Incorporating Financial Ratios and Intellectual Capital in Bankruptcy Predictions

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Abstract

Intellectual capital represents assets that frequently do not appear in the balance sheet. Intellectual capital has gained more and more attention since it is the core competence for many companies nowadays. The main purpose of this paper is to explore the performance of bankruptcy predictions incorporating financial ratios and intellectual capital by integrating artificial neural networks with the multivariate adaptive regression spines (MARS) approach. The obtained results are expected to greatly expand the application of intellectual capital, neural networks and MARS in bankruptcy predictions. And in terms of the successful identification of the relationship within data, better business modeling and investment decisions can be found and implemented.

Keywords: bankruptcy prediction, financial ratios, intellectual capital, neural networks, multivariate adaptive regression splines

1. Introduction

Bankruptcy predictions have long become important research topics after Beaver (1966) and Altman (1968) used the financial ratios methodology in predicting bankruptcies. As the world's economy has been experiencing severe challenges during the past decade, more and more companies, no matter large or small, are facing the problems of filing bankruptcy. Hence bankruptcy predictions have drawn serious attention from both researchers and practitioners aiming to provide on time signals for better investment and government decisions. Many different useful techniques, known as the bankruptcy prediction models, have been developed by researchers in order to solve the problems involved during the evaluation process. Basically the bankruptcy prediction models use appropriate independent variables to "predict" a company is a healthy company or a bankrupt one. Therefore the bankruptcy prediction problems are in the scope of the more general and widely discussed discrimination and classification problems (Johnson and Wichern, 2002).

After we carefully review the literature of bankruptcy prediction models, several important conclusions can be observed. Firstly, after Beaver (1966) and Altman (1968) used the financial ratios methodology in conducting bankruptcy predictions, almost all the literature only considered financial ratios as independent (input) variables. As intangible assets are often the major determinants of a company's competitiveness, factors other than financial ratios may also need to be incorporated in bankruptcy predictions. The high market to book ratios, often termed as P/B ratios, which have increased drastically for companies like, Microsoft, Intel, Cisco, and Oracle during the past decade, often justifies the existence and importance of intellectual capital (IC, Stewart, 1997). Intellectual capital has drawn serious attention from companies that derive their profits from non-traditional or intangible assets such as customer relations, skills of their employees, innovations and knowledge-incentive services. As the 21st century is the century of knowledge economics, IC is definitely going to play an even more important role for companies achieving continuous growth and maintaining competitiveness. We therefore, in this research, try to consider both financial ratios as well as intellectual capital variables in bankruptcy predictions to test whether IC will be decisive factors affecting the predictive capability.

Secondly, almost all the literature adopted the same cross sectional research design during the empirical study stage. It means that they use independent variables one, two or even three years prior to the bankruptcy, a fixed point before the bankruptcy happens, in predicting the status-healthy or bankruptcy of a company. However, bankruptcy is a continuous process. Even though the appraisal of bankruptcy happens at a certain time, it is the result of some policies of that company for a number of years. Therefore, the independent variables used in bankruptcy predictions should be observed over time to provide full information about the progress of a company (Dimitras *et al.*, 1996). Besides, as the influence of different variables in different time lags to the status of a company may not be the same, the traditional cross sectional analysis approach suffers from the fact that some important variables, in different time lags, may not be included in the final prediction model during the variable selection procedure. In order to solve the above-mentioned drawbacks, this paper tries to handle this issue in a totally different alternative. All the independent variables used in the prediction model will consist 8 consecutive quarterly data points before the bankruptcy occurred. In doing so, we can observe the influence of the progress of a variable to the status of a company. Besides, variables in different time lags could also be selected at the same time in the final prediction model as long as it is important in predicting the status of a company.

Finally, the most commonly discussed classification techniques in building bankruptcy prediction models are linear discriminant analysis (LDA), logistic regression analysis, and artificial neural networks (ANNs). However, the utilization of linear discriminant analysis has often been criticized because of its assumptions of the linear relationship between dependent and independent variables, which seldom holds, and the fact that it is sensitive to deviations from multivariate normality assumptions (Karels and Prakash, 1987, Reichert, *et al.*, 1983). Theoretically, quadratic discriminant analysis (QDA) should be adopted when the covariance matrices of the underlying populations are not equal. However, QDA seems to be more sensitive to the model assumptions than LDA and LDA has reported to be a more robust method (Dillon and Goldstein, 1984, Sanchez and Sarabia, 1995, Sharma, 1996). Therefore QDA is seldom applied to bankruptcy predictios (Laitinen and Laitinen, 2000).

Logistic regression analysis is another commonly adopted alternative in building bankruptcy prediction models. Logistic regression was emerged as the technique of choice in predicting dichotomous outcomes. Logistic regression does not require the multivariate normality assumption, however, exposed to a full linear compensation between independent variables in the exponent of the logistic function. Basically, both LDA and logistic regression are designed for the case when the relationship among variables are linear and therefore are reported to be lack of enough classification accuracy in modeling bankruptcy prediction problems.

Artificial neural networks provide a new alternative to LDA and logistic regression, particularly in situations where the dependent and independent variables exhibit complex nonlinear relationships. Even though neural networks have shown to have better predictive capability than LDA and logistic regression in modeling bankruptcy prediction problems (Coleman *et al.*, 1991, Rahimian *et al.*, 1993, Salchengerger *et al.*, 1992, Sharda and Wilson, 1996, Tam and Kiang, 1992, Wilson and Shrada, 1994, Zhang *et al.*, 1999). It is, however, also being criticized for its long training process in designing the optimal network's topology, hard to identify the relative importance of potential input variables and certain interpretative difficulties, and limiting its applicability in handling the general classification and bankruptcy prediction problems (Laitinen and Laitinen, 2000, Lee and Chen, 2002, Lee *et al.*, 2002, Trigueiros and Taffler, 1996).

In addition to the above-mentioned techniques, multivariate adaptive regression splines (MARS) is another commonly discussed classification technique nowadays. MARS is widely accepted by researchers and practitioners for the following facts. Firstly, MARS is capable of modeling complex nonlinear relationship among variables without strong model assumptions. Besides, MARS can identify "important" independent variables through the built basis functions (more details will be discussed in section 4) when there are many potential independent variables. Thirdly, the training time for MARS is significantly shorter than neural networks and hence can save lots of model building time when the data set is huge. Finally, one strong advantage of MARS over other classification techniques is the resulting model can be easily interpreted. It not only points out which variables are important in classifying objects/observations, but also indicates a particular object/observation belongs to a specific class when the built rules are satisfied. The final fact has important managerial and interpretative implications and can help make better/appropriate decisions.

Aiming at improving the above-mentioned drawbacks of neural networks and increasing the classification accuracy of the existing approaches, the objective of the proposed study is to explore the performance of bankruptcy predictions using both financial ratios and intellectual capital variables with a two-stage hybrid modeling procedure in using multivariate adaptive regression splines with neural networks technique. The rationale underlying the analyses is firstly to use MARS in modeling the bankruptcy prediction problems with both financial ratios and intellectual capital variables as independent variables. Then the obtained significant independent variables are served as the input nodes of the designed neural networks model. Please note that it is valuable to use MARS as a supporting tool for neural networks, as there still does not exist a theoretical method in determining the best input variables of a neural network model, MARS can be implemented as a generally accepted method for identifying important variables when many potential variables are considered.

To demonstrate the feasibility and effectiveness that the inclusion of the obtained significant independent variables from MARS would improve the classification accuracy of the neural networks model, bankruptcy prediction tasks are performed using the public companies filing bankruptcy between 1998 and 2000 in Taiwan. As to the structure of the designed neural networks model, sensitivity analysis is employed to solve the issue of finding the appropriate setup of the network's topology. Analytic results demonstrated that, in comparison with the traditional neural networks approach, the classification accuracy increases in terms of the proposed hybrid methodology. Moreover, the superior classification capability of the proposed technique can be observed by comparing the classification results with those using linear discrimintant analysis, logistic regression and MARS approaches.

The rest of the paper is organized as follows. We will give a brief review of intellectual capital in section 2. The literature of bankruptcy predictions will be outlined in section 3. Section 4 gives a brief overview of multivariate adaptive regression splines. The developments as well as the analytic results of bankruptcy prediction models using discriminant analysis, logistic regression, MARS, neural networks, and the hybrid models are presented in section 5. Finally section 6 addresses the conclusion and discusses the possible future research areas.

2. Intellectual Capital

2.1 Introduction to Intellectual Capital

Intellectual capital (IC) was first proposed by John Kenneth Galbraith trying to bridge the gap between a company's book value and its market value. With the tremendous growth of service industry in major industrialized countries, more and more researchers and practitioners have recommended that non-traditional or intangible assets of business operations such as customer relations, skills of their employees, innovations and leaderships tend to be the major determinants of a company's competitiveness and the resulting profits. Therefore more attention should be paid to justify and measure their impact on the core competence of a company (Kaplan and Norton, 1996, Edvinsson and Malone, 1997).

The management of intellectual capital has a history dated back to the early 1980s as researchers and practitioners were aware that a company's intangible assets, its intellectual capital, were often the major determinants of it's profit and continuing growth. In 1991 and 1994, Tom Stewart wrote two articles at Fortune magazine on brainpower discussing the idea of intellectual capital. In these two articles, Stewart pointed out that the employees of a company had a lot to do with its profitability and success. Also in 1991, Skandia AFS inaugurated its first intellectual capital office with Leif Edvinsson appointed as the first vice president of that office. Dow Chemical, interested in profiting from its intellectual capital, named Gordon Petrash as its first director of intellectual assets in 1993. The purpose of doing so was trying to identify innovations and ideas that might have been overlooked in the past and developing them into profits (Harrison and Sullivan, 2000).

Edvinsson conducted pioneering researches regarding the development of diversified measures of the performance of a company (Edvinsson and Malone, 1997). Edvinsson defined intellectual capital to be knowledge that can be converted into value. The intellectual capital system derived by Edvinsson, used five dimensions to measure a company's performance: Financial, what appears on the regular balance sheet; Human, the skills and performance of the employees; Customer, goodwill, relationships, and the brand name; Process, measures the efficiency of the internal functions; and Innovation, measures the growth and long-term research and developments. Edvinsson tried to use different variables in the above-mentioned five dimensions in measuring the values of intangible assets. He believed that the obtained information should be useful guidelines in implementing strategies such as allocation of expenditure to different areas, new investments and on-the-job training, to maintain or strengthen the competitiveness of a company.

2.2 The Structure and Classification of Intellectual Capital

As to the measurements and scopes of intellectual capital, Brooking (1996), Edvinsson and Malone (1997), Kaplan and Norton (1996), Stewart (1997), Roos *et al.* (1998), and Sveiby (1997) all proposed their concepts. Almost all the above literature focused on the construction of a general categorization of its elements. Brooking (1996) believe that the main elements of IC are market assets, human centered assets, intellectual property assets, and infrastructure assets; Sveiby (1997) instead proposed that internal structure, external structure, and employee competence are the core elements of IC; Stewart (1997) identified human capital, structural capital, and customer capital; while Edvinsson and Malone (1997) divided IC into human capital and structural capital, which can further be categorized as organizational capital and customer capital. The above structure/scheme can be summarized in table 1. As to the detailed contents of the above-mentioned assets and/or capital, please refer to Brooking (1996), Edvinsson and Malone (1997), Kaplan and Norton (1996), Stewart (1997), Roos *et al.* (1998), and Sveiby (1997) for more details.

Even though there are various schemes about the structure and classifications of IC, some conclusions can be observed after careful inspections. Some assets are related to employees, like human centered assets, employee competence, and human capital, are very difficult to manage since these assets cannot be kept or preserved. Other assets, like the infrastructure assets, internal structure, structural capital, and organizational capital can be better managed, relates to the process and procedure of a company. Finally, the third category of assets include market assets, customer capital, and external structure, are basically relied on the relationship with customers.

Table 1. Different systems of intellectual capital

	Contents of intellectual capital
Brooking (1996)	market assets, human centered assets, intellectual property assets, infrastructure assets
Sveiby (1997)	internal structure, external structure, employee competence
Stewart (1997)	human capital, structural capital, customer capital
Edvinsson and Malone (1997)	human capital, customer capital, process capital, innovation capital

3. Literature Review

Bankruptcies are destroying and devastating. Hence it is important to give on time signals to investors, creditors, and auditors to lessen the resulting impact. Beaver (1966, 1968) conducted pioneering research regarding bankruptcy predictions. He analyzed several financial ratios to evaluate their predictive capability by developing cut-off scores for each ratio to classify companies as bankrupt or non-bankrupt ones. Beaver's study was further discussed by Altman (1968) and Ohlson (1980) using discriminant analysis and logistic regression approaches. In this section we will review the work of Altman (1968) and Ohlson (1980) as well as other articles using discriminant analysis and logistic regression. The literature regarding neural networks will also being discussed in this section.

3.1 Altman's Model

Altman (1968) introduced the well-known Z-score model using the discriminant analysis approach. In this study, Altman (1968) used five financial ratios in identifying the discriminant function which best classifies the companies into bankrupt and non-bankrupt companies. The obtained Z-score is then used to determine the cut-off point in getting the highest classification accuracy. Altman's Z-score model has good classification result using variables one year prior to the bankruptcy. However, the model's predictive capability decreases drastically with variables two and three years before bankruptcy. The matched sample design proposed by Altman (1968) has been adopted thereafter in almost all the bankruptcy prediction models.

Moyer (1977) pointed out that Altman' (1968) model had poor classification capability and instead proposed a stepwise discriminant analysis (Johnson and Wichern, 2002) procedure in constructing a better model. Several other studies by Zmijewski (1984), Holmen (1988), and Begley *et al.* (1996) have also been conducted to test the applicability of Z-score models. Besides, the same matched research design using the same five financial ratios and/or other financial ratios with discriminant analysis have also been investigated by Blum (1974), Deakin (1972), Altman *et al.* (1974, 1977), Edmister (1972), Elam (1975), Johnson (1970), Jones (1987), Laitinen (1991, 1992), Norton and Smith (1979), Taffler (1982), and Wilcox (1973).

3.2 Ohlson's Model

Ohlson (1980) adopted logistic regression analysis in building the bankruptcy prediction models. Ohlson (1980) used 105 bankrupted and 2058 matched non-bankrupt industrial firms between 1970 and 1976 in building the prediction models. Ohlson used the cumulative logistic function in transforming the value of dependent variable to the bankruptcy probability. Then the obtained probability was compared with 0.5 to determine the company will be classified as the healthy company or the bankrupt one. Ohlson's model, in general, has very good predictive capability. The correct classification rate is above 95% with independent variables one and two years prior to bankruptcy.

Logistic analysis was also explored by other researchers to obtain better classification accuracy. Zavgren (1985) developed a logistic function using measures of entropy to evaluate the uncertainty of failure. Keasey and McGuinness (1990) criticized Zavgren's result (1985) since it cannot be applied to the case in UK. Based on the research findings in Keasey and McGuinness (1990), Keasey *et al.* (1990) instead proposed a mulitlogit model in classifying the bankrupted firms. Logistic regression has become a popular alternative in bankruptcy predictions after 1980. Gilbert *et al.* (1990), Laitinen (1999), Laitinen and Laitinen (2000), Lau (1987), Luoma and Laitinen (1991), Platt and Platt (1990), and Tennyson *et al.* (1990) all used logistic regression in building prediction models.

3.3 Artificial Neural Networks Prediction Models

Even though linear discriminant analysis and logistic regression are most widely adopted statistical approaches in building bankruptcy prediction models. However, the validity and effectiveness of these statistical methods depend on some restrictive assumptions such as linearity, normality, independence between independent and dependent variables and hence limited their applications in modeling bankruptcy prediction problems. Artificial neural networks (ANNs) are powerful tools for pattern recognition and pattern classification problems and have already been successfully applied to many financial related problems including bankruptcy predictions. ANNs were widely adopted in modeling the bankruptcy prediction problems after the 1990s with the need in improving the prediction accuracies.

Odom and Sharda (1990) first proposed using neural networks to build the bankruptcy prediction models. In their study, three-layer feedforward networks are adopted and the modeling results were compared with those using linear discriminant analysis. With different combinations of training sample sizes to testing sample sizes, the predictive capability of ANNS and linear discriminant analysis were tested and compared. The research findings concluded that neural networks provide more accurate and robust results. Rahimian *et al.* (1993) and Coleman *et al.* (1991) both used the same data of Odom and Sharda (1990) and provide better prediction results in their studies.

Tam and Kiang (1992) had a great impact on using ANNs in the general classification problems and bankruptcy predictions. They provided detailed analysis of the potentials and limitations of using ANNs in modeling the business classification problems. They also tried to compare the predictive capability of neural networks with linear discriminant analysis, logistic regression, k-nearest neighbor, and decision trees. Their results indicated that neural networks provide more accurate and robust results.

Neural networks have also been explored by Altman *et al.* (1994), Coats and Fant (1993), Fanning and Cogger (1994), Fletcher and Goss (1993), Lacher *et al.* (1995), Lenard *et al.* (1995), Lennox (1999), Leshno and Spector (1996), Piramuthu *et al.,* (1994), Raghupathi (1996), Rahimian *et al.* (1993), Salchengerger *et al.* (1992), Sharda and Wilson (1996), Udo (1993), Wilson and Shrada (1994) and Zhang *et al.* (1999) in handling bankruptcy prediction problems. The majority of the above references have concluded that the prediction accuracies of neural networks are higher than those using discriminant analysis and logistic regression techniques.

4. Multivariate Adaptive Regression Splines

Multivariate adaptive regression splines (MARS), a non-linear and non-parametric regression approach, is first proposed by Friedman (1991) as a flexible procedure in modeling relationships that are nearly additive or involve interactions with fewer variables. The modeling procedure is inspired by the recursive partitioning technique governing classification and regression tree (CART, Breiman *et al.*, 1984) and generalized additive modeling (Hastie and Tibshirani, 1990), resulting in a model that is continuous with continuous derivatives. It excels at finding optimal variable transformations and interactions, the complex data structure that often hides in high-dimensional data. And hence can effectively uncover important data patterns and relationships that are difficult, if not impossible, for other methods to reveal.

MARS essentially builds flexible models by fitting piecewise linear regressions; that is, the nonlinearity of a model is approximated through the use of separate linear regression slopes in distinct intervals of the predictor variable space. Therefore the slope of the regression line is allowed to change from one interval to the other as the two “knot” points are crossed. The variables to be used and the end points of the intervals for each variable are found via a fast but intensive search procedure. In addition to searching variables one by one, MARS also searches for interactions between variables, allowing any degree of interaction to be considered during the modeling procedure.

The general MARS function can be represented using the following equation (Friedman, 1991):

$$\hat{f}(x) = a_0 + \sum_{m=1}^{M} a_m \prod_{k=1}^{K_m} [s_{km} \cdot (x_{v(k,m)} - t_{km})]_+$$

where a_0 and a_m are parameters, M is the number of basis functions, Km is the number of knots, s_{km} takes on values of either 1 or -1 and indicates the right and left sense of the associated step function, v(k, m) is the label of the independent variable, and t_{km} indicates the knot location.

The optimal MARS model is selected in a two-stage process. Firstly, MARS constructs a very large number of basis functions are selected to overfit the data initially, where variables are allowed to enter as continuous, categorical, or ordinal- the formal mechanism by which variable intervals are defined, and they can interact with each other or be restricted to enter in only as additive components. In the second stage, basis functions are deleted in order of least contribution using the generalized cross-validation (GCV) criterion (Craven and Wahba, 1979). A measure of variable importance can be assessed by observing the decrease in the calculated GCV values when a variable is removed from the model. The GCV can be expressed as follows:

$$LOF(\hat{f}_M) = GCV(M) = \frac{1}{N}\sum_{i=1}^{N}[y_i - \hat{f}_M(x_i)]^2 \Big/ \left[1 - \frac{C(M)}{N}\right]^2$$

where there are N observations, and C(M) is the cost-penalty measures of a model containing M basis function (therefore the numerator measures the lack of fit on the M basis function model $f_M(x_i)$ and the denominator denotes the penalty for model complexity C(M)).

Missing values can also be handled in MARS by using dummy variables indicating the presence of the missing values. By allowing for any arbitrary shape for the function as well as interactions, and by using the above-mentioned two-stage model building procedure, MARS is capable of reliably tracking the very complex data structures that often hide in high-dimensional data. Please refer to Friedman (1991) for more details regarding the complete model building process.

The interpretation of the resulting MARS model is achieved through individual plots of risk. For variables that enter into the model additively, a risk line plot showing each variable’s individual contribution to the risk may be constructed. This is simply a plot of the risk (or log odds) represented by each basis function in the model that involves the variable of interest, for the range of values that the variable takes on in the data. Interactions can also be visualized as risk images showing the combined contribution of the variable’s risk in the model. Points are only plotted for the data that are available. High and low level of risks is indicated by dark and light gray areas on the plot respectively. These types of plots are not only restricted to interactions but can also be used to visualize the contributions of variables that enter into the model additivity and are highly correlated with one another.

MARS has been widely used in handling problems in the areas of forecasting and classifications (De Gooijer *et al.*, 1998, Friedman and Roosen, 1995, Griffin *et al.*, 1997, Kuhnert *et al.*, 2000, Lewis and Stevens, 1991, Nguyen-Cong *et al.*, 1996, Ohmann *et al.*, 1996). For other detailed list of the referred articles using MARS, the readers can login in to website http://www.salford-systems.com/MARSCITE.PDF provided by Salford Systems for more details.

5. Empirical Study

In order to verify the feasibility and effectiveness of the proposed two-stage hybrid modeling procedure, the public companies filing bankruptcy between 1998 and 2000 in Taiwan are used in this study. There are totally 35 companies, in 13 different industries, filing bankruptcy during the studying period. As there should be more healthy public companies than the bankrupt ones (apparently the prior probability of two types of companies should not be equal), 70 companies in the same industry which have been in business for at least two years, with similar total assets and number of employees are used as the matched sample. The numbers of bankrupt and matched healthy companies by industry are listed in table 2. Among the 105 companies used in this study, 23 bankrupted and 46 healthy companies (two thirds of the total sample size) are randomly selected as the training sample while the remaining 12 bankrupted and 24 healthy companies (one third of the sample size) are retained as the testing sample.

As to the independent variables to be included in the prediction model, it is a real challenge for the authors. Several factors have contributed to the difficulty in collecting the required variables. Firstly, like we have described before, all the independent variables used in the prediction model will consist 8 consecutive quarterly data points before the bankruptcy occurred for all the bankrupt and matched healthy companies. As not every company failed at the same time, it is therefore quite time-consuming in collecting all the quarterly data points. Secondly, unlike financial ratios, not all the intellectual capital variables can be found in the published financial statements. And since it is not required by government laws to provide all the information regarding intellectual capital, hence make it even more difficult to collect the IC variables. The graduate students/assistants involved in this project have to get related IC information through intensive personal and/or telephone interviews. Even by all these efforts, we still encounter serious difficulty in procuring all the required IC variables. Lots of companies do not update all the IC information from time to time. Besides, some of then are even reluctant to provide help using privacy and/or other excuses. Therefore the authors experienced serious problems of missing values in lots of variables. After deleting variables with too many missing values, the experiences from past decisions, and the knowledge of financial experts in that industry, 10 financial ratios and 9 IC variables can be obtained and summarized in table 3 (each variable will consist 8 quarterly data points before the bankruptcy occurred).

Table 2. Number of bankrupt companies and matched samples in different industry

Industry	Number of bankrupt companies	Number of healthy companies
Food	8	16
Steel and Metal	5	10
Construction Firms	5	10
Information Technology	4	8
Textiles	3	6
Mechanics	2	4
Cable and Wire	1	2
Ceramics	1	2
Rubbers	1	2
Auto dealer	1	2
Plastics	1	2
Recreation	1	2
Various	2	4
Total	35	70

Even though only 10 financial ratios have been collected for this study, the authors believe that they have covered the majority of the important variables adopted in most literature. The 10 financial ratios can be grouped into 3 categories as profitability, financial leverage, and turnover ratios. According to Dimitras *et al.* (1996), the most commonly used ratios in bankruptcy prediction are working capital/total assets, total debt/total assets, and current assets/current liabilities. Besides, quick assets/current liabilities is also among the top 10 commonly adopted ratios. All the other ratios have also been used in other studies (Altman, 1968, Altman, *et al.*, 1977, Beaver, 1966, Blum, 1974, Deakin, 1972, Dimitras *et al.*, 1996). We therefore believe that the obtained financial ratios should provide necessary information in predicting the status of a company.

For the intellectual capital variables, as there is no literature has been done regarding their applicability in bankruptcy predictions and it is very difficult to collect them as we have mentioned. We mainly refer to Edvinsson and Malone (1997), Sveiby (1997) and Stewart (1997), several experts' opinion and consider the data availability in obtaining the 9 intellectual capital variables as listed in table 3. The IC variables can also be classified as 3 categories, namely, human capital, customer capital, and the structure capital.

The main purpose of this article is to test whether intellectual capital will be helpful in bankruptcy predictions, and hence our approach is based on the rationale that with financial ratios already been included as independent variables, to test whether the inclusion of IC variables will provide extra information in improving the classification accuracy of the prediction model. As we also like to see whether MARS can be a good supporting tool in deciding the input variables of the neural networks prediction model, therefore the empirical study will firstly build two MARS prediction models. The first built model solely using financial ratios while the second one considers both financial ratios and intellectual capital variables as independent variables. In doing so, we can observe the prediction results of two MARS models as well as the obtained significant independent variables. The second stage of the study will use the obtained significant independent variables from MARS prediction models as inputs of two neural networks models. The obtained results can then be compared to see whether the one including IC variables will give better classification accuracy or not. Finally, in order to evaluate the effectiveness of the proposed two-stage prediction model, the results will also be compared with those using discriminant analysis, logistic regression, and solely using neural networks.

Table 3. List of financial ratios and intellectual capital variables

Variables	Category	Ratios and/or quantities
Financial Ratios	Profitability	Net income/Sales ($X_{1,t-1}$-$X_{1,t-8}$)
		Profit before taxes/Sales ($X_{2,t-1}$-$X_{2,t-8}$)
	Financial leverage	Current assets/Current liabilities ($X_{3,t-1}$-$X_{3,t-8}$)
		Total debt/Total assets ($X_{4,t-1}$-$X_{4,t-8}$)
		Earnings before interests and taxes/Total interest payments ($X_{5,t-1}$-$X_{5,t-8}$)
		Quick assets/Current liabilities ($X_{6,t-1}$-$X_{6,t-8}$)
		Working capital/Total assets ($X_{7,t-1}$-$X_{7,t-8}$)
		Networth+Long term debt/Fixed assets ($X_{8,t-1}$-$X_{8,t-8}$)
	Turnover ratios	Inventory turnover ratio ($X_{9,t-1}$-$X_{9,t-8}$)
		Accounts receivable turnover ratio ($X_{10,t-1}$-$X_{10,t-8}$)
IC Variables	Human capital	Number of employees with graduate degree/Number of employees ($IC_{1,t-1}$-$IC_{1,t-8}$)
		Average seniority of employee ($IC_{2,t-1}$-$IC_{2,t-8}$)
		Average age of employee ($IC_{3,t-1}$-$IC_{3,t-8}$)
	Customer capital	Accounts receivable of related party/ Sales to related party ($IC_{4,t-1}$-$IC_{4,t-8}$)
	Structure capital	R&D expenses/Total expenses ($IC_{5,t-1}$-$IC_{5,t-8}$)
		Auditor switching times ($IC_{6,t-1}$-$IC_{6,t-8}$)
		Financial forecasts adjusting times ($IC_{7,t-1}$-$IC_{7,t-8}$)
		Salary expenses/Sales ($IC_{8,t-1}$-$IC_{8,t-8}$)
		Fixed assets/number of employees ($IC_{9,t-1}$-$IC_{9,t-8}$)

The neural network simulator Qnet 97 (1998), developed by Vesta Services Inc, was utilized to develop the neural networks as well as the two-stage hybrid prediction models. It is a C based simulator that provides a system for developing backpropagation neural network configurations using the generalized delta learning algorithm. The discriminant analysis and logistic regression models will be implemented using the popular SPSS 1997 (1998) software. And MARS 2.0 (2001) provided by Salford Systems is used in building the MARS prediction models. All the modeling tasks are implemented on an IBM PC with Intel Pentium III 750 MHz CPU processor. The detailed prediction results can be summarized as follows.

1. MARS Prediction Models

In this section we will build two MARS prediction models. The first model only uses financial ratios as independent variables while the second one includes both financial ratios and intellectual capital variables. Table 4 summarizes the obtained significant independent variables and their relative importance for both models. From the results revealed in table 4, several important conclusions can be observed. Firstly, it is not surprisingly to figure out that total debt/total assets is the most important independent variable in both models. A company with a high ratio of total debt to total assets suffers from the risk of not being able to pay the debt on time and increases the chance of filing bankruptcy. Besides, quick ratio (quick assets/current liabilities) is the second most important variable in both models. A company with a low quick ratio may not have enough quick assets in paying short-term debt, related expenses and/or emergency cash requirements and also increases the possibility of filing bankruptcy.

Secondly, three intellectual capital variables, R&D expenses/total expenses, auditor switching times, and financial forecasts adjusting times, are significant in the model incorporating IC variables. These findings are also consistent with our conjecture in the beginning-IC variables should provide extra information in bankruptcy predictions. A company with low R&D expenses may not be able to provide innovative products/services and hence unable to keep itself competitive. Besides, a company keeps changing their auditors implying that they may have financial problems and the auditors do not wish to endorse their financial statements. Finally, a company keeps lowering their sales forecasts may also indicate that they encounter problems in selling their products/services. All the above three IC variables should be important indicators for predicting bankruptcies after the above justifications.

Thirdly, as we have mentioned before, the influence of different variables in different time lags to the status of a company may not be the same. It can be observed that the above arguments are reasonable and justified in this study. From table 4 we can see that almost all the time lags of the important variables are not the same. We have also pointed out that variables in different time lags may also be significant in the prediction models. For example, the quick ratios 6, 8, and 4 quarters before the bankruptcy are all significant in the model only considering financial ratios. Similar phenomenon can also be observed when considering both financial ratios and IC variables. These two points can give us strong supports that the cross sectional research design for all the literature may need to be modified in order to obtain more insights about the influence of independent variables.

Table 4、Obtained significant independent variables and their relative importance

MARS prediction model results			
Model 1：Financial ratios		**Model 2：Financial ratios＋IC variables**	
Variable name	Importance	Variable name	Importance
Total debt/Total assets (t-1)	100.00 %	Total debt/Total assets (t-1)	100.00 %
Quick assets/Current liabilities (t-6)	66.08 %	Quick assets/Current liabilities (t-8)	68.36 %
Quick assets/Current liabilities (t-8)	27.06 %	Quick assets/Current liabilities (t-6)	49.52 %
Quick assets/Current liabilities (t-4)	23.42 %	***R&D expenses/Total expenses (t-4)***	45.36 %
Networth+Long term debt/Fixed assets (t-8)	8.10 %	***Auditor switching times (t-8)***	38.66 %
		Financial forecasts adjusting times (t-4)	33.35%
		Networth+Long term debt/Fixed assets (t-3)	23.57 %
		Profit before taxes/Sales (t-1)	8.31 %

Thirdly, as we have mentioned before, the influence of different variables in different time lags to the status of a company may not be the same. It can be observed that the above argument is reasonable and justified in this study. From table 4 we can see that almost all the time lags of the important variables are not the same. We have also pointed out that variables in different time lags may all be significant in the prediction models. For example, the quick ratios 6, 8, and 4 quarters before the bankruptcy are all significant in the model only considering financial ratios. Similar phenomenon can also be observed when considering both financial ratios and IC variables. These two points can give us strong supports that the cross sectional research design for all the literature may need to be modified in order to obtain more insights about the influence of independent variables.

Finally, two financial ratios, networth+long term debt/fixed assets (t-3) and profit before taxes/sales, were not significant when only considering financial ratios but turning to be significant after the IC variables were added. MARS should be the reason behind this issue since one of the main features of MARS is that it also searches interactions between variables, allowing any degree of interaction to be considered during the modeling procedure. Networth+long term debt/fixed assets (t-3) and profit before taxes/sales became important financial ratios after considering their interaction with the IC variables.

The prediction results of the testing sample (the confusion matrix) using the obtained two MARS models can be summarized in tables 5 and 6 respectively. From the results in tables 5 and 6, we can observe that the average correct classification rate is 72.22% for the model only considering financial ratios and 75.00% for the model considering both financial ratios and intellectual capital variables. From the improved correct classification rate of the model considering both financial ratios and IC variables, IC should be helpful in improving the classification accuracy of the prediction model.

Table 5. MARS classification results with only financial ratios

	Classified Class	
Actual Class	1 (bankrupt)	2 (healthy)
1 (bankrupt)	8 (66.67%)	4 (33.33%)
2 (healthy)	6 (25.00%)	18 (75.00%)
Average correct classification rate: 72.22%		

Table 6. MARS classification results with both financial ratios and IC variables

	Classified Class	
Actual Class	1 (bankrupt)	2 (healthy)
1 (bankrupt)	8 (66.67%)	4 (33.33%)
2 (healthy)	5 (20.83%)	19 (79.17%)
Average correct classification rate: 75.00%		

2. Two-Stage Hybrid Model in Integrating MARS and BPN

Since Vellido *et al.* (1999) pointed out that around 80% of business applications using neural networks will use the BPN training algorithm, this study will also use the popular BPN in building the two-stage hybrid prediction model. As recommended by Cybenko (1989) and Hornik *et al.* (1989) that the network structure with one hidden layer is sufficient to model any complex system with any desired accuracy, the designed network model will have only one hidden layer. Due to the two hybrid prediction models will use the obtained significant independent variables from the two built MARS models, the two hybrid BPN models will have 5 and 8 input nodes respectively (refer to table 4 for more details). After comparing the prediction results of the testing sample with different combinations of hidden nodes and learning rates, the {5-9-1} topology with a learning rate of 0.06 and the {8-17-1} topology with a learning rate of 0.04 gives the best prediction results (minimum testing RMSE) for the model consider only financial ratios and the model considering both financial ratios and IC variables, respectively. Here {ni-nh-no} stands for the number of neurons in the input layer, in the hidden layer, and in the output layer, respectively. The prediction results of the testing sample (the confusion matrix) using the two hybrid prediction models are summarized in tables 7 and 8 respectively.

Table 7. Hybrid model classification results with only financial ratios

	Classified Class	
Actual Class	1 (bankrupt)	2 (healthy)
1 (bankrupt)	9 (75.00%)	3 (25.00%)
2 (healthy)	5 (20.83%)	19 (79.17%)
Average correct classification rate: 77.78%		

Table 8. Hybrid model classification results with both financial ratios and IC variables

	Classified Class	
Actual Class	1 (bankrupt)	2 (healthy)
1 (bankrupt)	10 (83.33%)	2 (16.67%)
2 (healthy)	4 (16.67%)	20 (83.33%)
Average correct classification rate: 83.33%		

From the results revealed in tables 7 and 8, we can observe that the average correct classification rate is 77.78% for the model only including financial ratios and 83.33% for the model incorporating both financial ratios and intellectual capital variables. Again from the improved correct classification rate of the model considering both financial ratios and IC variables, we can also conclude that IC should provide extra information other than financial ratios in improving the classification accuracy of the prediction model.

3. Results Compared with LDA, Logistic Regression, and Neural Networks

In order to evaluate the effectiveness of the proposed two-stage hybrid bankruptcy prediction models, the prediction results are compared with those using LDA, logistic regression and the model solely using BPN. Table 9 summarizes the classifications results of LDA, logistic regression, MARS, BPN, and the hybrid two-stage prediction models with only financial ratios as independent variables while table 10 summarizes the results of the same five models when considering both financial ratios and intellectual capital variables.

Table 9. Classification results of the five models with financial ratios

	Classification results		
Prediction method	{1-1}	{2-2}	Average correct classification rate
Discriminant analysis	66.67%	75.00%	72.22%
Logistic regression	66.67%	75.00%	72.22%
Multivariate adaptive regression splines	66.67%	75.00%	72.22%
Backpropagation neural networks	75.00%	79.17%	77.78%
Two-stage hybrid model	75.00%	79.17%	77.78%

*Here 1-1 (2-2) means a bankrupt (healthy) company is also classified as a bankrupt (healthy) company

Table 10. Classification results when considering financial ratios and IC variables

	Classification results		
Prediction method	{1-1}	{2-2}	Average correct classification rate
Discriminant analysis	66.67%	75.00%	72.22%
Logistic regression	75.00%	75.00%	75.00%
Multivariate adaptive regression splines	66.67%	79.17%	75.00%
Backpropagation neural networks	83.33%	83.33%	83.33%
Two-stage hybrid model	83.33%	83.33%	83.33%

After comparing the results in table 9 and table 10, several conclusions can be observed. Firstly, the models including both financial ratios and IC variables provide better classification results than the corresponding models only using financial ratios. The above phenomenon implies that IC variables do provide valuable information in predicting bankruptcies. Secondly, like similar results reported in the literature, BPN still provides better classification results than those using linear discriminant analysis and logistic regression approaches, no matter when only considering financial ratios or the model including both financial ratios and intellectual capital variables. Finally, both the two-stage hybrid model and the model solely using BPN obtain identical results for cases no matter including IC variables or not. However, we believe the two-stage hybrid model should be a better alternative since it exhibits the capability in identifying important independent variables which may provide valuable information for further diagnostic purposes.

4. Type I and Type II Errors of the Constructed Models

It is well known that, in order to evaluate the overall classification capability of the designed bankruptcy prediction models, the misclassification costs also have to be taken into account. It is apparent that the costs associated with Type I errors (a healthy company is misclassified as a bankrupt company) and Type II errors (a bankrupt company is misclassified as a healthy one) are significantly different. In general, the misclassification costs associated with Type II errors are much higher than those associated with Type I errors (Kiviluoto, 1998). And hence special attention should pay to Type II errors of the five constructed models in order to evaluate the overall classification capability. Table 11 and table 12 summarize the Type I and Type II errors of the five constructed models when considering only financial ratios and both financial ratios and IC variables. From the results revealed in table 11 and 12, we can figure out that the two-stage hybrid model and the model solely using BPN has the lowest Type II errors in both models in comparison with the other three approaches. Hence we can conclude that the two-stage hybrid model and the model solely using BPN not only have the best average correct classification rate, but also have the lowest Type II error.

Table 11. Type I and Type II errors of the five models with financial ratios

	Performance Assessment	
Approach	Type Ⅰ error	Type Ⅱ error
Discriminant analysis	25.00%	33.33%
Logistic regression	25.00%	33.33%
Multivariate adaptive regression splines	25.00%	33.33%
Back-Propagation neural networks	20.83%	25.00%
Two-stage hybrid model	20.83%	25.00%

Table 12. Type I and Type II errors with both financial ratios and IC variables

	Performance Assessment	
Approach	Type Ⅰ error	Type Ⅱ error
Discriminant analysis	25.00%	33.33%
Logistic regression	25.00%	25.00%
Multivariate adaptive regression splines	20.83%	33.33%
Back-Propagation neural networks	16.67%	16.67%
Two-stage hybrid model	16.67%	16.67%

6. Conclusions and Areas of Future Research

The world's economy has been experiencing severe challenges during the past few years, more and more companies in different industries, no matter large or small, are facing the problems of filing bankruptcy. Hence bankruptcy predictions have drawn serious attention from both researchers and practitioners in order to provide on time signals for better investment and governmental decisions. As this topic is getting more and more important, fruitful literature using various prediction models has been developed.

After we carefully review the literature, several important conclusions can be observed. Firstly, almost all the literature only adopted financial ratios as independent variables; Secondly, it is also quite surprised to figure out that almost all the literatures utilized the same cross sectional research design during the empirical study stage. It means that they use independent variables one, two or even three years prior to the bankruptcy, a fixed point before the bankruptcy happens, in predicting the status-healthy or bankrupt of a company; Finally, distriminant analysis and logistic regression are the most commonly used statistical prediction techniques, but often being criticized due to its strong model assumptions. On the other hand, the artificial neural networks has become a very popular alternative in bankruptcy predictions due to its associated memory characteristic, generalization capability and outstanding classification capability. However, it is also being criticized for its long training process, hard to identify the relative importance of potential input variables and certain interpretative difficulties.

In order to improve the drawbacks of only using financial ratios as independent variables, using the cross sectional research design, the shortcomings of neural networks and increasing the classification accuracy of the existing approaches, the objective of the proposed study is to explore the performance of bankruptcy predictions using both financial ratios and intellectual capital variables with a two-stage hybrid modeling procedure in integrating multivariate adaptive regression splines with neural networks technique. The rationale underlying the analyses is firstly to build a MARS prediction model with both financial ratios and intellectual capital variables as independent variables. Then the obtained significant independent variables are served as the input nodes of the designed neural networks model.

For verifying the feasibility on this proposed two-stage hybrid approach, bankruptcy prediction tasks are performed using the public companies filing bankruptcy between 1998 and 2000 in Taiwan. The research findings can be summarized as follows. Firstly, IC variables do provide valuable information other than financial ratios in bankruptcy predictions. Therefore investments in building or strengthening the intellectual capital contents should be good directions in improving the core competence and maintaining continuous growth of a company. Secondly, as the time lags of almost all the important variables are not same and the same variable in different time lags are all significant, the traditional cross sectional research design may need to be modified. Thirdly, the two-stage hybrid model and the model solely using BPN have higher average correct classification rate in comparison with those using linear discriminant analysis, logistic regression, and MARS approaches. However, the two-stage hybrid model should be an efficient alternative since it can identify important independent variables in predicting bankruptcies and contribute to better managerial implications. The above-mentioned research findings justify the presumptions that the two-stage modeling procedure should be a better alternative in conducting bankruptcy prediction tasks. Besides, the two-stage model not only has better classification accuracies, but also has the lowest Type II errors associated with high misclassification costs. Finally, the two-stage hybrid model can save lots of implementation time on the computer and therefore reserve more time for on time decisions.

As the authors encounter serious difficulties in collecting relevant information, especially the IC variables, and hence may limit the predictive capability of the built models due to the fact that without enough/important independent variables. Future researches may aim at collecting more important variables that should result in a model with higher prediction accuracy. Using other classification techniques, like classification and regression tree (CART) and support vector machines (SVM), in evaluating their applicability to bankruptcy predictions are also recommended. Integrating other artificial intelligence techniques, like fuzzy discriminant analysis and genetic algorithms, with neural networks in further refining the network structure and improving the predictive capability may also being investigated.

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Bibliography

1. Altman, E. I., "Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy", Journal of Finance, 23, 1968, 589-609.
2. Altman, E. I., Haldeman, R. G. and Narayanan, P. "Zeta Analysis: A New Model to Identify Bankruptcy Risk of corporations", Journal of Banking and Finance, 1, 1977, 29-54.
3. Altman, E. I., Marco, G., and Varet, F., "Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience)", Journal of Banking and Finance, 18, 1994, 505-529.
4. Altman, E. I., Margaine, M., Schlosser, M., and Vernimmen, P., "Statistical Credit Analysis in the Textile Industry (A French Experience)", Journal of Financial and Quantitative Analysis, 9, 1974, 195-211.
5. Beaver, W. H., "Financial Ratios and Predictors of Failure", Empirical Research in Accounting: Selected Studies, Supplement to Journal of Accounting Research, 4, 1966, 71-111.
6. Beaver, W. H., "Market Prices, Financial Ratios, and the Prediction of Failure", Journal of Accounting Research, 6(2), Autumn 1968, 179-192.
7. Begley, J., Ming, J., and Watts, S., "Bankruptcy Classification Errors in the 1980s: An Empirical Analysis of Altman's and Ohlson's Models", Review of Accounting Studies, 1, 1996, 267-284.
8. Blum, M., "Failing Company Discriminant Analysis", Journal of Accounting Research, 1974, 12(1), 1-25.
9. Breiman, L., Friedman, J. H., Olshen, R. A., and Stone, C. J., *Classification and Regression Trees*, Wadsworth, Pacific Grove, CA, 1984.

10. Brooking, A., *Intellectual Capital*, International Thomson Business Press, London, 1996.

11. Coats, P. K. and Fant, L. F., “Recognizing Financial Distress Patterns Using a Neural Network Tool,” Financial Management, 22, 1993, 142-155.

12. Coleman, K. G., Graettinger, T. J., and Lawrence, W. F., “Neural Networks for Bankruptcy Prediction: The Power to Solve Financial Problems”, AI Review, 1991, 48-50.

13. Craven, P. and Wahba, G., “Smoothing Noisy Data with Spline Functions. Estimating the Correct Degree of Smoothing by the Method of Generalized Cross-Validation”, *Numberische Mathematik*, 31, 1979, 317-403.

14. Cybenko, G., “Approximation by Superpositions of a Sigmoidal Function”, Mathematical Control Signal Systems, 2, 1989, 303-314.

15. Deakin, E. B., “A Discriminant Analysis of Predictors of Business Failure”, Journal of Accounting Research, 10, Spring 1972, 167-179.

16. De Gooijer, J. G., Ray, B. K., and Krager, H., “Forecasting Exchange Rates Using TSMARS”, Journal of International Money and Finance, 17(3), 1998, 513-534.

17. Dillon, W. R. and Goldstein, M., *Multivariate Analysis Methods and Applications*, Wiley, New York, NY, 1984.

18. Dimitras, A. I., Zanakis, S. H., and Zopounidis, C., “A Survey of Business Failures with an Emphasis on Prediction Methods and Industrial Applications”, European Journal of Operational Research, 90, 1996, 487-513.

19. Edmister, R., “An Empirical Test of Financial Ratio Analysis for Small Business Failure Predictions”, Journal of Financial and Quantitative Analysis, 7, 1972, 1477-1493.

20. Edvinsson, L. and Malone, M. S., *Intellectual Capital*, Harper Collins, New York, NY, 1997.

21. Elam, E., “The Effect of Lease Data on the Predictive Ability of Financial Ratios”, The Accounting Review, 50, 1975, 15-43.

22. Fanning, K. M. and Cogger, K. O., “A Comparative Analysis of Artificial Neural Networks Using Financial Distress Prediction”, Intelligent Systems in Accounting, Finance, and Management, 3, 1994, 241-252.

23. Fletcher, D. and Goss, E., “Forecasting with Neural Networks: An Application Using

Bankruptcy Data", Information and Management, 24, 1993, 159-167.

24. Friedman, J. H., "Multivariate Adaptive Regression Splines (with discussion)", Annals of Statistics, 19, 1991, 1-141.

25. Friedman, J. H. and Roosen, C. B., "An Introduction to Multivariate Adaptive Regression Splines", Statistical Methods in Medical Research, 4, 1995, 197-217.

26. Gilbert, L. R., Menon, K., and Schwartz, K. B., "Predicting Bankruptcy for Firms in Financial Distress", Journal of Business Finance and Accounting, 17(1), 1990, 161-171.

27. Griffin, W. L., Fisher, N. I., Friedman, J. H., and Ryan, C. G., "Statistical Techniques for the Classification of Chromites in Diamond Exploration Samples", Journal of Geochemical Exploration, 59, 1997, 233-249.

28. Harrison, S. and Sullivan, P. H., "Profiting from Intellectual Capital-Profiting from Leading Companies", Journal of Intellectual Capital, 1(1), 2000, 33-46.

29. Hastie, T. and Tibshirani, R., Gene*ralized Additive Models*, Chapman and Hall, London, 1990.

30. Holmen, J. S., "Using Financial Ratios to Predict Bankruptcy in Evaluation of Classic Models Using Recent Evidence", Akron Business and Economic Review, 19(1), 1988, 52-63.

31. Hornik, K., Stinchcombe, M., and White, H., "Multilayer Feedforward Networks Are Universal Approximations", Neural Networks, 2, 1989, 336-359.

32. Johnson, C., "Ratio Analysis and the Prediction of Firm Failure", Journal of Finance, 25, 1970, 853-868.

33. Johnson, R. A. and Wichern, D. W., *Applied Multivariate Statistical Analysis (Fifth Edition)*, Prentice-Hall, Upper Saddle River, NJ, 2002.

34. Jones, F. L., "Current Techniques in Bankruptcy Prediction", Journal of Accounting Literature, 6, 1987, 131-146.

35. Kaplan, R. S. and Norton, D. P., *The Balanced Scorecard: Translating Strategy into Action*, Harvard Business School Press, Harvard, MA, 1996.

36. Karels, G. and Prakash, A., "Multivariate Normality and Forecasting of Business bankruptcy", Journal of Business Finance and Accounting, 14(4), 1987, 573-593.

37. Keasey, K. and McGuinness, P., “The Failure of UK Industrial Firms for the Period 1976-1980: Logistic Analysis and Entropy Measures”, Journal of Business Finance and Accounting, 17(1), 1990, 119-135.

38. Keasey, K., McGuinness, P., and Short, H., “Multilogit Approach to Predicting Corporate Failure-Further Analysis and the Issue of Signal Consistency”, OMEGA, International Journal of Management Science, 18(1), 1990, 85-94.

39. Kiviluoto, K., “Predicting Bankruptcies with the Self-Organizing Map”, Neurocomputing, 21, 1998, 191-201.

40. Kuhnert, P. M., Do, K-A., and McClure, R., “Combining Non-Parametric Models with Logistic Regression: An Application to Motor Vehicle Injury Data”, Computational Statistics and Data Analysis, 34, 2000, 371-386.

41. Lacher, R. C., Pamela, K. C., Shrama, S. C., and Fant, L. F., “A Neural Network for Classifying the Financial Health of a Firm”, European Journal of Operational Research, 85, 1995, 53-63.

42. Laitinen, E. K., “Financial Ratios and Different Failure Processes”, Journal of Business Finance and Accounting, 18(5), 1991, 649-673.

43. Laitinen, E. K., “Prediction of Failure of a Newly Founded Firm”, Journal of Business Venturing, 7, 1992, 323-340.

44. Laitinen, E. K., “Predicting a Corporate Credit Analyst's Risk Estimate by Logistic and Linear Models”, International Review of Financial Analysis, 8(2), June 1999, 97-121.

45. Laitinen, E. K. and Laitinen, T., “Bankruptcy Prediction: Application of the Taylor's Expansion in Logistic Regression”, International Review of Financial Analysis, 9(4), Winter 2000, 327-349.

46. Lau, A. H. L., “A Five-State Financial Distress Prediction Model”, Journal of Accounting Research, 25(1), 1987, 127-138.

47. Lee, T. S. and Chen, N. J., “Investigating the Information Content of Non-Cash-Trading Index Futures Using Neural Networks”, Expert Systems with Applications, 22(3), 2002, 225-234.

48. Lee, T. S., Chiu, C. C., Lu, C. J., and Chen, I. F., “Credit Scoring Using the Hybrid Neural Discriminant Technique”, Expert Systems with Applications, 23(3), 2002, 245-254.

49. Lenard, M. J., Alam, P and Madey, G. R., “The Application of Neural Networks and a Qualitative Response Model to the Auditor’s Going Concern Uncertain Decisions”, Decision Sciences, 26(2), 1995, 209-226.

50. Lennox, C., “Identifying Failing Companies: A Reevaluation of the Logit, Probit and DA Approaches”, Journal of Economics and Business, 51, 1999, 347-364.

51. Leshno, M. and Spector, Y., “Neural Network Prediction Analysis: The Bankruptcy Case”, Neurocomputing, 10, 1996, 125-147.

52. Lewis, P. A. W. and Stevens, J. G., “Nonlinear Modeling of Time Series Using Multivariate Adaptive Regression Splines (MARS)”, Journal of American Statistical Association, 86, 1991, 864-877.

53. Luoma, M. and Laitinen, E. K., “Survival Analysis as a Tool for Company Failure Prediction”, OMEGA, International Journal of Management Science, 19(6), 1991, 673-678.

54. *MARS 2.0—for windows 95/98/NT,* Salford Systems, San Diego, CA, 2001.

55. Moyer, R. C., “Forecasting Financial Failure-A Re-Examination”, Financial Management, 6, 1977, 11-17.

56. Nguyen-Cong V., Van D. G., and Rode, B. M., “Using Multivariate Adaptive Regression Splines to QSAR Studies of Dihydroartemisinin Derivatives”, European Journal of Medical Chemistry, 31, 1996, 797-803.

57. Norton, C. L. and Smith, R. E., “A Comparison of General Price Level and Historical Cost Financial Statements in the Prediction of Bankruptcy”, The Accounting Review, 54, 1979, 72-87.

58. Odom, M. and Sharda, R., “A Neural Network Model for Bankruptcy Prediction”, Proceedings of the IEEE International Conference on Neural Networks, II, 1990, 163-168.

59. Ohlson, J. A., “Financial Ratios and the Probabilistic Prediction of Bankruptcy”, Journal of Accounting Research, 18, Spring 1980, 109-131.

60. Ohmann, C., Moustakis, V., Yang, Q., and Lang, K., "Evaluation of Automatic Knowledge Acquisition Techniques in the Diagnosis of Acute Abdominal Pain", Artificial Intelligence in Medicine, 13, February 1996, 23-36.

61. Platt, H. and Platt, M., "Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction", Journal of Business Finance and Accounting, 17 (1), 1990, 31-51.

62. Piramuthu, S., Shaw, M. J., and Gentry, J. A., "A Classification Approach Using Multilayered Neural Networks", Decision Support Systems, 11(5), 1994, 509-525.

63. Qnet 97 – *Neural Network Modeling for Windows 98/NT*, Vesta Services, Winnetka, IL, 1998.

64. Raghupathi, W., "Comparing Neural Network Learning Algorithms in Bankruptcy Prediction", International Journal of Computational Intelligence and Organizations, 1(3), 1996, 179-187.

65. Rahimian, E., Singh, S., Thammachote, T., and Virmani, R., "Bankruptcy Prediction by Neural Networks", in: Trippi, E. and Turban, E. (Eds), Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance, Probus Publishing, Chicago, 1993, 159-176.

66. Reichert, A. K., Cho, C. C., and Wagner, G. M., "An Examination of the Conceptual Issues Involved in Developing Credit-Scoring Models", Journal of Business and Economic Statistics, 1, 1983, 101-114.

67. Roos, J., Roos, R., Edvinsson, L., and Dragonetti, N., *Intellectual Capital: Navigating in the New Business Landscape*, New York University Press, New York, NY, 1998.

68. Salchengerger, L. M., Cinar, E. M., and Lash, N. A., "Neural Networks: A New Tool for Prediction Thrift Failures", Decision Sciences, 23, 1992, 899-916.

69. Sanchez, M. S. and Sarabia, L. A., "Efficiency of Multi-Layered Feedforward Neural Networks on Classification in Relation to Linear Discriminant Analysis, Quadratic Discriminant Analysis and Regularized Discriminant Analysis", Chemometrics and Intelligent Laboratory Systems, 28, 1995, 287-303.

70. Sharda, R. and Wilson, R. L., "Neural Networks Experiments in Business-Failure Forecasting: Predictive Performance Measurement Issues", International Journal of Computational Intelligence and Organizations, 1(2), 1996, 107-117.

71. Sharma, S., *Applied Multivariate Techniques*, Wiley, New York, NY, 1996.

72. SPSS 1997 – *Statistic Modeling for Windows 95/98/NT*, SPSS Inc., 1998.

73. Stewart, T. A., *Intellectual Capital: The New Wealth of Organizations*, Bantam Doubleday Dell, New York, 1997.

74. Sveiby, K., *The New Organizational Wealth-Managing and Measuring Knowledge-Based Assets*, Berrett-Koehler, San Francisco, CA, 1997.

75. Taffler, R., "Forecasting Company Failure in the UK Using Discriminant Analysis and Financial Ratio Data", Journal of Royal Statistical Society, Series A, 145, 1982, 342-358.

76. Tam, K. Y. and Kiang, M., "Managerial Applications of Neural Networks: The Case of Bank Failure Predictions", Management Science, 38(7), 1992, 926-947.

77. Tennyson, B. N., Ingram, R. W., and Dugan, M. T., "Assessing the Information Content of Narrative Disclosures in Explaining Bankruptcy", Journal of Business Finance and Accounting, 17(3), 1990, 391-410.

78. Trigueiros, D. and Taffler, R., "Neural Networks and Empirical Research in Accounting", Accounting and Business Research, 26(4), 1996, 347-355.

79. Udo, G., "Neural Network Performance on the Bankruptcy Classification Problem", Computers and Industrial Engineering, 25, 1993, 377-380.

80. Vellido, A., Lisboa, P. J. G., and Vaughan, J., "Neural Networks in Business: A Survey of Applications (1992-1998)", Expert Systems with Applications, 17, 1999, 51-70.

81. Wilcox, J. W., "A Prediction of Business Failure Using Accounting Data", Journal of Accounting Research (Supplement), 11, 1973, 163-179.

82. Wilson, R. L. and Sharda, R., "Bankruptcy Prediction Using Neural Networks", Decision Support Systems, 11, 1994, 545-557.

83. Zavgren, C. V., "Assessing the Vulnerability to Failure of American Industrial Firms. A Logistic Analysis", Journal of Business Finance and Accounting, 12(1), 1985, 19-45.

84. Zhang, G., Hu, M. Y., Patuwo, B. E., and Indro, D. C., "Artificial Neural Networks in Bankruptcy Predictions: General Framework and Cross-Validation Analysis", European Journal of Operational Research, 116, 1999, 16-32.

85. Zmijewski, M. E., "Methodological Issues Related to the Estimation of Financial Distress Prediction Models", Studies on Current Econometric Issues in Account Research, Supplement to Journal of Accounting Research, 22, 1984, 59-86.