

Auditing in the modern era: The effect of using the AI tools on external auditors' ability of detecting fraud

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Abstract

This research has investigated how the application of AI-based tools has affected external auditors in their detection of fraud in Oman. Analysis of responses from 70 auditors indicates that mid-career auditors with from 10 to 15 years of such experience are the best at implementing AI tools, while professionals with over 15 years' experience seem to threaten the returns less with some competencies. The regressions indicate an assurance that integrity and competence have a significant bearing on the audit result. The research points towards the positive influence of AI in augmenting audit quality as well as in the detection of fraud, while it also highlights the challenges of low AI adoption, skills scarcity, and ethical issues confronting Oman. In essence, the investigation confirms the benefits of AI integration in auditing while calling for further training, legal evolution, and organizational preparedness for the exploitation of AI's full potential towards fraud detection.

Keywords: Auditing, External Auditors, Fraud Detection, Audit Tools, AI Adoption, Artificial Intelligence (AI).

INTRODUCTION

Given the unique and advanced digital technologies that the Fourth Industrial Revolution has introduced, which include digital, physical and biological interaction. Which in turn produces new techniques and means of financial and non-financial fraud and embezzlement in the business field, it has become important to respond to this problem. It is not yet clear which way the future will go, but one thing is sure: the response to this fourth revolution It needs to be integrated and comprehensive, with all stakeholders in the global system, from the public and private sectors, including academia and civil society. "(Klaus Schwab - Founder and Executive Chairman of the World Economic Forum. 2017). The solution to this predicament lies in utilizing the technologies of artificial intelligence during the audit, review, analysis, and examination of recorded financial and non-financial data and the ability to detect and identify cases of ambiguity and fraud in them.

Research Objectives

1. Explore general perceptions of AI in auditing, its role in fraud detection, its impact upon auditors' decisions, and its challenges and limitations.
2. Explain the relevance and effects of AI technologies in fraud detection during auditing to enhance auditor opinion.
3. Integrity needs to be improved, corruption reduced, stakeholder rights protected, economic stability supported, and fraud risk lowered through AI.
4. impact of AI on decision-making of auditors towards enhancing auditing efficiency and effectiveness related to fraud detection.
5. Encourage auditing firms to embrace and prepare for future challenges with AI.

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Significance of the Study

Auditing, in particular, is an important area of study in the modern era because of the changing challenges and opportunities created by technology, globalization, and the increasing sophistication of financial transactions. Among the most critical areas of auditing is fraud detection and prevention, which continues to be one of the major threats to business and financial stability. The integration of Artificial Intelligence tools in auditing has emerged as a transformative factor that reshapes the competency and methodology used by external auditors in fraud detection.

Research Questions

From these objectives, the following research questions arise:

1. Determine whether there are specific criteria that can distinguish fraud and identify its source?
2. How can artificial intelligence technologies be an effective strategy for dealing with fraud dynamics (Fraud Hexagon)?
3. How can the research gap in artificial intelligence topics within the application environment in Oman be effectively addressed?
4. How can artificial intelligence address gaps in the efficiency, accuracy, and quality of external auditing in Oman?
5. What are the current applications of artificial intelligence in external auditing practices in Oman?

Hypothesis

H1: General Attitude towards AI in Auditing

The auditors' attitude towards utilization of AI for auditing and the extent of its trustworthiness.

H2: Importance of AI in Detecting Frauds

The extent to which auditors are aided by AI in detecting frauds.

H3: Integrity and Lesser Corruption

The integrity and ethical behaviour of the auditing process.

H4: Impact on Auditors' Decision-Making

The extent to which auditors' decision-making is affected.

H5: Challenges and Limitations

Points of concern or limitations that prevent AI from working effectively in audits.

LITERATURE REVIEW

Over time, the auditing profession has progressed well, considering the current level of technology, globalization, and complication of financial systems. An auditor in today's contemporary era is required to make sure that financial transparency and fraud detection take place with a view to protecting stakeholders' interests. In all these challenges, the issue of detection and mitigation of fraud assumes critical importance since the financial misfeasance tends to have far-reaching consequences. Traditional auditing methods are straining to cope with the dimensions of big data, sophisticated fraud schemes, and demands for real-time insights. One of the most important recent developments is the use of artificial intelligence technology. AI methods provide potential for enhancing auditors' ability to analyse huge datasets, identify unusual patterns, and more accurately and successfully identify fraud. This study of the literature review at the relationship between auditing and AI, paying special focus to how AI tools will eventually change the ability of external auditors to spot fraud. The review will try to establish a critical analysis of existing studies, theories, and technological frameworks related to AI in auditing. It discusses strengths and weaknesses of AI tools, their implications for auditors' roles, and the ethical considerations arising in using them. The section thus synthesizes extant literature with the intention of underlining both

opportunities and challenges that come with adopting AI in the auditing profession, therefore setting a basis for further investigation of its practical and theoretical effects.

Al-Fatlawi, Al-Khazaali, & Hasan, (2024). The purpose of this passage is to emphasize how the problem of fraud is becoming more and more serious in this modern world, which also faces greater banking and e-commerce issues. Nowadays, it is obviously stated that fraud has already become an international problem with new technologies, which give so many opportunities for committing crimes. With this growing threat, the techniques for fraud detection have become vital not only to identify and analyze the fraudulent activities taking place at the moment but also to predict future behavior to help reduce the risks. The passage also puts weight on security in the online banking systems, which involves factors such as authentication, confidentiality, and trust. This methodology focuses on fraud detection through techniques that identify and predict fraudulent activities by analyzing user behavior. It underscores the role of modern technologies for secure transactions in authentication, confidentiality, and data integrity. It mines data to identify trends in large datasets, the analysis of which could identify patterns in fraud cases. Secondly, the approach secures fraud detection design in online service access, particularly at financial institutions, reducing risks and losses. It combines predictive analytics with the necessary secure practices to offer an improved fraud prevention scenario, which in turn offers enhanced trust in online banking.

Bello, & Olufemi, (2024). The purpose of this study is to analyse the relationship between the IAF and fraud prevention and detection within organizations. This paper describes current internal auditing practices in order to investigate factors that influence the involvement of IAFs in fraud risk management. The study thus investigates how corporate governance, the positioning of the IAF between management and the audit committee, and the use of technology-based auditing techniques impact the extent to which the IAF engages in fraud prevention and detection. The overall objective of this study is to provide recommendations that will enhance fraud protection within organizations and provide further clarity on the responsibility of internal auditing in the management of fraud risk. Such findings imply that the research study will articulate a framework showing the key data analytics elements, how they can be integrated into the audit process, and best practices for using them. This study will be developing a framework that stipulates the key elements of data analytics, their integration into the audit process, and best practices. A pilot study with selected organizations will be conducted in order to ensure its practicality, with feedback used to refine and improve upon the framework for real-world implementation. To ensure practicality of the framework, a pilot study of selected organizations is put into place, ensuring that refinements to the feedback received are well considered to realize the framework in actual practice.

Ilori, Nwosu, & Naiho, (2024). The idea behind this concept is to present a framework that would incorporate advanced analytics into internal auditing to make risk management and fraud detection more efficient. The paper therefore seeks to ensure that organizations have a more comprehensive way of underpinning risks through the diversification of data sources, use of machine learning and predictive analytics, and real-time monitoring. It stresses that adaptive risk assessment models should be developed, with data-driven insights to enhance audit efficiency by uncovering complex fraud schemes and reinforcing measures of prevention. Internal audits need to become proactive, precise, and effective in managing the emerging risks. This study adopts qualitative research. It is followed by the case study analysis of those organizations which have implemented data analytics in their audits with much success and lists down the best practices and challenges. Expert interviews with auditors, data analysts, and IT professionals provide supplementary insights into current practices, technological challenges, and emergent trends. In the light of these findings, it develops a conceptual framework which outlines key components of using data analytics in audits, including strategies for integration and best practices.

Kuttiyappan, & Rajasekar, (2024). This research both conceptually and empirically validates AI-powered approaches to cope with increasingly sophisticated and dynamic fraudulent activities. In this regard, the present study acknowledges that all those aforementioned conventional fraud detection techniques, which vary between rule-based systems, statistical techniques, and traditional machine learning models, have no such capacity to learn in order to adapt with evolving fraud. To overcome these problems, the paper suggests three new AI-based methods: Graph Neural Networks, Generative Adversarial Networks, and Temporal Convolutional Networks. Each of these techniques brings individual strengths in data modelling and pattern recognition to further enhance fraud detection in terms of accuracy and efficiency. Performance evaluation on a comprehensive scale is presented that compares AI-based approaches against traditional ones involving rule-based systems, logistic regression, and random forest models. The findings support that the edge of the proposed AI solutions sets up their potential to become innovative and adaptive fraud detection tools. Advanced AI techniques are used in this work to perform fraud detection; hence, this work focuses on three innovative approaches: GNNs to spot fraud networks with high precision and very strong AUC-ROC performance, adversarial machine learning for effective anomaly detection featuring exceptional recall and capturing even unseen patterns, and TCNs for reliable real-time fraud detection by balancing precision and recall. This has been tested extensively, where these AI models outperformed the traditional methods using rule-based systems, logistic regression, and random forests with convincing margins across all metrics. The system merges real-time processing with adaptive learning and wraps it in a user-friendly interface, where fast, accurate, proactive fraud prevention becomes possible.

Kamuangu, P(2024) .This research paper aims at exploring the advanced approaches being undertaken for the detection of financial fraud, with a particular emphasis on the effectiveness of Machine Learning and Artificial Intelligence techniques. The research critically analyses the current fraudulent detection scenario by reviewing the shortcomings of traditional methods of fraud detection and the effectiveness of the ML and AI techniques. It also intends to map out future research directions by discussing successful implementations and bringing out the potential of various ML and AI algorithms. Another objective is to go beyond performance metrics like accuracy, precision, and recall, and look into the real-world implications and further refinement avenues that fraud detection can be taken to. Some of these AI and ML methods include pattern spotting and anomaly detection in data for financial fraud detection. The approach adopted by a particular method will depend on the type of fraud being sought and a trade-off between the level of accuracy and efficiency. One of the most key approaches is supervised learning, where logistic regression is at the forefront. These algorithms learn from past transactions in the training data pre-labelled as fraud or not fraud to predict whether a new transaction is fraudulent. Logistic regression, for instance, is a popular technique for binary classification that will return an estimate of the probability of fraud. Although easy to interpret and computationally efficient, it may struggle with complex nonlinear patterns.

Mohammed, & Rahman (2024). This study explores the role of AI in fraud detection in Saudi Arabia's private sector. It looks into challenges, opportunities, and the effectiveness of AI technologies while addressing research gaps in this field. The combined quantitative-qualitative method provides insights and recommendations to enhance fraud detection processes using AI. The method which has been used there were a mixed method such quantitate and qualitative. Qualitative data shall be retrieved from interviews with key stakeholders and in-depth case studies of organizations using AI to detect fraud; thematic analysis will be used for the analysis. Ethical considerations, such as participant confidentiality and research approvals, are integral to the process that ensures a thorough and responsible investigation.

Mitan, (2024) Artificial Intelligence has reworked the face of the audit profession, and this study investigates its implications for methods of auditing, the role of the auditor, and audit quality. This study will look into such benefits accruing from the integration of AI with a view to emphasizing how tools such as machine learning, deep learning, and natural language processing enhance audit processes in terms of efficiency, accuracy, and enriched risk assessment capabilities. It also discusses how auditors' responsibilities are changing with AI, from traditional ones to more analytical and decision-making functions; the development of expertise in data analytics and AI by auditors themselves should be considered. The paper also places into perspective the ethical challenges that are bound to arise, from data privacy to algorithmic transparency, in respect to AI implementation and calls for standardization, regulation, and training that ensures ethics are upheld and audits are accurate. The application of AI technology in auditing has been transformed in part by big data. The Big Four have made significant investments in their AI capabilities in response to the growing demand; in 2023, each company announced multibillion-dollar commitments. As AI algorithms have become more sophisticated and cloud computing capacity has increased over the past few years, additional catalysts have responded to increased investment. Data and AI have grown rapidly as a result. All AI systems are built on algorithms. An artificial intelligence algorithm is a sophisticated collection of guidelines that allow the system to learn from data and function on its own. In contrast to algorithms used in data analytics and automation, artificial intelligence (AI) models use algorithms to mimic human-like intellect and adaptability.

Wang, Shen, Bi, & Fu, (2024) .The current research seeks to put forward and enhance a workable financial fraud detection and prevention scheme based on AI as well as data mining techniques. The use of Internet finance has greatly increased and with that, the use of traditional fraud management has been found... This paper seeks to study these advances and the implications of such threats to the threats posed in carrying out financial activities. While relying on AI with its benefits in big data, and understanding how fraud has been advanced, the paper argues that some new technologies like advanced artificial intelligence have a unique influence in this regard. Machine learning algorithm application, data preprocessing and feature engineering for better detection, and operational monitoring and early warning system architecture, have all been discussed. The paper's contribution is its provision of the systematic design and testing of the system and establishment of its appreciable robustness. Finally, it goes on to provide the reasons for believing that the system has considerable potential to provide a strong backbone and risk management approach to financial security in the contemporary world. This methodology integrates statistical techniques with machine learning algorithms for an efficient anti-fraud system. The statistical module includes variable selection, preprocessing of data, and correlation analysis in order to improve the quality of data and identify the most relevant variables linked to fraud. A binary classification supervised model will be implemented, enabling the capability to forecast fraudulent behavior with high-dimensional, complex data supported by machine learning algorithms and large samples. This integrated approach results in improved accuracy, scalability, and adaptability. The system incorporates model training, optimization, and real-time monitoring and its effectiveness in real-world financial fraud detection is validated with experiments.

Xu, Yang, Zhuang, Li, & Lu, (2024). This paper investigates the application of deep learning algorithms to improve the accuracy and reliability of credit card fraud detection. The researchers have considered two methods: the Isolation Forest algorithm and the advanced neural network model known as Autoencoder. The results prove that deep learning has the capability of learning patterns and adapting to data complexity and could, thus, do a better job than classical methods. However, the research also points out the challenge of working with highly imbalanced datasets, where fraudulent transactions are uncommon. The results stress that these models need further refinement and provide valuable insights into extending

fraud detection systems. In this regard, they utilized deep learning techniques for preventing and detecting fraud in credit cards by utilizing an anomaly detection technique. To begin with, the standard credit card fraud dataset was subjected to the Isolation Forest algorithm which revealed a 26% success rate in identifying fraud among the top 1,000 transactions. Then, they utilized a framework called Autoencoder, which is an unsupervised deep learning algorithm designed to detect anomalies and was able to achieve a 33.6% accuracy in identifying fraud, though with some variations. Considering the Autoencoder's ability in relation to conceiving detection techniques in cases of fraud, the research also highlighted the importance of optimizing the structure of the model along with its hyper parameters so as to enhance its performance and stability. That is, additional experimentation and tuning will be necessary for effective and better deep learning systems for detecting credit card fraud.

Kemuma (2023) research seeks to explore the many facets through which artificial intelligence is affecting audit professions. This study will look at how AI enhances audit quality, efficiency, risk assessment, and fraud detection, among other aspects. The research will also go on to find those opportunities and challenges that come with this integration, such as data privacy, security, and ethics facing the auditing profession. These will be explored through the use of qualitative methods, namely in-person interviews, to understand how collaboration between human auditors and AI tools can support responsible integration. The study shall conclude with views on how matching technology with ethical practice can create the future of auditing. Qualitative data collection in the study involved thorough interviews that involve participants in semi-structured discussions. Audio recordings of the interviews were made and subsequently transcribed. Participants gave their agreement for the interview to be recorded even though they did not want to be audio recorded. In this sense, document analysis is particularly beneficial for extracting useful information from both digital and tangible published records. When combined, these methods offer a wealth of qualitative data, enhancing the research's authenticity and depth. In fact, the level and extent of our examination have been greatly aided by the deliberate sampling technique used for this qualitative study. By carefully selecting participants based on their direct knowledge of the research topic, the researcher has produced a sample that may offer deep insights into and a thorough understanding of it.

Mpofu, (2023) study examines the role of Artificial Intelligence in the external audit function and debates surrounding the adoption and implementation of AI within auditing. It aims at considering the pros and challenges concerning integrating AI into auditing: enhanced efficiency, enhanced quality of the audit, the enhancement of the sampling process, ethical issues, possible biases, and coordination between humans and machines by adopting a qualitative research approach, the paper has sought to make an inventory of controversies and convergences concerning the application of AI in external auditing as developed by scholars. The study shall, therefore, dig out gaps in research and bring out various insights that will have both theoretical and practical implications. Machine learning enables huge leaps forward in quality and speed of audit, but also carries some significant risks. Machine learning is part of AI that focuses on the ability of machines to receive data and learn from such data through altering algorithms accordingly as they continue to learn more about the information. It came about from the idea that machine scan learn to perform certain tasks as well as humans can. According to Kokina and Davenport, 2017; Raphael, 2017 all indicate the use of machine learning and it's potential to change the audit profession - fundamentally changing the manner of which audit is performed. The algorithms of machine learning come in different forms. For instance, unsupervised learning, supervised learning, and devices reinforcement learning (ISACA, 2018). In the case of supervised learning. Bao, Hilary, & Ke, (2022). The research is hence dedicated to the comprehensive discussion of the problems one may have when

trying to reveal fraud with the help of machine learning, taking as a basis accounting fraud. Employing a data-methods-evaluation framework, this study aims to explore practical issues that may affect the actual performance of machine-learning models in fraud prediction. It also surveys relevant academic literature from different disciplines to identify strategies that may be used to surmount such challenges. It also attempts to propose some promising future directions that may be an assistant to the area of fraud detection with machine learning novelties. Since analysts and researchers tend to code fraud into an indicator variable, logistic regressions have been the most dominant learning approach in the business literature before the recent development of the field of machine learning, for example see Dechow et al. 2011. In the recent years with the presence of many unstructured databases and the development of methodological breakthroughs, researchers and analysts start to employ some more recent advanced learning methods to train and predict 13 accounting fraud. For example, Cecchini et al. (2010), and Perols et al. (2017) use the SVM to train a fraud prediction model. Amiram et al., 2015 use Benford's Law to predict fraud.

Noordin, Hussainey, & Hayek, (2022). This paper tries to analyze the perception of external auditors about the use of AI in the UAE. Tries to establish any perceived contribution which AI is making to audit quality by the external auditors. It is also tending to assess the level of difference in opinions regarding the use of AI by local and international auditors, which influences their assessments of audit quality. Accordingly, an online questionnaire-based survey has been employed in this research with an access to 22 and 41 within or outside the country of auditing companies respectively. These respondents could either be by anyone involved in the audit world like managers, partners, the auditing seniors, or anyone who may be have some experiences in terms of accounting parts & the audit parts fields. Hypotheses has been tested after analysing the information & data undertaken through reliable and valid tests like, the tool of descriptive statistics & separate samples tests. In fact, the statistics indicates an insignificant of perceived with a differential of contribution of AI to the quality of audit between auditing companies within or outside the country. Most or probably all the auditing companies equally contribute to understand audit quality. The target population includes answerers from both within & outside auditing companies in UAE. Survey targets different types of respondents who can be classified as external auditors. Participators are anyone involved in auditing includes managers, partners, the auditing seniors, or anyone who may have some experiences in terms of accounting parts & the audit parts. Last of the samples has been received from 22 auditing companies within the country & 41 auditing companies outside the country. The results that has been included in findings from this research provide the measurements of the idea about AI assistance that may help anyone who want to do a research or a study could apply this technological advance.

Andrade, (2021).The research aims to discuss the effect of intelligent systems, such as Artificial Intelligence, Big Data, and the Internet of Things, upon the financial and auditing profession. In this study, it is intended to be shown how such technologies can improve efficiency by automating repetitive tasks that auditors currently do, also considering the perceptions of financial auditors about the adoption of intelligent systems. It also aims to determine the benefits and impediments related to the adoption of these technologies into routine auditing practices and their respective potentials to change the profession during the short to medium run. From a methodological perspective, the study relied on a quantitative approach as the basis for its source, using an online survey to answer each of the research questions. According to Bhattacharjee (2012), this methodological approach is described as a research instrument that "instruments range from broad topics" and which allows for the systematic gathering of answers. For Vilelas (2020), this is the most appropriate approach when the analytic unit of the study is a person; it is the most utilized in the management area and has the biggest advantages in terms of cost, processing of data, and reduction of fraud.

Hooda, Bawa, & Rana, (2018). One of the serious problems that companies faces is frauds throughout the world. Businesses that use unfair tactics without worrying about facing legal repercussions they will face sever effects on people and the economy in society. Fraud detection is responsibility of auditing procedures. The practice of looking into financial transactions of the organization for verifying the financial statements present if it's follows the accounting rules and their standards. Cosserat Citation2009. An extremely demanding test to identify organizations while detecting frauds, identifying errors, as well as unearthing employees involved in aiding and abetting illegal transactions. The tools that analyse data for fraud management effectively and efficiently have now become an absolute need of the audit. The auditors undertaking the external auditing have a clear responsibility with vital to the sound functioning of the businesses. To clarify, their task is the receipts of the audits, expenditure, accounting of pertaining to revenues, contingency fund, balance of sheets, accounts of the public, etc., maintained in any government office. The present paper is a case study on to an outside auditing firm in order to investigate the potential of machine learning algorithms to improve the calibre of audit work. Data is gathered annually from 777 businesses across 14 industries. Feature selection is done using the PSO algorithm.

Conceptual Framework:

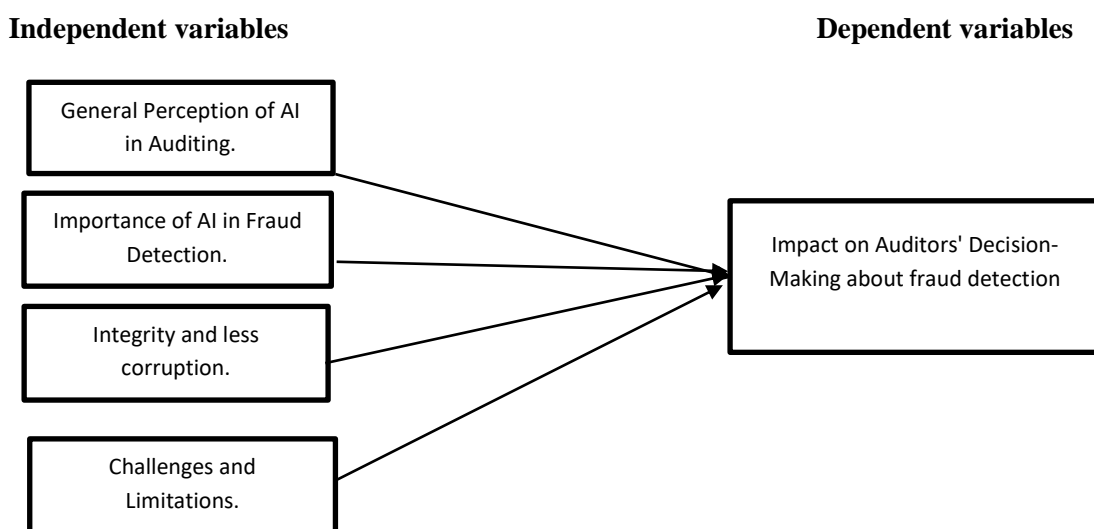


Figure 1: Conceptual Framework

Dependent Variable

Impact on Fraud Detection by Auditors' Judgment:

This variable identifies the impact on auditors' judgments and decisions on detecting fraud during audits. It indicates the quality, confidence, and accuracy that auditors portray when detecting fraud.

Independent Variables

1. General Perception of AI in Auditing

This measures how far auditors in general perceive and consider using artificial intelligence to use in applying to auditing practices, which could affect whether they use and depend on AI tools.

2. Importance of AI to Detect Fraud:

This refers to how far auditors think about AI technologies specifically for fraud detection, and this will shape how far they use aggressive AI in their audit practices.

3. Integrity and Less Corruption:

This is the ethical environment within which auditing occurs. More integrity and less corruption result in more transparent, honest decision-making.

4. Challenges and Limitations:

This construct encompasses the obstacles and constraints—e.g., technological problems, ignorance, or resistance—theory—is capable of hindering the efficient application of AI to auditing and thus influencing auditors' decision-making.

Research Gap

Notwithstanding globally increasing interest in the integration of AI into auditing practice, specific research concerning Oman is scant. It is the general economic, regulatory, and cultural environment in Oman that brings out unique challenges and opportunities, arguably one of the causes for this phenomenon as related to the adoption of the AI tool by an external audit firm. These factors have been identified to place in context the impact of AI on fraud detection skills in the Omani auditing industry.

Importance of Addressing the Research Gap

The identification of such a gap is helpful as a building block toward determining how application of AI tools for external auditing in Oman should be done. As a result, policymakers, regulators, and auditing firms will be better positioned to devise plans and ways of implementing AI technology that improves fraud detection while taking into consideration the peculiar challenges of the Omani context. This research will also contribute significantly to the global discussion with a perspective from a developing economy with unique legal and cultural characteristics.

Following are some of the research gaps that indicate the need for focused investigations *Very Limited Research on AI Adoption in the Omani Auditing Sector:*

While the topic has been empirically investigated more and more worldwide, the adoption of AI audit technologies among external auditors in Oman is very thin. In fact, not much is yet known about the technology infrastructure, other auditors' perceptions of AI, and the readiness of audit organizations.

Legal and Regulatory Issues: The regulatory framework for auditing and fraud detection in Oman is still in its infancy

Again, very few focused studies have been carried out on how integration of AI technologies aligns with such developments. For example, discussions on how existing laws and standards influence the adoption of AI technologies in auditing practices, whether the already existing regulatory updates need modification in line with technological developments.

Cultural and Organizational Issues

Probably the most influential factors that would affect the successful diffusion of the AI tools are cultural attitudes toward technology and organizational readiness. Business and workplace culture in Oman could easily shape auditors' perception and use of AI in the detection of fraud. For this reason, this has received little attention in the literature reviews.

Effectiveness of AI in Fraud Detection in Omani Context

The effectiveness of AI tools in fraud detection in selected economic sectors such as oil and gas, banking, and SMEs in Oman has to be established. Various sectors pose different fraud risks and have different characteristics of data which may impact the performance of AI tools.

Skills Gap among External Auditors

A shortage of the relevant technical skills and training thus limits the ability to make effective use of the AI tools by the external auditors of Oman. Of course, it needs to be determined by research studies as to what auditors' current skill levels actually are and the extent that programs of training are available and effective.

Comparative Studies with Regional and Global Practices

There is a pressing lack of comparative studies which place the auditing practices of Oman within some form of regional or global context. In this way, light may be shed on parallels

and discrepancies, along with many takeaways from other countries that have already integrated AI into their auditing systems.

Ethical and Trust Issues

Data privacy, algorithmic bias, and auditors' overdependence on AI-generated outputs in Oman are various faces of these ethical implication gaps. On one side, these are said to be integral issues in responsible adoption of this technology.

RESEARCH METHODOLOGY

The paper discusses the impact of AI tools on the capability of external auditors to detect fraud in the modern-day context of Oman. The methodology has been devised in such a way that the research analysis will be holistic and systematic quantitative approaches to attain the objectives of the research.

Research Design

This study uses quantitative method of data analysis that is numerical data approach. This kind of design would ensure that the numerical data analyses are balanced with deep insights into auditors' experiences and perceptions.

Type of Research Approach

Descriptive Research: The paper tries to describe the present extent to which AI tools are applied in auditing and the associated abilities related to fraud detection.
Exploratory Research: the study will identify the various challenges, opportunities, and trends that surround the adoption of AI tools by external auditors in Oman.

Data Collection Methods

Questionnaires

Structured questionnaires will be forwarded to external auditors in Oman for the collection of quantitative data regarding their experiences, perceptions, and usage of AI tools in fraud detection.

Techniques for Sampling

Population: These include local and foreign external auditors working in audit firms around Oman. Purposive sampling will be used to collect the sample, and the respondents must have relevant experience with the usage of AI tools or must have knowledge in fraud detection techniques.

Sample Size

Around 50 to 100 for questionnaires.

Methods of Data Analysis

Quantitative Data Analysis: Descriptive statistics through summary of survey responses
Inferential statistics on, for example, the regression analysis of relationships on how the use of AI tools will affect efficiency in fraud detection.

Statistical Tools: The collected data will be analyzed by an appropriate statistical method by using SPSS and AMOS.

Ethical Considerations

The researcher has obtained the required informed consent from all willing participants in this study. Its purpose and their respective individual rights in the research were likewise explained to them. Also, protection of respondent privacy can guarantee data confidentiality and anonymity. Ethical clearance will be sought from any relevant institutional review board or ethical committee.

Limitations of Study

1. Inability of audit firms to gain a proper information about AI as fraud detection is a very sensitive issue, the responses might be biased.
2. Location has to be considered: there are many audit firms in Oman, it will take a long time to have more information that need to be conducted from them as these information are

very important and sensitive that need to be discussed face to face especially for us as students.

RESULTS AND DISCUSSION

The data analysis has found evidence of years of experience significantly affecting some professional attitudes and competencies, but extreme age performers on the tail ends of the spectra seem to be in contradiction to this general trend. Mid-career professionals with 10-15 years of experience manifest the highest positive scores along relevant measures while making those with more than 15 years score lower on the standards. This general trend along these variables is observable except for one measure (CHA3) with few exceptions, which did not show any significant variation among groups based on years of experience. Meanwhile, regression analysis portrays the predictors together accounting for 77.5% of variation in the dependent variable IOA. The predominantly positive and statistically significant impact of ILC and CHA indicates the most pivotal factor influencing audit outcomes. GP and IM, on the other hand, lacked significance, hence considering integrity and competence (ILC and CHA) as the building blocks for enhanced audit performance will pave the way for research and practice. As the results will be presented in Frequency Analysis below for better understanding. As the focus was about four things, gender, qualifications, experience, and Profession.

Meaning of the Terms

(IOA) impact on auditors' decision making on fraud detection. The independent variables, General Perception of AI in Auditing (GP), : Importance of AI in Detecting Frauds (IM) , Integrity and Lesser Corruption (ILC) and Challenges and Limitations (CHA) ,will have an effect on the impact on auditors' decision making on fraud detection . Specifically, ILC and CHA have a strong positive effect on IOA. GP and IM do not have a significant effect.

Table 1
Frequency Analysis

Gender	Frequency	Percent
Valid male	37	52.9
Valid female	33	47.1
Total	70	100.0

Gender Distribution

The study population is nearly balanced in terms of gender, with males constituting 52.9% and females 47.1% of the sample. Such almost equal representation removes positivity from gender-based bias in the findings and implications of the study. It also shows inclusivity in data collection which further supports the study results' generalizations.

Table 2
Qualification

Qualification	Frequency	Percent
Diploma degree	9	12.9
Advanced Diploma degree	7	10.0
Valid Bachelor degree	44	62.9
Master degree	8	11.4
Ph.D degree	2	2.9
Total	70	100.0

Levels of Qualification

Most respondents (62.9%) are holders of a Bachelor's degree, representing a reasonably well-educated sample with solid grounding in their respective fields. In addition, 11.4% of respondents are Master's holders, and 2.9% have acquired a PhD degree, suggesting that some participants have high academic qualifications. The lesser Diploma (12.9%) and Advanced Diploma (10.0%) holders may suggest that some participants have vocational or technical qualifications, but the study mainly involves university-level professionals. Such variations in levels can draw attention to how the academic level may correlate with variables under stud

Table 3
Experience

Experience	Frequency	Percent
less than 5 years	28	40.0
5 years - 10 years	12	17.1
Valid 10 years - 15 years	13	18.6
more than 15 years	17	24.3
Total	70	100.0

Years of Experience

The dispersion of years of professional experience shows that 40% are between the less than 5 years category, suggesting the presence of a relatively young workforce or a group in the initial career stages. On the contrary, 24.3% have worked for 15 years and above, thereby constituting an experienced and very competent group. The rest lie somewhere between the 5- and 15-year range, thus creating an evenly divided cluster across all career levels. With such a distribution, one can start analyzing the influence of the experience on professional competencies or attitudes, thus providing a holistic view across the spectrum. Most of the respondents (40%) are less than five years in the field. A substantial group (24.3%) is way above 15 years. This reflects a variety of experience level.

Table 4
Profession

Profession	Frequency	Percent
Auditing	31	44.3
Accounting	17	24.3
Valid Academic	13	18.6
other	9	12.9
Total	70	100.0

One-way Anova

Table 5

Descriptive

ILC3	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean			
					Minimum		Maximum	
					Lower Bound	Upper Bound	Lower Bound	Upper Bound
less than 5 years	28	3.9643	1.03574	.19574	3.5627	4.3659	1.00	5.00
5 years - 10 years	12	4.1667	.93744	.27061	3.5710	4.7623	2.00	5.00
10 years - 15 years	13	4.6923	.48038	.13323	4.4020	4.9826	4.00	5.00
more than 15 years	17	3.6471	.86177	.20901	3.2040	4.0901	2.00	5.00
Total	70	4.0571	.94617	.11309	3.8315	4.2827	1.00	5.00

Table 6

ANOVA

ILC3	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.489	3	2.830	3.505	.020
Within Groups	53.283	66	.807		
Total	61.771	69			

Table 7

Multiple Comparisons

Dependent Variable: ILC3

Tukey HSD

(I) Years_Experience	(J) Years_Experience	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
less than 5 years	5 years - 10 years	-.20238	.31001	.914	-1.0195	.6147
	10 years - 15 years	-.72802	.30155	.084	-1.5228	.0668
	more than 15 years	.31723	.27626	.661	-.4109	1.0454
5 years - 10 years	less than 5 years	.20238	.31001	.914	-.6147	1.0195
	10 years - 15 years	-.52564	.35969	.466	-1.4737	.4224
	more than 15 years	.51961	.33877	.423	-.3733	1.4125
10 years - 15 years	less than 5 years	.72802	.30155	.084	-.0668	1.5228
	5 years - 10 years	.52564	.35969	.466	-.4224	1.4737
	more than 15 years	1.04525*	.33104	.013	.1727	1.9178
more than 15 years	less than 5 years	-.31723	.27626	.661	-1.0454	.4109
	5 years - 10 years	-.51961	.33877	.423	-1.4125	.3733
	10 years - 15 years	-1.04525*	.33104	.013	-1.9178	-.1727

*. The mean difference is significant at the 0.05 level.

ANOVA of ILC3 by Experience

The analysis shows that ILC3 scores were significantly different between different experience groups. ILC3 showed the strongest performance or attitude for the group that has 10 to 15 years of experience (mean = 4.69), while those that have more than 15 years of experience showed weaker scores (mean = 3.65), which show the difference or decline in this measure for the ILC3 group that is most experienced. The ANOVA test confirms that such differences are statistically significant ($p = 0.020$), i.e., the difference is unlikely due to chance. Post hoc tests also show significant difference between 10-15 years group and more than 15 years group, reconfirming mid-career professionals differ from senior ones in this aspect.

Profession

About 44.3% of respondents are auditors, thus emphasizing the domination of this profession within our study sample. Almost one-quarter (about 24.3%) comprise the accounting professionals, while another 18.6% are assigned to academic duties, and the remaining 12.9% belong to other professions. This shows that the sample is largely constituted by professionals working in financial oversight and education in the accounting and auditing domain. Such a dispersion might restrict the generalization of results to other professions, but this nevertheless strongly nourishes insight into these vital sectors.

Table 8

One-way Anova: Descriptive

ILC4	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
less than 5 years	284	1.786	.86297	.16309	3.8439	4.5132	1.00	5.00
5 years - 10 years	124	0.833	1.16450	.33616	3.3434	4.8232	1.00	5.00
10 years - 15 years	134	5.385	1.12660	.31246	3.8577	5.2193	1.00	5.00
more than 15 years	173	4.706	1.17886	.28592	2.8645	4.0767	1.00	5.00
Total	704	0.571	1.08862	.13011	3.7976	4.3167	1.00	5.00

Table 9

ANOVA, ILC4

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9.282	3	3.094	2.817	.046
Within Groups	72.490	66	1.098		
Total	81.771	69			

Table 10

Multiple Comparisons

Dependent Variable: ILC4

Tukey HSD

(I) Years_Experience	(J) Years_Experience	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
less than 5 years	5 years - 10 years	.09524	.36160	.994	-.8578	1.0483
	10 years - 15 years	-.35989	.35173	.737	-1.2869	.5672
	more than 15 years	.70798	.32223	.135	-.1413	1.5573
5 years - 10 years	less than 5 years	-.09524	.36160	.994	-1.0483	.8578
	10 years - 15 years	-.45513	.41954	.700	-1.5609	.6507
	more than 15 years	.61275	.39514	.414	-.4287	1.6542
10 years - 15 years	less than 5 years	.35989	.35173	.737	-.5672	1.2869
	5 years - 10 years	.45513	.41954	.700	-.6507	1.5609
	more than 15 years	1.06787*	.38613	.036	.0502	2.0856
more than 15 years	less than 5 years	-.70798	.32223	.135	-1.5573	.1413
	5 years - 10 years	-.61275	.39514	.414	-1.6542	.4287
	10 years - 15 years	-1.06787*	.38613	.036	-2.0856	-.0502

*. The mean difference is significant at the 0.05 level.

ANOVA on ILC4 by Experience

Similarly, there is a significant difference in ILC4 scores by experience groups ($p = 0.046$). The highest mean scores fall in the range of 10 to 15 years (mean = 4.54), while the lowest scores fall in the range of more than 15 years (mean = 3.47). This trend suggests that mid-career participants are predicted to experience better results or a more favorable reaction regarding ILC4 than their older counterparts. Post hoc examination confirms that the

comparison between these two cohorts is statistically significant, confirming the trend in ILC3.

Table 11
One-way Anova

Descriptives								
IOA4								
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
less than 5 years	28	3.7500	1.20570	.22786	3.2825	4.2175	1.00	5.00
5 years - 10 years	12	4.4167	.66856	.19300	3.9919	4.8414	3.00	5.00
10 years - 15 years	13	4.6923	.48038	.13323	4.4020	4.9826	4.00	5.00
more than 15 years	17	3.8824	.85749	.20797	3.4415	4.3232	2.00	5.00
Total	70	4.0714	.99741	.11921	3.8336	4.3093	1.00	5.00

Table 12
ANOVA

IOA4					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9.942	3	3.314	3.726	.015
Within Groups	58.701	66	.889		
Total	68.643	69			

Table 13
Multiple Comparison

Multiple Comparisons						
Dependent Variable: IOA4						
Tukey HSD						
(I) Years_Experience	(J) Years_Experience	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
less than 5 years	5 years - 10 years	-.66667	.32539	.181	-1.5243	.1910
	10 years - 15 years	-.94231*	.31651	.021	-1.7765	-.1081
	more than 15 years	-.13235	.28997	.968	-.8966	.6319
5 years - 10 years	less than 5 years	.66667	.32539	.181	-.1910	1.5243
	10 years - 15 years	-.27564	.37753	.885	-1.2707	.7194
	more than 15 years	.53431	.35558	.442	-.4029	1.4715
10 years - 15 years	less than 5 years	.94231*	.31651	.021	.1081	1.7765
	5 years - 10 years	.27564	.37753	.885	-.7194	1.2707
	more than 15 years	.80995	.34747	.101	-.1059	1.7258
more than 15 years	less than 5 years	.13235	.28997	.968	-.6319	.8966
	5 years - 10 years	-.53431	.35558	.442	-1.4715	.4029
	10 years - 15 years	-.80995	.34747	.101	-1.7258	.1059

*. The mean difference is significant at the 0.05 level.

ANOVA on IOA4 by Experience

For IOA4, there is once more a statistically significant difference in mean score across experience levels ($p = 0.015$). The 10-15 years category once more has the highest mean score (4.69), indicating good performance or positive attitudes in this category. Those with less than 5 years of experience are meanwhile the lowest in mean score (3.75), and this

indicates that increased experience has a positive influence on IOA4. The dramatic difference between the least experienced and the 10-15 years group shows an improvement in the measured characteristic as experience is greater among professionals.

Table 14
One-way Anova

Descriptives								
CHA3								
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
less than 5 years	28	3.9286	1.05158	.19873	3.5208	4.3363	1.00	5.00
5 years - 10 years	12	4.2500	.96531	.27866	3.6367	4.8633	2.00	5.00
10 years - 15 years	13	4.0000	1.08012	.29957	3.3473	4.6527	2.00	5.00
more than 15 years	17	4.2941	.58787	.14258	3.9919	4.5964	3.00	5.00
Total	70	4.0857	.94398	.11283	3.8606	4.3108	1.00	5.00

ANOVA						
CHA3						
	Sum of Squares	df	Mean Square	F	Sig.	
Between Groups	1.849	3	.616	.682	.566	
Within Groups	59.637	66	.904			
Total	61.486	69				

Table 15
Multiple Comparison

Multiple Comparisons

Dependent Variable: CHA3

Tukey HSD

(I) Years_Experience	(J) Years_Experience	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
less than 5 years	5 years - 10 years	-.32143	.32798	.761	-1.1859	.5430
	10 years - 15 years	-.07143	.31903	.996	-.9123	.7694
	more than 15 years	-.36555	.29227	.597	-1.1359	.4048
5 years - 10 years	less than 5 years	.32143	.32798	.761	-.5430	1.1859
	10 years - 15 years	.25000	.38053	.913	-.7530	1.2530
	more than 15 years	-.04412	.35840	.999	-.9888	.9005
10 years - 15 years	less than 5 years	.07143	.31903	.996	-.7694	.9123
	5 years - 10 years	-.25000	.38053	.913	-1.2530	.7530
	more than 15 years	-.29412	.35023	.835	-1.2172	.6290
more than 15 years	less than 5 years	.36555	.29227	.597	-.4048	1.1359
	5 years - 10 years	.04412	.35840	.999	-.9005	.9888
	10 years - 15 years	.29412	.35023	.835	-.6290	1.2172

ANOVA on CHA3 by Experience

Unlike the other variables, CHA3 scores also do not vary significantly by experience groups ($p = 0.566$). Mean scores are very stable across all the groups ranging from around 3.93 to 4.29. This suggests that the attribute or attitude defined by CHA3 is not influenced by years of experience and is the same irrespective of the number of years they have worked in their area of choice.

Table 16
Regression Analysis

Model Summary										
Model R	R Square	Adjusted Square	RStd. Error of the Estimate	Change Statistics R Change	SquareF Change	df1	df2	Sig. F Change		
1	.881 ^a	.775	.761	1.60287	.775	56.063	4	65	.000	
a. Predictors: (Constant), CHA, IM, GP, ILC										
ANOVA^a										
Model		Sum of Squares	df	Mean Square	F	Sig.				
1	Regression	576.146	4	144.036	56.063	.000 ^b				
	Residual	166.997	65	2.569						
	Total	743.143	69							
a. Dependent Variable: IOA										
b. Predictors: (Constant), CHA, IM, GP, ILC										
Coefficients^a										
Model		Unstandardized Coefficients		Standardized	t	Sig.				
		B	Std. Error	Coefficients Beta						
1	(Constant)	.298	1.329		.224	.823				
	GP	-.025	.090	-.024	-.273	.785				
	IM	-.079	.104	-.076	-.754	.454				
	ILC	.775	.101	.794	7.654	.000				
	CHA	.332	.071	.303	4.696	.000				
a. Dependent Variable: IOA										

Regression Analysis Summary

The overall regression model is a good fit, explaining 77.5% of variation in the dependent variable IOA. This implies that the predictors employed—CHA, IM, GP, and ILC—are extremely good as predictors for IOA combined. In particular, ILC and CHA both have statistically significant positive impacts on IOA, i.e., higher scores in these predictors are associated with higher IOA. In contrast to that, GP and IM have no significant role in this model. Results of these studies indicate that a number of these factors (CHA and ILC) are significant predictors of IOA outcomes and would be informative for future studies or real-world applications.

Meaning of the Terms

(IOA) impact on auditors' decision making on fraud detection. The independent variables, General Perception of AI in Auditing (GP), : Importance of AI in Detecting Frauds (IM) , Integrity and Lesser Corruption (ILC) and Challenges and Limitations (CHA) ,will have an effect on the impact on auditors' decision making on fraud detection . Specifically, ILC and CHA have a strong positive effect on IOA. GP and IM do not have a significant effect.

RESULTS AND DISCUSSION: CONTINUE

Respondents Overview

The study had 70 participants with nearly equal numbers of males (53%) and females (47%), which avoids any gender-related bias in the result. Participants were mostly degree holders (63%), with some holding diplomas or higher qualifications. Participants' work experience was also diverse, from less than 5 years to more than 15 years, giving us ample variety of observations at different levels of career development.

Key Findings

Experience and Its Impact on Performance

Our findings showed that years of experience have a clear impact on many major indicators: 10 to 15 years of experience had the best scores on crucial parameters, which reflect that they are at the top of their professional skills.

The subgroup with more than 15 years of experience did less well on some of the assessments, which may mean that some attitudes or abilities depreciate or change after a certain period of time in a profession. One of the variables did not vary much by level of experience, meaning that there are some qualities that are consistent regardless of how long one has been on the job. This would be in line with what other research has found—mid-career professionals are at the peak of performance, and longer-tenured professionals can experience shifts in engagement or priorities.

What Predicts Better Outcomes?

The regression analysis revealed some interesting findings:

Cumulatively, these variables explain about 78% of the variance of the main outcome (IOA), which signifies that our model fits well to the data.

Two variables proved to be the most optimal predictors: ILC and CHA. Scoring higher on these dimensions predicts with strength scoring higher on IOA. The other two factors, GP and IM, played a weaker role in this study, which means that either they have a lesser contribution or their contribution is more context-dependent. It validates earlier research which had established some leadership and ability factors as being important to organizational effectiveness.

Contribution of this Study to Existing Knowledge

Overall, our findings support existing research on the role of experience and key competencies in professional success. The clear peak in the performance of mid-career professionals adds further insight into the role of experience in affecting work outcomes. Furthermore, confirmation of the importance of ILC and CHA helps in the consolidation of these factors as being critical in this profession. The decline among professionals with more than 15 years of experience is an interesting finding that needs closer examination. This may be because of changes in job content or motivation, which has not been examined in detail as yet.

Development of Refined Conceptual Framework

Based on the findings, the conceptual model based on the literature review can be refined as:

Put more focus on the influence of ILC and CHA on IOA.

Recognize that years of experience, especially the mid-career phase, is a key variable.

Keep in mind that GP and IM are not immediate predictors of IOA here.

This new model better reflects the reality of our participants and can guide future research and practical action

CONCLUSION

The paper at hand takes on the topic of the role that AI technologies play in fraud identification by external auditors in the modern digital age, with a special emphasis on Oman. Traditional auditing techniques are brushed into oblivion by the enormous information and sophisticated design of frauds, and AI methods like machine learning and deep-learning help in the speed and accuracy of the identification of frauds. The study uses surveys and interviews with auditors in Oman and finds that the mid-career auditors (10–15 years) fare best and AI enhances audit quality. It also points to challenges that include lack of adoption of AI within Oman and competency gaps, along with legal, cultural, and ethical concerns. Overall, this study lays bare the positive impact of AI in fraud detection and audit, urges more training and development of the field, and provides some lessons for auditors, organizations, and policymakers alike, both within and beyond Oman.

Recommendation:

1. Audit firms in Oman should actively invest in training auditors and imparting new skills with regards to AI technologies through adequate training courses, particularly those which are ongoing and comprehensive. Hence, auditors would efficiently apply AI tools

in fraud detection within audit-related areas while further enhancing audit quality to keep up with fast-occurring changes within the digitalization of the audit profession.

2. While policymakers and regulators in Oman work toward the development, revision, and enforcement of solid legal, ethical, and regulatory frameworks for the impact that AI brings to auditing, clear rules should enable responsible, transparent, and secure use of AI technologies for apt protection of all stakeholders and to foster trust towards the audit process

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