporting, and compliance objectives. Thus, streamlining the original Framework; codifying the underlying principles; increasing focus on operations, non-external financial reporting, and compliance objectives; and enhancing usability were additional drivers behind COSO’s Internal Control— Integrated Framework (ICIF) Refresh Project (COSO, 2003).

The COSO Board has emphasised that the fundamental concepts and principles embedded in the original Framework remain fundamentally sound for designing, implementing, and maintaining systems of internal control and assessing their effectiveness (COSO, 2003). Therefore, COSO continued to make the original Framework available through December 15, 2014, at which point the 1992 Framework was considered superseded. During this transition period, COSO believed continued use of the 1992 Framework was acceptable. COSO's Internal Control Integrated Framework for external reporting purposes during the transition period required firms to disclose whether they used the 1992 or 2013 version, however. In the spirit of continuous improvement, companies should periodically reassess their system of internal control over external financial reporting to identify opportunities to improve efficiency and effectiveness in any case (COSO, 2017).

The COSO 2013 Framework, which formalised the principles embedded in the original more explicitly, also incorporated business and operating environment changes over the past two decades, as well as improving the operation and application of the framework. Specifically, the 2013 Framework makes it easier for management to see what is covered and where gaps exist in their current SOX 404 compliance programmes. For example, some companies may not have fully documented their internal control applications in line with the 1992 Framework (COSO, 2013), while others may have misinterpreted or misapplied the narrative in the original, thus falling short of an adequate assessment process in respect of one or more principles, or may have missed a principle outright. The new framework thus points out the missing parts of compliance, which makes it easier for management to apply the compliance process (COSO, 2013) fully.

The COSO 1992 framework introduced 17 principles associated with the components of internal control, and these were the focus of the COSO 2013 framework. The internal control consists of five integrated components: control environment, risk assessment, control activities, information and communication, and monitoring activities. The control environment is the set of standards, processes, and structures that provide a basis for internal control across the organisation (COSO, 2017). The board of directors and senior management establish the tone at the top regarding the importance of internal control, including expected standards of conduct (COSO, 2017). Management also reinforces expectations at various levels of the organisation. The control environment represents the integrity and ethical values of the organisation; the parameters enabling the board of directors to carry out its governance oversight responsibilities; the organisational structure and assignment of authority and responsibility; the process for attracting, developing, and retaining competent individuals; and the rigor around performance measures, incentives, and rewards that drive accountability for performance. The resulting control environment has a pervasive impact on the overall system of internal control, and the risk assessment contribution must consider a variety of risks from external and internal sources (COSO, 2017).

The risk is defined as the possibility that an event will occur and adversely affect the achievement of objectives and risk assessment is a dynamic and iterative process for identifying and assessing these possible impediments to the achievement of objectives. Thus, risk assessment forms the basis for determining how risks will be managed (UNC, 2018). The purpose of risk assessment is the establishment of objectives, which are linked at different levels of the entity. Management must specify these objectives within categories relating to operations, reporting, and compliance with sufficient clarity to be able to identify and analyse risks to those objectives (Alexander, 2017). Management must also consider the suitability of the objectives for the entity. Risk assessment further requires management to consider the impact of possible changes in the external environment and within its business model that may render internal control ineffective (UNC, 2017).

Control activities help ensure that management's directives to mitigate risks to the achievement of objectives are carried out; these are performed at all levels of the entity, at various stages within business processes, and over the full technology environment (COSO, 2017). They may be preventive or detective in nature and may encompass a range of manual and automated activities such as authorisations and approvals, verifications, reconciliations, and business performance reviews. Information is necessary for the entity to carry out internal control responsibilities to support the achievement of its objectives, and management must obtain or generate and use relevant, high-quality information from both internal and external sources to support the functioning of other components of internal control (UNC, 2017).

Communication is the continual, iterative process of providing, sharing, and obtaining the necessary information. The communication is external or internal. Both of the communications can pass information to the whole company. The final part of monitoring activities are an on-going evaluation, separate evaluation, or some combination of the two; these are used to ascertain whether each of the five components of internal control is in place and active. On-going evaluations, which are built into business processes at different levels of the entity, provide timely information, while separate evaluations, conducted periodically, vary in scope and frequency depending on assessment of risks, effectiveness of on-going evaluations, and other management considerations. Findings must be evaluated against criteria established by regulators, recognised standard-setting bodies, or management and the board of directors, and deficiencies should be communicated to management and the board of directors as appropriate.

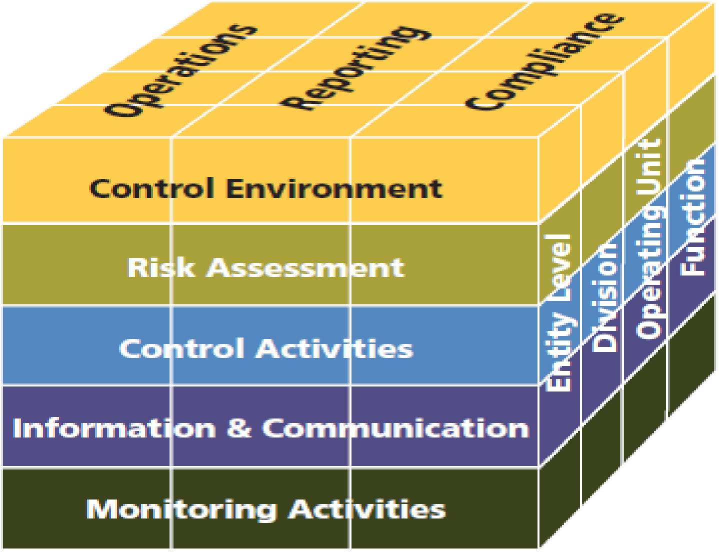


Figure 2.3 COSO 2013 framework cube (COSO, 2013)

The COSO framework can be presented as a cube as shown in Figure 2.3 (COSO, 2013). A direct relationship exists between objectives as an entity strives to achieve all components. It also shows the organisational structure of the entity (the operating units, legal entities, and other sections). The three categories of objectives, which are operations, reporting, and compliance, are represented by the columns, and the rows represent the five components. An entity's organisational structure is thus represented in three dimensions. The five components should operate together in an integrated manner, allowing all components to collectively work to reduce the risk of not achieving objectives to an acceptable level. Thus, all five components should be considered to be an integrated system, as they are interdependent, with a multitude of interrelationships and linkages among them. Organisations thus cannot conclude that they meet the standards of effective systems of internal control when any deficiency could affect these functions or principles.

If organisations want to secure the efficiency of internal control systems, senior management and board members should, therefore, ensure the control system achieves effective and efficient operations when external events are unlikely to have a significant impact on the objectives or the organisations can predict external events to an acceptable level. It is also essential for organisations to prepare reports based on applicable rules, regulations, and standards to demonstrate compliance with the laws, rules, regulations, and external standards. The COSO framework requires the judgment of management to ensure internal control and its efficiency. The use of such judgment could enhance management ability to make better decisions; however, it cannot guarantee perfect outcomes.

The COSO framework has a few limitations: although internal control provides reasonable assurance of achieving objectives, internal controls cannot prevent bad decisions, wrong predictions, or external events causing failure in achieving target objectives. The internal control system must be established based on suitable objectives, and the decision making progress could be biased and faulty due to human errors. Another reason for internal control failure may be management overriding the internal control systems. Furthermore, the management or third parties could override the control system by collusion. Finally, external events could cause the internal control system to fail where such external events are beyond the maximum ability of the system. Although such control systems can provide reasonable assurance, the board and management cannot, therefore, guarantee to achieve target objectives, and the management should be aware of these limitations when selecting, developing, and applying internal controls.

After review, it can be concluded that the COSO framework provides theoretical support. The COSO (2004) framework states that the process should be “applied in strategy setting across the enterprise” and “designed to identify potential events that may affect the entity, and manage risks to be within its risk appetite to provide reasonable assurance regarding the achievement of entity objectives” (COSO, 2004, p. 2).

2.4 The Concepts of Risk Management

2.4.1 Introduction

A well-thought-out risk management plan is essential to the future of a current or forthcoming venture (Kim and Vonortas, 2014). Risk management must focus on risk control, aiming to reduce loss by preventing, avoiding, or reduce issues leading to such loss. Bekefi et al. (2008) also stated, however, that risk management should consider the upside gains of risk. The primary goal of risk management then becomes to maximise shareholder value (CAS, 2003; COSO, 2004; Beasley et al., 2008; Pagach and Warr, 2011; Quon, Zeghal and Maingot, 2012). The approach named enterprises risk management (ERM) seeks to manage risks holistically (Kim and Vonortas, 2014). Nocco and Stulz (2006) stated that the ERM system could provide competitive advantages in the long run by optimising the trade-off between risk and return. As the existing literature has focused on large incumbent companies (Kim and Vonortas, 2014), however, there is a dearth of empirical evidence about risk management in SMEs.

The identification of the process of risk management is also essential. Many scholars have used failure or non-failure (Altman et al., 2010), ST or non-ST (Chen and Yi, 2007; Xie and Me, 2013), Z-scores (Altman, 1968 and Li et al., 2017), and the mean of financial ratios (Koyuncugil and Ozgulbas, 2012). However, the determination of risk impact could be yet more logical and precise. As the effects of risk have both upsides and downsides, while risk management seeks to reduce the loss caused by downside effects, enterprise risk management aims to maximise the shareholder value (Verbano and Venturini, 2011). Therefore, it could be concluded that enterprise risk management is likely to make the firms using it generate more profit. As their ability to make profits frequently measure the performance of firms, this is a comprehensive measure of both the positive and negative impacts of risks. It also indicates how risks impact the performance of firms. Thus, if management or scholars neglect the effects of risks and apply risk management procedures, they will not identify the where, when, how, and why of those risks. The risks can be identified and assessed after their impacts are measured and classified.

Scholars have used different classification of risks. According to Kim and Vonortas (2014), there are four risk domains for small companies: technology risk, market risk, financial risk, and operational risk. Meanwhile, Wu and Olson (2009) developed specific indicators of four perspectives, similar to these four risks, which were financial, customer, internal business, and innovation and learning perspectives, used in bank risk management. They also pointed out the goals and measures of the four different perspectives. Changes in financial ratios can measure financial risk, and the goal of financial risk management is to survive, succeed, and prosper (Wu and Olson, 2009). Market risk as described by Kim and Vonortas (2014) can be matched to customer perspective described by Wu and Olson (2009). The measurement of market risk relates to sales of new products and proprietary products; inventory turnover ratios, which could indicate a new product; responsive supply; and preferred suppliers and customer partnerships. The internal business perspective could be treated as a measurement of operational risk. The selected variables thus include cycle time, unit cost, schedules, and competition. These indicators can reflect the technological capability, manufacturing excellence, design productivity, and new product innovation of a firm. Finally, the technology risk can be measured by time to develop the next generation, process time to maturity, and new product introduction versus the competition. The technology perspective incorporates technology leadership, product focus, time to market, and manufacturing learning.

2.4.2 Enterprise Risk Management Risk types

Identifying the effect of risks by types is to control them more effectively and purposefully; after the effect of risks is precisely measured, the procedures for risk management can be invoked (Florio and Leoni, 2017). It is thus necessary to discover what could affect the performance of firms in order to find these risk indicators. This research applied an enterprise risk management framework and followed the classification of risk types given by CAS (2003). Before identifying the risk indicators in companies, it is important to identify the types of risks face by those companies. Sweeting (2011) pointed out that the particular risks differ from firm to firm, and that risk develops over time. Thus, it is not possible to consider every single risk in a given project. However, it is possible to discuss the main categories of risk faced by firms and their consequences (Sweeting, 2011). Based on the descriptions offered by the Casualty Actuarial Society (2003), there are four types of risk: hazard risk, financial risk, operational risk, and strategic risk. It is thus important to know the definitions and impacts of each type of risk in order to reduce the potential loss of firms affected by these factors.

Classification of Risks			
Hazard risks	Financial risks	Operational risks	Strategic risks
Fire and other property damage	Price	Business operations	Reputational damage
Wisdom and other natural perils	Liquidity	Empowerment, information technology	Competition
Theft and other crime, personal injury	Credit	Information/business reporting	Customer wants
Business interruption	Inflation/purchasing power		Demographic and socio-cultural trends
Disease and Disability (Including work-related ones)	Hedging/basis risk		Technological innovation
Liability claims			Capital availability
			Regulatory and political trends

Figure 2.4.2 ERM risk catalogues (CAS, 2003; Verbano and Venturini, 2011)

Figure 2.4.2 shows the types of risks and the aspects of each risk under consideration (CAS, 2003). The details of each risk type are discussed below.

2.4.2.1 Hazard Risk

- **Definition**

Several different classifications of hazard risk emerge from the CAS report. These include the possibility of fire or tornadoes damaging plant and equipment, which could result in loss of revenue and assets (CAS, 2003). Other hazard risks include injury or illness of employees, including employees' compensation claims for work-related injuries; similarly, the hazard risk also includes product liabilities. Thus, the hazard risk can be summarised as the risk from fire and other property damage; windstorm and other natural perils; theft and other crime; personal injury; business interruption; disease and disability; and liability claims.

- **The Importance of Hazard Risk**

Based on the description of hazard risk, it is clear that the hazard risk includes events that can cause harm or damage to humans, property, or the environment (William, 2001). William (2001) further stated that traditional risk management minimises exposure to product liability, employee compensation, etc. Many managers prefer to assume as much risk as deemed affordable and only transfer exposures where there may be a material impact on financial results, such as in hurricanes or fire. There are also many tools used to manage such exposures, such as captive insurers, self-insurance, and deductible arrangements (William, 2001).

There are several methods of classifying hazard, but most systems use the factor likelihood of the hazard turning into an incident and the impact of that incident if it happens. The hazard risk can thus be given as a formula:

Hazard risk = Hazard * Vulnerability / Capacity

When management believes that transferring risk to an insurer may be more expansive than accepting that risk, they may decide to accept the risk. The goal of hazard risk management thus also includes considering risk as precisely as possible in order to avoid premium charges by retaining relatively predictable losses (William, 2006). Hazard risks generally contain only the possibility of loss and are usually not reversible. Hazard risk management therefore usually works differently than other risks, for both practical and accounting purposes, as there are no upside gains to hazard risk. For example, a company may recognise a forecast of employee compensation based on its best measurement of such loss during a previous year. For accounting purposes, the management will take out insurance and show the reverse accrual. At the end of the year, an adjustment will be made based on the experience, and this may impact on further accounting periods.

2.4.2.2 Operational Risk

- **Definition**

Operational risk is the risk of losses resulting from inadequacy or failure of internal processes, people, and systems, or from specific potentially controllable or predictable external events. Operational risk is thus comprised of business operations (human resources, product development, capacity, efficiency, product/service failure, channel management, supply chain management, and business cyclicality); empowerment (leadership and change readiness); information technology (relevance and availability); and information/business reporting (budgeting and planning, accounting information, pension funds, investment evaluations, and taxation) (Kim and Vonortas, 2014). Operational risk refers to the internal organisation and management of the firm's operations team in so far as it promotes development, production, supply, and distribution. Sweeting (2011) stated that operational risk had attracted increasing attention over the past few years, while Deloitte (2011) found that about two-thirds of surveyed financial institutions calculated their economic capital for operational risk. As more corporate scandals such as Enron, WorldCom, and J.P. Morgan have emerged, the urgency of discussions regarding operational risk has increased, especially about corporate governance and compliance.

- **The Importance of Operational Risk**

Operational risk is a broad term capturing the business dangers and challenges arising mainly from the people, systems, and processes a company utilises. Broader use of the term can also include other business challenges related to the supply chain, the physical environment, legal liabilities, and other directly influential external environment factors. Among these diverse sources of operational risk, human resource availability is a crucial factor (Epstein and Rejc Buhovan, 2005), as one of the most significant difficulties for any firm is to attract employees with the requisite skills and motivate them appropriately. This problem is exaggerated in small fledgeling companies, which may face acute difficulties in attracting top candidates, and may have inadequately trained people, which creates the potential for significant loss when internal systems and processes fail. Sweeting (2011) stated that senior management often acts solely regarding operational risks being interrelated with other risks, such as credit risk and market risk. If the operational risk is not treated as a distinct discipline of risk, the other parts of the company will, however, become more challenging to manage. Sweeting (2011) further stated that poor operational management could lead to the neglect of key risk issues and too biased performance measurements, which could impede decision making progress based on inaccurate information.

According to a CAS report (2003), operational risks include risks from business operations (human resources, product development, capacity, efficiency, product/service failure, channel management, supply chain management, business cyclicality); empowerment (leadership, change readiness); information technology (relevance, availability), and information/business reporting (budgeting and planning, accounting information, pension funds, investment evaluations, taxation). As stated by Sweeting (2011), people are thus a factor in a large number of risks faced by organisations, and this hazard risk also overlaps with the possibility of criminal actions, beginning with the risk of hiring the wrong people for open positions. It is critical that employees have the proper skills for their positions and the company as a whole. Recruitment costs time and money and losing current employees results in a loss of valuable intellectual capital, thus leading to potential damage.

The term empowerment refers to the kind of agency risk suggested by Sweeting (2011), where one party that is supposed to act on behalf of another instead acts on its behalf. For example, managers may act for themselves rather than protecting the benefits of shareholders, whose benefits they are supposed to be protecting. Sweeting (2011) also pointed out that regulatory risk is another kind of operational risk, which has a negative impact using changes in legislation or regulation. These may lead to extra costs in compliance, existing activities being prohibited, or sales of parts of a business being required. There are also residual risks, which refers to risks regarding pension funds and investments. For example, a pension scheme may use interest rates and inflation swaps to reduce interest risk. However, these actions may result in other risks, such as another party refusing to make payment. These particular types of residual risk are known as basis risk, as they arise from imperfect hedging (Sweeting, 2011). Overall, the consequences of operational risks can be both critical and harmful to a company's equity, reputation, shareholders, and employees.

2.4.2.3 Financial risk

- **Definition**

Financial risk always refers to the tangible losses experienced when a firm suffers from business failure, but it is especially relevant to the financial aspects. Most scholars consider the financial risk to be a significant risk in corporate operation (Horcher, 2005). Financial risk arises from all transactions of a financial nature, including sales and purchases, investments and loans, and most other business activities (Horcher, 2005). However, financial risk is prevalent in new projects, mergers and acquisitions, debt financing, and the activities of management, shareholders, and counterparts. Horcher (2005) stated that there are three main sources of financial risk: a firm’s exposure to changes in market prices, such as interest rates, exchange rates, and commodity prices; transactions with other organisations such as vendors, customers, and counterparties in derivatives transactions; and internal actions or failures, especially with regard to people, processes, and systems.

- **The Importance of Financial Risk**

Financial risk management is thus a process that deals with the uncertainties resulting from financial markets (Horcher, 2005), due to the importance of managing those financial risks. Horcher (2005) stated that addressing financial risks gives an organisation a competitive advantage. The financial risks in such circumstances include risks from prices (asset values, interest rates, foreign exchanges, and commodities), liquidity (cash flows, call risk, and opportunity costs), credit (defaults or downgrading), inflation/purchasing power, and hedging and basis risks (CAS, 2003). These can be categorised as interest risks, foreign investment risks, liquidity risks, market risks, and credit risk. The process of financial risk management enables an organisation to manage these risks associated with financial markets. However, as risk management is a dynamic process, it is essential to include both internal and external analysis in the process and to examine the products, management, customers, suppliers, competitors, pricing, industry trends, balance sheet structure, and position of the firm in the industry overall (Horcher, 2005).

Horcher (2005) pointed out that significant market risks, which include foreign exchange risks, interest rate risks, commodity price risks, and equity price risks, are the most obvious types of financial risk. Charles and Betty (2005) also proved that foreign exchange risk is a significant financial risk among companies. They stated that regarding FX (Financial Exchange) risk management; there was a positive relationship between FX risk management and the value of the firm. Lam (2014) also noted that market risk was defined as exposure to potential loss resulting from changes in market prices or rates. The most common measure of market risk is thus Value-at-Risk (VaR) (Horcher, 2005), which offers a systematic methodology to quantify potential financial loss based on statistical estimates of probability. Horcher (2005) also emphasised that the use of value-at-risk could focus both nonfinancial and financial managers on the issue of measuring risk. To measure equity price risk, Charles and Betty (2005) referred to the capital asset price model (CAPM), which specifies a linear relationship between the rate of return on particular equity and the rate for the market portfolio. It can be written using a formula:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

which calculates the expected return on capital asset E(Ri), which equals the risk free rate of interest Rf plus the beta (the sensitivity of the expected asset returns to the expected market returns) times the market premium (the difference between the expected market rate of return and the risk free rate of return).

As mentioned by CAS (2003), credit risk is also crucial regarding measuring financial risk. Horcher (2005) stated that credit risk is the probability of loss as a result of the failure or unwillingness of a counterparty or borrower to fulfil a financial obligation; it is thus one of the most common risks of finance and business. Credit risk can be measured by the probability of counterparty default, the exposure in case of counterparty default, and the loss gave counterparty default. Credit risk increases as the time to expiry, time to settlement, or time to maturity increases. All organisations are exposed to credit risk throughout any business and financial tractions that depend on payment from or obligations of others. The traditional way of handling credit risk is to monitor borrowers carefully; many variables should be considered, such as financial stability, acceptable ratings, familiarity, political stability, satisfactory geographic location, and appropriate legal forms of organisation (Horcher, 2005).

Interest rate risk is a type of market risk that affects the value of long-term financial liabilities and the value of fixed interest investments. Interest rate risk arises from changes in the level of interest rates; changes in the shape of the yield curve; or mismatches between exposure and the risk management strategies (Horcher, 2005). Usually, the interest rate risk is managed using forward rate agreements, futures, and swaps. Horcher (2005) stated that interest rate derivatives, however, replace interest rate exposure with exposure to risks from the performance of counterparties and raise other issues that mean the interest rate risk cannot be considered independently. It has also been argued that the interest rate risk and credit risk are key components of overall market risk (Horcher, 2005), making it essential to focus on these risks and consider them as a whole.

2.4.2.4 Strategic Risk

- **Definition**

Strategic Risk Management is a process for identifying, assessing, and managing risks and uncertainties that are affected by internal and external events or scenarios and which could inhibit an organisation's ability to achieve its strategy and strategic objectives; its ultimate goal is to create and protect shareholder and stakeholder value (Frigo and Anderson, 2011). Strategic risks include fluctuations in the demand and market price for finished products and substitute products, competition from suppliers of other products, regulatory or political issues associated with the industry, and technological advances that could potentially render products obsolete or undesirable

(CAS, 2003). In general, strategic risks include risks from reputational damage (trademark or brand erosion, fraud, and unfavourable publicity), competition, changes in customer demand, demographic and social or cultural trends, technological innovation, capital availability, and regulatory and political trends.

- **The Importance of Strategic Risk**

According to a Harvard Business Review (2005) article, Gates (2006) stated that there are seven major classes of strategic risk. Industry margin squeeze is one of these seven strategic risks. To deal with industry competition, it is thus better to adjust the competitive or collaborative ratio, varying competition or collaboration between counterparts. Technology changes also result in strategic risk. The recommended practice is to use double bet counter-measures to solve this issue (Gates, 2006). Reputational damage is also important, and the CAS (2003) stated that brand erosion is a major source of reputational damage. It is wise to redefine the scope of brand investment and to reallocate brand investment in order to deal with brand or trademark erosion, (Gates, 2006). Sweeting (2011) also pointed out that reputational risk may also include the consequences of losing data, which could result in a loss of confidence and thus should be enthusiastically avoided.

Regarding competition, one-of-a-kind competitors also present the strategic risk (Gates, 2006). Competitors are always major risks to a firm, as they may create the threat of new products or lower price substitutes. Gates (2006) stated that it is thus important to develop non-overlapping business designs; firms must create different strategies and establish unique, profitable positions. Changes in customer demand also represent an important strategic risk. It is possible to avoid customer priorities shifting unexpectedly by creating and analysing proprietary information and conducting market experiments, which can be relatively quick and cheap (Gates, 2006).

The sixth strategic risk is the failure of new projects. It is not possible to avoid failure by avoiding launching new projects if a business wishes to thrive. Therefore, to reduce the impact of this risk, Gates suggested that the firms should engage in smart sequencing, developing excess options and employing the stepping-stone method. Market stagnation is the final kind of strategic risk. The economic environment is changing all the time, and Sweeting (2011) noted that there are some depictions of business cycles, which include stagnation phases. When the market is in a stagnation phase, Gates (2006) suggested that firms should generate demand-innovation, while Slywotzky (2003) opined that many companies had been stuck in a "no growth zone" for the last decade or more because their businesses have failed to move on from strong growth in the past into a future state of low or no growth. Demand innovation starts by examining current products and uncovering the issues and hassles inherent in those products for current customers. Gates (2006) stated that management should adjust their capital allocation decisions by applying higher rates of capital to riskier projects as well as building more flexible structures in more competitive environments. Taylor (2012) also stated that it is not possible to avoid strategic risks if a firm seeks to achieve its goals. Thus, the best solutions to strategic risks are to transfer the risks using insurances and to adjust acceptable risk levels.

2.4.3 Risk Management in SMEs

- **SME Definition**

There is no single globally agreed definition of the SME segment (Altman et al., 2009). According to Altman et al. (2009), in the United States, the Small Business Administration deals with policies relating to all SMEs, and North American Industry Classification System provides a basic definition of those SMEs, which states that the small business should have a maximum of 500 employees and average receipts of less than 28.5 million dollars. However, this standard may differ between industries. The

Basel Committee, in contrast, defined small and medium companies based mainly on annual turnover such that the annual turnover of small and medium companies should be less than 50 million dollars (Altman et al., 2009). In Europe, SMEs are defined as businesses employing fewer than 250 members of staff with annual turnovers of less than 50 million euros, or annual balance sheets of less than 43 million euros (European Commission, 2006). The Interim Categorizing Criteria on Small and Medium-sized Enterprises (SMEs), published in 2003 and based on the SME Promotion Law of China, also set guidelines for classifying SMEs in that country. This new standard replaced the old guidelines from 1988 and the additional criteria of 1992. The current definitions of SMEs in China are thus shown below in Table 2.4.3:

Size Category	Industries	Employment	Total assets	Business revenue
Small	Industry	Less than 300	Less than 40 million	Less than 30 million
	Construction	Less than 400	Less than 40 million	Less than 30 million
	Wholesale	Less than 100		Less than 30 million
	Retail	Less than 100		Less than 30 million
	Transport	Less than 500		Less than 30 million
	Post	Less than 400		Less than 30 million
	Hotel and restaurant	Less than 400		Less than 30 million
Medium	Industry	300 to 2000	40 million to 400 million	30 million to 300 million
	Construction	600 to 3000	40 million to 400 million	30 million to 300 million
	Wholesale	100 to 200		30 million to 300 million
	Retail	100 to 500		10 million to 150 million
	Transport	500 to 3000		30 million to 300 million
	Post	400 to 1000		30 million to 300 million
	Hotel and	400 to 800		30 million to 150 million

	restaurant			

Table 2.4.3 Definitions of SMEs in China (SME promotion law of China, 2003)

Medium enterprises should meet the three listed conditions, and small enterprises should meet one or more of the conditions. The standard is mainly focused on the industry, staff numbers, total assets, and annual business revenue of each organisation. As seen in the table, the maximum number of employees for SMEs in China is 3,000 people, and total assets should not exceed 400 million Chinese Yuan (about US$ 63.5 million); similarly, annual business receipts should not be over 300 million Chinese Yuan (about US$ 47.6 million) (Zhao et al., 2012). The definition of SMEs in China is thus very complicated and retains a great deal of ambiguity, as some large companies hire very few people. In the Asia-Pacific Economic Cooperation, the definition of SMEs differs again from that applied in China. The primary standard used to classify SMEs there is the number of employees; SMEs commonly employ 100 to 500 people (Liu, 2008). However, in China, companies with up to 3,000 employees are also classified as medium companies, and when judged by standards such as the 250 people marker used in the EU or the 500 people used in the US, small companies in China may quickly fall into the large firm category in other regions. Thus, SMEs in China are comparatively large than SMEs in other areas; however, the annual receipt limitations are not dramatically different.

2.4.3.1 SME Situation

- SMEs Worldwide

As SMEs have begun playing increasingly important roles throughout the world, the study of SMEs has drawn additional attention. Small and medium enterprises are now the primary sector of business in all economies. In the United Kingdom, SMEs account for 99.7 per cent of all 4.7 million businesses. These SMEs also account for 47.5 per cent of employment and 48.7 per cent of turnover (Wilson et al., 2012). In Italy, SMEs account for over 90 per cent of companies and employ over 80 per cent of the workforce (Gordini, 2014). SMEs also play an important role in developing economies. Rogerson (2001) stated that the growth of small and medium enterprises in Africa is closely related to the promotion of economic growth, job creation, and the mitigation of poverty. However, the performance of many SMEs is inferior, when examined individually. Mead and Liedholm (1998), for example, stated that many small and medium enterprises face business failure, and there are more SME closures than expansions, with only around 1 per cent of microenterprises growing from five or fewer employees to ten or more.

It has nevertheless long been proposed that SMEs are pivotal to employment creation and economic growth, particularly in countries such as South Africa with high unemployment rates, which have been estimated at up to 40 per cent (Friedrich, 2004; Watson, 2004). Upgrading the role of the SME sector in the South African economy to improve economic growth by increasing competitiveness and by generating employment and redistributing income (Rogerson, 2004, 2006) has thus been the focus of new development policies in that country since its democratic transition (Berry et al., 2002; GCIS, 2002). In order to aid in the facilitation of the SME environment, the South African government tabled the National Small Business Act of 1996, amended by Act 29 of 2004, to provide equal standing to SME enterprises (Rwigema and Venter, 2004; Ntsika, 2001) in South Africa's economy. The vital role the SME sector plays in the South African economy regarding addressing sustainable development was also highlighted by the 2003 Human Development Report (UNDP, 2003) for South Africa (Rogerson, 2004). It is estimated that 90 per cent of all formal businesses in South Africa is small, medium, or micro enterprises (Rwigema and Karungu, 1999), and the SME sector is, therefore, one of the most significant contributors to the South African economy.

SMEs are not only seen as an employment creator but also as an absorbent of retrenched people from the private and public sectors (Ntsika, 2001). Although the SME sector in South Africa is responsible for 75 per cent of new jobs, mainly due to the emergence of new microenterprises, this nevertheless compares poorly to Asian countries, where SMEs' employment contribution is estimated at 80 per cent overall (Friedrich, 2004; Watson and Godfrey, 1999). Even in countries that are less developed than South Africa in that region, the SME sector contributes a much higher proportion to the GDP and employment (UNDP, 2003; OECD, 19971 cited by Watson and Godfrey, 1999). This may be because the majority of South African SMEs are micro and survivalist enterprises which show no signs of enterprise growth due to inadequate firm dynamics, constraining SMEs to a conservative contribution to employment compared to other countries; even in dynamic South African SMEs, a "jobless growth" strategy (Kesper, 2000) tends to be employed.

- SMEs in China

In the past two decades, small and medium-sized enterprises in China have generally undergone three development phases (Chen, 2006). The first phase, from 1978 to 1992, saw the number and scale of SMEs expanded dramatically. During the first stage, the Chinese government provided a great deal of help and support for entrepreneurs from towns, collectives, and self-employed firms. The rapid expansion of these enterprises made a significant contribution to economic development, and the government benefited from the taxes as the people involved benefited from increased income. The second phase was from 1992 to 2002. In this stage, the most important targets for the government were the reform of the state-owned SMEs formed in the prior stage and the development of non-public economic sectors (Liu, 2006). China’s economic situation is unique, and the government plays a particularly important role in its development, making the majority of relevant decisions. In the second stage, restructuring, mergers and acquisitions, joint partnerships, leasing, contracting, and sell-offs between SMEs were thus encouraged. Several SMEs owned by the government were reformed to become self-owned or partly self-owned, and simultaneously privately-owned SMEs experienced rapid development as the market economy began to take hold. As China's economy changed from a non-public economy to a market economy, this phase was critical regarding the development of Chinese SMEs.

The third phase began in June 2002, when China launched the small and medium-sized enterprises promotion law, which set the standards and rules for SMEs. The main purpose of this government action was to implement laws to promote SMEs by further improving policies and measures supporting the development of SMEs; removing institutional barriers that hindered the development of SMEs, especially private-owned ones; creating a level playing field for the development of SMEs; promoting scientific and technological innovation and upgrades; optimising the industrial structure of SMEs; and enhancing the overall quality and competitiveness of SMEs (Liu, 2006). Generally, Chinese SMEs have experienced fast growth since the reform, measured regarding size, number, financial status, or profitability.

Two factors played significant roles in this period. The first was the rapid development of township enterprises, that is, the enterprises established in towns and small cities. Most township enterprises are small and medium-sized, and as the distributed population in China is enormous, such township enterprises quickly became one of the key elements supporting the development of Chinese SMEs. This development of township enterprises transferred labour from rural and farm work to non-agricultural sectors, increasing the remaining farmers' income. Other policies were thus developed based on this to establish a solid foundation for the strategy of reform and development.

The second factor was the rapid growth of the non-public sectors of the economy, especially privately-owned SMEs. As the economic reforms proceeded, privately-owned SMEs played an increasingly important role in the economy as state-owned businesses retreated from the market economy. In the initial phase of the reform and opening-up period, the government was aware that the non-public sector of the economy would have to be developed into a necessary supplement to the socialist public economy (Liu, 2006). In 2004, the government, therefore, amended the constitution in order to grant the non-public economy legal status in the socialist market economy. This legislative move reflected China's deepening understanding of the role of the non-public sector in the economy, which in turn gave greater impetus to the development of privately-owned enterprises

In 1980 in China, the number of industrial enterprises at the level of collectives, townships, and village enterprises was about 377,300 (Wang, 2004). There were only 1,400 large enterprises. There were 3,400 medium enterprises and 372,500 small enterprises, representing about 0.90 and 98.73 per cent of all firms, respectively (National Bureau of Statistics, 1981, p. 204). In that year, China also had 1.81 million commercial enterprises (including private businesses), more than 99 per cent of which were SMEs (Wang, 2004). There were 686,000 individually owned enterprises, which accounted for about a third of all commercial enterprises. The number of SMEs was boosted rapidly with the development of China's economy in the 1980s, and in 1990, there were nearly 8 million industrial enterprises. The proportions of large, medium and small enterprises were 0.95, 2.27 and 96.78 per cent, respectively. The number of small and medium enterprises had increased dramatically. Furthermore, the number of construction, commercial, food-and-beverage, and service enterprises had all increased by over 300 per cent since 1980 (NBS, 1991, p. 16-17).

By the end of 2001, there were about 2.4 million small and medium-sized enterprises in China, accounting for 99 per cent of all registered corporations. Including less apparent forms of SMEs such as self-employed businesses, leasehold farm households, and individual partnerships not registered as legal persons, this number becomes larger. Chinese SMEs have thus clearly played an important role in stimulating economic growth, increasing employment, expanding exports, and promoting science and technology innovation. Regarding economic growth, the output value, sales revenue, and tax revenue of SMEs in the industrial sector accounted for 60, 57, and 40 per cent of their sector totals, respectively (Liu, 2006). Since the 1990s, SMEs have created 75 per cent of the incremental industrial output value in the country, and SMEs also dominate in most industrial sectors, with over 70 per cent of the gross output value in the food, papermaking, and printing industries. The SMEs also dominated over 80 per cent of the garment tannery, recreation and sports outfits, plastic, and metalwork industries; and over 90 per cent of the wood and furniture industries (Liu, 2006). Due to the limitations of statistical data, such data is only available at industrial sector level; however, it is reasonable to extend this data to reach a conclusion about SMEs in other sectors based on observation. For example, SMEs in the wholesale and retail industry accounted for about 33 per cent of the total number of SMEs and must thus have played a crucial role in enhancing commodity circulation. Employees in SMEs account for a significant proportion of the total employees nationwide, with more than 85 per cent in the industrial sectors, 90 per cent in the retail industry, and over 65 per cent in the construction industry.

In recent years, the development of privately-owned SMEs has dramatically expanded employment opportunities and caused a significant increase in the labour force. The government started to reduce the number of employees in state-owned enterprises in the 1990s, and since that time, SMEs have played an important role in supporting this change in economic structure by hiring workers laid-off or dispersed from both state-owned enterprises and urban collective enterprises. From 1998 to 2003, nearly 19 million workers laid-off from state-owned enterprises were re-employed, most of whom went to SMEs (Information Office of the State Council, 2004).

SMEs have also played an important role in China’s foreign trade. China's total export value in 2003 was over US$ 430 billion, the fourth highest global figure, and SMEs played a significant role in the export of commodities such as garments, shoes and hats, handicrafts and metal goods, light industrial products, textiles, and toys; the impact was seen mainly in high-tech or labour-intensive products (Liu, 2006). Regarding technology innovation, SMEs in China have also achieved significant progress and gradually become the leading force behind the spread and application of new technologies and innovations. Liu et al (2012) noted that SMEs have contributed significantly to technology innovation and engineering in China, and by the end of 2003, China had established more than a hundred high-tech enterprise parks, over 30 university science parks, over 20 enterprise parks for returned overseas students, over 40 service centres for SME technology innovation, and more than 500 productivity promotion centres (Liu, 2006). All these institutions provide strong support for the technological innovation of SMEs.

Compared with large enterprises, SMEs have numerous advantages for such development. As SMEs are so small and low level, they can make highly efficient business decisions. In smaller companies, research and development (R&D) staff and production and marketing staff can remain in closer contact, facilitating better communication and cooperation. SMEs also have high business conversion adaptability and rapid technology absorption, as well as tending to display innovative spirits. Due to low creation cost, high-quality, and the potential to create more exclusive products, the majority of SMEs also have enhanced professional features. However, SMEs are generally inferior to large enterprises about technical reserves, R&D capabilities, and financing capabilities, as well as risk tolerance.

Differences in Risk Management for SMEs

In recent decades, a significant change in the role of risk management among companies has been seen as risk management has expanded well beyond the insuring and hedging of financial exposures to include many other types of risks (Nocco and Stulz, 2006). Nocco and Stulz (2006) stated that corporations could manage risks on a largely compartmentalised and decentralised basis. They also stated that preventing underinvestment problems, which make the cost of issuing equity very high, is the most important reason for managing risk. By managing risks, firms can limit the probability of massive cash shortfalls to acceptable levels. However, it can be challenging to decide which kind of risks companies should accept in order to grow. Currency and interest risk and commodity prices can be hedged with inexpensive derivatives such as forwards, futures, swaps, and options. However, these kinds of risks are mainly financial risks, and companies also need to face business and strategic decisions. Nocco and Stulz (2006) pointed out that companies cannot create economic hedges when they are launching promising business plans, and that proper risk management does not aim to reduce the risk level to zero. Failure is the cost associated with total risk, and it should be accounted for while assessing the risk-return trade-off of all major new investments. If the company takes on a project that increases the firm's total risk, the project should be predicted to be sufficiently profitable to provide an adequate return on capital after compensating for the costs associated with that increase in risk. Thus, a risk-return trade-off must be evaluated for all corporate decisions that are expected to have a material impact on total risk.

The traditional method for predicting business failure is to pair up failed and non-failed firms, which first requires distinguishing failed firms from non-failed firms (Wu, 2010). However, Wu (2010) stated that this traditional method could not adequately detect business failure. For instance, when a firm becomes a business failure, the traditional method succeeds or fails based on the extent of classification accuracy rather than predicting failure. It is also unhelpful for risk management to focus on the question of whether bankruptcy or zero-profit represents failure. The most important thing is to identify the common features of failed firms directly and to ascertain why they failed. Wu (2010) therefore recommended financial ratio analysis as a more effective and direct method to explore the model of business failure prediction.

Credit risk is the risk of not receiving promised repayments on outstanding investments such as loans and bonds due to default by the borrower; this is thus also known as default risk (Sweeting, 2011). Credit risk is the most critical risk faced by small and medium enterprises, as whenever debtors cannot fulfil their legal obligations to the debt holders, default occurs. Such defaults may, therefore, happen on many types of debt obligations, such as bonds, mortgages, and loans. As the development of new debt products never stops, the detection and measurement of credit risk have become increasingly important. Chen et al. (2010) stated that SMEs caused 64 per cent of gross bad bank loans in China in the period 2003 to 2005 in six major cities. As SMEs are therefore often deemed to have a lack of collateral and guarantees, banks are often not willing to lend to them. Chen et al. (2010) further stated that, according to a credit rating issued by the ICBC in 2001, only 16.31 per cent of 350,041 SMEs achieved an A rating or higher. Most SMEs were graded BBB or below, indicating that most of the SMEs in China find it very difficult to get loans from banks. The situation creates an issue, as sufficient access to capital is one of the essential elements in their development.

Financial statements are companies' basic documents, which should reflect their financial status. It is thus necessary to analyse financial statements to detect whether a company is running well or is in crisis (Ravisankar, Ravi, Rao, and Bose, 2011). By reading financial statements critically, it is possible to uncover the current situation of the firm, the most important elements in the financial statement, and the most important departments of the firm in the period covered. Financial ratios are a valuable and simple way to understand the facts behind the numbers shown in the financial statement (Ravisankar et al., 2011), and the application of financial ratio analysis is thus widespread. The study of business failure based on the use of financial ratios (Z-scores) began in 1966 with Beaver (Koyuncugil and Ozgulbas, 2012); later, Altman (1968) established a Z-score model based on five key financial ratios, and in the ensuing decades, several scholars focused on similar questions to discover ways of reducing risk. Different models and methods, such as logistic regression, multivariable statistical models, neural network methods, early warning systems, Chi-Square automatic interaction detector decision trees, were used; however, although the methods differed between studies, all of the research was based on financial ratios used to create models.

There are four aspects to financial ratio application, which are liquidity, safety, profitability, and efficiency (Ravisankar et al., 2011). Liquidity focuses on calculating a company’s capacity to pay off short-term debts; the most important ratios for this are the current ratio and quick ratio. Safety indicates the ability to pay the long-term debt; here, debt to equity, interest cover, and cash flow to long-term debt ratio play significant roles. The profitability reflects a company's ability to achieve returns from its operation; for this, scholars focus on gross profit margin, net profit margin, return on assets, and return on equity. Also, DuPont analysis (Groppelli and Ehsan, 2000) has been promoted as the most useful way to calculate return on equity, as this considers three or five essential ratios’ effect on the return on equity. Finally, efficiency measures whether the managers manage assets well or not; thus, the relationships between sales, accounts receivable, cost of goods sold, and inventory are most relevant.

About 20 years ago, risk management mainly involved the use of swaps and options to hedge interest rates and commodity prices. Back then, risk management was thought of as a generally decentralised or compartmentalised activity that helped a firm mainly by making modest contributions to its P&L statistics. The purview of today's risk manager is much broader, however, encompassing all aspects of the corporation, including investment and operating decisions as well as financing, with a particular focus on anything that affects the level and variability of cash flows going forward. It is seen as a way of ensuring the company's access to capital and thus its ability to carry out its strategic plans, and, in this sense, it has become a critical part of the business model. Nocco and Stulz (2006) stated that a corporation could manage all risks together as a single concern within a coordinated and strategic framework; this approach is often called enterprise risk management (ERM). An effective ERM approach offers a long-term competitive advantage over firms that manage and monitor risks individually. Nocco and Stulz (2006) also stated that ERM helps a firm maintain access to capital markets and other resources that are necessary to implement its strategic and business plan. In SMEs, the risk management function is usually based on the owner's assessment of threats and opportunities pertaining to the enterprise (Watt, 2007), and although risk management principles are common in all types of enterprises, the owner-managers risk perception and attitudes towards risk management influence the adequacy of the risk management actions deployed (Ntlhane, 1995). Smit and Watkins (2012) suggested that most SME owners and managers do not have systems in place for structured risk identification; thus, in most SMEs, risks are left unmanaged until they become apparent, and only then are managers spurred into action to address these (Ntlhane, 1995). Furthermore, while SME managers may be able to identify obvious risks, but their unsystematic risk knowledge may impede attempts to identify indirect risks, or to recognise the internal relationships of risks (Watt, 2007). It is important to embed a structured, matured, and incremental framework to help SMEs identify, assess, control, evaluate, and monitor risks.

2.4.4 Indicators in Risk Management

2.4.4.1 KPIs and KRIs

Several scholars have applied the special treatment (ST) and non-special treatment (Non-ST) as a classification standard when studying Chinese listed companies (Chen and Yi, 2007; Xie and Me, 2013). The ST system is unique; it was introduced on 22nd April 1998 (Green, Czernkowski, and Wang, 2009). A company is a special treatment company, if it satisfies one or more of the following criteria: the company has negative net profits for two consecutive fiscal years; the shareholders' equity for the company is lower than the registered capital (the par value of the share); the auditors of the firm have issued negative opinions or have been unable to issue an opinion; the company's operations have been stopped due to natural disaster or serious accident and cannot be restored within three months; the company is involved in a damaging lawsuit or arbitration; or the company is bankrupt (Green et al., 2009). However, the usefulness of the ST procedure is debatable. The ST standards do not require a strict measurement of performance of firms, acting more like a regulation system, which emphasises operational activities. In contrast, the potential risks faced by firms cause damage or unexpected loss of the value of these firms. The ST standard operates as activity regulation, while risk management is more like a value-increase system. Thus, judgements unlike those used for ST standards must be used to measure performance.

The ERM framework also mentioned the use of KRIs and KPIs (CAS, 2003; Mestchian and Cokins, 2006; Keith, 2014). The use of KPIs and KRIs can make the ERM process more efficiently. Performance measurement is a fundamental principle of management (Weber and Thomas, 2006). The most intuitive and simple measurement of a firm's performance is the increase in profit or value. As key performance indicators (KPIs) are similarly used to assess and evaluate the performance of target objectives, it is also important to define KPIs before commencing measurement (Yuan, Zeng, Skibniewski, and Li, 2009). Yuan et al. (2009) stated that KPIs compare actual and estimated performance regarding effectiveness, efficiency, and quality. However, the purposes of KPIs and their ranges of application may differ between investigations. Yuan et al. (2009) also pointed out that appropriate KPIs must be decided on before focusing on and measuring performance. As part of the risk management process, a successful result should increase the firm’s value (Verbano and Venturini, 2011). Thus, in this research, any KPIs used should be able to measure the firm's performance effectively as well as being easily obtained. Also, Keith (2014) stated that KPIs could be used to develop key risk indicators (KRIs). Therefore, it is necessary to select KPIs based on the characteristics of the research, and these may then be used in other studies.

Scarlat, Chirita, and Bradea (2012) claimed that many researchers are concerned about the problem of risk indicators and the extent to which they help to detect and reduce risk at an enterprise level. Risk indicators can provide forward direction and information about risk, which can thus be used as a warning system; also, many scholars have noted that whether an indicator is a key indicator or not can provide very important information (Davies, Finlay, Mclenaghen, and Wilson, 2006). Coleman (2009) claimed that KRIs could provide information about companies’ risk positions that can thus alert companies to relevant changes; this information could then be used by management to ascertain the risk level of proposed activities and projects. Scarlat, Chirita, and Bradea (2012) argued that risk varies from one enterprise to another, from one process to another, and from one system to another. To ensure the implementation of KRIs, it is thus important to maintain the qualification of indicators, usage of standards and methodologies, and connections between KRIs and business objectives. Scarlat, Chirita and Bradea (2012) also emphasised that KRIs must not be mistaken for KPIs, which are focused on historical performance, although these can also be used to measure management performance. While KPIs help management to understand whether the firm has reached its objectives, KRIs can help management to understand ongoing changes in risk profile, impact, and likelihood, better permitting them to complete the firms' goals (Scarlat, Chirita and Bradea, 2012). They also claimed that KRIs could be used as metrics for measuring risk levels, which requires the use of the right number of indicators. For instance, where firms select too many indicators, the efficiency of other tasks will be reduced, and the information may be excessive for decision makers; similarly, if firms select too few indicators, it might be too complicated for decision-makers to capture critical information. This makes it clear that the selection of KRIs and KPIs is a very important part of the risk management process.

Davies, Finlay, Mclenaghen, and Wilson (2006) argued that there are distinct criteria for selecting the right KRIs. KRIs should be efficient, comparable, and easy to use. For efficiency, indicators should be applied to at least one specific risk and one business function or activity; be measurable at specific points in time; reflect objective measurements rather than subjective judgements; track at least one aspect of the loss profile or event history; and provide useful management information. For comparability, indicators should be quantified regarding comparable values, such as ratios or percentages; be reasonably precise and of definite quantity; be comparable internally across the business, and be auditable and identifiable across organisations. The chosen indicators should be available reliably on a timely basis; cost-effective to collect, and readily understood and communicated; to promote ease of use. (Davies et al., 2006). High-quality KRIs should also include full definitions and descriptions of what was collected, the measurement and calculation, and offer guidance for implementation. Following research by Davies et al. (2006), KRIs may be financial indicators or non-financial indicators; they also argued that the selection of KRIs should begin by identifying the areas of highest risk for the business. Scandizzo (2005) further stated that a KRI could be either quantitative (e.g. turnover rate) or qualitative (e.g. adequacy of the system), and thus either objective or subjective. In any case, KRIs should be regularly reviewed and updated to remove irrelevant or redundant data; identification and location of the risk indicators is thus a significant step in the overall risk management process.

2.4.4.2 The Importance of Non-financial Indicators

This study applied the non-financial factors as risk indicators in risk management procedures as assessed using business intelligence (BI) approach. Although financial ratios are essential elements in the analysis of risk management, it is also important to consider non-financial indicators. Meyer (1998) pointed out the value of non-quantitative information for evaluating the credit levels of firms, while Cooper (1991) noted that the educational level of management, experience, and capital gained could contribute to predicting firms' performance. Also, Lussier (2001) found that the cycle of economy and production and the owner's age should be included in predictive models. Wu (2010) pointed out that the general environment, immediate environment, management/entrepreneur characteristics (education, motivation, qualities, skills, and personal characteristics), corporate policy, and company characteristics were also important factors for predicting business failure; however, his study was focused on large companies rather than SMEs. As Wang and Zhou (2011) stated, large companies always have different scales of measurement, and although auditors are responsible for detecting financial fraud, it is difficult for them to find clues within a manipulated financial statement. Financial fraud can be detected by human experts mainly based on experience, and thus the subjective bias of experts cannot be avoided (Ravisankar et al., 2011). Also, many corporate governance factors can affect risk management in large firms. Based on Cressey's Triangle theory, there are three elements of financial fraud: opportunity, incentives/pressures, and attitudes/rationalisation. The measurements of these three elements may not be numerical, however. For instance, to measure opportunity, it is common to use high or low ratings rather than a precise number.

The enterprise life cycle is also an important part of the prediction of business failure (Cao, Chen, Wu, and Mo, 2011). To determine the potential risk for firms, the analysis of company life stage is also important, as entering the decline stage always leads to financial distress (Cao, Chen, Wu and Mo, 2011). This makes it important to take pre-emptive steps before firms fall into the decline stage. The best solution for avoiding business failure is to detect the earliest signals of entering the decline stage. Many scholars also mention the existence of early warning systems based on business intelligence analysis (Yu et al., 2011, Koyuncugil and Ozgulbas, 2011, Gordini, 2014). By analysing internal and external information, such a system could warn managers where firms are likely to encounter financial distress.

Shuai and Li (2005) also emphasised the significance of non-financial information such as abnormal changes of CEO, financial managers, or auditors in the year before failure. Seeking to improve the accuracy of existing models, some scholars have thus suggested that the use of both qualitative data and quantitative data could improve the prediction of financial failure. Altman and Sabato (2007) showed that an applied Z-score model could result in 30 per cent less accuracy than applied logistic regression, and noted that Multiple Discriminant Analysis (MDA) default prediction models are even less capable of distinguishing defaulting and non-defaulting clients than logistic models. Furthermore, based on the enterprise risk management framework suggested by CAS (2003), some risks cannot be fully explained using either financial indicators or non-financial indicators alone. Thus, a combination of financial and non-financial indicators is necessary to measure all types of risks.

Many scholars have done studies using only either financial factors or non-financial factors. Koyuncugil and Ozgulbas (2012) constructed a CHAID model including 18 ratios to analyse 7,853 firms. In their research, they found that only using financial ratios did not wholly explain the risks faced by SMEs; hence, they suggested the use of non-financial factors can support their findings in further study. Rubin and Rubin (2013) applied a GARCH model by using time series data from 2000 to 2007; this proved that the use of business intelligence could improve company performance. Wu (2010) used 15 financial ratios to predict business failure, applying automatic clustering methods to detect 163 failed firms. Chen et al. (2010) used a KMV model based on Merton Option Pricing Theory to try to compare ST and non-ST companies in China, while Ravisanker et al. (2010) used support vector machines and genetic programming to detect financial fraud, including 33 financial ratios. However, none of the above studies included non-financial indicators. They suggested that non-financial factors should be included to improve model accuracy. Derelioglu and Gurgen (2011) tried to explain credit risk using binary class variables, while Lussier and Pfeifer (2001) used 15 non-financial factors within a true/false questionnaire. None of these scholars actively included both financial and non-financial factors in their models, despite many suggesting that the combination of both factors would improve model accuracy.

Altman et al. (2008) tried to apply both financial and non-financial factors to credit risk modelling, using seventeen financial ratios and eight dummy variables in a Z-scores model, based on Altman's initial risk management model from the 1970s. They concluded that non-financial factors could improve the accuracy of financial models. Cao et al. (2011) similarly used the business cycle as a non-financial factor, combined with twenty-nine financial ratios, to attempt to create an early warning system. Wang and Zhou (2011) used eight financial ratios and five non-financial ratios to conduct logistic regression to create a model based on data from 193 firms to try to explain

SMEs' defaults. The number of indicators in the previous work is relatively small. As stated by Han et al. (2012), the data mining process can discover knowledge from a large amount of data. The amount of financial and non-financial indicators can be increased to improve the prediction accuracy of the model or enhance the analytical ability of the model.

Overall, non-financial indicators have been more widely used by scholars since 2001, though the amount of research of this type remains limitations, and most existing studies in risk management for SMEs focus on one risk type only. For instance, 64 per cent of studies were not empirical studies, and some applied questionnaires as their research method (Verbano and Venturini, 2013). Although most of the risk features can be explained by using both financial and non-financial indicators, the study considered all risks and the whole risk management process is still understudied. This belies the need to conduct research, based on entirely objective indicators using a method to include all the risks in a model for risk management process in SMEs. According to Verbano and Venturini (2013), previous studies from 1999 to 2009 mainly focused on operational risk (54 percent), with the other three types of risks featuring in only 46 percent of previous studies (financial risk, 29 percent; strategic risk, 14 percent; and hazard risk, 3 percent). It indicated that there are fewer studies considered all the risks at the same time. There are fourteen out of thirty-four papers applied ERM framework in this risk management model (Verbano and Venturini, 2013). However, in the fourteen studies, there are only five of them studied total risk management process. It emerges from the results of other studies that the study of how to use ERM framework for the whole risk management process is needed. Also, the use of financial and non-financial indicators in the risk management process should also be evaluated.

Verbano and Venturini (2013) also noted that internal and external effects created production risks, human resource risks, and market share; and financial losses amongst SMEs. The analysis indicates that, for risk management in SMEs, non-financial indicators play a large part in risk identification; in particular, several key indicators should be non-financial rather than financial, including human resources-related indicators such as educational background, which are not numerical variables, and thus must be indicated by non-financial indicators. The use of non-financial indicators in models that comprehensively explain risk management in SMEs is thus obligatory.

2.4.5 Data Mining and Business Intelligence

Data mining is the process of discovering interesting patterns and knowledge within large quantities of data (Han, Kamber, and Pei, 2012). The data resources used could come from databases, data warehousing, the internet, or any other information repositories (Han et al., 2012). Negash and Gray (2008) mentioned that business intelligence could assist with corporate performance management and provide decision support; they also stated that business intelligence includes both structured and unstructured data in ways that provide actionable information. Business intelligence gathers unstructured information from spreadsheets, emails, and similar sources.

▪ Business processes ▪ Chats ▪ E-mails ▪ Graphics ▪ Image files	▪ Letters ▪ Marketing material ▪ Memos ▪ Movies ▪ News items	▪ Phone conversations ▪ Presentations ▪ Reports ▪ Research ▪ Spreadsheet files	▪ User group files ▪ Video files ▪ Web pages ▪ White papers ▪ Word processing text

Figure 2.4.5-a The Collectable information types by BI (Negash, 2004)

Figure 2.4.5-a shows, unstructured data or semi-structured data can be used in the analysis and decision-making process. In a similar manner to structured data, the unstructured data can be used in models via acquisition, integration, and clean up.

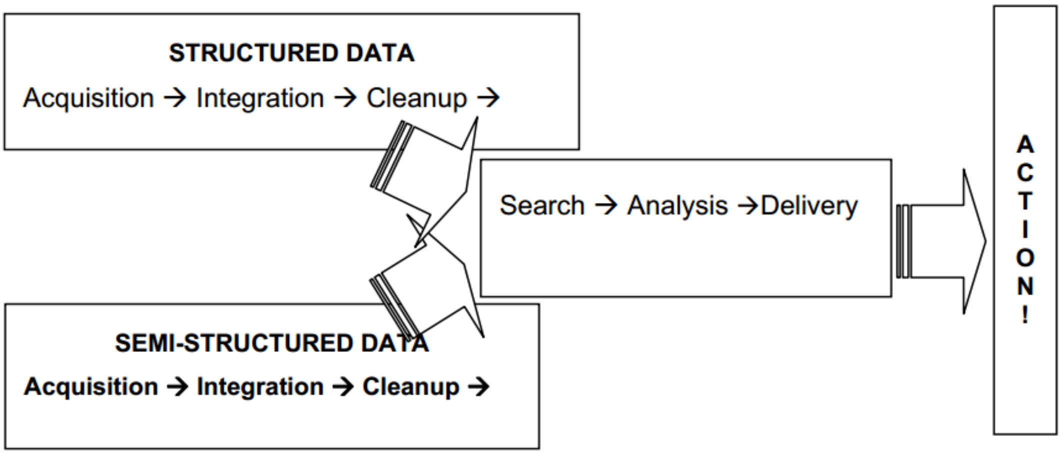


Figure 2.4.5-b The Process of BI (Negash, 2004)

Figure 2.4.5-b shows the process of using structured data and unstructured data to support the decision-making process. Chaudhuri, Dayal, and Narasayya (2011) also stated that business intelligence plays a vital role in building predictive models, allowing integration of data mining into the overall process. As business intelligence can provide data input to the data mining process, the efficiency of the data mining process is improved (Chaudhuri et al., 2011). Han et al. (2012) also pointed out that business intelligence provides historical, current, and predictive views of business operations, stating that data mining is the core of business intelligence and that data mining supports business decisions.

Han et al. (2012) stated that the data mining process can use relational database data, data warehouse data, and transaction data, along with other kinds of data (such as internet sources, graphs, maps, and videos), and that the output of data mining may be either descriptive or predictive. They also mentioned that data mining is inherently connected with statistical analysis.

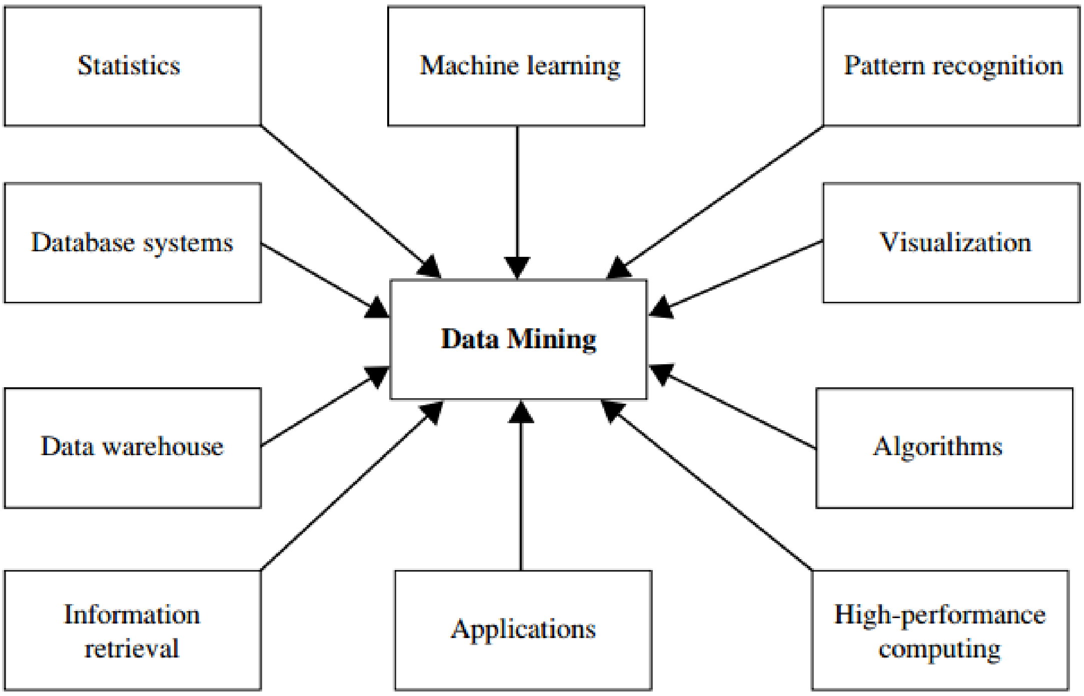


Figure 2.4.5-c Elements in Data Mining (Han et al., 2012)

Data mining incorporates many techniques from other domains, as shown in Figure 2.4.5-c (Han et al., 2012). Statistics and machine learning were the main methods used in this research, and these will thus be discussed in the next chapter. Information retrieval is the science of searching for whole documents or particular information in documents (Han et al., 2012). As mentioned when discussing the business intelligence approach, unstructured data, such as information from the web or information in documents, can be cleaned up and transformed into structured data. The enterprise risk management framework thus defines four different risks, based on features including financial information and non-financial information. Verbano and Venturini (2011) claimed that enterprise risk management is a proactive approach and that data mining with business intelligence is another proactive approach (Negash and Gray, 2008). As a result, these elements may well be integrated into a more comprehensive predictive model.

2.5 Gap Analysis

As risk may bring both losses and gains, research on risk management is a highly contentious issue. However, although a great deal of the literature shows an interest in applying risk management in SMEs, the number of published papers remains limited, which means that many areas are still understudied. Islam et al. (2006) claimed that while many studies have been done on risk and risk management, most of them focus on particular industrial contexts, and in particular on the industries associated with safety and occupational health hazards. As a result, risk management in the SME sectors has been given lower priority, as it is generally considered less catastrophic. Risk management for SMEs requires the adoption of risk management strategy and methodology, unlike risk management in larger organisations (Verbano and Verturini, 2013). Islam et al. (2006) also argued that the SMEs have specific limitations which lead to their risk types and factors differing from those of other organisations, requiring risk identification and categorisation to be developed specifically for this sector.

Verbano and Verturini (2013) argued that the tasks of risk management include identifying risks, measuring the potential consequences of events, and reducing or mitigating any possible loss. Vergas-Hernandez (2011) also claimed that SMEs needed to obtain competitive advantages and succeed in the market by protecting their innovative projects. Risk management in SMEs thus presents new challenges for scholars, requiring more specific and systemic methods for risk identification, evaluation, and treatment. The three mains steps mentioned previously as part of risk management are called risk assessment in the ISO 31000 standard, and the elements and factors in each step should be adjusted based on the features of SMEs to provide more helpful information to decision makers. It has also been argued by Samani et al. (2017) that the integration of the RM process with other processes or systems is possible. It concluded that the three main steps in the risk management process could be integrated with other process and components to improve efficiency and effectiveness.

The data mining process provided a solution to the whole risk management process. Johnson (2010) attempted to provide a conceptual mapping of risk management and data mining. In Johnson's study, he did not select a standard risk management process like ISO 31000 standard. Also, he applied the Cross-Industry Standard Process (CRISP) for the data mining process. However, compared with the data mining process developed by Han et al. (2012), the CRISP-DM process does not show a significant advantage in the whole process. On the other hand, the standard risk management by ISO 31000 was widely used and mentioned by scholars (Verbano and Venturini, 2013; Samani et al., 2017). Meanwhile, follow the ERM framework and risk management process, the use of KRIs and KPIs mainly belongs to feature selection, which may not require all the functions provided by the CRISP-DM process. According to Di Serio et al. (2011), the risk management is a dynamic process, where the 'monitor and control' step in ISO 31000 standard also required to adjust goals upon the need of specific firms. The risk management process in this study will also be embedded with other elements such as BI approach, EWS and ERM framework. Therefore, the standard risk management process can be integrated with other processes more effectively and efficiently, while the standardised data mining process is not suitable for the risk management process in this study for SMEs.

The application of non-financial indicators presents new challenges. Altman et al. (2010) studied the value of non-financial information in the prediction of SMEs; however, although they used a combination of financial and non-financial indicators in their models, the financial indicators were selected from their previous study, and only five were used. Further, the performance of firms had already been decided by the provider of the data. It could thus be concluded that that research did not follow the whole procedure of risk management laid out by ISO 31000 standards or COSO. According to Verbano and Venturini (2013), of the thirty-three relevant papers from 1999 to 2009, none covered all types of risks in a single piece of research, and only a third of researchers covered the whole risk management process (identification, evaluation, treatment, and context analysis). As risk management requires the adoption of the whole process to support decision makers, it is necessary to create a model that includes the processes mentioned in the ISO 31000 standards. The application of non-financial indicators should not be solely instituted at the risk treatment step, but instead, should be integrated into the whole risk management process. The current study's application and integration of financial and non-financial indicators is thus an innovative attempt to examine the risk management process.

Regarding risk assessment processes following ISO 31000 standards, several scholars have studied these using their methods (Altman et al., 2010, Geng, Bose and Chen, 2015, Koyuncugil and Ozgulbas, 2012). Geng et al. (2015) stated that several classification algorithms are available for financial distress prediction. In their research, they compared four different algorithms to predict the distress of firms; however, it was not possible to identify which algorithm provided the most accuracy before a comparison of methods. If only one method were applied, there might thus be a lack of evidence that the selected method was the most suitable and accurate choice. Moreover, risk indicators may change over time, as they are determined by the external and internal environments (COSO, 2003). It is thus not meaningful to use the same indicators for varying time periods or countries, as the situations are different and change over time. As each method uses different core algorithms, the results should naturally be different, and the significant indicators may differ from one method to another. Several methods should, therefore, be applied in the risk assessment process to achieve more convincing results, and these methods should be compared with each other to help select the most suitable.

Business intelligence provides a unique way of thinking about data analysis. Negash (2004) defined business intelligence as “a system combined data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers”. Comparing this with the definition of the risk management process provided by ISO 31000 standards, which includes establishing the context, risk assessment, and risk treatment, each risk management process can be matched with business intelligence steps to a certain extent. For example, when decision-makers need to establish context, they must determine the purposes and objects of actions; data gathering, and data storage could provide enough information to allow the decision makers or planners to ascertain patterns or rules for specific groups. Business intelligence can thus convert data into useful information, which people could use to develop knowledge (Negash, 2004). According to Negash (2004), business intelligence makes use of both structured and unstructured data, where the unstructured data is gathered from reports, research, spreadsheet files, and so on. As discussed, this non-financial information and some financial information can be classified as unstructured data. Thus, the use of business intelligence approach can help the DM process, which also improves the risk identification step in the risk management process.

The identification of KPIs and KRIs in SMEs is also a relatively new area. Scarlat et al. (2012) stated that KPIs are focused on the historical performance of firms and their key operations, while KRIs provide real-time information about future risks. The main difference between KPIs and KRIs is thus that the former indicates whether goals are achieved or not, while the latter explains the changes in risk profiles, the situation of firms and the probability of achieving the target goals (Scarlat et al., 2012). As a result, the key performance indicators should indicate whether the past performance of the firm has been good or not. Davies et al. (2006) also pointed out that the key indicators provide important information, serving this purpose very well. Based on this characteristic, the key risk indicators should not be solely decided by decision makers or management. Instead, the key risk indicators should be founded on rational and logical algorithms, considering their importance, threshold values, significance, and sequencing. Although Scarlat, Chirita and Bradea (2012) noted the importance of KPIs and KRIs, they did not suggest a method of identification and classification of key indicators. The resulting lack of procedures for the assessment of KPIs and KRIs thus requires amendment; results will be more convincing where one or more sophisticated algorithms guide the process.

There are thus several gaps in the existing research: the application of enterprise risk frameworks in SMEs, the value of non-financial indicators in risk management in SMEs, the selection of algorithms in risk assessment for SMEs, the method of identification of KPIs and KRIs, and the use of business intelligence in risk management in SMEs. Furthermore, the integration of the whole process within risk management remains a challenge, as the risk management process is not a single-step method. Following ISO 31000 standards helps to establish a more precise procedure for management or decision makers, but the selection of algorithms is also an important part of the risk management process, which requires efficiency and efficacy (Scarlat et al., 2012). It is therefore clear that the challenges of risk management for SMEs should be further studied, based on the existing framework and theories.

After reviewed existing literature, the current gap can be then identified. Firstly, the integration of the DM process to the RM process is needed. Although Johnson (2010) used the CRISP-DM process to a RM process, the RM process in his research is not a standardised process. Gjerdrum and Peter (2011) thoroughly described the ISO 31000 and COSO ERM framework. They concluded that the ISO 31000 increased ‘accountability and strengthens communication’, which means the standardised RM process has advantages. Therefore, the integration of the DM process to a standardised RM process can increase the ability of SMEs to deal with potential risks. Secondly, the BI approach has been used to visualise and quantities data for years (Nagash, 2004). The BI approach can provide a general view of dataset from the beginning of the DM process. It can also transfer non-numerical information into numerical format that can be directly used as input data for the DM process. But the use of BI approach can extract a high level of knowledge from raw data (Cortez and Silva, 2008). But the use of BI approach with the DM process in the RM process is still a new area, which requires more guidance on relevant theory and practice. Thirdly, the effectiveness of ERM framework in the RM process should be examined. There are two components in the ERM framework were used, which are risk types, KRIs and KPI (CAS, 2003). The ERM framework is a holistic framework, which aims to capture both financial and non-financial features from the risk management views. There are four different risk types, which cover financial and non-financial features of firms. On the other hand, the use of KPI and KRIs can reduce the number of indicators that the SMEs should focus on. The SMEs can monitor KRIs rather than all indicators, since the other indicators are not important as KRIs. The cost will be reduced, and the efficiency of the RM process will be then increased. Fourthly, the EWS can be used in the risk treatment step. The rules and pattern generated from the DM process can be analysed in detail. The threshold value of KRIs and the importance of KRIs will be found out, which provides explanations about the KRIs. Based on this information, it can know how and why the risks affect firm performance. Fifthly, The Financial and Non-financial factors have been used together in the DM process, which captured more comprehensive features of the RM. In the other studies, the financial indicators have been applied at the most time, while the use of non-financial indicators was only suggested by many scholars (Altman, 2007). However, some scholars tried to find out the value of non-financial indicators in relative topics (Altman et al., 2010; Geng et al., 2015). In this study, there are more financial indicators have been considered and included, which followed the risk catalogues of the ERM framework. Followed the existing framework, the explanatory and meaningfulness of non-financial indicators can be addressed and specified more clearly. As a result, through comparing prediction accuracy of the data mining methods with different groups of financial and non-financial indicators, the value of non-financial indicators can be shown directly. Finally, the performance of DM methods in RM for SMEs will be compared. In the RM process for SMEs, it is important to reduce the costs and increase accuracy. To achieve these goals, the feature selection functions of DM methods will be mainly considered. To evaluate the performance of DM methods, the prediction accuracy, comprehensiveness of the results, and complexity of the methods will be compared. The comparison of different DM methods has been applied in other studies (Geng et al, 2015). However, the comparison of the methods (LR, CHAID, GA, BPNN) in this study is a new set. Therefore, based on the evaluation of these four methods, it is possible to find out the most suitable DM method for RM in SMEs.

2.6 Summary

In this chapter, general background to risk management was introduced. As the development of risk management has occurred over only a few decades, the stages of risk management are not yet mature. As Verbano and Venturini (2011) stated, there are nine main paths of development in all the fields of risk management. The paths differ from one another, and depend on the different approaches used, risks considered, techniques and methodologies proposed, and fields of application. Therefore, if the research target selected is enterprise risk management for SMEs, the corresponding financial theories and tools for risk identification and assessment must be selected (Verbano and Venturini, 2011). The ISO 31000 standard and COSO framework for enterprise risk management were reviewed, and it was noted that enterprise risk management considers all the risks suggested by CAS (2003), which is the most holistic and integrated framework of the seven main risk management methods (Verbano and Venturini, 2011). To identify the most accuracy and efficient risk management method for SMEs, it is appropriate to use the enterprise risk management framework, while to determine the correct risk management process for SMEs, it is also important to introduce the background and definition of SMEs. Furthermore, the application of enterprise risk management frameworks to SMEs is a new field, which requires a careful selection of indicators and methods. Verbano and Venturini (2013) pointed out that there were only thirty-three papers about risk management for SMEs between 1999 and 2009, and that only fourteen out of the thirty-three papers used enterprise risk management frameworks. Further, only one paper included more than two risk types. Consequently, the framework of risk management processes for all types of risks in SMEs requires an introduction and a more detailed discussion.

3. Development of the Theoretical Framework for Risk Management in SMEs

3.1 Introduction

The previous chapter has reviewed the risk management process, risk management framework and ERM framework, the related concepts of risk management and identified the gaps in research, which is focusing on the risk management process, data mining process and ERM framework. It emphasised the usage of non-financial indicators and the solution of combining the data mining process and risk management process. The purpose of this chapter is to develop a theoretical model for risk management, which combined with the data mining process, ERM framework and BI approach in order to address the purpose of this research.

The structure of this chapter is shown as followed. The Theoretical Background discussed the frameworks in detail. After that, the components of the purposed framework have been introduced. Then, the hypotheses are developed and justified based on previous research.

3.2 Theoretical Background

Risk management in small and medium-sized enterprises has been less developed because SMEs have a comparative lack of resources and reliable mechanisms (Brustbauer, 2014). The risk management processes in SMEs are thus mainly based on the perception of the owners rather than expert boards of directors as in large companies (Herbane, 2010; Leopoulus, Kirytopoulos and Malandrakis, 2006; Nocco and Stulz, 2006). In recent years, the overarching view of risk management has changed from evaluating risks from an individual perspective to taking a more generally encompassing perspective, which is also known as enterprise risk management (Brustbauer, 2014). However, Florio and Leoni (2017) stated that the empirical evidence on the relationship between ERM and performance is still limited. Florio and Leoni (2017) argued that the reason for little empirical evidence is that it is difficult to explain the relationship between ERM and firm performance. Verbano and Venturini (2011) stated that ERM is the application of financial theories (Value Maximisation and RM) and the adoption of tools for risk identification and risk assessment, with the aim of maximising the firms' value. Therefore, the risk management process could combine with ERM framework to specify the risk catalogues, reduce the impact of uncertainty and then increase the firms' value.

In this section, the discussion will point out the theoretical foundations of this research. This chapter was divided into subsections: the first one introduces the ERM framework and risk management process. The second subsection focuses on the data mining process and the combination of the data mining process and risk management process. The third subsection describes the process of constructing the risk management framework with ERM framework with all the components together. The last one developed the hypotheses.

3.2.1 The ERM Framework

Enterprise risk management can increase risk management awareness by supporting a firm-wide risk management approach, which translates more effectively into mature operational and strategic management decisions (Nocco and Stulz, 2006). The enterprise risk management framework provides general guidance and key principles, leaving details to the individual firm (Brustbauer, 2014); even the definitions of risks may thus be different. However, the general agreement about risks in recent years is that the risks include both downside effects and positive effects. As defined by COSO (2017), enterprise risk management is a process that it is effected by an entity's board of directors, management, and other personnel, applied in both strategy setting and across the enterprise, that is designed to identify potential events that may affect the entity and thus manage risk such that it remains within the entity's risk appetite, thus providing reasonable assurance of the achievement of objectives. Pagach and Warr (2011) stated that the enterprise risk management framework aims to identify, assess, and monitor all threats and opportunities faced by the firms. As mentioned in Chapter 2, there are four main kinds of risks faced by SMEs under the ERM framework: hazard risk, operational risk, financial risk, and strategic risk. In many studies, scholars have constructed models to predict company performance by analysing financial ratios (Altman and Sabato, 2007; Altman et al., 2010; Lussier and Pfeifer, 2001). It can be concluded, however, that the risks faced by companies can be monitored more effectively using the changes in both financial ratios and non-financial ratios. To systematically manage different risks, this research will thus adopt existing developed frameworks and add additional variables to explain the risks and thus improve the efficiency of risk assessment and monitoring procedures.

As Verbano and Venturini (2011) stated, ERM is an extension of financial risk management (FRM) to non-financial circumstances, where the non-financial part is not studied as much as the financial part. Beaver (1967) and Altman (1968) first applied financial ratios to building business failure prediction models, while Nocco and Stulz (2006) found that financial risk management and firm value are correlated. Chen et al. (2010) applied a KMV model in the analysis of credit risk, and Wu and Olson (2009) demonstrated validation of predictive scorecards for large bank risk management. However, none of these previous studies provided a holistic and integrated model in the term of all risks. Verbano and Venturini (2013) stated that integrated risk management (also called enterprise risk management or holistic risk management) began in 2000 as an approach to align strategy, processes, people, technology, and knowledge with the process of evaluating and managing risks (threats and opportunities) (De Loach, 2000). Verbano and Venturini (2013) also stated that this required a re-ordering of the risk management discipline into a single framework to identify and characterise the different approaches to risk management. Based on this complete framework, future scholars would then be able to pool knowledge accumulated from individual development experiences (Verbano and Venturini, 2013).

Verbano and Venturini (2013) also pointed out that the ERM is the most studied framework since it covers all risk types. Enterprise risk management framework adopts the tools for risk identification and assessment to maximise the expected value of a firm; there are thus many advantages of applying an enterprise risk management framework in the risk management process. Several organisations also provide frameworks to help risk management, including COSO, ISO, and CAS. However, in the past, only a few researchers, such as Fraser and Simkins (2016) and Bromiley et al. (2014), focused on the usefulness of enterprise risk management in companies. According to many scholars (Lam, 2001; Liebenberg and Hoyt, 2003), enterprise risk management framework provides a higher probability of reaching a firm's goals; a reduction in the cost of capital; a greater understanding of the main risks; optimisation of the portfolio of risks; a reduction in the volatility of cash flows; a definition for intervention priorities; improvement in compliance to norms; a smaller number of unforeseen events and consequent losses; a more significant push for change; greater response speeds to varying business conditions; and a greater tendency to accept risk in order to gain higher returns (Verbano and Venturini, 2013).

Key performance indicators (KPIs) and key risk indicators (KRIs) can be identified and monitored more efficiently by integrating the four major types of risks into one complete framework in order to improve the prediction of business failure and to detect potential risks. The KPIs are used to measure firms' performance, which allowed the firms to set goals on performance (Delcea et al., 2013). The KRIs can provide information about unfavourable trends (Delcea et al., 2013). Delcea et al. (2013) also mentioned using EWS to monitor KRIs to control risks. CAS (2003) also stated the KPIs and risks are linked to the ERM framework. Keith (2014) also pointed out that the ERM framework linked KPIs and KRIs to manage the risks effectively. The risk management process could be simplified to control KPI and KRIs instead of considering and monitoring all indicators. Therefore, the application of ERM framework in the risk management process could provide an integrated view, which may also improve the efficiency of the whole risk management process.

Many scholars have studied risk management in different aspects, including its elements, steps, methods, and so on. Kloman (1976) started such research with "The Risk Management Revolution", and many practitioners have since advocated a coordinated approach to risk management. Kloman (1992) described the concepts coming out of Europe from the mid-'70s to the early '80s, with theory now associated with ERM. Gustav Hamilton, a risk manager in Sweden, argued for "a new and collective view of risks" (Kloman, 1992). Kloman (1992) also argued that the elements of risk management for enterprises must be based on the enterprise being treated as a system. The process of risk management in enterprises could thus be considered as a kind of information system. In such a system, the risk managers need to keep sending risk and uncertainty information from enterprise to managers and other departments to deal with future risk. Gleason (1999) stated that the risk management process includes the processes of identifying, measuring, and solving. Initially, it is imperative to measure the risks faced by the firm, and after this risk measurement, a process for evaluating the impacts of those risks should be applied. It is also important to set up a department to manage and control risk and to evaluate the potential loss inherent in any risk accepted.

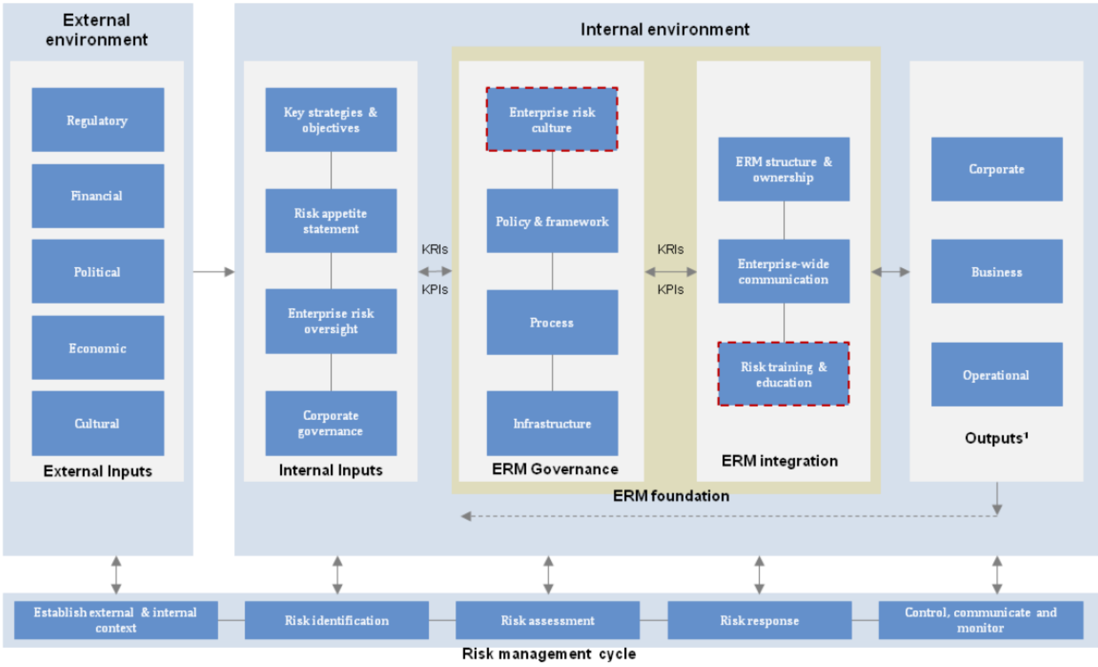


Figure 3.2.1-a The Risk management cycle with ERM (Source: Keith (2014))

The five steps required by ISO standards are thus accomplished within the framework (Keith, 2014). As shown in Figure 3.2.1 a, the external environment mainly affects only the first step of the framework, while the ensuing four steps are closely linked with the internal environment. The most important elements in the internal environment are the key risk indicators and key performance indicators. The KRIs and KPIs build links between risk identification, risk assessment, and risk response steps, and these three steps are the main processes in the ISO framework, collectively known as the risk assessment phase. Keith (2014) argued that KPIs and KRIs work simultaneously in the enterprise risk management framework, interacting with risk identification risk assessment and risk response. However, these risks could thus be only identified after firms have been affected; meaning that KPIs can be considered ineffective, as they measure events that have already happened, and which have thus already had an impact on the enterprise's performance (Kaplan, 2009). The key performance indicators can be used to see whether performance has been achieved or not, while key risk indicators can indicate how the risk profile has changed within desired tolerance levels. Thus, while KPIs provide information about past events, KRIs can thus potentially provide insights into future potential risk events (Taylor and Davies, 2003). For example, performance metrics can be used to measure expected performance, and KRIs can predict the downside risk or volatility of such performance (Smart and Creelman, 2009).

KRIs play critical roles in the whole risk management process. For instance, if organisations use self-assessment tools for risk identification and control, KRIs can facilitate the monitoring process at set intervals. They can also indicate what the entity's risk appetite is (Immaneni et al. 2004). When used appropriately, these tools can provide the insight needed to track business strategies and thus drive through the benefits of change (Kaplan and Norton, 1992; Frigo 2002). Developing a set of effective KRIs should, therefore, enable managers to identify relevant measures. It can also provide information about the impact of risks on the accomplishment of target objectives. Based on this, developing a good understanding of target objectives is more important than creating enterprise-wide KRIs, though developing effective KRIs is treated as the most important process in most organisations. Financial organisations usually focus on indicators of credit risk and market risk (Lam, 2005), and thus some of them may be challenged when required to develop KRIs for financial risk, technology risk, or operational risk.

Lam (2003) stated that KPIs could be developed from various sources such as policies and regulations, strategies and objectives, previous losses and incidents, stakeholder requirements, and risk assessments. According to Immaneni et al. (2004), there are two approaches to effectively addressing KPIs, which are top-down or bottom-up. The top-down method assesses general objectives and risks, then designs appropriate risk indicators. In contrast, the bottom-up approach defines specific processes and risks. Some unique business areas may be better suited to the bottom-up approach; for example, where there are special requirements in some corporations, the bottom-up approach could provide more accurate information on targeting objectives, which could be used to develop unique KRIs based on those unique corporate environments. One proposed way to overcome this challenge in other cases is to select measures that edge over the limit and to transform them into an index that acts as a tool to merge findings from different indicators and report them in aggregate (Immaneni et al., 2004).

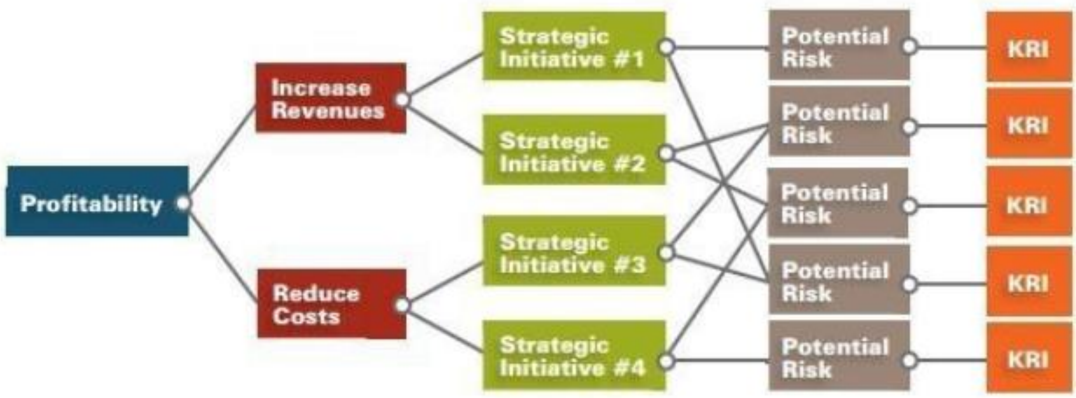


Figure 3.2.1-b The Use of KRIs (Immaneni et al., 2004; Keith, 2014)

The objective of KRIs is to create a better business performance. Thus, management will always set goals to increase profitability. An entity can either increase revenues or reduce costs to increase revenue. If firms want to achieve these two different results, different strategies must be applied, and whenever strategies are set to achieve target goals, these may come with potential risks. As stated in COSO 2010, potential risks can be highlighted and mapped to core strategic initiatives so that management can create metrics to contribute most effectively to the execution of the strategic goal. As the framework represents a dynamic process, continuous monitoring and analysis of internal and external environmental changes are also important. The framework thus demonstrates that the use of KRIs and KPIs can enhance monitoring and control risk to achieve target objectives (COSO, 2010).

3.2.2 The Risk Management Process

The risk management follows a stage-gate process (Verbano and Venturini, 2013). The process of risk management is thus shown in Figure 3.2.2 below:

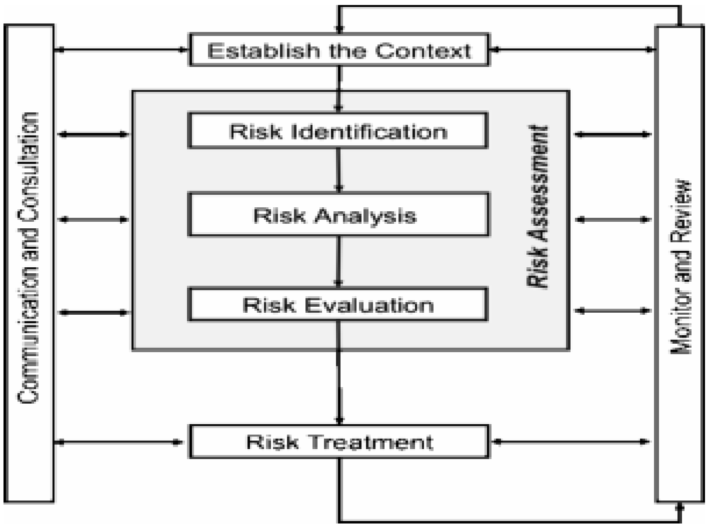


Figure 3.2.2 ISO standard risk management process (ISO 31000, 2009)

There are total of three main parts of the risk management process, which are Establish the Context, Risk Assessment and Risk Treatment. Additionally, the Risk Assessment part contains three sub-steps, which are Risk Identification, Risk Analysis and Risk Evaluation. Meanwhile, the Communication and Consultation step and Monitor and Review step will constantly interact with all other steps to control the quality of the risk management. The most important step is the Risk Assessment, which contains three sub-steps (Verbano and Venturini, 2013). They stated that the first sub-step aims to identify all the risks that the firms faced. The second sub-step aims to determine the probability and magnitude of the potential damage. The third substep is to identify the most suitable actions to reduce the effect of risk. The whole risk management process is a long-term, dynamic and interactive process (Di Serio et al., 2011). As a result, a process that considers all the steps and complies with long-term, dynamic and interactive is ideal for the risk management process.

During daily activities, enterprises may realise they will face future risks. However, it is not easy for them to identify what kind of risks and how those risks will affect their operational activities. There might be many indicators under each risk category, and these the indicators may or may not be related to firm performance. This makes it important to uncover these risks and to figure out how to assess them effectively. The biggest issue is to identify the firm's performance at the very beginning, which makes the risk management process more difficult. It is also necessary to identify one or more key performance indicators (KPIs) to measure the firm's performance, which should be readily comparable and allow classification of firms into different groups. So that firms can be classified, it has been assumed that the performance of firms differs and that selected KPIs can explain these differences. Based on these different performance levels, it would thus be possible to identify the risk indicators adopted by annual reports and government institutions. Risk indicators could also be classified by types of risk under the enterprise risk management framework created by CAS (2003). This makes it possible to identify key risk indicators under four risk categories. If these key risk indicators are confirmed, the risks can be ranked, evaluated, and explained by management in many different ways. The risks faced by SMEs have unique features, which are not same as in other sizes of the enterprise; thus, to assess these risks, it is important to discover directly effective methods rather than using universal methods. Unique threshold values, road maps, classifications and sequencing must thus be used to capture the features of SMEs, which should also guide decision makers. More specifically, decision-makers can use those methods to build an early warning system to control the risks and improve performance.

The risk assessment process can thus be explained as follow. Before any risk assessment steps, the performance of the firm should be assessed from the data sets. Delcea et al. (2013) stated that enterprise performance could be measured by using key performance indicators (KPIs). They also noted that the Risk Management Associations (RMA) had developed a project about Key Risk Indicators (KRIs) that can be helpful regarding accessing, measuring, and controlling different types of risks. Enterprise performance is most generally reflected in financial status, and based on the information provided by KPIs; it is possible to set objectives and monitor progress within a reasonable interval. Taylor et al. (2008) mentioned that enterprises could also monitor and predict the value of key performance indicators using a simulation tool. However, since the purposes of KPIs and KRIs are different, there might be conflicts in setting KPIs and KRIs. The risks faced by each company are different, and every company has its unique focus on risk management. Once again, it should be emphasised that KPIs and KRIs must not be confused with each other, and the application of KPIs should come before the identification of KRIs. Risks may affect the performance of firms, which indicates that risks can, therefore, be identified by comparing the performance of different firms.

As there are four different types of risks, and each different display characteristics, it becomes necessary to treat different risks separately; KRIs and KPIs are both important in this risk management process. KRIs, for example, can be used to detect unfavourable trends (Delcea et al., 2013). The risk identification step should come first, to classify the different risks. In the risk identification phase, the problems faced by companies can be classified using the four major risk types to help them focus the problems more efficiently. For example, where companies find that financial problems are the main issue, it is likely that financial risk has existed and not been treated in the past.

When a company is expanding, its operations and progress become more complex, and within these more complicated situations, the potential risks also grow. Risk indicators at that point could be either financial or non-financial, but Altman et al. (2010) argued that using non-financial variables could improve the accuracy of predicting company failure. Islam et al. (2006) agreed that the indicators could be financial or non-financial depending on the problems to be solved. For example, if decision makers want to know the financial situation of a firm, the most direct form of measurement is financial ratios, while if they need to measure other information, such as industry, employee education, or audit information, the non-financial indicators could more directly indicate this kind of information. Both financial and non-financial indicators can be integrated into a combined model as risk indicators, where they can be filtered and treated via business intelligence tools to determine key risk indicators. It is important to reassess and measure key risk indicators regularly in order to detect risks before they become harmful. Whenever one or more variables meet the thresholds set, it is possible that the company will be affected by future risks. KPIs are also important in the risk management process, and thus if enterprises set their goals and define their risk requirements, both KPIs and KRIs can be appropriately used in risk analysis progress. Although KPIs and KRIs are helpful in the risk management process, the application is still needed to be specified and optimised.

3.2.3 The Early Warning System

Based on the different types of risks, it is possible to evaluate most enterprise situations and to use key risk indicators to set up an early warning system, which could be useful to Risk Evaluation step. According to Bussiere and Franzscher (2006), early warning systems are developed to detect underlying economic weaknesses and vulnerabilities; furthermore, an early warning system can make it possible to reduce risks before a crisis by allowing management to take some pre-emptive steps. Koyuncugil and Ozgulbas (2012) defined an early warning system as an analysis technique used to predict the achievement conditions of enterprises and to decrease their risk of the financial crisis. It is thus apparent that KPIs and KRIs can be adequately fitted within early warning systems. Koyuncugil and Ozgulbas (2009) noted that a good early warning system can provide identification of changes in environment; identification of speed and direction of changes projected into the future; identification of the importance of the degree of changes; determination of deviations and signals; determination of possible reactions in the direction of privileged deviations; and investigation of the factors which cause changes and transactions between these factors. Such an early warning system is the type of predictive model, offering the chance to take corrective precautions in the long-term (Koyuncugil and Ozgulbas, 2009). An early warning system based on financial ratios could predict the profits of firms, potential bankruptcy risks, and any impending crisis for enterprises' economic trends. More importantly, it could make use of KRIs and KPI to increase the efficiency of the RM process.

The application of early warning systems is complicated. As Koyuncugil and Ozgulbas (2009) noted, financial early warning systems are based on financial ratio analysis. In these financial ratio based systems, administrative and structural factors are ignored, as are human factors. Thus, financial early warning system does not consider all of the relevant variables, which may lead to bias in the results. Striving to complete and improve on the application of early warning systems, many scholars have contributed studies on the use of early warning systems. Canbas, Cabuk, and Kilic (2005) created an integrated early warning system by combining three parametric models based on the principal component analysis (PCA). Oh, Kim, Lee, and Lee (2005) further stated that it is important to establish an alarm zone to predict potential crises. The basic process of establishing an early warning system is shown in Figure 3.2.3:

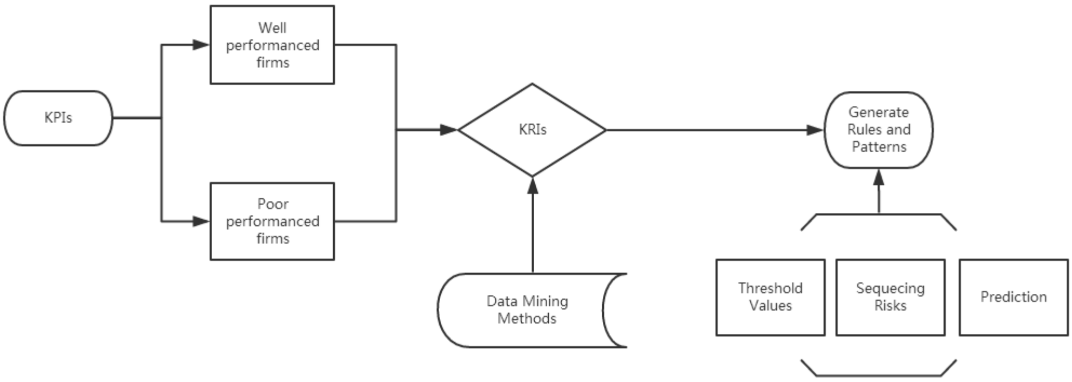


Figure 3.2.3 The Process of establishing EWS

Firstly, the firms should be classified into two groups based on the KPI, which indicates the performance of firms. The target Canbas et al. (2005) pointed out that, in bank failure studies, banks were split into two different groups: healthy and failed. Thus, to establish an early warning system for SMEs, it is important to classify the enterprises into two or more different groups, where the features of indicators could be studied. Based on the classification results, different sets of characteristics can then be generated in order to uncover the differences between groups. It is also necessary to define the standards of good and poor performance. Secondly, the most important step in this system is the generation of characteristics, as the conditions and thresholds defined later are based on the results of this step. Thus, to obtain more accurate results, it is necessary to apply more than one data mining method in the selection of KRIs.

Furthermore, the focuses and process of each data mining method are not the same, where using more methods may provide more comprehensive views of KRIs. Finally, the Rules and Patterns are explored by evaluating KRIs. The KRIs will be deeply analysed in order to generalise the ranges and significances of them, which will help the decision makers to focus on fewer indicators. Since the early warning system starts with the firms' performance, the aim of the early warning system and risk management process could be synchronised. As a result, the early warning system could increase the efficiency of the risk management process, especially for Risk Evaluation step.

After generating characteristics, the groups of sample data can be classified clearly. The characteristics of poorly performing enterprises may then indicate why they have been classified into this group. The classification of different risks was discussed in chapter two, and following categorisation into the four different risk types, it is possible to uncover the thresholds between high-performance enterprises and poor performance enterprises. These thresholds can be defined by using one or more variables above or below pre-set values. It may also be much easier to generate patterns of financial ratios and non-financial ratios from one of the groups. Based on these patterns, it is possible to uncover the influences of different risks and to determine the most important risk-related ratios. After this, the weights and independent variables should be optimised based on the results of the previous steps. For example, if the financial risk is the most significant risk, it is necessary to increase the weight of the financial risk related ratios, so that these ratios will play more important roles in the model and other, less significant, variables will take on less weight.

Setting up an early warning system also requires defining the desired values. To understand the performance of enterprises, examining examples of poor performance could be helpful to identify the risks and the weakness of an enterprise. In contrast, defining and identifying the desired values could be also helpful in understanding the good performance and the achievement of objectives for enterprises. Any indicator exceeding or missing a specified threshold value could thus be interpreted as a signal. There are many signals amongst the ratio analysis results of most enterprises. If these signals indicate that the enterprise is performing well, these signals could be adopted into desired variables. On the other hand, if the signals indicate that the enterprise is performing poorly or getting into financial distress, these signals should be taken as warning signals. In high-performance groups, the desired variables will thus outweigh warning signals. The features of different types of risks could also be identified during this process, and the weights of different risks in different groups ascertained. For instance, the sequencing could provide the rank of risk importance. As a result, warning signals based on the various risk categories can be created within the early warning system, making it possible to build integrated models, which indicate a range of potential risks for enterprises. Such integrated models can allow enterprises to improve their performance purposively, tactically setting their objectives to focus on the improvement of one or more targets.

3.2.4 The Data Mining Process

This research used data mining theory to build models and select methods for the risk management process. Soman, Diwakar, and Ajay (2009) pointed out that data mining algorithms are included in the knowledge discovery in databases (KDD). A data mining system allows users of databases to discover new knowledge from the data (Adriaans and Zantinge, 1996). Some data mining algorithms use statistical methods, but in essence, data mining refers to any means of discovering patterns within and extracting hypotheses from the data. Soman et al. (2009) also stated that the data mining differs from the traditional statistics in that data mining is used to extract qualitative models using logical rules or visual representations. Rokach and Maimon (2014) further noted that data mining is a term which describes the process of sifting through large databases in search of interesting, previously unidentified patterns. Data mining thus can make predictions about specific phenomena, and Soman et al. (2009) argued that data mining is a part of the KDD process, providing algorithms to support the overall KDD process.

Rokach and Maimon (2014) stated that data mining describes the process of finding unknown patterns through large databases; it is the accessibility and abundance of data that makes data mining possible. Data mining is also part of the Knowledge Discovery in Database (KDD) process, which is shown in Figure 3.2.4:

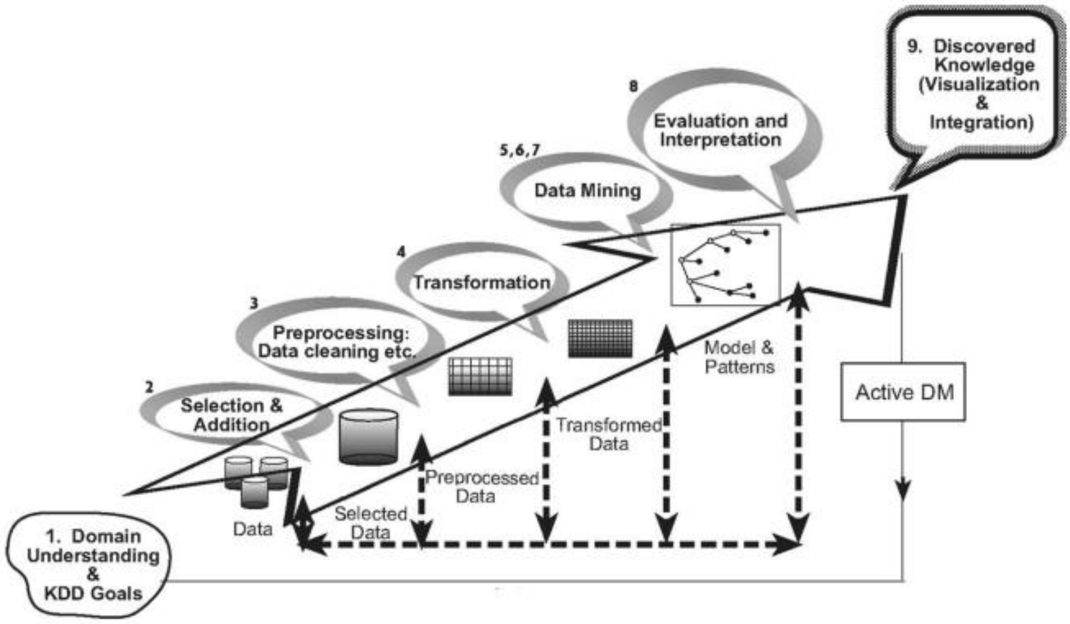


Figure 3.2.4 Data mining Steps (Rokach and Maimon, 2014)

Rokach and Maimon (2014) defined the KDD process, including the data mining process, as choosing the appropriate data mining task; choosing the data mining algorithm, and employing the Data Mining algorithm. Figure 3.2.4 also shows the steps taken to prepare data for mining, as well as showing how the data is transferred to knowledge. Han and Kamber (2001) pointed out that many people treat data mining as identical to KDD; they also stated that the data mining is often used to refer to the entire KDD process in the industry, media, and research milieus. Soman et al (2009) reaffirmed the four steps of the data mining process as data selection, data transformation, mining the data, and interpreting the results, while Han, Kamber, and Pei (2012) argued that there are seven steps to KDD, which are data cleaning; data integration; data selection; data transformation; data mining; pattern evaluation, and knowledge presentation. They also pointed out that the first four steps refer to different forms of data processing, which prepare the data for mining. The data mining step is the essential process, where intelligent methods are applied to extract data patterns (Han et al., 2012), and the final two steps identify the patterns and present knowledge to users. This affirms that the data mining process aims to uncover useful information from large datasets which can then be applied to risk management procedures to uncover potential risk factors.

3.2.4.1 Business Intelligence

BI approach could provide many helpful functions regarding ERM framework and data mining process. McBride (2014) stated that BI provides the information and tools for statistical analysis of large-scale trends, which also includes detailed characters. McBride (2014) also pointed out that the KPIs could be examined and monitored at every point, which is also complied with the risk management process. Han et al. (2012) also stated that the BI approach provides reporting, business performance management, benchmarking, and so on. The data collection is the basic step in the data mining process, which will construct the database. The BI approach could support the construction of data base by using software to collect the data from websites (Chen et al., 2010; Han et al., 2012). Additionally, the BI approach also includes data cleaning and arranging functions (McBride, 2014). It is evident that the whole data mining process could be supported by using the BI approach. Moreover, the ERM framework required both financial information and non-financial information to cover all four risk types. It is important to collect information from any possible resources. As a result, the database could be built by using BI approach in the data mining process.

Business intelligence can help decision makers to make decisions through the application of both structured and unstructured data (Negash, 2004). Structured data includes information from data warehouses, data mining, executive information systems, online analytic processing, and enterprise requirement planning, while unstructured data may include conversations, graphics, images, movies, news, and web pages. BI converts data into useful information, which helps to transform the data into knowledge using human analysis (Negash, 2004). The listed firms provide annual reports to the public, which contains the balance sheet, cash flow sheet and other related information (CFA, 2015). The financial information is more accessible to collect than non-financial information, where the financial indicators could be directly calculated by information in the balance sheet and cash flow sheet. However, the non-financial indicators required to be cleaned and standardised before applied in data mining methods, which should also be complied with the risk features under the ERM framework. As a result, it is necessary to use the BI approach to generate financial and non-financial information in order to use them in the data mining process.

The application of BI approach in data collection and data cleaning is very important in this research. By using BI approach, it is possible to select any available resources According to Tutunea and Rus (2012), BI in SMEs is variously perceived. Tutunea and Rus (2012) noted that the BI solutions and products include dashboards, localisation and business data visualisation, what-if analysis, interactive reports, and readily interpretable formats for users. The most important part of BI in this research is in the data collection and data cleaning steps. The SMEs required different focuses on risk management (Kim and Vonortas, 2014). As a result, the BI approach may provide more flexible adjustments, which could also dynamically adjusted (Chen et al., 2010). The BI approach is also helpful in other parts of the data mining process. For example, ‘mining the data’ and ‘rules and patterns’ may require BI approach to provide classification and clustering. Specifically, data mining is the core of BI (Han et al., 2012). Therefore, it would be helpful to use the BI approach in the whole data mining process to provide support for most steps in the model.

3.3 The Conceptual Model

As discussed earlier, the conceptual model for this research includes the risk management process, the data mining process, which also adopts the ERM framework, EWS and BI approach.

Following the risk management process in ISO 31000 (2009), risk management is a stage gate process (Henschel, 2009; ISO 31000, 2009) described in Figure 3.3-a:

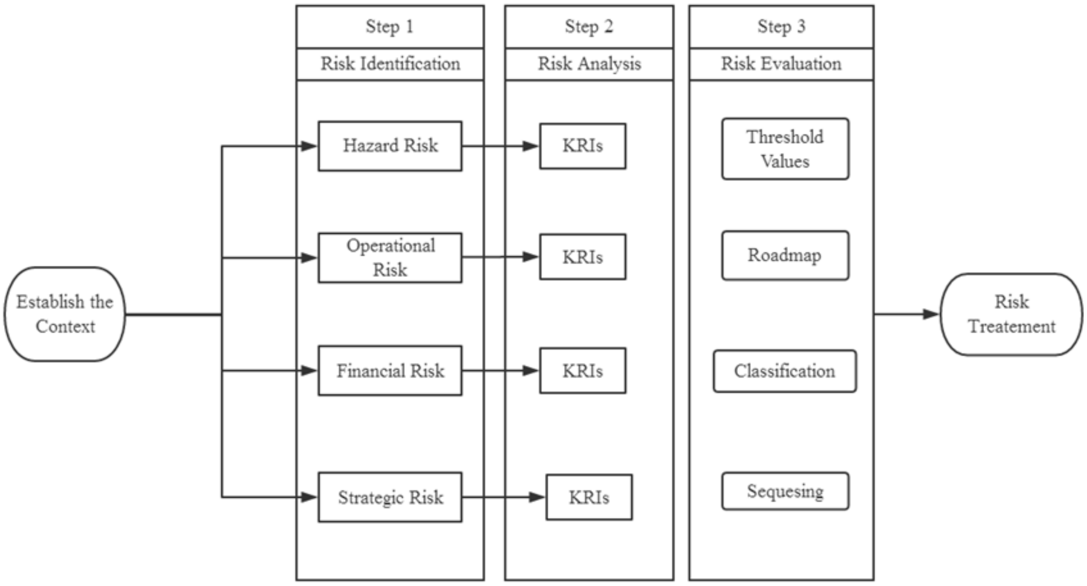


Figure 3.3-a The Detailed RM process

The purpose of RM should be recognised in the "Establish the Context" step (Verbano and Venturini, 2013) before the three sub-steps in the risk assessment phase are completed. In the risk identification step, the risk should be thoroughly investigated regarding what, how, when, and why risk may occur. The risk analysis is the most complicated section of the risk assessment step and should provide a generally complete understanding of each risk, the consequences of those risks, and the likelihood of those consequences. Finally, the risk treatment phase provides possible solutions and improvements for the firms concerned. It is possible to conclude that data mining steps can be used to support the risk management process naturally by combining this risk management process with a data mining process. For example, the Establish the Context process specifies the purposes of risk management, making it important to decide the KPIs and KRIs at this stage; this can be related to the data selection step in the data mining process.

Similarly, in the risk assessment step, the target risks should be analysed and explained in detail; the data transformation and mining the data stages of the data mining process can thus provide theoretical and practical support for these stages, including selecting and transforming appropriate information to create risk indicators. Further, based on the interpretation stage of the results of the data mining process, decision makers could decide on the actions to be used in the risk treatment step of the risk management process. In this way, it is possible to use data mining methods in the risk management process to achieve risk management goals.

The data mining process includes four steps: data selection; data transformation; mining the data and interpretation of results (Soman et al., 2009). The most important part of this process is data selection, which provides the resource for the ensuing steps. Soman et al. (2009) stated that the variables selected, and the range of the data to be examined should be specified in this step before data transformation is used to shift the data into the particular formats required by the chosen data mining tools. After that, the data is analysed using those data mining tools, and the results of the data analysis represented numerically or visually. The data mining process is not a one-step process, making it similar to the risk management process as outlined in ISO 31000.

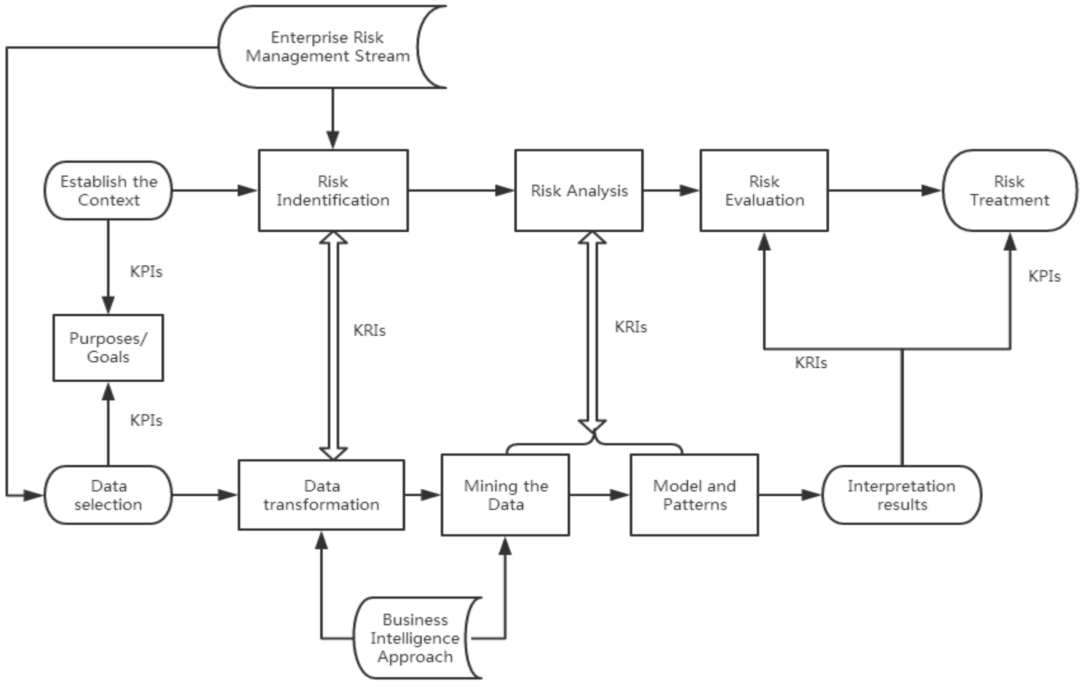


Figure 3.3-b Flowcharts of DM-RM model

Figure 3.3-b shows the combination of risk management procedures with a business intelligence approach in an enterprise risk management framework in the flowchart. The data mining process and risk management process are combined via KRIs and KPIs. As the purpose of the risk management process and data mining are similar, it is possible to combine the two processes to achieve risk management goals. The two frameworks can be connected by using KPIs and KRIs, where the KPIs provide a measurement of purposes or goals and the KRIs provide insight into rules and patterns. Also, the business intelligence approach supports the use of information from databases, data warehouses, the internet, and other information repositories. While the information collected from the internet or other external information repositories may not be basic forms of data (Han, Kamber and Pei, 2012), these non-basic forms can be transferred into basic forms of data to be used in the data mining process.

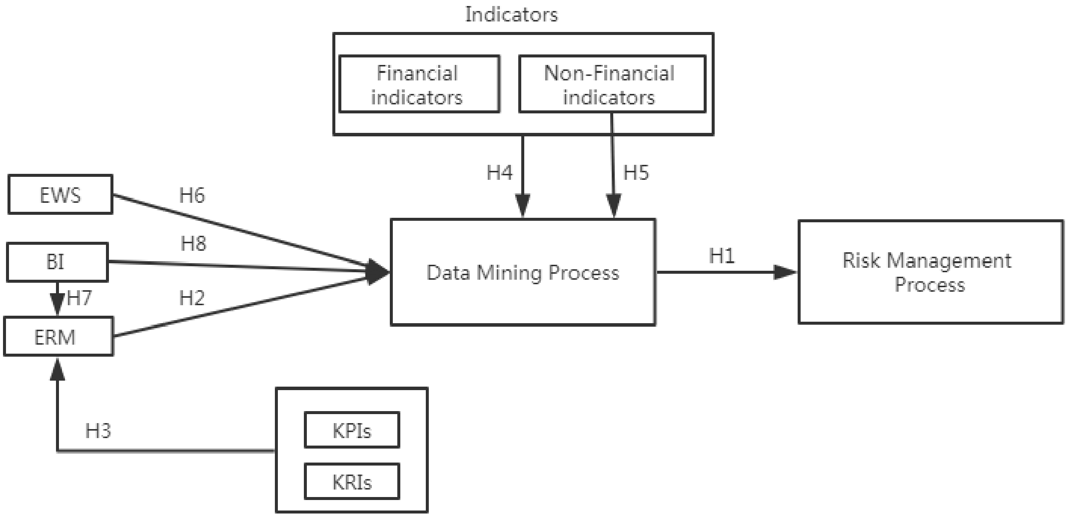


Figure 3.3-c The Research Conceptual model

Figure 3.3-c shows the conceptual model of this research. The model indicates the idea of combining the data mining process to the risk management process, which also considers enterprise risk management (ERM), early warning system (EWS), business intelligence (BI). Also, the research objectives are selected as SMEs. The RM process is a stage gate-process, which includes three main steps (Verbano and Venturini, 2013). The data mining process could also be presented as a stage-gate process. It is possible to combine two processes in one model, which could achieve risk management goals by using the data mining process. Han et al. (2012) defined data mining is: “the process of discovering interesting patterns and knowledge from a large amount of data”. Therefore, in the data mining process, the data is the most important component. The data mining process also includes several steps, such as four steps by Soman et al. (2009) and seven steps by Han et al. (2012).

The ERM, EWS, BI will support the data mining process by providing guidance on data selection, data collection and data analysis for SMEs. Since these systems or models cannot be directly applied in the model, it is necessary to introduce the mediators to link them together. Initially, the information provided by firms and government or other institutions will be transferred into the indicator format. The BI approach can collect the data and clean the data by using Web clawer, classification tools, etc. The listed Chinese SMEs were selected as research targets, where the annual reports were downloaded by using Web claws and the useful information are generated and cleaned by using classification tools. The ERM provided risk catalogues, which includes four different risk types (CAS, 2003). The indicators can explain the risk features defined by the ERM. As many scholars emphasised the importance of non-financial indicators (Altman et al., 2010; Geng et al., 2015; Li et al., 2017; Koyuncugil and Ozgulbas, 2012), the indicators were classified as Financial Indicators (FIs) and Non-Financial Indicators (Non-FIs) in this research. Then, these indicators will be used as candidates of KPIs and KRIs based on the ERM framework, which provides the linkage between the components shown in Figure 3.3-c. After that, the KPIs and KRIs could be used as input data to the data mining process and risk management process, where KPIs and KRIs will link each component of the two processes. The EWS will use the rules and patterns of KRIs and KPIs to achieve the goals of the risk management process by providing threshold values, risk sequencing, etc. Based on the results of EWS, the warning signals and desirable trends can be found out, which will support the decision-making. As a result, the data mining process has been supplemented by many components to fit in the risk management process. The data mining process will be discussed in the rest of this section, where the steps in the process will be explained. Therefore, the developed model is called DM (Data Mining) -RM (Risk Management) model in the following parts of this research.

The enterprise risk management framework can work throughout the whole model. Based on the risk categories provided by CAS (2003), risks are divided into four different groups, which guide capturing the features of each risk. As a result, the data selection step follows the enterprise risk management framework, while it also supports the risk identification step. The transferred data can then be used in the mining the data and model and patterns steps to identify KRIs among all risk indicators.

All of the basic form data and non-basic form data can be used as risk indicators, and the model and patterns step identifies the rules and patterns behind that data. The patterns identified are based on the needs of the risk management procedure, though the purposes of the two processes may be the same. As these patterns can be used as thresholds, ranges, or other descriptors of KRIs, the risk evaluation and risk treatment processes focus on dealing with these KRIs. Thus, problems are simplified by identifying KPIs and KRIs for risk management.

Soman et al. (2009) stated that there are many classes of tools that can be used in data mining processes, including Associations; Sequential patterns; Classifiers/Regression analysis; Decision trees, Clustering; Data transformation and cleaning; Estimation and forecasting; and Statistical analysis. According to the stage gate processes defined by Henschel (2009) and ISO 31000 (2009), the entire risk management process may require more than one method to achieve risk management goals. For instance, at the beginning of the RM process, the decision makers may not know what the future risks are precise. They must, therefore, identify potential risk factors and find out how to detect risks before those risks become harmful to their firms. At that point, associations, clustering, and classifier analysis could support decision-makers in the identification of risk indicators and performance indicators for potential risks, while other tools could be used to provide solutions for the on-going process of risk management. Estimation and forecasting could provide prediction accuracy for the applied models, and based on statistical analysis; the most important indicators could be selected for observation to improve the efficiency of the decision-making process. The decision makers could also generate patterns and rules in order to control KRIs to facilitate risk reduction. In this way, data mining tools could be helpful throughout the risk management process.

Data collection is one of the most important stages in data analysis (Rokach and

Maimon, 2014). Soman et al. (2009) pointed out that there are several research challenges in the data mining process, which include improving the scalability of data mining algorithms, mining non-vector data, mining distributed data, improving the ease of use of data mining systems and environments, and privacy and security issues. In the risk management process, the risk analysis part of the risk assessment step requires decision makers to focus on dealing with data. Soman et al. (2009) stated that information could be generalised into different types of data. Klieštik, Kočišová, and Mišanková(2015) also argued that there are several different types of classification variables: nominal variable, ordinal variable, interval variable, and ratio variable. Nominal variables are quantitative, and cannot be identified into certain categories, but only expressed by words or numerical codes (Kliestik et al., 2015). These include the names of people or the names of places, which can be expressed as numerical codes (such as 1, 2…, n) in modelling. Ordinal variables can be rationally listed in some order (Soman et al., 2009) and included all the features required from nominal variables (Kliestik et al., 2015). For example, the educational background of employees is an ordinal variable, as it follows a set of levels such as primary, college, masters, and so on. However, while it is clear that the master's degree is higher than the college education, the ordinal listing does not specify how much higher. An interval variable could be used to define the quantified difference between them (Kliestik et al., 2015); however, this type of quantified difference may be arbitrary (Soman et al., 2009). Taking temperature as an example, while 10 degrees is higher than 0 degrees, 10 degree is not 10 times higher than 0 degrees. Ratio variables are defined based on a "rational zero", which means that ratio variables have a true zero point (Kliestik et al., 2015; Soman et al., 2009). Ratio variables can thus demonstrate how many times one variable is higher or lower than another (Kliestik et al., 2015). Mass is a ratio variable, as 100 kg is two times as massive as 50 kg.

In the data sets used in risk management processes, all the financial indicators are ratio variables, such as quick ratio and net profit margin. Some non-financial indicators are nominal variables, such as the names of provinces and audit opinions, while some are ordinal variables, such as the educational background of employees. As most models required input variables to be ratio variables, it is essential to quantise and standardise the information into indicators. Data transformation steps thus play an important role in both data mining and risk management processes.

In the 'mining the data' and 'interpretation of results' steps, data mining methods are used to select KRIs, generate rules and develop roadmaps. The CHAID and Logit regressions were used in this research, based on statistical probability theory (Geng et al., 2015). The CHAID was developed by Kass (1980), based on AID (automatic interaction detection). The CHAID utilises a nominal scaled dependent variable, with an applied chi-squared statistic at each node (Kass, 1980). CHAID also reduces the operative difficulty for inexperienced researchers due to its significance testing framework. By using the significance of a statistical test as a criterion, CHAID can evaluate all of the potential predictors (IBM, 2011). It can then merge all the values, making them statistically homogeneous with the chosen dependent variable and distinguishing all the different values to create branches. As the tree is grown based on statistical testing, CHAID is thus based on statistical probability theory.

The Logit regression model is a well-established statistical method for the prediction of binomial or multinomial outcomes (IBM, 2011). The Logit regression was used for the selection of KRIs in this study, to provide a binary classification based on the performance of firms (good or poor). The model assumed a dichotomous dependent variable with a probability dependent on the weighted independent variables. For the selection of KRIs, the likelihood ratio statistic was used to determine whether a variable should be included in the model or not. The likelihood ratio statistic is defined as two times the log of the ratio of the likelihood functions of the two models evaluated at maximum likelihood estimates. The likelihood ratio statistic is asymptotically Chi-square distributed with a degree of freedom equal to the difference between the numbers of estimated parameters in the two models (IBM, 2011). Akaike (1987) stated that the minimum AIC represents the best fit among models; as a result, the Logit regression for selection of KRIs is a process of identifying the minimum AIC among different combinations of indicators applied in the Logit, regression model. As both CHAID and Logit regression apply statistical probability theory in their inner algorithms, it is important to consider the threshold value of such statistical tests long side other parameters.

As well as statistical methods, several other methods have been popular in addressing similar problems in risk management. Artificial Neural Networks (ANN or NN) and Genetic algorithms are also commonly used in data mining (Koyuncugil and Ozgulbus, 2012). An ANN is a non-linear predictive model that mimics the impulses from biological neural networks. An ANN thus consists of a large number of "neurons" and connections between those neurons, where the weights of factors are associated with neurons (Back, Laitinen, and Sere, 1996). The weights can then be optimised for certain outputs using a learning process. Genetic Algorithms simulate the Darwinian evolutionary process. The algorithm defines a fitness value regarding the performance of each basic component. The component is treated as a gene in biology, as each component can produce different results in different permutations (Back, et al., 1996). The whole process resembles a biological process whereby a population evolves to become stronger by optimising the genes of its members. Three operators can thus be used to optimise the results: reproduction, crossover, and mutation. Reproduction allows the copying of the strings of information with higher fitness values to the next generation, which makes that generation's fitness value closer to the desired result. Crossover refers to one string being combined with another; the combination creates a new string with more good parts (Back, et al., 1996). Mutation indicates a randomly selected gene in a string becoming amended. Both of these data mining methods have machine learning mechanisms, which mean that the results self-optimise via iteration according to their algorithmic settings. These data mining methods try to find the patterns for KPIs and KRIs from other aspects, which help reduce the possible bias introduced by using statistical methods.

So far, the process of data mining was explained in details, and how the supplemented components were introduced as well. Each component in Figure 3.3-c will be linked with each other by the proposed hypotheses, which will be thoroughly discussed in the next section.

3.4 Hypotheses Development

In this study, a research model to explain the combination of the risk management process and data mining process has been proposed. Moreover, this research also implied several elements to improve the two main processes, such as the Early Warning System, BI approaches and ERM framework.

Based on the review of the previous literature, the following hypotheses were developed to provide explicit verification of the research questions. The whole model could be described as Figure 3.4, which will be discussed in the following part of this section.

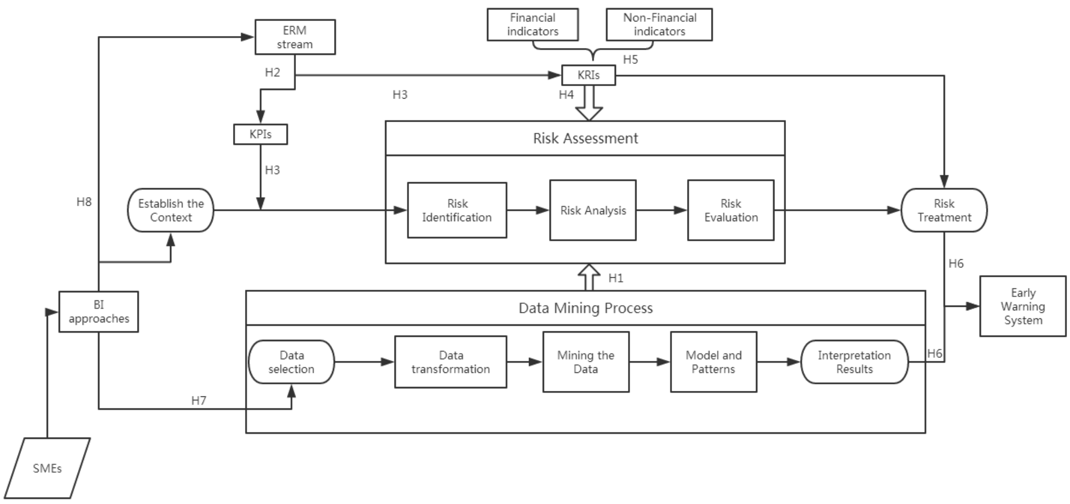


Figure 3.4 Flowcharts of DM-RM model

Figure 3.4 shows each component of this research in the flowchart, which is connected by hypotheses. The idea of combining risk management process and data mining process was purposed at the beginning. Followed that idea, the ERM framework will provide empirical evidence for the whole risk management process. Specifically, the usage of KPIs and KRIs is attempted to cover all risk features mentioned by the ERM framework. The early warning system is also attempted to be embedded into the risk management process, especially for risk treatment and interpretation result steps. After that, the application of BI approach to collect data of SMEs is introduced. Since this research focused on the risk management process for SMEs, it is necessary to build a suitable database, especially for SMEs. Meanwhile, the BI approach may be helpful in transferring information into both financial and non-financial indicators. Therefore, the model provides very detailed and logical methods of monitoring and reviewing risks, which is often helpful in the decision-making process.

3.4.1 Data Mining Process and Risk Management process

Data mining includes four steps: data selection; data transformation; mining the data and interpretation of results (Soman et al., 2009). The most important part of this process is data selection, which provides the resource for the ensuing steps. Soman et al. (2009) stated that the variables selected, and the range of the data to be examined should be specified in this step before data transformation is used to shift the data into the particular formats required by the chosen data mining tools. After that, the data is analysed using those data mining tools, and the results of the data analysis represented numerically or visually. The data mining process is apparently not a one-step process, making it similar to the risk management process as outlined in ISO 31000 standard.

The purpose of RM should be recognised in the “Establish the Context” step (Verbano and Venturini, 2013) before the three sub-steps in the risk assessment phase are completed. In the risk identification step, the risk should be thoroughly investigated regarding what, how, when, and why risk may occur. The risk analysis is the most complicated section of the risk assessment step and should provide a generally complete understanding of each risk, the consequences of those risks, and the likelihood of those consequences. Finally, the risk treatment phase provides possible solutions and improvements for the firms concerned. Combining this risk management process with a data mining process, it is possible to conclude that data mining steps can be used to support the risk management process naturally. For example, the ‘establish the context’ process specifies the purposes of risk management, making it important to decide the KPIs and KRIs at this stage; this can be related to the data selection step in the data mining process. Similarly, in the risk assessment step, the target risks should be analysed and explained in detail; the data transformation and mining the data stages of the data mining process can thus provide theoretical and practical support for these stages, including selecting and transforming appropriate information to create risk indicators. Further, based on the interpretation stage of the results of the data mining process, decision makers could decide on the actions to be used in the risk treatment step of the risk management process. In this way, it is possible to use data mining methods in the risk management process to achieve risk management goals.

As previously discussed, whether the risk management process and data mining process could be combined is uncertain. However, since the flows of the two processes are similar, it is very likely that the two processes could be synchronised. As a result, the hypothesis could be developed as:

H1: If the data mining process and risk management process could be synchronised together to achieve risk management purposes.

3.4.2 ERM Framework, KPIs and KRIs

Liebenberg and Hoyt (2003) defined enterprise risk management as a global approach to risk management, which aims to increase and protect the value of enterprises in both the short and long term. The integrated enterprise risk management framework used in this research is based on the ISO 31000, COSO, and enterprise risk management frameworks. Freeman, Harrison, Wicks, Parmar, and Colle (2010) pointed out that management scholars have entertained the proposition that firms have objectives beyond profits or shareholder wealth; however, as noted by Verbano and Venturini (2011), the purpose of risk management is to maximise shareholder value. It is thus important to be clear that the measurements of firms' performance, include increasing the probability of achieving the firm's goals, reducing the costs of raising capital, understand the risks faced by the firm, smoothing the volatility of cash flows, improving compliance to norms, decreasing loss in unforeseen circumstances, adapting to changes in external environment appropriately, and creating more profits by accepting manageable risks. As a result, the KPIs should be selected with the aim to maximise the firm's value, which is the same as the purpose of the ERM framework. Meanwhile, since indicators could measure the firms' performance, it is also important to select KRIs to link with KPIs in order to increase the efficiency of the risk management process. Since the indicators are collected based on ERM framework, the usage of KRIs also complies with the ERM framework. Therefore, the application of ERM framework, KPIs and KRIs could be in sync with the same aim, which is to maximise the firm’s value.

After the purpose of using the model has been clarified, the risks faced by the enterprises must be identified. The risk identification step also provides the necessary input for subsequent steps. According to Verbano and Venturini (2011), enterprise risk management is the extension of financial risk management to non-financial circumstances. They also pointed out that the number of types of recognised risks has proliferated in recent decades, and that definition, methods, techniques, and approaches have been developed for a wide range of fields. The Casualty Actuarial Society (CAS) has classified risks in four different types: hazard risks, financial risks, operational risks, and strategic risks. These risks can be measured using both financial and non-financial factors, based on information obtained from annual reports. The most challenging part of this step is to classify the risks accurately and to categorise the variables within each type of risk accurately. Based on the definitions given by CAS, it is, however, possible to distinguish between the different types of risks. Moreover, the risks as described by the CAS can be used to map risk overall based simply on annual reports and other information provided by enterprises. CAS (2003) stated that risk management is with enterprise risk management regarding the creation of enterprise value and impact on the firms’ goals. Therefore, the risk identification step should strictly follow the purpose decided in the previous step in order to maximise the efficiency of the model. The risk identification step also includes integrating risks, which means aggregating the risk distributions, reflecting on any correlations and portfolio effects, and expressing the results of the impact on KPIs (CAS, 2003).

The KRIs based on ERM framework could be helpful to improve the risk management process, where KRIs could be decided on after identifying the risks. After the samples are grouped, it is possible to determine the features of the variables in each group and to identify common and distinct variables. Based on the results, the reasons why some enterprises are classified as failed companies may emerge from financial-related ratios. Other variables could be selected as control variables in the data mining methods to distinguish between groups; thus, classification can be improved by optimising variable selection. The accuracy of grouping results could be improved by repeating the classification step and adding more variables, while the features of the failed group and non-failed group could be generated, by utilising the KPIs of each group. Based on this, the desired value and warning signals could be identified and monitored within the model. There are four different risk types under the ERM framework, where only financial indicators cannot adequately cover them. As a result, the usage of non-financial indicators is necessary in order to capture all the risk features under the ERM framework. The KRIs will be selected from financial and non-financial indicators. Although the use of non-financial indicators is suggesting and applied by many scholars (Altman et al., 2010; Li et al., 2017; Koyuncugil and Ozgulbas, 2012), the usefulness and effectiveness of them are still not evident. Therefore, it is necessary to specify the usefulness and effectiveness of non-financial indicators by the KPIs and KRIs by ERM framework.

As discussed above, the application of ERM framework, KPIs and KRIs should be specified, the research hypotheses could be developed as follow:

H2: The ERM framework could be embedded in the risk management process.

H3: The usage of KPIs and KRIs is complied with the ERM framework and can improve the risk management process

H4: Combining financial and non-financial indicators in the selection of KRIs can explain most of the features required by the enterprise risk management framework.

H5: Non-financial indicators are essential in the whole risk management process.

3.4.3 Early Warning System and Risk Treatment

The early warning system could be built based on the result of risk assessment. In the risk evaluation step, it is important to decide which factors are the most significant variables that affect the enterprises' performance. The features of different groups could be used to determine performance, and each group will have different values for these variables. The key performance indicators can be used as control variables and decision trees drawn to uncover the nodes of relative performance development paths. Meanwhile, the key risk indicators are helpful in identifying the most important risks faced by enterprises. Threshold values should be used to filter the KPI and KRI values in the target range in order to meet common objectives. When these objectives are targeted, it is thus also important to classify which types of risks are the major problems faced by the enterprise, thus making identifying the different paths in the decision tree model possible using tracking the nodes. The different nodes thus identify which variables are the most important determinants in an early warning system. It is also possible to create different profiles by using different control variables. For example, Koyuncugil and Ozgulbas (2012) applied a decision tree method with over thirty variables as independent variables to classify samples in thirty-one different profiles. They also linked the key performance indicators with financial ratios using correlation coefficients. These profiles could be used to identify which control variables created most nodes and thus uncover the target control variables. In this way, the variables affecting the four types of risks can be identified and monitored within the early warning system. The risk profiles thus show the variables within risk categories, allowing decision makers to uncover problems more efficiently. The relative weights of different risks can also be ascertained if the system uses variables based on the risk type categories within the enterprise risk management framework, making it possible to identify the effects of each type of risk and thus to improve the risk indicators in order to reduce the possibility of failure.

In the risk treatment step, managers must decide how to deal with results from previous steps. Koyuncugil and Ozgulbas (2012) posited that decision makers could create risk profiles by selecting different indicators as control variables. By distinguishing the sample into two groups based on financial performance, it is possible to choose profiles based on the logical application of real economic rules. In these cases, profiles with no good performance indicators or only good performance indicators would not include the best profiles to choose from. A chosen profile should make it easy to create filter variables and select the ranges for risk identification. The possible risk factors could solidify in this step, with each possible risk factor measured and considered along with all the possible effects on enterprise performance. The data mining methods could provide the relationship between KPIs and KRIs, and the rules and patterns in KRIs. For instance, Koyuncugil and Ozgulbas (2012) found that risk profiles could identify as good or bad, providing a financial roadmap in the decision making step. The key performance indicators were also used to detect distress positions of enterprises. When the risk profiles and key risk indicators were considered together, early warning signals could be identified. For example, where two risk indicators were found, these were more likely to affect enterprise positions significantly. Similarly, key risk indicators located in a specific range showed that the enterprises with such features were more likely to be in financial distress. Where the risk profiles indicated that the enterprises were performing well, the risk profile was then used as a benchmark for road maps. Firms were thus encouraged to reduce risks by improving variables falling within the ranges of the warning signals, and to develop higher level risk profiles by increasing the target indicators closer to desired values. In this way, both warning signals and desired values can be used to improve enterprise performance, while the road maps produced by the early warning system provide a bright look at relevant variables. As a result, the usage of an early warning system could be helpful in complying with the risk management process.

As discussed above, the use of an early warning system in the risk treatment step could provide the information on desired signals and warning signals of selected KRIs. If the results of early warning system were combined with rules and patterns found by the data mining process, it is clear that the threshold values and sequencing of KRIs will be specified. As a result, the efficiency of the risk management process will be improved. The hypothesis could be described as follow:
H6: The early warning system could provide solutions for KRIs in the risk treatment step.

3.4.4 BI approach and SMEs

The BI approach could be useful in all the data mining process. The BI approach will be helpful in building the database of research targets, which will be SMEs in this research. The database will be built upon the purpose of the data mining process, which is an essential part of the whole process. Since this research considers both financial and non-financial indicators, the traditional data-based will not be helpful in the assessment of non-financial indicators. Meanwhile, the non-financial information will be transferred to non-financial indicators in the data cleaning step, which could be supported by BI approach and tools (Chaudhuri et al., 2011). Therefore, the important things are the way of collecting data and transferring information into indicators.

The BI approach could build a database by using the information on SMEs, which will make the risk management process focused on SMEs. The financial information will be easier to collect since listed SMEs will publish their annual reports annually. The financial information could be directly collected from the balance sheet and cash flow sheet. As Koyuncugil and Ozgulbas (2012) did, the financial data will be calculated for financial indicators. For non-financial indicators, the process is complicated. Since the risk management process followed the ERM framework, the indicators should cover as much risk features as they can. As a result, the non-financial indicators need to support financial indicators in order to explain all risk features in the ERM framework. Therefore, the BI approach could help the risk management process follow the ERM framework in the term of indicators selection.

As discussed in this section, the BI approach may be useful in the risk management process. The hypothesis will be described as follow:

H7: The business intelligence approach can help the enterprise risk management framework become embedded into the risk management process.

H8: The business intelligence approach can enhance the ability to capture useful information to be used as indicators in the risk management process for SMEs.

3.5 Summary

The research questions and hypotheses of this study can be linked. The research questions and hypotheses were listed in Figure 3.5 and Table 3.5 respectively.

Q1	Is it possible to integrate the data mining process with risk management process and increase the effectiveness and efficiency of risk management process?
Q2	How could the business intelligence approach increase the explanatory and provide a more comprehensive view of risk management process with financial and non-financial indicators for SMEs?
Q3	Can the risk types, KRIs and KPIs in enterprise risk management framework improve the performance of risk management process?
Q4	How can early warning system increase the explanatory and efficiency of risk management process?
Q5	Are financial and non-financial indicators helpful regarding creating a model to measure firm performance, and if so, to what extent?
Q6	Which data mining method has the best performance in the risk management process for SMEs?

Figure 3.5 Research Questions

No.	Research Hypotheses
H1	The data mining process and risk management process could be synchronised together to achieve risk management purposes.
H2	The ERM framework could be embedded in the risk management process.
H3	The usage of KPIs and KRIs is complied with the ERM framework and can improve the risk management process
H4	Combining financial and non-financial indicators in the selection of KRIs can explain most of the features required by the enterprise risk management framework.
H5	Non-financial indicators are essential in the whole risk management process.
H6	The early warning system could provide solutions for KRIs in the risk treatment step.
H7	The business intelligence approach can help the enterprise risk management framework become embedded in the risk management process.
H8	The business intelligence approach can enhance the ability to capture useful information to be used as indicators in the risk management process for SMEs.

Table 3.5 The Summary of hypotheses

The Q1 aims to find a way of integrating the RM process with the DM process, which will be further explained by H1. If the two processes were successfully integrated, the prediction accuracy of the DM methods will be significantly more than 50%. The Q2 is going to find out how the BI approach can be used in gathering financial and non-financial indicators. Since the BI approach can quantise and standardise the information into indicators, the numbers of indicators can be expanded. These indicators can cover more aspects of risk catalogues, which is not only limited in the financial aspect. The H7 and H8 can further explore how the BI approach helps in the whole process. If the indicators generated by the BI approach work in the process, the results of DM methods can include and be improved by these indicators. The Q3 attempted to discover the usefulness of the ERM framework in the RM process. The most useful parts of the ERM framework in this study is risk types, KPI and KRIs. The risk types provide a more comprehensive and clear view of risks, while the use of KPI and KRIs can improve the efficiency of the RM process. The H2, H3 and H4 are therefore developed to provide insight views of these parts of the ERM framework. The risk types can be used to provide guidance in data selection, where the indicators will cover the features under risk types. The KPI provides a benchmark of the performance measurement, which can be modified upon the request of the RM process. The KRIs can be found among all the risk indicators, where the significant ones can be treated as KRIs. The KRIs can reduce the time and costs in the RM process, since the number of focused indicators will be significantly reduced.

The Q4 is going to find out the usefulness of EWS in the RM process. Since the EWS can explain rules and patterns, it is possible to conclude clearer views of the results. The H6 tried to find out how the EWS works in the RM process. The results of the DM process can provide some insightful information on the data, where can be used in EWS to generate more comprehensive and organised rules and patterns. The Q5 attempted to explore the value of non-financial indicators. Although the usefulness of non-financial indicators is studied by some scholars, it is still not clear that the value of non-financial indicators in the RM process for SMEs. The H5 attempted to find out the value of non-financial indicators. If the prediction accuracy of the data set including non-financial indicators has been improved, the value of non-financial indicators can be verified. It, therefore, can confirm the usefulness and effectiveness of non-financial indicators. The Q6 is going to compare the four data mining methods applied in this study. The data mining methods provide the empirical evidence to support the findings of previous questions, where the accuracy, comprehensiveness and effectiveness will be shown. The H4, H5 and H8 can be examined by using empirical evidence from DM methods. The different DM methods produced the different format of results, which can be used to support findings and verify the hypotheses. Therefore, the research questions and hypotheses in this study have been linked together.

4. Research Methodology

4.1 Introduction

This chapter provides detailed information about the methodology of this research. The process of the DM-RM model will be introduced, which will thoroughly describe each step of the model. After that, the data collection part will be introduced. Since the research is going to use the data mining process with BI approach, the building up of the database is important. Furthermore, the raw data will be transferred into indicators. The candidates of potential KRIs and the path of development will be shown. Since the data mining methods supported the risk management process, the details of the four methods will be introduced.

4.2 Research design

The research is developed based on risk management process by enterprise risk management framework (Verbano and Venturini, 2011). The purposed model is also a data mining process, which includes data collection, data selection, mining the data, model and patterns and interpretation results steps (Han, et al., 2012; Soman et al., 2009). The model is shown as follow:

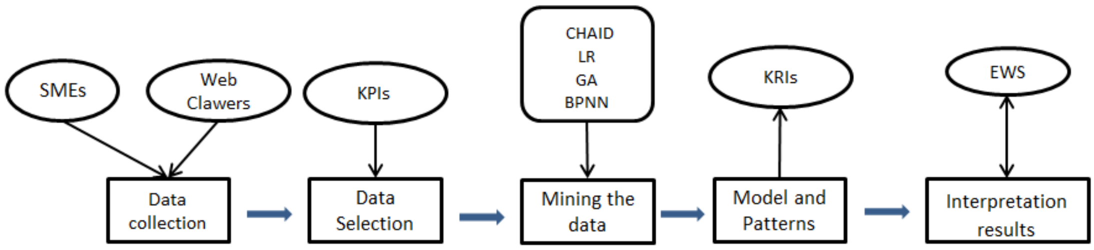


Figure 4.2 The Detailed DM process

As Figure 4.2 shows, the process of data mining started with Data collection step. In this step, the research used Web clawers to collect listed Chinese SMEs from Chinese

Shenzhen Stock Exchange website (www.szse.cn). Then, the raw data was cleaned and inputted into the database. The second step is Data selection. In this step, the KPIs will be selected, which indicated the performance of the firms. All of the information collected by the previous step will be transferred into indicators. The indicators will be classified into financial indicators group and non-financial indicators group. After that, the third step is mining the data. There are four different data mining methods were applied in this step, which is CHAID, LR, GA and BPNN. The main purpose of this step is to find out the significant indicators from all the indicators generated by the previous step and produce the preliminary results for the next step. After that, the model and patterns step is going to generate KRIs based on the results of mining the data step. In this step, the results of different data mining methods will be tested and compared in order to discover the hidden rules and patterns in the data. Meanwhile, the meaningfulness and robustness of the KRIs will also be examined. Finally, in the interpretation results step, the early warning system will be applied. Based on the results of previous steps, the KRIs are identified based on selected KPIs, where the roadmaps and threshold values have been found out based on the KRIs and KPIs. The firms will improve their performance and control their risks by monitoring KRIs. As a result, the DM-RM model will directly monitor and control the all the risks in an integrated model.

An important step in risk management is a selection of KRIs, which means the key problems in achieving risk control in selected groups. The selection of KRIs could be achieved by using a statistical test to check the significance of the indicators or by comparing the coefficient of the indicators. However, it is more challenging to choose potential KRIs based on enterprise risk management framework, which required four risk catalogues in total. It is necessary to use the balance sheet, cash flow sheet and the statistical reports published by the Chinese Statistical Bureau (www.stats.gov.cn) to collect related information to build financial indicators and non-financial indicators as potential KRIs. Since data mining requires a considerable number of samples to support the whole process, the database should include as much as possible raw data in order to transfer into indicators. After gathering enough indicators, the indicators were used into different data mining tools to find out KRIs based on selected KPI. After interpreted by the listed data mining tools, the most important indicators, which contain the most information to decide KPIs, will be picked out of potential indicators as KRIs. In the following stage, the threshold values and patterns of KRIs, which indicated the importance and the ranges, could be used to build roadmaps for selected groups (SMEs in this research). It is also important to verify the prediction accuracy of the data mining methods to ensure the performance of selected data mining tools and information gathered by the BI approach. If the prediction accuracy meets the expected, the result indicated that the process worked well with existing indicators, which could go forward to the explanation and discussion stage for decision makers to control risks. If the prediction accuracy does not meet the expected level, it means the indicators could not thoroughly explain the KPI, while the KRIs should be reselected in order to increase the prediction accuracy and model meaningfulness.

Since Altman et al. (2011), Lussier and Pfeifer (2001), Wu and Olson (2009), Wang and Zhou (2011) and Eckles, Hoyt and Miller (2014) mentioned, it could be more reliable to include qualitative data in their financial ratio analysis. It is possible to achieve better accuracy of risk management by combing the two kinds of variables. Following the framework developed in Chapter 3, the risk management process in this research is combined with the data mining process. Recently, there are several scholars have applied different methods in risk management of SMEs. Koyuncugil and Ozgulbas (2012) used data mining to construct an early warning model based on both qualitative and quantitative (major) data of SMEs, but the number of qualitative indicators are limited, and the performance measurement may not be able to tell the performance of the firms directly. Wu (2010) selected financial ratios and tested them in three different automatic clustering algorithms (EM, X-means, Filtered Clusterer). Ravisankar, Ravi, Rao and Bose (2011) used SVM, LR and other methods to distinguish financial failed firms from 202 Chinese companies. Therefore, it is possible that the business method could be helpful in generating features of financial distress firms. Kim and Vonortas (2014) used probit models to detect different risks in business. There are 15 variables in their model: technology strategy, market strategy, financial strategy, operational strategy, technology risk, market risk, financial risk, operation risk, firm size, founder education, previous work, life cycle and new product. Based on their research, they concluded that there were some relationships between non-numerical data and risks. However, their researches are based on questionnaires and only in European countries. Thus, there might be some subjective biases from interviewees. Meanwhile, due to the selected samples, it is difficult to compare the competitive advantage and market performance.

In this study, it is argued that the financial ratios are crucial. It has been proved and applied by many scholars that the changes in financial ratios could tell the potential business failure and business success. However, the value of non-financial information and the methods/models for applications of non-financial information are still in development. The study is to identify the value of the non-financial information and try to synchronise the non-financial information and the financial ratios in a promising model. The combination of two variables could result in more accurate predicting result. Therefore, it could help managers to make decisions on projects and alert the potential risks in advance.

4.3 Data Collection

The data collection part is very important, which includes setting up the database, data gathering, data clean up and data input. The database will be consisted of information from annual reports, government report and information from websites. The database will mainly specify the range of information, which is upon the purpose of the risk management process. The data gathering step will collect the information based on the range of the data, which provided by the database in the previous step. Since the annual reports could be downloaded from the Chinese Shenzhen Stock Exchange websites, it is possible to gather the information by using Web Clawer that could automatically collect the data. The data is required to be used to clean up the step in order to provide useful data for the model. Han et al. (2012) stated that the real-world data is incomplete, noisy and inconsistent. The data clean up step will try to smooth the noise and make the indicators usable in the model. Furthermore, the data clean up step also included the ratio calculation, where most of the indicators will be calculated in this step. Lastly, the data input step is to use the indicators in the model, which will produce the results of the selection of KPI and KRIs.

The variables have different types, where could be classified into four groups: nominal, ordinal, interval and ratios. The nominal variable is classified only qualitative, where the value could belong to any particular category. Words or numerical codes could express the values of nominal variables. For example, the marital status (single, married, divorced, widowed) could be coded as 1, 2, 3 and 4. The place of birth (name of cities), nationality (name of countries) could also be coded, which makes it easier to process with computers. The ordinal variables have all the features that nominal variables have, where the order of ordinal variables could be determined. For example, the level of education, which could be classified as primary, secondary, bachelor and so on, is one of the ordinal variables.

Another example is the level of customer satisfaction, such as low, medium and high. The interval variables provide more information than ordinal and nominal variables. The interval variables have value, but it does not have “rational zero” in its scale of values (Kliestik et al., 2015). For example, the temperature is one of the interval variables; it could be compared, where the 30 degrees is higher than 15 degrees. However, it cannot be said that the 30 degree is twice higher as 15 degree. Finally, the ratios variables could provide the most information amongst four different kinds of variables. The ratios variables could be compared with each other, where the ratios variables can indicate more information. For example, the profit of firms is one of the ratio variables. The profit could be compared with each other, while it could also be divided by sales to calculate the profit margin. The nominal and ordinal variables are marked as qualitative, while the interval and ratios are known as quantitative. In other word, the qualitative variables could provide the non-financial related information, while the quantitative variables could provide the financial related information.

The data was collected from the annual reports of listed SMEs in China to gather financial indicators. Since the listed companies could provide financial data annually, it is the better choice for tracking the performance of the companies. Meanwhile, since the managers and board members should be public information, it could be easier to find the background and other information about them. The information could be used in the analysis of characters, education background, attitude, strategic planning and other non-financial information. In the research of Quon et al. (2012), they applied EBIT margins, changes in sales and Tobin's Q as indicators to measure the performance of enterprises. Meanwhile, in Gordini (2014)'s research, the return on equity, return on investment, EBITDA/turnover, Interest charges/EBITDA, cash flow/total debt, financial debt/equity, total debt/EBITDA and current ratio were selected as main measurements to predict bankrupt problems in SMEs. Based on the research of Koyuncugil and Ozgulbas (2012), the financial indicators could be applied includes: current ratio, quick ratio, absolute liquidity, inventories to current assets, current liabilities to total assets, debt ratio, current liabilities to total assets, long-term liabilities to total liabilities, equity to asset ratio, current assets turnover rate, fixed assets turnover rate, days in accounts receivables, inventories turnover rate, asset turnover rate, equity turnover rate, profit margin, return on equity, return on assets. Therefore, the financial indicators are required to reflect the profitability, liquidity, leverage and stakeholder's interest of firms.

There are also many non-financial indicators would be selected in the research. However, most of the non-financial indicators were not clearly listed in the annual reports. Followed the BI thinking, the information in resources could be quantised and standardised into indicators, which could be used in models. As suggested by Li et al. (2017), there is the non-linear relationship between CEO power and capital structure in SMEs. They also applied dummy variables to measure the CEO power of the company, such as whether the CEO is the founder of the company or not; whether the CEO is the chairman of the company or not; whether the CEO owns more than 10% of the firm's share or not. In the research of Altman et al. (2010), there were several non-financial indicators could be selected in measurements of the performance of companies. Altman et al. (2010) stated that the type and sector, size and age (less than 3 years/ 3 to 9 years), reporting and compliance (provide full statement/ cash flow statement/ audited company) and court actions to recover debt/auditor opinions could be included in the research as potential non-financial indicators. Based on the research of Li et al. (2017), it is evident that the role of the CEO in the SMEs is significant. Therefore, it is possible to consider the manager's ability and characteristic in the analysis to conclude a more accurate predicting model.

However, there might be other aspects, which are not covered by other studies. Since the researchers also needed to follow the ERM framework by CAS (2003), it is important to find out indicators that could cover information as more as it can. Therefore, follow the other scholars' work (Koyuncugil and Ozgulbas, 2012; Altman et al., 2010; Geng et al., 2015), the candidate indicators should include the information about both financial and non-financial aspects, which should also be complied with four risk catalogues by ERM framework.

Current ratio	x1
Quick ratio	x2
Absolute liquidity	x3
inventory to current asset	x4
inventory to total asset	x5
current account receivables to total assets	x6
total loans to total assets	x7
equity to total assets	x8
equity to total loans	x9
short-term liability to total liability	x10
long-term liability to total liability	x11
long-term liability to long-term liability + equity	x12
tangible fixed asset to equity	x13
tangible fixed asset to long-term liability	x14
fixed asset to total loans	x15
fixed assets to equity	x16
fixed assets to equity + long-term loans	x17
short-term liability to total loans	x18
bank loans to total assets	x19
bank loans to short-term liability	x20
bank loans to total loans	x21
current asset to total asset	x22
tangible fixed asset to total asset	x23

receivable turnover	x24
working capital turnover	x25
net working capital turnover	x26
tangible fixed asset turnover	x27
fixed asset turnover	x28
equity turn over	x29
total asset turn over	x30
net profit to equity	x31
profit before tax to equity	x32
EBIT/EBT + finance expense	x33
net profit to asset	x34
operating profit to net sales	x35
interest expense to net sales	x36
gross profit to net sales	x37
net profit + interest expense + finance expense to interest expense	x38
cost of goods sold to net sales	x39
capital employed to total liability	x40
inventory/working capital	x41
inventory turn over	x42
Industry	y1
Number of employees	y2
Develop and life index	y3
Economic development index	y4
Wellbeing index	y5
Development of society index	y6
Environment index	y7

Technology innovation index	y8
Employees education	y9
Audit opinions	y10
Cost of Audited	y11
Numbers of subsidiary	y12
CEO shareholding	y13
Numbers of research staff	y14
CEO tenure	y15
Tax rate	y16
Listed duration	y17
Goodwill and intangible asset	y18
Size of firms	y19

Figure 4.3 The List of F and NF indicators

The Figure 4.3 shows all of the 42 financial indicators and 19 non-financial indicators used in this research. The total 61 ratios are designed to cover all of the risks catalogues under ERM framework. These ratios will be used as input indicators, which are also the candidates of KRIs. It is also important to standardise the indicators in order to use the indicators in data mining methods smoothly. However, the significance of each indicator cannot be obtained in this step. As a result, all of the indicators will be treated as candidates of KRIs, which means all of the indicators will be input in the models at the same time. The calculations of financial indicators are quite straightforward, while the calculation of non-financial indicators required detailed discussed. The y1 (Industry) classified the manufacture or not, where the manufacture equals to 1 and others equal to 0. There are three groups in y2 (Number of employees), which are less than 1000, between 1000 and 3000, and above 3000. The three groups are based on the distribution of employees in target firms. The indicators y3 to y8 are from the government reports by National Statistical Bureau of China (NSBC), which are based on the idea of human development index. The y9 (Employee education) classified the educational background of employees, which are based on the portion of high school or under the high school. The threshold values of the portion are 0.1, 0.25 and more than 0.25 respectively. The y10 (auditor’s opinion) and y11 (audition expense) are related to firm’s audition. The y10 classified standard unqualified equals to 1 and others equal to 0. For y11, the expense is under three groups, which are less than 500k, between 500k and 1M, and more than 1M (in RMB). The indicator y12 (Number of subsidiaries) tells the number of subsidiaries of the listed firm, which are grouped as 5, 15 and more than 15. The y13 (CEO shareholding) indicated the portion of shares held by CEO, which are classified as 0.05%, between 0.05% and 0.25%, and more than 0.25%). The y14 (Number of research staff) indicates the number of employees in the research and development department, which are classified as less than 150, between 150 and 500, and more than 500. The y15 (CEO tenure) indicates how long the CEO has held on this position, which are classified as 12 months, between 12 months and 36 months, and longer than 36 months. The y16 (tax rate) indicates which tax rate applied to the firm, where the tax rate less than 20% is group 0, and the tax rate greater than 20% is group 1. The y17 (listed duration) indicates the duration since IPO for the firm, which are grouped as 5 years, 5 to 10 years and more than 10 years. The y18 (goodwill and intangible asset) indicates the goodwill and intangible assets of the firm, which is measured by the actual value of goodwill and intangible assets provided in the balance sheet. The size of firms indicates the logarithm value of the firm, which could reduce the effect of the large size firms and small size firms. The use of financial and non-financial indicators attempted to cover all the risk features in ERM framework, where including non-financial indicators may explain some parts that cannot be covered by financial indicators.

4.4 Variable Selection

Based on the report by CAS (2003), the four risk types of enterprise risk management could be defined as follow: hazard risk, financial risk, operational risk and strategic risk. The CAS provided the general descriptions of each risk. Verbano and Venturini (2013) adopted the catalogues of risk types based on the CAS committee.

Classification of Risks			
Hazard risks	**Financial risks**	**Operational risks**	**Strategic risks**
Fire and other property damage	Price	Business operations	Reputational damage
Wisdom and other natural perils	Liquidity	Empowerment, information technology	Competition
Theft and other crime, personal injury	Credit	Information/business reporting	Customer wants
Business interruption	Inflation/purchasing power		Demographic and socio-cultural trends
Disease and Disability (Including work-related ones)	Hedging/basis risk		Technological innovation
Liability claims			Capital availability
			Regulatory and political trends

Figure 4.4 ERM risk catalogues (CAS, 2003)

As shown in Figure 4.4 above, the four types of risks are provided with brief descriptions. The variables selection is the most complicated and challenging process in this study.

In order to describe the hazard risks, the variables could be selected as geography, natural disasters, products recall and crime rate. According to CAS (2003), the hazard risks are more likely about nature and external physical environment, such as fire, crime, disease, etc. Therefore, the variables could include the geography information of the target enterprises. For example, in China, the developed levels of cities are not the same. The capital or large cities, such as Shanghai, Shenzhen, could be considered as the top level. Moreover, there will be less developed cities, such as provincial capitals, or the prefecture-level cities, which usually are less developed than provincial capitals. Therefore, the developed levels of the enterprises could affect the external environment of the enterprises, which includes the cost, the salary of employees, etc. Meanwhile, nature disasters will be another hazard risk variable. If a company located above earthquake zones, it is possible that the company will spend more on insurance and other welfare than companies in other areas. The probability of products recalls also could be considered as a component of hazard risk. The reasons for products recall could be quality problems or the frauds in customers. If the quality of products did not change significantly, the suddenly increased in the rate of products recall is possibly caused by frauds. Finally, the crime rate should also be considered. If the crime rate is very high around the company, it is possible that the company will spend more on securities, the insurance on steal, stock damage, and possible lost on equipment. Therefore, if the crime rate around the company is relatively lower than another area, the potential cost could be saved. The hazard risk could affect the cost of companies. If a company could significantly reduce the hazard risk, it is possible that they will have more available funds in their other activities.

The financial risk is the most important risk in companies. Verbano and Venturini (2013) stated that financial risks are a firm’s choice in debt, investments, which include credit risk and market risk. Kim and Vonortas (2014) stated that financial risk is referring to the tangible value of the financial aspects of a business. However, in their research, the variables that measured the financial risk and other risks are the levels of the risks perceived by the firms. The level of the risks is from 1 (not at all) to 5 (to a great extent). It could be more accurate if the financial ratio analysis measures the financial risk. In order to quantitatively measure the financial risk, it is better to apply financial ratios analysis. As stated by CAS (2003), the financial risk includes the price, liquidity, credit, inflation and hedging/basis risk. The CFA Institute (2015) also stated that the activity ratios, liquidity ratios, solvency ratios, profitability ratios and valuation ratios. The activity ratios referred to the asset utilisation or turnover ratios, which often indicated how the firms use various assets like inventory and fixed assets. The credit risk could be measured by the ratios about the interest, the working capitals, and cash flow ratios, etc. The CFA Institute also mentioned that the liquidity ratios and solvency ratios reflected the firm's ability to pay short-term and long-term debts, which matched the needs of credit risk management. Therefore, the liquidity and solvency ratios, which suggested by the CFA Institute, could be used to measure credit risk. The profitability ratios measure how well the firms get operation profits. As mentioned by Quon et al. (2012), the changes in sales, EBIT margins could be selected. Nocco and Stulz (2006) also pointed out that a firm could choose from market, credit and operational risk by Value at Risk (VaR) measures. Although the catalogues of the risks are not the same, it still provides a suggestion in measuring the probability of financial distress for a firm. In their study, they pointed out that the typical distributions in VaR of market risk, credit risk and operational risk are different. Therefore, it is important to select variables for each aspect of the financial risk respectively. Gordini (2014) also mentioned that there were twenty-eight financial ratios were selected by other scholars to measure the firms' liquidity, profitability and solidity as predictive variables. In this research, the financial risk will be explained within activity ratios, liquidity ratios, solvency ratios and profitability ratios in order to describe the more comprehensive result.

The operational risk includes business operations, such as human resources, product research and development, product or service failure, supply chain management; empowerment, such as leadership, change readiness; information technology, such as relevance, availability and information/business reporting, such as budgeting and planning, accounting information, pension fund, investment evaluation, taxation (CAS, 2003). The operational risk is about human errors, the employees, the supply chain management and the R&D. Therefore, the ratios for operational risk should be able to explain these aspects. The research by Li et al. (2017) suggested that the CEO power is related to the performance of SMEs to measure the human resource. For instance, the CEO power could be measured by the control power of the CEO to the firm. The board membership shows the CEO control power, the portion of the share ownership and the founder or not.

Furthermore, the CEO and senior management educational background could also affect the firm performance, which could be included in the operational risk in order to get a more comprehensive result. The quality of the management is also included in the empowerment aspect, which is under the catalogue of operational risks. The supply chain management could be measured by stock turnover ratios and the cash flow ratios. These ratios could explain the efficiency of a firm in managing its capital, stock and cash to create more value. In the research of Li et al. (2017), they also mentioned that the firm's official tax rate is also related to firm performance. According to CAS (2003), the information/business reporting includes the firm's behaviours such as budgeting and planning, accounting information, pension fund, investment evaluation, taxation. For instance, the new project investment, the tax ratios, the format of accounting should be all considered. Furthermore, Altman et al. (2010) also found out that the age of the firms is significant in measuring the performance. For example, they classified the age into two groups, which are less than 3 years and between 3 to 9 years. They suggested that the risk level of the firms of different ages not be the same. They also stated that auditing is another important factor in measuring operational risk. They suggested that the auditors' opinions, auditors switched should also be considered. On the other hand, Li et al. (2017) stated that the opportunity cost of the new project and the beta of the industry could provide information about how much a firm needs to spend when it is launching new projects. These variables could explain the operational risk to some extent. However, it is also important to adjust the weights of each variable in order to measure the credit risk comprehensively.

The strategy risk includes the risk of reputational damage, competition, the customer wants, demographic and social/culture trends, technological innovation, capital availability and regulatory and political trends (CAS, 2003). The reputational damage could be caused by the trademark/brand erosion, which could result from the scandals. It is true that the risk levels of different industries are not the same. Therefore, the industrial catalogues could be considered as a variable. Meanwhile, the situation of the industry, which is the external environment of the firms, should also be included. For example, if a firm is in a new and unstable industry, where the prospect of the firm and the industry cannot be forecasted based on experienced, the risk level should be increased as a result. The regulatory and policy could be affected by the industrial news. As a result, the external industrial environment could be affected by political changes. Altman et al. (2010) also stated that the size of the firm is also related to the total risk of the firm. They suggested that the log of the firms' sizes could be included in the model as an independent variable, where the relationship between asset size and insolvency rate is significant. The demographic and social/cultural trends could also affect the risk level of firms. For instance, the changes in demographics will potentially affect the sales, the structure of customers and the new projects. Social or cultural trends could also affect the profit of the firms similarly. It is possible that the interest of customers for products or services will change when there is a significant change in the social or cultural trends. In the circumstance, the sales and profits of firms will be affected, and the firms may spend more capital on the development of their new products or services. The strategic risk is more likely about how the firms deal with the changes from the external environment. Therefore, the ratios and variable that indicate the changes from the external economic environment should be considered carefully in measuring strategic risk.

4.5 Methods Introduction

4.5.1 Decision tree

Decision tree learning is one of the widely used and practical methods for inductive learning. Rule induction refers to the rules derived from the decision tree techniques in data mining. The data set is separated into many partitions in a way to increase the purity, which is the degree to which the dependent variable belongs to a certain class. The rules that are applied for splitting the data are called the inducted rules. A decision tree is a non-parametric method and suitable for figuring out the interaction effect or non-linearity. In many cases, a decision tree is used for the sake of interpretation of the analysis results. Decisions trees have four types of methods such as CHAID (Kass, 1980), CART (Breiman, Friedman, Olshen, and Stone, 1984), QUEST (Loh and Shih, 1997), and C5.0 (Quinlan, 1993). CHAID (Chi-squared automatic interaction detection) method is based on the chi-square test of association. A CHAID tree is a decision tree that is constructed by repeatedly splitting subsets of the space into two or more child nodes, beginning with the entire data set (Michael and Gordon, 2004). In order to determine the best split at any node, any allowable pair of categories of the predictor variables is merged until there is no statistically significant difference within the pair concerning the target variable. This CHAID method naturally deals with interactions between the independent variables that are directly available from an examination of the tree. The final nodes identify subgroups defined by different sets of independent variables (IBM, 2011). CART (Classification and regression tree) is a recursive partitioning method to be used both for regression and classification. The CART is constructed by splitting subsets of the data set using all predictor variables to create two child nodes repeatedly, beginning with the entire data set. The best predictor is chosen using a variety of impurity or diversity measures (Gini, towing, ordered towing, and least-squared deviation). The goal is to produce subsets of the data which are as homogeneous as possible concerning the target variable (Breiman et al., 1984). QUEST (Quick, unbiased, efficient statistical tree) is a binary-split decision tree algorithm for classification and data mining.

QUEST can be used with uni-variate or linear combination splits. A unique feature is that its attribute selection method has a negligible bias. If all the attributes are uninformative concerning the class attribute, then each has approximately the same chance of being selected to split a node (Loh & Shih, 1997). C5.0 (Commercial version 5.0) is a supervised learning classification algorithm used to construct decision trees from the data (Quinlan, 1993). Most empirical learning systems are given a set of pre-classified cases; each described by a vector of attribute values and constructs from them a mapping from attribute values to classes. C5.0 is one such system that learns decision tree classifiers. It uses a divide-and-conquer approach to growing decision trees. The main difference between C5.0 and other similar decision tree building algorithms is in the test selection and evaluation process.

4.5.1.1 Chi-Square Automatic Interaction Detector (CHAID)

Chi-Square Automatic Interaction Detector can be used for classification and threshold value selection, in addition to this several classification segmentation methods can be mentioned. However, in the process of finding the methods for SMEs, one of the basic objectives is to help SME administrators and decision makers to understand their situations. It has been argued by Wu (2010) that some of the managers do not have financial expertise, knowledge of data mining and analytic perspective, which makes the managers not easy to understand, easy to interpret and easy to apply results about the risk condition of their enterprises. Therefore, Decision Tree algorithms that are one of the segmentation methods can be used because they are easy to understand and easy to apply visualisation. Although several DT algorithms have widespread usage today, CHAID is separated from other DT algorithms because CHAID can produce different numbers of the branches. The difference between CHAID and other Decision Tree algorithms is that the other algorithms are branched in binary, but CHAID manifests all the different structures in data with its multi-branched characteristic. Hence, the CHAID is a better choice with the non-binary data, such as financial ratios.

In CHAID analysis, the following are the components of the decision tree: Root node, Parent’s node, Child node and Terminal node. Root node contains the dependent variable. For example, CHAID is appropriate if a firm wants to predict the performance based upon information like profit margin, inventory turnover, etc. The performance is the Root node in this example and remain indicators are independent variables. The algorithm splits the dependent variable into two or more categories. These categories are called parent node or initial node. In the firm example, good or poor performance is the parent’s node. Independent variable categories, which come below the parent’s categories in the CHAID are called the child node. The last categories of the CHAID are called the terminal node. In the CHAID model, the category that is a major influence on the dependent variable comes first, and the less important category comes last. Thus, it is called the terminal node. The Child node and terminal node could be the same one if the hierarchy of the CHAID is not greater than 3.

Assume that X1 to XN denote discrete or continuous independent variables and Y denotes the dependent variable as the target variable. Y is classified into two groups: good and poor. 'Poor' shows poor financial performance, where the growth of ROA is less than 0; 'Good' shows good financial performance, where the growth of ROA is greater than 0. The CHAID Decision Tree is given in Figure 4.5.1.1.

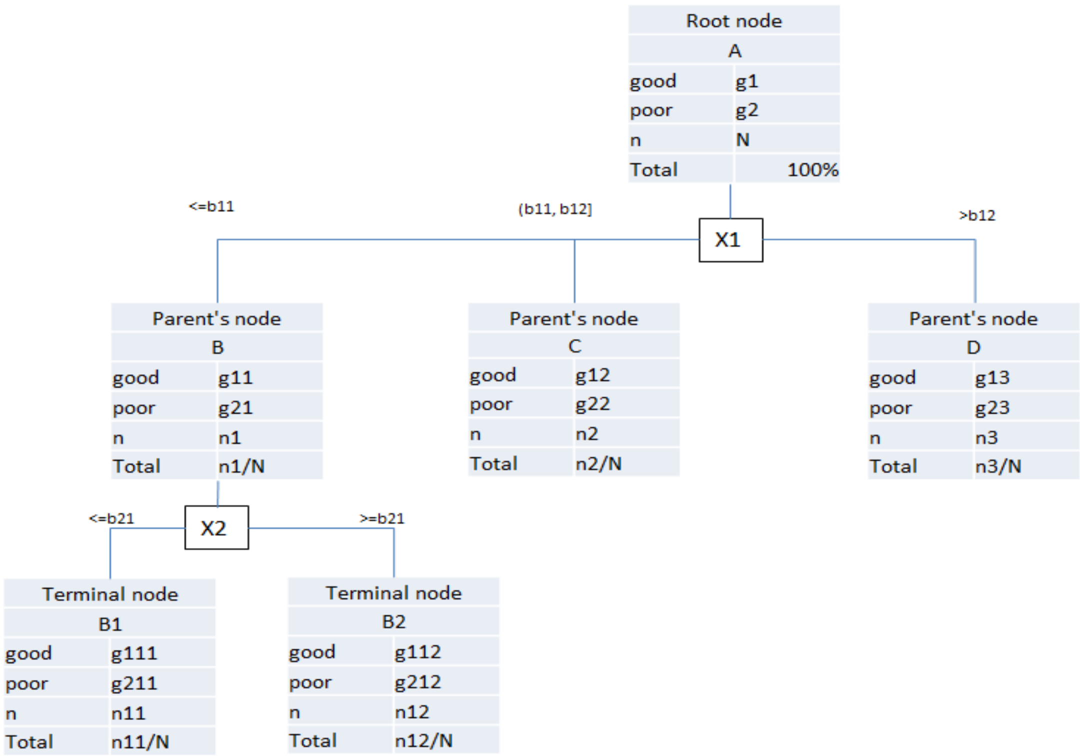


Figure 4.5.1.1 The Process of CHAID

In Figure 4.5.1.1 a, there are only two variables of N have a statistically significant relationship with the target Y, X1 has most statistically significant relation with target Y, X2 has statistically significant relation with X1, where X1 is less than b11. Determination of risk profiles CHAID algorithm organises Chi-square independence test among the dependent variable and independent (predictor) variables. The test starts from the branch of the variable, depends on which one has the closet relationship and statistically significant variables on the branches of the tree. Thus, all of the important relationships in data can be investigated until the subtle details have been found. In general, the study identifies all possible nodes by using the Chi-square test.

For instance, it shows that there are five risk profiles, where the interval indicates the profile is at risk or not. For example, profile B1 shows that there are n11 samples where X1 is less than or equal to b11 and X2 is less than or equal to b21, where g111 has poor financial performance, g211 has good financial performance. Similarly, profile B2 shows that there are n12 samples where X1 is less than or equal to b11 and X2 is greater than b21, where g112 has poor performance, g212 has good performance. Since there are no further child nodes under B1 and B2, the B1 and B2 are terminal nodes.

All of the risk profiles are investigated separately. Profile B1 shows that if any firm's variables X1 and X2 have values with X1 is less than or equal to b11 and X2 is less than or equal to b21, poor financial performance rate or risk rate of the firm will be rate (B1) = g111. Profile B2 shows that if any firm's variables X1 and X2 have values where X1 is less than or equal to b11 and X2 is greater than b21, poor financial performance rate or in another words risk rate of the firm will be rate (B2) = g112. After identified for the current situation of firms according to risk profiles and early warning signs, the result could be used to define the relationships between the dependent variable and independent variables as well as the risk profiles. This identification is realised by taking the group of variables in the risk profiles into consideration. All of the firms will look for the values of independent variables, in the light of the statistically significant variables in the Decision Tree.

According to the risk profiles, it is possible to detect the early warning signs that show the highest risk. In other words, this method could help managers to locate the most important variables and observe the changes in variables. According to Figure 4.5.2.1 a, it is not difficult to determine the risk grades of the firms. For example, if the risk rates of the firms in the order of B, C, D > B2 > B1. There are two variables X1 and X2 related with profile B1. If any firm wants to be in Profile B1, the firm must take steps to ensure values X1 is less than or equal to b11 and X2 is less than or equal to b21. The firms can identify the path to reach upper-level risk level and the indicators that require improvement for the variables on the roadmap. As a result, the path of improving performance has been obtained by focusing on the value of certain independent variables.

4.5.2 Logit Regression

The Logit Regression is a standard statistical method, which has been developed from the 1970s in early warnings of bank failure (Klistik, Kocisova and Misankova, 2015). In order to improve the MDA method, the conditional Logit analysis has been used for predicting the probability of default, which requires less restrictive statistical assumptions. The Logit regression could explain binary variables, which could be used to classify whether the firm is failed or not. Spuchl'kova and Cug (2014) stated that the classic regression could not be used under this circumstance if the value of the variable indicates the status of "yes or no". Thus, the Logit and Probit model was introduced to solve this kind of problems. The aim of logistic regression is expressed dependence of magnitude Y on the independent variable X. The observed data are interleaved by a logistic curve instead of a line, so that the regression is not linear. The Logit analysis is designed to predict the probability of the event occurs or not. The interval of the probability is from 0 to 1. The Logit transformation is based on the "ratio of chances and hopes" (Klistik et al., 2015). The relationship between dependent variable Y and a vector of independent variables X could be interpreted with the Logit transformation.

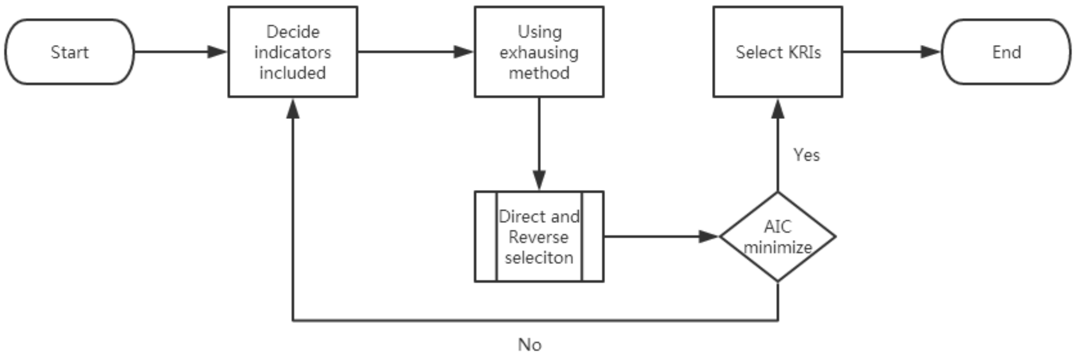


Figure 4.5.2 The Process of LR

The Figure 4.5.2 described the process of Logit regression for KRIs selection. Firstly, the target indicators need to be specified. In this research, there are three target groups of indicators, which are financial and non-financial, financial only and non-financial only. The target indicators could be changed upon the purpose of the study or the requirement of a specific question. Secondly, the performance of the model requires to be measured. For instance, there are about 60 different indicators were included in the model. Based on the AIC developed by Akaike (1987), the minimum AIC value indicates the model is the most accurate one. Meanwhile, the AIC value depends on the combinations of included indicators. Therefore, to select the minimum AIC value, it is necessary to adjust the indicators included in the model. There are two methods of methods used, where both of the methods are based on the idea of the exhausting method. The direct and reverse selection of indicators included in the Logit regression would calculate each AIC value of different combinations and select the minimum one as a financial selection. The exhausting direct selection method means including a few indicators at the beginning and increasing the number of indicators applied, while the AIC values of different groups will be compared to choose the minimum one. The reverse selection is on the contrary, which means excluding indicators from all indicators. Based on exhausting method, it is possible to calculate AIC values of all the combinations of indicators. Finally, based on the previous step, the minimum AIC value could be found out and the indicators included in the Logit regression equation could be listed by software. The rest indicators are still needed to pass the significant test to insure they are significant variables to the dependent variable. Furthermore, if scholars or decision makers need stronger judgments in the KRIs selection, the feature importance method could also be applied to decide significance. Therefore, the KRIs were selected by several steps to make sure the significance and meaningfulness to explain target question.

The Logit regression could explain the dependence variable Y by the independent variable X. However, the Logit regression is not using a linear dependence. Logistic curve interleaves the data instead of a line, and its prescript is (Kliestik et al., 2015):

$$\ln \frac{P}{1-P} = a + \sum_{i=1}^{m} b_i x_i$$

P is the probability of a firm becomes a business failure or financial distress given the independent variable (X1, X2…Xi), while 1 minus P is the probability of the firm that did not become a failure. The coefficient a, bi, are the estimated parameters, while Xi (i=1, 2,⋯, m) is the independent variables. The equation could be transferred as:

$$P = \frac{\exp\left(a + \sum_{i=1}^{m} b_i x_i\right)}{1 + \exp\left(a + \sum_{i=1}^{m} b_i x_i\right)} \quad \text{or} \quad 1 - P = \frac{1}{1 + \exp\left(a + \sum_{i=1}^{m} b_i x_i\right)}$$

The variables Xi are the financial indicators with the coefficient bi, where maximal likelihood could estimate the coefficients. The probability of default does not have a theoretical threshold value, which means the probability should be manually selected upon the macroeconomic environment. The target should be carefully selected as well as the financial indicators. The indicators could be optimised with principal component analysis. There are many indicators could express the performance of the firms (CAS, 2003). However, Chen and Shimerda (1981) stated that many of the ratios are highly correlated with other ones, which is the overlapping problem in the ratio analysis. Chen and Shimerda (1981) stated that the use of principal component analysis with other methods could produce a more powerful and basic analysis. The principal component analysis is going to group variables in a few factor groups, which retains the maximum of information contained in the original variable set. The purpose of using principal is to reduce the selected variables, which could help scholars to focus on few variables in order to get more accurate results. Chen and Shimerda (1981) pointed out that the ratios classified by the same factor are highly correlated, which may lead to multicollinearity. Therefore, it is important to select one ratio to represent a factor, which could account for most of the features provided amongst all the ratios of the factor.

4.5.3 Genetic algorithms

Genetic algorithms (GA) are population-based evolutionary searching methods. These algorithms have used probability-based search methods, which gained ideas drawn from natural genetic and evolutionary principles (Chamber, 1995). Genetic algorithms are particularly suitable for solving scheduling and machine layout problems. There were many scholars deeply research this method and applied it in the textile and apparel production (Chan, Hui, Yeung, & Ng, 1998; Wong, Mok, & Leung, 2006). Furthermore, genetic algorithms are very useful for product packing optimisation and product assortment management as well (Leung, Wong, & Mok, 2008).

The genetic algorithms differ from other non-linear optimisation techniques. The search by maintaining a population (or in this case a database) of solutions from which better solutions are created rather than making incremental changes to a single solution to the problem (Min, Ko and Ko, 2006). Genetic algorithms mimic Darwinian forces of natural selection to find optimal values of some function (Mitchell, 1996). An initial set of candidate solutions are created, and their corresponding fitness values are calculated (where larger values are better). This set of solutions is referred to as a population and each solution as an individual. The individuals with the best fitness values are combined randomly to produce offspring, which make up the next population. Individuals are selected, and cross-over and also are subject to random mutations. For real-world applications of GAs, choosing the fitness function is the most critical step. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population (Gordini, 2014). The new population is then used in the next iteration of the algorithm. This process is repeated again and again, while many generations are produced (i.e. iterations of the search procedure) that should create better and better solutions.

The random forest has been applied in multi-dimensions analysis in recent years (Zhao, Zhang, and Li, 2016). The random forest applied bootstrap sampling to generate trees from a subset of the total number of features (Elyan and Gaber, 2017). Kumar and Sahoo (2017) stated that the feature selection reduces the dimension of data and the computational time of the process. Since this study aims to select KRIs among all indicators in the DM process, the importance of feature selection is obvious. The combination of GA and RF has been applied in the classification in order to increase accuracy and efficiency. Each tree in RF method only contains some features selected by GA, which aimed to increase the prediction accuracy. Meanwhile, the mutation function in GA method can increase the diversity of the included features, which can potentially increase the comprehensiveness of the results.

The GARF is going to be used to select features among all indicators in order to find out KRIs. For feature selection, the individuals are subsets of predictors that are encoded as binary; a feature is either included or not in the subset. The fitness values are some measure of model performance, such as the root-mean-square error or classification accuracy (Max, 2018). One issue with using GARF for feature selection is that the optimisation process can be very aggressive and is possible to cause overfitting problems. Technically, the fitness function for this research is accuracy in cross-validation of the models for predicting the firm performance. The training data are split into many groups, which are depending on the resampling method in the control function. It is normal to verify the result based on the idea of K-fold cross-validation (Max and Kjell, 2018). For example, if 10-fold cross-validation is selected, the entire genetic algorithm is conducted ten separate times. In the first fold, nine-tenths of the data are used in the model while the remaining one out of ten is used to estimate the external performance since these data points were not used in the model. The algorithm terminates when either a maximum number of generations have been reached, or a satisfactory fitness level has been achieved for the population. In the 10-fold cross-validation, the accuracy of prediction will be compared to select the combination of variables.

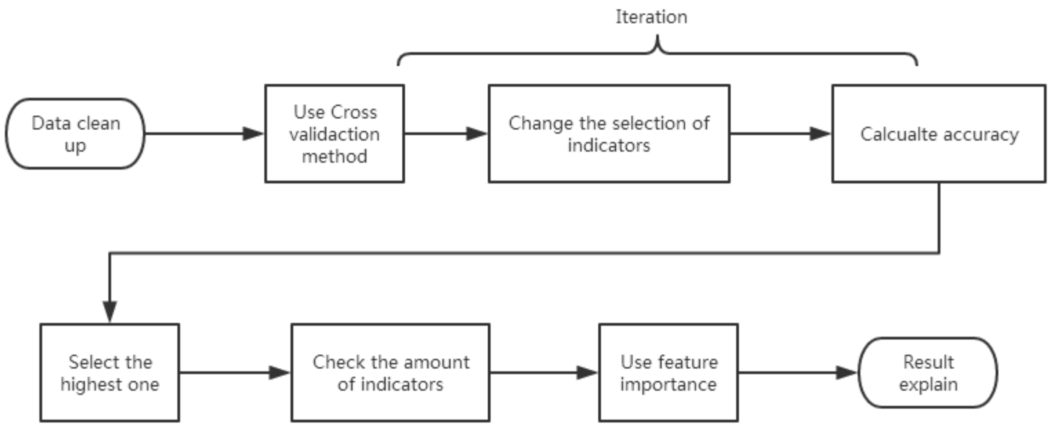


Figure 4.5.3 The Process of GAs

The Figure 4.5.3 shows the process of the genetic algorithm. Mitchell (1996) stated that the method mimics natural selection to find optimal values of the function. In order to solve a certain question, the potential combinations of indicators were created to calculate the corresponding solutions. The set of the solutions could be considered as a population, which are referred to as an individual, just like in biology. In order to measure the performance of the individuals, the fitness values were used. As a result, the individuals with the best fitness value will be gathered to produce the next generation. This process will be repeated several times, which is called iteration. The fitness values could be the measurements of model performance to select the most important indicators, such as RMSE or accuracy. The indicators were split into several groups, which are used to conduct the cross-validation method in order to select the best performance of predicting model. After several iterations, the process will terminate as long as the set times reached. Then, the combinations of the indicators will be obtained, which could be listed by using the feature importance method. Finally, the result will be used to predict for the target question, which is the performance of the firms in this research.

4.5.4 Artificial Neural Network

In business research, the back propagation artificial neural network (BPNN) could be used to calculate scores for the determination of attributes (Mikulić and Prebežac, 2012). The BPNN particularly used for forecasting purposes by many scholars (Enke and Thawornwang, 2005; Law and Au, 1999), while other scholars used it for the importance of determinants (Tsaur, Chiu and Huang, 2002). There are several advantages to BPNNs. Compared with traditional regression methods, BPNNs do not strictly require normal distributions of data and could explain large portions of variance among dependent variables (Mikulić and Prebežac, 2012). Furthermore, the BPNNs could learn from the data, which is a basic concept of knowledge mining. Mikulić and Prebežac (2012) stated that the BPNNs could use iterative methods to make the output closing to specified target outputs, which is going to minimise the mean square error between predicted and target values by applying backpropagation.

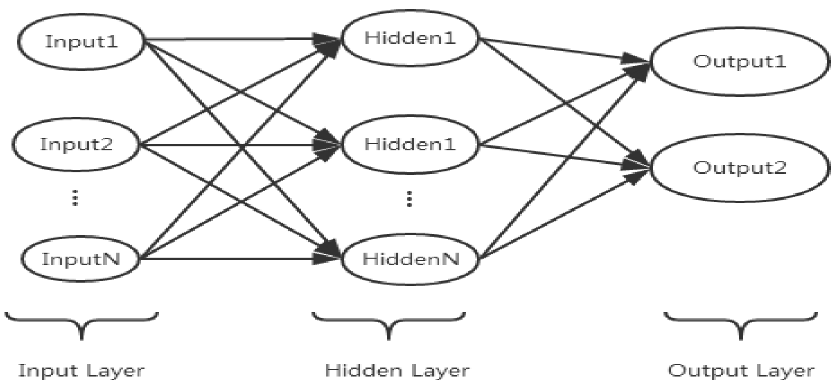


Figure 4.5.4-a The Structure of BPNN

As Figure 4.5.4-a shows, there usually are three hierarchy layers in a BPNN model, which are the input layer, the hidden layers and the output layer. The neurons comprised the layers, which contained information linked to provide answers to the given questions (Mikulić and Prebežac, 2012). The information linked together with different weights, which depends on the importance of information to the target problems. Unlike in other regression methods, the neurons in input layers and output layers are not directly related to each other but indirectly connected by neurons in hidden layers. The neural network could have many hidden layers. However, Lippman (1987) has proved that the one layer hidden BPNN can provide enough accuracy for any reflections between input and output layers and two hidden layers cannot significantly increase the prediction accuracy. In this research, there are two output values, which are good performance and poor performance of firms. Moreover, the input values are different, which depend on the types of indicators.

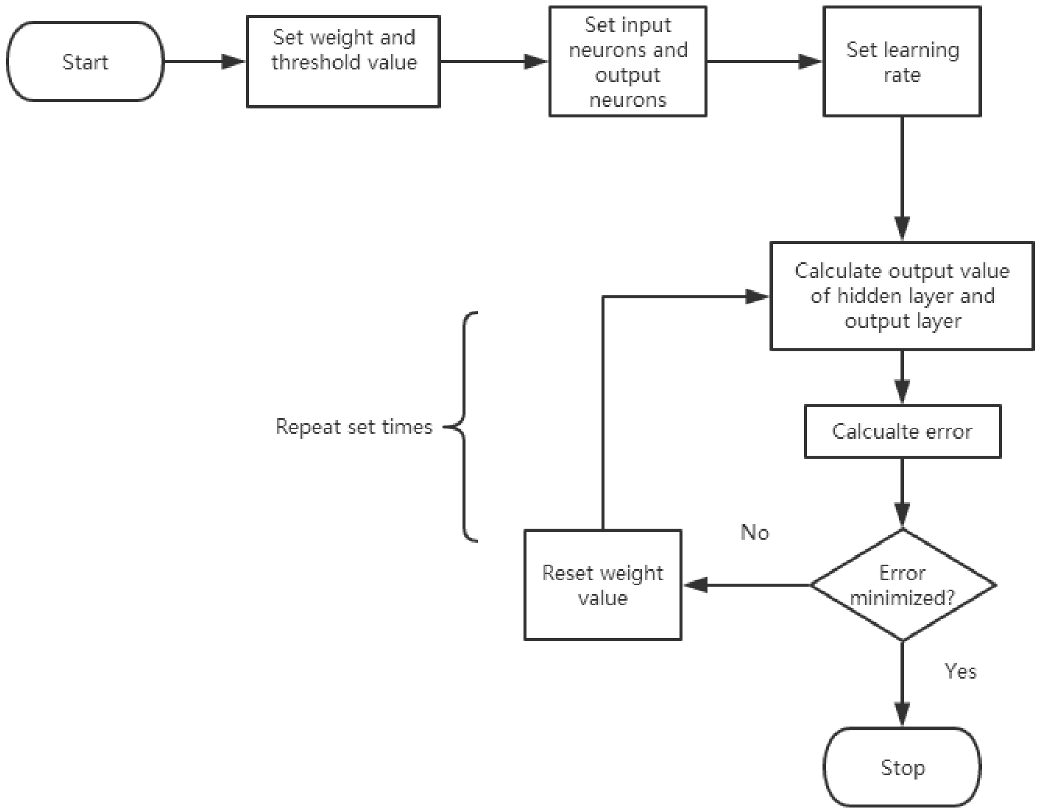


Figure 4.5.4-b The Process of BPNN in flowcharts

Figure 4.5.4-b shows the process of BPNNs in this research. The data should be transferred to a certain format in order to be used in the BPNNs model, since the BPNNs used neurons as data format rather than other methods. To conduct neurons, the data should be transferred to a value between 0 and 1. This research applied the function "norm Training And Test Set" in R programming, where the function is:

$$y = (x - x_{min}) / (x_{max} - x_{min})$$

Since the BPNN is a flexible method in data mining methods, there are many selections to decide the number of neurons in hidden layers, which could depend on the specific case. The amount of input neurons depends on the target question, specifically, financial and non-financial indicators, financial indicators only or non-financial indicators only. The output neurons are the performance of selected firms (good or poor). The initial weight and threshold value could be set as any value, which will be automatically adjusted by the method. The learning process of BPNNs is as follow: Firstly, the number of input neurons, hidden neurons and output neurons should be determined, where are set as n, p, m respectively. Secondly, the output value of hidden layers needs to be calculated, the formula for hidden layer output is: $H_j = f\left(\sum_{i=1}^{n} w_{ij} - b_j\right)$, where w is the weight value; b is a threshold value. To make sure the value is between 0 and 1, the activation function is $f(x) = \frac{1}{1+e^{-x}}$ (Mikulić and Prebežac, 2012). Thirdly, the value of neurons in output layers could be calculated based on the hidden layer output and weights, which is equal to $O_k = \sum_{j=1}^{m} w_j w_{ik} - b_k$. The learning mechanism of BPNN is to minimise the error between the actual value and the output value of output layers, which is equal to $e = Y_k - O_k$, where Y is the actual value. Finally, to minimise the error, it is necessary to adjust the weight value and repeat the step in order to make sure the error is minimised within a set iteration. The formula to explain this step is: $w_{jk} = w_{jk} + \eta H_j e_k$, where η is the learning rate. The learning rate could be used a different value to get expect error (Warren, 1995). However, low learning rate will make the method running slowly. As a result, the learning rate was set as 0.1 in this research to make sure the method could finish within the expected time. In this research, the repeat time was set as 200. If the error reached the expected value, the method could be used to predict firm performance.

4.5 Summary

This chapter started by introducing the research design, where the process of data mining process was thoroughly discussed. The data collection part described how did the researcher collect potential indicators in order to select KRIs based on KPI. Then, the variable selection part discussed how the indicators were fitted into the ERM framework, which provided an integrated model for risk management. After that, the main research paradigms and approaches are provided and the reasons for choosing the positivism approach with a quantitative method. The GA, CHAID, Logit

Regression and ANN have been thoroughly introduced, where each of the methods will be applied in the data mining process. Since all the methods are based on different statistical or data mining theories, they could be applied to discover different rules and patterns. As a result, after the rationales of these methods were introduced, all the methods could be applied in the whole process, since they comply with the usage of KRIs and KPI.

The four DM methods aimed to achieve a feature selection function to select KRIs among all candidate indicators. Recalled the research questions listed in Figure 3.5, the Q2, Q3, Q4, Q5 and Q6 required the results of DM methods. The use of KPI and KRIs, the value of non-financial indicators and the best DM methods need to be investigated from the results of DM methods. The financial and non-financial indicators have been divided into three different groups, which are financial indicators and non-financial indicators, financial indicators only, and non-financial indicators only. To find out the value of non-financial indicators, the results of different groups of indicators will be compared. The indicator group with the most accurate prediction will illustrate the effectiveness of the indicators group. The results of this step can be used to answer Q2 and Q3. On the other hand, the prediction accuracy of four different DM methods will be also compared. To evaluate the performance of four DM methods, the comprehensiveness, accuracy, time and costs will be examined. The Q5 and Q6 can be answered with the results of this step. The rules and patterns generated from the DM process will be applied to draw an overall picture of SMEs, where can show the roadmaps for the RM process. The Q4 can be examined in this step. Therefore, the research questions and applied methods can be linked together.

5 Results and Analysis

5.1 Introduction

The previous chapter has described and discussed the methodology used in this study. The purpose of this chapter is to apply data mining methods to analyse the collected data and describes the results emerged from different data mining methods. In order to analyse the data, this study applied SPSS and R programming. The Chapter starts with the variable selection, which includes the data collection, data selection and risk identification. After the initial preparation, the CHAID, LR, GAs and BPNN were used to select KRIs upon the selected KPI. The additional test, such as variable importance and receiver operation curve (ROC) was used to support the results of data mining methods. At last, a summary has been provided for the whole chapter.

5.2 Indicators Selection

5.2.1 Financial and Non-financial Indicators

The research is going to use both financial and non-financial indicators in the data mining progress. The research used 849 listed SMEs on Chinese Shenzhen Stock board from 2012 to 2013. The relationship between firm performance and risk indicators was thoroughly investigated by using CHAID, LR, GAs and BPNN. The financial indicators and non-financial indicators are selected based on ERM framework (Verbano and Venturini, 2011; CAS, 2003). There were forty-two financial ratios, and nineteen non-financial indicators were included in the data mining methods. The financial indicators considered four areas of firms, which are *profitability ratio, liquidity ratio, activity ratio and solvency ratio*. The financial indicators were obtained from the balance sheets, income statements and cash flow statements. The non-financial indicators were generated from the reports published by National Statistical Bureau of China (NSBC, www.stats.gov.cn); the suggestions by other scholars (Altman et al., 2010; Li et al., 2016; etc.); and the risk features suggested in ERM framework by CAS (2003). The non-financial indicators considered risk catalogues under ERM framework by CAS (2003), such as *human resource, leadership, research and development investmen*t, *age of the firms*, *size of the firms, industry catalogues*, *social trends, etc.* The detailed indicators will be introduced in the following part.

In this study, the financial indicators have been collected from annual reports, which are used to calculate financial ratios in order to find the hidden rules from the data. The calculations of the financial indicators are shown below:

Current ratio	x1	long-term liability to total liability	x11	bank loans to total loans	x21	net profit to equity	x31	inventory/working capital	x41
Quick ratio	x2	long-term liability to long-term liability + equity	x12	current asset to total asset	x22	profit before tax to equity	x32	inventory turn over	x42
Absolute liquidity	x3	tangible fixed asset to equity	x13	tangible fixed asset to total asset	x23	EBIT/EBT + finance expense	x33		
inventory to current asset	x4	tangible fixed asset to long-term liability	x14	receivable turnover	x24	net profit to asset	x34		
inventory to total asset	x5	fixed asset to total loans	x15	working capital turnover	x25	operating profit to net sales	x35		
current account receivables to total assets	x6	fixed assets to equity	x16	net working capital turnover	x26	interest expense to net sales	x36		
total loans to total assets	x7	fixed assets to equity + long-term loans	x17	tangible fixed asset turnover	x27	gross profit to net sales	x37		
equity to total assets	x8	short-term liability to total loans	x18	fixed asset turnover	x28	net profit + interest expense + finance expense to interest expense	x38		
equity to total loans	x9	bank loans to total assets	x19	equity turn over	x29	cost of goods sold to net sales	x39		
short-term liability to total liability	x10	bank loans to short-term liability	x20	total asset turn over	x30	capital employed to total liability	x40		

Table 5.2.1-a Selected F indicators

There were forty-two financial indicators in Table 5.2.1-a selected from annual reports, which measured the performance, operational risk and financial risk. The financial indicators were selected from the indicators used in the study by Altman et al. (2010), Koyuncugil and Ozgulbas (2012), CAS (2003), and Beaver (1966). The financial indicators indicated the profitability, liquidity, activity and solvency of firms. Based on the ERM framework (Verbano and Venturini, 2011), the financial indicators can indicate all features in financial risks and most of features in operational risks.

The non-financial indicators selection is a relatively new area. Li et al. (2017) stated that the variables about non-financial indicators about CEOs are significant in their study. Altman et al. (2010) stated that the audit information is significant in their estimated model. They also stated that the age of the firms followed “Liability of newness” theory by Stinchicombe (1965), which means the age of the firm could be classified into different groups. Bunn and Redwood (2003) stated that the subsidiary’s performance could affect the parent company. Therefore, the CEO related variables, audit information and subsidiary related variables should be collected from the annual reports of listed SMEs. Furthermore, the human resources variables have also been mentioned by Wu, Zhu, Wu and Ding (2014). The educational background of employees and employers was mentioned by Kim and Vonortas (2014). The business environment variables were suggested by Kim and Vonortas (2014). They stated that the external environment, such as country or industry, could affect the risk level of firms. However, in their studies, they only applied surveys method and defined the variables form “completely disagree” to “completely agree”. It will be more logical and convincible if the indicators were quantised and standardised from calculations of other variables. As a result, the Development and Life Index (DLI) reports providing by NSBC (2013) were selected supplementary materials in order to consider the non-financial aspects of risk features in the ERM framework.

The non-financial indicators provided additional explanations of the financial indicators. The ERM framework described the classification of risks, which was detailed discussed in Section 4.4. Some of the risk features cannot be explained by financial indicators, such as Wisdom and other natural perils (Hazard risks); Information/Business reporting (Operational risks); and Demographic and socio-cultural trends (Strategic risks). The non-financial indicators are then designed to consider these aspects. As stated in the reports by the Development Research Centre (DRC) of NBSC, there were a few indicators could indicate the macroeconomic environment (Zhao and Wang, 2015). This information explains part of Strategic risks, such as socio-cultural trends, customer wants; etc. They listed four aspects of Development and Life Index. Based on the report by (Zhao and Wang, 2015), the thirty-one provinces of China were rated in public services, public security, living environment and citizen lives. These indicators could also explain some aspects of Hazard risks and Strategic risks.

Furthermore, the National Bureau of Statistics of China (2013) investigated the development and life index (DLI) for thirty-one provinces in China. They calculated development and life index, economic development index, development of society index, environment index, well-being index and technology innovation index (NBSC, 2013). The report by NBSC (2013) stated that the indexes are based on the Human Development Index by the United Nations, which can provide information about Operational risks. Altman et al. (2010) suggested the goodwill and intangible asset may be possible significant variables in measuring the performances. The goodwill and intangible assets can be collected from balance sheets and income statement. Therefore, there are total nineteen non-financial indicators selected, in order to capture the information which cannot be told in the annual reports of listed Chinese SMEs.

y1	Industry
y2	Number of employees
y3	Develop and life index
y4	Economic development index
y5	Wellbeing index
y6	Development of society index
y7	Environment index
y8	Technology innovation index
y9	Employees education
y10	Audit opinions
y11	Cost of Audited
y12	Numbers of subsidiary
y13	CEO shareholding
y14	Numbers of search staff
y15	CEO tenure
y16	Tax rate
y17	Listed duration
y18	Goodwill and intangible asset
y19	Size of firms

Table 5.2.1-b Selected NF indicators

This research also includes several non-financial indicators which are not discussed or included in other previous studies, which were listed in Table 5.2.1-b. The hazard risks contained information about *disease and disabilities*; *wisdom and other natural perils*; *theft and other crime*, and *personal injury*. Geographic information and DLI can explain these features by NBSC (2013). Strategic risk includes *technological innovation*, *demographic and socio-cultural trends* and *regulatory and political trends*. The DLI reports by NBSC (2013) calculated indexes, which contains this kind of information. In a 2013 report by NBSC, the development and life indexes were published, which disclosed development and life index and other social indexes of total thirty-one provinces in China. Since the provinces of firms could be obtained from annual reports by firms, the necessary information for measuring hazard risk and strategic risks has been obtained. NBSC (2013) stated that there are six indexes measure the social development situation of different provinces. They have calculated development and life index, economic development index, well-being index, development of society index, environment index and technology innovation index.

NBSC (2013) stated that the indexes were calculated based on the statistical data and the Delphi method to evaluate the weights. The main calculation has based the method used in the Human Development Index (HDI) provided by the United Nations (NBSC, 2013).

Index	Development and life	Economic development	Well-being	Development of society	Environment	Technology innovation
Beijing	90.57	99.88	93.5	80.04	79.65	99.56
Tianjin	79.74	96.18	83.31	74.72	74.64	63.26
Hebei	61.08	67.19	72.7	70.95	60.4	13.56
Shanghai	86.44	99.98	88.82	79.51	80.61	71.5
Jiangsu	77.98	87.48	81.62	72.31	72.11	74.25
Zhejiang	77.8	83.55	87.53	69.12	75.45	67.13
Fujian	70.86	80.64	78.04	71.08	77.53	30.84
Shandong	67.79	76.43	76.77	70.23	69.33	30.2
Guangdong	74.79	89.62	77.74	67.65	76.51	54.97
Hainan	62.4	71.95	69.05	71.12	68.16	11.49
Shanxi	61.54	68.63	67.54	72.3	57.92	26.8
Anhui	63.62	67.03	69.32	70.27	70.34	25.93
Jiangxi	62.07	66.93	71.2	71.52	66.92	13.64
Henan	60.91	64.21	68.19	68.24	64.63	23.74
Hubei	63.98	71.41	70.82	68.7	66.24	27.76
Hunan	62.42	69.33	68.6	71.08	67.26	17.97
Neimenggu	59.64	77.05	65.02	67.07	60.19	9.28
Guangxi	59.48	65.47	66.57	67.12	67.63	11.22
Chonqing	68.67	77.9	72.67	67.61	73.8	40.29
Sichuan	63.82	68.7	67.87	70.35	66.15	34.06
Guizhou	55.83	64.25	60.86	66.9	60.56	7.64

Yunnan	57.59	65.27	60.84	67.97	65.06	11.05
Tibet	52.54	60.64	58.14	69.58	51.31	3.25
Shanxi	63.94	70.02	62.96	72.36	66.28	39.37
Gansu	54.1	62.44	60.43	64.42	54.65	11.07
Qinghai	52.6	66.18	60.12	63.03	47.97	6.91
Ningxia	55.75	67.97	62.92	65.73	53.11	10.55
Xinjiang	53.47	66.79	65.42	60.92	46.89	7.13
Liaoning	67.07	81.61	72.64	70.24	71.81	21.17
Jilin	61.54	72.71	70.18	69.25	62.7	12.86
Heilongjiang	60.89	73.76	67.83	67.47	61.64	15.47

Table 5.2.1-c DLI in China

In Table 5.2.1-c, the six indexes of thirty-one provinces in China were shown. NBSC (2013) also provided detailed calculation methods for the indexes. Since firms provided the geographic information in their annual reports, the six different indexes have been into the models, which provided information about strategic risk and hazard risk.

Province	Frequency	Province	Frequency
Anhui	28	Qinghai	1
Beijing	50	Shandong	67
Fujian	39	Shanxi	4
Gansu	5	Shan(3)xi	5
Guangdong	217	Shanghai	30
Guangxi	6	Sichuan	27
Guizhou	7	Tianjin	9
Hainan	4	Tibet	4
Hebei	10	Xinjiang	12
Henan	25	Yunan	10

Heilongjiang	4	Zhejiang	137
Hubei	12	Chongqing	6
Hunan	27	Jiangxi	9
Jilin	6	Liaoning	13
Jiangsu	106	Neimenggu	2
Ningxia	1	Total	833

Figure 5.2.1 The Frequency of locations

Figure 5.2.1 shows the frequency of locations of all the listed SMEs. The difference of the listed SMEs was significant in some provinces. For example, there are 217 listed firms in Guangdong, but only one firm in Qinghai. If the rank of the index was implied, it is possible that the result will be biased since the imbalance of the frequency. Therefore, in this research, the indexes calculated by the Delphi method were selected and used in all the models (NBSC, 2013).

5.2.2 K-means Clustering

The K-means Clustering is used to verify the meaningfulness of using KPIs. Altman (1968) proposed the original Z-score model use five ratios: working capital/ total assets, retained earnings/ total assets, earnings before interest and tax (EBIT)/ total assets, market value equity/ book value of total debt and sales/ total assets. Based on this formula, the Z-score of a firm could be divided into three catalogues: bankruptcy might be bankruptcy and stable. It is evident that the Z-score is a ternary variable. Another option for the dependent variable is the growth rate of ROA (ROA for short), ROE or Net profit ratio. The return of assets, return on equity and net profit ratio could directly measure the performance of the firms in profitability aspect, while the positive growth rate of profitability ratios means the good performance, and vice-versa. There are many studies concluded that the changes in ROA significantly affect the earnings growth (Altman et al., 2010; Heikal, Khaddafi and Ummah, 2014).

Most of the studies in Chinese firms applied ST and Non-ST as dependent variables (Geng et al., 2015; Xie and Me, 2013). In their studies, they used special treatment (ST) and non-ST as the dependent variable. For instance, Yao and Shen (2005) selected 80 firms, where 40 non-ST firms and 40 ST firms in China. The ST firms in the Chinese stock market are special treatment firms, which the profits are negative two years in a row or the net asset per share is lower than the book value per shares. However, in their study, there were 80 firms selected, and the classifications of the firms were based on ST or non-ST. Although the special treatment (ST) is the official standard in the Chinese stock market, it may be biased since there were over 1,000 firms listed. For the datasets used in this research, there are only 11 out of 839 firms are ST firms. If the ST classification was applied, the samples in two groups would be a biased result due to too fewer samples in the ST group. Meanwhile, the sample size is significantly larger than other studies in China (Yao and Shen, 2005; Li et al., 2017; Xie and Me, 2013). Therefore, it could make more sense to use statistical classification methods but not ST/Non-ST as KPI for this study.

The purpose of using K-means is to verify that there are at least two groups with different performance. The K-means method is one of the well-known methods for clustering. K-means clustering method could group the data based on their closeness to each other according to the Euclidean distance (Arora, Deepali and Varshney, 2016). K-means method takes k_y as input parameter and partition a set of n objects from k_y cluster. The cluster mean or centre is formed by the random selection k_y object. The primary step is:

1. Select initial cluster centres
2. Assign each record to the nearest cluster
3. Update the cluster centres based on the records assigned to each cluster
4. Repeat step 2 and 3 until in step 3 there is no change in the cluster centre or the

number of iterations exceeds the maximum parameter

Suppose it is going to classify two different groups, which are good performance and poor performance. The results were shown below:

Groups	x34	x31	x32	x37	x39
1	0.0157	0.0262	0.0243	0.0253	0.8213
2	0.0615	0.0911	0.1058	0.1367	0.6893

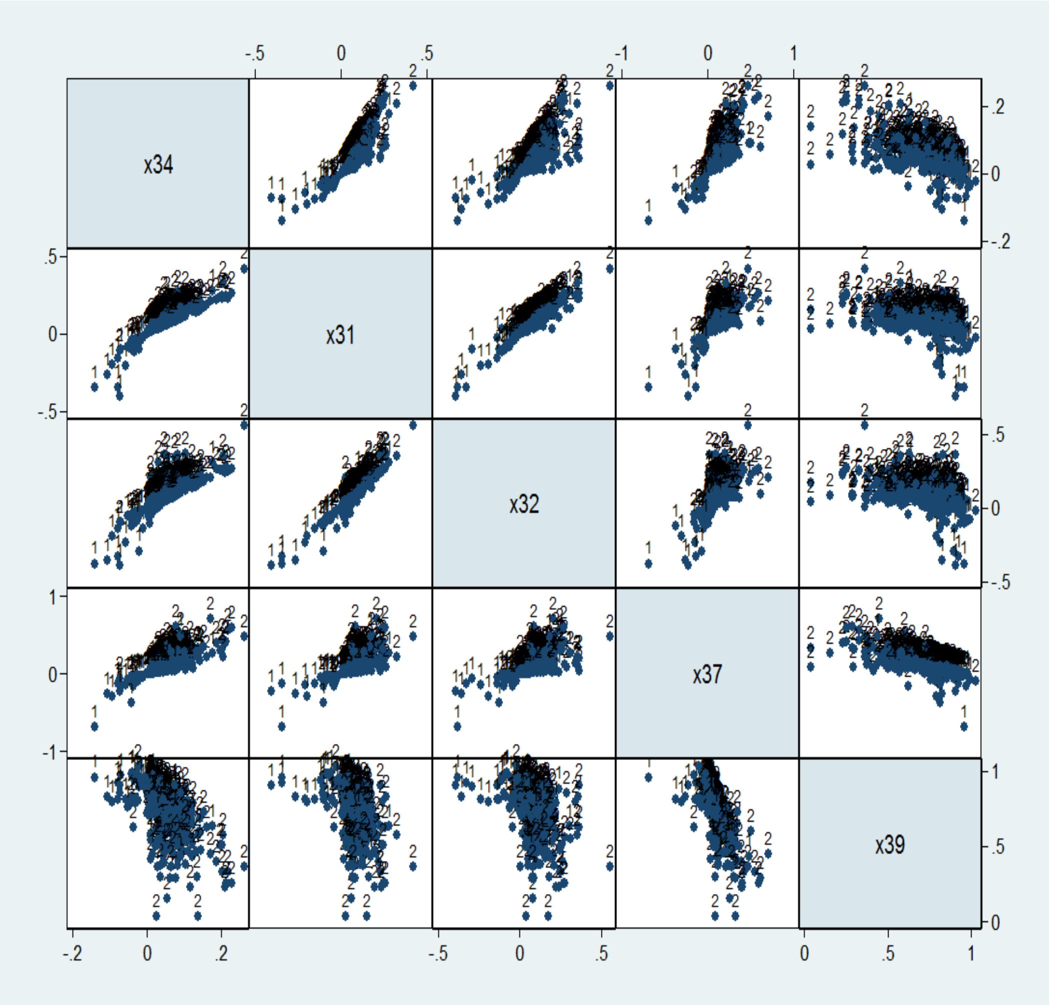


Figure 5.2.2 The Result of K-means

The result of K-means is shown above in Figure 5.2.2. Since the two groups are shown in a different colour, it is clear that the sample data includes at least two different groups. For example, there are two groups in x34; the means are 0.0157 and 0.0615 respectively. It could also be seen from the graphic that there are two kinds of spots with different colours. It indicated that there are different groups in the sample data. The results of K-means also supported that there is another classification method other than ST/Non-ST in the study of listed Chinese SMEs. Therefore, the KPI can be selected from Z-score or ROA

5.3 CHAID Results

5.3.1 CHAID algorithms

The CHAID method is started from the raw data treatment. Firstly, the dependent variables should be selected, where are the results of Z-score and ROA. Then, the independent variables could be selected as nodes, and the chi-square value was calculated in order to choose the first node. After the first node was decided, the first step will be repeated in order to decide the following nodes until the p-value of the chi-square is greater than the α_{split}. The algorithm is shown below:

1. For each independent variable X, there will be a distribution that the difference in regards to the dependent variable is minimum. In other word, the difference between the two groups will be very small. Thus, the p-value will reach the maximum. If the dependent variable is a continuous variable, the F-test will be applied. If the dependent variable is a nominal variable, the Pearson Chi-squared test will be applied. The dependent variable will be the column and the dependent variable will be the raw of the conducted two cross-classification chart. The Chi-square is:

$$\chi^2 = \sum_i \sum_j \frac{f_{ij} - \hat{F}_{ij}}{\hat{F}_{ij}} \quad (1),$$

where $f_{ij} = Y_{ij}/n$ is the real distribution frequency, n is the number of samples. Y_{ij} is the distribution frequency Y with the number i, and number j. the Y_{ij} is the theoretical estimated value corresponding to f_{ij}. $\hat{F}_{ij} = (Y_j/n) \times (Y_i/n)$, where Y_j is the sum of row i, Y_i is the sum of column j.

2. For all the independent variables, compared the p-value to the merging value, α_{merge}. If the p-value is greater than the α_{merge}, the two independent variables should be merged as a new independent variable.

3. The Bonferroni method is used to calculate adjusted p-value. $B=\sum_{i=0}^{r-1}(-1)^i\frac{(r-i)^c}{r!(r-i)!}$

Where c is the number of the independent variables, r is the number of the independent variables after merged.

4. Moreover, the independent variables with the minimum p-value will be compared with the α_{split}. If the p-value is less than the α_{split}, the nodes should be split. If the p-value is greater than the α_{split}, the node is the end node.

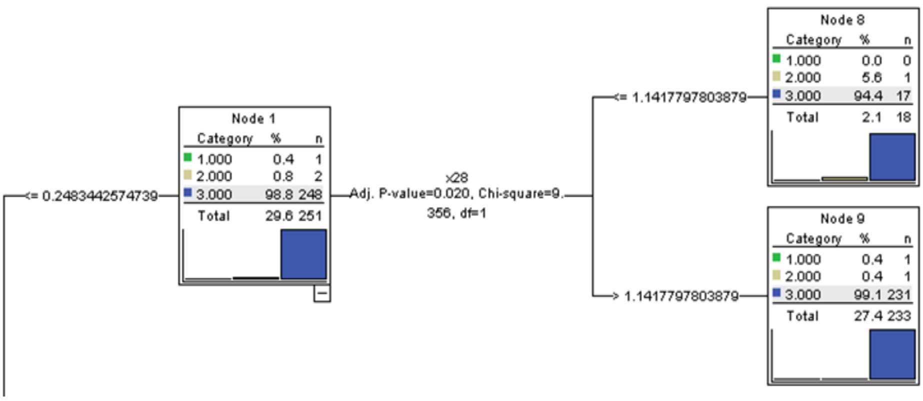
This research will select Z-score and ROA as dependent variables respectively, and the independent variables will be selected from Table 5.2.1-a and 5.2.1-b. The α_{split} is set equal to $\alpha_{merge} = 0.05$. The Z-score as dependent variable will be shown firstly. The train set selected the 75% data in 2012 from listed SMEs board in Shenzhen, China (www.szse.cn). And the test set selected the corresponding data in 2013 from listed SMEs board in Shenzhen, China. The maximal depth is 5 and the minimal size for split is 50, while all other settings are default.

5.3.2 Dependent variable: Z-score

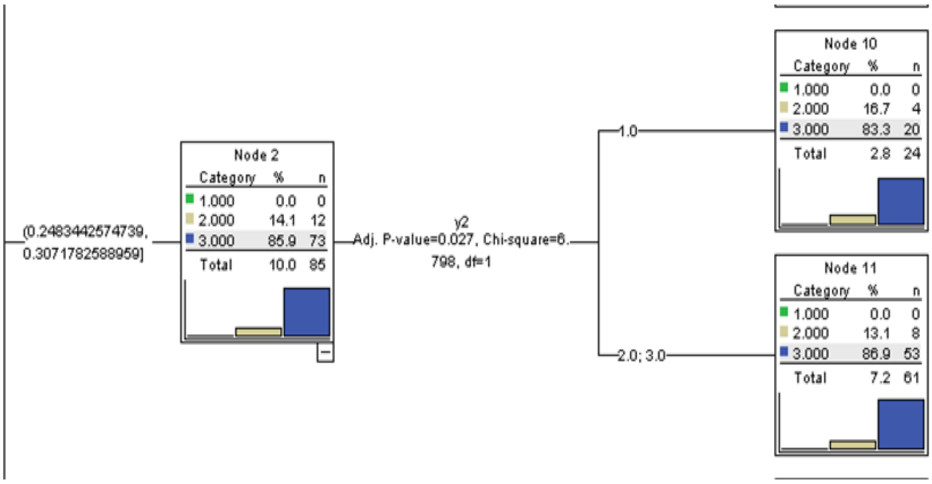
A. Independent variables: financial and non-financial indicators

The dependent variable of CHAID is chosen as Z-score, while the independent variables are financial indicators and non-financial indicators. The full decision tree was shown in Appendix 1, Figure 5.3.2-a. The detailed explanations of each branch and node are provided flowingly, which includes the threshold values of each independent variable. Meanwhile, the detailed values of nodes and classification were listed in Appendix 1, Table 5.3.2-a1.

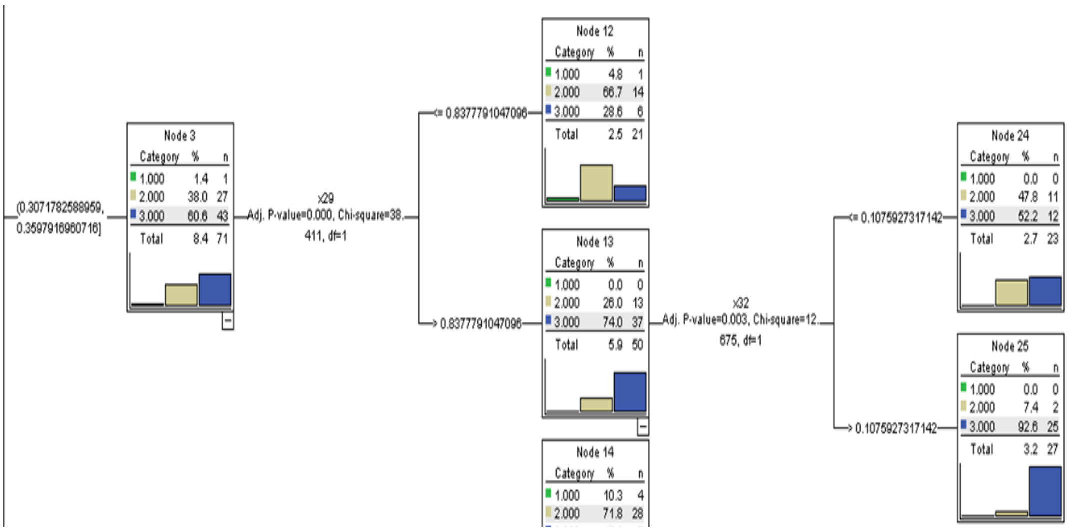
The results from SPSS were shown above in Figure 5.3.2-a. The Z-score was selected as the dependent variable, while the catalogues were bankrupt, might be bankrupt and stable, (respectively 1, 2 and 3). The parent node is x7, which is debt to asset ratio. There are seven child nodes were split from the Z-score, the range of the debt to asset ratio is from 0.248 to 0.635. The second nodes are x28, y2, x29 and x30, which are fixed asset turnover, number of employees, equity turnover and total asset turnover respectively. The threshold value of x28 is 1.141. The y2 variable was classified into three groups, less than 1000, between 1000 and 3000 and higher than 3000. The x29 was classified into two groups, and the threshold values of x29 are 0.8378 and 0.9421 respectively. There are two different second hierarchy nodes were classified by variable x30. The first one is from 0.7945 to 1.2677, which contains three threshold points, 0.6015, 0.7946 and 1.2677. Moreover, the threshold value of the second one is 0.9421. The terminal nodes are x32, x39 and x17, which are profit before tax to equity, cost of goods sold to net sales and fixed assets to equity and long-term loans. The threshold value of x32 is 0.1075. The threshold value of x39 is 0.7417, and the threshold value of x17 is 0.3036. The x7, debt to assets ratio has the strongest relationship with performance under the Z-score model, and it could bring out seven branches from the root node.



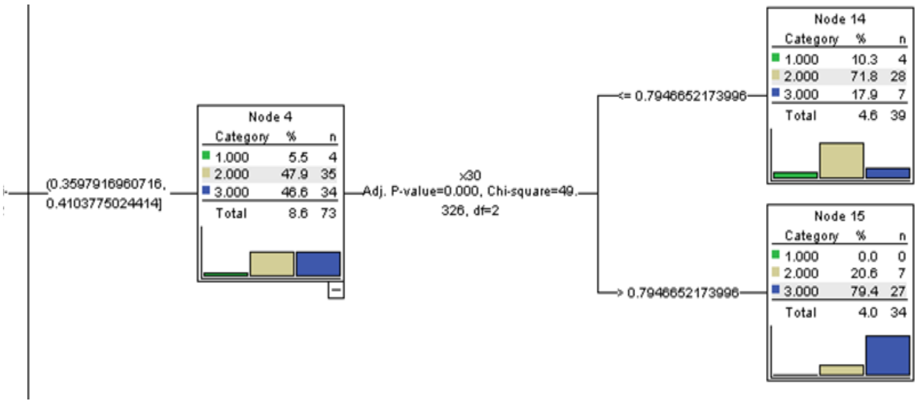
The classified rule for the first branch is when x7 less than 0.2483 and x28 less than 1.1477. The stable firms are 17 out of 18, and the might be bankrupt firm is 1 out of 18. The second rule is when x7 is less than 0.2483 and x28 is greater than 1.1477. The stable firms are 231 out of 233, while the bankrupt firm and might be bankrupt firm is 1 out of 233 respectively.



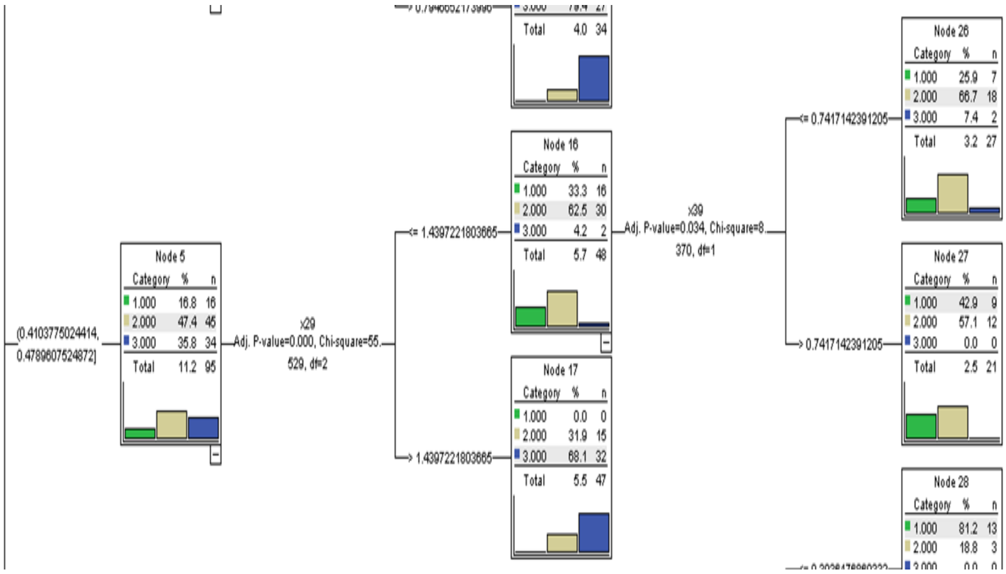
The classified rule for the second branch is x7 between 0.2483 and 0.3071. Given y2 is belong to group 1, there are 20 out of 24 stable firms and 4 out of 24 might be bankrupt firms. The second rule is given x7 between 0.2483 and 0.3071, and y2 belongs to group 2 and 3. There are 53 out of 61 stable firms and 8 out of 61 might be bankrupt firms.



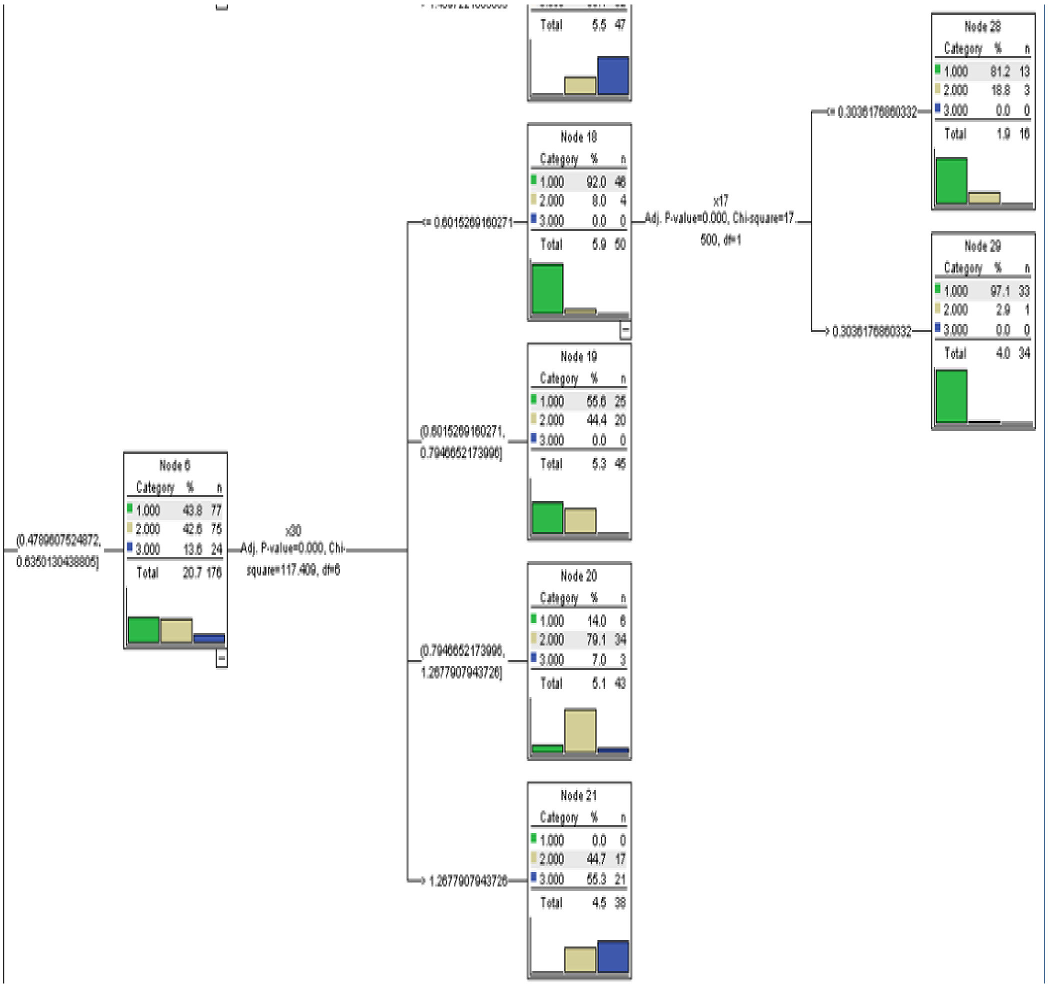
The third branch is the x7 between 0.3071 and 0.3597. Given x29 is less than 0.8377, there are 1 out of 21 bankrupt firms, 14 out of 21 might be bankrupt firms and 6 out of 21 stable firms. Given x29 is greater than 0.8377 and x32 is less than 0.1075, there are 12 out of 23 stable firms and 11 out of 23 might be bankrupt firms. Given x29 is greater than 0.8377 and x32 is greater than 0.1075, there are 25 out of 27 stable firms and 2 out of 27 might be bankrupt firms.



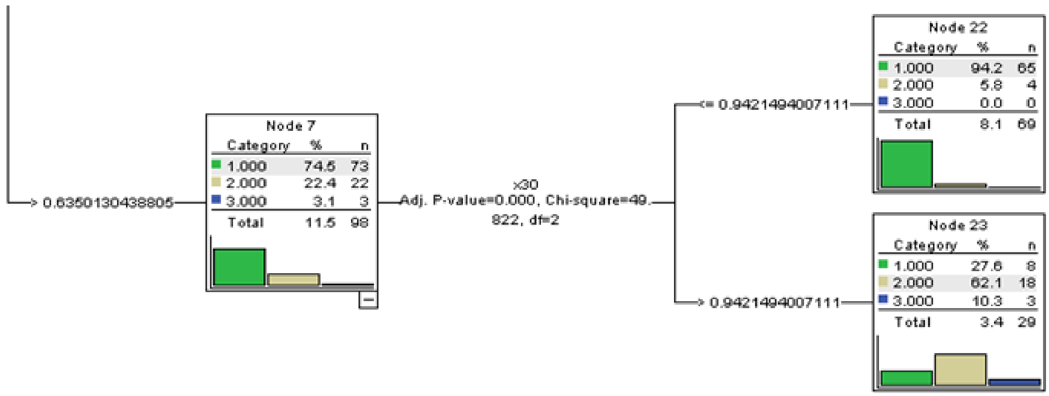
The fourth branch is the x7 between 0.3597 and 0.4103. Given x30 is less than 0.7946, there are 4 out of 39 bankrupt firms, 28 out of 39 might be bankrupt firms and 7 out of 39 stable firms. Given x30 is greater than 0.7946, there are 27 out of 34 stable firms and 7 out of 34 might be bankrupt firms.



The fifth branch is x7 between 0.4103 and 0.4789. Given x29 greater than 1.4397, there are 15 out of 47 might be bankrupt firms and 32 out of 47 stable firms. Given x29 is less than 1.4397 and x39 is less than 0.7417, there are 7 out of 27 bankrupt firms, 18 out of 27 might be bankrupt firms and 2 out of 27 stable firms. Given x29 is less than 1.4397 and x39 is greater than 0.7417, there are 9 out of 21 bankrupt firms and 12 out of 21 might be bankrupt firms.



The sixth branch is x7 between 0.4789 and 0.6350. Given x30 is greater than 1.2677, there are 17 out of 38 firms might be bankrupt and 21 out of 38 stable firms. Given x30 is between 0.7946 and 1.2677, there are 6 out of 43 bankrupt firms, 34 out of 43 might be bankrupt firms and 3 out of 43 stable firms. Given x30 is between 0.6015 and 0.7946, there are 25 out of 45 bankrupt firms and 20 out of 45 might be bankrupt firms. Given x30 is less than 0.6015, there will be another leaf nodes. Given x30 is less than 0.6015 and x17 is less than 0.3036, there are 13 out of 16 bankrupt firms and 3 out of 16 might be bankrupt firms. Given x30 is less than 0.6015 and x17 is greater than 0.3036, there are 33 out of 34 bankrupt firms and 1 out of 34 might be bankrupt firms.



The seventh branch is x7 greater than 0.6350. Given x30 is less than 0.9421, there are 65 out of 69 bankrupt firms and 4 out of 69 might be bankrupt firms. Given x30 is greater than 0.9421, there are 8 out of 29 bankrupt firms, 18 out of 29 might be bankrupt firms and 3 out of 29 good performance firms.

Classification

	Predicted			
Observed	1	2	3	Per cent Correct
1	145	26	1	84.3%
2	40	129	49	59.2%
3	0	42	417	90.8%
Overall Percentage	21.8%	23.2%	55.0%	81.4%

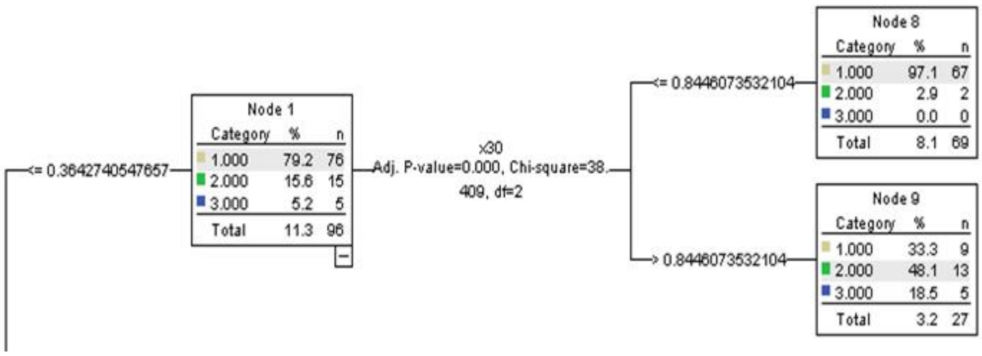
Table 5.3.2-a2 The Prediction accuracy of CHAID with F and NF (Z-score)

The prediction accuracy is shown above in Table 5.3.2-a2, where for bankrupt firms, there are 84.3% predicted correct, 59.2% predicted correctly for might be bankrupt firms and 90.8% predicted correctly for good performance firms. Overall the prediction accuracy is 81.4 per cent.

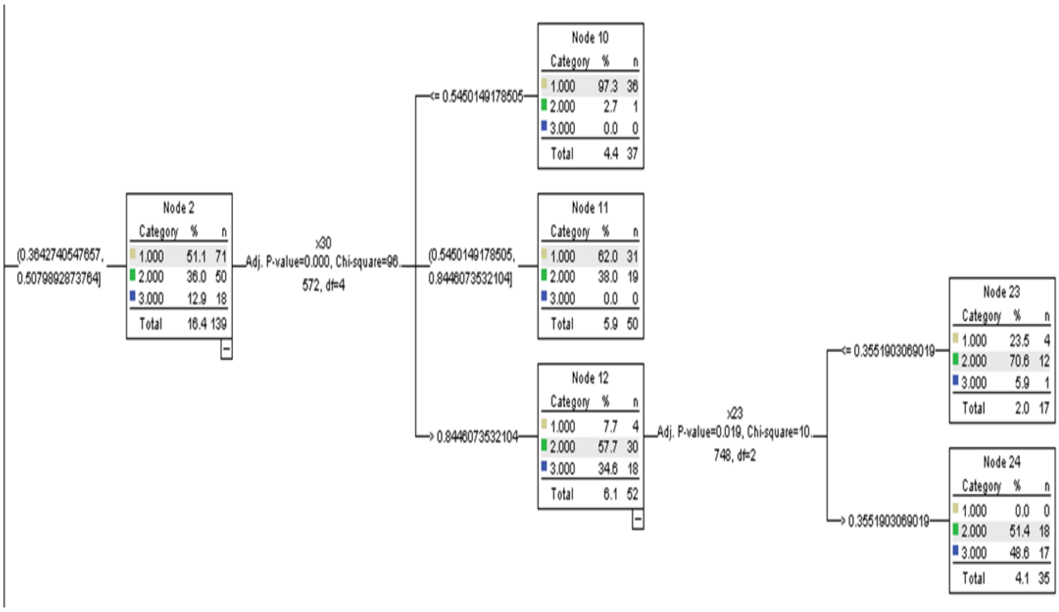
B. Independent variable: financial indicators

In this section, the dependent variable is selected as Z-score, while the independent variables are financial indicators only. The results of SPSS was shown in Appendix 1, Figure 5.3.2-b and the exact values of the nodes were shown in Appendix 1, Table 5.3.2-b1. The decision tree was detailed explained below.

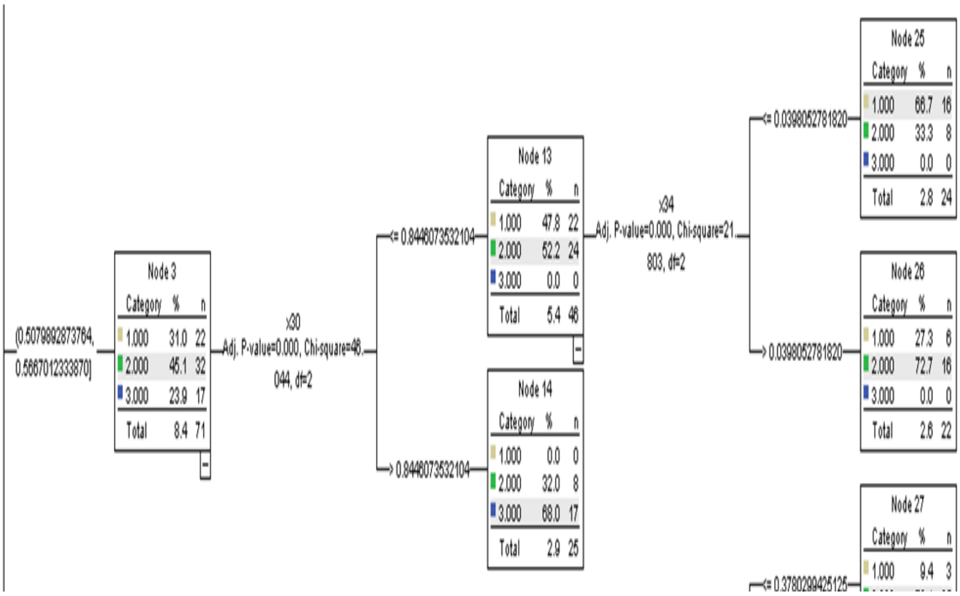
The parent node of this CHAID is x8, equity to total assets. There are seven different branches. The second hierarchy nodes are x30, x29, x17 and x23, which are total assets turnover, equity turnover, fixed assets to equity and long-term loans, and tangible fixed assets to total assets respectively. The third hierarchy nodes are x23, x34 and x17, which are tangible fixed assets to equity, net profit to assets and fixed assets to equity plus long-term loans.



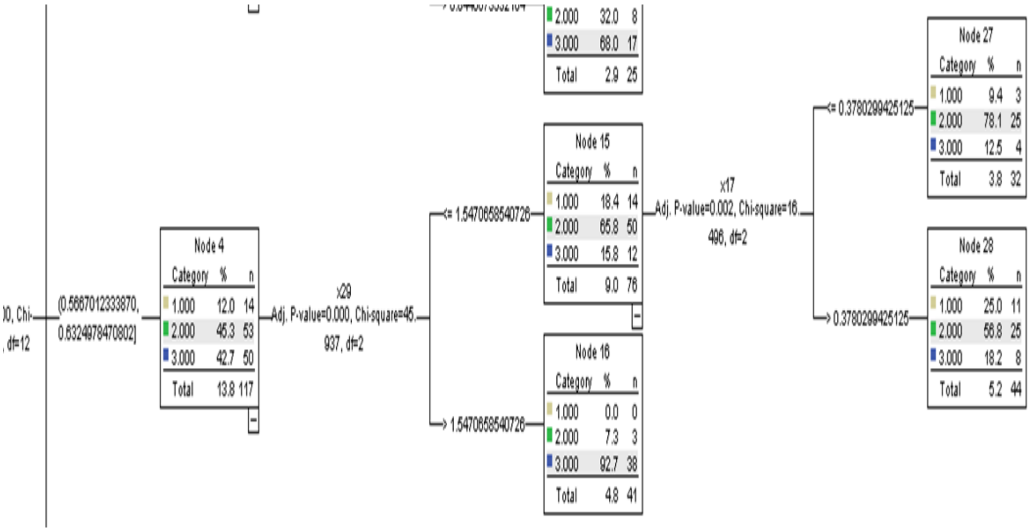
The first branch is x8 less than 0.3642. Given x30 is less than 0.8446, there are 67 out of 69 bankrupt firms and 2 out of 69 might be bankrupt firms. Given x30 is greater than 0.8446, there are 9 out of 27 bankrupt firms, 13 out of 27 might be bankrupt firms and 5 out of 27 stable firms.



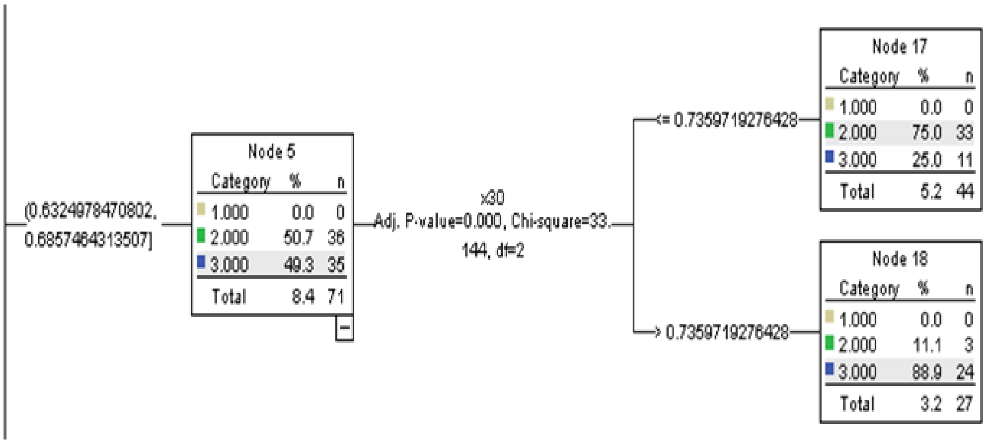
The second branch is x8 between 0.3642 and 0.5079. Given x30 is less than 0.5450, there are 36 out of 37 bankrupt firms and 1 out of 37 might be bankrupt firm. Given x30 is between 0.5450 and 0.8446, there are 31 out of 50 bankrupt firms and 19 out of 50 might be bankrupt firms. Given x30 is greater than 0.8446 and x23 is less than 0.3551, there are 4 out of 17 bankrupt firms, 12 out of 17 might be bankrupt firms and 1 out of 17 stable firms. Given x30 is greater than 0.8446, and x23 is greater than 0.3551, there are 18 out of 35 might be bankrupt firms and 17 out of 35 stable firms.



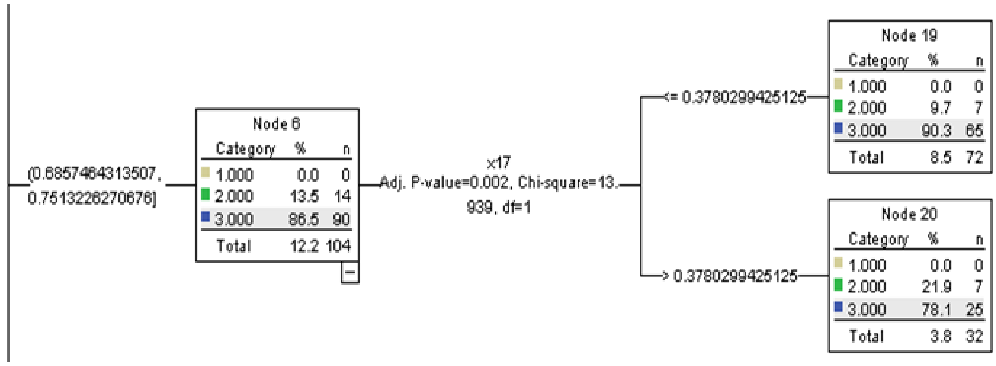
The third branch is x8 between 0.5079 and 0.5667. Given x30 is greater than 0.8446, there are 8 out of 25 might be bankrupt firms and 17 out of 25 stable firms. Given x30 is less than 0.8446 and x34 is less than 0.0398, there are 16 out of 24 bankrupt firms and 8 out of 24 might be bankrupt firms. Given x30 is less than 0.8446 and x34 is greater than 0.0398, there are 6 out of 22 bankrupt firms and 16 out of 22 might be bankrupt firms.



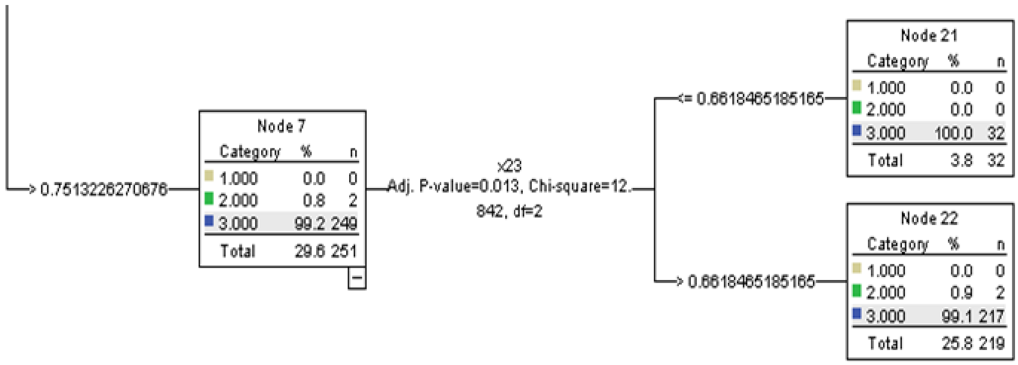
The fourth branch is x8 between 0.5667 and 0.6324. Given x29 is greater than 1.5470, there are 3 out of 38 might be bankrupt firms and 35 out of 38 stable firms. Given x29 is less than 1.5470 and x17 is less than 0.3780, there are 3 out of 32 bankrupt firms, 25 out of 32 might be bankrupt firms and 4 out of 32 stable firms. Given x29 is less than 1.5470 and x17 is greater than 0.3780, there are 11out of 44 bankrupt firms, 25 out of 44 might be bankrupt firms and 8 out of 44 stable firms.



The fifth branch is x8 between 0.6324 and 0.6857. Given x30 is less than 0.7359, there are 33 out of 44 might be bankrupt firms and 11 out of 44 stable firms. Given x30 is greater than 0.7359, there are 3 out of 27 might be bankrupt firms and 24 out of 27 stable firms.



The sixth branch is x8 between 0.6857 and 0.7513. Given x17 is less than 0.3780, there are 7 out of 72 might be bankrupt firms and 65 out of 72 stable firms. Given x17 is greater than 0.3780, there are 7 out of 32 might be bankrupt firms and 25 out of 32 stable firms.



The seventh branch is x8 greater than 0.7513. Given x23 is less than 0.6618, there are 32 out of 32 stable firms. Given x23 is greater than 0.6618, there are 2 out of 219 might be bankrupt firms and 217 out of 219 stable firms.

Classification

Observed	Predicted			
	1	2	3	Percent Correct
1	150	33	0	82.0%
2	30	142	30	70.3%
3	0	46	418	90.1%
Overall Percentage	21.2%	26.0%	52.8%	83.6%

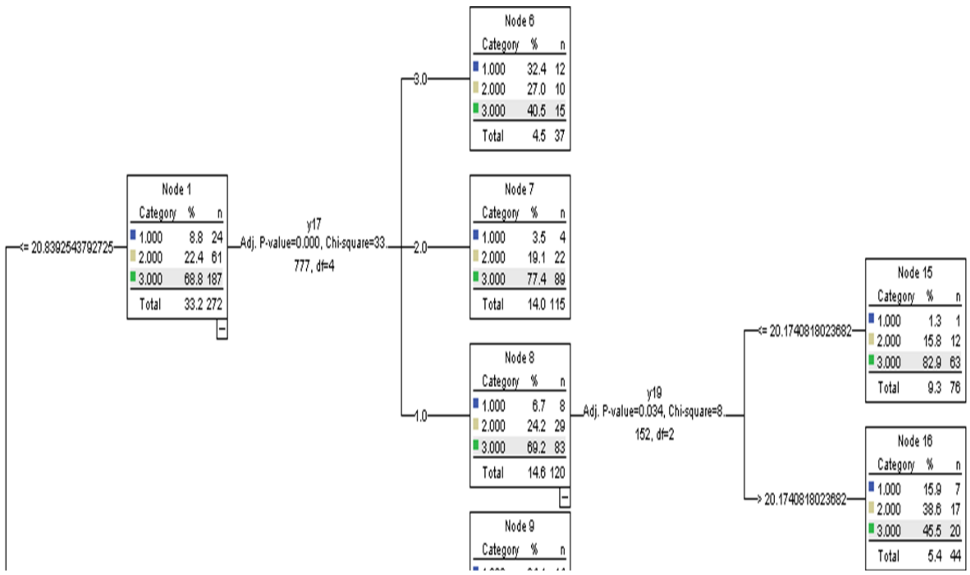
Table 5.3.2-b2 The Prediction accuracy of CHAID with F indicators (Z-score)

The table 5.3.2-b2 shows the accuracy of bankrupt firms is 82.0%, the accuracy of might be bankrupt firms is 70.3%, and the accuracy of stable firms is 90.1%. The overall prediction accuracy is 83.6%.

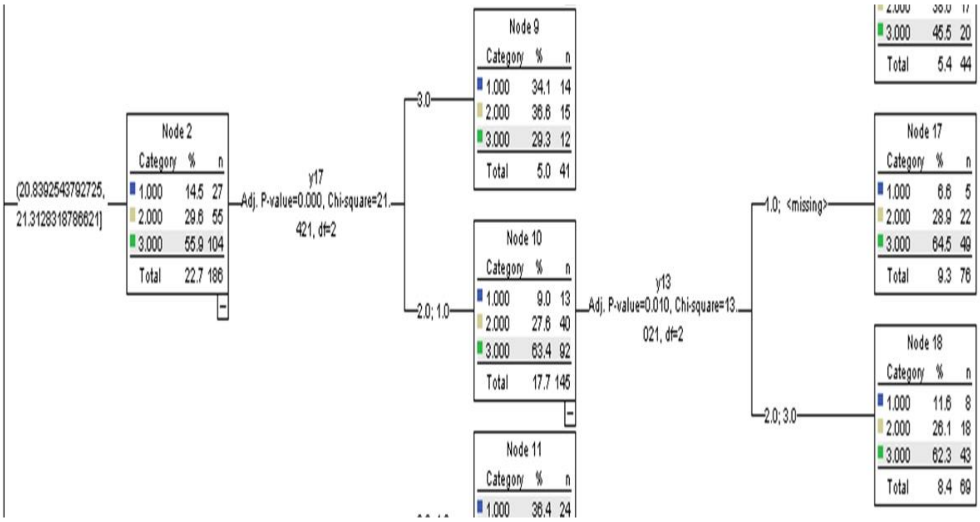
C. Independent variable: non-financial indicators

In this section, the dependent variable is selected as Z-score, while the independent variables are non-financial indicators only. The results of SPSS was shown in Appendix 1, Figure 5.3.2-c and the detailed values of the nodes were shown in Appendix 1, Table 5.3.2-c1. The decision tree was detailed explained below.

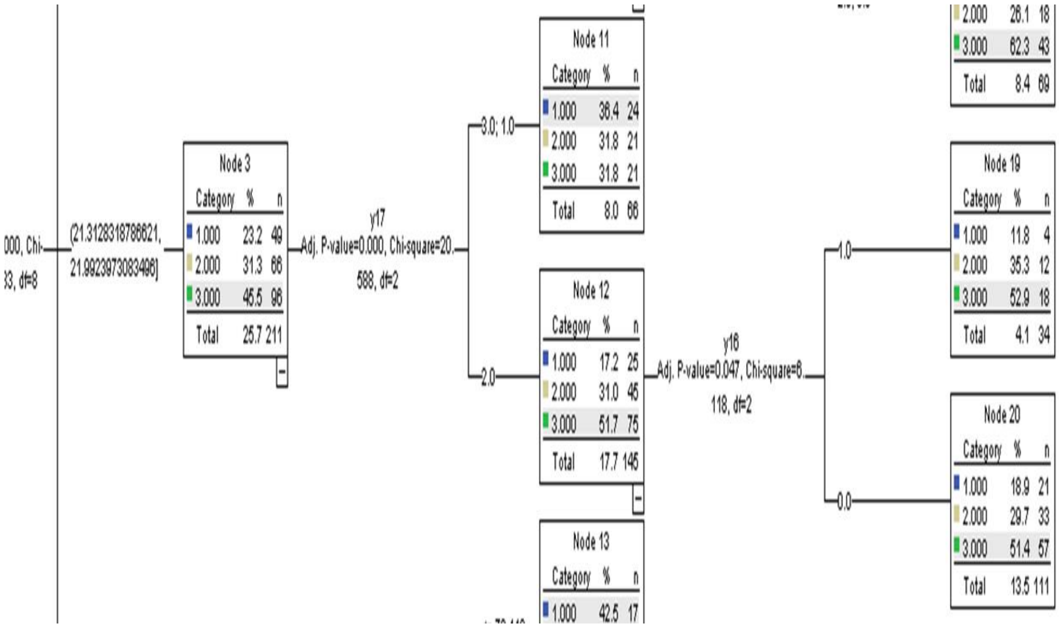
The parent node is y19, the size of firms. The child nodes are y17 and y7, which are listed duration and environment index. The terminal nodes are y19, y13 and y16, which are the size of firms, CEO shareholdings and tax rate. The size of firms was modified by logarithm. The CEO shareholdings are classified into three groups, less than 0.05, between 0.05 and 0.25 and greater than 0.25, which represent 1, 2 and 3 respectively. The tax rate is classified into two groups, greater than 0.20 and less than 0.20, which represent 1 and 0 respectively.



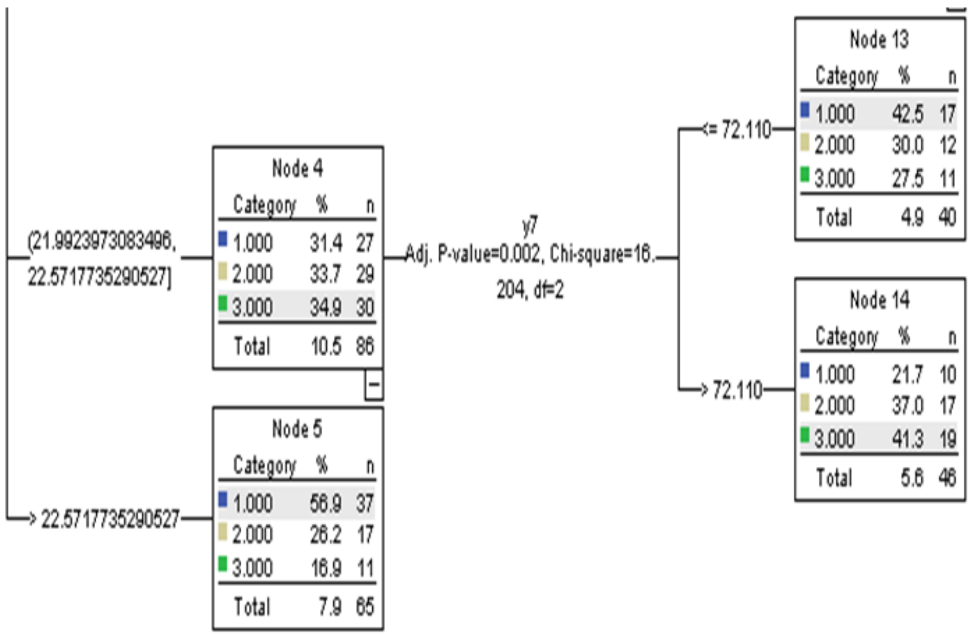
The first branch is y19 less than 20.8392. Given y17 is belong to group 3, there are 12 out of 37 bankrupt firms, 10 out of 37 might be bankrupt firms and 15 out of 37 stable firms. Given y17 is belong to group 2, there are 4 out of 115 bankrupt firms, 22 out of 115 might be bankrupt firms and 89 out of 115 stable firms. Given y17 is belong to group 3 and y19 is greater than 20.1740, there are 7 out of 44 bankrupt firms, 17 out of 44 might be bankrupt firms and 20 out of 44 stable firms. Given y17 is belong to group 3 and y19 is less than 20.1740, there are 1 out of 76 bankrupt firms, 12 out of 76 might be bankrupt firms and 63 out of 76 stable firms.



The second branch is y19 between 20.8392 and 21.3128. Given y17 is belong to group 3, there are 14 out of 41 bankrupt firms, 15 out of 41 might be bankrupt firms and 12 out of 41 stable firms. Given y17 is not in group 3 and y13 is belonged to group 1, there are 5 out of 76 bankrupt firms, 22 out of 76 might be bankrupt firms and 49 out of 76 stable firms. Given y 17 is not in group 3 and y13 is belonged to group 2 and gourp3, there are 8 out of 69 bankrupt firms, 18 out of 69 might be bankrupt firms and 43 out of 69 stable firms.



The third branch is y19 between 21.3128 and 21.9923. Given y17 is belong to group 1 and group 3, there are 24 out of 66 bankrupt firms, 21 out of 66 might be bankrupt firms and 21 out of 66 stable firms. Given y17 belongs to group 2 and y16 is belong to group 1, there are 4 out of 34 bankrupt firms, 12 out of 34 might be bankrupt firms and 18 out of 34 stable firms. Given y17 is belong to group 2 and y16 is belong to group 0, there are 21 out of 111 bankrupt firms, 33 out of 111 might be bankrupt firms and 57 out of 111 stable firms.



The fourth branch is y19 between 21.9923 and 22.57. Given y7 is less than 72.110, there are 17 out of 40 bankrupt firms, 12 out of 40 might be bankrupt firms and 11 out of 40 stable firms. Given y7 is greater than 72.110, there are 10 out of 46 bankrupt firms, 17 out of 46 might be bankrupt firms and 19 out of 46 stable firms. The fifth branch is y19 greater than 22.5717; there are 37 out of 65 bankrupt firms, 17 out of 65 might be bankrupt firms and 11 out of 65 stable firms.

Classification

	Predicted			
Observed	1	2	3	Per cent Correct
1	78	0	86	47.6%
2	50	0	178	.0%
3	43	0	385	90.0%
Overall Percentage	20.9%	.0%	79.1%	56.5%

Table 5.3.2-c2 The Prediction accuracy of CHAID with NF indicators (Z-score)

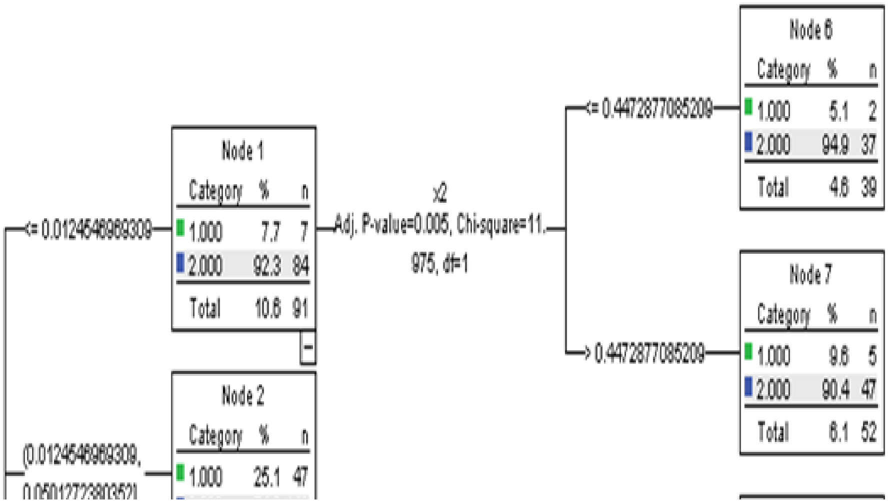
The Table 5.3.2-c2 shows the prediction accuracy of bankrupt firms is 47.6%, and the prediction accuracy of stable firms is 90.0%. However, the developed tree cannot detect the group 2 of Z-score, which is might be bankrupt firms. Therefore, the overall accuracy is 56.5%.

5.3.3 Dependent variable: growth of ROA;

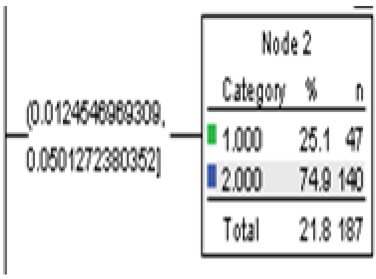
A. Independent variable: financial and non-financial indicators

In this section, the dependent variable is selected as growth of ROA, while the independent variables are financial indicators and non-financial indicators. The results of SPSS were shown in Appendix 1, Figure 5.3.3-a and the detailed values of nodes were shown in Appendix 1, Table 5.3.2-a1. The decision tree was detailed explained below.

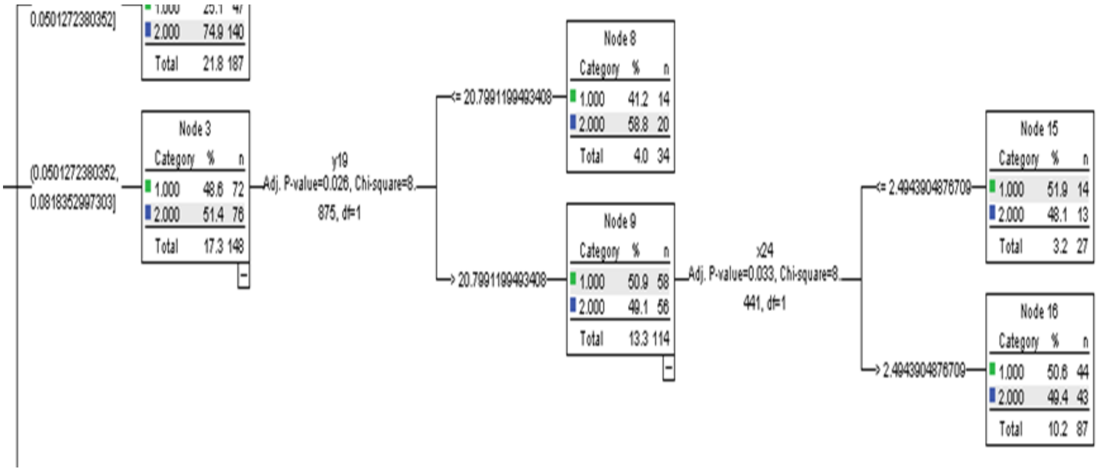
The growth of return on assets (ROA) could directly reflect the growth of profitability of firms. Based on the ratio, the performance of firms could be classified into two different groups: good and poor, where the classification rule is ROA greater or less than 0. The root node is the ROA, and the most significant ratio of ROA is x31, net profit to equity. There are five different branches from the root node. The range of net profit to equity is from 0.0124 to 0.2000. The child nodes are x2, y19 and y17 respectively, which are quick ratio, logarithm size of firms and listed ages. The secondary child nodes are x24 and x34, which are receivable turnover and net profit to asset. Moreover, the terminal node is x15, which is fixed assets to total loans.



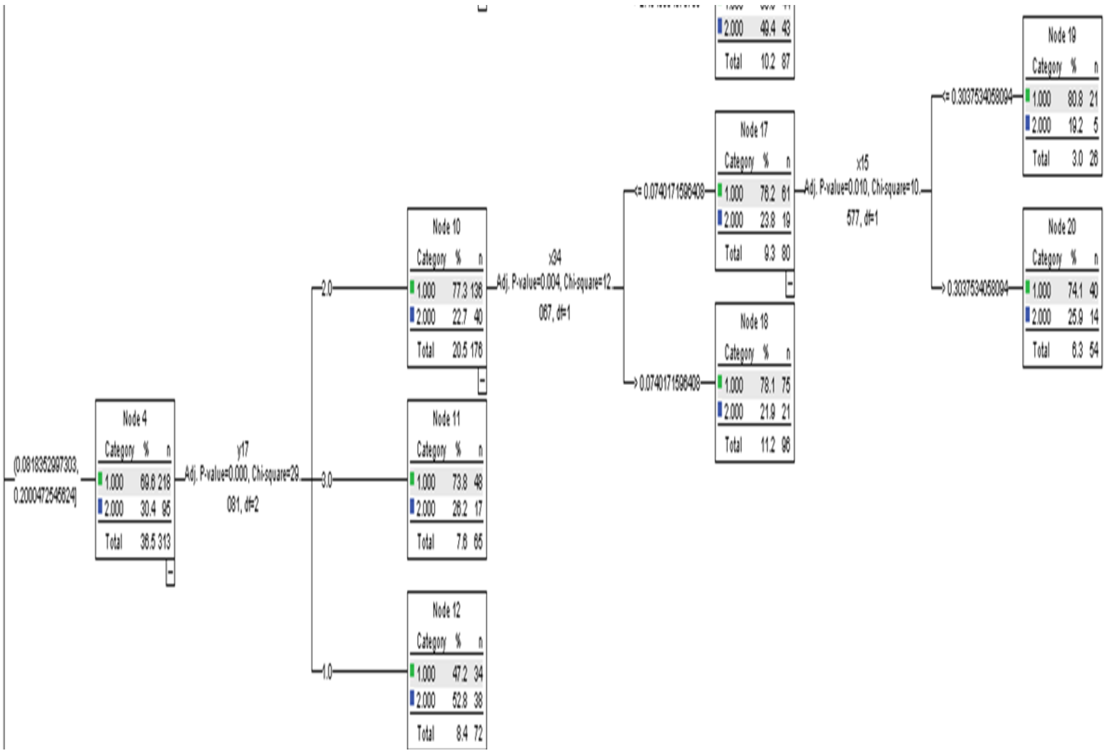
The first branch is shown above. Given x31 is less than 0.0124 and x2 is less than 0.4472, there are 2 out of 39 good performance firms and 37 out of 39 poor performance firms. Given x31 is less than 0.0124 and x2 is greater than 0.4472, there are 5 out of 52 good performance firms and 47 out of 52 poor performance firms.



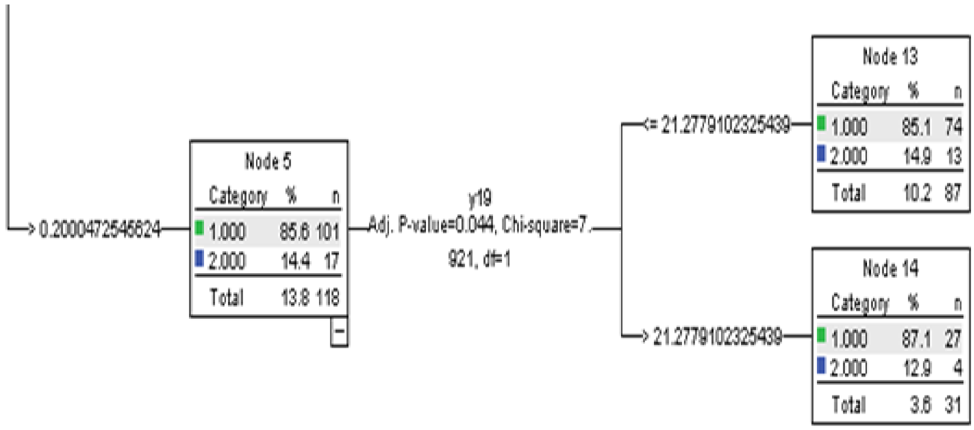
The second branch is relatively simple. If x31 is between 0.0124 and 0.0501, there are 47 out of 187 good performance firms and 140 out of 187 poor performance firms.



The third branch is x31 between 0.0501 and 0.0818. Given y19 is less than 20.7991, there are 14 out of 34 good performance firms and 20 out of 34 poor performance firms. Given y19 is greater than 20.7991 and x24 is less than 0.2494, there are 14 out of 27 good performance firms and 13 out of 27 poor performance firms. Given y19 is greater than 20.7991 and x24 is greater than 0.2494, there are 44 out of 87 good performance firms and 43 out of 87 poor performance firms.



The fourth branch is x31 between 0.0818 and 0.2000. Given y17 is belong to group 1, there are 34 out of 72 good performance firms and 38 out of 72 poor performance firms. Given y17 is belong to group 3, there are 48 out of 65 good performance firms and 17 out of 65 poor performance firms. Given y17 is belong to group 2 and x34 is greater than 0.0740, there are 75 out of 96 good performance firms and 21 out of 96 poor performance firms. Given y17 is belong to group 2, x34 is less than 0.0740 and x15 is less than 0.3037, there are 21 out of 26 good performance firms and 5 out of 26 poor performance firms. Given y17 is belong to group 2, x34 is less than 0.0740 and x15 is greater than 0.3037, there are 40 out of 54 good performance firms and 14 out of 54 poor performance firms.



The fifth branch is x31 greater than 0.2000. Given y19 is less than 21.2779, there are 74 out of 87 good performance firms and 13 out of 87 poor performance firms. Given y19 is greater than 21.2779, there are 27 out of 31 good performance firms and 4 out of 31 poor performance firms.

Classification

Observed	Predicted		
	1	2	Per cent Correct
1	333	112	74.8%
2	125	287	69.7%
Overall Percentage	53.4%	46.6%	72.3%

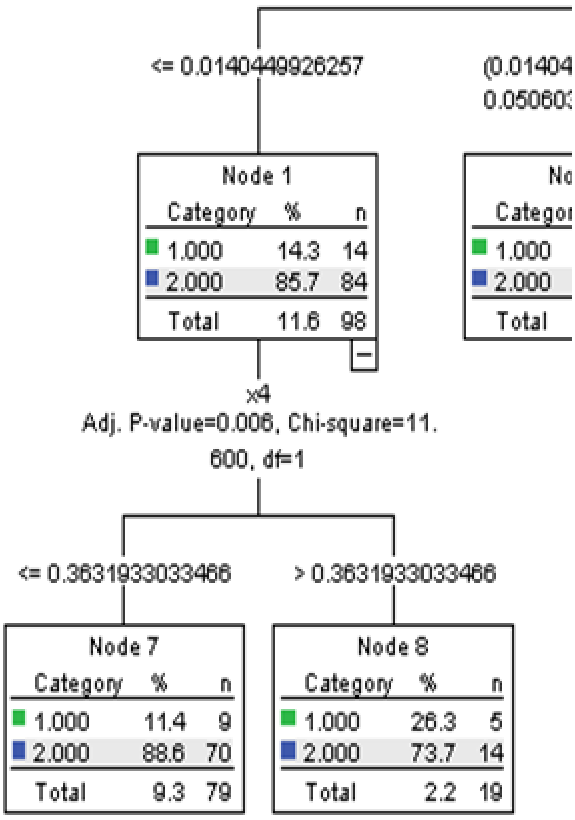
Table 5.3.3-a2 The Prediction accuracy of CHAID with F and NF indicators (ROA)

The predicted accuracy is shown above in Table 5.3.3-a2. The root node indicates that there are 445 good performance firms, which takes 51.9% of the total sample and 412 poor performance firms, which takes 48.1% of the total sample. Based on the CHAID method, there are 333 good performance firms, the predicted accuracy is 74.8% and 287 poor performance firms, and the predicted accuracy is 69.7%. The overall predicted accuracy is 72.3%.

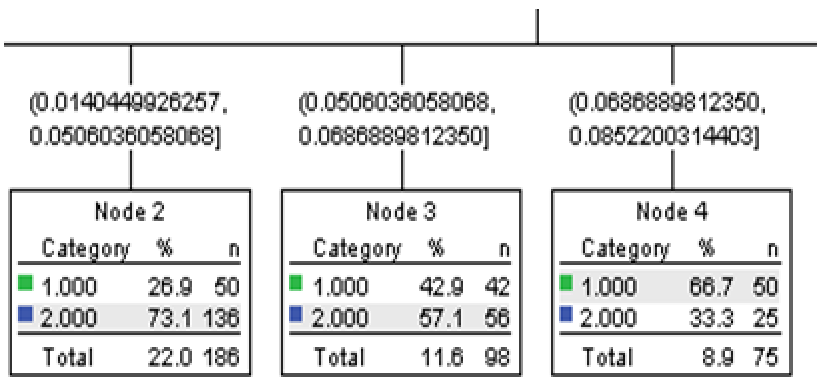
B. Independent variable: financial indicators

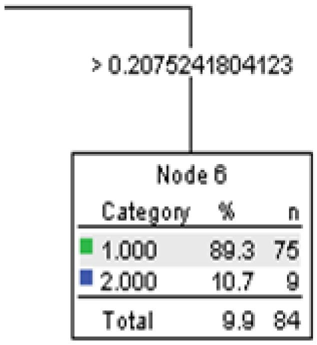
In this section, the dependent variable is selected as growth of ROA, while the independent variables are financial indicators only. The results of SPSS were shown in Appendix 1, Figure 5.3.2-b the detailed values of the nodes were shown in Appendix 1, Table 5.3.2-b1. The decision tree was detailed explained below.

The parent node of this CHAID is x31, net profit to equity. The range of x31 is between 0.0140 and 0.2075. The child nodes are x4 and x12, inventory to current assets and long-term liability to long-term liability and equity. The terminal nodes are x19 and x5, which are bank loans to total assets and inventory to total assets respectively. The group 1, 2 at the root node represents good performance and poor performance respectively.

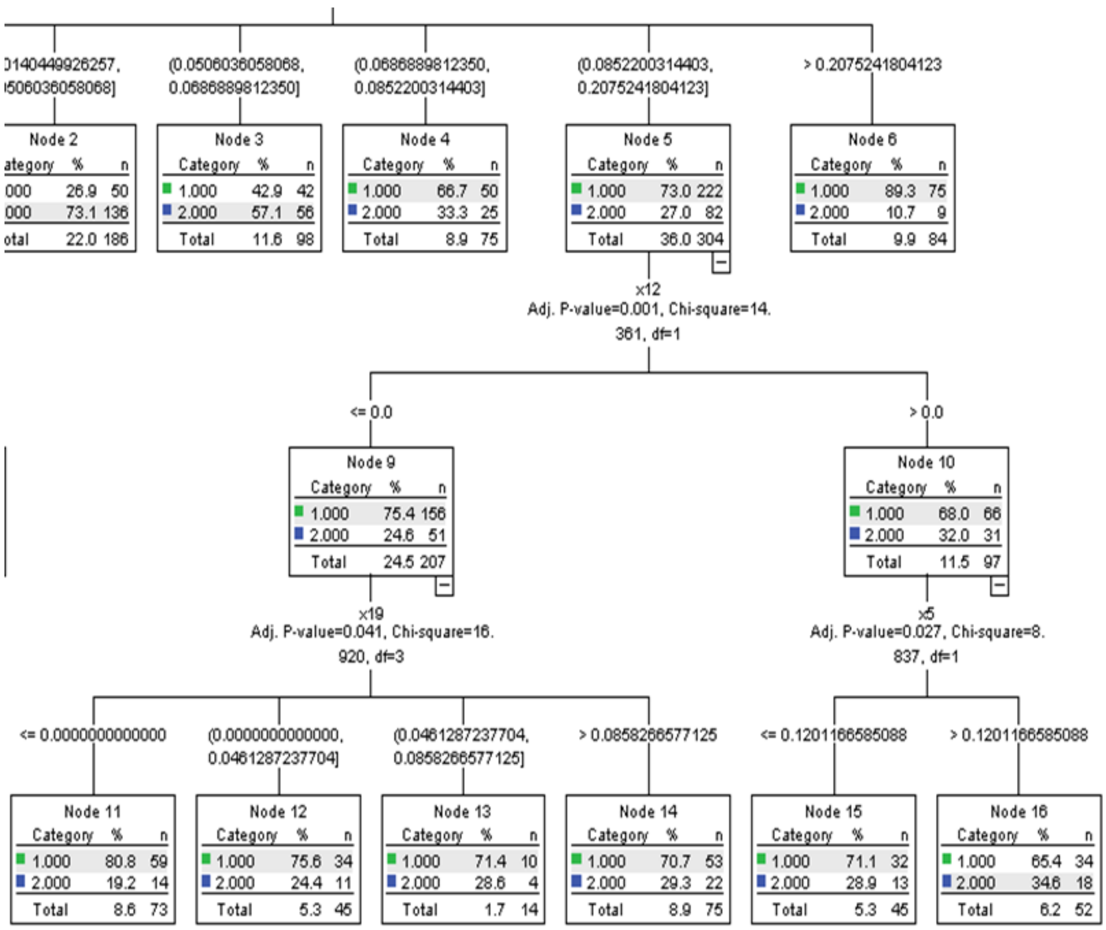


The first branch is x31 less than 0.0140. Given x4 is less than 0.3631, there are 9 out of 79 good performance firms and 70 out of 79 poor performance firms. Given x4 is greater than 0.3631, there are 5 out of 19 good performance firms and 14 out of 79 poor performance firms.





The second branch is x31 between 0.0140 and 0.0506; there are 50 out of 186 good performance firms and 136 out of 186 poor performance firms. The third branch is x31 between 0.0506 and 0.0686; there are 42 out of 98 good performance firms and 56 out of 98 poor performance firms. The fourth branch is x31 between 0.0686 and 0.0852; there are 50 out of 75 good performance firms and 25 out of 75 poor performance firms. The sixth branch is x31 greater than 0.2075; there are 75 out of 84 good performance firms and 9 out of 84 poor performance firms.



The fifth branch is x31 between 0.0852 and 0.2075. Given x12 is less than 0 and x19 is less than 0, there are 59 out of 73 good performance firms. Given x12 is less than0 and x91 is between 0 and 0.0461, there are 34 out of 45 good performance firms and 11 out of 45 poor performance firms. Given x12 is less than 0 and x19 is between 0.0461 and 0.0858, there are 10 out of 14 good performance firms and 4 out of 14 poor performance firms. Given x12 is less than 0 and x19 is greater than 0.0858, there are 53 out of 75 good performance firms and 22 poor performance firms. Given x12 is greater than 0 and x5 is less than 0.1201, there are 32 out of 45 good performance firms and 13 out of 45 poor performance firms. Given x12 is greater than 0 and x5 is greater than 0.1201, there are 34 out of 52 good performance firms and 18 out of 52 poor performance firms.

Classification

Observed	Predicted 1	2	Per cent Correct
1	313	140	69.1%
2	98	294	75.0%
Overall Percentage	48.6%	51.4%	71.8%

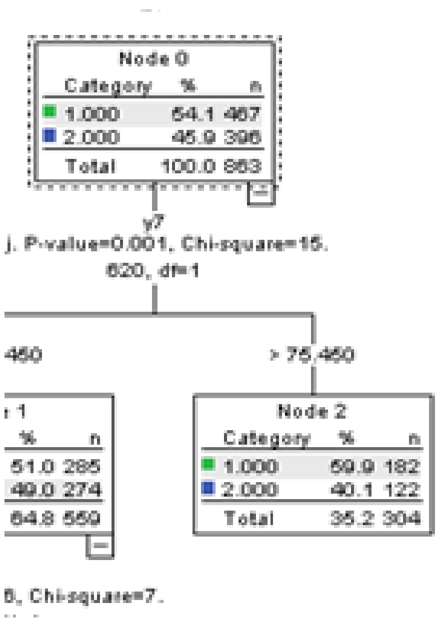
Table 5.3.3-b2 The Prediction accuracy of CHAID with F indicators (ROA)

The Table 5.3.3-b2 shows the predicted accuracy of good performance firms is 69.1%, while the predicted accuracy of poor performance is 75%. The overall accuracy is 71.8%.

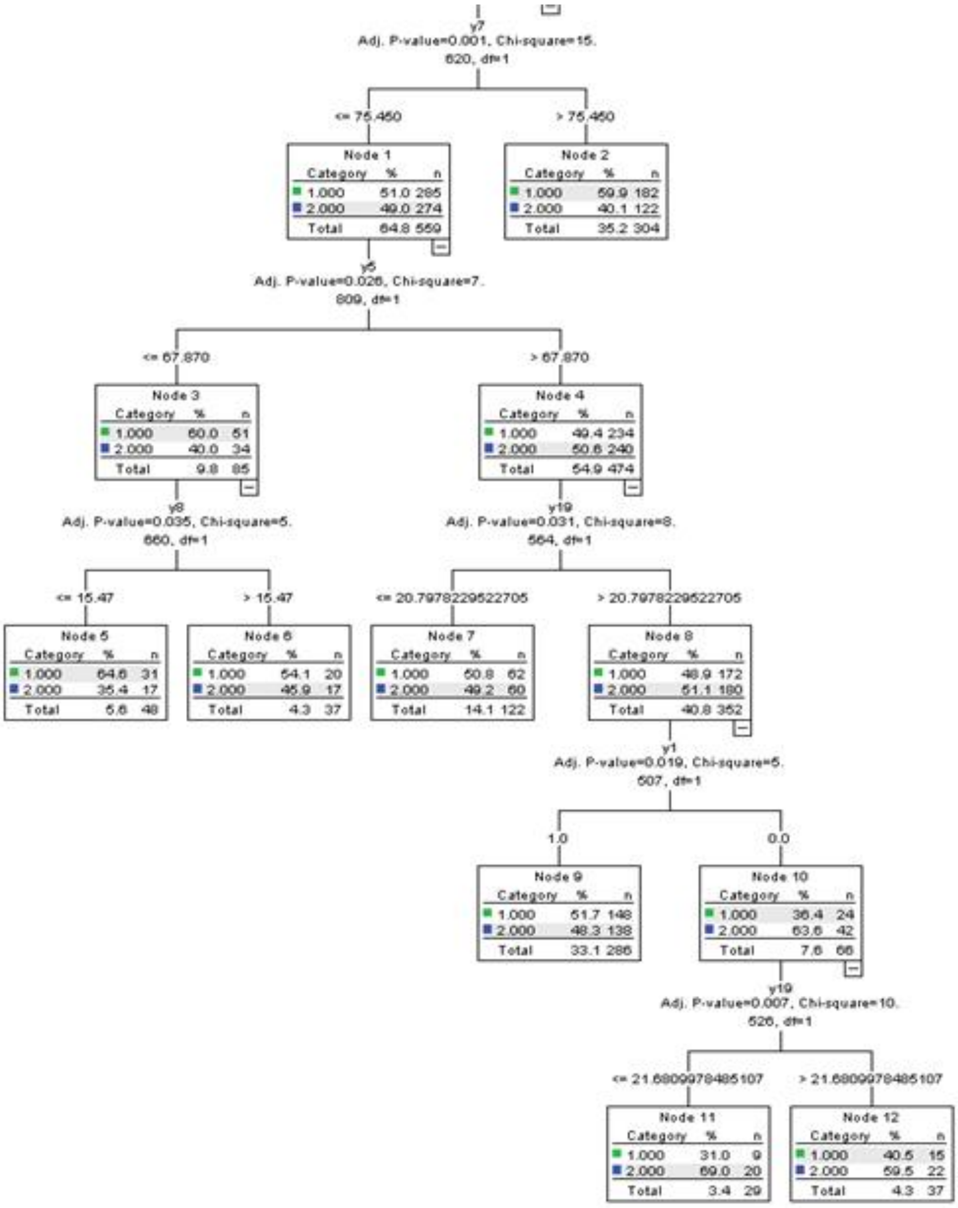
C. Independent variable: non-financial indicators

In this section, the dependent variable is selected as growth of ROA, while the independent variables are non-financial indicators only. The results of SPSS were shown in Appendix 1, Figure 5.3.3-c, the detailed values of the nodes were shown in Appendix 1, Table 5.3.2-c1. The decision tree was detailed explained below.

The result from SPSS is shown above. The variable y7, environmental index is the most significant variable to dependent variable. The second hierarchy node is y5, well-being index. The third hierarchy nodes are y8 and y19, which are technology innovation index and size of firms. The fourth hierarchy node is y1, industry. Moreover, the fifth hierarchy node is y19, the size of firms.



The first branch is that y7 is greater than 75.45. There are 182 out of 304 good performance firms and 122 out of 304 poor performance firms.



The second branch is y7 less than 75.45. Given y5 is less than 67.87 and y8 is less than 15.47, there are 31 out of 48 good performance firms and 17 out of 48 poor performance firms. Given y5 is less than 67.87 and y8 is less than 15.47, there are 31 out of 48 good performance firms and 17 out of 48 poor performance firms. Given y5 is less than 67.87 and y8 is greater than 15.47, there are 20 out of 37 good performance firms and 17 out of 37 poor performance firms. Given y5 is greater than 67.87 and y19 is less than 20.7978, there are 62 out of 122 good performance firms and 60 out of 122 poor performance firms. Given y5 is greater than 67.87, y19 is greater than 20.7978 and y1 is belonged to group 1 (manufacture), there are 148 out of 286 good performance firms and 138 out of 286 poor performance firms. Given y5 is greater than 67.87, y19 is greater than 20.7978, y1 is belonged to group 0 (non-manufacture) and y19 is less than 21.6809, there are 9 out of 29 good performance firms and 20 out of 29 poor performance firms. Given y 15 is greater than 67.87, y19 is greater than 20.7978, y1 is belonged to group 0 and y 19 is greater than 21.6809, there are 15 out of 37 good performance firms and 22 out of 37 poor performance firms.

Classification

	Predicted		
Observed	1	2	Pre cent Correct
1	147	320	31.5%
2	73	309	80.9%
Overall Percentage	25.9%	74.1%	53.7%

Table 5.3.3-c2 The Prediction accuracy of CHAID with NF indicators (ROA)

The Table 5.3.3-c2 shows the prediction accuracy of good performance firms is 31.5%, and the prediction accuracy of poor performance firms is 80.9%. The overall accuracy is 53.7%.

5.3.4 Summary

This research has included 849 firms listed on the small and medium-size enterprises board in Shenzhen in China. There are only ten firms is special treatment firms (ST firms). Although the special treatment is the official announcement of firm performance, there might be lack of accuracy in the procedure. If the sample data used ST and non-ST as a classification rule, the sample would be grouped as 839: 10. Xie and Me (2013) have selected 2207 from A-share listed companies, where there are 158 ST firms. They have randomly selected 30% of the full sample with 158 ST firms as a sample set, where the sample set includes 766 firms in total. Moreover, they randomly selected 70% of the sample set as train set and 30% of the sample set as a test set. Chen and Yi (2007) also applied the CHAID method in Chinese stock market. They selected the listed firms that total shares of the firms are less than 50 million Yuan and operational revenue or total assets are less than 500 million Yuan. They manually excluded the special treatment firms and selected 111 firms as sample data. Koyuncugil and Ozgulbas (2012) have collected financial data of 7,853 firms in Turkey from Turkey Centre Bank database. They measured the financial performance using all financial variables of a firm. In their study, financial performance indicators are the target variable, and all other financial variables are predictor variable. However, in their study, there is not a uniform standard to select the dependent variable. The performance measure could follow an existing standard or the objective fact. Therefore, the Z-score, which was developed by Altman in 1968, was selected as the existing standard. The profitability of firms could be considered as performance measurement, such as return on assets, return on equity, net profit growth, etc. Moreover, the growth rate or return on assets has been selected as the dependent variable in this study. If the growth rate is positive, the firm was considered as good performance, while the firms with negative growth rate on ROA are poor performance. Therefore, this research has applied two different dependent variables in order to compare the difference in prediction accuracy.

The independent variables are also different from other studies. This research has applied two different ratios as the dependent variable (Z-score and ROA) and two groups of independent variables (financial and non-financial). The model came from the Enterprise risk management framework suggested by CAS (2003) and concluded by Verbano and Ventruini (2013). It is going to find the relationship between financial and non-financial indicators and firm performance. There are six combinations of dependent variable and independent variables, which are Z-score with financial and non-financial indicators, Z-score with financial indicators, Z-score with non-financial indicators, ROA with financial and non-financial indicators, ROA with financial indicators and ROA with non-financial indicators. The model accuracy for Z-score with both financial and non-financial indicators model is 81.4%, for Z-score with financial indicators is 83.6% and for Z-score with non-financial indicators is 56.5%.

Classification Z-score with financial and non-financial				
Observed	Predicted			
	1	2	3	Percent Correct
1	145	26	1	84.30%
2	40	129	49	59.20%
3	0	42	417	90.80%
Overall Percentage	21.80%	23.20%	55.00%	81.40%
Classification Z-score with financial				
Observed	Predicted			
	1	2	3	Percent Correct
1	150	33	0	82.00%
2	30	142	30	70.30%
3	0	46	418	90.10%
Overall Percentage	21.20%	26.00%	52.80%	83.60%
Classification Z-score with non-financial				
Observed	Predicted			
	1	2	3	Percent Correct
1	78	0	86	47.60%
2	50	0	178	0.00%

3	43	0	385	90.00%
Overall Percentage	20.90%	0.00%	79.10%	56.50%

Table 5.3.4-a The Overall prediction accuracy of CHAID (Z-score)

The Table 5.3.4-a shows the prediction accuracy. It could be seen that the prediction accuracy for the group 2 (might be bankrupt firms) is relatively lower than the other two groups. It is clear that the grey area of Z-score, which is group 2, is very difficult to accurately predict by using CHAID with any combinations of independent variables. The highest accuracy is 83.6%, which is Z-score with financial indicators as independent variables. Since the calculation of Z-score is mainly based on financial ratios, it is reasonable that the financial indicators are the most significant variables in the Z-score based CHAID models. However, if we excluded the group 2 in the result, it could be seen that the overall accuracy for Z-score with financial and non-financial indicators is the most accurate predict model (84.3% and 90.8% versus 82% and 90.1% or 47.6% and 90%). Followed the Z-score with financial and non-financial model, it could be concluded that x7, x28, y2, x29, x30, x32, x39 and x17 are significant to the Z-score, where are total loans to total assets, fixed asset turnover, number of employees, equity turnover, total assets turnover, profit before tax to equity, cost of goods sold to net sales and fixed assets to equity and long-term loans. There are several roadmaps could be developed based on the CHAID model. If x7 (total loans to total assets) is less than 0.2483 and x28 (fixed asset turnover) is greater than 1.1417, the firms have 99.1% to be stable firms. If x7 (total loans to total assets) is between 0.3071 and 0.3597, x29 (equity turnover) is greater than 0.8377 and x32 (profit before tax to equity), the firms have 92.6% to be stable firms. If x7 (total loans to total assets) is between 0.4789 and 0.6350, x30 (total assets turnover) is less than 0.6015 and x17 (fixed assets to equity and long-term loans) is greater than 0.3036; the firms have 97.1% to be bankrupt firms. If x7 (total loans to total assets) is greater than 0.6350 and x30 (total assets turnover) is less than 0.9421, the firms have 94.2% to be bankrupt firms.

Classification ROA Financial and non-financial			
Observed	Predicted		
	1	2	Percent Correct
1	333	112	74.80%
2	125	287	69.70%
Overall Percentage	53.40%	46.60%	72.30%
Classification ROA Financial			
Observed	Predicted		
	1	2	Percent Correct
1	313	140	69.10%
2	98	294	75.00%
Overall Percentage	48.60%	51.40%	71.80%
Classification ROA Non-financial			
Observed	Predicted		
	1	2	Percent Correct
1	147	320	31.50%
2	73	309	80.90%
Overall Percentage	25.90%	74.10%	53.70%

Table 5.3.4-b The Overall prediction accuracy of CHAID (ROA)

The prediction accuracy of CHAID with ROA was shown in Table 5.3.4-b. The classification rules for ROA are relatively simple, which are good performance (group 1) and poor performance (group 2). The sample includes 863 firms. The prediction accuracy of ROA with financial and non-financial indicators for good performance firms is 72.3%, where the accuracy of good performance firms is 74.8%, and accuracy of poor performance firms is 69.7%. The prediction accuracy of ROA with financial indicators only is 71.8%, where the accuracy of good performance firm is 69.1%, and accuracy of poor performance is 75%. The prediction accuracy of ROA with non-financial indicators only is 53.7%, where the accuracy of good performance is 31.5%, and accuracy of poor performance is 80.9%. It is true that including non-financial indicators in the CHAID model could increase the accuracy of prediction. For instance, in the ROA with financial and non-financial indicator model, the prediction accuracy of good performance firms is 74.8%, which is higher than 69.1% in ROA with the financial indicators model and 31.5% in ROA with the non-financial indicators model. However, the prediction accuracy of poor performance firms in ROA with financial and non-financial is 69.7%, which is lower than the other two models (75% and 80.9% respectively). In the ROA with the non-financial indicators model, the prediction for poor performance firms is exceptionally high. Therefore, it is important to find out the roadmap for ROA with financial and non-financial and the poor performance firms in ROA with non-financial indicators.

There are several variables significant in measuring firm performance in ROA based CHAID models. The x31, x2, y19, y17, x24, x34 and x15, which are net profit to equity, quick ratio, size of firms, listed time, receivable turnover, net profit to assets and fixed assets to total loans, are significant to the dependent variable ROA. There are several roadmaps could be obtained from the CHAID model. In the ROA with the financial and non-financial indicators model, if x31 (net profit to equity) is less than 0.0124 and x2 (quick ratio) is less than 0.4472, there is 94.9% that the firms are poor performance firm. If x31 (net profit to equity) is less than 0.0124 and x2 (quick ratio) is greater than 0.4472, there is 90.4% that the firms are poor performance firms. If x31 (net profit to equity) is between 0.0818 and 0.2000, y17 (listed time) is in group 2, x34 (receivable turnover) and x15 (fixed assets to total loans) are less than 0.3037, there is 80.8% that the firms are good performance firms. If x34 (net profit to equity) is greater than 0.2000 and y19 (logarithm size of firms) is greater than 21.277, there is 87.1% that the firms are good performance firms. Since the ROA with non-financial indicators is superior in the prediction of poor performance firms, it is necessary to find out the roadmap for poor performance firms in the model. In the model, y7, y5, y8, y19 and y1, which are environment index, well-being index, technology innovation index, logarithm size of firms and industry, are significant to the ROA. If y7 (environment index) is less than 75.45, y5 (wellbeing index) is greater than 67.87, y19 (logarithm size of firms) is greater than 20.7978, y1 (industry) belongs to group 0 (not manufacture) and (logarithm size of firms) is less than 21.68, there is 69% that the firms are poor performance firms.

The result of CHAID model is not quite the same compared with other studies. In the research by Koyuncugil and Ozgulbus (2012), the sample includes 7,853 firms. Since they have way more samples in their model, they could build CHAID tree with more branches and hierarchies. Meanwhile, with more detailed nodes, they could also obtain the 100% roadmaps with enough samples at end nodes. However, they did not provide the prediction accuracy in their research. Instead of predict accuracy, they provide several roadmaps of no risk for the firms. In the other study in China stock market, Chen and Yi (2007) only applied 14 financial ratios with 111 sample firms built a CHAID model, in which the accuracy is 88.6%. The CHAID model in their study is relatively simple, where there are only three hierarchies.

Meanwhile, their study manually selected 111 firms and excluded all the ST (special treatment) firms. Xie and Me (2013) also applied CHAID in the Chinese stock market. They selected the combination of 158 ST firms and non-ST firms as sample data, which includes 766 firms. Moreover, they built a train set and a test set from the same sample data. The accuracy of the test set is 81.14%. However, they applied the CHAID model to identify whether the firm is ST firm or not. Moreover, they used the same year to test the accuracy of the model, which may be argued the meaningfulness of the test set may be biased. Therefore, it could be concluded that this research has applied the more logical method in building sample data, train set and test set. The accuracy is acceptable, and the result is more convincing since the train set was all the listed SMEs in 2012 and the test set is the same data set in 2013. There are also several roadmaps have been obtained for firms in order to improve the performance or reduce the probability of being bankrupt.

The result also complied with the studies of other scholars. Altman et al. (2010) have applied Logit regression to test the significance of financial ratios and qualitative information. They suggested twenty-two potential non-financial variables. In this study, the age bands, auditor information, total assets and subsidiary information were included. Li et al. (2017) also suggested potential non-financial about CEO power. In the balance sheet of listed SMEs in China, CEO tenure and CEO shareholdings could be obtained, which were included in the non-financial variables in this study. In this study, the size of firms and age of firms on board (listed duration) were significant to the firm performance. However, the CEO related information is different from the research of Li et al. in 2017, where only CEO shareholdings are significant in CHAID model. Since the research by Li et al. (2017) used linear regression and principal components analysis (PCA) to conduct their main variables. It is possible that the CEO power related variables are not significant in CHAID model. In the research of Koyuncugil and Ozgulbas (2012), there are 15 financial variables significantly related to the firm performance. There are several variables overlapped in this study, which are receivable turnover, bank loans to total assets, fixed assets to long-term loans and equity, return on equity, profit before tax to equity and equity turnover. It could be concluded that the result for financial indicators result is quite similar in different research, while there is still part of non-financial ratios are overlapped with other scholars' studies. Therefore, it has been proved that the CHAID model verified the significance of financial and non-financial ratios in the analysis of firm performance.

In order to deeply investigate the risk indicators in the DM-RM model, it is necessary to find out the variables under risk catalogues developed by CAS (2003). Followed the ERM framework by CAS (2003), the selected variables could be generated under each risk catalogue.

Model	Significant variables	
Z-score with financial and non-financial indicators	x7, x28, y2, x29, x30, x32, x39, x17	total loans to total assets, fixed assets turnover, number of employees, equity turnover, total assets turnover, profit before tax to equity, cost of goods sold to net sales, fixed assets to equity and long-term loans
Z-score with financial indicators	x8, x30, x29, x17, x23, x34	equity to total assets, total assets turnover, equity turnover, fixed assets to equity and long-term loans, tangible fixed assets to total assets, net profit to total assets
Z-score with non-financial indicators	y19, y17, y7, y13, y16	size of firms, listed duration, environment index, CEO shareholding, tax rate
ROA with financial indicators and non-financial indicators	x31, x2, y19, y17, x24, x34, x15	net profit to equity, quick ratio, size of firms, listed duration, receivable turnover, net profit to assets, fixed assets to total loans
ROA with financial indicators	x31, x4, x12, x19, x5	net profit to equity, inventory to current assets, long-term liability to long-term liability and equity, bank loans to total assets, inventory to total assets.
ROA with non-financial indicators	y7, y5, y8, y19, y1	Environment index, well-being index, technology innovation index, size of firms, industry

Table 5.3.4-c Significant indicators in CHAID models

From Table 5.3.4-c above, it indicates that there are several financial and non-financial indicators are significant in the CHAID model. The hazard risks could be explained by the development of society index, environment index. The financial risks could be explained by profit before tax to equity, cost of goods sold to net sales, net profit to total assets, equity to total assets, net profit to assets, long-term liability to long-term liability and equity, bank loans to total assets and fixed assets to equity and long-term loans. The operational risks could explain by fixed assets turnover, equity turnover, total assets turnover, quick ratio, receivable turnover, inventory to current assets, CEO shareholdings and inventory to total assets. The strategic risks could be explained by listed duration, industry, development of society index, economic development index, tax rate, size of firm and number of employees. Therefore, it is clear that the risk indicators from the CHAID models matched the risk catalogues provided by CAS (2003).

Followed the result of CHAID model, it is possible to generate the warning signals for each risk indicator based on four different risks. Firstly, the hazard risk includes wellbeing index and environment index, which are three non-financial indicators. When the environment index is greater than 75.45, there is 60% that the firms are good performance firms. The environment index includes the resource consumption and environment improvement (NBSC, 2013). NBSC (2013) stated that resource consumption includes energy consumption per GDP, water consumption per GDP and construction land occupancy per GDP. The environment improvement includes investment in environmental improvement, industrial waste compliance rate, domestic wastewater treatment rate, environmental quality index and domestic garbage treatment rate. The wellbeing index includes the income allocation, life quality and employment. NBSC (2013) stated that income allocation reflects the relationship between income and GDP. The life quality includes disposable income, average net income of rural population, Engel coefficient of urban and rural families, average living space, council housing proportion, internet popularising rate, average vehicles per 10,000 people; average expected lifespan, water supply rate and social service bad spaces per 1,000 people. The employment tells the unemployment rate of rural and urban areas. Followed the catalogues under hazard risks by CAS (2003), it could be concluded that the environment index could tell wisdom and other natural perils and fire and other property damage. Meanwhile, there are other indicators included in other variables, which may be not significant in this model, such as development of society index, economic development index, etc. Although not all of the indexes are significant with the CHAID method, it could be concluded that theft and other crime, personal injury, disease and disability (include working related ones). According to NBSC (2013) report, the indexes could indicate social security, social welfare, etc. Therefore, it is true that the hazard risks could be mainly explained by selected non-financial indicators, which could also provide accepted predicted accuracy.

The financial risks consider the price, liquidity, credit, inflation/purchasing power and Hedging/basis risk (CAS, 2003). The ratios that measure the ability to make profit, credit, liquidity could be catalogued under financial risks. In the CHAID models, profit before tax to equity, costs of goods sold to net sales, fixed assets to equity and long-term loans, net profit to total assets, net profit to equity and bank loans to total assets are significant with firms performance. Koyuncugil and Ozgulbas (2012) stated that the profitability ratios include net profit to equity, profit before tax and cost of goods sold to net sales. These ratios indicate that the ability of making profit, which is the main financial related function for firms. The liquidity and credit are similar in measuring the ability of paying debts of firms. In the CHAID models, fixed assets to equity and long-term loans, quick ratio, long-term liability to long-term liability and equity, inventory to current assets and bank loans to total assets are significant to firm performance. These ratios could explain the liquidity and credit-related problems faced by firms. Koyuncugil and Ozgulbas (2012) also selected quick ratio and inventory to current assets as liquidity indicators. Moreover, they chose long-term liability to long-term liability and equity and bank loans to total assets and fixed assets to equity as an indicator for 'financial position', which indicates the situation of long-term and short-term debts.

The operational risks include business operations, empowerment information technology, information/ business reporting (CAS, 2003). It could be concluded that the firms' turnover ratios represent the business operations. In the CHAID models, fixed assets turnover, equity turnover, total assets turnover and receivable turnover are significant with firm performance. Meanwhile, the information/business reporting could be indicated by audit related variables, such as auditor opinions, auditor fees. However, empowerment information technology cannot be found in the annual report provided by listed firms. Although not all of the information about operational risks was included in CHAID models, the turnover rations and audit information could explain significant operational risks. Therefore, it could be concluded that the CHAID models could explain the operational risks.

The strategic risks indicated the macro-environment of firms, which included competition, firms' strategic, technology support and policy support (CAS, 2003). The inventory to current assets and inventory to total assets could indicate the customer wants and purchasing trends. When the inventory to current assets is less than 0.3631 or inventory to total assets is less than 0.1201, there is 88.6% or 71.1% respectively; the firm is a good performance firm. Meanwhile, the costs of goods sold to sales could also partly explain the trends in customers. Similarly, in financial risks, the cost of goods sold to sales should not exceed a certain range, which means the cost of principal operating activity should maintain an acceptable level in order to avoid poor performance. The technology innovation index explained the technology innovation under strategic risks. When technology innovation index is less than 15.47, there is

64.6% that the firms are good performance firms. The industry catalogue indicates if the firms are not in the manufacture, there is 63.6% the firms are good performance firms. The tax rate stated that if the tax rate of firms is greater than 0.2%, there is 52.9% that the firm is a good performance firm. It could be concluded that the tax rate is not a dominated variable in the classification of firm performance since the probability is more like a fifty-fifty chance. The technology innovation is not the higher, the better in listed Chinese SMEs. It is possible that the spending on research and development could increase the burden on SMEs' capital usage. The SMEs in manufacture are more likely become poor performance since the manufacture required more capital and large-scale than other industries. Therefore, it is clear that the major business is the most important element in strategic risks, which reflected the customer wants. The technology innovation may have negative impact on the firm performance, and the policy support does not take an essential part in the classification of firm performance.

Variables	Importance	Variables	Importance
x34	0.070	x18	0.014
x31	0.059	x23	0.014
x32	0.057	x27	0.014
x37	0.031	x11	0.013
x39	0.025	x26	0.013
x17	0.019	y17	0.013
x4	0.018	x7	0.013
x6	0.018	x8	0.013
x16	0.018	y5	0.013
x30	0.017	y8	0.013
x15	0.017	y15	0.013
x35	0.017	y3	0.013

x22	0.016	y11	0.013
x28	0.016	x12	0.013
x38	0.015	x24	0.013
x33	0.015	x19	0.013
y19	0.015	x2	0.013
x21	0.015	y9	0.013
y18	0.015	x20	0.013
x5	0.015	y14	0.012
x29	0.015	x1	0.012
x25	0.014	y4	0.012
y13	0.014	y12	0.012
y6	0.014	y7	0.012
x10	0.014	y2	0.012
x42	0.014	x14	0.010
x40	0.014	y1	0.009
x13	0.014	y16	0.008
x3	0.014	y10	0.005
x41	0.014	x36	0.001
x9	0.014		

Table 5.3.4-d The Feature importance of all indicators

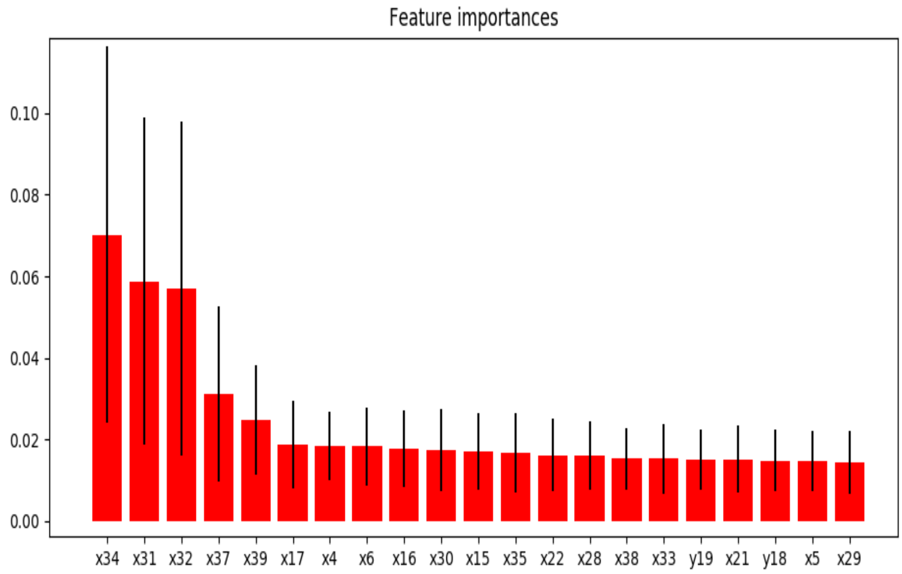


Figure 5.3.4-a The Visualisation of Feature importance

In order to decide the importance of four risks, the importance of variables could be conducted. As Table 5.3.4-d and Figure 5.3.4-a shown above, all-importance of the financial and non-financial indicators was included in the variable importance test. There are all of the indicators with importance over 0.015 were shown on the graphic. Followed the variable importance graphic, it is possible to find out the variable from the enterprise risk management framework and decide the importance of the risks. For the hazard risks, the two significant variables in CHAID models are environment index (y7) and well-being index (y5). The importance of these two variables is 0.012 and 0.013 respectively. Under the financial risks catalogue, there are profit before tax to equity (x32), costs of goods sold to net sales (x39), fixed assets to equity and long-term loans (x17), net profit to total assets (x34), net profit to equity (x31), quick ratio (x2), long-term liability to long-term liability and equity (x12) and bank loans to total assets (x19), where the importance of the variable is 0.057, 0.025, 0.019, 0.070, 0.059, 0.013, 0.013 and 0.013 respectively. For the operational risks, there are fixed assets turnover (x28), equity turnover (x29), receivable turnover (x24), total assets turnover (x30) and size of firms (y19), where the importance of variable is 0.016, 0.015, 0.013, 0.017 and 0.015 respectively. Finally, under strategic risks, there are technology innovation index (y8), tax rate (y16), cost of goods sold to net assets (x39), inventory to current assets (x4), industry (y1) and inventory to total assets (x5), where the importance of the variable is 0.013, 0.008, 0.025, 0.018, 0.009 and 0.015 respectively. Therefore, it could be concluded that the financial risks are the most important risk amongst total four risk types, where the most important indicators are net profit to total assets (x34), profit before tax to equity (x32) and net profit to equity (x31). The most important aspect of financial risks is profitability. The strategic risks and operational risks are similarly important risks. The most important indicators for operation risks are turnover ratios, while the most important indicators for strategic are inventory and prime operating-related ratios. Accordingly, the most important element under operational risks is business operations. Moreover, the most important element under strategic risks is costumer wants and competition. For hazard risks, the two indicators are similarly important, where could not be decided the importance. Therefore, if the Chinese listed SMEs need to improve the performance, the financial risks are the most critical risk they need to consider. The strategic risks and operational risks are the secondary risks to be considered, while the Chinese listed SMEs can not neglect the capital efficiency and prime operating activities.

In order to test the accuracy of the predicted models, the further test could be applied. Since the result is a binary result, which means the performance could be only good or poor in CHAID models, the receiver operation characteristic (ROC) curve could be used to test the prediction accuracy. The ROC curve plots the true positive rate against the false positive rate (SPSS, 14.2). For a good model, the curve will rise sharply near the left axis and cut across near the top, which will draw a graph like a semicircle. For an uninformative model, the curve will like a line with slope equal to 1.

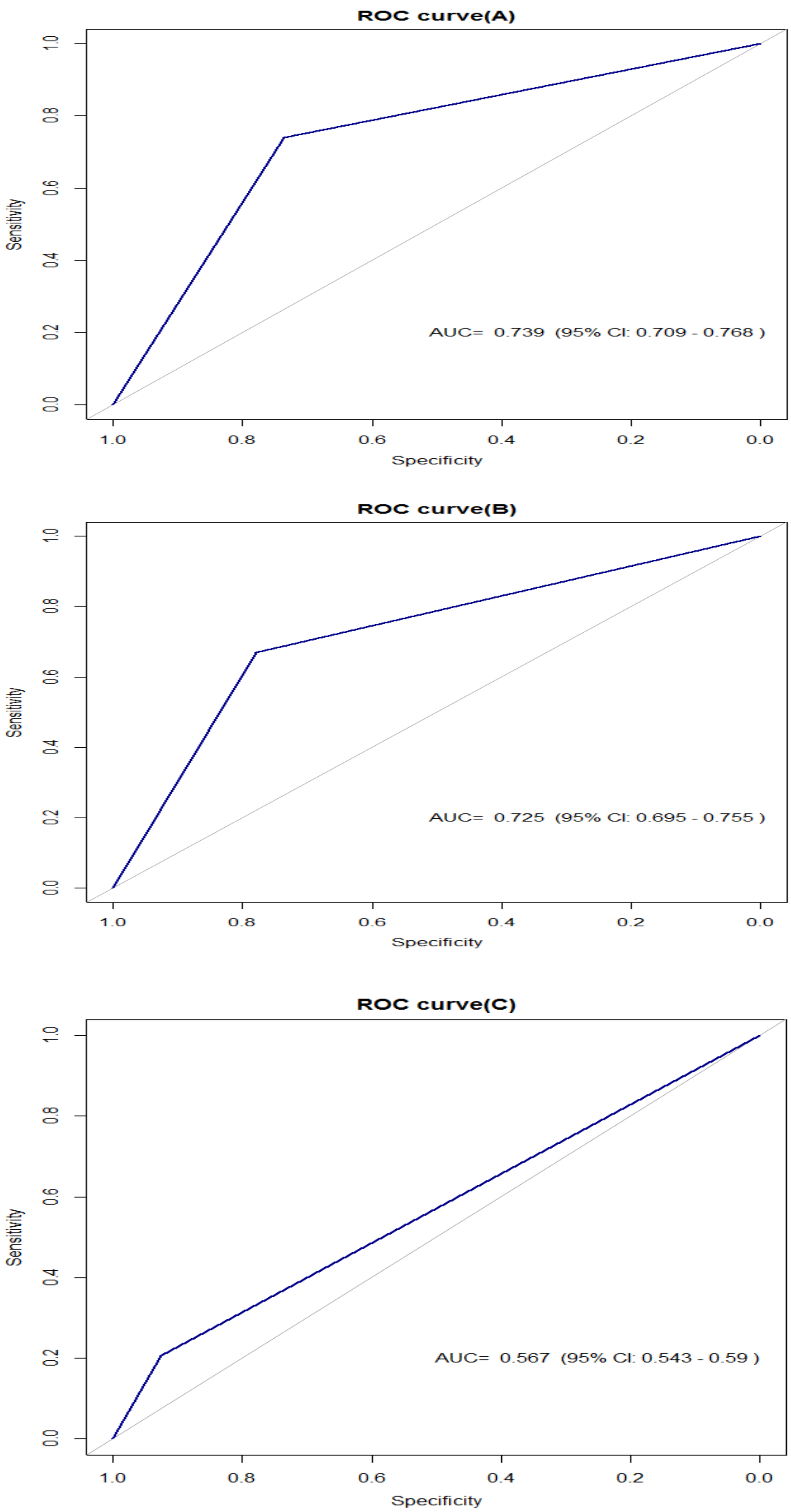


Figure 5.3.4-b The Result of ROC curve of CHAID (ROA)

As the result of ROC shows, the highest AUC value is in the model A with CHAID, which is 0.739. The AUC value is higher than the model B with CHAID (0.725) and model C with CHAID (0.567). Fawcett (2006) introduced that the AUC is a portion of the area of a unit square under the ROC curve, which means the AUC value should always be between 0 and 1.0. For a unit square within a coordinate system, a randomly guess could produce an area with the minimum square of 0.5 (Fawcett, 2006). Therefore, it could be concluded that the model A with CHAID has the highest accuracy in predicting firm performance and finding risk indicators. The model C with CHAID could not explain the question well.

5.4 Logit Regression Results

5.4.1 Logit Regression

The Logit Regression is a standard statistical method, which has been developed from the 1970s in early warnings of bank failure (Klistik, Kocisova and Misankova, 2015). The LR could explain binary variables, which could be used to classify whether the firm is failed or not. Spuchl'kova and Cug (2014) stated that the classic regression could not be used under this circumstance if the value of the variable indicates the status of "yes or no". Thus, the Logit model was introduced to solve this kind of problems. The aim of LR has expressed dependence of magnitude Y on the independent variable X. The observed data are interleaved by a logistic curve instead of a line, so that the regression is not linear. Meanwhile, the Logit Regression does not require the data should follow a strictly normal distribution. The Logit transformation is based on the "ratio of chances and hopes" (Klistik et al., 2015). Each LR function could provide the AIC for the model, which could measure the effectiveness of the regression. This research used LR to determine the KRIs and verify the value of non-financial indicators.

The exhaustive method is used in LR regression for this research. In LR regression, the AIC value will measure the accuracy of the model, so that the question was transferred as finding out the minimum AIC value. The AIC value depends on the independent indicators applied in the regression model, where the minimum AIC means the most accurate result. As a result, the minimum AIC could be found by attempting all the different combinations of indicators applied. The exhaustive method will be applied in the selection of indicators included in the model. There are two different ways of exhaustive, where the applied indicators could be from more to less or less to more. The AIC values of each combination will be calculated, which will be compared with each other to find out the minimum one. This step will be repeated several times, where the repeated step could be considered as an iterative process.

5.4.2 Logit Regression with financial and non-financial indicators

The dependent variable is selected as growth rate of ROA (ROA for short in the following parts), which is a binary variable. The independent variables were selected as financial indicators and non-financial indicators in this section.

```
Step:  AIC=1036.73
lg_trainy ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 +
    x11 + x12 + x13 + x15 + x16 + x17 + x19 + x21 + x22 + x23 +
    x24 + x25 + x26 + x27 + x28 + x29 + x30 + x31 + x32 + x33 +
    x34 + x35 + x37 + x38 + x39 + x40 + x41 + x42 + y1 + y2 +
    y3 + y4 + y5 + y6 + y7 + y8 + y9 + y10 + y11 + y12 + y13 +
    y14 + y15 + y16 + y17 + y18 + y19
```

```
Step:  AIC=973.79
lg_trainy ~ x2 + x4 + x8 + x10 + x11 + x13 + x17 + x21 + x31 +
    x34 + x38 + x42 + y2 + y4 + y10 + y12 + y14
```

```
> lg_ms

Call:  glm(formula = lg_trainy ~ x2 + x4 + x8 + x10 + x11 + x17 + x21 +
    x31 + x34 + x38 + x42 + y2 + y4 + y10 + y12 + y14, family = binomial(link = "logit"),
    data = lg_train)

Coefficients:
(Intercept)           x2           x4           x8          x10
 -6.876e-01    9.552e-02    1.386e+00    2.871e+00   -1.289e+07
        x11          x17          x21          x31          x34
 -1.289e+07    8.214e-01    1.289e+07    7.329e+00   -4.019e+01
        x38          x42           y2           y4          y10
  1.697e-03    3.154e-04    3.230e-01    1.843e-02   -2.072e+00
        y12          y14
 -2.001e-01   -2.509e-01

Degrees of Freedom: 841 Total (i.e. Null);  825 Residual
Null Deviance:      1166
Residual Deviance: 939  AIC: 973
```

Figure 5.4.2-a Result of LR with F and NF indicators

The Logit Regression could also be used to find the key risk indicators and explain the risks. Figure 5.4.2-a above shows the model from the beginning, which contains forty-two financial indicators and nineteen non-financial indicators. The AIC value is 1036.73 in the beginning model. In order to achieve a better result, it is necessary to delete the insignificant variables in order to maximise the AIC value. After 42 times of iteration steps, there are twelve financial indicators and five non-financial indicators left in the Logit model.

	Estimate	Std.Error	z	value	Pr(>|z|)
(Intercept)	-6.90E-01	1.40E+00	-0.483	0.629	.
x2	9.60E-02	3.80E-02	2.487	0.013	*
x4	1.40E+00	6.00E-01	2.296	0.022	*
x8	2.90E+00	6.70E-01	4.29	0	***
x10	-1.30E+07	7.40E+06	-1.751	0.08	.
x11	-1.30E+07	7.40E+06	-1.751	0.08	.
x17	8.20E-01	3.80E-01	2.174	0.03	*
x21	1.30E+07	7.40E+06	1.751	0.08	.
x31	7.30E+00	2.00E+00	3.638	0	***
x34	-4.00E+01	5.00E+00	-8.109	0	***
x38	1.70E-03	1.10E-03	1.481	0.139	.
x42	3.20E-04	1.80E-04	1.718	0.086	.
y2	3.20E-01	1.40E-01	2.299	0.021	*
y4	1.80E-02	8.00E-03	2.292	0.022	*
y10	-2.10E+00	1.10E+00	-1.899	0.058	.
y12	-2.00E-01	1.10E-01	-1.854	0.064	.
y14	-2.50E-01	1.30E-01	-1.945	0.052	.

Table 5.4.2-a Significant indicators of LR with F and NF indicators

The significance values of indicators were shown in Table 5.4.2-b. If the significance value of variables was set as 0.05, there are x2, x4, x8, x17, x31, x34, y2 and y4 are significant, which are quick ratio, inventory to current assets, equity to total assets, fixed assets to equity and long-term loans, net profit to equity, net profit to assets, number of employees and economic development index.

	Predicted group		1	0	
LOGIT	Profit	1	66.88%	33.12%	70.71%
	Loss	0	24.60%	75.40%	

Table 5.4.2-b Prediction accuracy of F and NF indicators with LR

The prediction accuracy of Logit Regression is shown in Table 5.4.2-b. The data in 2012 was chosen as a training group, and the data in 2013 was chosen as a test group. The overall prediction accuracy is 70.71%.

5.4.3 Logit Regression with financial indicators

The dependent variable is selected as growth rate of ROA. The independent variables were selected as financial indicators only in this section.

```
Step:  AIC=1026.97
lg_trainy ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 +
    x11 + x12 + x13 + x15 + x16 + x17 + x19 + x21 + x22 + x23 +
    x24 + x25 + x26 + x27 + x28 + x29 + x30 + x31 + x32 + x33 +
    x34 + x35 + x37 + x38 + x39 + x40 + x41 + x42


Step:  AIC=984.1
lg_trainy ~ x2 + x5 + x10 + x11 + x13 + x21 + x22 + x23 + x31 +
    x34 + x38 + x42

> lg_ms

Call:  glm(formula = lg_trainy ~ x2 + x5 + x10 + x11 + x13 + x21 + x22 +
    x23 + x31 + x34 + x38 + x42, family = binomial(link = "logit"),
    data = lg_train)

Coefficients:
(Intercept)           x2           x5          x10          x11
  1.575e+00    1.004e-01    2.213e+00   -1.220e+07   -1.220e+07
        x13          x21          x22          x23          x31
 -1.304e+00    1.220e+07   -1.829e+00    2.590e+00    6.153e+00
        x34          x38          x42
 -3.794e+01    1.398e-03    2.811e-04

Degrees of Freedom: 841 Total (i.e. Null);  829 Residual
Null Deviance:      1166
Residual Deviance: 958.1        AIC: 984.1
```

Figure 5.4.3-a Result of LR with F indicators

The results of Logit Regression with financial indicators only were shown in Figure 5.4.3-a. After 26 iterations, there are only 12 variables left. The AIC value was improved from 1026.97 to 984.1. The iteration steps were stopped since the AIC value cannot be reduced. There are x2, x5, x10, x11, x13, x21, x22, x23, x31, x34, x38 and x42 were left in the formula.

	Estimate	Std.Error	z	value	Pr(>|z|)
(Intercept)	1.58E+00	5.49E-01	2.867	0.004	**
x2	1.00E-01	3.91E-02	2.568	0.01	*
x5	2.21E+00	8.91E-01	2.483	0.013	*
x10	-1.22E+07	7.26E+06	-1.679	0.093	.
x11	-1.22E+07	7.26E+06	-1.679	0.093	.
x13	-1.30E+00	8.44E-01	-1.545	0.122	
x21	1.22E+07	7.26E+06	1.679	0.093	.
x22	-1.83E+00	6.41E-01	-2.852	0.004	**
x23	2.59E+00	7.64E-01	3.392	0.001	***
x31	6.15E+00	1.98E+00	3.115	0.002	**
x34	-3.79E+01	4.82E+00	-7.878	0	***
x38	1.40E-03	1.12E-03	1.253	0.21	
x42	2.81E-04	2.06E-04	1.362	0.173	

Table 5.4.3-a Significant indicators of LR with F indicators

The Table 5.4.3-a shows the z-values of indicators. If the significance level is 0.05, the x2, x5, x22, x23, x31 and x34 are significant, which are quick ratio, inventory to total assets, current assets to total assets, tangible fixed assets to total assets, net profit to equity and net profit to assets.

	Groups		1	0	
LOGIT	Profit	1	64.94%	35.06%	68.98%
	Loss	0	26.98%	73.02%	

Table 5.4.3-b The Prediction accuracy of F indicators with LR

Table 5.4.3-b above shows the model accuracy of Logit Regression with financial indicators, where the overall accuracy is 68.98%. The training set and test set selection is the same as the Logit Regression with financial indicators and non-financial indicators model.

5.4.4 Logit Regression with non-financial indicators

The dependent variable is selected as the growth rate of ROA. The independent variables were selected as non-financial indicators only in this section.

```
Start:  AIC=1162.72
lg_trainy ~ y1 + y2 + y3 + y4 + y5 + y6 + y7 + y8 + y9 + y10 +
    y11 + y12 + y13 + y14 + y15 + y16 + y17 + y18 + y19

Step:  AIC=1151.89
lg_trainy ~ y3 + y4 + y5 + y6 + y7 + y8 + y10 + y14 + y17 + y19

> lg_ms

Call:  glm(formula = lg_trainy ~ y3 + y4 + y5 + y6 + y7 + y8 + y10 +
    y14 + y17 + y19, family = binomial(link = "logit"), data = lg_train)

Coefficients:
(Intercept)           y3           y4           y5           y6
     3.6898      -1.0058       0.2176       0.2710       0.2171
         y7           y8          y10          y14          y17
     0.2045       0.1265      -2.3122      -0.2704       0.3113
        y19
    -0.1911

Degrees of Freedom: 841 Total (i.e. Null);  831 Residual
Null Deviance:      1166
Residual Deviance: 1130        AIC: 1152
```

Figure 5.4.4-a Result of LR with NF indicators

Figure 5.4.4-a above showed the result of Logit Regression with non-financial

indicators only. In the beginning, there are nineteen non-financial indicators were included in the model. After eight times iterations, there are only eight variables left in the model. The AIC was improved from 1162.72 to 1151.89. The eight variables are y3, y4, y5, y6, y7, y8, y10, y14, y17 and y19.

	Estimate	Std.Error	z	value	Pr(>|z|)
(Intercept)	3.68977	3.83546	0.962	0.33604	
y3	-1.00576	0.46441	-2.166	0.03034	*
y4	0.21761	0.10262	2.121	0.03396	*
y5	0.27097	0.1258	2.154	0.03124	*
y6	0.2171	0.12652	1.716	0.08617	.
y7	0.20449	0.09145	2.236	0.02534	*
y8	0.12651	0.0576	2.196	0.02807	*
y10	-2.31224	1.07007	-2.161	0.03071	*
y14	-0.27044	0.10283	-2.63	0.00854	**
y17	0.31125	0.15378	2.024	0.04297	*
y19	-0.19107	0.09527	-2.005	0.04492	*

Table 5.4.4-a Significant indicators of LR with NF indicators

Table 5.4.4-a shows the z-values of indicators. If the significance level was set as 0.05, the variables y3, y4, y5, y7, y8, y10, y14, y17 and y19, which are develop and life index, economic development index, well-being index, environment index, technology innovation index, audit opinions, number of employees, listed duration and size of firms.

	Group		1	0	
LOGIT	Profit	1	50.92%	49.08%	53.67%
	Loss	0	43.59%	56.41%	

Table 5.4.4-b The Prediction accuracy of NF indicators with LR

Table 5.4.4-b shows the overall accuracy of the Logit Regression model with non-financial indicators is 53.67%. The training set and test set selection is the same as the Logit Regression with financial indicators and non-financial indicators model.

5.4.5 Summary

The Logit Regression method also selected forty-two financial variables and nineteen non-financial variables. The dependent variable was selected as the growth in ROA rather than Z-score since the Logit Regression requires a binary dependent variable. The Logit Regression is also used for the selection of KRIs among risk indicators. To select the KRIs amongst risk indicators, it followed a combination of financial and non-financial indicators, only financial indicators and only non-financial indicators. The usage of different groups could be helpful to find the KRIs and the value of non-financial indicators. The measurement of performance is AIC value, which could produce a satisfactory solution to the target problems based on the number of factors (Akaike, 1987). Akaike (1987) stated that the minimum AIC represents the best fit. In this research, the process to select the variables with the LR regression could be described as follow: include all the groups of indicators first and get the result; exclude one of the indicators and get the result; compare the AIC from two groups and choose the minimum AIC; repeat the process until the AIC reached the minimum. It is also important to check the significant value of indicators, where the insignificant variable should be excluded from KRIs. After using three different groups of indicators, it is possible to conclude the KRIs from indicators.

Groups	Code	Indicators
F and NF	x2	quick ratio
	x4	inventory to current assets
	x8	equity to total assets
	x17	fixed assets to equity and long-term loans
	x31	net profit to equity
	x34	net profit to assets
	y2	number of employees
	y4	economic development index
F	x2	quick ratio
	x5	inventory to total assets
	x22	current assets to total assets
	x23	tangible fixed assets to total assets
	x31	net profit to equity
	x34	net profit to assets
N	y3	develop and life index
	y4	economic development index
	y5	wellbeing index
	y7	environment index
	y8	technology innovation index
	y10	audit opinions
	y14	number of employees
	y17	listed duration
	y19	size of firms

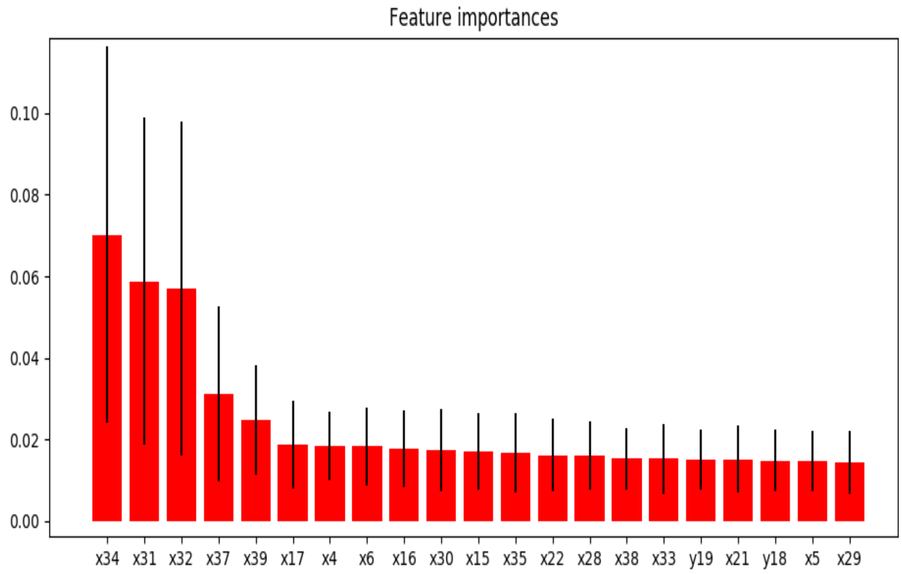


Figure 5.4.5-a Significant indicators in all LR models and feature importance

Figure 5.4.5-a shows the significant variables and feature importance. Although the significance of indicators to firm performance could be detected, it is not possible to decide the threshold values and the order of importance based on the LR method only. As a result, it is necessary to use extra methods to decide the KRIs, where the variable importance could be a choice. As the graph above shows, the 21 indicators with the highest importance have been detected. It could be concluded that x4, x5, x17, x31, x34 and y19 matched the result of variable importance. Therefore, it could say that the x4, x5, x17, x31, x34 and y19 are KRIs from the LR method, where the threshold values and roadmaps could not be detected by using LR method.

The research also considered applying the CHAID and LR method together in order to find threshold values and roadmaps. Since the CHAID method runs a Chi-square test on each independent variable to dependent variable and every node, it is clear that the CHAID potentially consider all the variables to build the decision tree. If the Logit Regression was implied before building CHAID, it is possible that the hierarchy nodes and branches will be reduced. There is a problem called overfitting. Hawkins (2004) stated that models and procedures should contain all necessary but nothing more. For example, if a regression model with two indicators can explain the dependent variable, there should no more than these two indicators be included. The overfitting problem is that the usages of models or procedures violate such parsimony, which includes more terms than necessary or uses more complicated approaches than necessary. Therefore, since the CHAID and Logit Regression may overlap on the variable classification or test, it is better to use only one of these methods separately.

5.5 Genetic Algorithm Results

5.5.1 Genetic Algorithm in variable selection

Genetic algorithms (GA) are population-based evolutionary searching methods. These algorithms have used probability-based search methods, which gained ideas drawn from natural genetic and evolutionary principles (Chamber, 1995). Genetic algorithms are particularly suitable for solving scheduling and machine layout problems. The genetic algorithms differ from other non-linear optimization techniques. In a genetic algorithm, a population of strings, which encode a potential solution to the problem, is evolved toward a better solution (Chamber, 1995). A population of candidate solutions, whose individuals are characterised by possessing a chromosome, is maintained, and after a generation is accomplished, the population evolves until converges at levels regarded as optimal. The evolution (initialisation stage) usually starts from a population of randomly generated individuals and happens in generations. Each chromosome is evaluated utilising a user-defined fitness function. For real-world applications of GAs, choosing the fitness function is the most critical step. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. The algorithm terminates when a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

In this study, the fitness value is the Cross Validation, which indicates the accuracy of the predicting result. For example, if 10-fold cross-validation is selected, the entire genetic algorithm is conducted ten separate times. For the first fold, nine-tenths of the data are used as comparing groups, while the remaining tenth is used to estimate the result. Moreover, this process will be repeated ten times, while the accuracy will be compared after that. This function determines the optimal number of generations for the GA. In order to get the best results, the indicators were regrouped as many as possible. If the indicators produced lower accuracy predicted results, the indicators would be removed from the training set. Since the iteration process needs exceptionally high computing power, the maximum iteration times were set as three times.

5.5.2 Genetic Algorithm with financial and non-financial indicators

In this section, the individuals were selected from forty-two financial indicators and nineteen non-financial indicators. The method aims to select the most important indicators from all input neurons.

Iterations	Variables	Accuracy	Kappa	Accuracy SD	Kappa SD
1	1	0.6269	0.2476	0.09421	0.1906
2	2	0.7265	0.448	0.07791	0.1578
3	3	0.7449	0.486	0.06549	0.1307

4	4	0.7495	0.4943	0.07077	0.1436
5	5	0.7517	0.5008	0.06889	0.1374
6	6	0.7494	0.496	0.1024	0.2066
7	7	0.7676	0.5311	0.08542	0.1733
8	8	0.7607	0.5179	0.07919	0.1606

Table 5.5.2 Result of GA with Financial and Non-Financial Indicators (1)

There are forty-two financial indicators, and nineteen non-financial indicators were used as individuals. Table 5.5.2 shows the iterations, number of variables and accuracy of the method. For the financial indicators and non-financial indicators group, the accuracy of the predicted result reached the maximum at seven variables left.

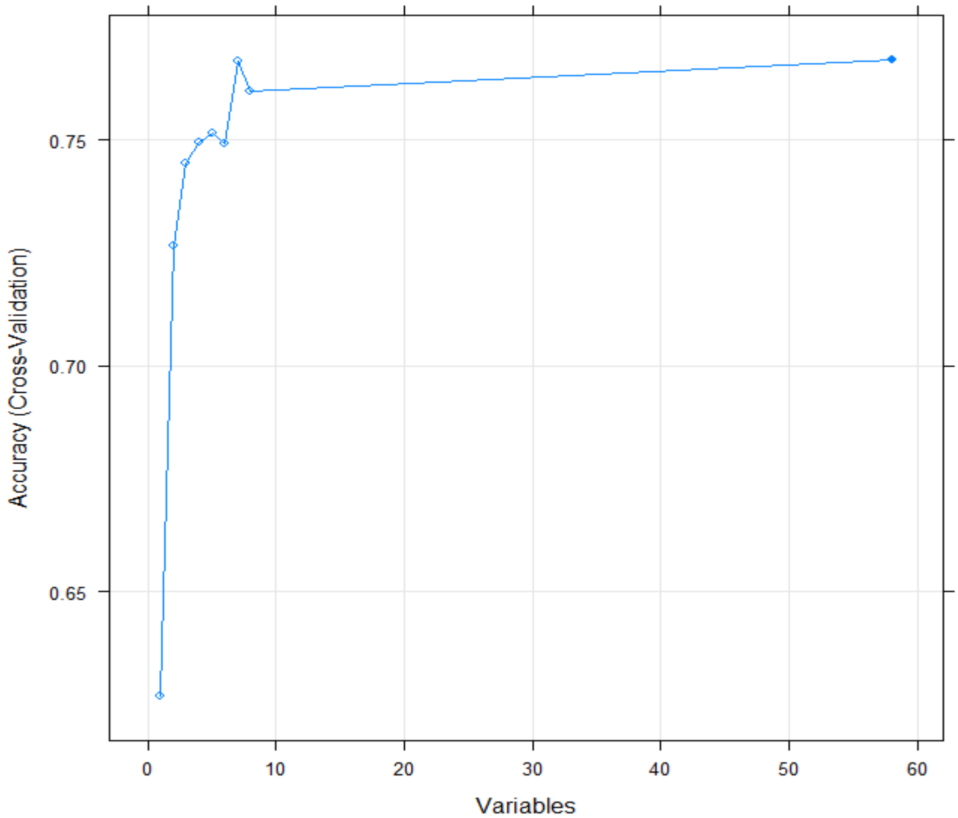


Figure 5.5.2-a Result of GA with Financial and Non-Financial Indicators (2)

As Figure 5.5.2-a shows, the maximum accuracy is 0.7676. To find out the most important indicators, it is also necessary to apply the feature importance method.

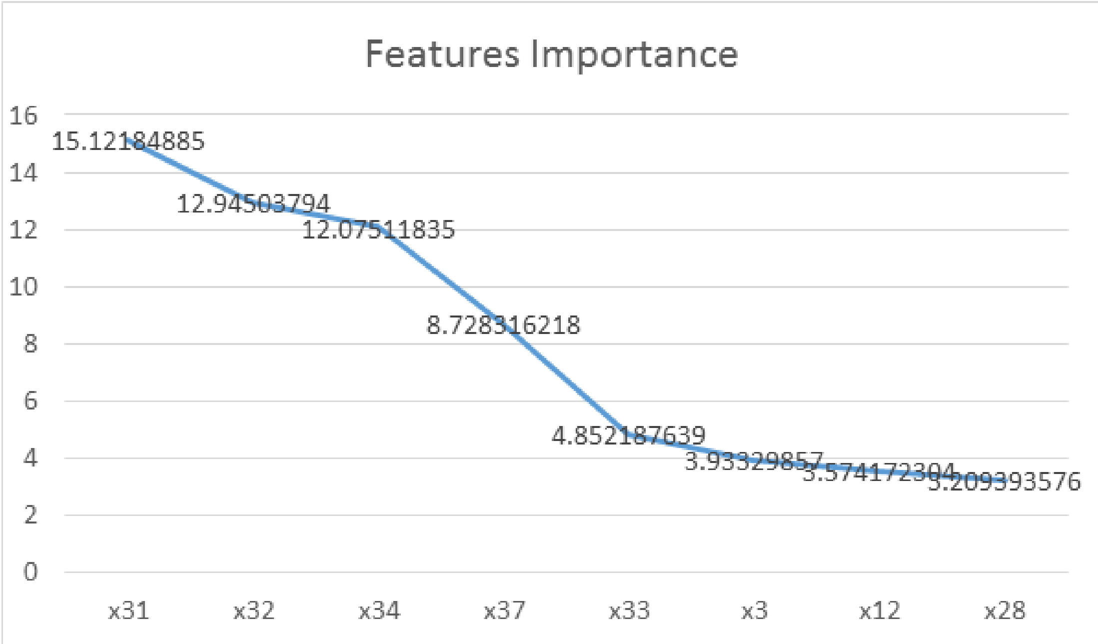


Figure 5.5.2-b The Features Importance of GA with F and NF Indicators

As Figure 5.5.2-b above shown, the most important indicators are x31, x32, x34, x37, x33, x3 and x12, which are net profit to equity, profit before tax to equity, net profit to assets, gross profit to net sales, EBIT to EBT and finance expense, absolute liquidity, and long-term liability to long-term liability and equity. The seven indicators are all financial indicators. It means that the firm performance prediction with the GA method mostly depended on the financial indicators than non-financial indicators.

5.5.3 Genetic Algorithm with financial indicators

In this section, the individuals are selected as financial indicators only. There are total forty-two financial indicators were used in this part.

Iterations	Variables	Accuracy	Kappa	Accuracy SD	Kappa SD
1	1	0.646844	0.2900703	0.05338264	0.10295596
2	2	0.7378201	0.4732482	0.04489754	0.08560919
3	3	0.7630796	0.5237937	0.04315571	0.08598116
4	4	0.7586375	0.5150284	0.04773482	0.09330309

5	5	0.7472187	0.4914868	0.04845589	0.09483429
6	6	0.7518147	0.5001206	0.06731957	0.13304206
7	7	0.7496453	0.4967097	0.05543584	0.10863941
8	8	0.7519204	0.5001481	0.05826773	0.11675416

Table 5.5.3 The Result of GA with Financial Indicators (1)

Table 5.5.3 shows the iterations, number of variables and accuracy in this method. The method reached the highest accuracy when the number of variables equals to 3. At this point, the predicted accuracy is 0.7630.

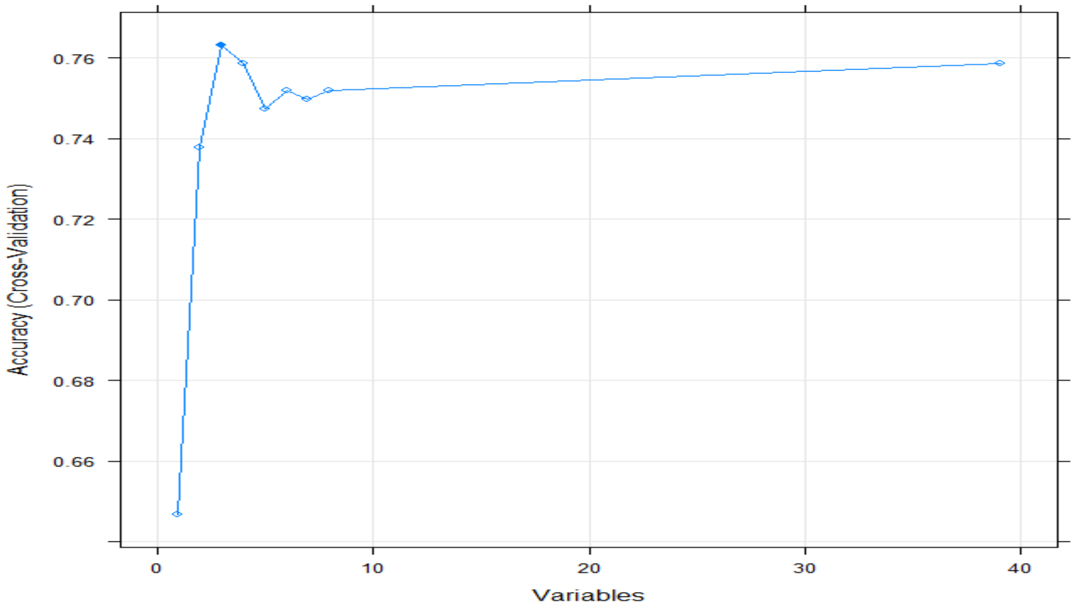


Figure 5.5.3-a The Result of GA with F indicators (2)

As Figure 5.5.3-a shown, the accuracy is increased significantly as the number of variables increased until there are three variables were included. After this point, the accuracy fluctuated until the number of variables reached eight. Then, the accuracy was increasing slowly as the number of variables increases. The accuracy of prediction could not exceed 0.76 as the number of indicators increased until the number of variables reached the maximum.

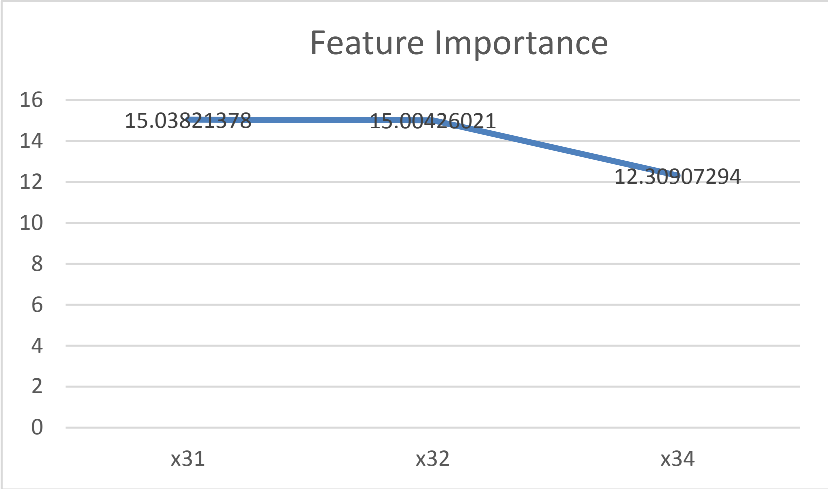


Figure 5.5.3-b Features Importance of GA with F Indicators

In order to detect the most important indicators, it is necessary to use feature importance method to measure the importance of indicators. As Figure 5.5.3-b shows, the most important indicators are x31, x32 and x34, which are *net profit to equity*, *profit before tax to equity* and *net profit to assets* respectively.

5.5.4 Genetic Algorithm with non-financial indicators

In this section, the individuals are selected as non-financial indicators only. There are total nineteen non-financial indicators were used in this part.

Iterations	Variables	Accuracy	Kappa	Accuracy SD	Kappa SD
1	1	0.5239464	-0.0102644	0.0211053	0.0270737
2	2	0.5262192	-0.0079348	0.0121068	0.0135439
3	3	0.5105626	-0.0172180	0.0542413	0.1042585
4	4	0.4984202	-0.0206483	0.0768341	0.1604554
5	5	0.4988384	-0.0123038	0.0545900	0.1154158
6	6	0.4851492	-0.0421573	0.0517080	0.1079851
7	7	0.5078788	0.0034385	0.0500580	0.1024859

8	8	0.4850987	-0.0407024	0.0683793	0.1327973

Table 5.5.4 The Result of BPNN with NF Indicators (1)

Table 5.5.4 shows the iterations, number of variables and accuracy in this method. The highest accuracy has been reached, when the number of variables equals to two. At the moment, the accuracy is 0.526.

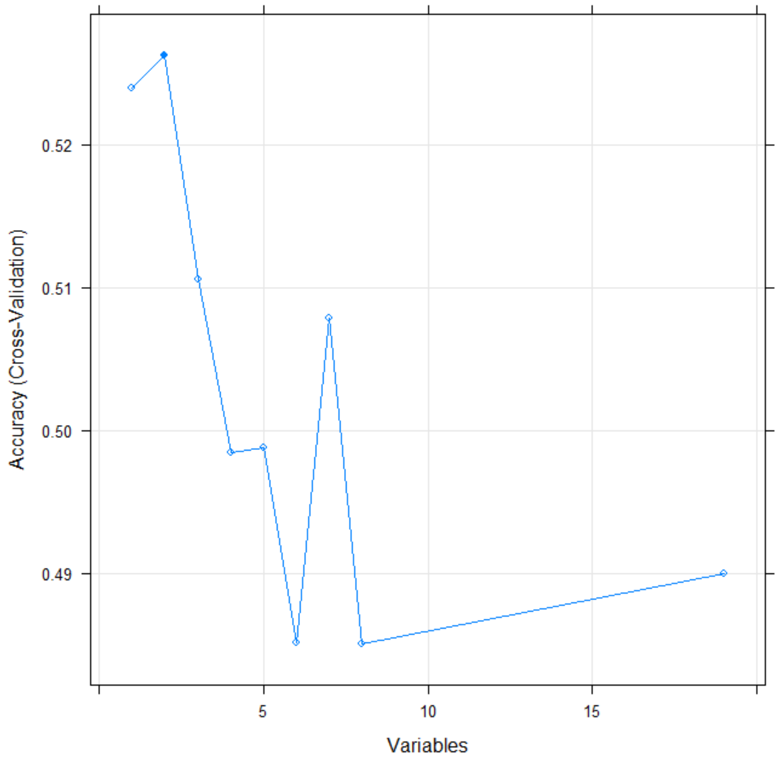


Figure 5.5.4-a The Result of GA with NF indicators (2)

As Figure 5.5.4-a shows, the accuracy of GA with non-financial indicators is fluctuating dramatically. After the highest accuracy has been reached at number of variable equals 2, the accuracy dropped significantly till number of variable equals 6. Afterwards, the accuracy of prediction could not exceed 0.52 as the number of indicators increased.

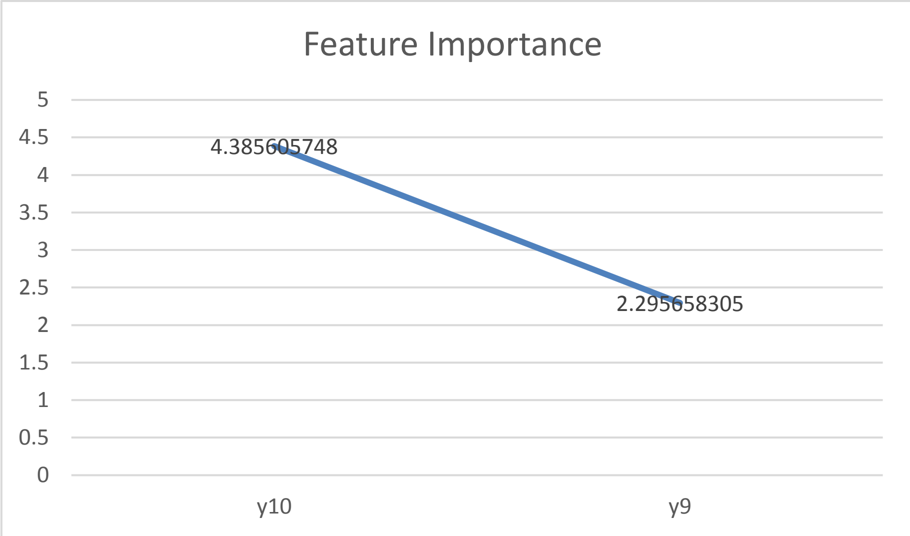


Figure 5.5.4-b Features Importance of GA with NF Indicators

Figure 5.5.4-b shows the result of feature importance. In order to detect the most important indicators, it is necessary to use feature importance method to measure the importance of indicators. As Figure 5.5.4-b shown, the most important indicators are y10 and y9, which are *audit opinions* and *education background of employees* respectively.

5.5.5 Summary

The GA methods have applied three different groups of indicators, which are financial and non-financial indicators, financial indicators only and non-financial indicators only. The fitness value of GA is selected as the accuracy of cross validation, where the value is going to measure internal performance. In other word, the accuracy of cross-validation has been applied in selecting the number of indicators. Specifically, for the GA methods, including non-financial indicators could slightly increase the accuracy of cross validation from 0.763 (financial indicators only) to 0.767 (financial indicators and non-financial indicators. It is clear that the non-financial indicator groups have the worst performance in the GA method, where the accuracy is only 0.526. It is clear that the GA method determines the firm performance mostly depending on the financial indicators since the accuracy of non-financial indicators group is only 0.526. However, it has been confirmed that including the non-financial indicators could increase the accuracy of the GA method. After three iterations, the financial and non-financial indicators group has 4 more indicators than financial indicator group only, which means including non-financial indicators could provide more comprehensive information.

GA	Real group		Predicted group		Firms correctly (incorrectly) classified
			1	0	
Financial and non-financial indicators	Profit	1	70.59%	29.41%	74.87%
	Loss	0	20.85%	79.15%	
Financial indicators	Profit	1	73.53%	26.47%	75.91%
	Loss	0	21.70%	78.30%	
Non-financial indicators	Profit	1	0.00%	100.00%	47.38%
	Loss	0	1.70%	98.30%	

Figure 5.5.5-a The Prediction accuracy of all GA models

Figure 5.5.5-a shows the prediction accuracy of GA models with three different groups of indicators. There is only a slight difference between the accuracy of GA with financial and non-financial indicators model and GA with financial indicators model. Comparing two models, the GA with financial and non-financial indicators model predicted poor performance firms better than the GA with financial indicator model. The prediction accuracy of both models is acceptable, where the accuracy is around 75%.

On the contrary, the accuracy of GA with non-financial is only 47.38%, which means the model cannot be used to predict the firm performance. However, the prediction accuracy of poor performance firms with the model is 98.3%, while the prediction accuracy of good performance firms with the model is 0%. The result indicates that the non-financial indicators groups cannot be used to predict the firm performance. The predicted group could be classified all of the samples in one catalogue, which may result in the fifty-fifty result. This kind of result is more like the statistical experiment ‘coin tossing’, which result randomly 50% for each catalogue. For instance, the model classified all of the samples in poor performance, which will result in the 100% for poor performance firms prediction, but 0% for good performance firms. Therefore, it could be concluded that the non-financial indicators cannot be independently used to predict firm performance. On the other hand, the financial and non-financial indicator group and financial indicator group models could be used to predict firm performance. Since both models have more than 74% accuracy for two predicted groups, it means that the result is not like non-financial indicators model. The accuracy was slightly dropped by including non-financial indicators to the model, where the highest accuracy among GA models is the one with financial indicators group.

Groups		Overall	Var	
F and NF	1	15.12184885	x31	net profit to equity
	2	12.94503794	x32	profit before tax to equity
	3	12.07511835	x34	net profit to asset
	4	8.728316218	x37	gross profit /net sales
	5	4.852187639	x33	EBIT/EBT and Finance expense
	6	3.93329857	x3	absolute liquidity
	7	3.574172304	x12	long-term liability to long-term liability and equity
F	1	15.03821378	x31	net profit to equity
	2	15.00426021	x32	profit before tax to equity
	3	12.30907294	x34	net profit to asset
NF	1	4.385605748	y10	audit opinions

	2	2.295658305	y9	employees education

Figure 5.5.5-b Significant indicators of GA models

Figure 5.5.5-b indicated the different significant indicators in three different models by GA methods. Although the accuracy of GA with financial indicators is slightly higher than GA with financial and non-financial indicators, more variables are significant in the latter one. Compared the two different models, the financial and non-financial indicators considered the cost, tax, liquidity and liability than financial indicators model, which may provide more comprehensive information regarding the enterprise risk management framework. It could be concluded that the non-financial indicators will indirectly improve the predictive results in the risk management process, which included the features under operational risks and strategic risks. Figure 5.5.5-b also shows the GA model with financial indicators model only included three risks, which are the features of financial risks only. As a result, the non-financial indicators could provide more information to decision makers in considering all the risks.

5.6 Neural Network Results

5.6.1 BPNN

The (artificial) neural network (NN) is made up of a large number of neurons and connections between them (Back, Laitinen and Sere, 1996). The neurons in the networks are arranged in the layers, which included input layers, hidden layers and output layers. Each layer is fully interconnected to the preceding layer and the following layer (SPSS, 2011). It is necessary to determine the weights of neurons, which are used to connect each layer. Based on the weights, the importance of the neurons could be described. Meanwhile, the weights could be adjusted iteratively in order to generate better prediction results. The network starts to mimic the biological neural network, which one neuron passes information to another. In the neural network, the input layers contained input neurons, which determined the neurons in output layers via hidden layers. Since the weights are learned using iteration, the network could get a desirable input to output by a learning mechanism (Back et al., 1998). There are two different types of learning mechanism of learning, which are supervised learning and unsupervised learning. The supervised learning is used to get the answers to a specific question, which is firm performance in this study. Unsupervised learning is to get answers to unknown questions. The target problems are defined by KPIs and the target data set is used to select KRIs, all of the output and input are certain, so that unsupervised learning may not be suitable for this study.

The backpropagation artificial neural network (BPNN) means the model is not a simple feed-forward neural network, where it uses backpropagation to iteratively adjust the weights of neurons to get the minimum error output (IBM, 2011; Back et al., 1996). The information flow goes through the network from the input layer to the output layer, then get a prediction result. The prediction result is compared with the recorded value of the output layer to calculate the error, while the difference between the predicted and actual output is propagated backward through the network (IBM, 2011). At the start of training, the weights of neurons are randomly valued between -0.5 and 0.5. During cycles from the input layer to the output layer, the weights of the neurons will be continuously adjusted based on the errors of prediction results. After several iterations, the error could be minimized, and the prediction results will be close to the actual result. The errors were measured by the sum of squared errors of prediction (SSE). Therefore, the final result shows the minimised error between the actual value and prediction result by iteratively adjusting the weights of input neurons.

5.6.2 BPNN with financial and non-financial indicators

In this section, the input neurons were selected as financial and non-financial indicators. There are forty-two financial indicators, and nineteen non-financial indicators were used in this part. The detailed results were listed in Appendix 2, Table 5.6.2-a and Table 5.6.2-b.

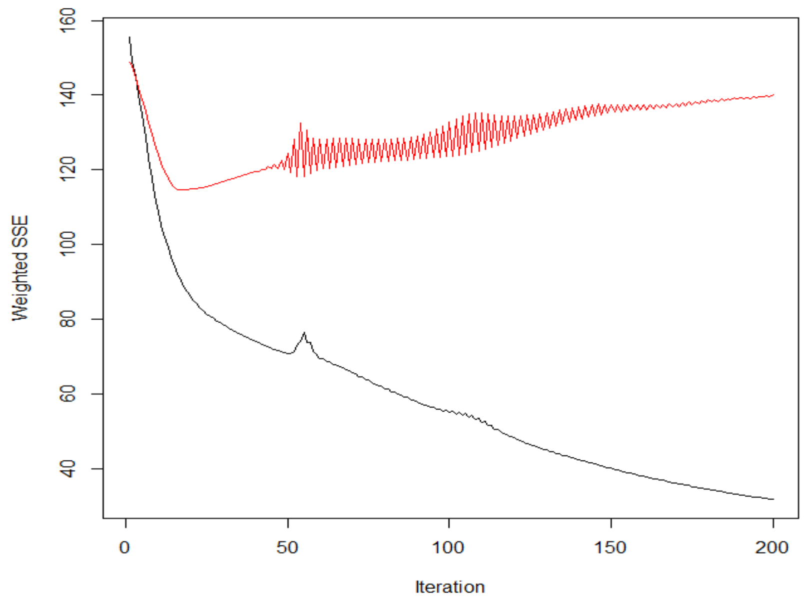


Figure 5.6.2-a The Result of BPNN with F and NF indicators

Figure 5.6.2-a shows the SSE of BPNN with financial and non-financial indicators. The weighted SSE, which shows as a black line, is converged with less than 40 after 200 times iterations. In the beginning, the SSE decreased significantly from 150 to 75. After 50 times iterations, the SSE decreased slowly from 75 to 35. The difference between the highest SSE to the lowest is about 120. The red line shows the SSE in the test set, which is around 110. The converging speed of the test set line is respectively lower than the training set. During the 50^{th} iteration and 150^{th} iteration, there are continually fluctuating between 110 and 130. The SSE of the test set finally converged to around 130. The table 5.6.2-a shows all the neurons applied in the BPNN method. The performance is measured as a binary variable, where value 1 represents good, and 0 represent poor. As the table 5.6.2-a shown, it is clear that the value of output neurons

converged to 1 and 0. In order to verify the training result, the rules should be applied to the test set.

Model	Real group membership		Predicted group		Firms correctly(incorrectly) classified
			1	0	
BP	Profit	1	68.97%	31.03%	67.59%
	Loss	0	33.78%	66.22%	

Figure 5.6.2-b Prediction accuracy of BPNN with F and NF indicators

As Figure 5.6.2-b shows, the overall prediction accuracy of BPNN with financial and non-financial indicators is 67.59%. The prediction accuracy of good performance firms is 68.97%, while the prediction accuracy of poor performance is 66.22%. The prediction accuracy of good performance firms is a little bit higher than the other one.

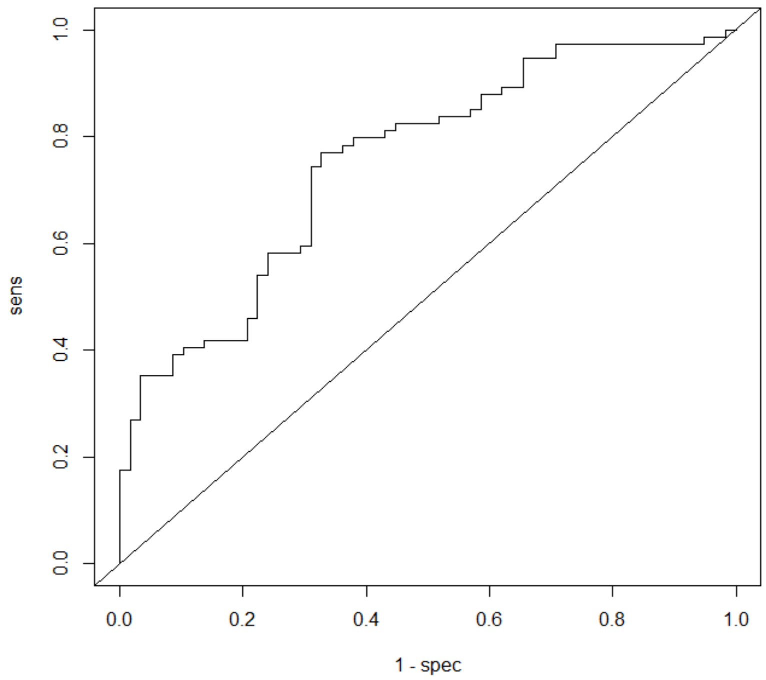


Figure 5.6.2-c The ROC curve of BPNN with F and NF indicators

Figure 5.6.2-c shows the result of the ROC test. In order to test the accuracy of the predicted models, the ROC test could be applied. The receiver operation characteristic (ROC) curve could be used to test the accuracy since the results are binary. The area

under the curve (AUC) is the measurement of performance in the ROC test, where the area under the curve is the more, the better. The ROC curve plots the true positive rate against the false positive rate (SPSS, 2011). As Figure 5.6.2-c shows, the ROC curve used sensitivity (sens) and specificity (1-spec) as X-axis and Y-axis. In the good model, the curve increased sharply near the left axis and came close to the top, while the AUC should be close to 1. In Figure 5.6.2-c, the area covered more than 75% of the square, which means the model result is acceptable.

5.6.3 BPNN with financial indicators

In this section, the input neurons were selected as financial indicators only. There are forty-two indicators were used in this part. The detailed results were shown in Appendix 2, Table 5.6.3-a and Table 5.6.3-b.

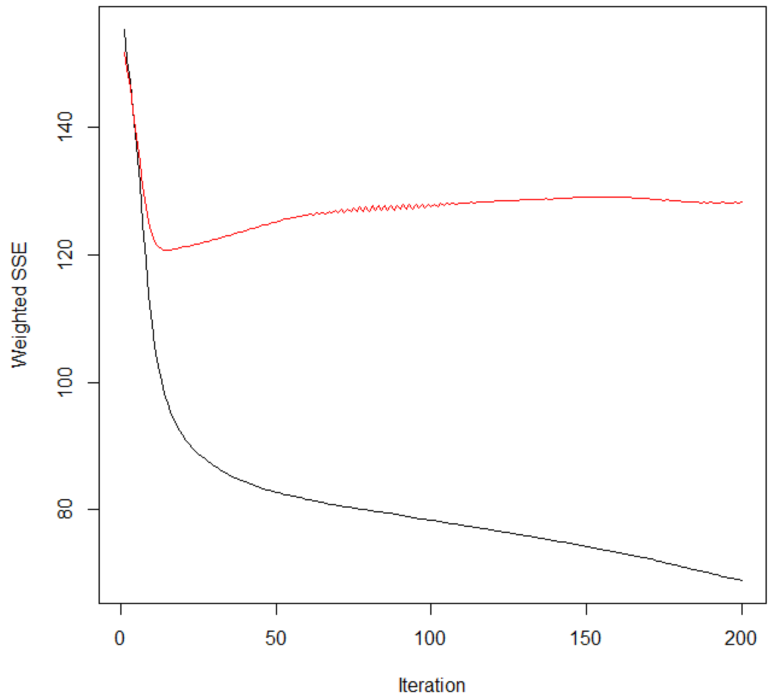


Figure 5.6.3-a The Result of BPNN with F indicators

Figure 5.6.3-a shows the SSE of BPNN with financial indicators only. After 200 times iteration, the weighted SSE decreased from 160 to around 20, which dropped

significantly from 160 to 90 at around 40^{th} iteration. After that, the weighted SSE decreased slowly to 200^{th} iteration. The difference between the highest SSE to the lowest SSE is 140. The SSE of training set decreased significantly from 150 to 120 in the first 20 iterations. After that, it smoothly increased about 5, while finally converged to 125. Table 5.6.3-a shows the values of each neuron, while the important ones are the value of output layers. Table 5.6.3-b shows the weighted value of hidden neurons and output neurons. The most important thing is that the converging values of the model are not close to 0 and 1, which means the result may not be able to classify the poor performance and good performance firms.

Model	Real group membership		Predicted group		Firms correctly(incorrectly) classified
			1	0	
BP	Profit	1	68.97%	31.03%	68.94%
	Loss	0	31.08%	68.92%	

Figure 5.6.3-b The Prediction accuracy of BPNN with F indicators

The prediction result is shown in Figure 5.6.3-b. The overall prediction accuracy for BPNN with financial indicators is 68.94%. The prediction accuracy for good performance firms is 68.97%, while the prediction accuracy for poor performance result is 68.92%. There is not a significant difference between the prediction accuracy for good or poor performance firms.

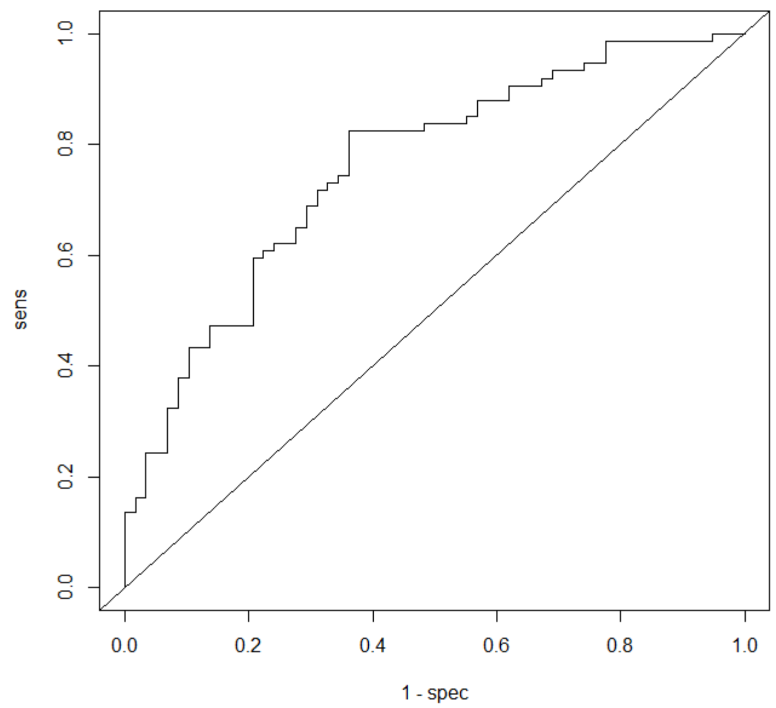


Figure 5.6.3-c ROC curve of BPNN with F indicators

Figure 5.6.3-c shows the result of the ROC test. As mentioned before, the AUC should be close to 1, which indicates the prediction accuracy is good. As the figure shows, the AUC is greater than 0.5, while the total AUC is around 75% of the full area. Therefore, it indicates that the result could explain well.

5.6.4 BPNN with non-financial indicators

In this section, the input neurons were selected as non-financial indicators. There are nineteen non-financial indicators were used in this part. The detailed results were listed in Appendix 2, Table 5.6.4-a and Table 5.6.4-b.

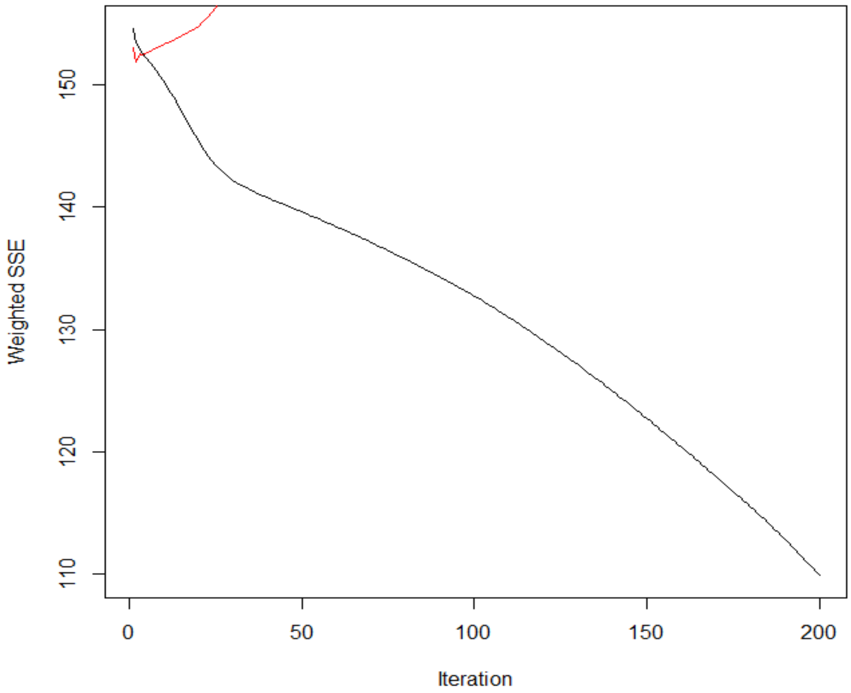


Figure 5.6.4-a The Result of BPNN with NF indicators

Figure 5.6.4-a shows the result of BPNN with non-financial indicators only. The weighted SSE smoothly dropped from around 160 to 110 after 200 times iteration. Although the process is smooth, the absolute difference between the highest SSE to the lowest is about 50. The SSE of training set cannot converge to a stable value. It shows the SSE of training set increased over 150, while the converged value does not exist during the 200 iterations. Table 5.6.4-a shows the value of each neuron in the network. The value of the output layer did not converge to 0 and 1, where is around 40:60. Table 5.6.4-b shows the weighted value of each neuron in the hidden layer.

Model	Real group membership		Predicted group		Firms correctly(incorrectly) classified
			1	0	
BP	Profit	1	27.59%	72.41%	41.50%
	Loss	0	44.59%	55.41%	

Figure 5.6.4-b The Prediction accuracy of BPNN with NF indicators

Figure 5.6.4-b shows the prediction accuracy of the model. The overall prediction accuracy is 41.50%. The prediction accuracy for good performance firms is very low, which is only 27.59%. On the contrary, the prediction accuracy of poor performance is around fifty-fifty, which is 55.41%.

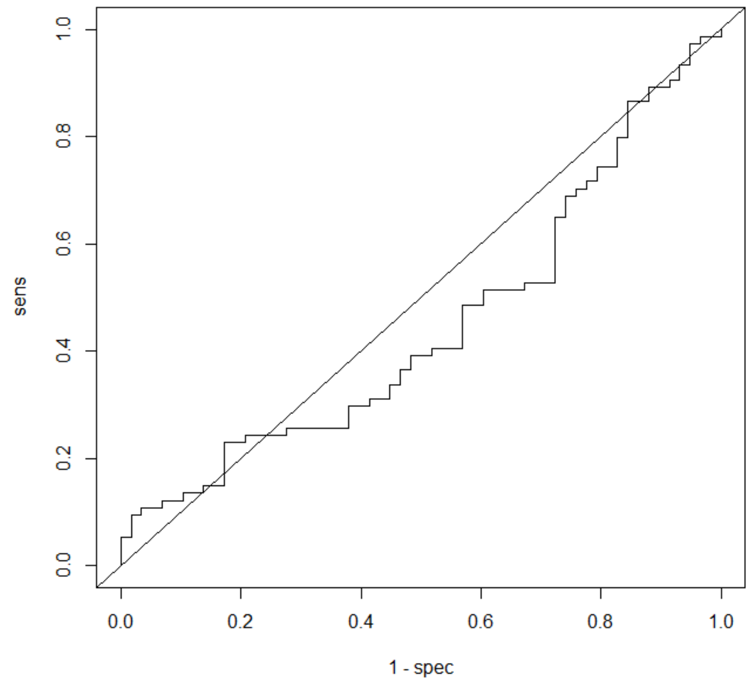


Figure 5.6.4-c The ROC curve of BPNN with NF indicators

Figure 5.6.4-c shows the result of the ROC test for the model. As mentioned before, the AUC should cover more than 70% of the full area to indicate a well-explained model. However, the AUC shows above cannot even cover half of the full area. Therefore, the ROC result shows the model cannot conclude meaningful explanation, which means the prediction result based on the model cannot be used in supporting decision making.

5.6.5 Summary

Since the BPNN model with financial indicators group did not converge to 0 and 1, it is possible to optimise the result by increasing the iteration times and the number of hidden neurons. The detailed results were shown in Appendix 2, Table 5.6.5-a.

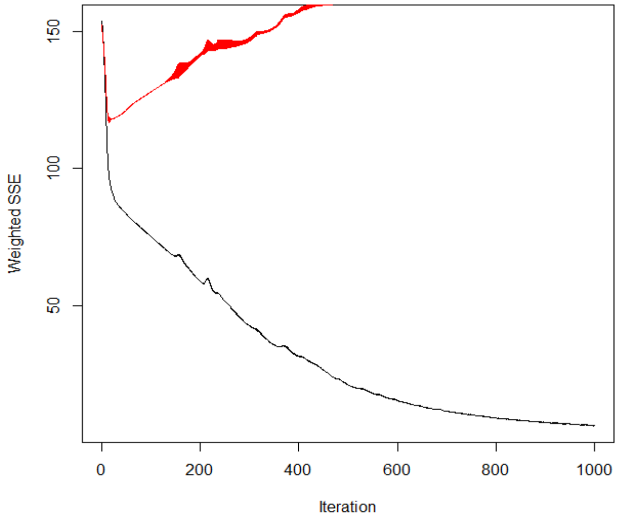


Figure 5.6.5-a Result of BPNN with F indicators (1000 times iterations)

Figure 5.6.5-a shows the weighted SSE in 1000th iterations, where the black line shows the SSE of the training set and the red line shows the SSE of the test set. The table 5.6.5-a shows the values of output neurons, which are 0.998 and 0.00. The values of output neurons are close to 0 and 1. However, the result still could not be used to predict firm performance. The SSE of the test set in Figure 5.6.5-a did not coverage to a constant value, on the contrary, the SSE of training set continually decreased as iteration times increased. Although the SSE of the training set is quite low as iteration increased, the increasing SSE of test set indicates that the rules cannot be applied with other samples than the training set. More specifically, increased iterations led to the problem of overfitting, which means the patterns or rules found by the training set could only explain itself only. Therefore, the result in section 5.6.3 was selected as a final result, since increasing iteration times cannot improve the model.

Indicators	Real group membership		Predicted group		Firms correctly(incorrectly) classified
Financial and non-financial			1	0	
	Profit	1	68.97%	31.03%	67.59%
	Loss	0	33.78%	66.22%	
	Real group membership		Predicted group		Firms correctly(incorrectly) classified
Financial			1	0	
	Profit	1	68.97%	31.03%	68.94%
	Loss	0	31.08%	68.92%	
	Real group membership		Predicted group		Firms correctly(incorrectly) classified
Non-financial			1	0	
	Profit	1	27.59%	72.41%	41.50%
	Loss	0	44.59%	55.41%	

Figure 5.6.5-b The Prediction accuracy of three BPNN models

Figure 5.6.5-b shows the summary of the prediction accuracy of BPNN models with three different indicator groups. The most accurate one is the BPNN with financial indicators model, which is 68.94%. The BPNN with financial and non-financial indicators model is the second accurate one, which the prediction accuracy is 67.59%. There is not a significant difference between these two models. The prediction of good performance firms is same for two models, while there is a slight difference (2.7%) with the prediction of poor performance firms. However, the prediction accuracy of BPNN with non-financial indicators model is inferior, which is only 41.5%. Specifically, the prediction of good performance firms in BPNN with non-financial indicators is the worst one, which is only 27.59%. Therefore, it could be concluded that the most accurate model is BPNN with financial indicators. The prediction

accuracy will slightly decrease when the financial indicators and non-financial indicators are used simultaneously in the model. According to the result, the non-financial indicators cannot be solely used as input neurons to build the BPNN model.

SSE	Converging speed (Training set)	Converging speed (Test set)	Absolute difference	AUC
Financial and non-financial	quick at beginning	Quick at the beginning, fluctuating	120	0.75
Financial	quick at beginning	Quick at the beginning, Smooth	140	0.75
Non-financial	slow	Does not converge	40	less than 0.5

Figure 5.6.5-c Description of three BPNN models

Figure 5.6.5-c shows the result of weighted SSE calculated by BPNN with three different indicator groups. The result of the financial and non-financial indicators group is very similar to the financial indicator groups. The Converging speeds of SSE in training set in both groups are quick at the beginning, while the shape of the curve is also similar. The converging speeds of SSE in the test set are different. As shown in Figure 5.6.5-b, the converging speed of SSE for the test set in financial and non-financial indicators group is quick at the beginning, but the whole process comes with fluctuations. The converging speed of SSE for the test set in financial indicators group is quick at the beginning but smoother than the previous group.

On the other hand, the SSE for the test set in non-financial indicators group does not converge to a specific value after 200 iterations, which means the methods cannot be used to predict with non-financial indicators group. There is only a slight difference in the Absolute difference of weighted SSE, where the value of the Absolute difference in financial indicators group is 20 higher. The AUC of both groups is the same, which is shown in Figure 5.6.2-c and Figure 5.6.3-c. On the contrary, the Converging speed of weighted SSE in non-financial indicator group is slow, where the value of the Absolute difference is only 40. Most importantly, the AUC is less than 0.5, which means it cannot explain the result well. Therefore, for BPNN models, the best one is BPNN with financial indicators and including non-financial indicators simultaneously with financial indicators cannot increase the prediction accuracy.

5.7 Summary

This chapter has shown the analytical procedures and the results of the analysis. There are 849 listed Chinese SMEs in Shenzhen Stock Exchange has been selected. The data was collected by Web Clawer. The main steps of applied data mining methods were using SPSS 20.0 and R programming.

Firstly, the data was collected as discussed in previous chapters, which includes financial information and non-financial information. Then, all the information was transferred into indicators. After that, the financial ratios were calculated, and the non-financial indicators were generated. The results of K-means clustering supported that there are two different groups of firms, which means the classification should not strictly follow ST/Non-ST standards in Chinese stock market.

Then, the CHAID, LR, GAs and BPNN were applied as data mining methods. Followed the ERM framework, the dependent variables are KPIs and independent variables are candidates of KRIs. To investigate the value of non-financial indicators in DM-RM model, the KRIs were selected from three indicator groups, which are financial and non-financial indicators groups, financial indicators group and non-financial groups. In the CHAID method, the dependent variables are selected as Z-score (Altman et al., 2010) and growth of ROA. In the rest three methods, the dependent variables are selected as the growth of ROA. In order to provide additional tests to verify the meaningfulness and robustness of the results, the variable importance and RUC test have also been applied. At the end of each subsection, the results of the data mining methods were summarised. Also, the rules and patterns found by the data mining methods have also been initially discussed. The subsequent chapter will discuss the results generated from this part and provide links between results, hypothesis and findings.

6. Discussion

6.1 Introduction

This Chapter is going to discuss the main findings of the data mining methods. The data mining process examined the usefulness and meaningfulness of KPIs and KRIs in the DM-RM model. In order to test the relationship between the KPIs and KRIs, four different data mining methods were applied in the empirical examination. The data mining methods examined the selection of KPIs, selection of KRIs, the value of non-financial indicators and the combination of data mining process and risk management process.

The study has developed a research model that linked data mining process and risk management process together. In order to improve the risk management process, the data mining process was fitted into all steps in the risk management process. The two processes were linked by using KPIs and KRIs. Meanwhile, the usage of EWS and BI helped the DM-RM model focused on a specific purpose in this study. These components improved the DM-RM model in risk treatment, data collection, and data clean up. The usage of DM-RM model successfully captured the rules and patterns in listed Chinese SMEs, which indicated the model is suitable for analysis of specific targets. Furthermore, the results of this research were compared with other scholars' work to verify the effectiveness of accuracy.

The purpose of this chapter is to provide a thorough discussion of all results obtained from empirical examinations in the previous chapter. In doing so, this chapter was divided into seven sections, including this introductory part. The following section 6.2 and 6.3 discusses the selection of KPI and KRIs. Next, the rules and patterns found by the DM-RM model were detailed explained. After that, the hypotheses of this research have been verified. Then, the results of this study have been compared to other studies in order to verify the effectiveness. At last, a summary of this chapter is provided.

6.2 Selection of KPI

Coleman (2009) claimed that key risk indicators (KRIs) provided the information about companies' risk positions to alert the companies about the changes, which can be used by management to show the risk level of activities and projects. Meanwhile, according to Verbano and Venturini (2011), the purpose of ERM is to maximise the firms' value. It is also important for firms to present their profitability to stakeholders and investors. As a result, some indicators that could represent the firm performance could be selected as KPI, which will provide information regarding the profitability of the firm. Altman et al. (2009) stated that the Z-score, which was developed by Altman, could be used to measure the situation of the firms. To measure the firms' risk positions, Li et al. (2017) selected Altman's Z-score as the performance indicator. On the other hand, there are some other indicators could be used for the measurement of firm performance. The growth rate of return on assets (short for ROA) is one of the measurements of firms' performance since the growth rate could indicate the life-cycle of firms (Young, 1996). The ROA measures the change in ROA, which is not only considering the absolute value of ROA. It is more objective to use the change rate of ratios to measure the profitability since the absolute value of the ROA depends on the size of the firms.

There are some scholars used ST and Non-ST in the analysis of Chinese companies. However, there are limitations to using ST standards in Chinese stock market, which was detailed discussed in Section 2.4.4.1. It concluded that the ST/Non-ST might be biased since it is subjectively selected by many scholars (Xie and Me, 2013; Yao and Shen, 2005). On the other hand, Koyuncugil and Ozgulbas (2012) used the mean of financial ratios as performance measurement, which may not directly reflect the performance of firms. Therefore, the possible KPIs could be selected from Z-score and ROA. Since the Z-score provides a ternary classification, the result may be lack of evidence to support the performance in the grey area. The ternary variable should be transferred to a binary variable to use Logit regression and GA method. Meanwhile, after comparing the accuracy of CHAID models, the accuracy of Z-score models is less than ROA models. Therefore, the KPI is finally decided to use ROA.

The prediction accuracy of data mining methods can support chosen ROA as KPI. The highest average accuracy is around 75% for financial and non-financial indicators group with ROA as KPI. On the other hand, there are three groups of performance with Z-score as KPI, which are bankruptcy, might be bankruptcy and stable (Altman, 1968; Altman et al., 2010). Since there is a grey area in the Z-score, it means the risks positions of the firms in this area are uncertain (Gerantonis, Vergos and Christopoulos, 2009). The prediction accuracy of CHAID with Z-score for three different performance groups cannot avoid calculating the accuracy of the grey area, which does not make sense in performance prediction. On the contrary, the ROA only classified two groups, which are good or poor performance. Choosing ROA as KPI is more straightforward and meaningful. As a result, the ROA has been selected as KPI in this study.

6.3 Selection of KRIs

The selection of KRIs is complicated since the number of candidate indicators is much more than KPIs. In order to find the hidden rules and patterns from data for decision makers to improve risk management, the accuracy, function, and operability of the models are very important. This research has applied four different data mining methods in the selection of KRIs. As stated by Han et al. (2012), Mining the data step is essential in the data mining process. To find out the rules of KRIs, it is also important to analyse the result of Patterns and Models step (discussed in section 3.4.2). The accuracy of the prediction models is important, where it indicates the meaningfulness and robustness of the rules. This research has applied four different methods (CHAID, LR, GAs and BPNN) with three different indicator groups (F and NF, F, NF). The results are shown below:

Financial and Non-financial indicators					
Model	Real group membership		Predicted group		Firms correctly(incorrectly) classified
			1	0	
CHAID	Profit	1	74.80%	25.20%	72.30%
	Loss	0	30.30%	69.70%	
GA	Profit	1	70.59%	29.41%	74.87%
	Loss	0	20.85%	79.15%	
LOGIT	Profit	1	66.88%	33.12%	70.71%
	Loss	0	24.60%	75.40%	
BPNN	Profit	1	68.97%	31.03%	67.59%
	Loss	0	33.78%	66.22%	

Financial indicators					
Model	Real group membership		Predicted group		Firms correctly(incorrectly) classified
			1	0	
CHAID	Profit	1	69.10%	30.90%	71.80%
	Loss	0	25.00%	75.00%	
GA	Profit	1	73.53%	26.47%	75.91%
	Loss	0	21.70%	78.30%	
LOGIT	Profit	1	64.94%	35.06%	68.98%
	Loss	0	26.98%	73.02%	
BPNN	Profit	1	68.97%	31.03%	68.94%
	Loss	0	31.08%	68.92%	

Non-financial indicators					
Model	Real group membership		Predicted group		Firms correctly(incorrectly) classified
			1	0	
CHAID	Profit	1	31.50%	68.50%	53.70%
	Loss	0	19.10%	80.90%	
GA	Profit	1	0.00%	100.00%	47.38%
	Loss	0	1.70%	98.30%	
LOGIT	Profit	1	50.92%	49.08%	53.67%
	Loss	0	43.59%	56.41%	
BPNN	Profit	1	27.59%	72.41%	41.50%
	Loss	0	44.59%	55.41%	

Table 6.3-a The Comparison of prediction accuracy of four data mining methods

Table 6.3-a indicated all three combinations of indicators used in this research, the accuracy of data mining methods with different indicator groups are listed. The information included in Table 6.3-a has been visualised in order to find the patterns more straightforward.

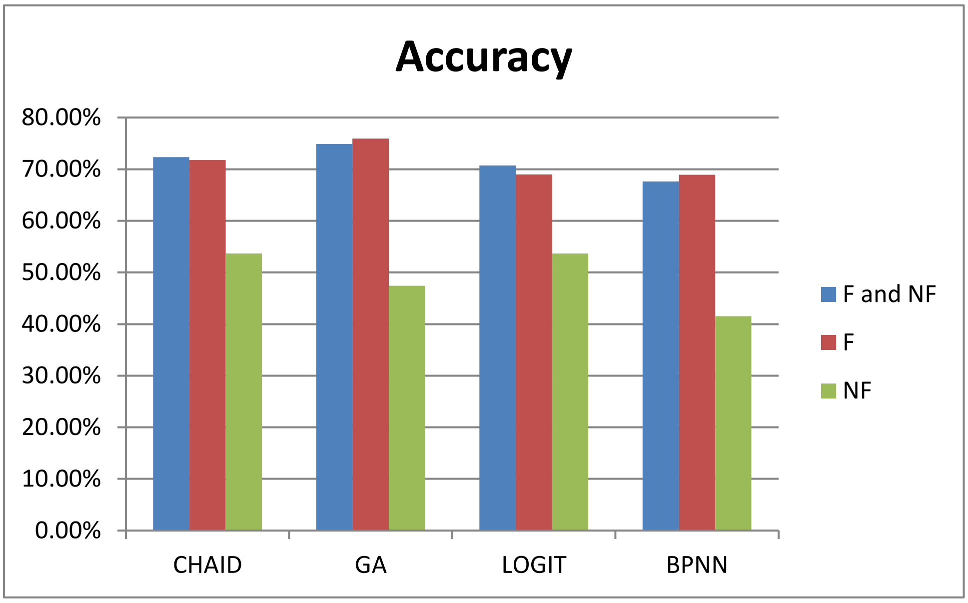


Figure 6.3-a, The Visualisation of prediction accuracy (1)

Figure 6.3-a indicated the Accuracy of four methods. It is evident that the highest prediction accuracy is the GA model with financial indicators. Including non-financial indicators could increase the accuracy of prediction models was proved in CHAID and Logit model. Although the value of non-financial indicators is not directly shown on the GA and BPNN models, there is other evidence shows the usefulness of non-financial indicators. Individually, in the GA models, the significant indicators in the Financial and Non-Financial model are more than in Financial indicators group. As previously discussed in Section 5.5.5, the GA model with financial and non-financial indicators may be more comprehensive in explaining the features of operational and strategic risks.

On the other hand, as discussed in Section 5.6.5.1, the BPNN model with financial indicators did not converge to target output value, which means the predictive result cannot be used in risk evaluation. Compared the result of BPNN model with three different indicator groups, there is only the BPNN model with financial and non-financial indicators converged to target output value within set iteration times. Although the results of the ROC test and prediction accuracy of BPNN model with the financial indicators group were acceptable, the output value cannot converge to target ranges of KPI. The overfitting problem will occur as the iteration times increased to 1000. As a result, the BPNN model provides a meaningful result only with financial and non-financial indicators. The usefulness of non-financial indicators was examined in four different models, which included statistical methods and non-statistical methods. Therefore, the non-financial indicators played an important role in the selection of KRIs in increasing accuracy, providing a more comprehensive explanation and optimising the predictive result.

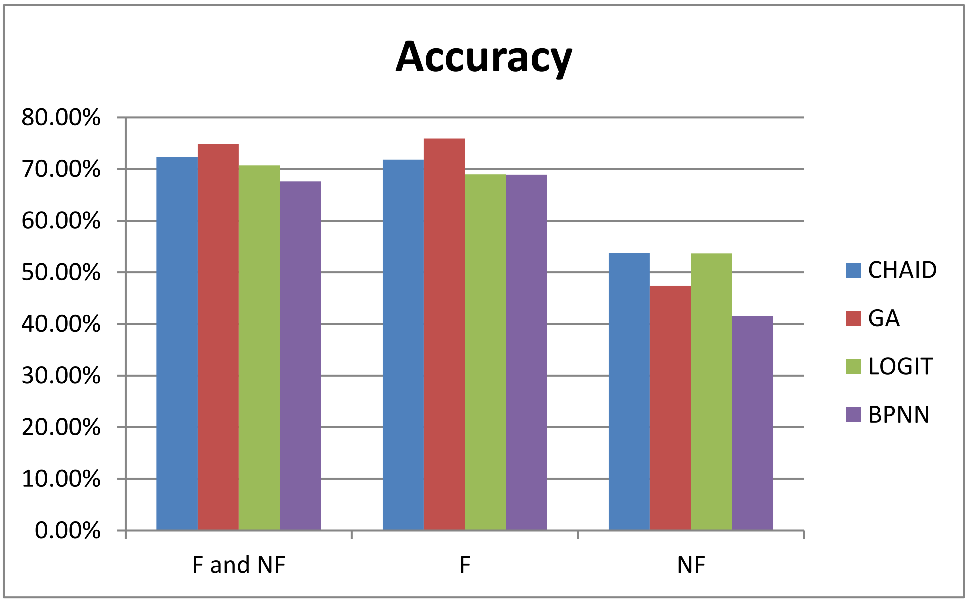


Figure 6.3-b The Visualisation of prediction accuracy (2)

Figure 6.3-b shows the prediction accuracy of the same indicator groups in the different four models. As it shows, there is not a significant difference between financial indicators group and financial indicators and non-financial indicators group. The accuracy of all models with non-financial indicators group is relatively low, which cannot be used to predict. Since the selected KPI is the firm performance, the selected KRIs should be able to measure the firm performance well. However, only around 50% accuracy cannot support the risk evaluation, since the tossing coin process is also with a fifty-fifty chance. The accuracy of GA and CHAID model is similar, which is higher than the other two models. Compared to the mechanism of two GA and CHAID model, the CHAID model could provide information about significant indicators and the

value of the indicator, while the GA model could only provide the significant indicators. In the risk management process, it is also important to know the treatment of the risks, where the information of KRIs is the more, the better. Therefore, it could be concluded that the CHAID model will be selected as the primary model since the information provided by the CHAID model will be more than the other three models.

6.4 Result Evaluation

The Risk Treatment is to interpret the rules and patterns generated in the Risk Assessment step, which will also be supported by Interpretation result step in Data mining process. Based on the enterprise risk management framework, the features of risks have been classified into four different risk catalogues. Since the two processes have been connected via KPI and KRIs, the threshold values of KRIs could be used to find out to reduce risks.

Risks	Model	Rules	Group Good
F,O	ROA with F and NF	x31<0.012,x2<=0.447	5.10%
F,S	ROA with F and NF	x31>0.2, y19>21.278	87.10%
F,O,S	ROA with F and NF	0.082<x31<0.2, y17=2,x34<=0.07, x15<=0.304	80.80%
F	ROA with F	x31>0.208	89.30%
F,O,	ROA with F	0.085<x31<0.208, x12<=0, x19<=0	80.80%
F,O,S	ROA with F	x31<=0.014, x4<=0.363	88.60%
H	ROA with NF	y7>75.45	60%
H, S	ROA with NF	y7<=75.45,y8<=15.47	64.60%
H, S	ROA with NF	y7<=75.45,y19>=20.79, y1=0	36.40%
	H=Hazard risks F=Financial risks O=operational risks S= strategic risks		

Figure 6.4-a Rules by CHAID models

Figure 6.4-a described the roadmaps of firms, which generated by CHAID method. The yellow rows indicated the strong rules, which the rules could determine the firm performance with probability around 90%. To comprehensively consider the risks, it is necessary to find patterns and rules from all the three combinations of the indicators for selected methods. The probability of performance good around 90% or less than

10% could be considered as convincible rules, which have been marked as yellow. It could also be concluded that the variables in the rules are KRIs, which are more important to detect the potential risk.

Furthermore, the rules generated by other methods could also be used to interpret the result. The financial risks are the most important risk among other three risks. There are total of six out of nine convincible rules are related to financial risks. There are also five out of nine convincible rules are related to strategic risks, and four out of nine convincible rules are about operational risks. All of the convincible rules are related to financial risks, which indicated the importance of financial risks. From the Figure 6.3-a, the KRIs generated by CHAID model are net profit to equity (x31), Quick ratio (x2), Size of firms (y19), Listed duration (y17), fixed assets to total loans (x15), long-term liability to long-term liability and equity (x12), bank loans to total assets (x19), environment index (y7), technology innovation index (y8) and industry (y1).

F and NF		Estimate	Std.Error	z	value	Pr(>|z|)
	x2	9.60E-02	3.80E-02	2.487	0.013	*
	x4	1.40E+00	6.00E-01	2.296	0.022	*
	x8	2.90E+00	6.70E-01	4.29	0	***
	x17	8.20E-01	3.80E-01	2.174	0.03	*
	x31	7.30E+00	2.00E+00	3.638	0	***
	x34	-4.00E+01	5.00E+00	-8.109	0	***
	y2	3.20E-01	1.40E-01	2.299	0.021	*
	y4	1.80E-02	8.00E-03	2.292	0.022	*
F	x2	1.00E-01	3.91E-02	2.568	0.01	*
	x5	2.21E+00	8.91E-01	2.483	0.013	*
	x22	-1.83E+00	6.41E-01	-2.852	0.004	**
	x23	2.59E+00	7.64E-01	3.392	0.001	***
	x31	6.15E+00	1.98E+00	3.115	0.002	**
	x34	-3.79E+01	4.82E+00	-7.878	0	***
NF	y3	-1.00576	0.46441	-2.166	0.03034	*
	y4	0.21761	0.10262	2.121	0.03396	*
	y5	0.27097	0.1258	2.154	0.03124	*
	y7	0.20449	0.09145	2.236	0.02534	*
	y8	0.12651	0.0576	2.196	0.02807	*
	y10	-2.31224	1.07007	-2.161	0.03071	*
	y14	-0.27044	0.10283	-2.63	0.00854	**
	y17	0.31125	0.15378	2.024	0.04297	*
	y19	-0.19107	0.09527	-2.005	0.04492	*

Figure 6.4-b Significant indicators by LR methods

Figure 6.4-b shows the result of Logit Regression. There are eight significant

indicators in the financial and non-financial group, where the top three z-value indicators are net profit to equity (x31), net profit to assets (x34) and equity to assets (x8). There are six significant indicators in the financial group, where the most significant indicators are net profit to assets (x34) and tangible fixed assets to total assets (x23). There are nine indicators are significant in the non-financial group, where the most significant indicator is a number of research staffs (y14). Although the KRIs are significant to the KPI, the coefficient of the KRIs cannot interpret how the importance of the indicators in measuring KPI. Since Logit regression can not generate the threshold values of the KRIs, the rules and patterns of KRIs may not be able to describe all aspects of the KPI.

Group	Iteration	Importance	Accuracy	Indicator	Name
Financial and non-financial	1	15.12184885	0.6269	x31	Net profit to equity
	2	12.94503794	0.7265	x32	Profit before tax to equity
	3	12.07511835	0.7449	x34	Net profit to asset
	4	8.728316218	0.7495	x37	Gross profit /net sales
	5	4.852187639	0.7517	x33	EBIT/EBT and finance expense
	6	3.93329857	0.7494	x3	Absolute liquidity
	7	3.574172304	0.7676	x12	Long-term liability to long-term liability and equity
Financial	1	15.03821378	0.646844	x31	Net profit to equity
	2	15.00426021	0.7378201	x32	Profit before tax to equity
	3	12.30907294	0.7630796	x34	Net profit to asset
Non-financial	1	4.385605748	0.5239464	y10	Audit opinions
	2	2.295658305	0.5262192	y9	Employees education

Figure 6.4-c Significant indicators in GAs method

Figure 6.4-c indicated the most significant indicators in all the three indicators groups with the GAs method. The financial and non-financial group generated the most KRIs, where the amount of the KRIs is seven. The financial group generated 3 KRIs, and the non-financial group only has two KRIs. As discussed in Section 5.6.5, the accuracy of the non-financial group cannot be used to predict KRI. There is less KRIs in financial indicators group than the financial and non-financial group, which means including the non-financial indicators could provide more comprehensive result in selecting KRIs. Therefore, in GA models, the financial and non-financial will be the optimised choice in the selection of KRIs, which is considered the comprehensiveness and the accuracy.

F and NF	Output_0	0.94401	0.34138
	Output_1	0.05605	-0.3466
F	Output_0	0.76269	-0.11104
	Output_1	0.2396	0.0811
NF	Output_0	0.36506	0.12428
	Output_1	0.63826	-0.02857

Figure 6.4-d Converging results of BPNN models

Figure 6.4-d shows the converging results of three indicators group in BPNN models. The KPI was coded as 0 and 1, which means poor performance and good performance respectively. It is clear that there is only financial and non-financial group converged to target output value, where the other two indicator groups cannot converge to 0 and 1. As discussed in Section 5.6.5, although the accuracy of financial and non-financial indicators group is the second one, the model converged to target output indicated this one predicted the KPI better than the other two models. Compared with other methods, the BPNN model cannot indicate the threshold and the patterns of the KRIs. As there is the black box mechanism built in the algorithm, it is not possible to interpret the result with the certain rules. Therefore, in the BPNN models, the prediction accuracy

is not the most important aspect, while the converged value and accuracy should be considered at the same time.

After compared all four models with three different indicator groups in addressing the KRIs and KPIs problems, the optimum algorithm is CHAID method, which provided the second highest accurate prediction and threshold values of KRIs. Although the CHAID is better than other algorithms, it is necessary to consider the results of other algorithms to get the most comprehensive view. To sum up, the roadmaps and threshold values were described as follow: to achieve good performance, the listed SMEs in China can follow such rules:

1. Net profit to equity greater than 0.12 and quick ratio greater than 0.447
2. Net profit to equity greater than 0.2 and firm size (log) greater than 21.278
3. Net profit to equity less than 0.014 and inventory to current assets less than 0.363
4. Net profit to assets has a native effect on firm performance, and the research stuff is important to firm performance
5. Profitability and liability are the most important aspects generated by GA algorithms, while the employee education and audit opinion are critical non-financial indicators in GA algorithms
6. The profitability ratios, liability ratios, firm size and Goodwill and intangible asset are essential aspects, which are belonging to financial risks, operational risks and strategic risks.

6.5 Hypotheses Verification

There are eight hypotheses have been purposed to verify the DM-RM model. The hypotheses were listed below:

No.	Research Hypotheses
H1	The data mining process and risk management process could be synchronised together to achieve risk management purposes.
H2	The ERM framework could be embedded in the risk management process.
H3	The usage of KPIs and KRIs complied with the ERM framework and can improve the risk management process
H4	Combining financial and non-financial indicators in the selection of KRIs can explain most of the features required by the enterprise risk management framework.
H5	Non-financial indicators are essential in the whole risk management process.
H6	The early warning system could provide solutions for KRIs in the risk treatment step.
H7	The business intelligence approach can help the ERM framework become embedded into the risk management process.
H8	The business intelligence approach can enhance the ability to capture useful information to be used as indicators in the risk management process for SMEs.

Table 6.5-a The Summary of hypotheses

Table 6.5-a shows the contents of eight research hypotheses. The hypotheses attempted to examine the relationship between the data mining process and risk management process. KPIs and KRIs have linked the data mining process and risk management process. Also, the ERM framework, EWS, BI and SMEs have also been examined. The value of non-financial indicators in DM-RM model has also been tested.

Figure 3.3-c shows the connections with hypotheses in DM-RM model discussed in Section 3.4. The results were recalled verifying the hypotheses. There are total eight hypotheses were initially proposed as follow:

H1: If the data mining process and risk management process could be synchronised together to achieve risk management purposes.

H2: The ERM framework could be embedded in the risk management process.

H3: The usage of KPIs and KRIs complied with the ERM framework and can improve the risk management process

H4: Combining financial and non-financial indicators in the selection of KRIs can explain most of the features required by the enterprise risk management framework.

H5: Non-financial indicators are essential in the whole risk management process.

H6: The early warning system could provide solutions for KRIs in the risk treatment step.

H7: The business intelligence approach can help the enterprise risk management framework become embedded into the risk management process.

H8: The business intelligence approach can enhance the ability to capture useful information to be used as indicators in the risk management process for SMEs.

The H1 is the foundation of this study. In order to test H1, the results need to show the data mining process and risk management process have been integrated together. There are three main steps in the RM process (ISO 31000, 2009). Moreover, there are five data mining steps (Han et al., 2012). The connections were shown below:

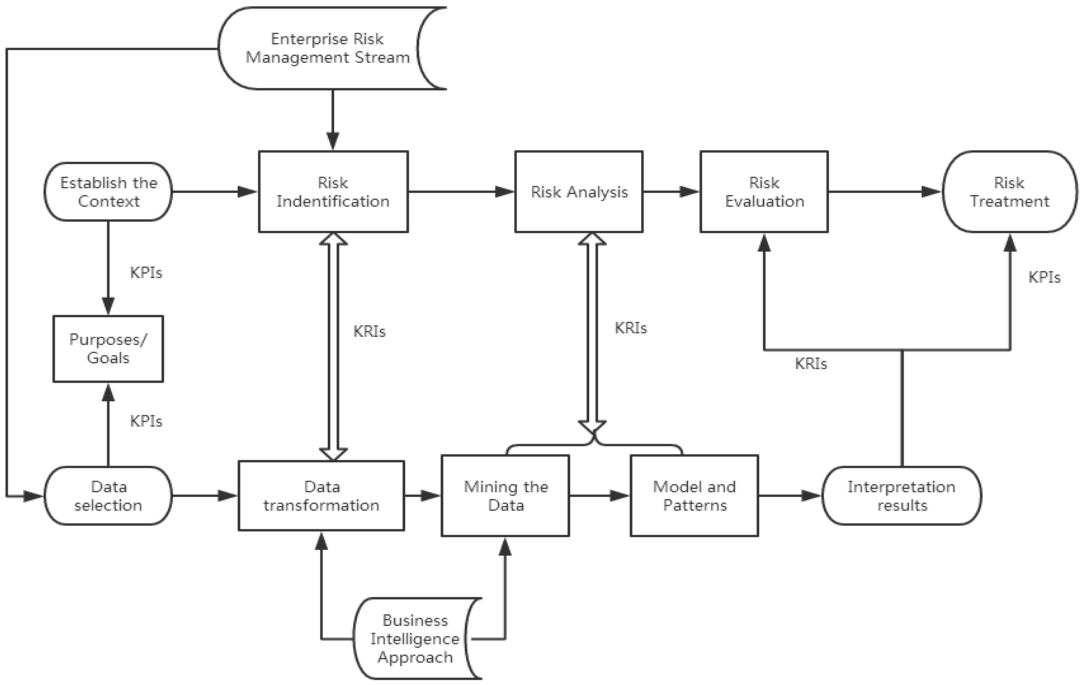


Figure 6.5-b Flowcharts of DM-RM model with hypotheses

Figure 6.5-b shows the explicit connections between the DM process and risk management process. It is clear that each sub-step was synchronised by using KPIs and KRIs. If the KPIs and KRIs were found and meaningful, it indicated that the two processes had been integrated. The results of the data mining methods have found out the KPI and KRIs, where the usefulness and meaningfulness of KPI and KRIs have

also been proved. Therefore, if the usage of KPI and KRIs was successful, the H1 can be proved. From the empirical view, the results of DM should support the RM process, which means the feature selection functions should be effective. As discussed in the previous section, the overall prediction accuracy is over 75% for all models, it means the two different performance groups can be distinguished by using DM methods in this study. As a result, the empirical evidence supports that the DM process can be integrated to the RM process.

For H2 examined, it is necessary to specify the risk catalogues mentioned in the ERM framework, and the results should also follow the ERM framework. The four risk catalogues under the ERM framework (CAS, 2003; Verbano and Venturini, 2011) have been applied in order to capture all the risk features. In Section 4.4, the information was collected based on the risk catalogues under the ERM framework. Meanwhile, the indicators have been calculated upon the ERM framework as well. In Section 5.7, the results of four different data mining methods have been verified, which indicated that the results are meaningful and reasonable. Moreover, the empirical findings in Section 6.4 illustrated that the four different risk types are all important in the RM process. The results from the CHAID model directly show the connections and importance between rules and risk types. Therefore, the H2 has been proved that the ERM framework has been embedded into the RM process.

The H3 examined the effectiveness of using KPIs in the DM-RM model. The KPIs aimed to provide measurements for the research targets. The KPIs have been used in 'Establish the Context' step in the RM process, where the purpose of the RM process was specified. In Section 5.3.4, the usage of different KPIs (Altman's Z-score and ROA) has been compared. Based on the empirical results, the ROA has been selected as KPI in this study. Verbano and Venturini (2011) stated that the ERM aims to maximise the firms' value. The ROA directly measured the performance of the firms, which was used by other studies as well (Altman et al., 2010; Heikal et al.; 2014). Also, the selection of KRIs is also complied with the risks features by ERM framework. Since the KRIs determined the prediction accuracy of KPIs, the KPIs are also based on the ERM framework. The data mining methods helped in reducing the number of indicators that decision-makers need to focus, which means the efficiency of the whole RM process has been simplified. Therefore, it concluded that the usage of KPIs enhanced the efficiency of the RM process and complied with the ERM framework.

The H4 required that both a financial indicator and non-financial indicators were applied in data mining methods, where the results required proving the value of non-financial indicators. In the applied four data mining methods, there were three different indicators groups (financial and non-financial; financial; and non-financial) indicators have been applied in order to verify the value of non-financial indicators. In Section 5.3 to 5.6, each data mining method applied three different indicator groups. It concluded that the non-financial indicators are essential in the DM-RM model, because including non-financial indicators can increase the accuracy of the prediction. However, as stated in Section 6.4, the non-financial indicators cannot solely predict the performance. Using financial and non-financial indicators together is necessary. On the other hand, the results indicated that the financial indicators could not explain some of the characters of strategic risks and hazard risks. The usage of non-financial indicators considered the aspects that financial indicator cannot explain. The effectiveness and meaningfulness of using non-financial indicators were thoroughly discussed in Section 6.4. Also, because the prediction accuracy of all models is over 75%, it means the results are meaningful. Especially, the KRIs were selected from financial and non-financial indicators, which proved the usefulness of the indicators in the whole RM process. Therefore, with over 70% accuracy, the financial and non-financial indicators could be used to explain the risk features under the ERM framework.

H5 examined the usefulness and meaningfulness of non-financial indicators in the model. The non-financial indicators were generated based on the risk catalogues in ERM framework by CAS (2003), where some information was transferred into indicators based on the understanding of the risk features. As discussed in Section 6.3, the prediction accuracy increased as non-financial indicators included in the CHAID and Logit regression models. In the GA method, the non-financial indicators can provide a more comprehensive view of the KPI, which takes four more indicators into account. In the BPNN model, only the financial and non-financial indicators group could converge to the target result. However, the result also proofed that the non-financial indicators cannot independently predict the KPI as KRIs. Since the selected KPI should clearly state the financial position of firms, the KPI is more like a financial indicator. As a result, the non-financial indicators cannot explain the feature of financial indicator makes sense, where the result of prediction accuracy with non-financial indicators group is acceptable. Although the non-financial indicators cannot predict KPI independently, it still can proof the usage of non-financial indicators is meaningful and useful.

To examine H6, the usefulness of EWS required to be proved. The EWS monitored and reported alerts of the potential risks (Koyuncugil and Ozgulbas, 2012). In the risk treatment step in the RM process, the EWS provided explanations of rules and patterns found by the data mining process. Risk treatment thus also includes improving the existing control methods and developing new controls (ISO 31000, 2009). As discussed in Section 6.4, the threshold values provided the specific ranges of KRIs in good and poor performance firms. If the decision makers followed the path of KRIs in good performance firms, the effect of risks would be reduced to a minimum level. As stated in Section 6.4, there are several convincible rules have been found out. The RM roadmaps for the SMEs have been developed. If the ratios in convincible rules were reached, it means the performance will be in danger or getting better. As a result, the EWS provided solutions for controlling risks by improving KRIs.

To verify H7, the usefulness of BI approach in helping the ERM framework for RM process required to be proved. The BI approach suggested that the information could be anything useful, which may be obtained from websites, reports, emails, etc., while the non-financial indicators generated by the BI approach considered this information. Most of the aspects described by the ERM framework were considered with the non-financial indicators generated by the BI approach. The BI approach provided solutions in data collection, data clean up and data transferred. As discussed in Section 6.4, the KRIs have been selected from all indicators, the effectiveness of the data mining methods has been confirmed. Therefore, the BI approach can help the ERM framework by providing candidates of KRIs, which was embedded in the RM process.

To examine H8, the functions of the BI approach in data collection required to be specified. This study has collected 849 listed Chinese SMEs in the Shenzhen Stock Exchange. There are forty-two financial indicators, and nineteen non-financial indicators were collected from each frim. The BI approach provided solutions in transferring information into indicators (Chen et al., 2012). The useful information can be transferred into indicators upon the requirements by ERM framework, which has been discussed in Section 6.4. Since the prediction accuracy is acceptable, the DM-RM model for SMEs is successfully developed. Also, the risk features of SMEs have also been captured by analysing the indicators provided by the BI approach. As a result, the BI approach provided solutions in transferring information into data, which captured the risk features of SMEs.

No.	Result	Explanation
H1	Verified	The model prediction accuracy over 70%
H2	Verified	ERM risk types covered most of the features

H3	Verified	KPIs and KRIs have been selected and can be used to predict
H4	Verified	The FIs and Non-FIs can do feature selection with over 70% accuracy
H5	Verified	Including both FIs and Non-FIs can increase the prediction accuracy
H6	Partly Verified	The rules and patterns can build a roadmap for SMEs, but can be improved with more information
H7	Verified	The indicators can be visualised by using BI approach
H8	Partly Verified	The information can be quantised by using the BI approach, but can be expanded

Table 6.5-b Hypotheses verification

Table 6.5-b shows the hypotheses verification. All the eight hypotheses have been thoroughly discussed above, where each clarification of each hypothesis has also been provided. This study shows the detailed steps in integrating the RM process and DM process. Meanwhile, as shown in Figure 6.5-b, all connections among all the components have been linked with hypotheses. Meanwhile, the quantised measurements of the model performance have shown, which illustrated the prediction accuracy of DM methods. Three combinations of data groups have been compared, where the value of non-financial indicators has been recognised. Furthermore, the most suitable DM method for RM in SMEs has been found out by comparing the comprehensiveness and accuracy of the prediction. On the other hand, the BI approach and EWS can be improved by using broader information and more systematic framework, which means these two components can be improved. Therefore, all the hypotheses have been verified.

6.6 Comparison with other studies

The data mining methods in financial distress prediction is a classic topic. Geng et al. (2015) stated that the statistical techniques were commonly applied in the prediction of this area. However, due to the unrealistic assumptions, some of the statistical methods may not perform well in the area. Some scholars used Logit regression to overcome the drawbacks of traditional statistic methods, while others tried to use machine learning methods based on artificial intelligence. Geng et al. (2015) stated that researchers applied neural network (Fletcher & Goss, 1993; Wilson & Sharda, 1994), decision trees (Frydman, Altman, & Kao, 1985), genetic algorithms (Shin & Lee, 2002). In this research, the data mining methods: LR, CHAID, GAs and NN were applied, which were used to build the integrated model to manage risks. The main purpose of DM-RM model is to select KRIs to determine KPI, which is used to link the data mining process and risk management process. Therefore, these data mining methods were purposed to find out KRIs based on KPI to support the whole framework, which means these methods focused on the feature selection aspect.

The prediction accuracy of the DM-RM model has also been compared with other studies. According to Geng, et al. (2015), the most accurate model is Neural Network in their research, where the accuracy is around 78%. Shin and Lee (2002) applied the GA method to predict bankrupt, where the accuracy is about 80%. Gordini (2014) stated that the accuracy of GA, SVM and LR were 78%, 77.2%, 72% respectively. Since the purpose of studies may not be the same, some of the research will not only focus on the prediction of firm performance to achieve risk management process. Compared with other studies, the result of this research is about 77% accuracy with four different methods, which is not entirely different from other studies. Therefore, it is possible to conclude that the result of this research is acceptable in the academic aspect.

6.7 Summary

This chapter evaluated the result of all methods applied in this research, verified the constructed framework, and compared the result with other methods. The main finding is that there are connections between KRIs and KPI, which could be used to link the data mining process and risk management process. Furthermore, the selection of KRIs and KPI provided evidence that the ERM framework could be used to risk management process. The successful usage of KRIs and KPI also proved that the meaningfulness and usefulness of two different processes. Meanwhile, the value of non-financial indicators has also been verified, which was clearly described by the comparison of different methods. Furthermore, the CHAID model provided the roadmap and threshold values of KRIs, which is complied with the idea of the early warning system. The ERM steam was also explained by the model, where the rules generated by the four models followed the risk catalogues classified by the ERM framework. Additionally, the result of this research was also compared with other studies in order to verify the meaningfulness and robustness of models. Since there is not a significant difference between the result of this research and other scholars' work, it is concluded that the result is acceptable and useful.

This section has discussed the results of four different data mining methods. It detailed introduced four data mining methods for KRIs selection. In general, the results obtained from this study empirically suggested that the data mining process and risk management process has been combined. The results also supported that the usage of KPIs and KRIs is successful, where the KRIs have been selected upon the selected KPI. The DM-RM model also successfully embedded with ERM framework in risk identification; EWS in risk treatment; BI approach in data collection and SMEs in data selection.

The results of this study also supported that the usage of non-financial indicators is essential to building the DM-RM model for SMEs. It has been proved that the non-financial indicators can provide supports to financial indicators.

7. Conclusion

The study aims to improve the risk management process with the data mining process. In doing so, it incorporated the data mining process with ERM framework, BI approach, EWS and SMEs as components. This study also examined the usage of KRIs and KPIs in addressing risk management to capture all the risk features. Also, the study also examined the value of non-financial indicators in the risk management process. The DM-RM model was developed in this study, which can consider all the risks together in order to improve the firms' performance purposively. The study has also introduced the importance of risk management and discussed the four types of risks based on the ERM framework by CAS in 2003. The study also made initial attempts in the integrated risk management process with the data mining process and successfully concluded the listed SMEs in China can be grouped based on the performance.

The purpose of this chapter is to provide a conclusion of the study. The chapter discussed how the study's aim and objectives are achieved; outlined the theoretical and practical contributions; identified the limitations of this study; and provided recommendations for future research.

7.1 Overview

This study has combined the data mining process and risk management process and concluded a method in the application of KPIs and KRIs by BI approach for SMEs. The ISO and COSO risk management framework provided a solution for improving the efficiency of the risk management process. The risks are required to be detected and identified in the risk management process, which required detailed practical guidance. However, the ISO framework only provided the brief process in the risk management, which included the build the context, risk assessment and risk treatment. In order to achieve risk management goals in daily operating, it is necessary to explain more specific guidance in risk management. The COSO framework gives the management prototype of the framework in their risk management activities, which includes control environment, risk assessment, control activities, information and communication and monitoring activities. In order to apply an enterprise risk management framework in firms, there should be more practical guidance from the theory of enterprise risk management (Nocco and Stulz, 2006). The enterprise risk management framework has been studied by many scholars (Verbano and Venturini, 2011), which considers both financial and non-financial aspects of firms' operation. Verbano and Venturini (2011) claimed that enterprise risk management is one step further from traditional financial risk management. O' Donnel (2005) pointed out that the strategies, market, processes, financial resources, human resources and technologies were all structured into enterprise risk management. To measure all aspect of firms operation, the application of only financial indicators is not enough. As a result, the non-financial indicators have been suggested and developed to improve the risk management process. This study developed the DM-RM model with the ERM framework, BI approach, EWS, and SMEs components. The usage of data mining process will also be discussed and recommend other studies in different areas.

7.2 Achievements of aims, objectives and research questions

This section reviews the aims, objectives and research questions presented in Chapter 1 in order to verify that they have been achieved. The research aim is:

To investigate how financial and non-financial indicators can be used in risk management procedures with the data mining process based on ERM framework by applying a BI approach for SMEs.

The aim has been achieved. Chapter 2 has introduced the relationship between other concepts and financial and non-financial indicators. Chapter 3 has thoroughly discussed how to use financial and non-financial indicators in the proposed DM-RM model. Since the usage of non-financial indicators is a recent development, there are many scholars have proposed to apply it with their existing financial indicators research (Geng et al., 2015; Koyuncugil and Ozgulbas, 2012). To use non-financial indicators in the models, it is necessary to apply BI approach to capture the information required in the ERM framework by CAS (2003). On the other hand, practical guidance was obtained as the DM-RM model has been successfully built. As discussed in Chapter 5 and 6, the result of the data mining process could support that the model is valid. Therefore, the step-by-step practical guidance was obtained, which was shown by the process of model development.

There are also six detailed research objectives:

1. To develop a risk management process with enterprise risk management framework and data mining process.
2. To measure risks with both financial and non-financial information by using a business intelligence approach.
3. To comprehensively consider the risks applicable to the enterprise risk management framework and to integrate all necessary risk management and data mining steps for this consideration into one model.
4. To examine different data mining methods that can be applied in the analysis of the risk management process in SMEs.
5. To evaluate the usefulness of non-financial indicators in the risk management procedure.
6. To establish a robust early warning system to predict the likelihood and impact of different kinds of risks for SMEs based on financial and non-financial factors using data mining methods.

Chapter 2 and 3 reviewed concepts in the risk management process and data mining process, which introduced the fundamental components of the theoretical framework. Furthermore, the two chapters also discussed the usage of BI approach in capturing non-financial indicators, which could support the risk catalogues by ERM framework. Meanwhile, since the theoretical framework was developed and verified in this research, the model could comprehensively explain all the four risks under the ERM framework in one-step. Chapter 5 and 6 discussed different data mining methods in KRIs selection, which also provided an insight view of the risk management process. In Chapter 6, the total of four different methods applied in this research were compared with each other to evaluate the prediction results. Also, the prediction results also indicated the usefulness of non-financial indicators. Since the added non-financial indicators could either improve the accuracy or indicate more KRIs, it could be concluded that the non-financial indicators are usefulness in this research. Finally, the early warning system could be built via the rules and patterns found in Chapter 5 and 6. The threshold values and significance of KRIs could be generated with all four models, which could provide the essential components of building an early warning system. As a result, the early warning system could be built with the results gathered in this research.

The aim and objectives of this research were used to address six research questions:

1. Is it possible to use the risk management framework in SMEs by using Enterprise risk management framework?

In order to address this question, it is important to obtain the prediction result based on the ERM framework, which indicates the risk positions of the target firms. Since there are different types of risk management framework (Verbano and Venturini, 2011), it is necessary to specify the risk management framework. After that, the risk catalogues of the risk framework should be followed in the whole risk management process. In this research, the risk management process is followed the ERM framework. Also, the database is selected from the listed Chinese SMEs, which is also complied with the question.

2. How to conduct the risk management procedure under the enterprise risk management framework with business intelligence approach?

According to Han et al. (2012), the data mining process could use BI approach to generate data and build a database. Under the ERM framework, there are total of four different risk catalogues, which cannot be fully covered by financial indicators only. As a result, it is necessary to use some non-financial indicators to explain features of all risks. Since BI approach could support the data collection step, it is possible to gather enough information and transfer information to indicators to complete the risk management process.

3. Is the business intelligence approach useful in quantising and standardising the information into indicators?

The BI approach is useful in transferring the information to data, where the information gathered from Websites and other reports could be used in the data transfer step. Han et al. (2012) stated that the data mining process includes data cleaning up and data transferring steps. The raw data required to be cleaned and transferred before it becomes indicators that could be directly used in the model. The BI approach could be used to clean up and transfer the data format via coding or software. Therefore, the question could be answered, since BI approach provided supports to quantising and standardising the data.

4. How to use financial indicators and non-financial indicators in the prediction models to capture the risks under the enterprise risk management framework?

The financial indicators and non-financial indicators could be used as input indicators in data mining methods. Since there are four different risk catalogues in ERM framework suggested by CAS (2003), the indicators should cover financial risks, operational risks, hazard risks and strategic risks. As discussed in Section 4.4 and Section 5.2.1, the indicators are collected from the risk catalogues by CAS (2003). Since selected indicators could cover most of the features mentioned in the ERM framework, it is true that the indicators could capture most of the features. Therefore, the question could be solved, since the indicators were developed based on the requirements by ERM steam.

5. Are the non-financial indicators helpful in the promising model to measure firm performance? If yes, how much can it help?

In order to address this question, it is necessary to use at least two groups of indicators, where the results of financial indicators and non-financial indicators should be able to be compared. As discussed in Chapter 5 and 6, there are total of three different indicators groups, which are financial and non-financial indicators, financial indicators only and non-financial indicators only. The prediction accuracy could be used as the measurements of each indicator group. As discussed in Chapter 6, including non-financial indicators in the model could increase the prediction accuracy or increase the range of KRIs selection. The detailed discussion about how much non-financial indicators can help was listed in Section 6.4. Therefore, it can prove that the non-financial indicators are helpful.

6. Could the BI approach and the enterprise risk management framework integrate together in addressing risk management in SMEs?

In order to address this question, it is necessary to find out the function of BI approach in the risk management process and ERM framework. As discussed in Chapter 2 and 4, the BI approach could gather risk features required by the ERM framework. Also, the risk management process is required to follow one of the frameworks (Verbano and Venturini, 2011), where the ERM framework would be more suitable for this research. The important thing is to capture enough information require by ERM framework to complete the risk management process. The BI approach will provide information to support ERM and not limited to specific risk frameworks. The ERM framework provides risk catalogues for the risk management process, which limited the range of indicators selections. The ERM framework and BI approach played different roles in the whole risk management process. As a result, it is necessary to use both the ERM framework and BI approach in this research to complete the risk management process.

The decision makers may concern how to improve the performance and reduce the uncertainty. In section 6.4, the advantages of each method were discussed, which could be selected by decision makers. In order to reduce risks, the decision makers could control the ranges of KRIs or monitor the values of KRIs in order to improve the performance, which is complied with the purpose of risk management mentioned by Verbano and Venturini (2011). Furthermore, as discussed in Chapter 3, the purpose of this model could be changed upon required, which could provide more broad applications for different decision-making processes. The scholars may concern the implementation of data mining process into other areas. The data mining process can be easily adjusted based on a general purpose in another area, which will be used to find hidden rules and patterns. The BI approach in data mining process provided supports in data collection and data clean-up, which can be used in collecting data for other areas and topics. Also, the embedded ERM framework and usage of KPIs and KRIs provided a more comprehensive view of the risk management process, which improved the efficiency and coverage for the current knowledge. Therefore, these questions provided theoretical extension and practical guidance of the developed model in this study, which was answered by the discussion in section 6.4.

7.3 Contributions

7.3.1 Theoretical Contributions

Although the study in risk management started decades ago, the risk management is still a relatively new topic in SMEs, especially with the data mining process and BI approach. By providing empirical evidence on the enterprise risk management amongst SMEs in China, the study contributes to risk management literature by integrating numbers of processes and concepts from risk management, enterprise risk management, early warning system and business intelligence. Specifically, this research combined risk management process and data mining process and built a comprehensive framework to improve the current risk management process. Although the combination of the data mining process and risk management process was attempted before (Johnson, 2010), but the use of standard risk management process is the first time. The attempt of combing the data mining process and risk management process is a new area, which provided a different view of the data mining process. Furthermore, the application of ERM framework in risk management for SMEs is also be developed, which was considered understudied by Verbano and Venturini (2013). The total risk process and four risk types were fully considered in this study, which followed the ERM framework (Verbano and Venturini, 2013). As a result, this study provides a boarder view extended from existing literature by combining risk management process with the data mining process, with ERM, BI and EWS.

The business intelligence approach provided the support in data collection and indicator selection for the data mining process. This study followed the ERM framework in SMEs risk catalogues, which has developed the risk indicators under four risk types claimed by CAS (2003). Furthermore, this study extends the enterprise risk management framework by applying business intelligence concepts. It solved the problem of building up database, which provides the foundation of a data mining process. It has contributed to the current risk management process in model selections, variable selections and methods integration. In the studies of Chinese listed firms, many scholars applied ST and non-ST as a classifier. Differently, in this study, the classification did not follow the ST and non-ST classification, while the classifier was objectively selected by using statistical methods. This study also tried to provide the dependent variables other than ROE in other studies and attempted to provide more dimensions to explain the risks faced by SMEs. The study considered all the risks in an integrated framework rather than analysing the risks separately, which could provide a more comprehensive view of decision makers. As stated by Verbano and Venturini (2011), most of the studies did not cover all of the four risk catalogues, since collecting all the information required by the ERM framework is relatively tricky. However, this study attempted to capture all the risk features mentioned in the ERM framework and achieved acceptable prediction accuracy. The use of EWS in the DM-RM model has successfully found the convincible rules from all the rules and patterns and detected the warning signals. It indicated that the EWS was integrated into the risk management process and data mining process. Therefore, it concludes that this study has contributed to this topic and expanded the data mining process to other similar areas.

7.3.2 Practical Contributions

The findings contribute to the SMEs in China as well as broader risk management participants in other areas and industries. The developed process of building the integrated DM-RM model provides detailed steps for using the data mining process. Additionally, the data mining process has been developed based on the risk management process, which means the purpose of the data mining process is defined by the purpose of the risk management process. For a specific research target, it is possible to apply the DM-RM model to build a specific model, which was used to find potential rules and patterns for targeted objectives. This study thoroughly discussed the steps for risk management and the essential steps in decision-making. It specified the necessary steps in integrating data mining process and risk management process, which required symmetrically developed.

The risk management process provides the targets and goals for the data mining process, which resulted in closer connections between the two processes. It also proved that risk management would require more complex and integrated methods to find the benchmarks to avoid business failure. It also proved that a data mining method might not provide full explanations of the ERM framework since the risk features can be insignificant with different data mining methods. The study provided a detailed variable selection based on the four types of risks. Moreover, it is also possible to conduct models with different catalogues of risks. It also suggested that the difference between good performance and poor performance enterprises may not only depend on the financial ratios. This study also provided a different view in listed Chinese SMEs, which did not apply ST/Non-ST classification as many previous studies (Xie and Me, 2013; Geng et al., 2015). The classification was completely objective, which comes from the results of statistical data mining methods. This study has successfully avoided using imbalance database (Xie and Me, 2013), where the Non-ST firms are much more than ST firms in the imbalance database. It indicated that the ST and Non-ST is not the only classification rule in the studies of listed Chinese SMEs.

Meanwhile, the KPI and KRIs under different risk catalogues were redefined, which provided more accurate predictions and more efficient monitors in the whole process. The use of BI approach collected the information from annual reports, and government reports, which transferred useful information into indicators. The BI approach provided more abundant information on the requirements of the risk framework. The use of EWS efficiently explained the rules and patterns generated by data mining methods. Based on the ERM framework, the rules and patterns were obtained by risk catalogues, which provides a more specific view of the risk management process. The convincible rules, significant variables were concluded in Section 6.4, where the warning signals and desired trends were generated by EWS. It thus indicated that the EWS supported risk treatment in the risk management process and result interpretation step in the data mining process. At last, the study also allowed the companies to benchmark themselves to their peers and competitors across different KPI and KRIs.

7.4 Limitation

This section identifies three critical limitations to this research, based on the knowledge of the subject, the availability of time, access to information and skills.

- Confining information to create indicators

There are total of four aspects of risk catalogues defined by ERM framework, which includes hazard risks, financial risks, operational risks and strategic risks. Since the study of financial risks and operational risks are the primary interest of the previous studies (Verbano and Venturini, 2013), this research tried to capture the features of hazard risks and strategic risks. Although the information was tried to collect as much as possible, there are still some areas may not be covered. Specifically, the theft and other crime, personal injury in Hazard risks can only be explained by geographic information provided by firms. Similarly, the Disease and disability and Liability claim can only be described with the closest indicators that could be found in the reports, web information or annual reports. For strategic risks, there are also some features could not be perfectly captured by using existing information as well. Therefore, the result may be improved by using more appropriate indicators to describe the features listed in the ERM framework.

- Possible more data mining methods

Although there are total of four different data mining methods were used in this research, it is possible to apply more data mining methods to select KRIs more comprehensively. Other studies are using different methods to select KRIs, Rough set analysis (Xiao et al., 2012); Clustering methods (Chen, 2013); Support vector machines (Geng et al., 2015). Although section 6.6 discussed the results of this research and other studies, it is possible to include more data mining methods to show the difference of methods directly.

- Limited sample size and access to information

This research analysed over 800 listed Chinese SMEs. However, as the big data study developed, the sample size could be increased as many as possible in order to train the model. Furthermore, since the data of unlisted SMEs in China cannot be directly obtained by researchers, this research only publicly available data to build a database. It is true that the listed SMEs takes only a small portion of all SMEs all over the world, which means the rules provided by this database cannot explain part of the risk management process among SMEs.

Although there are some limitations to this research, the researcher has attempted to minimise the effects of the limitations. As discussed in Chapter 4 and 5, the variable selection was attempted to capture as much information as it can, which covered most features required by the ERM framework. Furthermore, as discussed in Chapter 6, this research has already completed the tasks of the framework, which means currently applied data mining methods are somehow enough.

7.5 Recommendation

Further research could be applied in several aspects based on the result of this research.

Firstly, the study targets may be not limited to SMEs. Since the DM-RM model has been developed, the purpose of the model could be changed upon the users. The research questions could then expand to other topics as long as the purposes are similar to this research. Since Verbano and Venturini (2013) stated that risk management in SMEs is understudied, there might be other aspects of risk management are understudied as well. As a result, the model could be used in other risk management related topics. Secondly, the usage of non-financial indicators could be developed. As many scholars stated, the non-financial indicators are useful in the prediction of firms' performance. This study has examined the usefulness of the non-financial indicators. However, the non-financial indicators are based on the ERM framework. As Verbano and Venturini (2011) stated that there are other risk management frameworks, it is possible to expand the usage of non-financial indicators to other topics. Furthermore, there is not a standard range of non-financial indicators. The range of non-financial indicators could be different from this research to cover different features.

Further research could focus on the selection of non-financial indicators to develop the universe ranges of non-financial indicators applied in risk management related topics or other topics. Thirdly, the usage of data mining method to deal with large data sample could be expanded to other topics in management academic studies. Since the data mining method could found hidden rules and patterns from the database, it is possible to collect related data and find out potential connections in other areas. As the development of data mining methods, there might be other frameworks could be combined with the data mining process to gather more rules and patterns from existing findings. Finally, the comparison of different data mining methods could be applied. There are many different data mining methods based on different theories. Although the popular data mining methods were used in this research, there are still many methods could be used, such as SVM, MV, etc. For a certain database, the different method may conclude a similar result with a slight difference, which could be used to find out the insufficiency of applied methods. Other scholars have made a similar comparison as well, such as Geng, et al. (2015) applied three methods to predict financial distress. Therefore, there are still many possible areas could be developed from this research, which may produce a better understanding of the risk management process and data mining process.

7.6 Summary

The final chapter has drawn upon the thesis to conclude the study. Some findings in this study have been summarised, which led to several practical and theoretical contributions. The development of DM-RM model provided a combination of risk management process and data mining process. There are many scholars supported that risk management process could effectively deal with risks (Cumming and Hirtle 2001; Liebenberg and Hoyt 2003; Miccolis and Shah 2000). The developed model provides the theory of how to assess risks after the purpose of risk management was settled. It concluded the four different types of risks, which gives decision makers and scholars the research direction of variable selection. Followed the catalogues by ERM framework, the indicators have been classified and clustered within specific risk type. If the decision makers followed the DM-RM model, the efficiency of the process would be improved.

This study has built DM-RM model with the data from listed SMEs in China, followed the ERM framework; and provided practical guidance in details. The predictive results verified the accuracy of the model. The usefulness of financial factors and non-financial factors was studied and examined in the model, where both financial and non-financial indicators were selected as KRIs. This study also compared different data mining methods in the selection of KRIs. The whole process of risk management, such as variable selection; risk indicators filtering; and risk identification, was studied and explained in details. As BI developed, the decision makers can get information from structured and unstructured data by using the idea of a business intelligence system (Negash, 2004). In order to consider risk features, this research has used forty-two financial indicators and nineteen non-financial indicators. This study achieved data mining methods by using SPSS, and the R Programming, which finally selected CHAID model as the best approach. By using the data mining methods and other tests (ROC and variable importance), the DM-RM model has successfully found out KRIs from risk indicators and made the sequencing of four types of risk.

Moreover, the usage of non-financial risk indicators increased the accuracy of the model, which has been proved the usefulness of non-financial indicators in SMEs. The roadmap for improving firm performance was developed by finding threshold values of KRIs, which is compiled with EWS. Since this study provided a solution to improve the risk management process, the DM-RM model can be used in other related topics that can be applied data mining process. This chapter was closed by discussing the main findings and recommendations for further study areas.

8. Reference

ACCA, 2017, COSO Enterprise Risk Management Framework, ACCA, www.accaglobal.com

Adriaans, P.W. and Zantinge, R., 1996, Data mining. Addison-Wesley, 1996.

Alexander, A.G., 2017, Enterprise risk management and business continuity, continuity central.com.

Altman, E.I., Sabato, G., 2007. Modeling credit risk for SMEs: Evidence from the US market. Abacus 43,332–357.

Altman, E.I., Sabao, G., Wilson, N., 2010. The value of non-financial information in small and medium-sized enterprise risk management. Journal of Credit Risk 6 (2), 95–127.

Altman, E.I., Narayanan, P., 1996. Business failure classification models: an international survey, Working paper series, 1996.

Alquier, A.M.B., Tignol, M.H.L., 2006. Risk Management in Small and Medium-sized Enterprises. Production Planning & Control, 17(3), 273-282

Akaike, H., 1987, Factor analysis and AIC, Psychometrika, September 1987, Volume 52, Issue 3, pp. 317–332

Andersen, T.J., 2008. The performance relationship of effective risk management: exploring the firm-specific investment rationale. Long Range Planning 41

(2), 155e176

Arnott, D., & Pervan, G., 2008. Eight key issues for the decision support systems discipline. Decision Support Systems, 44(3), 657-672

Arora P., Deepali, and Shipra V.,2016, Analysis of K-Means and K-Medoids Algorithm For Big Data", International Conference on Information Security & Privacy, India, Science Direct, Vol. 78, pp. 507-512, 2016.

BBA – British Bankers' Association, International Swaps and Derivatives Association, Price water house Coopers LLP, 1999. Operational risk: the next frontier, RMA, Philadelphia.

Beaver, W., 1967 , Financial ratios predictors of failure. Empirical research in accounting: selected studies 1966, Journal of Accounting Research, Supplement to Vol. 4, 1967, pp.71-111.

Bajo J., Borrajo M. L., De Paz J. F., Corchado J. M., Pellicer M., 2012. A multi-agent system for web-based risk management in small and medium business. Expert Systems with Applications, Volume 39, Issue 8, 15 June 2012, Pages 6921-6931

Back B., Laitinen T., Sere K., 1996, Neural networks and genetic algorithms for bankruptcy predictions, Expert Systems with Applications, Volume 11, Issue 4, 1996, Pages 407-413, ISSN 0957-4174,

Barrieu, P., El Karoui, N., 2004. Optimal derivative design under dynamic risk measures. In Mathematics of Finance, Contemporary Mathematics.

Beasley, M.S., Clune, R., Hermanson, D.R. (2008). The impact of enterprise risk management on the internal audit function, Journal of Forensic Accounting,

Becchetti, L., and Sierra J., 2002. Bankruptcy risk and productive efficiency in manufacturing firms. Journal of Banking and Finance 27, 2099–2120.

Berman, K., Knight, J., Case, J., 2006. Financial Intelligence: A Managers Guide to Knowing What the Numbers Really Mean. Massachusetts: Harvard Business School Press

Bunn P, and Redwood V., 2003. Company accounts based modelling of business failures and the implications for financial stability. Bank of England Working Paper 210.

Bussiere M. and Franzscher M., 2006, Towards a new early warning system of financial crises. Journal of International Money and Finance, Volume 25, Issue 6, October 2006, Pages 953-973

Breiman, L., Friedman, J., Olshen, R. A., & Stone, C. J., 1984. Classification and regression trees. Belmont, Calif: Wadsworth International Group.

Brustbauer J., 2016, Enterprise risk management in SMEs: Towards a structural model, International Small Business Journal, 2016, Vol. 34(1) 70–85

Calandro J., 2015. "A leader’s guide to strategic risk management", Strategy & Leadership, Vol. 43 Issue: 1, pp. 26-35

Cao Y., Chen X., Wu D. D., Mo M., 2011.Early warning of enterprise decline in a life cycle using neural networks and rough set theory. Expert Systems with Applications, Volume 38, Issue 6, June 2011, Pages 6424-6429

Canbas S., Cabuk A., and Kilic S.B., Prediction of commercial bank failure via multivariate statistical analysis of financial structures: The Turkish case, European Journal of Operational Research, Volume 166, Issue 2, 2005, Pages 528-546, ISSN 0377-2217,

Chamber L., 1995, Practical Handbook of Genetic Algorithms, CRC Press, Boca Raton, FL (1995)

Chan C.C. K., Hui C.L. P., Yeung K.W., and Ng S.F. F., (1998) "Handling the assembly line balancing problem in the clothing industry using a genetic algorithm", International Journal of Clothing Science and Technology, Vol. 10 Issue: 1, pp.21-37,

Casualty Actuarial Society (CAS), 2001, Final Report of the Advisory Committee on Enterprise Risk Management

Casualty Actuarial Society (CAS), 2003, Overview of Enterprise Risk Management

Chen X. and Yi S., 2007, Financial crisis research: Evidence from listed SMEs based on CHAID, Research of Economic and Management，2007，3：50 - 54

Choi T., Chan H. K. and Yue X., 2017, Recent Development in Big Data Analytics for Business Operations and Risk Management, in IEEE Transactions on Cybernetics, vol. 47, no. 1, pp. 81-92, Jan. 2017.

COSO, 2003, 2004, 2017. Enterprise Risk Management Integrated Framework. The

Committee of Sponsoring Organizations of the Treadway Commission.

Chen H., Chiang R. H.L., Storey V. C., 2012, Business intelligence and analytics: From big data to big impact, MIS Quarterly Vol. 36 No. 4, pp. 1165-1188/December 2012

Chen K. H., Shimerda T. A, 1981, An Empirical Analysis of Useful Financial Ratios, Financial Management, Vol. 10, No. 1 (Spring, 1981), pp. 51-60

Chen M., 2011. Bankruptcy prediction in firms with statistical and intelligent techniques and a comparison of evolutionary computation approaches, Computers & Mathematics with Applications, Volume 62, Issue 12, December 2011, Pages 4514-4524

Chen X., Wang X., Wu D. D., 2010.Credit risk measurement and early warning of SMEs: An empirical study of listed SMEs in China. Decision Support Systems, Volume 49, Issue 3, June 2010, Pages 301-310

Cisko, Š., & Klieštik, T., 2013. Finančný manažment podniku II. Žilina: EDIS Publisher.

Cooper, Arnold C., 1991, A resource-based prediction of new venture survival and growth, Academy of Management Proceedings, 1991, pp. 68-72.

Corazza, M., Funari, S., and Gusso, R. 2016. Creditworthiness evaluation of Italian SMEs at the beginning of the 2007–2008 crisis: an MCDA approach, North American Journal of Economics and Finance 38: 1–26.

Cumming C. M. and Hirtle, B., 2001. The challenges of risk management in diversified financial companies, Economic Policy Review, Federal Reserve Bank of New York, issue Mar, pages 1-17.

Davies J., Finlay M., Mclenaghen T., and Wilson D., 2006, Key Risk Indicators – Their Role in Operational Risk Management and Measurement. Risk Business International Limited

Delcea, C., Cotfas, L., Bradea, I. Scarlat E., and Maracine V., 2013, KRI and firms' performance—a grey theory approach. Proceedings of 2013 IEEE International Conference on Grey Systems and Intelligent Services (GSIS), pp. 260–264 (2013c)

De Loach, J. 2000. Enterprise-wide risk management: Strategies for linking risk and opportunities. London: Financial Times/Prentice Hall

Den Hamer, P., 2004, Business Intelligence, Academic service; 01 edition (1 July 2004)

Derelioglu, G., and Gurgen, F., 2011. Knowledge Discovery Using Neural Approach for SME's Credit Risk Analysis Problem in Turkey. Expert Systems with Applications (38), 9313-9318. http://dx.doi.org/10.1016/j.eswa.2011.01.012

Di Serio, L.C., de Oliveira, L.H., and Siegert Schuch, L.M., 2011. Organizational Risk Management: A Study Case in Companies that Have Won the Brazilian Quatity Award Prize. Journal of Technology Management and Innovation, 6(2), 230-243.

Dickinson G., 2001, Enterprise risk management: Its origins and conceptual foundation, The Geneva Papers on Risk and Insurance Vol. 26 No. 3 (July 2001) 360–

Dora-Anca B., 2014. Study Regarding the Perception of the Concept of “Business Intelligence” Among Application Designers. Procedia - Social and Behavioural Sciences, Volume 109, 8 January 2014, Pages 402-406

Doering, D.S., and Parayre, R., 2000. Identification and assessment of emerging technologies. In: Day, G., et al., Whartonon Managing Emerging Technologies. Wiley, NewYork, pp.75–98.

Ebben, J.,2005. Managing risk in a new venture. www.Inc.com.

Eckles D. L., Hoyt R. E., and Miller S. M, 2014. The impact of enterprise risk management on the marginal cost of reducing risk: Evidence from the insurance industry. Journal of Banking & Finance, Volume 43, June 2014, Pages 247-261

Elyan, E., and Gaber, M. M., 2017. A genetic algorithm approach to optimising random forests applied to class engineered data. Information Sciences, 384, 220–234.

Epstein, M., and Rejc Buhovan, A., 2005. The Reporting of Organizational Risks for Internal and External Decision-making. Society of Management Accountants of Canada and American Institute of Certified Public Accountants

Enke D., Thawornwong S., 2005, The use of data mining and neural networks for forecasting stock market returns, Expert Systems with Applications, Volume 29, Issue 4, 2005, Pages 927-940, ISSN 0957-4174,

Fawcett T., 2006, An Introduction to ROC Analysis, Pattern Recognition Letters, vol.

27, no. 8, pp. 861-874, 2006.

Fraser J. R.S., Simkins B. J., 2016, The challenges of and solutions for implementing enterprise risk management, 2016 Kelley School of Business, Indiana University

Freeman, R.E., Harrison, J.S., and Wicks, A.C., Parmar, B.L., Colle, S. 2010. Stakeholder theory: The state of the art. Cambridge: Cambridge University Press.

Frigo, M. L., 2002, Strategy, Business Execution and Performance Measures. Strategic Finance, May (2002).

Frigo M. L., Anderson R. J., 2011, What is Strategic Risk Management, Strategic Finance, April 2011

Florio, C., & Leoni, G., 2017. Enterprise risk management and firm performance: The Italian case. British Accounting Review, 49(1), 56–74.

Gates S., 2006, Incorporating Strategic Risk into Enterprise Risk Management: A Survey of Current Corporate Practice, Journal of Applied Corporate Finance, Vol. 18 Number 4, Fall 2006.

Geng R., Bose I., Chen X., 2014., Prediction of financial distress: An empirical study of listed Chinese companies using data mining, European Journal of Operational Research, 241 (1) (2015), pp. 236-247

Gerantonis, N., Vergos, K. and Christopoulos, A.G., 2009. Can Altman Z-score Models Predict Business Failures in Greece?, Research Journal of International Studies, 12: 21-28

Glancy, F.L and Yadav S.B, 2011. Business Intelligence Conceptual Model Volume 2, Issue 2. 19 pages. International Journal of Business Intelligence Research.

Gjerdrum, D. and Peter, M. 2011. The New International Standard on the Practice of Risk Management – A Comparison of ISO 31000:2009 and the COSO ERM Framework. Risk Management 21, 8–12.

Gordini N., 2014. A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy. Expert Systems with Applications, Volume 41, Issue 14, 15 October 2014, Pages 6433-6445

Green W., Czernkowski R., Wang Y, 2009. "Special treatment regulation in China: potential unintended consequences", Asian Review of Accounting, Vol. 17 Issue: 3, pp.198-211

Grunet, J. Norden L and Weber M, 2004.The role of Non-financial Factors in Internal Credit Ratings, Journal of Banking and Finance, Vol 29 No.2.

Hawkins, D. M., 2004, The Problem of Overfitting, Journal of Chemistry Information Computer Science, 2004, 44 (1), pp 1–12

Han J., and Kamber M., 2001, Data Mining Concept and Technology. Beijing: Higher Education Press, 2001

Han J., Kamber M., and Pei J., 2012, Data mining: concepts and techniques, Morgan Kaufmann Publishers, Elsevier. 225 Wyman Street, Waltham, MA 02451, USA

Head, L.G., 2009. Risk Management - Why and How. International Risk Management Institute, Dallas, Texas.

Headd B., 2003, Redefining business success: distinguishing between closure and failure, Small Business Economics, 21 (1) (2003), pp. 51-61

Henschel, T., 2009. Implementing a Holistic Risk Management in Small and Medium Sized Enterprises (SMEs). Edinburgh Napier University School of Accounting, Economics and Statistics, UK.

Herbane B., 2010. Small business research: time for a crisis-based view, Strategic Direction, Vol. 26 Issue: 8,

Hill, P., and Wilson, N., 2007. Predicting the insolvency of unlisted companies. Unpublished manuscript, Credit Management Research Centre, Leeds University

Horcher K. A., 2005, Essentials of Financial Risk Management, Published by John Wiley & Sons, Inc., Hoboken, New Jersey

Huang, G., & Song, F. M., 2006. The determinants of capital structure: Evidence from China. China Economic Review, 17(1), 14–36.

IBM, 2011, SPSS Modeller 14.2 Algorithms Guide, IBM Corporation 1994, 2011

International Organizations for Standardization, 2009, Risk management - Principles and guidelines.

Islam, M.A., Tedford, J.D., Haemmerle, E., 2006. Strategic Risk Management

Approach for Small and Medium-Sized Manufacturing Enterprises (SMEs): A Theoretical Framework. Proceedings of IEEE International Conference on Management of Innovation and Technology, Singapore pp.694-698.

Immaneni, A., Mastor, C. and Haubenstock, M., 2004. A Structured Approach to Building Predictive Key Risk Indicators. The RMA Journal, May (Operational Risk: A Special Edition), pp. 42-47

Johnson T., 2010, Conceptual Mapping of Risk Management to Data Mining, 2010 3rd International Conference on Emerging Trends in Engineering and Technology, Goa, 2010, pp. 636-641.

Kaplan, R.S., 2009, Conceptual Foundations of the Balanced Scorecard, Handbooks of Management Accounting Research, Elsevier, Volume 3, 2009, Pages 1253-1269, ISSN 1751-3243, ISBN 9780080554501,

Kaplan R. S. and Norton D. P., 1992, The balanced scorecard: measures that drive performance. Harvard Business Review, Jan – Feb, pp. 71-80.

Kass, G. V., 1980, An Exploratory Technique for Investigating Large Quantities of Categorical Data. Applied Statistics, Vol. 29, No. 2. (1980), pp. 119- 127

Keizer, J., Halman, J., Song, M., 2002. From experience: applying the risk diagnosing methodology. J. Prod. Innovation Manage.19, 213–232

Keith J. L., 2014, Enterprise Risk Management: Developing a Strategic ERM Alignment Framework – Finance Sector, PhD Thesis, Brunel University

Klieštik T., Kočišová K., Mišanková M., 2015, Logit and Probit Model used for prediction of financial health of company. Procedia Economics and Finance 23 (2015) 850 – 855

Kloman, H.F., 1992. Rethinking risk management. The Geneva Papers on Risk and Insurance-Issues and Practice 17 (3), 299e313.

Kim Y. J., Vonortas N. S., 2014. Managing risk in the formative years: Evidence from young enterprises in Europe, Technovation, Volume 34, Issue 8, August 2014, Pages 454-465

Koyuncugil A. S. and Ozgulbas N., 2009, Measuring and hedging operational risk by data mining, Proceedings Book of World Summit on Economic Financial Crisis and International Business, Washington, p.1-6, 2009

Koyuncugil A.S, Ozgulbas N, 2012. Financial early warning system model and data mining application for risk detection, Expert Systems with Applications, Volume 39, Issue 6, May 2012, Pages 6238-6253

Kumar, S., & Sahoo, G., 2017. A random forest classifier based on genetic algorithm for cardiovascular diseases diagnosis. International Journal of Engineering, Transactions B: Applications, 30(11), 1723–1729.

Kumar P. R, Ravi V., 2006. Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review, European Journal of Operational Research, Volume 180, Issue 1, 1 July 2007, Pages 1-28

Lam, J., 2003. Enterprise Risk Management: From Incentives to Controls. Hoboken, NJ: John

Wiley & Sons, Inc.

Lau R., and Au N., 1999, A neural network model to forecast Japanese demand for travel to Hong Kong, Tourism Management 20 (1999) 89—97

Leopoulos, V. N., Kirytopoulos, K. A., and Malandrakis C., 2006. Risk Management for SMEs: Tools to Use and How. Production Planning & Control 17 (3): 322–332.

Leung S.Y.S., Wong W.K., Mok P.Y., 2008, Multiple-objective genetic optimization of the spatial design for packing and distribution carton boxes, Computers & Industrial Engineering, Volume 54, Issue 4, 2008, Pages 889-902, ISSN 0360-8352,

Liebenberg, A. and Hoyt, R., 2003. The Determinants of Enterprise Risk Management: Evidence from the Appointment of Chief Risk Officers. Risk Management and Insurance Review. 6. 10.1111/1098-1616.00019.

Li T., Munir Q., Abd Karim M.R., 2017, Nonlinear relationship between CEO power and capital structure: Evidence from China's listed SMEs, International Review of Economic and Finance 47, 2017, 1-21

Liu M., Li M., and Zhang T., 2012, Empirical Research on China's SMEs Technology Innovation Engineering Strategy, Systems Engineering Procedia, Volume 5, 2012, Pages 372-378, ISSN 2211-3819,

Liu, Q. G., and Tian, G. G., 2009. Leverage ratio and determinants of capital structure in SMEs: Evidence from China. University of Wollongong (Working Paper)

Lippman R.P., 1987, An introduction to computing with neural nets, IEEE

Transactions on Acoustics, Speech, and Signal Processing Magazine (1987), pp. 4-22

Loh, W., and Shih, Y., 1997. Split selection methods for classification trees. Statistica sinica, 7(4), 815-840.

Lussier, R. N., 1995. A non-financial business success versus failure prediction model for young firms. Journal of Small Business Management 33, 8–20.

Lussier, R.N. and Pfeifer S, 2001, A cross national prediction model for business success," Journal of Small Business Management, Vol.39 (3), 2001, pp.228-239.

Martin D., 1977, Early warning of bank failure: a logit regression approach, Journal of Banking and Finance 1 (1977) 249-276.

Max K. and Kjell J., 2018, Applied Predictive Modelling, Springer, ISBN-13: 978-1461468486

Mehr R. I. and Hedges B. A., 1963. Risk Management in the Business Enterprise. Richard D. Irwin, Inc. Homewood, IL

Mestchian P. and Cokins G., 2006, Risk-based performance management - making it work. Business Credit, 108 (5), pp. 28-30.

Miccolis J., & Shah, S, 2000. Enterprise risk management: An analytic approach: Tillinghast-Towers Perrin Monograph. Retrieved April 8, 2005, from http://www.tillingast.com.

Mikulić J., Prebežac, D., 2012, Accounting for dynamics in attribute-importance and for competitor performance to enhance reliability of BPNN-based importance–performance analysis, Expert Systems with Applications, Volume 39, Issue 5, 2012, Pages 5144-5153, ISSN 0957-4174,

Mitchell M., 1996, Introduction to Genetic Algorithms, MIT Press, Cambridge, MA, 1996.

Miles D.A, 2010. Risk factor and business models: Understanding the Five Forces of Entrepreneurial Risk and the Causes of Business Failure. Boca Raton, Florida.

Mikulić J, Prebežac D, 2012, Accounting for dynamics in attribute-importance and for competitor performance to enhance reliability of BPNN-based importance–performance analysis, Expert Systems with Applications, Volume 39, Issue 5, 2012, Pages 5144-5153, ISSN 0957-4174,

Min H., Ko H. J., Ko C. S., 2006, A genetic algorithm approach to developing the multi-echelon reverse logistics network for product returns, Omega, Volume 34, Issue 1, 2006, Pages 56-69, ISSN 0305-0483,

McBride, N., 2014, Business intelligence in magazine distribution, International Journal of Information Management, Volume 34, Issue 1, February 2014, Pages 58-62

NBSC, 2013, The analysis of development and life index of 2013, http://www.stats.gov.cn/tjsj/zxfb/201412/t20141231_661933.html

Negash S., 2004, Business intelligence, Communications of the Association for Information Systems, Volume 13, Article 15

Negash S., Gray P. , 2008, Business Intelligence. In: Handbook on Decision Support Systems 2. International Handbooks Information System. Springer, Berlin, Heidelberg

Ntlhane K.E., 1995. The application of risk management principles to smaller enterprises. A research report submitted in partial fulfilment of the requirements for the degree of Masters of Business Administration in the Faculty of Management at the University of the Witwatersrand.

Nofal M.I. and Yusof Z.M., 2013, Integration of Business Intelligence and Enterprise Resource Planning within Organizations, Procedia Technology, Volume 11, 2013, Pages 658-665, ISSN 2212-0173,

Nocco B.W., Stulz R.M., 2006, Enterprise risk management: Theory and Practice, Journal of Applied Corporate Finance, Vol. 18, Number 4, Fall 2006.

O'Donnell Ed, 2005, Enterprise risk management: A systems-thinking framework for the event identification phase, International Journal of Accounting Information Systems, Volume 6, Issue 3, 2005, Pages 177-195, ISSN 1467-0895,

Oet M. V., Bianco T., Gramlich D., Ong S. J., 2013, SAFE: An early warning system for systemic banking risk, Journal of Banking & Finance 37 (2013) 4510–4533

Oh K.J., Kim T.Y., Lee H.Y., Lee H., 2005, Using Neural Networks to Support Early Warning System for Financial Crisis Forecasting. In: Zhang S., Jarvis R. (eds) AI 2005: Advances in Artificial Intelligence. AI 2005. Lecture Notes in Computer Science, vol 3809. Springer, Berlin, Heidelberg

Pagach, D., and Warr, R., 2011. The characteristics of firms that hire chief risk officers, The Journal of Risk and Insurance, Vol. 78, No. 1, pp. 185-211.

Peng W. M., 2010, Research streams, Provost's Distinguished Professor of Global Strategy, University of Texas at Dallas, 2010

Pirttimäki, V., 2007, Business intelligence as a managerial tool in large Finnish companies, Tampera University of Techology, PhD thesis.

Quinlan, J. R., 1993. C4.5: Programs for machine learning. San Mateo, Calif: Morgan Kaufmann Publishers.

Quon T. K., Zeghal D., Maingot M., 2012. Enterprise Risk Management and Firm Performance. Procedia - Social and Behavioral Sciences, Volume 62, 24 October 2012, Pages 263-267

Rokach L. and Maimon O., 2014. Data Mining with Decision Trees: Theory and Applications, Published by World Scientific Publishing Co. Pte. Ltd., #9789814590082, 2014

Ravisankar P., Ravi V., Rao G. R., and Bose I., 2011.Detection of financial statement fraud and feature selection using data mining techniques, Decision Support Systems, Volume 50, Issue 2, January 2011, Pages 491-500

Rubin E., Rubin A., 2013. The impact of Business Intelligence systems on stock return volatility, Information & Management, Volume 50, Issues 2–3, March–April 2013, Pages 67-75

Samani M. A., Ismail N., Leman Z. and Zulkifli N., 2017, Development of a conceptual model for risk-based quality management system, Total Quality Management & Business Excellence.

Scarlat, E., Chirita, N., and Bradea, I. A., 2012. Indicators and Metrics Used in the Enterprise Risk Management (ERM). Economic Computation and Economic Cybernetics Studies and Research Journal, (4), 5-18

Seghezzi, H. D., Schweickardt, S., and Sinha, M. N., 2001. Integration of quality management into business management: An IAQ project report. The Best on Quality, 12, 3–50

Smart, A. and Creelman, J., 2009. Embedding Risk Appetite within the strategy process. London, UK: Manigent.

Shen Y., Shen M., Xu Z., and Bai Y., 2009. Bank Size and Small- and Medium-sized Enterprise (SME) Lending: Evidence from China, World Development, Volume 37, Issue 4, April 2009, Pages 800-811

Siegel J. G.; Shim J. K. and Hartman S, 1997. Schaum's quick guide to business formulas: 201 decision-making tools for business, finance, and accounting students. McGraw-Hill Professional

Shuai, J. J., & Li, H. L., 2005.Using rough set and worst practice DEA in business failure prediction. Lecture Notes in Computer Science, 3642(2), 503–510.

Shollo A, 2013. The Role of Business Intelligence in Organizational Decision-making, 2013, PhD thesis.

Smit Y., Watkins J. A., 2012, A literature review of small and medium enterprises (SME) risk management practices in South Africa, African Journal of Business Management Vol. 6(21), pp. 6324-6330, 30 May 2012

Soman K.P., Diwakar S. and Ajay V., 2009, Data mining: theory and practice, PHI Learning Pvt. Ltd., ISBN 9788120328976.

Spuchľáková, E., & Cúg, J., 2014. Lost Given Default and the Credit risk. International Conference on Management, Education, Business, and Information Science, 12-15.

Sperber, William H. , 2001. "Hazard identification: from a quantitative to a qualitative approach". Food Control. 12: 223–228.

Stephen M., 2013, The 2013 COSO framework and SOX compliance, The Committee of Sponsoring Organizations of the Treadway Commission (COSO).

Stinchcombe, A. L., 1965. Social Structure and Organizations. In The Handbook of Organizations, James G. March (Ed.). Chicago: Rand McNally & Co.

Sweeting P., 2010, Financial Enterprise Risk Management, Cambridge University Press

Taylor, C., Davies, J., 2003, Getting traction with KRIs: Laying the groundwork. RMA J. 2003, 58–62.

Tyson, K., 1986. Business Intelligence Putting It All Together. Leading Edge

Publications, Illinois, 275.

Tsaur S., Chiu Y., and Huang, C, 2002, Determinants of guest loyalty to international tourist hotels—a neural network approach, Tourism Management, Volume 23, Issue 4, 2002, Pages 397-405, ISSN 0261-5177,

Tutunea M. F., Rus R. V., 2012. Business Intelligence Solutions for SME's, Procedia Economics and Finance, Volume 3, 2012, Pages 865-870

UNC, 2018, Components Of The Internal Controls Process – Finance, https://finance.unc.edu/departments/internal-controls/components-ic-process/

Urciuoli, V., Crenca, G., 1989, Risk management: strategie e processi decisionali nella gestione dei rischi puri d'impresa. ISBA, Rovereto

Valverde R., 2011. A Business Intelligence System for Risk Management in the Real Estate Industry, International Journal of Computer Applications (0975 – 8887), Volume 27– No.2, August 2011

Vergas-Hernandez, J. G., 2011, Modeling Risk and Innovation Management. Advances in Competitiveness Research, 19 (3-4), 45-57.

Verbano, C., and Venturini, K., 2011.Development paths of risk management: approaches, methods and fields of application. Journal Risk Research 14(5-6),519–550.

Verbano, C., and Venturini, K., 2013. Managing Risks in SMEs: A Literature Review and Research Agenda, Journal of Technology Management and Innovation. 2013, Xiao Z., Ye S., Zhong B., and Sun C., 2009, BP neural network with rough set for short term load forecasting, Expert Systems with Applications, Volume 36, Issue 1, 2009, Pages 273-279, ISSN 0957-4174,

Xie and Me, 2013, The financial crisis model based on CHAID method in Chinese listed companies, Statistic and Decision, 2013, Vol 1, 83-85

Watson H. J. and Wixom B. H., 2007, The current state of business intelligence," IEEE Computer, vol. 40, no. 9, pp. 96–99, Sep. 2007.

Watt J, 2007, Strategic risk management in small businesses. In: Reuvid J (ed.) Managing Business Risk: A Practical Guide to Protecting your Business (2nd edn). London: Kogan Page, pp.31–40.

Wang W, and Zhou X, 2011, Could traditional financial indicators predict the default of small and medium-sized enterprises?, International Conference on Economics and Finance Research, IPEDR vol.4 (2011) © (2011) IACSIT Press, Singapore

Wang Y, 2004, Financing Difficulties and Structural Characteristics of SMEs in China, China and World Economy / 34-49, Vol.12, No.2, 2004

Warren S. S., 1995, Stopped training and other remedies for overfitting, Proc. 27th Symposium of Interface Computer Science Statistics, pp. 352-360, 1995.

Weber A., Thomas R., 2006, Key Performance Indicators: Measuring & Managing the Maintenance Function, Ivara Corporation

Wong, W., Mok, P. and Leung, S., 2006, The International Journal of Advanced Manufacturing Technology (2006) 28: 387.

Wu W., 2010, Beyond business failure prediction, Expert Systems with Applications, Volume 37, Issue 3, 2010, Pages 2371-2376, ISSN 0957-4174,

Wu D.D, and Olson D. L., 2009, Introduction to the Special Section on “Optimizing Risk Management: Methods and Tools”, Human and Ecological Risk Assessment: An International Journal, 15:2, 220-226,

Wu X., Zhu X., Wu G. and Ding W., 2014, Data mining with big data, in IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 1, pp. 97-107, Jan. 2014

Wu W.W., 2009. Beyond business failure prediction. Expert Systems with Applications, Volume 37, Issue 3, 15 March 2010, Pages 2371-2376

Yao H., and Shen Y., 2005, Predicting the financial distress of firms using genetic, neural networks, Journal of central China Normal University (Vol 39 No.2, Jun 2005)

Young, M., 1996, Critical Business Knowledge and Competencies: diagnostic through the business life-cycle. Academy of Entrepreneurship Journal. (1), 25-26.

Yuan J., Zeng, Y. A. Miroslaw, Skibniewski J., and Li Q., 2009, Selection of performance objectives and key performance indicators in public–private partnership projects to achieve value for money, Construction Management and Economics, 27:3, 253-270

Zhao and Wang, 2015, The analysis and design of development and life index, Development Research Centre of NBSC, 201

Zhao F., Zhang T., and Li K., 2016, An Optimized Random Forest Based on Genetic Algorithm and its Application to Feature Selection for Gene Data, Chinese Statistics, 2016 Aug, volume 33

Appendices

Appendix 1: Results of CHAID

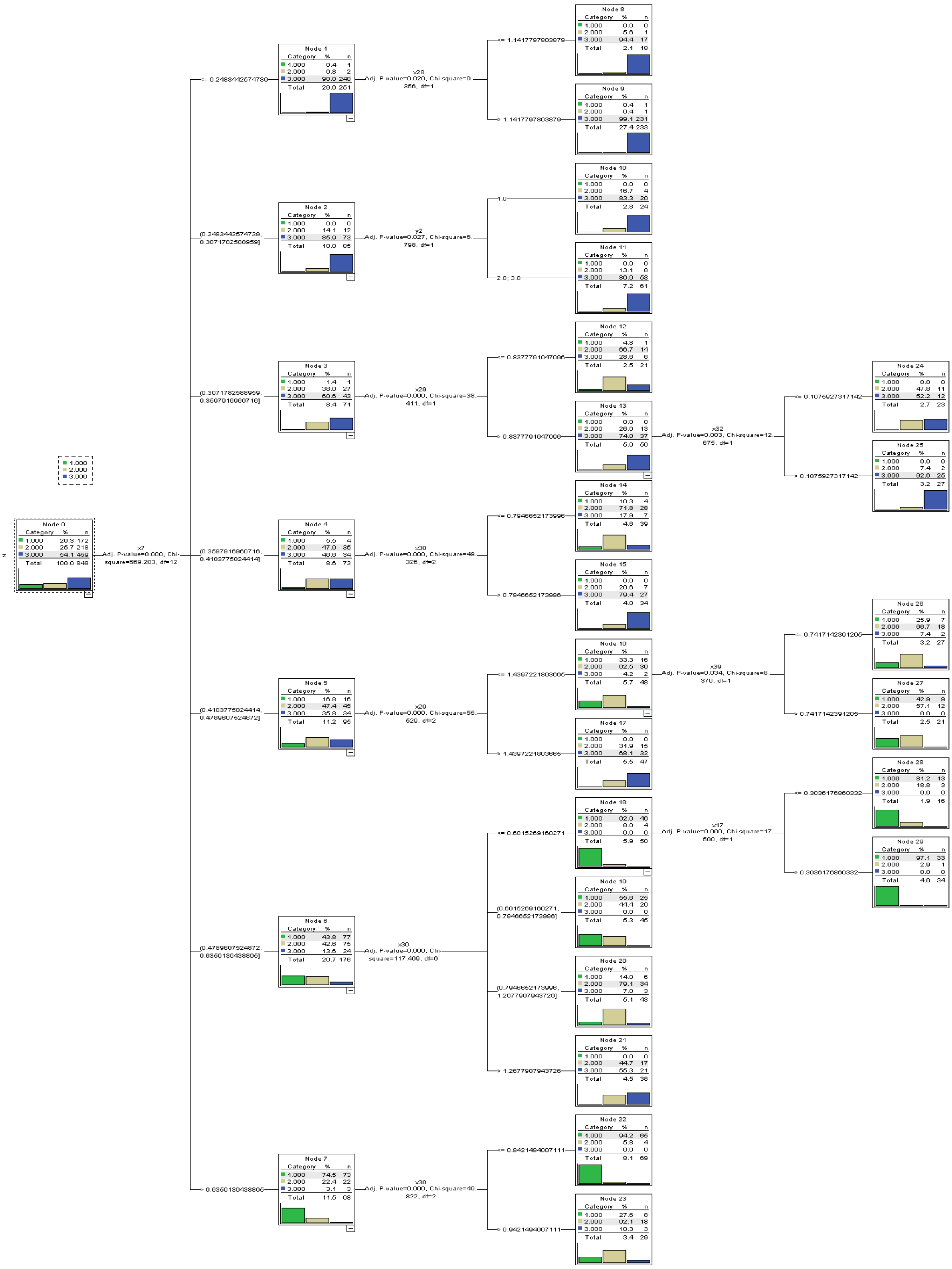


Figure 5.3.2-a The Result of CHAID with F and NF indicators (Z-score) (1)

Node	N	N	N	Percent	Predicted Category	Parent Node	Variable	Sig.a	Chi-Square	df	Split Values
0	172	218	459	100.00%	3						
1	1	2	248	29.60%	3	0	x7	0	669.203	12	<= .2483442574739
2	0	12	73	10.00%	3	0	x7	0	669.203	12	(.2483442574739, .3071782588959]
3	1	27	43	8.40%	3	0	x7	0	669.203	12	(.3071782588959, .3597916960716]
4	4	35	34	8.60%	2	0	x7	0	669.203	12	(.3597916960716, .4103775024414]
5	16	45	34	11.20%	2	0	x7	0	669.203	12	(.4103775024414, .4789607524872]
6	77	75	24	20.70%	1	0	x7	0	669.203	12	(.4789607524872, .6350130438805]
7	73	22	3	11.50%	1	0	x7	0	669.203	12	> .6350130438805
8	0	1	17	2.10%	3	1	x28	0.02	9.356	1	<= 1.141779780388
9	1	1	231	27.40%	3	1	x28	0.02	9.356	1	> 1.141779780388
10	0	4	20	2.80%	3	2	y2	0.027	6.798	1	1
11	0	8	53	7.20%	3	2	y2	0.027	6.798	1	2.0; 3.0
12	1	14	6	2.50%	2	3	x29	0	38.411	1	<= .8377791047096
13	0	13	37	5.90%	3	3	x29	0	38.411	1	> .8377791047096
14	4	28	7	4.60%	2	4	x30	0	49.326	2	<= .7946652173996
15	0	7	27	4.00%	3	4	x30	0	49.326	2	> .7946652173996
16	16	30	2	5.70%	2	5	x29	0	55.529	2	<= 1.439722180367
17	0	15	32	5.50%	3	5	x29	0	55.529	2	> 1.439722180367
18	46	4	0	5.90%	1	6	x30	0	117.409	6	<= .6015269160271
19	25	20	0	5.30%	1	6	x30	0	117.409	6	(.6015269160271, .7946652173996]
20	6	34	3	5.10%	2	6	x30	0	117.409	6	(.7946652173996, 1.267790794373]
21	0	17	21	4.50%	2	6	x30	0	117.409	6	> 1.267790794373
22	65	4	0	8.10%	1	7	x30	0	49.822	2	<= .9421494007111

23	8	18	3	3.40%	2	7	x30	0	49.822	2	> .9421494007111
24	0	11	12	2.70%	3	13	x32	0.003	12.675	1	<= .1075927317142
25	0	2	25	3.20%	3	13	x32	0.003	12.675	1	> .1075927317142
26	7	18	2	3.20%	2	16	x39	0.034	8.37	1	<= .7417142391205
27	9	12	0	2.50%	1	16	x39	0.034	8.37	1	> .7417142391205
28	13	3	0	1.90%	1	18	x17	0	17.5	1	<= .3036176860332
29	33	1	0	4.00%	1	18	x17	0	17.5	1	> .3036176860332

Table 5.3.2-a1 The Result of CHAID with F and NF indicators (Z-score) (2)

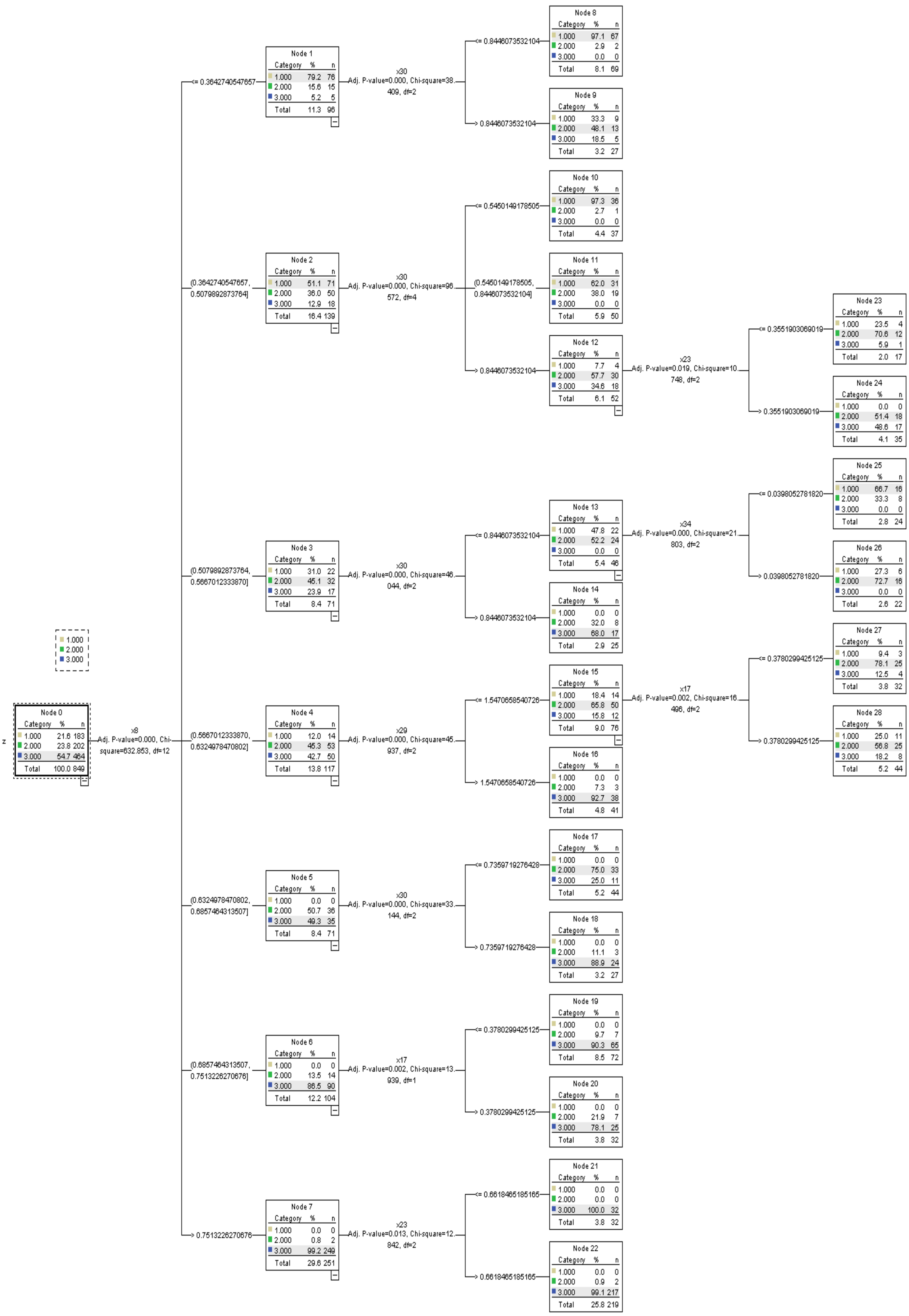


Figure 5.3.2-b Result of CHAID with F indicators (1)

Node	N	N	N	Predicted Category	Parent Node	Variable	Sig.a	Chi-Square	df	Split Values
0	183	202	464	3						
1	76	15	5	1	0	x8	0	632.853	12	<= .3642740547657
2	71	50	18	1	0	x8	0	632.853	12	(.3642740547657, .5079892873764]
3	22	32	17	2	0	x8	0	632.853	12	(.5079892873764, .5667012333870]
4	14	53	50	2	0	x8	0	632.853	12	(.5667012333870, .6324978470802]
5	0	36	35	3	0	x8	0	632.853	12	(.6324978470802, .6857464313507]
6	0	14	90	3	0	x8	0	632.853	12	(.6857464313507, .7513226270676]
7	0	2	249	3	0	x8	0	632.853	12	> .7513226270676
8	67	2	0	1	1	x30	0	38.409	2	<= .8446073532104
9	9	13	5	2	1	x30	0	38.409	2	> .8446073532104
10	36	1	0	1	2	x30	0	96.572	4	<= .5450149178505
11	31	19	0	1	2	x30	0	96.572	4	(.5450149178505, .8446073532104]
12	4	30	18	2	2	x30	0	96.572	4	> .8446073532104
13	22	24	0	2	3	x30	0	46.044	2	<= .8446073532104
14	0	8	17	3	3	x30	0	46.044	2	> .8446073532104
15	14	50	12	2	4	x29	0	45.937	2	<= 1.547065854073
16	0	3	38	3	4	x29	0	45.937	2	> 1.547065854073
17	0	33	11	2	5	x30	0	33.144	2	<= .7359719276428
18	0	3	24	3	5	x30	0	33.144	2	> .7359719276428
19	0	7	65	3	6	x17	0.002	13.939	1	<= .3780299425125
20	0	7	25	3	6	x17	0.002	13.939	1	> .3780299425125
21	0	0	32	3	7	x23	0.013	12.842	2	<= .6618465185165
22	0	2	217	3	7	x23	0.013	12.842	2	> .6618465185165

23	4	12	1	2	12	x23	0.019	10.748	2	<= .3551903069019
24	0	18	17	2	12	x23	0.019	10.748	2	> .3551903069019
25	16	8	0	1	13	x34	0	21.803	2	<= .0398052781820
26	6	16	0	2	13	x34	0	21.803	2	> .0398052781820
27	3	25	4	2	15	x17	0.002	16.496	2	<= .3780299425125
28	11	25	8	2	15	x17	0.002	16.496	2	> .3780299425125

Table 5.3.2-b1 The Result of CHAID with F indicators (2)

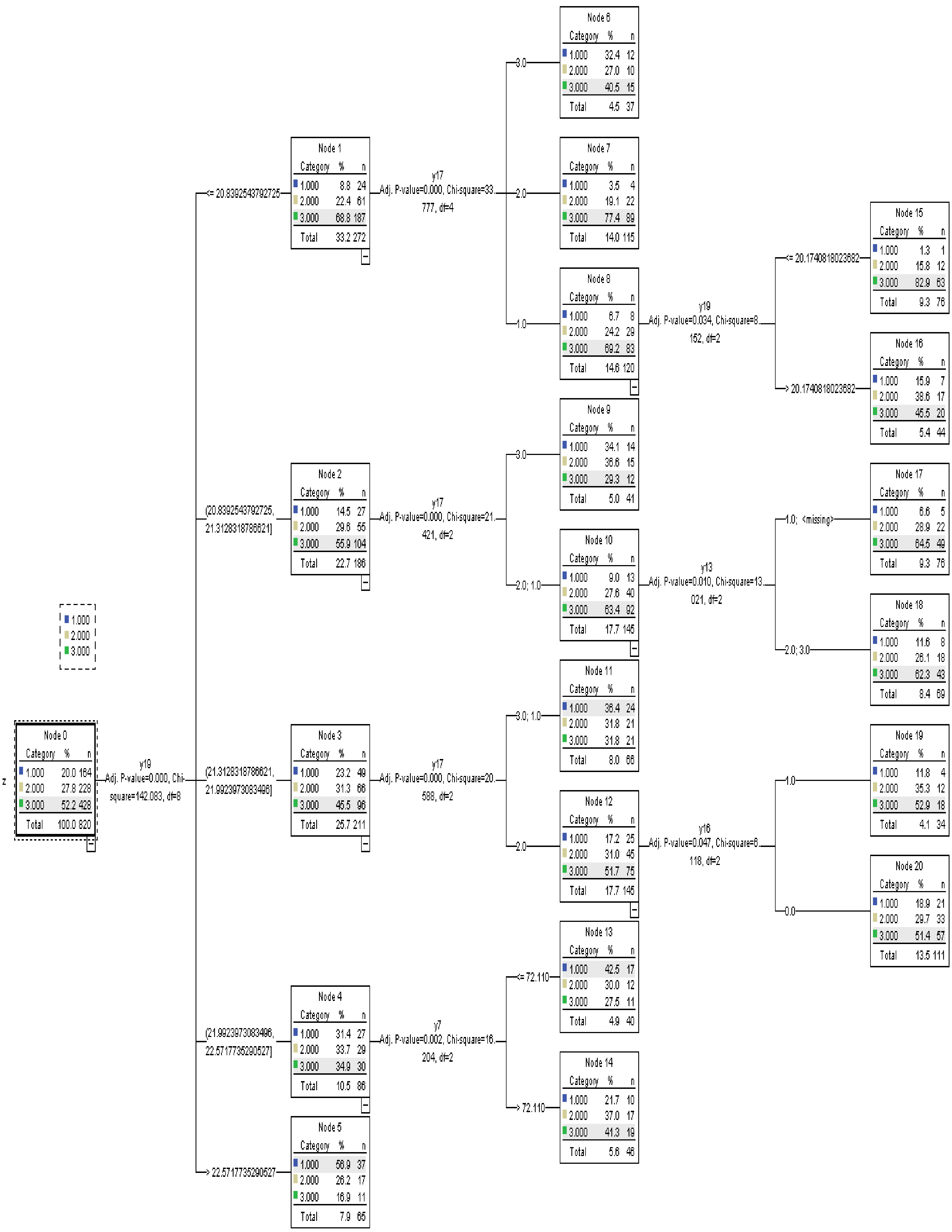


Figure 5.3.2-c The Result of CHAID with NF indicators (Z-score) (1)

Node	N	N	N	Percent	Predicted Category	Parent Node	Variable	Sig.a	Chi-Square	df	Split Values
0	164	228	428	100.00%	3						
1	24	61	187	33.20%	3	0	y19	0	142.083	8	<= 20.83925437928
2	27	55	104	22.70%	3	0	y19	0	142.083	8	(20.83925437928, 21.31283187867]
3	49	66	96	25.70%	3	0	y19	0	142.083	8	(21.31283187867, 21.99239730835]
4	27	29	30	10.50%	3	0	y19	0	142.083	8	(21.99239730835, 22.57177352906]
5	37	17	11	7.90%	1	0	y19	0	142.083	8	> 22.57177352906
6	12	10	15	4.50%	3	1	y17	0	33.777	4	3
7	4	22	89	14.00%	3	1	y17	0	33.777	4	2
8	8	29	83	14.60%	3	1	y17	0	33.777	4	1
9	14	15	12	5.00%	3	2	y17	0	21.421	2	3
10	13	40	92	17.70%	3	2	y17	0	21.421	2	2.0; 1.0
11	24	21	21	8.00%	1	3	y17	0	20.588	2	3.0; 1.0
12	25	45	75	17.70%	3	3	y17	0	20.588	2	2
13	17	12	11	4.90%	1	4	y7	0.002	16.204	2	<= 72.110
14	10	17	19	5.60%	3	4	y7	0.002	16.204	2	> 72.110
15	1	12	63	9.30%	3	8	y19	0.034	8.152	2	<= 20.17408180237
16	7	17	20	5.40%	3	8	y19	0.034	8.152	2	> 20.17408180237
17	5	22	49	9.30%	3	10	y13	0.01	13.021	2	1.0, <missing>
18	8	18	43	8.40%	3	10	y13	0.01	13.021	2	2.0; 3.0
19	4	12	18	4.10%	3	12	y16	0.047	6.118	2	1

20	21	33	57	13.50%	3	12	y16	0.047	6.118	2	0

Table 5.3.2-c1 Result of CHAID with NF indicators (Z-score) (2)

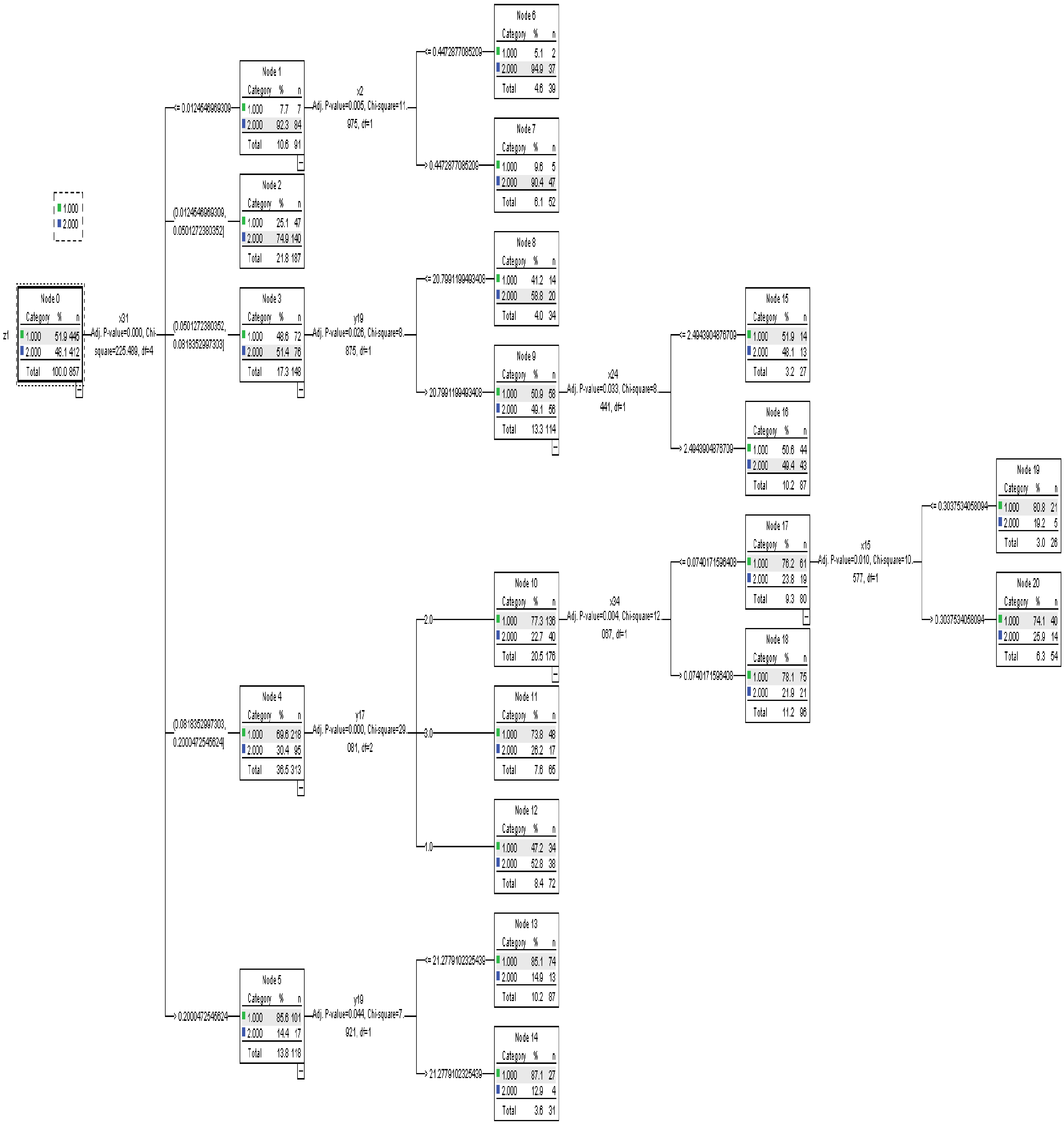


Figure 5.3.3-a The Result of CHAID with F and NF indicators (ROA) (1)

Node	N	N	Predicted Category	Parent Node	Variable	Sig.a	Chi-Square	df	Split Values
0	445	412	1						
1	7	84	2	0	x31	0	225.489	4	<= .0124546969309
2	47	140	2	0	x31	0	225.489	4	(.0124546969309, .0501272380352]
3	72	76	2	0	x31	0	225.489	4	(.0501272380352, .0818352997303]
4	218	95	1	0	x31	0	225.489	4	(.0818352997303, .2000472545624]
5	101	17	1	0	x31	0	225.489	4	> .2000472545624
6	2	37	2	1	x2	0.005	11.975	1	<= .4472877085209
7	5	47	2	1	x2	0.005	11.975	1	> .4472877085209
8	14	20	2	3	y19	0.026	8.875	1	<= 20.79911994935
9	58	56	1	3	y19	0.026	8.875	1	> 20.79911994935
10	136	40	1	4	y17	0	29.081	2	2
11	48	17	1	4	y17	0	29.081	2	3
12	34	38	1	4	y17	0	29.081	2	1
13	74	13	1	5	y19	0.044	7.921	1	<= 21.27791023255
14	27	4	1	5	y19	0.044	7.921	1	> 21.27791023255
15	14	13	1	9	x24	0.033	8.441	1	<= 2.494390487671
16	44	43	2	9	x24	0.033	8.441	1	> 2.494390487671
17	61	19	1	10	x34	0.004	12.067	1	<= .0740171596408
18	75	21	1	10	x34	0.004	12.067	1	> .0740171596408
19	21	5	1	17	x15	0.01	10.577	1	<= .3037534058094

20	40	14	1	17	x15	0.01	10.577	1	> .3037534058094

Table 5.3.3-a1 Result of CHAID with F and NF indicators (ROA) (2)

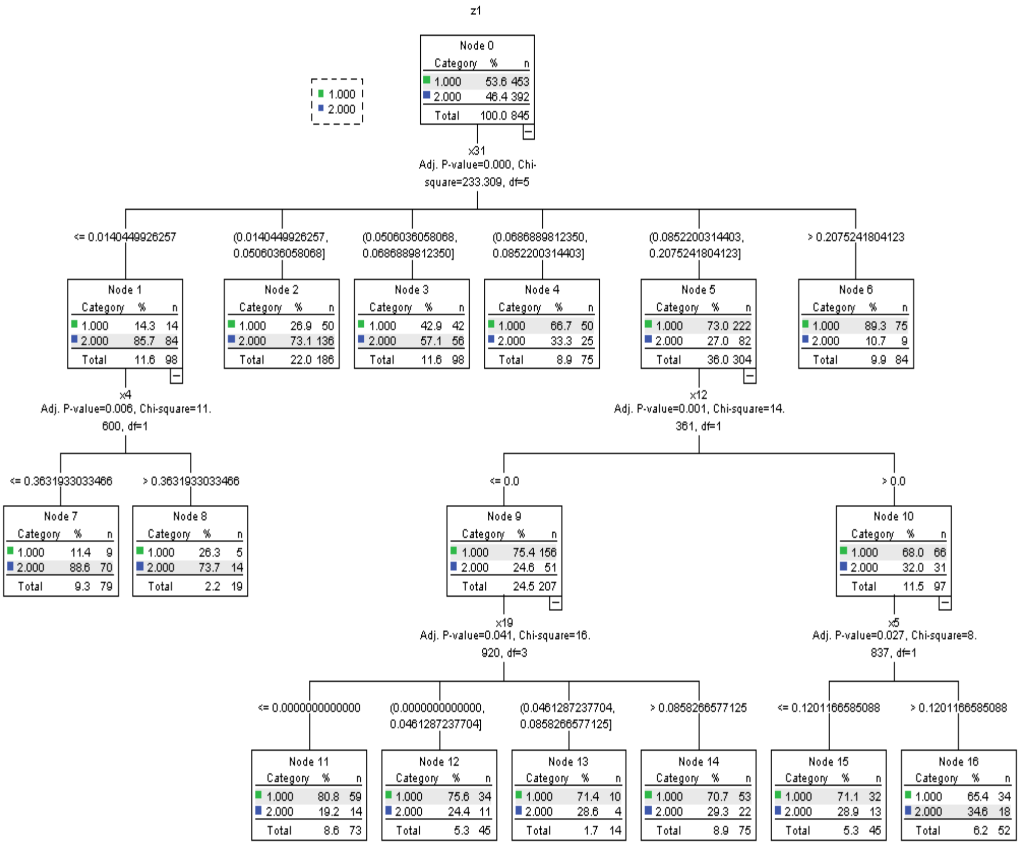


Figure 5.3.3-b The Result of CHAID with F indicators (ROA) (1)

Node	N	N	N	Per cent	Predicted Category	Parent Node	Variable	Sig.a	Chi-Square	df	Split Values
0	453	392	845	100.00%	1						
1	14	84	98	11.60%	2	0	x31	0	233.309	5	<= .0140449926257
2	50	136	186	22.00%	2	0	x31	0	233.309	5	(.0140449926257, .0506036058068]
3	42	56	98	11.60%	2	0	x31	0	233.309	5	(.0506036058068, .0686889812350]
4	50	25	75	8.90%	1	0	x31	0	233.309	5	(.0686889812350, .0852200314403]
5	222	82	304	36.00%	1	0	x31	0	233.309	5	(.0852200314403, .2075241804123]
6	75	9	84	9.90%	1	0	x31	0	233.309	5	> .2075241804123
7	9	70	79	9.30%	2	1	x4	0.006	11.6	1	<= .3631933033466
8	5	14	19	2.20%	2	1	x4	0.006	11.6	1	> .3631933033466
9	156	51	207	24.50%	1	5	x12	0.001	14.361	1	<= .0
10	66	31	97	11.50%	1	5	x12	0.001	14.361	1	> .0
11	59	14	73	8.60%	1	9	x19	0.041	16.92	3	<= .0000000000000
12	34	11	45	5.30%	1	9	x19	0.041	16.92	3	(.0000000000000, .0461287237704]
13	10	4	14	1.70%	1	9	x19	0.041	16.92	3	(.0461287237704, .0858266577125]
14	53	22	75	8.90%	1	9	x19	0.041	16.92	3	> .0858266577125
15	32	13	45	5.30%	1	10	x5	0.027	8.837	1	<= .1201166585088
16	34	18	52	6.20%	2	10	x5	0.027	8.837	1	> .1201166585088

Table 5.3.3-b1 The Result of CHAID with F indicators (ROA) (2)

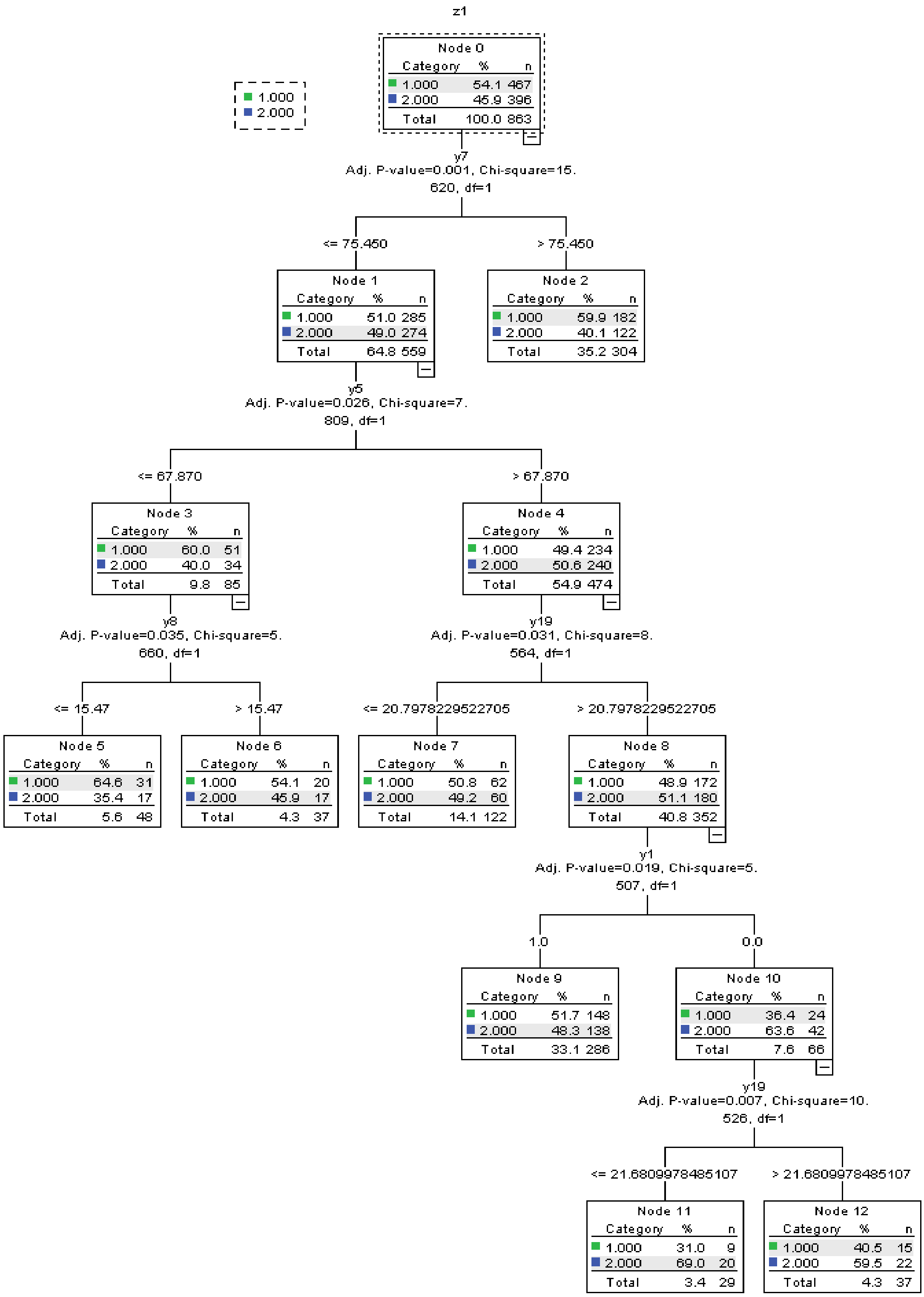


Figure 5.3.3-c The Result of CHAID with NF indicators (ROA) (1)

Node	N	N	N	Percent	Predicted Category	Parent Node	Variable	Sig.a	Chi-Square	df	Split Values
0	467	396	863	100.00%	1						
1	285	274	559	64.77%	1	2	y7	0.001	15.62	1	<=75.450
2	182	122	304	35.23%	1	2	y7	0.001	15.62	1	>75.450
3	51	34	85	15.21%	1	3	y5	0.026	7.89	1	<= 67. 870
4	234	240	474	84.79%	2	3	y5	0.026	7.89	1	>67.870
5	31	17	48	17.58%	1	4	y8	0.035	5.66	1	<=15.47
6	20	17	37	13.55%	1	4	y8	0.035	5.66	1	>15.47
7	62	60	122	44.69%	1	4	y19	0.031	8.564	1	<= 20. 798
8	24	42	66	24.18%	2	4	y19	0.031	8.564	1	>20.798
9	148	138	286	81.25%	1	5	y1	0.019	5.507	1	1
10	24	42	66	18.75%	2	5	y1	0.019	5.507	1	0
11	9	20	29	43.94%	2	6	y19	0.007	10.526	1	<=21.68
12	15	22	37	56.06%	2	6	y19	0.007	10.526	1	>21.68

Table 5.3.3-c1 The Result of CHAID with NF indicators (ROA) (2)

Appendix 2: Results of BPNN

no.	unitName	act	bias	st	position	act func
1	Input_1	2.03472	-0.18352	i	1, 0, 0	Act_Identity
2	Input_2	2.68214	-0.02815	i	2, 0, 0	Act_Identity
3	Input_3	2.27534	0.14185	i	3, 0, 0	Act_Identity
4	Input_4	-1.42709	0.15137	i	4, 0, 0	Act_Identity
5	Input_5	-1.18488	-0.20774	i	5, 0, 0	Act_Identity
6	Input_6	-1.25795	0.27966	i	6, 0, 0	Act_Identity
7	Input_7	-1.45902	-0.14182	i	7, 0, 0	Act_Identity
8	Input_8	1.45902	0.13926	i	8, 0, 0	Act_Identity
9	Input_9	1.94211	0.248	i	9, 0, 0	Act_Identity
10	Input_10	-1.05788	-0.24611	i	10, 0, 0	Act_Identity
11	Input_11	0.21919	-0.1203	i	11, 0, 0	Act_Identity
12	Input_12	-0.38945	-0.23118	i	12, 0, 0	Act_Identity
13	Input_13	0.65765	-0.09012	i	13, 0, 0	Act_Identity
14	Input_14	1.63515	-0.00444	i	14, 0, 0	Act_Identity
15	Input_15	-0.67607	0.23669	i	15, 0, 0	Act_Identity
16	Input_16	-0.68781	0.08777	i	16, 0, 0	Act_Identity
17	Input_17	-1.05788	0.24082	i	17, 0, 0	Act_Identity
18	Input_18	-0.88773	-0.22832	i	18, 0, 0	Act_Identity
19	Input_19	-0.87146	0.00825	i	19, 0, 0	Act_Identity
20	Input_20	0.79674	0.20714	i	20, 0, 0	Act_Identity
21	Input_21	1.51821	0.21426	i	21, 0, 0	Act_Identity
22	Input_22	-0.05866	0.27631	i	22, 0, 0	Act_Identity
23	Input_23	-1.00537	0.05787	i	23, 0, 0	Act_Identity
24	Input_24	0.05992	0.12943	i	24, 0, 0	Act_Identity
25	Input_25	-0.02228	-0.02239	i	25, 0, 0	Act_Identity

26	Input_26	-0.33038	0.09706	i	26, 0, 0	Act_Identity
27	Input_27	-0.83448	0.09594	i	27, 0, 0	Act_Identity
28	Input_28	-0.96232	0.16474	i	28, 0, 0	Act_Identity
29	Input_29	-0.03289	0.18164	i	29, 0, 0	Act_Identity
30	Input_30	-0.03926	-0.24957	i	30, 0, 0	Act_Identity
31	Input_31	-0.2179	-0.13303	i	31, 0, 0	Act_Identity
32	Input_32	0.2952	-0.15458	i	32, 0, 0	Act_Identity
33	Input_33	-0.96214	0.19384	i	33, 0, 0	Act_Identity
34	Input_34	1.39562	-0.14243	i	34, 0, 0	Act_Identity
35	Input_35	-0.13433	0.00666	i	35, 0, 0	Act_Identity
36	Input_36	-2.19603	0.28572	i	36, 0, 0	Act_Identity
37	Input_37	1.95652	0.05107	i	37, 0, 0	Act_Identity
38	Input_38	0.06145	0.08015	i	38, 0, 0	Act_Identity
39	Input_39	-0.07863	-0.11133	i	39, 0, 0	Act_Identity
40	Input_40	0.58267	0.2258	i	40, 0, 0	Act_Identity
41	Input_41	-1.49648	-0.26504	i	41, 0, 0	Act_Identity
42	Input_42	-1.29219	0.11004	i	42, 0, 0	Act_Identity
43	Input_43	-0.79411	0.25829	i	43, 0, 0	Act_Identity
44	Input_44	-1.28472	-0.11792	i	44, 0, 0	Act_Identity
45	Input_45	-0.81881	0.10516	i	45, 0, 0	Act_Identity
46	Input_46	-1.64085	-0.11339	i	46, 0, 0	Act_Identity
47	Input_47	-1.401	-0.23513	i	47, 0, 0	Act_Identity
48	Input_48	1.32313	-0.29008	i	48, 0, 0	Act_Identity
49	Input_49	0.11471	-0.09941	i	49, 0, 0	Act_Identity
50	Input_50	-0.98276	-0.25477	i	50, 0, 0	Act_Identity
51	Input_51	-0.39354	0.26855	i	51, 0, 0	Act_Identity
52	Input_52	-0.91511	-0.27535	i	52, 0, 0	Act_Identity

53	Input_53	-1.31459	0.24542	i	53, 0, 0	Act_Identity
54	Input_54	0.63289	-0.21322	i	54, 0, 0	Act_Identity
55	Input_55	-0.51236	-0.01758	i	55, 0, 0	Act_Identity
56	Input_56	-0.7198	-0.06969	i	56, 0, 0	Act_Identity
57	Input_57	0.04606	-0.23804	i	57, 0, 0	Act_Identity
58	Input_58	0.13257	-0.11413	i	58, 0, 0	Act_Identity
59	Hidden_2_1	0.97381	0.00798	h	1, 2, 0	
60	Hidden_2_2	0.94407	0.14939	h	2, 2, 0	
61	Hidden_2_3	0.00003	0.15256	h	3, 2, 0	
62	Hidden_2_4	0.22891	-1.1014	h	4, 2, 0	
63	Hidden_2_5	0.9987	0.82715	h	5, 2, 0	
64	Output_0	0.94401	0.34138	o	1, 4, 0	
65	Output_1	0.05605	-0.3466	o	2, 4, 0	

Table 5.6.2-a The Result of BPNN with F and NF indicators (1)

target	source:weight							
59 | | 58: 0.86315	57: 0.13271	56:-0.81009	55: 2.15298	54:-0.22827	53:-1.14306	52: 0.21397	51: 0.68260	50:-1.00892
49:-1.01955	48:-0.71456	47:-0.53835	46: 0.31776	45:-0.38124	44:-0.39049	43:-0.11878	42:-0.54213	41: 0.99769
40:-0.44505	39:-0.02372	38:-0.43764	37: 0.82045	36:-0.06025	35: 0.62044	34:-1.07023	33: 0.14152	32:-1.63176
31: 0.24948	30:-1.64284	29:-1.54067	28: 0.16166	27: 0.63244	26:-0.82932	25: 0.28943	24:-0.05935	23: 0.13846
22:-0.18754	21: 0.83414	20: 0.25647	19:-0.91347	18:-0.52938	17:-0.55235	16:-0.36725	15:-0.10872	14:-0.94928
13:-0.17491	12: 0.16769	11:-0.48960	10:-0.34178	9: 0.40588	8: 0.41751	7: 0.06347	6:-0.21746	5:-0.73396
4:-0.71043	3:-0.93706	2: 0.42252	1:-0.27900					
60 | | 58: 0.19610	57:-0.00321	56: 0.27474	55:-0.24051	54:-0.81437	53:-0.65934	52:-0.08972	51:-0.54014	50:-0.50347
49: 0.14730	48:-0.13140	47:-0.31921	46: 0.08213	45:-0.68156	44:-0.72782	43:-0.48943	42:-0.49704	41: 0.89821
40: 0.66229	39:-0.11344	38: 0.22455	37:-0.23512	36:-0.35714	35:-0.53756	34:-0.10220	33:-0.45813	32: 0.19310
31: 0.87249	30: 0.34376	29: 0.41712	28:-0.57570	27:-0.43320	26: 0.01692	25:-0.11633	24: 0.08245	23:-0.47349
22: 0.13158	21:-0.35611	20: 0.67960	19: 0.48446	18: 0.62243	17: 0.24959	16: 0.53163	15: 0.66580	14: 0.47146
13: 0.20093	12: 0.10271	11: 0.18347	10: 0.30263	9:-0.15744	8:-0.32232	7: 0.41664	6: 0.11591	5: 0.24789
4:-0.27966	3: 0.40519	2: 0.07179	1:-0.14698					
61 | | 58: 0.05207	57: 0.29956	56: 1.03111	55:-0.79173	54:-0.66042	53:-0.26212	52:-0.36488	51:-0.31742	50:-0.06268
49:-0.28453	48:-0.14051	47: 0.36591	46: 1.01339	45: 0.50498	44:-0.13727	43: 0.67929	42: 0.48435	41: 0.58811
40: 0.43258	39: 0.35189	38: 0.01836	37:-0.20727	36:-0.63487	35: 0.63460	34:-0.52677	33: 0.35522	32:-0.57897
31: 0.16071	30: 0.16252	29:-0.75727	28: 0.50173	27: 0.39720	26:-0.27704	25:-0.01981	24:-0.00269	23: 0.76397
22: 0.17111	21:-0.08884	20:-0.67800	19: 0.37254	18:-0.17086	17:-0.21942	16: 0.37788	15: 0.51089	14:-0.30609
13:-0.64547	12:-0.46839	11:-0.12895	10: 0.26400	9:-0.40389	8:-0.26955	7: 0.09667	6: 0.25534	5:-0.17355
4: 0.62786	3:-0.36915	2: 0.28967	1: 0.15120					
62 | | 58: 0.37752	57:-0.85420	56:-0.26453	55:-0.61845	54:-0.50917	53: 0.73625	52:-0.04294	51:-0.98660	50: 0.43770
49:-0.44662	48: 0.78295	47: 0.38602	46:-1.62533	45: 0.79516	44: 0.29603	43:-0.74942	42:-0.03910	41: 1.29002
40: 0.25368	39: 0.56073	38:-0.27787	37: 0.10570	36:-0.63605	35: 0.31112	34:-0.34143	33:-0.41845	32:-1.67934
31: 0.13106	30:-0.51413	29:-1.27957	28:-0.73896	27: 0.55945	26: 0.52674	25: 0.01925	24:-0.13181	23: 0.06112
22:-0.00637	21:-0.07530	20:-0.20410	19: 0.07593	18:-0.85965	17: 0.98564	16: 0.08283	15:-0.36221	14:-0.33649
13: 0.24431	12:-0.78165	11:-0.86469	10: 0.92677	9: 0.27926	8:-0.19787	7:-0.10093	6:-0.50395	5:-0.28937
4: 0.38640	3:-0.45863	2: 0.24772	1:-0.00180					
63 | | 58: 1.21113	57: 0.07533	56:-0.47499	55: 0.90143	54:-0.10694	53: 0.24621	52: 0.86965	51: 0.40055	50:-1.26146
49: 0.45147	48:-0.74859	47:-0.00201	46:-0.81177	45: 0.61419	44: 0.39921	43:-0.56570	42: 0.03660	41:-0.17160
40:-0.92570	39: 0.17816	38:-0.10126	37:-0.51860	36:-1.49180	35:-0.29513	34: 2.02681	33: 0.90436	32: 1.82112
31: 0.25689	30: 0.10532	29: 1.77975	28: 1.16407	27: 1.07690	26:-0.06915	25:-0.00326	24:-0.38944	23: 0.24213
22: 0.11101	21:-0.62658	20: 0.86880	19:-0.43364	18: 0.69260	17: 0.03492	16:-0.55020	15:-0.77881	14: 0.23665
13:-0.72104	12:-0.46595	11:-0.81113	10: 0.02616	9:-0.26296	8:-0.45518	7: 0.24595	6:-1.26030	5:-0.11882
4:-0.87906	3: 1.00657	2: 0.32924	1:-0.43981					
64 | | 63: 3.87418	62:-2.95038	61:-1.98943	60: 2.75882	59:-3.40385				
65 | | 63:-3.87166	62: 2.94871	61: 1.99137	60:-2.75520	59: 3.40469				

Table 5.6.2-b The Result of BPNN with F and NF indicators (2)

no.	unitName	act	bias	st	position	act func
1	Input_1	2.03472	0.01687	i	1, 0, 0	Act_Identity
2	Input_2	2.68214	0.11197	i	2, 0, 0	Act_Identity
3	Input_3	2.27534	0.22449	i	3, 0, 0	Act_Identity
4	Input_4	-1.42709	0.2065	i	4, 0, 0	Act_Identity
5	Input_5	-1.18488	-0.06445	i	5, 0, 0	Act_Identity
6	Input_6	-1.25795	0.27793	i	6, 0, 0	Act_Identity
7	Input_7	-1.45902	-0.02359	i	7, 0, 0	Act_Identity
8	Input_8	1.45902	0.02358	i	8, 0, 0	Act_Identity
9	Input_9	1.94211	0.1827	i	9, 0, 0	Act_Identity
10	Input_10	-1.05788	-0.05847	i	10, 0, 0	Act_Identity
11	Input_11	0.21919	-0.24741	i	11, 0, 0	Act_Identity
12	Input_12	-0.38945	-0.02286	i	12, 0, 0	Act_Identity
13	Input_13	0.65765	0.20017	i	13, 0, 0	Act_Identity
14	Input_14	1.63515	0.19673	i	14, 0, 0	Act_Identity
15	Input_15	-0.67607	0.01568	i	15, 0, 0	Act_Identity
16	Input_16	-0.68781	0.10069	i	16, 0, 0	Act_Identity
17	Input_17	-1.05788	0.12169	i	17, 0, 0	Act_Identity
18	Input_18	-0.88773	0.18044	i	18, 0, 0	Act_Identity
19	Input_19	-0.87146	0.22609	i	19, 0, 0	Act_Identity
20	Input_20	0.79674	-0.21055	i	20, 0, 0	Act_Identity
21	Input_21	1.51821	0.07094	i	21, 0, 0	Act_Identity
22	Input_22	-0.05866	-0.17011	i	22, 0, 0	Act_Identity
23	Input_23	-1.00537	0.0319	i	23, 0, 0	Act_Identity
24	Input_24	0.05992	0.00595	i	24, 0, 0	Act_Identity
25	Input_25	-0.02228	0.07595	i	25, 0, 0	Act_Identity
26	Input_26	-0.33038	-0.29817	i	26, 0, 0	Act_Identity
27	Input_27	-0.83448	-0.18838	i	27, 0, 0	Act_Identity

28	Input_28	-0.96232	-0.04042	i	28, 0, 0	Act_Identity
29	Input_29	-0.03289	0.0446	i	29, 0, 0	Act_Identity
30	Input_30	-0.03926	-0.10025	i	30, 0, 0	Act_Identity
31	Input_31	-0.2179	0.1956	i	31, 0, 0	Act_Identity
32	Input_32	0.2952	-0.09041	i	32, 0, 0	Act_Identity
33	Input_33	-0.96214	-0.08698	i	33, 0, 0	Act_Identity
34	Input_34	1.39562	0.05403	i	34, 0, 0	Act_Identity
35	Input_35	-0.13433	0.24434	i	35, 0, 0	Act_Identity
36	Input_36	-2.19603	0.23533	i	36, 0, 0	Act_Identity
37	Input_37	1.95652	0.24119	i	37, 0, 0	Act_Identity
38	Input_38	0.06145	0.12269	i	38, 0, 0	Act_Identity
39	Input_39	-0.07863	0.17077	i	39, 0, 0	Act_Identity
40	Hidden_2_1	0.92712	0.84756	h	1, 2, 0	
41	Hidden_2_2	0.00364	1.15699	h	2, 2, 0	
42	Hidden_2_3	0.81123	0.66103	h	3, 2, 0	
43	Hidden_2_4	0.81468	-0.25265	h	4, 2, 0	
44	Hidden_2_5	0.88775	-1.12039	h	5, 2, 0	
45	Output_0	0.76269	-0.11104	o	1, 4, 0	
46	Output_1	0.2396	0.0811	o	2, 4, 0	

Table 5.6.3-a The Result of BPNN with F indicators (1)

target	source:weight								
40	39:-0.36622	38: 0.18323	37:-0.15617	36: 1.06645	35:-0.34002	34: 0.49887	33: 0.69974	32: 0.49647	31: 0.03024
	30:-0.67205	29: 0.39794	28: 0.30276	27: 0.26678	26:-0.25704	25: 0.05773	24:-0.03517	23:-0.47354	22: 0.17909
	21:-0.25681	20: 0.43555	19:-0.20669	18: 0.20438	17: 0.15648	16:-0.03484	15:-0.34923	14: 0.98363	13:-0.18235
	12:-0.09396	11: 0.28519	10:-0.19626	9: 0.05360	8:-0.45971	7: 0.14897	6:-0.42744	5: 0.03043	4:-1.25753
	3: 0.32169	2:-0.09082	1: 0.09926						
41	39: 0.49810	38: 0.00468	37: 0.41692	36: 1.02813	35: 0.23698	34:-1.45852	33:-0.50585	32:-1.88176	31: 0.05071
	30:-1.16904	29:-1.32183	28:-0.43371	27: 0.02154	26:-0.27899	25:-0.14123	24: 0.23882	23:-0.31546	22:-0.16196
	21: 0.42675	20:-0.33529	19: 0.29613	18: 0.37772	17: 0.20086	16:-0.11300	15: 0.35473	14: 0.13602	13:-0.47693
	12:-0.23064	11:-0.05660	10: 0.74050	9: 0.51601	8: 0.26388	7:-0.07554	6: 0.10058	5: 0.17701	4: 1.27311
	3:-0.71290	2:-0.43997	1: 0.38176						
42	39:-0.39136	38: 0.35948	37: 0.03949	36:-0.57001	35:-0.64610	34: 0.99839	33:-0.26407	32: 2.29160	31:-0.15073
	30: 1.27618	29: 2.07567	28:-0.03494	27:-0.03635	26: 0.60939	25:-0.04874	24:-0.20113	23:-0.21883	22: 0.02035
	21:-0.04011	20:-0.16542	19: 0.82856	18: 0.54415	17: 0.31701	16:-0.18170	15:-0.00022	14: 0.47255	13:-0.80030
	12: 0.11520	11: 1.23426	10: 0.67562	9: 0.14431	8: 0.10766	7:-0.41569	6: 0.23238	5: 1.14159	4: 0.47312
	3: 0.59865	2:-0.44900	1:-0.00558						
43	39: 0.03241	38: 0.05196	37:-0.18080	36:-0.78385	35: 0.06616	34: 0.30094	33: 0.34178	32: 0.44636	31:-0.15136
	30: 0.11910	29: 0.32160	28: 0.39600	27:-0.14434	26:-0.11513	25: 0.11077	24: 0.00849	23: 0.32002	22:-0.13699
	21: 0.11769	20:-0.53950	19: 0.43475	18:-0.10428	17: 0.16897	16: 0.39545	15: 0.34718	14: 0.18898	13: 0.07421
	12:-0.42784	11: 0.18606	10:-0.11182	9:-0.05322	8: 0.08442	7:-0.30220	6:-0.26104	5:-0.31453	4: 0.20600
	3: 0.02586	2: 0.15734	1:-0.06765						
44	39:-0.41448	38:-0.08919	37: 0.15639	36: 0.34686	35: 0.14648	34:-0.82866	33: 0.55010	32:-0.67137	31:-0.83494
	30:-0.58886	29:-1.14233	28: 0.37575	27: 0.41839	26: 0.06705	25:-0.00985	24:-0.22794	23: 0.08527	22:-0.11006
	21: 0.56167	20: 0.05294	19:-0.48757	18:-0.50818	17:-0.34169	16:-0.54710	15:-0.05303	14:-0.66920	13:-0.08094
	12: 0.33258	11: 0.36211	10:-0.24125	9: 0.48847	8: 0.17858	7: 0.09375	6:-0.73251	5:-0.65905	4:-0.46077
	3:-0.48604	2: 0.61502	1: 0.25824						
45	44:-1.59936	43:-1.24231	42: 2.42213	41:-2.33299	40: 1.89194				
46	44: 1.64884	43: 1.24603	42:-2.39272	41: 2.35178	40:-1.92251				

Table 5.6.3-b The Result of BPNN with F indicators (2)

no.	unitName	act	bias	st	position	act func
1	Input_1	0.58267	0.15474	i	1, 0, 0	Act_Identity
2	Input_2	-1.49648	0.26845	i	2, 0, 0	Act_Identity
3	Input_3	-1.29219	-0.25543	i	3, 0, 0	Act_Identity
4	Input_4	-0.79411	-0.28789	i	4, 0, 0	Act_Identity
5	Input_5	-1.28472	0.0059	i	5, 0, 0	Act_Identity
6	Input_6	-0.81881	-0.07621	i	6, 0, 0	Act_Identity
7	Input_7	-1.64085	0.04427	i	7, 0, 0	Act_Identity
8	Input_8	-1.401	0.29467	i	8, 0, 0	Act_Identity
9	Input_9	1.32313	0.16074	i	9, 0, 0	Act_Identity
10	Input_10	0.11471	0.19406	i	10, 0, 0	Act_Identity
11	Input_11	-0.98276	0.09941	i	11, 0, 0	Act_Identity
12	Input_12	-0.39354	0.26137	i	12, 0, 0	Act_Identity
13	Input_13	-0.91511	-0.23197	i	13, 0, 0	Act_Identity
14	Input_14	-1.31459	-0.22719	i	14, 0, 0	Act_Identity
15	Input_15	0.63289	-0.01107	i	15, 0, 0	Act_Identity
16	Input_16	-0.51236	0.05668	i	16, 0, 0	Act_Identity
17	Input_17	-0.7198	0.04922	i	17, 0, 0	Act_Identity
18	Input_18	0.04606	0.08854	i	18, 0, 0	Act_Identity
19	Input_19	0.13257	0.09284	i	19, 0, 0	Act_Identity
20	Hidden_2_1	0.01192	-0.58406	h	1, 2, 0	
21	Hidden_2_2	0.59197	-0.17259	h	2, 2, 0	
22	Hidden_2_3	0.29163	0.08967	h	3, 2, 0	
23	Hidden_2_4	0.09723	-0.78529	h	4, 2, 0	
24	Hidden_2_5	0.50892	0.31	h	5, 2, 0	
25	Output_0	0.36506	0.12428	o	1, 4, 0	
26	Output_1	0.63826	-0.02857	o	2, 4, 0	

Table 5.6.4-a The Result of BPNN with NF indicators (1)

target		source:weight							
20	19:-0.42313	18: 0.91401	17:-1.20651	16: 1.93711	15:-0.58579	14:-1.14252	13:-0.45185	12:-0.69424	11:-0.06442
	10:-0.58003	9:-0.95132	8: 0.08238	7: 1.03387	6:-0.48668	5: 0.28789	4: 0.06985	3: 0.25727	2: 1.26771
	1:-0.31462								
21	19:-1.43734	18:-2.23469	17: 0.39984	16: 0.94921	15: 0.98284	14: 1.55306	13:-0.61593	12:-0.18694	11: 0.01682
	10:-0.62133	9: 1.02811	8:-0.34195	7:-1.38929	6:-0.38243	5:-0.22671	4: 0.19681	3:-0.19218	2: 1.63259
	1: 0.18914								
22	19:-0.80067	18:-0.06453	17:-0.43753	16:-0.11501	15:-0.49494	14: 0.32990	13:-0.82690	12:-1.82681	11:-0.63707
	10: 0.31421	9:-0.57742	8: 0.22732	7: 0.41648	6:-0.45566	5: 0.39863	4: 0.10171	3: 0.30870	2:-0.00374
	1:-0.43558								
23	19: 0.66303	18: 1.32619	17:-0.68877	16: 1.81563	15: 1.08309	14:-0.80267	13: 0.87177	12: 0.72924	11: 0.76703
	10: 0.37807	9: 0.40701	8:-1.26280	7: 2.42271	6: 0.76337	5:-0.93118	4:-0.42043	3:-0.37570	2: 0.18839
	1:-0.93389								
24	19:-0.01459	18: 0.49176	17:-0.04458	16:-0.24610	15: 0.14186	14:-0.17130	13: 0.34324	12: 0.12525	11: 0.46552
	10:-0.05562	9: 0.24655	8: 0.00914	7: 0.01039	6:-0.07494	5: 0.11180	4: 0.48561	3:-0.10112	2:-0.07766
	1:-0.02792								
25	24:-0.76046	23: 2.35380	22: 1.99332	21:-1.81081	20:-2.42925				
26	24: 0.65086	23:-2.35350	22:-2.03285	21: 1.78704	20: 2.43079				

Table 5.6.4-b The Result of BPNN with NF indicators (2)

no.	unitName	act	bias	st	position	act func
1	Input_1	2.03472	0.24513	i	1, 0, 0	Act_Identity
2	Input_2	2.68214	0.27887	i	2, 0, 0	Act_Identity
3	Input_3	2.27534	0.24243	i	3, 0, 0	Act_Identity
4	Input_4	-1.42709	0.1706	i	4, 0, 0	Act_Identity
5	Input_5	-1.18488	-0.29382	i	5, 0, 0	Act_Identity
6	Input_6	-1.25795	-0.014	i	6, 0, 0	Act_Identity
7	Input_7	-1.45902	0.22704	i	7, 0, 0	Act_Identity
8	Input_8	1.45902	0.29965	i	8, 0, 0	Act_Identity
9	Input_9	1.94211	-0.20991	i	9, 0, 0	Act_Identity
10	Input_10	-1.05788	0.06647	i	10, 0, 0	Act_Identity
11	Input_11	0.21919	0.24854	i	11, 0, 0	Act_Identity
12	Input_12	-0.38945	-0.09044	i	12, 0, 0	Act_Identity
13	Input_13	0.65765	0.22868	i	13, 0, 0	Act_Identity
14	Input_14	1.63515	0.29447	i	14, 0, 0	Act_Identity
15	Input_15	-0.67607	0.13917	i	15, 0, 0	Act_Identity
16	Input_16	-0.68781	-0.04322	i	16, 0, 0	Act_Identity
17	Input_17	-1.05788	0.18876	i	17, 0, 0	Act_Identity
18	Input_18	-0.88773	-0.11444	i	18, 0, 0	Act_Identity
19	Input_19	-0.87146	0.16055	i	19, 0, 0	Act_Identity
20	Input_20	0.79674	-0.01594	i	20, 0, 0	Act_Identity
21	Input_21	1.51821	0.12243	i	21, 0, 0	Act_Identity
22	Input_22	-0.05866	0.26107	i	22, 0, 0	Act_Identity
23	Input_23	-1.00537	0.27886	i	23, 0, 0	Act_Identity
24	Input_24	0.05992	0.1431	i	24, 0, 0	Act_Identity
25	Input_25	-0.02228	0.2697	i	25, 0, 0	Act_Identity

26	Input_26	-0.33038	0.20235	i	26, 0, 0	Act_Identity
27	Input_27	-0.83448	-0.2445	i	27, 0, 0	Act_Identity
28	Input_28	-0.96232	0.23263	i	28, 0, 0	Act_Identity
29	Input_29	-0.03289	0.20071	i	29, 0, 0	Act_Identity
30	Input_30	-0.03926	-0.10768	i	30, 0, 0	Act_Identity
31	Input_31	-0.2179	-0.23593	i	31, 0, 0	Act_Identity
32	Input_32	0.2952	0.01207	i	32, 0, 0	Act_Identity
33	Input_33	-0.96214	-0.04806	i	33, 0, 0	Act_Identity
34	Input_34	1.39562	0.28215	i	34, 0, 0	Act_Identity
35	Input_35	-0.13433	-0.00466	i	35, 0, 0	Act_Identity
36	Input_36	-2.19603	-0.22074	i	36, 0, 0	Act_Identity
37	Input_37	1.95652	0.25147	i	37, 0, 0	Act_Identity
38	Input_38	0.06145	-0.24621	i	38, 0, 0	Act_Identity
39	Input_39	-0.07863	0.11184	i	39, 0, 0	Act_Identity
40	Hidden_2_1	0.90838	1.94591	h	1, 2, 0	
41	Hidden_2_2	0.21332	0.89579	h	2, 2, 0	
42	Hidden_2_3	0.99996	-2.10405	h	3, 2, 0	
43	Hidden_2_4	1	1.9028	h	4, 2, 0	
44	Hidden_2_5	0	-2.65348	h	5, 2, 0	
45	Hidden_2_6	0.14673	-1.57451	h	6, 2, 0	
46	Hidden_2_7	0.08457	-1.31883	h	7, 2, 0	
47	Hidden_2_8	0.42111	1.92943	h	8, 2, 0	
48	Hidden_2_9	0.82852	0.49692	h	9, 2, 0	
49	Hidden_2_10	0.78993	-1.40775	h	10, 2, 0	
50	Output_0	0.99842	-1.2202	o	1, 4, 0	
51	Output_1	0.00158	1.20597	o	2, 4, 0	

Table 5.6.5-a The Result of BPNN with F indicators (1000 times iterations)