Research Article

The Impact of Machine Learning and Deep Learning on Accounting Information Quality in Yemeni Banks in Light of Internal Auditing Effectiveness: The Moderating Role of Organizational Culture (Survey Study)

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Abstract

Objectives: The study aimed to measure the impact of machine learning and deep learning techniques on the quality of accounting information in Yemeni banks, through the effectiveness of internal audit as an intermediate variable, and explored the interactive impact of organizational culture of these variables.

Prior Work: The subject of the study is characterized by its novelty, especially after its emergence in peer-reviewed scientific journals, where it contributes to enriching the applied scientific literature related to the impact of AI on the accounting information quality and internal auditing through the interactive effect of organizational culture.

Approach: The descriptive method of analysis, and the questionnaire, a tool for data collection, represented the study population in of all (18) Yemeni banks in the capital, Sana'a, and it is considered a survey study as it took the whole society

Results: There is a high explanatory power of the proposed models, as it explained (63%) of the changes in the quality of accounting information, which supports its validity, and there is a positive effect of machine learning and deep learning on the quality of accounting information and the effectiveness of internal audit in Yemeni banks, in addition to a positive mediating effect of internal audit on the relationship between machine learning, deep learning, and the quality of accounting information. There is an interactive effect of organizational culture on the effectiveness of internal audit, and on the relationship between machine and deep learning and the quality of accounting information, with the intermediary role of internal audit stabilizing as organizational culture levels change.

Implications: The study benefits executives, financial managers, auditors, regulatory institutions, and researchers.

Keywords: Machine Learning; Deep Learning; Accounting Information Quality; Internal Audit; Yemeni Banks

Introduction

In recent decades of the twenty-first century, the world has witnessed rapid technological advancements that have caused fundamental transformations in the business and management environment. These developments have materially contributed to enhancing institutional performance efficiency, improving control mechanisms, and reinforcing transparency. Modern digital technologies have become among the most prominent tools supporting decision-making processes, providing a secure and effective informational environment that enhances the quality of administrative and financial operations.

With technological progress, Artificial Intelligence (AI) has become a critically important factor in improving the quality of internal auditing (Shivram, 2024: 24). Due to its capabilities in processing data rapidly and accurately, and analyzing it in an advanced manner, AI can contribute to enhancing the effectiveness and efficiency of the internal audit process and assist in detecting errors and inconsistencies in financial reports (Alnajjar, 2024: 2). As the volume of data increases and financial operations become more complex, intelligent technologies such as machine learning (ML) and deep learning (DL) techniques are considered vital tools for improving accounting information quality (AIQ) and contributing to the enhancement of internal audit (IA) effectiveness.

Framework and Literature Review

Study Problem

All Yemeni banks have recently engaged in a significant race toward automating their operations. Although internal auditors have relied on technology in previous years to enhance the efficiency of the auditing process, this reliance remained confined to routine tasks and low-level skills, coupled with a lack of technical expertise in detecting risks and manipulation within financial accounting systems. Technology alone has been unable to address these issues, which necessitates that internal auditors provide their services at the highest quality level. Consequently, there is a trend toward utilizing new technologies such as AI, by simulating AI processes that occur within the human brain, enabling computers to solve problems and make sound decisions logically and systematically. This approach aims to overcome some aspects of human limitations by employing AI dimensions (ML, knowledge representation and reasoning, and DL) during the execution of auditing operations through automated programs that support internal auditing functions in Yemeni banks to achieve their objectives by elevating the quality of internal auditing to the highest level.

Based on the foregoing, the following main research question can be formulated:

What is the impact of ML and DL on AIQ in Yemeni banks in light of internal auditing (IA) effectiveness as a mediating variable and organizational culture (OC) as a moderating variable?

This question branches into the following sub-questions:

1. What is the impact of machine learning (ML) on the AIQ in Yemeni banks?

2. What is the impact of DL on AIQ in Yemeni banks?

3. What is the impact of ML on the effectiveness of IA in Yemeni banks?

4. What is the impact of DL on the effectiveness of IA in Yemeni banks?

5. What is the impact of IA effectiveness on AIQ in Yemeni banks?

6. What is the interactive role of OC in the relationship between ML and DL and AIQ in Yemeni banks?

Study Objectives

The study aims to achieve the primary and main objective, which is to identify the impact of ML and DL on the AIQ in Yemeni banks, in light of the effectiveness of IA as a mediating variable and OC as a moderating variable. The following subsidiary objectives branch from these:

1. To clarify the impact of ML on the AIQ in Yemeni banks.

2. To clarify the impact of DL on the AIQ in Yemeni banks.

3. To explore the impact of ML and DL on the effectiveness of IA in Yemeni banks.

4. To determine the impact of IA effectiveness on AIQ in Yemeni banks.

5. To identify the interactive role of OC in the relationship between ML and DL and AIQ in Yemeni banks.

Study Importance

This research derives its scientific and practical significance from the importance of the topic it addresses, which is summarized as follows:

1. The importance of the study stems from forecasting the impact of deep machine learning on AIQ in Yemeni banks and exploring the effect of deep machine learning on the IA, as well as the moderating role of OC in the relationship between ML and DL and AIQ, especially in light of the challenges faced by the IA profession amid rapid technological developments.
1. 2- The study addressed a topic characterized by its modernity, especially after its emergence in peer-reviewed scientific journals, both foreign and Arabic. This study also contributes to enriching the scientific literature related to the impact of modern digital technologies on the quality of IA by focusing on modern techniques that have not yet been sufficiently studied in the Yemeni context. It is a cognitive and scientific foundation thru the collection of important theoretical information that forms the theoretical framework for this study and increases confidence in the sources used.
2. 3- The study gains practical importance as it investigates field and applied study the impact of DL technology on AIQ in light of the effectiveness of IA as a mediating variable, which will contribute to the development of IA processes, starting from planning and ending with the preparation and delivery of internal audit reports and monitoring their implementation using DL technology. This will lead to increased effectiveness and quality of IA processes, as well as accuracy and speed, reducing time and effort to the minimum possible, and enhancing AIQ.

Framework Model

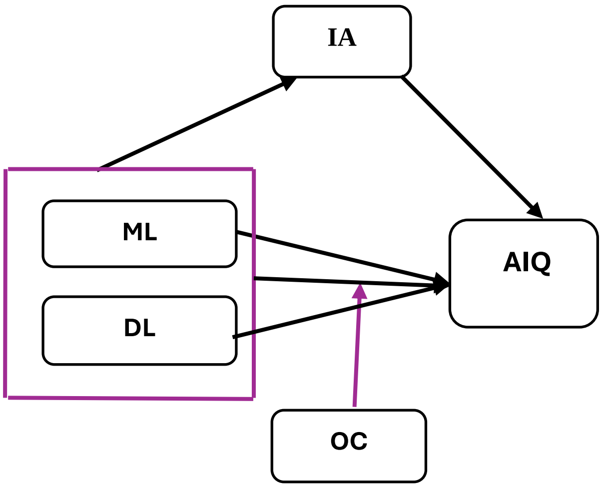

Figure 1: The cognitive model of the study (study variables)

Study Hypotheses

According to the study's problem, questions, objectives, and previous studies, the hypotheses can be formulated as follows:

First Main Hypothesis: There is no statistically significant effect of ML and DL on AIQ in Yemeni banks.

1. There is no statistically significant effect of ML on AIQ in Yemeni banks.
2. There is no statistically significant effect of DL on AIQ in Yemeni banks.

Second Main Hypothesis: There is no statistically significant effect of ML and DL on the effectiveness of IA in Yemeni banks.

1. There is no statistically significant effect of ML on the effectiveness of IA in Yemeni banks.
2. There is no statistically significant effect of DL on the effectiveness of IA in Yemeni banks.

Third Main-Hypothesis: There is no statistically significant effect of IA effectiveness on AIQ in Yemeni banks.

Fourth Main Hypothesis: There is no statistically significant effect of ML and DL on the AIQ in Yemeni banks through the mediating effect of IA effectiveness.

Fifth Main Hypothesis: There is no statistically significant interactive effect of OC on the relationship between ML &DL and AIQ, with the effect of IA as a mediating variable in Yemeni banks.

Literature Review

The study by Shawaqfeh, et al. (2025) aimed to determine the impact of AI on improving the quality of DL in Jordanian commercial banks, with the moderating role of Accounting Information Systems (AIS). The study employed a descriptive-analytical methodology and questionnaires for data collection. It concluded that AI technologies have an impact on the quality of DL in commercial banks, and that AIS plays a mediating role in the effect of AI on enhancing the quality of DL in these banks.

The study by Que, et al. (2025) examined the relationship between AIQ, information technology (IT), and the effectiveness of IA in Philippine companies. It used a descriptive-analytical approach and questionnaires for data gathering. The study found that the use of IT is essential to enhance the effectiveness of IA, and that AIQ plays a vital mediating role in the relationship between IT and internal audit effectiveness.

The study by Hadji, et al. (2025) aimed to explore the impact of AI and auditors' technological knowledge on the quality of IA in Iranian organizations. The study relied on a descriptive-analytical methodology and questionnaires for data collection. It concluded that AI and auditors' technological knowledge have a positive and statistically significant effect on the quality of IA. Additionally, AI has a positive and statistically significant impact on auditors' technological knowledge. The study inferred that the development and application of AI and the enhancement of auditors' technological knowledge are key factors in improving the quality of internal auditing in Iranian organizations.

Whereas the study by Awwad, et al. (2024) aimed to determine the impact of adopting AI technologies (Expert Systems, Machine Learning, Neural Networks, and Algorithms) on improving the quality attributes of accounting information, such as relevance, faithful representation, and verifiability, the study employed a descriptive-analytical methodology and used a questionnaire as a data collection tool from employees in companies listed on the Palestine Exchange. The study concluded that the use of AI technologies (Expert Systems, Machine Learning, Neural Networks, and Algorithms) has a positive effect on enhancing the quality attributes of accounting information (relevance, faithful representation, and verifiability). Expert Systems, Neural Network applications, and Algorithms contribute to developing solutions for various problems in industrial companies; detecting fraudulent practices in financial data; and achieving more accurate, faster, and reliable results. It is also beneficial to link Machine Learning technologies simultaneously and integrally with company systems in an effective manner.

The study by Sanjiwani et al. (2024) aimed to examine the impact of AI on accounting information systems and addressed the challenges faced in adopting AI technologies. The study relied on a review of previous research and studies and concluded that integrating AI into fraud detection processes has proven effective in enhancing the interpretability of fraud detection methods, addressing emerging fraud patterns, and mitigating challenges posed by imbalanced datasets. Additionally, the emphasis on education and training in AI techniques for accountants highlights the necessity of equipping professionals with the skills required to effectively implement AI-based solutions in fraud detection and prevention. The study also underlined the urgent need for deeper exploration of ethical considerations surrounding AI in financial reporting, with particular focus on mitigating biases, ensuring data privacy and security, and maintaining transparency and accountability in the use of AI systems.

The study by Khorsheed et al. (2024) aimed to explore the impact of AI and ML on professional roles within the context of financial reporting and auditing practices in Iraq. Employing a quantitative approach, data were collected via a structured questionnaire assessing perceptions of efficiency, accuracy, fraud detection, compliance, and professional impact. The study concluded that there is no significant effect of AI and ML on perceived efficiency, accuracy, fraud detection capabilities, or compliance in the professional roles of accountants. Furthermore, a gap exists between the theoretical benefits of AI and ML technologies and their practical perception among professionals in this field.

The study by Al-Akour (2024) aimed to demonstrate the impact of AI on the quality of accounting information in Jordanian commercial banks. The study employed a descriptive-analytical methodology and a questionnaire to collect data. The study concluded that there is a statistically significant impact of AI, using DL and ML, on the quality of accounting information in Jordanian commercial banks.

The study by Al-Taie (2023) aimed to clarify the role of AI in its various dimensions, represented by expert systems, knowledge representation, reasoning, and machine learning, in improving the quality of the auditing process in Iraqi banks. The study relied on the descriptive method and the questionnaire as its tool. The study concluded that there is a significant role for the dimensions of artificial intelligence systems in supporting the IA process within Iraqi banks.

While the study by Anantharaman et al. (2023) aimed to examine whether the adoption of AI in business operations improves the quality of financial reports, it relied on a sample of American public companies that adopted AI from 2014 to 2018. The financial statements of these companies were analyzed, and the study concluded that companies relying on AI achieved higher profitability than those that did not adopt AI technologies. Additionally, these companies were more stable and had greater accounting/operational complexity. The study also found that companies adopting AI did not experience significant changes in many of the fundamental bases of those companies and measures of accounting/business complexity. Furthermore, it indicated that the adoption of AI by companies improves the quality of earnings, as measured by discretionary allocations and the degree of alignment between allocations and cash flows.

The study (Ali et al., 2022) aimed to demonstrate the impact of activating artificial intelligence technologies on enhancing internal audit activities. The study relied on a descriptive-analytical approach and survey method. It concluded that traditional manual systems used in internal audit activities do not align with the continuous economic development in the business environment. The study indicated that the application of artificial intelligence helps internal auditors conduct comprehensive evaluations and prepare periodic reports that include the most important observations, discuss them with the board of directors, and provide appropriate recommendations and corrective actions to ensure the quality of financial reports.

The study (Abu Zeina, 2022) addressed artificial intelligence (expert systems, neural networks, genetic algorithms, intelligent agents) and its impact on improving the quality of internal auditing in Jordanian commercial banks. The study adopted a descriptive and analytical approach and used the survey method to obtain primary data. The study concluded that the level of AI in commercial banks was average, and the level of DL quality in commercial banks was high. Additionally, there is a statistically significant impact of AI and its contribution to improving the quality of IA in Jordanian commercial banks.

Theoretical Framework

This section provides a brief overview of the study variables, namely ML, DL, AIQ, IA, and OC.

Machine Learning (ML)

ML is a branch of AI that deals with enabling computer systems and software to learn and improve task performance autonomously without explicit programming. In ML, computational algorithms are used that allow systems to process data and extract patterns and knowledge from available data. These algorithms enable systems to learn from past experiences and improve their performance over time (Al-Masri, 2022), making them powerful tools for data analysis and decision-making in a more intelligent and effective manner. ML relies on analyzing large volumes of data and using technology to train computer systems capable of detecting patterns and relationships within this data. This is achieved using a variety of techniques, which allow computer systems to perform complex tasks faster and more accurately, thereby contributing to improved efficiency in service delivery to customers in banks (Metwally, 2022). Among the most important applications of ML are behavior prediction, data classification, image analysis, speech recognition, user recommendations, autonomous driving, machine translation, and many other fields that depend on effective data usage and analysis (Al-Akkour, 2024).

There are three types of machine learning. The first type is supervised learning, where the algorithm is provided with pre-labeled inputs that include the correct answers. The objective is to learn the relationship between inputs and outputs so that the algorithm can accurately predict outputs for new, unlabeled inputs. The second type is unsupervised learning, where pre-labeled answers are not provided; instead, the algorithm must discover patterns and relationships within the data on its own. The goal is to understand the internal structure of the data and identify clusters and significant variables based on these patterns (Canhoto & Clear, 2020). The third type is reinforcement learning, which involves continuous improvement of the model by providing it with some initial data, then evaluating the model based on its accuracy. This type aims to assess, update, and enhance the model, which evolves autonomously over time (Hopkins, 2022).

Ml technology is characterized by several advantages that make it an effective tool in various fields. These include the ability of computational models to adapt to changes in data and the surrounding environment, contributing to improved efficiency and accuracy in analysis, forecasting, and faster, more precise decision-making. Additionally, machine learning has the capability to recognize patterns and changes that are difficult to detect using traditional methods, thereby saving time and effort in analyzing and processing large datasets (Chen et al., 2020). The machine learning process involves seven steps as follows (Granata et al., 2022):

1. Data Collection: Gathering the necessary datasets to train and test the model.

2. Data Preparation: Processing and cleaning the data to prepare it for training.

3. Selection of the ML Model: Choosing the appropriate algorithm for the problem, such as neural networks.

4. Model Training: Training the model on the training data to learn the pattern in the data.

5. Model Evaluation: Testing the performance of the trained model on independent test data.

6. Model Tuning: Enhancing the model's performance by adjusting parameters and structure.

7. Model Deployment: After completing training and testing, the model is used to make predictions on new data.

Deep Learning (DL)

DL is a branch of ML based on the architecture of neural networks inspired by the neural networks in the human brain, which consists of billions of neurons. These neurons are interconnected to form complex networks, and this pattern of communication between neurons is simulated by computational units called nodes. Each node processes information and transmits it to the next node in a manner similar to the function of neurons in the brain (Bennett et al., 2022). Dl consists of multiple layers known as hidden layers, where each layer processes information progressively and represents a certain level of abstraction. Neural networks in DL are characterized by their ability to utilize large amounts of data to improve model performance and better analyze patterns. These networks can operate at a deep level to understand and analyze data and extract important features. Through DL, models can learn automatically and continuously improve their performance over time without the need for repeated human intervention, making them powerful tools for data analysis and extraction of valuable information that supports decision-making with greater accuracy and efficiency (Janiesch et al., 2021).

Neural networks are utilized in DL to process complex and large-scale data containing multiple levels of hierarchical representations. This approach is characterized by its ability to analyze data in a manner similar to human thinking, enabling effective pattern recognition and precise information extraction (Haiba, 2022). DL technology encompasses numerous algorithms (Pouyanfar et al., 2020; Al-Ramadna, 2024), with the most common being:

1. Convolutional Neural Networks (CNNs).

2. Long Short-Term Memory Networks (LSTMs).

3. Recurrent Neural Networks (RNNs).

4. Generative Adversarial Networks (GANs).

5. Radial Basis Function Networks (RBFNs).

6. Self-Organizing Maps (SOMs).

7. Deep Belief Networks (DBNs).

8. Restricted Boltzmann Machines (RBMs).

Accounting Information Quality (AIQ)

Information is considered the fuel that drives management; without information, management remains constrained and unable to make decisions. The quality of accounting information is an indicator of the efficiency of such information in serving its users by enabling them to make correct decisions. The quality of accounting information requires a set of attributes that make it relevant and effective, known as the qualitative characteristics of information. The quality of accounting information includes a set of qualitative characteristics that make it reliable and useful for its users. These characteristics are completeness, neutrality, and freedom from error, in addition to adherence to legal, professional, and regulatory standards. By achieving these standards, accounting information is secured in a manner that ensures its credibility and effectiveness in supporting users' decision-making processes, thereby contributing to achieving the desired benefits and objectives (Shalabi and Tarirat, 2021).

The qualitative characteristics of accounting information can be addressed as follows:

Fundamental Characteristics

These characteristics aim to provide accounting information that benefits internal officials within banks, in addition to external parties such as shareholders and auditors. When accounting information lacks any of the fundamental characteristics, it will not be useful to users. Therefore, it is essential to have two main characteristics to ensure the usefulness of accounting information to users: relevance and faithful representation (Abu Nasar & Hamidat, 2020). The characteristic of relevance is considered one of the primary attributes of AIQ, playing a crucial role in influencing decision-making processes. This importance is highlighted through its predictive and confirmatory value. Predictive value refers to the bank's ability to forecast future cash flows and provide a forward-looking perspective on the bank's business outcomes, enabling users to make better future decisions (Qasaimeh, 2021). Confirmatory value means the ability of accounting information to provide feedback that confirms previous evaluations, thereby enhancing users' confidence in the presented data. The characteristic of faithful representation is one of the main attributes of accounting information, consisting of three essential components: completeness, neutrality, and freedom from error. This means that the information must comprehensively cover all relevant aspects of the financial event, be free from any influence that could bias the evaluation of financial facts, and be free from errors to ensure the accuracy and reliability of the data (Qasaimeh et al., 2022).

Enhancing (Secondary) Characteristics

Secondary qualitative characteristics of accounting information are as important as the primary characteristics, as they complement and enhance the latter to make the information more effective and efficient. These secondary characteristics encompass several important aspects that distinguish useful information from information that does not add value. These secondary characteristics include verifiability, comparability, timeliness, and understandability. Through the availability of these secondary characteristics, users can better identify and analyze information, thereby making more accurate and effective decisions (Al-Samurai et al., 2019; Al-Akkour, 2024).

Internal Auditing (IA)

The Institute of Internal Auditors (IIA) defines IA as "an independent, objective assurance and consulting activity designed to add value and improve an organization's operations. It helps the organization accomplish its objectives by bringing a systematic, disciplined approach to evaluate and improve the effectiveness of risk management, control, and governance processes" (IIA, 2023). IA is considered an essential part of the financial reporting process and has been proven to assist companies in maintaining effective governance. The success of the internal audit function contributes to the quality of integrated financial reports and affects the disclosure of financial information in a more comprehensive manner (Muhtar et al., 2020). It is noteworthy that the internal audit function needs to adapt to the evolving nature of AI and leverage its capabilities to meet the requirements of the increasingly complex corporate environment, which has adopted AI technologies in its systems and certain operations. Internal auditors must possess a sound level of awareness and knowledge of modern technology to effectively manage the advantages and challenges arising from the integration of AI into audit processes (Fedyk et al., 2022). The use of AI technologies impacts the audit environment, including procedures, evidence, and audit outcomes. After collecting and evaluating information, auditors must draw audit conclusions and formulate audit opinions based on their expertise, experience, and professional judgment aligned with current developments (Gao & Han, 2021). Ml assists auditors by automating manual and repetitive rule-based tasks and highlighting higher-order thinking skills that aid in planning and executing audit tasks (Nonnenmacher et al., 2021).

IA can immediately participate in AI initiatives and provide guidance to support their successful implementation. It is important to ensure that the internal audit function manages risks related to the reliability of core algorithms and the data on which they are based (III, 2017). Instead of focusing on repetitive tasks, ML techniques assist auditors in concentrating more on core areas such as error detection, sample expansion, forecasting, and risk potential assessment, which reveal anomalous items that require greater attention (Puthukulam et al., 2021). It is increasingly evident that the objective of IA in light of AI needs to shift from sample-based and compliance auditing to more advanced, comprehensive, useful, and systematic audits capable of problem-solving, forecasting, and detecting fraud cases before they occur (Khan et al., 2020). This can significantly improve audit efficiency by reducing costs and facilitating effective handling and processing of large volumes of data (Eulerich & Wood, 2023).

Organizational Culture (OC)

OC can be defined as "a system of values, beliefs, assumptions, or norms that have been valid for a long time, agreed upon, and followed by members of the organization as a guide for behavior and solving organizational problems" (Syaifu, 2024). Jerab & Mabrouk (2023) state that OC "consists of shared values, beliefs, traditions, behaviors, and norms that form the identity of the organization. These elements influence employee interactions, decision-making, collaboration, and act as 'unwritten rules' guiding behavior." There are six characteristics of OC: values and beliefs, norms and behaviors, socialization, adaptation, influence on decision-making, and impact on performance. When a strong OC exists, the risk of fraud can be reduced, as fraud often arises from the ingrained behaviors of individuals or groups within the organization.

In the application of OC, the concept used in the fraud triangle is justification, which is the attitude displayed by the perpetrator through rationalizing the actions they have taken. This refers to the attitude, personality, or value system adopted by the perpetrator. It can be concluded that fraud is likely to occur when the work environment has weak integrity, lacks strong controls, loses accountability, or is under significant pressure; therefore, it is probable that someone will commit fraud. The higher the OC and the better the work climate formed, the more effective the prevention of fraud will be. Conversely, if there is high awareness and culture, this will lead to the prevention of fraudulent behaviors.

Survey Study

Study Procedures and Data Analysis:

Study Methodology

The study relied on the descriptive-analytical method to achieve its objectives and answer its specific questions. By using this method, the study phenomenon was described in detail and analytically allowing for a deep understanding of the variables and their relationships.Study population and sample. The study targeted all Yemeni banks totaling (18) banks according to the statistics of Central Bank of Yemen (CBY) (Sana'a) for the year (2025) represented by executive directors, department heads, financial and accounting department employees, internal auditors, and IT specialists, totaling (220). The entire population was targeted, with (220) questionnaires distributed to all banks, (192) questionnaires retrieved and (188) questionnaires subjected to analysis.

Data Collection

The study relied on secondary sources to cover the study topic, its main variables, and its sub-dimensions. These sources included scientific books, previous studies, scientific theses, and peer-reviewed scientific articles, in order to obtain a comprehensive and integrated analysis of the various dimensions of the study topic. Primary sources were mainly represented by the questionnaire through the preparation of the practical aspect of the study, reflecting the desire to obtain direct opinions and observations from the targeted groups and specialists in the field. The questionnaire was carefully and thoughtfully designed, using secondary sources and based on the theoretical framework and the questions that were directed.

Structure Tool

A questionnaire was prepared to measure the variables related to ML technology, DL, the quality of accounting information, the effectiveness of IA, and OC. The questionnaire was constructed according to the five-point Likert scale and was designed as follows:

Section (1): This section consists of personal data about the respondent (Educational Qualification, Specialization, Level, Years of Experience).

Section (2): Represents the fields of the questionnaire, in five axes. The first axis contains (6) items to measure the first independent variable represented by ML. The second axis includes (6) items and measures the study sample's opinions on the second independent variable, DL. The third axis contains (7) items and measures the dependent variable represented by AIQ. The fourth axis includes (7) items and measures the mediating variable represented by the effectiveness of IA. The fifth axis includes (6) items and measures the moderating variable represented by OC.

Instrument Reliability

To verify the instrument's reliability, the internal consistency coefficient (Cronbach's alpha) was calculated using statistical software (SPSS v27, Process v5, AMOS v24), which is a reliability coefficient indicating the instrument's dependability for research purposes, as shown in Table (1). These values were deemed sufficient for the study's purposes, and thus the questionnaire is considered a standard to ensure that the sample's opinion is consistent. The results obtained from it can be relied upon to generalize to the study population, and Table (1) shows the results of the Cronbach's alpha test.

Table 1: Test The Reliability Study Tool (Cronbach’s Alpha)

Variable	The No of Questions	Sig.	Alpha Coefficient Value
ML	6	0.000	0.916
DL	6	0.000	0.923
AIQ	7	0.000	0.935
IA	7	0.000	0.899
OC	6	0.000	0.947
Total	**32**	**0.000**	**0.973**

It is clear from Table (1) that the reliability degree (Cronbach's alpha value) is high for each dimension, ranging between (0.899 - 0.947), while the overall reliability degree for all items of the questionnaire (α) is

(%97.3). This means that the reliability of the study tool is very high, as it exceeds the acceptable rate (70%). This indicates the stability of the questionnaire and the consistency of the items with the dimensions, which qualifies the questionnaire to be a suitable and effective measurement tool, and allows for reliance on it in testing hypotheses and generalizing the results to the study population to a great extent.

Multiple linear correlation test for the study variables:

Table 2: Results of Multi Collinearity Test Between Dimensions of Study Using Pearson Correlation Coefficient

Variables	AIQ	ML	DL	IA	OC
AIQ	1	*	*	*	*
ML	0.742	1	*	*	*
DL	0.732	0.78	1	*	*
IA	0.748	0.75	0.735	1	*
OC	0.563	0.701	0.664	0.815	1

Table 2 shows that the highest correlation coefficient value between the dimensions of the independent, mediating, moderating, and dependent variables reached (0.815) between the variables of IA effectiveness and OC. Meanwhile, the Pearson correlation coefficient values between the other variables were lower than that, indicating the absence of high multi collinearity among the dimensions of the variables. The variables obtained correlation coefficient values ranging between (0.563-0.815) with a significance level of (0.000), all of which were less than one and less than the significance level adopted in the study (0.05). Therefore, the sample is free from the problem of high multi collinearity in the study data.

To confirm the previous result, the Variance Inflation Factor (VIF) was measured for the dimensions of the independent variables, where the decision rule indicates that the data is free from the problem of high multi collinearity if the VIF values range between (1.00- 10.00), and the tolerance values range between (0.100- 1.00). The results of the multi collinearity problem test between the dimensions of the independent variable using the VIF are shown in Table 3.

Table 3: Results of Variance Inflation Factor Test Between Dimensions of Independent Variable Using Tolerance and VIF

Variables	VIF	Tolerance
ML	3.187	0.314
DL	2.947	0.339
IA	3.950	0.253
OC	3.165	0.316

It is observed from Table (3) that the values of the VIF ranged between (2.947- 3.96), while the Tolerance values ranged between (0.253- 0.339). Therefore, the variables are free from the problem of multi collinearity.

Hypothesis Testing and Discussion of Results

Analysis of Descriptive Statistics of Study Variables

Table 4: Descriptive Statistics (Means & Standard Deviations) for Study Variables

NO	ML		DL		AIQ		AI		OC	
	M	**S.D**	**M**	**S.D**	**M**	**S.D**	**M**	**S.D**	**M**	**S.D**
1	3.72	0.80	3.72	0.83	3.85	0.80	3.64	0.97	4.10	0.86
2	3.87	0.87	3.65	0.92	3.79	0.84	3.86	0.97	3.91	0.86
3	3.96	0.78	3.65	0.84	3.73	0.95	3.93	0.73	3.93	0.89
4	3.87	0.81	3.68	0.83	3.73	1.07	4.05	0.87	4.03	0.87
5	3.85	0.88	3.75	0.80	3.73	1.02	3.87	0.92	4.10	0.91
6	3.66	0.90	3.75	0.85	3.54	1.02	3.96	0.92	4.11	0.81
7	---	---	---	---	3.62	1.00	4.04	0.96	---	----
	3.82	**0.71**	**3.70**	**0.72**	**3.71**	**0.81**	**3.91**	**0.72**	**4.03**	**0.77**

It is noted from Table 4 that all independent, mediating, moderating, and dependent variables of the study obtained high arithmetic means above the hypothesized mean (3), in addition to having standard deviations that deviate from the exact one, indicating the agreement of the sample members with the items included in the axes (variables), and the consistency of those responses without variation. The OC variable ranked first with the highest arithmetic mean of (4.03) and a standard deviation of (0.773), followed by the IA effectiveness variable in second place, with an arithmetic mean of (3.9) and a standard deviation of (0.718). The ML variable came in third place with an arithmetic mean of (3.82) and a standard deviation of (0.706). In fourth place was the dependent variable of AIQ, and in fifth place was the DL variable with an arithmetic mean of (3.7) and a standard deviation of (0.717).

Hypothesis Testing and Discussion of Results

Result of The First Main Hypothesis Test:

Null hypothesis H_0: There is no statistically significant effect of ML and DL on AIQ in Yemeni banks.

Alternative hypothesis H_a: There is a statistically significant effect of ML and DL on AIQ in Yemeni banks.

This hypothesis aims to measure the impact of ML on the AIQ in Yemeni banks, and simple linear regression analysis was used, as shown in Table (5).

Table 5: Results of Multiple Regression Analysis Between ML and DL Techniques and AIQ

AIQ		ML	DL
T.Test	**β**	0.504	0.444
	T.Value	5.96	5.34
	Sig.	0.001	0.11
ANOVA	**F.Value**	**145**	
	Sig.	**0.000**	
R		**0.781**	
R^2		**0.611**	
Dependent Variable		**AIQ**	
Independent Variable		**ML and DL**	

Table 5 presents the results of the multiple linear regression analysis between the ML and DL techniques and AIQ in Yemeni banks. The results of the multiple linear regression analysis indicate that the F-value reached 145 with a statistical significance of 0.000, which is less than the significance level ($\alpha \leq 0.05$) at a confidence level of 0.95. The correlation coefficient (R) was 0.781, indicating the presence of an effect of ML and DL techniques on AIQ in Yemeni banks. The coefficient of determination (R^2) was 0.611, meaning that 61.1% of the variation in AIQ is explained by changes in ML and DL techniques, while 39% of the effect on the quality of accounting information is attributed to other variables not included in the model. As observed from Table 5, the two independent variables achieved a level of statistical significance below the significance threshold (0.05), leading to the rejection of the null hypothesis and acceptance of the alternative hypothesis, i.e., there is a statistically significant effect of ML and DL techniques on AIQ in Yemeni banks. Additionally, no independent variable was excluded since the calculated significance level for all independent variables was below the adopted significance level (0.05).

Result of The First Sub-Hypothesis Test

Null Hypothesis H_0: There is no statistically significant effect of ML on AIQ in Yemeni banks.

Alternative hypothesis H_a: There is a statistically significant effect of ML on AIQ in Yemeni banks.

This hypothesis aims to measure the impact of ML technology on AIQ, and simple linear regression analysis was used, as shown in Table 6.

Table 6: Result of Simple Linear Regression Analysis for The First Sub-Hypothesis

R	R2	T.Test			ANOVA	
		B	T.Value	Sig.	F.Value	Sig.
0.742	0.55	0.856	15.091	0	227.743	0.000

Table 6 shows that the results of the simple regression analysis to measure the presence of a statistically significant effect of the ML technology on the quality of accounting information, as the value of the correlation coefficient R (0.742), and the value of the determination coefficient R^2 (0.550), that is, (0.742) of the changes in the level AIQ is the result of the change in the ML technology, while what we perceive (55%) of the changes in the level of AIQ for other factors, and the value of linear regression was (B (0.856), which indicates that the increase in the ML technology by (1%) leads to an increase in the level of AIQ by (0.856), and the level of significance (0.000), which is less than the approved level of significance (0.05), and therefore the null hypothesis is rejected and the alternative hypothesis is accepted, that is, there is a positive and statistically significant effect of the ML technology on AIQ in Yemeni banks.

Result of The Second Sub-Hypothesis Test

Null hypothesis H_0: There is no statistically significant effect of DL on AIQ in Yemeni banks.

Alternative hypothesis H_a: There is a statistically significant effect of DL on the AIQ in Yemeni banks.

This hypothesis aims to measure the impact of DL technology on AIQ, and simple linear regression analysis was used, as shown in Table 6.

Table 7: Result of Simple Linear Regression Analysis for the Second Sub-Hypothesis

R	R2	T.Test			ANOVA	
		B	T.Value	Sig.	F.Value	Sig.
0.732	0.536	0.830	14.651	0.000	214.646	0.000

Table 7 presents the results of the simple regression analysis measuring the presence of a statistically significant effect of DL technology on the AIQ. The correlation coefficient R value reached (0.732), and the coefficient of determination R^2 value was (0.536), indicating that 73.2% of the variations in the level of AIQ are attributable to changes in DL technology, while approximately 53.6% of the variations in the level of AIQ are explained by other factors. The linear regression coefficient (B) was (0.830), indicating that a 1% increase in DL technology leads to a 0.830% increase in the level of AIQ. The significance level was (0.000), which is below the accepted significance threshold of (0.05). Accordingly, the null hypothesis is rejected, and the alternative hypothesis is accepted, confirming that there is a positive and statistically significant effect of DL technology on AIQ in Yemeni banks.

Result of Testing the Second Main Hypothesis:

Null Hypothesis H_0: There is no statistically significant effect of ML and DL on the effectiveness of IA in Yemeni banks.

Alternative Hypothesis H_a: There is a statistically significant effect of ML and DL on the effectiveness of IA in Yemeni banks.

This hypothesis aims to measure the impact of ML and DL on the effectiveness of IA in Yemeni banks. Multiple linear regression analysis was used, as shown in Table 8.

Table 8: Results of Multiple Regression Analysis Between ML and DL Techniques and IA Effectiveness

IA Effectiveness		ML	DL
T.Test	β	0.459	0.384
	T.Value	6.234	5.310
	Sig.	0.000	0.000
ANOVA	F.Value	151.342	
	Sig.	0.000	
R		0.788	
R^2		0.621	
Dependent Variable		IA	
Independent Variable		ML & DL	

Table 8 illustrates the results of the multiple linear regression analysis between the ML and DL techniques and the effectiveness of IA in Yemeni banks. The results of the multiple linear regression analysis indicate that the F-value reached 151.342 with a statistical significance of 0.000, which is less than the significance level ($\alpha \leq 0.05$) at a confidence level of 0.95. Additionally, the correlation coefficient (R) was 0.788, indicating an effect of ML and DL techniques on the effectiveness of IA in Yemeni banks. The coefficient of determination (R^2) was 0.621, meaning that 62.1% of the variance in IA effectiveness is attributable to changes in ML and DL, while 37.9% of the effect on IA effectiveness is due to other variables not included in the model.

As observed in Table 8, both independent variables achieved a significance level below 0.05, leading to the rejection of the null hypothesis and acceptance of the alternative hypothesis, indicating a statistically significant effect of ML and DL techniques on the effectiveness of IA in Yemeni banks. Furthermore, no independent variable was excluded since the computed significance level for all independent variables was below the adopted significance threshold of 0.05.

Result of Testing First Sub-Hypothesis

Null Hypothesis H_0: There is no statistically significant effect of ML on the effectiveness of IA in Yemeni banks.

Alternative Hypothesis H_a: There is a statistically significant effect of ML on the effectiveness of IA in Yemeni banks.

This hypothesis aims to measure the impact of ML technology on the effectiveness of IA, and simple linear regression analysis was used, as shown in Table 9.

Table 9: Result of Simple Linear Regression Analysis for The First Sub-Hypothesis

R	R2	T.Test			ANOVA	
		β	T.Value	Sig.	F.Value	Sig.
0.750	0.563	0.763	15.475	0.000	239.482	0.000

Table 9 illustrates the results of the simple regression analysis measuring the presence of a statistically significant effect of ML technology on the effectiveness of IA. The correlation coefficient R was (0.750), and the coefficient of determination R^2 was (0.563), indicating that 75.0% of the variations in the level of IA effectiveness are attributable to changes in ML technology, while approximately 56.3% of the variations in IA effectiveness are explained by other factors. The linear regression coefficient B was (0.763), indicating that a 1% increase in ML technology leads to a 76.3% increase in the IA effectiveness. The significance level was (0.000), which is below the accepted significance threshold of (0.05). Accordingly, the null hypothesis is rejected, and the alternative hypothesis is accepted, confirming a positive statistically significant effect of ML technology on the effectiveness of IA in Yemeni banks.

Result of Testing the Second Sub-Hypothesis:

Null Hypothesis H_0: There is no statistically significant effect of DL on the effectiveness of IA in Yemeni banks.

Alternative Hypothesis H_a: There is a statistically significant effect of DL on the effectiveness of IA in Yemeni banks.

This hypothesis aims to measure the impact of DL technology on the effectiveness of IA, and simple linear regression analysis was used, as shown in Table 10.

Table 10: Result of Simple Linear Regression Analysis for the Second Sub-Hypothesis

R	R2	T.Test			ANOVA	
		β	T.Value	Sig.	F.Value	Sig.
0.735	0.541	0.736	14.805	0.000	219.190	0.000

Table 10 presents the results of the simple regression analysis to measure the presence of a statistically significant effect of DL technology on the effectiveness of IA. The correlation coefficient R value reached (0.735), and the coefficient of determination R^2 was (0.541), indicating that 73.5% of the changes in the level of internal audit effectiveness are due to changes in DL technology, while approximately 54.1% of the changes in the level of IA effectiveness are explained by other factors. The linear regression coefficient B was (0.736), indicating that a 1% increase in DL technology leads to a 73.6% increase in the level of IA effectiveness. The significance level was (0.000), which is below the accepted significance level of (0.05). Accordingly, the null hypothesis is rejected, and the alternative hypothesis is accepted, meaning that there is a positive and statistically significant effect of DL technology on the effectiveness of IA in Yemeni banks.

Result of Testing the third Main-Hypothesis

Null Hypothesis H_0: There is no statistically significant effect of IA effectiveness on AIQ in Yemeni banks.

Alternative Hypothesis H_a: There is a statistically significant effect of IA effectiveness on AIQ in Yemeni banks.

This hypothesis aims to measure the impact of IA effectiveness on AIQ in Yemeni banks, and simple linear regression analysis was used, as shown in Table 11.

Table 11: Result of Simple Linear Regression Analysis for The Third Hypothesis

R	R2	T.Test			ANOVA	
		β	T.Value	Sig.	F.Value	Sig.
0.748	0.559	0.848	15.369	0.000	236.220	0.000

Table 11 presents the results of the simple regression analysis measuring the presence of a statistically significant effect of IA effectiveness on the AIQ. The correlation coefficient R was (0.748), and the coefficient of determination R^2 was (0.559), indicating that 74.8% of the variations in the level of AIQ are attributable to changes in IA effectiveness, while approximately 55.9% of the variations in AIQ are explained by other factors not included in the model. The linear regression coefficient (B) was (0.848), indicating that a 1% increase in IA effectiveness leads to an 81% increase in AIQ. The significance level was (0.000), which is below the accepted significance threshold of (0.05). Accordingly, the null hypothesis is rejected, and the alternative hypothesis is accepted, meaning there is a positive statistically significant effect of IA effectiveness on AIQ in Yemeni banks.

Result of Testing the Fourth Main Hypothesis

Null Hypothesis H_0: There is no statistically significant effect of ML and DL on the AIQ in Yemeni banks through the mediating effect of IA effectiveness.

Alternative Hypothesis H_a: There is a statistically significant effect of ML and DL on the AIQ in Yemeni banks through the mediating effect of IA effectiveness.

Hierarchical linear regression analysis was used, incorporating the use of Progress v5, in addition to path, regression, and correlation tests through AMOS v24. The results of testing the previous hypotheses confirmed the fulfillment of the three conditions:

1. There is a statistically significant effect of the independent variable (ML & DL) on the dependent variable (AIQ).
2. There is a statistically significant effect of the independent variable (ML & DL) on the mediating variable (IA effectiveness).
3. There is a statistically significant effect of the mediating variable (IA) on the dependent variable (AIQ).

Therefore, the test of the mediating effect of the variable (IA) on the dependent variable (AIQ) in the presence of the independent variable (ML & DL) can be conducted, as shown in Table 12.

Table 12: Hierarchical Multiple Regression Analysis of the Mediating Role Statement:

DEP.V (AIQ)	IND.V (ML&DL)	First Model β	First Model T	First Model SIG	Second Model β	Second Model T	Second Model SIG
AIQ	ML&DL	0.842	17.44	0.000	-	-	-
	$(ML\&DL)^X$ IA	-	-	-	0.613	5.03	0.000
	R		0.787			0.810	
	R^2		0.62			0.656	
	ΔR^2		0.618			0.653	
	Δ F		303.54			176.93	
	SIG. Δ F		0.000			0.000	

Table 12 in Model One shows that the coefficient of determination (R^2) was 0.787, indicating that 78.7% of the variance in AIQ is attributable to changes in ML and DL techniques. The effect size (B) was 0.842, suggesting that a one-unit increase in the level of ML and DL techniques leads to an increase of 84.2% in the AIQ. This implies that ML and DL techniques explain 84.2% of the variance in AIQ.

In Model Two, the mediating variable (IA effectiveness) was added to the regression model, resulting in an increase in the correlation coefficient (R) to 0.810, and the coefficient of determination (R^2) rose to 65.6%. Furthermore, this proportion is statistically significant, as the F-value changed to 176.93 with a significance level of 0.000, which is less than 0.05. The effect size β for the mediating variable (internal audit effectiveness) was 0.613, and the calculated T-value was 5.03 with a significance level (Sig) of 0.000. This confirms the important role of the mediating variable (IA effectiveness) in enhancing the impact of the relationship between ML and DL techniques and AIQ, where the explained variance in AIQ improved from 61.8% to 65.3%.

Accordingly, we reject the null hypothesis and accept the alternative hypothesis, that is, there is a statistically significant positive effect of IA effectiveness on the relationship between ML& DL techniques, and the AIQ.

Table 13: Hypothesis Testing of Model:

Path	ESTM	S.E	C.R	P.value
ML → IA	0.459	0.046	10.010	0.000
DL → IA	0.384	0.045	8.525	0.000
ML → AIQ	0.322	0.061	5.261	0.000
DL → AIQ	0.292	0.057	5.098	0.000
IA → AIQ	0.396	0.079	5.019	0.000

Table 14: Path analysis results that both Machine Learning (ML) and Deep Learning (DL)

Model	Path	Direct Effect	Indirect Effect	BootLLCI	BootULCI	P.V	R^2
1	ML → IA → AIQ	0.4768	0.3787	0.2423	0.5217	<0.001	63.4%
2	DL → IA → AIQ	0.4493	0.3811	0.5039	0.5039	<0.001	63.1%

Table 13 shows the results of the path analysis showed that both machine learning (ML) and deep learning (DL) have a direct and positive impact on the quality of accounting information (AIQ), with the direct coefficient of ML (0.4768) and DL (0.4493), indicating that the adoption of these technologies directly contributes to improving the quality of accounting information in Yemeni banks.

The results also confirmed that there is a significant indirect effect of both ML and DL on AIQ through the effectiveness of internal audit (IA), where the indirect effect values were 0.3787 for ML and 0.3811 for DL, which means that an important part of the impact of advanced technologies on the quality of accounting information is achieved by improving the effectiveness of internal audit, while the interpretation ratio (R^2) in both models exceeded 63%, indicating a high explanatory power of the proposed model.. Therefore, the relationship is partial and not total. The following figure illustrates the relationship among the variables:

Figure 2: Illustrates The Mediating Effect of the Relationship Between the Independent Variable and The Dependent Variable.

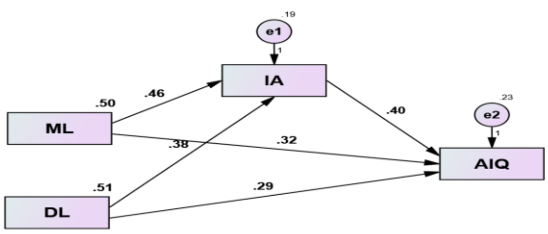

Figure 2 illustrates the mediating effect of the relationship between the independent variable and the dependent variable

Result of Testing the Fifth Main Hypothesis

Null Hypothesis H0: There is no statistically significant interactive effect of OC on the relationship between ML and DL and AIQ, with the effect of IA Effectiveness as a mediating variable in Yemeni banks.

Alternative Hypothesis Ha: There is no statistically significant interactive effect of OC on the relationship between ML and DL and AIQ, with the effect of IA Effectiveness as a mediating variable in Yemeni banks.

Table (15) Hypothesis Testing of Model:

Path	ESTM	S.E	C.R	P.value
ML → IA	0.024	0.037	0.640	0.000
DL → IA	0.587	0.037	15.977	0.000
OC → IA	0.562	0.034	16.482	0.000
INTMLCO→ IA	0.057	0.005	10.552	0.000
INTDLCO→ IA	0.086	0.005	15.787	0.000
ML → AIQ	0.322	0.049	6.518	0.000
DL → AIQ	0.292	0.056	5.246	0.000
IA → AIQ	0.396	0.046	8.557	0.000

The results in the table indicate that organizational culture has a strong and direct positive impact on internal audit effectiveness. The higher the positive organizational culture in the bank, the greater the internal audit effectiveness by 0.562 standard units, with other factors remaining constant.

The results indicate that organizational culture enhances the relationship between machine learning and internal audit effectiveness. In the presence of a strong organizational culture, the impact of ML on IA becomes more positive.

The results indicate that organizational culture also enhances the relationship between deep learning and internal audit effectiveness. It was observed that the indirect effect of both ML and DL on AIQ thru IA remains significant at all selected levels of organizational culture (low, medium, and high), as the bootstrap confidence intervals do not include zero in any case. This confirms the stability of the mediation effect regardless of the level of organizational culture in the Yemeni banks under study.

Figure 3 Illustrates The Moderating Effect of the Relationship Between the Independent Variable and The Dependent Variable

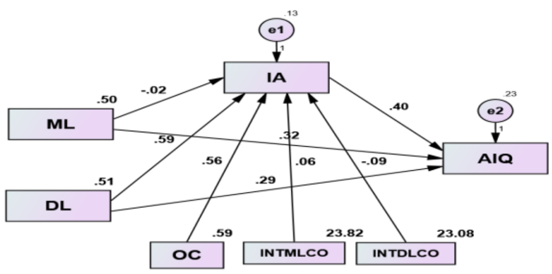

Figure 3: illustration of the moderating effect of the relationship between the independent variable and the dependent variable

Conclusion

The study explored a high explanatory power of the proposed models, as they explained more than 63% of the variance in the quality of accounting information, supporting the validity of the research models. The results showed a direct and strong positive impact of artificial intelligence technologies, particularly machine learning and artificial learning, on the quality of accounting information in Yemeni banks. Additionally, the effectiveness of internal auditing had a direct, strong, and positive impact on the quality of accounting information.

The findings strongly suggest that the impact of these technologies significantly affects the quality of accounting information and the effectiveness of internal auditing, due to their advantages that lead to the rapid execution of processes, in addition to moving away from personal judgments based on personal experience and professional evaluations of specialists in this field. In addition, their high ability to handle large and complex data makes them qualified to positively impact AIQ on one hand, and IA effectiveness on the other. It is worth noting that the study found a statistically significant positive impact of machine learning and deep learning on internal auditing in Yemeni banks, which underscores the importance of adopting these technologies in Yemeni banks.

There is a statistically significant interactive effect of organizational culture on the relationship between machine learning, deep learning, and AIQ. Additionally, there is an interactive effect of organizational culture on the effectiveness of internal auditing. There is also a partial and significant mediating role in transmitting the impact of both ML and DL on the quality of accounting information, confirming the robustness of the mediating relationship between artificial intelligence technologies and the quality of accounting information thru the effectiveness of internal auditing. The impact of the mediating variable (IA) remained stable across different levels of organizational culture, with mediation accounting for approximately 45% of the total effect.

Suggestions

Based on the conclusions, the study recommends that Yemeni banks work diligently to benefit from ML and DL techniques and other AI technologies due to their significant effects in improving and developing the functions performed by banks. It is essential to train and develop the performance of financial statement preparers and internal auditors in using AI techniques and modern technologies that can be utilized in the banking sector.

The study also recommends that Yemeni banks benefit from the experiences of banks in developed countries that have adopted AI techniques, adapting them for application in the Yemeni environment. It emphasizes the necessity of adhering to the ethics of applying AI techniques and establishing an OC among bank employees, particularly positive values and beliefs that contribute to improving and developing performance.

The study advises the Central Bank of Yemen and the regulatory bodies overseeing the banking sector in Yemen to update laws, regulations, guidelines, and instructions in line with developments in AI technologies and to establish a culture of positive use of these technologies.

Efforts should be made to enhance and improve the effectiveness of IA by adhering to international auditing standards and the positive use of ML and DL techniques, given their significant and extensive advantages that can be harnessed to detect errors, prevent manipulation, and perform auditing tasks with the required accuracy, speed, and quality, meeting the aspirations and ambitions of boards of directors.

Finally, the study recommends conducting studies and research that measure the extent of the application of AI techniques and their impact on IA, accounting information systems, and external auditing profession in other sectors.

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