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MODEL FOR EVALUATING THE CREDITWORTHINESS OF SMALL AND MEDIUM ENTERPRISES IN BOSNIA AND HERZEGOVINA

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Abstract

This paper presents the development of a credit model for predicting the likelihood of timely repayment of credit obligations by small and medium enterprises (SMEs) in Bosnia and Herzegovina (BiH). The model was developed using a sample of 100 enterprises, consisting of 50 enterprises that are timely in repaying their credit obligations and 50 enterprises that are overdue in payments for more than 90 days. The presented credit model is based on the financial statements of SMEs at the time of loan approval and allows for the prediction of delays within a one-year period. The model's average accuracy rate is 84% for correct classifications, correctly classifying 80% of enterprises that timely meet their obligations and 88% of enterprises that are late in payments. The use of this credit model would enable financial institutions in BiH to manage credit risk more effectively and lend more efficiently to the SME sector, thereby contributing to the faster economic growth of the national economy.

Keywords: Small and medium enterprises, credit model, creditworthiness, banks

INTRODUCTION

An adequate assessment of an enterprises' creditworthiness, when generating decisions in the process of approving loans to legal entities, is a crucial factor for the successful operation of banks and the stability of the financial system in Bosnian and Herzegovinian banks. This aspect gains particular importance given that credit risk is the most significant risk in Bosnian and Herzegovinian banks, as the credit portfolio constitutes the most substantial item of total assets in the banking sector in BiH. Assessing creditworthiness is particularly challenging for small and medium enterprises (SMEs), which make up a significant part of BiH's economy.

According to available data, the estimated total number of enterprises in BiH ranged from 26,000 to 29,000. Considering this number, it is estimated that over 97% of enterprises fall into the category of micro, small, and medium enterprises. SMEs in BiH are the backbone of the economy, creating over 60% of the gross domestic product (GDP) and the majority of new jobs (CPU, 2010, p. 3). Considering this, it is evident that providing favorable conditions for the operation and growth of SMEs is crucial for the growth of the national economy. Bank lending to SMEs is undoubtedly one of the critical conditions for the growth and development of SMEs. To enhance lending to SMEs in the banking sector, the use of models or rating systems for the quality assessment of these enterprises' creditworthiness is desirable.

Recent research has established that credit models developed using samples of enterprises operating in the USA and the EU do not have adequate accuracy for assessing the creditworthiness of enterprises in transitional countries. Therefore, there is a clear need to develop models for assessing creditworthiness or bankruptcy for enterprises operating in transitional economies.

The aim of this paper is to develop a credit model for predicting the likelihood of timely repayment of credit obligations by small and medium enterprises (SMEs) in Bosnia and Herzegovina. We will present the sample selection, the use of statistical methods for the development and evaluation of the model's efficiency, and provide recommendations for banking practice, as well as further research on this topic.

METHODOLOGY OF EMPIRICAL RESEARCH

The database for the sample of enterprises used to develop the credit model for determining the creditworthiness of enterprises in BiH is the credit portfolio of loans issued to SMEs (small and medium enterprises) by a commercial bank. This bank operates across the entire territory of BiH (the Federation of BiH, the Republic of Srpska, and Brčko District) and consistently achieves good business results, indicating that the bank's credit policy is at a satisfactory level. Using the expert sampling method, 100 enterprises were selected and divided into two equal groups:

- "Good" (PL – performing loans) enterprises: clients who are timely in repaying their credit obligations, that is, with repayment delays of up to 30 days;
- "Bad" (NPL – non-performing loans) enterprises: clients who are overdue in repaying obligations to the bank for more than 90 days.

The reason for this division is the Basel definition of default, which considers a delay to have occurred if the debtor is more than 90 days late in fulfilling any credit obligation. The selected enterprises have sales revenues of less than 7 million BAM and employ, on average, fewer than 250 people, thus qualifying as small and medium enterprises. According to the Basel agreement, SMEs are defined as enterprises with sales revenues of less than 50 million Euros (Altman & Sabato, 2005, p. 3).

For the calculation of coefficients, the official financial statements (balance sheets and income statements) of the debtors at the time of loan approval were used. The delays in fulfilling credit obligations occurred within 12 months after the loan was approved, thus meeting the Basel agreement's requirement for considering the possibility of predicting delays for a period of one year.

Table 1 presents the types of activities of the "good" and "bad" enterprises. It can be observed that trade is the most represented activity, followed by manufacturing.

Table 1. Structure of the Sample by Activities of "Good" and "Bad" Enterprises

Activity	„Good" enterprises	"Bad" enterprises
Transport	6	3
Trade	22	28
Manufacturing	11	11
Services	5	6
Construction	6	2
Total	50	50

According to sales revenue (Table 2), the largest number of "good" enterprises, 11 of them, had sales revenue between 2 and 3 million BAM, while the largest number of "bad" enterprises (23) had sales revenue of less than 500,000 BAM.

Table 2. Structure of the Sample by Sales Revenue of "Good" and "Bad" Enterprises

Sales Revenue	„Good" enterprises	"Bad" enterprises
Up to 500,000 KM	4	23
500,001 KM − 1,000,000 KM	9	11
1,000,001 KM − 2,000,000 KM	10	10
2,000,001 KM − 3,000,000 KM	11	3
3,000,001 KM − 4,000,000 KM	9	2
4,000,001 KM – 5,000,000 KM	6	0
5,000,001 KM – 6,000,000 KM	1	0
6,000,001 KM – 7,000,000 KM		1
Total	50	50

Looking at the number of employees in "good" enterprises, it is evident that enterprises with over 20 employees dominate (19), while the largest number of "bad" enterprises (24) employ fewer than 5 workers (Table 3).

Table 3. Structure of the Sample by Number of Employees in "Good" and "Bad" Enterprises

Number of Employees	„Good" enterprises	"Bad" enterprises
1-5	9	24
6-10	9	11
11-15	3	9
16-20	10	2
Over 20	19	4
Total	50	50

In Table 4, the duration of the enterprises' operations at the time of loan approval is presented, and it is evident that the majority of both "good" (23) and "bad" (22) enterprises operated between 6 to 10 years.

Table 4. Structure of the Sample by Duration of Business Activity of "Good" and "Bad" Enterprises

Duration of Business Activity (in years)	„Good" enterprises	„Bad“ enterprises
1-5	15	18
6-10	23	22
11-15	7	8
16-20	4	2
Over 20 years	1	0
Total	50	50

BUILDING A MODEL FOR ASSESSING THE CREDITWORTHINESS OF SMALL AND MEDIUM ENTERPRISES IN BIH

When constructing the credit model, that is, determining the interrelationships and influences of financial indicators on the probability of an enterprise falling into arrears with its obligations, the first question that arises is the selection of an appropriate statistical model. Since regression analysis has often been used in the development of recent credit models (Zenzerović, Peruško, Bohača, Šarlija, Benšić, and so forth), and models developed using regression analysis have shown high accuracy in assessment, we will use logistic regression as the statistical model for prediction of (non)compliance of enterprises in meeting credit obligations.

As independent variables in developing the credit model, financial indicators of the enterprises were observed. The dependent variable is the compliance with obligations towards the bank, where we have two possibilities: the enterprise regularly meets its obligations, or the enterprise has a delay in fulfilling obligations to the bank for more than 90 days from the moment the loan was approved. Binary logistic regression was used to develop the credit model, which is applied when the dependent variable is binary, that is, it can take two values (0 and 1). Thus, the dependent variable in developing the credit model for assessing the creditworthiness of small and medium enterprises in BiH is dichotomous, with a value of 0 assigned to legal entities that are compliant in meeting obligations to the bank, while a value of 1 is assigned to legal entities that are overdue in meeting credit obligations for more than 90 days.

Based on the analysis of research addressing bankruptcy prediction and credit model development, and based on available financial data on enterprise operations from the sample, 40 financial indicators were selected, as presented in Table 5.

Table 5. Overview of Initial Financial Indicators of the Model

Variable Label	Financial Indicators
VAR01	Working capital/Assets
VAR02	EBIT/(Assets - Current liabilities)
VAR03	Equity/Total Debt
VAR04	(Profit + Depreciation + Amortization) / Sales Revenue
VAR05	(Profit + Depreciation + Amortization) / Total Debt
VAR06	(Profit + Depreciation + Amortization)/Current liabilities
VAR07	(Profit + Depreciation + Amortization)/Capital
VAR08	Total liabilities - Cash/Cash flow
VAR09	Short-term assets/Short-term liabilities
VAR10	Cash/Short-term assets
VAR11	Working capital/Total liabilities
VAR11	Total liabilities/Total assets
VAR13	Capital/Assets
VAR14	Subscribed capital/Total assets
VAR15	Total liabilities/(Retained earnings + Depreciation)
VAR16	Total income/Total expenses
VAR17	EBIT/Revenues
VAR18	EBIT/Assets
VAR19	EBIT/Total liabilities
VAR20	Cash/Short-term liabilities
VAR21	Current assets/Sales Revenue
VAR22	Cash/ Sales Revenue
VAR23	Working capital/Sales Revenue
VAR24	Retained earnings/Total assets
VAR25	Net Profit/Assets
VAR26	Net Profit/Capital
VAR27	(Current assets-Inventory)/Current liabilities
VAR28	Net profit /Sales Revenue
VAR29	Total liabilities/Sales Revenue
VAR30	Cash flow/ Sales Revenue
VAR31	EBITDA/Total liabilities
VAR32	Cash flow/Total assets
VAR33	Cash flow/Total liabilities
VAR34	Inventory/Total Revenue
VAR35	(Capital + Long-term liabilities)/Fixed assets
VAR36	P&L Cash flow/(Total liabilities - Cash)
VAR37	Sales Revenue/ Total assets
VAR38	Operating Cash Flow / Sales Revenue
VAR39	Net profit/Total debt
VAR40	Working capital/EBITDA

Before analyzing the data, it is necessary to remove any data that may affect the accuracy of the final result. It is essential to eliminate the possibility of errors in data entry. To verify this, for categorical variables, we used the Descriptive Statistics/Frequencies function to determine if all data fall within the range of possible values and if any data are missing. We found that there are no selected categorical variables for the model.

Logistic regression is sensitive to outliers, that is, extreme values that are outside the range of possible values for the variable. It is possible that the collected data in the sample contain outliers, that is, non-standard, deviating values that may negatively affect the model outcome by leading to incorrect conclusions. Outliers are observations that significantly deviate from the overall data distribution. They can be identified by arranging the data in a variational series and then calculating the means of the variables without the top 5% and bottom 5% cases. This mean is then compared to the true mean of a particular characteristic. If these two means significantly differ, the top 5% and bottom 5% cases are likely outliers.

To verify the correctness of the data, we calculated the mean, standard deviation, and minimum/maximum values for the independent variables. We have 40 initial variables, all of which are continuous. Based on the minimum and maximum values from the results obtained, we conclude that all data make sense, that is, their values fall within possible ranges. However, for the variables Total liabilities - Cash/Cash flow, Total liabilities/Retained earnings + Depreciation, and Working capital/EBITDA, it is noticed that the average value is not in the expected intervals. Therefore, we check for the existence of outliers for these variables.

Table 6. Descriptive Statistics for Independent Variables

	N	Minimum	Maximum	Mean	Std. Deviation
Working capital/Assets	100	-,39	,93	,1587	,25813
EBIT/(Assets - Current liabilities)	100	-1,16	1,16	,1481	,30959
Equity/Total Debt	100	-,11	18,96	1,1888	2,15513
(Profit + Depreciation + Amortization)/Sales Revenue	100	-,06	,43	,0989	,09514
(Profit + Depreciation + Amortization)/Total Debt	100	-,13	6,52	,3348	,76761
(Profit + Depreciation + Amortization)/Current liabilities	100	-,14	6,52	,4549	,83143
(Profit + Depreciation + Amortization)/Capital	100	-,02	2,44	,4137	,43256
Total liabilities - Cash/Cash flow	100	-517,00	757,70	-17,8903	145,34953
Short-term assets/Short-term liabilities	100	,26	15,00	1,9555	2,32337
Cash/Short-term assets	100	,00	,97	,1338	,18321
Working capital/Total liabilities	100	-,67	13,37	,5279	1,49209
Total liabilities/Total assets	100	,05	1,12	,6093	,23192
Capital/Assets	100	-,12	,95	,3891	,23208
Subscribed capital/Total assets	100	,00	,70	,1220	,18632

Total liabilities/ (Retained earnings + Depreciation)	100	-18,28	917,00	19,8776	94,44561
Total income/Total expenses	100	,72	1,93	1,1130	,16125
EBIT/ Revenues	100	-,45	,43	,0483	,12293
EBIT/ Assets	100	-,46	,57	,0749	,13712
EBIT/Total liabilities	100	-,77	6,48	,2503	,78960
Cash/Short-term liabilities	100	,00	1,37	,1973	,28392
Current assets/Sales Revenue	100	,05	3,96	,5942	,55155
Cash/Sales Revenue	100	,00	,98	,0770	,14339
Working capital/Sales Revenue	100	-1,18	1,79	,1449	,36581
Retained earnings/Total assets	100	-,17	,77	,1772	,18136
Net Profit/Assets	100	-,15	,51	,0745	,10323
Net Profit/Capital	100	-,14	1,24	,2334	,26983
(Current assets- Inventory)/ Current liabilities	100	,02	11,00	1,0960	1,25352
Net profit /Sales Revenue	100	-,06	,38	,0594	,07679
Total liabilities/Sales Revenue	100	,02	3,47	,6395	,56343
Cash flow/ Sales Revenue	100	-,29	,30	,0215	,07776
EBITDA/Total liabilities	100	-,63	7,63	,3493	,88632
Cash flow/Total assets	100	-,53	,56	,0198	,10457
Cash flow/Total liabilities	100	-1,60	,82	,0247	,22748
Inventory/Total Revenue	100	,00	1,09	,2055	,24435
(Capital + Long-term liabilities)/ Fixed assets	100	-,76	31,50	3,2450	5,96014
P&L Cash flow/ (Total liabilities - Cash)	100	-16,00	9,68	,2596	2,01935
Sales Revenue/ Total assets	100	,17	12,14	1,5873	1,46812
Operating Cash Flow/ Sales Revenue	100	-,35	1,54	,0754	,23782
Net profit/Total debt	100	-,14	5,37	,2352	,66882
Working capital/EBITDA	100	-34,33	107,67	2,6579	14,22569
Valid N (listwise)	100				

The information in the following table illustrates the extent of the problem posed by cases with outliers. The concept of the 5% Trimmed Mean is a value obtained by disregarding the top and bottom 5% of cases and recalculating the mean without them. By comparing the original mean with the new mean calculated without the extreme values, we can determine whether the outliers significantly affect the mean or not (Pallant, 2009, p. 61-62).

Observing the mean calculated without the top and bottom 5% of cases (Trimmed Mean) and the "true" mean, it is noted that these values for the variables "Total liabilities/Retained earnings + Depreciation" and "Total liabilities - Cash/Cash flow" are not particularly close. Therefore, these values will be omitted to avoid complicating further analysis.

Table 7. Outliers

			Statistic	Std. Error
Total liabilities - Cash/Cash flow	Mean		-17,8903	14,53495
	95% Confidence Interval for Mean	Lower Bound	-46,7308	
		Upper Bound	10,9502	
	5% Trimmed Mean		-12,5768	
	Median		2,5700	
	Variance		21126,487	
	Std. Deviation		145,34953	
	Minimum		-517,00	
	Maximum		757,70	
	Range		1274,70	
	Interquartile Range		42,04	
	Skewness		,268	,241
	Kurtosis		10,945	,478

			Statistic	Std. Error
Total liabilities/(Retained earnings + Depreciation)	Mean		19,8776	9,44456
	95% Confidence Interval for Mean	Lower Bound	1,1375	
		Upper Bound	38,6177	
	5% Trimmed Mean		6,4003	
	Median		3,0650	
	Variance		8919,974	
	Std. Deviation		94,44561	
	Minimum		-18,28	
	Maximum		917,00	
	Range		935,28	
	Interquartile Range		7,77	
	Skewness		8,917	,241
	Kurtosis		84,416	,478

			Statistic	Std. Error
Working capital/EBITDA	Mean		2,6579	1,42257
	95% Confidence Interval for Mean	Lower Bound	-,1648	
		Upper Bound	5,4806	
	5% Trimmed Mean		1,4443	
	Median		,9000	
	Variance		202,370	
	Std. Deviation		14,22569	
	Minimum		-34,33	
	Maximum		107,67	
	Range		142,00	
	Interquartile Range		3,32	
	Skewness		5,018	,241
	Kurtosis		35,032	,478

As logistic regression is sensitive to high correlations between independent variables, in the next step, we tested for multicollinearity. For this purpose, we calculated the Pearson correlation coefficient matrix, where a coefficient greater than 0.7 indicates high multicollinearity between independent variables (Pervan & Kuvek, 2013, p. 192) and they were consequently omitted. Additionally, additional tests for multicollinearity were conducted, namely the Variance Inflation Factor (VIF) test and the Tolerance test. A tolerance level below 0.10 indicates high correlation of the independent variable with other independent variables in the logistic regression model, thus indicating the presence of multicollinearity. Similarly, if the Variance Inflation Factor (VIF) values (the reciprocal of Tolerance) exceed 10, it indicates the presence of multicollinearity. Hence, common cutoff points for determining multicollinearity are Tolerance values less than 0.10 or VIF values greater than 10 (Pallant, 2009, p. 158). We re-evaluate the correlation between independent variables and omit independent variables with high correlation with other independent variables but low correlation with dependent variables. The following table displays the retained independent variables, showing no high correlation among them.

Table 8. VIF Test and Tolerance Test of Independent Variables

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-,133	,244		-,545	,588		
Working capital/Assets	-,215	,401	-,111	-,537	,593	,163	6,138
(Profit + Depreciation + Amortization)/Capital	,065	,146	,056	,448	,656	,437	2,287
Total liabilities/Total assets	,650	,358	,300	1,815	,073	,253	3,945
EBIT/ Assets	-,649	,470	-,177	-1,379	,172	,420	2,381
Cash/Short-term liabilities	-,080	,294	-,045	-,271	,787	,251	3,989
Cash/Sales Revenue	,735	,601	,210	1,223	,225	,235	4,253
Retained earnings/Total assets	-,076	,308	-,027	-,245	,807	,561	1,782
Net Profit/Capital	-,202	,257	-,108	-,783	,436	,362	2,761
(Current assets- Inventory)/Current liabilities	,021	,085	,051	,241	,811	,153	6,542
Net Profit/Sales Revenue	,438	,981	,067	,447	,656	,308	3,248
Total liabilities/Sales Revenue	,198	,164	,222	1,204	,232	,204	4,910
Cash flow/Sales Revenue	-,631	1,191	-,098	-,530	,598	,204	4,911
EBITDA/Total liabilities	,028	,075	,049	,373	,710	,397	2,518
Cash flow/Total liabilities	,157	,496	,071	,317	,752	,137	7,293
Inventory/Total Revenue	,641	,331	,312	1,936	,056	,267	3,743
Capital + Long-term liabilities)/Fixed assets	-,011	,009	-,126	-1,132	,261	,557	1,796
P&L Cash flow/(Total liabilities - Cash)	,004	,027	,018	,159	,874	,567	1,763
Sales Revenue/Total assets	,017	,043	,051	,409	,684	,444	2,253
Operating Cash Flow/Sales Revenue	,204	,229	,096	,889	,377	,590	1,695
Working capital/EBITDA	-,002	,005	-,048	-,372	,711	,410	2,440

The statistical program SPSS offers several techniques for logistic regression, which serve to test the predictive power of sets or blocks of independent variables and allow for specifying the method of inputting independent variables into the regression model. Here, we will utilize the Stepwise Backward LR method of binary logistic regression, as it begins with all independent variables of the model and then gradually eliminates those with lower correlations with the dependent variable, presenting the obtained results below.

Table 9 provides details on the sample size. The observed sample consists of 100 enterprises, half of which regularly met their credit obligations to the bank, while the other half had delays exceeding 90 days in meeting their credit obligations.

Table 9. Sample Size

Unweighted Cases		N	Percent
Selected Cases	Included in Analysis	100	100,0
	Missing Cases	0	,0
	Total	100	100,0
Unselected Cases		0	,0
Total		100	100,0

Enterprises that regularly met their credit obligations to the bank are assigned a value of 0 for the dependent variable, while enterprises with delays in meeting credit obligations exceeding 90 days are assigned a value of 1 for the dependent variable, as shown in the following table.

Table 10. Values of Dependent Variables

Original Value	Internal Value
„Bad" enterprises NPL	1
„Good" enterprises PL	0

In Table 11 (in SPSS Block 0), the results of the analysis without any independent variables included in the model are displayed. It is evident that 50% of the cases are correctly classified. The goal of modeling is to improve the accuracy of this prediction after the inclusion of independent variables in the model (NPL-non-performing loans, PL- performing loans).

Table 11. Classification Accuracy of the Model without Independent Variables

Block 0 Classification Table					
Observed			Predicted		
			PL ili NPL		Percentage Correct
			NPL	PL	
Step 0	PL ili NPL	NPL	0	50	.0
		PL	0	50	100.0
	Overall Percentage				50.0

The Stepwise Backward binary logistic regression procedure, based on the Likelihood Ratio Test, for selecting significant independent variables explaining the dependent variables, was conducted in 17 steps of gradual statistical regression. The final 17th step is presented in the following table.

Table 12. Variables Included in the Model

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 17[a]	VAR07	1.139	.714	2.544	1	.111	3.125	.770	12.677
	VAR18	10.341	6.357	2.646	1	.104	30991.776	.120	7989009272.327
	VAR29	2.595	.948	7.487	1	.006	13.400	2.088	85.987
	VAR31	-11.603	4.102	8.002	1	.005	.000	.000	.028
	Constant	-.534	.747	.510	1	.475	.586		

The table titled "Variables Included in the Model" provides the final appearance of the sought model. It informs us about which variables are included in the model and provides information about the contribution or importance of each predictor variable. The coefficients B actually represent the coefficients that enter the final equation for calculating the probability that the analyzed case falls into a particular category (enterprises regular or irregular in meeting credit obligations).

The following table displays the selected financial indicators, their B values, model labels, and the calculated constant.

Table 13. Names and Values of Variables in the Model

Variable	Financial Indicators	Values	Label in the Model
VAR07	(Net profit + Depreciation + Amortization)/Capital	1.139	X1
VAR18	EBIT/Assets	10.341	X2
VAR29	Total liabilities/Sales revenue	2.595	X3
VAR31	EBITDA/Total liabilities	-11.603	X4
Constant		-0.534	

Therefore, the equation for predicting the probability of timely repayment of credit obligations for small and medium-sized enterprises in BiH takes the following form:

Log (p/1-p) = - 0.534 + 1.139X1 + 10.341X2 + 2.595X3 - 11.603X4,

The equation above can be simplified as:

p = 1 / 1 + e^(-(-0.534 + 1.139X1 + 10.341X2 + 2.595X3 - 11.603X4)),

where, e is the base of the natural logarithm, i.e., e ≈ 2.71828.

VERIFICATION OF THE RELIABILITY OF THE DEVELOPED MODEL FOR ASSESSING THE CREDITWORTHINESS OF SMALL AND MEDIUM-SIZED ENTERPRISES IN BIH

After developing the model, it is important to establish the statistical level of its validity and reliability, for which the following statistical tests for evaluating the adequacy of logistic regression models are used:

• Omnibus test (Goodness of fit test);

• Cox & Snell and Nagelkerke test; and

• Hosmer-Lemeshow test.

We will present the results of these tests for the developed model.

The model contains only quantitative indicators and has the following form:

Log (p/1-p) = - 0.534 + 1.139X1 + 10.341X2 + 2.595X3 - 11.603X4,

Where,

X1 − (Net profit + Depreciation + Amortization)/Capital,

X2 − EBIT/Assets,

X3 – Total liabilities/Sales revenue,

X4 − EBITDA/Total liabilities.

Table 14, titled "Summary Performance Indicators for the Model" records the difference compared to Block 0 when independent variables were not entered into the model. This test is called the Goodness of Fit test and shows how well the model predicts results. It is desirable that this set of results is significant, that is, the Sig. (significance) value should be less than 0.05. In this case, at the 17th iteration step (Step 17), the significance is 0.000, which actually means $p < 0.0005$. Based on this, we can conclude that the derived model predicts data better than the initial model shown in Block 0. The chi-square test statistic in the final model is 60.862 with 4 degrees of freedom.

Table 14. Summary Performance Indicators for the Model

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	81,390	20	,000
	Block	81,390	20	,000
	Model	81,390	20	,000
Step 2[a]	Step	-,161	1	,688
	Block	81,229	19	,000
	Model	81,229	19	,000
Step 3[a]	Step	-,247	1	,619
	Block	80,982	18	,000
	Model	80,982	18	,000

Step 4[a]	Step	-,176	1	,675
	Block	80,806	17	,000
	Model	80,806	17	,000
Step 5[a]	Step	-,403	1	,526
	Block	80,404	16	,000
	Model	80,404	16	,000
Step 6[a]	Step	-,189	1	,664
	Block	80,214	15	,000
	Model	80,214	15	,000
Step 7[a]	Step	-,319	1	,572
	Block	79,895	14	,000
	Model	79,895	14	,000
Step 8[a]	Step	-1,291	1	,256
	Block	78,605	13	,000
	Model	78,605	13	,000
Step 9[a]	Step	-2,301	1	,129
	Block	76,304	12	,000
	Model	76,304	12	,000
Step 10[a]	Step	-1,494	1	,222
	Block	74,809	11	,000
	Model	74,809	11	,000
Step 11[a]	Step	-1,459	1	,227
	Block	73,350	10	,000
	Model	73,350	10	,000
Step 12[a]	Step	-2,226	1	,136
	Block	71,124	9	,000
	Model	71,124	9	,000
Step 13[a]	Step	-2,089	1	,148
	Block	69,035	8	,000
	Model	69,035	8	,000
Step 14[a]	Step	-1,639	1	,200
	Block	67,395	7	,000
	Model	67,395	7	,000
Step 15[a]	Step	-1,994	1	,158
	Block	65,402	6	,000
	Model	65,402	6	,000
Step 16[a]	Step	-2,461	1	,117
	Block	62,941	5	,000
	Model	62,941	5	,000
Step 17[a]	Step	-2,079	1	,149
	Block	60,862	4	,000
	Model	60,862	4	,000

The Cox & Snell R Square and Nagelkerke R Square values indicate the proportion of variance in the dependent variable explained by the model. For the final obtained model (Step 17), these values are 0.456 and 0.608, respectively. In other words, the set of variables comprising the obtained model explains between 45.6% and 60.8% of the variance.

Table 15. Cox & Snell R Square and Nagelkerke R Square for the Model

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	57,240[a]	,557	,742
2	57,400[a]	,556	,742
3	57,647[a]	,555	,740
4	57,823[a]	,554	,739
5	58,226[a]	,552	,737
6	58,415[a]	,552	,736
7	58,734[a]	,550	,734
8	60,025[b]	,544	,726
9	62,326[b]	,534	,712
10	63,820[b]	,527	,702
11	65,280[b]	,520	,693
12	67,506[b]	,509	,679
13	69,595[b]	,499	,665
14	71,234[b]	,490	,654
15	73,228[b]	,480	,640
16	75,688[b]	,467	,623
17	77,767[c]	,456	,608

The results presented in the Hosmer-Lemeshow test table support the claim that the model is good. According to this test, the model is appropriate if the significance (Sig. value) is greater than 0.05, which is the case for the final model, as the chi-square indicator for the Hosmer-Lemeshow test is 10.484 with 8 degrees of freedom and a significance of 0.233. Therefore, we conclude that the model prediction is good, indicating that the model is appropriate.

Table 16. Hosmer-Lemeshow Test for the Model

Step	Chi-square	df	Sig.
1	13,864	8	,085
2	6,329	8	,610
3	6,260	8	,618
4	3,044	8	,932
5	10,339	8	,242
6	7,274	8	,507
7	13,703	8	,090
8	3,749	8	,879
9	1,485	8	,993
10	1,244	8	,996
11	4,676	8	,792
12	4,854	8	,773
13	6,701	8	,569
14	4,170	8	,841
15	1,173	8	,997
16	10,726	8	,218
17	10,484	8	,233

The table titled "Accuracy of Company Classification for the Model" illustrates how well the model predicts the category (company late in repaying credit obligations/company regularly repaying credit obligations) for each examined case, that is, for each individual step in the regression. The results presented for the final model demonstrate that it correctly classifies 84% of all cases, representing a significant improvement compared to the initial 50%. Specifically, the model accurately classifies 80% (40 out of 50) of enterprises regularly repaying obligations to the Bank and 88% (44 out of 50) of enterprises that are late in repaying obligations to the Bank.

Table 17. Accuracy of Company Classification for Model

Observed			Predicted		
			PL ili NPL		Percentage Correct
			PL	NPL	
Step 1	PL ili NPL	PL	43	7	86,0
		NPL	7	43	86,0
	Overall Percentage				86,0
Step 2	PL ili NPL	PL	43	7	86,0
		NPL	8	42	84,0
	Overall Percentage				85,0
Step 3	PL ili NPL	PL	43	7	86,0
		NPL	8	42	84,0
	Overall Percentage				85,0
Step 4	PL ili NPL	PL	43	7	86,0
		NPL	8	42	84,0
	Overall Percentage				85,0
Step 5	PL ili NPL	PL	43	7	86,0
		NPL	6	44	88,0
	Overall Percentage				87,0
Step 6	PL ili NPL	PL	44	6	88,0
		NPL	6	44	88,0
	Overall Percentage				88,0
Step 7	PL ili NPL	PL	42	8	84,0
		NPL	6	44	88,0
	Overall Percentage				86,0
Step 8	PL ili NPL	PL	43	7	86,0
		NPL	7	43	86,0
	Overall Percentage				86,0
Step 9	PL ili NPL	PL	43	7	86,0
		NPL	7	43	86,0
	Overall Percentage				86,0
Step 10	PL ili NPL	PL	41	9	82,0
		NPL	6	44	88,0
	Overall Percentage				85,0
Step 11	PL ili NPL	PL	41	9	82,0
		NPL	7	43	86,0
	Overall Percentage				84,0
Step 12	PL ili NPL	PL	40	10	80,0
		NPL	7	43	86,0
	Overall Percentage				83,0

Step 13	PL ili NPL	PL	40	10	80,0
		NPL	7	43	86,0
	Overall Percentage				83,0
Step 14	PL ili NPL	PL	40	10	80,0
		NPL	7	43	86,0
	Overall Percentage				83,0
Step 15	PL ili NPL	PL	40	10	80,0
		NPL	6	44	88,0
	Overall Percentage				84,0
Step 16	PL ili NPL	PL	39	11	78,0
		NPL	6	44	88,0
	Overall Percentage				83,0
Step 17	PL ili NPL	PL	40	10	80,0
		NPL	6	44	88,0
	Overall Percentage				84,0

The following table (Table 18) illustrates the types of errors of the developed model. Error type one (I) indicates how many enterprises with irregular repayment of credit obligations the model incorrectly classified as enterprises with regular operations. Error type two (II) denotes the misclassification of enterprises that regularly repay credit obligations, which the model wrongly categorized as enterprises with poor financial stability. The third column calculates the average of the realized errors of type I and II. The fourth column shows the average accuracy of the model's prediction, calculated as the difference between one and the average of errors of types I and II.

Table 18. Errors in Company Classification and Prediction Accuracy for the Developed Credit Model

Error type I (percentage)	Error type II (percentage)	Percentage of average error	Average accuracy of model prediction
12%	20%	16%	84%

CONCLUSION

By employing binary logistic regression on a sample of 100 SMEs, divided into two groups: "good" enterprises with a delay in repaying credit obligations up to 30 days and "bad" enterprises with a delay longer than 90 days, a credit model for predicting the probability of timely repayment of credit obligations was developed. The created credit model calculates the possibility of predicting delays for a period of one year. Only financial performance indicators of legal entities from the sample were used in model development. Official financial reports of SMEs at the time of loan approval were used to calculate these financial indicators. In the financial model, the most significant performance indicators in predicting the probability of timely repayment of credit obligations were identified as: (Net profit + Depreciation + Amortization)/Capital, EBIT/Assets, Total liabilities/Sales revenue, and EBITDA/Total liabilities.

The developed financial model correctly classifies 84% of all cases. Specifically, the model correctly classifies 80% (40 out of 50) of enterprises with timely repayment of obligations to the Bank, and 88% (44 out of 50) of enterprises with delays in repayment of obligations to the Bank. Using statistical methods such as the Omnibus test (Goodness of fit test), Cox & Snell and Nagelkerke test, and Hosmer-Lemeshow test, a satisfactory level of validity for the developed model was confirmed.

The results of this research indicate the efficiency of the developed credit model and its potential application in practice for better credit risk management when approving loans for SMEs. These findings also suggest that further refinement of the model could further improve decision-making processes in commercial banks, contribute to the stability of the financial system, and support economic growth through better financing of the SME sector.

LIMITATIONS OF THE STUDY

The limitations of the conducted research are as follows:

- The research included a limited sample of enterprises from only one bank in BiH;
- The research has methodological limitations since it was not possible to analyze the impact of all significant business indicators of enterprises.

SCOPE FOR FURTHER RESEARCH

The development of a credit model for assessing the creditworthiness of small and medium-sized enterprises (SMEs) in Bosnia and Herzegovina presented in this paper opens up several avenues for future research and improvement. Recommendations for further research include:

- Expansion of the sample and data: Research should include a larger sample of enterprises from different sectors of the economy to increase the model's generalizability. Additionally, including data from multiple banks can help reduce potential biases related to specific credit policies of individual banks.
- Long-term validation of the model: Future research should monitor the long-term performance of the credit model over a period longer than one year to determine its stability and accuracy over time. This would allow for the identification of possible seasonal or cyclical impacts on enterprises' creditworthiness.
- Inclusion of additional variables: Research could examine the impact of additional financial and non-financial variables on creditworthiness, such as liquidity indicators, indebtedness, as well as qualitative factors such as management capabilities, market conditions, and market position.

RECOMMENDATIONS FOR BANKS AND FINANCIAL INSTITUTIONS

Financing the SME sector by banks is crucial for economic growth and the stability of the financial system in Bosnia and Herzegovina. The development and implementation of sophisticated credit models, such as the model presented in this research, can significantly contribute to better credit risk management. Using such models could help banks more efficiently assess the creditworthiness of enterprises, resulting in risk reduction, improvement of the credit portfolio, and support for the growth of the SME sector, which is crucial for the economy of Bosnia and Herzegovina. Therefore, we recommend that banks actively work on adapting and improving existing credit models, and continuously monitor and evaluate their performance to ensure stability and growth of both their businesses and the overall economic system. Recommendations for banking practice include:

- Implementation and adaptation of the model: Banks in Bosnia and Herzegovina should consider implementing this credit model to improve decision-making processes when approving loans for SMEs. Adapting the model to the specificities of their own credit portfolio can further increase its efficiency.
- Expansion of analysis to multiple sectors: Future research should include a larger sample of enterprises from different sectors of the economy to further enhance the model and achieve greater generalizability. Developing specific models for different industries (for example, construction, trade, manufacturing) can provide more precise assessments of creditworthiness.
- Long-term performance monitoring: Monitoring the performance of the credit model over a longer period of time would allow banks to identify seasonal or cyclical changes in enterprises' creditworthiness and adjust their strategies accordingly.

These recommendations can help further improve the model and ensure its relevance and applicability in a dynamic business environment, contributing to better credit risk management and supporting sustainable economic growth through efficient financing of small and medium-sized enterprises in Bosnia and Herzegovina.

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