Integrated Economy and Society: Diversity, Creativity, and Technology
16–18 May 2018
Naples • Italy
Management, Knowledge and Learning International Conference 2018
Technology, Innovation and Industrial Management

RISK MANAGEMENT IN SMES WITH FINANCIAL AND NON-FINANCIAL INDICATORS USING BUSINESS INTELLIGENCE METHODS

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Abstract:
This study assesses the usage of financial and non-financial indicators in risk management process with a Business Intelligence (BI) approach and data mining methods. The paper focuses on the selection of Key Risk Indicators (KRIs) KRIs amongst risk indicators for performance measurement and risk control. 846 Chinese listed SMEs in the Shenzhen Stock Exchange have been studied as part of this research. After comparing Logit regression (LR), genetic algorithms (GA) and Chi-square automatic interaction detection (CHAID), it has been found that the CHAID is more accurate with non-financial indicators, which is also able to provide roadmaps to improve risk management performance. This study also used a BI approach to quantise and standardise information from government reports and firms' annual reports to generalise data for non-financial indicators. This study considered four completely different types of risks following the enterprise risk management framework. By using CHAID as the main method, the threshold values and roadmaps of KRIs have been found. This study provides an integrated method for the risk management process in SMEs by using financial and non-financial information generalised by a BI approach.

Keywords: data mining, enterprise risk management, business intelligence, KRIs, non-financial indicators, SMEs, CHAID

1. INTRODUCTION

Risk management (RM) is a systematic process of identifying, analysing and responding to business risks (Yeo & Lai, 2004). Sweeting (2010) argues that RM can reduce the volatility in a firm's return, which helps to increase the value of the firm and reduces the probability of insolvency. Sweeting (2010) also points out that improved RM could make more profit with certain risk levels. Enterprise risk management (ERM) has been introduced in latest 20 years, which means that all risks can be viewed together within a coordinated and strategic framework (Nocco & Stulz, 2006). The existing literature has mainly focused on RM in large companies (Kim & Vonortas, 2014). However, due to the increasing importance of SMEs, RM for SMEs has drawn the attention of many academics (Verbano & Venturini, 2013). Verbano and Venturini (2013) also point out that applying RM in SMEs is a relatively new topic, and most areas relating to it are under researched. As ERM considers hazard risk, financial risk, operational risk and strategic risk, there are some features of risks that cannot be described by just using financial indicators. To gain more useful information, it is necessary to also use business intelligence (BI) approach. BI can support decision making by converting any kind of data into useful information (Negash & Gray, 2008). Therefore, the application of RM in SMEs by using the ERM framework is a new innovation, especially due to combining BI approach in data gathering for financial and non-financial indicators.

Nocco and Stulz (2006) state that ERM provides a long term competitive advantage by optimising the trade-off between risk and return. However, the application of ERM in SMEs is still under researched (Verbano & Venturini, 2013). Every firm faces different risks, which depend on their external and internal environments (COSO, 2004). As developed in the BI approach, the effect of quantising and standardising information into indicators within models is still under researched. The effect of non-financial indicators on the ERM process also remains unclear. Furthermore, the effectiveness of different data mining methods for RM in SMEs could also be investigated and evaluated. This study investigates the ERM stream for RM in SMEs, attempts to use non-financial indicators under the ERM stream, compares different methods in the selection of KRIs among risk indicators and provides roadmaps and the order of risks under the ERM stream in the RM process. Therefore, this study has made the following contributions: evaluating the effect of using the ERM framework in RM for SMEs; examining the usefulness of non-financial indicators in RM for SMEs based on the ERM stream; comparing the performance of different data mining methods in selecting KRIs for ERM; and providing roadmaps and risk ordering to improve firm performance.

2. LITERATURE REVIEW

Risk management is defined as the process of planning, organising, directing, and controlling resources to achieve goals (Head, 2009). The International Organization for Standardization (ISO 31000, 2009) provided guidance for the RM process, which included three main steps.

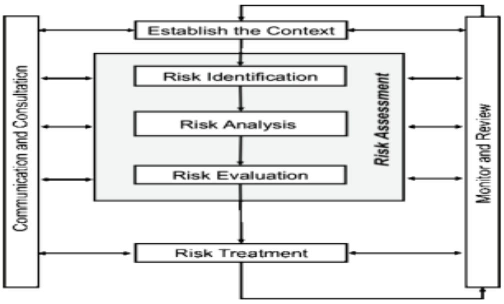

Figure 2a ISO 31000, 2009.

Figure 2a shows the ISO 31000 description of the RM process. In general, RM follows a stage-gate process (Henschel, 2009; ISO 31000, 2009). Firstly, the purpose of RM should be recognised, which is the establish the context step (Verbano & Venturini, 2013). There are then three sub-steps in the risk assessment step. In the risk identification step, the risk will be thoroughly investigated to discover what it is and how, when and why the risk may occur. The risk analysis is the most complicated stage in the risk assessment step. Risk analysis should provide an understanding of each risk, the consequences of the risks and the likelihood of the consequences. Finally, the risk treatment step provides possible solutions and methods for improvement for firms.

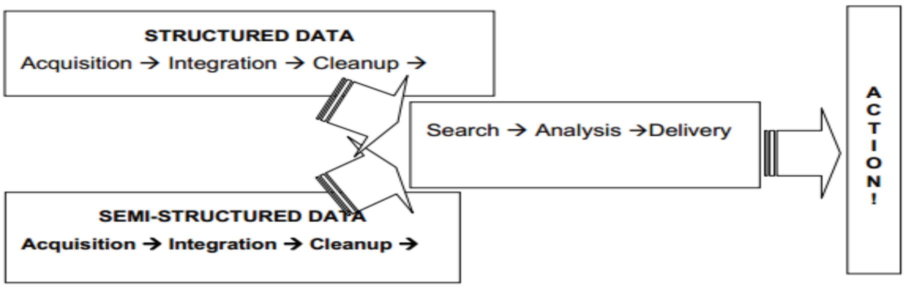

Figure 2b Negash, 2004.

Figure 2b explains the core idea of the BI approach. BI is a natural outgrowth of a series of previous systems designed to support decision making (Negash, 2004). The BI systems are data-driven decision support systems, where the main objective of BI is to provide timely and quality information for the decision making process by analysing large amounts of data about the firms and their activities (Tutunea & Rus, 2012). BI systems can help decision makers to make decisions by inputting structured and unstructured data, which can turn information into decisions. There are three main steps in the RM process (ISO 31000, 2009). In this study, RM integrated with BI can be described as follows. In the ‘establish the context’ step, the purposes and objectives are confirmed. In the ‘risk assessment step’, the risk types and risk indicators should first be identified. Then, the data should be analysed by using BI tools to obtain the result. Finally, the result should be explained and checked. In the risk treatment step, the rules and patterns generated from previous steps are applied to support decision making.

The most important phase in the RM process is risk assessment. In this step, the types of risk, the selection of risk indicators, the prediction accuracy and the usage of models should be decided. Many academics have used different classifications of risks and many academics have used different types of risks in similar studies for RM process (Kim & Vonortas, 2014;

Wu & Olson, 2009). Sweeting (2010) points out that the particular risks differ from firm to firm, while the risk develops over time. Therefore, it is difficult to consider every single risk in one project. However, it is still possible to discuss the main categories of risk faced by firms and their consequences (ibid). This study has selected the classifications of the four types of risk by the Casualty Actuarial Society (2003) for enterprise risk management, which are hazard risks, financial risks, operational risks and strategic risks.

Table 1. Classification of risks (adapted from Casualty Actuarial Society 2003).

Hazard risks	Financial risks	Operational risks	Strategic risks
• Fire and other property damage • Wisdom and other natural perils • Theft and other crime, personal injury • Business interruption • Disease and disability (including work-related ones) • Liability claims	• Price • Liquidity • Credit • Inflation/ purchasing power • Hedging/basis risk	• Business operations (e.g. product development, human resources, supply chain management, etc.) • Empowerment, information technology • Information/ business reporting (e.g. budgeting and planning, accounting information, investment evaluation, etc.)	• Reputational damage • Competition • Customer wants • Demographic and socio-cultural trends • Technological innovation • Capital availability • Regulatory and political trends

Figure 2c Verbano and Venturini, 2011.

Figure 2c indicates the four risk types for the ERM stream as concluded by the CAS (2003). Each risk type describes one potential risk aspect in firms, which requires the usage of indicators to measure it quantitatively and specifically. To address the RM process logically and precisely, it is important to introduce key performance indicators (KPIs) and key risk indicators (KRIs). Delcea et al. (2013) state that enterprise performance can be measured by KPIs. The aims of this study can be clarified by using KPIs to measure firm performance, which depend on the demands of decision makers or planners. The KRIs can detect unfavourable trends (Delcea et al., 2013). If the KRIs are confirmed, the risks can be ranked, evaluated and explained by management in many different ways.

The risk indicators could be either financial or non-financial. Altman et al. (2010) argued that using non-financial variables can improve the accuracy of predicting company failure. Both financial and non-financial indicators can be integrated into one model or combined with a model as risk indicators, while filtering and treating data via BI tools to determine KRIs. Islam et al. (2006) also point out that the indicators can be financial or non-financial, depending on the problems to be resolved. For example, if the decision makers want to know the financial situation of a firm, the direct measurement is financial ratios. In contrast, if the decision makers need to measure other information, such as industry, employee education or audit information, non-financial indicators could directly indicate this kind of information. To classify these different risks, the risk identification step should come first. In the risk identification phase, the problems faced by companies should be classified based on four major risk types. Therefore, if enterprises clearly establish their goals and define their risk requirements, KPIs and KRIs can be properly used in the risk analysis process.

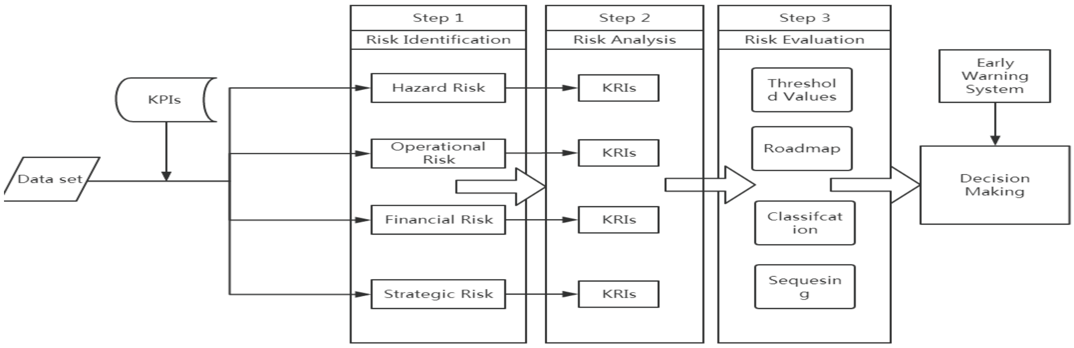

Figure 2d

Figure 2d indicates the entire process for applying the RM process under the ERM stream in SMEs. To classify these different risks, the risk identification step should come first. In the risk identification phase, the problems faced by companies should be classified into four major risk types. After the problems are specifically classified, the companies can focus the problems more efficiently. The most important part in the RM process is risk analysis, which can decide the threshold values, importance of risk indicators and the number of KRIs. Islam (2006) points out that the indicators can be financial or non-financial, depending on the problems to be solved. In the risk analysis section, the result from the final step can be used to evaluate the situation of enterprises by setting up an early warning system. This early warning system can reduce risks by implementing some pre-emptive steps (Bussiere & Franzscher, 2006). Koyuncugil and Ozgulbas (2009) define early warning systems as an analytical technique that is used to predict the achievement conditions of enterprises and to decrease the risk of financial distress. Koyuncugil and Ozgulbas (2009) state that an early warning system could provide: identification of changes in the environment before clarification; identification of speed and direction of change for projecting the future; identification of the degree of importance of changes; determination of deviations and taking signals; determination of possible reactions in the direction of privileged deviations; and an investigation of the factors that caused changes and transactions. The result of the risk evaluation step can provide threshold values, classifications, roadmaps and sequencing for KRIs and other risk indicators, which can be used to support the decision making process. Furthermore, the RM process is a dynamic system, which can also be monitored and reviewed depending on the changes in the external or internal environment. Therefore, it is possible to provide all the elements needed in the RM process in one integrated model.

3. RESEARCH METHODOLOGY

This study developed an integrated model for RM for SMEs with the ERM stream by using a BI approach, which strictly followed the RM procedure in ISO 31000. The selection of KPIs was related to the establish the context step, while the selection of algorithms was mainly concerned with the risk assessment step. To select risk indicators based on the KPIs, genetic algorithm (GA), logit regression and CHAID were used in this study. In the risk evaluation step, the performance of selected algorithms was compared based on the accuracy predictions. The variable importance and ROC curve were used as supplemental tools for choosing KRIs. Data from 2012 was selected as a training set, while data from 2013 was selected as a test set. In order to reduce the impact of over fitting, the sample data was randomly selected as 75:25 partition ratios.

3.1 Data collection

The data used in this study were selected from the annual reports of 846 listed SMEs in the Shenzhen Stock Exchange in China (www.szse.cn). The information was partly structured, and while some of the information required a clean-up, some of the information was not measured in a standard data format. The financial indicators could be directly obtained from balance sheets, income sheets and cash flow sheets in annual reports, which could be used in addressing financial risks and operational risks. The non-financial indicators were collected from general information, supplementary materials in annual reports and reports provided by the Chinese government. The non-financial indicators were mostly used to describe strategic risks and hazard risks.

3.2 Variable selection

This study has included 42 financial indicators and 19 non-financial indicators. The 42 financial indicators reflect profitability, solvency, structures and liquidity. The non-financial indicators were generated under the ERM stream (CAS, 2003). Followed the ERM framework, it is clear that only some of the features under hazard risks cannot be covered and quantitated by the annual reports and statistical reports from the Chinese government. The collection process was able to use coding via Ruby to download relevant annual reports and manually select variables. Afterwards, the unstructured data could be standardised and quantitated to be integrated in the data mining process.

3.3 Modelling

There are several methods that could be used to filter indicators and find hidden patterns. The most important part in this research has been to find the KRIs among all of the selected risk indicators. Meanwhile, the integration of non-financial indicators into prediction models has also been a challenge. Therefore, GA, logit regression and CHAID were selected as the main methods.

3.3.1 Genetic algorithms

Genetic algorithms (GA) are population-based evolutionary searching methods, which come from the concepts of natural genetics and evolutionary principles (Shin & Lee, 2002). GAs are particularly suitable for solving multi-parameter optimisation problems. Min et al. (2006) state that GAs differ from other non-linear optimisation techniques, which search by maintaining a population of solutions to find the best solutions for the problem. In GAs, a population of strings, which encode a potential solution to the problem, is evolved towards the best solution. GAs include initialisation, selection of better individuals, crossover and mutation. For the real-world applications of GAs, choosing the fitness function is the most critical step (Gordini, 2014). In this study, GA has been used to select KRIs by using the feature selection function, where the fitness value is set as the classification accuracy.

3.3.2 Chi-square automatic interaction detector

Chi-square automatic interaction detector (CHAID) is a decision tree-based method. Decision tree algorithms segmentation methods that can be used due to their easy to understand and easy to apply visualisation. Although several decision tree (DT) algorithms have widespread usage today, CHAID is distinct from other DT algorithms because of the number of the branches that are produced by it. CHAID can have more branches than other DT methods. It also embraces the Chi-square test in deciding branches and nodes, which can be used to select significant indicators out of all indicators. It can also provide the rules to find out roadmaps for the RM process (Koyuncugil & Ozgulbas, 2012).

3.3.3 Logit regression

Logit regression (LR) is a standard statistical method, which was developed in the 1970s to provide early warnings of bank failure (Klistik, Kocisova & Misankova, 2015). LR can explain binary variables, which can be used to classify whether a firm has failed or not. Spuchľáková and Cug (2014) stated that classic regression cannot be used if the value of the variable indicates that the status is ‘yes or no’. Therefore, the logit model was introduced to solve this kind of problem. The aim of LR is an 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, LR does not require data to strictly follow normal distribution. The logit transformation is based on the ‘ratio of chances and hopes’ (Klistik et al., 2015). Each LR function could provide the Akaike information criterion (AIC) for the model, which could measure the effectiveness of the regression. This study used LR to determine the KRIs and verify the value of non-financial indicators.

3.4 Test details

Annual reports of firms were downloaded by using programming in Ruby from quotes.money.163.com. The CHAID method was run by SPSS, while the GA and LR methods were run in R programming. A total of 849 firms with 42 financial indicators and 19 non-financial indicators were used in the modelling. To select KRIs, variable importance was run by Python. The data in 2012 was used as a training set to find patterns and the data in 2013 was used as a test set to verify the prediction accuracy.

4. RESULT AND ANALYSIS

4.2 Model evaluation

4.1.1 KPI selection

Coleman (2009) claimed that key risk indicators (KRIs) could provide information about companies’ risk positions to alert them about changes, which could be used by management to show the risk level of activities and projects. To measure firms' risk positions, Li et al. (2016) selected Altman's Z-score as a performance indicator. According to Verbano and Venturini (2011), enterprise risk management should maximise a firm's value. The growth rate of return on assets (ROA) is one of the measurements of a firm's performance, since the growth rate can indicate the life-cycle of firms (Young, 1996). Although there are some academics that use Special treatment (ST) and non-ST in analysis of Chinese companies, the ST standard has its limitations. Therefore, possible KPIs could be selected from the Z-score and ROA. Since the Z-score provides a ternary classification, the results of Z-score classification may lack evidence to support the performance in the grey area. The ternary variable should be transferred to a binary variable to use the LR method. Meanwhile, the accuracy of Z-score models is lower than in CHAID models. Therefore, ROA has been decided for KRI selection.

4.1.2 KRI selection

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

```
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
```

```
> 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 4.1 2a Result of LR with F and NF; F=financial indicators; NF=non-financial indicators

Figure 4.1.2a shows the process of LR model in selection of KRIs with financial indicators and non-financial indicators. Initially, all of the 42 financial indicator and non-financial indicators were included in the LR. Then, to achieve the minimum AIC, some of indicators were excluded. When it reaches the minimum AIC, the coefficient of each indicators were calculated.

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

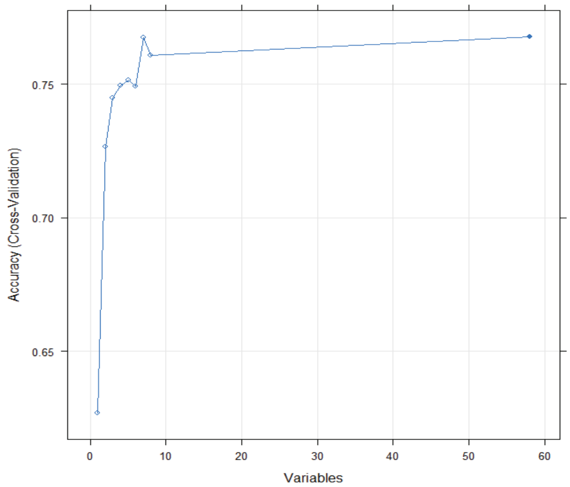

Figure 4.1.2b Result of GA with F and NF

Figure 4.1.2b shows the result of GA in selection of KRI. The table shows the accuracy of cross validation and the graph make it visualised. As it shows, the highest accuracy reached the maximum, when there are seven indicators included. After that, the accuracy of validation will not increase as more indicators included. However, only GA cannot find out which seven indicators are. It is necessary to apply variable importance to decide this question.

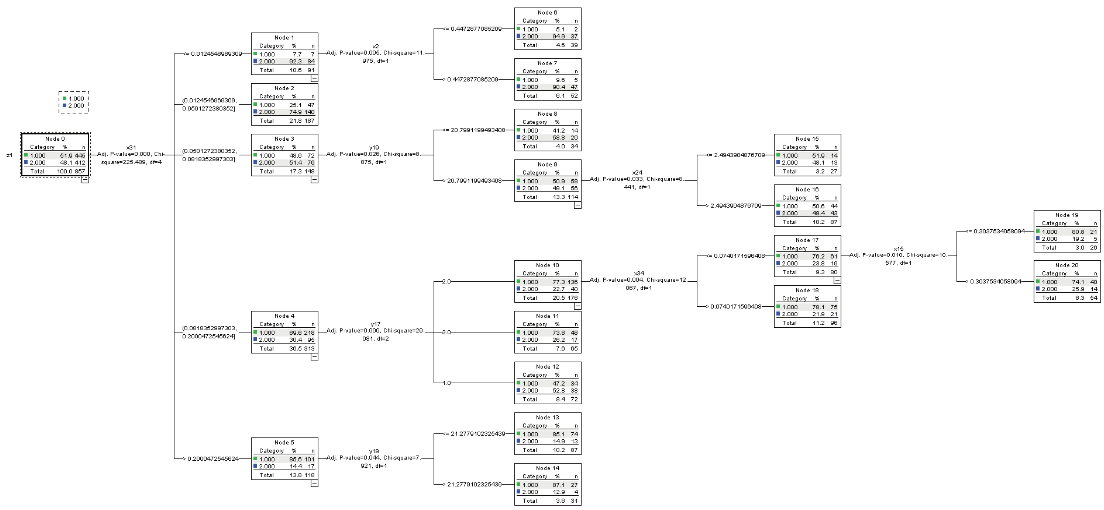

Figure 4.1.2c result of CHAID ROA with F and NF

Figure 4.1.2c shows the result of CHAID with F and NF based on ROA. Since the Z-score provided a ternary classification (distress, grey and safe), the performance cannot be decided in grey area. The ROA classification provided a binary (good or poor) result, which is more simply and direct in measuring firm performance. The result of CHAID also provided threshold values and roadmaps for firms to become good performance, which is easier to use compared with other two methods above.

The selection of KRIs is more difficult as the number of risk indicators is much higher than in KPIs. Since LR, GA and CHAID models are used to find hidden rules and patterns in data for decision makers to improve risk management, the accuracy, function and operability of the models are very important.

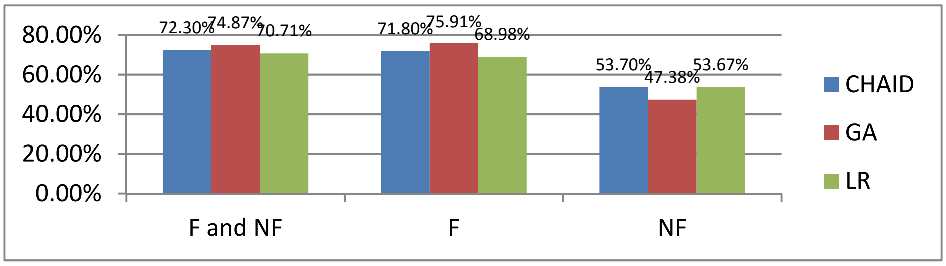

Figure 4.1 2d comparisons of three methods with F and NF, F and NF

The accuracy of the three methods is shown above. The prediction data was selected from 2013 to verify the forecast results. From the figure, it is clear that the GA has the highest accuracy in the financial and non-financial group and in the just financial group, while it is lowest in the non-financial group. CHAID has the second highest degree of accuracy in the F and NF group, and the F group, and the highest in the NF group. In the CHAID and LR algorithms, it is true that adding non-financial indicators into the data set could improve the prediction accuracy. However, for the GA, there is an inverse situation. The accuracy is higher in the F group than in the other two groups. The result of the GA with full indicators shows that the seven most important variables are all financial indicators. It can be concluded that the GA may have more affinity with financial indicators to measure firm performance. Indeed, the non-financial indicators still affect the result of GA. The accuracy of Cross-Validation reached the maximum with three indicators in the GA with the F model, while the accuracy of Cross-Validation reached the maximum with seven indicators in the GA with the F and NF model. However, just including the financial indicators may not explain all of the risks well. By comparing the GA with the other two methods, the affinity of non-financial indicators for GA is the worst, while the accuracy is only 2.57% higher than the CHAID model. Furthermore, CHAID can also provide threshold values and road map information, which may reduce the difficulty in operations. Therefore, the CHAID method was selected as the main method for choosing KRIs.

4.3 Analysis of results

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 4.2a

Figure 4.2a describes the roadmaps of firms, generated by the CHAID method. The yellow rows indicate strong rules, where the rules can determine the firm performance with a probability of around 90%. To comprehensively consider the risks, it is necessary to find patterns and rules from all three combinations of the indicators for selected methods. A good probability of a performance is at around 90% or less than 10% and can be considered to be convincible rule, which have been marked in yellow. It can also be concluded that the variables in the rules are KRIs, which are more important for detecting potential risks.

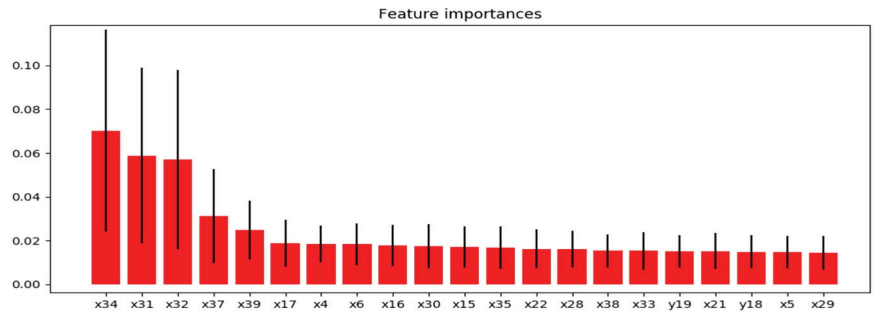

Figure 4.2b

To verify the results, the variable importance has also been checked as Figure 4.2b shows above. By comparing the high importance variables to the CHAID result, it is clear that most of the variables are overlapped. It also shows that the CHAID model can classify KRIs out of all risk indicators. As a result, it can be concluded that the financial risks and operational risks are the most important risks that affect firm performance.

To conclude, the roadmaps and threshold values are described as follows. To achieve good performance, the listed SMEs in China should:

1. Have a net profit to equity greater than 0.12 and a quick ratio greater than 0.447
2. Have a net profit to equity greater than 0.2 and a firm size (log) greater than 21.278
3. Have a net profit to equity less than 0.014 and inventory to current assets less than 0.363
4. Focus on profitability ratios, debt ratios, firm size and goodwill and intangible assets

5. CONCLUSION

More than 800 companies were used in this study to holistically achieve a RM process with Chinese SMEs listed in the Shenzhen stock market based on 42 financial and 19 non-financial indicators. The data set included all the listed SMEs in the Shenzhen stock exchange market, which was not subjectively selected based on special treatment (ST) like in other studies (Geng et al., 2014; Chen & Yi, 2007; Xie & Me, 2013; Li et al., 2017). The most suitable method for selection of KRI was chosen by comparing the accuracy, function and operability. The main findings are discussed below.

This study conducted the entire RM process under the ISO 31000 standard in one model, which included the risk assessment method and provided suggestions in risk evaluation. After comparing the prediction accuracy of three methods, CHAID was selected as the main method. The result also showed that quantitative and structured data could be helpful in addressing the ERM framework, which comes from the BI approach. It also successfully considered four risks in one model. Furthermore, it has been proven that including non-financial indicators can increase the prediction accuracy in measuring firm performance. After the BI approach was developed, decision makers could get information from structured and unstructured data by using the concept of a BI system (Negash, 2004). To include sufficient information, this study has used 42 financial indicators and 19 non-financial indicators. The features under the CAS (2003) risk catalogues were almost completely covered by using BI thinking to standardise and quantise information into indicators.

This study developed KRI selection methods by using the Python and R programming languages, and selected the CHAID model as the main approach out of GA, CHAID and LR. Firstly, by combining the CHAID models and variable importance, this research has successfully selected the KRIs from risk indicators and has made sequencing out of four types of risk. Secondly, the usage of non-financial risk indicators increased the accuracy of the modelling, which has proven the usefulness of non-financial indicators in ERM for SMEs. Thirdly, the attempt to use the ERM framework was also successful, which provided practical guidance for the ERM theory suggested by Nocco and Stulz (2006). Meanwhile, this study compared other filtering and clustering methods and selected one of the models with the highest accuracy to find the threshold values of the KRIs. It also provided risk sequencing and roadmaps to support decision making, which indicated the importance of the risks and thresholds values of the KRIs. Finally, this study also provided an integrated process for RM, where the KRIs and KPIs can also be changed or adjusted depending on management’s requirements. As a result, decision makers and academics can use the process developed in this study to build frameworks adjusted to their own purposes.

This study still has some limitations. The data set could be expanded to a longer period in order to verify its effectiveness. Although the patterns for listed SMEs in China have been found, it may not be a general rule for other areas as a result of different accounting standards. To investigate general rules, it is necessary to collect data from other areas and then conclude the more extensive rules and patterns. Since not all the features mentioned in the ERM framework (2003) have been covered, it is possible that more information can be found from other resources or institutions to quantise more information into indicators. Future research could be developed to investigate more general patterns for different groups to compare the KRIs in different areas and capture the features of research objects, to cover more aspects mentioned in the ERM framework, to adopt other RM frameworks and to verify the models for selection of KRI.

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