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EMERGING FORENSIC ACCOUNTING TECHNOLOGIES FOR FRAUD DETECTION: A COMPREHENSIVE SCOPING REVIEW

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Abstract:

As the world becomes digital, financial fraud too is evolving and is a challenge for organisations today to detect and prevent frauds. The fraud schemes get more involved and rely on the latest technology, and traditional audit methods are no longer able to catch up. This scoping review follows the PRISMA-ScR guidelines and the Arksey and O'Malley (2005) framework to analyse how forensic accounting is evolving with the development of new technologies, using a combination of Web of Science and Scopus for literature collection, which results in 116 empirical studies between 2022 and 2024 (89 from Web of Science and 27 from Scopus). Five themes were identified from the analysis. The technology-based fraud detection using artificial intelligence and machine learning was the most notable which was seen in 67 studies (57.8%) with a range of accuracy between 93% and 98.58%. Although the role of technology is becoming increasingly important, there were still 18 studies (15.5%) that emphasized the importance of the auditor's role in supporting the technological tools. Governance and internal controls were found in 21 studies (18.1%) and professional skepticism in 12 studies (10.3%) were organizational and individual factors, respectively. Specifically, the highest accuracy was obtained by using Random Forest (98.58%), K-Nearest Neighbor (95.89%) and Convolutional Neural Networks (95.8%). The hybrid combinations of Multiple Benford's Law models and the K-Means clustering technique were found to be useful for the accuracy of the detection increased from 40% to 93.33%. In terms of geographical distribution, Asian markets are the most prolific and more than 68 studies (58.6%) were published in Asia of which more than 24 (24.1%) were published in China and 12.9% in Indonesia, suggesting the region's high rate of digitalization and dire need for fraud detection. African and Latin American research was very little (4.3% combined) and therefore there was a huge research gap. There were a couple of limitations identified: Most studies (94.8%) were of cross-sectional

designs which overlooked longitudinal perspectives and research into implementation challenges is still limited, as is research into the cost benefit analysis and the ethical implications of AI-based fraud detection. This review provides a comprehensive, up-to-date literature review and integrates the latest developments in forensic accounting technology, providing recommendations for organizations, policy makers and researchers.

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Artificial Intelligence; Data Analytics; Digital Forensics; Emerging Technologies; Forensic Accounting; Fraud Detection; Machine Learning; Scoping Review.



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Introduction

Financial fraud is one of the most imminent threats to the organizations these days. The statistics are stark: Organizations around the world are experiencing the loss of about 5% of annual revenue to fraud, or approximately \$4.7 trillion lost annually. In fact, PwC's Global Economic Crime and Fraud Survey 2022 (the Survey) identifies almost half of the organisations surveyed having suffered a form of fraud within the last two years and losses per incident are typically around \$42,000. These are not mere figures, but a threat to the sustainability of businesses and the economic stability.

Digital technology has turned the world of fraud on its head. Technological advancements such as electronic transactions and digital financial services, and automated business processes have provided a huge boost in efficiency but have also created new opportunities for fraudsters. Manual sampling, retrospective analysis and rule-based detection systems were just not suitable for a world with massive amounts of data, moving much faster than ever before. As Appelbaum and colleagues (2020) mention, these traditional approaches face the challenge of dealing with a large volume of transactions, are difficult to apply to identifying complex patterns, and don't necessarily capture novel fraud schemes altogether.

That's where forensic accounting comes in, but in that case, it has had to evolve as well. Most of the initial investigation work has become more positive, technology-based and proactive. Forensic accountants today don't simply follow paper trails, they are using artificial intelligence, machine learning, blockchain technology and advanced data analysis to keep the fraudsters in check. Nowadays, the profession comprises of digital forensics specialists, data science specialists, cybersecurity specialists, and specialists in applications of artificial

intelligence (Crumbley, Heitger, & Smith, 2019). It's taking a different approach from the standard accounting method.

To date, many other technological advances have been made, but there are many areas of understanding that are still missing. In what ways are organizations using the new technologies? What is it about them that make them work in some instances and not others? What are some of the obstacles to overcome in organizations for implementing them? We were stimulated to do this thorough review of the latest research by these questions. We analysed 116 empirical studies from the period 2022–24, considering five main research questions: What are the major themes in the research of forensic accounting technology? What are the technologies being used? What are some of the factors that can affect their effectiveness? But how effective are their performance, how well do they do their jobs? And what is not yet known?

Theoretical Background

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, which was developed by Venkatesh et al. in 2003, was used to gain an understanding of technology adoption in forensic accounting. This framework is based on findings from eight technology acceptance models, to explain why people would embrace (or not embrace) new technologies. Four factors are believed to be most important: (1) the users' belief that the technology will enhance their performance, (2) their ease of use of the technology, (3) the users' belief that important others will think highly of their use of the technology, and (4) the organizational support for the technology. These relationships can also be affected by gender, age, experience and voluntary use. Future research researched the effects of other factors such as motivation, perceived value and habit (Venkatesh, Thong, & Xu, 2012).

Materials and Method

The six-stage process outlined by Arksey and O'Malley (2005) with some changes recommended by Levac and colleagues (2010) and Peters and colleagues (2020) was used to conduct this scoping review. In order to meet current standards for the transparency and reproducibility of our review we also followed the PRISMA Extension for Scoping Reviews guidelines (Tricco et al., 2018).

Defining Our Research Questions

We began by agreeing with each other what we were seeking to know. After conducting various team discussions, initial literature scanning, and discussions with forensic accounting practitioners, we decided on the 5 primary questions that relate to forensic accounting technology research that were published from 2022-2024. The questions were intentionally designed to be quite general in scope to cover the entirety of research and sufficiently narrow in scope to be able to conduct a systematic search.

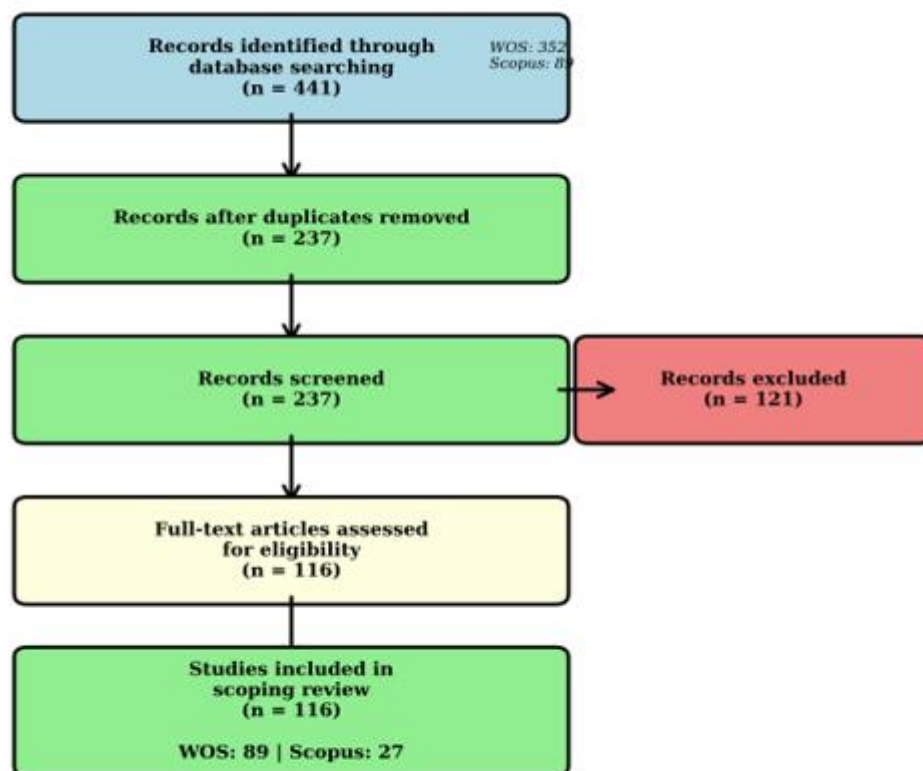
Finding Relevant Studies

Two academic databases, Web of Science and Scopus were searched. The databases selected were chosen due to their extensive coverage of peer-reviewed research from the various academic fields that are relevant to our research, such as accounting, information systems,

computer science and business management. The search terms included two sets of search terms: terms related to forensic accounting and fraud detection along with terms related to technology (AI, machine learning, data analytics, blockchain, etc.) and practitioner (accountants, auditors). These searches were conducted on 14th May 2024 and initially resulted in 441 potentially relevant studies being identified.

Selecting Studies for Review

441 studies were sent out but not all of them were included in the final review. We used the following inclusion criteria: The studies were empirical research published between 2022 and 2024 in English language peer-reviewed journals, with the focus on forensic accounting technology for fraud detection, and accounting professionals or auditing contexts. We did not include conference papers, dissertations, technical papers that did not have an accounting context, or papers focusing on studies of fraud perpetration, studies of fraud detection were included. Following the screening of titles and abstracts we were left with 237 studies. We reduced this to our last 116 articles after full-text review of these narrowed to 89 articles from Web of Science and 27 articles from Scopus. This selection activity is explained in a detailed manner in figure 1.



PRISMA 2020 Flow Diagram for Scoping Reviews

Figure 1: PRISMA Flow Diagram

Source: Author's own compilation, adapted from the PRISMA-ScR reporting guidelines (Tricco et al., 2018).

Extracting and Organizing Data

A standardized questionnaire was prepared to extract the common data from every study, including basic bibliographic data, methodological features, technologies investigated, key variables and outcomes, geographical location of the study and the main theme. This information was independently extracted by two reviewers who agreed on 96.3% of the information. If we did not agree with each other, we discussed the study till we reached some consensus. The systematic approach helped us to avoid missing key pieces of information from the studies and to avoid bias in our interpretation of the studies.

Analyzing and Synthesizing Findings

We used a thematic synthesis method in our analysis which included aspects of the grounded theory and meta-ethnography (Thomas & Harden, 2008). We discussed the results of each of the study lines, coding and identifying concepts and patterns. These codes were then clustered into descriptive themes and then, higher themes of analysis were drawn from across the descriptive themes. This was an iterative process of continually making comparisons across articles and then elaborating our understanding of what the research was telling us; it continued on until we felt we had the whole picture.

Findings

What We Found Overall

In 116 more recent studies (from 1986 to 2013) research interest has been growing in this area. Looking at when these studies were published, we see 28 in 2022 (24.1%), 51 in 2023 (44.0%), and 37 in 2024 (31.9%). This increase is quite alarming especially for 2023, with more than 80% of the research over the last two years. In terms of methodology, the majority of the studies (98, 84.5%) applied quantitative methods, and the rest applied a combination of methods (mixed methods). Interestingly, all the qualitative studies that met criteria were also mixed method studies, indicating that researchers in this field are more inclined to measure outcomes of effectiveness of technology than focus solely on qualitative outcomes. Most of the studies used surveys (55.2%), followed by the analysis of actual fraud cases (29.3%).

Where This Research Is Happening

Research was conducted in different regions of the country, and some interesting trends were noted. The majority of the countries were Asian with 68 studies or 58.6% of all studies. China led the way with 28 studies (24.1%), followed by Indonesia with 15 (12.9%) and India with 12 (10.3%). This Asian focus is probably due to a number of reasons: rapid digitalization in these areas, both opportunities and threats for fraud; a significant amount of investment in research infrastructure; and a focus on financial technology innovation by governments in these countries, especially since several high-profile fraud cases in these countries occurred recently. In other regions of the world, there were 17 studies conducted in North America (14.7%) mostly from the USA, 14 studies from Europe (12.1%) from the UK, Germany and Sweden and 12 studies from the Middle East (10.3%) from Iran, Egypt and Jordan). The actual divide seems to be between Africa and Latin America, with only 5 African studies (4.3%) with virtually no research in Latin America. This is especially troublesome because these areas already have

great fraud problems but may not be as well-equipped with technology and research to combat fraud.

Geographical Distribution of Studies (N = 116)

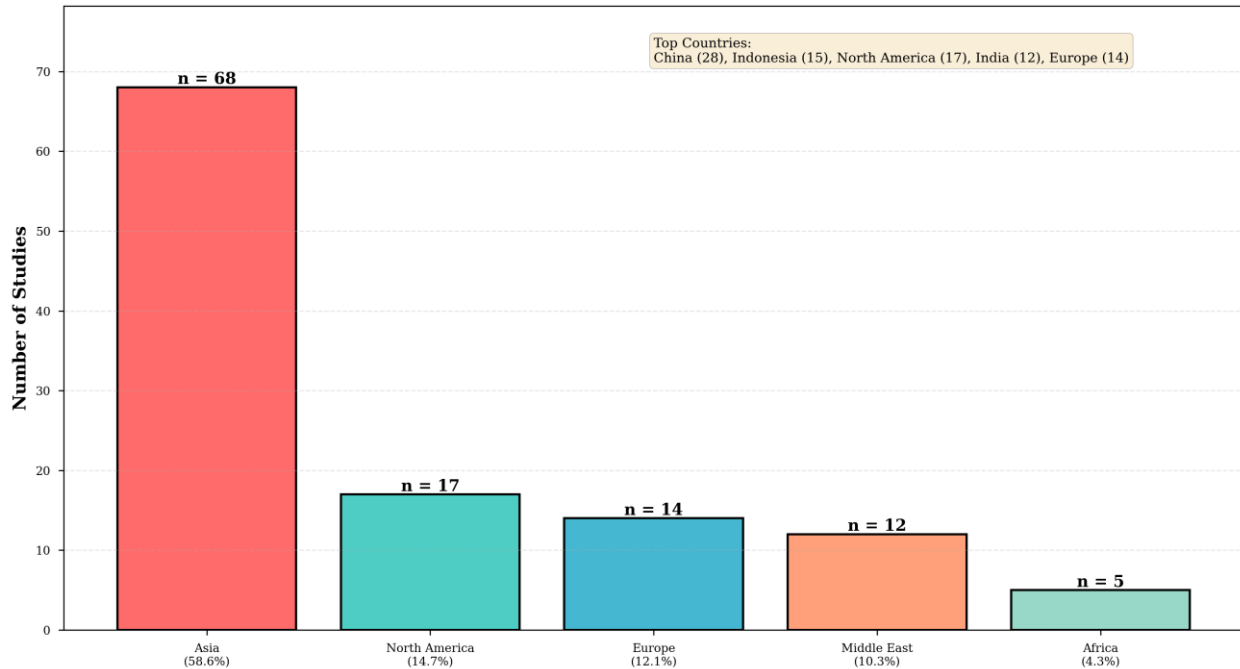


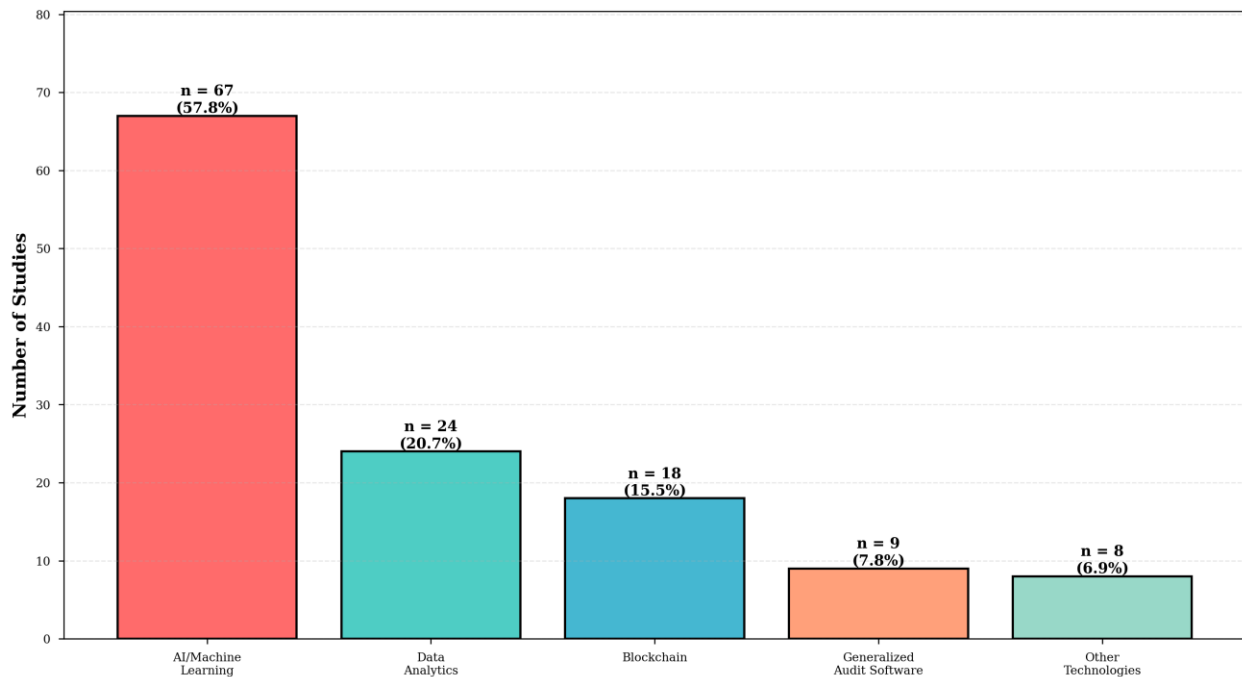
Figure 2: Where Studies Were Conducted

Source: Author's own analysis of the reviewed studies, showing a strong concentration in Asian markets.

What Technologies Are Being Used

Artificial intelligence and machine learning are definitively the stars of the study, and were included in 67 studies, or almost 58% of our review. In this category, there was a variety of strategies implemented. Logistic Regression was featured in 34 studies (29.3%) while Random Forest was used in 28 studies (24.1%) and gradient boosting techniques such as XGBoost and AdaBoost were used in 26 studies (22.4%). A more complex architecture of deep learning is also being investigated, namely Convolutional Neural Networks, that were mentioned in 15.5% of 18 studies, and Recurrent Neural Networks, in 10.3% of 12 studies. Special techniques for dealing with imbalanced data are gaining popularity as it is often a problem when dealing with fraudulent transactions, which are usually rare events in any data set.

In 24 studies (20.7%), the problem of data analytics, in general, was mentioned, not just AI and machine learning. This involved traditional statistics techniques such as analysis of Benford's Law in 8 studies (6.9%), and a number of data mining techniques. A particularly interesting result: By applying the Benford's Law several times to various subsets of data, instead of once on the entire data set, the accuracy was increased from 40% to 93.33%. 18 studies (15.5%) included blockchain technology, 9 (7.8%) included Generalized Audit Software and the rest of the studies used various other tools.

Distribution of Technology Types in Forensic Accounting Research (N = 116)**Figure 3: Technology Types Being Studied**

Source: Author's own analysis, illustrating the dominance of AI/machine learning approaches in current research.

Key Themes We Identified

In our thematic analysis five themes emerged that reflect the areas of focus that researchers are engaged in in this field.

The most obvious theme is technology-based fraud detection that was found in 67 studies (57.8%). These studies focused on the capabilities of AI and machine learning in pattern recognition, on a scale that is impractical for any human to manage; automated real-time detection systems; advanced predictive tools that can identify suspicious behaviour before it becomes a problem; and cutting-edge data processing methods for the structured and unstructured data that come with it. The accuracy figures obtained have been impressive - from 93% to 98.58% in comparison with the traditional methods.

Auditor capabilities and skills was the second theme that appeared in 18 studies (15.5%). The focus of this study was that technology will not take the place of human expertise, instead it will augment it. The studies examined the abilities required to be an auditor are technical/analytical skills to work with the tools, communication skills and interpersonal skills to act on findings, accounting and auditing specific skills to interpret the results, and forensic specific skills. The bottom line: Advanced technology isn't going to help people if they aren't properly trained to use it.

Our third theme was organizational factors with 21 studies (18.1%). This research focused on the impact of the context of the organization on the effectiveness of technology: the quality of internal controls, management support, strength of corporate governance, and organizational

commitment to fraud prevention. Appropriate controls and effective governance structures provide an environment where tools that help prevent fraud can flourish.

Individual factors were our fourth theme with 12 studies (10.3%). In this, the researchers considered personal traits that are important: professional skepticism, emotional intelligence, professional commitment and ethical orientation. The individual characteristics influence the use of the fraud detection tools and the interpretation of the output from the tools.

Lastly all but one of our studies addressed our final theme of detection effectiveness and performance measures. This is logical - after all, people want to know if it's real. It would seem that the answer is yes, but with the proviso. Random Forest (98.58%) can perform the best, followed by KNN (95.89%), CNN (95.8%) and innovative combination of multiple Benford's Law and K-Means clustering (93.33%). The effectiveness is critically reliant on the quality of the data, feature engineering, algorithm parameters and human judgment integration, however.

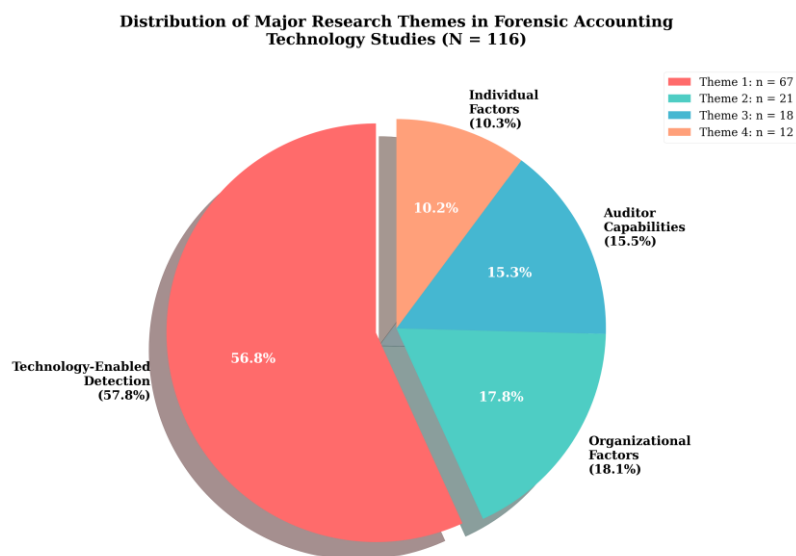


Figure 4: Major Research Themes

Source: Author's own analysis, showing technology-enabled detection as the dominant research focus.

Discussion

There are some important lessons to be learned from this collection of 116 studies.

The prevalence of the use of AI and machine learning (57.8% of studies) is a true paradigm shift in the area of forensic accounting. In an effort to prevent fraud before it happens, the field is shifting from a reactive investigation once fraud occurs to a proactive approach. Ensemble methods such as Random Forest (98.58%) and deep learning architectures, such as CNNs (95.8%), deliver superior performance and are not mere fads: they are indeed superior to the traditional statistical methods we see in the rest of the machine learning literature.

Secondly, the geographic focus in Asian markets (58.6%) provides us with an important clue as to why and where fraud detection innovation is occurring. These are areas experiencing a fast digital revolution, and governments are keen to invest in the research and development of financial technology and fraud prevention. There was a lack of African and Latin American

research (4.3% combined) and this is an opportunity as well as a gap because these areas have high levels of fraud but lack research which is specific to the local area to enable solutions to be developed.

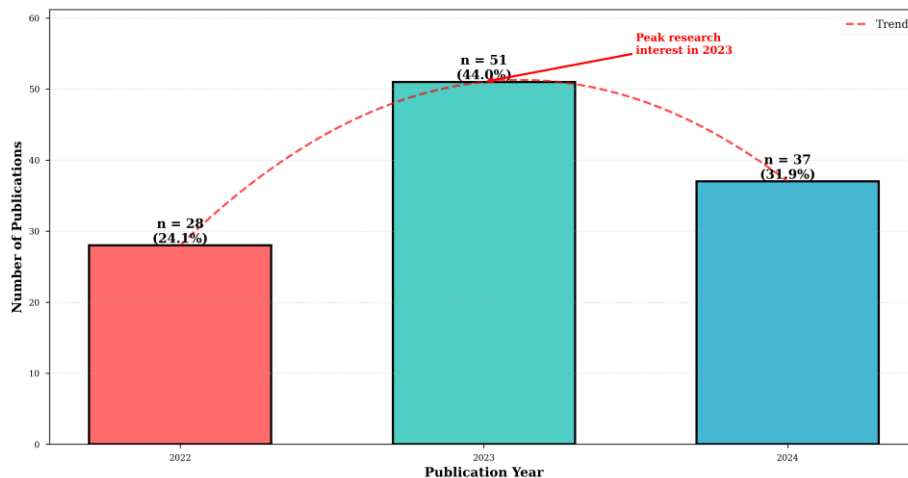
Third, although technology is clearly significant, the studies on the capabilities of auditors serve as a reminder that technology operates in a context. In the case of GAS, for example, it had a moderating influence on the relationship between auditor self-efficacy and detection effectiveness. That is, it is a technology that enhances human capacity, not that it displaces it. This is in line with the socio-technical systems thinking: Good technology combined with skilled people is the best way to detect fraud.

Lastly, the gaps in research that we identified are large. There are 94.8% of cross-sectional studies, snapshots, not movies – we don't really know how these technologies will perform over time, how their adoption will progress or what will happen after they are first implemented. Few studies have also addressed issues of the actual implementation challenges, costs and benefits, and ethical issues such as algorithmic bias and privacy issues. These are important lines of future enquiry.

Limitations and Future Directions

As with all reviews, there are things that our review could not capture. Only by limiting the search to Web of Science and Scopus was it possible to avoid the inclusion of some studies in less well-known databases. We didn't have a language barrier that prevented us from accessing other languages, but the requirement for English-language studies did mean that important research in other languages might have been missed, especially in other world areas where much research may be going on. A possible explanation for this is the publication bias – the fact that positive results are published more easily than negative results.

A number of research directions appear to be very relevant to the future. Longitudinal studies of the technology adoption and performance over time are needed. The barriers to successful implementation, changing organizational structures and processes, and practical challenges need to be explored in implementation research. Economic analyses should take a broad look at costs vs benefits. The study of multi-technology integration may experiment with different ways in which technologies can be integrated with each other so that their effectiveness is improved. Ethical implications of algorithmic bias, privacy issues, transparency and accountability measures for automated fraud detection should be a subject of impact studies.

Publication Timeline and Trends in Forensic Accounting
Technology Research (2022-2024)**Figure 5: Research Over Time**

Source: Author's own analysis of publication trends, showing accelerating interest with peak activity in 2023.

Conclusion

The results of this scoping review have surveyed the current research landscape related to forensic accounting technology published over the last five years (2022 – 2024) and analyzed 116 empirical studies. The result is a visualisation of a field that is undergoing a fast pace of change, largely due to developments in AI and machine learning.

The study shows that AI/ML techniques, especially ensemble methods and deep learning architectures, can attain a significant accuracy of 93% to 98.58%. These are not only incremental gains, but also big improvements on what has been done traditionally with detection. But technology is by no means the solution. The research on auditors' capabilities and organizational factors serves as a reminder that robust fraud detection capabilities take the right mix of powerful tools, intelligent people, effective governance structures and cultures.

The geographic focus in Asian markets is revealing the market where digital transformation and fraud detection innovation is most prevalent. But there is a huge lack of research in Africa and Latin America, especially since these parts of the world have been facing fraud issues and do not have as much technological resources as other parts of the world.

Most importantly, this review has identified gaps in knowledge that need to be addressed in the future to improve knowledge of the subject. As AI-powered fraud detection becomes increasingly common, there is a need for more long-term effectiveness data and implementation research to help inform the practical adoption of these technologies, cost-benefit analyses to help guide investment decisions, and more reflection on the ethical implications.

The take-home message for practitioners is that a hybrid strategy of advanced technologies and skilled practitioner is the most viable option. There is a need to invest in technological capabilities as well as in human expertise development in the organizations. The policymakers need to set ethical rules on how to use AI to fight fraud and encourage data quality. For researchers, there is a lot to be desired in terms of implementing, integrating, ethical issues,

and the long-term impact, which will influence the direction that forensic accounting will take in the upcoming future.

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Ethics Statement: The study is not one that would involve a human participant, animal or sensitive data that would require ethical approval but a scoping review of literature that has been published and available to the public. The authors have ensured that the research has been done with proper academic integrity and ethical standards of publication.

Author Contribution Statement: Ros Azilatul Nadiah Binti Md Isa conceptualized, designed the method, did literature search and screening, extracted data and analyzed it, and wrote the manuscript. Mohd Danial Afiq Bin Khamar Tazilah gave supervision, critically reviewed the manuscript and helped to improve methodology and interpretation of the findings. The authors have read and accepted the final manuscript.

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