Artificial Intelligence and the Future of Digital Forensic Engagements in Nigeria: Perceptual Evidence from Practitioners and Academics

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ABSTRACT

This study examined the perceptions of practitioners and academics on the use of artificial intelligence for digital forensic engagements in Nigeria. The study adopted a survey research design. Primary data were gathered through instrumentation and administration of questionnaire on selected respondents from audit firms (practitioners) offering forensic accounting services and university accounting academics in Nigeria. A sample size of 400 (approximated to 1 significant figure) was obtained from the entire population with the aid of Cochran formula and convenience sampling technique. Both descriptive and inferential statistical techniques were employed for data analysis. The formulated hypotheses were tested using structural equation modelling. The findings reveal a positive significant path from perceptual intelligence, cognitive intelligence and decision-making intelligence. The outcome of one-sample t-test conducted also shows no significant difference in the mean perceptions between both practitioners and academics on the relevance of artificial intelligence certification to digital forensic engagements. The study recommends that firms should invest in AI capabilities, ensure forensic accountants are adequately certified for AI usage and regulatory bodies should review laws to foster prudent use of these technologies.

Keywords: Artificial Intelligence; Academics; Digital Forensics; Engagements; Practitioners).

INTRODUCTION

Digital technology is undoubtedly bringing innovations and transformation to the world at a rapid pace. Developments over the years in digital technology have created vast opportunity of using the most cutting-edge information and communication technology (ICT) features for commercial activity engagements and government services thereby, shaping the lifestyle of many individuals. These developments with the emergence of artificial intelligence (AI) aggressively triggered the fourth industrial revolution. The implication of this is that it results in astronomic growth in the volume of data generation by companies (Smith, 2018; Ghanoum & Alaba, 2020).

In spite of indubitable multifarious benefits of digital technology worldwide, it also poses proliferation of new threats and cyber-security challenges ranging from identity theft to cyberbullying, data leakage exploiting social engineering or information hiding, malicious software turning, among others. Consequently, accountants in the developed countries have embraced waves of automation over the years to keep abreast of this change (KPMG, 2016). The forensic accounting profession is responding to this transformation with the integration of AI systems to stay abreast of the development.

AI is a technological advancement that is expected to inevitably influence the law and the forensic accountant as an expert witness for successful prosecution of cases (Metallo, 2020). The term was first coined in 1955 by a famous computer scientist called John Mcarthy. Interestingly, as the world is still struggling to replace natural human with an AI system, the certainty of such an achievement is increasing (Ilachinski, 2017). For instance, it spurs decision making that facilitates generation of large data (especially for a detailed forensic audit of all companies' transactions) within the shortest time than for humans to be employed in the process.

The term digital forensics (DF) has its origin dated back to 1970 when the only copy of a database that got lost was safely recovered by some engineers. According to Carrier and Spafford (2005), it remained a new field in developed economies up till mid-1990s when the only public examples of code and log analysis were for detecting intrusions and misuse, or perhaps making some unintentional observations about a potential online criminal, such as a malware author. By 1992, digital forensics started to emerge as an identifiable field. Today, digital forensic role has become an important aspect in the field of accounting that takes care of fraud investigation, mitigation of bribery and corruption, extension of legal support, looking after expert witnessing and cyber-security (Rezaee and Wang, 2019; Mittal , Kaur & Gupta, 2021).

This study therefore attempts to examine the perceptions of both the practitioners and academics on the current state of AI adoption for DF engagements in Nigeria, given the increasing volume of economic events and consequential spurt in accounting entries that have dramatically changed the nature of forensic auditor's job with the use of big data.

Statement of the Problem

The adoption of AI technology in forensic accounting investigation is taking place worldwide, hence Nigeria should not be an exception. Developed countries find AI highly beneficial because it creates an enabling environment for accountants to focus on more valuable tasks such as decision-making, problem solving, advising, strategy development, and leadership (FSB, 2017). The challenges faced by accounting profession to continue to maintain its credibility and trust as well as ensuring that its relevance as an information science is not misplaced, necessitate auditors and forensic accounting practitioners to be more forward-looking by acclimatizing on this trend of cognitive technology.

In Nigeria, the fear that AI compliant paradigm may eliminate the traditional human accounting career path is on the increase, which portends that the application of AI technique to fraud and digital forensics is very scarce, especially among accounting practitioners. As the popularity of AI technology continues to grow mainstream, identifying an aspect of forensic accounting services that requires the use of digital technology may be difficult in the nearest future.

Empirical evidence on the impact of AI on the future of digital forensics, especially in developing economies is scanty. Examples are: artificial intelligence and the future of accountancy (ICAEW; 2018); AI and its potential to revolutionize the accounting industry (Goh, et al., 2019); Integration of Artificial Intelligence in Auditing (Ghanoum & Alaba, 2020); impact of artificial intelligence on forensic accounting and testimony (Metallo, 2020). Most of these studies adopted a systematic review of literature of the major academic publications, professional reports and websites as a research methodology while little attention was devoted to the developmental process of AI which encompasses perceptual intelligence, cognitive intelligence and decision-making intelligence. The natural corollary from the gaps x-rayed above informs the imperative to incur into the dilemma of constraints of expanding the frontiers of forensic accounting knowledge by cross-examining the perceptions of practitioners and academics in this regard. The study also addresses the lacuna in the literature by building a framework that addresses issues bordering on certification and the appropriate organizational structure for decision making involving AI.

Research Objectives

The main objective of this study is to examine the effect of AI on the future of digital forensic engagements, drawing evidence from practitioners' and academics' perspectives.

Specifically, the study seeks to:

i) investigate the influence of perceptual intelligence on DF engagements.
ii) evaluate the extent of relationship between cognitive intelligence and DF engagements.
iii) ascertain if decision-making intelligence affects DF engagements.
iv) examine the adequacy of artificial intelligence certification for DF engagements in Nigeria.

v) determine if there is significant difference in the perceptions of practitioners and academics on the relevance of AI for DF engagements in Nigeria.

Research Hypotheses

The following hypotheses were set to guide the conduct of this research:

H_{01}: Perceptual intelligence does not have any significant influence on DF engagements.

H_{02}: Cognitive intelligence does not have any significant relationship with DF engagements.

H_{03}: Decision-making intelligence does not significantly affect DF engagements.

H_{04}: Artificial intelligence certification is not significantly adequate for DF engagements in Nigeria.

H_{05}: There is no significant difference in the perceptions between practitioners and academics on the relevance of AI for DF engagements in Nigeria.

LITERATURE REVIEW

Conceptual Issues

Concept of Artificial Intelligence (AI)

AI as defined by Pratik and Abhishek (2013) is the science of making machines do things that would require intelligence-requiring things if done by men. European Commission (2020) states that AI involves the systems that display intelligent behaviour by analyzing their environment and taking action – with some degree of autonomy – to achieve specific goals. Kolbjørnsrud et al. (2017) defined AI as computers and applications that sense, comprehend, act, and learn. Russell and Norvig (2010) refer to it as a term describing machines which mimic human cognitive functions like learning and problem solving. In other words, it consists of techniques which learn to recognize patterns in order to make predictions that facilitate decision-making.

According to Ransbotham et al. (2018), AI which is otherwise called machine intelligence, stands for the integration of human-like intelligence in machines with the basic idea of understanding the context and making intelligent decisions based on the information at hand. In the words of Makarius et al. (2020), it refers to a system's capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption.

Yang and Peng (2020) aver that the intention of AI is to use computers to simulate human intelligence, so that machines have consciousness, can think, learn autonomously, can listen, speak, understand language and solve problems based on intelligent reasoning and rapid decision-making. It specifically related to: perception, computation, cognition, and innovative intelligence. Summing up the key points from the aforementioned definitions, AI can simply be said to mean a cognitive technology in form of brainbox containing activities that enable machines to complete tasks ordinarily performed by humans.

Perceptual Intelligence (PI)

As described by Xu et al (2021), PI means that a machine has the basic abilities of vision, hearing, touch, etc., which are familiar to humans. In the views of Yang and Peng (2020), PI includes vision, hearing, touch and taste, in which case, the whole body of a person can be seen as a perceptron. From the few definitions provided above, PI can be briefly defined as to a system's ability to become conscious of its environment through the senses of hearing, visualizing, manipulating, etc., vision and hearing, being the most developed parts in AI system.

PI is therefore, an integral part that makes AI system work efficiently for digital forensic exercise and covers different aspects of the cyber fraud investigation procedure.

Cognitive intelligence (CI)

CI is a higher-level ability of induction, reasoning and acquisition of knowledge. It is inspired by cognitive science, brain science, and brain-like intelligence to endow machines with thinking logic and cognitive ability similar to human beings (Xu et al, 2021). CI refers to an artificial intelligence inspired by the brain, which understands how the brain makes the mind, how the brain works and communicates, how brain electrical signals control human activities, and how to build intelligent machines (Yang & Peng, 2020). In other words, CI is an artificial brain-like intelligence capable of inducting, reasoning and acquiring knowledge.

Issa et al. (2016) expatiate that this aspect of development process of AI has the capability of taking balanced decisions, mimicking cognitive function associated with the human mind and able to observe its environment and take actions that maximize its chances of attaining a goal. Among other things, Integrating AI in each step of audit engagement and forensic accounting investigation auditing process will delete tasks that are repetitive and ease analysis of numerous data to have an in-depth understanding of the business operation (Kokina & Davenport, 2017).

Decision-making Intelligence (DI)

Boucher (2020) describes DI as higher-level ability of AI to process data to make decisions in a way that is inspired by the structure and functionality of the human brain. It is defined by Philiphs-Wren (2012) as AI-integrated support systems used to aid decision-making in such areas as auditing, finance, marketing, commerce, digital forensics, cyber-security, among others. Due to **s**ome researchers' criticism of human biased and irrational decision making by nature, Parry et al. (2016) posit that **AI**-based decision-making systems are free of human preconceptions and present a better representation of the reality. Application of AI in auditing and digital forensic investigation is not new in developed economies (Hansen & Messier Jr., 1986) because it has greatly served as a useful decision support tool for digital forensic audit specialists for decades, but still in its infancy in Nigeria.

Concept of Digital Forensics (DF)

From forensic science angle, Goh, et al. (2021) describe DF as involving data sourcing from digital devices such as computers, servers, mobile devices, the cloud, and so on, to advance a much smaller subset of data for review. Anderson et al. (2021) describes DF as the preservation, identification, extraction, interpretation, and presentation of computer data which can be used by a court of law. It refers to the identification, preservation, acquisition, examination, analysis and presentation of digital evidence (Hewling, 2011).

From forensic accounting context, Fenu and Solinas (2016) define DF as the process of investigating a computer system (used for accounting, financial reporting or financial transactions purpose) to determine the cause of an incident.

However, DF from forensic accounting context is concerned with investigation, analysis and recovery of forensic accounting data for digital evidence of a financial crime at the law court or administrative proceeding. Failure to detect fraud not only exposes audit firms to risk, but also subjects the audit profession to increased public and governmental criticism (Albrecht, 2009), hence digital technology has been embraced by some audit firms in Nigeria for application in areas of audit or forensic accounting, where there is a need to identify fraudulent behaviour or errors.

Artificial Intelligence Certification

Cihon et al (2021) define AI certification as an attestation that a product, process, person, or organization satisfies some specified criteria. According to them, the object of certification is the entity to be certified which could be an organization, individual, a product or process, while the actor who does the certifying is the certifier. Before certification, it is necessary to confirm if the object of certification conforms to the specified criteria. Such confirmation is done by an assessor. Certification in this context is outside the scope of this study. Owing to AI increasingly gaining popularity among today's organizations worldwide, it becomes necessary for external stakeholders to know whether ethical standards are met by organizations and their AI systems.

Although, the primary role of AI system certification is to reduce information asymmetries, it is also important to know if forensic accountants in Nigeria have requisite credentials in AI that are adequate enough to undertake digital forensic investigation as obtained in most developed countries. This is because, certification adds value to career advancement, improve career prospects, and enhance earning power among the holders (Domino et al., 2017; Ibrahim, 2020).

Relevance of Artificial Intelligence Certification for Digital Forensic Engagements

Issues bordering on whether AI is going to transform every economic sector, including accounting industry have generated mixed reactions among stakeholders in the accounting domain like practicing accountants, forensic auditors, analysts and academic researchers. Evidences gathered in favour of AI's relevance for DF engagements include an argument from Ghanoum and Alaba (2020) that AI-based tools in auditing makes detecting such high-risk transactions easy unlike manual auditing may sometimes not capture fully as a result of sample population testing. This view is supported by Issa et al (2016) who posit that AI application makes adoption of tools that can mimic human-like activities possible in audit processes and perform the tasks much more effectively. Similarly, Deloitte (2015) asserts that with the use of AI for auditing fraud investigation, it potentially enables firms to accomplish set goal of quality enhancement and effective audit assignment within a reasonable time frame and cost. When looking to the future, audit function and risk management professionals will increasingly embrace AI technologies (Goh et al, 2019).

Contrary to the foregoing positions, Allen (2019) argues that possible disagreements on ethical virtues which most people would instinctively value over dishonesty of various actions or behaviour of AI systems underlie the difficulties that designers face in determining criteria for ascribing morality to the actions or behaviour of AI technology. The use of AI systems largely restricts the engagement of auditors and forensic accountants from examining the financial reports extensively which relatively contravenes the provision of the international accounting standards that requires auditors to scrutinize financial reports as verifiable after reviewing the financial reports to a satiable level (Bustinza et al., 2015). Lastly, colossal investment is required for adopting AI technology to address specific accounting problems. According to PWC (2018), AI technology is still very expensive to acquire for use by both big and small firms. More importantly, in spite of availability of a lot of free and open-source software in this area, utilizing established software providers may be needed on legal or regulatory justifications (ICAEW, 2015).

Therefore, it is imperative to have the active engagement of standard setters and regulators to achieve transformation in the areas of auditing, forensic accounting and financial reporting. This will give these stakeholders better understanding of AI application and be contented with any risk associated thereto.

Theoretical Review

Sternberg's Information Processing Theory

This is a psychological theory developed by Sternberg (1988) which mainly focuses on intelligence.

According to Sternberg, development is a continuum and skills-based as opposed to the belief of the stage theorists. While the theory does not accept the concept of incremental stages, it believes that development happens in similar way throughout life span differentiated only by the dexterity and expertise of the learner to process new information.

The theory mainly accommodates information processing facets of development but does not consider any aspect of biological development. More so, where cognitive development is seen as a greenhorn to expert progression, development changes as a result of feedback. The theory views intelligence as having three categories of information processing components, namely: meta-components, performance components and knowledge-acquisition components which work together to enhance learning and cognitive development. Meta-components exert influence on planning and decision making in relation to problem solving situations. This however, affirms the fact that perception, cognition and decision-making are key constructs traceable to each of the information processing components which form the integral parts of AI system. Apparently, psychology is concerned with the study of human brain and its nature, information processing theory of intelligence is an impulse to psychology. As a result, cognitive psychology and AI share many metaphors while AI is the branch which deals with the intelligence in machine (Pratik & Abhishek, 2013). The limitation of this theory borders on machines that have a restricted capacity as opposed to human capacity for memory. Also, machines process data serially while human capacity is not immense for either parallel data processing or sorting multiple pieces of data at a time.

Theory of Inspired Confidence (TIC)

A Dutch professor known as Theodore Limperg, developed TIC in late 1920s. The primary focus of the theory is on both the demand and supply of auditing services. According to the theory, the demand for audit services is a feedback triggered by the engagement of external stakeholders in a company. In order to avert conflict of interest and ensure accountability as demanded from the management, supply of audit service becomes necessary by the external stakeholders due to the likelihood of the managers being biased in the provision of financial information. In this respect, the theory maintains that the independent auditors while discharging their obligations, should conduct themselves in a professional manner that guaranties assurance of meeting the expectations of relevant users of such financial information without prejudice.

Since the essence of companies nowadays investing more in audit-friendly technologies is not only to prevent fraud but to meet the expectations of the rational users of financial information (Nwoye & Ogbodo, 2021), the idea of integrating AI technology for digital forensic investigation is also seen as following this strategic step as expounded by this theory. This therefore, confirms the justification for the adoption of the theory in this study. TIC has been criticized by some opponents that it puts the accountant at the mercy of the unpredictable expectations of the man on the street.

Theory of Professions

Talcott Parsons is the father of the studies of professions. The primary focus of this theory is on the nexus subsisting between occupational groups, theoretical knowledge and the chances of applying such knowledge by practitioners within their occupational practice. The theory which was rooted from the field of sociology was intended for identifying and understanding the essential elements of professions and to explain their functional role in society (Ibrahim, 2020). It enumerated the basic attributes of a profession as body of knowledge, mode of entry, ethical codes of conduct and protection of public interest; although more attributes were consequently discovered which were considered relevant. Examples are fiduciary relationship with clients (Lewis & Maude, 1953), loyalty to colleagues and acting above and beyond material incentives (Larson, 1977).

Leading researchers in organization studies and accounting, found this theory useful since 1990s in order to understand large professional organizations and how they differed from corporations. Obviously, accounting is confirmed as a generally accepted profession, having met the aforementioned criteria of professions. Certifications of practitioners in forensic accounting, artificial intelligence, auditing and other related professional practices are expected to meet the requisite conditions of a profession. This will undoubtedly improve their professional skills to conduct comprehensive and timely forensic investigation of financial records which in turn adds to the level of credibility, reduces the chances of information asymmetry mitigates opportunistic or deviant behaviors. The theory is found useful for providing some useful lens for further understanding of the role and characteristics of forensic accounting practitioners in Nigeria.

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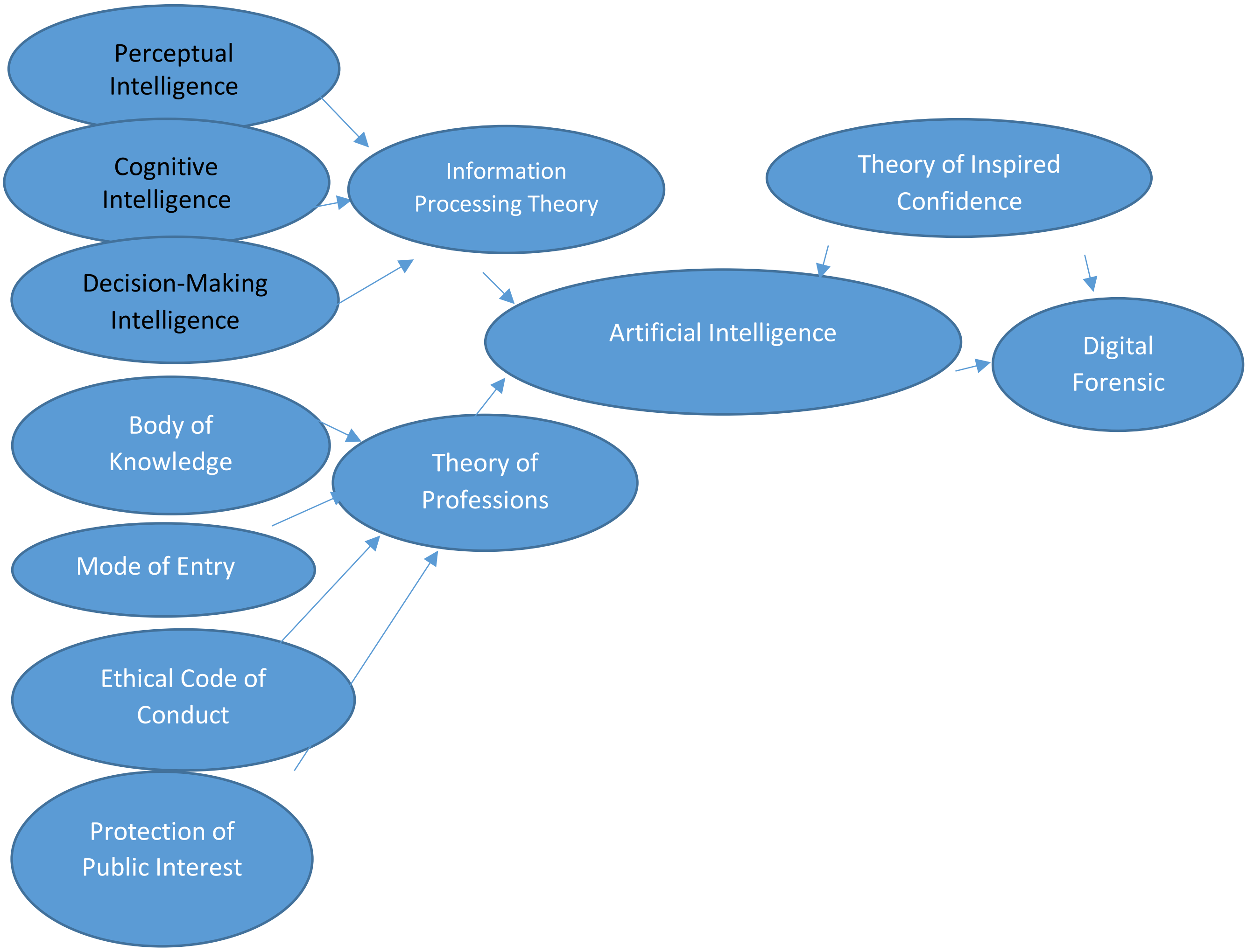
Conceptual Framework

Figure 2.1 Conceptual Framework of Artificial Intelligence for Digital Forensic Engagements



Source: Adapted Model from the works of Ghanoum and Alaba (2020).

The Theories of Professions, Information Processing and Inspired Confidence provide support for the final model that was developed for this study as revealed in figure 2.1. This model is the best for this study as it captures the essence and the research objectives that link the demand for, and supply of digital forensic services by practitioners with artificial intelligence credentials and expertise juxtaposing the required criteria that lead to the ultimate description of profession.

The application of each of the theories determines the interaction between AI technology and digital forensic engagements. AI technology facilitates optimal digital forensic engagements. The two-way interaction between the application of AI based tools and digital forensic engagements is presumed to result to an enhanced effectiveness of the process for the benefit of all stakeholders, which were subjected to further empirical investigation as the study progressed.

Review of Empirical Studies

Ghanoum, and Alaba (2020) investigated the effect of integrating artificial intelligence on auditing process in Sweden, using qualitative research design and adopting an abductive approach. Primary data were sourced through a semi-structured interview conducted with auditors from auditing firms within Sweden who have adopted the use of AI technology tools for auditing their clients' financial records. The study findings showed that, as a result of exponentially increasing data, auditors need to enhance the processing capability while maintaining the effectiveness and reliability of the audit process. The study findings also confirmed that the use of AI systems enhances effectiveness in all stages of audit process as well as increases professionalism and compliance with standards. The study however favored the use of AI-enabled auditing systems as opposed to the use of traditional auditing tools.

Albrecht (2009) examined fraud and forensic accounting in a digital environment by identifying four aspects of computer assisted fraud detection that are of primary interest to fraud investigators and forensic accountants, namely: data mining techniques for the detection of internal fraud, ratio analysis for the detection of financial statement fraud, the issues surrounding external information sources, and computer forensics during fraud investigations. It provides an informative background and then details the current status of research in each area.

Eriksson et al. (2019) tested the relationship between prevention and detection for risk and fraud in the digital age. The study explored the possibilities new technology used in fraud detection and prevention mechanisms could provide. The research findings revealed connection among the new technology mechanisms with the aspect of organizational culture that has been proved significant in fraud risk.

Yoon (2020) carried out a survey on transformation of accounting based on new technologies with empirical evidence from Korea to clearly identify the new technologies into cloud, AI, big data, and block-chain, to introduce the case of Korean companies applying new technologies to their accounting process. Systematic review of the literature of the major academic publications, professional reports and websites was used as a research methodology. During case section stage, analytical process of reviewing Korean major business and economic newspaper articles was done. The study findings suggest the need for the acceleration of technology transformation, especially after COVID-19 pandemic period of which it is considered necessary to understand and explore ways to effectively apply them.

Nwoye and Ogbodo (2021) examined the effective deployment of digital forensic techniques and the sustenance of material misstatement-free financial reporting in Nigeria, using secondary data source. A total of 50 manufacturing companies were purposively sampled with pre and post IFRS annual reports for the years 2006 – 2016 which were assessed using digital forensic technique such as Probit Model e-enabled spreadsheet. Relevant hypotheses were tested using Multiple Regression technique and Mann Whitney U test. Study findings showed that appropriate application of digital forensic technique deployed effectively predicts tendencies of material misstatement in the pre and post IFRS Financial Statements of selected manufacturing companies sampled.

Metallo (2020) studied the Impact of artificial intelligence on forensic accounting and testimony by exploring the current issues and legal implications surrounding the use of artificial intelligence by forensic accounting experts and its importance to forensic accounting research. The study reviewed existing law, proposed changes to the federal rules of evidence for using artificial intelligence in the courtroom, and covers emerging technology a forensic accountant may encounter, such as block-chain, cryptocurrency, smart contracts, machine learning and algorithmic entities. The study findings suggests that the changes to the rules should encompass standards to account for artificial intelligence reliability and argues forensic accounting experts and all forensic experts are needed even more in light of this new technology to assist the trier of fact in its deliberations.

Kokina and Davenport (2017) provided an overview of the emergence of artificial intelligence in accounting and auditing. Current capabilities of cognitive technologies and the implications they will have on human auditors and the audit process itself were reviewed with the provision of industry examples of artificial intelligence implementation by Big 4 accounting firms. The study findings revealed some potential biases associated with the creation and use of artificial intelligence.

Ogoun (2020) investigated the role of accounting professional practice in shaping the expansion of the frontiers of accounting knowledge based on the reality of the threat posed by developments in artificial intelligence premised on tech-developmental disruptions, the gap between accounting theoreticians and practitioners, and accounting's back-lead in new knowledge development and application. As gleaned from the preponderance of theoretical evidence, which underscores practitioners' continuing preference for normative, descriptive, and immediate problem resolution research, the study suggests that expanding the frontiers of accounting knowledge has been budged down, by the limited scope of practice accommodation given to new knowledge deployment.

METHODOLOGY

This study employed survey research design. The population of the study consists of 892 registered audit firms in Nigeria as well as 73,400 academic staff in Nigerian universities as at April, 2022. The sample size was therefore, determined from the entire population using a model developed by Cochran in 1963 as cited by Kasiulevicius , Sapoka and Filipaviciute (2006), and Singh and Masuku (2014). In line with Cochran's position, the required sample size in a descriptive survey study is calculated with the knowledge of three criteria, namely: level of precision (which is also known as margin of error), confidence level or risk level and the degree of variability which is also known as standard deviation. The Cochran formula as cited by Kasiulevicious et al, (2006) is:

$$n = \frac{z^2 \text{ x } p(l-p)}{e^2}$$

$$\text{Necessary Sample Size} = \frac{(\text{Z-score})^2 * \text{Standard Deviation}*(l - \text{Standard Deviation})}{(\text{Margin of Error})^2}$$

90% - Z - Score = 1.645

95% - Z - Score = 1.96

99% - Z - Score = 2.326

The study used 95% confidence level which has a Z-score of 1.96, a standard deviation as 50% (.5) and a margin of error as +/-5% (.05). This choice is due to the safety associated with midpoint standard deviation. Using Cochran's formula, a computed sample size of 383 was arrived at. Convenience sampling technique, a non-probabilistic method was considered appropriate for quantitative research approach of this nature. Showkat and Parveen (2017) accentuate that in this type of sampling, researchers prefer participants as per their own convenience.

The primary data used in this study were sourced through questionnaire administration on selected respondents from audit firms (practitioners) offering forensic accounting services and university accounting academics in Nigeria. The questionnaire (which is close-ended) is divided into two sections with respect to demographic information and the relevant variables to the study. A five-point Likert attitudinal scale which allows respondents to indicate a degree of agreement or disagreement in a multiple-choice type format was adopted. While validity test was conducted, Cronbach's Alpha was used to test the level of consistency and the reliability of a data set. The reliability statistic for all the variables is not expected to be significantly different from the 0.7 as minimum level recommended by Nunnally (I978).

The study employed both descriptive and inferential statistical techniques for data analysis. Specifically, Structural Equation Modelling was employed to test hypotheses 1, 2, 3 and 4 to confirm the cause-effect relationship between the dependent variable and the independent variables, while One Sample t-test was used to test hypothesis 5 in order to establish if any significant difference exists in the perceptions between practitioners and academics on the relevance of AI for digital forensic engagements.

However, the regression model for this study is specified as:

$$DFE_i = \beta_0 + \beta_1 PIN_i + \beta_2 CIN_i + \beta_3 DIN_i + \beta_4 AIC_{i\,+}\, \mathcal{E}_i$$

Where:

DFA = Digital Forensic Engagements,

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PIN = Perceptual Intelligence,

CIN = Cognitive Intelligence,

DIN = Decision-making Intelligence, and

AIC = Artificial Intelligence Certification.

β_0 = Regression constant

$\beta 1$, $\beta 2$, $\beta 3$ and $\beta 4$ = Regression coefficients, which represent the unit contribution that will be brought to the opinion on artificial intelligence by all the regressors respectively.

RESULTS AND DISCUSSION

Data Presentation

The sample consisted of 220 respondents, with 61.82% being male and 38.18% female. The age distribution indicates a diverse range, with the majority (39.09%) falling within the 41-50 age group, followed by 31.82% in the 31-40 age group. The educational qualifications of the respondents were also varied, with 44.55% holding a Bachelor's degree, 32.73% possessing a Master's degree or equivalent, and 17.27% having a PhD as shown in table 4.1.

Table 4.1 Demographic Spread

Gender	**Number**	**Percentage**
Male	136	61.82%
Female	84	38.18%
Total	**220**	**100%**
Age Range	**Number**	**Percentage**
18 - 30	30	13.64%
31 - 40	70	31.82%
41 - 50	86	39.09%
51 - 60	28	12.73%
Above 60	6	2.73%
Total	**220**	**100%**
Education Level	**Number**	**Percentage**
SSCE/OND	12	5.45%
BSc.	98	44.55%
MSc./MBA/MA/MPhil	72	32.73%
PhD	38	17.27%
Total	**220**	**100%**
Certification	**Number**	**Percentage**
ICAN	152	69.09%
ANAN	32	14.55%
ACFA	0	0.00%
ICFE	0	0.00%
IFAN	14	6.36%
IICFIP	2	0.91%

None	20	9.09%
Total	**220**	**100%**
Job Description	**Number**	**Percentage**
Auditor	50	22.73%
General Accountant	62	28.18%
Chartered Accountant	82	37.27%
Forensic Accountant	16	7.27%
Lecturer	10	4.55%
Other	0	0.00%
Total	**220**	**100%**

Table 4.2 Descriptive Statistics

Variable	**N**	**Mean**	**Min**	**Max**	**Std Dev**	**Skewness**	**Kurtosis**
PIN	220	13.82	7	20	2.963	-0.124	-0.543
CIN	220	13.55	5	20	2.988	-0.378	-0.215
DIN	220	15.89	7	20	2.464	-0.789	0.412
AIC	220	30.21	21	37	3.642	-0.302	-0.187
DFA	220	16.29	10	20	1.814	-0.576	1.243

In Table 4.2, The descriptive statistics provides an insight into the distribution and characteristics of the key variables in this study. Perceptual Intelligence (PIN) shows a mean score of 13.82, with a relatively wide range from 7 to 20. The standard deviation of 2.963 indicates moderate variability in responses. The slight negative skewness (-0.124) suggests a distribution slightly skewed to the left, while the negative kurtosis (-0.543) indicates a somewhat flatter distribution compared to a normal curve. Similarly, Cognitive Intelligence (CIN) has a mean of 13.55, also with a wide range from 5 to 20. The standard deviation of 2.988 is similar to PIN, indicating comparable variability. The negative skewness (-0.378) is more pronounced than PIN, suggesting a stronger tendency towards higher scores.

On the other Hand, Decision-making Intelligence (DIN) had a high mean of 15.89, the highest among the AI capabilities, with a range from 7 to 20. The lower standard deviation (2.464) indicates less variability in responses compared to PIN and CIN. The more substantial negative skewness (-0.789) and positive kurtosis (0.412) suggest a distribution with a longer left tail and a sharper peak than a normal distribution. Also, Artificial Intelligence Certification (AIC) has a mean of 30.21, with a range from 21 to 37. The standard deviation of 3.642 reflects considerable variability in responses, which is expected given the broader scale used for this construct.

The Dependent variable, Digital Forensic Engagements (DFA) showed a mean of 16.29, with a range from 10 to 20. The lower standard deviation (1.814) indicates more consistent responses compared to other variables. The negative skewness (-0.576) and positive kurtosis (1.243) suggest a distribution with a longer left tail and a sharper peak than a normal distribution. The descriptive statistics provides a track for understanding the data distribution and variability, informing subsequent analyses and interpretations of the relationships between these variables in the context of AI capabilities and digital forensic engagements in Nigeria.

Test of Assumptions

To ensure the validity of the statistical analyses, it is essential to test the underlying assumptions of the statistical techniques employed. In this case, the assumptions for structural equation modeling (SEM) will be tested.

Test for Normality

The normality assumption is crucial for SEM as it ensures that the parameter estimates are unbiased and efficient. The normality of the data can be assessed using various statistical tests and graphical methods. One common method is the Shapiro-Wilk test, which tests the null hypothesis that the data is normally distributed.

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Table 4.3: Shapiro-Wilk Test for Normality

Variable	Statistic	df	Sig.
PIN	0.984	220	0.013
CIN	0.987	220	0.040
DIN	0.976	220	0.001
AIC	0.982	220	0.007
DFA	0.974	220	0.000

The Shapiro-Wilk test results indicate that the null hypothesis of normality is rejected for all variables (p-value < 0.05). However, SEM is relatively robust to violations of normality, especially with large sample sizes.

Test for Multicollinearity

Multicollinearity occurs when two or more independent variables are highly correlated, which can lead to unstable and unreliable estimates. The variance inflation factor (VIF) is commonly used to assess multicollinearity.

Table 4.4: Variance Inflation Factors (VIF)

Variable	VIF
PIN	1.927
CIN	2.105
DIN	2.473
AIC	1.685

Generally, VIF values greater than 5 or 10 indicate potential multicollinearity issues. In this case, all VIF values are below 5, suggesting that multicollinearity is not a significant concern.

Reliability Analysis

Reliability analysis is conducted to assess the internal consistency of the measurement scales used in the

study. The most commonly used measure of reliability is Cronbach's alpha, which ranges from 0 to 1, with values above 0.7 considered acceptable.

Table 4.5: Cronbach's Alpha Reliability Analysis

Construct	Cronbach's Alpha	No. of Items
PIN	0.812	4
CIN	0.836	4
DIN	0.867	4
AIC	0.791	8
DFA	0.701	4

The results show that all constructs have Cronbach's alpha values above 0.7, indicating acceptable internal consistency and reliability of the measurement scales.

Structural Equation Modeling (SEM)

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is used to assess the validity of the measurement model, which specifies the relationships between the observed variables (survey items) and the latent constructs (PIN, CIN, DIN, AIC, and DFA). The CFA evaluates the model's goodness-of-fit and the significance of the factor loadings.

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Table 4.6: Confirmatory Factor Analysis Results

Model Fit Indices
$\chi2/df$ = 2.178 (acceptable range: < 3)
CFI = 0.928 (acceptable range: > 0.9)
RMSEA = 0.074 (acceptable range: < 0.08)
SRMR = 0.053 (acceptable range: < 0.08)

Standardized Factor Loadings:

Construct	**Item**	**Loading**
PIN	PIN1	0.792
	PIN2	0.811
	PIN3	0.827
	PIN4	0.701
CIN	CIN1	0.775
	CIN2	0.819
	CIN3	0.846
	CIN4	0.793
DIN	DIN1	0.821
	DIN2	0.858
	DIN3	0.839
	DIN4	0.777
AIC	AIC1	0.725
	AIC2	0.749
	AIC3	0.802
	AIC4	0.791
	AIC5	0.678
	AIC6	0.712
	AIC7	0.791
	AIC8	0.745
DFA	DFA1	0.832
	DFA2	0.819
	DFA3	0.841
	DFA4	0.698

The model fit indices suggest an acceptable fit for the measurement model ($\chi2/df < 3$, CFI > 0.9, RMSEA < 0.08, SRMR < 0.08). Additionally, all standardized factor loadings are greater than 0.6, indicating satisfactory convergent validity.

Convergent and Discriminant Validity

Convergent validity assesses the degree to which the observed variables (items) measure the intended latent construct, while discriminant validity evaluates the extent to which the constructs are distinct from one another.

Table 4.7: Convergent Validity Measures

Construct	AVE	CR
PIN	0.629	0.870
CIN	0.657	0.885
DIN	0.692	0.900
AIC	0.583	0.914
DFA	0.641	0.877

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The average variance extracted (AVE) values for all constructs are greater than 0.5, and the composite reliability (CR) values exceed 0.7, indicating acceptable convergent validity.

Table 4.8: Discriminant Validity (Fornell-Larcker Criterion)

Construct	PIN	CIN	DIN	AIC	DFA
PIN	0.793				
CIN	0.621	0.810			
DIN	0.674	0.719	0.832		
AIC	0.535	0.589	0.648	0.764	
DFA	0.602	0.673	0.732	0.587	0.801

The square root of the AVE (diagonal values) for each construct is greater than the correlations between that construct and other constructs, providing evidence of discriminant validity based on the Fornell-Larcker criterion.

Structural Model (Path Analysis)

The structural model examines the relationships between the latent constructs, allowing for the testing of hypotheses. The results (coefficients) are visualized in the path diagram in figure 4.1 and shown in table 4.9.

Figure 4.1 Path Diagram

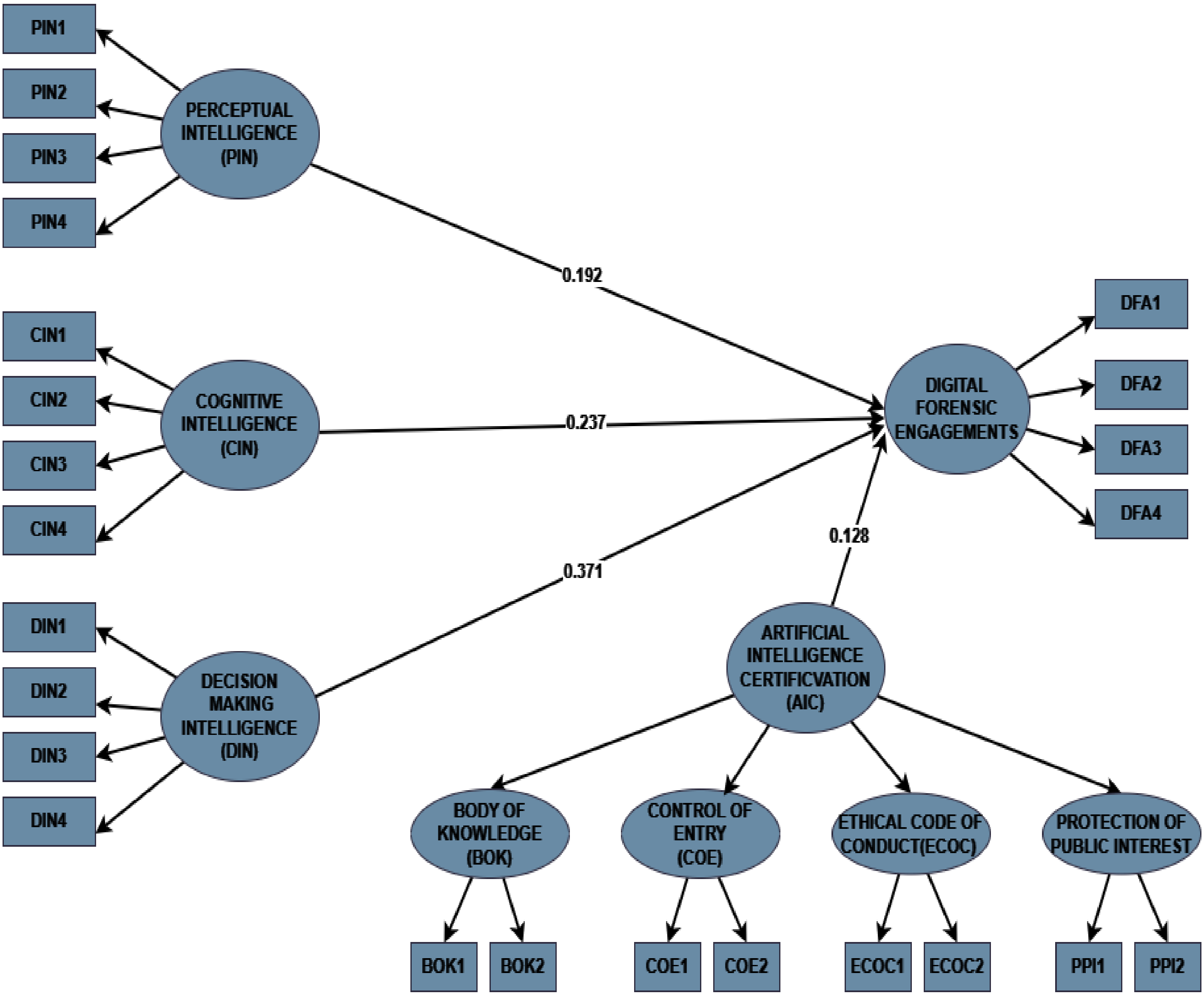

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Table 4.9: Structural Model Path Analysis

Path	Estimate	S.E.	C.R.	P-value
PIN → DFA	0.192	0.063	3.049	0.002
CIN → DFA	0.237	0.071	3.339	***
DIN → DFA	0.371	0.087	4.263	***
AIC → DFA	0.128	0.044	2.909	0.004

The path analysis results indicate that all four independent variables (PIN, CIN, DIN, and AIC) have a significant positive effect on the dependent variable (DFA) at the 0.05 significance level (or better).

One Sample T-Test

To test for the difference in the perceptions between practitioners and academics on the relevance of AI certification for digital forensic engagements, a one-sample t-test can be conducted. The responses from lecturers were used to represent the perceptions of academics, while the remaining responses were considered as those of practitioners.

The one-sample t-test compares the mean of a sample to a hypothesized population mean. In this case, the test compares the mean of the lecturers' responses on the relevant survey items (items 21-24) to the mean of the practitioners' responses. The mean of lecturers' responses is 16.60 while that of the practitioners' responses is 16.28 indicating a similarity in the response pattern of both practitioners and academics

Table 4.10 One-Sample T-Test

Test Value = 16.28 (Practitioners' Mean)					
Group	t	df	Sig.(2-tailed)	Mean Difference	95% Confidence Interval
Academics	0.549	9	0.596	0.32	-(0.97, 1.61)

The one-sample t-test results show a t-value of 0.549 and a p-value of 0.596 (greater than 0.05). This indicates that there is no statistically significant difference between the mean of the lecturers' responses (16.60) and the mean of the practitioners' responses (16.28) at the 0.05 significance level.

Hypothesis Testing

H01: Perceptual intelligence does not have any significant influence on digital forensic engagements.

Based on the structural model path analysis, the path coefficient from perceptual intelligence (PIN) to digital forensic engagements (DFA) was found to be significant (estimate = 0.192, p-value = 0.002). This result indicates that perceptual intelligence has a significant positive influence on digital forensic engagements. Therefore, the null hypothesis (H01) is rejected.

H02: Cognitive intelligence does not have any significant relationship with digital forensic engagements.

The path coefficient from cognitive intelligence (CIN) to digital forensic engagements (DFA) was estimate = 0.237, p-value < 0.001 in the structural model path analysis This suggests that cognitive intelligence has a significant positive relationship with digital forensic engagements. Hence, the null hypothesis is rejected.

H03: Decision-making intelligence does not significantly affect digital forensic engagements.

The path analysis results show a significant positive effect of decision-making intelligence (DIN) on digital forensic engagements (DFA) (estimate = 0.371, p-value < 0.001). Therefore, the null hypothesis (H03) is rejected, indicating that decision-making intelligence significantly affects digital forensic engagements.

H04: Artificial intelligence certification is not significantly adequate for digital forensic engagements in Nigeria.

The path coefficient from artificial intelligence certification (AIC) to digital forensic engagements (DFA) was found to be significant and positive (estimate = 0.128, p-value = 0.004) in the structural model path analysis. This result suggests that artificial intelligence certification is significantly adequate for digital forensic engagements in Nigeria. Consequently, the null hypothesis (H04) is rejected.

H05: There is no significant difference in the perceptions between practitioners and academics on the relevance of AI certification for digital forensic engagements in Nigeria.

The one-sample t-test results (Table 10) showed no significant difference between the mean of the lecturers' responses (representing academics) and the mean of the practitioners' responses on the relevance of AI for digital forensic engagements (t = 0.549, p-value = 0.596). Therefore, the null hypothesis (H05) is not rejected, indicating that there is no significant difference in the perceptions between practitioners and academics regarding the relevance of AI certification for digital forensic engagements in Nigeria.

DISCUSSION OF THE FINDINGS

The findings from the structural equation modeling analysis indicate that all three AI capabilities—perceptual intelligence, cognitive intelligence, and decision-making intelligence—have a significant positive influence on digital forensic engagements. These results align with the theoretical underpinnings and existing literature on the potential of AI technologies to enhance and transform various aspects of forensic accounting and auditing practices.

Perceptual intelligence, which refers to the ability of AI systems to perceive and process sensory input similar to humans, was found to have a significant positive effect on digital forensic engagements. This finding suggests that the integration of perceptual intelligence capabilities, such as computer vision, image recognition, and pattern recognition, can improve the efficiency and accuracy of forensic investigations by enabling the analysis of complex data sources, including digital evidence, multimedia files, and other visual or auditory inputs.

The significant positive relationship between cognitive intelligence and digital forensic engagements highlights the importance of AI systems' ability to mimic human behavior, reasoning, and problem-solving. Cognitive intelligence capabilities, such as natural language processing, knowledge representation, and machine learning, can enhance the analysis and interpretation of unstructured data, facilitate the identification of patterns and anomalies, and support decision-making processes in complex forensic investigations.

Decision-making intelligence, which encompasses the ability of AI systems to make optimal decisions based on data patterns and support decision-making processes, was found to have the strongest positive influence on digital forensic engagements among the three AI capabilities examined. This finding underscores the potential of AI-based decision support systems, expert systems, and automated planning tools to augment forensic accounting practices by providing data-driven insights, identifying potential fraud scenarios, and recommending appropriate courses of action.

Furthermore, the study revealed that artificial intelligence certification is significantly adequate for digital forensic engagements in Nigeria. This finding suggests that the existing professional certifications and regulatory frameworks related to AI in the field of forensic accounting and auditing are perceived as sufficient by practitioners and academics. However, it is important to note that the descriptive statistics indicated relatively lower mean scores and higher variability in responses related to the control of entry and standard regulations surrounding AI certification, which could warrant further investigation and potential improvements in these areas. The adequacy of AI professional certification is crucial for ensuring the competence, ethical conduct, and public trust in the application of AI technologies in forensic accounting practices. The findings highlight the need for continuous efforts to maintain and enhance the body of knowledge, ethical codes of conduct, and regulatory oversight mechanisms to keep pace with the rapid advancements in AI and its increasing integration into various domains, including digital forensics.

Additionally, the study did not find a significant difference in the perceptions between practitioners and academics regarding the relevance of AI certification for digital forensic engagements in Nigeria. This result

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suggests a general consensus among these two groups on the importance and potential impact of AI technologies in enhancing forensic accounting practices and addressing the challenges associated with digital forensic investigations. However, it is worth noting that the descriptive statistics revealed slight variations in the mean scores between practitioners and academics, with academics having a slightly higher mean score on the relevant survey items. While this difference was not statistically significant, it could indicate potential nuances or varying emphases in the perceptions of the two groups, which could be explored further through qualitative or mixed-methods research approaches.

The findings of this study have several implications for theory, practice and policy. From a theoretical perspective, the results contribute to the growing body of knowledge on the applications of AI in forensic accounting and auditing, particularly in the context of digital forensic engagements. The study provides empirical evidence supporting the positive influence of AI capabilities on forensic accounting practices, aligning with and extending existing theoretical frameworks and conceptual models in this domain .

Limitations of the study

While the study provides valuable insights, it is important to acknowledge its limitations. First, the sample was drawn from practitioners and academics in Nigeria, which may limit the generalizability of the findings to other geographic contexts with different regulatory environments and professional practices. Future research could explore cross-cultural comparisons or expand the scope to include a more diverse and internationally representative sample.

Additionally, the study relied on self-reported perceptions and attitudes through a survey instrument, which may be subject to response biases or limitations in capturing the nuances and complexities of the research topic. Complementing the quantitative approach with qualitative methods, such as interviews or focus groups, could provide deeper insights and a more holistic understanding of the interplay between AI capabilities, professional certification, and digital forensic engagements.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The integration of artificial intelligence (AI) technologies into digital forensic engagements has the potential to revolutionize the field of forensic accounting and auditing. This study aimed to investigate the influence of AI capabilities, namely perceptual intelligence, cognitive intelligence, and decision-making intelligence, as well as the adequacy of AI professional certification, on digital forensic engagements in Nigeria.

The findings revealed that all three AI capabilities have a significant positive influence on digital forensic engagements. Perceptual intelligence enhances the ability to perceive and process sensory input, cognitive intelligence enables mimicking human behavior and reasoning, and decision-making intelligence supports optimal decision-making based on data patterns. Additionally, the study found that AI professional certification is significantly adequate for digital forensic engagements in Nigeria, highlighting the importance of maintaining robust certification programs and regulatory frameworks. Furthermore, the study did not find a significant difference in the perceptions between practitioners and academics regarding the relevance of AI for digital forensic engagements, suggesting a general consensus on the importance and potential impact of AI technologies in this domain.

Recommendations

Based on the findings of this study, the study recommends that Forensic accounting and auditing firms should prioritize investments in developing and integrating AI capabilities, particularly perceptual intelligence, cognitive intelligence, and decision-making intelligence, to enhance their digital forensic engagements. This can be achieved through the adoption of relevant AI technologies, workforce training, and collaborations with technology providers or research institutions.

Professional bodies and regulatory authorities should continuously review and update AI professional certification programs, ensuring they align with the latest advancements in AI technologies and address emerging challenges and ethical considerations. This may involve incorporating AI-specific courses, certifications, and ethical guidelines into existing professional development frameworks.

Suggestions for Further Research

Though the findings of this study are of great importance, there are opportunities for further research in this area. Future studies could expand the scope of research to include a more diverse and internationally representative sample, allowing for cross-cultural comparisons and exploring potential differences in the adoption and perceptions of AI technologies in digital forensic engagements across different regions and regulatory environments. Also, Complementing the quantitative approach with qualitative methods, such as interviews or focus groups, could provide deeper insights and a more nuanced understanding of the interplay between AI capabilities, professional certification, and digital forensic engagements. Mixed-methods research designs could offer a comprehensive and holistic perspective on this research topic.

While this study focused on the general context of digital forensic engagements, future research could examine industry-specific applications and challenges of AI in forensic accounting and auditing. For example, investigating the use of AI in detecting and preventing financial fraud in specific sectors, such as banking, healthcare or government, could yield valuable insights and practical recommendations. By pursuing further research in these areas, the body of knowledge surrounding the intersection of AI and digital forensic engagements can be further enriched, facilitating the development of more effective and responsible applications of AI technologies in this critical field.

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