International Journal of Accounting and Economics Studies, 12 (3) (2025) 63-68

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/che1y197
Research paper

The Effectiveness of The Kida Model in Measuring Financial Failure Through Selected Financial Indicators Using Artificial Intelligence Tools: An Applied Study on Iraqi Commercial Banks (2018 – 2023)

Ahmed Adheem Alsaffar*, Dr. Jawad Kadhim AL-Bakri

University of Babylon / College of Administration and Economics
**Corresponding author E-mail:bus314.ahmed.atheem@student.uobabylon.edu.iq*

Received: June 9, 2025, Accepted: July 9, 2025, Published: July 15, 2025

Abstract

This study aims to assess the effectiveness of the Kida model in measuring the probability of financial failure in selected Iraqi commercial banks by analyzing the influence of a set of selected financial indicators. The study employed the Panel Autoregressive Distributed Lag (Panel ARDL) model, relying on four indicators that capture essential aspects of banking risk: (Capital Adequacy Ratio(CAR), Cash Liquidity Ratio(CLR), Non-Performing Loans ratio(NPL), and Credit Deployment Ratio(CDR). The empirical analysis covers a sample of three Iraqi commercial banks listed on the Iraq Stock Exchange, using quarterly data for the period 2018 - 2023. The findings reveal a statistically significant long-run relationship between the Kida index and the selected financial indicators, while the error correction term confirms a moderate speed of adjustment toward equilibrium following financial shocks. Considering the accelerating developments in artificial intelligence (AI), this study underscores the potential for integrating the Kida model into intelligent analytical systems capable of real-time monitoring and predictive assessment of financial distress, based on continuous and automated data feeding. Such an integration—leveraging machine learning algorithms (e.g., decision trees, neural networks) and real-time data processing platforms - could significantly enhance the ability of decision-makers to detect early signs of financial distress and respond more proactively. The study concludes that the Kida model, when aligned with critical financial indicators, serves as an effective tool for assessing financial risk. It recommends the periodic adoption of this approach within the Iraqi banking sector, while highlighting the future strategic role of AI in strengthening early-warning mechanisms and data-driven financial governance.

Keywords: *Financial failure; Kida model; Iraqi banks; Financial indicators; Artificial intelligence.*

1. Introduction

The banking sector is the main pillar of the stability of the national economy, especially in rentier states such as Iraq, which rely heavily on oil revenues. With increasing cases of financial defects, it has become necessary to provide accurate and effective quantitative tools that enable early warning of financial failure. In this context, the Kida model is an appropriate analytical tool for measuring compound financial risks, as it combines several fundamental financial indicators that reflect the health of the banking institution.

This study aims to analyze the relationship between the Kida index and several important financial indicators in the Iraqi environment, using the Panel ARDL model that allows understanding the short- and long-term relationships, thus contributing to enhancing the effectiveness of banking supervision.

In line with the rapid developments in artificial intelligence technologies, this study highlights the possibility of integrating the Kida model into intelligent analysis systems capable of monitoring financial indicators in real time and predicting financial failures with greater accuracy, through continuous and real-time data feeding. This integration of financial models and artificial intelligence will enhance the ability of bank decision-makers to assess the feasibility of financial policies and operational activities faster and more responsively to market changes. For instance, machine learning models such as Random Forests and Support Vector Machines (SVM) can be trained on historical financial indicators to classify banks' financial health into risk categories. Moreover, real-time dashboards powered by AI can continuously monitor changes in key ratios, such as capital adequacy and liquidity, and automatically flag potential anomalies, enabling faster decision-making and more agile supervisory responses.

2. The Theoretical Review of Financial Failure and The Kida Model

2.1 Financial failure: concept and dimensions

Financial failure is one of the most prominent challenges facing financial institutions, especially banks, due to its repercussions on financial stability and the entire economic system. Financial failure refers to a situation in which an enterprise is unable to meet its outstanding financial obligations, either in the short or long term, because of deterioration in financial performance, poor management or external shocks. Financial failure takes many forms, including:

- Technical insolvency: It occurs when an enterprise is unable to meet its short-term obligations despite having sufficient assets in the long term.
- Economic Failure: The inability of an institution to generate returns that cover the cost of invested capital.
- Legal Bankruptcy: A situation in which an enterprise is formally declared unable to pay and enters legal proceedings for liquidation or restructuring.

Understanding the nature of financial failure is the first step in building early warning systems that can detect signs of default before it occurs.

2.2 The Importance of Predicting Financial Failure in The Banking Environment

Predicting financial failure is particularly important in the banking sector, given the vital role banks play in financial intermediation and liquidity management within the economy. A disruption in the bank's performance may have an impact on depositors, borrowers, and the money market in general. From this standpoint, early forecasting is a strategic tool for crisis prevention and proactive monitoring, as it helps in:

- Enable regulators to take early precautionary measures.
- Directing risk management to make decisions based on quantitative indicators.
- Maintain public confidence in the banking system.
- Reduce the costs of sudden collapses.

These variables have prompted researchers and international institutions to develop quantitative indicators that predict the likelihood of failure, foremost of which are composite prediction indicators such as the Kida index.

2.3 The Evolution of Financial Failure Prediction Models

Attempts to predict financial failure began by using simple financial ratios such as those proposed by Beaver in the sixties of the last century, where he relied on the analysis of individual ratios such as the liquidity ratio and profit ratio to assess the financial position of institutions. Over time, these models have evolved to become more complex and accurate, most notably the Altman index model, which uses linear discriminant analysis to classify companies according to their probability of financial failure.

Later, research tended to develop simpler models without affecting their predictive power, and the Kida model appeared in Japan in 1980 to be one of the models characterized by focusing on five carefully defined financial indicators. These indicators have been combined into a single mathematical formula that generates a composite index that reflects the level of financial risk that an organization may face, making it a common tool in assessing the financial soundness of institutions.

With the rapid development of AI technologies in recent years, it has become possible to enhance the effectiveness of these models (including the Kida model) by integrating AI technologies with them. AI can process large amounts of financial data and update results in real time, making the model more able to predict financial failure accurately and in real time. AI also allows continuous learning from past and current data, analyzing the impact of various variables, improving the proactive ability of the model, and supporting decision-makers within banking institutions in making decisions based on accurate and responsive analyses of financial and banking variables.

2.4 Kida Model (Z-Score): Concept and Use

The Kida index is based on the integration of five financial ratios that represent the basic dimensions of financial performance, such as profitability, liquidity, leverage, and others. The strength of this indicator is its simplicity and ability to provide a reliable quantitative assessment of the probability of failure.

The performance of enterprises is classified according to the value of the Z-score as follows:

- $Z > 1.0$: A secure and non-fail-prone organization.
- $1.0 \geq Z \geq 0.5$: Enterprise within the gray area (average probability of failure).
- $Z < 0.5$: The organization is highly prone to financial failure.

In this study, the Z-Score model is used as a composite measure of financial failure and not as an equation, as it is studied as a dependent variable affected by a set of selected financial indicators, through the Panel ARDL model that enables the analysis of short- and long-term relationships.

Although traditionally the Z-score is computed and interpreted directly based on its formula, this study adopts a different approach by treating it as a dependent variable within the econometric model. This allows for capturing its dynamic interaction with key financial indicators over time, offering deeper empirical insights into the determinants and progression of financial distress in the banking sector.

3. Financial Indicators and Their Relationship to The Kida Model (Z-Score)

The assessment of financial failure in banking institutions is based on several financial indicators that reflect their stability and efficiency in risk management.

In this study, the impact of four qualitative indicators that are considered one of the main pillars in the supervisory evaluation of any bank is analyzed: (Capital Adequacy Ratio (CAR), Cash Liquidity Ratio (CLR), Non-Performing Loans Ratio (NPL), and Credit Deployment Ratio (CDR). These indicators were selected because they provide comprehensive coverage of the main risk dimensions facing banks: capital risk, liquidity, asset quality, and operational risk.

The following is a detailed analysis of each indicator in terms of concept, economic significance, and the expected relationship with the Z-score index of the Kida model.

3.1 Capital Adequacy Ratio (CAR)

The capital adequacy ratio is the cornerstone of a bank's ability to cope with unexpected losses, as it shows the extent to which capital covers potential risks. This ratio is calculated by dividing regulatory capital by risk-weighted assets and is a core indicator of Basel II and Basel III standards.
Economic significance: reflects the strength of the bank's solvency.
Expected relationship with (Z-Score): A positive relationship, the higher the capital adequacy, the higher the bank's ability to resist financial failure, and thus the higher the value of (Z-Score).

3.2 Cash Liquidity Ratio (CLR)

This ratio measures a bank's ability to cover its short-term liabilities through its liquid assets. This ratio is a direct measure of the bank's financial flexibility and ability to deal with sudden pressures and is one of the most important indicators of financial soundness.
Economic significance: reflects the bank's ability to respond promptly to financial claims.
Expected relationship with Z-Score: A positive relationship, where high liquidity indicates robustness in financial performance, leading to an increase in the value of the Kida indicator.

3.3 Non-performing Loans Ratio (NPL)

This ratio reflects the quality of the bank's credit portfolio, as it represents the ratio of non-performing loans to total loans granted. A higher ratio indicates a weakness in credit management and a higher risk of recovering funds.
Economic significance refers to deteriorating asset quality and a high risk of defects.
The expected relationship with the Z-Score: an inverse relationship, as the increase in non-performing loans leads to a decline in the value of Z-Score as an indicator of financial failure.

3.4 Credit Deployment Ratio (CDR)

Credit Deployment Ratio reflects the extent to which the Bank uses its financing resources to grant loans compared to available deposits. While a higher ratio may reflect good credit activity, it may also indicate excessive risk if it exceeds safe limits.
Economic significance: Reflects the bank's efficiency in managing credit and liquidity.
Expected relationship with the Z-Score: The relationship may be non-linear but often takes a moderately positive form in equilibrium situations, or inversely if the ratio rises to an unsafe level.

3.5 Theoretical Review of The Relationship Between the Four Financial Indicators and the Z-Score Index of The Kida Model

Based on the financial literature, indicators (CAR, CLR, NPL, CDR) are basic control tools used to assess financial performance and risk in banking institutions and form the basis for assessing the ability of banks to cope with potential defects. In the context of this study, it is assumed that the Z-score index extracted from the Kida model is directly affected by these variables, as they represent pivotal dimensions in determining the level of financial stability of the bank.
This relationship will be tested using the Panel ARDL model, which allows the analysis of long and short-term effects separately, with the direction of the relationship and the degree of causation determined with high methodological accuracy.
Considering technological development, this theoretical framework can be strengthened by integrating artificial intelligence techniques that allow real-time and in-depth analysis of financial data. AI can monitor changes in these indicators in real time and create Z-score predictions based on the data pattern, which adds a dynamic dimension to the analysis of the relationship between variables and enhances the model's efficiency in predicting financial failure proactively and more accurately.

4. Applied Analysis of the Relationship Between the Kida Model Index and the Four Financial Indicators

4.1 Sample Description

The study relied on quarterly data of three Iraqi commercial banks, listed on the Iraq Stock Exchange: (Bank of Baghdad, National Bank of Iraq, and Mansour Investment Bank. These banks were selected based on data availability and the continuity of activity during the study period. Although the sample includes only three banks, their selection was based not only on data availability but also on their systemic importance, diversity in size and ownership structure, and consistent listing on the Iraq Stock Exchange throughout the study period. These criteria ensure that the sample provides a representative reflection of key trends and dynamics within Iraq's commercial banking sector. The period extended from the first quarter of 2018 to the fourth quarter of 2023, with 24 observations per bank, total of 72 observations.
The study adopted officially published financial statements, through which the Z-Score indicator was calculated according to Equation 1:

$$Z = 1.042\ X1 + 0.42\ X2 + 0.461\ X3 + 0.463\ X4 + 0.271\ X5 \tag{1}$$

Whereas:
X1: Profitability
X2: Financial sustainability
X3: Liquidity

X4: Asset Utilization Efficiency
X5: Cash
Z: weighted rate of financial ratios (continuity index).
In addition to the quarterly values of the four financial indicators: (CAR, CLR, NPL, and CDR). The data is organized into a panel dataset, allowing for more accurate analysis compared to time series or only incidental data.

4.2 Variable Stability Test (LLC Test)

Before proceeding with the ARDL estimation, the stability of the variables was tested using the Levin, Lin Chu (LLC) test, one of the most popular unit root tests for panel data. The test results, presented in Table 1, showed that most of the variables (Z-Score, CAR, CLR, and CDR) are unstable at the level but become stable at the first difference, indicating they are integrated of order one [I(1)]. In contrast, NPL was stable at level [I(0)]. This justified using the ARDL model, which accommodates variables with different integration orders (I(0) and I(1)) provided none are integrated at the second order.

Table 1: Levin Lin Chu (LLC) Unit Root Test Results for Panel Data Variables

Dependent-Variable: D(Z_KIDA)
Method: PMG
Date: 05/22/25 Time: 08:36
Sample: 2018 Q3 2023 Q4
Included observations: 66
Number of cross-sections: 3
Lag-selection: Automatic (deplags = 2, reglags = 2)
Selected model: PMG (2,0,2,2,1) using AIC (162 models evaluated)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
		Long-run (Pooled) Coefficients		
CAR	0.145203	0.024781	5.859343	0.0000
CLR	0.962878	0.067614	14.24074	0.0000
NPL	-0.584753	0.129174	-4.526872	0.0000
CDR	0.074433	0.035456	2.099341	0.0399
C	-0.041873	0.040530	-1.033126	0.3056
		Short-run (Mean- Group) Coefficients		
COINTEQ	-0.349847	0.344387	-1.015854	0.0313
D (Z_KIDA (-1))	-0.191687	0.184509	-1.038906	0.3029
D(CLR)	0.348373	0.322929	1.078790	0.2849
D (CLR (-1))	0.056943	0.196818	0.289319	0.7733
D(NPL)	0.202430	0.212784	0.951342	0.3452
D (NPL (-1))	0.088608	0.116576	0.760085	0.4501
D(CDR)	0.013778	0.034425	0.400237	0.6904
R- squared	0.980318	Mean dependent var.		-0.023670
Adjusted R- squared	0.968016	S. D. dependent var.		0.062052
S.E. of regression	0.009112	Akaike-info criterion		-5.965845
Sum. squared resid.	0.004898	Schwarz-criterion		-5.103254
Log-likelihood	222.8729	Hannan-Quinn criterion.		-5.624994
F- statistic	117.5446	Prob (F- F-statistic)		0.000000

Source: - Prepared by the researcher based on:

EVIEWS (12) Program-Outputs
Iraqi Securities Commission / Annual & Quarterly Financial Report of the Mentioned Banks for the Period (2018-2023).
Iraqi Stock Exchange / Annual and Quarterly Financial Report of the mentioned banks for the period (2018-2023)
The long-run relationship between the variables and Z_KIDA was examined using the PMG estimation approach under the panel ARDL framework. The results indicate that CAR, CLR, NPL, and CDR significantly influence Z_KIDA in the long run, with CAR and CLR having positive effects, while NPL and CDR exhibit negative impacts. These findings are summarized in Table 2.

Table 2: Long-Run Coefficient Estimates and Interpretations from PMG Estimation

Variable	Estimated coefficient	P-Value	Interpretation
CAR	0.145203	0.0000	Significant and Positive
CLR	0.962878	0.0000	Significant and Positive
NPL	-0.584753	0.0000	Significant and Positive
CDR	-0.074433	0.0399	Significant and Negative

The corrected coefficient of determination (Adj. R-sq) was about 0.96, which reflects the high explanatory ability of the model, as 96% of the changes in the Z-Score index of the Kida model are explained by the four variables studied.
Error Correction Model (ECM), to ascertain a long-term equilibrium relationship between the variables, which was estimated, showing the speed of adjustment towards equilibrium after a shock. It reached (-0.349847) with a probability value (prob.=0.0313), which indicates a strong equilibrium relationship, where about 35% of deviations from equilibrium are corrected during one quarter.
This result confirms that temporary changes in the four indicators are quickly reflected in the Z-score of the Kida model, which enhances its reliability as an auditing index.
It is important to note that most short-run coefficients in the ARDL model were statistically insignificant, indicating a limited immediate responsiveness of the Z-score to quarterly variations in the selected financial indicators. This outcome may reflect underlying structural rigidities or delayed transmission effects within the Iraqi banking sector and should be carefully accounted for when designing short-term financial risk management strategies.

4.3 Analysis of differences between banks

Through the above, the average Z-Score index for each bank was calculated during the study period, and classified according to risk levels (Table 3):

Table 3: Average Z-Score, Risk Levels, and Interpretations for Sample Banks

Bank	(Z-Score) Average	Risk level	Interpretation
Mansour Bank	0.777	Average risk	Relatively stable financial performance, with acceptable liquidity and moderate control over non-performing loans.
Bank of Baghdad	0.559	Average risk	Average performance indicates relative equilibrium in financial indicators, but there are indications of potential liquidity or capital adequacy pressures.
National Bank of Iraq	0.462	prone to failure	A decrease in value below (0.5) indicates relative financial weakness, which may be the result of high non-performing loans or weakness in liquidity and operating efficiency

This analysis supports previous results, as the Z-score of the Kida model reflects an effective ability to rank banks according to their level of risk based on the four fundamental factors.

5. Conclusions and recommendations

5.1 Conclusions

Considering the results drawn using the Panel ARDL model, the study reached a set of important theoretical and applied conclusions:
1. The Z-Score index proved high accuracy in measuring financial risks and classifying banks according to the level of potential failure, which confirms its validity as an early warning tool in the Iraqi environment.
2. Both the Capital Adequacy Ratio (CAR) and the Cash Liquidity Ratio (CLR) have had a positive impact on Z-Score, indicating their vital role in promoting stability and reducing risk.
3. NPLs have a significant negative impact on Z-Score, reflecting the risk of declining credit quality on financial soundness.
4. The impact of the Credit Deployment Ratio (CDR) was weakly negative, which may indicate that uncontrolled credit expansion may contribute to raising the likelihood of financial failure, especially considering other weak indicators.
5. The error correction factor showed that banks were able to correct imbalances by 35% over a quarterly period, demonstrating a good degree of financial resilience.
6. Integrating the Kida model into intelligent AI-based systems can enhance its predictive capabilities and provide real-time mechanisms to monitor indicators and improve the effectiveness of banking decisions.

5.2 Recommendations

Based on the results of the study, the researcher recommends several measures to enhance the effectiveness of banking supervision and reduce the risk of financial failure:
1. Adoption of the Kida Index as a monitoring tool: The Z-score of the Kida model is recommended by the Central Bank of Iraq as an early warning mechanism applied quarterly, to support proactive intervention in cases of deterioration in financial performance.
2. Integration of basic indicators in risk assessment: The need to include indicators (CAR, CLR, NPL, CDR) in banks' internal assessment systems and dynamically link them to the outputs of the Kida model.
3. Improving Financial Disclosure: Encourage banks to provide accurate and regularly updated financial statements, particularly related to asset quality and liquidity, to support the accuracy of predictive models.
4. Enhancing analytical capabilities: Developing training programs for banking cadres to raise their efficiency in using standard models (such as ARDL) and analyzing financial performance indicators, and linking them to potential risks.
5. Extending the application to other sectors: It is recommended to apply the model in other financial institutions such as Islamic banks and finance companies, to verify its flexibility and adaptation in multiple financial environments.
6. Investing in AI in Financial Control: The study encourages the integration of the Kida model into smart control systems supported by artificial intelligence, allowing real-time monitoring and accurate proactive analysis that contributes to supporting decision makers.

References

[1] Iraqi Securities Commission (2018–2023), Quarterly and annual financial reports of Bank of Baghdad, National Bank of Iraq, and Al-Mansour Bank [Quarterly & Annual Reports], Iraqi Securities Commission, Baghdad, Iraq. Available at: https://www.isc.gov.iq/

[2] Iraq Stock Exchange (2018–2023), Public financial disclosures of Bank of Baghdad, National Bank of Iraq, and Al-Mansour Bank [Listed Company Reports], Iraq Stock Exchange, Baghdad, Iraq.

[3] Al-Daamee WAJ & Almowail TFA (2021), The role of visionary leadership in reducing the financial failure of banks: An exploratory study in a sample of Iraqi commercial banks, Turkish Journal of Computer and Mathematics Education 12(7), 1234–1245.

[4] Arkan T (2015), Detecting financial distress with the b-Sherrod model: A case study, Zeszyty Naukowe Uniwersytetu Szczecińskiego. Finanse, Rynki Finansowe, Ubezpieczenia 74(2), 45–56.

[5] Ash RL & Rao RKS (1992), Financial management: Concepts and applications, Macmillan Publishing Company, New York, NY.

[6] Banne VR, Kalangi JB & Wangke SJ (2019), Analysis of financial health level of PT. Garuda Indonesia based on financial aspect of Keputusan Menteri BUMN No. KEP, Journal Riset Ekonomi, Manajemen, Bisnis dan Akuntansi 7(3), 205–214.

[7] Baral A, Peters D & Muller H (2005), Financial health and sense of coherence, South African Journal of Human Resource Management 8(1), 15–22.
[8] Bessis J (2015), Risk management in banking (4th edn), John Wiley & Sons, Chichester.
[9] Bhattari BP (2019), Effect of credit risk management on financial performance of commercial banks in Nepal, European Journal of Accounting, Auditing and Finance Research 7(5), 45–58.
[10] Bodie Z, Kane A & Marcus AJ (2013), Investments (10th edn), McGraw-Hill Education, New York, NY.
[11] Brem A, Viardot E & Nylund PA (2020), The impact of artificial intelligence on business and society, in The impact of artificial intelligence on business and society, Springer, pp. 262–278.
[12] Brockwell PJ & Davis RA (2002), Introduction to time series and forecasting (2nd edn), Springer, New York, NY.
[13] Brooks C (2019), Introductory econometrics for finance (4th edn), Cambridge University Press, Cambridge.
[14] Davenport TH & Ronanki R (2018), Artificial intelligence for the real world, Harvard Business Review 96(1), 108–116.
[15] DuJardin P & Severin E (2012), Forecasting financial failure using a Kohonen map: A comparative study to improve model stability over time, European Journal of Operational Research 221(2), 378–396.
[16] Enders W (2015), Applied econometric time series (4th edn), Wiley, Hoboken, NJ.
[17] Gao Y, Jiang B & Zhou J (2023), Financial distress prediction for small and medium enterprises using machine learning techniques, arXiv, Available at: https://arxiv.org/abs/2302.12118
[18] Gujarati DN & Porter DC (2009), Basic econometrics (5th edn), McGraw-Hill/Irwin, New York, NY.
[19] Ha HH, Dang NH & Tran MD (2023), Financial distress forecasting with a machine learning approach, Corporate Governance and Organizational Behavior Review 7(3), 90–104. https://doi.org/10.22495/cgobrv7i3p8
[20] Huang D, Chang B & Liu ZC (2012), Bank failure prediction models: For the developing and developed countries, Quality 46(1), 54–63.
[21] Koch TW & McDonald SS (2000), Bank management (4th edn), Harcourt, Fort Worth, TX.
[22] Krim X et al. (2021), COVID-19 liquidity and financial health: Empirical evidence from South Asian economies, Asian Journal of Economics and Banking 10(3), 234–250.
[23] Maddala GS & Wu S (1999), A comparative study of unit root tests with panel data and a new simple test, Oxford Bulletin of Economics and Statistics 61(S1), 631–652.
[24] Nguyen M, Ngo T, Nguyen B & Hong S (2024), Using machine learning and counterfactual explanations for financial distress prediction, SSRN, Available at: https://doi.org/10.2139/ssrn.5032226
[25] O'Neill K et al. (2006), Change in health, negative financial events, and financial distress/well-being for debt management program clients, Journal of Financial Counseling and Planning 17(2), 23–35.
[26] Ross SA (2006), Banking management (2nd edn), McGraw-Hill, New York, NY.
[27] Ross SA, Westerfield R & Jaffe J (1999), Essentials of corporate finance (2nd edn), McGraw-Hill, New York, NY.
[28] Russell S & Norvig P (2021), Artificial intelligence: A modern approach (4th edn), Pearson, Hoboken, NJ.
[29] Sarhan SS & Alali AH (2022), The role of financial structure balance in ensuring Iraqi bank financial health: Analysis of banks listed in ISX-IQ (2015–2020), Tanmiat Al-Rafidain 41(13), 122–139.
[30] Shetty S, Mengi K & Sharma S (2012), Financial distress prediction models: A review, Journal of Commerce & Accounting Research 1(1), 1–9.
[31] Whitehead B & Bergeman C (2017), The effect of the financial crisis on physical health: Perceived impact matters, Journal of Health Psychology 22(7), 889–897.