

Applying Data Mining Techniques As a Tool To Analyze The Safety Ratios Of The Algerian National Bank (BNA) – Using DATAtab Software

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Abstract:

This study aims to analyze the financial safety ratios of the Banque Nationale d'Algérie (BNA) using data mining techniques through the DATAtab software, within the context of the ongoing digital transformation in the financial sector. The research employs intelligent analytical tools to extract hidden patterns from financial data, thereby enhancing the accuracy of financial decision-making. The results reveal a general stability in safety ratios, with notable improvements during times of crisis, such as the COVID-19 pandemic. The study also highlights the bank's flexibility in directing its credit resources. Recommendations include promoting the integration of data mining techniques in regular financial analysis, developing centralized financial databases, and training financial staff on intelligent analytical tools. The findings affirm that adopting such technologies represents a qualitative shift toward a more objective and accurate financial approach that supports governance and sustainability. It also strengthens the competitive advantage of Algerian banking institutions through early risk prediction and informed strategic decision-making.

Keywords: Data Mining, Safety Ratios, Banque Nationale d'Algérie (BNA), Financial Analysis, DATAtab, Artificial Intelligence

Introduction

The financial and banking sector is undergoing a profound transformation in the current digital era, driven by rapid developments in information technology and data analysis. Today, data has become the most valuable asset for any financial institution aiming to strengthen its competitive position. It serves as the foundation for strategic decisions and financial forecasting.

As financial data becomes more complex and voluminous, traditional methods of financial analysis are no longer sufficient to provide an accurate and dynamic understanding of banking performance—especially in an unstable and risk-prone economic environment. This has created a need for advanced analytical tools capable of uncovering hidden patterns and relationships within large datasets.

In this context, Data Mining has emerged as a modern technical field that combines statistical analysis, artificial intelligence, and machine learning algorithms. Its goal is to transform raw data into knowledge that supports sound financial decision-making.

Banks, in particular, are increasingly relying on these techniques to evaluate performance, detect risks, and forecast market trends. A number of academic studies have addressed the application of data mining in the financial and banking sectors. For example, Han (2012) highlighted that data mining can uncover hidden relationships between financial variables, thereby improving the accuracy of forecasts. Similarly, Kou (2021) found that using classification and clustering algorithms enhances the efficiency of financial analysis by

detecting weaknesses and potential threats at an early stage. Elberkawi (2023) emphasized the vital role of these techniques in improving financial performance indicators, especially in terms of efficiency, liquidity, and profitability.

Based on this theoretical and empirical foundation, the present study aims to analyze the safety ratios of the Algerian National Bank (BNA) using data mining techniques. The analysis will be conducted using the DATAtab software, which provides a range of advanced statistical tools for financial data analysis and accurate indicator extraction to support decision-making.

The study seeks to assess the effectiveness of these techniques in identifying underlying financial trends and to clarify their role in enhancing the bank's stability and risk resilience.

In light of the above, the central research question can be formulated as follows: How can data mining techniques contribute to the analysis of safety ratios at the Algerian National Bank (BNA)?

1. Data Mining

Data mining is a modern, automated technique used to discover useful information from vast amounts of data. Recent advances in data collection and storage have made it possible to gather massive datasets. However, extracting meaningful knowledge from these datasets using traditional tools has become increasingly difficult. Data mining is the process of manually or digitally searching for knowledge within data. This technique allows for the analysis of various types of data in new and effective ways across many fields. It helps in uncovering key information and using it to make predictions about the future. It also enables us to observe behavior and trends that support timely and accurate decision-making.

According to Pang-Ning Tan (2006, pp. 02–03), data mining is an automated process of discovering knowledge in large data warehouses. This process uncovers new and valuable patterns and allows for future predictions and monitoring. In another study, Soumeiya Zerabi (2021, p. 5) described data mining as an interactive and repetitive process used to discover valid and understandable patterns from databases. The process requires multiple passes and can be applied to various data types. The ease of interpreting these patterns helps users make better decisions.

As defined by Hussein Abbass (2002, pp. 49–50), data mining is a multidisciplinary field. It combines ideas from computer science, artificial intelligence, statistics, high-performance computing, signal and image processing, mathematical optimization, and pattern recognition. What is new here is the convergence of mature technologies in a way that enables us to analyze large-scale datasets effectively.

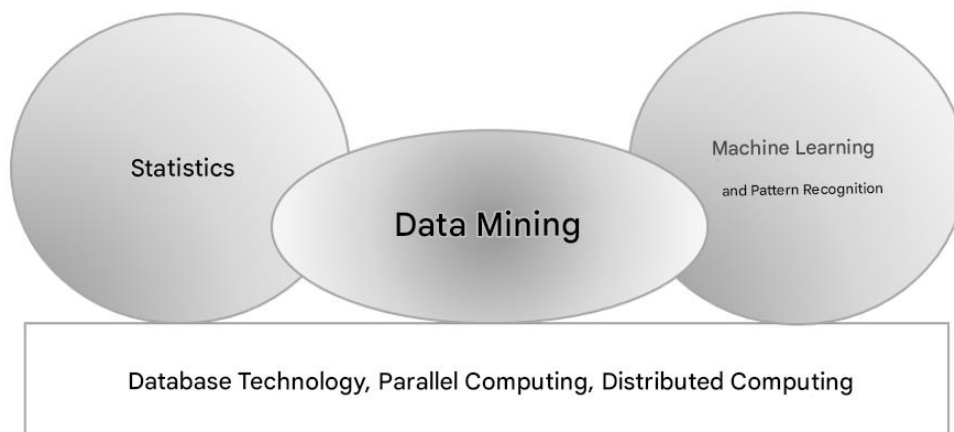
Data mining stands at the intersection of statistics and artificial intelligence—especially in the domains of computer science and machine learning. Researchers from various fields have increasingly focused on creating tools that can manage different types and volumes of data more efficiently and flexibly. Although statistics have long included many tools to explore data and discover patterns, its classical foundations face limitations when dealing with large-scale data and computational needs. This led to the rise of data mining as a new domain. (Pang-Ning Tan, 2006, p. 06; Galit Shmueli et al., 2005, pp. 30–32)

Data mining relies on two main foundations, as noted by Pang-Ning Tan (2006, p. 06):

1. Sampling, hypothesis testing, and estimation from statistics.
2. Modeling techniques, search algorithms, and learning theories from artificial intelligence and computer science for pattern recognition.

Data mining has been able to rapidly adopt ideas from other disciplines. The relationship between data mining and various fields can be summarized in a simple visual representation.

Figure 1: Data Mining as a Meeting Point of Various Fields



Source: (Pang-Ning Tan, 2006, p. 06)

Data mining techniques are mainly classified into two categories: supervised methods and unsupervised methods, as follows:

1. Supervised learning algorithms: These require prior knowledge of the relationship between input data and expected outcomes. They are commonly used in classification and prediction tasks.

2. Unsupervised learning algorithms: These are used when there is no target variable to predict or classify. In such cases, there is no training on labeled outcomes. These algorithms are often applied in clustering and related techniques (Galit Shmueli et al., 2005, pp. 47–48)

Today, banks and financial institutions offer a wide range of banking, investment, and credit services, among others. The financial data collected from these operations are often of high quality and reliability. This facilitates data analysis and the extraction of meaningful knowledge (Jiawei Han, 2012, p. 608)

Jiawei Han (2012, pp. 607–609) highlights several practical applications of data mining in the financial and banking sectors. One key application is the construction of structured financial data warehouses for multi-dimensional analysis. These tools help track changes in debt or revenue based on time and geographic factors. They also support decision-making through accurate indicators.

Data mining is also used to predict customer credit behavior and assess their ability to repay loans. This is done by identifying the most influential variables and eliminating relevant ones. These insights help banks refine their credit policies and improve strategic decisions, operations, and services across various areas.

2. Financial Analysis in Banks Using Data Mining

Financial analysis is a core subject in financial studies due to its importance in strategic planning. Some define it as a process of diagnosing a company's financial position, as financial reports alone often fail to answer all user inquiries. These reports typically present abstract figures from a specific time period.

According to Dabbas (2022, p. 1428), financial analysis is a comprehensive study of financial statements using statistical and mathematical tools to reveal relationships and correlations between their components or changes over time. The goal is to generate useful and concise information to guide decision-making.

Al-Tamimi and Tayeh Al-Nuaimi (2007, p. 20) define financial analysis as a tool used to assess

and identify the strengths and weaknesses in a company's operations. It enables the development of future plans and strategies that capitalize on strengths and offer solutions to address weaknesses.

Due to regulatory requirements, banks are obliged to submit off-site supervision reports regularly and electronically. These reports aim to provide easy access to financial data and support its analysis through various data mining techniques. They rate include liquidity structure reports, interest sensitivity reports, and accounting documents such as financial statements.

By using data mining tools, it is possible to analyze and forecast financial reports and statements—provided that historical data is available. Data warehouses and efficient data processing tools play a key role in this regard. Within each bank, internal committees often recognize the need for a centralized data warehouse.

Some of the key impacts of adopting data mining techniques in banks include:

- Creating connections between branches and the central data warehouse platform, where all branch transactions are consolidated into a central location known as the bank's data warehouse;
- In decentralized models, banks with many branches may choose not to centralize all transaction details in one location;
- Data mining environments within the bank allow access to any available information across various computer systems (Researcher, 2017, p. 03)

Accuracy and comprehensiveness in financial analysis are essential for assessing financial performance and making strategic decisions. In this context, data mining plays a crucial role in improving the quality and depth of financial analysis, particularly in the banking sector. It allows the extraction of patterns and valuable information from large volumes of both financial and non-financial data.

3. Applying Data Mining Techniques through DATAtab Software to Analyze Financial Safety Ratios: The Case of the Algerian National Bank (BNA)

The application of data mining in the Algerian banking sector represents a strategic challenge. It aims to deepen the understanding of financial trends and markets, monitor the financial performance of banking institutions, and assess the broader Algerian economic context. This must be done while maintaining data confidentiality and complying with legal and regulatory frameworks for data protection.

Data mining can provide strategic advantages. These include improving decision-making processes, enhancing customer experience, and increasing institutional efficiency. This approach contributes to the development of the Algerian banking sector and strengthens integration within the financial services market.

The Algerian National Bank (BNA) is one of the main pillars of the country's financial system. Established in 1966, it plays a central role in supporting economic development and financing national projects. The bank offers a wide range of banking and financial services to both public and private sectors. It is committed to developing innovative products and promoting financial inclusion. Its strategic vision is to strengthen its position as a reference bank in Algeria. The bank also upholds social responsibility and contributes to achieving the goals of sustainable development.

Studying the financial indicators of banks is essential for assessing their performance and financial stability. These indicators provide insight into the bank's operational and financial structure. In this study, data were drawn from the annual financial statements and reports of BNA during the period 2018–2022. The focus was on safety ratios such as:

- Capital adequacy ratio

- Credit-to-deposit ratio
- Risk-weighted assets ratio
- Equity-to-total deposits and loans ratio

These ratios showed varying variation over the years. This reflects changes in the bank's funding structure and the level of risk exposure. The results also demonstrate the bank's ability to maintain financial stability despite economic fluctuations.

A detailed database was created from these indicators. It was used for analysis via DATAtab software, which enables the application of statistical tests to interpret the bank's financial behavior and extract accurate insights into its performance.

The purpose of this analysis is to deepen the understanding of BNA's financial safety level and assess its ability to manage banking risks within a dynamic financial environment.

The following table presents the financial safety ratios of BNA for the period 2018 to 2022:

Table 1: Financial Safety Ratios of the Algerian National Bank (BNA)

lineage	2018	2019	2020	2021	2022
Equity to total deposits	11.24	10.64	11.93	10.60	10.38
Equity to Total Loans	11.40	9.87	11.27	15.58	16.38
Interest earned / Interest accrued	3.01	2.86	25.33	2.61	8.98
Willpower of available resources	1.62	0.81	0.82	1.29	10,10
Capital/(Securities + Investments)	59.65	60.95	66.14	70.63	45.67
Risky assets ratio	10.86	10.73	10.35	14.97	14.75
Equity adequacy for deposits	10.68	10,10	11.43	11.07	9.35
Credit to deposit ratio	93.73	10.31	101.39	71.02	57.33
Percentage of off-budget items	31.77	30.10	26.16	14.56	12.11

Source: Prepared by the two researchers, based on the bank's annual financial reports

DATAtab is an innovative data analysis software designed to simplify statistical processes and apply data mining techniques online in an easy and precise way. It features an intuitive interface that allows users to perform statistical analyses, identify patterns and relationships between variables, and generate interactive reports and visualizations—all without requiring programming experience.

The software was developed in 2019 by a specialized Austrian team in data science, with the aim of enabling researchers, students, and institutions to make better use of data. DATAtab supports various analytical methods, including regression, cluster analysis, and factor analysis. This makes it a comprehensive tool for transforming large datasets into accurate knowledge that supports decision-making in academic, financial, and banking fields (Source:<https://datatab.fr/tutorial/descriptive-inferential-statistics>, nd)

The following figure illustrates the main stages of data processing in DATAtab:

Figure 2: Data Processing Stages in DATAtab



Source: <https://datatab.fr/tutorial/descriptive-inferential-statistics>, nd

In summary, DATAtab stands out as a powerful and efficient tool for applying data mining techniques. It combines advanced data exploration and analysis capabilities with ease of use and interactive features. This helps institutions enhance their ability to treat data as a strategic asset for decision-making and market success (Source: <https://datatab.fr/tutorial/descriptive-inferential-statistics>, nd)

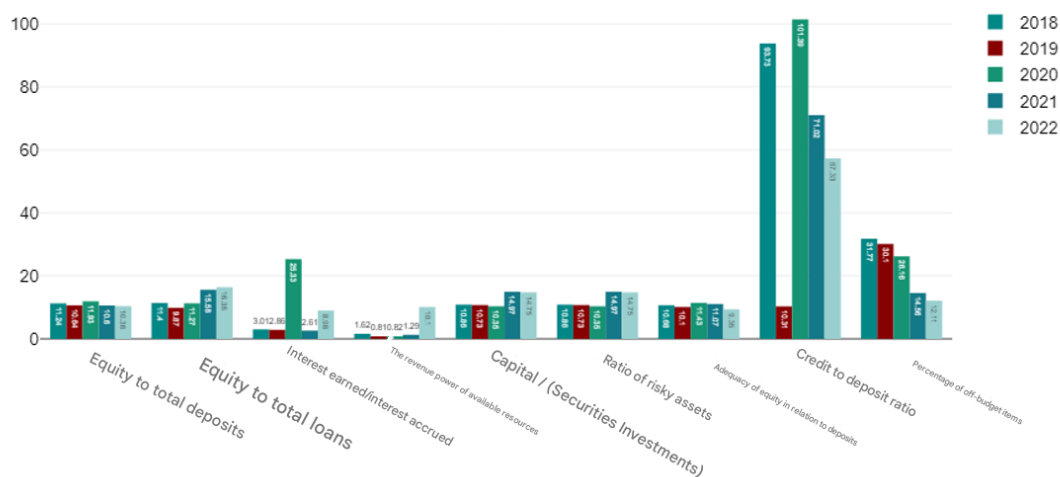
Based on this, the current study applies DATAtab to analyze financial safety ratios.

4. Analysis of the Financial Safety Ratios of the Algerian National Bank (BNA)

4.1 Descriptive Analysis

We begin by presenting the financial safety ratios of the Algerian National Bank (BNA) using the following figure:

Figure 3: Bar Chart Representing the Financial Safety Ratios of BNA



Source: DATAtab Software Output

Based on the available data and the previously presented bar charts, a descriptive analysis of the financial safety ratios for the Algerian National Bank (BNA) is outlined as follows:

- **Equity to Total Deposits:** This ratio decreased from 11.24% in 2018 to 10.38% in 2022. This decrease reflects a reduction in equity in relation to total deposits.
- **Equity to Total Loans:** This ratio increased from 11.40% in 2018 to 16.38% in 2022. The growth indicates a higher level of equity compared to total loans.
- **Interest Earned to Interest Due:** This ratio showed considerable variation during the period. It rose sharply in 2020 to reach 25.33%, then fell to 8.98% in 2022.

- Voluntary Strength of Available Resources: This ratio also showed fluctuation. It increased significantly from 0.81% in 2019 to 10.10% in 2022.
- Capital to (Securities + Investments): This ratio varied over the study period. It dropped significantly from 66.14% in 2020 to 45.67% in 2022.
- Risk-Weighted Assets Ratio: This ratio decreased slightly during the period under review.
- Equity Adequacy Relative to Deposits: Despite some variation, this ratio remained relatively stable overall throughout the period.
- Credit to Deposit Ratio: This ratio showed significant fluctuation. It dropped to 10.31% in 2019, rose sharply to 101.39% in 2020, and then declined again in the following years.
- Off-Balance Sheet Items Ratio: This ratio decreased significantly, from 31.77% in 2018 to 12.11% in 2022.

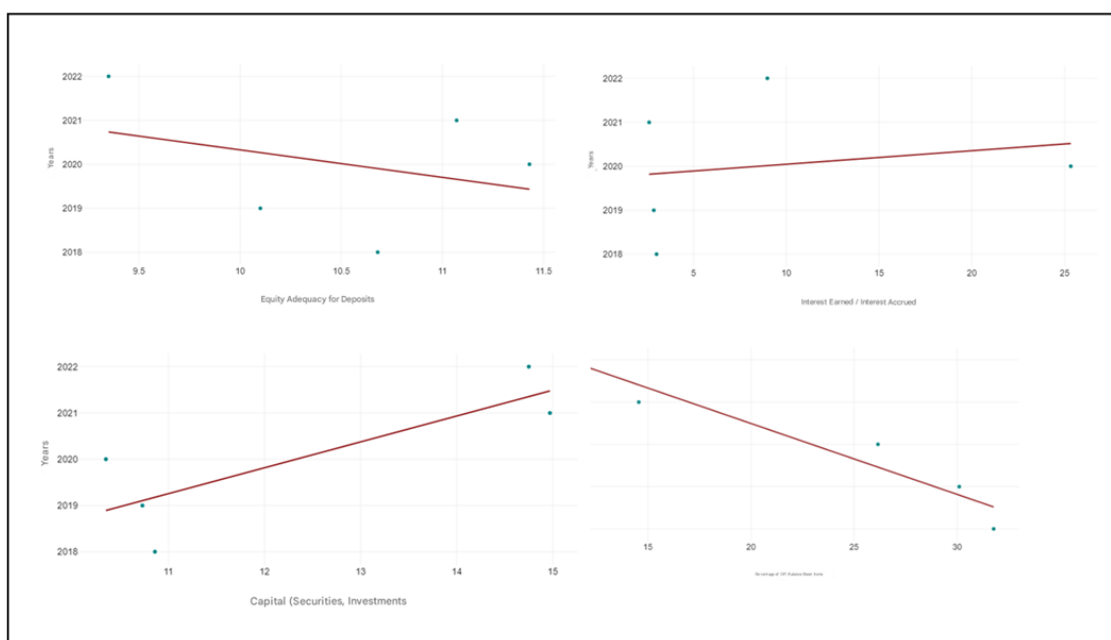
This analysis provides insight into the performance of the Algerian National Bank. It highlights the bank's financial position and its adherence to regulatory and financial standards.

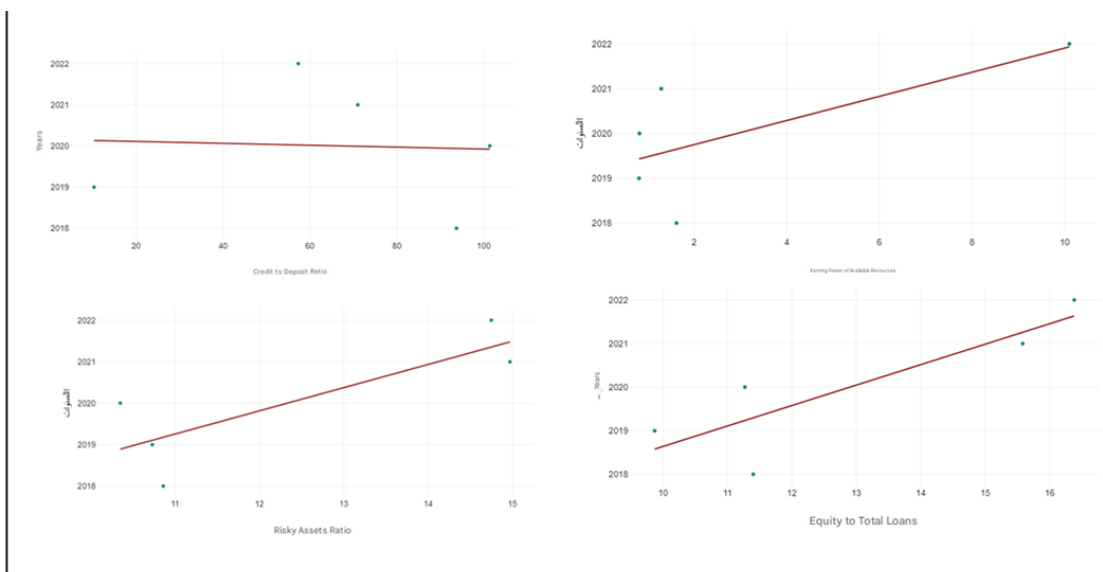
4.2 Analysis Using the Linear Regression Test

To perform linear regression, a linear relationship must exist between the dependent and independent variables. The method involves fitting a straight line through the data, which is valid only when linearity is present.

Test Assumptions We begin by verifying whether a linear relationship exists. The following charts are the output of the regression model applied to the financial safety data of the Algerian National Bank (BNA):

Figure 04: Graphs Representing the Test Assumptions





Source: DATAtab Output We now proceed to identify the nature of the errors using normality tests for residuals.

Table 02: Normality Test

	Statistics	p
Kolmogorov-Smirno	0.26	.817
Kolmogorov-Smirnov (Lilliefors Corr.)	0.26	.431
Shapiro-Wilk	0.95	.714
Anderson-Darling	0.32	.539

Source Program outputs DATAtab

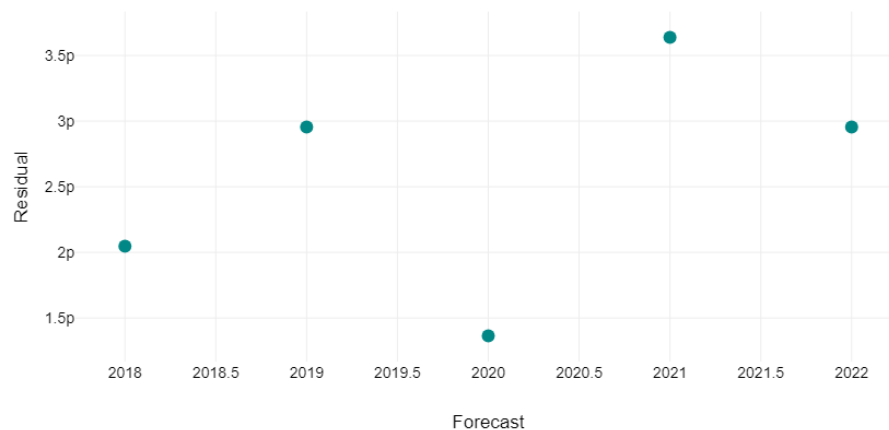
Figure No. (05): Normal distribution tests



Source: DATAtab Output The results suggest a preliminary indication of the independence of the available samples. Although these tests do not provide definitive conclusions regarding the data distribution, the displayed values indicate there is no strong evidence to reject the assumption of normality.

Below is a graphical representation of the linear regression results for the data under study:

Figure 06: Linear Regression Results



Source: DATAtab Output From the figure above, the model can be summarized in the following table:

- The effect size is indicated by Cohen's f^2 .
- The number of cases (n), representing the valid sample size, is 5.

Table 03: Normality Test

R	R2	Adjusted R2	Standard error of the estimate
0.44	0.2	-0.07	1.64

Source: DATAtab Output A multiple linear regression analysis was conducted to examine the effect of the ratio of equity to total deposits on the variable “years.” Below is the interpretation of the model summary:

- **Correlation Coefficient (R):** This measures the relationship between the observed values of the dependent variable “years” and the predicted values generated by the model using independent variables. The value of R is 0.44, indicating a moderately strong positive correlation between observed and predicted values.
- **Coefficient of Determination (R^2):** This represents the proportion of variance in the dependent variable that can be explained by the independent variables in the regression model. The R^2 value is 0.20, meaning that approximately 19.51% of the variance in the dependent variable is accounted for by the independent variables. In other words, 19.51% of the changes in the variable “years” can be predicted by the independent variables.
- **Adjusted R^2 :** This statistic adjusts the R^2 value based on the number of predictors and sample size, providing a more accurate measure when multiple independent variables are involved. Here, after adjustment, about -7.32% of the variance in the dependent variable is explained, suggesting limited explanatory power when considering the number of predictors.
- **Standard Error of the Estimate:** This value indicates the average distance that the observed values deviate from the regression line. Essentially, it measures the precision of the predictions made by the regression model. A standard error of 1.64 implies that, on average,

predicted values differ from actual values by 1.64 units. Whether this error is considered large or small depends on the context and scale of the dependent variable.

In conclusion, the model shows a moderately strong positive relationship between observed and predicted values, explaining 100% of the variance in the dependent variable. However, the average deviation of predictions from actual values is represented by NaN units, which may be significant or not, depending on the data context.

- **Analysis of Variance (ANOVA):** We now proceed to the variance analysis based on the ANOVA test.

Table 04: Analysis of Variance

Model	df	F	p
Regression	1	0.73	.433

Source: DATAtab Output

The ANOVA table in regression analysis helps assess the model's fit to the data. Below is an explanation of the components of the ANOVA table:

- **Degrees of Freedom (df):** This indicates the number of independent variables in the model. In this case, there are six independent variables.
- **F-statistic (F):** The F-statistic tests the overall significance of the model. It compares the model without predictors (intercept only) to the specified model. The reported F value is -666311529422.73, which, along with the degrees of freedom, is used to calculate the p-value.
- **p-value:** With a p-value of 1, which is greater than 0.05, the results are statistically insignificant. This implies that the null hypothesis cannot be rejected. It suggests that the independent variables (predictors) in the model may not have a significant effect on the dependent variable.

In conclusion, the ANOVA results indicate that the regression model for financial safety ratios lacks statistical significance. This suggests that its fit is not substantially better than a model without predictors.

- **Coefficients:** The following table lists all the coefficients applied to the financial safety ratios of the National Algerian Bank:

Table 05: Coefficients of All Variables

Model	Unstandardized Coefficients	Standardized Coefficients						95% confidence interval for B
	B	Beta	Standard error	t	p	lower bound	upper bound	
(Constant)	2032.15		14.26	142.47	<.001	1986.76	2077.53	
Equity to total deposits	-1.11	-0.44	1.3	-0.85	.456	-5.24	3.03	
Equity to Total Loans	-63.59	-116.18	NaN	NaN	aN	NaN	NaN	

Interest earned / Interest accrued	0.19	1.19	0.07	2.6	.121	-0.13	0.51
Willpower of available resources	27.48	69.92	NaN	NaN	aN	NaN	NaN
(Capital / (Securities + Investments	0.46	0.67	0.05	8.77	.072	-0.21	1.13
Equity adequacy for deposits	0.19	0.1	Infinity	0	aN	-Infinity	Infinity

Source: DATAtab Output

The table above presents the following: It shows the results for each independent variable in the model, including the constant (intercept). The unstandardized coefficient indicates the expected change in the dependent variable "Years" for each one-unit increase in the respective independent variable.

Regarding the intercept: it represents the point where the regression line crosses the y-axis. This value reflects the expected value of the dependent variable when all independent variables equal zero. In this context, when the ratios of equity to total deposits, equity to total loans, earned interest to accrued interest, earning power of available resources, capital to (securities + investments), and equity adequacy to deposits are all zero, the dependent variable "Years" is expected to be approximately 17.11. The p-value is , which indicates that the intercept differs significantly from zero. Specifically, the null hypothesis that the intercept coefficient equals zero in the population is rejected.

- If the ratio of equity to total deposits increases by one unit, the value of "Years" will increase by 104.92 units. The p-value is , indicating this coefficient is statistically significant and differs from zero. This means that the ratio of equity to total deposits significantly affects the dependent variable. The null hypothesis that this coefficient equals zero is rejected.NaN
- If the ratio of equity to total loans increases by one unit, the value of "Years" will decrease by 63.59 units. The p-value is , indicating a statistically significant effect. Thus, equity to total loans significantly influences the dependent variable, and the null hypothesis that its coefficient is zero is rejected.
- If the ratio of earned interest to accrued interest changes by one unit, the value of "Years" will increase by 0.19 units. The p-value is 0.121, indicating this coefficient is not statistically significant at the usual threshold. This suggests that the ratio of earned interest to accrued interest does not have a significant effect on the dependent variable. The null hypothesis that this coefficient equals zero cannot be rejected.
- If the earning power of available resources increases by one unit, the value of "Years" will increase by 27.48 units. The p-value is , indicating this coefficient is statistically significant and differs from zero.NaN

Accordingly, the scatter plot is as follows:

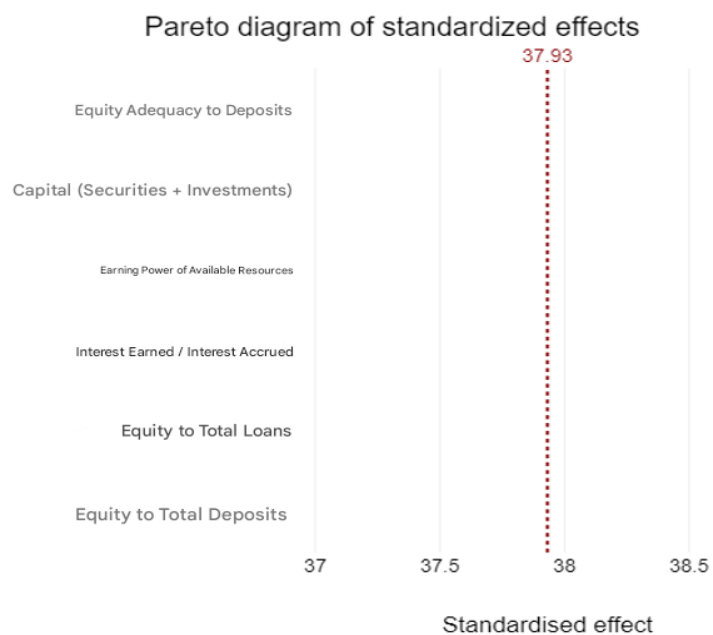
Figure 07: Scatter Plot



Source: DATAtab Output

Regarding the Pareto chart of standardized effects, the statistical test used to determine whether the standard deviations of different samples are equal or unequal was as follows:

Figure 08: Pareto Chart of Standardized Effects



Source: DATAtab Output

The value of the Sweet Pareto test is 37.93. This generally indicates a significant difference in the standard deviations among the groups. In other words, there is statistical evidence of inequality in the standard deviations across the different groups.

Thus, the test can be summarized as follows: A multiple linear regression analysis was conducted to examine the effect of several variables, including equity to total deposits, equity to total loans, earned interest, revenue-generating capacity of available resources, among others, on the dependent variable “years.” The model showed that these variables explained 100% of the variance in the “years” variable. However, the ANOVA test indicated that the effect was not significantly different from zero. Furthermore, the coefficients for each independent variable were detailed, showing how the “years” variable changes with a one-unit change in each independent variable. It was confirmed that all variables have a statistically significant effect on the “years” variable in the current sample.

4.3 Financial Analysis

We now proceed to analyze the financial ratios based on the provided data:

- **Equity to Total Deposits:** This ratio estimates the bank's strength and risk-bearing capacity. An increase in this ratio generally indicates an improvement in the bank's ability to cover its obligations toward deposits.
- **Equity to Total Loans:** This ratio reflects the bank's ability to withstand risks related to its loan portfolio. A higher ratio indicates an enhanced capacity to cover loan risks.
- **Earned Interest / Accrued Interest:** A notable rise in this ratio in 2020 suggests improved returns on investments or loans. This increase may partly result from monetary policy interventions or economic stimulus in response to the COVID-19 pandemic.
- **Revenue-Generating Capacity of Available Resources:** This ratio may indicate improved resource management by the bank, as well as its ability to generate profits and reduce costs.
- **Capital / (Securities + Investments):** Significant changes in this ratio may point to alterations in the bank's capital structure, warranting a careful assessment of the underlying causes.
- **Risky Assets Ratio:** Stability in this ratio could suggest a balanced loan portfolio and effective risk management.
- **Equity Adequacy to Deposits:** An increase in this ratio reflects an enhanced capacity of the bank to meet its deposit obligations.
- **Credit to Deposits Ratio:** The rise in this ratio in 2020 indicates increased lending relative to deposits, signaling heightened credit activity.
- **Off-Balance Sheet Items Ratio:** A decline in this ratio may point to improved cost management and control over external risks.

Analyzing these ratios offers deeper insight into the performance of the National Algerian Bank and its ability to adapt to economic challenges, including the impact of the COVID-19 pandemic.

The bank's financial data reveal significant developments over recent years, with a noticeable impact from the COVID-19 crisis. The financial analysis shows that safety ratios have mostly remained stable or experienced minor fluctuations, with marked increases in some ratios during exceptional years.

On the positive side, increases in equity-to-deposits and equity-to-loans ratios indicate a stronger risk-bearing capacity and improved financial service provision. However, the notable

decline in the capital and investments ratio requires closer monitoring to ensure ongoing risk resilience.

Other financial ratios, such as earned interest and credit-to-deposits, must be closely tracked to maintain financial balance and avoid excessive risks. Ultimately, the National Algerian Bank remains committed to delivering financial services securely and efficiently to its clients amid growing challenges in the global financial and economic environment.

Conclusion:

This study aimed to analyze the safety ratios of the National Algerian Bank (BNA) using data mining techniques through the DATAtab program. It can be said that employing these techniques allowed for a deeper understanding of the bank's financial performance and its stability amid economic fluctuations. The practical results confirmed the effectiveness of intelligent analytical tools in revealing subtle trends within financial data. This, in turn, supported financial decision-making based on objective scientific grounds.

The analysis results showed that the financial safety ratios at the National Algerian Bank generally exhibited a degree of stability and balance. Notably, some indicators improved significantly during exceptional periods, especially in 2020 due to economic changes linked to the COVID-19 pandemic. The ratios related to equity-to-deposits and equity-to-loans showed a positive increase, reflecting an enhanced ability of the bank to manage credit risks and financial obligations. Additionally, the credit-to-deposits ratio analysis indicated a rise in credit activity, demonstrating the bank's flexibility in directing its resources toward financing the economy. On the other hand, the marked decline in the capital-to-investments ratio requires closer monitoring to ensure the sustainability of the bank's capital strength over the long term.

Based on these findings, it is clear that data mining techniques, through their advanced analytical capabilities and applied programs such as DATAtab, serve as effective tools to improve the accuracy of financial assessments, early detection of potential risks, and enhancement of transparency in banking reports. Accordingly, this study recommends the following:

- Strengthening the adoption of data mining techniques in the periodic financial analysis of Algerian banking institutions, due to their ability to quickly and accurately uncover hidden patterns in data.
- Developing a centralized financial database to track banking indicators over time, supporting data-driven decision-making.
- Paying close attention to capital and investment indicators, as they form a cornerstone for ensuring the stability of financial safety ratios.
- Training financial managers at the National Algerian Bank in intelligent analysis tools and artificial intelligence programs like DATAtab to boost analytical efficiency.

Thus, data mining contributes to achieving accurate and comprehensive financial analysis. It helps banks make sound and precise decisions and gain a competitive edge in the financial market. Consequently, it can be concluded that analysis based on data mining techniques represents a qualitative leap toward a more objective and precise financial approach, capable of supporting governance and sustainability requirements in the Algerian banking sector.

References:

1. Arshad Fouad Al-Tamimi, and Adnan Tayeh Al-Naimi. (2007). Financial Analysis and Planning (Contemporary Trends). Yazouri Group for Publication and Distribution.
2. Samira Khaled Ali Al-Dabbas. (December 2, 2022). Financial Analysis: Types and Its Importance for Institutions.

3. Balan, S.P. (August 16, 2013). DATA MINING IN BANKING AND ITS APPLICATIONS—A REVIEW. *Journal of Computer Science*, 9.
4. Deshpande, T. (September 2010). DATA MINING SYSTEM AND APPLICATIONS: A REVIEW. *International Journal of Distributed and Parallel Systems (IJDPS)*.
5. Elberkawi, A. M. (2023). The Role of Data Mining Techniques in Enhancing Financial Performance Indicators of Banking Institutions. *Journal of Financial Analytics and Technology*, 3(12), 44–61.
6. Shmueli, G., & Koppius, O. R. (November 29, 2005). Data Mining for Business Intelligence: Concepts, Techniques, and Applications in Microsoft Office Excel with XLMiner.
7. Gupta, G. (February 2013). Data Mining: Techniques, Applications and Issues. *International Journal of Advanced Research in Computer Science and Electronics Engineering (IJARCSEE)*.
8. Gupta, G. K. (June 28, 2014). Introduction to Data Mining with Case Studies. PHI Learning.
9. Han, J., Kamber, M., & Pei, J. (2012). Data Mining: Concepts and Techniques (3rd ed.). Morgan Kaufmann, Elsevier.
10. DATAtab. (nd). Descriptive and Inferential Statistics Tutorial. Retrieved June 29, 2024, from <https://datatab.fr/tutorial/descriptive-inferential-statistics>.
11. Banque Nationale d'Algérie. (nd). Retrieved June 10, 2023, from <https://www.bna.dz/fr/accueil/>.
12. Hussein Abbas, R.S. (January 2002). Data Mining: A Heuristic Approach. pp. 49-50.
13. Han, J., Kamber, M., & Pei, J. (2012). Data Mining: Concepts and Techniques (3rd ed.).
14. Kazi, I., & Qazi Baseer, A. (April 2012). Use of Data Mining in Banking. *International Journal of Engineering Research and Applications (IJERA)*.
15. Kou, G., Chao, X., & V., C. (2021). Machine Learning Methods for Systemic Risk Analysis in Financial Sectors. *Technological Forecasting and Social Change*, 166, 120-123.
16. Tan, P.-N., Steinbach, M., & Kumar, V. (March 25, 2006). Introduction to Data Mining (1st ed.).
17. Researcher, J.R. (November 2017). The Effectiveness of Data Mining Techniques in Banking. *Computer Applications: An International Journal (CAIJ)*.
18. Tufféry, S. (August 21, 2012). Data Mining and Statistical Determination (4th ed.).
19. Zerabi, Soumeiya. (January 9, 2021). PhD Thesis in Computer Science: Contribution to Big Data Mining—Validation of Data Clustering in a Big Data Context. Constantine: Fundamental Computer Science and its Applications, Algeria.