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QUALITATIVE AND QUANTITATIVE CREDIT RISK RATING MODEL FOR SMEs IN BOSNIA AND HERZEGOVINA

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Abstract

This study focuses on developing an advanced credit assessment model for Small and Medium Enterprises (SMEs) in Bosnia and Herzegovina (BiH), integrating both quantitative and qualitative indicators. SMEs represent over 99% of the enterprises in the country and contribute more than 60% to GDP, underscoring their critical role in economic development. To address the unique financing needs of SMEs, the research employs binary logistic regression on a sample of 100 SMEs, classified into "good" enterprises with credit repayment delays of up to 30 days and "bad" enterprises with delays exceeding 90 days. Initially, 40 financial indicators were derived from official financial reports. The model was further enhanced by incorporating qualitative indicators such as management education and experience, quality of cooperation with the bank, accounting quality, planning and control, modernity and capacity of equipment, market development, market position, and the number of employees. The resulting model achieved a classification accuracy of 91%, significantly surpassing the 84% accuracy of models based solely on financial indicators. The model's validity was confirmed through statistical tests including the Omnibus test, Cox & Snell, Nagelkerke tests, and the Hosmer-Lemeshow test. This research highlights the importance of integrating qualitative factors to improve the predictive accuracy of credit models. The findings have significant implications for banks and financial institutions, enhancing risk management and supporting SME growth, which is vital for the broader economic development of Bosnia and Herzegovina. Recommendations for further research include expanding the sample size, incorporating additional qualitative indicators, and applying advanced machine learning techniques to further refine the model.

Keywords: Small and medium enterprises, credit model, quantitative and qualitative indicators, credit risk management

INTRODUCTION

SMEs in Bosnia and Herzegovina comprise over 99% of enterprises (out of 31,435 active enterprises – Agency for Statistics of BiH, 2020). According to the latest data from the Statistical Business Register of the Agency for Statistics of BiH, 74% of active enterprises are micro enterprises, 19% are small enterprises, and 6% are medium enterprises. Large enterprises account for less than 1%. SMEs generate over 60% of GDP and, consequently, should become the engine of economic development in BiH (Martinović et al, 2012, p. 34). Given the above, it is evident that it is necessary to ensure appropriate access to financing sources for the SME sector in order to enhance its development. It is important to emphasize that lending to SMEs requires a specific approach in the processing and approval of loans compared to large enterprises. Recent research has shown that banks should apply different procedures (in the application and behavioral process) to manage SMEs compared to large corporate firms and should also use scoring and rating systems specifically addressed to the SME portfolio (Altman et al, 2010, p. 4). Research on this topic has shown that rating systems for assessing the creditworthiness of SMEs usually have a significant proportion of qualitative modules, which decrease in favor of quantitative modules as the enterprise's sales revenue increases (Svítil, 2018, p. 39). Multiple studies have indicated that non-financial, qualitative indicators positively influence the assessment of an enterprise's business performance. In the aforementioned research, Altman and all concluded that qualitative information is likely to significantly improve the prediction accuracy of the model for SMEs by up to 13% (Altman et al, 2010, p. 24). Similar research was conducted in Sweden, where the authors included the following non-financial indicators in the model: changes of auditors and qualified audit opinions, company age, defaulted payments, industry risk weights and reporting delays. Adding qualitative factors to the prediction model is found to improve the classification results by up to 5.4 percentage points (Kernell & Wallin, 2011, p.1). Kohv and Lukason argued that the joint use of financial and non-financial factors significantly enhances the accuracy of loan-default prediction (Kohv & Lukason, 2021, p.13).

In addition to the aforementioned points, it is important to emphasize that recent research by eminent authors (Minussi, Soopramanien, & Worthington, 2006) has highlighted the need for credit models, predominantly developed for the American market, to be adapted and tailored for markets in other countries. Additionally, numerous authors (Zenzerović & Peruško, Muminović, Pavlović & Cvijanović, Salkić) have determined that credit models developed using samples of enterprises operating in the USA and the European Union lack adequate accuracy when assessing the creditworthiness of enterprises operating in transition countries, such as those in Bosnia and Herzegovina.

Therefore, the aim of this paper is to develop a credit model, which includes quantitative and qualitative indicators, for assessing the creditworthiness of SMEs in Bosnia and Herzegovina. The same sample of enterprises used for developing the quantitative model for assessing the creditworthiness of SMEs, which had a prediction accuracy of 84% (Salkić, 2024), will be used for the development of this model. Taking into account the results of the aforementioned research, we start from the hypothesis that this new model, which also includes qualitative business indicators, will have a higher level of accuracy than the already developed model, which contains only financial indicators. We will present the sample selection, the use of statistical methods for the development validation and evaluation of the model's efficiency. Finally, we will provide recommendations for financial institutions, as well as further research on this topic.

METHODOLOGY

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 below 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 (refer the 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 QUALITATIVE AND QUANTITATIVE 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 the influence of quantitative and qualitative 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, Salkić 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, quantitative and qualitative 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 Quantitative 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 whether all data fall within the range of possible values and whether 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 statistical 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 table 8 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

In accordance with the aforementioned research and experiences, and in order to improve the accuracy of the credit prediction model compared to the already developed model that includes only quantitative indicators, we have incorporated qualitative business indicators for the enterprises in the sample into this model. These indicators assess:

- education and experience of the enterprise's management,
- quality of the management's cooperation with the bank,

- quality of the accounting function in the enterprise,
- quality of planning and control,
- modernity and capacity of equipment,
- development of the market in which the enterprise operates,
- the enterprise's position in the market, and
- number of employees.

The assessment of the aforementioned qualitative indicators was provided by financial advisors (bank employees) at the time of loan approval. A scale from 1 to 5 was used for the evaluation of qualitative indicators, where 1 is excellent, 2 good, 3 average, 4 satisfactory, and 5 poor. The number of employees was also rated on a scale from 1 to 5, as follows: 5 poor − for fewer than 5 employees, 4 satisfactory − for 5 to 10 employees, 3 average − for 10 to 20 employees, 2 good − for 20 to 30 employees, and 1 excellent − for more than 30 employees.

Table 9. Overview of Qualitative Indicators of the Model

Variable Label	Qualitative Indicators
VAR41	Education and Experience of the Company's Management
VAR42	Quality of the Management's Cooperation with the Bank
VAR43	Quality of the Accounting Function in the Company
VAR44	Quality of Planning and Control
VAR45	Modernity and Capacity of Equipment
VAR46	Development of the Market in which the Company Operates
VAR47	Company's Position in the Market
VAR48	Number of Employees

The above ratings of qualitative indicators were added to the financial indicators retained in the analysis, after excluding outliners and multicollinear independent variables (they are shown in Table 8. Tolerance and VIF test).

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 10 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 10. 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 11. Values of Dependent Variables

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

In Table 12 (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 12. Classification Accuracy of the Model without Independent Variables

Block 0 Classification Table

Observed			Predicted		
			PL or NPL		Percentage Correct
			NPL	PL	
Step 0	PL or NPL	NPL	0	50	.0
		PL	0	50	100.0
	Overall Percentage				50.0

The Stepwise Backward LR binary logistic regression procedure, based on the Likelihood Ratio Test, for selecting significant independent variables explaining the dependent variables, was conducted in 15 steps of gradual statistical regression. The final 15th step is presented in the following table. 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.

Table 13. Variables Included in the Model

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 15[a]	VAR07	8.632	3.845	5.042	1	.025	5610.870
	VAR12	12.679	5.659	5.019	1	.025	320953.446
	VAR18	45.854	21.262	4.651	1	.031	82044370638317300000.000
	VAR22	18.497	9.898	3.492	1	.062	107964332.034
	VAR24	9.033	5.035	3.219	1	.073	8378.217
	VAR26	-11.384	4.478	6.461	1	.011	.000
	VAR31	-33.646	13.798	5.946	1	.015	.000
	VAR34	7.648	3.804	4.042	1	.044	2096.800
	VAR35	-.259	.102	6.398	1	.011	.772
	VAR37	-1.375	.628	4.792	1	.029	.253
	VAR38	16.320	7.190	5.152	1	.023	12238377.028
	VAR45	4.549	1.502	9.172	1	.002	94.528
	VAR47	-1.274	.639	3.974	1	.046	.280
	VAR48	.757	.382	3.928	1	.047	2.132
	Constant	-15.308	5.259	8.471	1	.004	.000

The table 14 presents the quantitative and qualitative variables that comprise the final model calculated in the 15th iteration, along with their assigned B coefficients. These B coefficients are incorporated in the final equation for calculating the probability of whether the enterprise, whose creditworthiness is analyzed, falls into a certain category (enterprises regular or irregular in the settlement of credit obligations).

Table 14. Names and Values of Quantitative and Qualitative Variables in the Model

Variable	Indicators	B Values	Label in the Model
VAR07	(Profit + Depreciation + Amortization)/Capital	8.632	X1
VAR12	Total liabilities/Total assets	12.679	X2
VAR18	EBIT/ Total assets	45.854	X3
VAR22	Cash/ Sales Revenue	18.497	X4
VAR24	Retained earnings/Total assets	9.033	X5
VAR26	Net Profit/Capital	-11.384	X6
VAR31	EBITDA/Total liabilities	-33.646	X7
VAR34	Inventory/Total Revenue	7.648	X8
VAR35	(Capital + Long-term liabilities)/Fixed assets	-0.259	X9
VAR37	Sales Revenue/ Total assets	-1.375	X10
VAR38	Operating Cash Flow / Sales Revenue	16.320	X11
VAR45	Modernity and Capacity of Equipment	4.549	X12
VAR47	Company's Position in the Market	-1.274	X13
VAR48	Number of Employees	0.757	X14
Constant		-15.308	

Established on the basis of our research the equation for predicting the probability of timely repayment of credit obligations for small and medium-sized enterprises in BiH, which contains quantitative and qualitative indicators, has the following form:

$$\text{Log}(p/1-p) = -15.308 + 8.632X1 + 12.679X2 + 45.854X3 + 18.497X4 + 9.033X5 - 11.384X6 - 33.646X7 + 7.648X8 - 0.259X9 - 1.375X10 + 16.320X11 + 4.549X12 - 1.274X13 + 0.757X14$$

The equation above can be simplified as:

$$p = 1 / 1 + e^{-(-15{,}308 + 8{,}632X1 + 12{,}679X2 + 45{,}854X3 + 18{,}497X4 + 9{,}033X5 - 11{,}384X6 - 33{,}646X7 + 7{,}648X8 - 0{,}259X9 - 1{,}375X10 + 16{,}320X11 + 4{,}549X12 - 1{,}274X13 + 0{,}757X14)}$$

where,

e is the base of the natural logarithm, that is, $e \approx 2.71828$.

The probability p can have values from 0 to 1, and these probabilities can be directly interpreted as delay probabilities. Making conclusions about the enterprise's ability to properly settle its obligations to banks is possible by comparing it with the calculated value, that is, the probability of the model, where the critical value is 0.5. A value of less than 0.5 means that the enterprise is classified as one with an orderly settlement of credit obligations, otherwise it is predicted that the enterprise will be late in the settlement of credit obligations.

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 second developed model contains both quantitative and qualitative indicators and has the following form:

Log (p/1 - p) = - 15.308 + 8.632X1 + 12.679X2 + 45.854X3 + 18.497X4 + 9.033X5 - 11.384X6 - 33.646X7 + 7.648X8 - 0.259X9 - 1.375X10 + 16.320X11 + 4.549X12 - 1.274X13 + 0.757X14

Table 15, 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 15th iteration step (Step 15a), 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 95.527 with 14 degrees of freedom.

Table 15. Summary Performance Indicators for the Model

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	108.773	28	.000
	Block	108.773	28	.000
	Model	108.773	28	.000
Step 2a	Step	-.043	1	.836
	Block	108.730	27	.000
	Model	108.730	27	.000
Step 3a	Step	-.040	1	.841
	Block	108.689	26	.000
	Model	108.689	26	.000

Step 4a	Step	-.316	1	.574
	Block	108.373	25	.000
	Model	108.373	25	.000
Step 5a	Step	-.217	1	.641
	Block	108.156	24	.000
	Model	108.156	24	.000
Step 6a	Step	-.476	1	.490
	Block	107.680	23	.000
	Model	107.680	23	.000
Step 7a	Step	-.225	1	.635
	Block	107.455	22	.000
	Model	107.455	22	.000
Step 8a	Step	-.380	1	.537
	Block	107.075	21	.000
	Model	107.075	21	.000
Step 9a	Step	-1.025	1	.311
	Block	106.050	20	.000
	Model	106.050	20	.000
Step 10a	Step	-1.345	1	.246
	Block	104.705	19	.000
	Model	104.705	19	.000
Step 11a	Step	-1.822	1	.177
	Block	102.883	18	.000
	Model	102.883	18	.000
Step 12a	Step	-.830	1	.362
	Block	102.053	17	.000
	Model	102.053	17	.000
Step 13a	Step	-2.221	1	.136
	Block	99.832	16	.000
	Model	99.832	16	.000
Step 14a	Step	-1.958	1	.162
	Block	97.875	15	.000
	Model	97.875	15	.000
Step 15a	Step	-2.347	1	.125
	Block	95.527	14	.000
	Model	95.527	14	.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 15), these values are 0.615 and 0.820, respectively. In other words, the set of variables comprising the obtained model explains 61.5% and 82% of the variance.

Table 16. Cox & Snell R Square and Nagelkerke R Square for the Model

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	29.857[a]	.663	.884
2	29.900[b]	.663	.884
3	29.940[b]	.663	.884
4	30.256[b]	.662	.882
5	30.474[b]	.661	.881
6	30.949[c]	.659	.879
7	31.175[c]	.659	.878
8	31.555[c]	.657	.876
9	32.579[c]	.654	.872
10	33.925[d]	.649	.865
11	35.746[e]	.643	.857
12	36.576[e]	.640	.853
13	38.797[e]	.632	.842
14	40.755[e]	.624	.832
15	43.102[e]	.615	.820

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 10.656 with 8 degrees of freedom and a significance of 0.222. Therefore, we conclude that the model prediction is good, indicating that the model is appropriate.

Table 17. Hosmer-Lemeshow Test for the Model

Step	Chi-square	df	Sig.
1	4.947	8	.763
2	5.256	8	.730
3	4.944	8	.764

4	5.417	8	.712
5	3.951	8	.862
6	3.122	8	.926
7	2.492	8	.962
8	2.825	8	.945
9	1.216	8	.996
10	2.759	8	.949
11	.309	8	1.000
12	1.244	8	.996
13	.320	8	1.000
14	.543	8	1.000
15	10.656	8	.222

The table titled "Accuracy of Company Classification for the Model" illustrates how well the model predicts the category (enterprise late in repaying credit obligations/enterprise 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 91% of all cases, representing a significant improvement compared to the initial 50%. Specifically, the model accurately classifies 90% (45 out of 50) of enterprises regularly repaying obligations to the Bank and 92% (46 out of 50) of enterprises that are late in repaying obligations to the Bank. Here we can conclude that this model also has a better percentage of classification accuracy compared to the model, which was based on only financial indicators (Salkić, 2024, p. 264) and whose classification accuracy is 84%.

Table 18. Accuracy of Company Classification for Model

Observed			Predicted		
			PL or NPL		Percentage Correct
			PL	NPL	
Step 1	PL or NPL	PL	45	5	90.0
		NPL	4	46	92.0
	Overall Percentage				91.0
Step 2	PL or NPL	PL	45	5	90.0
		NPL	3	47	94.0
	Overall Percentage				92.0
Step 3	PL or NPL	PL	45	5	90.0
		NPL	3	47	94.0

	Overall Percentage				92.0
Step 4	PL or NPL	PL	45	5	90.0
		NPL	4	46	92.0
	Overall Percentage				91.0
Step 5	PL or NPL	PL	45	5	90.0
		NPL	4	46	92.0
	Overall Percentage				91.0
Step 6	PL or NPL	PL	45	5	90.0
		NPL	3	47	94.0
	Overall Percentage				92.0
Step 7	PL or NPL	PL	45	5	90.0
		NPL	3	47	94.0
	Overall Percentage				92.0
Step 8	PL or NPL	PL	45	5	90.0
		NPL	3	47	94.0
	Overall Percentage				92.0
Step 9	PL or NPL	PL	46	4	92.0
		NPL	2	48	96.0
	Overall Percentage				94.0
Step 10	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 11	PL or NPL	PL	46	4	92.0
		NPL	2	48	96.0
	Overall Percentage				94.0
Step 12	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 13	PL or NPL	PL	46	4	92.0
		NPL	4	46	92.0
	Overall Percentage				92.0
Step 14	PL or NPL	PL	46	4	92.0
		NPL	3	47	94.0
	Overall Percentage				93.0
Step 15	PL or NPL	PL	45	5	90.0
		NPL	4	46	92.0
	Overall Percentage				91.0

The following table (Table 19) 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 19. 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
8%	10%	9%	91%

CONCLUSION

This study aimed to develop a credit model for predicting the probability of timely repayment of credit obligations by SMEs using binary logistic regression on a sample of 100 SMEs. These enterprises were categorized into two groups: "good" enterprises with delays in repaying credit obligations of up to 30 days, and "bad" enterprises with delays exceeding 90 days. The resultant credit model facilitates the prediction of delays over a one-year period.

In the initial phase of model development, 40 financial indicators were derived from the official financial reports of the enterprises. Subsequently, the model was enhanced by integrating qualitative business indicators, including the education and experience of the enterprise's management, the quality of the management's cooperation with the bank, the quality of the accounting function in the enterprise, the quality of planning and control, the modernity and capacity of equipment, the development of the market in which the enterprise operates, the enterprise's position in the market, and the number of employees.

The most significant qualitative and quantitative performance indicators included in the model for assessing the creditworthiness of SMEs are: (Profit + Depreciation + Amortization)/Capital, Total liabilities/Total assets, EBIT/Total assets, Cash/Sales Revenue, Retained earnings/Total assets, Net Profit/Capital, EBITDA/Total liabilities, Inventory/Total Revenue, (Capital + Long-term liabilities)/Fixed assets, Sales Revenue/Total assets, Operating Cash Flow/Sales Revenue, Modernity and Capacity of Equipment, Enterprise's Position in the Market, and Number of Employees. The developed credit model achieved a classification accuracy of 91%, correctly classifying 90% (45 out of 50) of enterprises with timely repayments and 92% (46 out of 50) of enterprises with delayed repayments. This significant improvement in prediction accuracy, compared to the model relying solely on financial indicators with an accuracy of 84%, validates our working hypothesis.

The validity of the developed model was further confirmed using statistical methods such as the Omnibus test (Goodness of fit test), Cox & Snell and Nagelkerke tests, and the Hosmer-Lemeshow test, demonstrating a satisfactory level of validity.

The development and utilization of credit assessment models tailored for SMEs hold significant importance for banks and the economy of Bosnia and Herzegovina. The advantage for banks and financial institutions is of course in the improvement of risk management. Accurate credit assessment models enable banks to make informed lending decisions based on both quantitative financial metrics and qualitative business indicators. This improves the allocation of capital, ensuring that funds are directed towards SMEs with the highest potential for success and repayment. Access to tailored credit products helps SMEs secure financing necessary for expansion, innovation, and market competitiveness, thereby fostering economic growth.

Limitations of the Study

Every research endeavor has its constraints and this study is no exception. Here are some limitations to consider:

- Sample Size and Scope: The study utilized a sample of 100 SMEs from a specific region or industry, which may limit the generalizability of findings to other contexts or sectors.
- Data Availability and Quality: The accuracy and reliability of the credit model heavily depend on the availability and quality of data obtained from SMEs' financial reports and other sources. Incomplete or inaccurate data could affect the validity of results.
- Time Constraints: The study focused on predicting credit repayment behaviors over a one-year period. Longer-term studies could provide insights into how creditworthiness evolves over time and during economic cycles.

Acknowledging these limitations is crucial for interpreting the study's results accurately and for guiding future research efforts aimed at improving credit assessment models for SMEs.

Scope for Further Research

Based on the conclusions drawn from this study, several avenues for further research are recommended to enhance the predictive capabilities and robustness of credit models for SMEs:

- Expansion of Sample Size and Diversity: Future studies should consider expanding the sample size to include a larger and more diverse set of SMEs. This can help in generalizing the findings and improving the model's applicability across different sectors and regions.
- Incorporation of Additional Qualitative Indicators: While the current model includes several qualitative indicators, further research could explore additional non-financial factors such as education and motivation of employees, customer satisfaction, and innovation capacity, which may also significantly impact creditworthiness.
- Longitudinal Analysis: Conducting a longitudinal study to track the performance of SMEs over an extended period could provide deeper insights into the dynamics of creditworthiness and allow for the development of models that account for changes in business conditions over time.
- Application of Advanced Machine Learning Techniques: Utilizing advanced machine learning algorithms and techniques, such as random forests, gradient boosting, and neural networks, could improve the accuracy and reliability of credit prediction models by capturing complex nonlinear relationships between variables.
- Integration of Macroeconomic Variables: Including macroeconomic indicators such as interest rates, inflation, and GDP growth in the model could enhance its predictive power by accounting for the broader economic environment that influences SME performance.

By addressing these areas, future research can build on the findings of this study to create more comprehensive and accurate credit assessment models for SMEs, ultimately contributing to better financial decision-making and support for this critical sector of the economy.

Recommendations for Banks and Financial Institutions

Based on the findings of this study, several recommendations can be made to banks and financial institutions to improve their assessment of SME creditworthiness and enhance their lending practices:

- Adopt Comprehensive Credit Models: Banks should adopt credit models that integrate both quantitative and qualitative indicators. This approach has been shown to significantly improve prediction accuracy compared to models relying solely on financial indicators.
- Enhance Qualitative Assessments: Financial institutions should place greater emphasis on qualitative assessments, including management quality, cooperation with banks,

accounting practices, and market position. Training loan officers to accurately evaluate these aspects can lead to better credit decisions.

- Develop Sector-Specific Models: Different sectors have unique characteristics and risks. Developing sector-specific credit models can enhance the accuracy of predictions and better address the specific needs of SMEs in various industries.
- Provide Financial Education and Support: Offering financial education programs to SMEs can improve their financial management practices, making them more creditworthy. Banks can also provide advisory services to help SMEs strengthen their business operations.
- User-Friendly Implementation Tools: Developing user-friendly software tools or applications that implement the credit model can facilitate its adoption by banks and financial institutions, thereby bridging the gap between academic research and practical application.

By adopting these recommendations, banks and financial institutions can improve their credit assessment processes, reduce default rates, and better support the SME sector, which is crucial for economic growth and development.

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