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ATTEMPT TO BUILD A QUANTITATIVE MODEL FOR PREDICTING FINANCIAL FAILURE OF A SAMPLE OF ALGERIAN ECONOMIC INSTITUTIONS

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ABSTRACT

This study aims to attempt to formulate a quantitative model with the capability to provide early prediction of the financial status of an economic institution, whether it is heading towards financial failure or in a sound financial position, through the composition of a combination of financial ratios that have the ability to discriminate between successful institutions and failing institutions. This was conducted using the Multiple Discriminant Analysis (MDA) method, which was applied to a sample consisting of 32 industrial institutions, of which 20 were successful institutions and 12 were failing institutions according to the criterion of consecutive losses for more than two years.
The study concluded that three (03) ratios out of twenty-eight (28) financial ratios have the ability to discriminate between successful institutions and failing institutions according to the discriminant analysis model, which achieved a classification accuracy of 96.9%.

KEYWORDS

Prediction, Early Warning, Financial Failure, Discriminant Analysis

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Introduction:

The global economy has experienced successive economic crises, the most prominent of which was the Great Depression, which led to the collapse of many institutions. Traditional financial tools had a positive effect in addressing many financial problems. However, with the enormous development in the institutional environment, traditional tools became incapable of measuring financial performance and predicting the financial risks that threaten their existence, and they began to produce conflicting results that could not be relied upon to judge the future of the institution.

As a result, institutions realized the necessity of seeking modern financial tools that enable them to predict future positions based on extrapolating the past and observing the present. These tools are known as quantitative forecasting models, which have been formulated according to precise statistical methods such as discriminant analysis, logistic analysis, artificial neural networks, and other statistical and mathematical methods. These tools are now relied upon to forecast financial needs and plan ways to meet them, in addition to predicting the financial status and providing early warning regarding the potential exposure of institutions to failure in the future. From this perspective, this study seeks to address the following problem:

How do quantitative models contribute to predicting financial failure for Algerian industrial institutions?

To address this problem, it is necessary to raise the following sub-questions:

- Is it possible to build a quantitative model using discriminant analysis based on a combination of financial ratios?
- Which ratios are the most appropriate for constructing a quantitative model based on discriminant analysis?

Study Hypotheses:

In light of the questions posed and to cover the aspects of the study, the main hypothesis was formulated as follows:

"Quantitative models have sufficient capability to predict the financial failure of Algerian industrial institutions."

Based on this hypothesis, the following sub-hypotheses can be identified:

- A quantitative model can be built using discriminant analysis based on the financial ratios that have the highest ability to discriminate between successful and failing institutions.
- The current liquidity ratio, quick ratio, and overall liquidity ratio are the best ratios that can be relied upon in formulating a predictive model according to the discriminant analysis method.

Study Methodology:

To achieve the objectives of the study and address them with a scientific methodology, we used the descriptive approach within the theoretical framework of the study by providing a brief overview of the phenomenon of financial failure. The method employed for conducting the field study is statistical, through selecting a sample of Algerian industrial institutions for a specific period, where data and information were collected from financial statements and analyzed based on the discriminant analysis method to build a quantitative model capable of predicting the risk of financial failure.

Study Objectives:

This study aims to achieve a primary objective, which is attempting to build quantitative models capable of diagnosing the future financial status of Algerian industrial institutions and predicting their risk of financial failure. This is particularly relevant after specialists and consulting offices recently relied on modern assessment tools by selecting the set of financial ratios that best discriminate between successful and failing institutions, and by using statistical methods such as discriminant analysis to formulate quantitative models characterized by accuracy in evaluation and saving effort and time.

1. Concept of Financial Failure:

There are multiple definitions of financial failure. One group of experts sees it as the inability of an institution to meet its short-term obligations when they become due, whereas another group of specialists, led by John Argenti (Argenti), views it as the process in which the institution has begun a long trajectory that ends in an event known as financial distress. Another group defined financial failure as the cessation of the institution from paying preferred stock dividends (Ghassan Al-Khairi & Dalal, 2013, p. 100). It is also an expression of insolvency that manifests at a certain moment when the institution is subject to economic, legal, and even judicial procedures encompassing all creditors at the moment the institution halts its payments (Hubert, 2010, p. 422).

Financial failure implies that the institution is heading toward retirement and liquidation, and that the institution ceases to exist in the economic life voluntarily. Financial failure represents its ultimate law, or the end of its organization and the death of the institution (Al-Zubaidi, 2011, p. 272).

From the above, it can be said that financial failure is a pathological condition affecting institutions due to numerous interacting factors that, over time, generate financial imbalances, causing a state of disequilibrium between its resources and obligations due in the short term. This may occur temporarily, and thus does not represent financial failure. However, if it occurs continuously, the institution’s assets will be unable to meet total liabilities, and the institution’s property may be placed under judicial custody or subject to reorganization procedures and settlements between the institution and its creditors.

1.1 Financial Symptoms:

These symptoms are associated with two main indicators that reflect the deterioration of the institution's financial situation:

- **Decline in profitability:** The institution's profitability is an important indicator reflecting its status, as it represents the performance achieved. The decline in profitability is often due to increased activity costs (fixed or variable), and may also be attributed to weak sales profits resulting from a decrease in sales or in their volume.
- **Treasury crisis:** Weakness in the treasury reflects a state of financial imbalance and poor treasury management, exposing institutions to financial imbalances that evolve into the inability to meet financial obligations at their due dates. Accumulation of treasury deficits may lead to long-term bankruptcy, often caused by increased working capital needs or a decrease in net working capital.

Other symptoms of financial failure, branching from the above two indicators, include:

- Paying medium-term loan interests through short-term borrowing;
- Delaying the settlement of bills and medium-term loan installments;
- Distributing profits to shareholders through loans;
- Not creating adequate provisions and reserves for asset replacement and renewal;
- Financing fixed assets with resources not from the same category (short-term loans);
- Decrease in working capital value due to shortage of receivables and debtors, and reduction in inventory value without a corresponding reduction in short-term liabilities.

1.2 Non-Financial Symptoms:

Non-financial symptoms appear in the following forms (Assawi & Ait Mohammed, 2018, p. 275):

- **Tense social climate:** A struggling institution experiences a climate of conflicts between workers and management, especially if the institution fails to pay wages or refrains from doing so under the pretext of severe financial difficulties;
- **Deterioration of the institution's reputation among customers:** Due to poor quality of products and services or non-compliance with customers' desires and preferences, negatively affecting demand for the institution's products;
- **Deterioration of the institution's reputation among suppliers:** Resulting from delays or refusal to fulfill obligations, creating supply difficulties;
- **Emergence of conflicts between partners or shareholders and management:** Increasing the financial crisis the institution is exposed to.

2. Concept of Predicting Financial Failure:

The process of predicting financial failure is an attempt to foresee the future status of the institution through its financial statements and to understand its capacity for continuity and handling potential risks. The prediction process is considered an effective method upon which the institution relies in financial decision-making and planning. This includes forecasting financial needs to complete operational processes. Predicting failure also refers to the computational process for estimating potential future changes through studying financial ratios obtained from financial statements (Assawi & Ait Mohammed, 2018, p. 276).

Predicting financial failure is considered an attempt to form a vision of the institution's future financial status based on past and current information to meet the institution's financial obligations, which is carried out through an evaluation process followed by appropriate decision-making (Hafsi, 2021, p. 91).

2.1. Components of the Financial Failure Prediction Process:

For the financial failure prediction process to succeed in achieving its intended objectives, a set of requirements or conditions must be available, which together form fundamental pillars that must be observed. If we consider that the ultimate goal of prediction is to provide information regarding the potential for an institution to reach a state of financial failure years before it occurs, in order to enable the institution to take appropriate corrective actions in a timely manner, then the success factors for this predictive process must be ensured. This involves providing a set of conditions, some of which relate to the methods, approaches, and analytical tools used in the predictive model, and others relate to the sources of information relied upon.

Various financial failure prediction models rely on quantitative methods, whose research emphasizes the necessity of relying on quantitative data to construct predictive models for failure. This perspective is supported by the fact that the predictive ability of accounting data is among the most important qualitative features that such data must possess to be considered suitable for decision-making.

Such accounting data are represented in financial statements, and their development in terms of preparation, classification, and the type of information and data available therein, especially with international standards that emphasize transparency and reliability of information, in addition to the analyst's ability to interpret the relationships between available data and the use of statistical and mathematical tools, facilitates the prediction of failure (Okashi, 2016, p. 69).

In general, the success of the financial failure prediction process depends on a set of conditions that must be met, most importantly (Ghazwan, 2020, p. 178):

- Objectivity of historical data and its comprehensiveness regarding all aspects of the institution's activities;
- Shortness of the time horizon for prediction, as the shorter the prediction period, the higher the accuracy, and vice versa;
- Realism of the assumptions underlying future forecasts, taking into account the external circumstances surrounding the institution;
- Construction of predictive models based on a scientific methodology;
- Accurate extrapolation in the prediction process, noting that models derived during a previous period may not be suitable for another period if the size or type of the institution's activity changes.

3. Concept of Discriminant Analysis:

Discriminant analysis is a statistical method typically used for classification. It estimates the linear function that can effectively classify elements (individuals) as follows (Hongkuy & Other, 2005, p. 98):

$$\mathbf{Z=C_1X_1 + C_2X_2 + \ldots + CnXn}$$

Where:

- Z: the discriminant value resulting from applying the above discriminant equation,
- C: discriminant coefficients of the discriminant variables,
- X: independent discriminant variables,
- n: number of independent variables forming the discriminant equation.

The element is classified into the appropriate group based on the result of this discriminant function.

Discriminant analysis is often referred to as Fisher's discriminant analysis, as it classifies items into one of two or more pre-defined populations based on the individual characteristics of those items. The term"discriminant analysis" first appeared in 1936 in an article by R. A. Fischer on"The Use of Multiple Measurements in Taxonomic Problems." Fisher defined the nature of discriminant analysis simply as relying on a method to discover the relationship between a set of independent variables (called features) and a qualitative dependent variable, which in the simplest case is binary with only two values. If the discriminant result takes the value (0), the element belongs to the first group with specific characteristics; if the value is (1), the element belongs to the second group. Depending on the number of variable distinctions, one can perform two-group discriminant analysis or multiple-group discriminant analysis (Kocisova & Misankova, 2014, p. 1149).

Discriminant analysis is the method used to find the linear combination of financial ratios that best distinguish between the groups being classified. Through the graphical representation below, the resulting model is better for discrimination the smaller the overlap between the two groups, meaning that the two groups on axis D1 provide better discriminatory power than the two groups on axis D2 (Beaver & Deakin, 1972, p. 173).

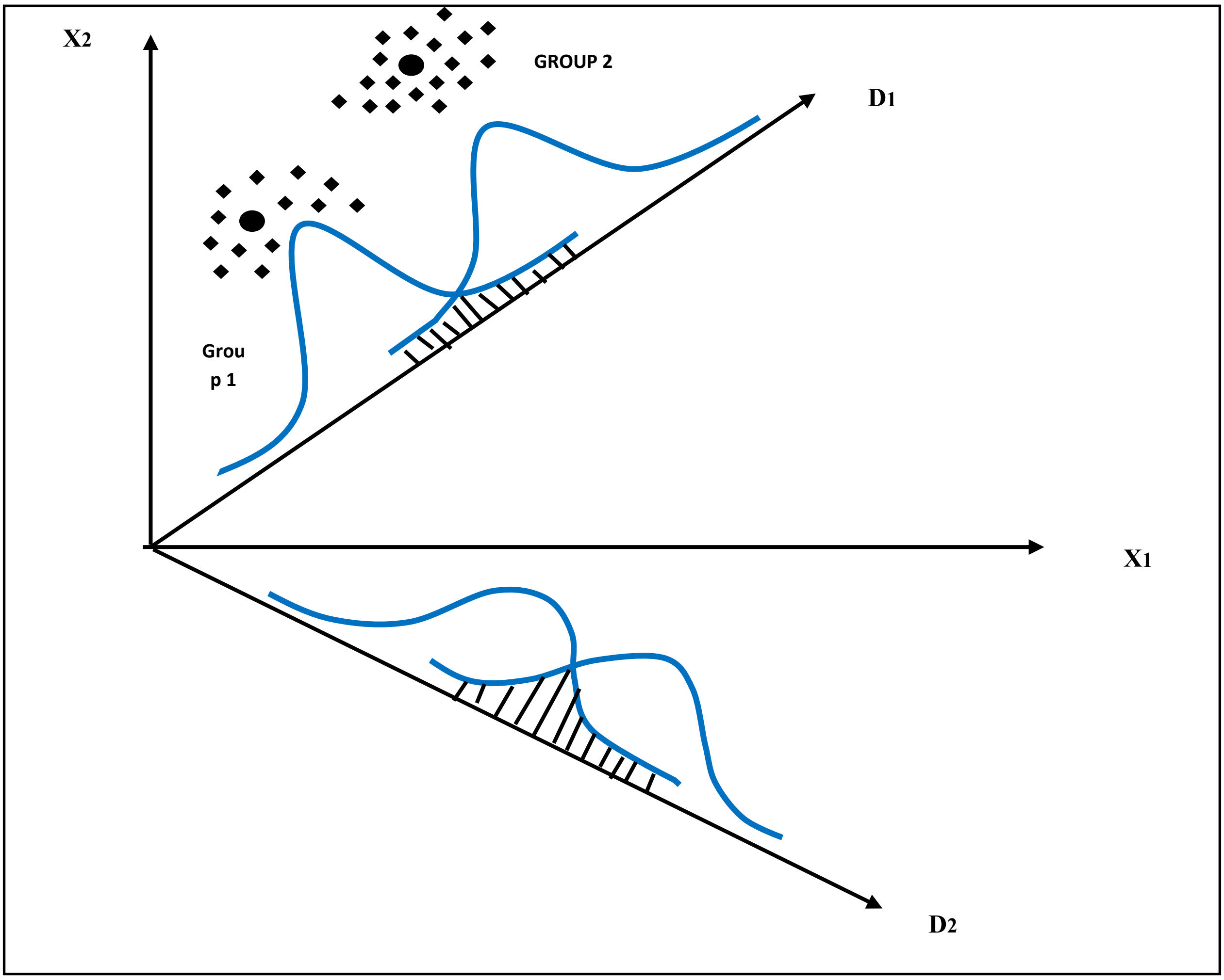

Fig 1. *Illustrates the discriminant function.*
Source: Edward Beaver and Deakin, A Discriminant Analysis of Predictors of Business Failure, Journal of Accounting Research, Vol. 10, No. 01, Spring 1972, p. 173.

3.1. Hypotheses of the Discriminant Analysis Method:

Discriminant analysis, like other statistical models, relies on a set of hypotheses, which are as follows (Jawda, 2008, p. 117):

• Quantitative variables are normally distributed for each population, and these populations define the levels of the grouping variable;

• The variances and covariances of dependent variables are the same across all factor levels. If sample sizes differ and the variances and covariances are unequal, discriminant analysis will not yield valid results;

• The sample is randomly selected, and the score of any individual in the sample for any variable should be independent of all other individuals' scores;

• No high correlation exists between independent variables. Discriminant analysis assumes no such correlation, and variables must be independent, or highly correlated variables must be removed from the analysis.

2.3. Steps for Building a Predictive Model According to Discriminant Analysis:

To build a predictive model according to the discriminant analysis method, several steps should be followed. It begins with selecting a sample representing the various subpopulations under study, based on which the most significant independent variables for the financial position of the institutions are derived. The model is then formulated after determining the discriminant coefficients.

To classify the predicted institutions, a statistical separation rule is established by defining a cut-off value between the populations of sound and struggling institutions and comparing it with the discriminant value of the institution resulting from applying the model. Finally, the model's effectiveness is verified by testing its accuracy in correctly classifying institutions. In general, this method derives a linear discriminant equation consisting of independent discriminant variables that are considered the best for distinguishing between groups. The importance of each of these variables in differentiating the two groups is reflected through the discriminant coefficients. The stages of building the model can be summarized as follows (Ben Omar, 2010, p. 25):

- Examination and identification of the dependent variable for the model;
- Determination of the independent variables for the model;
- Specification of the complete form of the model;
- Establishment of a separation rule;
- Testing the validity of the discriminant analysis model.

4. Presentation of the Study Methodology:

The methodological framework of the study will be illustrated by presenting the population and sample, deriving the explanatory (independent) variables and the dependent variable.

4.1. Study Population:

The study population consists of economic institutions operating in the industrial sector of several Algerian provinces, registered with the National Center of the Commercial Register (CNRC), with legal forms represented by joint-stock companies (SPA) and limited liability companies (SARL), totaling 263 institutions. Data for these institutions were obtained from the local branch of the CNRC in the Wilaya of M'sila, through the privilege of participation and unrestricted access to the portal to search all available databases, such as the list of traders. This allowed identifying the nature, essence, and components of the study population, confirming a degree of homogeneity that permits the selection of a representative sample and the applicability of results derived from this chosen sample.

4.2. Study Sample:

In such studies, where it is difficult to study the phenomenon through a comprehensive survey of all data, the sampling method is employed. Institutions with available data during the study period (2019–2023) were selected. Therefore, the type of sample suitable for this study is a purposive (intentional) sample, chosen for a specific objective and purpose. A sample of 32 institutions was selected, for which complete financial data were available and chronologically sequenced. Other institutions were excluded due to incomplete data. The sample was classified into two groups: the first represents successful institutions, while the second represents failing institutions, based on multiple criteria for this classification, the most important being achieving consecutive losses for two or more years for failing institutions, and achieving consecutive profits for successful institutions during the study period.

4.3. Study Variables:

The study variables consist of dependent and independent (explanatory) variables, as follows:

- **Dependent Variable:**
- This is a binary variable denoted by (Z) representing the financial failure of the institution. It takes the value zero (0) if the institution is failing, and one (1) if the institution is successful.
- **Independent Variables:**
- The independent variables consist of a set of financial ratios extracted from the financial statements of the institutions under study, including balance sheets and income statements, totaling 28 ratios. These ratios were relied upon in previous foreign and Arab studies and are believed to best express the financial performance of the institutions. These variables are divided into groups: liquidity ratios, activity ratios, profitability ratios, and financial structure ratios. Since various studies in this field agree on the impossibility of using standard ratios included in the model for previously mentioned reasons, their selection is made based on scientific criteria and justifications, and they are characterized by their classification ability and minimum error compared to other ratios.

Table 1. Financial Ratios Most Frequently Used for Constructing Quantitative Models According to Foreign and Arab Studies

Number	Code	Ratio Type	Number	Code	Ratio Type
Liquidity Ratios			15	X15	Operating Result / Sales
1	X1	Quick Ratio	**Profitability Ratios**		
2	X2	Current Ratio	16	X16	Net Income / Sales
3	X3	Net Working Capital / Total Assets	17	X17	Earnings Before Tax / Equity
4	X4	Current Assets / Current Liabilities	18	X18	Net Income / Equity
5	X5	Current Assets / Total Assets	19	X19	Net Income / Total Assets
6	X6	Net Working Capital / Current Assets	20	X20	Earnings Before Tax / Total Assets
7	X7	Current Liabilities / Total Assets	21	X21	Gross Operating Surplus / Total Assets
8	X8	Cash / Total Assets	22	X22	Operating Result / Total Assets
Activity Ratios			**Financial Structure Ratios**		
9	X9	Sales / Current Assets	23	X23	Total Debt / Total Assets
10	X10	Sales / Total Assets (NDA)	24	X24	Total Debt / Equity
11	X11	Inventory / Sales	25	X25	Equity / Total Assets
12	X12	Sales / Working Capital	26	X26	Long-Term Debt / Total Assets
13	X13	Cash / Sales	27	X27	Long-Term Debt / Equity
14	X14	Value Added / Sales	28	X28	Short-Term Debt / Equity

Source: Prepared by the researcher based on global studies and models.

5. Constructing a Model for Predicting Financial Failure Based on the Outputs of Discriminant Analysis:

With the aim of reaching the construction of a quantitative model for predicting the failure of industrial enterprises, including the most important financial ratios and those most capable of distinguishing between successful and failing enterprises, it is required to apply the appropriate statistical discriminant method for prediction by determining the membership of the individuals (enterprises) in the two groups.

5.1. Extracting the Most Discriminating Independent Variables:

In this step, the number of variables used in prediction is identified, amounting to 03 variables out of a total of 28. The *Statistiques pas à pas* (step by step statistics) method is employed, which is one of the techniques used to measure the ability of variables to discriminate, through the lowest value of the Wilks' Lambda statistic (*Lambda de Wilks*) and the highest value of the F statistic. The selected variables form the discriminant function of the model, and the following table shows this:

Table 2. Step-by-Step Statistics of the Selected Variables.

Steps	Entered	Wilks' Lambda	Statistic	df 1	df 2	df 3	F to Enter	Statistic	df 1	df 2	Significance
1	X21	0.549	1	1	30.000	24.638	1	30.000	0.000		
2	X10	0.476	2	1	30.000	15.961	2	29.000	0.000		
3	X9	0.347	3	1	30.000	17.576	3	28.000	0.000		

At each step, the variable that maximizes the smallest F-ratio between the group pairs is introduced.
a. The maximum number of steps is 56.
b. The minimum partial F to enter is 3.84.
c. The maximum partial F to remove is 2.71.
d. F threshold, tolerance, or insufficient VIN for continuing the calculation.
Source: Table prepared based on the statistical processing outputs of the SPSS program.

Depending on the results shown in the table above, we notice that there are 56 steps carried out by the program to extract the three variables. According to the F statistic and the significance level, it is observed that the variables included in the analysis are ordered according to their discriminating ability: X21, X10, X9. The significance value came equal to 0.000, which is less than 0.05, and this indicates the high ability of these ratios, when combined, to discriminate between the enterprises under study.

It can also be noted, in the table below, that by relying on variable X21 alone in the first step, the Wilks' Lambda value was null and the significance level of F was 0.000 (less than 0.05). This shows that the discriminating power between successful and failing enterprises is primarily due to the ratio Gross Operating Surplus / Total Assets. In the second step, the ratio Sales / Total Assets (X10) was added, and the Wilks' Lambda value rose to 0.766 for X21 and 0.549 for X10, while the significance value remained below 0.05. In the third step, the program added the ratio Sales / Current Assets (X9), where the Wilks' Lambda values for the first and second variables (X21 and X10) decreased to 0.642 and 0.540 respectively, while X9 recorded a value of 0.476 for Wilks' Lambda with a significance level of 0.003 (less than 0.05). According to the results of these statistics, the three ratios extracted from the analysis program possess predictive power in distinguishing between successful and failing enterprises. The following table shows the values of the statistics related to the discriminating variables:

Table 3. Values of F Statistics and Wilks' Lambda.

Step	Variable	Tolerance	Sig. of F to Remove	Wilks' Lambda
1	X21	1.000	0.000	
2	X21	0.999	0.000	0.766
	X10	0.999	0.044	0.549
3	X21	0.868	0.000	0.642
	X10	0.422	0.000	0.540
	X9	0.393	0.003	0.476

Source: Table prepared based on the statistical processing outputs of the SPSS program.

5.2. Testing Significance and Strength of the Relationship:

This test depends on the calculation of both the eigenvalue and Wilks' Lambda statistic.

• **Eigenvalue:**

• It is known that the number of functions extracted according to the discriminant analysis method equals the number of groups minus one. In this study, there are two groups (the group of successful enterprises and the group of failing enterprises), so we obtain one canonical discriminant function (01), as shown in the following table:

Table 4. Eigenvalue.

Function	Eigenvalue	Variance %	Cumulative %	Canonical Correlation
1	1.883[a]	100.0	100.0	0.808

a. First canonical discriminant functions used in the analysis.
Source: Table prepared based on the statistical processing outputs of the SPSS program.

The above table shows that the value of the canonical correlation is close to one, which is a good value for the model, estimated at 0.808. This indicates the good discriminating power of the function. As for the eigenvalue, it is estimated at 1.883, which is a good amount for the performance of the discriminant function. The larger the eigenvalues, the larger the shared variance in the linear composition.

The variance and cumulative variance were 100% because there is only one discriminant function in the first cell of the eigenvalue table.

• **Wilks' Lambda (Lambda de Wilks):**

After identifying the eigenvalues, it is required to test the values of Wilks' Lambda statistic as shown in the following table:

Table 5. Wilks' Lambda.

Function(s)	Wilks' Lambda	Chi-Square	df	Sig.
1	0.347	30.178	3	0.000

Source: Table prepared based on the statistical processing outputs of the SPSS program.

Wilks' Lambda statistic is used to test the discriminant function, as it expresses the amount of unexplained variance in the discriminant scores. The smaller this statistic, the better the analysis results. As for the Chi-square statistic, the higher it is, the better the quality of discrimination. From the table above, we notice that Wilks' Lambda value is low (0.347), while the Chi-square value is high (30.178) at a significance level equal to 0.000. This indicates that the extracted discriminant function meets the criterion of quality discrimination.

This test can also be interpreted through the following hypotheses:

$$\begin{cases} \boldsymbol{H_0}: \boldsymbol{\alpha} \geq \mathbf{0.05} \\ \boldsymbol{H_1}: \boldsymbol{\alpha} < 0.05 \end{cases}$$

Where:

H0: Null hypothesis (no differences between the two groups).

H1: Alternative hypothesis (existence of differences between the two groups).

From the results obtained from the Wilks' Lambda test, we note that the significance value equals 0.000, which is less than the significance level. Therefore, the null hypothesis is rejected and the alternative hypothesis is accepted, meaning that there are differences between the two groups (financial ratios).

5.3. Standardized Coefficients of the Canonical Discriminant Function

Based on the following table, it is possible to write the standardized canonical discriminant function.

Table 6. Standardized coefficients of the extracted canonical discriminant function

Coefficients of Standardized Canonical Discriminant Functions	Function
X9	-1.028
X10	1.139
X21	0.901

Source: Table prepared based on the statistical processing outputs of SPSS

On the basis of the data presented in the above table, the standardized canonical discriminant function can be formulated as follows:

Z = -1, 028 X9 + 1, 139 X10 + 0, 901 X21

Through this function, the importance of the coefficients of each variable in the predictive model becomes apparent. The higher the coefficient of a given variable, the more significant its role in the discriminant function. As observed in the extracted discriminant function, the most influential variable is the ratio of turnover to total assets, followed by the ratio of gross operating surplus to total assets. By contrast, the ratio of turnover to current assets exerts an inverse effect on the discriminant function.

5.4. The Discriminant Function at Group Centroids

Based on the results displayed in the table below, it is clear that each group is centered around specific points referred to as *group centroids*. These represent the mean values of the discriminant scores at the group centers, as shown in the following table:

Table 7. Coordinates of the group centroids

z	Function
Failed	-1.715
Successful	1.029

Source: Table prepared based on the statistical processing outputs of SPSS

From the function column, the centroid of each group is evident: the centroid of failed firms equals -1.715, whereas that of successful firms equals 1.029. These two values are diametrically opposed and together establish the separating boundary. By substituting the financial ratios of each firm into the discriminant function, one obtains what is referred to as the *discriminant score*, which is then compared against these centroids to determine the group to which the firm belongs.

Accordingly, it can be said that the value -1.715 serves as the threshold point for failed firms, while the value 1.029 represents the threshold point for successful firms. To determine whether a firm is successful or on the verge of failure, the following ranges are adopted:

- If $Z \geq 1.029$, the firm is successful and capable of continuity.
- If $Z \leq -1.715$, the firm is at risk of bankruptcy.
- If $-1.715 < Z < 1.029$, the firm lies within a grey zone where it becomes difficult to determine its financial standing, and further, more detailed studies are required.

6. Testing the Discriminatory Power of the Model

The quality of the model's outputs is determined by measuring classification results and assessing the accuracy of the model in predicting failure, in addition to measuring the degree of reliability.

6.1. Results of Classification Accuracy

This stage helps determine the precision of the final classification results. To identify correctly classified cases, the following table is examined:

Table 8. Discriminatory power of the model

z	Predicted Group Membership	Total
	Failed	Successful
Actual	Failed	12
	Successful	1
%	Failed	100.0
	Successful	5.0

a. 96.9% of original grouped cases correctly classified.

Source: Table prepared based on the statistical processing outputs of SPSS

From the above table, the following points are observed:

- Out of 12 cases from the first group (failed firms), 100% were correctly classified, and thus no misclassification occurred.
- Out of 20 cases from the second group (successful firms), 95% were correctly classified, with only one misclassified case representing 5%.

As a general conclusion, 96.90% of cases across both groups were correctly classified, reflecting the high quality of the classification results.

6.2. Reliability Testing

To further verify the quality of the achieved results and evaluate the discriminatory efficiency of the proposed model, the *Kappa test* was employed. This test is regarded as a robust measure of reliability, as it accounts for the element of chance in classifying observations. The following tables illustrate this:

Table 9. Classification predictions

	Expected Cases for the Analysis		Total
	Failing	**Successful**	
Z			
Failing – Effective	12	0	12
% of Total	37.5%	0.0%	37.5%
Successful – Effective	1	19	20
% of Total	3.1%	59.4%	62.5%
Total – Effective	13	19	32
% of Total	40.6%	59.4%	100.0%

Source: Table prepared based on the statistical processing outputs of SPSS

Table 10. Kappa test

Value	Asymptotic Standard Error[a]	Approximate T[b]	Significance Level
0.934	0.064	5.297	0.000

Source: Table prepared based on the statistical processing outputs of SPSS

The first table shows that 31 cases were correctly classified—that is, the total of correctly classified successful and failed firms (12 + 19)—representing 96.9% of all cases (37.5% + 59.4%).

The second table indicates that the Kappa statistic equals 0.934, which reflects the very high predictive accuracy of the model. It is not sufficient to rely solely on the significance value (0.000); one must also verify that the Kappa measure exceeds the threshold of 0.700. Accordingly, the test results confirm the reliability of the classification and demonstrate that the outcome was not the product of random chance.

7. Results of the study:

The process of predicting financial failure is considered a matter of high importance, and also a necessity, because it enables the institution to anticipate its future performance especially in light of the shift towards the market economy as well as the economic openness, therefore, the institutions that did not give attention to this process or that relied on traditional tools which do not go in harmony with this rapid development, they were exposed to financial crises that led to their inability to fulfill their obligations and, in many times, to their bankruptcy and disappearance. Therefore, it was necessary to support them with modern tools in the form of quantitative models that work on simplifying the practical reality in order to reach indications about the continuity of the institution in working in the future and the extent of its ability to pay its debts and obligations, and the application of this model on the study sample yielded the following results:

- The concepts that express financial failure are multiple such as financial distress, financial difficulty, and bankruptcy, but they do not represent its synonyms, rather they are stages of failure that begin with difficulty and then financial distress, and if this failure is not treated it becomes a financial failure and then bankruptcy and liquidation;
- Financial failure results from the inability of the institution to fulfill its obligations, but that does not represent the real cause, as most opinions agree on the existence of reasons inside the institution which are the result of the wrong policies adopted by the management of the institution, and external reasons that are outside

the scope of control of the institution such as monetary policies, exchange rate, external competition and other reasons;

- Financial ratios are considered the common element in most of the quantitative models used for predicting financial failure;
- The results of classification proved that the following ratios: turnover to current assets, turnover to total assets, gross surplus of exploitation to total assets are the best ratios in efficiency to distinguish between the successful institutions and the failing institutions by using the method of discriminant analysis;
- The application of the discriminant analysis method on a sample composed of 32 industrial institutions divided into the group of successful institutions and the failing institutions led to the building of a quantitative model with the following mathematical formula:

$$Z = -1,028\ X9 + 1,139\ X10 + 0,901\ X21$$

And the model achieved a correct classification rate estimated at 96.9% one year before the financial failure, and a rate of 90.6% two years before the occurrence of the financial failure.

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