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Risk Classification of SMEs by Early Warning Model Based on Data Mining

Nermin Ozgulbas, and Ali Serhan Koyuncugil

***Abstract*—**One of the biggest problems of SMEs is their tendencies to financial distress because of insufficient finance background. In this study, an Early Warning System (EWS) model based on data mining for financial risk detection is presented. CHAID algorithm has been used for development of the EWS. Developed EWS can be served like a tailor made financial advisor in decision making process of the firms with its automated nature to the ones who have inadequate financial background. Besides, an application of the model implemented which covered 7,853 SMEs based on Turkish Central Bank (TCB) 2007 data. By using EWS model, 31 risk profiles, 15 risk indicators, 2 early warning signals, and 4 financial road maps has been determined for financial risk mitigation.

***Keywords*—**Early Warning Systems; Data Mining; Financial Risk; SMEs.

I. Introduction

SMEs are defined as enterprises in the non-financial business economy (NACE, Nomenclature statistique des activités économiques dans la Communauté européenne (Statistical classification of economic activities in the European Community)) that employ less than 250 persons. The complements of SMEs - enterprises that employ 250 or more persons -are large scale enterprises (LSEs). Within the SME sector, the following size-classes are distinguished:

- Micro enterprises, employing less than 10 persons
- Small enterprises, employing at least 10 but less than 50 persons
- Medium-sized enterprises that employ between 50 and 250 persons.

This definition is used for statistical reasons. In the European definition of SMEs two additional criteria are added: annual turnover should be less than 50 million €, and balance sheet total should be less than 43 million € [1].

SMEs play a significant role in all economies and are the key generators of employment and income, and drivers of innovation and growth. Access to financing is the most significant challenges for the creation, survival and growth of SMEs, especially innovative ones. The problem is strongly exacerbated by the financial and economic crisis as SMEs have suffered a double shock: a drastic drop in demand for goods and services and a tightening in credit terms, which are severely affecting their cash flows [2]. As a result, all these factors throw SMEs in financial distress.

The failure of a business is an event which can produce substantial losses to all parties like creditors, investors, auditors, financial institutions, stockholders, employees, and customers, and it undoubtedly reflects the economics of the countries concerned. When a business with financial problems is not able to pay its financial obligations, the business may be driven into the situation of becoming a non-performing loan business and, finally, if the problems cannot be solved, the business may become bankrupt and forced to close down. Those business failures inevitably influence all businesses as a whole. Direct and indirect bankruptcy costs are incurred which include the expenses of either liquidating or an attempting to reorganize businesses, accounting fees, legal fees and other professional service costs and the disaster broadens to other businesses and the economics of the countries involved [3,4,5]. The awareness of factors that contribute to making a business successful is important; it is also applicable for all the related parties to have an understanding of financial performance and bankruptcy. It is also important for a financial manager of successful firms to know their firm's possible actions that should be taken when their customers, or suppliers, go into bankruptcy. Similarly, firms should be aware of their own status, of when and where they should take necessary actions in response to their financial problems, as soon as possible rather than when the problems are beyond their control and reach a crisis.

Therefore, to bring out the financial distress risk factors into open as early warning signals have a vital importance for SMEs as all enterprises. There is no specific method for total prevention for a financial crisis of enterprises. The important point is to set the factors that cause the condition with calmness, to take corrective precautions for a long term, to make a flexible emergency plan towards the potential future crisis.

An Early Warning System (EWS) is a system which is using for predicting the success level, probable anomalies and is reducing crisis risk of cases, affairs transactions, systems, phenomenona, firms and people. Furthermore, their current situations and probable risks can be identified quantitatively [6]. Financial EWS is a monitoring and reporting system that alerts for the probability of problems, risks and opportunities before they affect the financial statements of firms. EWSs are used for detecting financial performance, financial risk and potential bankruptcies. EWSs give a chance to management to take advantage of opportunities to avoid or mitigate potential problems. Nearly, all of the financial EWSs are based on

Nermin Ozgulbas, Ph.D. is with the Baskent University, Ankara, Turkey (phone:+90-312-2466666-2137; e-mail:ozgulbas@ baskent.edu.tr).

Ali Serhan Koyuncugil, Ph.D. is with Capital Markets Board of Turkey Ankara, Turkey (e-mail: askoyuncugil@gmail.com).

financial statements. Balance sheets and income tables are the data sources that reflect the financial truth for early warning systems. In essence, the early warning system is a financial analysis technique, and it identifies the achievement analysis of enterprise due to its industry with the help of financial ratios.

An EWS developed for SMEs must design according to the needs of SMEs managers. Therefore, system must be easy to understand and easy to use, must design according to financial and operational risk factors (as banks and BASEL II requirements), and must be intelligence for using update data.

The aim of this paper is to present an EWS model based on data mining. EWS model was developed for SMEs to detect risk profiles, risk indicators and early warning signs. Chi-Square Automatic Interaction Detector (CHAID) Decision Tree Algorithm was in the study as a data mining method. Remaining of this chapter is organized as follows: Section 2 contains data mining model for risk detection and early warning system. Implementation of data mining for risk detection and early warning signals is presented in Section 3. Concluding remarks and strategies were suggested in the Conclusion Section.

II. Data Mining Model for Risk Detection and Early Warning System

The identification of the risk factors by clarifying the relationship between the variables defines the discovery of knowledge. Automatic and estimation oriented information discovery process coincides the definition of data mining. Data mining is the process of sorting through large amounts of data and picking out relevant information. Fawley, Piatetsky-Shapiro and Matheus [7] has been described data mining as "the nontrivial extraction of implicit, previously unknown, and potentially useful information from data". Also, Hand, Mannila and Smyth [8] described data mining as "the science of extracting useful information from large data sets or databases". Data mining, the extraction of hidden predictive information from large databases, is a powerful new technology with great potential to help companies focus on the most important information in their data warehouses. Data mining tools predict future trends and behaviors, allowing businesses to make proactive, knowledge-driven decisions. The automated, prospective analyses offered by data mining move beyond the analyses of past events provided by retrospective tools typical of decision support systems. Data mining tools can answer business questions that traditionally were too time consuming to resolve. They scour databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations [9].

Koyuncugil and Ozgulbas [10] described the data mining as “collection of evolved statistical analysis, machine learning and pattern recognition methods via intelligent algorithms which are using for automated uncovering and extraction process of hidden predictional information, patterns, relations, similarities or dissimilarities in (huge) data”

Data mining is used by business intelligence organizations, and financial analysts to get information from the large data sets. Data mining in relation to enterprise resource planning is the statistical and logical analysis of large sets of transaction data, looking for patterns that can aid decision making [11]. Today, data mining technology integrated measurement of different kinds of is moving into focus to measure and hedging risk. Data mining techniques have been successfully applied like fraud detection and bankruptcy prediction by Tam and Kiang (1992), Lee, Han and Kwon (1996), Kumar, Krovi and Rajagopalan (1997), strategic decision-making by Nazem and Shin (1999) and financial performance by Eklund, Back, Vanharanta and Visa (2003), Hoppszallern (2003), Derby (2003), Chang, Chang, Lin and Kao (2003), Kloptchenko, Eklund, Karlsson, Back, Vanhatanta and Visa (2004), Magnusson, Arppe, Eklund and Back (2005) [12, 13, 14, 15, 16, 17, 18, 19, 20, 21]. Also, some earlier studies of Koyuncugil and Ozgulbas [22, 23, 24, 25, 26, 27, 28, 29, 30]. Ozgulbas and Koyuncugil [31,32, 6] conducted on financial performance, financial risk and operational risk of Small and Medium Enterprises (SMEs) and hospitals by data mining

Fayyad, Piatetsky-Shapiro and Symth (1996), proposed main steps of DM [33]:

- Retrieving the data from a large database.
- Selecting the relevant subset to work with.
- Deciding on the appropriate sampling system, cleaning the data and dealing with missing fields and records.
- Applying the appropriate transformations, dimensionality reduction, and projections.
- Fitting models to the preprocessed data.

Data mining techniques can yield the benefits of automation on existing software and hardware platforms, and can be implemented on new systems as existing platforms are upgraded and new products developed. When data mining tools are implemented on high performance parallel processing systems, they can analyze massive databases in minutes. The most commonly used techniques in data mining are [9, 34]:

- *Artificial neural networks:* Non-linear predictive models that learn through training and resemble biological neural networks in structure.
- *Decision trees:* Tree-shaped structures that represent sets of decisions. These decisions generate rules for the classification of a dataset. Specific decision tree methods include Classification and Regression Trees (CART) and Chi Square Automatic Interaction Detection (CHAID).
- *Genetic algorithms:* Optimization techniques that use process such as genetic combination, mutation, and natural selection in a design based on the concepts of evolution.
- *Nearest neighbor method:* A technique that classifies each record in a dataset based on a combination of the classes of the k record(s) most similar to it in a historical dataset. Sometimes called the k-nearest neighbor technique.

- *Rule induction:* The extraction of useful if-then rules from data based on statistical significance.

Decision trees are tree-shaped structures that represent sets of decisions. The decision tree approach can generate rules for the classification of a data set. Specific decision tree methods include Classification and Regression Trees (CART) and Chi Square Automatic Interaction Detection (CHAID). CART and CHAID are decision tree techniques used for classification of a data set. They provide a set of rules that can be applied to a new (unclassified) data set to predict which records will have a given outcome. CART typically requires less data preparation than CHAID [35].

During the developing EWS; an easy to understand, easy to interpret and easy to apply utilitarian model that is far from the requirement of theoretical background is targeted by the discovery of the implicit relationships between the data and the identification of effect level of every factor. Because of this reason, data mining is the ideal method for financial early warning system.

Developing an EWS for SMEs focused segmentation methods. The main approach in analysis is discovering different risk levels and identifying the factors affected financial performance. By means of Chi-Square metrics CHAID is able to separately segment the groups classified in terms of level of relations. Therefore, leaves of the tree have not binary branches but as much branches as the number of different variables in the data. So, it was deemed convenient to use CHAID algorithm method in the study.

CHAID modeling is an exploratory data analysis method used to study the relationships between a dependent measure and a large series of possible predictor variables those themselves may interact. The dependent measure may be a qualitative (nominal or ordinal) one or a quantitative indicator. For qualitative variables, a series of chi-square analyses are conducted between the dependent and predictor variables. For quantitative variables, analysis of variance methods are used where intervals (splits) are determined optimally for the independent variables so as to maximize the ability to explain a dependent measure in terms of variance components [9].

Model of EWS

The model of EWS based on data mining and data flow diagram of the EWS is shown in Figure 1.

The steps of the EWS are:

- Step I. Data Preparation
- Step II. Implementation of DM Method
- Step III. Determination of Risk Profiles
- Step IV. Identification for Risk Indicators and Early Warning Signs
- Step V. Classification of SMEs by Risk Profiles and Early Warning Signs

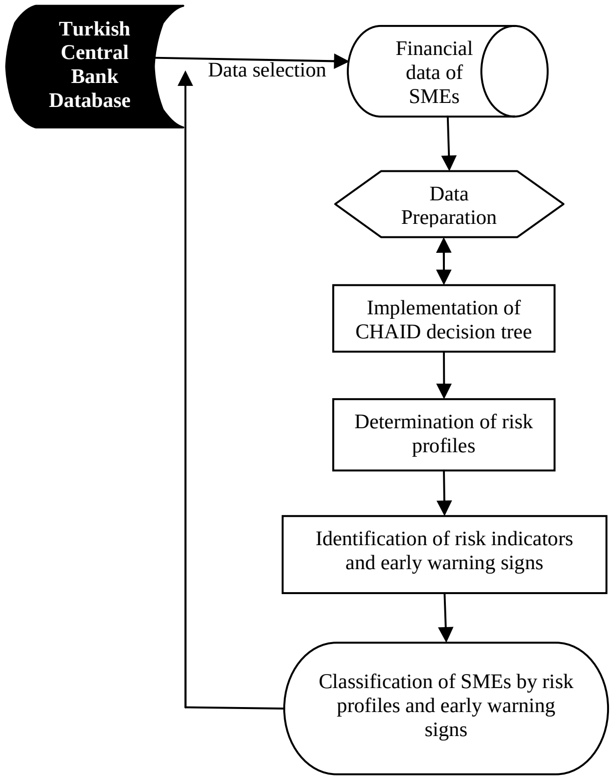

Fig. 1 Data flow diagram of EWS

III. Application of Model for Early Warning Signs and Risk Classification

Application of our model, early warning signs, financial road maps and other results are presented below.

Step I. Data Preparation

Application of our model covered SMEs in Turkey in 2007. Data of firms was obtained from Turkish Central Bank (TCB) after permission. Total number of firms had financial data were 8.979 in TCB in 2007. Since scope of our study only covered micro, medium, and small-scaled enterprises, which are often referred to as SMEs, those 7.853 firms were classified to identify the firms, which can be categorized as a SME. We based on SME definition of the EU in an attempt to participate to Turkey's efforts to align with the EU acquits and to ensure comparability of the analysis provided herein. The thresholds used to classify SME on basis of the EU's SME definitions are €50 million.

Financial data that are gained from balance sheets and income statements was used to calculate financial indicators of system. Steps of preparation of data:

TABLE I
FINANCIAL VARIABLES AND DEFINITIONS

Code	Variables	Definition
A	**Liquidity Ratios**	
A1	Current Ratio	Current Assets/ Current Liabilities
A2	Quick Ratio (Liquidity Ratio)	(Cash, Banks, Marketable Securities, Account Receivables)/ Current Liabilities
A3	Absolute Liquidity	(Cash, Banks, Marketable Securities)/ Current Liabilities.
A4	Inventories to Current Assets	Total Inventories / Current Assets
A5	Inventories to Total Assets	Total Inventories / Total Assets
A6	Inventory Dependency Ratio	(Short-Term Liabilities - (Liquid Assets +Marketable Securities))/ Inventories
A7	Current Account Receivables to Total Assets	Current Account Receivables/ Total Assets
A8	Short-Term Receivables to Total Assets Total Assets	Short-Term Receivables/Total Assets Total Assets
B	**Ratios Of Financial Position**	
B1	Total Loans to Total Assets	(Short-Term Liabilities + Long-Term Liabilities)/ Total Assets (Leverage Ratio)
B2	Own Funds to Total Assets	Own Funds/ Total Assets
B3	Own Funds to Total Loans	Own Funds/ (Short-Term Liabilities + Long-Term Liabilities)
B4	Short-Term Liabilities to Total Liabilities	Short-Term Liabilities/ Total Liabilities
B5	Long-Term Liabilities to Total Liabilities	Long-Term Liabilities / Total Liabilities
B6	Long-Term Liabilities to Long-Term Liabilities And Own Funds	Long-Term Liabilities /(Long-Term Liabilities And Own Funds)
B7	Tangible Fixed Assets to Own Funds	Tangible Fixed Assets / Own Funds
B8	Tangible Fixed Assets to Long-Term Liabilities	Tangible Fixed Assets / Long-Term Liabilities
B9	Fixed Assets to Total Loans	Fixed Assets/ (Short-Term Liabilities + Long Term Liabilities)
B10	Fixed Assets to Own Funds	Fixed Assets / Own Funds
B11	Fixed Assets to Long Term Loans+ Own Funds	Fixed Assets /(Long Term Loans+ Own Funds)
B12	Short-Term Liabilities to Total Loans	Short-Term Liabilities / Total Loans
B13	Bank Loans to Total Assets	Bank Loans / Total Assets
B14	Bank Loans to Short-Term Liabilities	(Short-Term Bank Loans + Principal Installments And Interest Payments Of Long-Term Bank Loans)/Short-Term Liabilities
B15	Bank Loans to Total Loans	(Short-Term Bank Loans + Principal Installments And Interest T Payments Of Long-Term Bank Loans + Long-Term Bank Loans)/ (Short-Term Liabilities + Long Term Liabilities)
B16	Current Assets to Total Assets	Current Assets / Total Assets
B17	Tangible Fixed Assets to Total Assets	Tangible Fixed Assets / Total Assets
C	**Turnover Ratios**	
C1	Inventory Turnover	Cost Of Goods Sold (Current Year) /(Previous Year's Inventory + Current Year's Inventory)/2
C2	Receivables Turnover	Net Sales/ (Short-Term Trade Receivables + Long-Term)
C3	Working Capital Turnover	Net Sales/Current Asset
C4	Net Working Capital Turnover	Net Sales/(Current Assets – Short-Term Liabilities)
C5	Tangible Fixed Assets Turnover	Net Sales/Tangible Fixed Assets (Net
C6	Fixed Assets Turnover	Net Sales/ Fixed Assets
C7	Own Funds Turnover	Net Sales/ Own Funds

Code	Variables	Definition
C8	Total Assets Turnover	Net Sales/ Total Assets
D	**Profitability Ratios**	
D1	Ratios Relating Profit To Capital	
D1a	Net Profit To Own Funds	Net Profit (Profit After Tax)/Own Funds
D1b	Profit Before Tax To Own Funds	Profit Before Tax/ Own Funds
D1c	Profit Before Interest And Tax To Profit Before Tax + Financing Expenses	Profit Before Interest And Tax /(Profit Before Tax + Financing Expenses)
D1d	Net Profit To Total Assets	Net Profit /Total Assets
D1e	Operating Profit To Assets Used In Carrying Out Of The Operations	Operating Profit / Total Assets-Financial Fixed Assets
D1f	Cumulative Profitability Ratio	Reserves From Retained Earnings/ Total Assets
D2	Ratios Relating Profit To Sales	
D2a	Operating Profit To Net Sales	Operating Profit / Net Sales
D2b	Gross Profit To Net Sales	Gross Profit / Net Sales
D2c	Net Profit To Net Sales	Net Profit / Net Sales
D2d	Cost Of Goods Sold To Net Sales	Cost Of Goods Sold / Net Sales
D2e	Operating Expenses To Net Sales	Operating Expenses / Net Sales
D2f	Interest Expenses To Net Sales	Interest Expenses / Net Sales
D3	Ratios Relating Profit To Financial Obligations	
D3a	Profit Before Interest And Tax To Profit Before Tax + Financing Expenses	Profit Before Interest And Tax /(Profit Before Tax + Financing Expenses)
D3b	Net Profit And Interest Expenses Net Profit + Financing Expenses To Interest Expenses	(Net Profit And Interest Expenses Net Profit + Financing Expenses) / Interest Expenses

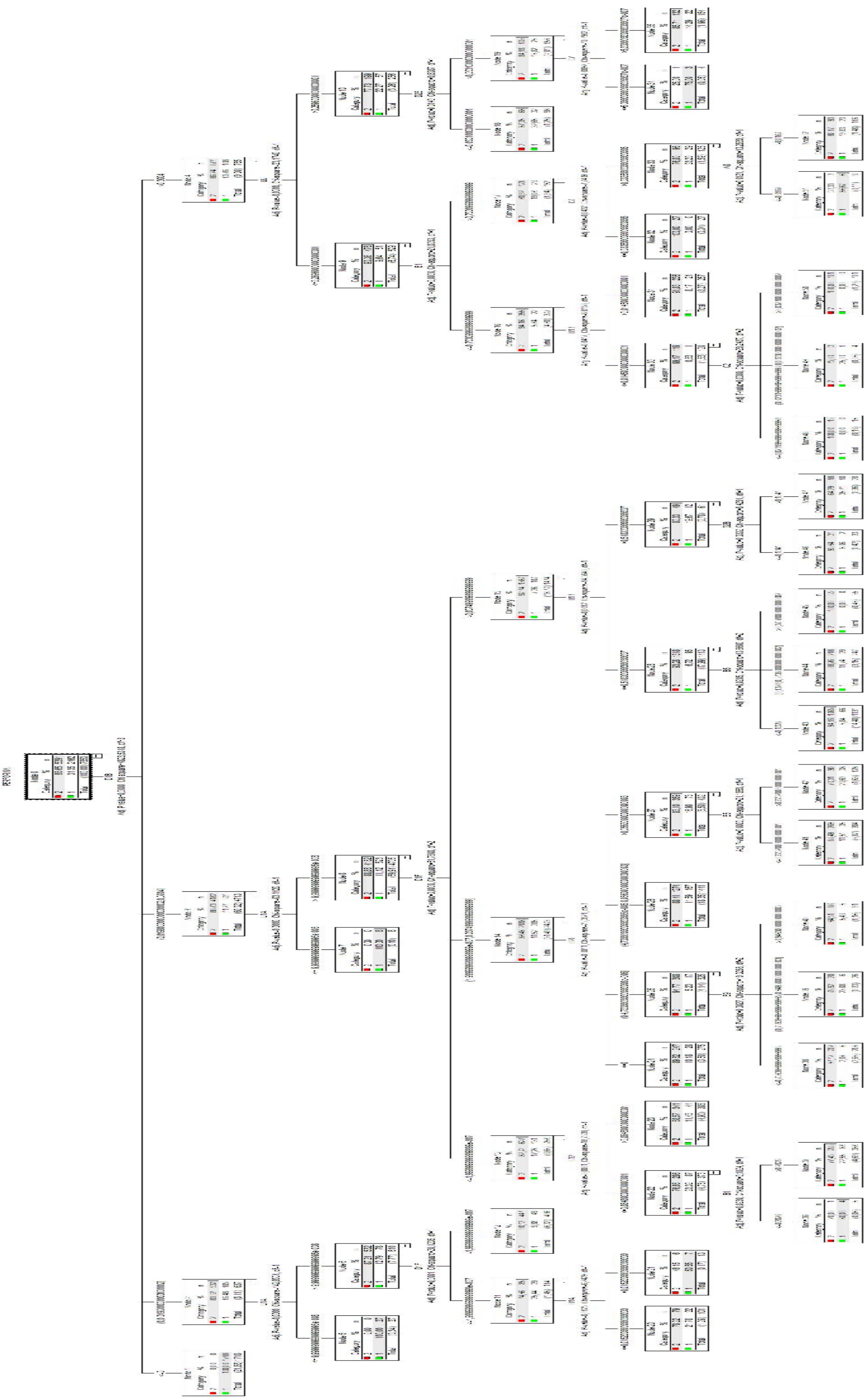

Fig. 2CHAID Decision Tree and Financial Profiles of SMEs

- Calculation of financial indicators like in Table I
- Reduction of repeating variables in different indicators to solve the problem of Collinearity / Multicollinearity
- Imputation of missing data
- Solution of outlier and extreme value problem

Financial ratios as financial risk indicators were calculated with variables collected from balance sheets of SMEs. These indicators and their definitions are presented in Table I.

Step II. Implementation of Data Mining Method (CHAID)

In the scope of the methods of data mining,

- Logistic regression,
- Discriminant analysis,
- Cluster analysis,
- Hierarchical cluster analysis,
- Self Organizing Maps (SOM),
- Classification and Regression Trees (C&RT),
- CHi-Square Automatic Interaction Detector (CHAID)

can be the principal methods, in addition to this several classification/segmentation methods can be mentioned.

However, during the preparation of an early warning system for SMEs, one of the basic objectives is to help SME administrators and decision makers, who does not have financial expertise, knowledge of data mining and analytic perspective, to reach 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 of their easy to understand and easy to apply visualization. Although, several decision tree algorithms have widespread usage today, CHAID is separated from other decision tree algorithms because of the number of the branches that are produced by CHAID. Other decision tree algorithms are branched in binary, but CHAID manifests all the different structures in data with its multi-branched characteristic. Hence; the method of CHi-Square Automatic Interaction Detector (CHAID) is used in the scope of this study.

CHAID algorithms used in this study are developed on basis of two groups of variables, namely target variable and predictor variables that will explain the target variable. In this study financial performance is explained by means of all financial variables of a SME. Therefore, the financial performance indicator is considered as the target variable and all financial variables (see Table I) are considered as the predictor variables. Figure 2 shows the CHAID Decision Tree and all profiles obtained from CHAID. Table II and Table III are explained and summarized the profiles in Figure 2.

Step III. Determination of Risk Profiles

CHAID has multi-branches, and all of the important relationships in data can be investigated until the subtle details. As can be seen from Figure 2 which explain SMEs profiling and financial performance statuses based on CHAID method, although it was possible to superficially categorize the covered SMEs into two groups as SMEs with good financial performance and with poor financial performance with CHAID method it was possible to categorize the covered SMEs in 31 different profiles in terms of level of financial performance. These profiles show us what financial indicators should focus on for good financial performance as well as those profiles those SMEs should take example to improve their financial performances.

As required under CHAID method SMES profiling is based on profit before tax to own funds ratio (D1B), which has the strongest relation with the financial performance ($p<0.001$). SMEs with this ratio lower than and equal to 0 are grouped in the 1st profile. According to this profile, all of 1,718 SMEs in this profile, or 21.88 % of all covered SMEs in the study have poor financial performance.

Those SMEs with profit before tax to own funds ratio between 0 and 0.20 are grouped in 2nd to 5th profiles given in Figure 2. Also, it was determined that return on equity ratio (D1A, $p<0.001$) and cumulative profitability ratio (D1F, $p=0.001$) affected financial risk of SMEs in these profiles. 2nd profile comprises 27 SMEs, or 0.34 % of total covered SMEs with return on equity ratio lower than and equal to 0, and all those SMEs have poor financial performance. 3rd profile with return on equity ratio between 0 and 0.02 and cumulative profitability ratio lower than and equal to 0.0000002 covered total 101 SMEs. In this profile 78.22 % (79 SMEs) have good financial performance and remaining 21.78 % (22 SMEs) have poor financial performance. On the other hand, 4th profile comprises 13 SMEs with return on equity ratio higher than 0.02 and cumulative profitability ratio lower than and equal to 0.0000002, and 46.15 % of which have good financial performance and 53.85 % of which have poor financial performance. Last profile with profit before tax to own funds ratio between 0 and 0.20 is 5th profile. In this profile, return on equity ratio is higher than 0 and cumulative profitability ratio is higher than 0.0000002. 90.12 % (447 SMEs) of SMEs have good financial performance and remaining 9.88 % (49 SMEs) have poor financial performance in this profile.

SMEs with profit before tax to own funds ratio between 0.20 and 0.36 are grouped in 6th to 21st profiles. Profiles 6th-16th given in Figure 2 and profiles 17th-21st given in Figure 2. Beside this ratio, return on equity ratio (D1A, $p<0.001$), cumulative profitability ratio (D1F, $p=0.001$), short-term liabilities to total loans (B12, $p=0.0001$), and total loans to total assets (B1, $p=0.0230$) affected financial risk of SMEs in 6th profile to 9th profile. 6th profile comprises 8 SMEs, or 0.1 % of total covered SMEs with return on equity ratio lower than and equal to 0, and all those SMEs have poor financial performance. 7th profile includes SMEs with return on equity ratio higher than 0, cumulative profitability ratio lower than and equal to 0.0000002, short-term liabilities to total loans lower than and equal to 0.86, and total loans to total assets lower than and equal to 0.20. In this profile, 20 % (1 SMEs) of SMEs have good financial performance, and 80 % (4 SMEs) of SMEs have poor financial performance. 8th profile contains SMEs with return on equity ratio higher than 0, cumulative profitability ratio lower than and equal to 0.0000002, short-term liabilities to total loans lower than and equal to 0.86, and total loans to total assets higher than 0.20. In this profile, 77.45 % (285 SMEs) of SMEs have good financial performance, and 22.55 % (83 SMEs) of SMEs have poor financial performance. 9th profile includes SMEs with return on equity ratio higher than 0, cumulative profitability ratio lower than and equal to 0.0000002, and short-term liabilities to total loans higher than 0.86. In this profile, 88.57 % (341 SMEs) of SMEs have good financial performance, and 11.43 % (44 SMEs) of SMEs have poor financial performance.

In 10th to 16th profiles, beside profit before tax to own funds ratio (D1B, p<0.001), return on equity ratio (D1A, p<0.001), cumulative profitability ratio (D1F, p=0.001), interest expenses to net sales (D2F, p=0.0011), fixed assets to long term loans+ own funds (B9, p=0.0027), and long-term liabilities to total liabilities (B5, p< 0.0001) affected financial risk of SMEs. 10th profile includes SMEs with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, and interest expenses to net sales lower than and equal to 0. In this profile, 89.82 % (247 SMEs) of SMEs have good financial performance, and 10.18 % (28 SMEs) of SMEs have poor financial performance. 11th profile covers SMEs with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, interest expenses to net sales between 0 and 0.000005, and fixed assets to long term loans+ own funds lower than and equal to 0.74. In this profile, 97.12 % (202 SMEs) of SMEs have good financial performance, and 2.88 % (6 SMEs) of SMEs have poor financial performance. 12th profile contains SMEs with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, interest expenses to net sales between 0 and 0.000005, and fixed assets to long term loans+ own funds ratio between 0.74 and 0.95. In this profile, 76.92 % (20 SMEs) of SMEs have good financial performance, and 23.08 % (6 SMEs) of SMEs have poor financial performance. 13th profile comprises SMEs with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, interest expenses to net sales between 0 and 0.000005, and fixed assets to long term loans+ own funds ratio higher than 0.95. In this profile, 94.51 % (86 SMEs) of SMEs have good financial performance, and 5.49 % (5 SMEs) of SMEs have poor financial performance. 14th profile with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, and interest expenses to net sales between 0.000005 and 0.06 covers total 1,441 SMEs. In this profile, 88.41 % (1274 SMEs) of SMEs have good financial performance, and 11.59 % (167 SMEs) of SMEs have poor financial performance. 15th profile includes SMEs with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, interest expenses to net sales higher than 0.06, and long-term liabilities to total liabilities lower than and equal to 0.22. In this profile, 88.49 % (269 SMEs) have good financial performance and remaining 11.51 % (35 SMEs) have poor performance. 16th profile contains SMEs with return on equity ratio higher than 0, cumulative profitability ratio between 0.0000002 and 0.04, interest expenses to net sales higher than 0.06, and long-term liabilities to total liabilities higher than. In this profile, 70.31 % (90 SMEs) have good financial performance and remaining 29.69 % (38 SMEs) have poor financial performance.

In 17th to 21st profiles, profit before tax to own funds ratio (D1B, p<0.001), return on equity ratio (D1A, p<0.001), cumulative profitability ratio (D1F, p=0.001), long-term liabilities to total liabilities (B5, p< 0.0001), gross profit to net sales (D2B, p=0.0332), and bank loans to total assets (B13, p< 0.0012) affected financial risk of SMEs. 17th profile with return on equity ratio higher than 0, cumulative profitability ratio higher than 0.04, long-term liabilities to total liabilities lower than and equal to 0.14, and bank loans to total assets lower than and equal to 0.52 contains total 1,131 SMEs. In this profile, 94.16 % (1065 SMEs) of SMEs have good financial performance, and 5.84 % (66 SMEs) of SMEs have poor financial performance. 18th profile comprises SMEs with return on equity ratio higher than 0, cumulative profitability ratio higher than 0.04, long-term liabilities to total liabilities between 0.14 and 0.38, and bank loans to total assets lower than and equal to 0.52. In this profile, 88.26 % (218 SMEs) of SMEs have good financial performance, and 11.74 % (29 SMEs) of SMEs have poor financial performance. All of 35 SMEs in profile 19th have good financial performance. This profile covers SMEs with return on equity ratio higher than 0, cumulative profitability ratio higher than 0.04, long-term liabilities to total liabilities higher than 0.38, and bank loans to total assets lower than and equal to 0.52. 20th profile contains SMEs with return on equity ratio higher than 0, cumulative profitability ratio higher than 0.04, gross profit to net sales lower than and equal to 0.13, and bank loans to total assets higher than 0.52. In this profile, 93.94 % (31 SMEs) have good financial performance and remaining 6.06 % (38 SMEs) have poor financial performance. 21st profile contains SMEs with return on equity ratio higher than 0, cumulative profitability ratio higher than 0.04, gross profit to net sales higher than 0.13, and bank loans to total assets higher than 0.52. In this profile, 64.29 % (18 SMEs) have good financial performance and remaining 35.71 % (10 SMEs) have poor financial performance.

SMEs profit before tax to own funds ratio higher than 0.36 are grouped in 22nd to 31st profiles given in Figure 2. Beside this ratio, total loans to total assets (B1, p=0.0230), inventory dependency ratio (B6, p<0.0001), bank loans to total assets (B13, p< 0.0012), own funds turnover (C7, p=0.0432), short-term receivables to total assets total assets (A8, p=0.0121), operating expenses to net sales assets (D2E, p=0.0149), receivables turnover (C2, p<0.0001) affected financial risk of SMEs in these profiles.

In 22nd to 25th profiles, total loans to total assets ratio is lower than and equal to 0.75, and inventory dependency ratio is lower than and equal to 0.26. Beside these ratios, 22nd profile contains SMEs with bank loans to total assets ratio lower than and equal to 0.015. All of 15 SMEs have good financial performance in this profile. 23rd profile covers SMEs with bank loans to total assets ratio lower than and equal to

0.015, and receivables turnover higher lower and equal to 0.03. In this profile, 75 % (3 SMEs) have good financial performance and 25 % (1 SMEs) have poor financial performance. All of 101 SMEs have good financial performance in 24th profile. This profile contains SMEs with bank loans to total assets ratio lower than and equal to 0.015, and receivables turnover higher 0.03. 25th profile contains SMEs with bank loans to total assets ratio higher than 0.015. In this profile, 91.83 % (236 SMEs) have good financial performance and 8.17 % (21 SMEs) have poor financial performance.

In 26th to 28th profiles, total loans to total assets ratio is higher than 0.75 and inventory dependency ratio is lower than and equal to 0.26. Beside these ratios, 26th profile contains SMEs with own funds turnover lower than and equal to 0.03. All of 27 SMEs have good financial performance in 26th profile. 27th profile covers SMEs with own funds turnover higher than 0.03, and short-term receivables to total assets ratio lower than and equal to 0.02. In this profile, 33.33 % (3 SMEs) have good financial performance and 66.67 % (6 SMEs).Last profile in this group covers SMEs with short-term receivables to total assets ratio higher than 0.02. In 28th profile, 80.17 % (93 SMEs) have good financial performance and 19.83 % (23 SMEs) have poor financial performance.

Step IV. Identification of Risk Indicators and Early Warning Signs

As you can see in Figure 2 and Table III, SMEs are classified in 31 different profiles, according to indicators that affected their financial performance and financial situation. Results of the study revealed that there are 15 indicators (in total 41 ratios), which had effects on financial performance or in other words distress of the covered SMEs.

TABLE II
FINANCIAL INDICATORS AFFECTED FINANCIAL DISTRESS

Code	Financial Indicators	p
D1B	Profit Before Tax to Own Funds	<0.0001
D1A	Return on Equity	<0.0001
D1F	Cumulative Profitability Ratio	=0.0001
B12	Short-Term Liabilities to Total Loans	=0.0001
B1	Total Loans to Total Assets	=0.0230
D2F	Interest Expenses to Net Sales	=0.0011
B9	Fixed Assets to Long Term Loans+ Own Funds	=0.0027
B5	Long-Term Liabilities to Total Liabilities	<0.0001
D2B	Gross Profit to Net Sales	=0.0332
B13	Bank Loans to Total Assets	=0.0012
B6	Inventory Dependency Ratio	<0.0001
C7	Own Funds Turnover	=0.0432
A8	Short-Term Receivables to Total Assets Total Assets	=0.0121
D2E	Operating Expenses to Net Sales	=0.0149
C2	Receivables Turnover	<0.0001

As seen in Table II, these are profit before tax to own funds ratio (D1B, p<0.001), return on equity ratio (D1A, p<0.001), cumulative profitability ratio (D1F, p=0.001), short-term liabilities to total loans (B12, p=0.0001), total loans to total assets (B1, p=0.0230), interest expenses to net sales (D2F, p=0.0011), fixed assets to long term loans+ own funds (B9, p=0.0027), long-term liabilities to total liabilities (B5, p< 0.0001), gross profit to net sales (D2B, p=0.0332), bank loans to total assets (B13, p< 0.0012), inventory dependency ratio (B6, p<0.0001), own funds turnover (C7, p=0.0432), short-term receivables to total assets total assets (A8, p=0.0121), operating expenses to net sales assets (D2E, p=0.0149), receivables turnover (C2, p<0.0001).

We determined that 15 indicators affected financial risk and distress position of SMEs. When we consider risk profiles and risk indicators together, only 2 indicators can be identified as early warning signals. These are profit before tax to own funds and return on equity (ROE).

i. If profit before tax to own funds was lower than and equal to 0

ii. If ROE was lower than and equal to 0

iii. If profit before tax to own funds was between 0 and 0.20, and ROE was lower than and equal to 0

iv. If profit before tax to own funds was between 0.20 and 0.36, and ROE was lower than and equal to 0 financial distress were indispensable for SMEs.

TABLE III
RISK CLASSIFICATION

Risk Classes				Financial Performance					
Risk Level			Profiles	Good		Poor		Total	
%	n	%		N	%	N	%	n	%
100	1753	22,32	1	0	0	1718	100	1718	21,88
			2	0	0	27	100	27	0,34
			6	0	0	8	100	8	0,1
80	5	0,06	7	1	20	4	80	5	0,06
75	4	0,05	30	1	25	3	75	4	0,05
67	9	0,11	27	3	33,33	6	66,67	9	0,11
54	13	0,17	4	6	46,15	7	53,85	13	0,17
<36	5891	75,02	21	18	64,29	10	35,71	28	0,36
			29	66	67,35	32	32,65	98	1,25
			16	90	70,31	38	29,69	128	1,63
			23	3	75	1	25	4	0,05
			12	20	76,92	6	23,08	26	0,33
			8	285	77,45	83	22,55	368	4,69
			3	79	78,22	22	21,78	101	1,29
			28	93	80,17	23	19,83	116	1,48
			31	132	85,71	22	14,29	154	1,96
			18	218	88,26	29	11,74	247	3,15
			14	1274	88,41	167	11,59	1441	18,35
			15	269	88,49	35	11,51	304	3,87
			9	341	88,57	44	11,43	385	4,9
			10	247	89,82	28	10,18	275	3,5
			5	447	90,12	49	9,88	496	6,32
			25	236	91,83	21	8,17	257	3,27
			20	31	93,94	2	6,06	33	0,42
			17	1065	94,16	66	5,84	1131	14,4
			13	86	94,51	5	5,49	91	1,16
			11	202	97,12	6	2,88	208	2,65

=0	178	2,27	19	35	100	0	0	35	0,45
			22	15	100	0	0	15	0,19
			24	101	100	0	0	101	1,29
			26	27	100	0	0	27	0,34
	7,853	100,0	**Total**	**5,391**	**68,65**	**2,462**	**31,35**	**7,853**	**100**

Step V. Classification of SMEs by Risk Profiles and Early Warning Signs

It was determined that 5,391 SMEs (68.6 %) out of 7,853 covered SMEs had good financial performance while 2,462 of them had poor financial performance. Results showed that 31.4 % of the covered SMEs financially distress. These distress firm are in 27 different profiles except 19th, 22 nd , 24 th, and 26th profiles depend on different financial indicators. All of SMEs in profiles 1st, 2nd, and 6th have poor financial performance and these SMEs are exactly distressed firms. These profiles contain SMEs with highest financial risk. All of SMEs in profiles 19th, 22 nd , 24 th, and 26th have good financial performance and these SMEs are exactly non distressed firms.

IV. Conclusion

Financial early warning system is a technique of analysis that is used to predict the achievement condition of enterprises and to decrease the risk of financial distress. By the application of this technique of analysis, the condition and possible risks of an enterprise can be identified with quantity. Risk management has become a vital topic for all institutions, especially for SMEs, banks, credit rating firms, and insurance companies. The financial crisis has pushed all firms to active risk management and control financial risks. All enterprises need EWS to warn against risks and prevent from financial distress. But, when we consider the issues of poor business performance, insufficient information and insufficiencies of managers in finance education, it is clear that EWS is vital for SMEs. Benefits of an EWS can summarize as early warning before financial distress, road maps for good credit rating, better business decision making, and greater likelihood of achieving business plan and objectives.

Developing practical solutions will not only help to SMEs but also to the economies of countries. Having information about their financial risk, monitoring this financial risk and knowing the required roadmap for the improvement of financial risk are very important for SMEs to take the required precautions. Data mining, that is the reflection of information technologies in the area of strategically decision support, develops a system for finding solutions to the financial administration as one of the most suitable application area for SMEs as the vital point of economy.

In this study, we developed a financial EWS based on financial risk by using data mining. As results of the study we classified 7,853 SMEs in 31 different risk profiles via CHAID. Results showed that 31.4 % of the covered SMEs financially distress. All of SMEs in profiles 1st, 2nd, and 6th have poor financial performance and these SMEs are exactly distressed firms. These profiles contain SMEs with highest financial risk. All of SMEs in profiles 19th, 22 nd, 24 th, and 26th have good financial performance and these SMEs are exactly non distressed firms.

According to these profiles, we identified that profit before tax to own funds ratio, return on equity ratio, cumulative profitability ratio, short-term liabilities to total loans, total loans to total assets, interest expenses to net sales, fixed assets to long term loans+ own funds, long term liabilities to total liabilities, gross profit to net sales, bank loans to total assets, inventory dependency ratio, own funds turnover, short-term receivables to total assets total assets, operating expenses to net sales assets, receivables turnover affect financial performance or in other words distress of the covered SMEs. When we consider risk profiles and these 15 risk indicators together, only 2 indicators can be identified as early warning signals. Financial early warning signs for covered SMEs are profit before tax to own funds and return on equity (ROE). If profits before tax to own funds and ROE ratios are lower than and equal to 0, financial distress is indispensable for SMEs.

Beside these findings we determine financial road maps for risk mitigation and improve financial performance. Financial road maps can use for decision making process as inputs. According to our study findings, we developed 4 financial road maps. All of 4 road maps provide risk indicators and their values for successful management and risk hedging.

EWSs should develop and implement in every business, to provide information relating to the actions of individual officers, supervisors, and specific units or divisions. In deciding what information to include in their early warning system, business should balance the need for sufficient information for the system to be comprehensive with the need for a system that is not too cumbersome to be utilized effectively. The system should provide supervisors and managers with both statistical information and descriptive information about the function of business.

In case of using our EWS model by SMEs, some of expected contributions can be summarized as:

- Determine financial performance and position of firms,
- Determine financial strategies by minimum level of finance education and information
- Financial and operational risk detection
- Roadmaps for risk mitigation
- Prevent for financial distress
- Decrease the possibility of bankruptcy
- Decrease risk rate
- Efficient usage of financial resources
- By efficiency in resources;
- Increase the competition capacity
- New potential for export,
- Decrease the unemployment rate
- More taxes for government
- Adaptation to BASEL II Capital Accord

Developing a financial EWS based on financial risk is not enough for to understand and manage the financial risks that can cause insolvency and distress. Managers need also to manage operational risks that can arise from execution of a company's business functions, and strategically risks that can undermine the viability of their business models and strategies or reduce their growth prospects and damage their market value. For this reason we suggest to develop EWS that contain all kind of risk factors.

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Ozgulbas Nermin is associate professor of finance at Baskent University in Turkey. She taught financial management, financial analysis and cost accounting in Baskent University, distance education program of Anadolu University and Turkish Ministry of Health. Her research and publication activities include finance, cost accounting, risk management, early warning systems, and data mining in especially SMEs, capital markets, health care organizations, and social security. She has been participating in a lot of international and national projects and conferences as an organizer, reviewer and advisor. Her latest researches are about early warning systems based on data mining.

Koyuncugil Ali Serhan is working as a statistician for Capital Markets Board of Turkey. He had his B.Sc., M.Sc. and Ph.D. degrees in statistics from Ankara University Department of Statistics. His current research interests are design and development of fraud detection, risk management, early warning, surveillance, information, decision-support and classification systems, design and development of datawarehouses and statistical databases, development of indicators, models and algorithms, conducting analysis on capital markets, finance, health, SMEs, large scale statistical researches (e.g. census), population and development, socio-economic and demographic affairs based on data mining, statistics, quantitative decision making, operational research, optimization, mathematical programming, fuzzy set, technical demography theory and applications. He is elected member (fellow) of the International Statistical Institute (ISI) and member of the IASC and IASS sections of ISI, Turkish Statistical Association, Turkish Informatics Society and was former vice head of Turkish Statisticians Association. He has been taking part in a lot of international and national projects (UN, IBRD, EU, etc.). He has been taking part in a lot of international and national journals, conferences as an editorial board member, organizer, reviewer and advisor. His latest researches are about early warning systems based on data mining.