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FORENSIC AUDITING SERVICES IN THE FIFTH INDUSTRIAL REVOLUTION: THE MEDIATED ROLE OF ARTIFICIAL INTELLIGENCE

Jean Damascene Mvunabandi[1]*, Celumusa Makepeace Chonco[2], Ferina Marimuthu[3]

[1]Durban University of Technology, Faculty of Accounting and Informatics, Department of Financial Accounting, Durban 4000 South Africa,JeanM2@dut.ac.za, https://orcid.org/0000-0002-3356-9493
[2]Durban University of Technology, Faculty of Accounting and Informatics, Department of Financial Accounting, Durban 4000 South Africa, Celumuc@dut.ac.za
[3]Durban University of Technology, Faculty of Accounting and Informatics, Department of Financial Accounting, Durban 4000 South Africa, ferinas@dut.ac.za

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Corresponding Author: Jean Damascene Mvunabandi (JeanM2@dut.ac.za)

ABSTRACT

Contemporary global crises and the rapid technological advancements have exacerbated the levels of uncertainties in financial systems, compelling forensic practitioners to re-analyse the necessity of paradigm shift in forensic auditing practices to adapt to the disruptive realities of the Fifth Industrial Revolution (5IR). Even though artificial intelligence (AI) has revolutionised fraud detection and data analysis, significant gaps remain in understanding its ethical, operational, and regulatory implications. This study adopts a scoping review methodology to systematically map peer-reviewed literature (2018–2024) on AI's merits (e.g., efficiency, fraud detection) and challenges (e.g., data bias, ethical concerns) in forensic auditing. The study's findings underscore the crucial role of adaptability in contemporary forensic auditing practices providing valuable key insights for forensic practitioners and entities confronting disruptors technologically. The study further reveals that AI-based forensic auditing can potentially assist the accuracy, efficiency in forensic investigations, identifying patterns and fraud risks in financial data, quicker detection of fraudulent activities and mitigating fraud risks. However, AI-based forensic auditing poses major challenges such as the quality and quantity of financial data that AI systems entirely depend on, the dire need of human expertise to validate the forensic output or evidence of AI generated systems. Another potential challenge revealed is inadequate and incomplete data which subsequently lead to invalid conclusions. Furthermore, the issue of privacy and ethical concerns, bias and accountability arise when AI-based forensic auditing systems are used to identify and detect fraudulent activities. This study proposed a remote forensic auditing framework-based conceptualised model in a disruptive environment. Policymakers are urged to develop robust legal frameworks to address ethical and regulatory gaps in AI-driven forensic auditing.

KEYWORDS: AI-based forensic auditing, Artificial Intelligence (AI) and 5IR.
JEL Classification: M4, M41, M42.

1. INTRODUCTION

1.1. Problematisation and Research Gap

Scholars such as Mehta, Mittal, Gupta, and Tandon (2022) and Mike and Olochukwu (2022) argue that artificial intelligence (AI) technologies are both gaining great attention and reshaping how many aspects and processes that were previously handled by hand are performed including auditing field. Given the speed with which digitalisation has spread across the world, coupled with anticipated changes occasioned by current and future technologies such as robotics and blockchain, Sharma and Biswas (2021) argue that the traditional forensic auditing system become less efficient and effective in dealing with big data and is not technologically ready to effectively prevent, detect and respond to the risks of fraud promptly. Sharma and Biswas (2021) highlight that due to exponential growth of data, AI-based technologies can significantly enhance accuracy and efficiency of forensic auditing procedures, necessitating a rethinking of forensic auditing procedures through automating forensic audit tasks. However, Mike and Olochukwu (2022) soundly criticise that AI-based forensic auditing poses challenges, limitations and opportunities.

The concept of AI was initially discussed by Greenman (2017) who described AI as the simulation of human intelligent or thoughts (intelligent automation) in machines through complex programming that mimics human thoughts and learning processes or intelligent computer programming. Helm et al. (2020) state that “software programmers simulate the functioning of the human brain, thereby creating the ability for the programme to imitate logical decision making”. Chowdhary and Chowdhary (2020) introduced the definition of AI as the innovative technique whereby machines are given capacity and ability to perform tasks such as reasoning and problem-solving, perception and learning that human being would normally perform.

The fourth industrial revolution (4IR) raised a question of human- centered design of factories and used technology to convert the workforce into new skills (Naqvi, 2020). Generically speaking, the 4IR shows the transformation of manufacturing agents from physical systems to cyber-physical systems, while the fifth industrial revolution (5IR) introduces robust modifications to previous stage of technological development in relation to the interaction between humans and artificial intelligence (human-machine or cobot/ human-robots coworking era) (Bose, Dey, & Bhattacharjee, 2023). The 5IR was first introduced in Japan in 2015, and where integration of humans and technology is used to solve the problems faced by Japan (Zengin, Naktiyok, Kaygın, Kavak, & Topçuoğlu, 2021). Zengin et al. (2021), state that in super smart society (SSS), the industrial revolution 5.0 is the super-intelligent society, and it also places mankind in the middle of cyberspace and physical space.

Hayek, Noordin, and Hussainey (2022) note that new fraud schemes emerged and fraud perpetrators and trust violators have become increasingly sophisticated due to the advancement in information and technology. Cybercrime such as crypto-jacking, fake investments schemes, money laundering, cryptocurrency fraud, attacking automated weakness systems, Internet of things competitivity systems and AI abuse require great attention and crucial role of forensic auditors in investigating and preventing such crimes in digital world. However, a robust debate among academics and forensic practitioners on the use of AI in forensic auditing intelligence is currently occurring (Ariga et al., 2020; Papadakis, Garefalakis, Lemonakis, Chimonaki, & Zopounidis, 2020; Sekar, 2022; y Mpofu, 2023). For instance, forensic practitioners believe that they need people to catch people and they no need robots to catch robots or robots to catch people. As pinpointed by Mehta, Kaushik, and Bhargav (2021), financial and economic criminals always profit the vulnerability in 4IR and 5IR as it is still in its infancy. Whether the AI in the 5IR directly or indirectly impact the services of forensic auditors is highly debated. The impact of the 5IR on digital forensic auditing services remains an elusive practitioner and an empirical question. This question for investigating the demerits and merits of the use of AI on the services of forensic auditors motivates the current study and builds on gaps in the literature and it holds the centre stage in the scientific inquiry. The aim of this study is to systematically examine the literature by reviewing peer reviewed and published studies on the merits and demerits of 5IR and forensic auditing services, mainly between 2019-2023 in order to convey the latest developments on the applicability of AI in forensic auditing field.

To predict misapplication, manipulation and misrepresentation in the financial statements, Mehta et al. (2022) proposed the use of digital forensic auditing tools and techniques as well as the use of AI as a revolutionary force which could potentially improve the efficacy and efficiency of forensic audits and significantly minimise the timeframe of work performed on detecting any anomaly in the financial statements. It is against this background that this study is conducted focusing on the 5IR and its impact to uncover key insights into the benefits and challenges of the use of AI on forensic auditing services. It addresses precisely the following two interrelated fundamental research objectives on the new challenges and opportunities brought by the 4IR and 5IR on forensic auditing with the aim of proposing a conceptual framework of using the AI in forensic auditing: (1) to critically assess the demerits of using the AI in forensic auditing, (2) to critically assess the merits of using the AI in forensic auditing.

This article added to the existing body of knowledge in the field of forensic auditing under three themes, namely its theoretical contribution in terms of emergent theory, methodological contribution relating to the scoping review framework followed by PRISMA, and practical contribution in terms of recommendations relevant to forensic practitioners, policymakers and academicians, standard setters and professional bodies. It thus adds to the current understanding of demerits and merits of using the AI in forensic auditing.

1.2. Underpinning Theoretical Framework

A multi-theoretical approach integrating multiple theories to analyse the transformative role of AI in forensic auditing was adopted as the underpinning theoretical framework. This approach addresses both technological disruption and human organisational dynamics through a comprehensive understanding of AI's opportunities, challenges, and adoption barriers within the context of the 5IR. The following theories are employed in the study.

1.3. The Disruptive Technology Theory (Dtt)

Propounded by Bower and Christensen (1995) and updated by Denning (2016), this theory anchors the study's exploration of AI as a disruptive force in forensic auditing. It explains how AI technologies initially emerge as niche innovations but eventually surpass traditional auditing methods in efficiency, accuracy, and scalability. For instance, AI's ability to process vast datasets and detect fraud patterns aligns with the theory's emphasis on technologies that redefine industry standards. As an underpinning theory, it explains systemic shifts caused by AI, such as replacing reactive forensic practices with proactive, data-driven approaches. Moreover, it highlights the destabilisation of traditional auditing systems and the need for adaptive strategies to harness the potential of AI.

1.4. Technology Acceptance Model (TAM)

The TAM is a widely used theoretical framework in the field of information and technology adoption, healthcare, education and e-commerce and according to Sagnier et al. (2020), it has been propounded by Davis (1989) who note that the TAM seeks to explain and predict the factors influencing individuals and corporate's acceptance to new technologies. Al-Adwan et al. (2023) concur adding that the TAM suggests that perceived usefulness and perceived ease to use are the key fundamental factors of the user's genuine intention to adopt a particular new technology which turn affects people actual usage. Na et al. (2022) validated the effectiveness of TAM in predicting and enhancement of performance and productivity. In the same vein, Aburbeian et al. (2022), state that TAM aids in the prediction of technology acceptance based on the constructs of perceived usefulness; perceived ease of use; attitudes; and behavioural intention. Technology Acceptance Model is thus considered relevant and appropriate for this research study because the theory both regulators and forensic auditors with regards to the adoption of remote forensic auditing.

1.5. Unified Theory of Acceptance and Use of Technology (UTAUT)

Despite the widespread use of TAM, Malatji et al. (2020), note that, this model has been soundly criticised for its focus on individuals' beliefs, attitudes and some instances overlooking social and contextual factors influencing technology adoption. Scholars continue to expand the model to address these limitations. For instance, in their research, Venkatesh and Davis (2000), the authors extended the TAM by incorporating cognitive instrumental process, social influence resulting in the UTAUT. Donmez-Turan (2020) holds a view that the social and organisational fundamental factors that can potentially impact technology acceptance beyond individual perceptions.

Venkatesh & Bala (2008) propounded the TAM3 model by incorporating the impact of external variables to provide a more robust and comprehensive understanding of technology acceptance. The unified theory of acceptance and use of technology and its extensions like UTAUT2 are also fast becoming leading theories to studies that focus on value, acceptance and use of digital technology products, services and platforms in several fields (Chatterjee et al., 2021, Arain et al., 2019). Venkatesh et al. (2003) in their empirical tests identified performance expectancy, effort expectancy and social influence as the three direct factors of behavioural intention in technology use. Venkatesh et al. (2003) found facilitating conditions and contingencies such as gender, age, experience and voluntariness would also alter the effect of the factors on the behaviour or intention. UTAUT is thus considered relevant and appropriate for this research study because the theory is crucial for both regulators and forensic practitioners with regards to the adoption of AI in revolutionalising forensic auditing services.

1.5. Artificial Intelligence Device Usage Acceptance Model (AIDUA)

AIDUA was developed by Ma and Huo (2023) as model tailored to tackle AI-specific ethical and operational challenges such as trust, ethical concerns, and human-AI collaboration. This model bridges gaps left by TAM/UTAUT by addressing issues like algorithmic bias, data privacy, and the need for human oversight. Hence, the model role in this study was to evaluate ethical dilemmas and the human expertise required to validate AI outputs. In addition, the model guides recommendations for balancing automation with human judgment in forensic investigations.

1.6. Adaptive Resonance Theory (ART)

Grossberg, S. (2013) aimed to explain how the brain can learn and recognize patterns in a stable and adaptive manner. Khan et al. (2021) elucidates how AI systems learn and adapt to evolving fraud patterns. Hence, the ART supports the study's findings on AI's ability to continuously refine fraud detection models through machine learning, ensuring relevance in dynamic environments. The ART strengthens the argument for AI's adaptive capabilities, such as identifying emerging fraud schemes (Table 2) and also aligns with the need for forensic auditors to stay ahead of sophisticated cybercrimes in the 5IR era.

Whilst the DTT is foundational for framing AI's transformative role in traditional forensic auditing practices, aligning with the study's focus on the 5IR and technological shifts, incorporating the multi-theoretical approach with TAM, UTAUT, AIDUA and ART, strengthens the analysis by addressing multifaceted aspects of AI adoption and creates a holistic framework.

2. LITERATURE REVIEW

2.1. Artificial Intelligence and Forensic Auditing

Kagombora and Mbogo (2024) argue that forensic auditing has always been criticized to be in a reactive and not a proactive, scandal after scandal, and corporate failure after corporate failure which proved that forensic auditing has been functioning as a follower not as a leader. The author recommends that forensic auditors should stay ahead of emerging fraud risks by using AI-based forensic auditing.

Dandotiya, Khatri, and Dandotiya (2020) define digital forensic as a digital forensic science branch that emphasises on the recovery and investigation of artifacts delivered from digital devices. The findings of Vitali and Giuliani (2024) indicate the extent to which the use of new software and artificial intelligence platforms potentially enhance the efficacy and efficiency of entities and accounting and auditing firms' audits and investigations to protecting, preventing, detecting, and investigating financial and economic crimes when internal audits and controls fail or are circumvented by trust violators.

Scholars such as Zhou (2017) and Zemankova (2019), have reported that accounting and auditing firms (big four) such as Deloitte, KPMG and PwC are intelligently automating their business operations through incorporation of AI. Both Kokina and Davenport (2017) and Vitali and Giuliani (2024), further argue that the AI has emerged as a powerful tool to dissecting financial data over many years to identify spending patterns and high-risk transactions of a forensic auditor to perform a high level of review. Mehta et al. (2022), concur with Mehta (2021), adding that the use of AI is the best alternative to allow forensic experts to analyse billions of transactions over multiple financial years within a significantly reduced timeframe. The issue of anonymity has also exacerbated the privacy issue as it evidenced in the case of Microsoft rejecting a warrant from United states of America for disclosing its customers emails and data in cloud.

The AI has been defined by Fan, Fang, Wu, Guo, and Dai (2020) as "the capability and ability of computer systems to performs tasks that require biological or human intelligence with different key functions" Fan et al. (2020) further outlined the following sub-fields namely: (1) natural language processing (NLP)-where the main goal is to develop a hardware and software that is able to understand human speech, speaking, reading text, writing text, spell check, text analytics and SMART search among others (2) expert systems and in forensic auditing is continuous process auditing system (CPAS), Chan, Kim, and Auditor (2020) concur with Fan et al. (2020) adding that the CPAS was created as internal audit for internal investigation to deal with the issues of auditing large paperless database systems (3) machine learning (ML) where machines are being trained to learn the same the way that humans learn,

(4) artificial neural network- which is a computational system for processing information as a response to external stimuli and it is also consists of a set of highly interconnected processing elements called " neuros" that emulates specific performance characteristics of biological neural networks , and (5) deep learning which is part of the AI. Nawaiseh, Abbod, and Itagaki (2020) further alluded that in order to prevent, protect and respond to frauds, entities have turned to forensic auditing and the utilisation of AI as a part of their internal fraud risk management strategy. The progression of artificial intelligence through several stages is presented to in Figure 1 below.

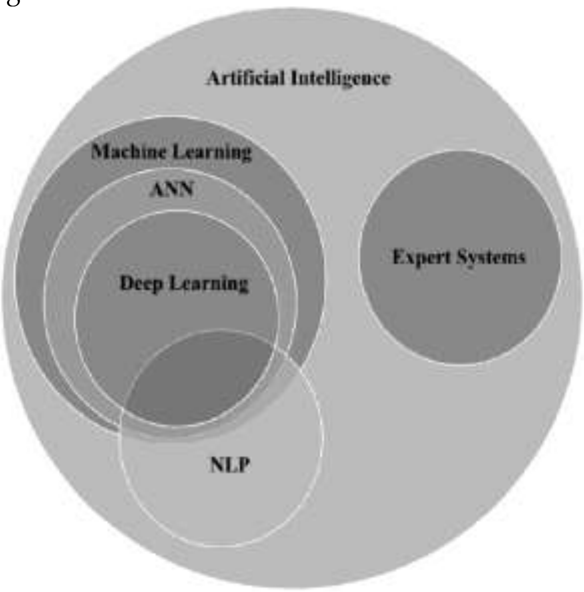

Figure 1:Categories of Artificial Intelligence. Source: Gurjar and Patel(2021).

2.2. A Brief Overview About Industrial Revolutions

Digital revolution started in the third industrial revolution with the development of a computer and the developments became rapid in the 4IR with AI, robotics, machine learning and internet of things taking the lead amongst other developments (Exceed, 2022). Chambers (2017) reiterates that the 4IR definition is the fusing of digital, biological and physical worlds that have impact on all disciplines, industries and economies. The 4IR is not just inspiring digital disruption and innovations but a paradigm shift in human experiences, socioeconomic norms, government and business and these seismic transformations is rewriting the unspoken contract between the business world and its stakeholders (Chambers, 2017).

Mollel et al. (2021) outline that the 4IR is encompassed with common words such as blockchain, big data, internet of things and machine learning amongst others and accountancy professionals can no-longer take a back seat since they are now forced to adopt, adapt and embrace technologies for them to remain relevant in the ever-evolving digital world. Bishop (2022) states that from the beginning of 2020 more than half of accountants in South Africa were moving away from traditional accounting service models and reinventing new core technologies and skill set to offer their customers an end-to-end consulting service. While it is difficult to predict how technology will shape the future, a careful examination of the preceding 4IR reveals that forensic auditing services should be the focal point of 5IR, not only because of its altruistic importance, but also because of its technological and economic feasibility (Raheman, 2022). Recent technological advancements indicate that the next industrial revolution is imminent, as several researchers have predicted. The 5IR also known as Industry 5.0. will focus on regaining the human hand and mind integrated into the industrial paradigm. The earliest definition of 5IR was introduced on 1 December 2015 with a main focus on industrial Economic, Social and Governance (ESG), and waste-prevention. Further, 5IR has three key pillars: human-centric, resilient and sustainable (Kraaijenbrink, 2019). The 5IR is the revolution in which humans and machines reunite and discover new ways to work together (George & George, 2020). A brief overview about industrial revolutions is diagrammatically presented in the Figure 2 below.

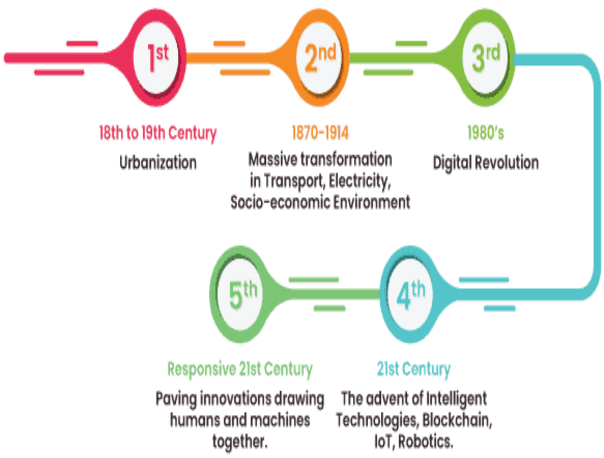

Figure 2:The progression of industrial revolutions (1.0-5.0) Source: Joseph (2020).

2.3. Pillars of IR 4.0 and 5.0

The 5IR places more emphasis on human intelligence than ever before. It eliminates dull and tedious work, but at the same time promotes curiosity, empathy, creativity and judgment, ensuring a balance between people and technology. The 5IR offers an opportunity to bridge historic divides and usher in a new socio-economic era (George & George, 2020). New employees no longer need to read piles of papers or attend meetings to get up-to-date and accurate information which implies that organizations and employers can easily recruit new employees without having to invest heavily in education and training. This technology helps organizations make the most of available resources, freeing up management teams to focus on more strategic tasks (George & George, 2020). According to current developments, this world stands on the edge of 5IR, where human creativity and craftsmanship coexist with cyber-physical systems. The pillars of IR 4.0 and 5.0 is schematically presented in the Figure 3 below.

Figure 3: Main Pillars of IR 4.0 and 5.0
Source: Pereira, Lima, and Santos (2020)

2.4. Artificial Intelligence, Automation and the Likely Effects on the Demand for Accountants in Future.

As helpful as AI will be, a lot of professionals have the aversion of using AI because they are fearing that they are going to make them obsolete, however humans are going to continue to have certain advantages over AI (Stahl et al., 2023). The best way to remain in demand faced with AI and automation is by being prepared (Jinwei Zhang, 2022). Accountants' self-education and continuing education as well as being early adopters to new technologies can make accountants irreplaceable in current or future positions. Muñoz-Izquierdo, Segovia-Vargas, and Pascual-Ezama (2019) indicate that the ability of accountants to evolve their technological skills in digital age is the pivotal competency to secure their career, remain relevant in the profession and competitive. Faced with ever changing manner of doing business, the professional competence of an auditor in digital era needs to be advanced to meet the new challenges. Adiloglu and Gungor (2019) mention that in the modern golden age of digitalisation data, data audit, data review is now the important challenge to the auditing and accounting profession. Oladejo and Jack (2020) view that digital quotient represents the competence that accountants and finance professionals must develop for them to remain relevant. AI is replacing manual tasks and eradicating the burden of repetition and jobs performed by average bookkeeper are going to be replaced or changed (Murphy, 2022). The approval processes, transaction entries, tax services or auditing will be performed through the bookkeeping AI software.

Oladejo and Jack (2020) further established that most if not all audit firms in Turkey provide service of tax audits and independent audits, but not all the firms are investing the necessary human resources and infrastructure for digitalisation that is defining new landscape for the audit profession.

Oladejo and Jack (2020) indicated the exciting developments that improves accuracy and efficiency of the technologies in doing work but also the anxiety regarding job security. The technological advances are replacing the type of human input required in different trades and professions and the risk of some jobs becoming redundant (Exceed, 2022). There are speculations in the discipline of accounting including auditing regarding the viability of bookkeeping, accounting and tax jobs within the next ten years as the role of human is evolving due to technology (Oladejo & Jack, 2020). Oladejo and Jack (2020) summarised that the effect that artificial intelligence has on the auditing profession is that, machine learning is to be used to record business transactions, analyse unstructured data, optimise audit time and require human judgement to analyse deeper set of documents and data. The technologies are certainly going to replace numerous repetitive accounting tasks but whether robots are going to take over jobs is dependent on the profession's preparedness to evolve and adapt to the technologies (Mollel et al., 2021). In line with these developments the clients for auditors are exploring and implementing some digital innovations which drives the efficiency of business operations, locate new markets, customer centricity and improve productivity (Ofoje & Aggreh, 2023).

Accountants with unique combination of digital skills, business acumen, data analytics and accounting principles will continue to have a bright future in the profession (Oladejo & Jack, 2020). Stahl et al. (2023) believe that human touch of accountants is one of the things that accounting professional need to have to stand out against digital technologies and no matter how the AI will perform the professionals capable of reasoning logically will continue to be in demand.

2.5. The Application of Learning Machine in Accounting and Auditing

As alluded by Dyball and Seethamraju (2021) the big four such as E&Y, PwC, Deloitte and KPM have only taken giant steps to follow the latest innovations but also made massive investments in technological innovations by incorporating the artificial intelligence and machine learning techniques into their forensic audit process. The table below provides snapshot of the AI and learning platforms and tools developed by big four accounting and auditing firms:

Table 1:AI and learning platforms and tools developed by big four accounting and auditing firms.

Tax &Legal	KMP	Deloitte	PwC	EY
Audit	Clara	Sonar	GL.ai	Canvas
		Argus	Cash.ai	Helix
		Optix	Halo	Blockchain analyser
		Signal		
		Cortex		
		Reveal		
		Omnia DNAV		
		GRAPA		
Consulting		HR Agent Edgy		
Risk advisory		DocQminer		
Financial Advisory		Eagle Eye		
		BrainSpace		

Source:http://www.internationalaccountingbulletin.com/events-archive.

Other scholars such as Richard III, Roussev, and Marziale (2007) and Chukwuma, Okolie, and Eneh (2022) argue that automated forensic auditing tools such computer aided audit tools, forensic audit tools, Encase, digital forensic framework, the workgroup and enterprise version, standalone version and digital investigation manager (DIM) can all potentially provide forensic investigative platforms to proactively search, scrutinise and analyse digital information. These scholars further state that these automated forensic audit tools are ideal for revealing accounting fraud, solving cyber-crimes and retrieving deleted files and data.

2.6. The Forensic auditing processes in digital environment.

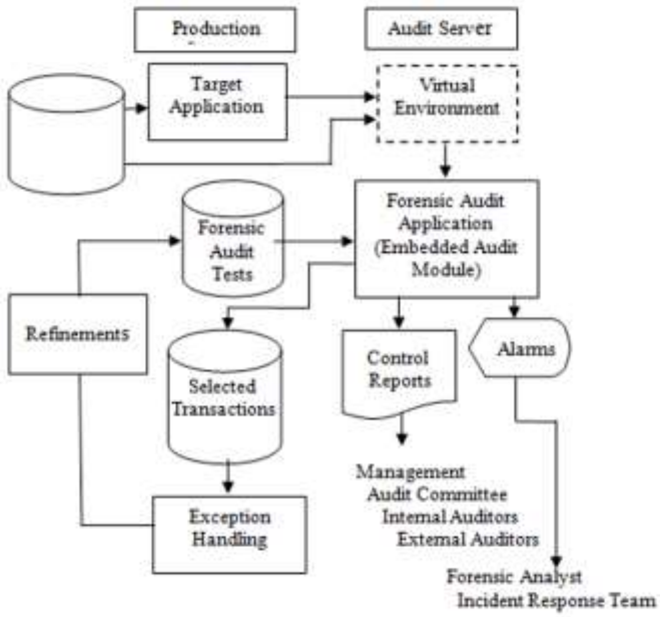

Figure 4:The Forensic Continuous Audit System Source: Adapted from Danese (2011:43).

eDiscovery in Digital Forensic Auditing

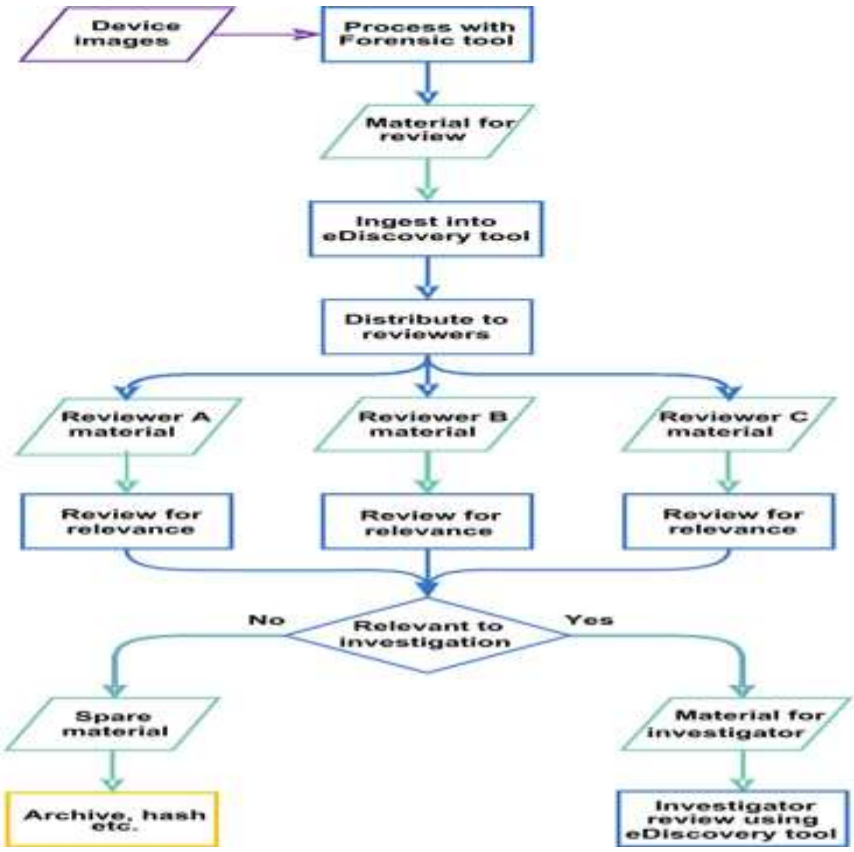

Figure 5: eDiscovery in Digital Forensic Auditing.
Source: Adapted from Lawton, Stacey, and Dodd (2014).

3. METHODOLOGY

Guided by Arksey and O'Malley's (2005) framework, this study employs a scoping review to map literature on AI in forensic auditing. According to Peters et al. (2020), scoping reviews prioritise breadth over depth, distinguishing them from systematic reviews or content analysis.

The review is composed of 27 evaluation items (checklist) that represent a minimum set of relevant information to convey in a systematic review report, covering the rationale for review, databases used to identify potential studies and the implications of review results, and the flow chart with four main strategic blocks namely: (1) identification, (2) screening, (3) eligibility, and (4) inclusion (Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow, Shamseer, Tetzlaff, & Moher, 2021). Hence a comprehensive literature search was conducted from popular and reputable databases.

Page et al. (2020) pointed out that six relevant steps to be followed namely: (1) selecting of research and objective of the study and outline the question(s) for review, (2) design of inclusion and exclusion criteria, (3) study identification, (4) study quality valuation, (5) extraction of data, and (6) synthetising of data (formulate a brief evidence for the results) and interpret them. Clark, Clark, Raffo, and Williams (2021) concur with Page et al. (2020) adding that systematic literature reviews include defining the objective of the study, scanning the literature, screening and selecting relevant articles, thereafter, analyzing and reporting the results. To achieve the objectives of this study we followed the protocol proposed by Fisch and Block (2018) and updated by Page et al. (2021).

The following steps were thoroughly followed for the two study's objectives.

Step 1: Identification of research objectives/questions: The research objectives which guided the study is: to critically analyse key merits/ benefits and demerits/challenges of incorporating AI into forensic audits justified by the existing theories and empirical literature that contribute to the remote forensic auditing.

Step 2: Identification of relevant studies: Having identified the research objective/question, the researcher proceeded to identify previous studies considered relevant to the research (See selections of Publications and PRISMA diagram flow).

Step 3: Study selection: the studies selected can be clearly seen in the figure 6.

Step 4: Charting data: In line with Arksey & O'Malley (2005) the data charting form was used for 27 articles which formed the final corpus of the literature use for the study (see Figure 6).

Step 5: Collating, summarising and reporting results: as recommended by Arksey and O'Malley (2005), thematic construction is needed to present a narrative account of existing literature. Thus, for the purpose of this research, themes were created and consequently used as a guide to provide answers to the questions/objectives of the study. Themes are presented in the discussion sections (5.1 and 5.2).

Selections of Publications: The exclusion criteria (EC) and inclusion criteria (IC) are used to exclude studies that are not relevant to answer the empirical research question.

3.1. Selections of Publications

The exclusion criteria (EC) and inclusion criteria (IC) are used to exclude studies that are not relevant to answer the empirical research question.

3.1.1. Inclusion Criteria

The inclusion criteria for this study focused on all theories and empirical studies that examined the key merits or benefits and demerits/ or challenges of incorporating AI into Forensic Audits. The systematic retrieval process used a number of search strings, namely "remote forensic auditing", "AI-based forensic audits tools", "fourth and fifth industrial revolution", "Artificial Intelligence" Searches were conducted between 2018 and 2024 and only articles published in English language were considered for this study. The search fields and research query are defined as follows:

- Search fields: Title and Keywords
- Search Strings as cited above
- Search filed: Abstract.

3.1.2. Exclusion Criteria

Articles published in French and other languages other than English were excluded from the search. The ECs are used to filter the irrelevant articles from the sources in terms of format, publication details and access. These are defined criteria:

- EC1: All articles published before 2018 were excluded from this study,
- EC2: the work of research study is not published as a scientific article,
- EC3: the article is not part of the computer science era
- EC4: The paper is not written in English
- EC5: The article without an abstract
- EC6: The article is a duplicate

The aims of the study were used to determine the eligibility for the study. In this research study 65 articles were excluded based on refinements. A considerable number of articles did not include given name of the authors within article metadata but only abbreviation, to address this issue an API called API metadata retrieval is used to extract extra data information based upon Digital Object Identifier (DOI) of the articles, after further refinements 22 articles were excluded, the PRISMA process is diagrammatically presented in the figure 6.

3.2. Selected Databases

The search process was carried using search engine to get relevant articles, Numerous databases were searched starting with the Google Scholar. The search was first done on Google Scholar to search for databases that consist high quality and impactful journals on 5IR, forensic auditing and AI. The Google Scholar search resulted in the following databases: Emerald insight, Springer Link, Semantic Scholar, Science Direct, Digital Library, Pro Quest and Scopus, Emerald, Taylor and Francis online, EconLit and Business Source Premier which were used to search for the journals used in the current study.

Databases were searched using a single search strings or multiple search strings with a combination of Boolean operators, namely "and", 'OR' and 'NOT' Relevant related literature and articles used for this research were then extracted from the cited above databases. The researchers decided whether the data found was suitable or not. A study is eligible to be selected if the data used is only related to the merits or benefits and demerits/ or challenges of incorporating AI into Forensic Audits. Gathered data was analysed to show and map the theories and merits and demerits of the fifth industrial revolution through AI in auditing profession. A systematic literature review research is carried out for various purposes, including to identify, review, evaluate and interpret available research on the topic area phenomenon of interest (Clark et al., 2021). This study specifically intends to critically analyse the merits and demerits of AI in forensic auditing justified by the existing theories and empirical literature with the aim of proposing a conceptual framework of using the AI in forensic auditing.

3.3. Data Validity

To ensure the validity and credibility in this research study, only peer-reviewed articles were considered.

3.3.1. Data Analysis

Data gathered was entirely analysed to show: the merits and demerits of AI on the in forensic auditing in Tables 2 and 3.

4. RESEARCH RESULTS DISCUSSION

The diagram flow of literature retrieval on the merits and demerits of AI on the in forensic auditing is set out in Figure 6 below.

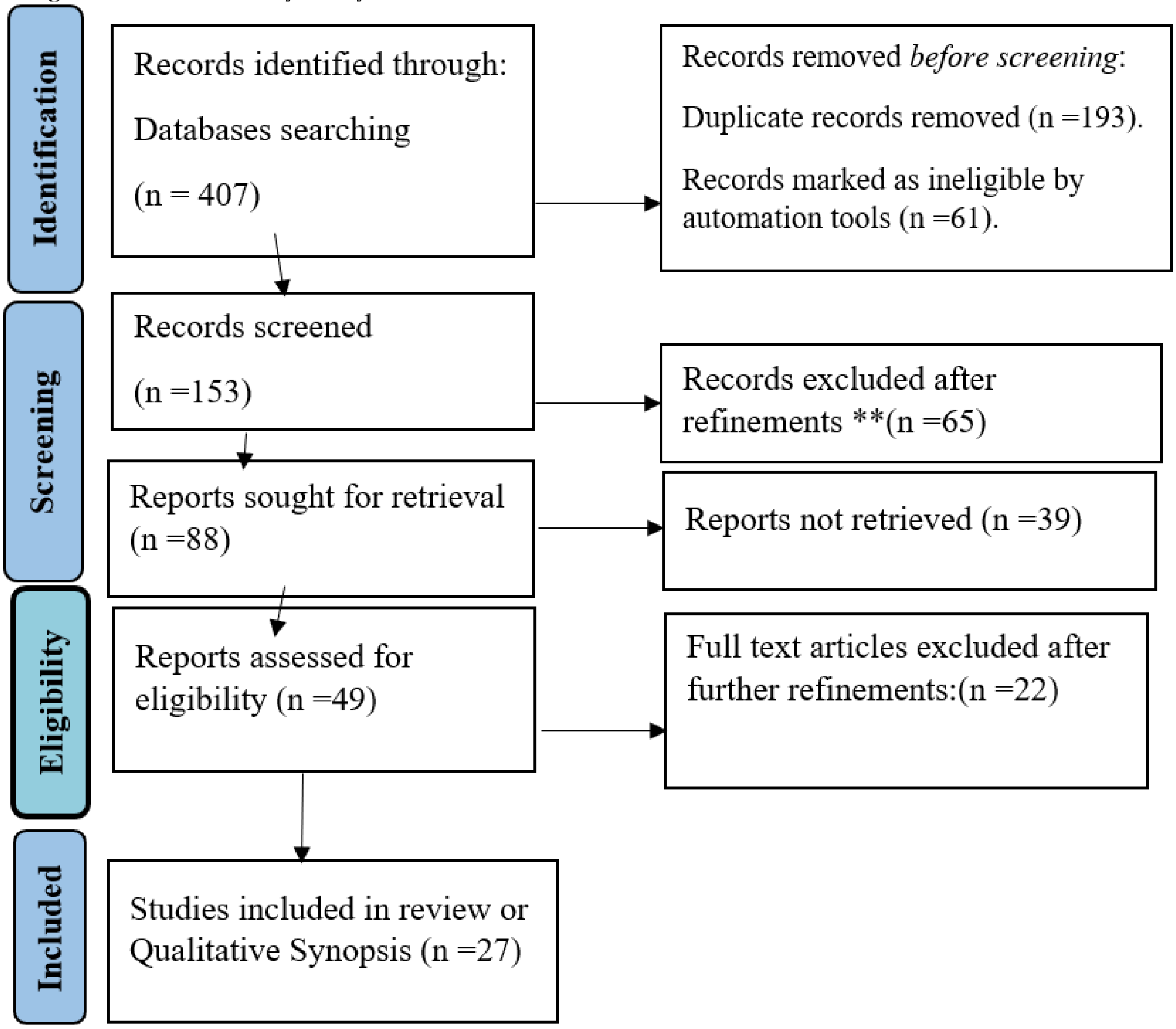

Figure 6: Flowchart of numbers of searched articles and final corpus.
Source: Drafted by the author (2024).

The results are fundamentally based on the review outcome of the prior 27 published studies in the area of the merits and demerits of AI on the in forensic auditing. We will discuss first the merits and demerits of AI-based on the in forensic auditing services, followed by the and demerits of AI on the in forensic auditing services and we concluded by proposing a conceptual framework of using the AI on the in forensic auditing services.

Table 2 below presents the studies that support the analysis to the research objectives as shown in the introductory section. After critical reading and analysing of the articles presented in table, the researcher tried to match the articles and papers with the objectives formulated, as presented in the last column of the table that is, Objective 1- to critically analyse the merits of AI-based on the in forensic auditing, and the objective 2- to critically analyse the demerits of AI-based on the in forensic auditing. The systematic literature review is presented below, trying to achieve the objectives formulated and set.

Table 1:Key merits/ benefits of incorporating AI into Forensic Audits.

Selected papers related to the research objectives			
Key merits/ benefits of incorporating AI into Forensic Audits		**Related References**	**Objective 1/2**
Reduction in staff-time and engagement timeline	AI platforms are capable of processing and analyzing far greater amounts of data within a significantly reduced timeline. This results in a reduction of staff time-allocated toward engagements which triggers cost-savings for both the accounting and auditing firm and the organisation under audit. Additionally, AI can help reduce the time needed to identify the cause of fraud, which can be critical in instances where the fraud is ongoing.	(Munoko, Brown-Liburd, & Vasarhelyi, 2020; Sharma & Biswas, 2021)	**Objective 1**
Enhance Speed and Efficiency, Enhanced fraud detection	AI algorithms can process data at a much faster rate than manual methods. This can potentially accelerate the forensic audits process which allows entities to respond swiftly to potential financial irregularities.	(Mike & Olochukwu, 2022)	**Objective 1**
Machine learning and Natural Language Processing Technology	AI uses Natural Language Processing Technology to identify key terms or performance indicators within contracts, administrative documents and financial reports. Additionally, AI systems are learning-machine technologies that allow organisations to tailor the systems to their organisations using a set of sample documents. The systems will continue to learn as they are utilized and do not require specific programming.	(Jing Zhang & Tao, 2020)	**Objective 1**
Removal of human error	Since AI, involves human interaction in processing and analysisng sets of data, the risk of human error through clerical errors, typos in formulas or values, etc. is significantly reduced. Additionally, AI helps to identify anomalies or inconsistencies in data sets that may help to identify human errors.	(Galante, Cotroneo, Furci, Lodetti, & Casali, 2023)	**Objective 1**
Fraud detection and investigation	AI can be trained to recognise patterns associated with fraudulent activities by leveraging machine learning models, forensic audits can automatically identify unusual transactions, unusual behavior or	(Bhagat, 2024; K. Mehta et al., 2022)	**Objective 1**

	other indicators of potential fraud, helping forensic auditors focus their efforts on high-risk areas.		
Predictive and Improved data analytics	Because AI is able to process a large amount of data, the platforms are also able to summarise data into user-friendly visuals to illustrate findings. This allows for more accurate, timely and understandable data analytics.	Alzeban et al., (2018) as cited in (Mike & Olochukwu, 2022) and (Insights, 2018)	**Objective 1**
Adaptive Learning	AI systems can adapt to changing patterns of fraud, continuously learning from new data. This adaptability is crucial in the dynamic landscape of financial crimes, allowing forensic auditors to stay ahead of emerging frauds and threats.	(Rodgers, 2020; Solanke, 2022)	**Objective 1**
Resource Optimisation	Automating routine tasks and leveraging Artificial intelligence, forensic auditors can optimize their resources, this allows entities to allocate human expertise strategically, focusing on high-value investigative work or more complex and strategic aspects of investigation.	(Hossain, 2023; Murphy, 2022)	**Objective 1**
Improved risk assessment	AI-based forensic audits provide forensic auditors with opportunity to assess fraud risks more accurately and proactively.	(Zhou et al., 2019) and Galante et al. (2023)	**Objective 1**
Enhanced Decision making	AI-based forensic audits tools allow forensic auditors to make informed decisions quickly and efficiently	(Kwon et al., 2018)	**Objective 1**
Improved fraud detection	AI-based forensic audits provide forensic auditors with opportunity to detect financial statement fraud more accurately and efficiently	(D'Auria and De Pietro, 2018)	**Objective 1**
Improved audit trial	AI-based forensic audit allows forensic auditors to create a comprehensive audit trail, documenting the entire audit process	(D'Auria and De Pietro, 2018)	**Objective 1**
Enhance client satisfaction	AI-based forensic auditing tools can improve client satisfaction by providing them with more accurate and timely information about their financial transactions.	(Zhou et al., 2019)	**Objective 1**

Source: Author's own investigation (2024).

Table 2:Key demerits or challenges of incorporating AI into Forensic Audits.

Selected papers related to the research objectives			
Key demerits/ Challenges of incorporating AI into Forensic Audits		**Key references**	**Objective**
Data Privacy and Security concerns	Forensic audits often involve sensitive financial and personal information. Implementing AI in this context requires strict adherence to data privacy regulations and robust security measures to prevent unauthorized access or data breaches	(Chukwuma et al., 2022; Munoko et al., 2020)	**Objective 2**
Gaps in data collection	AI-based forensic auditing is limited to the data available, hence gaps in data used for the analysis or if the quality of the data is poor. The issue is that **AI Algorithms may not able to identify all potential cases of frauds.**	Kehoe and Liyanage (2018) and Galante et al. (2023)	**Objective 2**
Lack of standardization	AI-based forensic auditing lacks standardization in data gathering and analysis across different industries, which is difficult for the AI algorithms to detect anomalies and potential fraud across different types of businesses.	Kim and Lee (2019) and (Hossain, 2023)	**Objective 2**
Interpretability and explainability	Many AI algorithms, especially deep learning models, operate as "black boxes," making it challenging to understand how they arrive at specific conclusions. Forensic auditors may face difficulties explaining AI-generated findings, which can be a critical issue in legal proceedings.	(Oberoi, Kumar, Sharma, & Gaur, 2021)	**Objective 2**
Bias in AI algorithms	AI systems can inadvertently inherit biases present in the training data. In forensic audits, biased algorithms may result in unfair or inaccurate assessments, especially if the training data reflects historical biases or imbalances. AI-based forensic auditing is potential for Algorithms Bias which affect the accuracy if the results. Because the AI systems entirely rely on historical data to make decision which trigger perpetuate practices that were present in the past leading to inaccurate and unfair results	(Leong and Vasarhelyi, 2020) and (Murphy, 2022)	**Objective 2**

Human Oversight of the AI system (Lack of interpretability of AI outputs)	Although AI-based forensic auditing can be effective in identifying fraud, human experts are still needed to interpret the data and make informed decisions based on the results.	Xu and Wang (2019) and (Hossain, 2023)	**Objective 2**
Lack of domain-specific expertise	Developing effective AI solutions for forensic audits requires a deep understanding of both AI technologies and forensic accounting. Organizations may face challenges in finding professionals with the necessary expertise in both domains.	(Bhagat, 2024; Solanke, 2022)	**Objective 2**
Implementation costs	Implementing AI solutions can be expensive, involving costs related to technology acquisition, training, and ongoing maintenance. Smaller organizations may find it challenging to allocate sufficient resources for AI adoption in forensic audits.	(Aitkazinov, 2023; Mehta, 2021)	**Objective 2**
Integration with existing systems	Integrating AI systems with existing forensic audit processes and legacy systems can be complex. Compatibility issues, data format discrepancies, and resistance to change within the organization may pose challenges during the integration process.	Xu and Wang (2019) and Bhagat (2024)	**Objective 2**
Ethical considerations	The use of AI in forensic audits raises ethical concerns, especially when it comes to issues such as employee privacy and the potential misuse of technology. Organizations need to establish ethical guidelines for the responsible use of AI in forensic investigations. AI-based forensic auditing is limited to data privacy and security concerns on sensitive financial data which inhibit entities from embracing AI-based forensic auditing as viable tool and solution for detecting fraudulent activities.	Li, Li, and Zhang (2020) and Mike and Olochukwu (2022); (Munoko et al., 2020)	**Objective 2**
Training and skills gaps.	AI implementation requires skilled professionals who can develop, deploy, and maintain the technology. There may be a shortage of individuals with the necessary expertise, creating a skill gap that organizations must address.	(K. Mehta et al., 2022; Solanke, 2022)	**Objective 2**

Resistance to change	Employees within an organization may resist the adoption of AI due to fear of job displacement, lack of understanding, or concerns about job role changes. Managing the human element and fostering a culture of collaboration with AI tools is crucial for successful implementation.	(Mike & Olochukwu, 2022; Oladejo & Jack, 2020)	**Objective 2**

Source: Author's own investigation (2024).

The contemporary systematic literature review of literature is briefly presented below, trying to achieve the objectives already formulated to answer the fundamental universal questions raised scholars. The presentation and discussion of the results are organised in the two sub-sections: (1) key benefits or merits of AI-based on the in forensic auditing, (2) key demerits, challenges and limitations of AI-based on the in forensic auditing

4.1. Theme 1: The Merits of AI-Based Technologies on the in Forensic Auditing

Mike and Olochukwu (2022) list the following key merits of using AI-based technologies on the in forensic auditing: (1) spotting errors and fraud in the financial statements more quickly, (2) AI-based technologies can quickly detect fraudulent activities with higher accuracy and quality, (3) enhancing client satisfaction, (4) enhancing decision making, (5) improving audit trial, (4) improving remote risk assessment. Naqvi (2020) and Bhagat (2024) concur with Mike and Olochukwu (2022) and add that AI-based technologies on the in forensic auditing assist forensic auditors in proactive fraud risk assessments and predicting fraud schemes. The argument in favour of AI-based technologies on the in forensic auditing has also been advanced by Aitkazinov (2023) who stated that AI-based technologies can potentially assist forensic auditors in early detection of emerging fraud schemes, tracing digital transactions and faster identifying and mitigating cyberthreats. Bhagat (2024) grouped empirical literature on the demerits of AI-based technologies on the in forensic auditing into five areas: (1) assist forensic auditors in enhancing the accuracy in identifying suspicious patterns, (2) increasing efficiency and speed of forensic investigations, (3) increasing the accuracy in unstructured data analysis, (4) streamlining data analysis for large datasets, (5) improving risk management and proactive fraud prevention and detection. This was also overwhelmingly confirmed by the research and articles linked to the use of AI-based technologies in various disciplines (Galante et al., 2023; Hossain, 2023; Vitali & Giuliani, 2024; Yebi & Cudjoe, 2022). IRBA (2024) agrees with these studies and adds that AI has a potential to save time and create value for accounting professionals and it can generate various forms of data including images, videos, audio which can assist in dealing with fraud and thus reduce agency problems created by information asymmetry.

4.2. Theme 2: The Demerits of AI-Based Technologies on the in Forensic Auditing

Empirical evidence, AI-based technologies could potentially enhance forensic auditing to effectively prevent, detect and respond to the risks of fraud promptly (Mike & Olochukwu, 2022). However, critisms ranging from pointing out that demerits, challenges and limitations associated with their use. Sharma and Biswas (2021) argue that AI-based technology is still at its infancy, especially in forensic auditing. Sharma and Biswas (2021) further raised serious concerns of reliability and accuracy of AI algorithms. Mike and Olochukwu (2022) soundly argue that even if AI-based technology can be effective in identifying and detection fraud, forensic auditors' experts are still needed to make sense and interpret data and make sound decisions based on the findings. Similarly, Oladejo and Jack (2020) explored limitations and challenges of AI-based forensic audits and highlighted that the AI cannot detect all potentially fraudulent activities. Oladejo and Jack (2020) and Mike and Olochukwu (2022) also raised issues about ethical concerns, data management and privacy, heavily reliance on human experts to interpret the data and results to make informed decisions. IRBA (2024) agrees with these studies as information produced can be incorrect, biased and unethical which would require professional skepticism from accountancy professionals when using AI technology. Furthermore, fabricated working papers may be generated by professionals which would impact on integrity and reliability of the work produced by auditing professionals. This would require policies and procedures to ensure authenticity of the work produced including monitoring unintended disclosures of confidential information. AI therefore does not address all the agency problems and accountancy professionals are required to apply professional skepticism when using the AI.

The research results of the review outcome of the 27-peer reviewed and published studies are congruent with the multiple theories adopted. DTT explains how AI disrupts traditional forensic auditing by introducing innovations that outperform existing methods, however its focus on market/industry disruption without addressing user acceptance or behavioral factors is regarded as a limitation. The inclusion of TAM and UTAUT address perceived usefulness, ease of use, and social/organisational influences, critical for understanding forensic auditors' adoption of AI tools. The challenges mentioned in Table 3 such as resistance to change and skill gaps align with these theories. The AIDUA model, which is tailored to AI device acceptance, provides insights into user trust, ethical concerns, and human-AI collaboration, which are key challenges highlighted in the study. Lastly, the ART supports understanding how AI systems learn and adapt to new fraud patterns, aligning with the study's emphasis on AI's adaptive capabilities as highlighted in Table 2.

Various empirical studies are in tally with current with the findings of the current study. Bhagat (2024) concluded that integrating AI systems with existing forensic audit processes and legacy systems can be complex. The study found that compatibility issues, data format discrepancies, and resistance to change within the organization may pose challenges during the integration process and intelligent automation forensic audit platforms is relatively new. The results concur with those of (Murphy, 2022). While the above empirical studies support the findings of the current study, other studies however, come with contradicting findings (Munoko et al., 2020; Sharma & Biswas, 2021).

5. CONTRIBUTION AND CONCLUSION

Since AI-based forensic auditing presents both challenges and opportunities the Remote forensic auditing framework-based conceptualised model in a disruptive environment is proposed and presented in the figure 7 below.

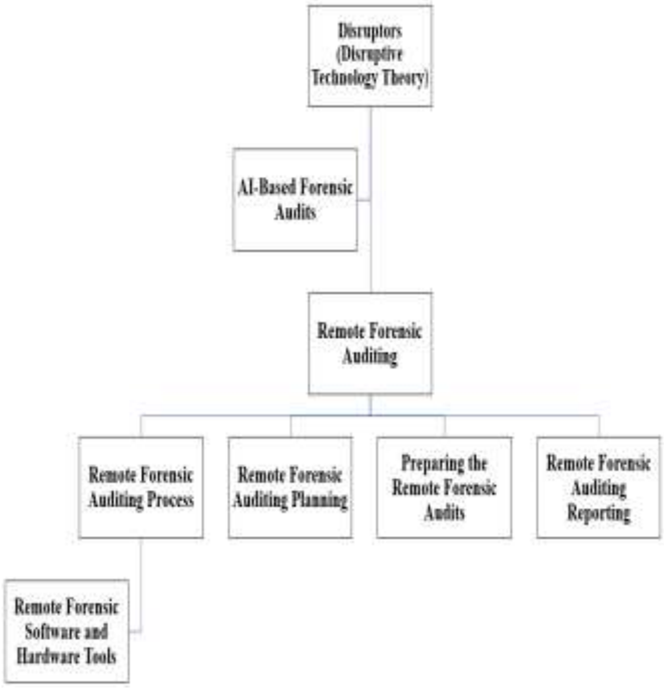

Figure 7: Remote forensic auditing framework-based conceptualised model
Source: Author's own (2024).

The study explored the discourse on the fifth industrial revolution and forensic Auditing Services from a scholarly point of view. Hence, the fundamental aims of this study were: (1) to critically assess the demerits of AI-based forensic auditing, (2) to critically assess the merits of AI-based forensic auditing. This article adopted a scoping review method by reviewing a selective bibliography of articles published between 2018 and 2024, The research results from extant contemporary literature revealed and recommended the following:

1. The impact of 4IR and 5IR on forensic audit services cannot be overlooked.
2. The use of sophisticated remote forensic software and hardware tools and technological innovations including AI-based forensic auditing in order to improve the collection of remote forensic audit evidence and eDiscovery.
3. The study highlights that the use of AI-based forensic auditing presents both limitations or challenges and opportunities. Hence, the researcher recommends policymakers, and legal framework to urgently address universal issues associated with AI-based forensic auditing and raised.
4. The use of AI-based forensic audit labs to improve forensic audit quality, to maximise the capability of AI-based forensic auditing to potentially collect big data for accurate and

faster analysis.

5. The use of neutral Language processing is also highly recommended to quickly identify high risk areas that can attract forensic auditors' attention.
6. Future researchers could develop AI-based forensic auditing models that are interpretable and understandable.
7. Policymakers and law-makers should address the issues of privacy and ethical concerns and bias
8. The international Standards on Auditing should be updated to incorporate AI-based forensic auditing process.
9. Thoroughly empirical research based on cases studies or case scenarios to validate the efficacy of AI-based forensic auditing is highly needed.
10. Future studies could produce empirical evidence field-based testing AI-based forensic auditing models in real world auditing scenarios.

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