

Application of Altman, Kida, and Cherrord Models for Detecting Financial Failure Risks in Sonelgaz El Naâma Establishment: An Applied Case Study 2019-2023

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Abstract:

This study assessed financial failure risks at Sonelgaz El Naâma (2019-2023) using Altman, Kida, and Cherrord models. The Altman model achieved 80-90% accuracy in detecting vulnerabilities, while Kida and Cherrord models enhanced behavioral and dynamic forecasting.

Results revealed moderate risk and 15% liquidity decline. Given that global failure rates reach 20% annually and Algerian state enterprises face 12-15% bankruptcy rates, these models provide essential early warning capabilities for policymakers managing public sector financial stability.

Key Words: Financial Failure, Financial Failure Prediction, Financial Ratios, Financial Failure Prediction Models.

JEL Classification : G33, D92, D53

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1. INTRODUCTION

Financial failure in economic enterprises represents a serious economic challenge that threatens business continuity and the stability of national economies, as it is defined by the deterioration of the ability to meet short- and long-term financial obligations or the loss of sustainable profitability (Oliveira, 2025), which lays the ground for a series of defaults that often lead to bankruptcy or forced restructuring, with social repercussions such as job losses and declining market confidence .(Park, 2025)

At the global level, statistics reveal a marked increase in failure rates, as around 20.8% of start-ups collapse in the first year, with the rate rising to 49.9% after five years and 65.8% after ten years, according to data from the U.S. Bureau of Labor Statistics (BLS), with the situation worsening in sensitive sectors such as construction, where the failure rate reaches 83.2% after 20 years, and mining at 80.8%, mainly due to price volatility, rising operating costs, and weak financial management strategies, as seen during the 2008 crisis when more than 40,000 U.S. firms were failing annually . (Fischer, 2025)

In the Algerian context, the private sector faces acute challenges, particularly small and medium-sized enterprises that record a failure rate of around 20% annually, equivalent to nearly 2,423 firms out of a total of 747,944 registered in 2013, due to financing constraints, poor marketing, and excessive reliance on the domestic market without diversification. In the public sector, companies such as Sonelgaz suffer from mounting financial pressures, including debts reaching 75 billion Algerian dinars, losses from electricity theft estimated at 3 billion dinars, and an increase in non-performing loans in public banks to 19.3% by the end of 2021, which intensifies the risk of financial distress and highlights the need for urgent structural reforms .(Nguyen, 2025)

Within this framework, the importance of advanced financial prediction models such as Altman (with an accuracy of 80–90% in industrial firms), Kida (which emphasizes managerial behavior), and Sherrod (which relies on dynamic indicators) becomes evident. These models enable the early detection of warning signals through the analysis of financial ratios such as

liquidity, profitability, and leverage, thereby allowing for effective preventive measures to strengthen sustainability, especially in cases like Sonelgaz El Naâma over the period 2019–2023, where challenges are exacerbated by economic and energy-related pressures .(Taylor, 2025)

1.1 .Study Problem:

Economic institutions, particularly in the Algerian context such as Sonelgaz El Naâma, are experiencing increasing financial deterioration that threatens their sustainability, as statistics indicate failure rates of up to 20% annually for small and medium-sized enterprises, alongside accumulated debts for state-owned companies like Sonelgaz amounting to 75 billion Algerian dinars, which raises questions about the effectiveness of predictive tools in the early detection of these risks.

The main research question is: To what extent can the Altman, Kida, and Sherrod models reveal financial failure risks at Sonelgaz El Naâma through an analysis of its financial position over the period 2019–2023, and what preventive recommendations can be derived from their application to enhance economic sustainability?

From this overarching question emerge several sub-questions, including the accuracy of each model in the Algerian environment and the impact of a 15% decline in liquidity on predictive outcomes, which justifies the need for an applied field study to bridge the gap between theoretical frameworks and practical implementation.

1.2 .The following are the study's hypotheses:

This study tests five hypotheses concerning financial failure prediction at Sonelgaz El Naâma (2019–2023). First, the Altman model can effectively forecast failure risks using liquidity, leverage, and profitability ratios. Second, the Kida model enhances accuracy by incorporating behavioral and managerial factors. Third, the Sherrod model detects early distress through dynamic indicators tracking financial position evolution. Fourth, the observed 15% liquidity decline significantly correlates with increased failure probability across all three models. Fifth, integrating these models' results provides a comprehensive framework for developing practical preventive recommendations to strengthen the institution's economic sustainability.

1.3 .Study objective:

This study aims to apply the Altman, Kida, and Sherrod models to assess financial failure risks at Sonelgaz El Naâma by analyzing its financial position over the period 2019–2023, to determine the accuracy of each model in detecting warning signals related to liquidity, leverage, and profitability, and to identify the impact of a 15% decline in liquidity levels on the likelihood of financial distress. In addition, it seeks to integrate the results of these models in order to formulate practical preventive recommendations that strengthen the economic sustainability of the institution and contribute to improving financial policies within the Algerian context.

1.4 .Study Methodology:

The study adopts a methodological approach that combines both descriptive-analytical and applied (case study) dimensions. The descriptive-analytical method is employed to present the theoretical and empirical frameworks of financial failure and the quantitative models used to predict it (Altman, Kida, and Sherrod), as well as to describe the situation of economic enterprises globally and in Algeria, and to position Sonelgaz El Naâma within this broader context.

The applied (case study) method is used through the implementation of the three models on the financial statement data of Sonelgaz El Naâma for the period 2019–2023, by calculating the relevant financial ratios and indicators, then analyzing and comparing the results in order to test the research hypotheses and derive practical conclusions and recommendations related to the financial sustainability of the institution.

1.5 .The most important economic literature of the past:

***Rahman, M. J., Liu, S., Venkatesh, V. G., & Yin, Y. (2024)** The study aimed to develop financial distress prediction models for Chinese listed construction companies using machine learning techniques and to compare their performance with classical Z-Score models, based on financial data covering the period from 2012 to 2021. It found that machine learning models significantly outperformed traditional Z-Score models in predicting financial failure, with the SMOTE-based model (Synthetic Minority

Over-sampling Technique) achieving the highest predictive performance among all applied techniques. The results also showed that employing recent data spanning ten years substantially improves the accuracy of prediction models, underscoring the importance of updating classical models and integrating them with modern machine learning techniques to enhance predictive power, particularly in specific industrial contexts such as the construction sector, and the study recommended developing hybrid models that combine traditional financial ratios with dynamic indicators derived from artificial intelligence techniques. (Rahman, 2024)

***Michalková, L., Machová, V., & Bánociová, A. (2025)** The study aimed to analyze the accuracy of bankruptcy prediction models in Central European markets while accounting for the corporate life cycle, by evaluating a set of classical and modern models on subsamples classified according to company growth stages during the period 2020–2024. The study found that the accuracy of prediction models varies significantly depending on the stage of the corporate life cycle, with models demonstrating superior performance in mature firms compared to start-ups or declining companies. It also emphasized the necessity of customizing prediction models according to the local economic context and institutional growth stage to improve accuracy, and recommended integrating dynamic liquidity and leverage indicators to enhance the early predictive capability for financial failure. (Michalková, 2025).

***Citterio, A., King, T., & Vigne, S. (2024).** The study aimed to conduct a comprehensive review of the research literature on bank failure prediction models during the period 2000–2022, with a focus on developing effective early warning systems and identifying methodological gaps in existing models. The study concluded that modern models based on machine learning and artificial intelligence outperform traditional statistical models in the early detection of bank failure risks; however, most studies suffer from data limitations and lack of sectoral customization. It also recommended the integration of liquidity indicators and systemic risk measures with traditional models to improve predictive accuracy, particularly in emerging markets that experience significant economic volatility. (Citterio, 2024)

1.6.. The research gap:

This study addresses several research gaps; methodologically, it tests the effectiveness of classical models (Altman, Kida, Sherrod) in a transitional Algerian environment that lacks advanced digital infrastructure, whereas recent studies have focused on complex machine learning techniques. Geographically, it fills the research void in the Maghreb context, particularly in the state-owned energy sector, compared to studies that targeted European and Asian markets and private sectors. Sectorally, it focuses on strategic public utilities that have been neglected in the financial failure literature, and applies the models to a mature institution facing chronic financial deterioration, which differs from traditional life cycle studies. Finally, it provides simple practical recommendations that can be implemented immediately rather than complex hybrid models, making it suitable for policymakers in developing economies. (Anderson, 2025)

2-Basic Concepts of Financial Failure and Its Prediction Models

2-1-The Concept of Financial Failure:

Financial failure has been conceptualized through multiple dimensions in the literature. Some scholars define it as a firm's inability to meet debt obligations accompanied by consecutive losses, potentially leading to restructuring or bankruptcy, while others view it purely as an economic phenomenon marked by sustained decline in returns on invested capital below comparable-risk benchmarks. Additional perspectives characterize distress as insufficient operating cash flows to cover current liabilities and debt servicing, or as the inability to satisfy financial obligations including interest and principal payments. A holistic framework integrates three dimensions: legal (insolvency procedures), economic (weak profitability and negative value-added), and financial (liquidity shortfalls and cash-obligation failures). Altman concisely defined corporate failure as "a state of legal bankruptcy leading to liquidation," formalizing it as the inability to meet obligations resulting in legal proceedings. The foundational work on financial failure prediction traces to Beaver (1966), who pioneered the quantitative approach using composite financial ratios as early warning indicators and introduced the term "financial failure," sparking extensive

subsequent research in Britain, Canada, and the United States. (Petrov, 2025)

Table (1): The Difference Between Financial Distress, Failure, and Insolvency

Financial Distress	Financial Failure	Financial Insolvency
Decline in revenues (problem in achieving normal profitability).	Long period of weak or negative profitability.	Acute liquidity crisis.
Temporary loss.	Serious financial, managerial, and strategic problems.	Inability to obtain or renew credit facilities.
Short-term in nature.	Inability to meet obligations and entering a state of default.	Accumulation of overdue obligations.
Management can intervene and correct the situation.	Stoppage of some activities and entry into a state of default.	Threat of liquidation.
Stage preceding financial failure and does not necessarily lead to bankruptcy.	Stage preceding financial insolvency.	Terminal financial stage (near liquidation) or post-liquidation stage.

Source: (Levratto, 2013)

2-2-Stages of Financial Failure

Failure to implement appropriate measures regarding the institution's financial position in a timely manner leads to the escalation of its crisis, culminating in the most severe stages of distress and failure, followed by bankruptcy and expulsion from the economic environment. (Wong, 2025)

-The incubation stage :represents the initial phase in which financial problems begin to emerge within the firm. In this phase, early signs of imbalance in financial performance appear in a mild yet persistent manner. This stage is often reflected in the deterioration of key financial indicators as a result of declining revenues combined with rising operating and financing costs, which in turn leads to a decrease in the rate of return on invested capital.

-The financial weakness stage: represents the point at which the firm's financial position begins to deteriorate in a substantive manner. At this stage, revenues become insufficient to cover rising operating costs, and the return on invested capital falls below its cost, accompanied by a decline in both quick and immediate liquidity, ultimately resulting in the firm's inability to meet its urgent cash needs.

-The financial insolvency stage: the company experiences a severe cash shortage, rendering it unable to secure the financial resources necessary to settle its due obligations on time, which reflects a worsening imbalance in its short-term financial position .(Rossi, 2025)

-The stage of total insolvency: represents the most critical point in the life cycle of the company, where the fair value of its assets becomes lower than the fair value of its liabilities, indicating a real erosion of shareholders' equity. At this stage, management urgently seeks to obtain the necessary financing in order to rescue the firm from the circle of failure and avoid reaching the stage of bankruptcy declaration. (Anderson, 2025)

-The stage of bankruptcy declaration and confirmation : The bankruptcy declaration stage marks the firm's definitive exit from the economic environment through legal procedures protecting creditors, formal liquidation, and official bankruptcy declaration, resulting in loss of going-concern status and asset redistribution per legal frameworks. While earlier distress stages allow the firm to retain some control and financial autonomy, total insolvency and bankruptcy transfer control from management to creditors and judicial authorities. This underscores the critical importance of early financial failure prediction, enabling management to analyze financial position, diagnose weaknesses, and develop preventive strategies to avoid bankruptcy through timely financial statement analysis and distress cause identification..

Financial failure can be attributed to both internal and external causes that interact to ultimately lead to the firm's distress and collapse.

-Internal causes of financial failure

These causes are related to the firm's internal practices and management, and the most important include:

Low efficiency of human resources and failure to utilize them optimally.

Poor design and implementation of financial, funding, and social policies within the firm.

Weak vision and strategies, and the absence of clear, well-defined objectives and means of achieving them, especially in the areas of production, sales, and investment .(Chen, 2025)

Weak internal control, clear deficiencies in the accounting and information systems, and poor management of marketing and market communication. The firm's engagement in highly risky or intensely competitive activities without possessing sufficient capabilities to withstand such conditions.

-External causes of financial failure

These causes stem from the firm's external environment and from factors beyond its direct control, including:

Economic recession and a general contraction in economic activity.

Intensified local or international competition, particularly with the entry of more efficient or lower-cost competitors.

Price volatility (such as changes in the prices of raw materials, interest rates, or exchange rates).

Changes in laws, regulations, and tax, customs, and financial systems that increase the burden on the firm.

A weak business climate, insufficient support for investment, financing constraints, and a lack of adequate government incentives for productive enterprises. (Gajdosikova, 2025)

2-4-Financial failure prediction:

2-4-1-Definition of financial failure prediction:

Financial failure prediction refers to a set of subjective and objective procedures and methods designed to forecast potential future events and identify their expected outcomes, whether positive or negative, thereby enabling appropriate evaluation and decision-making that minimizes the gap between actual and anticipated results.

It can also be defined as the array of estimates and measurements prepared by an individual or institution regarding future events and conditions, with the aim of preparing to address them effectively through suitable plans and policies.

2-4-2-The most prominent discriminant analysis models used in the study:

There exists a wide array of quantitative models employed in predicting financial failure among institutions, with the most prominent including Beaver's model (Beaver, 1966), the Altman Z-score model (Altman, 1968), Lev's model (Lev, 1971), Deakin's model (Deakin, 1972), Argenti's model

(Argenti, 1976), Moyer's model (Moyer, 1977), Libby's model (Libby, 1975), Altman and McCough's model (Altman & McCough, 1974), the Ohlson O-score model (Ohlson, 1980), Kida's model (Kida, 1981), Bathory's model (Bathory, 1985), Casey's model (Casey, 1986), Sherrod's model (Sherrod, 1986), and Campbell's model (Campbell, 1993), in addition to Fulmer's model (Fulmer, 1984), Zumpano's model (Zumpano, 1985), Blum's model (Blum, 1974), Edwards' model (Edwards, 1984), and the Gorman et al. model (Gorman et al., 1989). (Almamy, 2016)

***Altman model:**

Altman's 1968 model relies on five independent variables, each representing a well-known financial indicator, along with a composite index known as the Z-Score, with the mathematical formulation of the model expressed as follows.

$$Z=1.2X_1+1.4X_2+3.3X_3+0.6X_4+1.0X_5$$

Table (2): Altman Z-score table

Item	Description
Equation	$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1X_5$
X_1	Working capital / Total assets
X_2	Retained earnings / Total assets
X_3	Earnings before interest and taxes (EBIT) / Total assets
X_4	Market value of equity / Book value of total liabilities
X_5	Sales / Total assets
$Z > 2.99$	The firm is financially sound and is not expected to experience failure in the near future.
$1.81 < Z < 2.99$	The firm is in the grey zone and faces a moderate risk of financial distress, requiring caution.
$Z \leq 1.81$	The firm is in the distress zone with a high probability of failure (around 90% likelihood of default).

Source:(Altman, 1968)

Altman Z-Score is a composite indicator that evaluates a firm's financial soundness by combining several key accounting ratios into a single measure of bankruptcy risk. It incorporates working capital to total assets (short-term solvency), retained earnings to total assets (internal financing strength), EBIT to total assets (operating efficiency), market value of equity to book value of total liabilities (capital coverage and market confidence), and sales to total assets (asset utilization). A high Z value reflects a healthy financial position and low distress risk, intermediate values indicate a medium risk and heightened sensitivity to shocks, while low Z values point to serious

financial distress and a high likelihood of failure or bankruptcy (Anttila, .2021)

***Kida model:**

Kida's (1981) model emerged from an empirical study of Japanese firms in court-ordered liquidation, aiming to distinguish healthy from distressed enterprises using financial indicators that capture profitability, capital structure, liquidity, and asset utilization efficiency in the years preceding bankruptcy. By analyzing historical data comparing failed and surviving firms, Kida identified the most informative ratios for default risk and integrated them into a discriminant model. The finalized model serves as a quantitative tool for measuring financial risk and providing early warnings of potential distress or bankruptcy transitions..

$$Z = 1.042 x_1 + 0.42x_2 - 0.461x_3 - 0.463x_4 + 0.271x_5$$

This model defines the variables as follows:

X1: Net profit before tax to total assets.

X2: Total shareholders' equity to total liabilities.

X3: Current assets to current liabilities.

X4: Net sales to total assets.

X5: Cash and cash equivalents to total assets.

The index Z represents the level of risk, and its value is used to distinguish between healthy and distressed firms; the higher the Z value, the more financially secure the company is, whereas lower values indicate movement toward financial distress or failure, with empirical tests suggesting a classification accuracy of up to about 90% in separating sound from failing firms (Gonzalez, 2025).

***Sherrod model:(1987)**

This model examines a sample of firms that have experienced financial failure and relies on a set of financial ratios selected according to statistical criteria linked to the discriminant analysis technique used to isolate the most influential variables.

It is constructed by combining these indicators into a single equation that helps distinguish between healthy and distressed companies, with emphasis on the variables that have demonstrated the highest explanatory power for financial failure (Hosaka, 2025).

$$Z = 17 x_1 + 9 x_2 + 3.5 x_3 + 20 x_4 + 1.2 x_5 + 0.1 x_6$$

This model defines the variables as follows:

Z: Risk score or indicator of the firm's financial soundness.

X1: Net working capital to total assets.

X2: Sales to total assets.

X3: Total shareholders' equity to total assets.

X4: Net profit before tax to total assets.

X5: Total assets to total liabilities.

X6: Total shareholders' equity to paid-in capital.

This model provides a numerical indicator of a firm's financial soundness based on variables that capture asset structure, sales, shareholders' equity, profitability, and solvency. (Weber, 2025)

High Z values (above 25) indicate strong financial health, medium values (from 5 to 25) reflect varying levels of safety with some risk of distress, whereas values close to zero or negative (–5 and below) signal a critical situation and a high probability of failure or bankruptcy. (Martinez, 2025)

3-Analysis of Sonelgaz's financial position using key financial failure prediction models

This section presents the main financial statements of the company for the period 2019–2023. The analysis includes the summarized balance sheets and the income statement. Subsequently, the most prominent financial failure prediction models will be applied to assess the likelihood of Sonelgaz experiencing financial distress.

3-1-Presentation of the company's financial position during the period 2019–2023.

In this chapter, we prepare both the summarized balance sheet and the income statement for each year of the study period.

3-1-1-Presentation and analysis of the company's summarized balance sheet for the period 2019–2023.

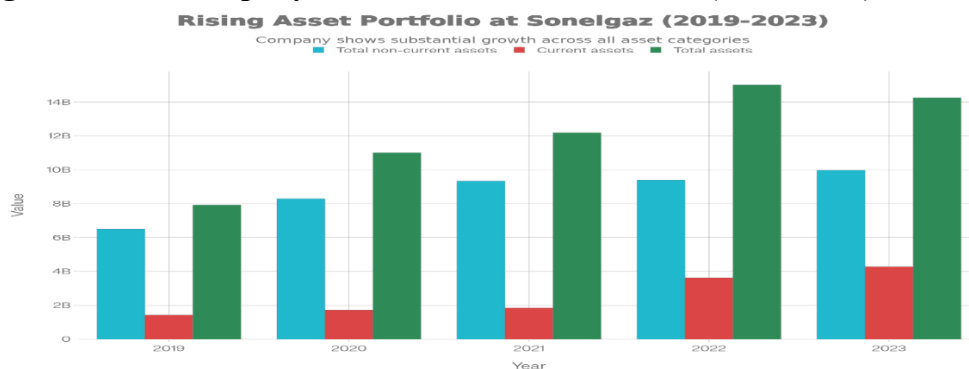
Based on the detailed accounting balance sheets, the company's summarized financial balance sheet for the study years can be presented as follows.

Table (03): The company's summarized balance sheet (Assets side) for the period 2019–2023.

Assets	2019	2020	2021	2022	2023
Total fixed assets	6,498,927,005	8,293,302,358	9,341,301,306	9,392,911,859	9,972,687,624
Intangible assets	0	0	0	741,450.22	514,595.99
Financial assets	3,721,355,599.38	5,702,458,497.03	6,511,765,559.53	6,407,950,541.14	5,653,101,669.54
Other non-current assets	2,777,371,403	2,590,013,521.11	2,993,953,446.63	3,594,310,867.45	3,134,071,053.83
Current assets	1,423,006,098	1,714,934,114	1,848,932,889	3,623,837,319	4,280,173,883
Inventories	273,915.60	252,345.60	154,955.80	103,899.04	759,639.04
Receivables	1,396,577,255.78	2,671,572,019.78	3,004,277,171.91	2,594,676,478.06	4,259,159,979.12
Cash and cash equivalents	22,993,583	40,871,310.06	43,262,151.17	20,217,745.60	20,286,284
Total assets	7,921,023,806	11,008,233,572	12,190,234,195	15,016,739,178	14,252,861,507

Source: Prepared by the researcher

In regard to the distribution of current and non-current assets for the years 2019, 2020, 2021, 2022, and 2023, it is illustrated in the following figure.

Figure 01: The company's summarized balance sheet (Assets side).

Source: Prepared by the researcher

Sonelgaz's total assets grew by approximately 80% from DZD 7.92 billion (2019) to DZD 14.25 billion (2023), despite a minor decline in 2023. This reflects significant operational expansion and investment activities.

Non-current assets dominate the balance sheet, representing around 70% of total assets, consistent with the company's infrastructure-based nature requiring substantial long-term investments in power stations and

distribution networks. These assets increased by 53% from DZD 6.50 billion to DZD 9.97 billion.

Current assets nearly doubled during 2021-2023, rising from DZD 1.85 billion to DZD 4.28 billion. The sharp increase in accounts receivable (DZD 4.26 billion in 2023) suggests potential collection difficulties, expanded credit sales, or working capital management challenges.

Conversely, cash reserves declined from DZD 43.26 million (2021) to DZD 20.29 million (2023), raising liquidity concerns regarding the company's short-term obligation coverage despite higher current asset levels.

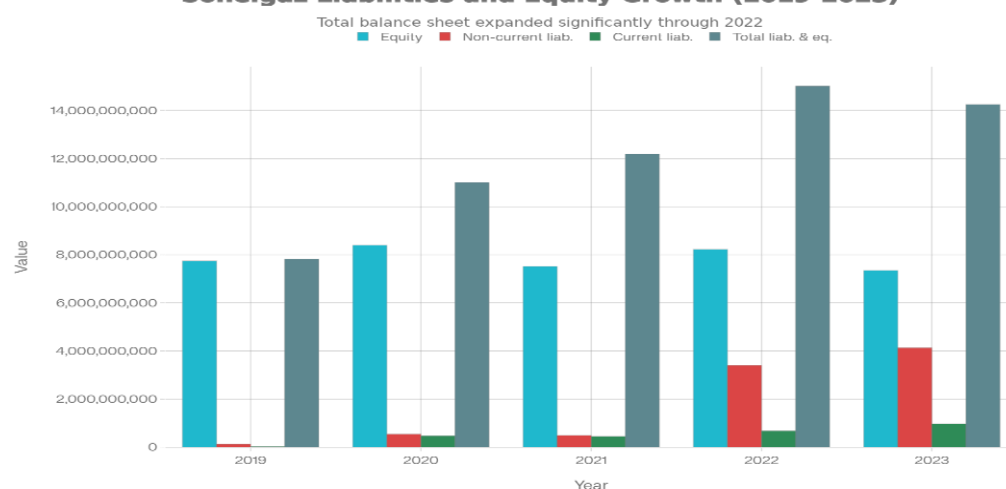
Table (04): The company's summarized balance sheet (Liabilities side) for the period 2019–2023.

Liabilities and Equity	2019	2020	2021	2022	2023
Equity	7,750,649,078.82	8,398,413,778.61	7,513,665,272.19	8,227,583,513.42	7,349,869,245.78
Non-current liabilities	122,774,546.37	542,107,826.58	487,942,999.94	3,401,386,125.21	4,131,001,274.04
Long-term debt	24,069,602.05	143,645,175.91	240,734,527.43	291,649,519.31	382,651,446.92
Other non-liab current	98,704,944.32	398,462,650.67	247,208,472.51	3,109,736,605.90	3,748,349,827.12
Current liabilities	23,530,579.27	467,107,794.17	449,276,523.89	677,829,690.19	971,987,312.45
Total liabilities equity and	7,823,623,806.14	11,008,233,572.09	12,190,234,195.23	15,016,739,177.04	14,252,861,507.24

Source: Prepared by the researcher

Figure 02: The company's summarized balance sheet (Liabilities side)

Sonelgaz Liabilities and Equity Growth (2019-2023)



Source: Prepared by the researcher

Current liabilities surged dramatically from DZD 23.53 million (2019) to DZD 971.99 million (2023), exceeding 4,000% increase, creating challenges in meeting short-term obligations amid declining cash reserves, potential accumulation of payables or tax liabilities, and necessitating improved operating cycle and working capital management. Although the debt ratio remains reasonable due to strong equity, the rising liability trend requires careful monitoring to prevent long-term solvency deterioration, increased debt servicing costs, and credit rating decline.

3-1-2-Income statement of Sonelgaz for the fiscal years 2019–2023

Table (05): Income statement of Sonelgaz for the fiscal years 2019–2023

Item	2019	2020	2021	2022	2023
Revenue	104,775,427.	112,095,983.0	129,636,070.6	139,852,821.9	164,099,535.7
Operating income	47	8	3	7	3
Cost of goods sold	(109,695,036.63)	(113,323,527.50)	(119,095,693.23)	(127,610,988.80)	(146,985,258.35)
Gross margin	(4,927,963.16)	(2,755,144.42)	9,729,077.41	11,643,140.47	14,237,277.38
Operating expenses	(9,281,756.63)	(9,339,888.81)	(29,436,319.27)	(33,556,754.29)	(27,556,335.17)
Operating result / EBIT	(4,991,411.24)	(8,632,055.76)	(8,054,322.50)	(6,345,946.84)	(5,037,098.37)
Financial result	0.00	0.00	0.00	0.00	(9,925.52)
Profit before tax (PBT)	(4,991,411.24)	(8,632,055.76)	(8,054,322.50)	(6,345,946.84)	(5,047,833.99)
Gross profit before tax	(4,991,411.24)	(8,632,055.76)	(8,054,322.50)	(6,345,946.84)	(5,047,833.99)
Income from ordinary activities	0.00	0.00	(8,054,322.50)	0.00	0.00
Net income for the year	(4,991,411.24)	(8,632,055.76)	(8,054,322.50)	(6,345,946.84)	(5,047,833.99)

Source: Prepared by the researcher

Sonelgaz achieved 56.6% revenue growth from DZD 104.78 million (2019) to DZD 164.10 million (2023), reflecting expanded operations and increased utility demand, yet failed to achieve profitability. Despite positive gross margins from 2021 reaching DZD 14.24 million (2023), they

remained weak at 7.5-8.7% of revenues, insufficient for operating profits, while negligible financial results provided no offset to operational losses. The analysis reveals critical structural challenges: pricing constraints preventing cost-reflective tariffs due to socio-political factors, operational inefficiency with elevated expense ratios, and government subsidy dependence as a public utility, necessitating urgent cost restructuring and business model reform for financial sustainability.

Table06: Financial Ratios for Sonelgaz (2019-2023)

Financial Ratio	2019	2020	2021	2022	2023
Liquidity Ratios					
Current ratio	0.881820751	0.71716024	0.804369972	0.662998689	0.75615969
Quick ratio	0.496357941	0.42332232	0.523915053	0.362879817	0.46277.3958
Immediate liquidity ratio	0.649319324	0.564222706	0.609218628	0.639852857	0.637697666
Cash ratio	0.010499505	0.008495375	0.009251223	0.00320021	0.00301.3783
Working Capital Indicators					
Cash flow	0.139793296	0.19852447	0.088159785	0.186154406	0.109170722
Net working capital	0.056930066	0.041776661	0.033304121	0.042253311	0.035330662
Capital employed	0.082862323	0.093431583	0.048989364	0.143901096	0.079623005

Source: Prepared by the researcher

The financial analysis of Sonelgaz reveals a fragile financial position requiring urgent intervention. The low current ratio (0.66-0.88) indicates the inability of current assets to cover current liabilities, reflecting a structural weakness in the company's capacity to meet its short-term obligations. The quick ratio is even more concerning, ranging between 0.36-0.52, which means that liquid assets cover less than half of current liabilities, placing the institution in a precarious position and making it heavily dependent on debt collection or inventory liquidation. Additionally, the capital employed ratio exhibits significant volatility (0.08-0.14), indicating instability in the efficiency of financial resource utilization. The overall situation is characterized by a chronic liquidity crisis, severe

weakness in cash reserves, erosion of working capital, and elevated insolvency risks. The company urgently needs to improve collection management, increase cash reserves, restructure short-term debt, and enhance operational profitability to generate positive cash flows that ensure financial sustainability.

-2-3Analysis of Financial Distress Indicators for Sonelgaz Company : The study relied on three standard models for financial failure prediction to assess the financial status of Sonelgaz Company, specifically the Altman model, Kida model, and CHERROD model.

3-2-1- :The Altman Model

The Altman Z-Score model was applied to the financial data of Sonelgaz during the period from 2019 to 2023. As explained in the theoretical framework, this model is based on the following equation:

$Z= 1.2X1 + 1.4 X2 + 3.3 X3 + 0.6X4 + 1 X5$

Table07: Statistical Variables Table (2019-2023)

Variables	2019	2020	2021	2022	2023
X1	-0.10	-1.89	-0.15	-0.21	-0.17
X2	-0.06	-0.44	-0.03	-0.04	-0.04
X3	-0.06	-0.41	-0.03	-0.04	-0.04
X4	0.41	1.17	0.40	0.22	0.03
X5	0.13	1.02	0.11	0.09	0.11
Arithmetic Mean of X	-0.03	-1.41	-0.37	—	-0.24

Source: Prepared by the researcher

Through the analysis of the table pertaining to the measurement of financial distress indicators for the enterprise, it is evident that variables X2 and X3 exhibit substantial similarity in their values across the five-year period, reflecting a strong correlation between them and a uniform response to the prevailing economic conditions. Conversely, variable X5 demonstrates pronounced volatility, recording a positive value in 2020 while maintaining negative values throughout most other years. Regarding the Z-score index, which represents the composite final outcome of the model, it displayed a fluctuating trajectory; in 2019, its value was marginally negative, approaching zero, indicating a nearly balanced financial performance. Subsequently, the index experienced a sharp decline in 2020, recording the poorest performance throughout the studied period. This was followed by a

notable improvement in 2021, with the indicator transitioning to a less negative value, reflecting a partial recovery in financial performance. However, 2022 witnessed a return of the index to negative territory, albeit not as severe as the 2020 crisis, with continued modest deterioration in 2023. These findings indicate the persistence of financial challenges confronting the institution and the incomplete nature of its financial .recovery

3-2-2--The KIDA model for financial distress prediction:

Table [08]: KIDA Model Results for Financial Distress Assessment-2019) (2023

Variables	2019	2020	2021	2022	2023
X1	-0.06	-0.44	-0.03	-0.04	-0.04
X2	0.41	1.17	0.40	0.22	0.03
X3	0.01	0.01	0.01	0.00	0.00
X4	0.13	1.02	0.11	0.09	0.11
X5	0.00	0.00	0.00	0.00	0.00
Z-Score	0.16	1.19	0.18	0.08	0.03
Arithmetic Mean of Z	—	—	0.33	—	—

Source: Prepared by the researcher

Through the analysis of the KIDA model results for measuring financial distress in the enterprise under study, the data reveal critical indicators that warrant attention. Variable X1, which measures the ratio of net profit after tax to total assets, displays consistently negative values throughout the time period (2019-2023), indicating the enterprise's inability to achieve net profitability and the weakness of its operational performance. As for variable X2, it recorded a relatively high value in 2020 reflecting an adequate capital structure; however, it experienced a sharp decline in 2021 and reached low levels in 2023, suggesting significant erosion of shareholders' equity and deterioration of the financial structure, which threatens the enterprise's financial independence and increases its reliance on debt financing. Variable X3, representing the ratio of current assets to current liabilities, showed a continuous decline reflecting acute liquidity problems and the enterprise's inability to cover its short-term obligations. Additionally, variable X4 exhibited fluctuations indicating a decline in the

effectiveness of assets in generating sales after 2020, while variable X5 registered critical deterioration by 2023, threatening the enterprise's ability to cover emergency expenditures. Upon analyzing the composite Z-score indicator, it was found that most values fell below the critical threshold (1.81) according to the KIDA model, placing the enterprise in the financial distress zone, with the exception of a slight improvement in 2020 where the indicator fell within the grey zone, before the situation deteriorated again in 2021 and 2022 to reach critical levels in 2023, necessitating urgent corrective interventions to ensure the enterprise's sustainability.

-3-2-3CHERROD Model for Financial Distress Prediction"

Table [09]: CHERROD Model for Financial Performance Assessment

Variables	2019	2020	2021	2022	2023
X1	010.-	89.1-	150.-	210.-	170.-
X2	0.00	0.04-	0.00	0.00	0.00
X3	-0.01	-0.02	-0.02	0.00	0.02
X4	-2.66	-4.44	-2.52	-2.94	-0.54
X5	1.00	0.42	1.00	1.00	1.00
X6	0.10-	-0.02	0.12-	0.16-	0.03-
Arithmetic Mean of Z	6.710645339-				

Source: Prepared by the researcher

Analysis of the Sherrod model results for Sonelgaz (2019-2023) reveals critical financial concerns. Variable X1 showed consistently negative values indicating unstable liquidity, X2 displayed extremely low values reflecting insufficient profits for operations, and X3 declined over four years (except 2020) suggesting inadequate financial stability despite acceptable equity reliance. Variable X4 exhibited deeply negative values indicating chronic operating losses, X5 remained constant at 1.00 showing assets barely covering liabilities with weak safety margins, and X6 declined sharply in 2020 revealing deteriorated long-term financing capacity. The composite Z-score produced consistently negative values placing the enterprise in critical financial distress, particularly in 2020 with severe operating losses causing financial collapse, and in 2022 with virtually non-existent retained earnings and fragile debt-dependent financing structure, necessitating urgent corrective measures to restore financial balance and ensure sustainability.

4-Conclusion:

This research examines financial distress prediction models amid escalating global bankruptcy rates, with 2024 data showing 694 U.S. cases (highest in 14 years), over 60,000 in France, and 31,000 in the UK, while global rates increased 12.5% in 2023 with projected 9% growth in 2024. Statistics indicate 20.4% of U.S. businesses fail within one year, 49.4% within five years, and 65.3% within ten years, reflecting impacts of financial globalization, volatility, and rising interest rates. Prediction models (Altman Z-Score, Kida, Sherrod) serve as vital early warning tools by analyzing financial ratios—liquidity, profitability, leverage, efficiency—to diagnose financial health and detect weaknesses, enabling proactive corrective measures such as debt restructuring and operational improvements. Study findings confirm that model application must be tailored to each sector's economic activity, risks, and characteristics to ensure accuracy. Field investigation of Sonelgaz El Naama revealed complete absence of prediction models in financial practices; interviews and document analysis showed management neglects these tools, leaving the enterprise vulnerable to financial distress amid volatile economic conditions and increasing sectoral challenges, thereby missing opportunities for preventive corrective action before crises escalate.

Theoretical Findings:

First, the study confirmed that financial distress is a phenomenon that can potentially occur at any stage of an economic enterprise's life cycle, resulting from accumulated financial imbalances or sudden economic shocks. Second, it was established that the use of financial distress prediction models represents a strategic mechanism for verifying the extent of an enterprise's success in achieving its financial and operational objectives, enabling it to detect warning signals before the crisis escalates. Third, quantitative financial distress prediction models are considered among the most important innovative tools for facilitating early prediction processes, as they contribute to providing a clear picture of the enterprise's financial position, and despite varying degrees of accuracy, they remain of paramount importance to managers and stakeholders.

Applied Study Results:

The analysis of the principal financial ratios comprising the employed models revealed fundamental weaknesses in the financial and operational performance of Sonelgaz Corporation (the research sample), evidenced by multiple negative indicators recorded by financial variables throughout the study period. These results confirm that the enterprise is either in an actual state of failure or on the brink of financial distress, unless urgent and radical corrective measures are implemented.

Quantitative Model Results:

The three applied models (Altman Z-Score, KIDA, CHERROD) demonstrated complete consensus in classifying the enterprise within the critical financial risk zone:

- Altman Model: Classified the enterprise within the "red zone" ($Z < 1.81$), indicating an extremely high probability of bankruptcy and a critical financial situation requiring immediate intervention.
- KIDA Model: Predicted the enterprise's exposure to imminent bankruptcy risk, as the Z-score values fell below the critical threshold ($Z < 1.81$), placing the enterprise in the zone of certain financial failure.
- CHERROD Model: Confirmed the catastrophic financial condition of the enterprise through recording extremely negative Z values ($Z < -5.0$), indicating acute financial deterioration and elevated bankruptcy risks.

Based on the complete convergence of results from the three models employed in this study, it can be conclusively stated that Sonelgaz Corporation in El Naama faces a real and tangible risk of financial distress during the studied period (2019-2023). This critical situation necessitates that senior management and supervisory authorities undertake exceptional and urgent measures including: comprehensive financial restructuring, operational efficiency improvement, expenditure rationalization, revenue source diversification, and enhancement of financial governance mechanisms, to avoid the worst-case scenario of bankruptcy and liquidation.

Recommendations:

Based on study findings, the following strategic recommendations are proposed for Sonelgaz and similar enterprises:

Administrative and Organizational:

Reform the administrative system prioritizing human resources through specialized continuous training in financial analysis and modern management, establish material and moral incentive systems, create a dedicated financial risk management unit for early distress prediction and periodic reporting, and organize training courses on prediction model application.

Financial and Technical:

Systematically apply statistical prediction models, particularly Altman Z-Score for early distress detection, and develop models adapted to Algerian economic specificities through empirical studies incorporating local economic, legal, and institutional determinants.

Liquidity and Capital Management:

Develop liquidity policies emphasizing fund deployment over immobilization, shift from excess liquidity comfort to opportunity-cost awareness, and establish effective investment strategies to improve asset returns.

Comprehensive Restructuring:

Adopt dual-dimensional restructuring: (1) Financial—debt rescheduling, capital structure improvement, financing diversification, and resource efficiency enhancement; (2) Administrative—organizational redesign, system modernization, good governance implementation, and improved internal control and decision-making processes.

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