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USING Z–SCORE MODELS TO FORECAST FINANCIAL STABILITY IN PHARMACEUTICAL FIRMS: A CASE STUDY OF SAIDAL

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Purpose. This research paper aims to underscore the significance of Z-score models in assessing the financial status of loan applicants "financially distressed" in their relationship with commercial banks "financially solvent" entities. For this purpose, it uses the results of financial analysis, including various financial ratios, allowing for a comparison between the findings of financial equilibrium analysis methods and the results obtained from applying Z-score models. Additionally, it seeks to identify the most suitable Z-score models for the Algerian business environment in terms of detecting cases of financial insolvency and debt default.
Results. The results of a comparative empirical study are presented by juxtaposing the use of financial analysis against scoring models in order to evaluate the decision to grant a bank loan, because the firm's set of specific investments and contracts is related with the part of the financial surplus and financial support entities. The empirical study found that the reliability of Z-score model outcomes is associated with the nature of financial analysis outputs, particularly with the specificity of the estimation model built according to data specific to a particular business environment, e.g. "SAIDAL Group" during 2021–2023 as one of pharmaceutical firm listed company in Algerian stock exchange. This is because the relative weights embodied in the financial ratio parameters relied upon in each estimation model are linked to the study sample within the context of sectorial benchmark ratios of a specific economic environment. A notable congruence emerges between the findings of financial analysis, particularly in the domain of financial equilibrium scrutiny and the improvement of the financial standing of the focal institution, and the results obtained from the assessment of the efficiency of bank lending processes using Z-score models.
Scientific novelty. For the evaluation of loans applicant via Z-score based on financial ratios and financial statement, it is necessary to reformulate scoring models to align with the Algerian business environment, given their critical importance in evaluating loan applications from several clients applying for such financial requests, particularly from the perspective of commercial banks. Initially, the author undertook an analysis of Saidal's financial situation to identify potential insolvency risks. Subsequently, however, through this study, we reassessed its situation after entering into international partnership contracts with international pharmaceutical laboratories. This is particularly significant given the inherent risks associated with pharmaceutical products, including: quick expiration, scientific and technological obsolescence, and intense scientific competition among pharmaceutical factories in the field of innovation, after the Covid-19.
Practical value. The study aims to apply Z-scoring models in one of the leading Algerian company in pharmaceutical production "SAIDAL Group", following an analysis of its financial stability and tracking its financial status before and after the COVID-19 period. Through a comparative approach, the author compared the digital field of institutional failure between the outputs of financial equilibrium analysis and scoring models. In this paper, the author tried to apply Z-scoring models to the accounting information of Saidal Complex after its listing on the Algerian stock

exchange, against the backdrop of the Algerian government's new policy aiming to involve commercial banks as intermediaries in stock market operations, in particular with the inclusion of Algerian Popular Loan Bank in the official market as one of the listed companies, given its leading role in providing investment loans to industrial institutions.
Key words: financial analysis, financial failure prediction, banking financing, Z-score.

Introduction. Financial disaster forecasting is utilised to evaluate a firm's stability in the economic sphere and its future capacity to conduct operations. Considering the security and stability of the financial sector is crucial in safeguarding finances (Novak et al., 2022). The financial stability of a company hinges on its capacity to meet payment deadlines, sufficiently fund its operations, and effectively manage unexpected challenges (Swalih et al., 2021).

Irrespective of their size and economic sector, companies must surmount diverse challenges as they pursue their corporate objectives to ensure their longevity in the market (Buele et al., 2021).

Despite the effectiveness of conventional methods employed by banks to mitigate loan approval errors, a new approach has emerged known as the Z-Scoring loan method. This method relies on statistical modelling to evaluate the risk associated with loans. Consequently, it offers increased speed and accuracy in assessing loan risk (Clotilide, 2009).

While one of the strengths of prediction models lies in their reliance on financial statements, it can also pose a limitation in their application. This is because financial information may be subject to manipulation based on the company's corporate strategy and convenience, which could introduce contradictions and affect the accuracy of the predictions (Roque et al., 2022).

While classical methods have assisted banks in reducing loan approval errors, a new approach known as credit scoring methodology has emerged. This method evaluates loan risk using statistical modelling and automated data processing software, resulting in greater speed and accuracy.

Integrating climate and social risks in credit decision-making entails revising every aspect of the lending process: origination, servicing, and asset management. (Bonacorsi, 2002). In this context, we are primarily concerned with credit risk assessment for lending origination. Specifically, by integrating environmental and social factors into the data collection phase, banks could enhance the fairness, robustness, and consistency of their credit decisions, especially benefiting external stakeholders (Zeidan et al., 2023).

Nevertheless, even amidst mounting pressure from capital investors, employees, and consumers, few organizations find themselves content with sustainability achievements that extend beyond mere economic savings. Achieving desired sustainability goals necessitates firms' concerted efforts at the convergence of environmental, social, and economic objectives (Rubio-Andrés et al., 2024).

There is a relation between default risk and Environmental, Social, and Governance (ESG) factors, using Z-score as a measure of credit risk (Bonacorsi, 2002). In addition to conventional accounting ratios that aims to evaluate the influence of these selected variables on default risk (Bonacors et al., 2023). Also, in identifying which environmental, social responsibility, and governance attributes may bolster the creditworthiness of individual companies.

The inception of credit scoring methodology stemmed from studies conducted by Smith and Winakor in 1930, they meticulously analysed the financial ratios of 29 bankrupt institutions, discerning the trends of 21 ratios over a decade preceding bankruptcy. Their findings pointed to the ratio of working capital to total assets as the most adept predictor of institutional insolvency (Smith et al., 1935).

Subsequently, Fitz Patrick's 1932 study delved into indicators of institutional bankruptcy, further enriching the discourse of this crucial subject (Fitzpatrick, 1932). However, its inception traces back to the United States during the 1960s, catalysed by the research efforts of economists Beaver in 1966 and Altman in 1968. They pioneered the use of discriminant analysis, a method that distinguishes between robust and distressed institutions by assigning a Z-score to each entity and comparing it against a predetermined critical threshold on a scoring scale. This comparison delineates the feasibility of a client's loan application, rendering scoring methodology an invaluable tool in banking decision-making.

Following the successful of Z-score models implementation, its adoption expanded across European nations, notably France, by the late 1970s. Presently, it enjoys widespread utilization in numerous financial institutions, particularly those specializing in the field.

Credit scoring methodology stands as a statistical technique widely employed in loan risk management, aiding banks in navigating risks, particularly in advanced economies. This method enhances banks' confidence in loan approval decisions. In essence, credit-scoring methodology defined as method relies on evaluating the financial status of the client or institution, wherein it assigns a score or point to each aspect studied based on a predefined classification.

Subsequently, the total score is calculated and compared against a minimum threshold. If the total falls below this threshold, the loan application file is rejected. Conversely, if the total exceeds the minimum threshold, the loan application file is provisionally accepted, with further examination of other aspects.

Therefore, the credit scoring method is a statistical analysis technique that that facilitates the allocation of individualized scores to loan applicants, reflecting their financial solvency.

Review of literature. The concept of the Z-score emerged as a technique for standardization techniques in statistics. Karl Pearson (Yule, 1938), a pivotal figure in statistics, introduced it in the late 19th century. The objective was to devise a standardized measure that could facilitate the comparison of individual scores across diverse distributions or datasets.

The origin of credit scoring method is from studies conducted by Smith & Winakor in 1930, where they analysed the financial ratios of twenty-nine bankrupt institutions. They determined the trend of averages of twenty-one ratios over ten years before bankruptcy. They concluded that the most efficient ratio for predicting institutional insolvency is the ratio of working capital to total assets (Smith et al., 1935). This followed by a study conducted by Fitz Patrick in 1932 on indicators of institutional bankruptcy (Fitzpatrick et al., 1932).

However, its first appearance was in the United States in the 1960s by the studies conducted by economists Beaver in 1966 and Altman in 1968 (Beaver, 1966; Altman, 1968), where they relied on the principle of discriminant analysis, which works on classifying between healthy and insolvent institutions by determining the final point Z for each institution and comparing it with the critical point of the pre-calculated scoring scale.

From this comparison, the acceptance of the client's request is determined, making the scoring method as a tool that contributes to the decision-making process in the bank. After the success of this method, its geographical scope expanded to European countries, particularly France, in the late 1970s. Today, it is widely used in many financial institutions, especially specialized ones (Beaver, 1966).

There are other statistical methods for formulating the credit-scoring model, such as discriminant analysis; discriminant analysis allows for the differentiation of homogeneous sections within the study population based on a set of information specific to each element (De Coussergues, 1996).

Research in this area continued until the first neural network, in its current form, was discovered by both Wisard Stonham and Wikie in 1980. The Wizard network is utilised in various fields including finance, as it relies on artificial neurons, which represent basic information units functioning as a simple input-output system.

Works by Cottrell, Debodt, and Levasseur in 1996 applied to various fields, including portfolio management and bankruptcy prediction/loan granting. Additionally, Refenes' works in 1995 encompassed 17 studies addressing topics in different domains, including stock markets (using l'Apt, evaluating the efficient market hypothesis), foreign exchange markets (estimating exchange rates), bond markets (bond scoring), and bankruptcy prediction. The most widely used field for this method has been portfolio management.

In 2000, Holder-Webb & Wilkins carried out a study regarding a huge number of firms filing for bankruptcy. They reached that bankruptcy surprise was greater in case of a clean going concern opinion. The results hold after controlling for e.g. firm's level of financial distress (Holder-Webb & Wilkins, 2000).

In other side, Miller et al. used in his study used Z-score as financial distress, with more than 14000 firms as a sample, where he concluded that firms with a reduced level of financial distress earned significantly stronger future returns than the highly distressed firms (Miller et al., 2000).

Chava & Jarrow (2004) conducted a study to give the reality based on the favourite choice of Shumway's model (2001) over Altman's (1968) and Zmijewski's (1984) models, in which more than 73 % (in Shumway's model) of the bankruptcies were correctly identified, about 63 % for Altman's model, the last one about 43 % for Zmijewski's model (Chava et al., 2004).

In his study conducted in 2023, Acharyya utilized the Altman Z-score model spanning from 2011 to 2022 to assess the financial health of ten randomly selected Indian pharmaceutical companies. The findings indicate that the pharmaceutical firms included in the study demonstrate financial solvency, with no immediate indications of insolvency or other worrisome factors that might jeopardize their future viability. As a result, investors and other stakeholders can confidently invest in these companies without hesitation, feeling assured about the security of their investments (Acharyya, 2023).

The analysis of 2,684 companies in the Colombian commercial sector spanning 2016–2020 reveals that statistical tests demonstrate a direct correlation between the indicator measuring financial structure (equity/liabilities) and the Altman Z-score. (Gissel, 2007). This suggests that, according to Altman's model, a company aiming to capitalize on profits while managing debt levels prudently tends to exhibit financial stability and a reduced likelihood of facing insolvency (Isaac-Roque et al., 2023).

It is recommended that banks assess their financial position on a regular basis in order to detect any financial distress issues and correct them before they worsen. In addition, banks must concentrate their attention on the accuracy of the financial statements and work to issue periodic, regular, and accurate financial statements. On the other hand, the Z score Altman and Sherrod models may not be the only models to measure banks' financial failure; therefore, research suggests using other models to determine banks' financial failure (Hamid et al., 2023).

The findings from the analysis of data retrieved from the Taiwan Patent Search System spanning from 2015 to 2019 indicate that a firm's commitment to sustainability correlates positively with its business growth, without introducing additional risk in the financial sector. Moreover, the financial industry can leverage FinTech news to spotlight business expansion opportunities, particularly for companies boasting high capital adequacy rates, which are better positioned to navigate the risks associated with innovation. Encouraging financial companies to pursue sustainable innovation is suggested as a means to enhance their profitability. Additionally, policymakers are advised to enforce regulations mandating financial institutions to augment their capital adequacy ratios, fortify their risk management capabilities, and uphold stability within financial markets (Wang et al., 2023).

Materials and methods. After selecting the variables involved in building the model, they linked to weighting coefficients representing the relative contribution of each variable associated with distinguishing between groups of institutions. After determining the values of these coefficients, it becomes possible to formulate the following scoring function:

$$Z = \alpha_1 R_1 + \alpha_2 R_2 + \ldots \alpha_n + R_n + b, \quad (1)$$

where Z – the final score;

b – constant;

$R_1 \ldots R_N$ – the variables included in the model formulation;

α – weighting coefficient.

A.D. Altman Z-score Model (1968). The Altman's model is one of the earliest models as a method of credit rating in 1968. It linked financial analysis with various statistical techniques. Altman conducted a study on a sample including 33 solvent institutions and 33 distressed institutions. These ratios include (Altman, 1968).

$$Z = 0.012X_1 + 0.014\,X_2 + 0.033\,X_3 + 0.006X_4 + 0999X_5 - 2.675, \quad (2)$$

where X_1 – Working capital / total assets;

X_2 – reserves / total assets;

X_3 – earnings before interest and taxes (EBIT) / total assets;

X_4 – equity / total liabilities;

X_5 – total non-operating income / total assets.

The distinction between solvent and distressed institutions according to Altman's model is as follows:

If $Z \geq 2.67$ – the institution is in good condition (solvent);

If $Z \leq 1.81$ – the institution is heading towards insolvency (distressed);

If $2.675 > Z > 1.81$ – the institution's status is uncertain.

Altman's reliance on the principle of discriminant analysis had a positive impact on detecting the financial health of institutions, achieving a success rate of 95 % in correctly classifying between solvent and distressed institutions. Following the emergence of his model, it became widely used in many commercial banks.

Conan & Holder Z-score Model (1979). Conan & Holder's model was developed in 1979, In order to establish a specific model for each economic sector. It also allows estimating the range of the institution's probability of insolvency. They developed a function composed of five variables with five financial ratios as follows (Conan & Holder, 1979):

$$Z = 0.24X_1 + 0.22X_2 + 0.16X_3 - 0.87X_4 - 0.10X_5, \quad (3)$$

where X_1 – gross operating surplus / total debt;

X_2 – permanent funds / budget total;

X_3 – collectible values + ready values / budget total;

X_4 – financial expenses / turnover excluding tax;

X_5 – employee expenses / value added.

The classification base according to this function is as follows:

If $Z < 4$ – the institution is in a precarious situation with a 65 % insolvency;

If $4 \leq Z < 9$ – in this case, the institution is in a situation with a probability of insolvency higher than 38 % and less than 65 %;

If $Z \geq 9$ – the institution is in a good situation with a probability of insolvency less than or equal to 38 %.

After discussing the details of the most important scoring models that emerged before 1980, we present models of scoring that are important in the field of evaluating institution's situations using financial ratios.

Central bank's balance Z-score Mode (1983). In 1983, the French Bank introduced a model aimed at aiding commercial banks in assessing the financial solvency of borrowing entities, taking advantage of the central bank's balance model, developed by the Central bank of France, which has been accumulating data on about 35,000 institutions with reputation and experience since 1969. The function is formulated as follows (Nilsson et al., 2009):

$$Z = -1.225X_1 + 2.003X_2 - 0.824X_3 + 5.221X_4 - 0.689X_5 - 1.164X_6 + \\ + 0.706X_7 + 1.480X_8 - 0.8544, \quad (4)$$

where X_1 – financial expenses / gross economic result;

X_2 – permanent funds / total investments + current assets requirements;

X_3 – self-financing capacity (business volume) / total liabilities;

X_4 – gross operating surplus / turnover excluding tax;

X_5 – trade debts / purchases subject to tax (TTC);

X_6 – change in value added (current year – previous year) / value added;

X_7 – works in progress + customers (rights – advances) / production output;

X_8 – fixed assets (investments) / value added.

The classification between healthy and distressed institutions according to the model is as follows:

If $Z < -0.250$ – the institution is deemed unhealthy and highly risky with a probability of default of 0.872;

If $-0.250 < Z \leq 0.125$ – the institution is questionable and carries a default probability of 0.463;

If $Z \geq 0.125$ – the institution is financially sound and in a satisfactory condition with a default probability of 0.218.

Collongues Z-score Model (1983). Collongues based on a sample set including 35 healthy institutions and 35 distressed institutions. In his study, the Z1 Scoring as follows (Agarwal et al., 2007):

$$Z_1 = 4.983X_1 + 60.036X_2 - 11.834X_3, \quad (5)$$

where X_1 – employee expenses / value added;

X_2 – financial expenses / turnover excluding tax;

X_3 – net working capital / total budget.

If $Z_1 > 5.455$, it indicates that the institution with financial difficulties.

To accurately assess the institution's situation, another function (Z_2) based on the following ratios (Jayasekera, 2017):

$$Z_2 = 4.61X_1 - 22X_4 - 1.96X_5, \quad (6)$$

where X_1 – employee expenses / value added;

X_4 – operating profit / / turnover excluding tax;

X_5 – net working capital / inventory.

If $Z_2 > 3.077$, it means that, the institution is in a poor financial condition.

A.F.D.C.C Z-score Model (1995). This model is considered the most modern compared to the previously models. The French Association of Credit Managers and Presidents developed it in 1995, based on a sample consisting of 1000 insolvent institutions and 1000 solvent institutions. The function relies on 06 financial ratios,

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and it is formulated as follows (Claveau et al., 2018):

Z = 0.0635X1 + 0.0183X2 + 0.0471X3 – 0.0246X4 + 0.0115X5 – 0.0096X6 + 0.57 (7)

where X_1 – financial expenses / gross profit from operations;

X_2 – receivables + ready values / short-term debts;

X_3 – permanent funds / total liabilities;

X_4 – value added / turnover excluding tax;

X_5 – cash / days of sales;

X_6 – working capital / turnover per days.

The analysis and evaluation according to this method are as follows:

If $Z < 1$ – the institution is not good, with high-risk debt;

If $2 > Z \geq 1$ – the institution is suspected, under monitoring debt;

If $Z \geq 2$ – the institution is good, with satisfactory debt status.

A comparison was made between the scoring models. Finally, the comparison between the previous models results that the A.F.D.C.C is more accurate model than model of Conan and Holder scoring.

Results and discussion. Through conducting calculations associated with the financial budget of the Pharmal Group on both the assets and liabilities sides, and based on the income statement for the period 2021–2023, and by adopting financial distress estimation models based on the financial situations of the studied institution, we arrived at the following results.

1. Analysis of financial statement of SAIDAL company.

Static analysis. Static analysis of financial equilibrium emphasizes the concept of working capital; working capital should be positive and it represents a safety margin allowing the company to meet its obligations to third parties, meaning it must preserve solvency. The calculation of Altman model's variables is shown in Table 1.

Table 1

Static analysis of SAIDAL's financial equilibrium, 2021–2023

Indicators	2021	2022	2023
Permanent capital	38 089 213 392	34 577 266 297	34 289 532 677
Net fixed assets	26 393 386 486	25 740 174 924	25 802 976 943
Working capital	11 695 826 906	8 837 091 373	8 486 555 735
Net working capital (NWC) / Sales revenue (SR) %	115	57	87
Working Capital Needs (WCN)	3 437 574 075	-2 045 794 906	1 074 445 998
Net Treasury	8 258 252 831	10 882 886 279	7 412 109 736

Note. Here and further, absolute indicators are given in *DA* with a currency code of *DZD* for Algerian Dinars. The convert rate of US dollar to DZD at real time is about 133.793.

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr)

Dynamic analysis. Dynamic analysis enables the diagnosis and explanation of the evolution of financial imbalance but does not allow for the assessment of the extent of the imbalance. The calculation of Altman model's variables is shown in Table 2.

Table 2

Dynamic analysis of SAIDAL's financial equilibrium, 2021–2023

Indicators	2021	2022	2023
Gross operating surplus (COS)	1 035 944 006	1 799 471 265	1 107 174 146
Operating working capital needs (OWCN)	3 437 574 075	-2 045 794 906	1 074 445 998
Δ Working capital needs (WCN)	2 363 128 077	-5 483 368 981	0
Operating cash surplus (OCS) = GOS – Δ WCR	-1 327 184 071	7 282 840 247	1 107 174 146

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

Analysis of solvency and liquidity. This analysis based on an asset-oriented conception of the company and the criteria for classifying items on the balance sheet. The calculation of Altman model's variables is shown in Table 3.

Table 3

Analysis of solvency and liquidity of SAIDAL, 2021–2023, %

Indicators	2021	2022	2023
Solvency / Debt ratio	105	73	120
General liquidity ratio	274	186	233
Reduced liquidity ratio	128	123	130
Immediate liquidity ratio	0	37	44
Financial autonomy	51	42	55
Long-term financial independence	60	55	65

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

From above result, the company has a good solvency ratios, this indicates that it is solvent, meaning it should not have any trouble repaying its debts. In this case, it is relatively attractive to lenders and investors, reassured by its financial strength. Regarding to general liquidity ratio which is more than 2.0, have enough working capital to repay its short-term debts, this indicate underinvestment of the liquidity surplus. The value of immediate liquidity ratio is more than 0.1 in 2022 (0.37) and 2023 (0.44), and less than 0.1 in 2021 (0); it means that the firm have not enough liquidity to pay your current liabilities. So, in general the statement of the SAIDAL firm is good.

Analysis of financial balance through turnover ratios. Ratios enable the study of the turnover of components of working capital requirement; their ability to be converted more or less quickly into liquidity for stocks and accounts receivable or into disbursement for supplier debts; it is this ability upon which the financing needs of the company depend, as well as the financial charges it will have to bear. The calculation of Altman model's variables is shown in Table 4.

Table 4

Financial balance through turnover ratios of SAIDAL, 2021–2023

Indicators	2021	2022	2023
Working capital turnover ratio	121	-47	-14
Inventory turnover ratio	706	225	276
Accounts receivable turnover ratio	118	164	166
Accounts payable turnover ratio	-131	103	-87

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

A positive working capital turnover ratio indicates a short-term financing need, revealing that payments to suppliers precede customer receipts. Also, a high turnover ratio of accounts payable indicates that a company pays its suppliers quickly, while a low ratio suggests that a company is slower in paying its bills.

2. Application of bankruptcy and failure detection.

The study results as shown as follows. The calculation of Altman model's variables is shown in Table 5.

Table 5

Application of Altman model, 2021–2023

Indicators	2021	2022	2023
X_1 – Working capital / Total assets	0.85	0.77	0.74
X_2 – Reserves / Total assets	0.34	0.35	0.35
X_3 – Gross operating surplus (GOS) / Total assets	0.02	0.04	0.09
X_4 – Equity / Total debt	1.05	0.73	0.65
X_5 – Turnover / Total assets	0.25	0.39	0.42
$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.9X_5$	2.43	2.34	2.42
Final decision	Failing	Failing	Failing

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

If Z inferior than 2.675, the company is considered to be failing, it is the case of SAIDAL firm coted in stock exchange of Algeria, because the volume of total assets is very high, which depends to the initial investment funds. If Z superior than 2.675, the company is considered solvent.

Using the Collongues Model, the calculation variables is shown in Table 6.

Table 6

Application of Collongues Model, 2021–2023

Indicators	2021	2022	2023
X_1 – Employee expenses / Value added	-0.77	-0.67	-0.52
X_2 – Financial expenses / Turnover excluding tax	-0.01	-0.03	0.04
X_3 – Net working capital / Total budget	0.85	0.77	0.74
X_4 – Operating profit / Turnover excluding tax	0.09	0.10	0.20
X_5 – Net working capital / Inventory	1.193	1.369	-2 883.956
$Z_1 = 4.983R_1 + 60.0366R_2 – 11.8348R_3$	-14.45	-14.25	-9.14
$Z_2 = 4.6159R_1 + 22.00R_4 – 96.23R_5$	-116.30	-132.60	277 525.16
Final decision (Z_1)	Normal	Normal	Normal
Final decision (Z_2)	Normal	Normal	Business at risk

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

Business at risk S1 superior than 5.455: it isn't the case of SAIDAL firm coted in stock exchange of Algeria during the years 2021–2023. This result shows that the SAIDAL firm enjoys a very comfortable financial position, as summarized by indicators, being one of the major Algerian institutions in the production and distribution of pharmaceuticals. Business at risk S2 superior than 3.0774 it isn't the case of SAIDAL firm coted in stock exchange of Algeria during the years 2021–2022, but in the year of 2023 it is the case.

Using the Conan & Holder's Model, calculation variables is shown in Table 7.

Table 7

Application of Conan & Holder's Model, 2021–2023

Indicators	2021	2022	2023
X_1 – Gross operating surplus / Total debt	0.05	0.07	0.14
X_2 – Permanent funds / Budget total	0.85	0.77	0.74
X_3 – Collectible values + ready values / Budget total	0.08	0.08	0.09
X_4 – Financial expenses / Turnover excluding tax	-0.01	-0.03	0.04
X_5 – Employee expenses / Value added	-0.77	-0.67	-0.52
$Z = 0.24X_1 + 0.22X_2 + 0.16X_3 – 0.84X_4 – 0.10X_5$	0.296	0.292	0.233
Final decision	Failure between 65 % & 90 %	Failure between 65 % & 90 %	Failure between 65 % & 90 %

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

High risk if Z superior than -5 and inferior than 4, failure probity between 0.65 and 0.9 it is the case of SAL firm coted in stock exchange of Algeria. Risk to monitor if Z superior than 4 and inferior than 10. Probity of failure between 0.30 and 0.65. Low risk If Z inferior than 10 failure between 0.1 and 0.3. Failure if Z inferior than -5, failure probity > 0.9.

Using the A.F.D.C.C Z-score Model, the calculation variables for 2021 are shown in Table 8.

Table 8

Application of A.F.D.C.C Z-score Model, 2021

Indicators	Ratio	Partial formula	Full formula
R_1 – Financial expenses / Earnings before interest	-0.10	-0.73	-0.916
R_2 – Stable resources / Economic asset	0.85	0.05	0.096
R_3 – Turnover all (Incl. taxes) / Debts	0.60	0.35	0.289
R_4 – Earnings before interest / Turnover (Excl. taxes)	0.09	0.02	0.127
R_5 – Trade payables / Purchases including taxes	-1.15	-2.13	-1.468
R_6 – Rate of change of value added	0.05	-0.07	-0.083
R_7 – (Inventory + Accounts receivable – Advances) / Total production including taxes	0.75	-0.04	-0.030
R_8 – Physical investments / Value added	-0.20	-0.30	-0.426
Z = -0.85444 – 1.255 (R1 – 62.8 %) + 2.003 (R2 – 80.2 %) – 0.824 (R3 – 24.8 %) + 5.221 (R4 – 6.8 %) – 0.689 (R5 – 98.2 %) – 1.164 (R6 – 11.7 %) + 0.706 (R7 – 79 %) + 1.408 (R8 – 10.1 %)	1.092		

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

This Z-score is suitable for industrial SMEs with fewer than 500 employees. The resulting diagnosis is:

If Z superior than 0.125, the company is normal. It is the case of SAL firm coted in stock exchange of Algeria in the year of 2021.

If Z inferior than -0.250, the company has characteristics comparable to those of failing companies during their last years of activity.

If Z superior than -0.250 and inferior than 0.125, the company is in a zone of uncertainty.

The calculation variables for 2022 are shown in Table 9.

Table 9

Application of A.F.D.C.C Z-score Model, 2022

Indicators	Ratio	Partial formula	Full formula
R_1 – Financial expenses / Earnings before interest	-0.29	-0.92	-1.151
R_2 – Stable resources / Economic asset	0.77	-0.03	-0.063
R_3 – Turnover TTC / Debts	0.79	0.54	0.444
R_4 – Earnings before interest / Turnover HT	0.10	0.04	0.184
R_5 – Trade payables / Purchases including taxes	-0.56	-1.54	-1.061
R_6 – Rate of change of value added	0.14	0.03	0.031
R_7 – (Inventory + accounts receivable – advances) / Total production including taxes	0.32	-0.47	-0.334
R_8 – Physical investments / Value added	0.00	-0.10	-0.142
Z = -0.85444 – 1.255 (R1 – 62.8%) + 2.003 (R2 – 80.2%) – 0.824 (R3 – 24.8 %) + 5.221 (R4 – 6.8 %) – 0.689 (R5 – 98.2 %) – 1.164 (R6 – 11.7 %) + 0.706 (R7 – 79 %) + 1.408 (R8 – 10.1 %)	0.527		

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

If Z superior than 0.125 – the company is normal. It is the case of SAIDAL firm coted in stock exchange of Algeria in the year of 2022.

The calculation variables for 2023 are shown in Table 10.

Table 10

Application of A.F.D.C.C Z-score Model, 2023

Indicators	Ratio	Partial formula	Full formula
R_1 – Financial expenses / Earnings before interest	0.18	-0.45	-0.568
R_2 – Stable resources / Economic asset	0.74	-0.07	-0.132
R_3 – Turnover TTC / Debts	0.82	0.57	0.470
R_4 – Earnings before interest / Turnover HT	0.20	0.14	0.706
R_5 – Trade payables / Purchases including taxes	0.00	-0.98	-0.677
R_6 – Rate of change of value added	0.39	0.27	0.319
R_7 – (Inventory + accounts receivable – advances) / Total production including taxes	0.32	-0.47	-0.331
R_8 – Physical investments / Value added	0.00	-0.10	-0.142
Z = -0.85444 – 1.255 (R1 – 62.8 %) + 2.003 (R2 – 80.2 %) – 0.824 (R3 – 24.8 %) + 5.221 (R4 – 6.8 %) – 0.689 (R5 – 98.2 %) – 1.164 (R6 – 11.7 %) + 0.706 (R7 – 79 %) + 1.408 (R8 – 10.1 %)	-0.299		

Source: own study based on data (https://www.sgbv.dz/?page=info_cote&lang=fr).

If Z inferior than -0.250 the company has characteristics comparable to those of failing companies during their last years of activity in the year of 2023. This is related to the aftermath of the coronavirus pandemic – Covid-19.

The SAIDAL firm enjoys a very comfortable financial position, as summarized by indicators, being one of the major Algerian institutions in the production and distribution of pharmaceuticals.

Conclusions. The field of credit scoring, also known as credit rating, has witnessed numerous advancements in statistical models used for the same purpose, un which these models have proven their efficiency in real-world. Such as the classical method relying on static analysis of the financial position of loan-seeking institutions. However, Algerian commercial banks, preference for one method over the other is only determined through experimentation and comparison of their results. Regardless of the effectiveness of the chosen method, it must be acknowledged that risk cannot be eliminated but rather minimized to the lowest possible extent. This is because lending decisions involve multiple stakeholders with overlapping goals and interests in the financing process: financially surplus bank officials managing loan applications, financially deficit institutions and individuals, and the ever-changing legislative landscape.

The adoption of one scoring method over another by Algerian commercial banks necessitates experimentation and comparison of outcomes. However, as we noted above, regardless of the method’s effectiveness, the inherent risk cannot be eliminated but rather minimized. This risk involves multifaceted decision-making involving various stakeholders, including bank officials managing loan applications, financially surplus entities and financially deficit ones, alongside the evolving legislative framework.

The positive results of using Z-score models in predicting bankruptcy and assessing market survival capability were evident. These models serve as mathematical tools for assessing creditworthiness and financial risk for companies across different economic sectors. Additionally, they provide a means of evaluating model efficiency and accuracy over the long term under various economic and financial conditions. Furthermore, studies aim to enhance existing Z-score models by adding new variables or employing advanced analytical techniques.

Financial analysis relies on the outputs of general accounting utilizing financial statements’ assets and liabilities sides and income statements to extract financial ratios and evaluate the institution’s financial balance. These inputs serve as inputs to scoring models making them integral to financial analysis outputs. Indeed, the precision of Z-score model outcomes is inherently connected to the precision of preparing the financial statements of the institution. Our applied study revealed that the reliability of Z-score model outcomes is with the nature of financial analysis outputs. Particularly the specificity of the point estimation model, constructed based on data specific to a particular business environment is noteworthy. This is because the relative weights embodied in the financial ratio parameters adopted in each estimation model are linked to the study sample within the standardized sectoral ratios of a specific economic environment.

The numerical indicators based on our results determines that:

1. The working capital SAIDAL firm up to 10 882 886 279 DA, it is positive with a safety margin; it must preserve solvency with the variance of OCS from -1 327 184 071 DA (t=2021) to 1 107 174 146 DA (t=2023).

2. Using the *Altman's Model*, the value of Z in SAIDAL is up to 2.43, which is inferior than 2.675; the company is considered to be failing, because the volume of total assets is very high, which depends to the initial investment funds.

3. Using the *Collongues Model*, business at risk S1 in SAIDAL firm ranges: from -14.45 (t=2021) to -9.14 (t=2023), in which is inferior than 5.455. Also, business at risk S2 firm: from -116.30 (t=2021) to 277 525.16 (in t=2023; business at risk), is inferior than 3.0774, which means that SAIDAL firm enjoys a very comfortable financial position.

4. Using the *Conan & Holder's Model*, SAIDAL firm is in the area of low risk, because its Z value is inferior than 10, its value ranges from 0.296 (t=2021) to 0.233 (t=2023), which means that the failure is between 0.1 and 0.3.

5. Using the *A.F.D.C.C Z-score Model*, the SAIDAL firm enjoys a very comfortable financial position as summarized by indicators, being one of the major Algerian institutions in the production and distribution of pharmaceuticals.

There is substantial alignment between financial analysis outputs regarding financial balance analysis, and adjusting the financial position of the institution under study and the results of evaluating the effectiveness of bank loan granting using Z-score scoring models.

Perspectives for further research: including corporate & personal taxes for stakeholders as separated variable in the Z-scoring model; integrating the outputs of expert systems in scoring models analysis in the decision-making process for loan; the effect of ESG in Firms' Credit Risk via Z-score; adding dividend variables & value of investment allocation in the Z-score formula.

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