Oeconomia
Copernicana

Volume 13 Issue 4 December 2022

p-ISSN 2083-1277, e-ISSN 2353-1827
www.oeconomia.pl

ORIGINAL ARTICLE

Citation: Gavurova, B., Jencova, S., Bacik, R., Miskufova, M., & Letkovsky, S. (2022). Artificial intelligence in predicting the bankruptcy of non-financial corporations. *Oeconomia Copernicana, 13*(4), 1215–1251. doi: 10.24136/oc.2022.035

Contact to corresponding author: Beata Gavurova, gavurova@utb.cz

Article history: Received: 28.07.2022; Accepted: 30.10.2021; Published online: 30.12.2022

Beata Gavurova
Tomas Bata University in Zlín, Czechia
orcid.org/0000-0002-0606-879X

Sylvia Jencova
University of Presov, Slovakia
orcid.org/0000-0002-0736-0880

Radovan Bacik
University of Presov, Slovakia
orcid.org/0000-0002-5780-3838

Marta Miskufova
University of Presov, Slovakia
orcid.org/0000-0003-1077-74733

Stanislav Letkovsky
University of Presov, Slovakia
orcid.org/0000-0001-9111-4940

Artificial intelligence in predicting the bankruptcy of non-financial corporations

JEL Classification: *C45; C53; G17; G33*

Keywords: *engineering industry; automotive industry; bankruptcy prediction; Logistic regression; artificial intelligence, neural network*

Abstract

Research background: In a modern economy, full of complexities, ensuring a business' financial stability, and increasing its financial performance and competitiveness, has become especially difficult. Then, monitoring the company's financial situation and predicting its future development becomes important. Assessing the financial health of business entities using various models is an important area in not only scientific research, but also business practice.
Purpose of the article: This study aims to predict the bankruptcy of companies in the engineering and automotive industries of the Slovak Republic using a multilayer neural network and logistic regression. Importantly, we develop a novel an early warning model for the Slovak engineering and automotive industries, which can be applied in countries with undeveloped capital markets.
Methods: Data on the financial ratios of 2,384 companies were used. We used a logistic regression to analyse the data for the year 2019 and designed a logistic model. Meanwhile, the data for the years 2018 and 2019 were analysed using the neural network. In the prediction model, we analysed the predictive performance of several combinations of factors based on the industry sector, use of the scaling technique, activation function, and ratio of the sample distribution to the test and training parts.
Findings & value added: The financial indicators ROS, QR, NWC/A, and PC/S reduce the likelihood of bankruptcy. Regarding the value of this work, we constructed an optimal network for the automotive and engineering industries using nine financial indicators on the input layer in combination with one hidden layer. Moreover, we developed a novel prediction model for bankruptcy using six of these indicators. Almost all sampled industries are privatised, and most companies are foreign owned. Hence, international companies as well as researchers can apply our models to understand their financial health and sustainability. Moreover, they can conduct comparative analyses of their own model with ours to reveal areas of model improvements.

Introduction

In an increasingly dynamic and complex world, ensuring a business' financial stability and sustainability has become ever more so difficult. To measure firms' economic sustainability in this turbulent world, researchers need to connect traditional and modern metrics, and create multidimensional models. Indeed, several key financial indicators for firm survival and sustainability have been recently identified through the application of mathematical and statistical tools (Kral *et al*., 2018).

Crucially, estimating a risky company or its probability of bankruptcy is always very important not only for creditors but also for the managers or owners themselves. Using this information, the latter can then undertake necessary interventions to prevent bankruptcy (Wang, 2019). Understanding financial risk is also very important for investors' decisions (Yousaf & Bris, 2021). Stehel *et al*. (2021) noted that this is especially important for *SMEs*, since they face even more financial obstacles (Civelek *et al.,* 2020a; Civelek *et al*., 2021; Derindag *et al*., 2021; Kljucnikov *et al*., 2021). This makes them more vulnerable to (Belas *et al*., 2020; Metzker *et al.,* 2021) and have a greater likelihood of bankruptcy than larger businesses (Khan *et al.,* 2020; Psarska *et al*., 2019).

Vochozka *et al.* (2020) observed that financial distress is affected by numerous internal and external factors. Then, examining the relationship between these factors and potential insolvency leading to bankruptcy is quite relevant. Bankruptcy models that can help identify these conditions as accurately as possible become very important (Krulicky *et al*., 2020). These bankruptcy models can provide warning signals of impending danger and allow early intervention, and can help lenders estimate potential risks (Horak *et al.,* 2020a).

Many statistical estimation methods have been developed and used for this, especially for understanding financial risk. One such method is discriminant analysis, which allows the variables to differ from known groups of statistical units in the file and helps formulate classification rules. The aim of discriminant analysis is to design a discriminant function as a linear combination of various discriminatory variables. Multidimensional discriminant analysis functions include Indexes IN, Altman's model, Springate's model, Taffler's model, Fulmer's model, Chrastinova's Ch-index, and Gurcik's G index (Kliestik *et al.,* 2018).

The categorical dependent variables, logistic regression has been used (Svabova *et al*., 2020) in many studies across various disciplines (Kljucnikov *et al*., 2020a; Kljucnikov *et al.,* 2020b), including in bankruptcy predictions (Civelek *et al.,* 2020b). However, as non-linear models for bankruptcy estimation, logit and probit models have some limitations, including the restriction of the outcome by bias of the regression function, sensitivity to exceptions in bankruptcy, and implicit Gaussian distribution in most conclusions (Neves & Vieira, 2006). With technological advancements and improvements in computing performance, artificial intelligence has helped in designing new prediction models or improved the precision of existing models. For instance, an artificial neural network (*ANN)* is considered a good instrument for bankruptcy prediction.

Several studies have examined bankruptcy in the context of the Slovak economy. Valaskova *et al.* (2020) demonstrated the predictive ability of bankruptcy models for the agricultural sector. Noga and Adamowicz (2021) constructed a bankruptcy model for the wood sector. To analyse the financial failure of Slovak heat management companies, Stefko *et al*. (2020, 2021) used multidimensional scaling (*MDS*), principal component analysis (*PCA*), and data envelopment analysis (*DEA*). Kolkova and Kljucnikov (2021) used many statistical methods, such as neural networks, hybrid models, and technical analysis. To validate profit scoring models with traditional credit scoring models, Lyocsa *et al.* (2022) used several statistical methods such as logistic and linear regression, lasso, ridge, elastic net, random forest, and neural networks.

This study aims to predict the bankruptcy of companies in the engineering and automotive industries of the Slovak Republic using a multilayer neural network and logistic regression. The Slovak Republic has a strong industrial tradition and long-term focus on technical skills. According to the European Union statistics, the Slovak Republic is one of the most industrialised countries in Europe. The country's engineering industry is one of the main drivers of the Slovak economy and has a strong historical background and stable position in the Slovak industry. Similarly, the automotive industry has a strong tradition and is the most important driving force of the Slovak economy.

Our aim is to construct appropriate models to evaluate the financial situation in selected branches of the industries. Assessing the financial health of business entities using various models is an important area not only in scientific research, but also in the practice of business entities. The biggest problems in constructing these models arise while choosing suitable indicators and methods for measuring, evaluating, and managing the financial situation of business entities. Universal models are often not suitable, because they are created for specific conditions of a given economy in a given period. The benefit and originality of this study is the construction of a novel early warning model for the Slovak engineering and automotive industries. These models will significantly enrich econometric models of financial management. Furthermore, our work is particularly important and can be applied to other geographies as well. Specifically, the Slovak Republic is one of the most industrialised countries in Europe and is the world leader in car production per 1,000 inhabitants. Almost the entire industries are privatised, and most companies are foreign-owned. Therefore, international companies can apply our created models for understanding their financial health and sustainability, and even compare them with their own models to identify the areas of improvement. Finally, our models are particularly applicable in countries with underdeveloped capital markets.

The remainder of this work proceeds as follows. The literature review offers a theoretical basis for logistic regression and neural networks, and an overview of studies which use these methods in which logistic regression and neural networks were used. The research sample and methods are described in the research methodology section. The last part of the article contains the results, discussion, and conclusions.

Literature review

The enormous consequences of financial failure for creditors, investors, and employees are why bankruptcy prediction has become significant in the last 30 years. For instance, the high cost of bankruptcy, with direct and indirect cost estimates ranging 11–17%, is one of the reasons for the increased interest in forecasting (Garcia, 2022). According to a European Commission study, half of the *EU* companies do not survive their first 5 years and 15% become bankrupt. With globalization and the stresses caused by the COVID-19 pandemic, it is appropriate to focus not on whether to use bankruptcy prediction, but on how to increase their accuracy and efficiency (Kitowski, 2022). An accurate prediction can reduce analysis costs and increase the debt-collection rate (Korol, 2019). A common feature of most models is a short-term horizon, with the standard forecasts being for 1–3 years. Bankruptcy itself is the result of several causes that lead to insolvency. Furthermore, owing to the impact of globalization and the dynamically changing business environment, we need to constantly update prediction models and increase their accuracy and efficiency. Finally, prediction of future development requires an expansion of the range of mathematical and statistical methods because several methods to clarify a company's financial health.

Logistic regression analysis is one of the basic methods for estimating enterprise failure. Models based on logistic regression assume a log probability distribution. In our context, the estimated result is the value of the probability of bankruptcy in the range of 0 to 1. Its advantage over discriminant analysis is that logistic regression does not require the fulfilment of certain assumptions, such as normality of financial indicators (normal distribution of independent variables) and homogeneity of variance-covariance matrices (Jencova *et al.,* 2020).

Several studies have used logistic regression. Tseng and Lin (2005) applied a quadratic interval logit model to forecast corporate distress in the *UK*. Marcinkevicius and Kanapickiene (2014) applied logistic regression in the context of the Lithuanian construction industry. Jabeur (2017) developed a logistic model for French companies using 33 financial ratios. Chen *et al.* (2021) predicted bankruptcy in Taiwan's electronics industry based on data from 2000 to 2019. Out of the 22 financial indicators used, the authors found that three affect corporate bankruptcy the most: liquidity ratio, debt ratio, and fixed assets turnover ratio. Shetty and Vincent (2021) examined the bankruptcy of 164 companies in the Indian industrial sector, using financial and non-financial indicators in a logistic model. Sousa *et al.* (2022)

constructed a model based on logistic regression combined with *PCA* on a sample of Portuguese construction companies from 2009 to 2019.

Hurtosova (2009) and Gulka (2016) used logistic regression to predict the bankruptcy of companies in the Slovak Republic. Mihalovic (2016) compared the predictions of discriminant analysis and logistic regression in a sample of 236 Slovak firms. The authors found that the most significant predictors were net income to total assets, current ratio, and current liabilities to total assets. Horvathova and Mokrisova (2020) compared logistic regression with *DEA* on a sample of 343 companies operating in the heat supply industry. Peat and Jones (2012) compared logistic regression with neural networks in a sample of Australian businesses between 2000 and 2002. Youn and Gu (2010) also used logistic regression and *ANNs* to predict the failure of *US* restaurant firms. Brozyna *et al.* (2016) compared predictions from classification and regression analyses, logistic regression, and multilayer perceptron (*MLP*) in the Slovak Republic and Poland using a sample of 47 transport companies. Other authors include Salehi and Mousavi Shiri (2016), Ayadi *et al.* (2017), Obradovic *et al.* (2018), and Rahman *et al.* (2021).

Kalinova (2021) saw that the current economic system often shows instability and is changing dynamically. Therefore, it is important to look for new procedures and models for estimating the financial and economic conditions of businesses and their future prospects. Classical prediction methods are often insufficient mainly because of the lack of useful information in historical data, which arises from the dynamics of the economic system. The authors found the use of *ANN*-based prediction procedures to be better owing to their nonlinearity and ability to recognise complex relationships between indicators.

Although classical prediction models are still used and justified, the estimate made by the artificial intelligence model may act as an indication of high potential risk, and thus, initiate a more detailed analysis to confirm the adequacy of the suspicion of financial and economic problems (Horak *et al*., 2020b).

ANNs refer to as a black box because it is impossible to know in detail the internal structure of the system (Privara & Rievajova, 2021; Stefancik *et al.,* 2021). However, neural networks can reveal non-linear relationships in data and learn (Fitriyaningsih *et al.,* 2018; Grumstrup *et al.,* 2021; Sahoo & Pradhan, 2021). Moreover, neural network models exhibit non-linear nonparametric properties. The advantage of neural networks is that they do not require the fulfilment of assumptions such as linearity, normal distribution, or independence of variables. They transform inputs into desired outputs by adjusting the weights of the signals between neurons (Jencova *et al.,* 2020).

There are two basic types of neural networks: feed-forward (*FF*) neural networks, which spread signals in only one direction, and recurrent neural networks, which have synapses oriented in different directions (Kabir, 2021; Privara & Rievajova, 2021).

'Backpropagation' neural networks are the most relevant form of neural network in financial management (Wang & Zha, 2019). This model is a type of multilayer neural network that typically consists of three layers: input, output layer, and hidden layers. The nodes of different layers, but not of the same layer, are connected (Horvathova *et al.,* 2021).

Kimoto *et al.* (1990) use neural networks to predict the Tokyo Stock Exchange Index. Tam (1991) believed that neural networks are a competitive tool for assessing the financial situation of banks.

O´Leary (1998) analysed the results of 15 studies that used *ANN* to predict bankruptcy (most of which are back-propagated (*BP*) or 'Generalized Adaptive *NN* Algorithm' [*GANNA*]). One of the most important problems of such an analysis is the diversity of the input data for prediction, besides the different models and network settings. The authors found that individual studies compared *ANN* with discriminant analysis, logistic regression, and heuristic models. The results are not unambiguous: some show approximately the same accuracy of the *ANN* prediction as the compared classical model, while some found significantly higher success rate in the *ANN*. Interestingly, no study showed a statistically significant higher accuracy of the classical model compared to *ANN* or excluded its use for prediction.

Nachev *et al.* (2010) used a neural network to predict the bankruptcy of 129 firms using five financial indicators: working capital/total assets, retained earnings/total assets, earnings before interest and taxes (*EBIT*) to total assets, market value of equity/book value of total debt, and sales/total assets. Iturriaga and Sanz (2015) developed a neural network to predict the bankruptcy of *US* banks between 2002 and 2012. Dube *et al.* (2021) used *ANN* to develop prediction models for financial services and manufacturing companies listed on the Johannesburg Stock Exchange for the period 2000–2019. Abid *et al.* (2022) used neural networks combined with 30 financial ratios to predict bankruptcy for 856 French companies from the industrial sector. Other authors who deal with bankruptcy prediction using a neural network include Tsai and Wu (2008), Tsai (2009), Salehi and Davoudi Pour (2016), Chung *et al.* (2016), and Kim *et al.* (2018).

Charambous *et al.* (2000) compared logistic regression with *BP ANN* on a sample of 139 *US* companies. Hsieh *et al.* (2006) and Horvathova *et al.* (2021) compared neural networks with multivariate discriminant analysis.

Tinoco and Wilson (2013) compared neural networks with Altman's original Z-score specification on a sample of 23,218 companies during 1980–2011. Kasgari *et al.* (2013) compared *MLP* and probit analysis using a sample of 136 Iranian corporations. Papana and Spiridou (2020) compared four approaches of predicting financial bankruptcy in Greece: discriminant analysis, logit, decision trees, and neural networks. Kim (2011) conducted an interesting study comparing multivariate discriminant analysis (*MDA*), logit, support vector machine (*SVM*) and *ANN* in the context of the hotel business, and demonstrated the superiority of artificial intelligence.

Deep learning-based models are being developed as well. Because deep learning is useful for image recognition, the authors represented a set of financial ratios as a grayscale image and then used it for training *CNN*. However, the disadvantage of this method was the unknown impact of each ratio on the prediction. Jardin (2018) proposed a model that relied on the estimation of failure patterns quantified using ensembles of Kohonen maps, which was found to be efficient than single-based models. Korol and Fotiadis (2022) developed several forecasting models for evaluating Polish and Taiwanese consumers' financial standing using fuzzy logic (*FL*), *ANN,* and *GA-ANN*. The authors demonstrated the high effectiveness and low-cost errors of *FL* over *ANN* and *GA-ANN*. According to Garcia (2022), non-linear-based machine learning models fit better than traditional techniques; however, they are still considered as 'black box' technologies.

However, Chen (2021) noted the lack of research on effective prediction models for specific industries in the context of a specific country. The author conducted a comparative study and proposed a suitable hybrid model for addressing financial bankruptcy in Taiwan. Many models have problems in the selection of financial indicators for prediction. Some indicators with high prediction potential are omitted because they have a non-linear relationship with the probability of bankruptcy. Shirata (1998) tried to solve this problem through the statistical selection of indicators. Takata *et al.* (2015) used the adaboost system. Ptak-Chmielewska (2019) also demonstrated that non-financial factors are important in predicting small enterprise success or failure, and that more advanced, complicated models are not necessary because simple models are as effective as more complex ones.

Importantly, bankruptcy rates are not high, and there is a problem with the data distribution. Garcia (2022) indicated that it is difficult to extract signal from imbalanced data to understand the effects of independent variables on the dependent variable. Thus, the bankruptcy prediction has a typical problem of unbalanced data classification. This imbalance can interfere with a performance of machine learning. Several attempts have been made and methods developed to reduce imbalance, such as algorithm-level modification, data pre-processing with changing the size of the dataset (oversampling or undersampling), and hybrid systems (Wang & Liu, 2021). An approach using oversampling (*SMOTE*, or a combination of *SMOTE* and under-sampling) can improve the accuracy of classifiers for minority classes (Arafat *et al.,* 2017; Tumpach, 2020; Garcia, 2022). In addition, ensemble methods can be used to improve the accuracy of *ANN* using bagging and boosting algorithms (Kim & Kang, 2010).

Research methods

Research sample

The Slovak Republic has a strong industrial tradition and long-term focus on technical skills. The country is one of the most industrialised countries in Europe. The automotive industry dominates the country's industrial base, and is closely linked to engineering and electrical industries. Overall, industrial production is a key element for ensuring Slovakia's economic growth.

The research sample consists of a set of 2,384 non-financial corporations in the Slovak engineering (SK NACE 28 [Manufacture of machinery and equipment], 30 [Manufacture of other transport equipment], and 33 [Repair and installation of machinery and equipment]) and automotive industries (SK NACE 29 [Manufacture of motor vehicles, trailers, and semi-trailers]) for the period 2018–2019. Owing to the nature of production, part of the group of SK NACE 25 belongs more to the metallurgical industry and is excluded. In the engineering and automotive industries, the sample consists of 2,070 and 314 non-financial corporations, respectively.

The engineering industry is one of the main drivers of the Slovak economy, and has a strong historical background and stable position in the Slovak industry. The automotive industry in Slovakia has a strong tradition and is the most important driving force of the Slovak economy. The Slovak Republic is one of the 20 largest car producers in the world, with an annual production of more than 1 million vehicles. There are currently four established carmakers in Slovakia: Volkswagen Slovakia, PSA Group, Kia Motors Slovakia, and Jaguar Land Rover. The country is the world leader in car production per 1,000 inhabitants. In 2020, Slovakia produced 229 cars per 1,000 inhabitants, while it was 126 in the Czech Republic, 12 in Poland, 62 in Germany, 44 in Hungary, 23 in Belgium and England, 49 in Spain, and 101 in Slovenia. There are more than 350 suppliers in the Slovak automotive industry (SARIO, 2021a, 2021b).

Methods

Neural networks

ANN is a mathematical structure implemented using software or hardware. It can process incomplete data and produce approximate results (Pozorska & Scherer, 2018). The basic element of an *ANN* is a neuron. The principle of a neuron is to obtain signals from an environment or other neurons, combine them in some way, make a non-linear operation (activation function), and produce the result on its output:

$$y = f\left(\sum_0^n x_i \cdot w_i\right) \tag{1}$$

where:

y an output,
x_i inputs,
w_i synaptic weights,
f an activation function.

The most popular *ANN* structure is *MLP* with *FF* connections (no recurrent loop) and *BP* learning systems. *BP* is part of the process in which the neuron weights are adapted according to the current output error signal. This process continues iteratively and makes the network 'learn' what is the response for actual inputs. This algorithm propagates the error toward the network input, where the error in some layers is defined as the sum of the errors in the next layer of neurons with corresponding weights. The activation function converts the inputs to a specific output depending on the type of network (or activation function used). These functions can vary from linear to non-linear. The most common transfer functions are step, threshold, sigmoid, htan, and *RBF* (Figure 1). The learning process consists of adjusting weights to minimise the error in the associated known input-output pairs (training data set):

$$w_{ij} = w_{ij}{}' + \Delta w_{ij} \tag{2}$$

where new weights (w_{ij}) are the sum of the old weight ($w_{ij}{}'$) and new delta (Δw_{ij}) (referred to as the generalized delta rule). The new delta (Δw_{ij}) is proportional to the negative change in the sum of squared errors (∂SSE) with respect to the change in weights (∂w_{ij}):

$$\Delta w_{ij} \propto -\frac{\partial SSE}{\partial w_{ij}} \tag{3}$$

ANNs can quickly adapt to changes because they are very flexible, resistant to chaotic information, and can use quantitative or qualitative data. They also have some limitations, such as long-term learning process, difficult weight selection, and need to select explanatory variables before creating the model (Ptak-Chmielewska, 2019). The number of neurons affects learning speed. Too many neurons require more time and increase the complexity of the system. In contrast, a small number of neurons can cause the network to be quickly over-fitted and cause generalized knowledge to be lost. To verify the correctness of the design, it is necessary to test the network on a sample of data that has not been used during training; that is, dividing the dataset into training and testing datasets. The number of hidden layers also affects the performance. This number increases with the difficulty level of the problem. Bankruptcy prediction is a relatively simple problem for *ANN*s, and most studies consider one to two hidden layers to be sufficient.

We used *IBM SPSS* Statistics, which includes neural networks (*MLP*) for our prediction problem. For the calculation, we used the financial ratios of non-financial corporations in the engineering and automotive industries. Financial ratios were calculated based on absolute indicators from the financial statements of non-financial corporations, which were accessed from the Register of Financial Statements of the Slovak Republic.

The choice of financial indicators is crucial for the results; therefore, we followed the literature on prediction of corporate failure. Fitzpatrik (1932) found that the ratios equity/liabilities and return on equity (*ROE*) are the most important in predicting the financial situation of a company. According to Smith and Winakor (1935), the ratio working capital to assets is the best indicator. Other financial indicators that influence bankruptcy are financial leverage, interest coverage, gross profit margin, inventory turnover, and cash ratio (Jakubik & Teply, 2011). According to Valecky and Slivkova (2012), return on assets (*ROA*), return on sales (*ROS*), cash ratio, quick ratio, total indebtedness, and added value to sales ratio affect bankruptcy. Harumova and Janisova (2014) included earnings before interest, taxes, depreciation, and amortization (*EBITDA*) to sales ratio, accounts payable turnover ratio, total assets turnover ratio, liabilities to cash flow ratio, and the overall liquidity ratio as important indicators. Slavicek and Kubenka

(2016) found that *ROA*, inventory turnover, current liquidity, and total indebtedness are financial indicators that influence bankruptcy. Kovacova and Kliestik (2017) found that eight variables influence bankruptcy: net return on total income, current ratio, net working capital ratio, retained earnings to total assets ratio, total debt to total assets ratio, current debt to total assets ratio, equity to assets ratio, and current assets to total income ratio.

We chose the following nine financial indicators as inputs for *ANN* prediction model:

x_1 – *Total Indebtedness (TI)* = $Total\ Debt/Total\ Assets$
x_2 – *Financial Leverage (FL)* = $Total\ Assets/Equity$
x_3 – *Return on Sales (ROS)* =
$Earnings\ before\ interest\ and\ taxes(EBIT)/Sales$
x_4 – *Return on Equity (ROE)* = $Earnings\ after\ taxes(EAT)/Equity$
x_5 – *Return on Investments (ROI)* =
$Earnings\ after\ taxes(EAT)/Total\ Capital$
x_6 – *Share of Value Added in Sales (VA / S)*
x_7 – *Turnover of Assets (TA)* = $Sales/Total\ Assets$
x_8 – *Net Working Capital to Assets ratio (NWC / A)*
x_9 – *Quick Ratio (QR)* =
$(Current\ Assets - Inventory)/Current\ Liabilities$

Table 1 presents the descriptive statistics of these variables in our research sample. The dataset was also split into several subsets (engineering industry without automotive, automotive industry, and both together), and each was used with both scaling techniques (standardisation and normalisation) for comparison. The datasets for training and testing samples were divided with ratios of 80:20, 70:30, and 60:40. The transfer and activation functions were set to sigmoid, hyperbolic tangent, and a combination of hyperbolic tangent and sigmoid functions. Extreme values in each subset were removed using the inter-quartile method. In 2018, after modifying the database, 164 and 1,183 enterprises in the automotive and engineering industries, respectively, were included in the analysis. In 2019, after modifying the database, 170 and 1,236 enterprises in the automotive and engineering industries, respectively, were included in the analysis.

The neural networks were assembled with one hidden layer (five hidden nodes). The output of the neural network provided information on whether the company was bankrupt (1) or not (0). Act no. 7/2005 Coll. on Bankruptcy and Restructuring defines bankruptcy and expresses it as the equity to debt ratio. Act no. 513/1991 Coll. Commercial Code establishes the minimum value of the ratio for each year. In 2018 and 2019, this value was 0.08. That is, if this ratio was less than 8%, the enterprise defaulted and a value of one was assigned, and zero otherwise.

Scaling techniques

Scaling is a pre-processing step which generally moves the centre of the coordinate system, and lengthens or shortens the scale on the axes. It is important for comparing measurements with different units, and is considered a requirement for machine learning algorithms. Importantly, it significantly affects the machine-learning performance.

Standardisation means eliminating the dependence on units and position parameters. It re-scales data to obtain a mean of 0 with a standard deviation of 1, and it not impacted by outliers because of the range of transformation is not defined. The standardised value y_{ij} of matrix $N \times M$ (*N* = number of cases and *M* = number of financial indicators) can be expressed as follow:

$$y_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \tag{4}$$

$$\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{ij}, \tag{5}$$

$$\sigma_j = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(x_{ij} - \mu_j\right)^2}, \tag{6}$$

where:

x_{ij} an original value of case *i* and indicator *j*,

μ_j a mean value across all cases of indicator *j*, and

σ_j a standard deviation across all cases of indicator *j*.

The normalisation scaling technique re-scales the data into a fixed range (usually {0,1}). This results in smaller standard deviations, while suppressing the effect of outliers. The normalised value y_{ij} of matrix $N \times M$ (*N* = number of cases and *M* = number of financial indicators) can be expressed as follows:

$$y_{ij} = \frac{x_{ij} - min_j}{max_j - min_j}, \tag{7}$$

where:

x_{ij} an original value of case *i* and indicator *j*,

min_j a minimum case value of indicator *j*,

max_j a maximum case value of indicator *j*.

Inter-quartile method

An outlier can be considered as an inconsistent observation in the dataset. This observation may not even be from the same statistical distribution as the rest. One of the commonly used methods for detecting outliers is the inter-quartile range (principle of boxplots). The lower quartile (Q_1) represents the 25th percentile and the upper quartile (Q_3) is the 75th percentile. The inter-quartile range ($Q_3 - Q_1$) produces 50% of most represented data (the middle 50% of a distribution). The deviated observation must be at the end of the distribution. The boundaries are set at a fixed distance from this range. The information contained in the values outside the boundaries is extreme and creates suspicion of an abnormality. We considered the boundary as three times the inter-quartile range, and observations outside these boundaries were removed.

Logistic regression

Logistic regression is used to model the unilateral dependence between variables when the dependent variable is not continuous but discrete (categorical). Independent variables can be continuous, discrete, or categorical (Jencova *et al.,* 2020).

Here, the logit-score lies between zero and one, which indicates the probability of a company's bankruptcy. Logistic models are extremely sensitive to the problem of multiple regression; therefore, it is necessary to avoid the inclusion of highly dependent variables.

To use a logistic regression, the dependent variable was transformed into a continuous value by calculating the logarithm of the odds ratio:

$$logit(p) = ln\left(\frac{p(Y=1|X)}{p(Y=0|X)}\right) = ln\left(\frac{p}{1-p}\right) \tag{8}$$

By logit transformation we go from non-linear to linear dependence, and the equation of the logarithmic model has the following form:

$$ln\left(\frac{p}{1-p}\right) = ln\left[p^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k)}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \tag{9}$$

The logistic function takes the form of an exponential function:

$$p = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k)}} = \frac{e^z}{1-e^z} = \frac{1}{1+e^{-z}} \tag{10}$$

where β is the vector of the estimated parameters and x_i is the individual input value. Estimates of the logistic model parameters were obtained using non-linear maximum likelihood estimation.

After adjusting the input database, 1,525 and 295 non-financial corporations in the engineering and automotive industries, respectively, were used for the analysis for 2019. We used the following financial ratios:

indicators of profitability:
Return on Assets (ROA) = $Earnings\ before\ interest\ and\ taxes\ (EBIT)/Total\ Assets$
Return on Sales (ROS) = $Earnings\ before\ interest\ and\ taxes(EBIT)/Sales$
Return on Investments (ROI) = $Earnings\ after\ taxes(EAT)/Total\ Capital$
Return on Equity (ROE) = $Earnings\ after\ taxes(EAT)/Equity$

indicators of activity:
Turnover of Assets (TA) = $Sales/Total\ Assets$
Turnover of Current Assets (TCA) = $Sales/Current\ Assets$
Inventory Turnover (IT) = $Sales/Inventory$
Receivables Turnover (RT) = $Sales/Receivables$

indicators of indebtedness:
Total Indebtedness (TI) = $Total\ Debt/Total\ Assets$
Financial Leverage (FL) = $Total\ Assets/Equity$
Debt-Equity Ratio (DER) = $Total\ Debt/Equity$

indicators of liquidity:
Quick Ratio (QR) = $(Current\ Assets - Inventory)/Current\ Liabilities$
Current Ratio (CR) = $Current\ Assets/Current\ Liabilities$
Net Working Capital to Assets ratio (NWC/A)

indicators of cost effectiveness:
Cost/sales (C/S)
Personnel costs/sales (PC/S)

indicators of productivity:
Share of value added in sales (VA/S)

The dependent (binary) variable was defined as before: If the equity to liabilities ratio was less than 0.08, the company was considered to have defaulted and the bankruptcy variable equalled one, and zero otherwise.

The data were processed using the open-source Gretl software.

Results

Neural network

We use the indicators of profitability (*ROS, ROI,* and *ROE*), activity (*TA*), indebtedness (*TI* and *FL*), liquidity (*QR* and *NWC/A*), and productivity (*VA/S*) to create an optimal neural network for 2018 and 2019. These indicators are part of the ex-post financial analysis and evaluate the financial situation of individual companies. Liquidity indicators assess whether a company can pay short-term liabilities. Activity indicators indicate how long a company has tied up finances in its assets. Indebtedness indicators provide a picture of the structure of financial resources and express the company's creditworthiness. Profitability indicators quantify entrepreneurs' ability to enhance invested capital and generate new sources of financing.

We constructed an optimal neural network for the automotive and engineering industries with these nine financial indicators on the input layer in combination with one hidden layer (Figure 2). This hidden layer has five neurons.

Figure 2 shows the connections between the neurons. Lines have different thicknesses and colours. When the weight between the variables is less than zero, the lines are blue. When the weight has a value greater than zero, the lines are grey. Lines are thinner (thicker) as one moves closer (farther) to zero.

We analysed several combinations based on the industry sector, use of the scaling technique, activation function, and ratio of the sample distribution of the test and training parts. The difference between the scaling techniques used was insignificant for all the subsets. Furthermore, the results show whether the selected ratios (80:20, 70:30, and 60:40) of the training and testing samples were significant.

Table 2 (3) shows the values of the weights between neurons for both industries together, scaling technique normalisation (standardisation), ratio 80:20, and year 2019.

The success of the models for all combinations (scaling techniques, industries, and division into training and testing sets) and the sigmoid activation function are shown in Tables 4 and 5. During the monitored period, the highest 100% success rate of the neural network was demonstrated in the engineering and automotive industries with the normalisation scaling technique, and 80:20, 70:30, and 60:40 ratios.

On average, the standardised and normalised data in 2018 for the automotive industry achieved a success rate of 99.5% for the test subset with the sigmoid function, 97.2% with a hyperbolic tangent function, and 99% with a combination of hyperbolic tangent and sigmoid functions. In 2019, the success rate for all functions in the automotive industry was 100%.

On average, standardised and normalised data in 2018 for the engineering industry achieved a success rate of 99.8% for the test subset with the sigmoid function, 99.6% with a hyperbolic tangent function, and 99.7% with the combination of hyperbolic tangent and sigmoid functions. The normalised data had a slightly lower success rate than the standardised data.

Table 6 shows the performance of the models for both years, for both industries, and compares the sigmoid, hyperbolic tangent, and a combination of hyperbolic tangent and sigmoid functions.

Logistic regression

Next, we estimated the parameters of the prediction model using a binary logistic regression. The aim of the model was to find a combination of indicators that showed the best predictive ability.

An *AEI* (automotive-engineering industry) model with predictors x_1 to x_6 was designed for a set of 1,820 non-financial corporations in the engineering and automotive industries. An *EI* (engineering industry) model with predictors x_1 to x_6 was proposed for a set of 1,525 non-financial corporations in the engineering industry. The Wald test showed the significant contribution of these predictors to the model.

All types of indicators were considered when we were searching for the optimal model based on company data for 2019. We did not include the *ROE* indicator because the share of negative economic results for the accounting period and negative equity gives a positive value.

The stepwise method was used to construct logistic regression models while testing the significance of adding or eliminating variables at each step. Despite the significant coefficients of the six predictors, the model does not fit well, as the probability $p < 0.001$ of the Hosmer-Lemeshow test indicates that the number of company defaults differs from the number predicted by the model.

OR is a positive number. If it exceeds 1, there is a higher chance of bankruptcy; and if it is less than 1, there is a lower chance of bankruptcy. The odds value (e^B) means that if, for example, the independent variable x_4

(*TA*) increases by a value of 1, then the estimated chance of bankruptcy at the values of the other fixed predictors increases by a multiple of e^B. Table 7 shows the estimated coefficients and odds ratios for the engineering and automotive companies together. Simultaneously, a logistics model for *AEI* companies of the following form was designed:

$$logit(\beta) = ln\left(\frac{p}{1-p}\right) = \\ = -1.7484 - 0.541.ROS + 0.0122.FL - 1.1796.\frac{PC}{S} + 0.2578.TA \\ - 2.6784.\frac{NWC}{A} - 0.1082.QR \tag{11}$$

Table 8 shows the estimated coefficients and odds ratio for enterprises in the engineering sector. Simultaneously, a logistic model for engineering companies was proposed in the following form:

$$logit(\beta) = ln\left(\frac{p}{1-p}\right) = \\ = -1.5649 - 0.5457.ROS + 0.0098.FL - 1.2313.\frac{PC}{S} + 0.1912.TA \\ - 2.6518.\frac{NWC}{A} - 0.1036.QR \tag{12}$$

The results show that they are very similar models. That is, the automotive companies did not determine the prediction model for the engineering companies, and thus, the *EI* model is fully applicable to automotive companies, and vice versa. Table 9 shows a comparison of the models using the information criteria. The Akaike (*AIC*), Bayesian (*BIC*), and Hannan-Quinn information criteria (*HQIC*) showed that we can apply the *EI* model in practice. For individual models, Table 10 shows the probability that a bankrupt (prosperous) enterprise is classified as bankrupt (prosperous) enterprise.

The sensitivity of the *EI* model is 98.8%, its specificity is 44.23%, the negative predictive value reaches 11.5%, and the false positive is 10%. Figure 3 shows the *ROC* curves for the *EI* model. We do not present the curve for the *AEI* model because the results are very similar to those of the *EI* model (Table 11). The *ROC* curve for the *EI* model defines an area under the curve equal to 0.899; (*AUC ROC* = 0.899; *S.E.* = 0.012; *p* = 0.000; 95% *CI* = [0.875 – 0.923]). Thus, the probability that a company in crisis has a higher predicted probability than that of a company that is not in crisis is 0.899. According to Jencova *et al.* (2019), the interval 0.9 - 1.0 for the relationship of *AUC* and model quality is excellent as it exceeds 0.8 - 0.9. Based on these six indicators, we model the binary variable bankruptcy. The logistic regression model was statistically significant. The financial indicators *ROS, QR, NWC/A,* and *PC/S* reduce the chances of bankruptcy; therefore, when these indicators increase, the probability (or chance) of the company going bankrupt decreases. Ceteris paribus, a one-unit increase in return on sales, quick ratio, and net working capital to assets decreases the chance of bankruptcy by 1.72, 1.1, and 14 times, respectively.

Discussion

We analysed the predictive ability of various financial ratios on non-financial firms' bankruptcy using data on 2,384 companies in the engineering and automotive industries of the Slovak Republic in 2018 and 2019. We used logistic regression to analyse the data for 2019, and a neural network for the data of 2018 and 2019.

Specifically, we constructed an optimal neural network for the automotive and engineering industries with nine financial indicators on the input layer in combination with one hidden layer. All networks were highly successful. We analysed several combinations based on the industry sector, use of the scaling technique, activation function, and ratio of the sample distribution of the testing and training parts. The differences between the scaling techniques, and the ratio of the sample distribution of the test and training dataset were insignificant.

Next, we used several indicators in our neural network on specific types of financial aspects of a firm which have been used in the literature. First, the indebtedness indicators were represented by the financial leverage (Purvinis *et al.*, 2008; Kim & Kang, 2010), and total indebtedness (Purvinis *et al.*, 2007; Purvinis *et al.*, 2008; Chen *et al.*, 2009; Nyitrai & Virag, 2019). Second, activity indicators were represented by the asset turnover ratio (Lee *et al*., 1996; Merkevicius *et al.*, 2006; Purvinis *et al.*, 2008; Kim & Kang, 2010; Nyitrai & Virag, 2019). Among liquidity indicators, we included the quick ratio (Tsakonas *et al*., 2006; Purvinis *et al.*, 2007; Purvinis *et al.*, 2008; Nyitrai & Virag 2019) and net working capital to assets ratio (Merkevicius *et al.*, 2006; Kim & Kang, 2010). Profitability indicators were *ROI* (Merkevicius *et al.*, 2006)*, ROE,* and *ROS* (Purvinis, Sukys & Virbickaite, 2007; Nyitrai & Virag, 2010).

We model the binary variable bankruptcy based on these six indicators using a logistic regression, which turned out to be statistically significant. We found that the financial indicators *ROS, QR, NWC/A,* and *PC/S* reduce the chances of bankruptcy; therefore, when these indicators increase, the probability (or chance) of the company going bankrupt decreases. A one-unit increase in return on sales, quick ratio, and net working capital to assets decreases the chance of bankruptcy by 1.72, 1.1, and 14 times, respectively. Meanwhile, *TA* and *FL* increased the chances of bankruptcy; therefore, when these indicators increase, the probability (or chance) of the company going bankrupt increases, but only slightly. The overall success rate of the engineering industry is 89.4 %.

We can compare our model with several existing logistic regression models that are used to predict the bankruptcy of companies. Our logistic model used the indebtedness indicators represented by financial leverage (Jakubik & Teply, 2011). Activity indicators were represented by the asset turnover ratio (Wrzosek & Ziemba, 2009; Genriha *et al.*, 2011; Harumova & Janisova, 2014; Nyitrai & Virag, 2019). Among liquidity indicators, we included the quick ratio indicators (Mihalovic, 2016; Nyitrai & Virag, 2019; Rahman *et al*., 2021) and the net working capital to assets ratio (Wrzosek & Ziemba, 2009). Profitability indicators that our model included were *ROS* (Wrzosek & Ziemba, 2009; Jakubik & Teply, 2011; Harumova & Janisova, 2014; Nyitrai & Virag, 2019). Overall, our model had the following four indicators in common with Jencova *et al.* (2020): return on sales, quick ratio, financial leverage, and net working capital to assets.

Conclusions

One can gain an overview of an industry's financial situation from the financial analysis of individual companies in that industry (Ocal *et al*., 2007). However, different financial indicators are essential for different industries. The advantage of using traditional financial indicators is that they are a relatively simple collection of data that are part of mandatory financial statements.

Estimating the riskiness of company or the probability of its bankruptcy is important, especially for investors and creditors, besides business owners. Therefore, searching for applicable models to predict bankruptcy is important. This is an important area not only in scientific research, but also in the practice of business entities. Notably, the biggest problems arise while choosing suitable indicators and methods for measuring, evaluating, and managing the financial situation of business entities. Universal models are often not suitable because they are created for specific conditions of a given economy in a given period. Currently, models based on artificial intelligence are being used in the field of prediction.

Here, our aim was to predict the bankruptcy of companies in the engineering and automotive industries of the Slovak Republic using a multilayer neural network and logistic regression. The intention was to construct appropriate models and evaluate the financial situation in selected branches of industry. Our main contribution is that we develop a novel early warning model for non-financial firms' bankruptcy in the Slovak engineering and automotive industries. These models substantially enrich econometric models of financial management. Moreover, our models are particularly applicable in countries with underdeveloped capital markets.

Moreover, we show that some crucial indicators can mitigate bankruptcy risks, while others can enhance it. Thus, managers and business owners can use this insight to guide their firms and inform future business plans. In addition, this article can be insightful for international readers because the Slovak Republic is one of the most industrialised countries in the European area and is the world leader in car production per 1,000 inhabitants. Almost the entire industries under study are privatised and most companies are foreign-owned. Thus, international companies can apply our created models to understand their financial health and sustainability, and even compare them with their own models to understand the areas where models can be improved.

This study had several limitations. First, we analysed data from only two years and focused only on some industries. Repeat the analysis for different years and over an extended period can reveal interesting insight. Researchers can also use the regional segmentation of companies and other qualitative data. They can also extend the analysis to other countries, besides focusing on other industries. Second, we did not consider the heterogeneity of effects across firm sizes. Future research can divide the sample into small, medium, and large enterprises, and explore the differences in the results. Moreover, in addition to neural networks and logistic regression, we suggest using *DEA* or panel regressions. Financial analysts should simultaneously use multiple methods to compare the results.

In essences, corporations must identify and prevent instability over time. Therefore, it is necessary to evaluate the financial health of companies using appropriate models. However, expanding the spectrum of mathematical and statistical methods to predict the future development of financial situations remains a crucial area of research. This study helps in advancing our understanding along these lines.

References

Abid, I., Ayadi, R., Guesmi, K., & Mkaouar, F. (2022). A new approach to deal with variable selection in neural networks: an application to bankruptcy prediction. *Annals of Operations Research, 313*(2), 605–623. doi: 10.1007/s10479-021-04236-4.

Act No. 513/1991 Coll. in commercial code; 2013. Bratislava: Iura Edition.

Act No. 7/2005 Coll. bankruptcy and restructuring; 2013. Bratislava: Iura Edition.

Arafat, M. Y., Hoque, S., & Farid, D. M. (2017). Cluster-based under-sampling with random forest for multi-class imbalanced classification. In *11th international conference on software, knowledge, information management and applications (SKIMA)* (pp. 1–6). Malabe: IEEE. doi: 10.1109/SKIMA.2017.8294105.

Ayadi, A. M., Lazrak, S., & Welch, R. (2017). Determinants of bankruptcy regime choice for Canadian public firms. *Research in International Business and Finance, 42*, 161–172. doi: 10.1016/j.ribaf.2017.04.043.

Belas, J., Cepel, M., Kliuchnikava, Y., & Vrbka, J. (2020). Market risk in the SMEs segment in the Visegrad group countries. *Transformations in Business and Economics*, *19*(3), 678–693.

Brozyna, J., Mentel, G., & Pisula, T. (2016). Statistical methods of the bankruptcy prediction in the logistic sector in Poland and Slovakia. *Transformations in Business and Economics, 15*(1), 93–114.

Civelek, M., Gajdka, K., Svetlik, J., & Vavrecka, V. (2020a). Differences in the usage of online marketing and social media tools: evidence from Czech, Slovakian and Hungarian SMEs. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 15*(3), 537–563. doi: 10.24136/eq.2020.024.

Civelek, M., Kljucnikov, A., Vavrecka, V., & Gajdka, K. (2020b). The usage of technology-enabled marketing tools by smes and their bankruptcy concerns: evidence from Visegrad countries. *Acta Montanistica Slovaca*, *25*(3), 263–273. doi: 10.46544/AMS.v25i3.1.

Civelek, M., Kljucnikov, A., Fialova, V., Folvarcna, A., & Stoch, M. (2021). How innovativeness of family-owned SMEs differ depending on their characteristics? *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(2), 413–428. doi: 10.24136/eq.2021.015.

Derindag, O. F., Lambovska, M., & Todorova, D. (2021). Innovation development factors: Switzerland experience. *Pressburg Economic Review, 1*(1), 57–65.

Dube, F., Nzimande, N., & Muzindutsi, P. F. (2021). Application of artificial neural networks in predicting financial distress in the JSE financial services and manufacturing companies. *Journal of Sustainable Finance & Investment.* Advance online publication. doi: 10.1080/20430795.2021.2017257.

Fitriyaningsih, I., Tampubolon, A. R., Lumbanraja, H. L., Pasaribu G. E., & Sitorus, P. S. A. (2018). Implementation of artificial neural network to predict S&P 500 stock closing price. *Journal of Physics: Conference Series*, *1175*, 012107. doi: 10.1088/1742- 6596/1175/1/012107.

Fitzpatrik, P. J. (1932). A comparison of the ratios of successful industrial enterprises with those of failed companies. *Certified Public Accountant, 6*, 727–731.

Garcia, J. (2022). Bankruptcy prediction using synthetic sampling. *Machine Learning with Applications, 9*, 100343. doi: 10.1016/j.mlwa.2022.100343.

Genriha, I., Pettere, G., & Voronova, I. (2011). Entrepreneurship insolvency risk management: case Latvia. *International Journal of Banking, Accounting and Finance, 3*(1), 31–46. doi: 10.1504/IJBAAF.2011.039370.

Grumstrup, E. J., Sorensen, T., Misiuna, J., & Pachocka, M. (2021). Immigration and voting patterns in the European Union: evidence from five case studies and cross-country analysis. *Migration Letters, 18*(5), 573–589. doi: 10.33182/ml.v18i5.943.

Gulka, M. (2016). Bankruptcy prediction model of commercial companies operating in the conditions of the Slovak Republic. *Forum Statisticum Slovacum*, *12*, 16–22.

Harumova, A., & Janisova, M. (2014). Rating Slovak enterprises by scoring functions. *Ekonomicky Casopis (Journal of Economy), 62*(5), 522–539.

Horak, J., Vrbka J., & Suler, P. (2020a). Support vector machine methods and artificial neural networks used for the development of bankruptcy prediction models and their comparison. *Journal of Risk and Financial Management*, *13*(3), 60. doi: 10.3390/jrfm13030060.

Horak, J., Krulicky, T., Rowland, Z., & Machova, V. (2020b). Creating a comprehensive method for the evaluation of a company. *Sustainability*, *12*(21), 1–23. doi: 10.3390/su12219114.

Horvathova, J., & Mokrisova, M. (2020). Comparison of the results of a data envelopment analysis model and logit model in assessing business financial health. *Information*, *11*(3), 160. doi: 10.3390/info11030160.

Horvathova, J., Mokrisova, M., & Petruska, I. (2021). Selected methods of predicting financial health of companies: neural networks versus discriminant analysis. *Information, 12*(12), 505. doi: 10.3390/info12120505.

Hsieh, W. K, Liu, S. M., & Hsieh, S. Y. (2006). Hybrid neural network bankruptcy prediction: an integration of financial ratios, intellectual capital ratios, MDA, and neural network learning. In *Proceedings of the 9th joint international conference on information sciences (JCIS-06). Advances in intelligent systems research*. Atlantis Press. doi: 10.2991/jcis.2006.323.

Hurtosova, J. (2009). *Construction of a rating model, a tool for assessing the creditworthiness of a company*. Bratislava: Economic University in Bratislava.

Charambous, C. H., Charitou, A., & Kaourou, F. (2000). Comparative analysis of artificial neural network models: application in bankruptcy prediction. *Annals of Operations Research*, *99*(1), 403–425. doi: 10.1023/A:1019292321322.

Chen, H. J., Huang, S. Y., & Lin, Ch. S. (2009). Alternative diagnosis of corporate bankruptcy: a neuro fuzzy approach. *Expert Systems with Applications, 36*(4), 7710–7720. doi: 10.1016/j.eswa.2008.09.023.

Chen, Y. S., Lin, Ch. K., Lo, Ch. M., Chen, S. F., & Liao, Q. J. (2021). Comparable studies of financial bankruptcy prediction using advanced hybrid intelligent classification models to provide early warning in the electronics industry. *Mathematics, 9*(20), 2622. doi: 10.3390/math9202622.

Chung, Ch. Ch., Chen, T. S., Lin, L. H., Lin, Y. Ch., & Lin, Ch. M. (2016). Bankruptcy prediction using cerebellar model neural networks. *International Journal of Fuzzy Systems, 18*(2), 160–167. doi: 10.1007/s40815-015-0121-5.

Iturriaga, F. J. L., & Sanz, I. P. (2015). Bankruptcy visualization and prediction using neural networks: a study of U.S. commercial banks. *Expert Systems with Applications, 42*(6), 2857–2869. doi: 10.1016/j.eswa.2014.11.025.

Jabeur, S. B. (2017). Bankruptcy prediction using partial least squares logistic regression. *Journal of Retailing and Consumer Services*, *36*, 197–202. doi: 10.1016/j.jretconser.2017.02.005.

Jakubik, P., & Teply, P. (2011). The JT index as an indicator of financial stability of corporate sector. *Prague Economic Papers, 20*(2), 157–176. doi: 10.18267/j.pep.394.

Jardin, P. (2018). Failure pattern-based ensembles applied to bankruptcy forecasting. *Decision Support Systems, 107*, 64–77. doi: 10.1016/j.dss.2018.01.003.

Jencova, S., Stefko, R., & Vasanicova, P. (2020). Scoring model of the financial health of the electrical engineering industry's non-financial corporations. *Energies, 13*(17), 1–17. doi: 10.3390/en13174364.

Kabir, H. (2021). Notion of belonging in the nation-state: gendered construction of international migration aspirations among university students in Bangladesh. *Migration Letters, 18*(4), 463–476. doi: 10.33182/ml.v18i4.1158.

Kalinova, E. (2021). Artificial intelligence for cluster analysis: case study of transport companies in Czech Republic. *Journal of Risk and Financial Management, 14*(9), 411. doi: 10.3390/jrfm14090411.

Kasgari, A. A., Divsalar, M., Javid, M. R., & Ebrahimian, S. J. (2013). Prediction of bankruptcy Iranian corporations through artificial neural network and probit-based analyses. *Neural Computing and Applications, 23,* 927–936. doi: 10.1007/s00521-012-1017-z.

Khan, K. A., Dankiewicz, R., Kliuchnikava, Y., & Olah, J. (2020). How do entrepreneurs feel bankruptcy? *International Journal of Entrepreneurial Knowledge, 8*(1), 89–101. doi:10.37335/ijek.v8i1.103.

Kim, S. Y. (2011). Prediction of hotel bankruptcy using support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis. *Service Industries Journal, 31*(3), 441–468. doi: 10.1080/02642060802712848.

Kim, M. J., & Kang, D. K. (2010). Ensemble with neural networks for bankruptcy prediction. *Expert Systems with Applications, 37*(4), 3373–3379. doi: 10.1016/j.eswa.2009.10.012.

Kim, S., Mun, B. M., & Bae, S. J. (2018). Data depth based support vector machines for predicting corporate bankruptcy. *Applied Intelligence, 48*(3), 791–804. doi: 10.1007/s10489-017-1011-3.

Kimoto, T., Asakawa, K., Yoda, M., & Takeoka, M. (1990). Stock market prediction system with modular neural networks. In *1990 IJCNN international joint conference on neural networks (IJCNM-90)*, *INT Neural Network SOC*, San Diego: IEEE. doi: 10.1109/IJCNN.1990.137535.

Kitowski, J., Kowal-Pawul, A., & Lichota, W. (2022). Identifying symptoms of bankruptcy risk based on bankruptcy prediction models - a case study of Poland. *Sustainability, 14*(3), 416. doi: 10.3390/su14031416.

Kliestik, T., Vrbka, J., & Rowland, Z. (2018). Bankruptcy prediction in Visegrad group countries using multiple discriminant analysis. *Equilibrium-Quarterly Journal of Economics and Economic Policy, 13*(3), 569–593. doi: 10.24136/eq.2018.028.

Kljucnikov, A., Civelek, M., Polach, J., Mikolas, Z., & Banot, M. (2020a). How do security and benefits instill trustworthiness of a digital local currency? *Oeconomia Copernicana, 11*(3), 433–465. doi: 10.24136/oc.2020.018.

Kljucnikov, A., Civelek, M., Voznakova, I., & Krajcik, V. (2020b). Can discounts expand local and digital currency awareness of individuals depending on their characteristics? *Oeconomia Copernicana, 11*(2), 239–266. doi: 10.24136/oc.2020.010.

Kljucnikov, A., Civelek, M., Fialova, V., & Folvarcna, A. (2021). Organizational, local, and global innovativeness of family-owned SMEs depending on firm-individual level characteristics: evidence from the Czech Republic. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 16*(1), 169–184. doi: 10.24136/eq.2021.006.

Kolkova, A., & Kljucnikov, A. (2021). Demand forecasting: an alternative approach based on technical indicator Pbands. *Oeconomia Copernicana*, *12*(4), 863–894. doi: 10.24136/oc.2021.028.

Korol, T. (2019). Dynamic bankruptcy prediction models for European enterprises. *Journal of Risk and Financial Management*, *12*(4), 185. doi: 10.3390/jrfm12040185.

Korol, T., & Fotiadis, A. K. (2022). Implementing artificial intelligence in forecasting the risk of personal bankruptcies in Poland and Taiwan. *Oeconomia Copernicana, 13*(2), 407–438. doi: 10.24136/oc.2022.013.

Kovacova, M. C, & Kliestik, T. (2017). Logit and probit application for the prediction of bankruptcy in Slovak companies. *Equilibrium. Quarterly Journal of Economics and Economy Policy*, *12*(4), 775–791. doi: 10.24136/eq.v12i4.40.

Kral, P., Musa, H., Lazaroiu, G., Misankova, M., & Vrbka, J. (2018). Comprehensive assessment of the selected indicators of financial analysis in the context of failing companies. *Journal of International Studies*. Szczecin, *11*(4), 282–294. doi: 10.14254/2071-8330.2018/11-4/20.

Krulicky, T., Kalinova, E., & Kucera, J. (2020). Machine learning prediction of USA export to PRC in context of mutual sanction. *Littera Scripta, 13*(1), 83–101. doi: 10.36708/Littera_Scripta2020/1/6.

Lee, K. Ch., Han, I., & Kwon, Y. (1996). Hybrid neural network models for bankruptcy predictions. *Decision Support Systems, 18,* 63–72. doi: 10.1016/0167-9236(96)00018-8.

Lyocsa, S., Vasanicova, P., Misheva, B. H., & Vateha, M.D. (2022). Default or profit scoring credit systems? Evidence from European and US peer-to-peer lending markets. *Financial Innovation, 8*(1), 32. doi: 10.1186/s40854-022-00338-5.

Marcinkevicius, R., & Kanapickiene, R. (2014). Bankruptcy prediction in the sector of construction in Lithuania. *Procedia Social And Behavioral Sciences. 156*, 553–557. doi: 10.1016/j.sbspro.2014.11.239.

Merkevicius, E., Garsva, G., & Girdzijauskas, S. (2006). A hybrid SOM–Altman model for bankruptcy prediction. In V. N. Alexandrov, G. D. VanAlbada, P. M. A. Sloot & J. Dongarra (Eds.). *Conference: computational science – ICCS 2006, 6th international conference, reading* (pp. 364–371). Berlin: Springer-Verlag.

Metzker, Z., Marousek, J., Zvarikova, K., & Hlawiczka, R. (2021). The perception of SMEs bankruptcy concerning CSR implementation. *International Journal of Entrepreneurial Knowledge, 9*(2), 85–95. doi: 10.37335/ijek.v9i2.133.

Mihalovic, M. (2016). Performance comparison of multiple discriminant analysis and logit models in bankruptcy prediction. *Economics and Sociology, 9*(4), 101–118. doi: 10.14254/2071-789X.2016/9-4/6.

Nachev, A., Hill, S., & Barry, Ch. (2010). Fuzzy, distributed, instance counting, and default artmap neural networks for financial diagnosis. *International Journal of Information Technology & Decision Making, 9*(6), 959–978. doi: 10.1142/S0219622010004111.

Neves, J. C., & Vieira, A. (2006). Improving bankruptcy prediction with hidden layer learning vector quantization. *European Accounting Review, 15*(2), 253–271. doi: 10.1080/09638180600555016.

Noga, T., & Adamowicz, K. (2021). Forecasting bankruptcy in the wood industry. *European Journal of Wood and Wood Products, 79*, 735–743. doi: 10.1007/s00107-020-01620-y.

Nyitrai, T., & Virag, M. (2019). The effects of handling outliers on the performance of bankruptcy prediction models. *Socio-Economic Planning Sciences, 67*, 34–42. doi: 10.1016/j.seps.2018.08.004.

Obradovic, D. B., Jaksic, D., Rupic, I. B., & Andric, M. (2018). Insolvency prediction model of the company: the case of the Republic of Serbia. *Economic Research-Ekonomska Istrazivanja, 31*(1), 139–157. doi: 10.1080/1331677X.2017.1421990.

Ocal, M. E., Oral, E. L., Erdis, E., & Vural, G. (2007). Industry financial ratios—application of factor analysis in Turkish construction industry. *Building and Environment, 42*(1), 385–392. doi: 10.1016/j.buildenv.2005.07.023.

O´Leary, D. E. (1998). Using neural networks to predict corporate failure. *International Journal of Intelligent Systems in Accounting, Finance & Management, 7*, 187–197. doi: 10.1002/(SICI)1099-1174(199809)7:3<187::AID-ISAF144>3.0.CO;2-7.

Papana, A., & Spyridou, A. (2020). Bankruptcy prediction: the case of the Greek market. *Forecasting, 2*(4), 505–525. doi: 10.3390/forecast2040027.

Peat, M., & Jones, S. (2012). Using neural nets to combine information sets in corporate bankruptcy prediction. *Intelligent Systems in Accounting Finance & Management, 19*(2), 90–101. doi: 2350/10.1002/isaf.334.

Pozorska, J., & Scherer, M. (2018). Company bankruptcy prediction with neural networks. In L. Rutkowski, R. Scherer, M. Korytkowski, W. Pedrycz, R. Tadeusiewicz & J. Zurada (Eds). *Artificial intelligence and soft computing. Lecture notes in computer science*. Springer, Cham. doi: 10.1007/978-3-319-91253-0_18.

Privara, A., & Rievajová, E. (2021). Migration governance in Slovakia during the COVID-19 crisis. *Migration Letters, 18*(3), 331–338. doi: 10.33182/ml.v18i3.1469.

Psarska, M., Haskova, S., & Machova, V. (2019). Performance management in small and medium-sized manufacturing enterprises operating in automotive in the context of future changes and challenges in SR. *Ad Alta: Journal of Interdisciplinary Research, 9*(2), 281–287.

Ptak-Chmielewska, A. (2019). Predicting micro-enterprise failures using data mining techniques. *Journal of Risk and Financial Management*, *12*(1), 30. doi: 10.3390/jrfm12010030.

Purvinis, O., Sukys, P., & Virbickaite, R. (2007). Adaptive network-based fuzzy inference system for enterprise bankruptcy prediction. In *2nd international conference on changes in social and business environment* (pp. 198–202). Kaunas University Technology Press.

Purvinis, O., Virbickaite, R., & Sukys, P. (2008). Interpretable nonlinear model for enterprise bankruptcy prediction. *Nonlinear Analysis: Modelling and Control, 13*(1), 61–70. doi: 10.15388/NA.2008.13.1.14589.

Rahman, M., Li Sa, Ch., & Masud, A. K. (2021). Predicting firms´ financial distress: an empirical analysis using the F-score model. *Journal of Risk and Financial Management, 14*(5), 199. doi: 10.3390/jrfm14050199.

Sahoo, M., & Pradhan, J. (2021). Adaptation and acculturation: resettling displaced tribal communities from wildlife sanctuaries in India. *Migration Letters, 18*(3), 237–259. doi: 10.33182/ml.v18i3.877.

Salehi, M., & Davoudi Pour, M. (2016). Bankruptcy prediction of listed companies on the Tehran Stock Exchange. *International Journal of Law and Management, 58*(5), 545–561. doi: 10.1108/IJLMA-05-2015-0023.

Salehi, M., & Mousavi Shiri, M. (2016). Different bankruptcy prediction patterns in an emerging economy: Iranian evidence. *International Journal of Law and Management, 58*(3), 258–280. doi: 10.1108/IJLMA-05-2015-0022.

SARIO (2021a). *Machinery & equipment industry in Slovakia*. Bratislava: Slovak Investment and Trade Development Agency.

SARIO (2021b). *Automotive sector in Slovakia*. Bratislava: Slovak Investment and Trade Development Agency.

Shetty, S. H., & Vincent, T. N. (2021). The role of board independence and ownership structure in improving the efficacy of corporate financial distress prediction model: evidence from India. *Journal of Risk and Financial Management, 14*(7), 333. doi: 10.3390/jrfm14070333.

Shirata, C. Y. (1998). Financial ratios as predictors of bankruptcy in Japan: an empirical research. In *Proceedings of the second Asian Pacific interdisciplinary research in accounting conference*. Retrieved from https://www.shirata.net/eng/APIRA98.html.

Slavicek, O., & Kubenka, M. (2016). Bankruptcy prediction models based on the logistic regression for companies in the Czech Republic. In *Proceedings of the 8th international scientific conference managing and modelling of financial risks* (pp. 924–931). Ostrava: VŠB-TU of Ostrava.

Smith, R. F., & Winakor, A. H. (1935). *Changes in the financial structure of unsuccessful industrial corporations.* Urbana, IL, USA: University of Illinois.

Sousa, A., Braga, A., & Cunha, J. (2022). Impact of macroeconomic indicators on bankruptcy prediction models: case of the Portuguese construction sector. *Quantitative Finance and Economics, 6*(3), 405–432. doi: 10.3934/QFE.2022018.

Stefancik, R., Nemethova, I., & Seresova, T. (2021). Securitisation of migration in the language of Slovak far-right populism. *Migration Letters, 18*(6), 731. doi: 10.33182/ml.v18i6.1387.

Stefko, R., Horvathova, J., & Mokrisova, M. (2020). Bankruptcy prediction with the use of data envelopment analysis: an empirical study of Slovak businesses. *Journal of Risk and Financial Management, 13*(9), 212. doi: 10.3390/jrfm13090212.

Stefko, R., Horvathova, J., & Mokrisova, M. (2021). The application of graphic methods and the DEA in predicting the risk of bankruptcy. *Journal of Risk and Financial Management, 14*(5), 220. doi: 10.3390/jrfm14050220.

Stehel, V., Horak, J., & Kruclicky, T. (2021). Business performance assessment of small and medium-sized enterprises: evidence from the Czech Republic. *Problems and Perspectives in Management, 19*(3), 430–439. doi: 10.21511/ppm.19(3).2021.35.

Svabova, L., Michalkova, L., Durica, M., & Nica, E. (2020). Business failure prediction for Slovak small and medium-sized companies. *Sustainability*, *12*, 4572. doi: 10.3390/su12114572.

Takata, Y., Hosaka, T., & Ohnuma, H. (2015). Financial ratios extraction using adaboost for delisting prediction. *Proceedings of the Seventh International Conference on Information*, 158–161.

Tam, K. (1991). Neural network models and the prediction of bank bankruptcy. *Omega*, *19*(5), 429–445. doi: 10.1016/0305-0483(91)90060-7.

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis, 30*, 394–419. doi: 10.1016/j.irfa.2013.02.013.

Tsai, Ch. F. (2009). Feature selection in bankruptcy prediction. *Knowledge-Based Systems, 22*(2), 120–127. doi: 10.1016/j.knosys.2008.08.002.

Tsai, Ch. F., & Wu, J. W. (2008). Using neural network ensembles for bankruptcy prediction and credit scoring. *Expert Systems with Applications, 34*(4), 2639–2649. doi: 10.1016/j.eswa.2007.05.019.

Tsakonas, A., Dounias, G., Doumpos, M., & Zopounidis, C. (2006). Bankruptcy prediction with neural logic networks by means of grammar-guided genetic programming. *Expert Systems with Applications, 30*(3), 449–461. doi: 10.1016/ j.eswa.2005.10.009.

Tseng, F. M., & Lin, L. (2005). A quadratic interval logit model for forecasting bankruptcy. *Omega, 33*(1), 85–91. doi: 10.1016/j.omega.2004.04.002.

Tumpach, M., Surovicova, A., Juhaszova, Z., Marci, A., & Kubascikova, Z. (2020). Prediction of the bankruptcy of Slovak companies using neural networks with SMOTE. *Journal of Economics*, *68*(10), 1021−1039. doi: 10.31577/ ekoncas.2020.10.03.

Valaskova, K., Durana, P., Adamko, P., & Jaros, J. (2020). Financial compass for Slovak enterprises: modeling economic stability of agricultural entities. *Journal of Risk and Financial Management, 13*(5), 92. doi: 10.3390/jrfm13050092.

Valecky, J., & Slivkova, E. (2012). Microeconomic scoring model of Czech firms' bankruptcy. *Ekonomicka Revue. Central European Review of Economic Issues, 15*, 15–26. doi: 10.7327/cerei.2012.06.02.

Vochozka, M., Vrbka, J., & Suler, P. (2020). Bankruptcy or success? The effective prediction of a company's financial development using LSTM. *Sustainability*, *12*(18), 7529. doi: 10.3390/su12187529.

Wang, H., & Liu, X. (2021). Undersampling bankruptcy prediction: Taiwan bankruptcy data. *Plos One, 16*(7), e0254030. doi: 10.1371/journal.pone.0254030.

Wang, L. (2019). Financial distress prediction for listed enterprises using fuzzy C-means. *Littera Scripta, 12*(1), 1–9.

Wang, R., & Zha, B. (2019). A research on the optimal design of BP neural network based on improved GEP. *International Journal of Pattern Recognition and Artificial Intelligence*, *33*(3), 1959007. doi: 10.1142/S0218001419590079.

Wrzosek, M., & Ziemba, A. (2009). Construction of a rating based on a bankruptcy prediction model. *Credit Research Center, The University of Edinburgh*, 1–19.

Youn, H., & Gu, Z. (2010). Predict US restaurant firm failures: the artificial neural network model versus logistic regression model. *Tourism and Hospitality Research, 10*(3), 171–187. doi: 2350/10.1057/thr.2010.2.

Yousaf, M., & Bris, P. (2021). Assessment of bankruptcy risks in Czech companies using regression analysis. *Problems and Perspectives in Management, 19*(3), 46–55. doi: 10.21511/ppm.19(3).2021.05.

Acknowledgments

This research was supported by the projects KEGA 001PU-4/2022.

This research was supported by the Scientific Grant Agency of the Ministry of Education, Science, Research, and Sport of the Slovak Republic and the Slovak Academy Sciences as part of the research project VEGA No. 1/0590/22: "Exploration of natural, social and economic potential of areas with environmental burdens in the Slovak Republic for the development of specific forms of domestic tourism and quantification of environmental risks".

Annex

Table 1. Descriptive statistics of used dataset

Variable	Min	Max	Range	Mean	Std. dev.	Q0.25	Q0.75	Median
				2018				
TI	-0.31	0.44	0.75	0.07	0.10	0.02	0.11	0.05
FL	-0.91	1.33	2.24	0.18	0.29	0.03	0.31	0.14
ROS	-0.37	0.52	0.89	0.08	0.13	0.01	0.13	0.05
ROE	-5.54	9.94	15.48	2.46	2.14	1.36	3.21	1.99
ROI	-0.69	0.98	1.68	0.29	0.20	0.16	0.41	0.27
SVA/S	0.04	6.69	6.65	1.83	1.12	1.04	2.35	1.61
TA	-4.27	11.19	15.46	2.48	2.18	1.08	3.08	1.65
NWC/A	-1.63	1.74	3.37	0.26	0.40	0.05	0.54	0.28
QR	-4.27	10.18	14.45	2.05	2.04	0.73	2.55	1.34
				2019				
TI	-0.28	2.52	2.80	0.56	0.36	0.32	0.73	0.53
FL	-5.44	9.97	15.41	2.45	2.17	1.35	3.16	1.98
ROS	-0.34	0.43	0.77	0.06	0.11	0.01	0.11	0.05
ROE	-1.02	1.32	2.35	0.17	0.29	0.02	0.30	0.12
ROI	-0.43	0.54	0.97	0.07	0.13	0.01	0.13	0.05
SVA/S	-0.54	1.00	1.54	0.29	0.20	0.15	0.40	0.27
TA	-0.001	7.34	7.33	1.87	1.23	1.04	2.44	1.58
NWC/A	-1.69	0.94	2.63	0.25	0.42	0.03	0.54	0.29
QR	-1.44	11.87	13.30	2.14	2.26	0.66	2.61	1.35

Table 2. The values of weights between neurons

Parameter Estimates – Normalised 80:20 (both – 2019)								
Predictor		**Predicted**						
		Hidden Layer 1					**Output Layer**	
		H(1:1)	**H(1:2)**	**H(1:3)**	**H(1:4)**	**H(1:5)**	**[bankruptcy=0]**	**[bankruptcy=1]**
Input Layer	(Bias)	-1.074	-1.334	-1.528	.724	.256		
	TI	-3.502	-4.932	-6.258	-0.644	0.206		
	FL	2.564	4.249	4.938	1.388	0.255		
	ROS	0.739	1.135	0.984	0.997	0.329		
	ROE	-0.775	-0.849	-1.261	0.096	0.529		
	ROI	0.837	0.932	1.743	0.721	0.774		
	SVA/S	0.076	-0.156	0.140	1.018	0.695		
	TA	-0.227	-0.693	-0.035	-0.219	-0.156		
	NWC/A	1.397	1.969	2.130	1.505	0.659		
	QR	0.758	0.268	0.381	0.705	0.016		
Hidden Layer 1	(Bias)						-2.921	3.065
	H(1:1)						2.115	-2.488
	H(1:2)						4.369	-4.346
	H(1:3)						6.047	-5.812
	H(1:4)						-1.404	1.070
	H(1:5)						-1.060	1.314

Table 3. The values of weights between neurons

Parameter Estimates – Standardised 80:20 (both – 2019)								
Predictor		**Predicted**						
		Hidden Layer 1					**Output Layer**	
		H(1:1)	**H(1:2)**	**H(1:3)**	**H(1:4)**	**H(1:5)**	**[bankruptcy=0]**	**[bankruptcy=1]**
Input Layer	(Bias)	2.570	2.885	3.014	-1.277	1.087		
	TI	-2.227	-1.865	-2.378	-1.632	-3.080		
	FL	2.328	2.216	2.651	1.365	2.626		
	ROS	-0.216	0.088	0.138	0.169	0.703		
	ROE	-0.361	-0.327	-0.485	0.102	-0.477		
	ROI	0.721	0.400	0.571	0.194	0.847		
	SVA/S	0.221	0.082	0.155	0.550	0.526		
	TA	-0.178	-0.097	-0.072	-0.086	0.035		
	NWC/A	0.564	0.162	0.694	1.704	1.894		
	QR	-0.260	-0.024	-0.417	0.729	0.247		
Hidden Layer 1	(Bias)						-5.519	5.469
	H(1:1)						3.563	-3.388
	H(1:2)						3.870	-4.546
	H(1:3)						4.466	-4.295
	H(1:4)						-2.064	2.353
	H(1:5)						1.855	-1.649

Table 4. Model performance for all subsets for year 2018

2018											
Sample			**Automotive predicted**			**Engineering predicted**			**Both predicted**		
			0	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**
standardisation											
80:20	Training	**0**	135	0	100.0	894	0	100.0	1009	0	100.0
		1	0	5	100.0	4	56	93.3	4	65	94.2
		Overall (%)	96.4	3.6	100.0	94.1	5.9	99.6	94.0	6.0	99.6
	Testing	**0**	25	0	100.0	215	0	100.0	241	0	100.0
		1	0	0	0	0	15	100.0	1	13	92.9
		Overall (%)	100	0	100.0	93.5	6.5	100.0	94.9	5.1	99.6
70:30	Training	**0**	121	0	100.0	762	0	100.0	925	0	100.0
		1	0	4	100.0	4	50	92.6	1	58	98.3
		Overall (%)	96.8	3.2	100.0	93.9	6.1	99.5	94.1	5.9	99.9
	Testing	**0**	39	0	100.0	347	0	100.0	325	0	100.0
		1	0	1	100.0	0	21	100.0	2	22	91.7
		Overall (%)	97.5	2.5	100.0	94.3	5.7	100.0	93.7	6.3	99.4
60:40	Training	**0**	90	0	100.0	680	0	100.0	773	0	100.0
		1	0	1	100.0	2	50	96.2	0	53	100.0
		Overall (%)	98.9	1.1	100.0	93.2	6.8	99.7	93.6	6.4	100.0

Table 4. Continued

			2018								
Sample			**Automotive predicted**			**Engineering predicted**			**Both predicted**		
			0	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**
					standardisation						
	Testing	**0**	70	0	100.0	429	0	100.0	477	0	100.0
		1	2	2	50.0	2	21	91.3	2	28	93.3
		Overall (%)	97.3	2.7	97.3	95.4	4.6	99.6	94.5	5.5	99.6
					normalisation						
80:20	Training	**0**	122	0	100.0	871	0	100.0	968	0	100.0
		1	0	4	100.0	4	62	93.9	5	56	91.8
		Overall (%)	96.8	3.2	100.0	93.4	6.6	99.6	94.6	5.4	99.5
	Testing	**0**	38	0	100.0	238	0	100.0	282	0	100.0
		1	0	1	100.0	0	9	100.0	0	22	100.0
		Overall (%)	97.4	2.6	100.0	96.4	3.6	100.0	92.8	7.2	100.0
70:30	Training	**0**	115	0	100.0	762	0	100.0	890	0	100.0
		1	5	0	0	3	54	94.7	4	56	93.3
		Overall (%)	100	0	95.8	93.4	6.6	99.6	94.1	5.9	99.6
	Testing	**0**	45	0	100.0	347	0	100.0	360	0	100.0
		1	0	0	0	1	17	94.4	1	22	95.7
		Overall (%)	100	0	100.0	95.3	4.7	99.7	94.3	5.7	99.7
60:40	Training	**0**	97	0	100.0	661	0	100.0	779	0	100.0
		1	0	5	100.0	2	43	95.6	4	51	92.7
		Overall (%)	95.1	4.9	100.0	93.9	6.1	99.7	93.9	6.1	99.5
	Testing	**0**	63	0	100.0	448	0	100.0	471	0	100.0
		1	0	0	0	2	28	93.3	2	26	92.9
		Overall (%)	100	0	100.0	94.1	5.9	99.6	94.8	5.2	99.6

Table 5. Model performance for all subsets for year 2019

			2019								
Sample			**Automotive predicted**			**Engineering predicted**			**Both predicted**		
			0	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**
					standardisation						
80:20	Training	**0**	132	0	100.0	929	0	100.0	1044	0	100.0
		1	0	5	100.0	0	57	100.0	1	71	98.6
		Overall (%)	96.4	3.6	100.0	94.2	5.8	100.0	93.6	6.4	99.9

Table 5. Continued

Sample			Automotive predicted 0	Automotive predicted 1	Automotive Correct (%)	Engineering predicted 0	Engineering predicted 1	Engineering Correct (%)	Both predicted 0	Both predicted 1	Both Correct (%)
			2019								
standardisation											
	Testing	**0**	31	0	100.0	231	0	100.0	273	0	100.0
		1	0	2	100.0	1	18	94.7	0	14	100.0
		Overall (%)	93.9	6.1	100.0	92.8	7.2	99.6	95.1	4.9	100.0
70:30	Training	**0**	117	0	100.0	799	0	100.0	934	0	100.0
		1	0	2	100.0	1	42	97.7	1	51	98.1
		Overall (%)	98.3	1.7	100.0	95.0	5.0	99.9	94.8	5.2	99.9
	Testing	**0**	46	0	100.0	361	0	100.0	383	0	100.0
		1	0	5	100.0	0	33	100.0	0	34	100.0
		Overall (%)	90.2	9.8	100.0	91.6	8.4	100.0	91.8	8.2	100.0
60:40	Training	**0**	88	0	100.0	712	0	100.0	797	0	100.0
		1	0	2	100.0	1	48	98.0	0	48	100.0
		Overall (%)	97.8	2.2	100.0	93.7	6.3	99.9	94.3	5.7	100.0
	Testing	**0**	75	0	100.0	448	0	100.0	520	0	100.0
		1	0	5	100.0	0	27	100.0	1	37	97.4
		Overall (%)	93.8	6.3	100.0	94.3	5.7	100.0	93.4	6.6	99.8
normalisation											
80:20	Training	**0**	133	0	100.0	927	0	100.0	1047	0	100.0
		1	0	5	100.0	1	52	98.1	0	70	100.0
		Overall (%)	96.4	3.6	100.0	94.7	5.3	99.9	93.7	6.3	100.0
	Testing	**0**	30	0	100.0	233	0	100.0	270	0	100.0
		1	0	2	100.0	0	23	100.0	1	15	93.8
		Overall (%)	93.8	6.2	100.0	91.0	9.0	100.0	94.8	5.2	99.7
70:30	Training	**0**	116	0	100.0	796	0	100.0	915	0	100.0
		1	0	4	100.0	1	51	98.1	1	58	98.3
		Overall (%)	96.7	3.3	100.0	94.0	6.0	99.9	94.0	6.0	99.9
	Testing	**0**	47	0	100.0	364	0	100.0	402	0	100.0
		1	0	3	100.0	0	24	100.0	0	27	100.0
		Overall (%)	94.0	6.0	100.0	93.8	6.2	100.0	93.7	6.3	100.0
60:40	Training	**0**	97	0	100.0	680	0	100.0	768	0	100.0
		1	0	3	100.0	0	44	100.0	1	51	98.1
		Overall (%)	97.0	3.0	100.0	93.9	6.1	100.0	93.8	6.2	99.9
	Testing	**0**	66	0	100.0	480	0	100.0	549	0	100.0
		1	0	4	100.0	1	31	96.9	0	34	100.0
		Overall (%)	94.3	5.7	100.0	93.9	6.1	99.8	94.2	5.8	100.0

Table 6. Model performance for both industries with different functions for year 2019

			Automotive and Engineering industry								
Sample			**sigmoid**			**htan+sigmoid**			**htan**		
			predicted			**predicted**			**predicted**		
			0	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**
standardisation											
80:20	Training	**0**	1044	0	100.0	1074	0	100.0	1045	0	100.0
		1	1	71	98.6	1	71	98.6	1	68	98.6
		Overall (%)	93.6	6.4	99.9	93.8	6.2	99.9	93.9	6.1	99.9
	Testing	**0**	273	0	100.0	243	0	100.0	272	0	100.0
		1	0	14	100.0	0	14	100.0	0	17	100.0
		Overall (%)	95.1	4.9	100.0	94.6	5.4	100.0	94.1	5.9	100.0
70:30	Training	**0**	934	0	100.0	935	0	100.0	927	0	100.0
		1	1	51	98.1	1	61	98.4	0	57	100.0
		Overall (%)	94.8	5.2	99.9	93.9	6.1	99.9	94.2	5.8	100.0
	Testing	**0**	383	0	100.0	382	0	100.0	390	0	100.0
		1	0	34	100.0	0	24	100.0	1	28	96.6
		Overall (%)	91.8	8.2	100.0	94.1	5.9	100.0	93.3	6.7	99.8
60:40	Training	**0**	797	0	100.0	792	0	100.0	794	0	100.0
		1	0	48	100.0	1	53	98.1	1	52	98.1
		Overall (%)	94.3	5.7	100.0	93.7	6.3	99.9	93.9	6.1	99.9
	Testing	**0**	520	0	100.0	525	0	100.0	523	0	100.0
		1	1	37	97.4	0	32	100.0	0	33	100.0
		Overall (%)	93.4	6.6	99.8	94.3	5.7	100.0	94.1	5.9	100.0
normalisation											
80:20	Training	**0**	1047	0	100.0	7070	0	100.0	1057	0	100.0
		1	0	70	100.0	1	70	98.6	1	63	98.4
		Overall (%)	93.7	6.33	100.0	99.0	1.0	100.0	94.4	5.6	99.9
	Testing	**0**	270	0	100.0	247	0	100.0	260	0	100.0
		1	1	15	93.8	0	15	100.0	0	22	100.0
		Overall (%)	94.8	5.2	99.7	94.3	5.7	100.0	92.2	7.8	100.0
70:30	Training	**0**	915	0	100.0	937	0	100.0	917	0	100.0
		1	1	58	98.3	1	65	98.5	0	59	100.0
		Overall (%)	94.0	6.0	99.9	93.5	6.5	99.9	94.0	6.0	100.0
	Testing	**0**	402	0	100.0	380	0	100.0	400	0	100.0
		1	0	27	100.0	0	20	100.0	1	26	96.3
		Overall (%)	93.7	6.3	100.0	95.0	5.0	100.0	93.9	6.1	99.8
60:40	Training	**0**	768	0	100.0	776	0	100.0	766	0	100.0
		1	1	51	98.0	1	54	98.2	0	46	100.0
		Overall (%)	93.8	6.2	99.9	93.5	6.5	99.9	94.3	5.7	100.0

Table 6. Continued

		Automotive and Engineering industry								
Sample		**sigmoid**			**htan+sigmoid**			**htan**		
		predicted			**predicted**			**predicted**		
		0	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**	**0**	**1**	**Correct (%)**
Testing	**0**	549	0	100.0	541	0	100.0	551	0	100.0
	1	0	34	100.0	0	31	100.0	1	39	97.5
	Overall (%)	94.2	5.8	100.0	94.6	5.4	100.0	93.4	6.6	99.8

Table 7. Model AEI

	Indicator	**(B)logit**	**S.E.**	**z**	**Waldov**	**OR**	**95% Wald CI**	
	Constant	-1.7484^{d}	0.1358	-13.14	-9.9872			
x_1	ROS	-0.5410^{d}	0.1620	-3.339	-3.0848	0.5821	0.424	0.800
x_2	FL	0.0122^{d}	0.0034	3.272	2.8059	1.0113	1.005	1.018
x_3	PC/S	-1.1796^{d}	0.3977	-2.966	-2.8424	0.3074	0.141	0.670
x_4	TA	0.2578^{d}	0.0257	10.02	4.5972	1.2941	1.230	1.361
x_5	NWC/A	-2.6784^{d}	0.1984	-13.50	-12.2429	0.0687	0.047	0.101
x_6	QR	-0.1082^{d}	0.0426	-2.541	-2.4853	0.8974	0.825	0.976

Note: B denotes coefficient, S.E. is standard deviation, OR denotes odds ratio, and ^{d} denotes statistical significance at the 0.1% level.

Table 8. Model EI

	Indicator	**(B)logit**	**S.E.**	**z**	**Waldov**	**OR**	**95% Wald CI**	
	Constant	-1.5649^{d}	0.1567	-9.983	-9.9872			
x_1	ROS	-0.5457^{d}	0.1769	-3.085	-3.0848	0.5794	0.410	0.820
x_2	FL	0.0098^{d}	0.0035	2.741	2.8059	1.0099	1.003	1.017
x_3	PC/S	-1.2313^{d}	0.4332	-2.842	-2.8424	0.2919	0.125	0.682
x_4	TA	0.1912^{d}	0.0416	4.593	4.5972	1.2108	1.116	1.314
x_5	NWC/A	-2.6518^{d}	0.2166	-12.24	-12.2429	0.0705	0.046	0.108
x_6	QR	-0.1036^{d}	0.0417	-2.485	-2.4853	0.9016	0.831	0.978

Note: B denotes coefficient, S.E. is standard deviation, OR denotes odds ratio, and ^{d} denotes statistical significance at the 0.1% level.

Table 9. Statistical validation of models

Criterion	**Model EI (1,525)**	**Model AEI (1,820)**
AIC	956.390	1155.028
BIC	993.698	1160.896
HQIC	970.277	1136.570
Logarithm of the likelihood	-471.195	-554.174
McFadden	0.323	0.3451

Table 10. Classification table for EI and AEI model

Model EI		Predicted			
		Y			
		0	**1**	**overall**	**Correct (%)**
Y	**0**	1250	15	1265	98.81
	1	145	115	256	44.92
	Overall	1395	130	1525	
Overall success rate (%)					89.5
Model AEI		**Predicted**			
		Y			
		0	**1**	**overall**	**Correct (%)**
Y	**0**	1480	20	1500	98.66
	1	170	150	320	53.31
	Overall	1650	170	1820	
Overall success rate (%)					89.6

Table 11. AUC

Model	Area	S.E.	Sig.b	95% CI	
Model EI	0.899	0.012	0.000	0.875	0.923
Model AEI	0.900	0.011	0.010	0.878	0.922

Note: S.E. denotes standard deviation, Sig.b denotes statistical significance, and CI denotes confidence interval.

Figure 1. Activation function

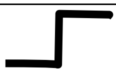
Function	Graphical representation	Mathematical representation
Step		$g^{step}(x) = [0,1]$
Threshold		$g^{theta}(x) = x\Theta(x)$
Sigmoid		$g^{sig}(x) = \frac{1}{1+e^{-x}}$
Hyperbolic Tan		$g^{tanh}(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$
RBF		$g^{gauss}(x) = e^{-x^2}$

Figure 2. ANN Architecture

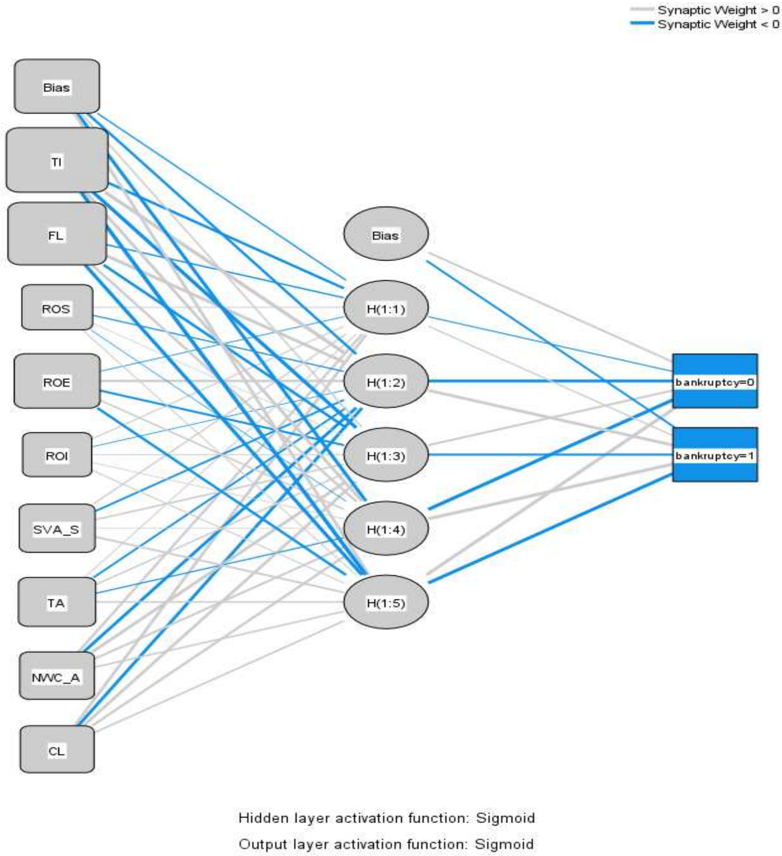


Figure 3. ROC for model EI