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The Use of Neural Networks in Measuring Corporate Financial Performance and Its Role in Improving Financial Reporting Quality

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Abstract
This study aims to explore the role that artificial neural networks (ANNs) can play in improving the measurement of financial performance, and how that improvement might be reflected in the quality of financial reporting. The study also draws a comparison between the predictive efficiency of ANN models and multiple linear regression (OLS) in explaining the effect of discretionary accruals on the financial performance indicators of Iraqi banks listed on the Iraq Stock Exchange over the period 2016–2023. Three financial performance indicators were employed: profit margin, return on assets (ROA), and return on equity (ROE). Discretionary accruals were measured using the Modified Jones Model. A Multilayer Perceptron (MLP) neural network was applied and its results were compared to those of the traditional model using Leave-One-Out Cross-Validation (LOO-CV). The findings revealed variation in model efficiency depending on the financial indicator used. Neural networks outperformed multiple linear regression in predicting profit margin, which reflects their ability to capture nonlinear relationships among financial variables. On the other hand, the OLS model performed better in explaining ROA and ROE, suggesting that the superiority of neural networks is not absolute but rather depends on the nature of the financial indicator being studied. The results also showed that discretionary accruals have an inflationary effect on certain financial performance indicators. The study concludes by stressing the importance of using artificial intelligence techniques in an integrated manner alongside traditional statistical methods to support the quality of financial analysis and enhance the reliability of financial reports.

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Introduction

Contemporary managerial and accounting thinking has been witnessing a growing shift towards incorporating artificial intelligence technologies in the areas of financial forecasting and decision-making (Artene & Domil, 2025: 1–2) [4]. Among the most prominent branches of AI that have emerged in this context are artificial neural networks, which are designed to mimic the way biological neurons transmit signals and recognize patterns (RAWAL, 2025: 6113) [19]. These networks represent a computational model inspired by the human nervous system, and they are distinguished by their capacity to learn and adapt through a matrix of weighted connections that form artificial synapses linking their processing units (Abu Lifa & Shtwan, 2023: 32) [1]. Computationally, they integrate to perform specific tasks through massively parallel distributed processing (Mahdi, 2025: 10), and this grants them unique characteristics such as learnability, generalizability, parallel processing, and fault tolerance (Alaameri & Faihan, 2022: 2674) [2]. The significance of these networks stems from their high capability to model complex and nonlinear relationships within data (Sezer, 2020: 2) [21], as well as their ability to learn and adapt to new and evolving datasets

(Celik & Vanschoren, 2021: 3071) [6].

From a structural standpoint, neural networks can be classified into four main types based on how data flows through their units: feedforward networks, where data moves in one direction only; recurrent networks, which include feedback connections to handle sequential data (Qaidoum, 2025: 69) [18]; feedback networks that reinforce outputs; and auto-associative networks (Houbad & Chaibi, 2022: 490) [9]. In terms of architecture, each network consists of an input layer that receives the raw data and defines its features (Mienye, 2024: 4) [15], hidden layers that carry out the intermediate computations and collectively form what is known as a deep neural network (Chaudhary, 2025: 2) [7], and an output layer that produces the final results of the study (Saleh & Salman, 2022: 188) [20]. These operations are mathematically regulated through weighted connections that determine the strength of relationships between processing units, an aggregation function that acts as an internal activator by summing the products of inputs and their weights, and an activation function that applies mathematical equations to continuously adjust these weights throughout the training process (Gharyani, 2024: 286).

On the other side, financial performance represents the essential compass that guides decision-makers towards achieving sustainable growth and consistent profitability (Vintila *et al*., 2024: 1) [23]. It reflects the overall financial health of an organization and its capacity and willingness to meet its long-term financial obligations in order to ensure the delivery of services in the foreseeable future (Msua, 2016: 13; Ganyam & Ivungu, 2019: 42) [9, 16]. Evaluating this performance holds considerable importance as a monitoring tool that helps correct strategies, allocate resources efficiently, assess how well an organization is fulfilling its mission, generate cumulative knowledge, and identify strengths and weaknesses in order to maintain viability in a competitive environment (Ali *et al*., 2025: 283–284). These elements collectively serve the strategic objectives of financial balance, company growth for value maximization, and profitability as a measure of management efficiency in generating net earnings (Khalaf, 2025: 196) [12].

For stakeholders to be able to properly evaluate economic performance, the need for financial reporting quality has become increasingly apparent. This concept refers to the degree of accuracy and faithfulness with which financial reports convey true information about a company's operations and cash flows (Mbawuni, 2019: 30; Soyemi & Olawale, 2019: 449) [14, 22]. Quality reporting requires the provision of complete, unbiased, clear, verifiable, and non-misleading financial and non-financial information (Magaji & Abubakar, 2023: 114; Hussein & Aziz, 2024: 347) [10, 13]. The importance of this quality lies in enhancing the credibility of accounting information to facilitate managerial accountability (Yusran, 2023: 3) [25], as well as providing management with high-quality information that helps in identifying profitable projects and making more informed investment decisions (Assad & Alshurideh, 2020: 199) [5].

This brings us to the research gap addressed by the current study. While traditional statistical methods may overlook complex financial patterns, the use of neural networks in accounting and auditing has proven to be superior to conventional statistical models due to their higher accuracy (Jumaa, 2012: 151) [11]. Neural networks possess a superior dynamic capacity to capture interactions among financial variables, resulting in more accurate earnings forecasts and better risk assessments (Artene & Domil, 2025: 1–2), as well as a proven ability to predict account balances and detect transactions with unusual or fictitious patterns. Accordingly, this study seeks to bridge the gap in the literature by leveraging the advanced analytical capabilities of artificial neural networks and demonstrating their direct impact on assessing financial performance and ensuring the quality of financial reporting for economic entities.

Research Methodology

First: Research Problem

The problem addressed in this study revolves around the fact that traditional methods used in financial performance evaluation and in assessing the quality of financial reporting within accounting systems are no longer sufficient to keep up with the rapid developments taking place in today's business environment, particularly given the significant increase in data volume and complexity. Economic entities are now dealing with large datasets that require high processing and analysis capabilities, and this limits the effectiveness of traditional approaches in providing reliable and timely financial information. Against this backdrop, there has emerged a pressing need to employ artificial intelligence technologies as advanced tools capable of processing large data, improving the accuracy of financial conclusions, and enhancing the quality of financial reports by delivering more efficient and reliable results. The central research question can therefore be stated as follows:

How can artificial neural networks — with their characteristics and structural components — be employed in evaluating financial performance and ensuring the quality of financial reports for economic entities?

Second: Research Objectives

The current study aims to achieve the following main objectives:

- Understand the nature of artificial neural networks, their structural components (input, hidden layers, output, weights, and aggregation and activation functions), and their various types.
- Demonstrate the role of neural networks in modeling complex and nonlinear relationships and adapting to new data, compared to traditional statistical models.
- Measure and analyze the financial performance of the sampled economic entities in terms of financial balance, company growth, and profitability, and identify their strengths and weaknesses.
- Explore the extent to which neural networks contribute to improving the quality of financial reports by providing complete, faithful, relevant, and distortion-free information.

Third: Research Importance

Scientific Importance: This study enriches accounting and financial thought by integrating artificial intelligence techniques — specifically neural networks — into accounting practices, and by clarifying their superior predictive capacity and ability to detect transactions with unusual or fictitious patterns (Artene & Domil, 2025; Jumaa, 2012) [4, 11].

Practical Importance: This study provides managers and stakeholders with an advanced and highly accurate tool that can assist in resource allocation, strategy refinement, and making more informed investment decisions based on high-quality financial reports (Yusran, 2023; Assad & Alshurideh, 2020) [4, 25].

Fourth: Research Hypotheses

Based on the established literature, the following hypotheses were formulated:

H0: Artificial neural networks do not outperform multiple linear regression (OLS) in measuring the effect of discretionary accruals on the financial performance indicators of Iraqi banks.

H1: Artificial neural networks outperform multiple linear regression (OLS) in measuring the effect of discretionary accruals on the financial performance indicators of Iraqi banks.

$H1_1$: Neural networks outperform the traditional method in measuring the effect of discretionary accruals on profit margin.

$H1_2$: Neural networks outperform the traditional method in measuring the effect of discretionary accruals on return on assets.

$H1_3$: Neural networks outperform the traditional method in measuring the effect of discretionary accruals on return on equity.

Fifth: Proposed Conceptual Framework

Drawing on relevant literature, the study posits that artificial neural networks play a role in improving the accuracy of measuring and analyzing corporate financial performance, and that this improvement reflects positively on the quality of financial reporting by providing more reliable and relevant information for decision-makers. The conceptual model consists of the following variables:

Artificial Neural Networks (ANNs)

These represent one of the artificial intelligence techniques used in analyzing financial data and uncovering complex and nonlinear patterns and relationships, thereby contributing to improved measurement, forecasting, and decision-making processes.

Mediating Variable: Financial Performance

This reflects the company's ability to achieve its financial goals, and is measured through the following dimensions: financial balance, company growth, and profitability.

Dependent Variable: Financial Reporting Quality

This refers to the extent to which financial reports provide information characterized by accuracy, reliability, and relevance. It can be assessed through the following characteristics: relevance, faithful representation, verifiability, clarity and understandability, freedom from material errors and distortions, and the hypothesized relationships between variables.

The conceptual model of the study is built on the assumption that using artificial neural networks contributes to improving the measurement and analysis of corporate financial performance, that improved financial performance reflects positively on the quality of financial reporting, and that there may also be a direct effect of neural networks on enhancing reporting quality by raising the level of accuracy in financial analysis and supporting managerial and investment decisions.

Theoretical Framework

Section One: Artificial Neural Networks

First: The Concept of ANNs and Their Importance in Accounting and Finance

Artificial neural networks are built on a computational model inspired by the way the human nervous system processes and interacts with information. They are constructed from interconnected processing units that work in an integrated fashion to receive data and transform it into meaningful outputs. The relationships between these units are managed through weight parameters that are continuously updated during the learning phases, allowing the system to improve its performance and enhance its ability to interpret hidden patterns in the data.

Artificial neural networks represent one of the advanced structures within machine learning technologies, operating through a layered hierarchy where data starts at the input nodes, undergoes a series of transformations within intermediate layers, and then produces final results at the output layer. This structural organization allows the system to extract complex relationships between variables and convert raw data into interpretable and analyzable information.

Artificial neural networks have become increasingly prominent within modern financial and accounting applications, largely due to their ability to handle complex information environments characterized by multiple variables and intertwined relationships. Their importance is evident in their capacity to absorb continuous changes in financial data and deliver deeper insights compared to traditional methods.

Companies today are facing a growing influx of financial and non-financial information, along with the interplay of numerous economic, operational, and regulatory factors that influence their business outcomes. This complexity has heightened the need for analytical tools capable of dealing with multidimensional data and extracting indicators with high explanatory value.

Findings from numerous recent studies indicate that employing ANNs enhances the quality of financial decisions by improving the efficiency of predictive models used in future data analysis. This is attributed to their ability to uncover non-apparent relationships between variables and reduce error levels associated with estimation and forecasting processes.

The applications of ANNs in accounting environments extend beyond improving financial analysis and forecasting. They also encompass the enhancement of monitoring functions by examining accounting data and detecting unusual patterns and indicators that may be associated with errors or manipulative practices, thereby supporting the credibility of financial information and raising the level of reliance on it.

In light of the above, the current study proceeds from the assumption that artificial neural networks are no longer merely a computational technology for data processing, but have become a knowledge and strategic resource that can be employed to improve financial measurement efficiency and enhance the quality of information produced within companies.

This role is expected to reflect positively on the accuracy of financial performance evaluation and the level of financial reporting quality, by providing more reliable and relevant information for users' needs.

Second: Components of ANNs

Artificial neural networks consist of a set of interconnected elements that perform complementary roles in the data processing operation, including:

- Input Layer: This represents the starting point of the neural network, where the raw data to be analyzed — whether numerical, financial, or accounting — is received. Each node in this layer represents a variable or feature of the input data (Mienye & Swart, 2024) [15].
- Hidden Layers: Located between the input and output layers, these carry out the computational operations, analyze the relationships between data, and extract the latent patterns within it. Having multiple hidden layers increases the network's ability to handle complex problems and improve the accuracy of results (Chaudhary *et al*., 2025) [7].
- Output Layer: This is the final stage of the network, where the required results or predictions are produced after the processing operations within the hidden layers are complete (Saleh & Salman, 2022) [20].
- Weights: These express the strength of the relationship between artificial neurons and are continuously adjusted during the training process with the goal of minimizing errors and improving accuracy (Saleh & Salman, 2022) [20].
- Aggregation Function: This aggregates the inputs arriving at a neuron after multiplying them by their respective weights, yielding a total value that represents the net input to the neuron (Saleh & Salman, 2022).
- Activation Function: This is the mechanism that determines whether the signal generated by the aggregation function will be passed on to the next neuron. It plays a pivotal role in enabling the network to represent nonlinear relationships between variables (Gharyani, 2024).

Third: Characteristics of ANNs

- The ability to learn and acquire knowledge from available data.
- The ability to generalize and predict future outcomes.
- Parallel processing of data, which enhances operational efficiency.
- The ability to detect errors, correct them, and progressively improve results (Alaameri & Faihan, 2022) [2].

Fourth: Types of ANNs

- Feedforward Neural Networks
- Recurrent Neural Networks
- Feedback Networks
- Auto-associative Networks (Qaidoum, 2025; Houbad & Chaibi, 2022) [9, 18]

Fifth: Applications of ANNs in Accounting and Finance

Artificial neural networks have become one of the modern tools used to advance accounting and financial practices. They are applied in predicting earnings and cash flows, analyzing financial risks, evaluating financial performance, detecting fraud and manipulation in financial data, and supporting investment and credit decisions. Recent studies have confirmed that this technology achieves high levels of accuracy compared to traditional methods, which reinforces the reliability and quality of financial information (Sezer *et al*., 2020; Artene & Domil, 2025) [4, 21].

Section Two: Financial Performance

First: The Concept of Financial Performance

Financial performance is one of the fundamental indicators that reflect a company's ability to utilize its resources efficiently and achieve its economic objectives. It refers to the level of success a company achieves in generating profits, maintaining financial balance, and attaining sustainable growth in ways that ensure its continuity and strengthen its competitive position (Nasser & Al-Hadrawi, 2024; Vintila *et al*., 2024) [17, 23].

Financial performance is also viewed as a measure of the company's overall financial health and its ability to meet its current and future financial obligations, in addition to its capacity to create added value for stakeholders (Msua, 2016; Ganyam & Ivungu, 2019) [9, 16].

Second: Importance of Evaluating Financial Performance

Evaluating financial performance is important as a monitoring and management tool that helps:

- Measuring the extent to which strategic objectives are being achieved.
- Rationalizing the use of available resources.
- Identifying strengths and weaknesses.
- Supporting the decision-making process.
- Strengthening the company's competitive position (Ali *et al*., 2025).

Third: Objectives of Financial Performance

Financial Balance: This refers to the company's ability to maintain equilibrium between its funding sources and their uses, ensuring financial stability and operational continuity.

Growth: This indicates the company's ability to expand its activities and increase the volume of its business and profits in ways that generate greater value for shareholders.

Profitability: This represents the company's ability to generate financial returns from its various activities and reflects management's efficiency in utilizing available resources (Khalaf, 2025) [12].

Section Three: Financial Reporting Quality

First: The Concept of Financial Reporting Quality

Financial reporting quality refers to the degree to which financial reports are capable of presenting accurate, reliable, and relevant information that honestly reflects the economic reality of the company, thereby helping users of financial information make sound economic decisions (Mbawuni, 2019) [14]. It also expresses the degree to which financial information is free from material errors and biases, and its ability to represent a company's financial performance and financial position in a fair and transparent manner (Magaji & Abubakar, 2023; Soyemi & Olawale, 2019) [13, 22].

Second: Importance of Financial Reporting Quality

- Enhancing the reliability of accounting and financial information.

- Supporting the monitoring and accountability process.
- Improving investment and financing decisions.
- Increasing investor and stakeholder confidence.
- Enhancing the efficiency of financial markets (Yusran, 2023; Assad & Alshurideh, 2020) [4, 25].

Third: Characteristics of Financial Reporting Quality
- Relevance
- Faithful Representation
- Comparability
- Verifiability
- Timeliness
- Understandability

Section Four: The Relationship Between Neural Networks, Financial Performance, and Financial Reporting Quality

Recent literature indicates that artificial neural networks have become an effective tool for improving financial analysis processes and forecasting economic and financial indicators. They enable companies to process complex data and discover patterns and relationships that are difficult to detect using traditional methods. As a result, their use contributes to improving the accuracy of financial performance measurement and providing more reliable indicators for decision-making.

Furthermore, improving the quality of financial performance measurement reflects positively on the quality of financial reports by providing more accurate, objective, and transparent information. In addition, neural networks can directly contribute to enhancing the quality of financial reports by detecting errors and distortions and improving the quality of accounting information. Accordingly, the study assumes a positive relationship between the use of artificial neural networks and financial performance measurement on one hand, and between financial performance and financial reporting quality on the other, as well as a direct effect of neural networks on improving the quality of financial reports.

How This Study Differs from Prior Research

Despite the scientific contributions made by previous studies in the area of applying artificial neural networks to accounting and finance, most of them focused on specific domains such as sales forecasting, earnings prediction, financial time series analysis, detecting errors and distortions in financial data, or supporting financial and investment decisions. Some studies also tested the efficiency of neural networks in improving the accuracy of financial indicator forecasting or in credit risk assessment, while others examined financial reporting quality as either an independent or dependent variable linked to governance mechanisms, audit quality, or accounting information systems.

Despite the value of these studies, a research gap has been identified. There is a notable scarcity of studies that have comprehensively examined the role of artificial neural networks in measuring corporate financial performance and how that relates to the quality of financial reporting. Moreover, most previous studies focused on bilateral relationships between variables without presenting a framework that clarifies the cascading effect of neural networks on improving financial performance measurement and its subsequent impact on reporting quality.

The current study differs from previous research in several key aspects:

- Difference in subject matter: The study examines the integrative relationship between ANNs, financial performance, and financial reporting quality within a single research model, rather than focusing on one of these variables separately.
- Difference in analytical perspective: The study does not limit itself to testing the predictive capacity of neural networks but rather investigates their role in improving the financial performance measurement process and the implications of that for reporting quality.
- Difference in conceptual framework: The study presents a model that links ANNs as an influencing variable, financial performance as a mediating variable, and financial reporting quality as a dependent variable.
- Bridging a knowledge gap in accounting literature related to integrating AI applications with financial performance indicators and financial reporting quality — an issue that still requires further investigation in developing environments in general, and the Iraqi environment in particular.
- Focusing on the accounting and monitoring dimension of ANNs rather than limiting the scope to prediction or financial analysis alone, specifically by studying their role in strengthening the credibility of financial information and improving financial reporting quality.

Contribution of the Current Study

First: Scientific (Theoretical) Contribution
- Enriching accounting and financial literature related to AI applications, particularly ANNs, by clarifying their role in measuring financial performance and improving financial reporting quality.
- Presenting an integrated theoretical framework that explains the interrelated relationships between ANNs, financial performance, and financial reporting quality.
- Contributing to widening the scope of accounting studies that link AI technologies to the quality of financial information in the context of accelerating digital transformation.
- Providing a scientific foundation that future studies interested in examining the impact of AI technologies on the development of accounting and monitoring practices can build upon.

Second: Practical (Applied) Contribution
- Clarifying how ANNs can be employed to improve the accuracy of financial performance measurement within companies.
- Supporting financial and accounting departments in benefiting from AI technologies to develop financial analysis systems, forecasting, and decision-making.
- Contributing to improving the quality of financial reports by enhancing the accuracy of accounting information and enabling early detection of potential errors and deviations.
- Providing practical indicators that help companies and regulatory bodies adopt AI applications in line with requirements for transparency, reliability, and financial disclosure.
- Supporting digital transformation efforts in institutions by highlighting the added value of ANNs in advancing accounting and financial practices.

Research Gap

The research gap can be summarized as follows: previous studies have established the effectiveness of ANNs in financial forecasting and analysis, while other studies have confirmed the importance of financial reporting quality in supporting economic decisions. However, there is a clear shortage of studies that have examined the role of ANNs in improving financial performance measurement and how that reflects on financial reporting quality within an integrated framework — and this is precisely what the current study seeks to address and contribute to scientifically.

Empirical Section: Measurement and Descriptive Analysis

Financial Performance Measurement

Financial performance indicators: The financial performance of the sampled banks will be measured using three indicators based on profitability and liquidity measures.

Table 1: Profit Margin = Net Profit / Total Revenue

Bank / Year	Ashur Intl.	Investment	National	Gulf Comm.	Middle East	Mansour	Mosul Dev.	Baghdad	Sumer
2016	0.4292	0.3897	0.5090	0.2251	0.3301	0.5795	0.3897	0.2750	0.3273
2017	0.6677	0.2130	0.0796	0.1630	-0.1792	0.5751	0.4345	0.1168	0.0319
2018	0.2763	0.0007	-0.4245	0.0356	-0.1684	0.6340	0.2485	0.1185	0.1286
2019	0.3747	0.0391	0.2653	-0.3600	0.0940	0.4659	0.3760	0.1825	0.1687
2020	0.1865	0.3159	0.3677	-0.0001	0.0295	0.4444	0.2315	0.3006	0.1340
2021	0.3381	0.1145	0.3143	-0.5604	-0.0008	0.4705	0.3767	0.3614	0.1873
2022	0.4194	0.0874	0.2545	-0.4025	0.0753	0.4689	0.3643	0.4745	0.1372
2023	0.6352	0.7241	0.5539	0.3005	-0.5722	0.6043	0.2865	-0.3360	-0.7802
Mean	0.4159	0.2355	0.2400	-0.0749	-0.0490	0.5303	0.3385	0.1867	0.0418
Std. Dev.	0.1654	0.2390	0.3072	0.3229	0.2654	0.0751	0.0733	0.2440	0.3422
Max	0.6677	0.7241	0.5539	0.3005	0.3301	0.6340	0.4345	0.4745	0.3273
Min	0.1865	0.0007	-0.4245	-0.5604	-0.5722	0.4444	0.2315	-0.3360	-0.7802

Table (1) shows that the majority of the sampled banks recorded profits as a result of sound investment activity, with the profitability indicator ranging between -0.78 and 0.724 across banks and years. The highest values were recorded for Investment Bank and Ashur International Investment Bank, while the lowest levels were seen at Sumer Bank and Middle East Bank.

Table 2: Return on Assets (ROA) = Net Profit After Tax / Total Assets
This indicator focuses on measuring the profits generated from invested assets and reflects the bank's ability to generate earnings.

Bank / Year	Ashur Intl.	Investment	National	Gulf Comm.	Middle East	Mansour	Mosul Dev.	Baghdad	Sumer
2016	0.0393	0.0193	0.0394	0.0073	0.0179	0.0130	0.0086	0.0169	0.0107
2017	0.0359	0.0081	0.0049	0.0070	-0.0063	0.0113	0.0120	0.0057	0.0010
2018	0.0101	0.0000	-0.0112	0.0010	-0.0041	0.0135	0.0063	0.0039	0.0022
2019	0.0142	0.0009	0.0145	-0.0072	0.0042	0.0057	0.0083	0.0064	0.0029
2020	0.0313	0.0091	0.0223	0.0000	0.0018	0.0054	0.0037	0.0128	0.0032
2021	0.0124	0.0045	0.0143	-0.0094	0.0000	0.0116	0.0048	0.0195	0.0031
2022	0.0165	0.0022	0.0114	-0.0093	0.0040	0.0172	0.0069	0.0308	0.0032
2023	0.0330	0.0397	0.0477	0.0116	-0.0213	0.0349	0.0068	-0.0286	-0.0231
Mean	0.0241	0.0105	0.0179	0.0001	-0.0005	0.0141	0.0072	0.0084	0.0004
Std. Dev.	0.0119	0.0134	0.0187	0.0081	0.0111	0.0093	0.0025	0.0174	0.0099
Max	0.0393	0.0397	0.0477	0.0116	0.0179	0.0349	0.0120	0.0308	0.0107
Min	0.0101	0.0000	-0.0112	-0.0094	-0.0213	0.0054	0.0037	-0.0286	-0.0231

Table (2) shows that most of the sampled banks recorded profits from their asset investments, with the profitability indicator ranging between 0.028 and 0.047 across the period. The highest values were found for Investment Bank and Ashur International Investment Bank, while the lowest levels were seen at Baghdad Bank and Sumer Bank.

Table 3: Return on Equity (ROE) = Net Profit After Tax / Equity This indicator measures owner returns, and a higher value signals the banks' ability to generate profits from owners' invested capital.

Bank / Year	Ashur Intl.	Investment	National	Gulf Comm.	Middle East	Mansour	Mosul Dev.	Baghdad	Sumer
2016	0.0584	0.0385	0.0792	0.0185	0.0409	0.0500	-0.0328	0.0716	0.0141
2017	0.0507	0.0164	0.0104	0.0132	-0.0185	0.0511	-0.0505	0.0225	0.0015
2018	0.0176	0.0000	-0.0229	0.0019	-0.0115	0.0147	0.0097	0.0162	0.0034
2019	0.0227	0.0018	0.9164	-0.0128	0.0098	0.0296	0.0086	0.0267	0.0037
2020	0.0545	0.0196	0.0600	0.0400	0.0041	0.0237	0.0057	0.0128	0.0041
2021	0.0271	-0.0432	0.0159	-0.0097	-0.0001	0.0290	0.0059	0.0970	0.0044
2022	0.0401	0.0148	0.0826	-0.0166	0.0096	0.0447	0.0082	0.1520	0.0039
2023	0.0814	0.0701	0.3763	0.0207	-0.0438	0.1271	0.0187	-0.1660	-0.0268
Mean	0.0441	0.0148	0.1897	0.0069	-0.0012	0.0463	-0.0033	0.0291	0.0010
Std. Dev.	0.0214	0.0325	0.3187	0.0196	0.0247	0.0352	0.0245	0.0926	0.0119
Max	0.0814	0.0701	0.9164	0.0400	0.0409	0.1271	0.0187	0.1520	0.0141
Min	0.0176	-0.0432	-0.0229	-0.0166	-0.0438	0.0147	-0.0505	-0.1660	-0.0268

Table (3) shows that results across banks range between -0.166 and 0.916, with the highest values recorded for National Bank and Baghdad Bank, reflecting sound management and healthy operational policies. The lowest levels were recorded for Baghdad Bank and Mosul Development and Investment Bank.

Modified Jones Model

Step One

Calculating total accruals by subtracting operating cash flows from net income from ordinary operations using the following equations:

$$TACC_{jt} = NI_{jt} - CFO_{jt}$$

Step Two

Estimating the regression model coefficients β0, β1, β2, β3 for each entity and each year separately using the following equation:

$$\frac{TACC_{jt}}{TA_{jt-1}} = \beta 0 + \beta 1 \frac{1}{TA_{jt-1}} + \beta 2 \frac{\Delta SALE_{jt} - \Delta REC_{jt}}{TA_{jt-1}} + \beta 3 \frac{PPE_{jt}}{TA_{jt-1}} + \varepsilon_{jt}$$

TAt-1: refers to total assets

ΔSALEjt: Refers to changes in sales

PPEjt: Refers to property, plant, and equipment

ε: Refers to regression residuals

j, t: Refers to entity, year

Step Three: Calculating Discretionary Accruals

$$DiscAcc_{jt} = TACC_{jt} - NON\_DiscAcc_{jt}$$

Table 4: Discretionary Accruals Results — Modified Jones Model

Bank / Year	Ashur Intl.	Investment	National	Gulf Comm.	Middle East	Mansour	Mosul Dev.	Baghdad	Sumer
2016	0.0907	0.0512	0.0844	0.0651	0.0053	0.0474	0.0245	0.1449	0.0422
2017	0.1194	0.0931	0.0524	0.1284	0.0086	0.1748	0.0005	0.0395	0.1441
2018	0.1366	0.0805	0.0604	0.1004	0.0025	0.1210	0.0142	0.0030	0.0077
2019	0.0381	0.0626	0.0258	0.1195	0.0548	0.0067	0.0503	0.0113	0.0581
2020	0.0382	0.0191	0.0102	0.0719	0.0365	0.2008	0.0086	0.2764	0.0331
2021	0.1245	0.0897	0.1021	0.0012	0.2986	0.2324	0.6069	0.3108	0.2735
2022	0.0097	0.0068	0.1304	0.0832	0.0021	0.0934	0.0038	0.1064	0.0094
2023	0.2740	0.0262	0.1034	0.1249	0.0247	0.2634	0.0566	0.0466	0.0929

Neural Network Model Applied

This study applied a Multilayer Perceptron (MLP) neural network with the following structure:

Table 5: Neural Network Model Structure

Layer	Neurons	Variables	Activation Function	Role
Input Layer	2	|DAC|, Log(TA)	—	Receiving inputs
Hidden Layer	5	Learned weights	Tanh	Learning
Output Layer	1	Prediction of dependent variable	Linear	Output

The Leave-One-Out Cross-Validation (LOO-CV) method was used to verify the model's generalizability, given the sample size of 72 observations. The Adam optimization algorithm was applied with a learning rate of 0.005 and a Tanh activation function in the hidden layer.

Table 6: Multiple Linear Regression (OLS) Results Three multiple linear regression models were estimated using OLS, and the results with LOO-CV are as follows:

Model	β0	β1 |DAC|	β2 Log(TA)	R^2 Full	R^2 LOO	RMSE LOO
Profit Margin (PM)	-2.8627	0.5410	0.1108	0.0841	0.0034	0.3001
Return on Assets (ROA)	-0.1106	0.0174	0.0043	0.0504	-0.0870	0.0146
Return on Equity (ROE)	-1.0945	-0.0150	0.0415	0.0341	-0.0507	0.1230

The results indicate that the DAC coefficient was positive in both the profit margin and ROA models, reflecting the inflationary effect of discretionary accruals on the financial performance indicator. It is also evident that bank asset size Log(TA) is positively associated with all indicators, which is consistent with economies of scale theory.

Table 7: Artificial Neural Network (ANN) Results The MLP model was applied with three separate models (one model for each dependent variable) using LOO-CV:

Dependent Variable	R^2 OLS (Full)	R^2 ANN (Full)	R^2 OLS (LOO)	R^2 ANN (LOO)	RMSE OLS (LOO)	RMSE ANN (LOO)
Profit Margin (PM)	0.0841	0.0415	0.0034	0.0189	0.3001	0.2978
Return on Assets (ROA)	0.0504	-0.1075	-0.0870	-0.1460	0.0146	0.0150
Return on Equity (ROE)	0.0341	-0.2182	-0.0507	-0.2456	0.1230	0.1339

The table results indicate that the neural network model outperformed the traditional model in predicting profit margin (RMSE = 0.2978 compared to 0.3001, and R^2 LOO = 0.0189 compared to 0.0034). However, the traditional OLS method outperformed the neural network model in measuring ROA and ROE.

Table 8: Summary of Hypothesis Testing Results

Hypothesis	Content	R^2(LOO) OLS	R^2(LOO) ANN	RMSE OLS	RMSE ANN	Decision
$H1_1$	ANN > OLS in PM	0.0034	0.0189	0.3001	0.2978	Reject H0 ✓
$H1_2$	ANN > OLS in ROA	-0.0870	-0.1460	0.0146	0.0150	Accept H0
$H1_3$	ANN > OLS in ROE	-0.0507	-0.2456	0.1230	0.1339	Accept H0
Main H	ANN > OLS across all financial performance indicators	—	—	—	—	Partially Accept H0

Conclusions

- The study findings showed that the efficiency of ANNs varies depending on the financial performance indicator used.
- ANNs outperformed the multiple linear regression model only in predicting profit margin.
- The multiple linear regression model retained higher efficiency in explaining ROA and ROE.
- Discretionary accruals affect certain financial performance indicators, suggesting that earnings management practices may be reflected in the banks' financial results.
- A single analytical model cannot be relied upon for all financial indicators; rather, it is necessary to select the model most appropriate to the nature of the data and the analytical objective.
- Neural networks serve as a complementary tool to traditional models, rather than a complete substitute for them, within the Iraqi banking environment.

Recommendations

- Adopt an integrated approach that combines artificial intelligence techniques with traditional statistical methods when analyzing financial performance.
- Encourage Iraqi banks to develop their digital infrastructure and take advantage of AI applications in financial analysis and forecasting.
- Strengthen oversight of discretionary accruals to limit earnings management practices and improve the quality of financial reports.
- Train accounting and financial staff to use modern analytical tools and AI technologies.
- Conduct future studies using larger samples and additional variables, as well as comparing different types of neural networks and machine learning algorithms.
- Expand the scope of research to include other economic sectors in order to verify the generalizability of the findings to different business environments.

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Appendix 1

Table 4: Discretionary Accruals — Modified Jones Model Results (2016–2023)

Bank	Year	a0	a1*(ΔREV-ΔAR)/A	a2*1/TA-1	a3*PPE	NDAi,t	TACCi,t/Ai,t-1	DACi,t	|DACi,t|
Ashur Intl.	2016	0.0627	0.0066	-0.0959	0.0018	-0.0248	0.0660	0.0907	0.0907
	2017	0.0073	-0.0316	0.0107	-0.0295	-0.0430	0.0764	0.1194	0.1194
	2018	-0.0393	-0.0022	-0.0693	0.0000	-0.1108	-0.2475	-0.1366	0.1366
	2019	0.0248	-0.0143	0.0229	0.0256	0.0590	0.0971	0.0381	0.0381
	2020	-0.1046	-0.0435	0.0877	0.0065	-0.0539	-0.0157	0.0382	0.0382
	2021	0.3717	-0.0319	-0.3257	-0.0815	-0.0674	0.0571	0.1245	0.1245
	2022	-0.1343	0.1666	0.1471	0.0025	0.1819	0.1916	0.0097	0.0097
	2023	-0.3678	-0.0494	0.1585	0.0299	-0.2289	0.0451	0.2740	0.2740
Investment	2016	0.0627	0.0008	-0.0711	0.0014	-0.0062	-0.0574	-0.0512	0.0512
	2017	0.0073	-0.0404	0.0070	-0.0264	-0.0525	0.0406	0.0931	0.0931
	2018	-0.0393	0.0559	-0.0454	0.0000	-0.0288	0.0516	0.0805	0.0805
	2019	0.0248	0.0039	0.0176	0.0148	0.0611	0.1237	0.0626	0.0626
	2020	-0.1046	-0.0093	0.0703	0.0040	-0.0396	-0.0587	-0.0191	0.0191
	2021	0.3717	-0.0248	-0.2701	-0.0534	0.0234	0.1131	0.0897	0.0897
	2022	-0.1343	0.1839	0.2572	0.0067	0.3134	0.3066	-0.0068	0.0068
	2023	-0.3678	-0.0501	0.1642	0.0422	-0.2115	-0.1854	0.0262	0.0262
National	2016	0.0627	0.0162	-0.0660	0.0014	0.0144	-0.0700	-0.0844	0.0844
	2017	0.0073	-0.0236	0.0069	-0.0177	-0.0270	-0.0794	-0.0524	0.0524
	2018	-0.0393	-0.0282	-0.0432	0.0000	-0.1107	-0.0503	0.0604	0.0604
	2019	0.0248	-0.0877	0.0203	0.0161	-0.0265	-0.0523	-0.0258	0.0258
	2020	-0.1046	0.0708	0.0588	0.0040	0.0290	0.0189	-0.0102	0.0102
	2021	0.3717	-0.0761	-0.1727	-0.0842	0.0387	-0.0634	-0.1021	0.1021
	2022	-0.1343	0.0222	0.0496	0.0025	-0.0601	-0.1905	-0.1304	0.1304
	2023	-0.3678	0.0782	0.0511	0.0272	-0.2113	-0.3148	-0.1034	0.1034
Gulf Comm.	2016	0.0627	0.0053	-0.0489	0.0021	0.0212	-0.0439	-0.0651	0.0651
	2017	0.0073	0.0823	0.0050	-0.0296	0.0650	0.1934	0.1284	0.1284
	2018	-0.0393	-0.0194	-0.0432	0.0000	-0.1019	-0.0015	0.1004	0.1004
	2019	0.0248	0.0236	0.0185	0.0351	0.1020	-0.0176	-0.1195	0.1195

	2020	-0.1046	-0.0121	0.0678	0.0101	-0.0388	0.0331	0.0719	0.0719
	2021	0.3717	0.0030	-0.3022	-0.1379	-0.0654	-0.0642	0.0012	0.0012
	2022	-0.1343	-0.0303	0.1676	0.0056	0.0086	-0.0746	-0.0832	0.0832
	2023	-0.3678	0.0020	0.2234	0.0713	-0.0711	0.0537	0.1249	0.1249
Middle East	2016	0.0627	-0.0095	-0.0579	0.0097	0.0050	-0.0003	-0.0053	0.0053
	2017	0.0073	-0.0105	0.0061	-0.1475	-0.1446	-0.1532	-0.0086	0.0086
	2018	-0.0393	0.0008	-0.0338	0.0000	-0.0724	-0.0749	-0.0025	0.0025
	2019	0.0248	0.0086	0.0130	0.0779	0.1243	0.1791	0.0548	0.0548
	2020	-0.1046	-0.0102	0.0544	0.0283	-0.0320	0.0045	0.0365	0.0365
	2021	0.3717	-0.0024	-0.2259	-0.4824	-0.3390	-0.0405	0.2986	0.2986
	2022	-0.1343	0.1160	0.1342	0.0280	0.1440	0.1418	-0.0021	0.0021
	2023	-0.3678	-0.0381	0.1368	0.3383	0.0691	0.0938	0.0247	0.0247
Mansour	2016	0.0627	-0.0017	-0.0364	0.0010	0.0257	-0.0216	-0.0474	0.0474
	2017	0.0073	-0.0009	0.0036	-0.0177	-0.0076	-0.1824	-0.1748	0.1748
	2018	-0.0393	-0.0002	-0.0198	0.0000	-0.0593	-0.1803	-0.1210	0.1210
	2019	0.0248	-0.0004	0.0068	0.0091	0.0404	0.0337	-0.0067	0.0067
	2020	-0.1046	-0.0011	0.0255	0.0027	-0.0774	0.1234	0.2008	0.2008
	2021	0.3717	-0.0018	-0.1199	-0.0452	0.2047	0.4372	0.2324	0.2324
	2022	-0.1343	0.0345	0.1293	0.0034	0.0330	0.1264	0.0934	0.0934
	2023	-0.3678	-0.0225	0.1677	0.0440	-0.1787	-0.4420	-0.2634	0.2634
Mosul Dev.	2016	0.0627	-0.0049	-0.1071	0.0006	-0.0487	-0.0732	-0.0245	0.0245
	2017	0.0073	0.0021	0.0098	-0.0079	0.0113	0.0108	-0.0005	0.0005
	2018	-0.0393	-0.0750	-0.0637	0.0000	-0.1780	-0.1638	0.0142	0.0142
	2019	0.0248	-0.0080	0.0261	0.0653	0.1083	0.0580	-0.0503	0.0503
	2020	-0.1046	-0.0192	0.0908	0.0186	-0.0144	-0.0230	-0.0086	0.0086
	2021	0.3717	0.0007	-0.3884	-0.3073	-0.3232	-0.9301	-0.6069	0.6069
	2022	-0.1343	0.0096	0.1168	0.0070	-0.0009	0.0029	0.0038	0.0038
	2023	-0.3678	0.2475	0.1557	0.0937	0.1290	0.1856	0.0566	0.0566
Baghdad	2016	0.0627	0.0055	-0.0264	0.0011	0.0429	0.1878	0.1449	0.1449
	2017	0.0073	0.0035	0.0033	-0.0290	-0.0148	0.0247	0.0395	0.0395
	2018	-0.0393	0.0042	-0.0239	0.0000	-0.0590	-0.0619	-0.0030	0.0030
	2019	0.0248	0.0091	0.0096	0.0222	0.0657	0.0544	-0.0113	0.0113
	2020	-0.1046	-0.0087	0.0329	0.0069	-0.0736	-0.3500	-0.2764	0.2764
	2021	0.3717	0.0039	-0.1087	-0.0920	0.1749	-0.1359	-0.3108	0.3108
	2022	-0.1343	-0.0271	0.0586	0.0042	-0.0987	0.0077	0.1064	0.1064
	2023	-0.3678	-0.1325	0.0716	0.0523	-0.3764	-0.4230	-0.0466	0.0466
Sumer	2016	0.0627	0.0026	-0.1069	0.0029	-0.0387	0.0035	0.0422	0.0422
	2017	0.0073	0.0323	0.0114	-0.0392	0.0118	-0.1323	-0.1441	0.1441
	2018	-0.0393	-0.0133	-0.0668	0.0000	-0.1194	-0.1118	0.0077	0.0077
	2019	0.0248	0.0015	0.0261	0.0349	0.0873	0.1455	0.0581	0.0581
	2020	-0.1046	-0.0325	0.1062	0.0116	-0.0192	-0.0523	-0.0331	0.0331
	2021	0.3717	0.0044	-0.4633	-0.1976	-0.2847	-0.0112	0.2735	0.2735
	2022	-0.1343	-0.0111	0.2423	0.0081	0.1050	0.1144	0.0094	0.0094
	2023	-0.3678	0.0267	0.3769	0.1617	0.1974	0.1044	-0.0929	0.0929