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PREDICTION OF INSOLVENCY USING LOGISTIC REGRESSION: THE CASE OF THE REPUBLIC OF SRPSKA

Abstract

Purpose: In this paper, the authors try to develop a model for predicting the insolvency of trading companies from the Republic of Srpska. The research seeks to determine the statistically most significant financial indicator in predicting the insolvency of trading companies in the Republic of Srpska.

Methodology: The research data sample in this paper consists of yearly data from 2017 to 2020 for two hundred trading companies from the Republic of Srpska. Binary logistic regression was used to develop the model.

Results: As a result of the research, a model was created that successfully classifies 82.9% of solvent and 80% of insolvent companies, with a general efficiency rate of 81.4%.

Conclusion: Based on the empirical research results, we can conclude that the hypothesis has been confirmed that the LR model can be formed on the basis of selected financial indicators as a tool for predicting the insolvency of trading companies in the Republic of Srpska.

Keywords: Insolvency, bankruptcy, financial indicators, logistic regression, Republic of Srpska, trade

1. Introduction

The modern business environment is characterized by numerous and frequent changes, i.e., an extremely dynamic environment, in which change is the only constant. In such an environment, companies, especially those in trade, operate in highly competitive conditions, in which the greatest challenge is to survive in the "market competition" (Mikerević, 2011). One of the most common causes of the disappearance of companies from the market scene, according to the author of this paper, is insolvency, which in most cases results in the bankruptcy of the company. Given that the company is part of the environment in which it operates and that there is interdependence between the company as a legal entity and its environment, the disappearance of the company creates a series of negative circumstances for various stakeholders related to the company (Mikerević, 2011). Consequently, it is very important to anticipate the onset of insolvency in order to take appropriate measures in a timely manner in order to prevent the negative social and economic consequences that insolvency entails.

Taking into account the above, and the fact that according to the data provided by the Statistical Office of the Republic of Srpska for the period 2011-2020 (except for 2018), trade has the largest share as an economic activity in the structure of the gross domestic product of the Republic of Srpska, a research hypothesis in this paper is: Based on the selected financial ratios, the LR model can be formed as a tool for predicting the insolvency of companies engaged in trade in the Republic of Srpska.

In the last half century, numerous models have been developed for the purpose of predicting company insolvency (Altman's model, Zmijewski model, Fulmer model, Kralicek model). These models differ in terms of the variables they are based on, the activities they are applicable to, and the countries they have been developed in. Consequently, according to the authors of this paper, the application of one model in different economic activities within the same country will not result in the same degree of precision in predicting bankruptcy or insolvency, nor will the application of the same model to the same economic activities but in different countries, given that there are differences in socioeconomic and institutional business conditions.

Bearing in mind the above, the problem of predicting the insolvency of companies is still relevant both in Bosnia and Herzegovina and in the countries in the region (Salkić, 2013; Mijić & Andrašević, 2017; Bogdan et al., 2019; Lukić, 2020).

The following is an overview of the results of some relevant research conducted around the world, the subject of which was the assessment of the reliability of the model for predicting company insolvency.

Kovacova and Kliestikova (2017) tested the applicability of Altman's model, Zmijewski's model, Taffler's model, Fulmer's model and Springate's model to the example of companies from Slovakia. Based on the obtained results, they conclude that all analyzed models have a low accuracy rate (50%), and that the analyzed models can hardly be used in business conditions that differ from the business conditions of the country in which they were originally developed.

Indriyanti (2019) analyzed the accuracy of models for predicting financial difficulties (Altman, Springate, Fulmer, Taffler, Grover, Zmijewski and Ohlson) on the example of the 25 largest global technology companies according to the Forbes list. The obtained results showed that the highest percentage of reliability was recorded by Grover's model (96%), followed by Altman's model (86%) and Taffler's model (85%), while Fulmer's model recorded the lowest reliability rate (40%).

Tanjung Sutra (2020) tested the accuracy of Altman's, Springate's, Ohlson's and Zmijewski's models on the example of 9 pharmaceutical companies listed on the Indonesia Stock Exchange. Based on the obtained results, the author concludes that Altman's model is the most accurate in predicting financial difficulties for pharmaceutical companies listed on the Indonesia Stock Exchange. The period of analysis was from 2013 to 2017.

Aguilar et al. (2021) tested Altman's model on the companies listed on the Mexican Stock Exchange. The analysis covers 155 companies and the period from 2012 to 2019. Based on the obtained results, the authors conclude that the level of accuracy of Altman's model in terms of predicting company bankruptcy decreases when it is applied to Mexican companies. The percentage of model error is 18% based on the original time frame. This model error is high enough to confirm the low accuracy of the model.

Bahaa and Bahaa (2021) tested the applicability of Altman's model to industrial companies listed on the Palestine Stock Exchange. The analysis included 12 industrial companies and covered the period from 2013 to 2017. Based on the obtained results, the main hypothesis, according to which Altman's models cannot predict business performance of the analyzed companies, was contested.

Wahyuningsih and Venusita (2022) tested the accuracy of the Altman model, the Springate model, the Zmijewski model, the Fulmer model and the Grover model for predicting corporate bankruptcy. The testing was conducted on a sample of 28 retail companies listed on the Indonesia Stock Exchange and the analysis period was from 2019 to 2020. Based on the obtained results, they conclude that the analyzed models give different accuracy rates and that all the analyzed models can be used to predict the financial difficulties of the retail companies in Indonesia.

Özparlak (2022) tested the applicability of the Altman, Springate, Ohlson, Fulmer, Zmijewski Canada and Grove models to 16 companies from the US energy sector. The research results showed that the Zmijewski model is the most successful model for predicting bankruptcy of companies in the energy sector in the USA. The model that best predicted bankrupt and non-bankrupt companies one and three years prior to bankruptcy was again Zmijewski's model. However, Fulmer's model is the best predictor of bankruptcy two years prior to bankruptcy. On the other hand, according to other research results, the accuracy rate of the Altman, Springate, Canadian, Fulmer and Grover models is significantly below average compared to other research studies.

Below is an overview of the results of some relevant research conducted in the region and the Republika Srpska.

In the Republic of Serbia, Muminović et al. (2011) tested the prognostic power of Altman's Z, Z' and Z" models in the period from 2006 to 2009 on a sample of 73 companies that belonged to the BELEX15 and BELEXline index, excluding companies from the financial sector. According to the obtained results, those models are not reliable for predicting the insolvency of companies in developing markets due to a relatively high value of a type II error.

Obradović et al. (2018) developed a model for predicting the insolvency of manufacturing companies operating in the Republic of Serbia, using binomial logistic regression, whose accuracy in the classification of solvent and insolvent companies is 82.9% and 93.3%, respectively, while the overall average accuracy of the model is 88.4%.

Zenzerović (2009) analyzed Croatian service and manufacturing companies in the period from 1996 to 2006 and developed two models for predicting bankruptcy, i.e., a model for predicting financial instability of manufacturing companies and a model for predicting financial instability of service companies. Both models resulted in a high degree of accuracy in predicting bankruptcy, even one year before bankruptcy.

Bogdan et al. (2019) tested the possibility of applying Altman's Z-score model in the Republic of Croatia and tried to adjust the weights of the Z" score model in order to obtain a model that will be more adapted to the Croatian market. By applying multiple discriminant analysis, based on which the variable X1 was eliminated from the original model, the authors concluded that the adapted model Zk has a lower percentage of prediction success than the original model.

In Bosnia and Herzegovina, Salkić (2013) tested the feasibility of applying Altman's models for assessing the creditworthiness of companies. Based on the obtained results, the author concludes that Altman's Z-score and Z'-score models do not have the appropriate level of forecasting accuracy, which is why they should be used with caution and only as a supplement to traditional financial analysis. This is because the Z-score model correctly classified 16 out of 20 companies that fail to meet their obligations, and it incorrectly classified 13 out of 20 companies that regularly settle their obligations. On the other hand, the Z'-score model did not classify any company that duly settles its obligations as financially problematic (Bešlić, 2016).

Mijić and Andrašević (2017) tested the reliability of the application of foreign models (Altman's, Bek's, Springate's, Zmijewski's, Kralicek's models) for predicting bankruptcy of companies in the Republic of Srpska. Based on the obtained results, these authors concluded that foreign models (Altman's, Bek's, Springate's, Zmijewski's, Kralicek's models) are not adequate for predicting bankruptcy of companies operating in the Republic of Srpska. Namely, the maximum accuracy (80%) of the model in the projection of bankruptcy of a company for which bankruptcy proceedings were opened the following year is achieved by the Springate and the Zmijewski model. The accuracy of the Altman Z-score model is 70%. The authors conclude that in order to reliably project business success of companies, especially bankruptcy, in the Republic of Srpska it is necessary to develop models according to the specifics of the economic environment of the Republic of Srpska.

Božić and Stevanović (2017) analyzed the applicability of certain models for predicting bankruptcy of companies in the Republic of Srpska. The obtained research results are as follows: for the corrected model Z', the degree of accuracy is 74.43% with error type I and error type II amounting to 25.06% and 27.37%, respectively. By testing the original EM score model, an accuracy degree of 67.03% was obtained; however, error type I was 33.05% and error type II was 32.63%. These results are consistent with the results of previous tests conducted by these authors in 2016.

Based on the above, it can be concluded that the model developed in the Republic of Srpska has the highest degree of classification accuracy (Božić & Stevanović, 2017).

Taking into account the above, the goal of the research is to develop a model for predicting the insolvency of trading companies registered on the territory of the Republic of Srpska using a binomial logistic regression model.

The paper is divided into four sections. A theoretical framework is given in the first section, in which insolvency is defined and the models most commonly used for forecasting insolvency are presented. The research methodology is presented in the second chapter. Research results are given in the third section, that is, the process of forming the model itself and the assessment of the reliability of the created model. The conclusion of the research is given in the fourth section.

2. Theoretical framework of research

2.1 The concept of (in)solvency

The notion of the ability to pay has been accepted in domestic theory and practice as a synonym for the notion of solvency, which originates from the Latin word *solvens*, meaning one who is able to pay - the ability of an economic entity to meet its obligations in the long run (Kukoleča, 1990). As such, the notion of solvency entered the economic sciences from the legal sciences, more precisely, from property law (Pavlović & Milačić, 2013).

Due to the widespread view that solvency is the ability of a company to meet due obligations, solvency is often equated with liquidity (Enyi, 2008). However, there is a difference between liquidity and solvency. Namely, liquidity is defined as the ability of a company to meet its due obligations, while solvency covers a wider time horizon. Solvency is thus equated with the solvency of the company, and it implies its ability to settle all its due obligations with the available money at one time, even from the bankruptcy estate (Mikerević, 2016).

The solvency of a company is quantified by solvency ratios, which represent the ratio between business assets and debts (Rodić & Filipović, 2013). It shows the ability of the company to settle all obligations after the liquidation of the assets at its disposal.

$$Solvency\ ratio = \frac{(Business\ assets)}{Debts} \tag{1}$$

Source: Mikerević, 2011

The solvency ratio should be greater than 1 for the company to be considered solvent.

Taking into account the definition of solvency, insolvency is a situation in which a company is unable to meet its obligations based on available assets, even from the bankruptcy estate. This actually means that the ratio of operating assets to total liabilities is less than 1, and in such a situation if the company liquidated all assets shown in the balance sheet (book value of assets), it could not settle total liabilities by the difference between total liabilities and operating assets (Bešlić, 2016). Therefore, insolvency is a situation in which the company is not able to settle due liabilities even from the bankruptcy or liquidation estate (Grdić et al., 2009). Insolvency is defined in a similar way by Professor Mikerević (2016) who states that insolvency is a threat to the survival of the company and that it is one of the main causes of the disappearance of the company from the market scene because it is unable to pay its obligations with available money. As such, insolvency is the reason for initiating bankruptcy proceedings pursuant to the Bankruptcy Law of the Republic of Srpska, according to which it takes place if the bankruptcy debtor does not settle its due financial obligations within 60 days, or if the bankruptcy debtor's account has been blocked for 60 days continuously (Official Gazette of the Republic of Srpska, 2016).

2.2 Insolvency prediction models

Bankruptcy prediction models can be divided into two groups: classic (traditional) models and modern models.

Classical models include (Bešlić, 2016) financial analysis based on the analysis of financial indicators, statistical techniques that can be subdivided into univariate data analysis techniques of one variable, multivariate techniques such as linear multiple discriminant analysis, logit and probit analysis, mathematical models for linear programming and expert systems. Modern models can include decision trees, artificial neural networks, genetic algorithms and rough sets.

In this paper, attention is focused on statistical techniques for predicting insolvency.

According to Zenzerović and Peruško (2006), linear probability models are models that use a combination of independent variables to estimate the probability of opening bankruptcy proceedings. The model is shown by equation (2):

$$P_i = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon_i \quad , \tag{2}$$

Source: Zenzerović & Peruško, 2006

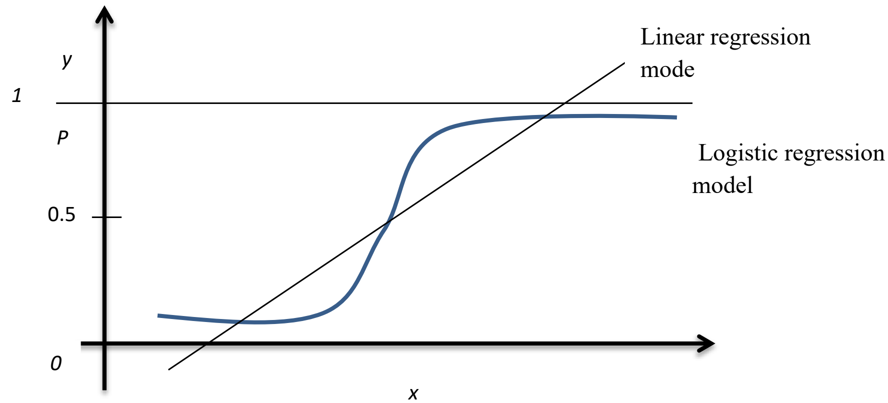
where:

- P_i is the probability of initiating bankruptcy proceedings,
- $X_1 \dots X_n$ is the value of the independent variable significant for bankruptcy prediction, n represents the number of variables,
- $\beta_1 \dots \beta_n$ is the weighted arithmetic mean of independent variables, and
- ε_i is the standard error.

Logit and probit analysis occur in response to the shortcomings of the linear probability model. Logit and probit prediction models result in the calculation of the probability of initiating bankruptcy in the interval between 0 and 1. In addition, the starting point is the assumption that the relationship between dependent and independent variables is nonlinear, which is much closer to reality.

In this paper, the logistic regression model will be used as a form of logit analysis for the purpose of predicting insolvency payments. Graph 1 provides an overview of the linear and logistic regression model.

Graph 1 Logistic regression model



Source: Pešić, 2016

Based on the shape of the functions of these two models, it can be concluded that the application of a linear regression model for predicting a binary event, such as corporate bankruptcy, may result in certain values of the independent variable *x*, probability *p(x)* can take nonstandard values, that is, it can have a negative value or, on the other hand, a value greater than 1, which is not acceptable from the aspect of possible probability values, because it ranges from 0 to 1. For this reason, the application of the logistic regression model is more adequate in this paper.

3. *Research methodology*

Based on the results of previous research on the development of bankruptcy prediction models (Obradović et al., 2018; Lukić, 2020; Pervan, 2017; Poljašević & Grujić, 2020), it can be concluded that the method of binomial logistic regression is used as the most common method for forming and developing a model for predicting corporate bankruptcy. Taking into account the above, the binomial logistic regression method was used for the purpose of developing a model.

The binomial logistic regression model is a statistical model that determines the influence of a set of n metric independent (predictor) variables x_i, which can be of any type (non-measurable or categorical), on the binary (dichotomous) dependent variable y_i (Bešlić, 2016). The dependent variable y_i in the binary logistics model is logit, i.e., the natural logarithm of the chance of success, which represents the ratio of the probabilities of the first and second choice, which can be written as follows:

$$logit[p(x)] = y_i = ln \frac{p(x))}{(1-p(x))} \tag{3}$$

Source: Adapted from Harrell, 2015

The dependent variable is coded by adding 0 to one outcome and 1 to the other possible outcome, where 0 most often means "failure" and 1 "success"

(Pešić, 2016). Thus, the expected value of the dependent variable in the binary logistic regression model for a given value of the independent variable ranges from 0 to 1.

The logistic regression model has the following form:

$$P(y_i = j) = p(x) = \frac{e^{y_i}}{1+e^{y_i}} = \frac{1}{1+e^{-y_i}}\ , \quad (5)$$

Source: Adapted from Obradović et al., 2018

where:

- *p(x)* - a predicted probability that the company will be in state j; *j = 0,1,2 ...n; j = 0: no bankruptcy and condition 1: bankruptcy*,
- y_i- dependent variable form

  $y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n$,
- e - the natural logarithm, e = 2.718281828459,
- β_0 - a constant, the value of the criterion when the predictor is equal to 0 (zero). This is a chance for a company to be classified into one of two categories before it is introduced into predictor variable analysis,
- $\beta_1 \dots \beta_n$- regression coefficients for *n* independent variables. They show how much the logarithm of the chances that the company will be in the group of companies that are in bankruptcy changes when the given independent variable is changed by one unit and the others are kept constant.

Logistic regression was applied in this paper in the IBM SPSS (Statistical Package for Social Sciences) 23 software platform. In this paper, the stepwise logistic regression method was applied - Backward LR - as a variant including independent variables, that is, the stepwise method was applied based on the probability quotient test, i.e., the LR test (*Likelihood Ratio Test*) for selected significant independent variables that explain the dependent variable. The Backward LR method assumes that all independent variables are initially included in the model, and then those with a lower degree of explanation of variations are eliminated.

A sample of 200 companies was selected for the purpose of developing a model for predicting the insolvency of trading companies from the Republic of Srpska.

The sample consists of companies in section G - wholesale and retail trade, which are registered on the territory of the Republic of Srpska, and which submitted financial reports to the Agency for Intermediary, IT and Financial Services (APIF) in the period from 2017 to 2020. The sample of 200 companies was divided into two groups in the ratio 70:30%, because this ratio was more frequently used in previous empirical research (Dvořáček et al., 2012; Bunyaminu & Issah, 2012; Andreica, 2013; Obradović et al., 2017). The first group, which is used for model development, consists of financial indicators of 140 companies, and the second group, which is used for model testing, consists of financial indicators of 70 companies. In addition to the 70:30% division of causes, an 80:20% division can also be used.

The sample of 140 companies, which is used for model development, is divided into two groups of companies: solvent (70) and insolvent (70) companies. For the purpose of this research, insolvent companies are those that, according to APIF data, had a blocked account for more than 60 days and over which, according to the Bankruptcy Law of the Republic of Srpska, bankruptcy proceedings should have been initiated. Solvency companies, on the other hand, are all those companies that have had a blocked account for less than 60 days.

Thus, the sample for model development consists of financial indicators of 70 insolvent companies and an equal number of solvent companies. Thirty percent of the companies from the total sample of 200 companies, as already mentioned, are used to test the model to determine whether the newly created model has the generalization ability, i.e., whether it can be applied to other data outside the sample. The test sample consists of 60 new companies outside the model development sample, which is divided into 30 solvent and as many insolvent companies.

All 200 companies were selected from a population that originally consisted of 2,166 companies applying the following elimination criteria:

- Companies that did not appear in the APIF records for at least two consecutive years were eliminated. This means that companies that did not appear in the APIF records in 2018 were eliminated from 2017, etc.
- Companies with the majority of AOP positions in the financial statements equal to zero were eliminated.

After atypical data analysis, it was determined that atypical data appear in a total of 26 analyzed companies included in the original sample of 226 companies. Taking into account the above, of the 226 companies that made up the sample, after eliminating 5% of the lower and upper cases, 200 companies remained, of which 100 were solvent and 100 were insolvent.

Different financial indicators from the following groups of indicators are used as independent variables: liquidity, solvency, profitability, activity and indebtedness, which are calculated on the basis of the financial statements of the sampled companies. From the previously mentioned groups of financial indicators, a total of 23 indicators were analyzed. The method of encoding the dependent variable, which is a categorical numerical variable, is given in Table 1.

For companies that are solvent, i.e., whose account has been blocked for less than 60 days, the value of the dependent variable is 0, and for companies that should have opened bankruptcy proceedings, i.e., those that had a blocked account for 60 or more days, the dependent variable takes on the value 1.

Table 1 Coding of variables

Dependent Variable Encoding	
Original Value	Internal Value
THE COMPANY IS SOLVENT	0
THE COMPANY IS NOT SOLVENT	1

Source: Authors, SPSS result

4. Research results

4.1 Creating a model for predicting insolvency

A model for predicting the insolvency of trading companies registered on the territory of the Republic of Srpska was developed after the 13th iteration (Table 2) by applying the stepwise logistic regression procedure based on the probability quotient test, i.e., the LR test (Likelihood Ratio Test) for selecting significant independent variables X_i, and Backward LR variants that explain the dependent variable y_i. The newly created model is based on seven of the initial 23 financial indicators: (1) the quick liquidity ratio (UL), (2) coverage level I (NP_I), (3) coverage level II (NP_II), (4) the total asset turnover ratio (KOUI), (5) the current assets turnover ratio (KOOI), (6) net profit margin (NPM), and (7) the financial stability ratio (KFS).

Table 2 Financial indicators included in the model for predicting the insolvency of commercial enterprises

Equation variables								**95% C.I. for EXP(B)**	
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
Step 13[a]	UL	.611	.346	3.125	1	.077	1.842	.936	3.627
	NP_I	.135	.074	3.309	1	.069	1.145	.990	1.325
	NP_II	-.086	.056	2.312	1	.128	.918	.822	1.025
	KOUI	-2.244	.615	13.297	1	.000	.106	.032	.354
	KOOI	.449	.232	3.728	1	.054	1.566	.993	2.470
	NPM	-.121	.050	5.734	1	.017	.886	.803	.978
	KFS	.004	.010	.191	1	.662	1.004	.985	1.024
	Constant	.153	.385	.157	1	.692	1.165		

Source: Authors, SPSS result

Starting from expression (5), the binomial model of logistic regression for predicting the insolvency of companies engaged in trade activities registered on the territory of the Republic of Srpska reads:

$$p(x)= \frac{e^{0,153+0,611X_1+0,135X_2-0,086X_3-2,244X_4+0,499X_5-0,121X_6+0,004X_7}}{1+e^{0,153+0,611X_1+0,135X_2-0,086X_3-2,244X_4+0,499X_5-0,121X_6+0,004X_7}} \quad (6)$$

or

$$p(x) = \frac{1}{(1+e^{-(0,153+0,611X_1+0,135X_2-0,086X_3-2,244X_4+0,499X_5-0,121X_6+0,004X_7)}} \quad (7)$$

where:

p(x) - the estimated probability of insolvency; e - natural logarithm; X_1 *- quick liquidity ratio;* X_2 *- coverage level I;* X_3 *- coverage level II;* X_4 *- total asset turnover ratio;* X_5 *- coefficient of current asset turnover;* X_6 *- net profit margin;* X_7 *- coefficient of financial stability.*

Based on the data from Table 2, we see that the ratio of accelerated liquidity, the coverage level, the coefficient of current asset turnover and the coefficient of financial stability have positive signs, which is not logical if we look at these indicators separately in relation to a company's solvency. However, it should be noted, as stated earlier, that these indicators are observed and interpreted together with other indicators that entered the model, that is, on the basis of which the model was created, and that based on their aggregate value, it is determined whether the company will be insolvent or not.

In the model equation for predicting the insolvency of a trading company, independent variables coverage level II, the total asset turnover ratio and net profit margin have negative regression coefficients (B3, B4 and B6), which means that an increase in the value of some of the mentioned independent variables by 1% will cause a decrease in the predicted probability of corporate insolvency by as much as the coefficient with the given independent variable. Other variables in the model have positive values of the coefficients (B1, B2, B5 and B7), and accordingly, their interpretation is opposite to the interpretation of the negative coefficients.

4.2 Reliability assessment of the newly created model for predicting the insolvency of trading companies in the Republic of Srpska

Different statistical procedures can be used to assess the reliability of the developed model. In this paper, the following tests and methods were used to assess the reliability of the developed model: the omnibus test (*goodness-of-fit*), Pseudo R^2 (the *Cox & Snell* R^2 *test* and *Nagelkerke* R^2), the Hosmer and Lemeshow test, and the classification table.

4.2.1 Omnibus test

Whether the developed model predicts the results well, i.e., how accurately it predicts the riskiness of a company, is shown by the omnibus test called goodness-of-fit. The goodness-of-fit test is based on the chi-square (x^2) distribution and this test tests the null hypothesis (H0) against the alternative hypothesis (HA). The null hypothesis actually implies that it is a justified step to include independent variables, i.e., financial indicators, in the logistic regression model (Obradović et al., 2018).

H0: The logit model is well-fitted, i.e., customized.

HA: The logit model is not well-fitted.

The results of the omnibus test are given in Table 3. The probability (p) value of obtaining the chi-square value is given in the column Sig. To say that the model is well-fitted, i.e., to accept the null hypothesis (H0), it is necessary that the value of Sig. is less than 0.05.

Table 3 Omnibus test for regression coefficients of the developed model

Omnibus Tests of Model Coefficients				
		Chi-square	**df**	**Sig.**
Step 1	Step	75.198	19	.000
	Block	75.198	19	.000
	Model	75.198	19	.000
...				
Step 12[a]	Step	-2.201	1	.138
	Block	66.891	8	.000
	Model	66.891	8	.000
Step 13[a]	Step	-2.665	1	.103
	Block	64.226	7	.000
	Model	64.226	7	.000
a. A negative chi-square value indicates that the chi-square value has decreased from the previous step.				

Source: Authors, SPSS result

For the model obtained in the last step (13), the chi-square is 64.226 with 7 degrees of freedom, and the p-value is 0.000, which is less than 0.05. Based on the p-value of the omnibus test from step 13, we conclude that the developed model is well-fitted, i.e., adjusted to the data from the sample.

4.2.2 Pseudo R^2

Pseudo R^2 indicators, the most common among which are the *Cox & Snell R Square* (R^2) and the *Nagelkerke R Square* (R^2) measure how much of the variance of the dependent variable is explained by the created model, i.e., variances of independent variables. The values of Cox & Snell R^2 and Nagelkerke R^2 range from 0 to 1, with values greater than 0.4, indicating that the logit model is well adapted (Braun et al., 2013). Table 4 presents the pseudo R^2 indicator values.

Table 4 Values of pseudo R^2 - Cox & Snell R^2 and Nagelkerke R^2

Model Summary			
Step	**-2 Log likelihood**	**Cox & Snell R^2**	**Nagelkerke R^2**
1	118.883[a]	.416	.554
...			
11	124.989[c]	.390	.519
12	127.190[a]	.380	.506
13	129.855[a]	.368	.491
a. Estimation terminated at iteration 9 because parameter estimates changed by less than .001.			
b. Estimation terminated at iteration 8 because parameter estimates changed by less than .001.			
c. Estimation terminated at iteration 10 because parameter estimates changed by less than .001.			

Source: Authors, SPSS result

Based on the data presented in Table 4, it can be seen that the model created in the last step of gradual logistic regression explains between 36.8% and 49.1% of the variance of the dependent variable. When it comes to the value of pseudo R^2, there is no agreement in the statistical literature on the value of pseudo R^2, which is why its value should be considered together with the values of other indicators in the overall evaluation of the model (Tušek & Gabrić, 2017). Given that the value of Nagelkerke's R2 is greater than 0.4 (0.491), taking into account the critical value of this indicator, which is 0.4, as mentioned earlier, it can be concluded that the developed model adequately explains the variations of the dependent variable. In addition, the authors in the study *Using Data Mining to Predict Success in Studying* (Simeunović & Preradović, 2014) state that the obtained value of the Cox-Snell index and the Nagelkerke index of 0.24 and 0.32, respectively, can be considered satisfactory. Taking into account the aforementioned research results, it can be concluded that the developed model can explain the variations of the dependent variable through all included predictor variables (financial indicators).

4.2.3 Hosmer-Lemeshow test

The claim that the model is good was also verified by using the Hosmer-Lemeshow test. It is the most reliable model prediction quality test. Unlike the omnibus test, in the Hosmer-Lemeshow test of small value statistics, the chi-square statistic indicates that the model is adjusted, while large values indicate that the model is not well adjusted to the data (Obradović et al., 2018). Accordingly, the model is supported if the p-value of the chi-square statistic is greater than 0.05.

Table 5 shows the p-value of the chi-square statistic of the Hosmer-Lemeshow test with 7 degrees of freedom for the developed model.

Table 5 Hosmer-Lemeshow test

Hosmer and Lemeshow Test			
Step	**Chi-square**	**df**	**Sig.**
1	8.967	8	.345
...			
11	6.990	8	.538
12	6.157	8	.630
13	8.138	8	.420

Source: Authors, SPSS result

The results given in Table 5 show that the value of the chi-square statistics of 8.138 is significant, i.e., the p-value of the Hosmer-Lemeshow test statistic is 0.420. As the p-value is greater than 0.05, it is concluded that the developed model agrees with the data.

4.2.4 Classification table and ROC curve

The classification table shows us how well the model predicts, that is, classifies each surveyed company into one of the two categories that the dependent variable can have. The classification table for both the model development sample and the test sample is given below.

Table 6 Classification table of the model for predicting the insolvency of trading companies in the Republic of Srpska

Classification Table[a]								
Observed			**Predicted**					
			Selected Cases[b]			**Unselected Cases[c]**		
			bankruptcy		**Perc. Correct**	**bankruptcy**		**Perc. Correct**
			0	**1**		**0**	**1**	
Step 1	bankruptcy	0	58	12	82.9	26	4	86.7
		1	12	58	82.9	11	19	63.3
	Overall Percentage				82.9			75.0
Step 12	bankruptcy	0	56	14	80.0	26	4	86.7
		1	14	56	80.0	5	25	83.3
	Overall Percentage				80.0			85.0
Step 13	bankruptcy	0	58	12	**82.9**	25	5	**83.3**
			14	56	**80.0**	6	24	**80.0**
	Overall Percentage				**81.4**			**81.7**
a. The cut value is .500								
b. Selected cases RT LT 1								
c. Unselected cases RT GE 1								

Source: Authors, SPSS result

Based on the model developed in the last logistic regression step (step 13), and from the previous table, it can be seen that within the sample for model development, the model accurately classifies 82.9% of companies that are solvent, which is the specificity of the model, and 80% of companies that are not solvent, which represents the sensitivity of the model. On the other hand, for the test sample, the model accurately classifies 83.3% of solvent companies and 80% of insolvent companies. If we look at the total accuracy of the model for the development sample, it is 81.4% (general efficiency of the model), and for the test sample, it is 81.7%. As the difference between classification accuracy of the developed model for the development sample and the test sample is only 0.3%, it is concluded that this prediction model is valid.

Taking into account the number of correctly and incorrectly classified companies from Table 7, type I error and type II error were calculated. Type I error, which implies that an insolvent company is classified as solvent, for the developed model, calculated for the model development sample, is 20% (100%-80%), while type II error, implying that a solvent company is classified as insolvent, amounts to 17.1% (100%-82.9%). Type I and type II errors for the test sample are 20% and 16.7%, respectively.

Table 7 Model efficiency

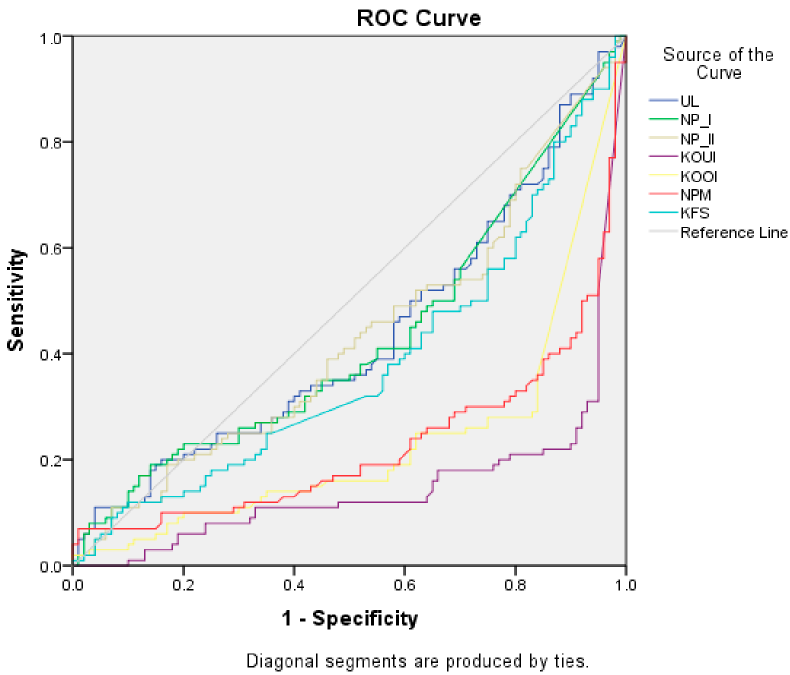
Observed	Predicted					
	Selected Cases			Unselected Cases		
	bankruptcy		TOTAL %	bankruptcy		TOTAL %
	0	1		0	1	
0	Specificity 82.9%	Type II error 17.1%	100.0	Specificity 83.3%	Type II error 16.7%	100.0
1	Type I error 20.0%	Sensitivity 80.0%	100.0	Type I error 20.0%	Sensitivity 80.0%	100.0

Source: Authors

It can be seen from Table 6 that the critical value for classifying companies into one of the two categories is $F^* = 0.50$. This means that if the calculated value of the predicted probability F is less than or equal to the critical value of insolvency F^* ($F \leq F^*$), then the company is classified into the group of solvent companies, otherwise it is classified as insolvent ($F > F^*$).

In addition to the statistical methods for estimating the newly created model that were presented previously, the ROC (*Receiver Operating Characteristic*) curve was also used. The ROC curve is a graphical representation of sensitivity and specificity for each possible result on the test (limit score) in the coordinate system, where the values of sensitivity are given on the ordinate (y) and on the abscissa (x) the specificity values are subtracted from 1 (Janičić & Novović, 2011). The ROC curve for the developed model is presented in Figure 1. As can be seen from Figure 1, the ROC curves of all financial indicators included in the model differ from the random outcome diagonal and are closer to the lower right corner of the coordinate system, which is why inverse values are given in Table 8.

Figure 1 ROC curve of the insolvency prediction model



Source: Authors, SPSS result

Table 8 Inverse values of the area under the ROC curve (AUC) of the model for predicting the insolvency of trading companies registered on the territory of the Republic of Srpska

Area Under the Curve					
Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
UL	.567	.041	.101	.487	.647
NP_I	.570	.041	.089	.489	.650
NP_II	.568	.041	.095	.488	.648
KOUI	.849	.029	.000	.792	.907
KOOI	.765	.035	.000	.697	.834
NPM	.773	.035	.000	.705	.841
KFS	.619	.040	.004	.541	.697
The test result variable(s) UL, NP_I, NP_II, KOUI, KOOI, NPM, KFS has/have at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.					
a. Under the nonparametric assumption					
b. Null hypothesis: true area = 0.5					

Source: Authors, SPSS result

Taking into account the AUC (Area Under the Curve), and based on the data presented in Table 8, it can be seen that the total asset turnover ratio has very good diagnostic power, while the area below its ROC curve is statistically significant (AUC = 0.849, $p < 0.05$). Net profit margin as well as the turnover ratio have good discriminant power, and the area under their ROC curve is also statistically significantly different from the random sample diagonal (NPM: AUC = 0.776, $p < 0.05$; KOOI: AUC = 0.765, $p < 0.05$). The financial stability coefficient has sufficient diagnostic power, and the area under its ROC curve is statistically significant (AUC = 0.619, $p < 0.05$). Other financial indicators in the model have insufficient diagnostic power, because the area below the ROC curve ranges between 0.5 and 0.6.

5. *Conclusion*

In the development of a binomial logistic regression model for predicting the insolvency of trading companies registered on the territory of the Republic of Srpska, 23 financial ratios were used, which were calculated on a sample of 200 companies included in the research study. Based on the empirical research results, we can conclude that the hypothesis the LR model can be formed on the basis of selected financial ratios as a tool for predicting the insolvency of trading companies in the Republic of Srpska has been confirmed. Out of a total of 23 financial ratios, which were used as independent variables, the following 7 variables were singled out as those that contribute statistically significantly to predicting the insolvency of trading companies in the Republic of Srpska: (X_1) - quick liquidity ratio, (X_2) - coverage level I, (X_3) - coverage level II, (X_4) - total asset turnover ratio, (X_5) - coefficient of current asset turnover, (X_6) - net profit margin, and (X_7) - coefficient of financial stability.

Within the development sample, the developed model accurately classifies 82.9% of companies that are solvent and 80% of companies that are not solvent. On the other hand, for the test sample, the model accurately classifies 83.3% of solvent and 80% of insolvent companies. Total model accuracy for the development sample is 81.4% (general efficiency of the model), and for the test sample it is 81.7%. Type I error and type II error calculated for the model development sample are 20% and 17.1%, respectively, while type I error and type II error for the test sample are 20% and 16.7%, respectively.

The obtained results are in accordance with the results obtained in previous research conducted in the Republic of Srpska, which were discussed in more detail earlier in this paper. Namely, it has been confirmed that the model developed for the needs of a certain economic branch within a given economic system gives a higher degree of general efficiency than foreign models (Altman's model, Zmijewski's model and other foreign models analyzed). This is because the model developed for the needs of a given economic branch within a certain economy takes into account the specificities of the given economic branch, as well as the specificities of the economy of the given country.

When it comes to the limitations of this research, they are reflected in the fact that financial statements were used that were not audited, because in accordance with the Accounting and Auditing Law of the Republic of Srpska, a great number of companies do not have the obligation to audit financial statements.

The scientific contribution of the paper is also reflected in the newly created model for predicting the insolvency of companies, which is aimed at trading companies from the Republic of Srpska. During the preparation of this paper and the creation of the model, new facts and empirical knowledge were presented about financial indicators that can be predictors of the future insolvency of trading companies in the Republic of Srpska.

As possible directions for further research, we can single out the examination of the possibility of applying the newly created model in other economic areas, i.e., the examination of the reliability of the newly created model in companies not engaged in trade. Furthermore, it is necessary to find out in future research why financial indicators are related to predicting the bankruptcy of commercial companies in the Republic of Srpska and whether they can be used as such to predict the insolvency of commercial companies in the region.

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