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DEVELOPING A COMPREHENSIVE CREDIT RATING MODEL FOR SMEs IN BOSNIA AND HERZEGOVINA: INTEGRATING QUANTITATIVE AND QUALITATIVE INDICATORS

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Abstract

The development of a comprehensive credit rating model for small and medium-sized enterprises (SMEs) in Bosnia and Herzegovina is critical to the stability and growth of both financial institutions and the broader economy. SMEs play a pivotal role in the nation's economic activity, however, they often face significant obstacles in securing financing due to their limited financial histories and reduced integration into global value chains. To address this, a holistic credit model was created, incorporating both quantitative and qualitative performance indicators. This model was developed using a sample of 100 SMEs, consisting of 50 enterprises that met their credit obligations on time and 50 that were over 90 days overdue on their obligations. Logistic regression was employed to develop the model, which can predict delays over a one-year period. Initially, 40 financial indicators were used for the development of the model. Non-financial indicators were then added, including the education and experience of management, the quality of management's cooperation with the bank, the quality of the enterprise's accounting function, the effectiveness of planning and control, the modernity and capacity of equipment, market development, the enterprise's market position, the number of employees, years of operation, and industry sector. The final model achieved a classification accuracy of 90%, outperforming a purely quantitative model with an 84% accuracy rate, though slightly lower than an alternative model with 91% accuracy. Despite the hypothesis that additional qualitative indicators would enhance model accuracy not being supported by empirical results, the newly developed holistic model demonstrates a significantly higher predictive capacity compared to the traditional quantitative approach. This *research underscores the necessity of integrating both quantitative and qualitative data for a more robust credit risk assessment, offering valuable insights for banks and financial institutions.*

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

INTRODUCTION

The Law on the Promotion of Small Business Development ("Official Gazette of the Federation of BiH", No. 19/06) outlines the criteria for small businesses, which include employing fewer than 250 persons annually and generating an annual turnover of up to 40 million BAM and/or having an annual balance sheet not exceeding 30 million BAM (Federal Ministry of Development, Entrepreneurship and Crafts, 2022).

Small and medium enterprises (SMEs) are pivotal to the economic landscape of Bosnia and Herzegovina, representing over 99% of enterprises and contributing more than 60% of the nation's GDP. SMEs account for 70% of total employment and generate 65% of added value. However, their integration into global value chains is low, and they are less competitive than similar enterprises in the region. Despite their critical role, SMEs frequently encounter challenges in securing financing, largely due to their lack of sufficient or reliable financial track records (Martinović et al, 2012).

The number of SMEs per 1,000 inhabitants in the EU averages around 50, and in 2020, it stood at 50.3. In contrast, data from 2021 for the Federation of BiH, which includes micro, small, and medium enterprises along with sole proprietorships, shows a ratio of 35.4 small business entities per 1,000 inhabitants (Federal Ministry of Development, Entrepreneurship and Crafts, 2022). The provided data imply that SMEs in Bosnia and Herzegovina have significant room for growth and improvement in their operations to reach the EU average.

In Bosnia and Herzegovina, the majority of banks have traditionally focused their lending activities on corporate enterprises, with SME financing only recently becoming a strategic priority. The development and implementation of a credit rating system with a high level of accuracy in assessing SME creditworthiness could have significant implications. On one hand, it would open up a new market for banks by enabling the growth of SME banking as a distinct segment. On the other hand, it would facilitate easier access to financial resources for SMEs, thereby fostering the development of the SME sector, creating new jobs, and ultimately contributing positively to the overall economic growth of Bosnia and Herzegovina.

The goal of this paper is the development of a new credit model, or more precisely, the improvement of the existing developed credit model with the inclusion of additional non-financial indicators. Specifically, we will add the following indicators to the model: the industry to which the SME belongs and its years of operation duration. We start from the hypothesis that a model that incorporates more non-financial indicators will have a higher level of accuracy in predicting the creditworthiness of SMEs than the previously developed model.

SHORT OVERVIEW OF MORE SIGNIFICANT STUDIES

In banking literature, we encounter various definitions of credit rating. It is highlighted as an assessment of an enterprise's creditworthiness summarized in a single grade or number. It provides an assessment of the current and future ability of an enterprise to fully and timely meet its obligations (payments and interests) (Bruckner et al, 2003, p.27). It can be said that credit rating is a standardized, objective, incremental, and current assessment of an enterprise's creditworthiness (Füser, 2001, p. 37).

Successful management of credit risk has been a topic of discussion among numerous eminent authors in contemporary banking literature, resulting in the development of a multitude of models for predicting the insolvency and/or bankruptcy of enterprises. Among the earliest models, Beaver's model (1967) stands out as a simple univariate statistical model that laid the groundwork for the application of statistical methods to credit risk analysis. Beaver's model utilized financial ratios, including cash flow/total assets, net income/total debt, and cash flow/total debt, derived from financial statements, and achieved notable success in predicting financial distress among enterprises (Altman & Sabato, 2005).

Building on Beaver's work, Altman (1968) introduced the Z-score model, one of the most renowned quantitative models for assessing the financial health of enterprises. This model utilized a combination of five key financial ratios—net working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value of equity/book value of total liabilities, and sales/total assets—to predict bankruptcy with a high degree of accuracy (Altman, 2000). Further refining these approaches, Edmister (1972) focused on small and medium enterprises (SMEs), using a multivariate discriminant analysis to develop a model that predicted financial instability. Edmister's research introduced innovations such as the use of three-year averages and trends in financial indicators, alongside comparisons with industry averages (Zenzerović & Peruško, 2006).

In a bid to enhance predictive accuracy over longer time horizons, Altman, Haldeman, and Narayanan (1977) developed the ZETA model, which were proven effective in forecasting the likelihood of enterprise bankruptcy up to five years in advance. This model incorporated seven financial indicators, including return on assets, earnings stability, and liquidity, and achieved an impressive 96.2% accuracy in classifying enterprises one year before bankruptcy (Altman, 2000). Ohlson (1980) later introduced a logistic regression model that further advanced the field by testing nine independent variables across a substantial sample of enterprises. His model yielded three distinct prediction tools for bankruptcy, offering varying time horizons with accuracy rates ranging from 92.84% to 96.12% (Zenzerović & Peruško, 2006).

This gap in financial history makes traditional credit assessment methods less effective for SMEs, necessitating alternative approaches. Research suggests that one of the most effective methods for evaluating SME creditworthiness is through an internal rating system, which relies on experts' subjective assessments and qualitative data rather than solely on quantitative data.

Numerous studies have underscored the importance of incorporating non-financial criteria into SME credit risk evaluations. For instance, Altman, Sabato, and Wilson (2010), Auken, Cánovas, and Guijarro (2010), and Berger, Miller, Petersen, Rajan, and Stein (2005) emphasize the significant role of qualitative factors such as market position, management quality, and industry risk. The development prospect of the industry has also been identified as a critical factor, with Gao and Zhang (2016) demonstrating that industry prospects significantly influence the probability of default.

In the context of German SMEs, Lehmann (2003) conducted a study comparing two models: one relying solely on quantitative financial information and the other incorporating qualitative judgments from credit analysts. The study found that the inclusion of qualitative information significantly enhanced the accuracy of the credit rating system, suggesting that subjective judgments can provide valuable insights that purely quantitative models might overlook.

Grunert, Norden, and Weber (2002) further explored the role of non-financial factors in credit ratings, concluding that a combined approach, using both financial and non-financial criteria, leads to a more accurate prediction of default than relying on either type of information alone.

Additionally, industry-specific risks play a crucial role in credit evaluations. Costa, Barroso, and Soares (2002) examined the bank ratings of client business areas and found that industry risk is a vital component of credit scoring models. This is particularly relevant in SMEs, where industry variability can significantly affect the accuracy of risk assessments.

This finding is consistent across various studies, highlighting the importance of a holistic approach to credit assessment. In light of all this, it is clear that evaluating the business performance of enterprises in modern business conditions cannot be based solely on the analysis of financial indicators. Instead, a combination of financial and non-financial data is essential for an adequate assessment of overall enterprise performance.

A credit model (Model II) has already been developed, incorporating both qualitative and quantitative performance indicators such as (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. This model achieved a classification accuracy of 91%, correctly classifying 90% of enterprises with timely repayments and 92% of enterprises with delayed repayments (Salkić, 2024, pp. 350-351). This significant improvement in prediction accuracy, compared to the model relying solely on financial indicators with an accuracy of 84% (Model I), validates our working hypothesis (Salkić, 2024, p. 264).

In this study, we seek to advance the existing credit rating model by integrating additional non-financial indicators, specifically the industry classification of the enterprise and its operational longevity. The development and validation of the new model will be conducted using the same sample of enterprises previously employed in the creation of the creditworthiness assessment model for SMEs (Salkić, 2024). This paper will detail the selection process of the sample, the application of statistical methods in the model's development, validation, and efficiency evaluation. Finally, we will offer recommendations for future research in this domain, as well as insights for banks and financial institutions to optimize their credit assessment processes.

METHODOLOGY

The study involves the construction and testing of a logistic regression model based on a sample of 100 SMEs: 50 enterprises that met their credit obligations on time and 50 that were over 90 days overdue on their obligations. Logistic Regression will be employed to analyze the relationship between the independent variables (quantitative and qualitative indicators) and the dependent variable (creditworthiness, measured as timely or delayed credit repayment). The model's validity and reliability will be confirmed through statistical tests, including the Omnibus test, Cox & Snell, Nagelkerke tests, and the Hosmer-Lemeshow test.

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 BAM	4	23
500,001 BAM − 1,000,000 BAM	9	11
1,000,001 BAM − 2,000,000 BAM	10	10
2,000,001 BAM − 3,000,000 BAM	11	3
3,000,001 BAM − 4,000,000 BAM	9	2
4,000,001 BAM – 5,000,000 BAM	6	0
5,000,001 BAM – 6,000,000 BAM	1	0
6,000,001 BAM – 7,000,000 BAM		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 MODEL FOR ASSESSING THE CREDITWORTHINESS OF SMALL AND MEDIUM ENTERPRISES IN BIH: INTEGRATING QUANTITATIVE AND QUALITATIVE INDICATORS

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.

Among the methodologies that can be employed for estimating default risk, the logistic regression (logit) is the preferred one for at least four reasons: a) its output is directly expressed as a measure of default probability; b) it is able to handle both qualitative and quantitative explanatory variables and allows simple testing of the significance of coefficients; c) it is sufficiently solid from a scientific perspective and from experimentation in applications; and d) currently, it is the most commonly applied methodology by bank credit risk systems. (Dainelli at all, 2013, p.26).

Since regression analysis has often been used in the development of recent credit models (Gao and Zhang, 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 obligation.

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 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

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.

In order to improve the credit model, we will add two more independent variables, which can have an impact on the dependent variables - the enterprise regularly/irregularly settles its credit obligations, namely belonging to a certain economic sector and the number of years of operation.

Namely, according to the data of the Banking Agency of the Federation of Bosnia and Herzegovina (for the year in which the loans were disbursed to the enterprises in the sample, and for which financial statements were used to calculate the indicators) in total approved loans to legal entities, the construction sector has the largest share of non-performing loans at 26.7%, followed by the agriculture sector with a high share of non-performing loans at 17%. The two economic sectors with the largest share in total loans are trade (19.8%) and production (14.3%). The percentage of non-quality loans placed in the production sector is 21.2%, while for the trade sector this percentage is significantly better and is 13.2%. In addition, in the catering sector, the share of non-performing loans is 12.7%, while for other sectors this percentage is 14.2% (Agencija za bankarstvo Federacije Bosne i Hercegovine, 2015, p. 39). We know the economic sector in which the enterprises from the sample operated. Based on the presented data, grades were assigned to each sector, from 1 to 5, where 1 is the best and 5 the worst grade. We assigned grades according to the percentage of non-quality loans for each sector, so the best grade 1 went to the catering sector, 2 to shops, 3 to agriculture and other, 4 to the manufacturing sector and 5 to the construction sector.

Furthermore, we assumed that enterprises that have been operating for many years are more financially stable, and that they have a built-up relationship with banks, as well as a credit history that can be checked. Guided by the above logic, a grade from 1 to 3 was assigned, where 1 is the best and 3 the worst grade. Grade 3 was given to enterprises that had been operating for up to and including 3 years at the time of loan approval. Rating 2 is awarded for the number of years of operation from 4 to 9, and 1 for over 10 years of operation. The above ratings of qualitative indicators were added, in addition to the existing qualitative indicators, to the quantitative indicators that were included in the previously presented model.

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
VAR49	Years of the Enterprise's Operation
VAR50	Industry/Economic sector

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 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 7 steps of gradual statistical regression. The final 7th 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 10. Variables Included in the Model

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 7a	VAR07	13.275	5.988	4.914	1	.027	582439.161	4.656	72862031234.055
	VAR12	17.105	6.940	6.075	1	.014	26836384.953	33.234	21670131683217.664
	VAR18	58.652	32.526	3.252	1	.071	29668667026156006000000000.000	.006	2037821804
	VAR22	38.128	15.352	6.168	1	.013	36209320344392976.000	3097.884	42322917194159810000000000000000,000
	VAR24	11.807	5.787	4.163	1	.041	134206.580	1.592	11310378568.384
	VAR26	-16.310	7.590	4.618	1	.032	.000	.000	.238
	VAR31	-42.449	20.430	4.317	1	.038	.000	.000	.090
	VAR34	6.198	3.834	2.613	1	.106	491.950	.268	902970.769
	VAR35	-.303	.115	7.010	1	.008	.738	.590	.924
	VAR37	-2.165	1.010	4.596	1	.032	.115	.016	.831
	VAR38	14.485	8.460	2.932	1	.087	1952333.394	.123	30995737924825.957
	VAR41	1.170	.744	2.472	1	.116	3.223	.749	13.863
	VAR45	5.944	1.794	10.980	1	.001	381.455	11.339	12832.625
	VAR47	-1.482	.654	5.132	1	.023	.227	,063	.819
	VAR50	-1.936	.844	5.259	1	.022	.144	.028	.755
	Constant	-14.144	5.694	6.170	1	.013	.000		

The following table presents the quantitative and qualitative variables that comprise the final model calculated in the 7th 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 11. Names and Values of Quantitative and Qualitative Variables in the Model

Variable	Indicators	B Values	Label in the Model
VAR07	(Profit + Depreciation + Amortization)/Capital	13.275	X1
VAR12	Total liabilities/Total assets	17.105	X2
VAR18	EBIT/ Total assets	58.652	X3
VAR22	Cash/ Sales Revenue	38.128	X4
VAR24	Retained earnings/Total assets	11.807	X5
VAR26	Net Profit/Capital	-16.310	X6
VAR31	EBITDA/Total liabilities	-42.449	X7
VAR34	Inventory/Total Revenue	6.198	X8
VAR35	(Capital + Long-term liabilities)/Fixed assets	-0.303	X9
VAR37	Sales Revenue/ Total assets	-2.165	X10
VAR38	Operating Cash Flow / Sales Revenue	14.485	X11
VAR41	Education and Experience of the Company's Management	1.170	X12
VAR45	Modernity and Capacity of Equipment	5.944	X13
VAR47	Company's Position in the Market	-1.482	X14
VAR50	Industry/Economic sector	-1.936	X15
Constant		-14.144	

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:

Log (p/1 - p) = - 14.144+13.275X1+17.105X2+58.652X3+38.128X4+11.807X5 -16.310X6–42.449X7+6.198X8-0.303X9–2.165X10+14.485X11+1.170X12+5.944X13-1.482X14-1.936X15

The equation above can be simplified as:

$$p = 1 / 1 + e^{-\ (-14.144\ +\ 13.275X1 + 17.105X2 + 58.652X3 + 38.128X4 + 11.807X5 - 16.310X6\ - 42,.449X7 + 6.198X8 - 0.303X9 - 2.165X10 + 14.485X11 + 1.170X12 + 5.944X13 - 1.482X14 - 1.936X15)}$$

where, e is the base of the natural logarithm, that is, e ≈ 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 HOLISTIC 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 developed model contains both quantitative and qualitative indicators and has the following form:

$$\text{Log}(p/1 - p) = -14.144 + 13.275X1 + 17.105X2 + 58.652X3 + 38.128X4 + 11.807X5 - 16.310X6 - 42.449X7 + 6.198X8 - 0.303X9 - 2.165X10 + 14.485X11 + 1.170X12 + 5.944X13 - 1.482X14 - 1.936X15$$

Table 12 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 7th iteration step (Step 7a), 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 102.320 with 15 degrees of freedom.

Table 12. Summary Performance Indicators for the Model

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	105.765	21	.000
	Block	105.765	21	.000
	Model	105.765	21	.000

Step 2[a]	Step	-.034	1	.854
	Block	105.731	20	.000
	Model	105.731	20	.000
Step 3[a]	Step	-.049	1	.824
	Block	105.681	19	.000
	Model	105.681	19	.000
Step 4[a]	Step	-.308	1	.579
	Block	105.373	18	.000
	Model	105.373	18	.000
Step 5[a]	Step	-.222	1	.638
	Block	105.152	17	.000
	Model	105.152	17	.000
Step 6[a]	Step	-1.005	1	.316
	Block	104.146	16	.000
	Model	104.146	16	.000
Step 7[a]	Step	-1.826	1	.177
	Block	102.320	15	.000
	Model	102.320	15	.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 7 these values are 0.641 and 0.854, respectively). In other words, the set of variables comprising the obtained model explains 64.1% and 85.4% of the variance.

Table 13. Cox & Snell R Square and Nagelkerke R Square for the Model

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	32.865[a]	.653	.870
2	32.899[a]	.653	.870
3	32.948[a]	.652	.870
4	33.256[a]	.651	.868
5	33.478[a]	.651	.867
6	34.483[b]	.647	.863
7	36.309[b]	.641	.854

The results presented in the table 14 support the claim that the model is good. According to the Hosmer-Lemeshow test, for the final model at the 7th step, the chi-square is 3.901 with a significance of 0.866, which is greater than 0.05, and 8 degrees of freedom, and we can conclude that the prediction of the model is good, that is, that the model is suitable.

Table 14. Hosmer-Lemeshow Test for the Model

Step	Chi-square	df	Sig.
1	2.970	8	.936
2	2.994	8	.935
3	3.323	8	.912
4	3.090	8	.929
5	10.555	8	.228
6	2.952	8	.937
7	3.901	8	.866

In the Table titled "Corporate classification accuracy for Model", it can be seen that the final model correctly classifies 90% of all cases. This model also has a better percentage of classification accuracy compared to the model, which was derived based on only financial indicators (Model I), and whose classification accuracy is 84%, but a slightly lower percentage of accuracy compared to Model II, which has an accuracy of 91 %. The model correctly classifies 88% (44 out of 50) of enterprises that are regular in settling their obligations to the bank, and 92% (46 out of 50) of enterprises that are late in settling their obligations to the bank.

Table 15. Accuracy of Enterprise Classification for Model

Observed			Predicted		
			PL or NPL		Percentage Correct
			PL	NPL	
Step 1	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 2	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 3	PL orNPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0

Step 4	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 5	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 6	PL or NPL	PL	45	5	90.0
		NPL	2	48	96.0
	Overall Percentage				93.0
Step 7	PL or NPL	PL	44	6	88.0
		NPL	4	46	92.0
	Overall Percentage				90.0

The following table (Table 16) 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 16. Errors in Enterprise 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%	12%	10%	90%

CONCLUDING REMARKS

Conclusion

In conclusion, the development of a comprehensive credit rating model that accurately assesses the creditworthiness of SMEs in Bosnia and Herzegovina is of paramount importance for both financial institutions and the broader economic landscape. SMEs constitute a significant portion of the country's economic activity, yet they encounter substantial challenges in securing financing due to their limited financial histories and lower integration into global value chains.

A holistic credit model has been developed, integrating both quantitative and qualitative performance indicators. This model was constructed using a sample of 100 SME enterprises, comprising 50 that are timely in meeting their credit obligations and 50 that have been overdue in fulfilling their credit obligations by more than 90 days. Logistic regression was employed in the model's development. The model enables the prediction of delays over a one-year period.

The model initially utilized a set of 40 financial indicators, to which several non-financial indicators were subsequently added. These include the education and experience of the enterprise’s management, the quality of management’s cooperation with the bank, the quality of the accounting function within 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, the number of employees, the years of the enterprise’s operation, and the industry or economic sector.

The final model achieved a classification accuracy of 90%, correctly identifying 88% of the enterprises that were regular in settling their obligations to the bank, and 92% of those that were late in doing so. This performance surpasses that of the quantitative model, which had an accuracy of 84% (Model I), though it is slightly lower than the 91% accuracy of an alternative model (Model II).

While the empirical results did not support the hypothesis that the inclusion of additional qualitative indicators, such as years of operation and industry sector, would enhance the model's accuracy, the newly developed holistic model still demonstrates significantly higher accuracy compared to the purely quantitative model. This advancement highlights the critical importance of a holistic approach to credit risk assessment that integrates both quantitative and qualitative data.

The implications of this research are far-reaching. For financial institutions, the adoption of a more comprehensive credit assessment model can unlock new opportunities within the SME sector, potentially leading to increased lending activities and improved financial stability. For policymakers and regulators, the findings provide a framework for enhancing the support mechanisms for SMEs, which are vital to the country's economic growth and creation of jobs.

Limitations of the Study

This study, while offering valuable insights into the development of a credit rating model for SMEs in Bosnia and Herzegovina, is subject to several limitations. First, the sample size of 100 enterprises, though carefully selected, may not fully capture the diversity of the SME sector across different industries and regions within the country. A larger, more representative sample could provide more generalizable results. Second, the study relies on data from a single commercial bank, which may introduce bias related to the bank's specific credit policies and practices. The inclusion of data from multiple financial institutions could enhance the robustness of the findings. Finally, the use of logistic regression as the primary statistical method, though effective, may have limitations in capturing complex, non-linear relationships between variables. Exploring alternative modeling techniques, such as machine learning algorithms, could further improve the accuracy and applicability of the credit rating model.

Recommendations for Further Research

Building on the findings of this study, several avenues for further research are suggested:

- Expansion of Non-Financial Indicators: Future research could explore the inclusion of additional non-financial factors, such as management quality, market position, technological adoption, and innovation capacity. These variables may provide deeper insights into the creditworthiness of SMEs and further enhance the accuracy of credit models.
- Addition of Financial Indicators: Further studies could examine the potential benefits of incorporating additional financial indicators. This could help in refining the existing credit models, providing a more detailed and nuanced understanding of an SME's financial health.
- Comparison Across Different Sectors: Conducting sector-specific studies could reveal how the creditworthiness of SMEs varies across different industries. Such research could lead to the development of industry-tailored credit models, offering more precise risk assessments.
- Incorporating Behavioral and Environmental Factors: The integration of behavioral finance aspects, such as the decision-making styles of SME owners, and environmental factors, like economic stability or regulatory changes, could offer a more dynamic understanding of credit risk.
- Use of Advanced Modeling Techniques: Exploring alternative statistical methods, including machine learning and artificial intelligence, could improve the predictive power of credit models. These techniques may capture complex, non-linear relationships between variables that traditional models might miss.
- Longitudinal Studies: Longitudinal research tracking the credit performance of SMEs over time could provide valuable insights into the long-term effectiveness of credit models and their adaptability to changing economic conditions.

Future research should continue to explore the integration of additional qualitative indicators and the potential application of advanced statistical techniques to further refine and validate credit models for SMEs. Such efforts will contribute to the development of more sophisticated tools that better align with the dynamic nature of the SME sector and the evolving economic environment in Bosnia and Herzegovina.

Recommendations for Banks and Financial Institutions

Here are several recommendations for banks and the financial sector regarding the application and development of credit models and internal rating systems:

- Industry-Specific Credit Models: Banks should consider developing credit models tailored to specific industries within the SME sector. Different industries have distinct risk profiles, market conditions, and operational challenges, which can significantly impact the creditworthiness of enterprises. By creating industry-specific models, banks can achieve more accurate risk assessments and provide better-aligned credit products that meet the unique needs of SMEs in various sectors.
- Customization of Credit Models to Match Bank Risk Appetite: Banks should develop credit models and internal rating systems that are aligned with their specific risk appetites. This approach allows banks to better manage their credit portfolios according to their strategic objectives, whether they are focused on growth, stability, or diversification. Tailoring credit models to reflect the institution's risk tolerance will enable more precise credit decisions and foster a more resilient credit portfolio.
- Integration of Non-Financial Indicators: Financial institutions are encouraged to integrate non-financial indicators, such as industry trends, management quality, and innovation capacity, into their credit assessment processes. These factors provide a broader view of an SME's overall health and potential, helping banks to identify promising borrowers that may not have strong financial histories but possess significant growth potential.
- Investment in Data Analytics and Technology: Financial institutions should invest in advanced data analytics and machine learning technologies to enhance their credit models. These tools can process vast amounts of data, identify complex patterns, and improve the accuracy and efficiency of credit assessments. Moreover, technology can facilitate the automation of credit scoring processes, reducing operational costs and speeding up decision-making.
- Development of SME-Specific Credit Products: Based on the insights gained from industry-specific credit models, banks can design specialized credit products tailored to the unique needs of SMEs in different sectors. These products could include flexible

repayment terms, industry-specific credit lines, and financing options that align with the cash flow cycles of SMEs in various industries.

- Enhanced Communication and Support for SMEs: Banks should focus on improving communication with SME clients, offering them support and guidance on how to enhance their credit profiles. Providing SMEs with clear feedback based on their credit assessments and offering advice on financial management can help them improve their creditworthiness and foster stronger relationships with their financial institutions.

By implementing these recommendations, banks and financial institutions can better serve the SME sector, enhance the accuracy of their credit assessments, and ultimately contribute to the economic growth and stability of Bosnia and Herzegovina.

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