A COMPARATIVE STUDY OF LOGIT AND ARTIFICIAL NEURAL NETWORKS IN PREDICTING BANKRUPTCY IN THE HOSPITALITY INDUSTRY

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CHAPTER I

INTRODUCTION

Background

The hospitality business has received scrutiny by many investors and lenders because of its unique risks (Elgonemy, 2002). Historically, the restaurant industry is well-known for its high failure rate, which prompted many researchers to search for the reasons of restaurants failures (Parsa, Self, Njite, & King, 2005). As Ernist (2002) stated, more than 30% of restaurant failed in their first two years of operation. The lodging industry is known to be capital-intensive and highly leveraged, and this can be a burden on managers wishing to obtain the required return and cash flow to meet their obligations.

In addition, the lodging industry is characterized by fluctuating demand. Hotels' profitability is tied to changes in the supply-demand balance. Moreover, overall operating environments for the hospitality industry, during the recession of the 1990s that followed the overbuilding of the 1980s dropped the profitability of many hotel businesses. (Rushmore, 1992).

Fortunately, after 2001, despite lingering fears of terrorist attacks, the lodging industry started to recover. In 2004, room revenue increased 9% over the previous year and it is achieved by a rise of only 6% in demand (Smith & Lesure, 2004, 2005, 2006).

Considering the combination of growing demand and rises in the average room rate (ADR), this steady growth is still a definite sign of recovery from recession.

In spite of the recovery, the industry still merits attention because it is affected by terrorism, recession, and other changes in its operating environment. Moreover, as the service industry has matured and the market is saturated, competition among hospitality firms has become intense. These characteristics of the hospitality industry can easily cause financial distress for lodging firms and force them to file for bankruptcy (Andrew & Schmidgall, 1993).

In particular, because a declaration of bankruptcy entails substantial costs including litigation, interest costs, and collection fees, auditors, senior executives, creditors and stockholders prefer early warning. These concerns are closely related to many previous studies that have identified the features of firms' financial stability using firms' financial information.

The use of financial ratios to diagnose a firm's financial condition led to many models designed to predict bankruptcy. Since the introduction of the Altman's Z-Score bankruptcy prediction model (Altman, 1968), a number of prediction models have been developed across industries, regions, and nations. Multivariate Discriminant Analysis (MDA) uses selective financial ratios. It is important to note that MDA is valid only under restrictive assumptions which may result in biased results when violated. This supports the theoretical superiority of the logit model in bankruptcy prediction (Kim & Gu, 2006).

Recently, Artificial Neural Networks (ANNs) have received a great deal of attention in the area of decision support system because of their outstanding ability to forecast and classify events to make a decision (Wilson & Sharda, 1994). ANNs are inspired by the function of human intelligence. Over the last half century, numerous researchers have studied ANNs. ANNs' ability to forecast and predict has been a serious contender for conventional statistical applications. In fact, several studies have found that ANNs are more accurate than statistical models such as Multivariate Discriminant Analysis (MDA) and logit models in accuracy rate (Lee, Booth, & Alam, 2005; Tam, 1991) and ANNs are free of restrictive statistical assumptions (Aminian, Suarez, Aminian, & Walz, 2006).

Despite many attempts to predict bankruptcy in the hospitality industry, there is still a great deal of room for methodological improvement. Harris and Brown (1998) stated that a more in-depth approach and sophisticated methodology are encouraged among researchers. A more in-depth approach and sophisticated methodology are to embrace the nature of the hospitality industry and draw more meaningful conclusions from research. In addition, the study by Chava and Jarrow (2004) concluded that industry groupings significantly affected in forecasting firms' bankruptcy because firms in the same industry group are assumed to be under the same legal, political, and economic influences. However, only a few empirical studies of bankruptcy prediction have focused on the hospitality industry, with its complexity and vulnerability. Furthermore, there is a dearth of bankruptcy prediction studies of the hospitality industry that have used ANNs.

Therefore, this study will use ANNs to predict bankruptcy among hospitality firms. This study will compare the performance of ANNs in predicting hospitality firms' bankruptcy to the more conventional statistical logit model.

The Purpose of the Study

The purpose of this study is to compare the accuracy of an Artificial Neural Networks to that of a logit model in predicting hospitality firms' bankruptcy.

Research Questions

The research questions are as follows:

Research Question 1: Does an Artificial Neural Networks outperform Logit, a conventional statistical technique, in predicting a hospitality firm's bankruptcy?

Research Question 2: What financial ratios significantly predict the classification of hospitality firms as bankrupt or non-bankrupt?

Definition of Terms

1. Bankruptcy: This is a legal status, one that involves many parties in litigation and requires a petition in federal court for filing for protection under either Chapter 7 of the legal code, which entails reorganization of its debts, or Chapter 11, which includes liquidation of its assets (Keown, Martin, Petty, & Scott, 1982).
2. Hospitality Industry: This consists of a variety of service industries including, lodging, food service, casinos, and tourism (Angelo & Vladimir, 2001).

3. Artificial Neural Networks: These are mathematical models based on biological neural networks of human brain. ANNs are configured for specific tasks such as pattern recognition or data classifications (Shah & Murtaza, 2000).

4. Logit Model: This statistical model is used to predict the probability of occurrence of certain events occuring. It is also referred to as logistic regression (Ohlson, 1980).

Organization of the Study

This investigation of the hospitality bankruptcy prediction model consists of five chapters. Chapter II will summarize the previous literature on business failure. It has four sections: studies of business failure, bankruptcy-predicting studies in the financial literature, studies of artificial neural networks, and bankruptcy-predicting studies in the hospitality industry. Chapter III provides the research methodology of the study: data collection procedure, logistic regression and artificial neural networks, and research variables. Chapter IV presents the empirical results. Chapter V discusses the implications and limitations of the study.

CHAPTER II

REVIEW OF LITERATURE

Business Failure

There is no clear and universally-accepted definition of business failure. The term 'business failure' is used to describe a firm's financial health study (Dimitras, Zanakis, & Zopounidis, 1996). Altman (1993) introduced three types of business failure: economic failure, insolvency, and bankruptcy. According to his study, 'economic failure' is a situation in which a firm has a lower return on investment than required level based on industry standards. 'Insolvency' is a situation in which a lack of liquidity prevents a firm from meeting its financial obligations. 'Bankruptcy' is a legal status that involves litigation and requires a petition in federal court.

Obviously, business failure threatens a firm's survival. It can harm its owners, managers, shareholders, employees, suppliers, clients, and even the government. Additional burdens of business failure are the high legal and collection fees that accompany bankruptcy. More importantly, business failures hurt society and the country's economy. For these reasons, many researchers and practitioners are interested in predicting business failure. Table 1 summarizes the number of companies that filed for bankruptcy, grouped by industry classification in the U.S, from 1962 to 1999. It shows that the manufacturing industry has the highest number of bankruptcy filings, followed by the retail trade and service industries.

Table 1. Bankruptcy by SIC (Standard Industrial Classification Code)

SIC Code	**Industry Name**	**Number (%) of Bankruptcies**
<1000	Agriculture, Forestry and Fisheries	30 (2.06%)
1000 to less than 1500	Mineral Industries	116 (7.96%)
1500 to less than 1800	Construction Industries	27 (1.85%)
2000 to less than 4000	Manufacturing	545 (37.38%)
4000 to less than 5000	Transportation, Communications, and Utilities	116 (7.96%)
5000 to less than 5200	Wholesale Trade	69 (4.73%)
5200 to less than 6000	Retail Trade	211 (14.47%)
6000 to less than 6800	Finance, Insurance, and Real Estate	160 (10.97%)
7000 to less than 8900	Service Industries	180 (12.35%)
9100 to less than 10000	Public Administration	0 (0%)
Total number of bankruptcy		1461 (100%)

Source : Chava, S., & Jarrow, R. (2004). Bankruptcy prediction with industry effects. *Review of Finance, 8,* 37-569.

Bankruptcy Prediction Studies in Financial Literature

Financial ratios are a typical method of assessing both firms' present and future financial performance, since the figures on balance sheets and income statements reflect a firm's financial status. One of the primary uses of financial ratios is the prediction of bankruptcy by using these ratios as variables. Beaver (1968) employed univariate analysis to estimate the predictive power of financial ratios on bankruptcy. The author tested six groups of ratios: cash flow, debt to total asset, net income, liquid assets to total asset, liquid assets to current debt, and turnover; the conclusion is that the combination of more than one ratio will give a researcher better predictability for further study (Beaver, 1968).

After Beaver's study of bankruptcy prediction utilizing financial ratios, Altman (1968) introduced the Altman Z score model, using Multiple Discriminant Analysis (MDA). Many researchers across disciplines have come to rely on MDA (Blum, 1974; Edmister, 1972). MDA uses a set of predictor variables to determine whether dependent variables indicate either bankrupt or non-bankrupt dichotomously. Altman chose 33 variables in the study to predict bankruptcy. After employing the step-wise procedure, to determine the extent of each variable's contribution, five ratios remained, which he considered to be significant predictors. The author cited limitations of the study in terms of industry scope and firm size, but his use of Multiple Discriminant makes this study the standard by which other models are measured (Altman, 1968).

Edmister (1972) was the first to examine the sizes of the firms being tested. The primary contribution of the study is the use of industry averages to generate standardized ratios. Blum (1974) broadened the scope of the study criteria by using a different indication to determine the population of the companies to be studied. The author looked beyond firms that had filed for bankruptcy in legal terms and included companies that made explicit agreements with creditors to reduce their debts. By doing this, the author obtained a data set that consisted of 115 failed and 115 non-failed firms. Moreover, the study grouped 12 ratios in terms of liquidity, profitability and variability. The inclusion of measures of variability differentiated this study from previous studies. Blum found a 93-95% predictive accuracy for the model in the first year prior to failure and cash flow/total debt as the best predictor, conforming Beaver's (1968) study.

Ohlson (1980) criticized prior studies that had been conducted using MDA technique because of its assumptions. With the MDA, the distributional properties of ratios are assumed to be normally distributed and the samples of companies are assumed to be randomly selected. However, financial figures are often not normally distributed because financial figures are skewed in the positive direction. This is due, in part, to the fact that a company may not necessarily be limited by the amount of money it can make, but by the amount of money it can lose. Violations of these assumptions can lead to inaccurate predictions. To overcome these pitfalls in collecting samples and variables for bankruptcy prediction models, the author used a logit analysis model and selected a simple data set. Logit analysis is a multivariate technique which uses all predictor variables simultaneously, but it does not carry the same assumptions of the MDA techniques. Ohlson's study is valuable because he conducted a logit model study whose theoretical soundness was supported by future researchers.

Following Ohlson's business failure study with a logit model, researchers conducted multiple studies to improve its classification accuracy using a logit model. Zavgren (1985) developed a measure, using a logit model with seven financial ratios, and tested its prediction capability for up to five years prior to bankruptcy. Hamer (1983) compared MDA to the logit technique using different data sets, and concluded that the two models were comparable in assessing the probability of failure. Lo (1986) studied corporate bankruptcies, comparing the logit model to MDA, and concluded that the logit model was more robust than MDA. Darayseh, Waples, and Tsoukalas (2003) conducted a study using a logit model to predict corporate bankruptcy and obtained 88 % accuracy for in-sample and holdout sample tests. Chi and Tang (2006) collected a sample of firms in seven Asia-Pacific capital markets to exam trade credit risk using a logit model. This study took a closer look into misclassification costs associated with cutoff value determination. Tseng and Lin (2005) used a quadratic interval logit model in attempt to achieve more accurate results by reducing a fuzzy relationship with explanatory independent variables and binary dependent variables.

Previous Studies of Artificial Neural Networks

The formal study of Artificial Neural Network (ANNs) was initiated by McCulloch and Pitts (1943). Inspired by biological networks and observations in the human brain, they built a simple binary neural network model using a number of interconnected neurons linked together. Since McCulloch and Pitts (1943) introduced their ANNs model, ANNs have received a great deal of attention as the theoretical foundations of building learning systems in the late 1950s and early 1960s (Sharda & Wang, 1996; Tam, 1991). However, Minsky and Paper's (1969) criticism of the functional limitations of its single-layer network led to a decline in the amount of research.

The stream of neural network studies was resuscitated 20 years ago with recent advances in neural networking topologies, activation function, and new learning algorithms such as back-propagation, radial basis functions networks (RBFs), and learning systems. Different ANNs' learning algorithms and topologies have been extensively studied and applied to various predicting/classifying tasks. For instance, ANNs have shown that a model can be trained to predict probabilities of occurrences, classifying events such as bankruptcy prediction, customer targeting, credit-risk evaluation, and even human resource practice analysis (Baesens, Setiono, Mues, & Vanthienen, 2003; Coats & Fant, 1993; Kim, Street, Russel, & Menczer, 2005; Stavrou, Charalambous, & Spiliotis, 2007).

In both academic and industrial tourism research, ANNs have recently received extensive attention due to their superiority over traditional statistical techniques in forecasting consumer behavior and demand in the tourism industry. This is because the nature of the tourism industry makes it particularly susceptible to such factors (Palmer, Montono, Sese, 2006; Pattie & Snyder, 1996; Wang, 2004). De Carvalho, Dougherty, Fowkes, and Wardman (1998) conducted a comparative study of logit and ANNs in forecasting travel demand. The study used three sets of data: synthetic data, which fulfills the logit assumptions; synthetic data, which violates the logit assumptions, and real data. The study results revealed that back-propagation neural networks achieved better accuracy when dealing with synthetic data, which breaches the logit assumptions. Of more interest is the discovery that same is true of real data. This indicates that ANNs do not require assumptions which are often violated by real data. Law and Au (1999) built a neural network model to forecast Japanese demand for travel to Hong Kong. The authors compared results derived from five different methods: neural networks, multiple regression, naïve, moving average, and exponential smoothing. The neural network model was supervised feed-forward perception consisting of five neurons in the input layers and a single neuron in the output layer. The study concluded that neural networks hold the superior forecasting efficiency than that of rest of four techniques. The authors pointed out that, though the neural network showed the best forecasting efficiency, the adequate techniques should be employed in certain situations to optimize the efficacy of analysis. Tsaur, Chiu, and Huang (2002) employed two prediction techniques: a neural network model and logistic regression to determine attributes of guest loyalty to international tourist hotels. The model adopted eight neurons, each representing responsiveness, tangibility, meal service, location, reliability, empathy, reputation, and business service. The results showed that the neural network model achieved more satisfactory model-fitting in determining attributes of guest loyalty to international hotels. Cho (2003) utilized three time-series forecasting techniques: exponential smoothing, Auto-Regressive Integrated Moving Average (ARIMA), and Neural Networks to forecast visitor arrivals to Hong Kong from six countries (USA, Japan, Taiwan, Korea, the UK, and Singapore). The results were compared to determine the best performing techniques. The results revealed that the neural networks outperformed the other two methods, especially when dealing with the less obvious patterns of Korean and Japanese visitors.

In bankruptcy prediction studies, the first attempt to use neural networks was made by Odom and Sharda (1990). They compared the performance of neural networks to Altman's MDA model using the five financial ratios that Altman had used in 1968. The empirical results demonstrated that neural networks outperformed MDA with regard to prediction accuracy and model robustness. Following the study by Odom and Sharda (1990), additional studies were conducted to investigate the effectiveness of neural network. For instance, Salchenberger, Cinar, and Lash (1992) used a network for the analysis of the bankruptcy of savings and loan institutions and showed that the neural networks outperformed logit models across different lead times. Tam and Kiang (1992) intended to prove the superiority of neural network in predicting bankruptcy. They compared several methodologies including MDA, logistic regression, *k*-nearest neighbor, and a machine learning method of a decision tree. This study concluded that neural networks showed better performance than any other techniques in predicting bankruptcy status.

Following previous ANNs studies, Wilson and Sharda (1994) conducted an exploratory study which compared predictive capability of neural networks to that of MDA. This study utilized the concept of Monte Carlo resampling techniques, in order to obtain better predictive accuracy, by reducing the impact of base rate on the performance of prediction techniques. The authors generated three composition levels of bankrupt and non-bankrupt firms in the training set and three composition levels of bankrupt and non-bankrupt levels in the testing set, generating nine different outputs. The empirical results revealed that neural network demonstrated significantly higher predictive accuracy than MDA. In the study by Boritz and Kennedy (1995), the proportions of bankrupt firms and non-bankrupt firms both in training and testing sets, were also a matter of concern. It demonstrated that different proportions of bankrupt firms and non-bankrupt firms in the training sample and testing samples affected prediction accuracy. They also found that different neural network approaches have varying effects on the levels of Type-I and Type-II error, which may result in misclassification of firms.

While recent studies focus on the relative performance of neural network over conventional statistical techniques, the study by Altman, Marco, and Varetto (1994) showed that the performance of neural network and other statistic techniques were comparable with regard to the degree of accuracy. Lee et al. (2005) examined on relative performances between supervised and unsupervised neural network models. This study used a back-propagation algorithm and Kohonen self-organizing feature map as a representative model of both supervised and unsupervised neural network models. The study revealed that supervised back-propagation is better when a target vector was available. During past decades, research in many fields has been conducted using neural networks by many researchers in various fields. Especially, great improvements in predicting and classifying tasks such as bankruptcy prediction have contributed to neural networks' sophisticated algorithms and advanced modeling systems (Belhadjali & Whaley, 2004).

Bankruptcy Prediction Studies in the Hospitality Industry

Gao (1999) analyzed firms' bankruptcy from both microeconomic and macroeconomic perspectives. From a microeconomic view, the study tested the multiple discriminant model with 25 hospitality firms (eight lodging companies and seventeen restaurant companies). Out of 17 financial variable tested, four ratios: total equity to total assets, retained earnings to total assets, EBIT to total liabilities, and sales to fixed assets were selected based on the result of stepwise procedure. The model incorporating the four ratios achieved an accuracy rate of 92% one year prior to bankruptcy and an 83% accuracy rate two years in advance. From macroeconomic perspective of the study, the result validated that change of real gross state product and change of disposable personal income have a significant impact on lodging firms' failure.

Gu and Gao (1999) also conducted a bankruptcy prediction study focusing on the hospitality industry. The study sample consisted of 14 hospitality companies and estimated a multivariate discriminant model to predict hospitality firm bankruptcy. The model reached 93% accuracy with in-sample firms in one year prior to bankruptcy.

Patterson (2001) analyzed bankruptcy in the casino industry. In his study, he developed a theoretical model based on the casino industry's unique characteristics. His model utilized 12 variables that differed significantly from those used in other studies: marketing costs/total revenue, net income/total assets, total revenues/total assets, operating margin, payroll costs/total assets, percent changes in marketing costs/total revenues ratio, percent changes in cash balance/total liabilities ratio, percent change in total revenues/total liabilities ratio, percent change in operating margin ratio, percent change in operating margin ratio, percent change in payroll costs/total revenues ratio, and percent change in payroll costs/total assets ratio. The results of a discriminant analysis generated a model using the 12 variables, showing an in-sample classification accuracy of 100% and a 92.3% accuracy rate with a holdout sample. This was significantly higher accuracy than that found in many previous studies.

Gu (2002) also studied restaurant firms' bankruptcy with a multiple discriminant model. The study selected two variables with the forward-stepwise procedure, which included total liabilities to total assets and earnings before interest and tax to total liabilities out of 12 initial variables. The model achieved a 92% accuracy rate in predicting firms' bankruptcy one year prior to the occurrences. The study suggested that more profitable operation policies and sound debt-financing strategies are crucial to keep companies from going bankrupt.

Kroeze (2005) investigated industry-specific bankruptcy. She used a modified Altman's Z-score model to predict bankruptcy in airline corporations. The study sample consisted of 16 airline companies. About three to four years of financial information for each sample company was collected and analyzed. This study achieved overall 62% of prediction accuracy when it applied Altman's Z-score model. The study developed a Kroeze Model by modifying Altman's Z score model. By applying the modified Kroeze Model, the study achieved overall 62% of prediction accuracy and found that retained earnings to total assets was the most significant financial variable in detecting an occurrence of bankruptcy. Despite the small sample size, the study demonstrated that the two models applied to the study were able to detect occurrences of bankruptcy up to four years before the events.

Kim (2006) made a first attempt to apply logistic regression to predict bankruptcy in the hospitality industry. He constructed the sample with 16 bankrupt firms and 16 non-bankrupt firms and achieved 84% and 91% accuracy in predicting the bankruptcy status of firms one year and two years prior to bankruptcy, respectively. This study recommended that future research should consider external impacts such as geographic diversification and market segmentation, into account for more sophisticated analysis and accurate examination.

To find the strengths of both the multiple discriminant model and the logit model in predicting bankruptcy, Kim and Gu (2006) compared the two models using the same set of data that Gu's (2002) study had previously used. They employed a logit forward stepwise statistical procedure and selected two financial variables, total liabilities to total assets and EBIT to total liabilities from 12 candidate variables. The result of logistic regression showed that the model correctly classified 93 % of sample firms, while the previous study achieved a 92% accuracy rate in classifying bankruptcy firms. The results of the study showed that both techniques have comparable ability to predict bankruptcy. However, the study concluded that the logit model was more preferable because of its theoretical soundness and that it does not require the statistical assumptions with which the MDA technique associates. Table 2 summarizes bankruptcy prediction studies in the hospitality industry.

Table 2. Summary of Bankruptcy Prediction Studies in the Hospitality Industry

Researcher(s) (Year)	Title	Sample used	Methodology(ies)
Gao (1999)	Study of business failure in the hospitality industry from both microeconomic and macroeconomic perspectives	Eight lodging companies 17 restaurant companies	MDA (Multivariate Discriminant Analysis)
Gu & Gao (1999)	A multivariate model for predicting business failures of hospitality firms	10 restaurants companies Four lodging companies	MDA (Multivariate Discriminant Analysis)
Patterson (2001)	Bankruptcy prediction: A model for the casino industry	Casinos*	MDA (Multivariate Discriminant Analysis)
Gu (2002)	Analyzing bankruptcy in the restaurant industry: A multiple discriminant model	18 restaurant companies	MDA (Multivariate Discriminant Analysis)
Kroeze (2005)	Predicting airline corporate bankruptcies using a modified Altman Z-Score model	11 airline companies	MDA (Multivariate Discriminant Analysis)
Kim (2006)	Logistic regression analysis for predicting bankruptcy in the hospitality industry	10 restaurant companies Six lodging companies	Logistic Regression
Kim & Gu (2006)	Predicting restaurant bankruptcy: A logit model in comparison with a discriminant model	18 restaurant companies	Logistic Regression/ MDA (Multivariate Discriminant Analysis)

Note: *Detailed information of the sample used in the study kept confidential.

CHAPTER III

METHODOLOGY

Sample and Data Collection

The sample data collection for the bankruptcy prediction model required a clear definition of failure and specification of the population. In this study, the sample firms included were selected solely based on the legal status of ‘bankruptcy’. The failed companies included in the study had already filed for Chapter 11 bankruptcy. The list of bankrupt firms was available from the New Generation Research Inc.’s Bankruptcy Database from1992 to 2007. Though a shorter period is more desirable, with respect to reducing economic effects on sample firms’ bankruptcy occurrences, the 15-year sample period was necessary in order to obtain an acceptable sample size for an analysis. Moreover, since the purpose of study is to compare the two methodologies, biases caused by external aspects can be ignored as long as the equal condition is provided. From the list of bankrupt firms, publicly-traded hospitality firms represented by the primary Standard Industrial Classification (SIC) code 5812 (Eating and Drinking Places), 7011 (Hotels and Motels) and 7990 (Services-Miscellaneous Amusement & Recreation), were included for the study. One hundred and twenty-eight firms were selected, 24 bankrupt firms and 104 non-bankrupt firms.

The primary purpose of the study is to compare the accuracy of an Artificial Neural Networks to that of a logit model in predicting hospitality firms' bankruptcy. Therefore, the same collection of sample companies was used for both neural network and logit analysis. In neural network analysis, out of 128 companies, 104 companies were used to train the neural network (also, referred to training phase) and 24 companies were used for testing phase. Similarly, the same proportion of sample was used for model estimation and holdout sample test to validate the estimated model created by logit analysis. A list of selected firms in the sample of this study is presented in Appendix A. After model estimation, in an attempt to test prediction accuracy, ten firms excluded for model estimation were used to test the model's predictive power for both ANNs model and a logit model. The holdout sample used in the model accuracy test is listed in Appendix B. In spite of attempts to match the number of firms in the holdout sample with the number of firms in the estimation sample, a lack of financial information made this impossible. For model estimation, financial information of sample firms such as total assets, cash flows, and net income was collected from Standard & Poor's Compustat database. Financial information used for bankrupt firms was from the last financial statement issued before the firms filed for bankruptcy. Thus, the bankruptcy prediction was made about one year prior to bankruptcy.

Research Variables

For the purpose of this study, 18 variables were examined as potential predictors of business failure. 18 financial indicators such as current ratio, ROA (Return on asset, profit margin of sample firms were used as research variables. These variables were determined on the basis of references to key attributes which prior studies found as important indicators of bankruptcy (Ferner & Hamilton, 1987; Kim, 2006).

Financial ratios are generally classified into several groups based on the information that each financial ratio represents (Andrew & Schmidgall, 1993). The variables used in the study have been grouped into five categories: liquidity, solvency, leverage, profitability, and efficiency.

Liquidity ratios measure a firm’s ability to meet its short-term obligations, that is, the ability of a firm to pay short-term expenses. The higher the value of the ratio is the more margins of financial securities that a company reserves enough liquidity to meet its obligation. A level of liquidity of a firm is very important to evaluate firms’ financial position. In this study, the current ratio, quick (acid) ratio, and working capital to total assets ratio were selected for model estimation.

Solvency ratios measure a firm’s ability to meet its long-term obligations, and solvency ratios indicate a firm’s degree of debt financing. When a company is insolvent, its chance of going bankrupt increases drastically. In this study, solvency was measured by liabilities to net worth and debt to earning before interest, tax, and depreciation and amortization (EBITDA).

Leverage ratio measures a level of money that investors or businesses borrowed from external resources to maximize shareholder's return. It shows the use of debt instead of equity to maximize a firm's speculative capacity. In this study, debt to market value of equity and tangible financial leverage were used to weigh firms' leverage.

The profitability ratios are important since they reflect the management team's operational effectiveness. The main concern of owners and investors is building their wealth, which is highly dependent on firms' profitability from operations. Therefore, the primary purpose of operation is to generate a profit. Gu (2002) indicated that unprofitable firms have a higher likelihood of going bankrupt. In this study, profitability was measured by five variables: gross profit margin, net profit margin, net income to the number of employees, return on assets (ROA), and return on sales (ROS).

Operating efficiency is a firm's ability to generate sales revenue by using its resources as efficiently as possible. Four ratios were used in the study to measure firms' operating efficiency: total assets turnover and fixed assets turnover, earning before interest, tax, and depreciation and amortization (EBITDA) to total assets, and earning before interest and tax to current assets (EBIT) were used to measure a firm's ability to maximize its revenue with a given amount of resources. Furthermore, additional two values from income statement; net income and EBITDA were selected as research variables as well as 16 ratios.

Data Analysis

In order to compare performance of two methodologies in classifying firms' bankruptcy, collected data were analyzed in two different ways. Empirical results of each analysis were the subject of comparison.

First, the data was entered into the Statistical Package for Social Sciences 15.0, (SPSS), for an independent t-test for mean comparison and logistic regression analysis. Prior to conducting the logistic analysis, the independent t-test was utilized to identify whether there was a difference in the mean value of each variable between bankrupt and non-bankrupt firms. T-values and p-values of each comparison were investigated. After the t-tests, logistic regression analysis was employed. The main advantage of this method is that no assumptions are necessary regarding the distributional properties of the predictors. In addition, it creates a non-linear transformation of the predictor variables, which reduces the impact of outliers. In estimating the logit model for predicting bankruptcy, dependent variable 1 was assigned to bankrupt firms and 0 was assigned to non-bankrupt firms. In logit analysis, the 'odds' of dichotomous outcomes are related to a set of independent variables. The odds were defined as, "the ratio of probabilities of bankruptcy to probability of non-bankruptcy," in turn, $p/(1-p)$, where p is probability of bankruptcy occurrence. It was expressed in logit form (1):

$$\text{Log}[P(x) / (1- P(x))] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \qquad (1)$$

Where,

$P(x)$ = Probability of the bankruptcy occurrence
β_0 = the intercept term
β_1 - β_i = the β coefficient associated with the corresponding explanatory variable X
X_1- X_i = the financial ratios

Several studies have attempted to find financial ratios as predictor variables which have a significant impact on determining firms' bankruptcy (Barniv, Agarwal, & Leach, 2002; Nam & Jinn, 2000). According to Theodossiou (1991), selecting financial ratios as independent variables can be onerous for researchers because representations of financial ratios are not necessarily associated with statistical significance in a model. Therefore, this study employed the forward stepwise procedure to select the variables for inclusion in a logit model among 18 candidate variables.

The dependent variable is the natural logarithm of the odds, which can be interpreted as the predicted probability (Hosmer & Lemeshow, 1989; Pampel, 2000). The probability of bankruptcy occurrence lies between 0 and 1 and is expressed in a dichotomy.

The natural logarithm of the odds can be interpreted according to Equation (2):

$$P(x) = \frac{1}{e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i)}} \tag{2}$$

Where,

e = the base of the natural logarithm

$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i$

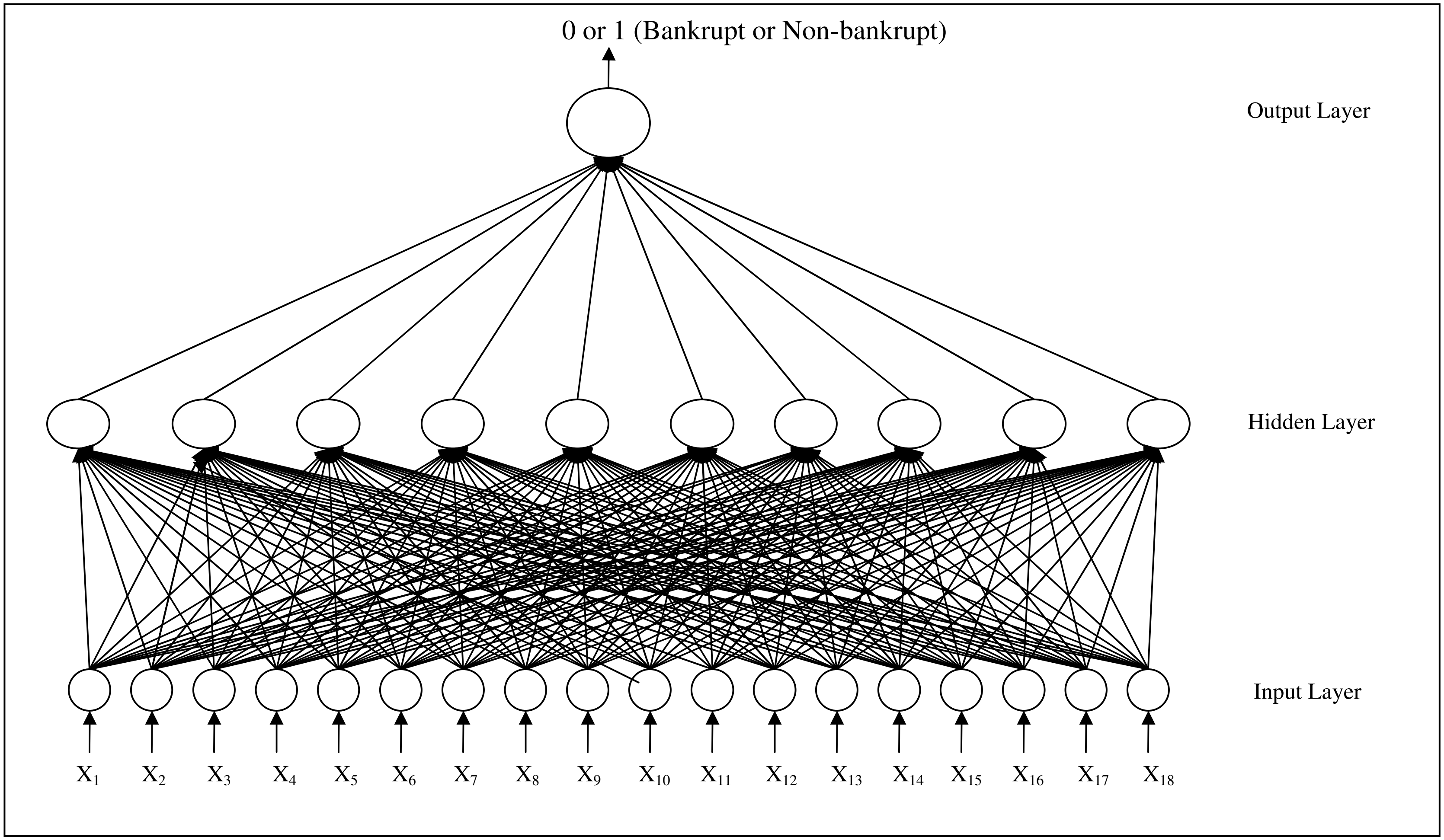
The probability of bankruptcy occurrence was calculated according to Equation (2) and the sample firms were classified into either a bankrupt or a non-bankrupt group based on its predicted probability of bankruptcy.

Second, collected data were imported in SPSS Clementine 11.0 for neural network analysis. Artificial Neural Networks (ANNs) are mathematical representations or computational models mimicking the neurobiological networks of the human brain function. The human brain's bewildering capabilities to process information, learn, and solve problems inspired researchers to construct a model that resembled its structure (Tam & Kiang, 1992).

ANNs are dynamic systems that consist of multiple parallel layers: an input layer, a hidden layer, and an output layers. Each layer is composed of interconnected interacting groups of artificial neurons. These neurons receive stimuli from the external and internal environment and exchange information by releasing neurotransmitters to the neighboring neurons (Shah & Murtaza, 2000). Repetition of the interacting process occurs during the training phase until the system recognizes a pattern of received information. In the current study, 18 financial ratios' of hospitality firms served as the external stimuli to train the model.

ANNs are designed to emulate the human brain's pattern recognition function through processing multiple inputs (Anandarajan, Lee, & Anandarajan, 2001). As a biological network produces a response in self-adaptive neurobiological connections and interactions among neurons, input-output mapping functions of ANNs are commanded according to computational algorithm designed to alter the weights of connections of homogeneous units. Most ANN models correspond to a mathematical function represented by $\boldsymbol{f}\mathbf{:}\ \mathbf{X} \rightarrow \mathbf{Y}$ and each type of ANNs model has each function of X. Figure 1 illustrates a neural network model used in this study for bankruptcy prediction. The neural network model used in this study is MLP (Multi-Layer Perceptron) network, multi-layer consisting an input layer, hidden layer, and output layer and feed-forwarding model meaning that data is fed forward from the input nodes to the output nodes without ever looping back on itself. An input vector in the input layer, Xi = ($\chi_{i1}, \chi_{i2}, \chi_{i3}, \chi_{i4}, \cdots, \chi_{i18}$), represents each financial ratios listed in the previous section.

Figure 1. A Network Configuration of Bankruptcy Prediction



Note: X_1= gross profit margin, X_2= EBITDA, X_3= net income, X_4= debt to EBITDA, X_5= liabilities to net worth, X_6= EBITDA to total assets, X_7= debt to market value of equity, X_8= current ratio, X_9= quick ratio, X_{10}= fixed asset turnover, X_{11}= net profit margin , X_{12}= total asset turnover, X_{13}= tangible asset leverage, X_{14}= working capital to total asset, X_{15}= EBIT to total current assets, X_{16}= net income to total employees, X_{17}= ROA, X_{18}= ROS.

In this study, the SPSS Clementine 11.0 neural network software package was used for data analysis. This software implements back propagation learning algorithm to train a neural network model. Back propagation algorithm refers to a method training a neural network model by adjusting each node's weights until it converges to desired value. Since the desired value is provided to the model while it is trained, it is referred to a supervised learning technique and it is designed to train feed-forward network (Anandarajan et al., 2001, Tam, 1991; Tam & Kiang, 1992).

Back-propagation Training Algorithm

In the training phase, an input vector $X_i = (\chi_{i1}, \chi_{i2}, \chi_{i3}, \chi_{i4}, \ldots , \chi_{i18})$, the numerical values of 18 financial ratios with varying weights associated with function f, generates intermediate y values, which can be defined as:

$$f(wx) = wx$$

In this current study, 18 financial variables served as the input nodes and each input node associates with varying weights. Inputs nodes in the input layer are connected to the hidden nodes in the hidden layer. In the hidden layer, each of these weights is adjusted through a number of iteration until the neural network model finds the best fit for the given answers. Expanding the simple equation to more than one variable along with the number of input nodes $f(wx)$ becomes:

$$f(wx) = \sum_{i=1}^{n} w_i x_i \qquad \text{(a)}$$

From the equation above, the sum of these weighted inputs can be derived. The sum of weighted input (a), which can be presented as intermediate y, is transformed to the sigmoid function with respect to the issue of discontinuity. By passing through the sigmoid function, the outcome can range between 0 and 1.

$$F(y) = \frac{1}{1+e^{-\alpha y}} \qquad \text{(b)}$$

In the equation, the parameter α is called Sigmoid's parameter, and simply causes the sigmoid to change from 0 to 1 more.

y is defined for a given set of inputs, this information can be combined:

$$f(wx) = y$$

$$f(wx) = \sum_{i=1}^{n} w_i x_i$$

$$y = \sum_{i=1}^{n} w_i x_i$$

$$F(y) = \frac{1}{1+e^{-\alpha y}}$$

$$F(y) = Y$$

$$Y = \frac{1}{1+e^{-\alpha \sum_{i=1}^{n} w_i x_i}}$$

In the training phase, the desired output of the neural network is given. Therefore, it is possible to define the error as the difference between the desired output and the actual calculated output. If the symbol T is assigned to the target output (either 1 for bankrupt or 0 for non-bankrupt) and a j subscript is used to denote individual specimens, the error to be adjusted e may be defined as:

$$e_j = Y_j - T_j$$

Therefore, the Mean Squared Error (MSE) may be defined as a function of the weights:

$$E(w) = \frac{1}{2}\sum_{j=1}^{p}(Y_j - T_j)^2 \qquad \text{(c)}$$

After carrying out the mathematical steps above, a Mean Squared Error (MSE) is be reached. It is the purpose of the iteration process to adjust these weights in such a way that reduces the Mean Squared Error.

If a certain weight produces a relatively small error, this weight does not need to be changed by the same factor as one which produces a large error. Therefore, by using an optimization algorithm, a local minimum of a function can be found with respect to the weights that were used. This is done mathematically by making adjustments to the weights using the gradient descent method. Using this method weights are changed by the equation:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}}$$

In this equation, the change in error with respect to the weights is defined as a partial derivative since the error is also a function of the inputs. A new term, η , is referred to as the "learning factor." This factor may be used to either increase or decrease the amount by which the weights are changed. This will either speed or slow the solution. In some cases, slowing the solution may be necessary in order to provide numerical stability. The partial derivative of the error was found by considering the three mathematical steps used to determine:

$$E(w):$$
$$E(Y)$$
$$Y(y)$$
$$y(w)$$

Therefore,

$$E(Y(y(w)))$$

Expanding the derivative:

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial Y}\frac{\partial Y}{\partial y}\frac{\partial y}{\partial w}$$

Derivative of y is simply x:

$$\frac{\partial y}{\partial w} = x$$

The derivative of the sigmoid is:

$$\frac{\partial Y}{\partial y} = \alpha y(1 - y)$$

Finally, the algebraic equation for the Mean Squared Error may be differentiated to yield:

$$\frac{\partial E}{\partial Y} = \sum (Y - T)$$

Substituting all of these derivatives into the equation for the adjustment of the weights:

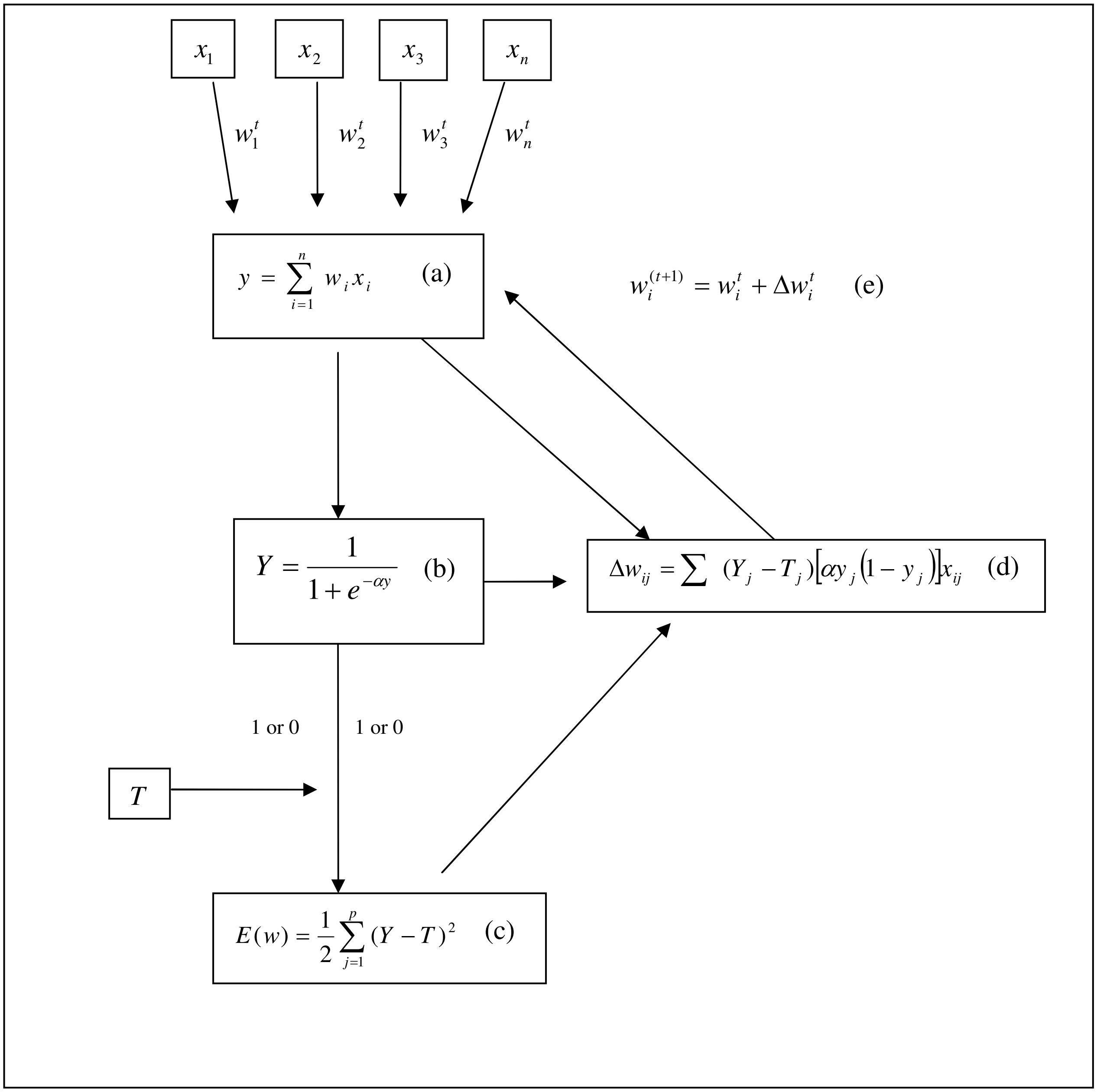
$$\Delta w_{ij} = \sum (Y_j - T_j)\left[\alpha y_j \left(1 - y_j\right)\right] x_{ij} \qquad \text{(d)}$$

The weights of the next iteration ($t + 1$) may then be found by:

$$w_{ij}^{(t+1)} = w_{ij}^{t} + \Delta w_{ij}^{t} \qquad \text{(e)}$$

With the ability to adjust the weights in a manner which reduces the Mean Squared Error, it is now possible to construct an iterative algorithm which will arrive at weights that produce minimal error. This process repeats until the error converges to a satisfactory value, which falls below threshold value. This back propagation learning algorithm is summarized in Figure 2.

Figure 2. Back-propagation Learning Algorithm



Note: $\chi_1, \chi_2, \chi_3, \chi_n$= input vectors, w_1^t , w_2^t , w_3^t w_n^t = varying weights associated with value χ, T= the target outputs (either 1 for bankrupt or 0 for non-bankrupt)

In order to validate the classifying performances of the logit analysis and the neural network analysis, 24 firms excluded in model estimations, consisting of eight bankrupt firms and 16 non-bankrupt firms, were used in out-of-sample test. The estimated model from logit analysis was tested with a holdout sample and the trained neural network model was tested with a testing sample.

Last, the number of firms correctly classified was counted as contrasted to the number of firms incorrectly classified to obtain the accuracy rates from logit and neural network analysis. The accuracy rates of two methodologies were compared to evaluate performances in predicting bankruptcy of hospitality firms.

CHAPTER IV

FINDINGS

Mean Comparison

Independent sample t-test

The financial information of bankrupt and non-bankrupt firms represented by 18 ratios was compared. In order to compare the mean value of the two groups, an independent sample t-test was employed. The results of the independent sample t-test show that eight financial ratios were significantly different between the two groups at the 0.10 level: current ratio, quick ratio, working capital to total assets, EBITDA, EBIT to total current assets, debt to market value of equity, return on assets, and net income to the number of employees. Among the eight ratios, five ratios: working capital to total assets, EBITDA, EBIT to total current assets, debt to market value, and net income to the number of employees were likewise significant at the .05 level, showing that there were significant differences in these five ratios between two groups. Table 3 shows each group's mean value of 18 financial ratios, independent t-test value, and p-value.

Table 3. Comparison of Financial Ratios of the Two Groups

Ratio	Mean (Bankrupt Firms)	Mean (Nonbankrupt Firms)	T-Value	P-Value
Current Ratio	.5600	1.2287	-1.962	.052*
Quick Ratio	.3992	.9779	-1.682	.095*
Working Capital to Total Assets	-.3250	-.0462	-2.999	.005**
EBITDA	10.8817	191.8539	-2.898	.005**
EBIT to Total Current Assets	-.4046	.3514	-2.056	.042**
EBIT to Total Assets	.1458	.1103	.288	.776
Debt to EBITDA	24.9504	5.6363	1.185	.248
Liabilities to Net Worth	146.3417	87.2173	.522	.606
Debt to Market Value of Equity	8.9346	.6549	2.227	.036**
Tangible Financial Leverage	-1.5808	8.6315	-.755	.452
Net Income	-11.1300	90.2663	-1.320	.189
Gross Profit Margin	30.2000	23.1200	1.253	.221
Net Profit Margin	-47.8654	-7.9851	-1.317	.200
Total Asset Turnover	1.5983	1.6371	-.162	.871
Fixed Asset Turnover	2.6254	3.9914	-1.360	.176
Return on Assets	-.1750	.0036	-1.986	.058*
Return on Sales	-.4467	-.0785	-1.206	.239
Net Income to the Number of Employees	-17.6392	2.1461	-2.068	.041**

Note: EBIT= earning before interest and tax, EBITDA= earning before interest, tax, and depreciation and amortization *Significant at the .10 level. **Significant at the .05 level.

In-Sample Model Construction

Estimated Logit Model

The logistic regression result selected four independent variables and a constant at significance level of 0.05: gross profit margin, EBITDA to total asset, debt to market value of equity, and EBIT to total current assets. Cox & Snell R^2 and Nagelkerke R^2 are pseudo-R squares. They show a goodness of fit of regression models. Omnibus test results demonstrated that the overall goodness of the estimated model was significant at 0.01 level associated with 48.257 chi-square value. Hosmer & Lemeshow Test was not significant at 0.05 level. Thus, the null hypothesis that there is no difference between the observed and predicted values of dependent was rejected, indicating the logistic model is a good fit. A value of (β) refers to coefficient of variables and constant. A Wald test was used to test the statistical significance of each coefficient (β) in the model. Four variables and constant were significant at 0.05 level. Table 4 presents a summary of the estimated Logit model for the hospitality firms' bankruptcy prediction.

Table 4. Summary of the Estimated Logit Model

Model Summary						**Value**
-2 log likelihood (-2LL)						41.042
Cox & Snell R^2						.371
Nagelkerke R^2						.644
Omnibus Test of Model Coefficients				**Chi-Square**	***df***	**Sig.**
Step				-1.107	*1*	.293
Block				48.257	*4*	.000
Model				48.257	*4*	.000
Hosmer & Lemeshow Test				**Chi-Square**	***df***	**Sig.**
				8.969	8	.345
Variable in Equation	**(β)**	**S.E**	**Wald**	**df**	**Sig.**	**Exp(B)**
Gross profit margin	.053	.019	8.074	1	.004	1.054
EBITDA to Total Assets	6.838	2.825	5.858	1	.016	933.044
Debt to Market Value	.782	.225	12.125	1	.000	2.186
EBIT to Total Current Assets	-.785	.291	7.260	1	.007	.456
Constant	-5.627	1.158	23.623	1	.000	.004

As a result of logit analysis for bankruptcy for the hospitality industry, the estimated logit model used to calculate the probability of bankruptcy was constructed in the manner previously described using the variables:

$$\text{Logit}\left[\frac{P(x)}{(1-P(x))}\right] = -5.627+0.053\ X_1-6.838\ X_2+.782X_3-.785X_4 \qquad (3)$$

Where,

X_1= gross profit margin
X_2= EBITDA to total asset
X_3= debt to market value of equity
X_4= EBIT to total current asset

From this logit analysis, 104 sample firms (16 bankrupt firms and 88 non-bankrupt firms) in analysis were classified into two groups. Firms with predicted probabilities above 0.5, the cut-off value, were classified as bankrupt and firms with predicted probabilities below 0.5 were classified as non-bankrupt. The estimated model correctly classified 95 firms, showing a 91.3% overall accuracy rate, or correspondingly, incorrectly classified 9 firms, an 8.7% overall error rate. A closer look showed that the 8.7% overall error rate was associated with type-I error, misclassification of failed firms into non-failed firms, as well as type-II error, misclassification of non-failed firms into failed firms. When divided into type-I and type-II errors, it was seen that these were 6.7% and 1.9%, respectively. Table 5 shows the classification results of the bankruptcy prediction model drawn from two analyses.

Table 5. Logit Model In-Sample Classification

Actual Status	Number Cases	Predicted Status		Accuracy Rate	Overall Accuracy
		Bankrupt	N-Bankrupt		
Non-Bankrupt	88	2	86	97.7	91.3
Bankrupt	16	9	7	56.3	

Trained Neural Network Model

After construction of the logit model, the same data were subjected to Clementine using neural network analysis. The model generated 25 neurons in the first hidden layer and 12 neurons in the second hidden layer. The output layer of the neuron took a value of either 1 (bankrupt) or 0 (non-bankrupt) depending on the case. Estimated accuracy of the model was 92.9%. The model selected five inputs depending on each input's contribution in the model training phase. Five inputs: fixed asset turnover, working capital to total assets, debt to market value of equity, liabilities to net worth, and gross profit margin were selected along with a degree of relative importance. Table 6 represents a summary of the trained neural network model.

Table 6. Summary of the Trained Neural Network Model

Model Summary				Value
Estimated Accuracy				**92.857 %**
Input Layer	**Hidden Layer 1**	**Hidden Layer 2**	**Output Layer**	
5 neurons	25 neurons	12	1 neurons	
Sensitivity Analysis				
Relative Importance of Inputs				
Fixed Assets Turnover				1.05
Working Capital to Total Assets				1.00106
Debt to Market Value of Equity				0.987545
Liabilities to Net Worth				0.918479
Gross Profit Margin				0.548275

Model Validation

Hold-out Sample Test

Each company's predicted probability of going bankrupt was calculated according to Equation 3, which was derived from logistic regression analysis with 104 in-sample firms. The logistic equation above (3) was transformed into the equivalent formulation below in order to obtain predicted probability of bankruptcy occurrence.

$$P(x) = \frac{e^{(-5.627 + 0.053\ X1 - 6.838\ X2 + .782X3 - .785X4)}}{1 + e^{(-5.627 + 0.053\ X1 - 6.838\ X2 + .782X3 - .785X4)}} \qquad (4)$$

Where,

X_1= gross profit margin
X_2= EBITDA to total asset
X_3= debt to market value of equity
X_4= EBIT to total current asset

Based on Equation (4), the predicted probability of each firm in the holdout sample was obtained, and firms were classified into two groups depending on their predicted probability using a cut-off value 0.5. Table 7 shows the predicted probability and membership of each firm. As Table 7 demonstrates, 20 out of the 24 firms were classified correctly indicating 83.3% of overall prediction accuracy. The model failed to place four bankrupt firms into the bankrupt group. This translated into 16.7% Type-I error. However, this particular model correctly identified all non-bankrupt firms, giving it no associated Type-II error.

Table 7. Holdout Sample Prediction from Logit Model

	Actual Group	**Predicted Group**	**P(E)**
American Restaurant group, inc	1	1	0.8569
Buffet Holdings, Inc.	1	1	0.8287
Einstein Noah Resaturant	1**	0	0.0106
ICH	1**	0	0.2431
Krystal co	1**	0	0.0028
Piccadilly Cafeterias	1**	0	0.0031
Planet Hollywood	1	1	0.9935
Prandium Inc	1	1	0.9485
BJ's Restaurants Inc.	0	0	0.0040
Carrols Corp	0	0	0.0010
Champps Entertainment Inc.	0	0	0.0030
Mortons Restaurant Group Inc	0	0	0.0012
Papa Johns International Inc.	0	0	0.0020
Texas Roadhouse Inc.	0	0	0.0009
Buca Inc.	0	0	0.0028
California Pizza Kitchens Inc.	0	0	0.0013
Champion Entertainment, Inc	0	0	0.0016
Diedrich Coffee Inc.	0	0	0.0432
Frisch's Restaurants Inc.	0	0	0.0008
Max & Ermas Restaurants	0	0	0.0021
KSL Recreation Group Inc.	0	0	0.0049
Starwood Hotels & Resorts World	0	0	0.0050
Sonesta International Hotels	0	0	0.1078
Steak N Shake Co.	0	0	0.0092

Note: Group 0= Non-bankrupt firms, Group 1= Bankrupt firms, **Misclassification

Testing Sample Test

In the neural network analysis, 24 firms were tested to validate the effectiveness of the trained neural network model. The confidence level simply indicated the degree of likeliness of output predicted by the trained model. As shown below, 21 out of the 24 firms were classified correctly demonstrating 87.5% overall prediction accuracy. In other words, the model had a12.5% error rate. This entire error rate was made up of Type-I error, a misclassification of failed firm as non-failed firm. However, it could again be seen that this model produces no Type-II error. Table 8 shows the confidence level of neural network analysis and a final membership of each firm.

Table 8. Testing Sample Prediction from Neural Network Model

	Actual Group	**Predicted Group**	**Confidence**
American Restaurant group, inc	1	1	0.7713
Buffet Holdings, Inc.	1	1	0.7713
Einstein Noah Restaurant	1**	0	0.7950
ICH	1	1	0.2757
Krystal co	1**	0	0.8147
Piccadilly Cafeterias	1**	0	0.7457
Planet Hollywood	1	1	0.7713
Prandium Inc	1	1	0.7713
BJ's Restaurants Inc.	0	0	0.8588
Carrols Corp	0	0	0.8112
Champps Entertainment Inc.	0	0	0.8382
Mortons Restaurant Group Inc	0	0	0.8112
Papa Johns International Inc.	0	0	0.8586
Texas Roadhouse Inc.	0	0	0.8112
Buca Inc.	0	0	0.8583
California Pizza Kitchens Inc.	0	0	0.8589
Champions Inc.	0	0	0.8497
Diedrich Coffee Inc.	0	0	0.8578
Frisch's Restaurants Inc.	0	0	0.8264
Max & Ermas Restaurants	0	0	0.7683
KSL Recreation Group Inc.	0	0	0.8112
Starwood Hotels & Resorts World	0	0	0.6871
Sonesta International Hotels	0	0	0.5341
Steak N Shake Co.	0	0	0.7713

Note: Group 0= Non-bankrupt firms, Group 1= Bankrupt firms, **Misclassification

CHAPTER V

CONCLUSION

Summary of the Study

This study compared the accuracy of an Artificial Neural Networks for predicting hospitality firms' bankruptcy occurrences to that of a logit model. The research questions were as follows:

Research Question 1: Does an Artificial Neural Networks outperform Logit, a conventional statistical technique, in predicting a hospitality firm's bankruptcy?

Research Question 2: What financial ratios significantly predict the classification of hospitality firms as bankrupt or non-bankrupt?

To achieve the purpose of study, 128 hospitality firms represented by the primary Standard Industrial Classification (SIC) code 5812 (Eating and Drinking Places), 7011 (Hotels and Motels) and 7990 (Services-Miscellaneous Amusement & Recreation) were included in the study. Eighteen financial ratios of 128 firms were collected from Standard & Poor's Compustat database and a total of 2304 input values were analyzed. Analytic techniques of the present study were a logit and an ANNs model. Collected data was imported to SPSS for Logit analysis and Clementine for a neural network analysis. The results of these two analyses were the subject of comparison.

Discussion and Implications

This study demonstrated the power of neural network by comparing its predictive capability with that of a logit model in predicting hospitality bankruptcy. From empirical results of the two methodologies, it was shown that neural network obtained a higher accuracy rate than did a logit model in an in-sample test as well as in holdout (testing) sample test. This result confirmed previous assertions made by many researchers stating the superiority of neural network over logit models in classification and prediction tasks.

Neural network analysis showed that the trained neural network model achieved 92.9% estimated accuracy. This was slightly higher than the accuracy rate achieved by the logit model. In the testing (holdout) sample test, the ANNs model confirmed the validity of the trained model with an 87.5% accuracy rate associated with 12.5% Type-I error and 0.0% Type-II error. It is noteworthy that not only did neural network achieve a higher overall accuracy rate than the logit model from in-sample test as well as from holdout test, but the higher accuracy rate was attained by lowering Type-I error, that is, lowering the misclassification of failed firms. Since Type-I error involves much higher costs than does Type-II error (Lee et al., 2005), it could be inferred that neural network models are a more sophisticated tool when used for classification tasks than are a logit models.

Second, the empirical results of analyses provided an instrument to take a closer look into companies' financial status. A t-test revealed the underlying structure of financial ratios between failed and non-failed firm. As shown in Table III, five ratios: working capital to total assets, EBITDA (earning before interest, tax, and depreciation and amortization), EBIT (earning before interest and tax) to total current assets, debt to market value of equity, and net income to the number of employees, demonstrated significant difference between the two groups. Each ratio measured a certain dimension of companies' financial status depends on contexts it contains. The five ratios found from the analysis belong to sub categories that represent liquidity, solvency, profitability, and efficiency. This implies that bankrupt firms are likely to have less liquidity and solvency to meet their short-term and long-term financial obligations than are non-bankrupt firms. Illiquidity could be caused by insufficient cash due to unprofitable and inefficient operations. Recalling that bankruptcy is defined as the inability of a firm to meet its payment obligations due to a lack of liquidity and solvency, this was no surprise. Although far more factors must be taken into account in order to diagnose a firm's financial position, implications drawn from the t-test could confirm the well-known cause of a company's bankruptcy.

In the estimated logit model, as shown in Table 4, four variables: gross profit margin, EBITDA to total assets, debt to market value of equity, and EBIT to total current asset were selected as significant variables from logit analysis. This does not mean that each of the four ratios provide conclusive evidence when taken individually.Gross profit margin, EBITDA to total assets, debt to market value, and EBIT to total current assets together constitute the most straightforward indicators for predicting bankruptcy in the logit model. In a sense of building a logit bankruptcy prediction model, a company's success or failure is a simple outcome of the complex function of inputs summed and transformed together weighing by importance of these four ratios' role.

Although a single ratio from each analysis does not provide conclusive evidence individually in deciding whether a firm goes bankrupt or not, special attention was paid to a ratio 'debt to total market value of equity'. Neural Network's trained model ranked debt to market value of equity as a highly important input in building a bankruptcy prediction model. Debt to market value of equity was a significant variable from both t-test and logit analysis. Debt to market value of equity is a leverage ratio indicating how a business or a firm utilizes debts instead of utilizing equity to maximize its speculative capacity. It is known that utilizing leverage could increase potential profits, gains, and growths. However, it is more important to note that it could amplify losses when investment returns do not meet its expected level, which simply includes, interest and principal payments. The results of the t-test showed that the mean value of debt to market value of equity of bankrupt firms was significantly higher than that of the non-bankrupt firm group, while a positive coefficient of debt to market value of equity in the logit model implied that a higher value of this ratio leads a classification into bankruptcy. Since the hospitality firms are especially well-known for being highly-leveraged, a conclusion could be drawn that extensive debt-financing not accompanied by competitive market value of equity could play a vital role in forcing firms to file for bankruptcy.

ANNs have received great attention as a tool for classification tasks. Research has revealed the superiority of neural network techniques over logit models. As shown in the results of the present study, the ANNs model achieved higher prediction accuracy than did the logit model when two sets of an identical sample were analyzed. This result could be attributed to neural networks' outstanding prediction accuracy when it carries out classification or prediction tasks. However, every technical methodology has drawbacks, and neural networks are no exception.

ANNs demonstrated a surprisingly accurate predictive ability compared to other techniques. In order to get a good result, extensive data preparation was required. An order and format or data setting can make a big difference in the results and neural networks cannot accommodate missing values. Thus, careful attention is required when preparing data. Moreover, ANNs involve complex mathematical equations, with a lot of transformations and exponential functions, to produce extensive networks in hidden layers, which are not easily understood and interpreted. This is why ANNs is not preferred if one is more concerned with the context of the results than with the results themselves. As the term 'hidden layer' implies, a complex networking inside a model, sometimes, can be obscure to human eyes. If one is simply concerned with the results, as in the case of detecting credit card fraud, a neural network may be the best choice. However, the contexts of such decisions are not quantifiable. A critique of the current study should take this into consideration.

It was a meaningful finding that a neural network model achieved higher accuracy rate attained by lowering type-I error compared to a logit model. This can be vital information when companies try to protect themselves from going bankrupt by being alerted to trouble early on. However, it was a bit difficult to interpret a network model to draw further implications. The model ranked inputs according to the magnitude of contribution in the model construction process, but it did not tell how inputs behaved inside of the model, whether its impact was positive to the output or negative to the output, whereas the logit model extracted significant variables along with the coefficient values, which allows one to construct a bankruptcy model after such analysis. Although intermediate variables are defined within the network, these parameters are of limited interpretive value and are certainly not comparable statistical values to which they appear analogous. This leaves neural networks open to criticism by researchers who wish to draw implications from the algorithm's convoluted, nonlinear data transformation (Delen & Sirakaya, 2006; Matheus, Chan, & Piathtsky-Shapiro, 1993). A neural network is a great detection tool, which will reveal whether an event will occur or not, however, further investigation is required. No technique is perfect for all situations. It can be thus concluded that a technical approach should be accompanied by an awareness of the strengths and weaknesses of each technique in order to obtain the best result with regard to its implication.

Limitations and Future Research

This study was not free of limitations. The small sample size, due to the lack of available financial data, precluded more sophisticated analysis. Despite an attempt to match bankrupt and non-bankrupt firms according to asset size and year of bankruptcy to minimize such limitations, such a data set could not be generated due to this study's focus on the hospitality industry.

For the same reason, this study could test only one year prior to bankruptcy. A one year period is not long enough for managers to make strategic plans for recovery. An early warning sign of bankruptcy could allow hospitality firms times to restructure the organization or debt-financing policies to prevent themselves from filing for bankruptcy.

In addition, the study analyzed business failure only from an internal perspective. Business entities interact with society and are affected by factors such as politics, economics, and culture. Hospitality firms are especially vulnerable to social and economic changes since the majority of revenue relies on disposable income. It is difficult for a social phenomenon to be explained by a single factor and from a single perspective. Therefore, it is recommended to take external aspects into account when analyzing hospitality bankruptcy.

These limitations suggest avenues for further research. First, a longer period of observation can be conducted in order to draw more practical implication. Investigation for bankruptcy occurrences can be conducted two years, five years, or even 10 year prior to bankruptcy in maximize the efficacy of prediction tools. To ensure comparability and minimize effects of factors not being addressed by the study, matching the bankrupt and non-bankrupt groups' asset size and year of bankruptcy is recommended. In particular, this could give researchers the possibility of using a more sophisticated analysis, which may result in more accurate observations.

Second, it is suggested that a study using another advanced techniques such as Support Vector Machine (SVM), genetic algorithms, or data envelopment analysis. These methods have recently been tested by many scholars and researchers and the outstanding capabilities of these methods have been proven. Thus, it is expected that using these technique will generate even more robust results.

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APPENDIXES

APPENDIX A

SAMPLE FIRMS USED IN MODEL ESTIMATION

Sample Bankrupt Hospitality Firms Used in Model Estimation

IDENTIFICATION	BANKRUPT FIRM	TOTAL ASSETS (MILLION $)
9	ROADHOUS GRILL	100.33
10	TAJ MAHAL	25.11
11	SCHOLATZSKY’S	125.79
12	STEAKHOUS PARTNERS	32.71
13	LODGIAN, INC	1163.95
14	PRIME MOTOR INN, INC.	122.28
15	ARLINGTON HOSTPITALIY, INC	103.36
16	INTEGRA- A HOTEL & RESORT	67.01
17	HOLLYWOOD CASINO SHREVEPORT	141.71
18	CCI GROUP	6.19
19	CLARIDGE HOTEL&CASINO	131.78
20	AMERICAN WAGERING INC	8.94
21	FITZGERALDS GAMING CORP	206.80
22	GB HOLDINGS INC	216.96
23	PREMIER EXHIBITIONS INC	10.76
24	WINDSOR WOODMNT BLK HWK REST	152.93

Note: Identification number was randomly assigned from 1 to 128 to each sample for convenience.

Sample Non-Bankrupt Hospitality Firms Used in Model Estimation

IDENTIFICATION	NON-BANKRUPT FIRM	TOTAL ASSETS (MILLION $)
41	GREAT WOLF RESORTS INC	173.49
42	PISMO COAST VILLAGE INC	8.48
43	PANERA BREAD CO	153.62
44	ARK RESTAURANTS CORP	43.63
45	BENIHANA INC -CL A	204.29
46	BERTUCCI'S CORP	125.20
47	BOB EVANS FARMS	1196.96
48	BRAZIL FAST FOOD CORP	21.95
49	BRINKER INTL INC	2221.78
50	BURGER KING HOLDINGS INC	2552.00
51	BUFFALO WILD WINGS INC	161.18
52	CALA CORP	0.86
53	CARIBOU COFFEE CO	136.31
54	CARROLS RESTAURANT GROUP INC	452.86
55	CBRL GROUP INC	1681.30
56	CEC ENTERTAINMENT INC	704.18
57	CHAMPPS ENTMT INC	332.37
58	CHEESECAKE FACTORY INC	1039.73
59	CHIPOTLE MEXICAN GRILL INC	604.21
60	CKE RESTAURANTS INC	794.422

IDENTIFICATION	BANKRUPT FIRM	TOTAL ASSETS (MILLION $)
61	COSI INC	75.76
62	DARDEN RESTAURANTS INC	2880.80
63	DENNYS CORP	443.91
64	DOMINO'S PIZZA INC	380.20
65	EAT AT JOES LTD	1.16
66	ELEPHANT & CASTLE	16.97
67	ELXSI CORP	74.31
68	FAMOUS DAVES OF AMERICA INC	65.64
69	FLANIGANS ENTERPRISES INC	27.40
70	FOG CUTTER CAPITAL GROUP INC	59.80
71	FRIENDLY ICE CREAM CORP	220.17
72	GOOD TIMES RESTAURANTS INC	10.69
73	GORDON BIERSCH BRWY RST-REDH	70.89
74	GRANITE CITY FOOD & BREWERY	63.86
75	GRILL CONCEPTS INC	32.24
76	J. ALEXANDER'S CORP	99.35
77	JACK IN THE BOX INC	1520.46
78	JAMBA INC	467.55
79	KONA GRILL INC	58.80
80	LANDRYS RESTAURANTS INC	1612.58
81	LUBYS INC	206.75
82	MCCORMICK & SCHMICKS SEAFOOD	228.42
83	MCDONALD'S CORP	29023.80
84	MERITAGE HOSPITALITY GROUP	46.72
85	MEXICAN RESTAURANTS INC	33.28
86	MORGANS FOODS INC	52.32
87	NATHAN'S FAMOUS INC	46.58
88	NUTRITION MGMT SVCS -CL A	13.97
89	O'CHARLEY'S INC	686.51
90	ORGANIC TO GO FOOD CORP	5.28
91	OSI RESTAURANT PARTNERS INC	2258.59
92	P F CHANGS CHINA BISTRO INC	514.04
93	PANERA BREAD CO	542.61
94	PAPA JOHNS INTERNATIONAL INC	379.64
95	PERKINS & MARIE CALLENDERS	352.14
96	RARE HOSPITALITY INTL INC	695.21
97	RED ROBIN GOURMET BURGERS	450.60
98	ROADHOUSE GRILL INC	25.11
99	RUBIO'S RESTAURANTS INC	67.50
100	RUBY TUESDAY INC	1171.57
101	RUTHS CHRIS STEAK HOUSE	209.72
102	SBARRO INC	388.54
103	SHELLS SEAFOOD RESTRNTS INC	13.84
104	SIXX HOLDINGS INC	3.47

IDENTIFICATION	BANKRUPT FIRM	TOTAL ASSETS (MILLION $)
105	SMITH & WOLLENSKY RSTRNT GRP	86.75
106	SODEXHO ALLIANCE SA -ADR	10636.10
107	SONIC CORP	638.02
108	SPEEDUS CORP	17.14
109	STAR BUFFET INC	34.17
110	STARBUCKS CORP	4428.94
111	STEN CORP	10.02
112	SYNDICATED FOOD SERVICE INTL	9.30
113	TIM HORTONS INC	1497.59
114	TULLYS COFFEE CORP -REDH	21.53
115	VICORP RESTAURANTS INC	395.24
116	VOLUME SERVICES AMERICA INC	280.19
117	WENDY'S INTERNATIONAL INC	2060.35
118	WESTERN SIZZLIN CORP	19.82
119	YUM BRANDS INC	6353.00
120	CHOCTAW RESORT DEV ENTRPRISE	489.97
121	GAYLORD ENTERTAINMENT CO	2632.52
122	HILTON HOTELS CORP	16481.00
123	HOME INNS & HOTELS MNGT -ADR	169.14
124	INTERCONTINENTAL HOTELS -ADR	3707.63
125	INTERSTATE HOTELS & RESORTS	333.69
126	MARRIOTT INTL INC	8588.00
127	ORIENT-EXPRESS HOTELS	1751.66
128	RED LION HOTELS CORP	351.44

Note: Identification number was randomly assigned from 1 to 128 to each sample for convenience.

APPENDIX B

HOLDOUT FIRMS USED FOR PREDICTION ACCURACY TEST

Sample Bankrupt Hospitality Firms Used in Accuracy Test

IDENTIFICATION	BANKRUPT FIRM	TOTAL ASSETS (MILLION $)
1	AMERICAN RESTAURANT GROUP, INC	72.82
2	BUFFET HOLDINGS, INC.	538.50
3	EINSTEIN NOAH RESTAUTANT	44.03
4	ICH	120.42
5	KRYSTAL CO.	130.79
6	PICCADILLY CAFETERIAS	133.70
7	PLANET HOLLYWOOD	146.21
8	PRANDIUM INC.	173.88

Note: Identification number was randomly assigned from 1 to 128 to each sample for convenience.

Sample Non-Bankrupt Hospitality Firms Used in Accuracy Test

IDENTIFICATION	NON- BANKRUPT FIRM	TOTAL ASSETS (MILLION $)
25	BJ'S RESTAURANTS INC	83.71
26	CARROLS CORP	452.86
27	CHAMPPS ENTMT INC	67.09
28	MORTONS RESTAURANT GROUP INC	124.41
29	PAPA JOHNS INTERNATIONAL INC	128.82
30	TEXAS ROADHOUSE INC	128.53
31	BUCA INC	123.44
32	CALIFORNIA PIZZA KITCHEN INC	145.34
33	CHAMPPS ENTMT INC	79.46
34	DIEDRICH COFFEE INC	34.13
35	FRISCH'S RESTAURANTS INC	138.64
36	MAX & ERMAS RESTAURANTS	54.93
37	KSL RECREATION GROUP INC	1034.46
38	STARWOOD HOTELS&RESORTS WRLD	263.41
39	SONESTA INTL HOTELS -CL A	109.54
40	STEAK N SHAKE CO	64.14

Note: Identification number was randomly assigned from 1 to 128 to each sample for convenience.

VITA

Soo-Seon Park

Candidate for the Degree of

Master of Science

Thesis: A COMPARATIVE STUDY OF LOGIT AND ARTIFICIAL NEURAL NETWWORKS IN PREDICTING BANKRUPTCY IN THE HOSPITALITY INDUSTRY

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Institution: Oklahoma State University Location: Stillwater, Oklahoma

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Pages in Study: 67 Candidate for the Degree of Master of Science

Major Field: Hospitality

Scope and Method of Study: The hospitality industry has been received scrutiny by many researchers because of its unique characteristics such as fluctuating supply-demand chain, seasonality, and high level of leverage. This is why much research has been conducted to find the best tool for early warning of bankruptcy. Artificial Neural Networks (ANNs) have received a great deal of attention in the area of decision support system because of their outstanding ability to forecast and classify events to make a decision This study employed Artificial Neural Networks (ANNs) to predict bankruptcy among hospitality firms and compared the performance of ANNs in predicting hospitality firms' bankruptcy to the more conventional statistical logit model.

Findings and Conclusions: From empirical results of the two methodologies, it was shown that neural network obtained a higher accuracy rate than did a logit model in an in-sample test as well as in holdout (testing) sample test. This result confirmed previous assertions made by many researchers stating the superiority of neural network over logit models in classification and prediction tasks. Even though ANNs achieved the higher prediction accuracy, they do not provide the user with useful information about how the model arrives at this prediction. Therefore, it is recommended that those who utilize such predictive tools be aware of advantages and disadvantages of the tools being used.