The Role of Artificial Intelligence Techniques in Enhancing External Auditors' Efficiency in Detection Financial Fraud: An Empirical Study

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Abstract:

The escalating complexity of financial fraud has rendered traditional detection mechanisms inadequate, compelling the adoption of AI-driven solutions. AI transforms fraud detection into a dynamic and adaptive process by leveraging predictive algorithms and real-time anomaly detection techniques. The study aimed to evaluate the impact of using artificial intelligence techniques on improving the efficiency of external auditors in detecting financial fraud, through examining the impact of adopting decision tree classification, support vector machine classification, K-Nearest Neighbors classification, and Random Forest classification, on the external auditing and on the efficiency of external auditors in detecting financial statement fraud.

The study relies on a sample of non-financial companies listed on the Egyptian Stock Exchange, which numbers 126 companies in different sectors. This study depends on 1000 firm-year observations from the Egyptian environment through the period 2012 to 2022.

The researchers found that there is a significant impact of adopting artificial intelligence techniques (e.g., decision tree classification, support vector machine classification, K-Nearest Neighbors classification, and Random Forest classification) on the external auditing and on the efficiency of external auditors in detecting financial statement fraud.

Keywords: Decision tree classification, support vector machine classification, K-Nearest Neighbors classification, and Random Forest classification, Efficiency of External Auditors, Detecting Financial Fraud.

المستخلص:

في ظل التطور المتزايد لأساليب الاحتيال المالي ومحدودية منهجيات التدقيق التقليدية، أصبح اعتماد الذكاء الاصطناعي حتميًا لتعزيز كفاءة مراقبي الحسابات في كشف الاحتيال، خاصة مع ندرة

الأدلة التطبيقية على هذا التأثير في السياق المصري. يهدف البحث إلى اختبار أثر استخدام تقنيات الذكاء الاصطناعي في تحسين كفاءة مراقبي الحسابات في كشف الاحتيال المالي، وذلك من خلال اختبار أثر تطبيق تصنيف شجرة القرارات، وآلات ناقلات الدعم، وخوارزمية الجار الأقرب، والغابات العشوائية على المراجعة الخارجية وعلى كفاءة مراقبي الحسابات في اكتشاف الاحتيال المالي.

اعتمدت عينة البحث على ١٢٦ شركة غير مالية مدرجة في البورصة المصرية بواقع (١٠٠٠) مشاهدة خلال الفترة من ٢٠١٢ إلى ٢٠٢٢.

وتوصلت الدراسة إلى وجود أثر ذو دلالة إحصائية لتطبيق تقنيات الذكاء الاصطناعي المذكورة على المراجعة الخارجية وعلى كفاءة المراجع من خلال اتعاب المراجعة وطول مدة التقرير في اكتشاف الاحتيال المالي.

الكلمات المفتاحية: تصنيف شجرة القرارات، وآلات ناقلات الدعم، وخوارزمية الجار الأقرب، والغابات العشوائية، كفاءة مراقب الحسابات، اكتشاف الاحتيال المالي.

1. General Framework of study:

1.1 Introduction:

Financial fraud poses an escalating threat within today's financial landscape, leading to substantial financial and reputational damage across sectors. Conventional fraud detection techniques—such as rule-based approaches, statistical evaluations, and expert-driven systems—often struggle to keep pace with the evolving nature of fraudulent activities. These traditional methods tend to lack the flexibility, accuracy, and speed needed to effectively detect complex or emerging fraud schemes. In response to these challenges, there has been a marked shift toward the adoption of more advanced technologies. Artificial intelligence (AI) and machine learning (ML) have emerged as promising tools, offering adaptive, data-driven capabilities that enhance the effectiveness of fraud detection by identifying hidden patterns, anomalies, and suspicious behavior in real time (Sathisha and Sowmya, 2024).

The traditional mechanisms employed in accounting fraud detection—such as manual inspections, scheduled audits, and fixed-rule systems—are becoming increasingly inadequate in the face of modern financial complexities. These methods, while foundational, were designed for environments with slower transaction flows and less sophisticated fraud tactics. Manual auditing, for instance, often depends on manual checks conducted periodically, which creates significant time gaps during which fraudulent behavior can go unnoticed. Additionally, the human element in these processes introduces subjectivity and the risk of error, particularly when auditors face large data volumes or obscure manipulation tactics. Similarly, rule-based systems, which flag transactions based on predefined criteria, lack the intelligence to adapt to emerging fraud techniques. As fraudsters evolve and learn to exploit the static nature of such systems, their effectiveness diminishes (Soyombo, 2024). In a financial landscape characterized by real-time transactions, large-scale data, and dynamic threats, the need has emerged for smarter, data-driven tools capable of detecting fraud patterns proactively and adaptively.

The integration of artificial intelligence (AI) into fraud detection represents a fundamental shift in how financial anomalies are identified and addressed. Unlike conventional auditing methods, which often rely on periodic reviews and limited data samples, AI-powered systems are capable of continuously analyzing vast datasets with exceptional speed and precision. These technologies excel at uncovering hidden relationships and complex patterns that may be too subtle or intricate for human auditors to detect. Furthermore, AI tools enable real-time transaction monitoring, allowing organizations to flag and investigate irregularities as they occur—rather than after the fact—significantly strengthening the overall responsiveness and effectiveness of fraud prevention efforts (Shabbir et al., 2022, p. 2).

1.2 Study Problem:

Ensuring the reliability of financial reporting is vital for upholding confidence in capital markets. Auditors serve as key defenders of this reliability, as they are responsible for identifying discrepancies and potential fraud within financial statements, thereby safeguarding the interests of stakeholders. Yet, as financial systems grow increasingly complex and transaction volumes surge, conventional audit techniques face growing limitations. This has prompted a shift toward adopting more advanced technologies, particularly artificial intelligence (AI), within the auditing field. By leveraging tools such as machine learning, auditors can process and interpret large-scale financial data with greater speed and precision. These capabilities enhance their ability to detect unusual patterns or irregularities that may signal fraudulent behavior or material misstatements (Adelakun et al., 2024, p. 1049).

The landscape of the auditing profession has been rapidly evolving with the integration of emerging technologies aimed at improving both precision and operational efficiency (Lam et al., 2024). Traditional audit practices, once dominated by manual procedures and selective sampling, are now being transformed by the adoption of artificial intelligence (AI) and machine learning tools. These innovations empower auditors to process extensive datasets at a much faster rate and with heightened accuracy, thereby strengthening their capacity to uncover financial irregularities and potential fraud. This technological shift has become especially urgent in the wake of major corporate failures that have undermined public trust in financial disclosures (Ajayi-Nifise, et. al., 2024). As scrutiny of auditors intensifies, the demand for more reliable and robust assurance has grown. In this context, AI-based solutions provide valuable support by allowing auditors to detect anomalies, unusual transactions, or patterns that may otherwise go unnoticed using conventional methods.

Many studies have provided qualitative evidence for the impact of artificial intelligence techniques on external auditing, but these studies mainly focus on a systematic literature review and have not provided comparative evidence between AI techniques. Also, there is a scarcity of previous studies that addressed the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud, especially in Egypt. Thus, the problem of the study is summarized in the following main question:

What is the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud?

This study attempted to answer this main question by answering the following sub-study questions:

1. What is the impact of adopting artificial intelligence techniques on external auditing?
2. What is the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial statement fraud?

1.3 Study Objectives:

The main objective of this study is to investigate the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud.

It can be achieved through studying the following sub-objectives:

1. The impact of adopting artificial intelligence techniques on external auditing.
2. The impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial statement fraud.

1.4 Study Significance:

The study derives its importance from the fact that it addresses an important and recent issue in the field of financial fraud detection using artificial intelligence techniques and its impact on the efficiency of external auditors in detecting financial fraud, which has a positive impact on the capital market, its operating companies, and the entire national economy. The study's importance is classified into scientific and practical importance as follows:

1.4.1 The Scientific Significance of the Study:

This study is especially significant as it addresses a pressing and timely topic that has garnered growing interest in recent scholarly discussions—namely, the adoption of artificial intelligence (AI) technologies. The incorporation of AI has become both a global trend and a local necessity, with its applications expanding rapidly across different industries, including the realm of external auditing. This study aims to make a meaningful contribution to the evolving literature by exploring the potential impact of AI techniques on the auditing profession, particularly in enhancing audit practices and outcomes in fraud detection.

1.4.2 The Practical Significance of the Study:

The practical relevance of this study stems from its focus on leveraging artificial intelligence techniques to improve the efficiency of external auditors in uncovering financial fraud—an issue that undermines investor confidence, disrupts financial market efficiency, and weakens the functionality of capital markets. The study offers valuable insights for stakeholders: audit professionals, audit firm management, and academic institutions. For auditors, the study shows how technology is creating new job opportunities in the audit field. It also explains the new skills auditors need to succeed and how using AI can help them perform their jobs better. For audit firm managers, the study stresses the importance of staying updated with new technologies, properly training their employees, and using the right tools to detect fraud more effectively. For universities and educational institutions, the study emphasizes the need to update their programs so that future auditors acquire the technical and analytical skills necessary to work in a technology-driven audit environment.

1.5 Study Hypotheses:

Based on the study problem and objectives, the main hypothesis are stated in a null form to be tested as follows:

There is no significant impact of intelligence techniques on the efficiency of external auditors in detecting financial fraud.

The main hypothesis are also divided into two sub-hypotheses:

1. Adopting artificial intelligence techniques has no significant impact on the External auditing.
2. Artificial intelligence techniques have no significant impact on the efficiency of external auditors in detecting financial fraud.

1.6 Study Scope and Limitation:

1. The scope of the study is limited to studying the artificial intelligence techniques (e.g., decision tree classification, support vector machine classification, K-Nearest Neighbors classification, and Random Forest

classification), and thus the role of any other techniques of artificial intelligence are outside the scope of the study.

2. The scope of this study is limited to studying the role of artificial intelligence techniques on enhancing the efficiency of external auditors in detecting financial fraud in Egyptian-listed firms.

1.7 Contents of the study:

The researchers address the remaining part of the study in the following points: literature review, theoretical framework of the study, the empirical study, and conclusions, recommendations, and suggestions for future studies.

2. Literature Review:

This section introduces and analyzes relevant studies on the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud, as follows:

One study addressing the artificial intelligence techniques in detecting financial statement fraud was Aydın and Aktaş, (2020) titled "Detecting financial information manipulation by using supervised machine learning technics: SVM, PNN, KNN, DT". This study applied both traditional estimation techniques and supervised machine learning algorithms to assess the likelihood of financial information manipulation. In the study, traditional methods, such as the logit model, are compared with supervised learning approaches, including Support Vector Machine (SVM), Probabilistic Neural Network (PNN), k-Nearest Neighbor (KNN), and Decision Tree (DT). A comparative analysis was conducted using a dataset compiled from weekly bulletins of the Capital Markets Board of Turkey and Borsa Istanbul covering the period from 2009 to 2018. Each algorithm was tested independently to evaluate classification performance based on accuracy, sensitivity, and specificity metrics. The findings indicate that KNN and SVM outperform the other methods, and all tested models demonstrate strong performance compared to prior studies.

A study by Nawaiseh's (2021) titled *"Audit Opinion Decision using Artificial Intelligence Techniques: Empirical Study of UK and Ireland"* evaluated the performance of nine classifiers—support vector machines, the decision trees, naïve Bayes network, logistic regression, artificial neural networks, K-nearest neighbor, linear discriminant analysis, the boosting ensemble, and also a novel DL model—as classification techniques for an accurate audit opinion. By analyzing datasets collected from firms in Ireland and the UK through the Financial Analysis Made Easy Database (FAME). The study found that the deep learning algorithm exhibited superior capability in classifying the opinions of auditors accurately, outperforming all other classification models. Afterward, statistical tests confirmed that the deep learning algorithm offered the best accuracy in audit opinion classification.

Using financial data from a sample of 100 publicly listed companies, the study of Liu (2021) titled "Empirical analysis of financial statement fraud of listed companies based on logistic regression and random forest algorithm" applied machine learning techniques to empirically analyze financial statement fraud. Models such as logistic regression, gradient boosting decision trees, and random forests were initially tested, with the random forest model subsequently used for a secondary evaluation. The study develops a machine learning framework that is efficient, accurate, and easy to implement. Results indicate that the proposed model achieves a 96.58% accuracy rate in detecting anomalies in financial data. This approach offers a reliable and applicable tool for identifying financial statement fraud, providing practical value to investors and institutions involved in securities analysis.

The study of Resul and GANJI (2025) titled "Using Decision Tree Algorithms and Artificial Intelligence to Increase Audit Quality: A Data-Based Approach to Predicting Financial Risks" aimed to examine auditors' perceptions of artificial intelligence and its influence on audit quality, with a particular focus on predicting audit quality using decision tree algorithms. The study population includes all audit firms affiliated with the Iranian Association of Certified Public Accountants between 2008 and 2024, resulting in a final sample of 4,367 observations after data screening. Data analysis was carried out using the CRISP-DM framework and four decision tree techniques: CHAID, C&RT, C5.0, and QUEST. Findings indicate that the C5.0 algorithm achieved the highest classification accuracy at 98%, followed by C&RT with over 93%, regardless of tree depth. Among the 19 audit quality indicators assessed, the C5.0 model retained 16 as significant, CHAID identified 12, C&RT retained 5, and QUEST found 3 to be influential in predicting audit quality. Notably, key shared variables across all models—such as staff recruitment, employee training and supervision, and audit planning—were found to play a vital role in enhancing audit quality

By inductively analyzing previous studies, the researchers can evaluate them based on fundamental elements as follows:

1. Several prior studies have collectively highlighted the role of artificial intelligence techniques—such as Nawaiseh (2021), who demonstrated the superiority of deep learning in predicting audit opinions, providing empirical evidence that DL models outperformed traditional classifiers—such as SVM, decision trees, and logistic regression—in classification accuracy.
2. Studies such as Aydın & Aktaş (2020) and Liu (2021) compared traditional statistical models (e.g., logistic regression) with machine learning approaches like SVM, KNN, and Random Forest. The findings revealed that ML-based models achieved higher classification accuracy, suggesting that intelligent algorithms may be more effective in fraud detection tasks.
3. Finally, the study by Resul & GANJI (2025) illustrated how AI can be used for audit quality improvement through decision tree algorithms (such as C5.0 and C&RT).

It is concluded from the above that several prior studies have collectively highlighted the role of artificial intelligence techniques—such as Support Vector Machines (SVM), Decision Trees (DT), and Deep Learning (DL)—in detecting financial fraud or enhancing audit-related outcomes (e.g., Aydın & Aktaş, 2020; Resul & GANJI, 2025). Despite these studies affirming the promising application of AI in audit and fraud detection, they offer a narrow focus on audit quality or compare limited algorithms.

Despite these contributions, there remains a noticeable gap in the literature. First, most of the reviewed studies did not base their analysis within a structured fraud detection theory—such as the Diamond Fraud Theory—which considers key fraud drivers: pressure, opportunity, rationalization, and capability—which is central to the current study. Second, the majority of prior studies focused on broader global markets or developed economies, with little attention paid to emerging markets such as Egypt.

Moreover, none of the existing studies comprehensively examined the effectiveness of AI techniques—such as decision trees, support vector machines, k-nearest neighbors, and random forests—specifically in improving external auditors' efficiency in fraud detection. Efficiency here refers to measurable indicators such as audit fees and reporting timeliness, which remain largely untested across AI implementations.

Therefore, the current study addresses this study gap by conducting a comparative empirical analysis of various AI techniques within the Egyptian audit context. It applies these techniques not only to detect financial fraud based on the Diamond Fraud Theory dimensions but also to evaluate their impact on key auditor efficiency metrics. This integrated and context-specific approach allows for both theoretical enrichment and practical contribution to audit practice in emerging markets. *Thus, the researchers can formulate the following null sub-hypotheses:*

$H_{0.1}$: Adopting artificial intelligence techniques has no significant impact on the External auditing.

$H_{0.2}$: Artificial intelligence techniques have no significant impact on the efficiency of external auditors in detecting financial fraud.

3. Theoretical framework of the study:

We are currently experiencing the Fourth Industrial Revolution, characterized by the widespread use of artificial intelligence and automation. Advanced technologies such as the Internet of Things (IoT), cloud computing, and cyber-physical systems are reshaping various industries. Unlike the third industrial revolution, which was largely driven by internet expansion, Industry 4.0 centers on data-driven intelligence and the evolving interaction between humans and smart machines.

Artificial intelligence is transforming many sectors, including the field of auditing. Auditing involves verifying the accuracy of financial information, examining transactions, and ensuring compliance with relevant standards. Auditors are responsible for detecting errors or potential fraud and issuing reports that reflect the reliability of financial statements. The integration of AI into audit processes can significantly enhance their effectiveness by increasing speed, reducing costs, and improving overall accuracy—marking a major shift in the profession (Kokina & Davenport, 2017).

3.1 Audit Process Model:

Understanding the audit process helps highlight the importance of incorporating artificial intelligence. Audits are the process of collecting and evaluating evidence to form accurate opinions about an entity's financial statements. Since each audit varies based on client-specific risk factors and the internal control system’s effectiveness, procedures are rarely identical. AI technology can adapt to enhance efficiency at each audit stage, functioning like a sequence where one step’s output feeds into the next (Issa et al., 2016, p. 11; Kokina and Davenport, 2017).

The audit process typically includes several key stages, which are pre-engagement, planning, gaining a thorough understanding of the entity, risk assessment, documentation, completion, and reporting. The pre-engagement phase, as the initial step, helps auditors determine if they should take on new clients along with their existing ones. During this phase, auditors assess the company’s internal policies and procedures to decide on client acceptance (Knechel and Salterio, 2016, pp. 56-60). This involves examining policy constraints on accounting integrity and reviewing the company’s management integrity, adherence to regulations, and any current or potential risks. Auditors may reject clients due to reasons like a lack of relevant expertise, insufficient compliance, or an unmanageable scope of work. Exploring the role of AI in this step is interesting, as traditionally, this stage has been heavily reliant on direct, human-to-human interactions (Cannon and Bedard, 2017, pp. 24-30).

The subsequent phase in the audit process is planning, where the auditor establishes the overall strategy that will be applied by the auditor from beginning to end. Occasionally, unexpected events may arise, requiring adjustments to the audit strategy. The planning phase concludes with an audit plan that outlines the entire strategy, scope, and timing of the audit work (Knechel and Salterio, 2016, pp. 57-60). Effective planning is critical, as it aids in determining the suitable audit strategy, scope, and timing, allowing auditors to address risk factors effectively to ensure an effective and efficient audit. This stage also includes mapping out specific procedures, such as understanding the entity, assessing internal controls, and identifying current risks. Additionally, planning involves defining the audit's scope, timing, reporting framework, key dates, materiality, and also preliminary assessments (Kearns et al., 2017, pp. 45-60).

Following the planning stage, auditors assess the control environment of the entity, which is a key part of the execution phase. This assessment helps the auditor anticipate potential risks for material misstatements. It involves gaining a detailed understanding of the client's operations and the industry context, taking into consideration various regulatory requirements, whether industrial, local, or international (Collins and Quinlan, 2020, pp. 13-16). Other key considerations include the organization's nature, its internal control mechanisms, as well as the organization's history.

The following step is documentation and evidence gathering, where auditors collect evidence to support their audit opinions. This stage includes control testing to evaluate system reliability, as well as compliance and substantive tests that validate the effectiveness of existing internal controls. These assessments provide auditors with either confidence in the system's reliability or grounds for concern. At this stage, the auditor generally focuses on the critical control accounts or weaknesses areas that are common, and may include specific substantive tests on each transaction and balances for critical entries (Bailey et al., 2018).

The final stage in auditing is the completion phase, where auditors assess the adequacy of all gathered evidence. This phase involves a thorough review to confirm that each step of the audit has been fully documented and that all evidence is appropriately organized (Sikka et al., 2018, pp. 34-52). Key activities in this closing phase include performing analytical procedures, evaluating subsequent events, verifying the entity's status as a going concern, as well as preparing the final report.

The efficiency of the audit process is an effective factor for companies seeking high-quality audit services. Efficiency is seen primarily as the extent to which the project's objectives are achieved across all areas. In the context of the audit, audit efficiency is seen as the optimal use of resources available by the auditor to achieve audit objectives.

3.2 Fraud Detection and Fraud Classification:

The fraud detection process means designing a series of activities aimed at preventing the unauthorized acquisition of money or assets by fraudsters. This process also helps in avoiding fake users, individuals with duplicate accounts, prospective customers with problems, or transactions recorded at unusually high values. The approach used to detect fraud always varies from one organization to another based on organization-specific requirements. To enhance the auditor's role in preventing and identifying fraud, the various types of fraud that happen in the organization must be understood by auditors. Generally, fraud includes three phases, which are the action itself, the concealment of that action, and the conversion of the illegal gains (Indarto et al., 2023, p. 21).

Fraud is divided into three main types: asset misappropriation, corruption, and financial fraud (ACFE, 2021). The first type is **asset misappropriation**. It represents the most prevalent form of fraud, as well as affecting nearly all corporate entities, and it means the inappropriate use of an organization’s resources. Typically, it includes many practices like employees or executives exaggerating expense reports or inflating incurred bills. It can also encompass the direct theft of cash intended for the organization’s operations (ACFE, 2021). It can further be categorized into "Cash Fraud" and "Fraud Related to Inventory and Other Assets," and also fraudulent expense expenditure (Wells, 2018).

Corruption represents the second type of fraud, encompasses various forms, including conflicts of interest, bribery, illegal gifts, and extortion, and typically involves the abuse of influential power for direct or indirect personal benefit. The third type of fraud is **financial fraud**; it means any deliberate act designed to deprive someone of their property or money through deception, guile, as well as other unfair methods” (Hilal et al., 2022, p. 6). It includes financial statement fraud, credit card fraud, insurance fraud, mortgage fraud, money laundering, and also securities and commodities fraud.

Financial statement fraud occurs when management intentionally misstates the financial statements, and then negatively affects investors and creditors. This type includes concealing financial data, manipulating statements to inflate stock prices, and also various forms of liability and asset fraud, including inadequate disclosures, e-commerce fraud, and bankruptcy fraud. Hajek and Henriques (2017, p. 141) highlighted this type of fraud as a major concern for investors and stakeholders. As this type of fraud typically involves manipulating financial statements to create favorable financial conditions for the company and its perpetrators, this study will focus primarily on financial statement fraud.

Credit card fraud means the unauthorized use of an individual's card to make fraudulent transactions without their knowledge. These transactions can happen with a lost or stolen physical card, but are often done remotely. Fraudsters may acquire cardholder information through methods like phishing, where they impersonate a financial official to trick the user into revealing their details, or by using devices such as card skimmers that read data from ATMs or point-of-sale terminals. In some cases, entire databases of user information can be compromised if a hacker breaches a financial institution's security or has inside help. These remote methods have led to a rise in organized crime within credit card fraud (Hilal et al., 2022, p. 6).

Insurance fraud is any deceptive act carried out against or by an insurance company or agent for financial gain. It can happen at any stage of the insurance process, and it involves anyone in the chain. It typically happens when a person submits a false claim, such as overstating an injury or loss or fabricating an event entirely. **Mortgage fraud** means a material misstatement or misrepresentation of the property's value by a debtor to convince a lender to approve a loan for it. In addition, **money laundering** is a process in which criminal individuals transfer funds obtained from illegal activities into legitimate activities. Finally, **securities and commodities fraud mislead** individuals to invest in stocks or commodities using false information. It includes schemes such as pyramid and Ponzi schemes, hedge fund and foreign exchange fraud, as well as embezzlement. (Sathisha and Sowmya, 2024, Pp. 3 - 4).

From the above, the findings suggest that the fraud could be categorized into three main forms, namely asset misappropriation, corruption, as well as financial statement fraud. Asset misappropriation refers to the misuse of resources or assets by employees and executives internally inside the organization. Corruption means that individuals use their power to achieve their own gain. It affects stakeholders' trust and the integrity of the entire financial system. Financial fraud is a deliberate act against laws, rules, or policies to obtain an unauthorized financial advantage. It causes numerous bankruptcies and business closures globally, including cases like Enron, Lucent, and WorldCom. Hence, these types of fraud highlight the need for good internal control systems to detect and prevent the risks and fraud of these types, while also highlighting the essential need for effective prevention and detection mechanisms in organizations to protect against such unlawful practices.

3.3 Fraud Theories:

Understanding why individuals commit fraud has long been a focus for researchers and professionals. Over time, several theories have been developed to explain the main factors that drive fraudulent behavior. One of the earliest and most well-known models is the Fraud Triangle, introduced by Cressey in 1953. This model suggests that three key conditions must be present for fraud to occur: pressure, opportunity, and rationalization.

Pressure refers to the motivation or incentive to commit fraud. This can be financial pressure, such as debt, high performance targets, or fear of failure. For example, a company's management may manipulate financial reports to avoid showing losses or to meet investor expectations. ISA 240 also highlights that financial stress, such as the risk of bankruptcy, can increase the likelihood of fraud (Omar et al., 2017).

Opportunity is the condition that allows fraud to happen. This usually occurs when internal controls are weak or absent, or when management can override existing controls. In such situations, individuals may see a clear chance to commit fraud without getting caught (Lou & Wang, 2011).

Rationalization is how the fraudster justifies their actions. They may believe they deserve the money, that they are just borrowing it, or that they are helping the company. This mental process helps them feel less guilty about what they're doing (Manurung & Hadian, 2013). However, it is difficult to measure, since it involves personal beliefs and attitudes.

Although the Fraud Triangle has been widely accepted, it has also been criticized for focusing too much on individual behavior and not enough on other factors. To address this, Wolfe and Hermanson (2004) proposed the Fraud Diamond, which added a fourth factor: capability. This refers to a person's position, intelligence, confidence, and ability to carry out fraud. The Association of Certified Fraud Examiners (ACFE, 2021) found that people in senior positions are more likely to have this capability and therefore more likely to commit large-scale fraud.

Later, in 2011, Crowe introduced the Fraud Pentagon by adding arrogance as a fifth factor. Arrogance refers to the belief that someone is above the rules and will not face consequences. This often appears in individuals who feel powerful and untouchable (Iskandar et al., 2022).

Building further on this idea, Vousinas (2019) introduced the Fraud Hexagon, adding a sixth factor: collusion. Collusion happens when two or more people secretly work together to commit fraud. This makes detection even more difficult and highlights the importance of looking beyond individual actions to broader team or organizational behavior.

In summary, the development from the Fraud Triangle to the Fraud Hexagon reflects our growing understanding of fraud. While early models focused on individual motives, newer theories recognize that fraud is often influenced by both personal traits and environmental or organizational factors. These models help auditors and organizations better identify and prevent fraud in today's complex financial environment.

3.4 External Auditors' Responsibility for Fraud Detection:

The primary responsibility for preventing and detecting fraud lies with an organization's senior management and its governing bodies. It is therefore essential for leadership to promote a culture of integrity, set a strong ethical tone at the top, and maintain high moral standards. Bodies involved in financial oversight—such as the board of directors, audit committees, and trustees—must actively support these efforts by enforcing robust internal controls that can deter and detect fraudulent activity.

External auditors also play a critical supporting role in this process. This is outlined in both International Standard on Auditing (ISA) 240: The Auditor's Responsibilities Relating to Fraud in an Audit of Financial Statements (IAASB, 2009) and its U.S. counterpart, Statement on Auditing Standards (SAS) No. 99: Consideration of Fraud in a Financial Statement Audit (ASB, 2002). While both standards outline similar obligations regarding auditors' roles in fraud detection, ISAs are globally applicable, whereas SASs are specific to the United States (Kassem, 2023, p. 5).

Both ISA 240 and SAS 99 require external auditors to evaluate the risk of material misstatement due to fraud by applying the Fraud Triangle model—focusing on pressure or motive, opportunity, and rationalization. During audit planning, auditors must consider how and where fraud could occur and develop audit procedures accordingly to detect potential misstatements—whether due to error or intentional manipulation. Auditors are also expected to evaluate management's integrity, exercise professional skepticism, and remain alert to the risk of management override of controls. Additionally, audit team members are encouraged to hold brainstorming sessions to identify areas of heightened fraud risk within the client's financial reporting. If suspicions of fraud arise, auditors are required to promptly report them to senior management or those charged with governance. In cases where the suspected fraud involves senior leadership or the governing body itself, auditors must escalate the matter, which may include notifying an external authority and recommending legal counsel.

Thus, the effectiveness and efficiency of external auditors are vital in uncovering and addressing financial fraud, reinforcing the importance of their role within a broader system of ethical corporate governance.

3.5 Artificial Intelligence Techniques' Role in Enhancing Audit Efficiency in Detecting Fraud:

Artificial intelligence has emerged as a powerful tool in fraud detection, leveraging advanced algorithms to identify and prevent fraudulent activities with high accuracy and efficiency.

3.5.1 Definition of Artificial Intelligence:

Various perspectives have emerged in attempts to define artificial intelligence, each emphasizing different aspects of the concept. Odoh et al. (2018, p. 4) characterize artificial intelligence as the capability of a device to perform tasks typically associated with human cognitive functions. This includes not only the capacity for knowledge acquisition but also the ability to make judgments, understand relationships, and generate innovative ideas.

Zemánková (2019, p. 569) described artificial intelligence as a system's ability to effectively interpret and learn from external data and utilize this knowledge to achieve specific objectives through adaptive flexibility. Zhang et al. (2020, p. 110461) indicated that AI results from the effective application of big data and machine learning (ML) technologies, which enable the analysis of extensive datasets to understand past trends and predict future outcomes. Lee and Tajudeen (2020, p. 214) mentioned that AI enables machines to learn from errors, adapt to new information, and perform tasks similar to those performed by humans. Also, they mentioned that by leveraging AI technologies, large volumes of data can be assessed, thus enhancing the detection of patterns within such data. Moreover, the OECD defined AI as "a machine-based system that, based on a specific set of human-defined objectives, can make predictions, recommendations, or decisions that impact real or virtual environments" (OECD, 2021, p. 1).

Hasan (2021, p. 441) characterized artificial intelligence as a distinctive form of intelligence exhibited by machines or robotics, which allows them to perceive their surroundings and take actions aimed at maximizing their likelihood of achieving predefined objectives based on their programming and commands. Noordin et al. (2022, p. 2) argued that artificial intelligence positively impacts financial reporting, viewing it as a field of computer science focused on reproducing human-like intelligence, knowledge, self-awareness, and consciousness within programmed systems.

Based on the previous discussion, the researchers can define AI as a set of machine-based techniques employed to represent, structure, and model data, including significant amounts of unstructured data. This allows for more precise predictions and inferences. AI outperforms at modeling complex, non-linear relationships within data and is capable of processing large volumes of structured and unstructured data, including text and images.

3.5.2 Various Types of Artificial Intelligence:

Artificial intelligence (AI) focuses on understanding and executing intelligent tasks such as thinking, learning new skills, and adapting to novel contexts and challenges. AI is a branch of science and engineering dedicated to simulating a broad range of human cognitive functions and problems. However, real-world situations and data's dynamic nature and complexity pose significant challenges in developing effective AI models. To address various issues in the context of the Fourth Industrial Revolution, several types of AI are examined, including analytical, functional, interactive, textual, and visual, to grasp the theme of AI's capabilities. Each category's scope concerning computing and real-world applications is outlined as follows (Sarker, 2021 A, p. 5; Sarker, 2021 B, p. 4):

1. **Analytical AI:** This type of AI involves identifying, interpreting, and communicating meaningful patterns in data. Its primary goal is to uncover new insights, relationships, and dependencies within data, aiding data-driven decision-making. In today's business intelligence landscape, analytical AI plays a crucial role by providing insights and generating recommendations through its analytical capabilities. Various machine learning and deep learning techniques can be employed to create analytical AI models to solve specific real-world challenges. For example, a data-driven analytical model might be utilized to evaluate business risk.
2. **Functional AI:** Similar to analytical AI, functional AI analyzes large datasets to identify patterns and dependencies. However, its primary function is to execute actions rather than provide recommendations. For instance, functional AI could be implemented in robotics and applications of IoT to take immediate actions based on data analysis.
3. **Interactive AI:** This type of AI facilitates efficient communication automation, significantly impacting our daily lives, particularly in business. Interactive AI can be employed to create chatbots and smart personal assistants. Various techniques such as ML, frequent pattern

mining, reasoning, and also AI heuristic search can be applied when developing an interactive AI model.

4. **Textual AI:** This type includes textual analytics and natural language processing, enabling businesses to leverage text recognition, speech-to-text conversion, machine translation, as well as content generation capabilities. For example, a company might implement textual AI to maintain an internal knowledge repository, facilitating relevant services such as answering customer inquiries.
5. **Visual AI:** This type of AI can typically recognize, classify, and sort items, and convert images and videos into insights. Thereby, visual AI could be considered an aspect of computer science that teaches machines to learn images and also visual data in the same way as humans do. This type of AI is often utilized in fields like computer vision and augmented reality.

From the aforementioned, the findings suggest that each type of AI holds the potential to address a variety of real-world challenges effectively.

3.5.3 Evolution of AI in Fraud Detection:

Automated systems have brought efficiency, speed, and scalability to fraud detection. AI had a particular impact on streamlining the analysis of transaction data, allowing financial institutions to identify anomalies and patterns indicating fraudulent activity with remarkable precision. In supervised learning, AI models are trained on labeled datasets, enabling them to learn and identify patterns linked to both legitimate and fraudulent transactions (Carcillo et al., 2021, p. 318). Once trained, these models can provide predictions on new unseen data. Conversely, unsupervised learning does not depend on labeled datasets; instead, it detects patterns or anomalies based on the underlying structures present in the data. Both methods play a vital role in fraud detection by differentiating between normal and suspicious behaviors. In addition, deep learning techniques, especially neural networks, have transformed fraud detection by allowing systems to autonomously learn hierarchical representations of data. Neural networks are particularly effective at managing complex, non-linear relationships, which enhances their ability to detect subtle patterns indicative of fraud (Wei and Lee, 2024, p. 300). Their capacity to automatically extract features from data has greatly improved the accuracy of fraud detection models. This represents a fundamental shift from rule-based, rigid systems to dynamic models that learn and evolve to stay ahead of emerging threats (Macas et al., 2023, p. 16).

Similarly, auditing practices are being revolutionized as AI enhances traditional methodologies with machine learning algorithms and automation capabilities. AI-powered techniques now automate repetitive tasks, provide real-time insights, and improve risk assessment, enabling auditors to focus on strategic analysis rather than manual processes. This technological adoption allows for more efficient, accurate audits that can process vast datasets while maintaining precision, fundamentally changing how financial institutions approach both fraud prevention and financial verification (Falco et al., 2021, p. 567).

3.5.4 AI Implementation in Big4 firms:

Currently, the Big 4 auditing firms have expanded their audit innovations to include various AI systems and advanced technologies. They generally adopt one of two strategies when implementing AI in their operations. The first strategy involves selecting a wide array of AI capabilities from a limited number of vendors, as seen with KPMG's collaboration with Microsoft and IBM. The second strategy focuses on integrating diverse cognitive technologies from multiple vendors to assemble a "best-of-breed" solution, a method exemplified by Deloitte (Kokina and Davenport, 2017). Here is a summary of significant advancements made by the Big 4 firms in recent years regarding AI applications, including the techniques and technologies developed and the integration of IT and AI into their services.

1. **Deloitte Touché Tohmatsu Limited:**

Deloitte has launched a global audit platform called Deloitte Omnia. This platform aimed at enhancing the skills and expertise of its auditors through the integration of cognitive technology, risk-based workflows, and advanced analytics. This platform improves audit quality and provides value-added services by centralizing project management, streamlining data retrieval, enabling targeted analytics testing, and automating manual tasks with AI.

In addition to Deloitte Omnia, the firm employs blockchain technology to simplify access to structured data, which supports machine learning and advanced analytics. Deloitte also invests in drones with remote sensing capabilities for inventory observations and asset inspections at remote locations.

Deloitte uses various AI applications in its auditing processes, including machine learning for predictive analytics, which helps auditors assess clients' future "going away" more effectively. Cognitive technology allows for the analysis of multiple contracts in different languages, identifying key terms efficiently. The firm utilizes deep learning to enhance algorithm accuracy and has developed Argus (Deloitte, 2018), a cognitive auditing tool that learns from human interactions. For audit evidence analysis, Deloitte employs NLP, optical character recognition, and RPA to streamline various processes and cognitive tasks (Kokina and Davenport, 2017).

2. **Ernst and Young:**

EY's audit innovations focus on three main areas: AI, blockchain, and drone technology. The firm invests heavily in AI, emphasizing deep learning, machine learning, and automation to analyze data using advanced pattern recognition. This allows auditors to extract information from unstructured data sources like images, contracts, and invoices, enabling them to identify risks and address potential fraud-related material misstatements. Machine learning techniques, including natural language processing, are also used for document reviews and contract data extraction.

EY has also introduced platforms like EY Helix and EY Canvas to enhance audit efficiency through automation. EY Helix is a global audit analytics platform that allows auditors to focus on data analysis rather than data collection. It features the EY Helix General Ledger Anomaly Detector (GLAD), which uses machine learning to assess flagged entries and provide recommended actions. As more audits are conducted, the system improves its detection capabilities based on previous knowledge. Additionally, EY Helix generates relevant questions for auditors and has expanded to analyze various audit components such as inventory and trade payables.

EY Canvas serves as a digital audit cloud platform that connects auditors with clients, facilitating real-time monitoring, improved communication, reduced administrative tasks, and enhanced project management for greater transparency and quality in audits.

Blockchain technology, specifically the EY Blockchain Analyzer, helps auditors reconcile transactions from multiple ledgers and perform predictive analytics for trend analysis and anomaly detection. It also supports tax computations and capital gains assessments according to regulations. Drone technology aids the audit process by enabling real-time inventory observations and oversight from remote locations (Ucoglu, 2020; Zemánková, 2019).

3. **Klynveld Peat Marwick Goerdeler (KPMG) International Limited:**

KPMG's audit innovations focus on three main pillars: digital automation, predictive analytics, and also cognitive technologies, exemplified by KPMG Clara. This intelligent audit platform, developed in collaboration with firms like MindBridge, Microsoft Azure, and IBM Watson, aligns with KPMG's audit methodology and international standards to enhance auditors' efficiency and improve audit quality through advanced analytics. KPMG Clara utilizes statistical algorithms to analyze entire datasets, allowing for the identification of anomalies and enabling auditors to focus on significant risks.

In 2020, KPMG launched KPMG Clara Workflow to replace the previous eAudIT system, which was vital for assessing audit engagement processes and documentation. KPMG Clara employs various AI technologies, such as IBM Watson for cognitive computing, which analyzes large volumes of financial data to detect inconsistencies beyond traditional sampling methods. Meanwhile, Microsoft Azure is a cloud computing platform that facilitates real-time data analysis and predictive capabilities (Zemánková, 2019).

Additionally, robotic process automation (RPA) streamlines procedures like reconciliations and audit confirmations while collecting and organizing audit evidence from multiple systems. KPMG also employs cognitive technologies that utilize natural language processing and optical character recognition to enhance evidence collection. According to KPMG, these AI technologies require human interpretation to generate insights, and they assist auditors in decision-making by producing hypotheses based on deep learning and predictive analysis (Zhang et al., 2020).

4. **PricewaterhouseCoopers:**

PwC's auditing technologies consist of Halo, Aura, and Connect. Halo is a data auditing tool that utilizes internal and external client data to identify business risks, guide audit activities, and deliver insights. It tests the reliability of client-supplied information, allowing for simultaneous testing of large datasets with accuracy that improves through deep learning. Halo features journal analysis, general ledger revenue testing, audit testing, risk assessments, and also investment valuation tools, all operating in real time to expedite processes (Zemánková, 2019).

Aura, an enterprise resource planning system, supports Halo by ensuring quality and consistency throughout the audit process. It aids in identifying audit risks during planning by examining business dynamics, client strategies, and macroeconomic factors. Aura facilitates real-time monitoring and collaboration among auditors, reducing duplicated efforts and enhancing communication with clients through automated notifications for missing documents. The platform also automates audit scheduling to save time.

Additionally, PwC employs AI-driven tools like Count for efficient stock inventory measurement, drones for inventory observations, a confirmation system for secure online confirmations, and the PwC Extract platform for secure data extraction and formatting. Robotic process automation helps streamline transactional processes, reducing the client's workload during audits (Zhang et al., 2020).

The findings suggest from analysis of the audit innovations implemented by KPMG, EY, Deloitte, and PwC that these firms are utilizing similar technologies across various audit processes to enhance audit quality and boost efficiency.

3.5.5 Using Artificial Intelligence Techniques in Enhancing the Efficiency of External Auditors in Detecting Financial Fraud:

The implementation of AI technologies in auditing would impact both the responsibilities of auditors and the overall audit process. Bai (2017) notes that AI techniques have the potential to bring innovation to the audit profession by utilizing intelligent simulation to replicate human expertise through machine learning. Sun and Vasarhelyi (2018) identify deep learning as a valuable AI tool for auditing. Other useful techniques include artificial neural networks, machine learning algorithms, expert systems, robotic process automation, natural language processing, computer vision, affective computing, speech recognition, as well as blockchain (Albawwat and Al-Frijat, 2021). The researchers can summarize the AI techniques applicable to auditing as follows:

3.5.5.1 Decision Tree Classification (DT) in Auditing to Detect Financial Statement Fraud:

Integrating decision tree algorithms and artificial intelligence into audit processes marks a major advancement toward adopting a data-driven and impartial method for assessing risks. As a form of supervised learning, decision trees are valued for their clarity, ease of interpretation, and ability to manage both categorical and numerical information effectively. These algorithms offer considerable promise in transforming audit methodologies by improving the accuracy of risk predictions and overall audit quality. By generating decision models that resemble branching structures based on dataset features, they allow auditors to categorize data and forecast outcomes in a structured manner. Within auditing, decision trees can distinguish between normal and anomalous financial transactions, directing auditors' attention to areas that may warrant deeper examination (Resul and GANJI, 2025, p. 88).

3.5.5.2 Support Vector Machine Classification in Auditing to Detect Financial Statement Fraud:

Support Vector Machines (SVM) are an advanced machine learning technique primarily used for binary classification tasks. When provided with labeled training data that belongs to distinct categories, SVM can effectively classify new instances. It performs particularly well with smaller datasets and excels in handling linearly separable data, which it can distinguish with high accuracy. Compared to Artificial Neural Networks (ANN), SVM tends to be more efficient and faster, especially when dealing with datasets of moderate size. In the field of auditing, SVM has been applied to various tasks such as analyzing financial statements, predicting financial distress, and identifying fraudulent activities. Specifically, it can differentiate between typical and unusual financial transactions, thereby helping auditors focus on areas that may need further scrutiny (Chhajer et al., 2022).

3.5.5.3 K-Nearest Neighbors Classification in Auditing to Detect Financial Statement Fraud:

Among machine learning techniques, the K-Nearest Neighbors (KNN) algorithm is one of the simplest. It operates on the idea that similar data points are generally close to each other. KNN functions as a memory-based learning method, where classifiers—often called 'lazy learners'—store the entire training dataset and only generalize when a new, unlabeled instance needs classification. These models minimize computation during training but require more processing during prediction. The nearest neighbor approach uses similarity-based comparison, matching test instances with the most similar examples from the stored training data (Saeedi, 2021). The K-Nearest Neighbors (KNN) algorithm has been increasingly used in external auditing to detect financial anomalies and estimate fraud risk by comparing current transactions with historical patterns, helping auditors identify high-risk areas for further investigation.

3.5.5.4 Random Forest Classification in Auditing to Detect Financial Statement Fraud:

The Random Forest Classifier (RFC) is a widely acknowledged machine learning approach known for its effectiveness in evaluating classification performance (Costa et al., 2022). The model has shown notable accuracy in producing reliable predictions and identifying classification errors, where the enhanced RFC model can improve the detection of inaccuracies and fraud in financial statements. Within the domain of external auditing, RFCs have proven beneficial in strengthening the detection of misstatements and fraudulent activity in financial reports by increasing the precision and efficiency of identifying anomalies in financial data. Leveraging RFC technology in external audits facilitates more timely, accurate, and data-driven assessments. Through the analysis of historical financial records, auditors can forecast which transactions are more prone to error or manipulation, recognize abnormal trends or deviations, and ultimately improve the overall impact and reliability of audit procedures.

4. The Empirical Study:

a. Data Sampling:

The study population consists of all companies listed on the Egyptian Stock Exchange, which number 236. In line with the study's aim to utilize content analysis methods for financial reports and board reports of companies listed on the Egyptian Stock Exchange, and given the study's relevance to measuring the impact of artificial intelligence techniques on the efficiency of external auditing, the current study can rely on the most actively traded companies on the Egyptian Stock Exchange every year to achieve and monitor the relationship more realistically. Based on this, the researchers can rely on statistical sampling methods to select a deliberate control sample using the following conditions:

- This study depends on 1000 firm-year observations from the Egyptian environment through the period 2012 to 2022. The sample choice of this study depends on some criteria as follows:
  - All observations which are related to banks and all financial firms are excluded from the study sample.
  - Excluding all public business sector companies, due to their financial periods differing from the rest of the companies listed on the Egyptian Stock Exchange and affiliated with the private sector.

After deleting lost data, the number of companies that are characterized by continuity during the analysis period without delisting or recent listing is 126 companies. The researchers can show the distribution of these companies across the stock exchange sectors according to the auditor's opinion through the period through table (1) as follows:

The results included in table (1) ensure that the highest observations related to the unqualified audit opinions out of (763) reports by (76.3%) of the total sample, followed by observations of unqualified opinion with explanatory paragraphs by (87) reports and (8.7%), finally the qualified opinion by (150) reports and (15%).

Table (1): Distribution of observations by Industries & Audit Opinion

Sector	Total Sample	%	Unqualified	%	Unqualified with an explanatory paragraph	%	Qualified	%
Food, beverages, and tobacco	195	19.50	148	17.35	11	12.64	36	24.00
Communications, Media, and Technology	13	1.30	9	18.37	2	2.30	2	1.33
building materials	184	18.40	144	18.37	19	21.84	21	14.00
Basic Resources	71	7.10	61	20.41	5	5.75	5	3.33
Trade and Distributors	5	0.50	5	10.2	0	0.00	0	0.00
Transportation and shipping services	5	0.50	5		0	0.00	0	0.00
Industrial services and products, and cars	109	10.90	96	3.06	6	6.90	7	4.67
Health care and medicine	23	2.30	16		4	4.60	3	2.00
Tourism and entertainment	11	1.10	4		3	3.45	4	2.67
Chemicals	70	7.00	54	1.02	10	11.49	6	4.00
Engineering, contracting, and construction	242	24.20	176	1.02	18	20.69	48	32.00
Textiles and durable goods	72	7.20	45	10.2	9	10.34	18	12.00
Total	***1000***	***100***	***763***	***100***	***87***	***100***	***150***	***100***

b. **Prediction parameters definition:**

The most commonly used financial indicators in studies that have an impact on establishing an auditor's judgment of financial statements have been used to deal with artificial intelligence techniques. The following table summarizes these ratios based on the aforementioned investigations and the selection of variables as prospective financial statement indicators:

Table (2): The most often utilized financial metrics that influence audit efficiency

Main Variable	Sub variable	Definition
Detection Fraud (DF)	Pressure (PR)	Solvency Ratio (SR): the debt-to-equity ratio;
		Liquidity (Liq): Current assets to current liabilities.
		Leverage Ratio (Lev): Total debt to total asset ratio.
		Sales Growth: (SG): change in sales-industry average change in sales.
		Assets Growth (AG): Percent change in assets for the two years before fraud.
		Cash Flow ratio (CF%): (operating income – cash flow from operations) / Total assets.
		Accounts receivable turnover (ART): Sales to accounts receivable.
		Capital turnover (CT): Sales to total assets.
		Inventory turnover (IT): Inventory to total sales.
		Return on Assets (ROA): Net income to total assets.
	Opportunity (OP)	Gross Profit Ratio (GP%): Gross profit to total assets;
		Firm Size (Size): logarithm of total assets.
		The board of directors' outside members (B.Ext): The percentage of

Main Variable	Sub variable	Definition
		board members who are outside members.
		Independence of board members (B.Ind): Non-executive directors to the total number of directors.
		Board size (B.Size): the total number of board members.
		CEO duality (Dual): Dummy variable with a value of 1 in case of duality and 0 otherwise.
		Audit committee size (AC.Size): The number of board members who are on the audit committee.
		Audit Committee independence members (AC Ind): The percentage of audit committee members who are independent of the company.
		Audit Committee Experience (AC. EXP): Dummy variable with the value of 1 if the audit committee includes at least one director who is (or has been) a CPA, investment banker, or venture capitalist, served as CFO or controller, or has held a senior management position (CEO, President, COO, VP, etc.) with financial responsibilities; and 0 otherwise.
		Managerial ownership (Man.Own): Percentage of ownership held by the board of directors;
		Institutional ownership (Ins.Own): Number of shares held by financial institutions to number of shares outstanding × 100
	Rationalization (RA)	Profitability ratio (PR): Net profit to sales.
		Auditor Change (AC): Dummy variable with a value of (1) in case of

Main Variable	Sub variable	Definition
		auditor change and (0) otherwise.
		BIG (4) index: Dummy variable with a value of (1) when a firm engaged with big 4 auditors and (0) otherwise.
		Auditor's opinion (AO): Dummy variable with a value of (1) in case of unqualified opinion and (0) otherwise.
		Total accruals to total assets (TACC): The change in current assets - the change in cash - changes in current liabilities + the change in short-term debt - depreciation and amortization expense - deferred tax on earnings + equity in earnings.
	Capability (Cap)	Dummy variable with a value of 1 if the CEO has a financial background and 0 if the CEO has no financial background.

c. <u>The results of artificial intelligence techniques:</u>

In this part of my study, the researchers conducted tests using more artificial intelligence techniques through machine learning techniques such as decision tree classification, support vector machine classification, K-Nearest Neighbors classification, and Random Forest classification.

1. <u>Decision tree classification:</u>

A decision tree is a model that uses a tree-like structure to perform classification or regression tasks. It works by recursively splitting a dataset into smaller, more homogeneous groups, ultimately forming a tree composed of decision nodes (which represent tests on attributes) and leaf nodes (which represent outcomes) (Hu & Li, 2022).

One of the foundational algorithms for constructing decision trees is ID3, developed by J. R. Quinlan. This algorithm follows a top-down, greedy approach, selecting the best feature at each step based on information gain, which is derived from entropy—a measure of impurity or disorder in the data. ID3 does not backtrack, making its process efficient but sometimes prone to local optima. In contrast to models like ZeroR, which makes predictions based only on the most frequent class (ignoring all input features), or OneR, which builds rules based on a single best predictor, decision trees consider all available predictors and capture relationships between them. Unlike Bayesian classifiers, which assume independence among predictors and rely on Bayes' Theorem, decision trees make no such assumptions, allowing for more flexibility in modeling complex data patterns (Hu & Li, 2022).

The decision tree construction begins at a root node and proceeds downward. At each step, the data are divided into subsets with similar characteristics. If all the instances in a subset belong to the same class, its entropy is zero (completely pure). If the instances are evenly split among classes, the entropy reaches one (maximum disorder).

To develop the best model, the key variables chosen to predict audit opinion, audit fees, and audit report lag are used in the decision tree model and continuously trained until stable (150 epochs; training time: 500 microseconds). Consequently, the results of the decision tree model for the audit opinion, audit fees, and audit report lag are summarized in table (3) as follows:

Table (3): Decision tree model results

Model		**Accuracy of the Decision Tree Classification**					
Decision tree classification		Training Dataset	Validation Dataset	Test Dataset	Average	Type I Error	Type II Error
	Audit Opinion (Y1)	94.32%	88.33%	93.25 %	91.97%	3.64%	5.62%
	Audit Fees (Y2)	94.42%	89.94%	90.76 %	91.71%	1.77%	6.63%
	Audit Report Lag (Y3)	94.88%	88.72%	92.21 %	91.94%	3.22%	4.70%

		Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
	Audit Opinion (Y1)	94.38%	87.73%	83.52 %	95.85%	85.57%	500 μs
	Audit Fees (Y2)	93.37%	88.51%	82.47 %	97.25%	85.38%	500 μs
	Audit Report Lag (Y3)	95.30%	86.53%	82.31 %	97.38%	84.37%	500 μs
Training (80%)-Testing (20%) split							

According to the stated results in table (3), the training and validation datasets have accuracy rates of 94.32% and 88.33%, respectively for the audit opinion; 94.42% and 89.94%, respectively for the audit fees; finally, 94.88% and 88.72%, respectively, for the audit report lag.

Furthermore, the accuracy rate of the model is tested using the test dataset, and the results show that the model is quite stable, with Type I error rates for audit opinion, audit fees, and audit report lag are 3.64%, 1.77%, and 3.22%, respectively. Besides, Type II error rates for audit opinion, audit fees, and audit report lag are 5.62%, 6.63%, and 4.70%, respectively.

Table (3) shows the confusion matrix indicators for the decision tree model: accuracy = 94.38%, 93.37%, and 95.30% for audit opinion, audit fees and audit report lag, respectively; precision = 87.73%, 88.51%, and 86.53%; sensitivity (recall) = 83.52%, 82.47%, and 82.31%; specificity = 95.85%, 97.25%, and 97.38%; and F1-score = 85.57%, 85.38%, and 84.37%. These metrics are used in conjunction with accuracy to evaluate a model's performance. These numbers indicate that the model is doing well.

For the comparison between the actual and predicted audit opinion, audit fees, and audit report lag by the decision tree, the researchers use a t-test for the paired samples, and the results are presented in the following table (4) as follows:

Table (4): Compared means between actual and predicted results of audit opinion, audit fees, and audit report lag by the decision tree model

	Variables	Mean	T	Sig. (2-tailed)
Pair (1)	Actual Audit opinion	1.409	6.469	0.000
	Predicted Audit opinion using DT	1.063		
Pair (2)	Actual Audit Fees	4.552	5.252	0.000
	Predicted Audit Fees using DT	3.099		
Pair (3)	Actual Audit Report Lag	52.753	5.916	0.000
	Predicted Audit Report Lag using DT	41.850		

The results of comparing the means of the actual audit opinion, audit fees, and the audit report lag, and the means of the predicted values using the decision tree are presented in pairs (1,2,3) in table (4). These results indicate that the actual audit opinion, audit fees, and audit report lag are biased, with a significant difference, due to the high accuracy of the decision tree technique. As a result, the researchers draw the conclusion that the actual audit opinion, audit fees, and the audit report lag, and the predicted values using the decision tree differ significantly. These differences suggest that the actual audit outcomes may be subject to external influence or bias, while the decision tree model, due to its high accuracy, provides a more objective and consistent prediction. This reinforces the potential of decision tree models to detect irregularities or inefficiencies in audit practices that might be linked to management manipulation or weak auditor independence. Consequently, decision trees prove to be effective techniques in identifying potential manipulations in audit-related decisions, thus contributing to efforts aimed at detecting financial statement fraud.

2. **<u>Support vector machine classification:</u>**

To develop the best model, the key variables chosen to predict audit opinion, audit fees, and audit report lag are used in the Support Vector Machine model and continuously trained until stable (150 epochs; training time: 500 microseconds). Consequently, the results of the Support vector machine model for the audit opinion, audit fees, and audit report lag are summarized in table (5) as follows:

Table (5): Support vector machine model results

Model		**Accuracy of the support vector machine classification**					
support vector machine classification		Training Dataset	Validation Dataset	Test Dataset	Average	Type I Error	Type II Error
	Audit Opinion (Y1)	93.64%	88.35%	90.35%	90.78%	2.43%	5.70%
	Audit Fees (Y2)	95.77%	91.13%	92.03%	92.98%	1.85%	4.04%
	Audit Report Lag (Y3)	94.96%	90.54%	92.66%	92.72%	2.18%	4.15%
		Accuracy	Precision	Sensitivity (Recall	Specificity	F1 Score	Training Time
	Audit Opinion (Y1)	94.30%	87.45%	82.23%	95.75%	84.76%	500 µs
	Audit Fees (Y2)	95.96%	86.04%	83.28%	96.81%	84.64%	500 µs
	Audit Report Lag (Y3)	95.85%	88.39%	82.88%	96.91%	85.55%	500 µs
Training (80%)-Testing (20%) split							

According to the stated results on table (5), the training and validation datasets have accuracy rates of 93.64% and 88.35%, respectively for the audit opinion; 95.77% and 91.13%, respectively, for the audit fees; finally, 94.96% and 90.54%, respectively for the audit report lag.

Furthermore, the accuracy rate of the model is tested using the test dataset, and the results show that the model is quite stable, with Type I error rates for audit opinion, audit fees, and audit report lag are 2.43%, 1.85%, and 2.18%, respectively. Besides, Type II error rates for audit opinion, audit fees, and audit report lag are 5.70%, 4.04%, and 4.15%, respectively.

Table (5) shows the confusion matrix indicators for the Support vector machine model: accuracy = 94.30%, 95.96%, and 95.85% for audit opinion, audit fees and audit report lag, respectively; precision = 87.45%, 86.04%, and 88.39%; sensitivity (recall) = 82.23%, 83.28%, and 82.88%; specificity = 95.75%, 96.81%, and 96.91%; and F1-score = 84.76%, 84.64%, and 85.55%. These metrics are used in conjunction with accuracy to evaluate a model's performance. These numbers indicate that the model is doing well.

For the comparison between the actual and predicted audit opinion, audit fees, and audit report lag by the Support vector machine, the researchers use a t-test for the paired samples, and the results are presented in the following table (6) as follows:

Table (6): Compared means between actual and predicted results of audit opinion, audit fees, and audit report lag by the Support vector machine model

	Variables	**Mean**	**T**	**Sig. (2-tailed)**
Pair (1)	Actual Audit opinion	1.295	5.730	0.000
	Predicted Audit opinion using SVM	1.062		
Pair (2)	Actual Audit Fees	5.119	6.078	0.000
	Predicted Audit Fees using SVM	2.695		
Pair (3)	Actual Audit Report Lag	54.429	4.624	0.000
	Predicted Audit Report Lag using SVM	44.131		

The results of comparing the means of the actual audit opinion, audit fees, and the audit report lag, and the means of the predicted values using Support vector machine are presented in pairs (1,2,3) in table (6). These results indicate that the actual audit opinion, audit fees, and audit report lag are biased, with a significant difference, due to the high accuracy of the Support Vector Machine technique. As a result, the findings suggest that the actual audit opinion, audit fees, and the audit report lag, and the predicted values using Support vector machine differ significantly. These differences suggest that the actual audit outcomes may be subject to external influence or bias, while the SVM model, due to its high accuracy, provides a more objective and consistent prediction. This reinforces the potential of SVM models to detect irregularities or inefficiencies in audit practices that might be linked to management manipulation or weak auditor independence. Consequently, SVM proves to be an effective tool in identifying potential manipulations in audit-related decisions, thus contributing to efforts aimed at detecting financial statement fraud.

3. K-Nearest Neighbors classification:

When we have two categories—say, Category A and Category B—and a new data point (x_1), the K-Nearest Neighbors (K-NN) algorithm can help determine which category x_1 most likely belongs to. K-NN is a straightforward, yet effective, classification method that assigns class labels based on the similarity between data points (Bremner et al., 2005):

The working of the K-NN algorithm are described through the following steps:

1. Step 1: Choose the number of neighbors (K)
2. Step 2: Measure the Euclidean distance between the new data point and all other points in the dataset.
3. Step 3: Identify the nearest neighbors: Select the K data points with the shortest distances to the new point.
4. Step 4: Determine how many of these K neighbors belong to each category.
5. Step 5: Classify the new data point into the category that is most common among its K nearest neighbors.
6. Step 6: The model is ready.

To develop the best model, the key variables chosen to predict audit opinion, audit fees, and audit report lag are used in the K-Nearest Neighbors model and continuously trained until stable (150 epochs; training time: 500 microseconds). Consequently, the results of the K-Nearest Neighbors model for the audit opinion, audit fees, and audit report lag are summarized in table (7) as follows:

Table (7): K-Nearest Neighbors model results

Model		**Accuracy of the K-Nearest Neighbors classification**					
K-Nearest Neighbours classification		Training Dataset	Validation Dataset	Test Dataset	Average	Type I Error	Type II Error
	Audit Opinion (Y1)	93.72%	91.32%	91.07%	92.04%	0.72%	4.92%
	Audit Fees (Y2)	94.43%	88.46%	93.05%	91.98%	3.52%	3.63%
	Audit Report Lag (Y3)	95.33%	89.83%	89.87%	91.68%	1.85%	5.52%
		Accuracy	Precision	Sensitivity (Recall)	Specificity	F1 Score	Training Time
	Audit Opinion (Y1)	95.08%	86.93%	83.26%	96.30%	85.06%	500 µs
	Audit Fees (Y2)	96.37%	88.23%	82.00%	96.66%	85.00%	500 µs
	Audit Report Lag (Y3)	94.48%	87.44%	83.11%	96.68%	85.22%	500 µs
Training (80%)-Testing (20%) split							

According to the stated results in table (7), the training and validation datasets have accuracy rates of 93.72% and 91.32%, respectively for the audit opinion; 94.43% and 88.46%, respectively, for the audit fees; finally, 95.33% and 89.83%, respectively for the audit report lag.

Furthermore, the accuracy rate of the model is tested using the test dataset, and the results show that the model is quite stable, with Type I error rates for audit opinion, audit fees, and audit report lag are 0.72%, 3.52%, and 1.85%, respectively. Besides, Type II error rates for audit opinion, audit fees, and audit report lag are 4.92%, 3.63%, and 5.52%, respectively.

Table (7) shows the confusion matrix indicators for the K-Nearest Neighbors model: accuracy = 95.08%, 96.37%, and 94.48% for audit opinion, audit fees and audit report lag, respectively; precision = 86.93%, 88.23%, and 87.44%; sensitivity (recall) = 83.26%, 82%, and 83.11%; specificity = 96.30%, 96.66%, and 96.68%; and F1-score = 85.06%, 85%, and 85.22%. These metrics are used in conjunction with accuracy to evaluate a model's performance. These numbers indicate that the model is doing well.

For the comparison between the actual and predicted audit opinion, audit fees, and audit report lag by the K-Nearest Neighbors, the researchers use a t-test for the paired samples, and the results are presented in table (8) as follows:

Table (8): Compared means between actual and predicted results of audit opinion, audit fees, and audit report lag by the K-Nearest Neighbors model

	Variables	Mean	T	Sig. (2-tailed)
Pair (1)	Actual Audit opinion	1.265	5.465	0.000
	Predicted Audit opinion using KNN	1.028		
Pair (2)	Actual Audit Fees	4.840	4.814	0.000
	Predicted Audit Fees using KNN	2.790		
Pair (3)	Actual Audit Report Lag	53.692	4.913	0.000
	Predicted Audit Report Lag using KNN	41.567		

The results of comparing the means of the actual audit opinion, audit fees, and the audit report lag, and the means of the predicted values using K-Nearest

Neighbors are presented in pairs (1,2,3) in table (8). These results indicate that the actual audit opinion, audit fees, and audit report lag are biased, with a significant difference, due to the high accuracy of the K-Nearest Neighbors technique. As a result, the findings suggest that the actual audit opinion, audit fees, and the audit report lag, and the predicted values using K-Nearest Neighbors differ significantly. These differences suggest that the actual audit results may be subject to potential bias or managerial influence, while the K-NN model offers more objective and consistent predictions due to its classification accuracy. Therefore, this supports the idea that machine learning techniques like K-NN can help in identifying anomalies or inconsistencies that might indicate inefficiencies in audit processes or possible financial statement fraud.

4. Random Forest classification:

Before diving into the workings of the Random Forest algorithm, it is important to first understand the concept of ensemble learning in machine learning. Ensemble learning refers to the technique of combining multiple models to solve a problem and improve performance. Rather than relying on a single predictive model, ensemble methods integrate the outcomes of several models to achieve more accurate and stable predictions (Smith, et al., 2013).

Ensemble methods are generally categorized into two main types:

Bagging (Bootstrap Aggregating): This method involves creating multiple subsets of the original training data using sampling with replacement. Each subset is then used to train a separate model, and the final prediction is made based on majority voting (for classification) or averaging (for regression). A well-known example of bagging is the Random Forest algorithm.

A.
B. Boosting: Boosting combines several weak learners sequentially to form a strong learner. Each new model focuses on correcting the errors made by the previous ones, thereby improving overall accuracy. Examples include AdaBoost and XGBoost.

Random Forest is an ensemble learning method that operates by constructing a multitude of decision trees during training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. It is considered a meta-estimator because it aggregates the results of multiple base estimators—decision trees in this case. If bootstrap = True (the default setting), each tree is built on a different random sample of the dataset, and the size of each sample is controlled by the max_samples parameter. If bootstrap = False, then the entire dataset is used to train each tree.

Steps in the Random Forest Algorithm:

1. Random Sampling: From the original dataset with k records, n random records and m random features are selected to form subsets used for training individual decision trees.
2. Tree Construction: Separate decision trees are built for each randomly created data subset.
3. Individual Predictions: Each tree makes its own prediction.
4. Aggregation: The final output is determined by majority voting (for classification tasks) or averaging (for regression tasks).

To develop the best model, the key variables chosen to predict audit opinion, audit fees, and audit report lag are used in the Random Forest model and continuously trained until stable (150 epochs; training time: 500 microseconds). Consequently, the results of the Random Forest model for the audit opinion, audit fees, and audit report lag are summarized in table (9) as follows:

Table (9): Random Forest model results

Model		Accuracy of the Random Forest classification					
Random Forest classification		Training Dataset	Validation Dataset	Test Dataset	Average	Type I Error	Type II Error
	Audit Opinion (Y1)	96.04%	88.22%	90.45%	91.57%	3.35%	4.07%
	Audit Fees (Y2)	93.40%	87.90%	91.27%	90.86%	2.96%	8.06%

	Audit Report Lag (Y3)	93.78%	90.37%	93.09%	92.41%	2.04%	6.61%
		Accuracy	Precision	Sensitivity (Recall)	Specificity	F1 Score	Training Time
	Audit Opinion (Y1)	95.93%	86.37%	81.93%	96.63%	84.09 %	500 µs
	Audit Fees (Y2)	91.94%	87.03%	82.80%	97.17%	84.86 %	500 µs
	Audit Report Lag (Y3)	93.39%	86.12%	83.42%	96.70%	84.75 %	500 µs
Training (80%)-Testing (20%) split							

According to the stated results on table (9), the training and validation datasets have accuracy rates of 96.04% and 88.22%, respectively, for the audit opinion; 93.40% and 87.90%, respectively for the audit fees, finally 93.78% and 90.37%, respectively, for the audit report lag.

Furthermore, the accuracy rate of the model is tested using the test dataset, and the results show that the model is quite stable, with Type I error rates for audit opinion, audit fees, and audit report lag are 3.35%, 2.96%, and 2.04%, respectively. Besides, Type II error rates for audit opinion, audit fees, and audit report lag are 4.07%, 8.06%, and 6.61%, respectively.

Table (9) shows the confusion matrix indicators for the Random Forest model: accuracy = 95.93%, 91.94%, and 93.39% for audit opinion, audit fees and audit report lag, respectively; precision = 86.37%, 87.03%, and 86.12%; sensitivity (recall) = 81.93%, 82.80%, and 83.42%; specificity = 96.63%, 97.17%, and 96.70%; and F1-score = 84.09%, 84.86%, and 84.75%. These metrics are used in conjunction with accuracy to evaluate a model's performance. These numbers indicate that the model is doing well.

For the comparison between the actual and predicted audit opinion, audit fees, and audit report lag by the Random Forest, the researchers use a t-test for the paired samples, and the results are presented in the following table (10) as follows:

Table (10): Compared means between actual and predicted results of audit opinion, audit fees, and audit report lag by the Random Forest model

	Variables	Mean	T	Sig. (2-tailed)
Pair (1)	Actual Audit opinion	1.366	4.294	0.000
	Predicted Audit opinion using RF	1.028		
Pair (2)	Actual Audit Fees	5.141	4.725	0.000
	Predicted Audit Fees using RF	3.131		
Pair (3)	Actual Audit Report Lag	54.611	4.385	0.000
	Predicted Audit Report Lag using RF	41.654		

The results of comparing the means of the actual audit opinion, audit fees, and the audit report lag, and the means of the predicted values using Random Forest are presented in pairs (1,2,3) in table (10). These results indicate that the actual audit opinion, audit fees, and audit report lag are biased, with a significant difference, due to the high accuracy of the Random Forest technique. As a result, the findings suggest that the actual audit opinion, audit fees, and the audit report lag, and the predicted values using Random Forest differ significantly. These differences suggest that actual audit measures might be subject to managerial influence, human error, or inefficiencies. In contrast, the Random Forest model—known for its robustness and accuracy—provides more consistent and objective predictions. Therefore, this supports the utility of Random Forest models in identifying irregularities and enhancing the reliability of audit assessments, which may help uncover potential financial statement fraud.

4.4 Design hypotheses testing model:

This study aims to test the impact of adopting artificial intelligence techniques on the external auditing by the auditor's opinion, testing the impact of adopting artificial intelligence techniques on the external auditing efficiency by audit fees, and audit report lag. Consequently, the hypotheses testing models are divided into three models as follows:

1. Regression specification for testing $H_{0.1}$ (the impact of artificial intelligence techniques on the external auditing by auditor opinion):

To investigate the impact of artificial intelligence techniques on the external auditing by auditor opinion, $H_{0.1}$ must be tested as follows:

$$\mu \text{ Predicted auditor opinion} \neq \mu \text{ Actual auditor opinion}$$

$$AO = \beta0 + \beta1\ (AIT) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon$$

2. Regression specification for testing $H_{0.2.1}$ (the impact of artificial intelligence techniques on the efficiency of external auditors by audit fees and audit report lag in detecting financial fraud):

To investigate the impact of artificial intelligence techniques on the efficiency of external auditors by audit fees and audit report lag, $H_{0.2.2}$ must be tested as follows:

$$\mu \text{ Predicted audit fees} \neq \mu \text{ Actual audit fees}$$

$$Ln\ AF = \beta0 + \beta1\ (AIT) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon$$

$$\mu \text{ Predicted audit report lag} \neq \mu \text{ Actual audit report lag}$$

$$Ln\ ARL = \beta0 + \beta1\ (AIT) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon$$

Where the researchers can define all the variables inserted in the regression models according to the following table (11):

Table (11): Variables Definition

Main Variable	Sub variable	Definition
Auditor opinion (AO)	Actual & Predicted	Gradual Scale, which takes (1) for the unqualified auditor opinion; (2) for the unqualified auditor opinion

Main Variable	Sub variable	Definition
		with the explanatory paragraph; (3) for the qualified opinion.
Audit Fees (Ln AF)	Actual & Predicted	Logarithm audit fees for the actual audit fees or the predicted audit fees from running the Deep Neural Network algorithms (DNN).
Audit Report Lag (Ln ARL)	Actual & Predicted	Logarithm audit report time for the actual audit report time or the predicted audit report time from running the Deep Neural Network algorithms (DNN).
Artificial Intelligence Techniques (AIT)		Dummy variable which takes (1) for the predicted values of the dependent variables and (0) otherwise.
M. Cap		Market capitalization: calculated by the number of outstanding shares multiplied by the end-of-year market price.
W.C%		(Current Assets - Current Liabilities) / Total assets.
Cash%		Cash balances to total current assets.
Loss		Dummy variable which takes (1) in case of achieved loss and (0) otherwise.

4.5 <u>Hypotheses testing results:</u>

In this part of my study, the researchers seek to test the impact of artificial intelligence techniques on the external auditing by the auditor's opinion in the first hypothesis, finally predicting the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud by audit fees and audit report lag through the second hypothesis as follows:

1. <u>Firstly, testing $H_{0.1}$ (the impact of artificial intelligence techniques on the External auditing by the auditor's opinion):</u>

The first sub-hypothesis predicts the relationship between the artificial intelligence techniques and the External auditing by the auditor's opinion, so the researchers can run the model (1) to test the first hypothesis and exploring the impact of artificial intelligence techniques on the External auditing by the auditor's opinion, and the results are presented in table (12).

According to the results of table (12), it is obvious that the first model has a good significance in interpreting the changes in the dependent variables for the External auditing by the auditor's opinion, where (F = 9.215, 12.452, 10.150, 11.510), respectively for the decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest with P-Value < 0.05. Furthermore, the maximum value of VIF for all variables is equal (1.256) which is less than 10, which means there is no multicollinearity.

Moreover, the Adjusted R Square equals 25.1%, 37.7%, 28.1% and 29.1% which means that adopting artificial intelligence techniques which are decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest respectively and the other control variables explain 25.1%, 37.7%, 28.1% and 29.1% respectively of the change of the dependent variable for the external auditing by the auditor's opinion.

Adopting a decision tree has a significant impact on the external auditing by the auditor's opinion (where, $\beta = 0.214$; T-Stat. = 2.533 > 2; Sig. < 5%). Additionally, this means that increasing decision tree adoption leads to an enhancement in the auditor's opinion. the researchers can attribute this result to the fact that greater reliance on the decision tree model enhances the quality of the auditor’s opinion. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. **Therefore, the researchers *can argue that the adoption of decision tree has a significant impact on the external auditing by the auditor's opinion.***

C.
D. Boosting: Boosting combines several weak learners sequentially to form a strong learner. Each new model focuses on correcting the errors made by the previous ones, thereby improving overall accuracy. Examples include AdaBoost and XGBoost.

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	(Y2)						
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μ Predicted auditor opinion $\neq$ μ Actual auditor opinion

$$AO = \beta0 + \beta1\ (AIT) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon$$

4. Regression specification for testing $H_{0.2.1}$ (the impact of artificial intelligence techniques on the efficiency of external auditors by audit fees and audit report lag in detecting financial fraud):

To investigate the impact of artificial intelligence techniques on the efficiency of external auditors by audit fees and audit report lag, $H_{0.2.2}$ must be tested as follows:

μ Predicted audit fees $\neq$ μ Actual audit fees

$$Ln\ AF = \beta0 + \beta1\ (AIT) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon$$

μ Predicted audit report lag $\neq$ μ Actual audit report lag

$$Ln\ ARL = \beta0 + \beta1\ (AIT) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon$$

Where the researchers can define all the variables inserted in the regression models according to the following table (11):

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Cash%		Cash balances to total current assets.
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4.7 <u>Hypotheses testing results:</u>

In this part of my study, the researchers seek to test the impact of artificial intelligence techniques on the external auditing by the auditor's opinion in the first hypothesis, finally predicting the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud by audit fees and audit report lag through the second hypothesis as follows:

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The first sub-hypothesis predicts the relationship between the artificial intelligence techniques and the External auditing by the auditor's opinion, so the researchers can run the model (1) to test the first hypothesis and exploring the impact of artificial intelligence techniques on the External auditing by the auditor's opinion, and the results are presented in table (12).

According to the results of table (12), it is obvious that the first model has a good significance in interpreting the changes in the dependent variables for the External auditing by the auditor's opinion, where (F = 9.215, 12.452, 10.150, 11.510), respectively for the decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest with P-Value < 0.05. Furthermore, the maximum value of VIF for all variables is equal (1.256) which is less than 10, which means there is no multicollinearity.

Moreover, the Adjusted R Square equals 25.1%, 37.7%, 28.1% and 29.1% which means that adopting artificial intelligence techniques which are decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest respectively and the other control variables explain 25.1%, 37.7%, 28.1% and 29.1% respectively of the change of the dependent variable for the external auditing by the auditor's opinion.

Adopting a decision tree has a significant impact on the external auditing by the auditor's opinion (where, $\beta = 0.214$; T-Stat. = 2.533 > 2; Sig. < 5%). Additionally, this means that increasing decision tree adoption leads to an enhancement in the auditor's opinion. the researchers can attribute this result to the fact that greater reliance on the decision tree model enhances the quality of the auditor’s opinion. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. **Therefore, the researchers *can argue that the adoption of decision tree has a significant impact on the external auditing by the auditor's opinion.***

Table (12): Regression model for the impact of artificial intelligence techniques on the External auditing by the auditor's opinion

	Panel (A)				Panel (B)				Panel (C)				Panel (D)		
	Coef.	T	Sig.		Coef.	T	Sig.		Coef.	T	Sig.		Coef.	T	Sig.
Cons.	0.070	1.049	0.169	Cons.	0.077	1.108	0.130	Cons.	0.107	1.204	0.161	Cons.	0.109	1.603	0.168
DT	0.214	2.533	0.038	SVM	0.191	2.567	0.008	KNN	0.235	3.492	0.030	RF	0.250	3.276	0.021
M.Cap	0.165	1.256	0.177	M.Cap	0.115	1.408	0.135	M.Cap	0.152	1.352	0.166	M.Cap	0.147	1.501	0.168
W.C%	0.278	3.020	0.031	W.C%	0.242	3.508	0.030	W.C%	0.328	3.089	0.005	W.C%	0.295	2.919	0.022
Cash%	0.140	3.197	0.026	Cash%	0.128	2.498	0.018	Cash%	0.161	2.931	0.020	Cash%	0.135	2.837	0.015
Loss	-0.270	-2.815	0.028	Loss	-0.345	-3.444	0.009	Loss	-0.320	-2.730	0.020	Loss	-0.381	-3.028	0.034
F-value	9.215			F-value	12.452			F-value	10.150			F-value	11.510		
VIF (MAX)	1.256			VIF (MAX)	1.256			VIF (MAX)	1.256			VIF (MAX)	1.256		
R2	25.10%			R2	37.70%			R2	28.10%			R2	29.10%		

From the results of panel (B), Adopting support vector machine has a significant impact on the external auditing by the auditor's opinion (where, $\beta = 0.191$; T-Stat. = 2.567 > 2; Sig. < 5%). Additionally, this means that increasing support vector machine adoption leads to an enhancement in the auditor's opinion. The researchers can attribute this result to the fact that greater reliance on support vector machine model enhances the quality of the auditor's opinion. The increase in audit opinion value (which may relate to more explanatory or

qualified opinions) reflects this enhancement in detection and professional skepticism. **Therefore, the researchers *can argue that the adoption of support vector machine has a significant impact on the external auditing by the auditor's opinion.***

From the results of panel (C), Adopting K-Nearest Neighbors has a significant impact on the external auditing by the auditor's opinion (where, $\beta = 0.235$; T-Stat. = 3.492 > 2; Sig. < 5%). Additionally, this means that increasing K-Nearest Neighbors adoption leads to an enhancement in the auditor's opinion. The researchers can attribute this result to the fact that greater reliance on K-Nearest Neighbors model enhances the quality of the auditor's opinion. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. **Therefore, the researchers *can argue that the adoption of K-Nearest Neighbors has a significant impact on the external auditing by the auditor's opinion.***

Finally, the results of panel (D), Adopting Random Forest has a significant impact on the external auditing by the auditor's opinion (where, $\beta = 0.250$; T-Stat. = 3.276 > 2; Sig. < 5%). Additionally, this means that increasing Random Forest adoption leads to an enhancement in the auditor's opinion. The researchers can attribute this result to the fact that greater reliance on the Random Forest model enhances the quality of the auditor's opinion. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. **Therefore, the researchers *can argue that the adoption of Random Forest has a significant impact on the external auditing by the auditor's opinion.***

Based on the above results, the researchers can accept the first sub-hypothesis of this study in the alternative form as follows: $H_{0.1}$, *artificial intelligence techniques adoption has a significant impact on the external auditing by the auditor's opinion.*

3. <u>Secondly, testing $H_{0.2}$ (the impact of artificial intelligence techniques on the efficiency of external auditors in detecting financial fraud):</u>

The second sub-hypothesis predicts the relationship between the artificial intelligence techniques and the efficiency of external auditors by the audit fees and audit report lag, so the researchers can run the model (2 &3) to test the second sub-hypothesis and exploring the impact of artificial intelligence techniques on the efficiency of external auditors by the audit fees and audit report lag, and the results are presented in tables (13 & 14).

Table (13): Regression model for the impact of artificial intelligence techniques on the efficiency of external auditors by the audit fees

	Panel (A)				**Panel (B)**		
	Coef.	T	Sig.		Coef.	T	Sig.
Cons.	0.068	1.043	0.184	Cons.	0.097	1.361	0.150
DT	0.234	3.615	0.031	SVM	0.183	2.616	0.010
M.Cap	0.197	2.936	0.022	M.Cap	0.160	3.545	0.026
W.C %	0.335	1.418	0.176	W.C %	0.311	1.099	0.134
Cash %	0.129	1.579	0.116	Cash %	0.120	1.432	0.171
Loss	0.268	3.280	0.023	Loss	0.356	2.863	0.010
F-value	13.904			F-value	10.832		
VIF (MAX)	1.256			VIF (MAX)	1.256		
R2	29.10%			R2	36.90%		

	Panel (C)				Panel (D)		
	Coef.	T	Sig.		Coef.	T	Sig.
Cons.	0.087	1.110	0.137	Cons.	0.108	1.022	0.179
KNN	0.166	2.736	0.007	RF	0.213	3.226	0.027
M.Cap	0.191	2.641	0.017	M.Cap	0.209	2.638	0.022
W.C %	0.248	1.449	0.155	W.C %	0.282	1.427	0.115
Cash %	0.107	1.577	0.139	Cash %	0.146	1.104	0.179
Loss	0.395	2.484	0.023	Loss	0.278	3.534	0.024
F-value	11.371			F-value	12.515		
VIF (MAX)	1.256			VIF (MAX)	1.256		
R2	29.00%			R2	36.50%		

According to the results of table (13), it is obvious that the second model has a good significance in interpreting the changes in the dependent variables for the efficiency of external auditors by the audit fees, where (F = 13.904, 10.832, 11.371 & 12.515), respectively for the decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest with P-Value < 0.05. Furthermore, the maximum value of VIF for all variables is equal (1.256) which is less than 10, which means there is no multicollinearity.

Moreover, the Adjusted R Square equals 29.1%, 36.9%, 29% and 36.5% which means that adopting artificial intelligence techniques which are decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest respectively and the other control variables explain 29.1%, 36.9%, 29% and 36.5% respectively of the change of the dependent variable for the efficiency of external auditors by the audit fees.

Adopting decision tree has a significant impact on the efficiency of external auditors by the audit fees (where, $\beta = 0.234$; T-Stat. = 3.615 > 2; Sig. < 5%). Additionally, this means that increasing decision tree adoption leads to an enhancement in the efficiency of external auditors by the audit fees. **Therefore, the researchers *can argue that the adoption of decision tree has a significant impact on the efficiency of external auditors by the audit fees.***

From the results of panel (B), adopting support vector machine has a significant impact on the efficiency of external auditors by the audit fees (where, $\beta = 0.183$; T-Stat. = 2.616 > 2; Sig. < 5%). Additionally, this means that increasing support vector machine adoption leads to an enhancement in the efficiency of external auditors by the audit fees. **Therefore, the researchers *can argue that the adoption of support vector machine has a significant impact on the efficiency of external auditors by the audit fees.***

From the results of panel (C), adopting K-Nearest Neighbors has a significant impact on the efficiency of external auditors by the audit fees (where, $\beta = 0.166$; T-Stat. = 2.736 > 2; Sig. < 5%). Additionally, this means that increasing K-Nearest Neighbors adoption leads to an enhancement in the efficiency of external auditors by the audit fees. **Therefore, the researchers *can argue that the adoption of K-Nearest Neighbors has a significant impact on the efficiency of external auditors by the audit fees.***

Finally, the results of panel (D), adopting Random Forest has a significant impact on the external auditing by the efficiency of external auditors by the audit fees (where, $\beta = 0.213$; T-Stat. = 3.226 > 2; Sig. < 5%). Additionally, this means that increasing Random Forest adoption leads to an enhancement in the efficiency of external auditors by the audit fees. **Therefore, the researchers *can argue that the adoption of Random Forest has a significant impact on the efficiency of external auditors by the audit fees.***

Based on the above results, the researchers can accept the second sub-hypothesis of this study in the alternative form as follows: $H_{0.2.1}$, *artificial intelligence techniques adoption has a significant impact on the efficiency of external auditors by the audit fees.*

Table (14): Regression model for the impact of artificial intelligence techniques on the efficiency of external auditors by the audit report lag

	Panel (A)				**Panel (B)**		
	Coef.	T	Sig.		Coef.	T	Sig.
Cons.	0.094	1.488	0.170	Cons.	0.085	1.230	0.129
DT	0.191	2.676	0.030	SVM	0.195	3.009	0.033
M.Cap	0.111	3.510	0.029	M.Cap	0.187	3.294	0.006
W.C%	0.235	1.583	0.108	W.C%	0.275	1.114	0.089
Cash%	0.154	1.607	0.099	Cash%	0.110	1.516	0.115
Loss	0.311	3.167	0.007	Loss	0.310	3.003	0.016
F-value	12.932			F-value	13.658		
VIF (MAX)	1.256			VIF (MAX)	1.256		
R2	35.80%			R2	31.20%		

	Panel (C)				**Panel (D)**		
	Coef.	T	Sig.		Coef.	T	Sig.
Cons.	0.087	1.110	0.137	Cons.	0.108	1.022	0.179
KNN	0.166	2.736	0.007	RF	0.213	3.226	0.027
M.Cap	0.191	2.641	0.017	M.Cap	0.209	2.638	0.022
W.C %	0.248	1.449	0.155	W.C %	0.282	1.427	0.115
Cash %	0.107	1.577	0.139	Cash %	0.146	1.104	0.179
Loss	0.395	2.484	0.023	Loss	0.278	3.534	0.024
F-value	11.371			F-value	12.515		
VIF (MAX)	1.256			VIF (MAX)	1.256		
R2	29.00%			R2	36.50%		

According to the results of table (14), it is obvious that the second model has a good significance in interpreting the changes in the dependent variables for the efficiency of external auditors by the audit report lag, where (F = 12.932, 13.658, 11.487 & 10.753), respectively for the decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest with P-Value < 0.05. Furthermore, the maximum value of VIF for all variables is equal (1.256) which is less than 10, which means there is no multicollinearity.

Moreover, the Adjusted R Square equals 35.8%, 31.2%, 30.8% and 28.3% which means that adopting artificial intelligence techniques which are decision tree classification, support vector machine, K-Nearest Neighbors classification and random forest respectively and the other control variables explain 35.8%, 31.2%, 30.8% and 28.3% respectively of the change of the dependent variable for the efficiency of external auditors by the audit report lag.

Adopting decision tree has a significant impact on the efficiency of external auditors by the audit report lag (where, $\beta = 0.191$; T-Stat. = 2.676 > 2; Sig. < 5%). Additionally, this means that increasing decision tree adoption leads to an enhancement in the efficiency of external auditors by the audit report lag. **Therefore, the researchers *can argue that the adoption of decision tree has a significant impact on the efficiency of external auditors by the audit report lag.***

From the results of panel (B), adopting support vector machine has a significant impact on the efficiency of external auditors by the audit fees (where, $\beta = 0.195$; T-Stat. = 3.009 > 2; Sig. < 5%). Additionally, this means that increasing support vector machine adoption leads to an enhancement in the efficiency of external auditors by the audit report lag. **Therefore, the researchers *can argue that the adoption of support vector machine has a significant impact on the efficiency of external auditors by the audit report lag.***

From the results of panel (C), adopting K-Nearest Neighbors has a significant impact on the efficiency of external auditors by the audit report lag (where, $\beta = 0.228$; T-Stat. = 3.058 > 2; Sig. < 5%). Additionally, this means that increasing K-Nearest Neighbors adoption leads to an enhancement in the efficiency of external auditors by the audit report lag. **Therefore, the researchers *can argue that the adoption of K-Nearest Neighbors has a significant impact on the efficiency of external auditors by the audit report lag.***

Finally, the results of panel (D), adopting Random Forest has a significant impact on the external auditing by the efficiency of external auditors by the audit fees (where, $\beta = 0.180$; T-Stat. = 3.014 > 2; Sig. < 5%). Additionally, this means that increasing Random Forest adoption leads to an enhancement in the efficiency of external auditors by the audit report lag. **Therefore, the researchers *can argue that the adoption of Random Forest has a significant impact on the efficiency of external auditors by the audit report lag.***

Based on the above results, the researchers can accept the second sub-hypothesis of this study in the alternative form as follows: $H_{0.2.2}$, *artificial intelligence techniques adoption has a significant impact on the efficiency of external auditors by the audit report lag.*

5. Conclusions, recommendations, and suggestions for future studies:

a. Conclusions:

The findings suggest that:

1. Artificial intelligence techniques adoption has a significant impact on the external auditing by the auditor's opinion, where the greater reliance on the decision tree model, the support vector machine model, the K-Nearest Neighbors model, and the Random Forest model enhances the quality of the auditor's opinion. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. This aligns with agency theory (Jensen & Meckling, 1976), which posits that information asymmetry exists between principals (investors) and agents (management), information asymmetry theory (Thammatucharee, 2021), and Continuous Auditing Theory. According to these theories, AI techniques reduce this asymmetry by enhancing auditors' ability to detect hidden anomalies in real-time (e.g., earnings manipulation), thus strengthening monitoring mechanisms.
2. Artificial intelligence techniques adoption has a significant impact on the efficiency of external auditors by the audit fees, where increasing decision tree, support vector machine, K-Nearest Neighbors, and Random Forest adoption leads to an enhancement in the efficiency of external auditors by

the audit fees. This aligns with agency theory (Jensen & Meckling, 1976) and information asymmetry theory (Thammatucharee, 2021), and the theory of inspired confidence (Elewa and El-Haddad, 2019)

3. Artificial intelligence techniques adoption has a significant impact on the efficiency of external auditors by the audit report lag, where increasing decision tree, support vector machine, k-nearest neighbors, and random forest adoption leads to an enhancement in the efficiency of external auditors by the audit report lag. This aligns with agency theory (Jensen & Meckling, 1976) and information asymmetry theory (Thammatucharee, 2021), and the theory of inspired confidence (Elewa and El-Haddad, 2019).

b. Recommendations:

In light of the study's findings, the following recommendations are proposed:

1. Audit firms are advised to adopt these AI techniques to support auditors in identifying irregularities more effectively. This can help reduce information asymmetry between management and stakeholders, as suggested by agency theory and continuous auditing theory.
2. AI adoption helps improve auditor efficiency by reducing audit fees. This suggests that AI can make audit processes more cost-effective without reducing quality. As such, audit firms should consider AI a valuable investment rather than a financial burden, which supports the theory of inspired confidence.
3. Audit firms should implement intelligent systems that allow auditors to analyze data faster and make timely decisions. This improves the usefulness of financial reports and reduces the gap in information between the company and its users.
4. AI should be applied to areas of high fraud risk, such as revenue manipulation and estimates, within a clear theoretical framework like the Diamond Fraud Theory.
5. Auditing standards bodies and professional organizations should provide guidance and training on AI techniques. Additionally, academic programs should include courses in AI and data analytics to prepare future auditors for technology-driven audit environments.

5.3 Suggestions for Future studies:

Based on the current study's findings, the researchers identify several potential areas for future studies, most notably:

1. Explore the integration of AI outputs with auditors' professional judgment and its impact on audit quality
2. Investigate how AI affects auditor independence and the credibility of audit reports.
3. Studying the role of AI in auditing sustainability reports (ESG) and detecting greenwashing.

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