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The use of discriminatory analysis in predicting the failure of Algerian small and medium enterprises, a sample study for the period 2005-2014

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Abstract
This study aims to develop a predictive model for financial failure in Algerian small and medium enterprises (SMEs) using discriminant analysis. The research utilized 63 financial ratios applied to a balanced sample of 70 enterprises (35 failed/non-active and 35 sound/active) over the period 2005-2014.
The findings yielded a robust predictive model comprising ten financial ratios with significant Distinguishing capability: working capital to turnover (TR7), total sales to operating result (EF9), net result to short-term debt (P6), short-term liabilities to total assets (FS2), non-current assets to total debt (D6), gross operating surplus to total debt (P4), equity to total debt (D3), turnover to short-term liabilities (TR4), operating cash flow to financial expenses (CFO6), and working capital requirement to total assets (FS5). The model demonstrated strong predictive capability with an overall classification accuracy of 82.3%. This research contributes to the development of early warning systems for financial distress in the Algerian SME sector, providing stakeholders with an effective tool for risk assessment and mitigation.

Keywords: financial failure; financial ratios; Discriminant Analysis; small and medium enterprise.

Introduction:
Financial failure constitutes a fertile domain for research and for the development of solutions and proposals that serve all stakeholders concerned with the institution as an entity within an economic community. The scope of research in this field is diverse; beyond the objective of diagnosing the phenomenon, studies address the principal causes and controlling factors, as well as the major repercussions for the institution at the micro level and for the economy at the macro level. Other research has focused on forecasting financial failure and anticipating related events, beginning with the foundational works of (W, 1966) and (E.I, 1968). Over the years, this line of inquiry has been sustained by numerous researchers and even governmental institutions such as the Bank of France, employing a variety of tools ranging from traditional statistical methods to advanced artificial intelligence techniques.
Researchers investigating financial failure prediction have employed a diverse spectrum of methodological frameworks and analytical techniques, ranging from classical statistical approaches to contemporary computational paradigms. Historically, statistical methods were the first to be applied, with the most prominent including: Linear Discriminant Analysis (LDA), Multiple Discriminant Analysis (MDA) (Altman, 1968; Beaver, 1966), Logistic Regression (A, 1980; E, 1984; Hua et al., 2007), and probabilistic models (Theodossiou, 1991).
The second category comprises artificial intelligence methods, which emerged as research advancement and were adopted in the field of financial failure prediction to address the limitations of traditional approaches in the mid-1980s. Notable examples include neural networks (Tam, 1992; Altman, 1994; ESSID Zina, 2009; Chandra, 2009; Ding, 2008) and genetic algorithms (GA) (Kyung-shik Shin, 2002; Hongkyu Jo, 1996; Hyunchul Ahn, 2009).
The suggestion here is that the discriminant model, if used correctly and periodically, has the ability to predict corporate problems early enough to enable corrective action. Hence, in our attempt to construct a model for predicting financial failure among Algerian small and medium-sized enterprises, we will employ Discriminant Analysis (DA). This paper is organized as follows: the second section discusses a literature review relevant to this research, the third section presents the study methodology, Section four details the study results and finally the last section (section 5) provides a conclusion.

Financial Failure: A Comprehensive Review
Beaver (1966) is considered the pioneer in developing a model for measuring corporate failure through his 1966 article. The model, named after him, relied on financial ratios and included a comparison of average financial ratios between 79 failed companies and 79 non-failed companies during the period 1954-1964.
Beaver selected 30 financial ratios for analysis and employed a univariate analysis approach, analyzing each ratio over five

consecutive years. He examined these ratios to identify those that most accurately and reliably indicated a company's success or failure.

Beaver concluded that the following ratios could be used more effectively than others in predicting corporate failure:
1. Cash flow to total debt.
2. Net income to total assets.
3. Total debt to total assets.
4. Working capital to total assets.
5. Current ratio.

Altman (1968) aimed to determine the capability of financial ratios and indicators in predicting financial distress for a sample consisting of 22 industrial companies, of which 11 were distressed. He selected 22 financial ratios as independent variables for his study and used linear discriminant analysis to construct the Z-score function. The study found that five ratios had the ability to predict the risk of distress, thus building a predictive model consisting of: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to total liabilities, and sales to total assets, denoted by the following symbols respectively: X1, X2, X3, X4, X5. The formula is as follows:

“$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$”

Zulkarnain Muhamad Sori's study (2009) aimed to build a model for predicting the failure of Singaporean institutions using discriminant analysis (DA) on 17 institutions and employing 64 financial ratios. The empirical study demonstrated that two of these ratios had Distinguishing capability, and the model achieved a classification accuracy of 82.1%.

Ouennoughi (2011) sought to identify conditions for early detection of bankruptcy risks in Algerian small and medium enterprises. The study included a sample of 210 institutions using Fisher's factor analysis method. The researcher relied on 24 financial ratios and 7 qualitative variables, which collectively represented the independent variables of the study. The research resulted in the following model:

" $Z = 5.144\ S4 + 3.99\ S7 - 0.97\ G4 - 9.38\ G7 + 0.7\ R2 + 1.64\ C2 + 1.02\ AGE - 6.03\ FORME - 11.65\ QLTMEG$"

The researcher also calculated the probability of bankruptcy, and the results demonstrated the model's ability to provide early detection of bankruptcy risk.

Bălan's study (2012) aimed to build a model for predicting bankruptcy in Romanian small and medium enterprises using the Score function on 84 institutions, employing 14 financial ratios. The researcher succeeded in constructing a model incorporating all the study variables.

II - Methodology and Tools:

First: Study Sample

The study sample consists of 70 enterprises, including 35 failed and 35 sound enterprises from the population of Algerian small and medium enterprises (SMEs), which reached a total of 934,569 enterprises as of December 31, 2015, this includes 934,037 from the private sector and 532 from the public sector. From the total enterprises, 8,646 were found to be inactive (providing 261 observations represented in the financial statements of these enterprises for the period 2005-2014). It should be noted that the study data were obtained through the National Center for Commercial Registry (CNRC).

Second: Study Variables

Dependent Variable

The dependent variable in our study represents the phenomenon of financial failure, where we classified the sample enterprises into two groups: the first group comprises failed enterprises, while the second group comprises sound enterprises.

Independent Variables

The independent variables for this study consist of financial ratios extracted from the financial statements of the sample enterprises, representing 63 financial ratios. It should be noted that the independent variables were derived based on the results of previous studies.

The financial ratios are distributed into seven classifications:
- Financial structure, comprising 11 ratios.
- Solvency-liquidity, comprising 9 ratios.
- Profitability, comprising 11 ratios.
- Efficiency, comprising 11 ratios.
- Cash flow, comprising 8 ratios.
- Turnover rate, comprising 7 ratios.
- Indebtedness, comprising 6 ratios (see Appendix 01).

Third: Study Tool

In order to achieve the objectives of the study and to build a model that helps in predicting the financial failure of small and medium enterprises, we will adopt one of the statistical methods used in prediction in such studies, which is Discriminant Analysis - step-wise method.

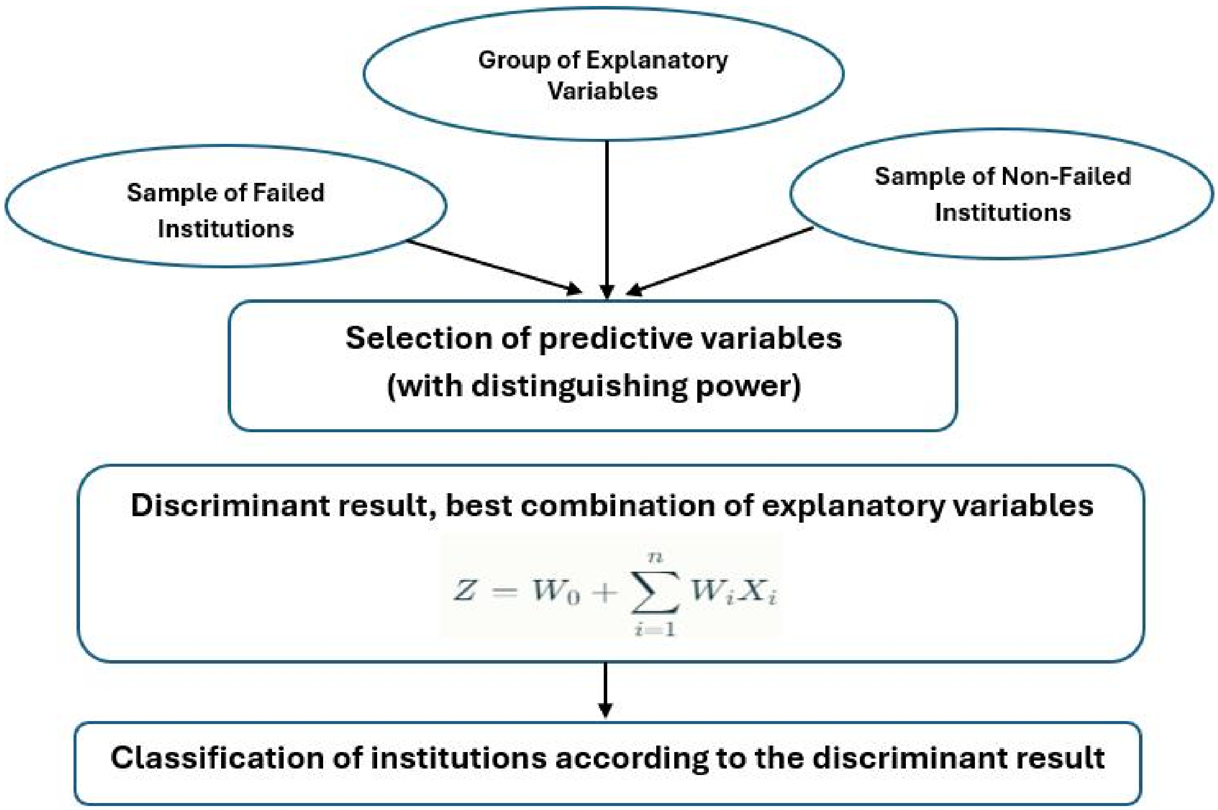
This method is implemented based on a set of tests:

- BOX test for equality of covariance matrices, expressed by the logarithm determinant that represents the difference in the covariance matrix, where discriminant analysis assumes homogeneity of the covariance matrix between groups, and is performed using the F-Fisher distribution.
- Wilk's Lambda statistic test (significance test and relationship strength) which expresses the amount of unexplained variance in the discriminant functions.

Note: The study data meet all the conditions for using the discriminant analysis method.

Therefore, we can summarize the most important steps of discriminant analysis in the following figure:

Figure 01: Most important steps of discriminant analysis



	Non-Failed	Failed
Non-Failed		(Sensitivity) Type Error II
Failed	(Privacy) Type Error I	

Source: Zopounidis, 1995

II - Results and Discussion:

Discriminant analysis begins with a model containing only one variable and then sequentially adds a set of several variables. The SPSS statistical program uses this algorithm, where we formed a matrix of variables and observations represented by financial ratios extracted from the financial statements of the studied enterprises. The following results were obtained, represented by a set of tests:

BOX Test for Equality of Covariance Matrices

The value of the logarithm determinant represents the difference in the covariance matrix; therefore, the larger its value, the more it indicates a difference in the joint variance matrix. As shown in Table (01) below, out of 63 variables, ten were predictive according to the content of the Rank column.
Discriminant analysis assumes homogeneity of the covariance matrix between groups; however, contrary to what is expected, the logarithm determinants are relatively unequal.

Table 01: Log determinants.

D	Rank	Log Determinants
0	10	-3.652
1	10	9.901
Pooled within groups	10	11.398

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.
Through Table (02), we can test the hypothesis of homogeneity of covariances using the BOX's M test. This test is performed using the F-Fisher distribution, where its value determines the hypothesis that should be accepted. If the significance indicator is less than 0.05, we reject the null hypothesis*, and accept the alternative hypothesis, which states that there is heterogeneity in the covariances between the two categories of the dependent variable—financial failure. Since the significance in this test is equal to 0.000, we adopt the alternative hypothesis.

Table 02: Test Results:

Box's M		**2142,108**
F	**Approx**	**37,340**
	df1	**55**
	df2	**207403,266**
	Sig.	**,000**

Test null hypothesis of equal population covariance matrices.
From Table (03) below, these variables collectively possess a high distinguishing capability, as evidenced by the significance value of the Exact F statistic being less than 0.05.

Table 03: Variables entered/removed[a,b,c,d]

					Wilk's Lambda		
							Exact F
Step	**Entered**	**Statistic**	**df1**	**df2**	**df3**	**Statistic**	**df1**
1	TR7	,889	1	1	254,000	31,669	1
2	EF9	,819	2	1	254,000	27,917	2
3	P6	,762	3	1	254,000	26,281	3
4	FS2	,729	4	1	254,000	23,286	4
5	D 6	,701	5	1	254,000	21,377	5
6	P 4	,674	6	1	254,000	20,099	6
7	D3	,656	7	1	254,000	18,579	7
8	TR4	,642	8	1	254,000	17,249	8
9	CF06	,630	9	1	254,000	16,054	9
10	FS5	,619	10	1	254,000	15,087	10
At each step, the variable that minimizes the overall Wilks' Lambda is entered.							
a. Minimum number of steps is 130.							
b. Minimum partial F to enter is 3.84.							
c. Maximum partial F to remove is 2.71.							
d. F level, tolerance, or VIN insufficient for further computation.							

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The stepwise method operates by ranking variables according to their distinguishing capability. However, before this ranking, it iteratively tests the variables' Distinguishing capability, beginning with a single variable and progressively adding variables one after another until identifying the group with the greatest distinguishing capability. The process of variable addition and exclusion comprised 130 steps.
Consequently, the variables with distinguishing capability are as follows:

- Working capital to turnover (TR7),
- Total sales to operating result (EF9),
- Net result to short-term debt (P6),
- Short-term liabilities to total assets (FS2),
- Non-current assets to total debt (D6),
- Gross operating surplus to total debt (P4),
- Equity to total debt (D3),
- Turnover to short-term liabilities (TR4),
- Operating cash flow to financial expenses (CFO6),
- Working capital requirement to total assets (FS5).

Significance Test and Relationship Strength
This test relies on values from a set of statistics that enable testing the strength of the relationship between the study variables. Table (04) below summarizes the results of this test, where we find: the **Eigenvalue**, whose value indicates the explanatory power of the variance in the dependent variable for the discriminant function. The larger the eigenvalue, the greater the explanatory power. In this study, it reached 0.616.

Table 04: Eigenvalue of the Discriminant Function

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,616[a]	100.0	100.0	,617

a. First 1 canonical discriminant functions were used in the analysis.
It is also evident from the previous table that the explained variance and cumulative explained variance ratios both reached 100%. The canonical correlation coefficient, shown in the last column, reached 0.617, indicating a strong correlation. The proportion of variance in the dependent variable[*], which equals the square of the correlation coefficient, was approximately 0,380.
To test the significance and strength of the relationship, it was necessary to conduct the Wilks' Lambda statistical test.
As shown in Table (05) below, this statistic reached 0.619, while the Chi-square statistic (X^2) was 119.479, with a significance (sig) of 0.000 at the 0.05 level, indicating the existence of differences between the two groups across the ten predictor variables.

Table 05: results of Wilks' Lambda test

Test of Function(s)	Wilks' Labda	Chi-square	Df	Sig.
1	0,619	1119,479	10	,000

Canonical Discriminant Function
The canonical discriminant function, which helps achieve the study's objective of predicting financial failure, takes the following form:
Z = -0.565 FS2 - 0.217 FS5 + 1.317 P4 + 0.905 P6 + 0.473 EF9 + 0.223 CFO6 - 0.498 TR4 + 0.631 TR7 - 5.960 D3 + 7.732 D6
Ten independent variables (financial ratios) were retained from the 63 proposed, which were found to be predictive and correlated with the discriminant function as follows:

- TR7 (Sales to working capital) correlates with the discriminant function at 45%, which is a positive correlation.

[*] This was discriminated through the independent variables of the study, which are the financial ratios.

- EF9 (Total sales to operating result) correlates with the discriminant function at 37.9%, which is a positive correlation.
- P6 (Net result to short-term debt) correlates with the discriminant function at 37.7%, which is a positive correlation.
- FS2 (Total sales to operating result) correlates with the discriminant function at -20%, which is a negative correlation.
- D6 (Non-current assets to total debt) correlates with the discriminant function at -12.4%, which is a negative correlation.
- P4 (Gross operating surplus to total debt) correlates with the discriminant function at 33.1%, which is a positive correlation.
- D3 (Equity to total debt) correlates with the discriminant function at -12.7%, which is a negative correlation.
- TR4 (Turnover to short-term liabilities) correlates with the discriminant function at 44.3%, which is a positive correlation.
- CFO6 (Operating cash flow to financial expenses) correlates with the discriminant function at 18.8%, which is a positive correlation.
- FS5 (Working capital to total assets) correlates with the discriminant function at -10.9%, which is a negative correlation.

Therefore, we can provide interpretations regarding the explanatory variables of the model as follows:

Working Capital to Turnover Ratio (TR7) (Turnover Rate):
We conclude that this ratio has distinguishing capability as it expresses the turnover rate of working capital, i.e., its contribution to turnover (the enterprise's activity), which represents the volume (surplus or deficit) that the enterprise achieves after paying short-term debts through current assets (financial equilibrium). This is referred to as the evolution of working capital (Ogien, 2008). Consequently, it reflects the ability of surpluses to cover the needs of its operating cycle. It also expresses a liquidity indicator through the position of its treasury, which contributes to avoiding or reducing the risk of failure as it is a source for settling the enterprise's obligations.

Operating Result to Total Sales Ratio (EF9) (Efficiency):
The appearance of this ratio among the explanatory variables of the proposed model demonstrates its ability to distinguish the element of failure as it expresses the operating profit margin (commercial profit), i.e., the contribution rate of the enterprise's main activity to turnover after covering sales costs, administrative costs, and distribution costs. This represents the proportion of profits through which the enterprise covers financial expenses (loan interest), taxes, and capital remuneration, which contributes to minimizing the probabilities of inability to pay these expenses and thus avoiding failure.

Net Result to Short-Term Debt Ratio (P6) (Profitability):
We conclude that this ratio has the ability to predict financial failure as it expresses the extent of the enterprise's ability to cover its short-term debts (cost of short-term debt) based on its net profit, which is considered a potential treasury if it is greater than investment and financing expenses. This explains the ratio's ability to distinguish the element of failure due to its direct correlation with short-term debt.

Short-Term Liabilities to Total Liabilities Ratio (FS2) (Financial Structure):
This ratio expresses the relative importance of short-term liabilities in the financial structure of small and medium enterprises, from which we infer its distinguishing capability. This ratio provides an indicator of the necessity to review the debt ratio (indebtedness) to enable the enterprise to cover it when due dates arrive, thereby avoiding payment default problems and capital erosion. On the other hand, controlling short-term liabilities may enable the enterprise to achieve financial balance by generating positive working capital.

Non-Current Assets to Total Debt Ratio (D6) (Indebtedness):
This ratio possesses the ability to distinguish the element of failure through its appearance in the model. It expresses the volume of debt that can be covered by non-current assets, where the ratio helps in estimating the debt that the enterprise's capacity can absorb, thereby reducing the probabilities of failure.

Gross Operating Surplus to Total Debt Ratio (P4) (Profitability):
The ratio expresses the extent to which the gross operating surplus can cover debts. We conclude that this ratio has a high predictive capability for failure and significant importance in detecting it. In financial accounting literature, the gross operating

surplus is considered a potential treasury when the enterprise controls its costs, thereby achieving a treasury surplus that covers part of its debts. This ratio is useful in monitoring the volume of indebtedness.

Total Debt to Equity Ratio (D3) (Indebtedness):
The presence of this ratio among the explanatory variables of the model indicates its high ability to distinguish between failed and sound enterprises. This ratio expresses the financial independence of the enterprise, i.e., the extent to which equity covers debts, which helps in taking necessary precautions and measures to prevent defaulting on payments when due. The ratio should not exceed 1.

Turnover to Short-Term Liabilities Ratio (TR4) (Turnover Rate):
We conclude that this ratio has the ability to distinguish through its presence in the proposed model as it expresses the turnover rate of short-term liabilities, i.e., the extent of their contribution to forming turnover (the enterprise's main activity).

Operating Cash Flow to Financial Expenses Ratio (CFO6) (Cash Flow):
Through its distinguishing ability, we conclude that this ratio is very influential as it relates to cash flows generated from the enterprise's main activity on one hand, and because small and medium enterprises rely on short-term debt to finance their operating cycle on the other hand. This ratio enables us to know the extent to which the enterprise's main activity can cover financial expenses. Its appearance in the model highlights the importance of information disclosed in the cash flow statement in predicting financial failure. The higher the ratio, the higher the ability to repay debt, thus reducing the probability of failure.

Working Capital to Total Assets Ratio (FS5) (Financial Structure):
We conclude that this ratio has the ability to diagnose the enterprise's situation and distinguish the element of failure as it expresses the volume (surplus or deficit) that the enterprise achieves after paying short-term debts through current assets and then the ability of the surplus to cover the needs of its operating cycle. Through its treasury position – surplus or deficit – which expresses liquidity in the enterprise, i.e., a source for settling its obligations and thus avoiding or reducing the risk of failure. This ratio is considered the best indicator of the cessation of the enterprise's activity (Altman, 1968).

Discriminant Values of the Model
Through this OLAP Cubes test, we can determine the status of the enterprise as to whether it is sound or failed, by calculating the model variables for this enterprise and then projecting them onto the model equation. This is followed by comparing the resulting balance value with the values shown in Table (06). It should be noted that this test allows us to know the strength of the model by applying it to years preceding the year of failure occurrence.

Table 06: OLAP Cubes

Sound = 0	Sum	N	Mean	Minimum	Maximum
Discriminant Scores from Function 1 for Analysis 1	102,11072	135	,7563757	-,79272	4,19705
Troubled = 1	**Sum**	**N**	**Mean**	**Minimum**	**Maximum**
Discriminant Scores from Function 1 for Analysis 1	-100,02563	125	-,8002051	-4,28743	1,49535

The aim of this test is to determine the predictive quality of the study observations using discriminant analysis. As observed in Table (07), the cases are correctly classified. We find that out of a total of 135 observations of sound enterprises (0), 106 were correctly classified, yielding a specificity of 78.5%, while 17 observations exhibited the behavior of the second group. As for the troubled enterprises (1), out of a total of 125 observations, 108 were correctly classified, yielding a sensitivity of 86.4%, while 13.6% of the observations exhibited the behavior of the first group.
Accordingly, the total number of correctly classified observations was estimated at 214, representing a classification accuracy of 82.3%.

Table 07: Classification Results[a,c]

D			Predictive Group Membership		Total
			0	1	
Original	Count	0	106	29	135
		1	17	108	125
	%	0	78,5	21,5	100

		1	13,6	86,4	100
Cross-validated[b]	**Count**	0	106	29	135
		1	17	108	125
	%	0	78,5	21,5	100
		1	13,6	86,4	100
a. 82,3% of original grouped cases correctly classified.					

Conclusion

In this study, we attempted to propose a model for predicting financial failure in small and medium enterprises by highlighting the role of discriminant analysis as an effective tool in building models capable of distinguishing between sound and failed enterprises. By applying this approach to a sample of 70 enterprises (35 sound and 35 failed) and using 63 financial ratios, we obtained a model with ten financial ratios that demonstrated high distinguishing capability. The model achieved a classification accuracy of 82.3%.

Based on the results obtained in our study and drawing on the findings of several scientific research studies on predicting this phenomenon using discriminant analysis, we can conclude that this tool is considered one of the most important methods used in prediction and has great effectiveness, which helps in making rational decisions that contribute to minimizing the risk of financial failure.

Finally, we suggest as a complementary study to conduct a comparison between discriminant analysis and other tools, whether statistical or in artificial intelligence, while relying on both quantitative and qualitative variables.

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