IS LOGISTIC REGRESSION RELIABLE IN BANKRUPTCY PREDICTION?

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ABSTRACT. Background: The fundamental foundation of financial and economic analysis is the implementation of financial and statistical models in business entities. Financial indicators help assess the company's financial situation and, at the same time, represent the most used tool in the detection of bankruptcy. A still significant method is the logistic regression, which ranks among classic statistical methods. **Aims:** The aim of the paper is to propose a scoring model for non-financial corporations in the electrotechnical industry and to estimate the probability of bankruptcy of enterprises in the electrotechnical industry of the Slovak Republic. **Sample:** The research sample consists of 1,241 companies operating in the electrotechnical industry of the Slovak Republic, according to SK NACE 26, 27 in the year 2020. **Methods:** We used logistic regression and designed a logistic model. Financial data were sourced from The Register of Financial Statements of the Slovak Republic. **Results:** In the bankruptcy model for the electrotechnical industry, the estimated odds ratios showed that the chances of bankruptcy significantly reduce the financial indicators *EBITDA/T, ROA, L2, and NWC/A*. When these indicators increase, the company's probability (or chance) of bankruptcy decreases. **Conclusions:** The estimate of a risky company or the probability of its bankruptcy is always very important. Therefore, it seems appropriate to look for applicable models. 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. **Implications:** The benefit of the paper is the construction of an early warning model for the Slovak electrotechnical industry. We constructed an appropriate model and evaluated the financial situation in the selected branch of industry.

Keywords: bankruptcy prediction, financial analysis, logistic regression, electrotechnical industry

JEL Classification: C53, G33

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Introduction

The state of the overall economy determines the ability of business entities to achieve the required profitability. A business entity is a symbiosis of a broad economic environment, be it regional, national, or global, which generates the conditions for its existence. However, the mentioned entity itself determines and creates this environment. The fundamental foundation of financial and economic analysis is the implementation of financial and statistical models in business entities. The issue of technical financial analysis is significantly reflected in decision-making processes in the field of business management.

Financial indicators help assess the company's financial situation and, at the same time, represent the most used tool in the detection of bankruptcy. Among the oldest and most popular models is the Altman model. A still significant method is the logistic regression, which ranks among classic statistical methods. Recently, new techniques based on artificial intelligence have emerged, and these have become promising hits.

The aim of the paper is to propose a scoring model for non-financial corporations in the electrotechnical industry and to estimate the probability of bankruptcy of enterprises in the electrotechnical industry of the Slovak Republic. The research sample consists of 1,241 companies operating in the electrotechnical industry of the Slovak Republic, according to SK NACE 26, 27 in the year 2020. We used the logistic regression and designed a logistic model.

Theoretical background

Logistic regression (LR) is used in cases where the dependent variable is not continuous but binary. It is characterised as a prediction of the probability of an event occurring or not. It eliminates the disadvantage of discriminant analysis in that it does not assume normal distribution and homogeneity of covariance matrices. Probit is an alternative that assumes a normal distribution of independent variables (Kliештik et al., 2015).

These statistical-mathematical methods were first used by Ohlson (1980) and Zmijewski (1984). Works by Bernhardsen (2001), Ogachi et al. (2020), Zultilisna et al. (2023), and Calabrese (2023) analysed these methods. Also, these methods have been compared with the latest techniques in the works by Sen et al. (2004), Du Jardin (2008, 2018), Lee (2015), Ptak-Chmielewska (2019), Jenčová et al. (2018, 2020), Korol (2020, 2021), Chen et al. (2021) and Kitowski (2022).

The improved PLS-LR ("partial least squares logistic regression") technique used in the prediction of Jauber (2017) achieved a slight increase in the accuracy of this method. Brygala (2022) used the Logit method to analyse the influence of the ratio of bankrupt and non-bankrupt samples (using the reduction of non-bankrupt ones - "downsizing"). Ohlson (1980) used 105 bankrupt and 2,058 non-bankrupt firms with a 9-indicators analysis that achieved 96% accuracy (one and two years before bankruptcy) using the Logit. Zavgren (1983) used 7 indicators with 69% accuracy (1-5 years before failure). Jenčová et al. (2020) proposed an LR model for the electrotechnical industry of the Slovak Republic, which had an accuracy of 94% (99% for non-bankrupt enterprises and 60% for bankrupt ones). Mućko and Adamczyk (2023) used LR to examine the accuracy of Altman's model and conclude that its unreliability is not caused by shutter manipulation. LR is a nonlinear model, although it is represented by a linear combination of parameters and values of explanatory variables. This function is bounded by 0 and 1 (Becerra-Vicario et al., 2020).

Logit analysis assumes a logarithmic probability distribution and Probit analysis a cumulative probability distribution. These methods can be considered as a kind of general version of the linear model of the estimation of the dependent variable. They allow the use of a continuous, categorical or discrete dependent variable. According to Jenčová et al. (2020), the main disadvantage of the logit model is its high sensitivity to the problem of multiple regression, which requires the exclusion of correlation between dependent variables.

We performed a bibliometric analysis to map the use of logistic regression in bankruptcy prediction. The input to the bibliometric analysis was the publications exported from the scientific database Web of Science. A query command was entered into the search line for the Topic option using the Boolean operator OR (or) in such a structure ("logistic regression" OR "ex-ante" OR "prediction bankruptcy"). Only the latest scientific outputs from 2023 to 2024 were used, which belonged to the category of Economics, Management, Business and Business Finance. After the mentioned restrictions, 1,246 articles were included in the bibliometric analysis. Bibliometric maps were created using the VOSviewer program.

First, the occurrence of countries dealing with the given issue was analysed. A country was included in the analysis only if at least 10 publications on the issue were associated with its affiliation. Figure 1 contains the created bibliometric map that classified 5 color-coded clusters of 33 cooperating countries. A larger point on the map represents a larger contribution of the country to the issue. The countries with the greatest influence are China and the USA. Thicker connections between countries represent more frequent cooperation. Classification of countries into individual clusters:

- red cluster (9 countries) – Austria, Belgium, Brazil, France, India, the Netherlands, Portugal, Romania, South Africa,
- green cluster (7 countries) – Australia, Canada, Indonesia, Japan, China, Singapore, the USA,
- blue cluster (6 countries) - Denmark, Germany, Sweden, Switzerland, Taiwan, Turkey,
- yellow cluster (6 countries) – Chile, England, Italy, Saudi Arabia, Scotland, Spain,
- purple cluster (5 countries) – Czech Republic, Poland, Slovakia, South Korea, Vietnam.

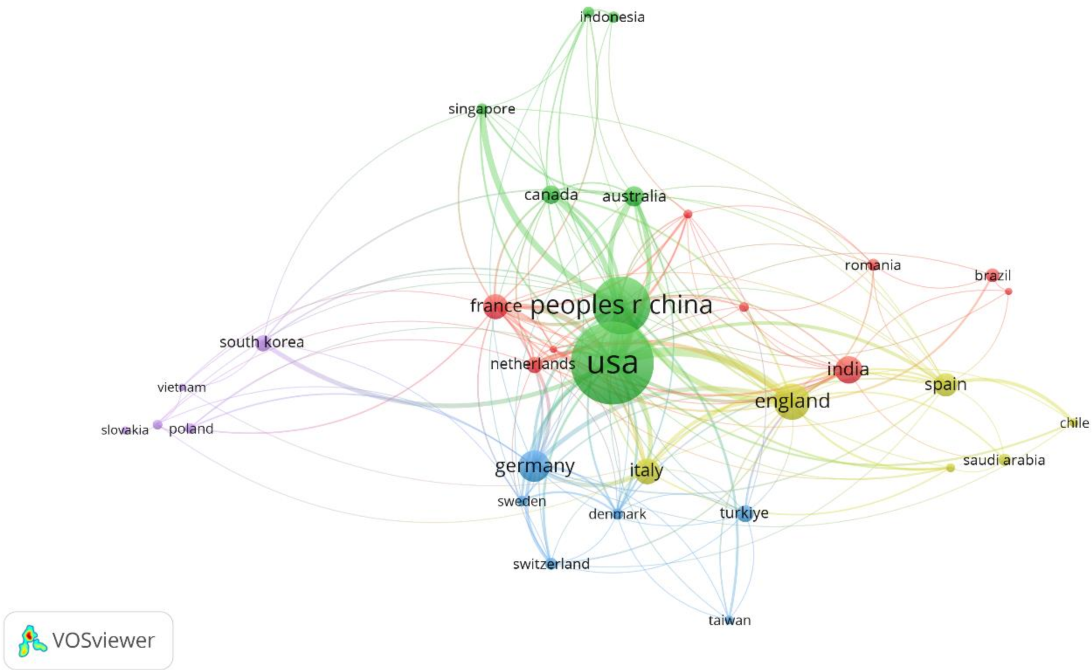

Figure 1 Bibliometric map of occurrence of countries
Source: *own processing in VOSviewer program*

Another part of the bibliometric analysis is the occurrence of keywords within the given issue. A keyword was included if it appeared at least 30 times in the underlying articles. Figure 2 offers the created bibliometric map that classified 3 color-coded clusters. A larger point on the map represents a more frequent occurrence of a keyword, and a thicker link between keywords means their more frequent occurrence together in publications.

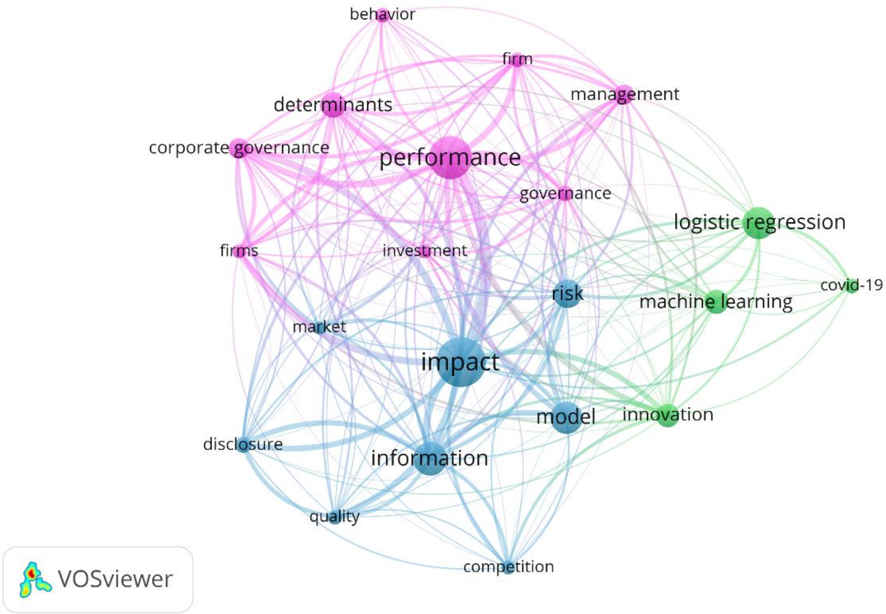

Figure 2 Bibliometric map of occurrence of keywords
Source: *own processing in VOSviewer program*

The classification of 21 keywords was carried out as follows:

- pink cluster (9 words) – behaviour, corporate governance, determinants, firm(s), governance, investment, management, performance,
- blue cluster (8 words) – competition, disclosure, impact, information, market, model, quality, risk,
- green cluster (4 words) – covid-19, innovation, logistic regression, machine learning.

Figure 3 detects the most discussed keywords from the underlying articles, specifically using Density Visualization. The greater the reach of the keyword, the larger the content of the coloured area around the specific word. We can see from the picture that the most discussed keywords include impact, performance, and information.

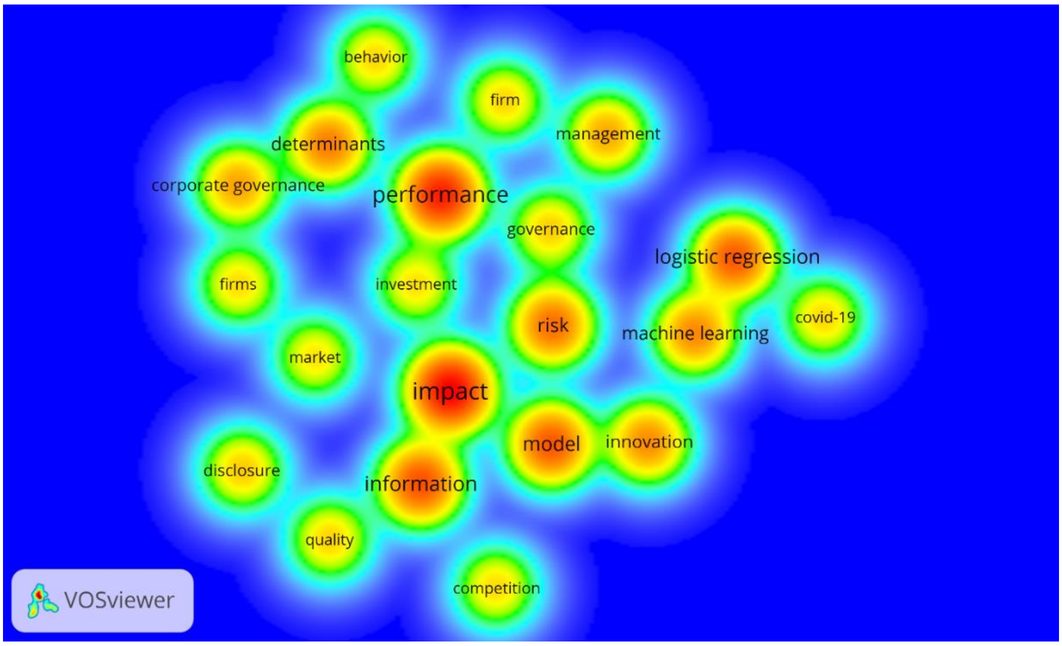

Figure 3 Bibliometric map of the most discussed keywords
Source: *own processing in VOSviewer program*

Methodology

Research Aim and Methods

The paper aims to propose a scoring model for non-financial corporations in the electrotechnical industry and to estimate the probability of bankruptcy for enterprises in the electrotechnical industry of the Slovak Republic.

Logistic regression (LR) is similar to linear regression, but unlike a continuous output variable, logit has a binary dependent variable. The model uses the probability density function in the large data to classify the explanatory variables and transform the numerical value into a probability distributed in the range 0-1. This simple model has flexible characteristics and is easy to understand, which is the reason for its frequent use in bankruptcy prediction. However, it has several strict assumptions (Chen et al., 2021). Unlike MDA, it does not require a normal distribution.

The conditional probability of the occurrence of the desired event under the condition of occurrence of the vector of independent variables *x* can be written as $p=P(Y=1|X)$, where *Y* is a binary variable that takes on two values. The logistic function expressing the relationship between the probability and the vector of explanatory variables has a nonlinear character and thus has the form of an exponential function:

$$p = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k}}{1+e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k}} = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k)}} = \frac{e^Z}{1+e^Z} = \frac{1}{1+e^{-Z}} \quad (1)$$

Using nonlinear maximum likelihood estimation in logistic regression, parameter estimates of the logit model were obtained according to (2). In order to use regression, the dependent variable is transformed to a continuous value by calculating the log of the odds (values from the interval (–∞; ∞)), with odds and probability expressing the same information in a different form.

Through the logit transformation, we get a linear one from a nonlinear dependence, the relationship between the logarithm of the chances and the vector of explanatory variables takes on a linear character, and the equation of the logarithmic model has the form according to (2).

$$\log it(p) = \ln\left(\frac{p}{1-p}\right) = \ln\left[e^{(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \quad (2)$$

Coefficients are estimated using the max-likelihood method. LR is suitable for predicting bankruptcy because its output is a value of 0-1. The cut-off point must ensure the most optimal distribution. The most commonly used split value is 0.5.

When using logistic regression, there is no equivalent statistic as for linear models, and pseudo-R^2 statistics are used. The Cox-Snell R^2 indicator is an alternative expression of the R^2 fit measure for linear models, which represents the proportion of variance explained by the model. It compares the model's credibility with a model without the use of regressors, i.e. with only an absolute term. It can be expressed as:

$$Cox\,\&\,Snell = 1-\left(\frac{L_0}{L_m}\right)^{\frac{2}{n}} \quad (3)$$

Lo is the likelihood of the model without regressors (use only with a constant), *Lm* is the maximum likelihood of the model with the use of regressors. A higher value indicates a better explanatory power of a specific model than a model without the use of regressors. The specific model fits the data better than the null model. The limit of the index is one minus the probability multiplied by *2/n*, which, under ideal conditions, reaches a maximum of 0.75. This bound is modified by the Nagelkerke correction, which is bounded to 1. Values approaching unity indicate that the specific model outperforms the model without regressors. This index simply normalizes Cox-Snell R^2 to the interval <0.1> :

$$Nagelkerke = \frac{CoxSnell}{\left(1-L_0\right)^{\frac{2}{n}}} \quad (4)$$

Tjur, unlike the other indices, is not relative to the model without regressors. Index values close to one indicate a clear separation of the prediction of bankrupt and non-bankrupt samples. The calculation is made up of the absolute value of the difference of the mean average forecast of the individual models.

$$Tjur = \left| \left(\overline{L}_0 - \overline{L}_1 \right) \right| \tag{5}$$

The basic criterion for assessing the classification model is its accuracy. It expresses the part of the prediction that was made correctly. The advantage is simple implementation and interpretability. The disadvantage is small robustness in case of an imbalance of data classes. In binary classification, it can be mathematically expressed as the ratio of correct estimates to the number of all samples. The ratio of positive prediction to positive samples expresses the sensitivity. The opposite is specificity, expressing the ratio of negative predictions to negative samples. Precision expresses the ratio of true positives to all positives.

The *ROC* curve is used to measure the goodness of fit to evaluate the LR model with a binary classifier. The curve is constructed based on the true positive rate on the vertical axis and the false positive rate on the horizontal axis for the various cut-off points of the model. The true positive rate is the rate of events that are predicted correctly and is usually referred to as sensitivity. The false positive rate is the rate of non-positive events, usually referred to as specificity. The *AUC* is the area under the *ROC* curve, which summarises the model's predictive power. The goal is to achieve the value of this metric as high as possible, approaching 1. The higher the value, the better the performance of the model for correct classification. A value of 1 would mean that the model estimated all values correctly (achieving a full 100%), whereas a value of 0 would mean an absolute failure and the inability to estimate a single value correctly. It can be calculated using a non-parametric approach known as the trapezoidal rule. The curve delimits the region and divides it into several trapezoidal intervals by sensitivity and 1-specificity. The sum of the area of the intervals creates the area under the *ROC* curve. This index is scale-invariant because it does not measure the absolute values of the prediction but how well they are evaluated, which is its great advantage. Other advantages include threshold invariance, which measures the quality of predictions regardless of the classification threshold.

The F1-score is a metric of predictive performance. It is an expression of the harmonic mean of precision and sensitivity. It is suitable for a higher imbalance of classification classes. The interpretation is relatively simple and reliable.

Modelling was done using the JASP program.

Research Sample

The research sample consists of 1,241 companies operating in the electrotechnical industry of the Slovak Republic, according to SK NACE 26, 27 in the year 2020. Financial data were sourced from The Register of Financial Statements of the Slovak Republic. We conducted outlier detection using the interquartile range method, where values outside the interval calculated as three times the interquartile range were flagged as outliers. After removing inconsistent samples and outliers, the research sample consists of 706 enterprises (667 healthy enterprises and 39 bankrupt enterprises). As part of the bankruptcy assessment in the analysed period, the ratio of equity to liabilities is set at 8%. Enterprises where the ratio of equity to liabilities is less than the defined ratio were considered bankrupt. The research sample was randomly split into two parts for training and testing, maintaining a ratio of 70:30. Financial indicators that were input to the analysis:

x_1 - *Total Indebtedness (TI)* = $Total\ Debt/Total\ Assets$
x_2 - *Financial Leverage (FL)* = $Assets/Equity$
x_3 – *Equity ratio (ER)* = $Equity/Assets$
x_4 – *Short-term Indebtedness (STI)* = $Current\ Liabilities/Assets$
x_5 - *Return on Sales (ROS)* = $EBITDA/Sales$
x_6 - *Return on Equity (ROE)* = $Earnings\ after\ taxes(EAT)/Equity$
x_7 - *Return on Assets (ROA)* = $Earnings\ after\ taxes(EAT)/Total\ Assets$
x_8 - *Share of Value Added in Sales (SVA / S)*
x_9 - *Turnover of Assets (TA)* = $Sales/Assets$
x_{10} - *Net Working Capital to Assets ratio (NWC / A)*
x_{11} - *Current Liquidity (L_2)* = $(Current\ Assets - Inventory)/Current\ Liabilities$
x_{12} – *Cash to Assets ratio (C/A)*

Results

To create prediction models for the electrotechnical industry, ratio indicators were selected from the group of liquidity (*L2, C/A*), indebtedness (*TI, FL, ER, STI*), activity (*TA*), profitability (*ROE, ROA, ROS*) and others (*SVA/S, NWC/A*), which, according to the analysed literature, significantly contribute to the estimation of the model. According to the literature, these 12 indicators show a high degree of causality to the explained variable (bankruptcy). Descriptive statistics of the data are presented in Table 1.

Table 1. Descriptive statistics

	SVA/S	***TI***	***ER***	***STI***	***FL***	***L2***	***C/A***	***ROE***	***ROA (EAT)***	***TA***	***NWC/ A***
Mean	03229	0.4657	0.5343	0.3372	2.2018	3.5164	0.3695	0.172	0.0885	1.618	0.4292
Med.	0.3004	0.4453	0.5547	0.2721	1.7324	2.0082	0.291	0.1327	0.0555	1.3699	0.4683
1Q	0.1612	0.2216	0.3304	0.1424	1.2577	1.2342	0.077	0.0109	0.0041	0.809	0.219
3Q	0.4649	0.6696	0.7784	0.4888	2.7715	4.4268	0.6309	0.3465	0.1651	2.1216	0.711
Var.	0.0693	0.0983	0.0983	0.0709	2.5447	13.6103	0.1086	0.1023	0.0285	1.3912	0.1309
Stand. dev.	0.2633	0.3135	0.3135	0.2663	1.5952	3.6892	0.3296	0.3198	0.1688	1.1795	0.3618
Kurto.	1.665	4.9559	4.9559	5.1871	2.5782	2.9997	-0.5838	1.8613	1.3992	3.1227	1.5744
Skew.	-0.0296	1.1468	-1.1468	1.2342	0.6307	1.8462	0.6225	-0.1168	0.3919	1.535	-0.6585
Min	-0.9176	-1.089	-1.4097	-1.1142	-3.8027	-4.7192	-0.3787	-1.0982	-0.4655	-0.6939	-1.0262
Max	1.0512	2.4097	2.089	1.8945	7.6719	17.9996	1.7908	1.3081	0.582	6.8881	2.1142

Source: *own processing*

Subsequently, the file was divided into two parts. The first part was used to create the model, and the second was used to validate it. The chosen ratio of 70:30 means that 70% (493) of the samples are involved in creating the model and 30% (213) in the validation.

The null model contained all the selected indicators, and using the stepwise method, those that were strongly correlated were gradually discarded. Covariates, in this case, are continuous variables that influence the dependent variable without experimental manipulation. The Wald statistic has an asymptotically *χ2* distribution with one degree of freedom under the null hypothesis. The test compares the original model with a sub-model without the given regression coefficient. The parameters in the model reached the significance of the Wald statistic. The probability of a company's bankruptcy is expressed by a model that consists of four predictors (*EBITDA/T, L2, ROA, NWC/A*) and an absolute term (Table 2).

$$\text{logit } (p) = \ln\left(\frac{p}{1-p}\right) = -0,698 - 2,103 \cdot EBITDA/T - 0,908 \cdot L_2 - 2,592 \cdot ROA - 1,912 \cdot NWC/A$$

Table 2. Model for electrotechnical industry

						Wald Test			95% Confidence interval	
	Estimate	Stand. dev.	Standardised dev.	Odds ratio	z	Wald Statistics	df	*p*	Lower limit	Upper limit
Constant	-0.698	0.188	-3.842	0.498	-3.716	13.807	1	<0.001	-1.066	-0.330
EBITDA/T	-2.103	1.020	-0.357	0.122	-2.062	4.253	1	0.039	-4.102	-0.104
L2	-0.908	0.194	-2.722	0.403	-4.691	22.006	1	<0.001	-1.287	-0.529
ROA (EAT)	-2.592	1.236	-0.403	0.075	-2.098	4.400	1	0.036	-5.014	-0.170
NWC/A	-1.912	0.340	-0.808	0.148	-5.620	31.589	1	<0.001	-2.579	-1.246

Source: *own processing*

A condition for logistic regression is that the samples are uncorrelated, so its modelling includes multicollinearity diagnosis. Multicollinearity diagnostics are calculated using VIF. For all financial indicators, the VIF was less than 5. All values meet the non-collinearity criteria (Table 3).

Table 3. Diagnosis of multicollinearity

Financial indicator	**Tolerance**	**VIF**
EBITDA/T	0.658	1.521
L2	0.948	1.054
ROA (EAT)	0.661	1.513
NWC/A	0.907	1.103

Source: *own processing*

The cut-off value is set to 0.5. Model quality is determined using *AIC* and *BIC*, chi-square. The R^2 value is a proportional expression of the total variance explained by the regression model. In this case, the chi-square alone is not a reliable indicator, so additional tests are also calculated - three pseudo-squares R^2. The value of the Cox-Snell, Nagelkerke statistics, and Tjur test were calculated in the model (Table 4).

Table 4. Statistical validation of a model

Model	**Deviation**	**AIC**	**BIC**	**df**	X^2	***p***	**McFadden R^2**	**Nagelkerke R^2**	**Tjur R^2**	**Cox & Snell R^2**
H_0	574.771	576.771	581.454	798						
H_1	398.879	408.879	432.296	794	175.891	<0.001	0.306	0.385	0.289	0.198

Source: *own processing*

The odds ratio expresses the increase in the odds ratio of bankruptcy when the predictor value is increased by 1. In the bankruptcy model for the electrotechnical industry, the estimated odds ratios showed that the chances of bankruptcy significantly reduce the financial indicators *EBITDA/T, ROA, L2, NWC/A*. When these indicators increase, the company's probability (or chance) of bankruptcy decreases. The return on sales, when it increases by one unit at the values of other fixed predictors, the chance of bankruptcy decreases by 8.19 times. Current liquidity will reduce bankruptcy by 2.48 times, and the share of net working capital in assets will reduce the chance of bankruptcy by 6.75 times.

By modelling a binary variable (*Y=1*, i.e. bankruptcy yes) depending on four predictors for the electrotechnical industry of Slovakia, the proposed logistic model was statistically significant as a whole. The overall success rate of the model for companies in the electrotechnical industry reached 91% (Table 5).

Table 5. Classification table for a model

	Predicted		
Real	**0**	**1**	**% accuracy**
0	700	6	99.150
1	64	29	31.183
Overall accuracy			91.239

Source: *own processing*

For comparison with other models, a more objective comparison is made using more advanced *AUC* and F-score metrics (Table 6). Figure 4 shows the *ROC* curve for the model. The *ROC* curve for the model defines an area under the curve equal to 0.865.

Table 6. AUC and F-score

	Value
Accuracy	0.912
AUC	0.865
Sensitivity	0.312
Specificity	0.992
Precision	0.829
F-score	0.453

Source: *own processing*

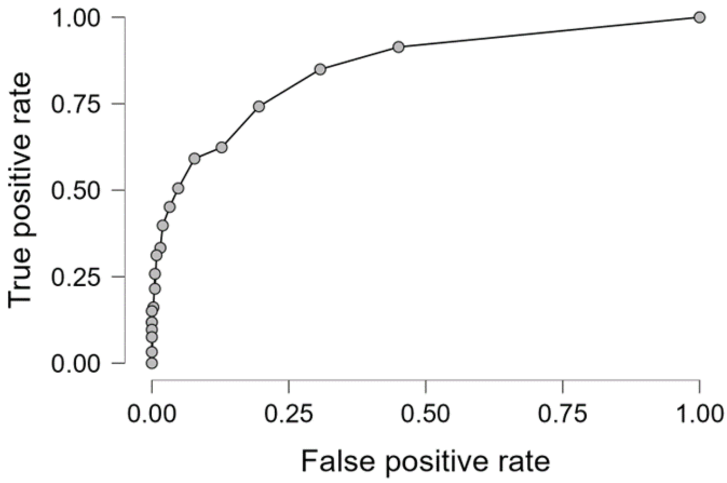

Figure 4 ROC curve
Source: *own processing*

We can compare our model with several existing logistic regression models. In our proposed logistic model, the liquidity indicators were represented by current liquidity (Mihalovic, 2016; Nyitrou & Virag, 2019; Rahman et al., 2021) and the share of net working capital in assets (Wrzosek & Ziemba, 2009; Jabeur, 2017; Valašková et al., 2018; Becerra-Vicario et al., 2020; Lohman et al., 2022). Profitability indicators were represented in our model by the return on sales indicator (Wrzosek & Ziemba, 2009; Jakubik & Teply, 2011; Harumova & Janisova, 2014; Lee & Su, 2015; Jabeur, 2017; Ptak-Chmielewska, 2019; Nyitrou & Virag, 2019) and return on assets (Režňáková et al., 2014; Lee & Su, 2015; Du Jardin, 2018; Ptak-Chmielewska, 2019; Becerra-Vicario et al., 2020; Korol, 2020; Yousaf & Bris, 2021).

Conclusion

Due to the impact of globalisation and worldwide problems, the need to monitor the business environment is inevitable. According to Samarin et al. (2022), bankruptcy is an important part of the market system, which aims to protect socio-economic processes from inefficient activities of such an entity. As a result, the entity is removed from the market, redistributing resources from inefficient owners to more efficient ones. Similarly, according to Kitowski et al. (2022), from a theoretical point of view, bankruptcy is part of the market's self-regulating mechanism and can be considered a condition for its development. According to Tsai and Jhen (2008), bankruptcy prediction has long been considered a critical topic and studied in financial literature.

We aimed to propose a scoring model for non-financial corporations in the electrotechnical industry and to estimate the probability of bankruptcy for enterprises in the electrotechnical industry of the Slovak Republic. The research sample consisted of 1,241 companies operating in the electrotechnical industry of the Slovak Republic, according to SK NACE 26, 27 in the year 2020. We used the logistic regression and designed a logistic model. In the bankruptcy model for the electrotechnical industry, the estimated odds ratios showed that the chances of bankruptcy significantly reduce the financial indicators *EBITDA/T, ROA, L2, NWC/A*. When these indicators increase, the company's probability (or chance) of bankruptcy decreases. The return of sales, when it increases by one unit at the values of other fixed predictors, the chance of bankruptcy decreases by 8.19 times. Current liquidity will reduce bankruptcy by 2.48 times, and the share of net working capital in assets will reduce the chance of bankruptcy by 6.75 times.

This paper has several limitations because we analysed it in only one year. Therefore, repeating the analysis for a different year would be interesting. In further analysis, we could use the regional segmentation of companies and other qualitative data. We could also consider the size of firms.

It is important for corporations to identify and prevent instability in time. For this reason, it is necessary to evaluate the company's financial health using appropriate models. To predict the future development of the financial situation, expanding the spectrum of mathematical and statistical methods is necessary.

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