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The Impact of Technology on Forensic Accounting and Fraud Detection: A Case Study of Omani Firms

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ABSTRACT

Rapid technological improvements have revolutionised several businesses, affecting financial fraud and accounting detection. Fraud practices are increasing and becoming more complicated nowadays, whereas the traditional methods of investigating and detecting fraud meet challenges in keeping pace. This study aims to improve forensic accounting efficiency by increasing accuracy and reliability, reducing task time, and adapting to technological advancement. Hence, the study objectives are to explore the impact of cutting-edge technology on forensic accounting and fraud detection within Omani firms, its applications, integration challenges, and solutions to overcome them. The research uses a mixed-method approach, using both quantitative and qualitative data. An online questionnaire is distributed to a sample of 30 forensic accountants and auditors across various Omani firms, focusing on their perspectives regarding the impact and challenges of technology in this field. Using Microsoft Excel, data are analysed through different statistical analyses like descriptive, correlation, regression, and ANOVA analyses. The findings demonstrate that forensic accounting efficiency is directly related to technology adoption and organisational challenges. However, organisational challenges do not correlate with technology adoption. The research suggests that continuous education and training for employees and targeted investments in cybersecurity are crucial for addressing these obstacles. This research enhances fraud detection techniques and increases trust in financial systems, benefiting regulators, organisations, and stakeholders.

Keywords: Artificial Intelligence, Blockchain, Forensic Accounting, Fraud Detection, Machine Learning, Technology

1. INTRODUCTION

Technological advances over the decades have had a significant role in shaping the development of forensic accounting processes. Frank Wilson, recognised as the "father of forensic accounting," employed early forensic methods that manually analysed fraud cases in the early 20th century. In 1930, these methods were primarily helpful in the tax evasion conviction of Al Capone, an infamous mobster (Adebayo et al., 2023). Since then, there has been a significant shift in the

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accounting field, with more sophisticated forensic accountant techniques, high-tech tools, and data analysis programs to examine vast amounts of information, determine trends, and identify abnormalities. According to Li (2010), Enron was established in 1985 and emerged as a prominent entity in the electricity, natural gas, communications, and pulp and paper industries before declaring bankruptcy in late 2001. Its annual revenues escalated from over $9 billion in 1995 to over $100 billion in 2000. The company's stated financial situation was controlled mainly by systematic, institutionalised, and creatively planned accounting fraud, which came to light at the end of 2001. Enron's stock price went from $90 per share in the middle of 2000 to under $1 per share by the end of 2001, resulting in a loss of approximately $11 billion for shareholders. For the five years before that, Enron looked at its financial statements again and found that it had lost $586 million. On December 2, 2001, the Enron scandal appeared as it declared its bankruptcy.

The increasing amount of financial fraud scandals nowadays has further emphasised the importance of technology in forensic accounting, as they have revealed weaknesses in conventional auditing practices. Patel et al. (2021) pointed out that auditors and forensic accountants have had to enhance their abilities to spot early indications of fraud due to these scandal incidents. Financial fraud is the leading cause of economic and financial disasters as it directly affects how well the stock, debt, and capital markets perform. Javaid (2024) sees that advancements in fraud detection technology have developed from simple rule-based systems to the integration of machine learning, artificial intelligence (AI), and data analytics. The forensic accountant conducts investigations of fraud and theft by using their expertise in auditing, accounting, and investigation. Alongside technological advancements, the responsibilities of a forensic accountant have expanded to include tracking money laundering and examining theft and evasion of tax practices (Rohmah et al., 2022). The escalating complexity of financial crimes in the contemporary digital age has revolutionised forensic accounting, where technology plays a pivotal role in augmenting fraud detection and prevention (Whitehouse, 2022). Contemporary forensic accounting incorporates innovative techniques like AI, data analytics, and blockchain technologies to detect and examine fraudulent activities efficiently. Hence helping forensic accountants manage large datasets and find complex fraud schemes that conventional approaches may miss.

Daraojimba et al. (2023) highlighted that forensic accounting now encompasses business management, psychology, crime science, and traditional financial analysis elements. Also, forensic accountants are now essential in court cases as they provide expert opinions and evidence to settle financial disputes and bring financial crimes to justice. Fraud theories establish a fundamental framework for perceiving the motivations and events that result in fraudulent activities. The Fraud Triangle, which identifies pressure, opportunity, and rationalisation as critical components of fraud, emphasises the significance of technology in the early detection of these aspects. Sophisticated instruments like data analytics and artificial intelligence can detect irregularities indicative of potential fraud, whilst ongoing surveillance can reduce the incentives that lead to fraudulent behaviour. Likewise, the Fraud Diamond, which incorporates "capacity" into the Fraud Triangle, corresponds with the application of technology to evaluate and mitigate the competencies of prospective fraudsters. Integrating these theories can concentrate on how technology addresses the underlying causes of fraud, thereby improving the efficiency and cost-effectiveness of forensic accounting practices while improving both detection and prevention.

According to Odeyemi et al. (2024), the rising complexity of financial fraud may be exceedingly challenging for traditional forensic accounting approaches, calling for innovative technological applications. Traditional forensic accounting techniques may be insufficient for detecting complicated fraud patterns in an environment characterised by the daily generation of extensive data (Onowu & Oludi, 2024). Therefore, manual detection approaches are time-consuming, expensive, inaccurate, and impractical in the massive data age, leading to failure to find fraudulent activities (West & Bhattacharya, 2016). Because of these issues, there is a growing need for modern technology-based tools and techniques that help to make forensic accounting more accurate, rapid and efficient. The application of innovative technologies to this field has a significant impact; however, the application is vulnerable to substantial obstacles and issues. This study addresses the challenges of traditional forensic accounting techniques and reveals modern forensic accounting techniques and their impacts. This study seeks to identify advanced technological applications in forensic accounting and fraud detection while evaluating their impact on improving efficiency within this discipline. This study will examine the challenges associated with integrating technology in forensic accounting and propose practical solutions to address these issues.

This study seeks to ascertain the influence of technology on forensic accounting in Omani firms. The characteristic will engage forensic accountants in Omani firms with a minimum of thirty accountants. The duration to complete this study will be three months and two weeks, from October 6th to January 11th. It will concentrate on theories of technology's influence on this accounting field. This study is significant because it examines how effectively technological advancements change fraud detection and forensic accounting. Fraud techniques are becoming more complicated nowadays, whereas the traditional methods of investigating and detecting fraud meet challenges in keeping pace. Moreover, the study aims to deliver an in-depth understanding of how technology can improve the efficiency of forensic accounting. It is possible to mitigate reputational risks caused by fraudulent activities, enhance adherence to regulatory standards, and minimise financial losses from fraud by implementing more extraordinary detection techniques. Technology can improve financial reporting accuracy, accountability, and transparency, which builds confidence in financial systems. Hence, the findings will seek to enhance detection methods and increase trust in financial systems, which will benefit regulators, organisations, and stakeholders.

2. LITERATURE REVIEW

2.1. Theoretical Framework

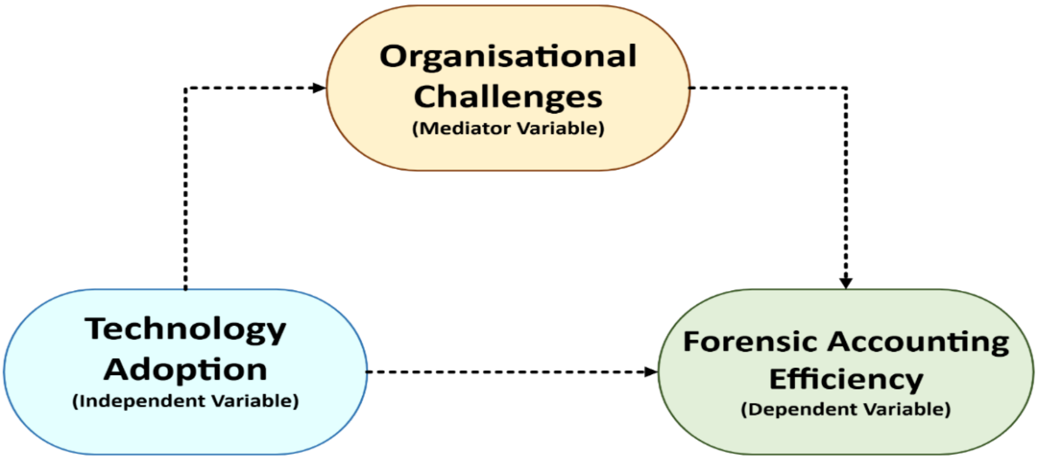

Figure 1 *Theoretical Framework*

Based on the study framework implied in Figure 1, it is hypothesised that implementing technology as an independent variable will improve the effectiveness of forensic accounting, the dependent variable, by providing advanced applications that automate and optimise the detection and analysis procedures. However, the magnitude of such enhancement is mediated by organisational challenges, which cover an organisation's obstacles that may be faced, like skilled employees, infrastructure, and a supportive environment. These challenges affect how the technology can be successfully utilised and incorporated within forensic accounting's finest practices, in which overcoming organisational barriers is crucial to this adoption's success. Hence, even though the adoption of technology can boost the efficiency of forensic accounting immediately, the full impact of this technology will become apparent when an organisation can eliminate the challenges of implementing technological advancements. Therefore, organisational challenges hinder the deployment of new technology and substantially impact the overall efficacy and efficiency of forensic accounting investigations.

2.2. Forensic Accounting

Forensic accounting is a specialised field within the accounting profession that provides many services besides fraud investigation. According to Akkeren et al. (2013), It is a domain within the accounting profession that addresses financial crime and its inherent complexities, necessitating a profound level of competence to analyse sophisticated financial transactions. Forensic accounting involves utilising specialised talents, including accounting, auditing techniques, finance, quantitative analysis, research, and investigative tactics. It also necessitates an understanding of specific legal domains. This expertise and these competencies empower forensic accountants to gather, analyse, and assess evidence subject matter and interpret and convey their conclusions (Crain et al., 2019). Fraud detection and prevention were recognised as components of accounting functions, with internal and external auditors tasked with identifying and mitigating fraud. Subsequently, it was observed that auditors are not accountable for fraud prevention and detection; their role is limited to verifying the adherence of the company's financial statements to applicable accounting standards and legislation governing financial reporting. Consequently, a new accounting field has emerged: "Forensic Accounting." The inception of Forensic Accounting was to identify fraudulent transactions occurring within commercial entities (Kaur, 2024).

2.2.1. Role of Forensic Accountant

Forensic accountants provide a crucial proactive risk mitigation function by serving as experts in statutory audits, devising and executing comprehensive procedures, advising audit committees, and supporting investment analyst research. Furthermore, when examining forensic accountants' duties, they are specialists in analysing what is behind the numerical data and addressing actual business scenarios (Wijerathna & Perera, 2020). Dalwadi (2023) stated that forensic accountants' primary roles are in detecting financial fraud; forensic accountants possess the expertise and insight to identify financial fraud, embezzlement, and various financial offences. They can examine dubious transactions, scrutinise financial records, and analyse financial data to detect anomalies or fraudulent acts. Also, forensic accountants may provide evidence for judicial processes, including criminal or civil cases. Their findings may be employed to substantiate legal claims or to convict persons or entities suspected of financial crimes (Alabdullah et al., 2013).

Additionally, to mitigate financial fraud, forensic accountants assist enterprises and organisations in preventing financial fraud by establishing robust internal controls, formulating anti-fraud policies, and performing risk assessments. Furthermore, avoiding financial losses, forensic accountants assist businesses in preventing financial losses caused by fraud or other financial offences. They can detect fraudulent actions promptly, allowing organisations to act swiftly and recapture lost revenue. Finally, to facilitate adherence to laws and regulations, forensic accountants assist in achieving compliance with financial regulations and legal rules. Forensic accountants can locate areas of non-compliance and offer recommendations for resolving such faults.

2.3. Financial Fraud

Financial fraud is a widespread and severe issue that adversely impacts individuals, organisations, and economies. Fraud is defined as a criminal act or sequence of illegal acts performed by nonphysical means and by secrecy or deceit to obtain money or property, prevent the payment or loss of money or property, or obtain trade or personal benefit (Free, 2015). According to the Global Fraud Study of the Association of Certified Fraud Examiners (ACFE) in 2016, fraud costs businesses an estimated 5% of their revenue annually, according to the median estimate of the Association (Association of Certified Fraud Examiners, 2016).

2.3.1. The Fraud Theories

The Fraud Triangle Theory (FTT) and the Fraud Diamond Theory (FDT), proposed by criminologists Donald Cressey, Wolf, and Hermanson, respectively, are the two leading theories of fraud that have been proposed and frequently referenced in literature over the years.

2.3.2. The Classic Fraud Triangle Theory

According to Eko (2022), the term ‘Fraud Triangle’ is attributed to Edwin Sutherland, who introduced it in his 1949 book, White Collar Crime. Thus, he becomes the principal contributor to the model. In 1953, Cressey formulated the idea to clarify the factors that drive individuals to commit fraud or criminal acts. The Fraud Triangle asserts that frauds encompass three elements: pressure, opportunity, and rationalisation. Opportunity is perceived as the prevailing gap that facilitates the commission of fraud. Moreover, the fertile soil is where the seed of fraud flourishes. An absence or poor internal control and governance structure primarily generates this opportunity. The Pressure factor necessitates that fraudsters feel compelled to engage in fraudulent activities and believe they cannot seek assistance or disclose their issues. Examples encompass pressure to fulfil or surpass analysts' earnings projections, cash flow difficulties, and constrictive loan covenants. The Rationalisation component refers to providing a justification that aligns with the fraudster's moral framework, or more precisely, an endeavour to mitigate cognitive dissonance among the individual (Gepp et al., 2023).

2.3.3. The Fraud Diamond Theory

The Fraud Diamond Theory expands upon the Fraud Triangle Theory. The Fraud Diamond Theory by Wolfe & Hermanson first appeared in 2004 in the Certified Public Accountant (CPA) magazine and is seen as an enhancement of Cressey’s (1953) Fraud Triangle Theory. The two theories are similar except for Wolfe and Hermanson's claims that the combination of pressure, opportunity, and rationalisation alone is inadequate for initiating fraud unless the potential perpetrator possesses the requisite intelligence, skills, and technical expertise to execute the intended fraud. Consequently, they incorporated the fourth factor

(Capacity) into Cressey's (1953) Fraud Triangle Theory to create their own Fraud Diamond Theory (Nwakeze et al., 2023). Several factors of "capability" encompassing position, cognitive capacity, self-assurance, resilience to stress and guilt, and the ability to manipulate and persuade others. Wolfe and Hermanson concluded that while opportunities, pressures, and rationalisations for fraud exist, the absence of the requisite capabilities in the fraudster prevents its occurrence. Figure 2 below shows the shift from the classic Fraud Triangle Theory to the Fraud Diamond Theory.

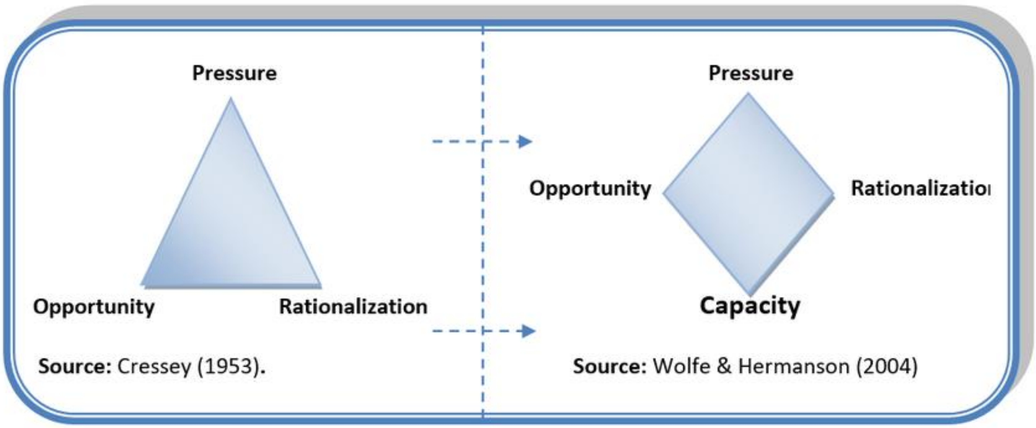

Figure 2 *Fraud Triangle (FTT) and Fraud Diamond (FDT) Frameworks*

2.4. Technology Applications in Forensic Accounting

Specialised software and tools in forensic accounting use data analysis, fraud detection and prevention, financial statement analysis, and investigative accounting. Blockchain, data analytics, and artificial intelligence technology are increasingly vital in detecting and preventing financial crime (Hossain, 2023).

2.4.1. Blockchain Technology

Financial investigations have entered a new age of transparency, accuracy, and efficiency through blockchain technology's application to forensic accounting techniques. Blockchain's decentralised and immutable nature assures a tamper-proof ledger, ensuring that financial records cannot be altered retrospectively, strengthening the credibility of evidence in court processes. Forensic accountants can utilise blockchain to authenticate the validity of financial data, trace transactions, and improve the general transparency of financial records (Odeyemi et al., 2024). Blockchain technology's immutability, decentralisation, and cryptographic security allow forensic accountants to solve many of their main challenges. By leveraging blockchain's decentralised characteristics, forensic accountants can obtain real-time transactional data directly from the source, minimising dependence on intermediaries and mitigating the risk of data manipulation. Moreover, many blockchain technology tools can be implemented to aid forensic accountants. One of them is the smart contract, a software application that conducts tasks on behalf of the user according to specified requirements (Zemánková, 2019). According to Brody et al. (2023), these computer codes autonomously run under specified conditions. The code can be saved and processed on a distributed ledger, which records any resultant changes. This category of smart contracts is characterised by an "internal model" framework. The code constitutes the complete agreement between the parties and replaces any other provisions expressed in plain language.

2.4.2. Artificial Intelligence and Machine Learning

The debate surrounding "artificial versus human intelligence" among scholars and professionals involves numerous contentious issues regarding the future of certain occupations, the necessary new skill sets and competencies, and the potential for effective collaboration between humans and machines (Mehta et al., 2021). Artificial intelligence relies on comprehending the essence of human intelligence by developing computer systems that can emulate human behaviour and supply users with the necessary information to facilitate prompt and informed decision-making. Machine learning applications in forensic accounting include decision trees, support vector machines, and clustering algorithms. These techniques train a model with pre-labelled data to predict new, unannotated data. Algorithms can be employed in forensic accounting to predict fraudulent transactions through real-time analysis and historical data examination. Decision trees and logistic regression are effective methods for predicting fraud using transaction data based on transaction information (Haddad et al., 2024). More recently, autoencoder networks have also been implemented in forensic accounting data analysis, which detects anomalies by applying fuzzy logic and autoencoder neural networks (ANN). For example, unusual accounting records, irregular combinations of general ledger accounts, and user accounts that multiple accounting departments use are examples of accounting anomalies. These local accounting anomalies are journal entries showing an unusual or rare combination of attribute values, while their attribute values occur frequently. This abnormality is far more challenging to identify, as fraudsters aim to conceal their actions by replicating a typical activity pattern. Consequently, such anomalies typically present a significant fraud risk related to procedures and activities that may not adhere to organisational rules (Schreyer et al., 2017).

2.4.3. Data Analytics and Big Data

Big data technologies are revolutionising corporate procedures and practices because traditional database management systems cannot manage large amounts of data. Akinbowale et al. (2023) divide three principal attributes typically employed to characterise "big data" as high volume (substantial size or quantity of data acquired), high velocity (the rapidity of data collection), and high diversity (the different sources of the data collected). Big data technologies enable organisations to extract real-time intelligence from vast data. These enhanced techniques empower forensic auditors to do thorough analyses to extract significant insights from the data, hence facilitating evidence-based decision-making. They can manage varied and extensive data efficiently to deliver critical information and find trends and patterns for decision-making. Predictive analytics can predict future entries and provide forward-looking insight based on historical data. The ability to analyse all data sets instead of relying just on sampling techniques enhances auditors ' confidence in their conclusions (Mittal et al., 2021). Also, advanced analytics detect anomalies in the behaviour of customers and vendors, including payments that are repeated or unusual invoice patterns. Clustering analysis can facilitate the identification of information with common characteristics in data mining, while association rules can help establish the extant relationships among the datasets. The regression analysis can ascertain how much the data pattern changes when specific variables are altered. Therefore, implementing data mining techniques can improve data processing and increase the dependability of the obtained information in pursuing fraud mitigation.

2.5. Role of Technology in Enhancing Forensic Accounting Efficiency

Forensic accounting is becoming increasingly critical in combating financial misconduct in the digital era. Digital forensic accounting, encompassing collecting and analysing data from electronic sources, is essential for identifying crimes like phishing and money laundering. Digital forensics has the potential to investigate and analyse digital data, including electronic transactions and email interactions, to detect fraudulent acts much faster and more efficiently through the use of data analysis techniques (Onamusi et al., 2024). According to Boylan and Hull (2022), an accounting information system (AIS) can monitor the individuals responsible for generating journal entries, the dates on which they were completed, and the accounts that were changed. Also, the fact that blockchains are challenging to modify is generally regarded as an advantage, enabling auditors and management to prevent criminal activity. Moreover, data mining aids in scanning transaction listings, finding gaps in cheque runs, payroll payments to the same payee during the inquiry period, finding duplicated invoice or payment voucher numbers, and matching returns. It also compares new invoice prices with archival inventory costs and filters transactions to find new suppliers (Eko, 2022). These advances facilitate the administration of extensive information and improve the identification of nuanced fraud trends. The detection of hidden fraud has been enhanced by sophisticated anomaly detection and pattern recognition algorithms. In contrast, data mining and visualisation tools have improved the analysis of complicated financial transactions, resulting in further refined forensic accounting practices. Data analytics has substantially improved the efficacy and accuracy of forensic investigations by reducing investigation timeframes and enhancing the accuracy of detecting fraudulent transactions. Advanced analytical approaches have improved data processing and decision-making, leading to more efficient investigations (Verma & Singh, 2024). This technology-based software, especially AI, is essential for forensic accountants, as it simulates the human intellect. It can also provide the required information and power at a rate that excels the speed and accuracy of human beings (Saluja et al., 2024).

2.6. Barriers to Integrating Technology in Forensic Accounting

Adopting emerging technology trends in forensic accounting may present significant challenges for businesses, such as the necessity of major investments in skilled personnel and technology infrastructures. These technologies need specific knowledge and skills that organisations or accounting professionals may not have (Al Abbadi et al., 2021). Additionally, companies may encounter barriers in implementation costs and system integration to use these technologies successfully. Businesses may struggle to integrate new technologies with the workflow of the existing system, which is one of the main challenges. In addition, employees or management may resist embracing new technologies due to concerns about job displacement or lack of familiarity with the new technology. According to Oladejo and Jack (2020), the challenges in data security risks can be shown in blockchain technology, where it may leak data, and hackers can penetrate blockchain technology's cryptography to perform fraud and other attacks, compromising its source documents and reliability. Moving to the legal aspect's challenges that may raise concerns and affect the application of techniques, Chinweike (2024) explains different legal challenges such as:

In the courts, the admissibility of digital evidence is governed by several rules and criteria like reliability, authenticity, and relevance. Digital evidence is regularly reviewed by courts, with authentication frequently requesting expert testimony to verify forensic processes, causing difficulties in guaranteeing the acceptance of this evidence. Additionally, as technology advances, digital forensics accounting faces new legal challenges. Blockchain and end-to-end encryption complicate traditional forensic methods. When laws do not keep up with technology, grey areas arise that impede investigations and court cases. Addressing these changing issues requires ongoing research and revised legislation. Moreover, since different nations have varied laws surrounding the collecting, sharing, and admissibility of evidence, cases that include investigations across international borders can be complicated. Despite this, international legal cooperation and agreements are frequently required, which can be time-consuming and complicated. Furthermore, digital evidence integrity depends on the chain of protection. From evidence gathering to court presentation, this process should be meticulously documented. Chain gaps can put suspicion on the evidence's authenticity and exclude it. Documenting and following procedures are essential to meeting admissible evidence criteria (Chinweike, 2024).

2.7. HYPOTHESES:

$\mathbf{H1_1}$: *Technology adoption positively influences forensic accounting efficiency.*
$\mathbf{H1_0}$: *Technology adoption negatively influences forensic accounting efficiency.*
$\mathbf{H2_1}$: *Organisational challenges mediate the relationship between technology adoption and forensic accounting efficiency.*
$\mathbf{H2_0}$: *Organisational challenges do not mediate the relationship between technology adoption and forensic accounting efficiency.*

3. METHODOLOGY:

3.1. Research Design

This research utilises descriptive design. The descriptive design offers a detailed overview of statistical data to reveal population characteristics or patterns related to this research. Also, it describes the different technology applications applied in this field and how it has enhanced its processes nowadays. The research design explains technology's integration challenges and solutions through recent literature reviews and forensic accountants' perspectives. Additionally, the research uses a mixed-method approach, where qualitative data is gathered through non-numerical data through open-ended questionnaire questions that focus on understanding experiences and perspectives. The quantitative method, such as the numerical data from the questionnaire, gathers actionable insights through statistical conclusions. Both statistical analysis and hypothesis testing are included in the data analysis process, and the results are shown as numbers and statistics.

3.2. Population of the Study and Sample Size

Professionals and organisations engaged in fraud detection and forensic accounting within Omani organisations encompass the population of this investigation. The research distributed a questionnaire to specific respondents to gain insights into the recent technology in forensic accounting. Overall, the population size of this research includes forensic accountants who are specialised in financial fraud detection, internal and external auditors who are engaged in investigating forensic practices or audits using fraud detection technologies, managers and people who make decisions in Omani companies; these are the people in charge of forensic accounting units or fraud detection teams. Hence, the sample size of this research will be 30 respondents. The population scope targets respondents from government and private sector entities as well as Omani small and medium enterprises (SMEs).

3.3. Sampling Technique

This research uses a non-probability sampling approach, wherein the researcher picks the sample based on subjective judgment rather than random selection. This strategy excludes some population members from participating in the research

(BYJU'S, 2024). Specifically, snowball sampling or a chain-referral sampling technique has been applied, which is used when samples with the desired characteristics are inaccessible (Naderifar et al., 2017).

3.4. Research Instruments and Validity and Reliability Testing

According to Afolayan and Oniyinde (2019), questionnaires are less expensive than interviews and can occasionally be mailed in without requiring skilled interviewers. It is simpler to use and can engage a larger audience. It enhances the reliability of data due to anonymity. Ultimately, it ensures that all participants are provided with identical questions, thus eliminating interviewer bias. The questionnaire consists of two parts: the demographic and the research objectives. Five demographic enquiries were included concerning the respondents' age, gender, education level, years of professional experience, and forensic accounting or fraud examination certifications obtained. The second part consists of fifteen questions related to the research objectives, which collects data using open-ended and closed-ended questions, including one dichotomous question (yes/no), two Multiple Choice Questions (MCQs), one rating scale, seven Likert scale responses (ranging from strongly agree to disagree and from very effective to very ineffective strongly) and two open-ended questions.

4. DATA ANALYSIS AND RESULTS

4.1. Descriptive Analysis

Table 1 *Descriptive Analysis of Demographics Data*

Measures	***Gender***	***Age***	***Academic Qualification***	***Work Experience***
Mean	1.5667	3.2	1.9333	2.6333
Standard Error	0.0920	0.2166	0.0951	0.1477
Median	2	3	2	3
Mode	2	3	2	3
Standard Deviation	0.5040	1.1861	0.5208	0.8087
Sample Variance	0.2540	1.4069	0.2713	0.6540
Kurtosis	-2.0621	-0.8356	1.0890	-0.3431
Skewness	-0.2834	-0.0159	-0.1092	-0.0459
Range	1	4	2	3
Minimum	1	1	1	1
Maximum	2	5	3	4

Sum	47	96	58	79
Count	30	30	30	30

- **Genders**

The mean gender value of 1.57 suggests a minor female (2) dominance among participants. The median and mode values 2 indicated that females comprised the majority. According to UN Women (2019), investments in women's economic empowerment establish a direct path to gender equality, poverty eradication, and inclusive economic development. Women significantly boost economies, whether working as employees or entrepreneurs in enterprises. With a standard deviation of 0.50, the gender representation is comparatively balanced and indicates moderate variability. With a sample variance of 0.25 for gender, the data shows minimal variation. This minor variation demonstrates that the replies are relatively consistent, with a slight inclination towards females. This corresponds with the standard deviation 0.50, further validating an equitable distribution across males and females. The gender range is 1, the difference between maximum females (2) and minimum males (1).

- **Ages**

A mean age value of 3.2 indicates that the average respondent belongs to the 35-39 age group (3). The median score of 3 implies a symmetrical distribution within this group. This signifies a central tendency within this age range. The mode of 3 further substantiates that the age group of 35-39 years is the most prevalent in the sample. A standard deviation of 1.19 indicates considerable variability, suggesting a broad age range among participants. A substantial amount of variation can be seen in the age categories of the respondents, as noted in the sample variance for age, which is 1.41. This shows that responders are scattered across age groups, but (35-39) is the main concentration. The age **range** is 4, encompassing the youngest group (1= 25-29) to the oldest group (5= 45 and above). This broad spectrum indicates a varied age demographic among the respondents, encompassing beginners to expert workers.

- **Academic Qualification**

With a mean qualification of roughly 1.93, it falls between a bachelor's degree (1) and a master's degree (2), with a small amount of bias towards the master. The median and mode are 2 (Master’s degree), indicating a significant prevalence of this category. The standard deviation is 0.52, indicating negligible variance in qualifications. The participants' educational qualifications are homogeneous, as evidenced by the low variance 0.271. The range is 2, encompassing a minimum of 1 (Bachelor’s degree) to a maximum of 3 (PhD degree). This small range shows that most respondents are between three educational levels.

- **Work Experience**

The mean job experience is roughly 2.63, ranging from 6-10 years (2) and 11-15 years (3). As indicated by the median and mode of 3, most responders have between 11 and 15 years of experience. A standard deviation of 0.81 signifies moderate variability in the job experience. The work experience sample variance is 0.65, indicating significant respondent variability. This encompasses a variety of people with different years of experience, ranging from early-career professionals 1-5 years to individuals with considerable expertise over 15 years. The range 3 extends from 1 (1-5 years) to 4 (over 15 years), representing a variety of participants across various experience levels.

4.2. Correlation and Regression Analyses

Table 2 *Correlation Table*

	Effectiveness of Data Mining	*Reduction in Fraud Detection Time*
Effectiveness of Data Mining	1	
Reduction in Fraud Detection Time	0.4884	1

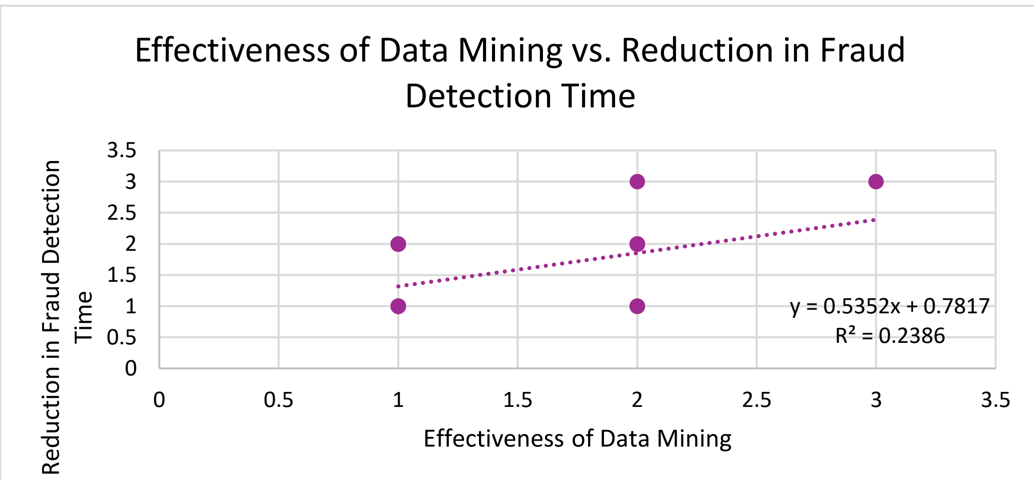

Figure 3 *Effectiveness of Data Mining vs. Reduction in Fraud Detection Time*

As shown in Figure 3 with a correlation coefficient of 0.488, the correlation analysis demonstrates a moderately positive relationship between the efficiency level of data mining and the reduction in the time required to detect fraudulent activity. The results support the hypothesis that a moderately strong correlation exists between the increased efficacy of using data mining (One of the technology applications) and significant reductions in fraud detection time (Efficiency of forensic accounting). The trendline indicates that enhancements in data mining efficacy correlate with decreased fraud detection time. At the same time, the explained variance implies that this relationship is very weak. Although data mining is crucial for improving fraud detection efficacy, other elements like AI or blockchain may also considerably affect results. Moreover, external factors such as training, cost, and management engagement may be facilitators or obstacles to efficiently utilising data mining. An in-depth examination of these aspects and focused actions may yield a comprehensive understanding and enhance the efficacy of technology in fraud detection.

Table 3 *Regression Analysis 1*

Regression Statistics	
Multiple R	0.4884
R Square	0.2386
Adjusted R Square	0.2114
Standard Error	0.5560
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.7117	2.7117	8.7729	0.00617
Residual	28	8.6549	0.3091		
Total	29	11.3667			

Forensic Accounting Efficiency

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.7817	0.2838	2.7544	0.01022	0.2004	1.3630	0.2004	1.3630
Technology Adoption	0.5352	0.1807	2.9619	0.00617	0.1651	0.9054	0.1651	0.9054

Table 3 shows the regression analysis by analysing the relationship between technology adoption as an independent variable and forensic accounting efficiency as a dependent variable, demonstrating a positive moderate correlation between them by Multiple R 0.488. The R Square of 0.239 suggests that the technology adoption score accounts for about 23.9% of the variance in forensic accounting efficiency. The model's statistical significance at the 1% level is confirmed by the F-statistic of 8.773 with p = 0.00617, which suggests that technology adoption accurately predicts forensic accounting efficiency. For technology adoption, the slope coefficient is 0.5352, which is statistically significant (p = 0.006). In other words, the forensic accounting efficiency increases by an average of 0.5352 units for every unit gain in forensic accounting efficiency. An F-statistic has a p-value of 0.00617, which means that the model is statistically significant, and the independent variable explains a meaningful amount of the variation in forensic accounting efficiency. Thus, the null hypothesis is resected, and ($H1_1$) is accepted, ensuring that technology adoption positively influences forensic accounting efficiency. This makes the case that technology adoption is a factor that can significantly explain the changes in forensic accounting efficiency.

Table 4 *Regression Analysis 2*

Regression Statistics	
Multiple R	0.0693
R Square	0.0048
Adjusted R Square	-0.0307
Standard Error	0.8843
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.1056	0.1056	0.1351	0.7160
Residual	28	21.8944	0.7819		
Total	29	22			

Organisational Challenges

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.1549	0.4514	4.7741	0.0001	1.2303	3.0795	1.2303	3.0795
Technology Adoption	-0.1056	0.2874	-0.3675	0.7160	-0.6943	0.4831	-0.6943	0.4831

Table 4 shows the regression of technology adoption and the organisational challenges. A Multiple R of 0.069 signifies a negligible positive correlation between both variables. R Square (0.0048) indicates that 0.48% of the variance in organisational challenges is elucidated by technology adoption. Technology adoption suggests no significant explanatory power for anticipating organisational challenges. Significance F represents the p-value for the complete model. A p-value of 0.716 signifies that the regression model does not have statistical significance, indicating that technology adoption fails to predict organisational challenges. The regression line's slope demonstrates that for each 1-unit rise in technology adoption, the organisational challenges diminish by 0.11 units. Hence, it accepts the null hypothesis (Organisational challenges do not mediate the relationship between technology adoption and forensic accounting efficiency ($H2_0$)) and rejects the alternative hypothesis.

Table 5: *Regression Analysis 3*

Regression Statistics	
Multiple R	0.3794
R Square	0.1440
Adjusted R Square	0.1134
Standard Error	0.5895
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.6364	1.6364	4.7088	0.0386
Residual	28	9.7303	0.3475		
Total	29	11.3667			

Forensic Accounting Efficiency

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.1121	0.2734	7.7244	0.0000	1.5520	2.6722	1.5520	2.6722
Organisational Challenges	-0.2727	0.1257	-2.1700	0.0386	-0.5302	-0.0153	-0.5302	-0.0153

The Multiple R of 0.3794 indicates a moderate linear correlation between organisational challenges and the efficiency of forensic accounting. R Square (0.14) signifies that about 14.4% of the variance in forensic accounting efficiency is attributable to organisational issues. The regression is statistically significant at just below 5%, as indicated by the F-Statistic of 4.7088 and a significance F of 0.0386. This suggests that organisational challenges have significantly impacted forensic accounting efficiency. The intercept of 2.11, accompanied by a highly significant p-value, indicates that in the absence of organisational challenges, the baseline efficiency of forensic accounting is 2.11. The organisational challenges negatively impact the efficiency of forensic accounting, with a p-value of 0.0386 (moderately significant) and a coefficient of -0.27. For every unit rise in organisational challenges, the efficiency of forensic accounting diminishes by 0.27 units.

Table 6: *Regression Analysis 4*

Regression Statistics	
Multiple R	0.5988
R Square	0.3586
Adjusted R Square	0.3111
Standard Error	0.5196
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	4.0757	2.0379	7.5467	0.0025
Residual	27	7.2909	0.2700		
Total	29	11.3667			

Forensic Accounting Efficiency

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.3196	0.3573	3.6935	0.0010	0.5865	2.0526	0.5865	2.0526
Technology Adoption	0.5088	0.1693	3.0056	0.0057	0.1615	0.8562	0.1615	0.8562
Organisational Challenges	-0.2496	0.1111	-2.2475	0.0330	-0.4775	-0.0217	-0.4775	-0.0217

Table 6 shows the relationship between forensic accounting efficiency (dependent variable) and technology adoption with organisational challenges (independent variables). Multiple R (0.599) represents the correlation coefficient indicating the strength and direction of the association among the predicted variables (technology adoption and organisational challenges) and the dependent variable, indicating a moderate positive correlation among variables. Technology adoption and organisational challenges combined include 35.9% of the variance in forensic accounting efficiency, as the R Square indicates (0.359). The coefficient of technology adoption in forensic accounting efficiency increases by 0.509 units for each unit, with organisational challenges held constant. The P-value of (0.0057) indicates a statistically significant relationship between technology adoption and forensic accounting efficiency. A higher perceived technology adoption is linked to a significantly higher perceived forensic accounting efficiency. The coefficient shows that with each 1-unit increment in organisational challenges, forensic accounting efficiency diminishes by 0.250 units. P-value (0.03298) indicates a statistically significant correlation between the two variables since $P < 0.05$. The regression analysis is statistically significant, indicating that technology adoption and organisational challenges are influential indicators of forensic accounting efficiency.

4.3. ANOVA Analysis

Table 7: *ANOVA Single Factor Analysis*

Groups	*Count*	*Sum*	*Average*	*Variance*		
1-5 Years	2	4	2	2		
6-10 Years	11	19	1.7273	1.4182		
11-15 Years	13	30	2.3077	1.5641		
Above 15 Years	4	6	1.5	0.3333		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.0156	3	1.0052	0.7270	0.5451	2.9752
Within Groups	35.9511	26	1.3827			
Total	38.9667	29				

Table 7 Shows an ANOVA analysis that compares the average of two groups: the years of experience in the fraud detection field and the level of agreement on the statement about AI improving fraud detection accuracy over the years. The group with (11-15 Years) of experience, 2.31, exhibited higher averages than others, followed by (1-5 Years) with an average of 2, 1.73 for group 6-10 Years, and 1.5 for the group above 15 Years of experience. The ANOVA table shows that the F-statistic is 0.73 and the p-value is 0.55, higher than the significance level (0.05). No statistically significant relationship exists between working experience (the grouping variable) and responses showing agreement that AI improves fraud prevention (the dependent variable). In other words, the job experience of respondents does not significantly affect their agreement on AI-enhancing fraud detection accuracy.

5. CONCLUSION

This research has studied the impact of technology on forensic accounting and fraud detection from Omani companies' perspectives. Through regression analyses, the first hypotheses of this research have been accepted and concluded that ($H1_1$) technology positively influences forensic accounting efficiency and ($H2_1$) rejected, showing that organisational challenges do not mediate the relationship between technology adoption and forensic accounting efficiency. Undoubtedly, forensic accounting efficiency has a direct relationship between technology adoption and organisational challenges separately. However, organisational challenges do not correlate with technology adoption, which shows that other challenges may affect this adoption. These findings shed deeper insight into the significance of technology in forensic accounting, enhancing fraud detection techniques and increasing trust in financial systems, benefiting regulators, organisations, and stakeholders.

These are the suggested recommendations for the companies: Encourage businesses to augment investments in artificial intelligence and machine learning technology. As evidenced by the research findings, these techniques have considerable potential in enhancing the rapidity and accuracy of fraud detection systems. Also, auditors must receive continuous training in digital fraud detection techniques to guarantee they can utilise sophisticated tools and keep up with technological advancements. Additionally, as forensic accounting increasingly depends on digital technology, enhancing and integrating comprehensive cybersecurity measures is crucial for protecting sensitive data and maintaining confidence within financial reporting systems.

5.1. Limitations

One of the main limitations encountered in this study was the scarcity of relevant journal articles on this specialised topic, which requires looking for specific articles related to this topic. This research discusses the new technologies used and applied nowadays, which are still developing regularly, and researchers are trying to catch the advancements of these technologies. Hence, most of the articles found were recently published a few months ago, and choosing journal articles over the last five years would enhance the accuracy of the data gathered. Finally, the audience of this study has specific characteristics, such as obtaining a certified fraud examiner (CFE), certified forensic accountant (CrFA), or other certificates focused on fraud detection. Forensic accountants or auditors specialising in fraud detection investigations in Oman are not easily reachable or accessible.

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