ISSN 2664-3995 (Print) & ISSN 2664-6757 (Online)
South Asian Research Journal of Business and Management
Abbreviated Key Title: South Asian Res J Bus Manag

| Volume-3 | Issue-6 | Nov-Dec -2021 | DOI: 10.36346/sarjbm.2021.v03i06.007

Original Research Article

Relevance of Qualitative Variables in Assessing the Risk of Business Bankruptcy

Mohamed Sofien Nouri[1*], Younes Boujelbene[2]

[1]Doctor in Economic Sciences, University of Sfax, FSEG of Sfax, Tunisia
[2]Professor in Economic Sciences and Dean of the Fseg of Sfax

***Corresponding Author**
Mohamed Sofien Nouri

Article History
Received: 19.10.2021
Accepted: 25.11.2021
Published: 30.11.2021

Abstract: The majority of studies in the area of corporate bankruptcy detection are generally concerned with the analysis of corporate financial ratios. Except these who are only symptoms of the process of the decline. The desire to better understanding the processes of bankruptcy obliges us to broaden the domain of expertise of financial analysis and integrate aspects of a qualitative order, relating more to the modes of organization of the company in relation with its environment. The objective in this paper, aims to broaden the debate by identifying the determinants of the bankruptcy of Tunisian SMEs through the use of qualitative variables alongside quantitative variables for forecasting the failure of companies, using the analysis in the main component and discriminant analysis. This approach allows a better explanation of the risks of bankruptcy and a better identification of the precursor signs of bankruptcy. In operational terms, this research aims to make a contribution to all decision makers inside and outside the company. In fact, to offer a clear vision to forecasting techniques and to show the contribution of qualitative variables in terms of early detection of business bankruptcy.

Keywords: Forecast, bankruptcy companies, qualitative variables, Principle Component Analysis, Discriminant Analysis.

I. INTRODUCTION

The increasing number of bankrupt companies confirms the necessity of searching causes and tools to detect immediately business bankruptcy, in order to take the necessary measures at the right time and limit their consequences. Indeed, it is necessary to ensure the protection of the interests of creditors, the sustainability of the company, by detecting the difficulties that companies may encounter, which requires an estimate of the risk of bankruptcy and possibly an improvement of the methods of evaluation.

The previous researches dealing with the prediction of the failure have been focused essentially on variables of quantitative type in spite of the importance which presents the variables of qualitative type in the explanation of the real causes of the failure, our objective in this study aims at widening the debate by the identification of the determinants of the failure of the Tunisian SME through the use of the qualitative variables beside the quantitative variables for the prediction of the failure of the companies, by using the method of the discriminating analysis. This approach allows a better identification of the precursory signs of the bankruptcy of companies and allows showing the contribution of the qualitative variables in terms of early detection of the failure of companies.

II. LITERATURE REVIEW

A. The state of the art

Predicting corporate bankruptcy forecast is a topic that has been studied in various fields: such as monitoring corporate credit worthiness and assessing the safety of corporate loans by financial institutions, assessing business continuity by corporate auditors, and assessing corporate financial health by corporate accounting and managers. ((Shumway, 2001; Duffie et Singleton, 2003; Altman, 2010; Jones and Wang, 2019).

The complexity of bankruptcy phenomenon has aroused participant's interests of pact and researchers for several years, and has justified the use of econometric and technical methods aimed to prevent this state. The theme of bankruptcy prediction is a field of investigation that dates back to the 1930s with the pioneering study of Fitzapatrick (1932). Throughout this study, we have seen several types of methods and models for the early detection of bankruptcy. Two techniques have marked the history of this type of prediction model, the parametric and non-parametric methods. Regarding parametric methods, the majority of studies have been based on standard discrete choice models, such as multiple discriminant analysis and Logit and Probit models (Jones and Wand 2019).

For non-parametric classification methods dealing with this domain, three predominant techniques have been commonly used: neural networks, decision trees, and support vector machines (SVM). The first use of neural networks to predict the risk of failure was carried out by Bell and al. (1990). The use of this method was then intensified by the work of Tam and Kiang (1992) and Altman and al (1994). Several studies have shown the superiority of the neural approach over discriminant analysis in terms of prediction (Odom and Sharda (1990), Abdou and Al (2008), Almaskati and Al (2021). Other studies suggest the use of discriminant analysis in the field of failure prediction given its performance (Edmister, R. (1972), Eisenbeis (1977), Bardos (1998)).

The prediction of the failure of a company can be appreciated as a classification problem, which consists, in general, of two categories of assignment: healthy company and failed company.

Discriminant analysis is part of the parametric techniques of statistical classification, it consists in establishing a functional relationship between the explanatory variables and the variable to be explained and it requires that the data be independent and normally distributed.

The 1960s marked the development of plenty of methods whose objective was to model the prediction of bankruptcy risk, one of the most famous is discriminant analysis. Among the approaches that have marked the use of this method is the uni-varied analysis of Beaver (1966) which was among the first research trying to distinguish between healthy and failing firms through the ratios financial of companies (up to 5 years before the bankruptcy event). A critical threshold was determined in order to best separate the group of healthy firms from the group of failing firms. Despite the fact that this method has produced effective results in terms of classification, it has been widely criticized. Indeed, the uniqueness of the ratio used does not allow for a global analysis of the financial health of the company, nor does it allow for the measurement of the interdependence criterion between the different financial ratios.

Despite the criticism of Beaver's unidimensional approach, this method has been the starting point for the development of other methods, such as multidimensional discriminant analysis, which allows a richer explanation of the company's situation. Multivariate Discriminant Analysis (MDA) is based on the application of Bayes' classification procedures and the strict assumptions that positive and negative classes have Gaussian distributions with equal covariance matrices. This method resulted in the construction of a score function, which is the linear combination of a number of variables. The z-score model published by Altman (1968) in the United States is the most popular bankruptcy prediction model in the literature. It calculates a Z-score function from a linear combination of many financial ratios.

The classification of a company as healthy or failing is done by comparing its score to the threshold set by the model. Altman (1968) used multivariate discriminant analysis to perform the classification of solvent and insolvent firms in the database and the financial state. He used five key financial ratios as inputs, including working capital/total assets, earnings before interest and taxes/total assets, which have been widely used in subsequent research.

B. The causes of business failures

Several researches have been conducted to determine the origins of bankruptcy or potential difficulties of companies. Despite methodological differences, all the studies show that failure rarely results from a sudden cause, but is the outcome of a continuous deterioration within the firm, due to the combination of several internal and external factors. The majority of theoretical approaches to this subject have classified the causes of failure under two categories: exogenous or contingent factors of the firm, and endogenous or organizational factors of the firm.

The endogenous factors

Since the end of the 1940s in the United States, the emphasis has been placed on the personal qualities of the leader. The research of Kaplan (1948) in which he found that the essential causes that lead to the failure of the company are the result of managerial inadequacies. Within this framework, Argenti (1976) noted that if the constraints exerted by the external environment favored the growth of the fragility of the companies, then they cannot however involve the bankruptcy of a well-managed company.

Other empirical studies have focused on the skills of managers and their role in the deterioration of the firm. Indeed, the results of studies of the national fund for state contracts (CNME) and of equipment credits for SMEs (CEPME) show that endogenous and cyclical (exogenous) accidental causes only represent relatively low frequencies: 7.5% and 8.2%. While all other causes representing 84.3% are the result of managerial behavior of the manager(s). In this context, Michoud (1995) noted that the performance of the company will be all the greater if the manager is capable of transforming the perception he has of his present, or even future, environment into a relevant strategy.

Following the ecological trend, Hannan and Freeman (1977) have highlighted the decreasing relationship between the mortality rate of industries and their size. Indeed, large industries can reduce their activities if necessary in order to cope with long periods of decline. While small industries can hardly reduce their activities and fail quickly when their wealth decreases.

In this context, Blazy and Combier (1995) have shown that the reasons for this finding are related to the effects of size on economies of scale, the experience effect and bargaining power with respect to business partners. Dembinski *et al.* (2003) concluded that age plays a fateful role in the failure process, since in the group of failed firms studied, the proportion of those that have not completed more than three financial years amounts to approximately 30% of the total.

The exogenous factors

These factors leading to business failure are due to the economic downturn and unpredictable changes in the business environment. The external environment of the company can contribute to the acceleration of the process of failure of companies: the law of the market, the aggressiveness of the competition, the technological development and the regulatory change constitute the principal factors likely to create a situation of difficulty for the companies '(Nahmias (2005)). Similarly, the latter noted that a comparison of trends in insolvencies with trends in gross domestic product (GDP) reveals a decreasing relationship between the number of insolvencies and economic activity; indeed, a fall in annual GDP growth coexists with an increase in the average annual growth rate of the number of insolvencies. Conversely, an upturn in economic activity coincides with a slowdown in the annual growth in the number of insolvencies. These factors are the most frequent and represent the major causes of difficulties and sometimes of the disappearance of any company that is dependent on or has exclusive business relations with single partners. In this context, Argenti (1976) considered that the presence of external factors such as imponderable natural events is likely to accelerate the process of business failure.

III. METHODOLOGY

There is a difficulty in accessing information on the causes, the direct consequences and the events that are at the origin of the triggering of the failure because it is a question of a deterioration of the organizational situation of the company, observable only at first internally. It is therefore very difficult, if not impossible, to detect failing firms when they are still in the early stages of the failure process if one does not have access to the internal data of these firms. And even if, in a second stage, this increasing deterioration of the organizational situation of the company becomes detectable by external observers, because of the deterioration of key financial indicators in the annual accounts, it is not always easy to know the origins (always organizational) of this failure. Indeed, managers generally find it difficult to talk freely about the causes that led to the failure of their companies, which they consider a personal defeat. Moreover, they generally do not have the time and they do not see the interest in talking about the failure of their companies with researchers because their common concern is to ensure the survival of their companies.

Aware of this difficulty in accessing information on the origins of business failures expressed by the managers of the companies themselves, we were obliged to resort to interviews with managers within the failing companies and in the majority of cases to send a questionnaire to the accountants and auditors who are familiar with the state of the companies). According to Jones and Wang (2019), qualitative factors are difficult to detect and data are difficult to collect. For the quantitative approach, our approach includes several steps: construction of the database, selection of companies and choice of failure indicators. As for the qualitative approach, a questionnaire was sent to the managers of the companies, in which they were given the opportunity to express their opinions concerning the micro and macroeconomic problems encountered by the company during its course.

A. Presentation of the database composed of quantitative variables

The database consists of financial statements of 300 healthy and failing companies that relate to the years 2019 and 2018. These firms are equally divided between healthy and failing firms. The financial ratios derived from these accounting data constitute our database of quantitative variables, which were selected on the basis of theoretical and empirical studies conducted in this area (Bardos (1998), Ooghe et Waeyaert (2004), Refait (2004), Bardos (2008), Ricca and al (2021).

Table-I: Selected Quantitative Variables

RATIOS	Code
Financial profitability	R01
Economic profitability	R02
Operating profitability	R03
Return on Investment	R04
Gross Profit Margin	R05
Asset Turnover	R06
Fixed Assets Turnover	R07
Turnover of equity	R08
Inventory turnover	R09
Days sales outstanding	R10
Time to pay suppliers	R11
Profitability rate	R12
Growth rate of the turnover	R13
General liquidity	R14
Reduced liquidity	R15
Immediate liquidity	R16
Asset liquidity	R17
Debt ratio	R18
Long-term debt	R19
Short term debt	R20
Financial Autonomy	R21
Financial balance	R22
Financial independence	R23
Coverage of financial expenses	R24
Capacity to repay debts	R25
General Solvency	R26
Equity Ratio	R27
Fixed Assets Ratio	R28
Size Indicator	R29

B. Presentation of the database composed of qualitative variables

Our database presenting the qualitative variables was constructed on the basis of a questionnaire sent to the various companies. This database presents the characteristic variables of 200 firms: 120 healthy firms and 80 failing firms. The results obtained from the answers to the questionnaire indicate the relevance of the following variables:

- **The decline in turnover**

The decrease in turnover is mainly due to the strong competition and the absence of a good commercial policy. Indeed, the majority of the companies we investigated evolve in strongly competitive sectors, without real niche and thus without real barrier to entry. Also, in the absence of a well-defined strategy, the companies behave as if they were in a monopoly situation whereas they live in a highly competitive environment, which means that no marketing strategy is adopted. This results in a limited vision that does not allow them to meet the needs of their customers.

- **Heavy commercial debt**

The decrease in turnover is generally accompanied by a lack of liquidity within the companies in difficulty, which leads to an increase in commercial debt.

- **Financial difficulties due to insufficient funds**

The situation of the companies is often characterized by financial a difficulty which is due to the lack of capital. Indeed, especially in the start-up phase, the companies have a reduced self-financing capacity since the contribution of the partners or creators is often limited (especially family contribution) and the absence of public aids (such as creation aid or investment subsidies) which allow these companies to increase their starting fund.

- **Difficulty in collecting accounts receivable**

Late payments of receivables weigh heavily on the profitability of the company. The absence of a collection service within companies leads them to have financial difficulties that can affect their survival. Also, few companies know the real financial situation of their customers; indeed a customer can be solvent today but his capacity of payment for tomorrow remains ambiguous.

- **Bankruptcy of a major customer**

Some companies have significant difficulties following the persistence of external shocks, even though they were performing well before the persistence of this or these events. In this context, the loss of an important customer following its bankruptcy or a failure to collaborate, on which the company is highly dependent, can affect the survival of the company.

- **Extension of customer payment terms**

Newly established companies or companies with difficulties in selling their products are obliged to extend the payment terms of their customers in order to attract new customers or market shares. The chosen solution is toodangerous for the financial health of the companies, which can lead to a state of insolvency due to the lack of available liquidity in the company.

- **Inability of the company to correctly evaluate the market in which it operates**

Some companies, too ambitious during the pre-creation phases, have overestimated the achievable turnover and have therefore given birth to a company with a very heavy structure in relation to its possibilities on the market.

- **Dysfunction in the internal organization**

The companies which know a dysfunction in the internal organization are necessarily the companies which survived since years. Indeed, these companies are experiencing difficulties because the managers are satisfied with their achievements. Indeed, since the company has existed for years, a kind of inertia is established within the company: establishment of rigid strategies, no questioning of the previous procedures.

- **Lack of product positioning**

The lack of a marketing strategy leads to the lack of product positioning which can even bankrupt the business. Indeed, to attract customers, the company must produce cheaper and with higher quality.

- **Management deficiency**

Companies created by unskilled people, i.e. people who have insufficient skills to manage an organization, are in trouble. The management skill set available within these companies is often very limited.

- **Poor social environment**

There are many factors that lead to a decrease in economic performance. Among these factors we can mention organizational deficiency and internal rigidity which are factors that can affect the social climate within the company. Also, the working conditions, the morale, the team spirit and the motivation of the staff can be affected by the imminence of bankruptcy on the one hand and by the misbehavior of the manager on the other hand, which creates a climate of stress and irresponsibility on the part of the staff.

- **A lack of staff responsibility and accountability**

In the first years of operation, the situation of the personnel and their remuneration do not seem to be a concern of the company's managers. This neglect leads to the departure of qualified personnel and creates a lack of accountability within the company.

- **Inadequate management and organization**

Companies run by unqualified people who lack management, organizational and especially financial skills are usually in trouble. Due to poor management, these companies will have difficulty developing strategic resources that create value.

- **Inability to anticipate and adapt**

A large number of companies go bankrupt due to inability to anticipate and adapt. Indeed, these difficulties are generally linked to management errors on the part of the managers, such as a bad anticipation of the evolution of the environment of the company, or the absence of competitive or strategic watch.

These variables obtained and which engender difficulties or even bankruptcy of companies have been verified by the research works of Runfola and al (2017), Ben arab and merdassi (2015), Ben Naseur et Boujelben (2014), Kammoun and Daoud (2011). All selected variables are presented in the table below with their coding (see Table II).

Table-II: Qaulitative Variables Selected

Variables	Code
Poor management and organization	MGESTORG
Inability to anticipate and adapt	INCANTIA
Management deficiency	DEFMANAG
Lengthening of customer payment terms	ALLODLP
Malfunctioning in the internal organization	DISFORG
Lack of analysis of the competition	ABSANCON
Inability of the company to correctly evaluate the market in which it operates	INCEVAL
Decrease in turnover	BAISSECA
Financial difficulties due to insufficient equity capital	DIFFINAN
Difficulty in collecting receivables	DIFFIREC
Increased commercial debt	ALLOUDTC
Lack of product positioning	ABSPOSPR
Bad social climate	MAUVCLIM
Lack of staff accountability	MQRESPER
Loss of an important customer	DEFACLT

Our database is divided into two sub-samples to be able to test the performance of the technique used: training sample and test sample. We initially have a so-called learning sample, the classification of which is known. This sample is used to configure the model and to learn the rules for classifying a company according to its characteristics. The second test sample is necessary to study the reliability of the technique used. For this reason, we will apply the discriminant analysis method on these two samples. The performance of the model is evaluated in a first step on the sample presenting the quantitative variables, then in a second step on the sample made up of quantitative and qualitative data.

C. Presentation of the software used

In order to prevent and model a potential business failure, we used SPSS software for data processing. This software was used for basic statistical processing and analysis (some recoding of variables, descriptive statistics, hypothesis testing...), principal component analysis to extract the factorial axes, and the application of discriminant analysis for the modeling of the bankruptcy.

IV. FACTORIAL ANALYSIS OF QUALITATIVE VARIABLES

Factor analysis refers to a set of methods used to select and synthesize data. In data analysis, there may be a large number of variables, often correlated, that need to be synthesized in order to derive useful information.

A. Relevance of the factor analysis

Bartlett's test of sphericity can be used to test the null hypothesis that the variables are uncorrelated in this study. This test is based on a chi-square transformation of the determinant of the correlation matrix. A high value will favor the rejection of the null hypothesis. Otherwise, the relevance of the factor analysis should be questioned. Another useful statistical test is the measurement of the Kaiser-Meyer-Olkin (KMO) goodness-of-fit index, which compares the magnitudes of the observed correlation coefficients with the magnitudes of the partial correlation coefficients. Small values of this index indicate that correlations between pairs of variables cannot be explained by other variables and that factor analysis may not be relevant. In general, a value greater than 0.5 indicates that the test is appropriate.

Table-III: Kmo Index and Bartlett Test

Precision measurement of Kaiser-Meyer-Olkin sampling.		**,831**
Bartlett sphericity test	**Khi-deux approximate**	1766,418
	Ddl	105
	Meaning of Bartlett	,000

The factorial analysis is then appropriate to synthesize the information contained in all the initial variables since the value of the KMO statistical test (0.831) is also high (>0.5). We can conclude, finally, from the statistics obtained that Factorial analysis is relevant for our study.

B. Interpretation of the selected axes

To facilitate the interpretation of the selected factorial axes, rotation algorithms were used. The objective of the rotation is that the factors have a non-zero or significant coefficient for some variables. To interpret the factors, it is necessary to go back to the initial variables and determine the weight of each variable in the formation of each factor. It is therefore necessary to go back to the principal components matrix and study the correlation coefficients between the new variables called principal factor and the old variables. (See Table IV).

Table-IV: Component Matrix

	Components			
	1	2	3	4
MGESTORG	,948	-,172	,188	,082
INCANTIA	,948	-,181	,174	,084
DEFMANAG	,946	-,161	,207	,073
ALLODLP	-,930	,155	-,125	- ,062
DISFORG	,892	,124	,156	,175
ABSANCON	-,828	,131	-,186	,366
INCEVAL	-,731	-,314	- ,055	,410
BAISSECA	,207	-,851	,138	-,135
DIFFINAN	,091	,786	,371	,026
DIFFIREC	-,312	,779	- ,087	-,313
ALLOUDTC	,151	-,756	,169	,096
ABSPOSPR	,393	,628	,282	,198
MAUVCLIM	,236	- ,008	,954	,016
MQRESPER	,240	,001	,953	,004
DEFACLT	-,046	,005	-,028	-,903
Extraction method: Principal component analysis Rotation method: Varimax with Kaiser normalization.				
The rotation has converged in 5 iterations.				

The active variables best correlated with factor 1 are: Poor management and organization of the different links in the internal value chain, Inability to anticipate and adapt, Malfunctioning in the internal organization, Lack of analysis of the competition, Inability of the company to correctly evaluate the market in which it operates. Furthermore, we can interpret the F1 axis as the management errors encountered within the company, which are among the causes that lead companies into difficulties and which are essentially due to managerial incompetence.

The active variables best correlated with factor 2 are: Decrease in turnover, financial difficulty due to insufficient equity, Difficulty in collecting trade receivables, increased commercial debt, Lack of product positioning. The F2 axis can be interpreted as the axis presenting the strategic errors within the company.

The active variables best correlated with factor 3 are: Poor social climate, Lack of staff accountability. Axis 3 presents the social responsibility of companies.

The active variables best correlated with factor 4 are: Loss or failure of a major customer. The F4 axis presents the dependence of the company on an external factor.

V. MODELING OF FAILURE USING QUANTITATIVE VARIABLES

A. *Choice of variables*

A set of twenty-nine financial ratios, coded from R01 to R29, was selected. The choice of these ratios was motivated by their recurrence in the studies relating to the subject of the prediction of the failure or those which present a significant informational character in the evaluation of the financial health of the companies. The themes chosen for the selection of these ratios are: profitability, productivity, management, liquidity and financing and finally the financial structure.

The modeling and the quality of prediction depend greatly on the choice and selection of financial ratios that significantly affect the probability of default.Given the large number of financial ratios initially set, our selection is based on the choice of ratios that best contribute to the discrimination between the two types of firms (healthy and failing). We apply Fisher's test to determine the most discriminating financial ratios that best differ between the two groups of firms (see Table V).

Table-V: Test of Equality of Means

Ratios	F	Signification
R01	35,280	,000
R02	8,256	,004
R03	,146	,703
R04	,128	,721
R05	,052	,820
R06	1,626	,203
R07	3,467	,064
R08	,147	,702
R09	,886	,347
R10	11,958	,001
R11	3,256	,072
R12	90,847	,000
R13	,312	,577
R14	9,585	,002
R15	7,443	,007
R16	4,588	,033
R17	1,060	,304
R18	72,257	,000
R19	33,794	,000
R20	33,389	,000
R21	13,161	,000
R22	,045	,831
R23	13,810	,000
R24	3,017	,083
R25	2,392	,123
R26	14,742	,000
R27	1,555	,213
R28	1,772	,184
R29	7,699	,006

Examination of the results obtained using the Fisher test in the table above, at the 5% level, shows the presence of a number of significant ratios and others that are not. The significant ratios that best discriminate between the two groups of firms belong to the four types of ratios used in this analysis. There are some profitability ratios (R01, R02), the second group of indicators relates to management ratios (R10, R12).

The ratios reflecting the company's liquidity are significant. These are the ratios R14, R15, and R16. The fourth group of indicators reflects financing and structure ratios. The significant ratios are R18, R19, R20, R21, R23, R26.

Finally, the ratio R29, which reflects the size of the firm, shows that large firms are less vulnerable to default. In conclusion, the analysis of the two groups of firms confirms that failing firms are characterized by poor economic and financial performance. The Fisher test, which allows us to test the relevance of a variable to differentiate between the two groups of firms, shows that failing firms have a high level of short-term debt in relation to their activity.

B. Application of Discriminant Analysis

- ***The Test of BOX***

Table-VI: Results of the Multivariate Box Test

M of Box		630,538
	Approximately	5,712
	ddl1	105
	ddl2	276659,610
	Signification	,000

The value of Box's M obtained by this test has a value equal to 630.538. The value obtained is high and the significant of the F-test tends to 0. These results indicate the relevance of the technique used.

- ***Lambda de wilks***

Table-VII: Value of the Multivariate Wilks Lambda Associated with the Discriminant Line Function

Test of the function(s)	Lambda of Wilks	Khi-deux	ddl	Signification
1	,519	190,631	14	,000

The statistic associated with Wilks' lambda follows a $\chi 2$ distribution with p (k-1) = 14 degrees of freedom under the null hypothesis of equality of the means of the k=2 groups for the 14 variables introduced in the model. The level of the first-species risk, less than one chance in a thousand, leads to the rejection of this hypothesis and to the assertion that the mean scores of the two groups according to the linear discriminant function differ significantly.

Following the verification of the validity of the discriminant analysis by the indicators analyzed above, we proceed to the elaboration of the linear discriminant function, score function.

- ***Formulation of the score function***

The score function with the highest discriminating power is a linear combination of all the ratios considered as the most discriminating. It is given by the vector given in the table below.

Table-VIII: Score Function Coefficient

	Function
R01	-,321
R02	-,179
R10	,177
R12	,545
R14	-,174
R15	-,190
R16	-,126
R18	,513
R19	,356
R20	,308
R21	-,210
R23	-,213
R26	,244
R29	,191

The established score function is written

Z = - 0.321R01-0.179R02+ 0.177R10 + 0.545R12 - 0.174R14 - 0.190R15 - 0.126R16+0.513R18 +0.356R19 + 0.308R20 - 0.21R21 -0.213R23+ 0.244R26+ 0.191R29

The Z-score value obtained can be compared to the average scores of the groups. The failure criterion is assigned to one of the groups based on the geometric rule developed from the midpoint of the segment joining the barycentre's of the two groups:

If Z > C, then the firm is classified as "healthy"
If Z < C, then the firm is classified as "failing
If Z = C, then the firm is classified by randomly drawing the groups
With C = - 0.959 + 0.959 = 0 (c: barycentre of the 2 groups)

C. ***Evaluation of the classification quality***

The objective of the established discriminant function is to use it to classify new companies into predefined groups based on the data provided in their financial statements. To ensure the predictive quality of the method, the discriminating power of the score is monitored. One measure of this discriminating power is the correct ranking rate. If the score of a company is positive, it is said to be well classified by the score function if it is assigned to the group of healthy companies. Similarly, if a firm's score is negative, it is said to be well classified by the score function if it is assigned to the group of failing firms.

Table-IX: Validation of Model

			Assignment class predicted by the model for the test sample		**Total**
		Corporate group	Failed company	Efficient company	
Original	Class	Failed company	133	17	150
		Efficient company	30	120	150
	%	Failed company	88,7	11,3	100
		Efficient company	20,0	80,0	100

We find that the model was able to classify 133 failing firms among the 150 initially introduced, which gives a correct classification rate of 88.7% for failing firms. Similarly, the model was able to identify 120 healthy firms among the 150 initially introduced, which gives a correct classification rate of 80% for healthy firms. On the other hand, the error rate of the first category is about 11.3%, while that of the second is 20%. We therefore conclude that the application of this model to our sample, one year before the default, allowed us to correctly classify 253 firms out of 300, i.e. a correct classification rate of 84.35%. The same score function applied to the test sample gave results that are presented in the following table:

Table-X: Classification Results of the Test Sample

			Assignment class predicted by the model for the test sample		**Total**
		Corporate group	Failed company	Efficient company	
Original	Class	Failed company	108	42	150
		Efficient company	30	120	150
	%	Failed company	72	28	100
		Efficient company	20	80	100

This score function made it possible to classify 108 failing firms out of the 150 in the test sample, which gives a correct classification rate of 72%. In the same way, this function allowed to classify 120 healthy firms among the 150 present in the test sample, that is to say a rate of 80% of good classification. To conclude, this model applied 2 years before the bankruptcy leads to a good classification rate of 76% for healthy firms**.**

VI. Failure modeling process using quantitative and qualitative variables

The analyses carried out in general are mainly based on the establishment of quantitative models built from financial data, and highlighting the various symptoms of the failure. The desire to better understand the process of failure obliges us to broaden the scope of the analysis and integrate qualitative aspects alongside the quantitative variables initially used. The factorial axes representing the qualitative variables initially selected will be associated with the quantitative variables to evaluate the predictive quality of the model.

A. Choice of variables

The test of equality of means will be carried out on all the quantitative variables and the factorial axes representing the qualitative variables in order to determine those which have the highest discriminating power and then to determine the score function which makes it possible to dissociate the healthy companies from the failures.

Table-XI: Test of Equality of Group Means

Ratios	Lambda de wilks	F	Signification
R01	,925	12,748	,000
R02	,956	7,237	,008
R10	,946	8,999	,003
R12	,901	17,344	,000
R14	,974	4,284	,040
R15	,959	6,736	,010
R18	,950	8,248	,005
R19	,892	19,219	,000
R20	,931	11,790	,001
R21	,911	15,504	,000
R23	,971	4,672	,032
R26	,962	6,210	,014
R27	,961	6,468	,012
R29	,943	9,550	,002
F1	,820	34,608	,000
F2	,830	32,376	,000
F3	,942	9,748	,002
F4	,949	8,500	,004

Examination of the Fisher test in the table above indicates that, at the 5% level, all the variables are significant. Similarly, the four factorial axes are significant and have a strong discriminating power

B. Identification of the score function

The same approach as the one used with the introduction of quantitative variables will be used.

Table-XII: Coefficient of the Score Function

	Fonction
R01	0,213
R02	0,160
R10	-0,179
R12	0,248
R14	0,230
R15	0,155
R16	0,171
R18	-0,261
R19	-0,205
R20	-0,235
R21	0,127
R23	0,133
R26	-0,152
R29	-0,184
F1	0,351
F2	0,339
F3	0,186
F4	0,174

Note that the score function with the most discriminating variables is presented as follows

Z = 0.213R01+ 0.160 R02 - 0.179R10 -0.248 R12 + 0.230R14+0.155R15 + 0.171R16 -0.261R18-0.205R19 -0.235R20 + 0.127 R21 + 0.133R23- 0.152 R26 - 0.184R29+0.351 FACT1+ 0, 339FACT2 + 0.186FACT3 + 0.174FACT4

C. Evaluation of the performance of the model

The validation criterion of the score function is the rate of good classification, resulting from the application of the decision rule derived from the discriminant function. This rate corresponds to the empirical frequency of firms well ranked by the model for each of the defaulting and healthy groups. For the discriminant tool to be effective, it is necessary that, for each of the groups, the rates of good classification differ very significantly. They must also be relatively balanced between the two groups in order to have a function that does not discriminate one group more than another.

The validation procedure of the selected function is divided into two steps:
- The first step consists in validating the specificity, through the measurement of the correct classification rates on the base sample.
- A second step consists in validating the discrimination on a test sample.
- Combining all the variables within the discriminant function yielded the following results:

Table-XIII: Ranking Results for the Learning Sample

			Assignment class predicted by the model for learning sample		**Total**
		Corporate group	Failed company	Efficient company	
Original	Class	Failed company	74	6	80
		Efficient company	8	72	80
	%	Failed company	92,5	7,5	100
		Efficient company	10	90	100

We find that this model was able to classify 74 failing firms among the 80 initially introduced, which gives a correct classification rate of 92.5% for failing firms. Similarly, this model was able to identify 72 healthy firms among the 80 initially introduced, which gives a correct classification rate of 90% for healthy firms. On the other hand, the error rate of the first category is about 7.5%, while that of the second is 10%. We therefore conclude that the application of this model to our sample, one year before the default, allowed us to correctly classify 146 firms out of 160, i.e. a correct classification rate of 91.2%. The same score function applied to the test sample yielded the results presented in the following table:

Table-XV: Classification Results for the Test Sample

			Assignment class predicted by the model for the test sample		**Total**
		Corporate group	Failed company	Efficient company	
Original	Effectif	Failed company	*63*	*17*	80
		Efficient company	*12*	*68*	80
	%	Failed company	78,75	21,25	100
		Efficient company	15	85	100

This score function made it possible to classify 63 failing firms among the 80 present in the test sample, which gives a good classification rate of 78.75%. In the same way, this function allowed us to classify 68 healthy firms among the 80 present in the test sample, that is to say a rate of 85% of good classification. To conclude, this model applied 2 years before the failure leads to a good classification rate of 81.75%.

D. Contribution of qualitative variables

To determine the contribution of categorical variables in terms of failure prediction, comparisons of the prediction performance of the model was conducted in the case of using quantitative variables and in the case of using a combination of quantitative and categorical variables (see Table XIV).

Table-XIV: Model Performance

	Quantitative variables		**Quantitative and qualitative variables**	
Rate of good evaluation	Test	Learning	Test	Learning
	76%	84,35%	81.75%	91,2%

The correct ranking rates from the model using quantitative variables are 76% for the test sample and 84.35% for the training sample. Following the insertion of qualitative variables next to the quantitative variables, it was found that the performance of the model improved for both the learning and the test samples, with rates of 81.75% for the test and 91.2% for the learning.

The association of qualitative variables with quantitative variables in the formulation of the default prediction model has allowed us to obtain quite satisfactory results that are more efficient than the results obtained from the models obtained only with the help of financial ratios, which proves the relevance of qualitative variables in the assessment of default risk.

VII. CONCLUSIONS

Our research focused first on the identification of the financial factors announcing the failure of companies. It emerges from the analysis that Tunisian SMEs that fail are characterized by low liquidity and a high level of debt. The principal component analysis applied on the qualitative variables allowed us to identify four factorial axes. The integration of these factors as additional variables in the discriminant analysis model allowed a significant improvement showing the importance of certain factors related to the external environment such as the domino effect, competitive pressure or the state of the economy as well as internal factors in terms of management quality and strategic orientation.

Our study showed the contribution of qualitative variables in predicting failure since the performance of the model improved whenever qualitative variables were associated with quantitative variables. The results reveal that the technique of discriminant analysis applied on quantitative and qualitative variables is an efficient and robust means of prediction.

In total, the results obtained in this research show that the application of qualitative variables alongside quantitative ones is very promising in the field of default risk assessment. In terms of future research, it is interesting to deepen this work, based on other new forecasting techniques such as neural networks and SVMs to confirm the results obtained with discriminant analysis and improve the predictive capacity of the models.

REFERENCE

- Abdou, H., Pointon, J., & El-Masry, A. (2008). Neural nets versus conventional techniques in credit scoring in Egyptian banking. *Expert Systems with Applications*, *35*(3), 1275-1292.
- Almaskati, N., Bird, R., Yeung, D., & Lu, Y. (2021). A horse race of models and estimation methods for predicting bankruptcy. *Advances in accounting*, *52*, and 100513.
- Altman, E. I., & Ratios, F. (1968). Discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589-609.
- Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of banking & finance*, *18*(3), 505-529.
- Altman, E. I. (1982). Accounting implications of failure prediction models. *Journal of Accounting, Auditing and Finance*, *6*(1), 4-19.
- Altman, E. I., Sabato, G., & Wilson, N. (2008). The value of non-financial information in SME risk management. *Available at SSRN 1320612*.
- Argenti, J. (1976). Corporate planning and corporate collapse. *Long range planning*, *9*(6), 12-17.
- Argenti, J. (1976). “Corporate Collapse : the causes and symptoms”, Holsted Press, McGraw-Hill, London, 1st Edition
- Arab, S. D. B., & Mardessi, S. M. (2015). Le Management des risques dans les entreprises Tunisiennes Un état des lieux après la révolution. *La revue gestion et organisation*, *7*(2), 106-115.
- Bardos, M. (1998). Detecting the risk of company failure at the Banque de France. *Journal of Banking & Finance*, *22*(10-11), 1405-1419.
- Bardos, M. (2008). Scoring sur données d’entreprises: instrument de diagnostic individuel et outil d’analyse de portefeuille d’une clientèle. *Revue Modula, 38,* 159-177.
- Beaver, W. H. (1966). Financial ratios as predictors of failure, Empirical research in Accounting: Selected studies [Text]. *Supplement to Journal of Accounting Research*.
- Bell, T. B., Ribar, G. S., & Verichio, J. (1990). Neural nets versus logistic regression: A comparison of each model's ability to predict commercial bank failures.
- Blazy, R., & Combier, J. (1997). La défaillance d'entreprise: causes économiques, traitement judiciaire et impact financier.
- Ben Nasr, K., Boujelben, Y. (2014). Assessing the Impact of Entrepreneurship Education”, *Procedia - Social and Behavioral Sciences*, *109*(8); 712-715
- Caisse Nationale des Marchés de l'Etat (CNME). (1976). "L'origine des difficultés des entreprises françaises tombées

en règlement judiciaire", Bulletin d'Information Economique, 73, 4ème trimestre, 41-70.

- CEPME, « Crédit d'équipement des PME ». (1986). Les causes de défaillance des entreprises industrielles, Rapport de synthèse
- Daoud, Y., & Kammoun, A. (2011). Contraintes Financieres Et Comportement D'Investissement: Cas Des Entreprises Tunisiennes. *Revue Libanaise de Gestion et d'Économie*, *4*(6), 125-157.
- Dembinski, P. H., Bonvin, J. M., Dommen, E., & Monnet, F. M. (2003). The ethical foundations of responsible investment. *Journal of Business Ethics*, *48*(2), 203-213.
- Duffie, D., Singleton, K.J. (2003). Risque de crédit, tarification, mesures et gestion. Princeton University Press, Princeton, New Jersey.
- Eliot Kaplan, H. (1948). "Concepts of Public Employee Relations" *Industrial and Labor relations Review*, *1*(2), January 1948
- Fitzpatrick, P.I. (1932). «A comparison of the successful industrial enterprise with those of failed companies», The Accountants Publishing Company.
- Hannan, M., & Freeman, J. (1977). "The Population Ecology of Public Organizations", *American Journal of Sociology, 82*(5).
- Jones, T., & Wang, T. (2019). "Predicting private company failure: A multi-class analysis". *J. Int. Financ. Markets Inst*. Money 61; 161–188
- Michoud, G. (1995b). Diagnostic: comportements managériaux et performances financières en PME, Communication à la conférence internationale de l'AIMS. HAL Id : hal-00818577, version 1
- Nahmias, L. (2005). Impact économique des défaillances d'entreprise. *Bulletin de la Banque de France*, (137), 59-74.
- Odom, M. D., & Sharda, R. (1990, June). A neural network model for bankruptcy prediction. In *1990 IJCNN International Joint Conference on neural networks* (pp. 163-168). IEEE.
- Ooghe, H., & Waeyaert, N. (2003). Oorzaken van faling en falingspaden: literatuuroverzicht en conceptueel verklaringsmodel. *Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium*, (03/187).
- Petersen, C. V., & Plenborg, T. (2012). *Financial statement analysis: valuation, credit analysis and executive compensation*. Pearson Longman.
- Refait-Alexandre, C. (2004). La prévision de la faillite fondée sur l'analyse financière de l'entreprise: un état des lieux. *Economie prevision*, (1), 129-147.
- Ricca, L. T., Jucá, M. N., & Junior, E. H. (2021). Tax benefit and bankruptcy cost of debt. *The Quarterly Review of Economics and Finance*, *81*, 82-92.
- Runfola, A., Perna, A., Baraldi, E., & Gregori, G. L. (2017). The use of qualitative case studies in top business and management journals: A quantitative analysis of recent patterns. *European Management Journal*, *35*(1), 116-127.
- Shumway, T. (2001). "Prévision plus précise de la faillite: un modèle de risque simple". *J. Bus. 74*(1), 101-124.
- Tam, K. Y., & Kiang, M. Y. (1992). Managerial applications of neural networks: the case of bank failure predictions. *Management science*, *38*(7), 926-947.

CITATION: Mohamed Sofien Nouri & Younes Boujelbene (2021). Relevance of Qualitative Variables in Assessing the Risk of Business Bankruptcy. *South Asian Res J Bus Manag*, *3*(6), 185-198.