Discriminant Analysis of Companies Failure: Application to Moroccan SME

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Abstract: ***Qualified as an abnormal event which marks the company's life cycle, business failure is an episode where the company endures serious malfunctions that endanger the continuity of its operations and its sustainability. This article is interested in both the prediction and prevention of the difficulties that the company can cross and this, via the use of a financial analysis. Thus, it remains a topic that draws from several directions: legal, economic, financial, managerial and social.***

Keywords: Failure, difficulties of the company, diagnosis and financial analysis, technical scoring, method of the ratios, suspension of the payments, risks bankruptcy, continuity of the exploitation

1. Introduction

The failure of companies is undoubtedly one of the most raised issues in the field of business management. Indeed, small and medium-sized enterprises (Smes) play an important economic role in many countries, particularly in developing countries. Their contributions to job creation and value added are significant. But despite this, most of them are exposed to the risk of failure and there is very little research and empirical studies on this subject, in Morocco as in many developing countries.

The current increase in the number of bankrupt companies confirms the usefulness of developing models for predicting failure. It is essential to ensure the protection of the interests of stakeholders, the sustainability of the company, by preventing the economic and financial difficulties that companies may encounter, which implies, in particular, a precise estimation of the probability of default and possibly a modification of the valuation methods.

Although the analysis of the causes of the failure is relatively old, the work on its prediction developed from the end of the sixties onwards. The most common approach is to use financial analysis to determine the variables, mainly accounting variables that best differentiate defaulting businesses from those that are not. The objective is to establish a stable statistical relationship between the explanatory variables for each of the two groups (Refait, 2004).

In this paper, we will present the main results for the prediction of failures using the discriminant analysis method.

2. Literature Review

In recent years, the annual flow of business failures has steadily increased and this trend is increasing during periods of crisis.

Economic bankruptcy is the state that characterizes a company whose financial performance is less than that of its main competitors[1]. Bescos (1987) defines the SME in difficulty as an enterprise in which the economic environment is unsuitable.

For Gresse (1994), the economic failure is reflected in negative value added. Koeing (1985) proposes a definition based on the relationship between profitability and liquidity. According to Ooghe and Van Wymeersch (1996).

Cata and Zerbib (1979) talk about the failure of the company by referring to a legal, economic and financial approach. According to these two authors, the legal failure concerns in principle a bankruptcy action linked to an insolvency situation. Economic failure refers to the lack of profitability and efficiency of the productive apparatus. Finally, financial distress is linked to cash flow problems and inability to repay debts. For Derni and Grucifix (1992), the company is threatened from the moment when profitability becomes insufficient, since it no longer makes it possible to remunerate own funds at market rates.The company no longer finds a solution to manage its debt, resulting in payment incidents (Gresse, 1994).

Zopounidis (1995) shows that there is no single definition of failure. It is therefore necessary to provide a broader definition, including qualitative variables in the analysis of financial distress (Sun & Li, 2009). Consideration of these qualitative variables alongside the financial variables will provide a more rational and comprehensive analytical framework for failure forecasting.

The financial failure

From a financial point of view, a company is considered deficient if it has cash flow problems and is unable to meet its commitments. Malecot (1981) considers that financial default occurs when the holding is no longer able to meet the liabilities due from its available assets. If profitability is insufficient, the operation of the company is threatened,

[1]Ooghe et Van Wymeersch ,1986

since it can no longer pay equity at market rates. Under these conditions, it will be less easy for the firm to obtain new capital since it is not in a position to remunerate it. It will then have to apply for a new credit line to ensure the continuation of its activity.

This use of external funds will lead to additional financial charges that will contribute to the deterioration of its financial results. Similarly, the company may experience liquidity problems if its operating resources are insufficient to cover all of its expenses (Bal et al., 2010).

The economic failure

Wtterwulghe (1998) believes that the survival of SME is explained by the willingness of large enterprises which have an economic interest in allowing the small enterprises with which they compete in a market to survive. For Michaux (1978), « *therefore, for the firm, bankruptcy or economic pre-bankruptcy is no longer the fatal outcome but only the possible outcome to which resistance can be opposed by the constitution of strategically maintained financial surpluses. The threat of exclusion of the firm from its market is inversely proportional to the powers of its prevailing or developing market in the sectors to which the firm belongs*. » According to Gresse (1994), the economic failure of the enterprise is a negative value added, which is an indicator of performance provided by the use of production factors. In such a situation, the firm uses more resources than it produces and is no longer able to guarantee at market price all the factors of production that contribute to the achievement of its economic activity. Van Wymeersch (1996) believes that, in a market economy, the remuneration offered by the firm to each of the production elements must be sufficient to ensure continuity and quality.

According to Quintart (2001), « *a positive value added represents a surplus of output compared to intermediate consumption. In absolute terms, this surplus is not significant because it must be put into perspective: the crucial question is whether the added value is sufficient to remunerate the factors of production to the extent that they are productive and used wisely*».

Ooghe and Van Wymeersch (1996) argue that the concept of a firm in difficulty is defined as one which is no longer able to achieve its economic objectives on an ongoing basis, taking into account social and environmental constraints.

Section 1: General Research Preparation

Through the general presentation of the research, we will try to give an overview of the spirit of the research. It will also include the preliminary stages of business modelling and reclassification.

2.1 Research Objective

The present research work is dedicated to the explanation of the various aspects of the failure that manifests in insurmountable financial difficulties for the company to end with the bankruptcy.

Predicting and preventing failure through discriminant analysis gives this research work a technical dimension that requires the design of a score function. So, the tool for detecting companies in distress raises other objectives that can be linked to the synthetic aspect of the revision method.

The objectives of the research will be as follows:

- Select variables with high discriminant power;
- Build a model whose combination of parameters is the most effective in discrimination;
- Validate the regression model;
- Mount a score function and determine the critical score;
- Reclassify companies into assignment groups;
- Assign a synthetic score to the companies in the sample.

2.2 Research methodology

The use of the scores for failure prediction is done using the statistical method "discriminant analysis".

In this section, we will explain the methodology followed, which we will break down into two points: the composition of the sample and the choice of indicators.

1) Sample Build – Database

The empirical investigation focused on a sample of Smes in the Rabat – Salé – Kenitra region that were taken care of. The sample distinguishes between two categories of enterprises: healthy enterprises, as well as defaulting enterprises which are the sample in our study, and will be excluded from start-ups as they carry a natural risk of failure (3 years of existence minimum). We will also ensure that the sample is as representative as possible of the economic fabric of the region. We will then collect data from accounting firms, audit firms and legal advisors**.**Indeed, for each of the companies observed, we will take some of its financial ratios, particularly those that constitute the explanatory variables of our econometric model. Again, following a colinemarity test, the ratios tend to translate the same information so as not to reduce the relevance of our results because of the redundancy of the information that these colinemarities may present.

The “failing companies” sample was randomly selected and provided to us by an official at the Rabat Commercial Court.

Our database consists of a sample of 43 companies:

- 23 healthy companies: 22 companies whose legal form is “SARL” and one company whose legal form is “SA”;
- 20 failing companies.

The data collected and used are financial in nature (Balance sheet and CPC). They are collected over a period of two years (2 financial years). The estimation of the regression model and the discriminant analysis were based on observations of variables (ratios) over two years; this amounts to the consideration of 86 observations selected for the study.

2) Choice of indicators

The choice of indicators represents the step in establishing the battery of ratios. The latter includes significant ratios capable of detecting and predicting failure. The construction of the predictive model requires preparatory work, namely the preliminary composition of significant variables with an explanatory capacity of the central problem: failure. The identification of indicators capable of marking and detecting the failure was solved thanks to the axes we were able to identify:

- Asset risk and illiquidity risk;
- Risk related to business, profitability, and financing;
- Debt risk.

The empirical work under SPSS requires a coding of the ratios for the selection of variables and the assembly of the forecast model, the codes relating to the indicators making up the ratio battery are explained in the following table :

Table 1: Coding the Ratio Battery[2]

	Battery of Ratios	
Code	Entitled	Components
	Heritage risk and illiquidity risk	
	The liquidity ratios	
R1	Immediate liquidity	(Cash assets + PST) / (Current liabilities + Cash liabilities)
R2	Reduced liquidity	((Current assets-Stock) + Cash assets) / (Current liabilities + Cash liabilities)
R3	General liquidity	(Current assets + Cash assets) / (Current liabilities + Cash liabilities)
	Management ratios	
R4	Stock turnover	(Stocks*360) / Resold purchases of goods
R5	Stock turnover	(Stocks of finished products*360) / Turnover
R6	Deadline for customer payments	(Clients and related accounts*360) / Turnover
R7	Deadline for supplier payments	(Suppliers and related accounts*360) / (Purchases including taxes + External charges)
	The structure ratios	
R8	Financial balance	(Stable resources/ Stable jobs) > 1
R9	Financial autonomy	Stable financial liabilities (MLT) / Equity
R10	Risk of illiquidity	Functional Working Capital / Working Capital Requirement
	Business risk, profitability, and financing	
	The activity ratios	
R11	Margin rate	Gross operating surplus/ Value added
R12	Gross operating margin rate	Gross operating surplus/ Turnover
	Profitability ratios	
R13	Operating profitability	Operating results/ Turnover
R14	Economic profitability	Operating Results/ Economic Assets
R15	Financial profitability	Net income / Equity
	Funding ratios	
R16	Solvency	Financial costs/ Gross operating surplus
R17	Ability to repay 1	Stable financial liabilities (LMT) / Self-financing capacity
R18	Ability to repay 2	Operating income/ Financial expenses
	Risk related to debt	
R19	Changes in equity	Changes in equity
R20	Debt	MLT Financing Debt / Permanent Capital

[2]Table prepared by us

Section 2: Developing the Prediction Model

It should be noted that the results presented are from SPSS 20. The preliminary processing of the financial data concerned the necessary and particularly significant restatements, the realisation of the statement of operating balances, the functional balance sheet, the balance sheet balance sheet balance sheet and the calculation of the pre-selected ratios statistiques descriptives

The development of the failure prediction model requires the production of descriptive statistics of the variables. These statistics represent an elementary step in the construction of the score function.

The use of the "*descriptive statistics*" command, the results of which are presented in the table below, makes it possible to study the diversity of the values taken by the ratios and their dispersion.

Table 2: Descriptive Ratio Statistics

	N	Minimum	Maximum	Moyenne	Ecart type
R1	86	-,011189	,390377	,04674640	,077622627
R2	86	,011807	2,271450	,76264165	,494105519
R3	86	,014073	3,380807	1,03755304	,631049362
R4	86	,000000	87140,81351	3262,652806	13473,10911
R5	86	,000000	1858,277831	45,17790497	208,6291128
R6	86	,000000	1800,839724	223,8744185	280,9656722
R7	86	,000000	948,463669	185,6338547	182,4431624
R8	86	-16,815072	22,094866	2,09603439	4,315252075
R9	86	-93,636101	24,385746	-2,61767744	14,56193760
R10	86	-330,703999	163,860582	-1,99578745	41,11843415
R11	86	-51,762176	9,909667	-,11266251	5,828487226
R12	86	-4,824673	,340491	-,06467781	,587798409
R13	86	-8,709588	,209917	-,25252643	1,260800797
R14	86	-6,770125	1,260055	-,05728317	1,087913333
R15	86	-7,050787	3,813084	,14969050	,987555254
R16	86	-4,639600	3,694710	,18019077	1,034914620
R17	86	-54,824029	131,593827	1,17670680	17,63400087
R18	86	-643,572635	140,128636	-4,60753322	76,80608701
R19	86	-72,370394	68,546512	,30758234	10,98521198
R20	86	-,813279	31,447112	,50318034	3,398126644
N valide (listwise)	86				

The "*descriptive statistics*" table shows the minimum and maximum values taken by the variables, namely, the completeness of the significant ratios used for the study. This command also makes it possible to calculate the averages of the values taken by the 20 ratios, each separately; as it makes it possible to obtain the standard deviation of the variables.

We note that the minimum values taken by the ratios are sufficiently distant from the maximum values (*e.g.: for the debt indicator "R20", the values taken by this ratio vary from -0.8132 to 31.4471)* ; this means that in principle the ratios take different values and therefore explain the failure and allow to reclassify these enterprises.

The averages of the variables take different values from one ratio to another which implies that the construction of the ratio battery is diversified and varied in order to cover the different aspects of the failure. In the same direction, the standard deviation column highlights the dispersion of the results taken by the ratios.

The selection of ratios is characterised by a diversity which will make it possible to cover the multiple aspects of the failure. In addition, the dispersion of values expresses the ability of the variables to explain the failure.

1) Estimation of the Linear Regression Model

In the context of the discriminant analysis, the selection of variables represents a decisive step in the construction of the score function. The objective of this step is to construct the forecast model, which will be used to produce the corresponding scores for each company in the sample.

The "Regression" function combines between the explanatory variables "*the ratios: R1, R2, ... , R20*" and the explained variable« *FTE*[3]» in a linear regression function. The objective is to highlight the relationship between the explained variable (V. dependent) and the explanatory variable (V. independent).

The estimation of the regression function, being a mathematical regression model with linear parameter, makes it possible to identify the most discriminating ratios among the preselected variables, these will mainly form the score function. The regression function is used to determine each company's score for early anticipation of failure.

2.3 Elimination of variables

The selection of variables will be done using the top-down method, moreover the table below shows the variables introduced (R1, R2, …, R20), as well as the elimination process performed based on the probability of Fisher. Variables with a probability greater than or equal to 0.1 are eliminated downwards.

Table 3: Elimination of variables using top-down method

Variables introduites/supprimées[a]

Modèle	Variables introduites	Variables supprimées	Méthode
1	R20, R9, R11, R5, R14, R17, R8, R19, R4, R16, R1, R15, R18, R3, R7, R10, R6, R2, R12, R13[b]	.	Entrée
2	.	R6	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
3	.	R8	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
4	.	R12	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
5	.	R9	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
6	.	R11	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
7	.	R4	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
8	.	R10	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
9	.	R15	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
10	.	R19	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
11	.	R1	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
12	.	R13	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
13	.	R7	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
14	.	R16	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).
15	.	R17	Elimination descendante (critère : Probabilité de F pour éliminer >= ,100).

a. Dependent variable: ETP
b. All required variables entered

Note that the ratio "*R6: Client Payment Time*" represents the first variable eliminated, the ratio "*R8: Financial Balance*" is the second variable eliminated, and in order, the ratio "*R12: Operating Gross Margin Rate*", the ratio "*R9: Financial self-sufficiency*", "*R11: Margin rate*", "*R4: Stock turnover*", "*R10: Illiquidity risk*", "*R15: Financial profitability*", "*R19: Changes in equity*", "*R1: Immediate liquidity*", " "*R13: Operating profitability*", the ratio "*R7: Supplier payment period*", the ratio "*R16: Solvency*", and finally the ratio "*R17: Repayment capacity 1*".

The elimination stops at model 15 by keeping the variables R2, R3, R5, R14, R18, R20. A priori, according to the top-down method of the linear regression function, the six ratios kept at the model 15 level are the variables that best explain the relationship between the ratios and the variables explained "FTE". However, this result is stated prematurely, to confirm that the combination of model 15 is the most discriminatory, we will observe some statistics explained in the tables that follow.

Table 4: Evolution of R-2 and Fisher statistics of SPSS models

Récapitulatif des modèles

Modèle	R	R-deux	R-deux ajusté	Erreur standard de l'estimation	Changement dans les statistiques: Variation de R-deux	Variation de F	ddl1	ddl2	Sig. Variation de F
2	,762[b]	,581	,460	,369	,000	,004	1	65	,953
3	,762[c]	,581	,468	,366	,000	,008	1	66	,930
4	,762[d]	,580	,476	,363	,000	,011	1	67	,915
5	,762[e]	,580	,483	,361	,000	,009	1	68	,925
6	,762[f]	,580	,490	,358	,000	,072	1	69	,789
7	,761[g]	,579	,496	,356	-,001	,120	1	70	,730
8	,760[h]	,578	,502	,354	-,001	,231	1	71	,633
9	,759[i]	,576	,506	,353	-,002	,355	1	72	,553
10	,757[j]	,572	,509	,352	-,003	,571	1	73	,452
11	,753[k]	,567	,510	,351	-,005	,881	1	74	,351
12	,750[l]	,562	,511	,351	-,005	,872	1	75	,353
13	,746[m]	,557	,511	,351	-,005	,943	1	76	,335
14	,741[n]	,549	,509	,352	-,008	1,315	1	77	,255
15	,735[o]	,540	,505	,353	-,009	1,611	1	78	,208

a. Valeurs prédites : (constantes), R20, R9, R11, R5, R14, R17, R8, R19, R4, R16, R1, R15, R18, R3, R7, R10, R6, R2, R12, R13
b. Valeurs prédites : (constantes), R20, R9, R11, R5, R14, R17, R8, R19, R4, R16, R1, R15, R18, R3, R7, R10, R2, R12, R13
c. Valeurs prédites : (constantes), R20, R9, R11, R5, R14, R17, R19, R4, R16, R1, R15, R18, R3, R7, R10, R2, R12, R13
d. Valeurs prédites : (constantes), R20, R9, R11, R5, R14, R17, R19, R4, R16, R1, R15, R18, R3, R7, R10, R2, R13
e. Valeurs prédites : (constantes), R20, R11, R5, R14, R17, R19, R4, R16, R1, R15, R18, R3, R7, R10, R2, R13
f. Valeurs prédites : (constantes), R20, R5, R14, R17, R19, R4, R16, R1, R15, R18, R3, R7, R10, R2, R13
g. Valeurs prédites : (constantes), R20, R5, R14, R17, R19, R16, R1, R15, R18, R3, R7, R10, R2, R13
h. Valeurs prédites : (constantes), R20, R5, R14, R17, R19, R16, R1, R15, R18, R3, R7, R2, R13
i. Valeurs prédites : (constantes), R20, R5, R14, R17, R19, R16, R1, R18, R3, R7, R2, R13
j. Valeurs prédites : (constantes), R20, R5, R14, R17, R16, R1, R18, R3, R7, R2, R13
k. Valeurs prédites : (constantes), R20, R5, R14, R17, R16, R18, R3, R7, R2, R13
l. Valeurs prédites : (constantes), R20, R5, R14, R17, R16, R18, R3, R7, R2
m. Valeurs prédites : (constantes), R20, R5, R14, R17, R16, R18, R3, R2
n. Valeurs prédites : (constantes), R20, R5, R14, R17, R18, R3, R2
o. Valeurs prédites : (constantes), R20, R5, R14, R18, R3, R2

In the table above, it is possible to observe the changes that affect Fisher's statistics. It is noted that this increases as the variables deemed unable to effectively explain the failure are eliminated. So the last model 15 expresses the best combination of variables.

Discriminant capacity is judged on the basis of the combination formed by the ratios and not by each ratio considered individually.

The above table also shows the value of R-2 statistics for all the proposed models. The values taken by R-2 are all greater

[3]The sample includes two sub-groups, a healthy business sample and a control sample that includes failed companies. Therefore, the FTE variable includes healthy companies coded "1" as well as failingcompanies coded "0".

than 0.30, especially for model 15, of which R-2 is equal to 0.540.

It can be concluded that the ratios selected for the study all explain the variable (FTE), which also includes the variables that make up model 15.

Ability to Discriminate Models

The analysis of the ANOVA variance presented in the table below makes it possible to assess the predictive capacity by observing Fisher's statistics. The options selected under the ANOVA variance allow to decline the sum of the squares, the degree of freedom, the mean of the squares, as well as the statistic D and the significance of its probability.

Table 5: ANOVA Variance Analysis

ANOVA[a]						
Modèle		Somme des carrés	ddl	Moyenne des carrés	D	Sig.
11	Régression	12,139	10	1,214	9,837	,000[l]
	Résidu	9,256	75	,123		
	Total	21,395	85			
12	Régression	12,032	9	1,337	10,851	,000[m]
	Résidu	9,364	76	,123		
	Total	21,395	85			
13	Régression	11,916	8	1,489	12,098	,000[n]
	Résidu	9,480	77	,123		
	Total	21,395	85			
14	Régression	11,754	7	1,679	13,584	,000[o]
	Résidu	9,642	78	,124		
	Total	21,395	85			
15	Régression	11,555	6	1,926	15,460	,000[p]
	Résidu	9,841	79	,125		
	Total	21,395	85			

On the ANOVA table we can observe the evolution of statistics D, it is in positive evolution. Statistic D achieves a satisfactory value of 15,460 points for the previously chosen model (model 15). Moreover, the significance of the probability of statistics D is zero, this can only confirm the good discriminant ability of the regression equations that emerged.

The table (Student Probability Meanings for Ratios) treats the model coefficients by highlighting the standardized and non-standardized coefficients, as well as the student "t" probability and its meaning.

They are retained variables with the highest beta statistic, as much beta is high, as the ratio is significant and highly discriminating. Beta statistics can be evaluated at three levels in order to interpret the elimination of a ratio:

- Low degree of discrimination when the absolute value of beta is less than 0.29;
- Average degree of discrimination when the absolute value of beta is between the absolute value of 0.3 and 0.49;
- High degree of discrimination when the absolute value of beta is greater than 0.5.

We are interested in the meaning of student probability of the eliminated ratios. Ratios with a significance greater than 0.005 are eliminated downwards. The most significant ratios have a high student probability.

It is noted that by moving from Model 13 to Model 14, the top-down method eliminates the ratio "*R16: Solvency*", which has the highest student significance (sig. = 0.255) among those of the same model. Then, by moving from model 14 to model 15, the ratio "*R17: repayment capacity 1*" with a meaning of 0.208 is eliminated.

Table 6: Student probability meanings for ratios

Coefficients[a]						
Modèle		Coefficients non standardisés		Coefficients standardisés	t	Sig.
		A	Erreur standard	Bêta		
	R14	,078	,035	,169	2,203	,030
	R16	-,042	,037	-,087	-1,121	,266
	R17	,003	,002	,112	1,363	,177
	R18	-,001	,001	-,140	-1,629	,107
	R20	,020	,011	,138	1,803	,075
13	(Constante)	-,102	,081		-1,268	,209
	R2	,457	,115	,450	3,962	,000
	R3	,258	,090	,325	2,871	,005
	R5	,000	,000	,139	1,822	,072
	R14	,081	,035	,175	2,281	,025
	R16	-,043	,037	-,089	-1,147	,255
	R17	,003	,002	,097	1,198	,235
	R18	-,001	,001	-,165	-2,012	,048
	R20	,020	,011	,133	1,748	,084
14	(Constante)	-,100	,081		-1,235	,221
	R2	,464	,115	,457	4,020	,000
	R3	,243	,089	,306	2,726	,008
	R5	,000	,000	,138	1,802	,075
	R14	,080	,035	,173	2,256	,027
	R17	,003	,002	,102	1,269	,208
	R18	-,001	,001	-,166	-2,016	,047
	R20	,020	,011	,135	1,773	,080
15	(Constante)	-,080	,080		-1,008	,317
	R2	,447	,115	,440	3,883	,000
	R3	,241	,089	,303	2,694	,009
	R5	,000	,000	,135	1,759	,083
	R14	,082	,035	,178	2,308	,024
	R18	-,001	,001	-,133	-1,697	,094
	R20	,021	,011	,140	1,830	,071

a. Dependent variable: ETP

2.4 Conclusion: Regression Model Selected

The selection of variables and the construction of the regression model of the parameters using the top-down method conclude that model 15 is the model whose parameters are the most discriminating, it is the most improved regression equation. The top-down method keeps the variables R2, R3, R5, R14, R18, R20 as predictors of failure.

Table 7: Student significance for the chosen model

Modèle		Coefficients non standardisés		Coefficients standardisés	t	Sig.
		A	Erreur standard	Bêta		
15	(Constante)	-,080	,080		-1,008	,317
	R2	,447	,115	,440	3,883	,000
	R3	,241	,089	,303	2,694	,009
	R5	,000	,000	,135	1,759	,083
	R14	,082	,035	,178	2,308	,024
	R18	-,001	,001	-,133	-1,697	,094
	R20	,021	,011	,140	1,830	,071

- R2: Reduced liquidity;
- R3: General liquidity;
- R5: Stock turnover;
- R14: Economic profitability;
- R18: Ability to repay 2;
- R20: Indebtedness.

The observation of student and Beta statistics for the variables excluded from the chosen model confirms the relevance of the variables chosen (model 15). The Beta of excluded ratios represents a low degree of discrimination, the meanings of student probability are also high.

Table 8: Variables excluded from the chosen model

Variables exclues[a]

Modèle		Bêta dans	t	Sig.	Corrélation partielle	Statistiques de colinéarité Tolérance
15	R6	,058[e]	,725	,471	,082	,907
	R8	,014[e]	,174	,862	,020	,860
	R12	,043[e]	,515	,608	,058	,850
	R9	,053[e]	,644	,522	,073	,856
	R11	-,070[e]	-,912	,364	-,103	,995
	R4	-,001[e]	-,010	,992	-,001	,967
	R10	,006[e]	,070	,944	,008	,955
	R15	,019[e]	,237	,814	,027	,938
	R19	,056[e]	,726	,470	,082	,976
	R1	-,086[e]	-1,015	,313	-,114	,819
	R13	,051[e]	,570	,570	,064	,735
	R7	,061[e]	,729	,468	,082	,828
	R16	-,094[e]	-1,221	,226	-,137	,968
	R17	,102[e]	1,269	,208	,142	,887

It can be concluded that the ratios used have a strong capacity to discriminate between healthy and failing companies.

3. Discriminatory analysis

Discriminant analysis is a method used to detect differences between groups. The method of discrimination is based on the regression equation that represents the score function. The objective being to calculate a score, it represents a statistical tool that allows to reclassify the explained variables, provide a forecast theoretical reclassification while basing on an original classification.

After selecting the ratios on which discrimination will be based, the discriminant analysis takes place in four stages in order to decline a reclassification and anticipate the failure:

- Study sub-groups (healthy/failing companies) to identify differences or similarities;
- Perform the necessary statistical tests to verify the validity of the study;
- Output weighting coefficients to construct the score function;
- Decline the reclassification of enterprises into theoretical subgroups and judge the quality of representation.

3.1 Verification of Sub-Group Differences

Verifying the existence of sub-group differences is the first step in the discriminant analysis under SPSS.

To do this, we will use three indicators, namely, the mean or variance, the Fisher test, as well as Wilks's Lambda.

Before proceeding with the differences analysis, we will verify the validity of the observations in our sample.

Study of diversity between subgroups

We note that the averages of the variables take different values from one subgroup to another. Indeed, this difference means that the values taken by the ratios of healthy enterprises differ from the values taken by the ratios of failing enterprises. For example, if we take the variable R5, the average is 21.3662 for failing companies versus 65.8836 for healthy companies. This is also the case for the standard deviation, for the same variable, it takes different values namely 58.9453 for defaulting companies compared to 279.7542 for healthy companies.

There is a difference between the averages and standard deviations of the overall ratios between failing and healthy enterprises.So there are differences between the subgroups.

Table 9: Group Mean Equality Test Results

	Lambda de Wilks	F	ddl1	ddl2	Signification
R2	,592	57,926	1	84	,000
R3	,634	48,534	1	84	,000
R5	,989	,974	1	84	,327
R14	,932	6,113	1	84	,015
R18	1,000	,033	1	84	,857
R20	,985	1,313	1	84	,255

Lambda de Wilks and Fisher can be seen on the table "*Group Average Equality Tests*".

According to the Lambda de Wilks criterion the selected variables are discriminant apart from R18, the Lambda de Wilks statistic takes a value equal to 1, this is explained by the means approaching between the sub-In addition, the Fisher criterion also allows the same observation to be made with a probability that far exceeds the significance threshold; this ratio was even considered in the regression model for the significance it brings to the model as a whole.

Fisher displays some meanings that exceed the significance threshold (but with acceptable thresholds) whose variables were included in the regression model.

3.2 Verifying the Validity of the Study

Verifying the validity of the study is the step to take once the diversity between the two sub-groups "*Healthy Enterprises*" and "*Failing Enterprises*" has been confirmed, it represents a crucial step and requires the use of three statistical decision criteria, namely, Box M statistics, canonical correlation, as well as Wilks Lambda statistics.

Table 10: Study validity, box test

M de Box		374,787
F	Approximativement	16,472
	ddl1	21
	ddl2	24882,517
	Signification	,000

Teste l'hypothèse nulle d'égalité de matrices de covariance des populations.

The "Test Result" table presents the results obtained for the multivariate Box test which makes it possible to test the null hypothesis of equality of covariance matrices via the neural logarithm of the determinants.

The results of the Box test show that the Box M statistic displays a value of 374.787, which is quite high. So the assumption of equal covariance matrices is rejected. Fisher's F displays an approximate value of 16,472 with zero meaning.

On the basis of the results of Fisher we can decide on the validity of the regression model, the significance of the test is zero then the model is validated.

The canonical correlation is the second criterion for assessing the validity of the model, the results of which are given in the table "Own values".

Table 11: Study validity, correlation

Valeurs propres

Fonction	Valeur propre	% de la variance	% cumulé	Corrélation canonique
1	1,174ᵃ	100,0	100,0	,735

a. The first 1 canonical discriminant functions were used for the analysis.

The canonical correlation tends towards 1 with a value of 0.735, it can be said that the chosen regression model is highly relevant with a fairly high discriminating ability.

The Lambda de Wilks statistic also makes it possible to assess the ability of the proposed regression model to distinguish between a healthy and a failing enterprise, which will give us the possibility of estimating the degree of discrimination in the regression equation.

Table 12: Validity of Study, Lambda de Wilks

Test de la ou des fonctions	Lambda de Wilks	Khi-deux	ddl	Signification
1	,460	62,908	6	,000

Lambda de Wilks is 0.460, low enough that the discriminant degree of the regression model is considered to be good. The value close to 0 of Lambda de Wilks shows that the averages of the subgroups are significantly different to reclassify the enterprises.

The significance of Lambda de Wilks confirms the quality of the discriminant degree of the proposed model by being null, the regression model is highly discriminant.

3.3 Estimation of Discriminant Function Coefficients

The purpose of the discriminant analysis is to bring out scores whose variance between the two subgroups is largely high compared to the variance of scores in the same group. Once the regression model proposed by SPSS is validated. The weighting coefficients of the discriminant function should be estimated. These coefficients make it possible to assign a weight to each ratio depending on its discriminating ability considered separately.

3.3.1 Score function

On the table «*coefficients of canonical discriminant functions*», we observe the discriminant power of the variables through their weightings:

Table 13: Coefficients of the discriminating function

Coefficients of canonical discriminant functions

	Fonction
	1
R2	1,777
R3	,958
R5	,001
R14	,326
R18	-,003
R20	,082
(Constante)	-2,446

Non-standardized coefficients

This table shows the non-standardized coefficients of the model, thus assign to the variables selected in the linear regression equation weighting coefficients that express the discriminating weight of each ratio selected in the validated regression model.

This discriminant ability of the function is the difference between the variance of the scores in the two separate subgroups and the variance of the scores between the groups.

Then the score function is written as follows:

Z = 1.777 R2 + 0.958 R3 + 0.001 R5 + 0.326 R14 - 0.003 R18 + 0.082 R20 – 2.446

3.3.2 Critical score

The "barycentres functions" table shows the mean discriminant scores of the two sub-groups that make up our sample, "failing FTE" and "healthy FTE".

Table 14: Assessment of NS discriminatory functions at group averages

ETP	Fonction
	1
Défaillante	-1,148
Saine	,999

Non-standardized canonical discriminant functions evaluated at group averages

The evaluation of the average scores of the discriminant function makes it possible to deduce from it the score which will represent the boundary that distinguishes healthy enterprises from failing enterprises at the time of the theoretical reclassification. This score represents the decision rule during assignments. The critical score, or boundary score, is equal to the sum of the means of the sub-group scores divided by 2: Sc = average failing FTE score + average healthy FTE score

Sc. = - 0.150

3.3.3 Decision Rule

The determination of the critical score makes it possible to set the decision rule in order to define the detection intervals. These intervals constitute the bounds of the classes to which the enterprises will be assigned during the theoretical reclassification:

Table15: Decision Rule

Scores intervals	Assignment Class
Z < or = - 0.150	Failing enterprises
Z > - 0.150	Healthy enterprises

At this stage we have achieved the main objective of the research, thanks to the critical score we will be able to appreciate the solidity of the companies in our sample, and move them to their theoretical categories. The predictive detection of the failure can be carried out by means of the discriminant function[4]constructed.

3.3.4 Fisher classification Functions

The table "coefficients of classification functions" allows to highlight the linear discriminant functions of Fisher. These two functions give the possibility of assigning a new score in order to classify the companies in their assignment class.

Table 16: Coefficients of sub-group classification functions

	ETP	
	Défaillante	Saine
R2	2,049	5,864
R3	1,948	4,004
R5	,002	,004
R14	-,177	,522
R18	-,007	-,014
R20	,077	,254
(Constante)	-1,816	-6,907

Fisher linear discriminant functions

The classification functions are written as follows:

$Z_{failing}$ = 2.049 R2 + 1.948 R3 + 0.002 R5 – 0.177 R14 – 0.007 R18 + 0.077 R20 – 1.816

$Z_{healthy}$ = 5.864 R2 + 4.004 R3 + 0.004 R5 + 0.522 R14 - 0.014 R18 + 0.254 R20 – 6.907

The above classification functions classify the sample enterprises into their theoretical subgroups. Indeed, after calculating the score of each company, they are assigned to the decision classes[5]. As a result, we get the situation of each company, namely, healthy or failing.

3.4 Quality of representation

The fourth and final stage of the study is logically that of estimating the quality of the representation of reclassifications. This phase makes it possible to observe the classifications carried out by the discriminating function. The evaluation of the quality of the theoretical groupings carried out by the score function is carried out via the confusion matrix in order to identify the correctly classified enterprises as well as those poorly classified.

3.4.1 Confusion Matrix

The "ranking result" table is used to describe the confusion matrix that groups the original groups of companies as well as their assignment classes predicted by the scores calculated via the score function. The discriminant function built allows to classify 85% of companies in their original subgroups. The quality of the function is therefore strong enough. This percentage expresses the quality of the score function as well as the degree of its discriminant power. By breaking down the reclassifications of the sample companies into sub-groups (healthy/failing FTE), it can be seen that:

- 85% of failing companies are well classified while 13% of companies are reclassified into a different theoretical group.
- 87% of healthy companies are correctly classified while 15% of businesses are assigned to another sub-group.

3.4.2 Q_{presse} test

The Q_{presse} statistic is used to assess reclassification by highlighting the degree to which assignments in theoretical subgroups were due to the discriminant power of the score function, not to a random distribution. The Q_{presse} statistic is calculated as follows:

Q_{presse}=(n− nc∗p)2n (p−1)

With:

- n: number of enterprises in the sample
- nc: number of enterprises correctly classified
- p: number of groups

digital application: $Q_{presse}=\frac{(180-74*2)2}{180\ (2-1)}$=44.6976744

Q_{presse}=44.69

This statistic follows a law of Chi-square to the degree of freedom 1 whose critical value is 3.84. In the case of our study, Q_{presse} takes a value of 44.69, the null hypothesis in this case is rejected. So, we can conclude that the theoretical assignments are not due to chance, and that the built score function is able to detect the failure and reclassify the companies thanks to its discriminant power.

Section 3: Applying the Score Function to the Core Sample

The scores for each company will be presented to assign them to their theoretical subgroups. The results of the reclassification within the sub-categories will then be presented. Finally, a synthesis of the results will be produced accompanied by the main limitations that have hindered the present research.

3.5 Failure detection

3.5.1 Healthy companies Scores

The following graph shows the dispersion of theoretical scores calculated for healthy companies in our sample. It is easy to see that most companies are ranked well above the critical score marked in red.

[4]See Table: Coefficients of canonical discriminatory functions
[5]See table: Decision rule

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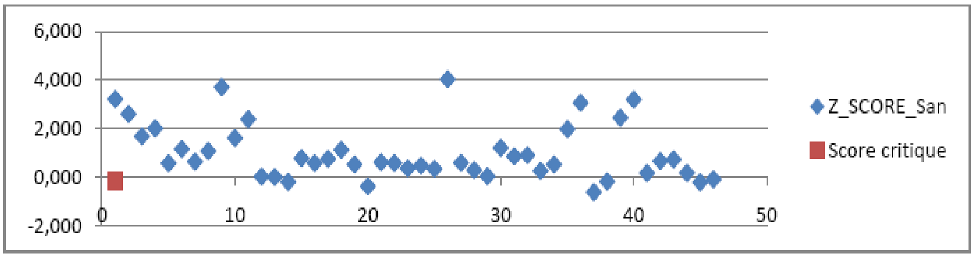

Figure 1: Subgroup 1 scores, healthy businesses

3.5.2 Failing Companies Scores

The following graph shows the distribution of the theoretical scores of the failing companies in the sample. It is noted that most companies are ranked well when they are at the bottom of the border score marked in red.

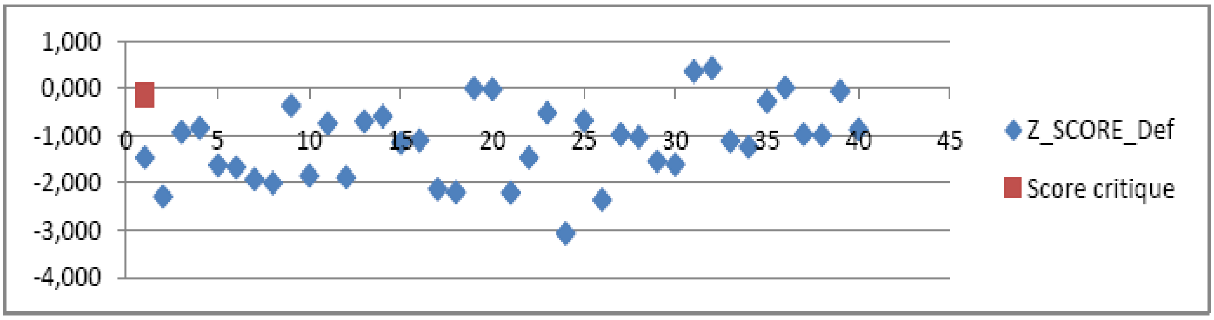

Figure 2: Subgroup 0 scores, failing companies

3.6 Conclusion: Combination of Healthy and Failing companies Scores

Discriminatory function scores reclassified 12 observations [See Table: Classification of observations into theoretical subgroups], the confusion matrix shows the cross results of the ranking. The calculation of the companies' scores highlights the observations to be assigned to a subgroup different from their original category. This reclassification is achieved thanks to the critical score and the decision rule resulting from the frontier value that distinguishes between healthy and failing enterprises.

The following table displays all scores for our sample observations. It should be noted that the red values for sound undertakings refer to observations where the undertakings are theoretically insolvent. Reverse reasoning applies to values in green.

Table 17: Company scores by origin subgroups

ETP SAINES	Scores N-1	Scores N	ETP DEFAILLANTES	Scores N-1	Scores N
ETP 1	3,20316883	2,594812024	ETP 1	-1,472861678	-2,296432358
ETP 2	1,675050975	1,995509559	ETP 2	-0,933837454	-0,843798903
ETP 3	0,565636918	1,145745088	ETP 3	-1,631383897	-1,676595633
ETP 4	0,633742807	1,067749542	ETP 4	-1,933009883	-2,007553678
ETP 5	3,702743316	1,605814146	ETP 5	-0,370353285	-1,853626262
ETP 6	2,375847999	0,013278959	ETP 6	-0,747465971	-1,888851391
ETP 7	-0,001024598	-0,204740464	ETP 7	-0,705319419	-0,597696937
ETP 8	0,774417714	0,571542408	ETP 8	-1,158306134	-1,106635535
ETP 9	0,746153878	1,116611075	ETP 9	-2,138194889	-2,202727399
ETP 10	0,518963063	-0,37934226	ETP 10	-0,011797228	-0,026120887
ETP 11	0,612337249	0,574585937	ETP 11	-2,211610264	-1,472509612
ETP 12	0,352217584	0,467530201	ETP 12	-0,528393479	-3,077093388
ETP 13	0,333822408	4,024341018	ETP 13	-0,686290198	-2,365832547
ETP 14	0,584086711	0,2849652	ETP 14	-0,986076311	-1,036090779
ETP 15	0,03659558	1,200277351	ETP 15	-1,55112408	-1,614068721
ETP 16	0,854255208	0,90112614	ETP 16	0,350748843	0,416865591
ETP 17	0,252890986	0,518374903	ETP 17	-1,119401044	-1,246454711
ETP 18	1,968573217	3,055147485	ETP 18	-0,282656238	0,003095956
ETP 19	-0,626173354	-0,191197209	ETP 19	-0,981164396	-1,0016351
ETP 20	2,43774017	3,18622489	ETP 20	-0,068783917	-0,87580606
ETP 21	0,165084346	0,660826799			
ETP 22	0,716632389	0,165700087			
ETP 23	-0,219502272	-0,10129471			

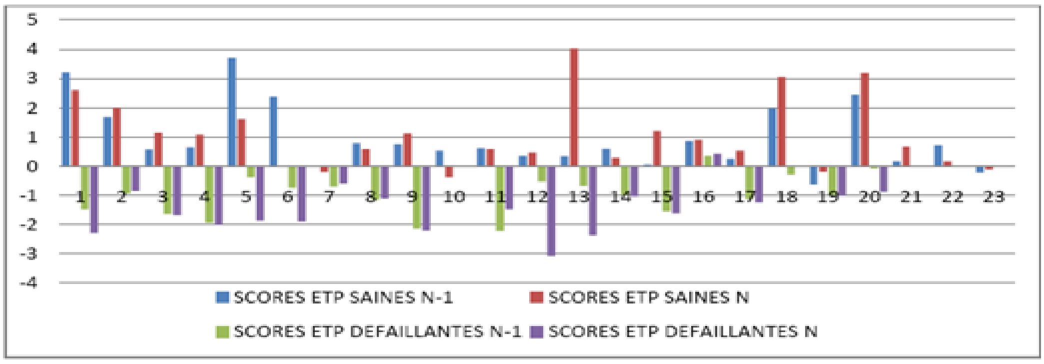

Figure 3: Healthy and Failing Companies Combined Scores

The graph at the top expresses the scores of the two sub-categories:

- Scores of healthy business observations over two fiscal years;
- The scores of failing companies' observations over two fiscal years.

3.7 Synthesis of the research

The research resulted in the design of a discriminant function and the classification functions corresponding to each sub-group:

- Main score function:

Z = 1.777 R2 + 0.958 R3 + 0.001 R5 + 0.326 R14 - 0.003 R18 + 0.082 R20 – 2.446

- Classification functions:

$Z_{failing}$ = 2.049 R2 + 1.948 R3 + 0.002 R5 – 0.177 R14 – 0.007 R18 + 0.077 R20 – 1.816

$Z_{healthy}$ = 5.864 R2 + 4.004 R3 + 0.004 R5 + 0.522 R14 - 0.014 R18 + 0.254 R20 – 6.907

The study also made it possible to select the most discriminating variables by means of a linear regression system in order to combine the discriminating parameters and form an effective discrimination model capable of distinguishing between healthy and failures:

Table 18: Selected ratios in regression model

Variables	Dénomination	Ratios	Coefficients de pondération
R2	Liquidation réduite	N* : (Actif circulant - Stock) + Trésorerie actif D** : Passif circulant + Trésorerie passif	+ 1.777
R3	Liquidation générale	N : Actif circulant + Trésorerie actif D : Passif circulant + Trésorerie passif	+ 0.958
R5	Rotations des stocks	N : Stocks de produits finis * 360 D : Chiffre d'affaires	+ 0.001
R14	Rentabilité économique	N : Résultats d'exploitation D : Actif économique	+ 0.326
R18	Capacité de remboursement 2	N : Résultat d'exploitation D : Charges financières	- 0.003
R20	Endettement	N : Dettes de financement MLT D : Capitaux permanents	+ 0.082

* : Numérateur, ** : Dénominateur.

From the ratios selected to compose the score function, we can conclude about the factors of the failure, according to our study:

First, the factors of failure if we limit ourselves to the sample of companies we collected. Indeed, since the regression model selected the most discriminating variables to predict the failure, this said that the failure is mainly due to liquidity problems.

Moreover, the first two ratios (R2 and R3), relating to reduced liquidity and general liquidity, represent the strongest ratios of our discriminant function. In addition, the statistics calculated for these two ratios showed very favourable values, the interpretation of which expresses their performance in distinguishing between insolvent and healthy enterprises, they are considered separately or combined in the regression equation.

Secondly, the failure is linked to problems of profitability, particularly economic ones. Indeed, the operational problems that a company may have significantly increase the risk of the failure to which it is exposed. Economic profitability expresses the relationship between the company's operating performance and the assets it uses for its core business[6]. So the failure may be due to the misuse of assets in the operating cycle.

Third, debt policy can also cause a company to fail. The selected payback ratio is the ratio that follows the amortization of financial expenses with the resources that flow from the operating cycle. It can be said that the ability of the company to repay its financial expenses with the resources generated by the activity is decisive when it comes to the risk of failure. The degree of indebtedness or over-indebtedness of the enterprise may affect the structure and financial soundness of the enterprise.

The following table sets out the statistical tests which represented the decision criteria throughout our study, and the set of significant results with decisive interpretations is also clearly described:

Table19: Summary of research results[7]

Decision criterion	*Result*	*Interpretation*
Mean/ Variance	See Table on Sub-Group Diversity	The averages between the groups are different and widely dispersed, which expresses the discriminant power of the model chosen among the subgroups.
Fisher test	Variation of Fisher: 1.1611 Sig: 0.208	The Fisher significance of Model 15 is the lowest so it is the most efficient and discriminating model.
R-two	R-2: 0.540	The value of R-two is higher than the minimum statistic of 0.30, which says that the variables R2, R3, R5, R14, R18, R20, are explanatory of the failure.
Student Test	Student test: 15.460 Sig: 0.000	The student test value for Model 15 is the highest. Therefore, Model 15 is the preferred model.
Box test	Box M: 374.87 Approximate F: 16.472 Sig: 0.000	The displayed value of Box and Fisher statistics shows that there is no similarity between the covariance matrices of the subgroups. So the model is able to distinguish the subgroups.
Canonical correlation	The canonical correlation: 0.735	The value of the canonical correlation is close to 1, this being said that the regression model is highly discriminating.
Wilks' Lambda	Wilks' Lambda: 0.460 sig:0.000	The Wilks Lambda value is close to 0. The model is validated for the null significance of the test.
Observations correctly classified	Correct ranking: 86%	The percentage obtained from correctly classified observations expresses a high degree of discrimination of the designed score function.
Critical score	Sc: -0.015	According to the constructed model, companies with scores below the critical score fail.

[6] LOCHARD J. (2008), les ratios qui comptent, 2nd éd. Paris : Organisation Edition, Eyrolles group, page 23.

[7]Table prepared by us

		While, companies with a score higher than the critical score are healthy.
Q press	Q press: 44.69	The null hypothesis is rejected since the Q press is different from the cross-value provided by the Chi-square table. So the reclassification is due to the discriminatory power and not to chance.

4. General Conclusion

After this above all empirical examination of the problem of failure, we can conclude that all the variables tested explain the failure. This is due to the fact that defaulting companies report poor trade policy conduct (poor market positioning, poor understanding of customer needs and expectations, poor forecasting of demand developments, price mismatch, etc.) (Brilman (1982); Ooghe et al. (1983); Koenig (1985); Jaminon (1986) ; Ooghe and Waeyaert (2003), but also in terms of financial and investment since they do not generate sufficient profitability, which is in line with and confirms the work of the authors cited.

In conclusion, the development of the failure prediction model has identified factors that compromise the proper functioning of the company, and which will be useful to pay attention to when implementing a tracking system. The factors of the default, resulting from the selection of the component variables of the score function, cover three aspects, namely, "**liquidity**", "**profitability**" and "**debt**".

Thus, the main contributions of our work are on two levels : academic and professional. With regard to the first, our work aims to contribute to the understanding of a phenomenon that is very little understood in academic circles and whose existing contributions, few indeed, limit themselves to the theoretical aspect of the question without however moving to an empirical verification applied to the Moroccan context. As for the second, this work would be very useful for managers of companies, consultancies and consultancies wishing to equip themselves with tools for forecasting and/or preventing business failures. In this sense, the factors we identified would be used to develop dashboard indicators to alert leaders to the symptoms of the failure. In any case, the present work is of a certain contribution both academically and professionally.

However, such contributions must not obscure the inherent or even specific limits of any scientific contribution. In the first place, we quote the unavailability of certain information (lack of open access databases on this subject) and the confidential nature of the data we needed (access to company balance sheets), which explains the refusal of some institutions to give us access to their documentation. To this are added the limited size of our sample, especially by sector, which would have visibly influenced the statistical tests carried out, and the non-exhaustive nature of the ratios taken as variables in this work.
For this reason, we consider that these limits can be remedied by proposing some future avenues of research on this subject. For purposes of improvement, it would be interesting to increase the sample size to include several sectors and regions of the kingdom. For the purposes of deepening, we propose, on the one hand, to broaden the choice of independent variables by integrating, in addition to those used, other quantitative variables such as productivity, margin and value added ratios, rotation, etc. but also qualitative such as the death of the principal associate, conflicts between associates, etc. On the other hand, it is important to deepen the issue of failures by focusing on a particular sector, the sector where failures occur most, for example.

Our interest in this topic abounds with academic reasons and initiation to scientific research. Indeed, the reasons why we have dealt with the prediction and prevention of failure go beyond the aspects addressed in this work to take on a greater dimension, it is "the social dimension". The failure of the enterprises compromises the chances of work, it is closely linked to the loss of job.

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