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Integration of Artificial Intelligence in Auditing:

The Effect on Auditing Process

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Abstract

Business growth comes with complexity in operations, leveraging on the use of technology-based decision tools are becoming prominent in today's business world. Consequently, the audit profession is tuning into this change with the integration of artificial intelligence systems to stay abreast of the transformation.

The study is a qualitative research. It adopted an abductive approach. Data used for the study was collected through a semi-structured interview conducted with auditors from auditing firms within Sweden that has adopted the use of AI-based tools in their audit process. 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 strongly agree 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.

Acquiring adequate skills in handling the AI tool and sound professional skepticism of auditors was seen to be an underlying factor that would further boost the interaction between AI tools and audit process. This prompted the need to modify the initially drawn research model to include skills in handling IT tools and audit professional competency. This which substantiated the abductive approach of the study.

Keywords: Artificial Intelligence (AI), Audit Process, AI in Auditing, Audit Effectiveness

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CHAPTER 1

1. INTRODUCTION

1.1. Background to the Study

Technological advancement is transforming the world at an ever-increasing pace. Business growth comes with complexity in operations, leveraging on the use of technology-based decision tools are becoming prominent in today's business world. This means more data are being produced by companies (Gepp, Linnenluecke, O'Neill, & Smith, 2018, p. 23-34), as such; audit firms have the responsibility to stay abreast of this change with equal investment in advanced technology-based tools to effectively examine the high volume of data been generated for efficient analysis of a company's businesses and its risks (KPMG, 2016). Consequently, the auditing profession is tuning into this change with the integration of artificial intelligence systems to stay abreast of the transformation.

Artificial Intelligence (AI) is a term first coined by John McCarthy, a renowned computer scientist, in 1955-56 at the Logic Theorist program initiated by Allen Newell, Cliff Shaw, and Herbert Simon presented at the The Dartmouth College Artificial Intelligence Conference to showcase how machines can be made to mimic the problem solving skills of humans (Havard Business School, 2017). McCarthy defined AI as "the science and engineering of making intelligent machines"(Hernández-Orallo, 2017 p.397). Also, AI which stands for the use of computerized systems to complete tasks ordinarily completed by human intelligence, is quickly becoming a topic of interest (Sotoudeh et al., 2019 p. 45-50). The first AI-based project occurred over sixty years ago when scientists attempted to design software that could translate between the Russian and English languages (Ilachinski, 2017 p. 14-29). This project happened at the height of the cold war, with America acting the principal financier. Although the project was feasible, the progress was the only average due to the limited computer-capabilities of the day. Recent advancements such as IBM Watson, together with the AlphaGo programs, moved scientists closer to artificially intelligent systems. Although the globe is yet to design an AI system capable of replacing the natural human, the possibility of such an achievement is increasing (Ilachinski, 2017 p. 10-25). The upcoming overreliance on AI makes it difficult to imagine a sector that will not be affected by AI. AI is comparable to computers and spreadsheets. Initially, the inventions seemed to change a few industries. As time passed, technology became an integral part of all sectors. It is playing a significant and evolving role in how we understand and interact with the world around us. For instance, Deep Shift survey report on *Technology Tipping Points and Societal Impact* presented at the World Economic Forum 2015 indicated that 75% of the respondents (which are made up of 816 executives and experts from information technology and communication sector) agreed that a tipping point of 30 percent of corporate audit performed by AI will be achieved by 2025 (World Economic Forum, 2015).

The idea of artificial intelligent technology in auditing is not entirely new because it has been useful as a decision support tool for computer audit specialists in decades past (Hansen & Messier Jr., 1986, p. 10-17). However, due to continuous advancement in technology, availability of big data and processing power, there is reason to believe that it will continue to make a significant impact in auditing field now and in future years (Kokina & Davenport, 2017, p. 115-122). As a result of exponentially increasing data, auditors need to enhance the processing capability while maintaining the effectiveness and reliability of the audit process. One of the strategies of attaining this objective is the introduction of AI-based technology to automate tasks initially completed through manual input. As AI systems continue to grow mainstream, it is difficult to visualize an aspect of auditing that will not require AI-related assurance or AI-assisted advisory services (Kokina & Davenport, 2017, p. 115-122).

Despite the technological evolution over the past years, the aim of the audit profession remains "providing independent third party opinion" on the truth and fairness of the financial statement of an organization and the compliance of this information with the applicable standards (Omoteso, 2012, p.84-90). Kokina & Davenport (2017, p. 115-122), posits that auditing is particularly suitable for applications of data analytics and artificial intelligence because it has become challenging to incorporate the vast volumes of structured and unstructured data to gain insight regarding financial and nonfinancial performance of companies. According to Zhang (2019,p. 69-88), audit procedures are processes involving the progression of activities to "transform inputs into output." In this scenario, data stands for the input which is the information being audited while the output stands for the opinions of auditors (I.F.A.C., 2019). Along the same lines, automating audit tasks potentially speed up completion of audit assignments while maintaining the integrity of the data. One of the ways through which A.I. is transforming auditing is through automatic analysis of accounting entries (Baldwin, Brown, & Trinkle, 2006). The benefit of using A.I. to make automatic entries is the reduction of human error. Other than reducing human interference, A.I., in some cases, can also detect fraudulent intrusion and raise the alarm at the head office (Moffitt, Rozario, & Vasarh, 2018).

This function is exceptionally high when companies apply deep learning (an A.I. expert tool) (Zhang, 2019).

Deep learning is the part of machine learning that engages in the deep analysis of trends by learning the underlying frameworks as opposed to the "outer" behavior of systems (Zhang, 2019). Once applied in auditing, deep learning requires machines to understand how and why transactions are entered in a particular way (Zhang, 2019, p. 14-16). Initially, the focus of the machines would be to understand the trends of transactions as opposed to the reasons for the transactions (Raji & Buolamwini, 2019, p. 20-98). For instance, AI systems can review contracts regularly to determine the progress or make recommendations. At the same time, AI systems pool and analyze information hence making it easy for auditors to identify important areas that require increased attention (CPA, 2017).

1.2. Problematization

The increasing pace of the use of information technology (IT) tools by modern businesses has changed the ways in which companies record and disclose financial information (Mansour, 2016; Shaikh, 2005). Collation of transactions and disclosure of financial information are increasingly done with various technological tools to gather and preserve data electronically with less paper documentation (Arens, Elder, & Beasley, 2014; Foneca, 2003; Khemakhe, 2001; Zhao, Yen, & Chang, 2004 in Mansour, 2016), this which comes with a lot of complexity increases the capabilities of auditing to add value (DeFond & Zhang, 2014). These development pose a challenge to auditors of these businesses, for in order to stay abreast of the technology, competition, and audit effectively in such highly technologically advanced business environment (Shaikh, 2005; Mahzan & Lymer 2014; Mansour, 2016), it is expedient auditors are equally informed and equipped with advanced technology that can guide in exploring and understanding how the entity's financial transactions and other data has been collected, recorded, and processed (Mansour, 2016; Issa et al, 2016). In order to plan effectively and execute the audit assignment efficiently to form appropriate opinions on the entity's financial statements (Messier Jr., 2014; Shaikh, 2005; Mansour, 2016). Implementing AI-based technology in auditing meets this challenge for auditors with the possibility of automation of auditing procedure from stage to stage (Moffitt, et al,. 2018). This is already being done by some leading auditing firms. For example; KPMG adoption of AI capabilities from IBM Watson, this is done with the broad agreement to apply Watson - which has a wide variety of "application program interfaces (APIs)", to the firm's various auditing processes

(Lee 2016; Melendez 2016 in Kokina & Davenport, 2017). Another example of this is Halo developed by PricewaterhouseCoopers (PwC) - an analytics platform that serves as a pipeline to AI and augmented reality products (M2 Presswire, 2016). So also, is Argus for AI developed by Deloitte (Kokina & Davenport, 2017). These developments are in the bid to enhance effectiveness of each stage of auditing processes.

Understanding steps involved in the process of auditing makes it possible to understand the importance of integrating AI for the effectiveness of the tasks. There are structured and repetitive tasks to be performed all through each step of audit assignment which are labour intensive (Rapoport 2016; Kokina &Davenport, 2017). From pre-engagement to presenting opinion through an audit report, effectiveness is crucial to each of these stages (Kokina & Davenport, 2017). One of the components of the auditor's work is to sample the data under analysis. Both random and non-random sampling introduces the risks of omission and commission (Bailey, Collins & Abbott, 2018, p.159-180). Traditionally, auditors were only capable of reducing risks as opposed to eliminating them. One of the ways of lowering auditing risks is to increase the sample size hence ensuring that all items have an equal chance of inclusion. Despite an increase in the size of the sample, auditors could not eliminate the risk of failing to detect material errors. Currently, auditors rely on CAATs, commonly referred to as Computer Assisted Auditing Techniques (Mansour, 2016). These tools enabled auditors to perform data analysis without the need to pull sample sizes. At the same time, tools such as Interactive Data Extraction and Analysis (IDEA) also introduce this capacity, but the ultimate data organization and processing still requires intensive human efforts. Another exhausting activity in auditing is the review of critical documents (Mansour, 2016). For instance, auditors must review all key contract documents to extract vital information such as pricing, discount rates, and timing of payments. The introduction of AI systems enables auditors to review records and obtain critical information in a short time (Omoteso, 2012).

Despite the outstanding ability of AI systems in improving the quality and effectiveness of auditing, there is a list of challenges which is gradually being improved on as AI technology keeps evolving, with the adoption of deep learning and capacity for larger storage space and large data population (Issa, Sun, & Vasarhelyi , 2016). The first of these challenges is the lack of sound data management and governance. After the increase in the capture, processing, as well as storage of new data, organizations need to scrutinize the organization of company data. Other than ensuring proper organization and accessibility of data, the management also ensures maintaining integrity at all levels of the organization by proper adherence to control measures through audit automated systems that can scrutinize the data on an ongoing process(Cannon & Bedard, 2017; Knechel & Salterio, 2016). As part of auditing processes, risk assessment is done to be aware of the susceptibility of the entity to threats. Risk assessment according to (Ramamoorti, Bailey, & Traver, 1999) "is a systematic process for identifying and analyzing relevant risk or the identification and analysis of relevant risks threatening the achievement of an entity's objectives, risk assessment is helpful for assessing and integrating professional judgments about probable adverse conditions and/or events"p.159. In audit planning, risk assessment has to do with "pattern recognition", of which unanticipated deviation from such gives an indication of risk (Ramamoorti et al, 1999)p.160. AI technologies can be deployed to effectively automate this task by "identifying patterns within a large volume of transactions" to detect and flag any unexpected change in the pattern (ACCA GLOBAL, 2019). According to Raji and Buolamwini (2019), AI automates many auditing tasks such as data entries that previously required manual efforts. Unlike human auditors, AI systems can analyze 100% of data, create audit tests, and prepare scripts. The system used requires machines that have in-built algorithms that enable the machines to learn the incoming data. Risk assessment is a crucial task to carry out when planning an audit, as such, leveraging an AI-based system would aid the effectiveness and efficiency of the job.

Some internal audit teams are already applying machine learning to the control of transactions and the completion of general auditing roles (Omoteso, 2012). In particular, the teams are using machine learning to some of the areas that are prone to fraud (Boillet, 2018). For instance, purchasing and manual system entries. This invention is proving to be helpful not only to auditors but also to other stakeholders who intend to oversee the transactions. In the end, the stakeholder finds it easy to visualize the trends and raise queries when anomalies arise (Moffitt, et al,. 2018). The use of machine learning is enabling machines to predict the trends in critical transactions (Boillet, 2018). The systems also provide insight into risk assessment, project scoping, issue identification, sub-population identification, and quantification. The internal audit teams can execute these AI systems with limited configuration using off the shelf configurations. Examples of these configurations include the decision tree, affinity analysis, and k-means clustering (Chiu, & Scott, 1994; Connell, 1987; Fanning, Cogger, & Srivastava. 1995). NPL is enabling auditors to scan through large volumes of documents, which may consist of contracts, loans, and other types of unstructured data (Knechel & Salterio, 2016). According to Knechel and Salterio (2016), NPL is a programming language with the capability of pattern matching designs. The software can easily match and compare the pattern of accounting entries. The ability of A.I. systems to work with unstructured data and extract relevant data points is an essential advancement from the traditional models where automation was only for structured and clearly labeled data.

As current and interesting the topic of AI in auditing appears to be, only limited study is available on the on-going transformational effect the emerging technology is having on the audit process most especially on the effectiveness it brings to audit processes. Some studies provide potential biases associated with the introduction and use of AI (Brown-Liburd & Vasarhelyi, 2015; Yoon, et al., 2015), it has been documented in some that big data can be used as more audit evidence (Alles and Gray, 2016 in Vasarhelyi, 2018) while others discuss the characteristics of Big Data analytics in auditing, which differentiate it from traditional auditing (Kokina & Davenport, 2017; Omoteso, 2012).

The exhausting nature of auditing largely contributes to the lack of effective and efficient audit processes (Ransbotham et al., 2018, p. 76). As it has been documented in studies that when it comes to complex tasks that required pulling together excessive information from numerous sources, humans do not perform at their best (Kleinmuntz 1990; Iselin 1988; Benbasat and Taylor 1982 in Issa et al, 2016). The modern corporate world is facing serious corruption incidences hence the need for sophisticated, stealth, and automated auditing systems (Knechel & Salterio, 2016, p. 15-69; Siriwardane, Hoi Hu, & Low, 2014, p.193). The need to examine audit effectiveness and methods of improving it is further necessitated by the number of published cases in both financial and quality auditing from time to time (Beckmerhagen, Berg, Karapetrovic, & Willborn, 2004; Siriwarde et al, 2014). In view of this, this study aims to add to knowledge by exploring how this emerging technology - AI, is transforming the audit process. Particularly explore the interaction between AI-based systems and auditing processes and how this enhances effectiveness of the process from the perspectives of the users of the tools.

1.3. Purpose of the study

The purpose of this study is to explore the effects of AI-based systems in enhancing effectiveness of auditing process by exploring the interaction of auditing process with AI tools. Since AI is still at the infancy stage, it is hoped that determining this benefits will contribute to knowledge in this emerging study area and equally spur corporate governors to advocate for the integration of AI systems with the consideration of Accounting and Auditing departments (Hussain, Rigoni & Orij, 2018)p.9-23. In the end, it is hoped that companies will enhance the quality of audits through effective audit processes improved by accurate AI systems. (Hussain et al., 2018).

1.4. Research question

- How is AI enhancing the effectiveness of audit processes?

1.5 Structure

The rest of the paper is structured as follows: the next chapter presents theoretical framework

CHAPTER 2

2. THEORETICAL FRAMEWORK

The purpose of this section is to review the existing literature regarding the role of AI in auditing and discuss in detail the applicable theories to our study. The chapter starts with the presentation of the theoretical model for the study. This is followed by the overall process of auditing, AI and the use of AI in auditing. Next to that is the discussion on audit effectiveness and the variety of ways in which the use of AI based tools are enhancing the effectiveness of audit process. Finally, the chapter ends with discussing the professional approach to auditing, and a comprehensive research model drawn up for the study, capturing how these are all connected.

2.1. Theoretical Model

2.1.1. The Agency Theory

One of the main auditing theories is the agency model, which translates the relationship between managers and investors. The agent is the manager or another person appointed to act on behalf of investors who represent the principal. The principal assigns assignments to the agent for compensation (Bosse & Phillips, 2016, p. 6-15). The managers must act in the best interest of the investors. Research shows that in some instances, the agents fail to act in the best interest of the investors. As a result, auditing is important since it assures the investors that the managers are upholding the interests of the investors (Commerford et al., 2019). The responsibility of auditors in such a case is to provide guidelines to investors while playing the oversight roles. At the same time, the audit reports guide investors in making a purchase, sell, or hold decisions (Shogren, Wehmeyer & Palmer, 2017). For example, the reports enable investors to determine the probability of a company's bankruptcy. The inability of investors to access and use verified auditing results could result in excessive financial losses (Shogren et al., 2017, p. 89-99).

The growth in the size of companies leads to a growth in the volume of data requiring to be audited. As a result, auditors must continue to provide timely and reliable information to investors. The provision of this information must continue to meet the reliability standards which require auditors to significantly peruse the financial reports (Blair & Stout, 2017, p. 23-37). Providing both timely and reliable auditing reports is an exhausting task. AI systems is expected to provide a strategic advantage in the attainment of these objectives. First, AI enables remoteness, which is the analysis of financial statements from different locations (Blair & Stout, 2017, p. 36-40). Usually, remoteness arises from the separation of the source of information and users. Since investors cannot travel to the company's premises every time, AI systems will provide remote access and remotely assisted analysis.

Another way through which AI is expected to facilitate the agency theory is by eliminating the effects of the complexity of handling financial information and reports. Since information has become complex over the past years, users find it difficult to attain a high-value assurance of the quality of the financial reports at hand. Since the growth in company sizes increases the risk of errors, AI systems reduce the complexity of operations (Blair & Stout, 2017, p. 37-45). At the same time, AI supports agency theory by eliminating the conflict of interest. The release of financial reports resembles a situation where directors are reporting their performance (Blair et al., 2017, p. 45-56). The directors are, therefore, likely to report skewed performance. On the other hand, investors prefer to receive an accurate report reflecting the financial performance of the company. The use of AI systems will invariably facilitate the audit of financial reports, thus eliminating the conflict of interest.

2.1.2. The stakeholder theory

The stakeholder theory was started by Edward Freeman in 1984. It focuses on the organizational management of business ethics, addressing the values and morals of corporate management. Over the past years, the theory has become a focus of most studies with academicians integrating it into concepts such as corporate social responsibility (Jachi and Yona, 2019, p. 78-102). The theory stresses the interconnectedness of relationships between varying stakeholders. Examples include suppliers, employees, investors, and communities. The theory argues that rather than create value for investors alone, it should also create value for all stakeholders. The theory insists that corporate managers must select the best line of action (Noor, and Mansor, 2019, p. 24-35). In the industry of auditing, the appropriate line of action is the provision of verified and timely financial information. Since the volume of information is increasing, the integration of AI in auditing will enhance the value created for all stakeholders.

Also, Jachi and Yona (2019) add that for pursuing the stakeholder theory, managers should also pursue the reliability of the information. In particular, the availability of an extensive amount of data and decreased room for errors will significantly enhance the reliability of the automated audit process. In auditing, safety is a result of producing quality work and sufficient information for clients. The use of artificial intelligence enhances effectiveness and quality, which will increase the reliability of audit reports by customers (Jachi and Yona, 2019, 14-20). According to the majority of auditors, automating auditing with AI reduces the room for human error, expanding the popularity and security among clients (Omoteso, 2016). Through AI, auditors can draw reliable conclusions rather than speculate on what could have gone wrong as in the conventional audit methods. Also, an automated audit process is efficient and dependable in data recovery as compared to traditional audit processes.

2.1.3. The theory of inspired confidence

The theory of inspired confidence was developed by Limberg, a Dutch Professor. The theory focuses on both the demand and supply of auditing services. The theory provides that the demand for audit services is a direct outcome of the engagement of a company's external stakeholders. The stakeholders demand accountability from the management. Since the reports provided by managers may be biased, there emerges a sharp conflict of interest (Mathias & Kwasira, 2019, p. 90-102). As a result, the need to audit these financial reports arises. The theory adds that the overall purpose of audit should be to meet the expectations of an average interested party. As a result, auditors should strive to meet these expectations.

A close analysis of the theory of inspired confidence shows that the integration of AI systems is a strategic step with long term positive advantages. Modern companies are increasingly having large operations and an enormous amount of data to be audited (Mathias & Kwasira, 2019, p. 90-102). Since human auditors are unable to cover that vast amount of information promptly, the entire auditing profession could gradually become a failure in that regard. The relationship between the theory of inspired confidence is available from Mathias and Kwasira (2019), who find that timely provision of information will enhance the quality of audits. The use of artificial intelligence in auditing saves time through a fast and accurate collection of data. Less time in data collection allows the auditor to embark on data analysis, quickly enhancing the timing of results. Automation of the auditing process improves the speed of audit since auditors can continue auditing in real-time. Artificial intelligence in auditing will enable the auditors to acquire accurate and up to date data whenever there is a need (Elewa & El-Haddad, 2019). An automated audit is essential since it allows the auditors to provide sufficient information to stakeholders and detect anomalies in time.

2.1.4. The credibility theory

The credibility theory provides that the primary function of auditing is to increase the credibility of financial statements. The financial statements are used by corporate managers to enhance the faith of the agents by reducing the asymmetry of information (Chen, Dong, & Yu, 2018). Since the management desires to influence the decisions of investors, there arises a conflict of interest, which then decreases the credibility of financial statements from the perspective of investors (Al-Shaer & Zaman, 2018, p. 78-85). In the end, it becomes necessary to hire independent auditors who can review the financial information and inspire confidence. The ability of auditors to conduct comprehensive and timely reviews of financial reports largely determines the level of credibility achievable. Since the integration of AI systems increases the speed and quality of auditing, it emerges as a necessary step.

The relationship between AI in auditing and the credibility theory is also affirmed by Chen, Dong, and Yu (2018), who find that automation of audit process will primarily increase audit quality. The standardization of the auditing process and the data will reduce the capacity for human errors. It will be possible for auditors to view the exact level of data correctness, for instance, indicating 60% instead of indicating that the materiality is correct (Matonti, 2018, p. 12-20). Besides, automation of the auditing process will improve the quality since instead of sampling, the auditors can view the entire population drawing practical conclusions based on the data available (Matonti, 2018, p. 12-27). Audit quality will increase with the automation of the auditing process to enhance its effectiveness and progress with continued technological innovations. As identified earlier, some firms are exploiting audit software, which has immensely increased the quality of recent audits and the effectiveness of the process. It is valid that the use of AI audit software might not immediately result in overall benefits because of the observed cons in the emerging technology, but the auditing process effectiveness and quality will increase as the program becomes more stable.

2.2. The process of auditing

Understanding the process of auditing makes it possible to understand the importance of integrating AI. Audit processes are the activities undertaken by auditors to obtain evidence to form appropriate opinions on the financial statement of an entity. No two audit processes are exactly the same because the procedures usually depend on the risk factors and effectiveness of the internal control system of the client (Kearney, 2013,p.142). AI is adaptable to enhancing effectiveness in each step of activities in audit process. It is likened to an assemblage in which an output of one step becomes the input of the next step to it (Issa et al, 2016; Kokina & Davenport, 2017).

The main steps of auditing include pre-planning (Pre-engagement), planning, understanding the entity, risk assessment, documentation, completion, and reporting (Knechel & Salterio, 2016). The first stage of auditing is the pre-engagement steps. The purpose of pre-engagement is to enable the auditors to decide whether it is appropriate to accept new clients in addition to the existing ones. For this purpose, the auditors check the internal procedures and policies of the company to decide whether the client should be accepted (Knechel & Salterio, 2016, p. 56-60). At this stage, the auditors review the extent to which the policies limit the integrity of accounting procedures. Also, the auditors check for the integrity of the company's management, compliance, and the existing or potential threats (Cannon & Bedard, 2017, p. 24-30). Some of the reasons that cause auditors to decline incoming clients include lack of expertise, poor compliance, and overwhelming scope of work. It will be interesting to explore how AI influences this step of the process because this step has been known to mainly involve auditor to client, human-to-human interaction.

The next step in the auditing process is planning. The purpose of planning is to develop the overall strategy to be applied by the auditor from the start to the end of the process. Although, unforeseen events may sometimes occur that may warrant changing the audit strategy (Kearney, 2013, p. 169). The outcome of the planning process is the auditing plan that defines the entire audit strategy, the extent, nature, and timing of work (Knechel & Salterio, 2016, p. 57-60). Good planning is key as it helps in the determination of the appropriate audit strategy, scope and how to handle the risks factor timely to have an effective and efficient complete audit(Cannon, 2017, p. 90-91). Also, the planning process involves the outlining of the steps to be followed. Some of the measures include understanding the entity, internal controls, and the existing risk. Additionally, the planning also entails the definition of the scope of the auditing, timing, financial reporting framework, key dates, materiality, and the initial assessment (Kearns,Neel , Roth , & Wu, 2017, p. 45-60).

Next to that step is the understanding of the entity's control environment (Bailey, Collins & Abbott, 2018. p159-180). This is part of the execution phase. This understanding enables the auditor to foresee the risk of material errors. Auditors are expected to get a thorough view of the client and the industry it operates in (Cannon, 2017, p. 92). Some of the items considered at this stage include industrial, local, and international regulations (Collins & Quinlan, 2020, p. 13-16). Other key considerations include the nature of the organization, internal controls, and the history of the organization. This step is followed by the documentation and audit evidence. The purpose of this step is to gather evidence to support the audit opinion. At this stage, the auditor can perform the test of controls to test the system (Bailey et al., 2018). Adequate compliance test on procedures and substantive test is required to ascertain the effectiveness of the internal control in place. These tests enable the auditor to believe in the system's credibility or to question it. At this stage, the auditor only concentrates on the critical control accounts or areas where weaknesses are common (Shen, Chen, Huang, & Susilo, 2017, p. 12-15). Also, the auditor can engage in substantive procedures. Examples include the assessment of each transaction and the balance of critical entries.

The final step in the auditing process is closure (Żytniewski, 2017). This step requires the auditor to evaluate the appropriateness of the evidence gathered for the auditing process. The completion process requires the auditor to ensure that the entire process has been documented, and the evidence is appropriately organized (Sikka, Haslam, Cooper, Haslam, Christensen, Driver, & Willmott, 2018, p. 34-52). Some of the activities included in the completion process include the analytical procedure, review of subsequent events, the going concern confirmation and reporting.

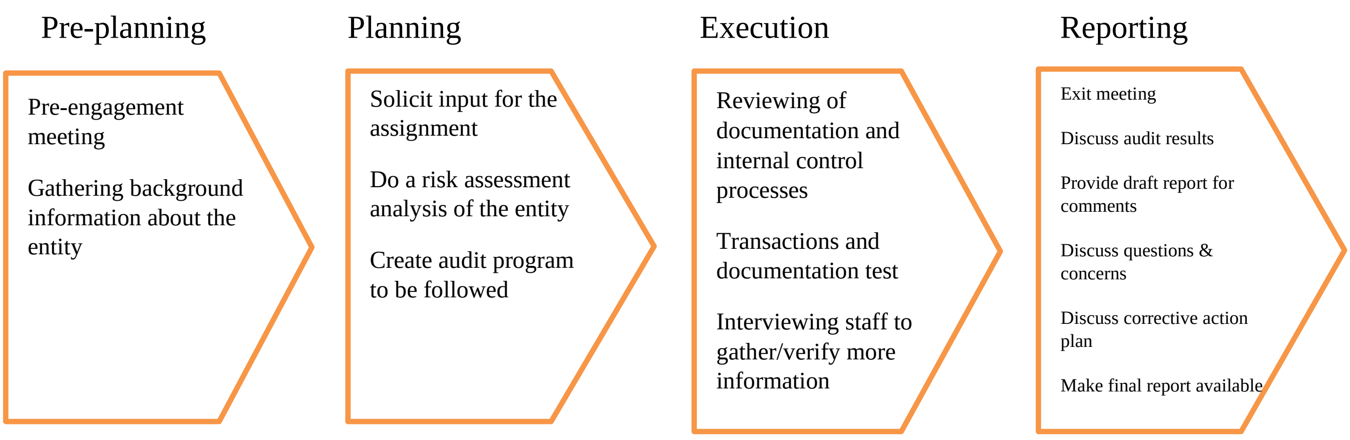

figure 1

Audit process model

2.3. Artificial Intelligence

Artificial Intelligence (AI), also known as machine intelligence according to Ransbotham, Gerbert, Reeves, Kiron & Spira, (2018) stands for the integration of human-like intelligence in machines. The basic idea in AI is to understand the context and make intelligent decisions based on the information at hand. Kokina & Davenport, 2016 view AI as synonymous to cognitive technology or cognitive computing with the level of intelligence suitable to perform cognitive tasks. While O'Leary (1987, p. 123) defines AI as a broad term that includes various activities like pattern recognition by computers, expert systems, deep learning and reasoning by computers, natural language use by computers and the likes. AI is also described as a "computer program that can take balanced decisions, observe its environment and take actions that maximizes its chances of achieving a goal"(Issa et al, 2016). Lu, Li, Chen, Kim, and Serikawa (2018, p. 34-37) define AI as the umbrella of activities that enable machines to complete tasks ordinarily completed by natural humans. Examples include expert systems, recognition of patterns, learning as well as reasoning by computers. In comparison, Gunning (2017, p. 45-59) defines AI as a computer program capable of making balanced decisions based on the existing context. The overall outcome of using such a system is the enhancement of decision goals. For this attainment, the AI system must be capable of mimicking human actions such as image identification. Jackson (2019, p. 45-47) adds that the proper operation of an AI system requires high operation capacity and large volumes of data. Artificial intelligence for the audit area is described as "a hybrid set of technologies supplementing and changing the audit" (Issa et al, 2016). Gartner, 2017 in his study posits that AI is anticipated to be prevalent in almost all "new software products and related services by 2020" (Sulaiman, Yen, & Chris, 2018)p.3. This is evident in the development of most software so far.

2.4. AI in Auditing

AI as described by Issa et al. (2016) is a computer program with the capability of taking balanced decisions, mimicking "cognitive" function associated with the human mind, and able to observe its environment and take actions that maximizes its chances of attaining a goal. Integrating AI in each step of auditing process will remove the repetitive tasks common in the process and make analysing large volumes of data to have an in-depth understanding of the business operation easier for auditors (Kokina & Davenport, 2017). Making it easier to concentrate on activities that will bring utmost value to the clients (Luo et al., 2018). As assessing the risk of material misstatement is a crucial part of the auditing. Auditors are expected to carry out tests on the transactions to make certain that there are no misstatements, for if financial impacts are not accurately recorded, financial statements are bound to be materially misstated. If unauthorized transactions and/or other irregularities are not detected in time, it may be challenging for auditors to capture such later (Shaikh, 2005, p. 16-20). AI-based tools in auditing makes detecting such high-risk transactions easy. This which manual auditing may sometimes not capture fully as a result of sample population testing unlike the AI technology that allows for full population testing.

According to Oldhouser, (2016) in the implementation of technologies, auditing profession is seen to be lagging behind the business field (Issa et al, 2016). The field however is researched to be well suited for advanced technology and automation as a result of its "labor intensiveness and range of decision structures" (Issa et al, 2016)p.1. Rapport, (2016) equally posits that AI capabilities in audit is especially centered on "automation of labor-intensive tasks" (Kokina & Davenport, 2017. p.116). Baldwin, Brown, and Trinkle (2006) in their study recap prior uses of variety of AI-based systems in auditing to involve performance of analytical review procedures and risk assessment, assist with classification tasks (e.g., collectible debt or a bad debt), materiality assessments, internal control evaluations, and going concern judgments. As the advent of computers transformed the scope and methods of audit examination, the advent of analytics is also changing the timing of audit, making it more proactive than reactive and generally increasing the effectiveness and efficiency. The advent of AI brings in cognition into automation. Making possible adoption of tools that can mimic human-like activities in audit processes and perform the tasks much more effectively (Issa et al, 2016). Potentially enabling organizations to achieve set objectives of quality and effective audit assignment within a reasonable time frame and cost (Deloitte, 2015).

2.5. Audit Effectiveness

Audit effectiveness has different meanings to different people. While some judge audit effectiveness from the result of an audit assignment, others view it from their perception of the audit firm itself. The formal meaning revolves round "the quality, competence, procedures and independence of the audit firm" (Audit Committee Chair Forum ACCF, 2006). Audit effectiveness can formally be regarded "as a composite of competence, procedural arrangements, quality control and quality assurance. The procedural arrangements can be regarded as the tools used by firms and individuals to ensure that audits comply with technical standards, i.e. legal requirements, regulators' requirements and auditing standards set by the

APB [Auditing Practices Board], and taking into account the supplementary material in APB Practice Notes and Bulletins"(Audit Committee Chair Forum ACCF, 2006). Audit procedures can be seen as "direct consequence of available technologies" (Issa et al, 2016). ISO 9000 (2000) defines effectiveness as the "extent to which planned activities are realized and planned results achieved" (Beckmerhagen, Berg, Karapetrovic, & Willborn, 2004). This invariably means comparing the audit process and its achieved outcomes with the set objectives.

This study sees AI-based systems in auditing as those tools adopted in the auditing process for ease of the assignment and that still ensure compliance with all required standards thereby enhancing the effectiveness of such process.

Audit effectiveness stands for the extent to which an audit accomplishes the primary objectives. On the other hand, audit efficiency stands for the extent to which an audit exercise delivers the highest possible value based on a fixed level of input. Examples of inputs include managerial time, training, and company funds (Noraini et al., 2018, p. 23-46). There are a variety of ways through which AI is introducing both audit effectiveness and efficiency. Commerford, Dennis, Joe, and Wang (2019, p. 56-62) opined that AI is maturing at the "right time". These days, auditors must peruse a large pool of information and make sense over a short period. For instance, entering the accounting information in the auditing software can enable auditors to collect processed data in the background (Van Liempd et al., 2019). After receiving the outcome, the auditors must judge the outcomes of the research exercise professionally, applying the professional knowledge of auditing. At the same time, the auditors must continue to observe the professional requirements, such as sharing the auditing information through data-sharing platforms (Rezaee et al., 2018). The sharing of information will enable the auditors to receive and compare data with other auditors across the industry.

Other than the methods classified above, Noor and Mansor (2019, p. 64), also finds that AI enhances auditing through the proper exchange of information between the auditors and the systems. The authors note that AI enhances the conversation between all stakeholders involved in the auditing process (Noor and Mansor, 2019, p. 64-65). In some embodiments, the AI systems use machine learning models to classify messages and increase the level of confidence for the auditors. If the threshold of the messages is low, the systems send the messages for further human analysis (Noor & Mansor, 2019, p. 64). This process is referred to as prioritization. In ordinary auditing methods, the same process is possible through the intervention of human auditors, albeit the slow classification process by a human. At the same time, the automated classification is effective because machines provide keywords that the auditors use to identify the priority areas.

Another way through which AI is transforming auditing is the elimination of redundant tasks. For instance, blockchain technology will revolutionize bookkeeping by eliminating the double-entry bookkeeping method (Omoteso, 2016, p. 23-65). The records of transactions between creditors and debtors will be recorded in blockchain networks. Both the debtors and creditors will have private accounts in the blockchain networks. This change will change bookkeeping from a process to an instantaneous entry. Once the first entry occurs, it reflects across the financial books at an instant. This ability will enable auditors to transfer all book entries into the blockchain technology, thus removing the conflict of interests that could affect the network (Omoteso, 2016, p. 45-52). At the same time, the immutability of blockchain technology as a general ledger will increase the value of AI to auditors (Raschke et al., 2018, p. 36-41). Rather than store the information on a central database, the system will provide a quality trail of the flow of information. A proper example of the applicability of technology relates to regulatory compliance. Usually, regulatory compliance is a costly and inefficient requirement for most companies. For instance, Kira systems created software that can analyze contracts as well as other documents such as leasing and merger agreements. Another example is the H&R system introduced by IBM through the AI platform (Commerford, Dennis, Joe & Wang, 2019, p. 10-15). The use of these systems assists clients in complying by filing reports in an orderly and verifiable manner.

Rather than foiling multiple documents for review, the regulators and firms can easily create data sharing points for easy exchange of information. The system takes care of factors that determine the compliance of the company in question. Examples include the date of filing, status, and ordinary income. IBM trained Watson by entering thousands of tax-related answers and questions. Through the use of this system, auditors can leverage the machine's knowledge to analyze information about the client (Joe et al., 2019). Similarly, Accenture uses AI to enhance the chances of fraud detection. The software analyzes data generated from transactions on a real-time basis. As a result, auditors can detect fraud at the time of occurrence. After detection, auditors intercept the transactions and prevent fraudulent networks that have a pattern of fraud. AI thus brings proactiveness into the audit process.

Another way through which AI is transforming auditing is the integration of real-time data analysis. Elliot (1994) studied the effects of AI on the auditing profession. The authors found that the integration of AI systems has both positive and negative effects on auditing. Initially, auditors focused on past information where auditors would verify the financial performance reported by managers. The introduction of AI in auditing systems changed the focus from past information to real-time data analysis (Elliot, 1994, p. 34-56). Modern investors prefer to make investment decisions based on real-time data as opposed to the past performance reports of companies. The appropriate approach to this requirement is continuous auditing, as opposed to auditing conducted after a fiscal period (Van Liempd et al., 2019). Rather than audit companies after the end of specific financial reports, companies should strive to provide relevant and timely information to investors. As companies record and conduct transactions, the AI systems would relay information to companies.

AI also makes the concept of continuous auditing which has been widely researched in modern academia a lot more easy. For instance, Alles et al. (2008) investigated the adoption and use of continuous auditing at Siemens. The company is large and can integrate continuous auditing. The outcomes showed that for the system to operate smoothly, there was a need to automate and formalize some auditing functions. Equally, PwC (2006) investigated the extent of continuous auditing in the United States. The report found that the extent of adoption is low, but the rate of adoption is gathering speed. Rikharddson and Dull (2016) also completed a similar study regarding the implementation of continuous auditing in medium-sized companies located in Iceland. The results showed that most companies applied AI technology to ensure that the data was both relevant and reliable. In most medium-sized firms, continuous auditing was a function of the internal audit. The ideal method would be to use it as a function of both internal and external functions. Even for companies that used continuous auditing for internal functions, managers could use more reliable and recent data. In the end, there emerged high-value cost control, increased revenues, and strong managerial strategies.

Another way through which AI is transforming the field of auditing is by enabling speedy and accurate collection of the audit evidence. According to Cascarino (2012, p. 37-103), audit evidence stands for the entire information collection that auditors collect to decide whether the financial reports presented by a company are honest presentations of the firm's financial position. AI is transforming auditing by enhancing the collection of auditing evidence. Yoon et al. (2015, p. 431) defined audit evidence as "the entire set of information collected and evaluated by auditors when deciding whether a firm's financial statements are stated following generally accepted accounting principles". Auditors are not required to examine every transaction or activity. Instead, it is required that they must have sufficient and appropriate evidence to justify their audit opinion (Yoon et al., 2015, p. 431). Auditors gather evidence that they deem relevant and useful in forming an audit opinion using various techniques such as inquiry, observation, interview, and test.

Over the past years, real-time accounting has been a challenge to auditing firms, and only a little progress has been made. However, the emergence of AI has given hope, and real-time accounting will cease to be a challenge (Cascarino, 2012, p. 37-103). Although the technology is new, auditors have confirmed that large companies have implemented the method on various transactions (Yoon et al., 2015, p. 431). Transactions with estimates and valuations cannot be processed in real-time due to the processing and recording, which require the assistance of an accountant. The first step after routine auditing is informing the management of the results and then the stakeholders. Real-time verification indicates a shift in the rational management of information since the accountants will report transactions to auditors directly as they happen (Cascarino, 2012, p. 37-103). In real-time auditing, the internal control system of a client needs to be continually monitored by the auditor to ensure the reliability of the information. In an efficient auditing environment, more focus will be to ensure the effectiveness and integrity of the internal controls (Shen et al., 2017). Through the real-time audit, the auditors can easily detect and identify errors and anomalies hence notifying the client in ample time. A real-time audit gives the auditors ability to monitor with the exception by setting a material level in the internal control system to uncover why anomalies and errors occur.

The automation of the auditing process will have an impact on the audit evidence and continue to change the collection manner of audit evidence (Omoteso, 2016, p. 32-41). Similarly, a black box file will be created to create an audit trail listing the errors, anomalies, and the occurred exceptions (Sikka et al., 2018, 47-56). The data will also act as evidence that the audit process was carried out and was up to standard.

The automation of auditing processes will enable companies to reduce the extent and frequency of human errors. Also, it will increase productivity, performance, and speed (Gunning, 2017, p. 89-92). Besides, the integration of AI systems will enable computers to complete tasks that require enhanced human cognitive abilities. Usually, people are reluctant to accept new technologies, especially when they disrupt the existing status quo (Commerford et al., 2019). One of the methods of disruption is the reduction in the number of jobs available. However, this cannot be proven as it is still a subject for further research.

When handling corporate information, there are two categories- structured and unstructured information. On one hand, structured information stands for organized data and which is easy to handle (Commerford et al., 2019, p. 96-104). On the other hand, unstructured data stands for information with minimal organization and which is challenging to handle. Other than the two categories, there are also semi-structured data which stands for information with a limited level of structures. According to Omoteso (2016), about 39% of the data audited is structured, 41% is semi-structured, while the remaining 20% is unstructured. Even though semi-structured tasks are higher than the other two categories, the structured tasks are especially susceptible to automation. This difference is because the semi-structured data also include substantive procedures as well as testing for internal controls. Elewa and El-Haddad (2019) believe that in the future, semi-structured data will become automated because the level of judgment required in handling this data is limited. Besides, the level of data employed in auditing is increasing over the recent past since auditors need AI and data analytics, thus meaning that structured tasks will be performed using AI technology as opposed to human auditors (Omoteso, 2016, p. 63-58).

2.6. Audit Ethics

An increase in automation will change the focus of auditing, as well as the roles and involvement levels of auditors. Despite these changes, the responsibility of auditors will remain unchanged. AI promises to enable the review of unstructured data while also enabling the review of information in real-time. These benefits apply to dispersed data as opposed to centralized information, thus widening the scope of accessing data (Samsonova-Taddei & Siddiqui, 2016, p. 23-44).

Despite the above-said advantages, auditors are supposed to use professional judgment while also maintaining professional skepticism. The benefit of skepticism is to ensure that auditors verify data before adopting it as the honest representation of a company's financial position (Raschke et al., 2018). The balance of professionalism and skepticism is a sensitive requirement which needs deep cognitive abilities. Although technology can mimic human abilities, it is unclear whether AI systems can maintain a high standard balance of the two functions. Besides, auditors are required to perform the concrete fraud risk assessment. According to Arfaoui, Damak-Ayadi, Ghram, and Bouchekoua (2016), the ability to conduct these assessments is important to the quality of auditing. Both entry-level auditors and AI systems may lack the capacity to conduct reliable risk assessment. Lombardi and Dull (2016) studied the benefits of implementing AudEx, another expert AI system meant to assess fraud risk factors. The system was for entry-level auditors or auditors with just an average experience. Lombardi and Dull (2016) discovered that using expert systems enabled entry-level auditors to make better findings in fraud risk assessment. Also, Lombardi and Dull (2016) found that the AudEx trained auditors to make better judgments in subsequent audits.

Another ethical implication facing auditors is the materiality concept. The concept provides that information is material if omitting, misstating, or obscuring it from the financial statements causes significant effects on the decision of investors (Arfaoui et al., 2016, p. 78-89). Before starting an audit, auditors must separate material from non-material information. Usually, materiality relates to misstatements that affect the entire financial statements. In some instances, materiality can arise from the accumulation of multiple immaterial errors (Arfaoui et al., 2016, p. 80-98). The integration of automated AI systems introduces minor errors that risks that can accumulate to cause material errors.

2.7. Professional approach to the Adoption of AI

A look at the professional angle to the adoption of AI in auditing profession is also expedient. Information technology advancement and availability of capable systems is not only changing how businesses are done but also transforming professions and professional work (Susskind & Susskind, 2015). This in a way will have a resemblance of how industrialization transformed the traditional craftsmanship according to Susskind & Susskind, 2015. Auditing is a knowledge intensive profession, knowledge of business law, accounting, corporate governance, taxation and principle of auditing are part of the training in the professional qualifications required of an auditor. Including other great personal qualities like integrity, objectivity, independence, ability to express and communicate and make good judgement are also qualities expected of an auditor in order to excel in the audit profession (Saxena & Srinivas, 2010). There is a guideline published in International Organization for Standardization (ISO), ISO 19011:2011, for auditing management systems which includes auditor competence requirements. Outlined in the guideline is an extensive list of competence requirements to ensure auditors and an audit teams have adequate skills to achieve audit objectives (International Organization for Standardization ISO, 2011). Using professional judgement and maintaining professional skepticism all through an audit process is required of an auditor (Eilifsen, Messier, Glover, & Prawitt, 2014).

“What one needs to know also depends in part on what others expect one to know” (Wilson, 1983: p. 150 in Olof & Jenny, 2005) as quoted from “cognitive authority” developed by Patrick Wilson on his study on that which relates to theory of professions. This is interpreted to mean “that both the status assigned to information as well as the kind of professional solutions that are considered socially appropriate, are negotiated by experts in different professional domains"(Olof & Jenny, 2005). Apart from the competence and skills required of professionals in their field, when making technology acceptance decisions, professionals can also be influenced by various factors such as personal inclinations to try out new technologies, social network interaction and/or cognitive resources “required for its effective utilization” (Yi, Jackson, Park, & Probst, 2006).

Away from the previous electronic systems that replaced paper-based systems in auditing, audit firms are increasingly adopting sophisticated, high-tech audit support systems to enhance effectiveness and efficiency of audit procedures(Dowling and Leech 2007; Banker, Chang, and Kao 2002). Which potentially gives firms competitive advantages above their peers (Carson & Dowling, 2012; Banker, Chang, and Kao 2002) by signifying the innovation and “sophistication of the firm’s audit process”(Dowling & Leech, 2014). As can be seen from the leading audit firms’ (the Big 4) adoption of AI-based systems in their auditing process. The models of future auditing must be different from the current ones due to the increased rates of transformation in technology. Examples of technologies transforming the industry of auditing include big data analytics, machine learning, and AI. Auditors slowly realize that the adoption of these technologies is increasing the efficiency of auditing.

Marcello et al. (2017) conducted a round table discussion on how the audit profession changed over the past years. One of the main discussions in the meeting was the use of technology in auditing. One participant was skeptical about the use of technology hence the belief that humans are better than machines. The underlying argument is that humans can independently analyze a context (Adler et al., 2018). This ability is widespread even in cases where humans lack previous exposure to such a scenario in the past. In comparison, AI systems can only handle a context after previous exposure to similar scenarios. Other participants in the meeting believed that machines could collect, analyze, and classify large volumes of data. This level of performance is difficult for humans. Other than that, Marcello et al. (2017) believe that in addition to learning patterns, machines will also learn to reason like humans.

The argument by Marcello et al. (2017) is valid since there are companies that have already adopted AI technologies in auditing. An example of these companies is PwC, a company that recently started to integrate AI systems into auditing. The technology is known as “Halo,” facilitates the scanning of massive information, which then enables auditors to make reliable risk assessments (Marcello et al., 2017). Furthermore, the technology can investigate and test accounting entries. After that, the system can identify high-risk transactions and align them for further analysis. Another example of AI systems is IBM Watson, a creation of both KPMG and IBM (PwC, 2016). The system enables companies to meet leasing requirements as stipulated in the IFRS 16. IBM Watson extracts data from lease documents and presents it for analysis. This ability ensures that the transactions involved in the agreement are accounted for in the right manner.

Although there may not be a radical change yet, the role of auditors will continue to change over time. This can be attributed to the technological side where developments are continuously evolving. Momodu et al., (2018) posits that various parts of the auditing process will be automated soon, while the full functioning technical integration will take a while to be realized (Momodu et al., 2018). Automation of the auditing process will bring changes in the normal auditing process, such as time spent in auditing. It will be an advantage to all the stakeholders in the industry since automation is not believed to reduce employment in the audit sector (Momodu et al., 2018). According to the responses in Momodu et al., 2018, auditors and AI can complement each other efficiently. Artificial intelligence would be focused on data extraction while the auditors concentrate on analyzing data and making decisions. Auditors can direct more time to consult with clients offering them more value for money and time. Studies given students in auditing should enhance their capacity to handle future technological developments in the auditing sector (Momodu et al., 2018). Research has indicated that universities have been slow in the adoption of curricula that match the technological changes in the auditing field.

2.8. Research Model

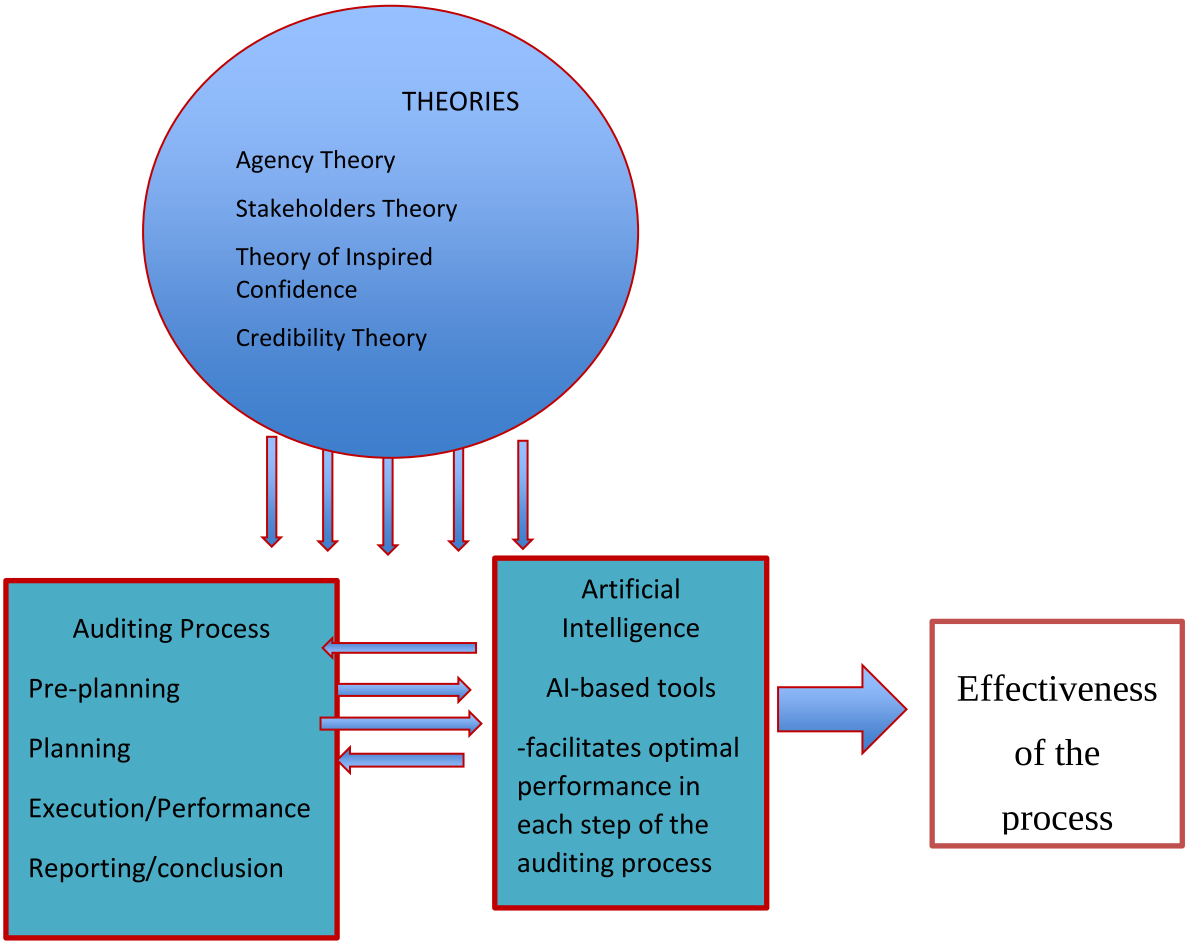

figure 2 Research Model

This depicts the graphical presentation of the theories and how it determines the interaction between the other key concepts of the study. From the relationship between the theories to its reflection on the interaction between AI tools and each step of the auditing process.

Starting from the agency theory which ensures assurance of protection of investors right to the stakeholders' theory that addresses interconnectedness of relationship between varying stakeholders to a business and that value for all stakeholders is upheld through the integration of AI in the auditing process of the entity, all through to the theory of inspired confidence that reiterates that the overall purpose of audit is to meet the expectation of an average interested party in the company's financial statement to the credibility theory which stresses the primary function of audit is to increase credibility of financial statements to enhance the faith of principals and other stakeholders in the financial report. The application of each of the theories determine the interaction between AI tools and the auditing process. AI based tools facilitate optimal performance in each step of the process. The two-way interaction between AI and auditing process is presumed to leads to an enhanced effectiveness of the process for the benefit of all stakeholders. This would be further authenticated/verified as the study progresses.

CHAPTER 3

3. METHODOLOGY

Research methodology refers to research strategy that explains the principle of epistemology and ontology into guidelines that denote how research is to be conducted (Sarantakos, 2005 in Tuli , 2010), and procedures, principles, and practices that guides research (Kazdin, 1992, 2003a cited in Marczyk , DeMatteo and Festinger, 2005 cited in Tuli, 2010). While quantitative research methodologies search for “regularities and principles” that are lawlike and are meant to give the same result every time it is tested in all given situations. Qualitative research seeks to “understand the complexities of the world through participants’ experiences. Knowledge through this lens is constructed through social interactions” (Tuli, 2010)p.103. The method to be used for this study is qualitative. As qualitative methodologies are usually known to be discovery and process oriented, with “high validity”, more particular about deeper understanding of the research problem in its “unique context” , and are less concerned with “generalizability” (Ulin, Robinson and Tolley, 2004 in Tuli, 2010)p.103 . This paradigm sees reality as human construct (Mutch, 2005). The answer to the research question “How is AI enhancing the effectiveness of audit processes” is shown at the end of the study after exploring and gathering empirical data from the auditors in the auditing firms that are already using AI technology for their audit process and were able to give detail analysis from their experience and reality of the difference AI makes in the effectiveness of audit process compare with traditional auditing or other previous technology they may have been using before the implementation of AI. This study follows an abductive approach. Abductive approach to research is the mixture of both inductive and deductive approach that allows researchers engage in a movement between theory and data back and forth so as to modify the existing theory/model or come up with a new one (Reichertz, 2004; Awuzie & McDermott, 2017). As posited by Malterud that “knowledge never emerges from data alone, but from the relation between empirical substance and theoretical models and notions” (Malterud, 2001p.486)

3.1. Epistemology position/ Interpretivism

The main epistemological debate in conducting social science research is "whether the social world" can be studied in accordance with "the same principles as the natural sciences" or not (Bryman, 2001 in Tuli, 2010)p.99. There are two broad worldviews to this epistemology positions; the positivism and the interpretivism-constructivism worldview. The positivists are of the opinion that the purpose of research is scientific explanation, this belief evolved largely from a nineteenth-century philosophical approach. The positivists explanation of social reality is that: empirical facts exist separately from personal thoughts or ideas; "they are governed by laws of cause and effect; patterns of social reality are stable and knowledge of them is additive" (Crotty, 1998; Neuman, 2003; Marczyk, DeMatteo and Festinger, 2005 in Tuli, 2010)p.100. As posited by Ulin, Robinson and Tolley (2004), the main assumption for this positivist paradigm is that science has the goal to come up with "the most objective methods possible to get the closest approximation of reality" (Tuli, 2010)p.100. Emphasis on closest approximation to reality not reality. Invariably, this paradigm separate people from their reality, with the position that knowledge is "objective and quantifiable" (Antwi & Hamza, 2015). Quantitative research mainly falls within this school of thought for it is basically "concerned with investigating things which could be observed and measured in some way" (Antwi & Hamza, 2015, p.1). While the interpretivist-constructivist view the world "as constructed, interpreted, and experienced by people" in how they interactions with one another and with social systems in general (Maxwell, 2006; Bogdan & Biklen, 1992 in Tuli, 2010, p.100). The nature of inquiry in this paradigm is "interpretive and the purpose of inquiry is to understand a particular phenomenon, not to generalize to a population" (Farzanfar, 2005). This is where most qualitative researchers draw inferences from. Interpretivism is the epistemology position employed for this study.

3.2. Ontology Position/ Constructionism

Objectivism and constructionism are the two broad contrasting positions of the ontology perspective; While objectivism posits that reality is independent of social processes, it is constructionism assumption that reality is the product of social processes (Neuman, 2003). Constructionism is chosen as the ontology position for this study because all participants in this research are social actors that have their individual reality and are constantly influenced by social processes.

3.3. Data Collection

Data collection is noted to be a crucial process in research, because the data is meant to contribute to a better understanding of a theoretical framework. As such it is important to select the method of data collection that will indicate such data is obtained with sound judgement, as no amount of analysis can make up for “improperly collected data” (Etikan, Musa , & Alkassim, 2016). Since interpretive researchers put great emphasis on how the world can be understood better through personal experiences, "truthful reporting and quotations of actual conversation from insiders perspectives" (Merriam, 1998 in Tuli, 2010,p.100) rather than just testing the laws of human behavior (Bryman, 2001; Farzanfar, 2005), methods of data gathering that denote sensitivity to context and enable the rich and detailed description of the social phenomena under study are being employed (Neuman, 2003; Tuli, 2010), where participants are encouraged to speak freely and understand the researcher's quest for insight into the phenomenon that the participant has experienced (Tuli , 2010). The method decided for data collection in this study is interview of auditors in different firms where A.I. has been implemented for their audit processes to get their in-depth perspectives from the experience of the phenomenon being studied. Nine auditors from various firms were interviewed. Seven male and two female. Two of whom are from the Big 4 audit firm. Interview session analysis with the dates of the interviews, positions of the auditors at the firm, gender, means through which the interview was conducted and length of the interview is presented in table 1 below to lend credence to the data for trustworthiness of the study. Names of the firms were omitted to keep to the assurance of anonymity promised the interviewees. All the interview sessions were conducted through social network medium as a result of the current situation of covid-19 pandemic ongoing in the world, which ruled out going to their offices for physical meeting as a result of the social distancing measures in place. However, the interviews were conducted through video means that made it possible to still see the participants and have a cordial interaction. The interviews were conducted in English language, the sessions were audio recorded and later transcribed into word file for ease of analysis and reliability purpose.

Interview Dates	**Participants**	**Position at the Firm**	**Gender**	**Interview means**	**Length of interview**
6 may	Auditor 1	Middle level auditor	Male	Skype	44 mins
7 may	Auditor 2	Senior auditor	Female	Zoom	48 mins
7 may	Auditor 3	Entry level auditor	Male	Zoom	40 mins

8 may	Auditor 4	Middle level auditor	Male	Skype	49mins
11 may	Auditor 5	Independent Senior auditor	Male	Skype	55 mins
14 may	Auditor 6	Entry level auditor	Male	Skype	40 mins
15 may	Auditor 7	Middle level auditor	Female	Skype	45 mins
18 May	Auditor 8	Entry level auditor	Male	Zoom	44 mins
15 May	Auditor 9	Entry Level Auditor	Male	Google meet	35mins

Table 1 Interview session analysis

3.4. Sampling Method

There are several sampling methods to choose from when conducting research. In the case of this study with the goal which is to explore the role of A.I. in auditing. It involved interviewing auditors to obtain their expert opinion on the topic under study. The targeted respondents are from Sweden's s top-rated auditing and consulting firms. Sampling methods are generally split into the probability methods and non-probability methods. Non-probability sampling is said to have limitations due to the subjective nature in choosing the sample, however, it is quite useful when the researchers has limited resources and time and does not aim to generalize result to entire population (Etikan, Musa , & Alkassim, 2016). As is the case in this study. Purposive sampling method which is grouped under non-probability sampling method is used for this study. “The purposive sampling also called judgement sampling is defined as the deliberate choice of a participant due to the qualities the participant possesses”(Etikan et al, 2016).

It is suitable for use in this study because the researchers have a purpose in mind which is to get knowledge on the experience of auditors on the implementation of AI in audit process and how it is contributing to the effectiveness of the process. As such the target was on auditors from audit firms within Sweden that has adopted the use of AI in their audit process. Interview request letters were initially sent to the selected firms' general email, when no response was forthcoming after three days, internet search was done to get contacts of office managers in the various audit firms in different locations within Sweden. Office managers were chosen because they coordinate affairs of the office, as such they can act as the contact persons in the firm and are in the best position to disseminate the information making it easy to reach those who will show interest in partaking in the study. Interview request letters were sent out to 18 official email addresses of the managers made available in the company profile online. The direct message yielded result as feedbacks came after 24hours and we got promises for participation. A manager was contacted through linkedin but no response came back. The request contained a brief overview of what the research is about, why their participation will be appreciated, ethical concerns they may have with assurance of anonymity, freedom to withdraw from participation at any time, and maximum amount of time the interview is expected to last (see the attached appendix 1 for the interview request letter). Out of the eighteen requests sent out, nine positive responses came back, and the time for interviews were fixed with the individuals separately. While two of the remaining nine requests declined participation as a result of busy schedules in their reply email, the remaining seven did not respond to the request for the interview atall.

3.5. Interview Process

Interviews for research are usually divided into structured format, unstructured format or the semi-structured format. Structured interviews are noted to be rigid in nature, will not help uncover all the information required about the role of A.I. in auditing because they offer very limited scope for follow-up questions to explore responses requiring deeper and exhaustive perceptions. An unstructured interview is the other interview method which is described as a conversation with an objective but often time without a set of predetermined questions because it is designed to allow the interviewee to discuss at length whatever questions asked by the interviewer(Saunders et al., 2009, p. 321). It is a method of the interview that has been described as shared experiences where those interviewed, and the interviewer come together in developing a background of personal familiarity where respondents are open to sharing their tales. It seems to be an oddly private method and a bit ill-suited for a professional environment, where the researchers are interested in seeking the opinion of auditors within a reasonable time frame not to waste too much of their time. Because of the drawbacks of both structured and unstructured interview methods, the semi-structured method is the method of choice for this study because it combines the benefits of the other two. It is described as a flexible technique that gives the interviewee a fair degree of freedom in expressing further opinion on a question asked (Drever, 1995). Its limitation been that it is not particularly suitable for studies involving a large number of participants. It fits well for the study because of the small sample size.

3.6. Interview Guide

To have questions that will delve deep into the experiences of the interviewees and gain rich data from the interview, the researchers in this study searched for inspiration and ideas to prepare the interview questions guide from systematic review of some literature such as; Daniel W. Turner III's Qualitative Interview Design (Turner, III, 2010), John W Creswell's Qualitative Inquiry & Research Design (Creswell, 2007), Kokina Davenport's The emergence of Artificial Intelligence: How Automation is Changing Auditing, Creswell (2003; 2007). And also from a few prior theses on audit process and automation that is available from online google search: Keskinen & Tarwireyi, 2019; Kostić & Tang, 2017. Although there are limited studies on AI in audit to get more ideas from mainly because the phenomenon is a new research topic area that is just evolving. The questions were then formed based on examining the interaction of AI on each stage of the audit process to gain knowledge from the experience of the participating auditors in order to achieve the aim of the study. (see the attached appendix 2 for the interview guide questions).

First section of the questions was on background information of the interviewees, these were asked to get ideas on their position at the firm, years of audit experience, professional certification and their main duties. The next section touched on the competence of the auditors in the use of IT tools (how well they use IT tools) this is deemed necessary to know their level of comfortability and familiarity with the general usage of IT tools both for work and personal use. While the next two consecutive sections of the interview guide focussed on the auditors' perspectives on how AI influences each stage of audit process. A particular question under this section, asked the auditors to rate the effectiveness of audit process with the adoption of AI tools on the scale of 1 to 10, this is a bit of an interesting twist in interview question style because it has a semblance of questionnaire used for survey, however, it is introduced to get their individual personal opinion on how they would rate AI influence on the process as first hand users of the tools in auditing. The last section of the interview was on ethical concerns of AI. It was asked to check their opinion of AI compliance to required audit/accounting standards and their opinion on if AI promotes or impairs professional judgement of auditors. A brief question was equally asked on the pros and cons of implementing AI in audit process and the challenges they have encountered in the use so far.

3.7. Interpreting the data: Structure used for the analyses

Making sense out of the data collected is another important and quite tasking part of the study. As a qualitative research, the data has to be structured in such a way that will follow a pattern and give an easy understanding to the readers of the work. Segmenting the data according to sections or groups of information, otherwise called themes or codes (Creswell, 2007 in Daniel W. Tuner III, 2010). The themes or codes are common phrases, expressions, or ideas that were common among interviewees (Kvale, 2007 in Tuner, 2010). For this study, the data were structured into sections according to the interview guide which also follow the pattern of the research model drawn up at the beginning of the study (in chapter two). The participants are referred to as interviewee, auditor, and informants interchangeably. The background information which is important to get the foundational knowledge were analysed first while other sections that followed which were check of competence in the use of IT tools, interaction of AI on the audit process and ethical concerns surrounding AI were analysed according to each stage of the process. Sample of interviewee responses are quoted, so they are seen to be presenting their own viewpoints themselves. The underlying assumption of this strategy is so that the data is treated as fact, that speaks for itself (Wolcott, H. F., 1994b)p.10 for reliability purpose. Discussion is done after each section to show the interpretation drawn from the common theme in the responses. As researchers maintained healthy skepticism so as to include every bit of important information gathered from the data that is different from the earlier preconceived framework (or may add to it) in order to build on the framework to buttress the abductive approach the study employed. Linking all relevant parts of the analysis with the theories that it supports the most.

3.8. Bias in data collection

Bias refers to the tendency that inhibits the unprejudiced reflection of a question, and in research, bias may occur at several phases of the process such as; data collection, planning, during analysis, and when the results are published. According to Pannucci and Wilkins (2010), bias should not be considered a dichotomous variable, and hence the interpretation of bias cannot be restricted to a simple inquisition and that which seeks to know whether it was present or not. Instead, Pannucci and Wilkins (2010, pp. 8-12) suggest that the reviewers of research data collection must evaluate the degree to which the bias was controlled by proper study design. As some level of bias is always present in every research, reviewers must consider the bias influence on the results and conclusions. Selection bias might occur during identification of the population to be interviewed/investigated. In the case of this study, it is obvious that there was a selection bias in data collection. This is because the study aims for a perfect population that can achieve the aim of the study. The population which is auditors that are already using AI in their audit processes and not auditors generally. The perfect population is one that is clearly defined and is reliable and accessible (Creswell,2007).

3.9. Trustworthiness, Credibility and Authenticity of the Study

Two important measures are proposed by Guba and Lincoln (1994) for assessing qualitative research. First of this is trustworthiness then authenticity. The trustworthiness in this regard talks about credibility and transferability of the data. Credibility here refers to if the researchers got the contributions of the interviewees correctly without bias. i.e “If the data can be attested to again by triangulation” (Smallbone & Quinton, 2004)p.156. The interviews for the study were audio recorded and transcribed word for word for credible analysis, voices of the interviewees are made heard by quoting their words and both researchers were involved in the interview as well as the analysis of the data. This is done to increase the credibility of the data without assumption or bias. As well noted by Gill, Stewart, Treasure & Chadwick that to guide against bias and presents evidence as it is expressed or not, is best done by transcribing interview in the same way they are recorded (Gill, Stewart, Treasure & Chadwick, 2008 p. 292). While the main test for the transferability is to check if the research data is enough to enable possible transference for research in other contexts by other researchers. According to Malterud Kirsti, producing information that is sharable and applicable beyond the study settings is the primary aim of research. However, there is no study, no matter the method employed that can provide findings that are transferrable universally (Malterud, 2001). It usually depends on the research question and what additional fact is required to effectively answer the research question in the context it is being applied (Malterud, 2001). For the authenticity of the study, which is about the wider context of the study, this involved confirming if all viewpoints in a certain setting is well represented (Smallbone & Quinton, 2004). The population represented in our research represents basically all levels of auditors involved in auditing process. This denotes fairness in representation.

CHAPTER FOUR

4. EMPIRICS, ANALYSIS AND DISCUSSION

The purpose of this chapter is to display and analyse the data collected. The research is concentrated on Sweden, one of the least corrupt countries in the world (from 2019 Corruption Perceptions Index). The previous chapter discussed the process by which primary data was collected from nine interviewees, all of whom are auditors from firms in the country. The interviews comprised of six key sections. The analysis is structured according to these sections as contained in the interview guide.

Analysis is explained as consisting of three simultaneous flow of activities which are reduction of text from the data collected, data display or exploration of the data and conclusion drawn from the data (Miles & Huberman, 1994; Attride-Stirling, 2001). All these streams of activities with interpretation at each stage, are interwoven and combined to make up the principle used for this analysis phase of the study.

4.1. Demographic Information

The first section of the interview comprised general questions. The purpose of these questions was to establish the background information of the interviewees. The first question is to establish the role and title of the interviewees at the auditing firms. The three levels included entry or junior, middle-level and senior/managerial levels. And there are three interviewees represented in each of the levels. These shows a good representation of audit team in the participants interviewed. “An audit is usually conducted by an audit team, which is characterized by a hierarchical structure and division of labor” (Bamber, 1983)p.396. The size and complexity of the audit determine the number of people that will be at each hierarchical level (Muczyk, Smith, & Davis , 1986).

In the same section of the interview, the interviewees were asked if they were part of the audit team at their various organization. Since the interview only adopted participants with experience regarding the AI based system, all of the interviewees replied “yes” to this question. Using teams with diverse skills boost audit effectiveness, as team members bring together their “knowledge and expertise” (Owhoso, Messier Jr., & Lynch Jr., 2002), while distributing the work by allocating audit sections to each team members (Vera-Muñoz et al., 2006 cited in Udeh, 2015).

Also, in this section, interviewees were asked about their years of experience in auditing profession. Their experience ranges between two to fifteen years in this field. For example, the second and fifth interviewee have 15 years of experience and work as senior auditors in the managerial position. While the sixth interviewee has 10 years of experience and also works as a senior auditor. The experience of the rest of the interviewees ranges between two to six years, and they work in the junior and middle-level position. The need for audit firms' managements to leverage their resources, by forming teams based on audit staff knowledge, experiences and expertise" to achieve quality audit is re-iterated by Gardner et al., 2012 cited
in Udeh, 2015

Participants	Auditor 1	Auditor 2	Auditor 3	Auditor 4	Auditor 5	Auditor 6	Auditor 7	Auditor 8	Auditor 9
Role at the firm	Middle level	Senior auditor/managerial level	Entry Level	Middle level	Senior auditor/managerial level	Senior auditor/managerial level	Entry level auditor	Entry level auditor	Middle-level auditor
Years of Experience	5 years	15 years	2 years	6 years	15 years	10years	3 years	2.5 years	4 years
Duties	Implement audit schedule	Make audit policies and Oversee audit process	Assist middle-level and senior-level auditors in audit schedule implementation	Implement audit schedule	Supervise audit process	Oversee audit process	Assist in audit process	Assist in implementing audit program	Participate in entire audit process as outline by the senior auditor
Professional certification	CPA Certified	CPA Certified	CPA certified	CPA Certified	CPA Certified	CPA Certified	-	CPA certified	CPA certified
Educational Background	Business Studies	Accounting	Economics	Economics	Economics	Accounting	Business	Accounting	Accounting
Gender	Male	Male	Male	Female	Female	Male	Male	Male	Male

Table 2 Background Information of the participants

Auditor 1 is a middle level auditor with five years of experience in auditing and CPA certification. His duties are… "implementing the audit schedule as outlined by the senior auditors while adhering to the existing accounting standards".

Auditor 2 is a senior auditor at the managerial level with 15 years of experience in auditing field and CPA certification. His role is to make audit policy for the firm and oversee audit process.

Auditor 3 is an entry level auditor with 2 years audit experience on the job. CPA certified. Duties involved assisting other middle level and senior auditors in audit process.

Auditor 4 is a middle level auditor with six years of experience and has CPA certification. His duties are to partake in audit process outlined according to the instructions of the senior auditor and use AI systems to complete substantive tests.

Auditor 5 is a senior auditor with 15 years professional experience in auditing and CPA certified. His responsibility is to supervise the entire audit process.

Auditor 6 is a senior auditor at the managerial level with 10 years of experience on the job and CPA certified. He oversees and give guidance to other subordinates in the entire audit process.

Auditor 7 is another entry level auditor with 3 years of experience on the job. He works at one of the big four auditing firm and gave no response on CPA certification. His duties are to assist the senior auditors in audit process and uses AI to “roll forward documents from previous year”.

Auditor 8 is also an entry level auditor with two and half years of experience on auditing job, CPA certified. His duties are to assist in implementing audit programs

Auditor 9 is a middle-level auditor with 4 years of experience and he is CPA certified. His duties involve Participate in entire audit process as outline by the senior auditor.

The section also sought to establish whether the interviewees are CPA certified. Usually, CPA certified auditors are seen as much more professional and competent in the field than their counterparts who lack this accreditation of certification. All interviewees but one answered this question in the affirmative, thus implying that majority of the informants are CPA certified. Also, the section sought to determine the role of each interviewee in the respective organization and audit team. The leading roles ranged from providing supportive services, following or giving directions related to auditing. For instance, the 1st interviewee cited that the primary role was to organize the entire audit team and supervise the remaining team members. The interviewee qualifies for this role due to the qualification as a senior auditor (Altındağ & Kösedağı, 2015, p. 12).

In comparison, the 8th interviewee mentioned his professional role as implementing the audit program developed by the team, providing advice and working with colleagues to generate favourable results. This interviewee works at the entry-level with an experience of 2.5 years. The observation is that experienced auditors have managerial roles while entry-level auditors assume supportive roles (Ax & Greve, 2017, P. 34). The end of this section sought to establish the educational background of interviewees. The main categories included accounting, economics, and business. The outcome for this section is as follows: two interviewees have business educational background, three have economic educational background and four interviewees have accounting educational background. As a result, the accounting has the highest number of interviewees followed by economics before the final category of business which has only two interviewees. The reason for this distribution is that accounting has the highest relationship with auditing (Bathc, 2017, p. 45).

4.2 Competence in the use of IT tools

The second section of the interview sought to determine the competence of interviewees' while using IT tools. The first question that was asked in this section read as- “how tech-savvy are you?” The responses ranged from “moderately good” to “extremely good.” Worth to note, that none of the informants was “extremely poor” or “poor”. Only two interviewees emerged as having entry-level knowledge of technology. The interviewees also agreed to be comfortable with IT tools both for personal use and office use. The other question asked whether the informants are familiar with the software used for accounting processes. The reason for this question is to determine how informed the auditors are about the softwares used for accounting purposes. As mentioned in the literature review at the opening chapter, collation of transactions and disclosure of financial information are increasingly done with various technological tools to gather, analyse and preserve accounting data electronically with less paper documentation (Arens, Elder, & Beasley, 2014; Foneca, 2003; Khemakhe, 2001; Zhao, Yen, & Chang, 2004 in Mansour, 2016), this which comes with a lot of complexity increases the capabilities of auditing to add value when auditing these accounts(DeFond & Zhang, 2014). The auditors' familiarity with various accounting software is evident in their responses. For instance, the 8th informant admitted familiarity with Sage, Xero, Pably, and Wave software. In comparison, the 1st informant indicated familiarity with Sage, Quickbooks, and Odoo. These responses are similar to the one made by the 3rd informant who quoted familiarity with Sage. Although the 3rd informant only listed one accounting software, the trend is that all informants are familiar with at least one accounting software.

Another significant trend seen in this is that Sage is the most popular accounting software known among this group of auditors. All of the 3rd, 8th, and 1st informants, the Sage software was common. Besides, the 9th informant quoted that “*The software I understand most is the Sage Accounting software. My company used it for over seven years. Recent changes have however rendered the software less useful since it requires intensive human efforts. This fact made it necessary to adopt the upcoming AI software such as Apace Mahout”*. At this juncture, the observation is that most ordinary accounting software is losing grip of the market. As a result, there is a need for industry stakeholders to focus on new and innovative software even for accounting purposes. AI seem a good example of this software from this interviewee response.

In the same way, the 4th informant indicated familiarity with the Raken accounting software. The information cited for this section reads as “*Yes, I am especially familiar with Raken, which* *is a cloud-based announcing arrangement intended for the development business. It assists with monitoring development extends and gives clients site refreshes continuously. It permits venture supervisors to keep up every day work logs, plan and allot occupations to representatives, send updates to handle operators, create and share depictions of a task's advancement. The arrangement additionally assists organizations with monitoring subcontractor hours. Combinations with Procore, Prolog, Egnyte and Box are accessible*". The information provided by this informant is not only precise but also shows outstanding confidence regarding the usefulness of the accounting software. The information regarding the software indicates that the existing accounting software is necessary but not sufficient tools for audit reliance (Bondarenko et al., 2017). It is important that auditors are equally equipped with advanced technology that can guide in exploring and understanding how the entity's financial transactions and other data has been collected, recorded, and processed (Mansour, 2016). Which is where AI tools for auditing comes in. As over-reliance on accounting software only will reduce the quality of audit, thus violating one of the primary principles of the auditing theories, which is to provide assurance that the company's accounts are accurate and represent a true and fair view of the financial position of the organization.

4.2. Personal views on the importance of automation of the auditing process for the audit profession

This first question in this section sought to determine the understanding of audit automation. Although the descriptions varied amongst interviewees, the general observation is that automation entails the use of software to automate auditing processes as opposed to the traditional method. For instance, the 3rd interviewee stated that audit automation is the use of automatic systems to audit financial reports as opposed to the use of traditional methods. In the same line, the 2nd interviewee defined audit automation as the use of automatic audit software as opposed to the conventional approach to auditing where natural humans complete the tasks. The 9th interviewee responded that "*Automation is about the use of non-manned or barely manned accounting software to overcome the challenges of using heavily manned software. An example of manned software is Sage while an example of non-manned software is the DeepLearning4J software"* Although the interviewees used different wording, the general theme is that audit automation entails the revolutionary integration of automatic audit software to reduce the limits attached to the use of traditional method or ordinary audit software that require intensive human engagement.

Another question sought to establish the familiarity of these auditors with AI tools and whether they use the AI tools for their auditing work. They answered with affirmation and gave names of AI software used in each of their firms. The reason for this identification was to check for a fact that the auditors have sufficient exposure to AI software to give credence to their opinion on the phenomenon.

The 6th interviewee responded "*Yes, I am familiar with the AI tools. The main ones we use include AI-one, DeepLearning4J and Apache Mahout. Yes. The firm relies on auditing in nearly all instances. Unless the scope required is narrow, the use of AI is mostly guaranteed".*

Interviewee 9th also noted his familiarity with AI tools "*Yes, I am familiar. The tools acquire intelligence about accounting systems as companies based on the financial context of the organization. My company used these software for the past five years. When I joined the company, the software was just new and the auditing team was just learning to use it. Up to now, the company has learned about the software by a large margin".*

At the same level of responses, the 1st interviewee answered "*Yes. I am familiar with them. They are software trained by auditors to complete tasks previously completed by natural humans. Yes, we use the MindBridge AI software".* These same response is common to the rest of the interviewees.

The opinions provided by the majority these interviewees indicates that auditing in this context is dependent on the existing AI for the implementation of the existing frameworks of applying the critical auditing theories. This is in line with the agency theory in the case of auditing, which requires stakeholders such as auditors to act in the best interests of investors (Blair et al., 2017, p. 45-56). This requirement needs auditors to ensure professional and widespread auditing of financial reports.

Other than the responses from the experienced and middle-level auditors showing that they had widespread knowledge about the AI software used in auditing, other responses show that the interviewees who are junior level auditors also have knowledge about the software used in auditing and accounting. For example, the 3rd interviewee indicated familiarity with just two auditing software. The response read as "*I am only familiar with a few tools- IBM Watson and Cygna Audit, Engati. Yes, the firm uses these tools but I am new and still learning. Software such as Engati is used to create chatboxes that enhance the interactions between the audit team and corporate accountants".* This response shows that even entry-level auditors have significant exposure to modern accounting and auditing software.

The above question closely resembled with another asking the informants whether the respective firms use AI software for auditing. The trend for this question is that the firms are increasingly adopting AI systems. For instance, the 6^{th} interviewee responded that “the firm relies on auditing software in nearly all instances. Unless the scope required is narrow, the use of AI is mostly guaranteed”. The words used by the interviewee in this instance shows that the use of AI is becoming a significant source of competitive advantage for the company that uses it. Shows their interest and commitment to improve their processes and turn out quality audit which is one of the main purpose ad expectation required of an audit process. One of the important models is the confidence model which requires auditors to increase the confidence in AI software through proper perusal (Naser & Al Shobaki, 2016, p. 90-97). The 1st interviewee confirms this argument by showing that there is widespread exposure to modern auditing software. The interviewee provided that “*Yes. I am familiar with them. They are software trained by auditors to complete tasks previously completed by natural humans*”. *Yes, we use the MindBridge AI software.*

Another key observation about these interviewees is their response to the question about their comfortability to using these systems. While some expressed that they are extremely comfortable (interviewee 5,1,2,8, 7) others noted that they are only “moderately comfortable” with the use of AI auditing software (interviewee 4, 6, 9). Some of the reasons given for this is that:

interviewee 6 “*I am moderately comfortable. The reason is that the system is new and it is in its “infancy.” The company needs to learn the software while the software must also learn the organization*”.

Interviewee 9 “*I am just comfortable, but I would prefer to be extremely comfortable. The reason is that I only have a few years of experience and the company has only used the software for a short time. As years continue to pass, I believe that I will extremely comfortable”.*

While interviewee 3 says “I *am not comfortable. The reason is that I am new to the field and auditing software require a lot of skills”*.

The observation at this juncture is that although companies may adopt AI-enabled auditing software, there is a need for additional training. In chapter 2, the literature review indicated that one of the challenges facing modern auditing companies is the lack of proper training for auditors and accountants (Noraini et al., 2018; Gonzalez-Padron, 2016, p. 89-92). As skills in using technological tools, ability to adapt to new technology as well as an understanding of how technology can affect the environment are all part of the competencies necessary for entry-level accountants and CPA professionals to thrive in the field as detailed in AICPA (American Institute of Certified Public Accountants) functional competencies (AICPA, 2018). "Due to the rapidly changing accounting profession, the framework focuses on critical skills instead of traditional subject-content areas or accounting services. Although knowledge requirements will change with time, the core set of competencies the framework identifies will have long-term value and will support a variety of career opportunities for future CPAs" (AICPA, 2018).

4.3. Auditing Process

This section sought to establish the role of AI in enhancing the process of auditing based on each of the stages.

Pre-engagement

This stage of the process is where the auditors review the extent to which the policies of the firm limit the integrity of accounting procedures. And also check for the integrity of the company's management, compliance, and the existing or potential threats (Cannon & Bedard, 2017, p. 24-30).

Majority of the participants agreed that AI is quite useful for the pre-engagement stage of audit process. With only one exception, a participant that says his firm does not presently use AI for this stage of the process. The common theme here is client evaluation.

"*AI has extensive roles in this stage with its capability to check and analyze historical information and make predictions of in all likelihood of risks and activities"* Interviewee 3

"AI acts as the link between auditors and financial documents as well as the financial framework of the organization" Interviewee 4

"AI has tremendous role in the pre-engagement stage. The purpose of this stage is to determine whether to accept or reject a client. As such, auditors need to verify the financial framework of the organization to determine the risk of financial fraud. Also, the stage enables the determination of the scope of work. AI systems review the trends in financial data without the need for extensive human engagement" Interviewee 9

"*AI helps with the important preliminary work at this stage with speed and accuracy which relieves auditors of the need to identify areas that need further scrutiny. As a result, the auditors have additional time to interact with corporate officers such as accountants".*
Interviewee 2.

These examples of the common responses from the auditors, re-affirms that client's evaluation is a common procedure for audit firms in order to decide if to accept a prospective client or not as noted by Eilifsen, Messier, Glover, & Prawitt (2014). Although the auditors acknowledged the role of AI in the entire audit process, there was a particular emphasis on the pre-engagement stage. Pre-engagement activities take place before the acceptance of an audit assignment and the stage has been noted as involving a lot of repetitive tasks and back & forth with exchange of documents between the potential client and the auditors for accurate evaluation of the client-to-be. This AI technology designs towards automating or streamlining the recruitment workflow parts, especially the parts that are repetitive or voluminous (Rahimi and Gunlu, 2016, p. 34-41).

However, AI interaction with the pre-engagement stage enhances the process with the speed at which it peruses the company's information and the accuracy it brings to the predictions without the need for extensive human engagement. As such freeing up time for auditors to make quick decisions on acceptance and move to attend next other important tasks geared towards having a complete and quality audit that would inspire confidence in all stakeholders' to the financial statement in accordance with the theory of inspired confidence.

<u>Planning Stage</u>

All the auditors agreed that AI helps greatly with this stage. With the speed at which it checks through multiple files to flag questionable documents for further analysis. The general theme from the responses is that AI helps with classifying materiality and in pattern identity. Here are some of the responses;

"AI can pass through multiple files in an instant. classifying files that show minimal variation as "less materials." those with a high variability, AI classifies them as 'highly material'" Interviewee 6

"the focus is on checking the patterns of transactions so that sudden changes can qualify for further analysis" Interviewee 4

"*AI peruse documents and compare the trends to "raise red warnings" in cases of sudden changes"* Interviewee 5

The overarching theme here is that AI helps with classifying materiality and in pattern identity. In audit planning, risk assessment has to do with “pattern recognition”, of which unanticipated deviation from such gives an indication of risk (Ramamoorti et al, 1999.p.160). Materiality judgement is a very cogent ingredient to accurate decision making. For auditors setting a materiality threshold that is higher than that of the users, may warrant useful information being omitted from the financial statement which will make the audit exercise results in an inefficient means of controlling agency cost (Kinney & Burgstahler, 1990). In the same vein, if auditors’ materiality threshold is set to be lower than that of the users, audit cost may end up being greater than the value of the information the audit exercise has provided (Chewning, Wheeler & Chan , 1998). Thus, balanced materiality classification and pattern identity is crucial as it enhances the process and brings effectiveness to this stage of the process. Good planning is noted as key as it helps in the determination of the appropriate audit strategy, scope and how to handle the risks factor timely to have an effective and efficient complete audit (Cannon, 2017, p. 90-91).

Execution Stage

With the intensity of tasks this stage of the process entails, it is general agreed by all participating auditors that AI reduces the burden of the tasks while enhancing the effectiveness

“*AI allows auditors to conduct substantive tasks in a “sweeping exercise”. rather than audit one level of financial entries and proceed to the next one, the systems can review multiple stages in an instant”* Interviewee 4

“*Uses AI to detect errors of omission, commission or fraud. An example of the activities undertaken by the company AI is re-calculating the values”.* Interviewee 5

*“AI plays a key role in carrying out internal control tests more so observation, inspection and recalculation. enabled systems to adapt to changes in the accounting framework and approach thus giving firm that use it far-reaching advantages over competitors”*Interviewee 6

The overarching theme in the responses here is that AI brings swiftness, effectiveness and ease to the test of controls for auditors. Adequate compliance test on procedures and substantive test is required to ascertain the effectiveness of the internal control in place. These tests enable the auditor to believe in the system’s credibility or to question it. With the swiftness with which AI goes through all the population to be tested instead of a sample that is usually tested with manual process, the auditor can fully concentrates on the critical control accounts or areas where weaknesses are common (Shen, Chen, Huang, & Susilo, 2017, p. 12-15). This agrees with literature on using machine learning models to classify messages and increase the level of confidence for the auditors. If the threshold of the messages is low, the systems send the messages for further human analysis (Noor & Mansor, 2019, p. 64).

Reporting Stage

This stage of the process depends on the outcomes of the previous stages. The information gathered at this stage finally determines the quality of reports generated by AI systems. The stage requires discussing with clients on discoveries made during the process that could not be made conclusions on yet, using professional judgement, as well as generate reports expressing their opinion on the true and fair view or otherwise of the account statements that stakeholders' are looking forward to.

Majority of the participants agreed that AI plays an important role in this stage too with an exception of one participant who noted that his firm does not use much of AI in this stage yet.

"*Yes. The information gathered at this stage finally determines the quality of reports generated by AI systems"* Interviewee 6

"Yes, AI joins the outcomes of the initial stages of auditing. Without the integration of AI systems, it would be difficult to manoeuvre the concluding stage" Interviewee 5

"The benefit of AI to the last stage of auditing depends on two main fronts- the accuracy and timeliness of the other stages. For instance, the proper collection of auditing documents followed by automated analysis makes it easy for auditors to make verifiable conclusions" Interviewee 2

The combination of the initially proposed theories (Agency theory, Stakeholders' theory, Inspired confidence theory and Credibility theory) shows that the ideal procedure of reporting requires companies to increase the verifiability of financial reports. This type of verifiability requires auditors to access, organize, peruse, and verify the credibility of a wide variety of financial data. The audit of these levels of data requires auditors to access and analyze comprehensive data over a short period. This which AI brings to the process with the speed and accuracy with which it peruses files and generate reports for ease and enhanced effectiveness of the process. AI tools brought a difference in speed and accuracy in the execution of the auditing process (Altındağ & Kösedağı, 2015, p. 63). This fact buttresses the data obtained from the auditors in their interaction with the AI system as reliable. This which enhances effectiveness in the process of executing auditing tasks.

4.4. The role AI plays in the process of auditing

In addition to the sections discussed above, the study sought to determine the difference the adoption of AI tools in audit process makes from the previous method used based on the auditors' opinion from their experience. This is deemed necessary to ascertain the extent to which AI facilitates or improves the process of auditing. Previously, the literature review showed that auditing has four main steps, namely pre-engagement, planning, execution, reporting/conclusion (Rahimi and Gunlu, 2016, p. 34-37). The first three steps form the basis for a reasonable conclusion . The implication for this observation is that the advantages of AI to the auditing profession spread across the entire auditing process. Interviewee 5 commented that "*AI is a perfect tool that allows auditors to analyses a full data set for the identification of outliers and exceptions. AI tools are also useful in the extraction of lease contracts using given selected criteria. It, therefore, leads to high levels of precision than using manual methods. Furthermore, AI can be used to analyze unstructured data from emails media post and audio files, a feature that cannot be easily done by human".*

According to Interviewee 6 "*The main difference is the reduction of human reliance. Initially, the process required intensive human efforts. The introduction of AI systems reduces the need for supervision, manual analysis of transactions and contracts"*

Interviewee 9 *"An artificial intelligence system reads data files and extracts what the auditors need. The system applies the risk indicators to massive datasets detecting risk that could have remained unnoticed. AI can analyze and categorize expenses, read texts and expose unauthorized claims. Also, the AI systems are used in indication of fraud by reviewing invoice pattern changes which is more effective than in ordinary auditing. Additionally AI systems have made idea of continuous auditing possible which was mere dream in ordinary auditing"*

Another auditor indicated that the AI system promotes the judgment of auditors by ensuring the efficiency of the auditing process. In each step of the auditing process, the AI system ensures that there is accuracy implemented in the execution of the processes involved. In the same way, the AI, therefore, leads to high precision as opposed to the use of other software or traditional methods (Altındağ & Kösedağı, 2015, p. 63-67).

The statements quoted from these three interviewees provide evidence that the use of AI for auditing is superior to manual or the use of traditional auditing tools (Altındağ & Kösedağı, 2015, p. 67-70).

In the same vein, the question asked on whether or not AI increases the quality of auditing, the 7th interviewee response confirmed the findings gathered from the literature review and the preceding three informants. In particular, the 7th interviewee noted that the integration of AI is more effective because it has benchmark tools that are useful in analyzing the transactions in the general ledger. The transactions will then classify where there is conformity to the level of risk. Therefore, AI is useful because it shows where the risks are, and that will be the area of attention. In manual auditing, random sampling was used for analysis and therefore was less effective. The 2nd interviewee supports this argument by indicating that modern organizations are grasping and actualizing innovations to smooth out their business tasks. One of the activities with the highest priority on their rundown is bookkeeping. That is because AI is giving positive outcomes, for example, expanded profitability, improved precision, and decreased expense. With such a significant number of advantages, AI is utilized progressively for regulatory errands and bookkeeping, bringing about different auxiliary changes. In the same way, the last respondent supported these arguments by citing that AI enhances both the efficiency and effectiveness of auditing.

4.5. Scale rating

Another critical question in this section asked respondents to determine the effectiveness of AI in the auditing process. The interviewees were asked to rate the systems on a scale of 1-10 where 10 is the highest score. The observable trend for this section is that the systems have a minimum score of seven out of ten. For instance, the 5th interviewee buttress his rating by citing that Artificial intelligence plays a tremendous role in today's finance department. In particular, the systems ease the financial audit, which requires a lot of time, has lots of workload in perusing financial statements also in giving accurate and efficient services. However, it still needs more research for its adoption. In the scale of ten, the interviewee awarded a score of seven. All of the remaining interviewees awarded a score of at least seven points. The average score for the section is 7.80, which indicates that AI strongly enhances both the effectiveness and efficiency of auditing.

4.6. Ethical concerns

The last section of the interview sought to determine the ethical concern of using auditing software. Usually, the ethical principles of auditing require auditors to act in the best interests of investors. Failing to act in this manner becomes a severe violation of the roles of auditors (Bieberstein et al., 2005, p. 78-82). The first question asked about the pros and cons of the auditing process. For this section, the interviewees showed similar trends in the list of pros and cons listed. On the advantages side, the informants stated that AI increases the accuracy of auditing. The said accuracy occurs at multi-levels which starts with the perusal of the primary documents. For instance, the 7th interviewee cited that Artificial intelligence would have a low blunder rate in contrast with human, whenever coded appropriately. They would have unbelievable exactness, precision, and speed. They will not be influenced by antagonistic situations, in this manner ready to finish risky assignments.

Regarding the disadvantages of AI, most interviewees indicated that AI is capital and skills intensive. For instance, the 7th interviewee indicated that "AI software is expensive and skill intensive. These challenges may force companies to skim necessary steps, thus failing to meet the regulatory standards." The argument by this informant corresponds with the outcomes of the literature review where AI emerged as an expensive alternative to accounting and auditing. At the same time, the 4th interviewee added to the arguments by providing that one of the benefits is increased innovation.

The same interviewee also indicates that AI has a list of adverse outcomes. He goes further, saying the installation of AI software requires intensive managerial efforts. Artificial intelligence can rework most enterprises. However, one of the essential demanding situations of artificial intelligence is the shortage of a transparent implementation approach. To be successful, a strategic approach desires to be established even as enforcing AI. This includes identifying regions that need development, putting goals within reality described blessings, and making sure a non-stop system improvement remarks loop (Bourne et al., 2007, p. 12-15). The informant further added that to compound the issue, managers will want to have a strong understanding of modern AI technologies, their possibilities and obstacles, in addition to maintaining updates at the cutting-edge demanding situations with AI. This step will allow companies to discover areas that may advance through AI.

The 2nd interviewee goes further that the advantage of the use of AI in auditing is that the AI system has the capability of learning the methodology of execution of its processes leading to the elimination of human error. However, the disadvantage of the system is that it cannot replicate the intricate human intelligence in the auditing process. The arguments by this informant also compare with the 5th interviewee who says that the pros of AI are digital assistance in everyday duties, rational decision-maker, and overcoming the human limitation of getting exhausting. The cons include; high costs, cannot be boosted through experiences since it keeps doing the same thing and lack of human replication in terms of emotions and moral values. Also, they lack improvement in the course of the time, therefore not reliable in a dynamic environment as per nature the demands in the contemporary market.

Equally, the 6th interviewee provided that AI systems in the auditing process provide highly accurate results that are beyond human efforts. As artificial intelligence develops, it improves human effort through error elimination. Besides, artificial intelligence systems can optimize and automate accounting tasks. Additionally, AI enhances the processing of large volumes of data. However, AI has various shortcomings which include the large amount of data required for the learning process. Besides, since the models specified in terms of data, it is hard to determine the extent of machine learning.

4.7. Challenges during the implementation of AI systems

Another relevant section in the interview was about the challenges facing the implementation of AI systems. The pattern of this question was about the complexity of the systems. During the literature review, the primary outcomes showed that bias is a common challenge associated with the use of AI systems. Literature review further showed that bias reduces the professionalism of AI systems since they limit the engagement of human auditors. The international accounting standards require auditors to verify financial reports as verifiable after reviewing the financial reports to a satiable level. The use of AI systems largely reduces the engagement of auditors, thus eliminating the ability of auditors to examine the financial reports widely. The 8th interviewee confirms this argument by providing that bias is one in all the most critical challenges facing AI systems in the auditing departments. *"Bias is one in all the most important challenges going through AI. Try as we'd to have information that is an absolute fact, there is inevitable bias when you explore the depths to which AI might be used. Forbes India explains the inherent bias in information, "An inherent trouble with AI systems is that they may be handiest as top – or as terrible – as the statistics they may be educated on. Bad information is frequently laced with racial, gender, communal or ethnic biases. Proprietary algorithms are used to decide who's known as for a job interview, who's granted bail, or whose loan is sanctioned. If the unfairness lurking within the algorithms that make essential decisions is going unrecognized, it is able to result in unethical and unfair* *effects…In the future, such biases will probable be greater accentuated, as many AI recruiting structures will continue to be skilled the use of terrible facts. Hence, the need of the hour is to train those structures with unbiased statistics and broaden algorithms that may be without difficulty defined. Microsoft is growing a device which could routinely pick out bias in a series of AI algorithms."*

Interviewee 6 also said *"Because of bias, the systems requires a lot of training data and staff training. Secondly, the system is expensive and is not as flexible as natural human beings". "With the end goal for AI to carry out its responsibility, models should be prepared on information. Be that as it may, information carries many deterrents to the table. 'The most inescapable constraint to AI reception is information. Artificial intelligence needs information to figure out how to play out its capacity,' said Purcell. Shockingly, I've yet to address an organization that has its information house totally all together. In many organizations, information is normally sealed and once in a while reliably recorded and administered. Without great, significant preparing information, an organization will discover it very difficult to begin with AI."* Interviewee 5

"Integration of AI with the existing auditing system is challenging. This challenge is because it requires more funds and training time. Additionally, data loss due in various processes is another issue facing AI usage as confidential data can be a lot through system inconsistencies". Interviewee 1

The AI system utilized in auditing processes face the challenge of collecting and using relevant data associated with the process of implementation of its tasks. As a result of this fact, the data that has been obtained from the system in some cases have been ascertained to be biased. Interviewee 2

Therefore, the overall outcome of this section is that AI faces the challenges of possible complexity in algorithm and skills gap. Also, AI struggles from the lack of adequate training for auditors. The training gap listed in the section spreads across auditors of all levels including entry, middle and senior levels. This observation implies that firms must not assume that auditors are capable of applying AI systems without proper training. Instead, auditing firms must prepare to invest in enhancing the skills of employees.

Another interesting observation from these responses is the fact that the challenges encountered in the use of AI in auditing so far are dynamic. An interviewee noted that the challenges depend on the extent and context of the organization. He argued that the everyday challenges witnessed in the use of AI in auditing depend on the degree of maturity for auditing applications. "*Artificial intelligence would have a low blunder rate contrasted with people, whenever coded appropriately. They would have unbelievable exactness, precision, and speed. They won't be influenced by antagonistic situations, in this manner ready to finish risky assignments.*

On the negative side, the software is expensive and skill intensive. These challenges may force companies to skim important steps thus failing to meet the regulatory standards".

To the question on the challenges encountered so far, he goes "*The common challenges witnessed in the use of AI in auditing depends on the degree of maturity for auditing applications. Therefore, the implication is that there is an abnormally long time seen in the normalization of data. The use of AI for auditing has no standards and an inherent lack of transparency. There is also a shortage of skilled accountants that can use this technology. Once these challenges come together, they reduce the ability of auditors to make professional judgments, which is a fundamental requirement in the auditing processs".* Interviewee 4

4.8. Compliance to the international auditing standards

Another critical question was whether AI enables auditors to satisfy the international standards of accounting cum auditing. The purpose of this question was to ensure alignment of AI to the overall auditing and accounting standards, which form the primary verification criteria. The interviewees largely agreed that AI enables the attainment of international accounting standards (Bustinza et al., 2015, p. 34-42). They also agreed that compared to the traditional tools of accounting, AI provided superior solutions. For this question, the 6th interviewee responded that Artificial intelligence gives companies the capacity to improve their efficiency and effectiveness to operations and compliance through continuous analysis of data and model transformation. However, artificial intelligence also has the existing regulation and compliance challenges that the management should address up front. The most outstanding observation in this response is that AI systems fail to meet compliance in some perspectives (Bustinza et al., 2015, p. 34-42). Although the respondent failed to identify specific international requirements that AI fails to meet, it gives an indication for management the needs to investigate the loopholes and identify immediate solutions.

The same interviewee further noted that although AI in auditing reduces human errors, professional judgment remains vital and auditors need to improve their technological skills to coexist with the system. Artificial intelligence allows auditors to perform better diligently and make decisions appropriately. Also, AI system continually updates data which improves the auditor's efficiency. In the same way, the 7th interviewee noted that the evolution of technology is sharply accelerating in modern times. The rapid growth in a way has left many corporations using AI technologies for the auditing process without clear standards for compliance. The AI comes with infused features that have a lot of data to analyze before making professional judgments. Adequate analysis indicates that AI systems are compliant to the auditing standards lack of which would indicate otherwise. If anything, professional judgment is a critical standard in auditing. The same informant further notes that even though adequate standards of auditing may not have been met fully, AI promotes professional judgment of auditing through augmentation of existing business models, giving them a better way of accuracy. It also provides a better ground unto which due diligence will be attainable while also ensuring the success of many deals. Comparatively, the 2nd informant indicated that even though AI leads to remarkable improvements in the auditing process, the indication for full compliance to the auditing standards is not certain. This argument occurs because AI systems may fail to incorporate human intelligence completely throughout the process. This point however cannot be further substantiated because AI is programmed to imitate human cognitive reasoning 'not incorporating human intelligence' may denote programming failure in some AI systems. In the same line, the informant cited that AI system promotes the judgment of auditors by ensuring the efficiency of the auditing process.... "in each step of the auditing process, the AI system ensures that there is accuracy implemented in the execution of the processes involved". This shows a bit of a contradiction from the interviewee, which makes his earlier statement on ethical concern not fully substantiated.

The most conspicuous response for this section was from the 5th interviewee. the auditor argued that AI has expansive roles in enabling the professional judgement of auditors. The respondent further added that a unique example of the way synthetic intelligence algorithms enable the detection of fabric misstatements is the use of "unsupervised learning." These strategies leverage the science of figuring out what is standard as opposed to unusual to record on outliers in ledger information without bias or records, letting the statistics talk for itself. K·Coe Isom, a leading consulting and accounting firm for the meals and agriculture enterprise, makes use of AI to offer unique insights and a complete view on financial fitness for customers. Brittany Ferguson, the Senior Associate at K·Coe, explains, "We used AI-based analysis for materiality limits and extracted medium and high-danger gadgets to run samples on for the duration of our starting stage. This risk evaluation diagnosed two transactions that could now not occur beneath general testing conditions. The locating, although immaterial, was a value-brought education possibility that we have been able to offer to the client." AI warrants a re-assessment of how audit making plans and testing becomes achievable. Historically, the most straightforward feasible approach for substantively testing significant portions of statistics turned into to sample transactions statistically or non-statistically, preceding the attempt essential to look at the entire dataset. This step frequently required widespread backward and forward time with the client to reap the considered necessary data no longer obtained at some stage in fieldwork.

It is noted that acquiring adequate skills in handling the AI tool and sound professional skepticism of auditors came to play all through the interview as the underlying factor that would further boost the interaction between AI tools and audit process, this discovery necessitates the need to modify the initially drawn research model to include skills in handling IT tools and audit professional competency as shown below:

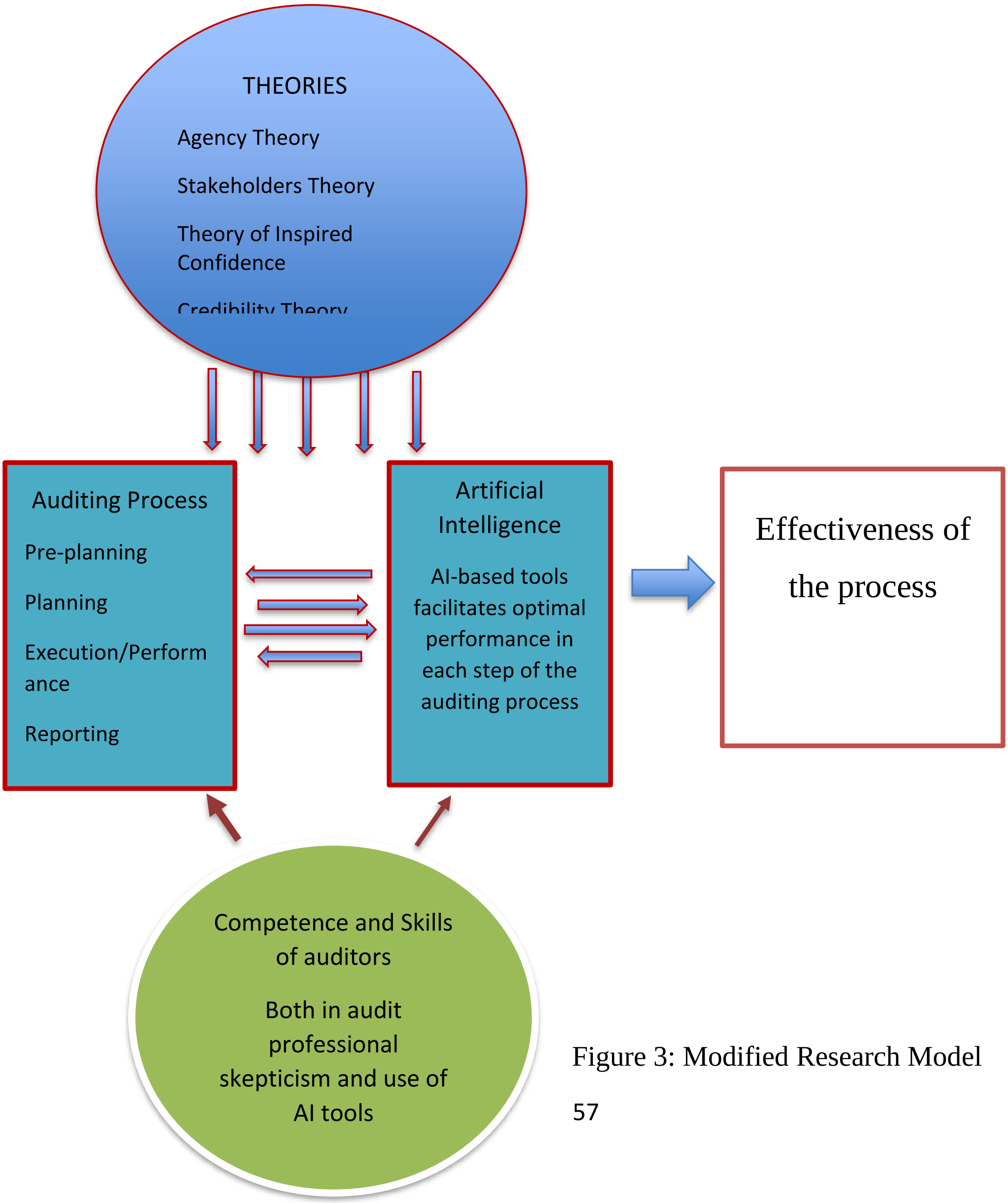

Figure 3: Modified Research Model

As earlier noted in the initially drawn model, the application of each of the theories determine the interaction between AI tools and the auditing process. However, in modification, this interaction coupled with the professional competence and skills both in IT tools proficiency and professional skepticism applied by the auditors on the tasks facilitate AI optimal performance in each step of the process. The two-way interaction between AI and auditing process and the competence with which the assignment is handled eventually leads to an enhanced effectiveness of the process for the benefit of all stakeholders.

CHAPTER FIVE

5. RESULT AND CONCLUSION

The overall purpose of this research was to explore the role of AI in enhancing effectiveness in auditing process. The analysis of the responses gathered from the nine professional Swedish auditors provide evidence that AI has a widespread positive effect on the overall quality of audits. AI enhances the quality of auditing by facilitating and enhancing effectiveness in the four main steps involved in the process of auditing. The area which this study explored extensively.

It is deduced from the study that the main link between AI and effectiveness of audit process is the reduction in errors which formerly cause auditors to repeat the work. For instance, AI systems can collect and peruse financial records, coherently, and effectively. AI reduces the time needed for classification and comparison of transactions more so the first entries in the journal. Auditors using manual methods often fail to cover these transactions. In all, interviewees agreed that the use of AI reduces exhausting human labour which increases the risk of error, manipulation, and omission. At the level of the literature review, the outcome was that AI is useful because it has benchmark tools that are useful in the analysis of the transactions in the general ledger. Therefore, AI is useful because it shows where the risks are, and that will be the area of attention. In manual auditing, random sampling was used for analysis and therefore was less effective. All these findings satisfactorily answered the research question of how AI enhances effectiveness of auditing process.

Also, the respondents strongly agreed that the use of AI systems increases professionalism and compliance with international standards. As a result, the study uniformly agrees that the use of AI systems will continuously increase the effectiveness of auditing. The respondents, therefore, favored the use of AI-based auditing systems as opposed to the use of traditional auditing tools.

As a result of the emphasis on the importance of acquiring adequate skills in handling the AI tool and sound professional skepticism of auditors that came to play all through the interview as the underlying factor that would further boost the interaction between AI tools and audit process, this prompted the need to modify the initially drawn research model to include skills in handling IT tools and audit professional competency.

Some of the cons associated with the implementation of AI is that it is expensive to adopt and quite skill intensive. Also, the possibility of bias associated with the AI programming which could reduce the professionalism of AI systems since they limit extensive human engagement. For wrong information in algorithm frequently has with it racial, gender, communal or ethnic biases (The Brookings Institution, 2019). If this kind of unfairness is left to lurk within the algorithms that make essential decisions undetected, it can result in unethical and unfair effect which could potentially reduce the reliance and credibility of the AI system. If this is not immediately paid attention to, such biases will probably become heightened, as many AI recruiting structures will continue to be skilled in the use of terrible facts. Hence, the need of the hour is to train those structures with unbiased statistics and broaden algorithms that may be without difficulty defined. However, the pros identified with system outweighed the cons. Apart from the general agreement on the speed, accuracy and enhanced effectiveness mentioned as pros to the adoption of AI in audit process, increased innovation is another interesting pro identified in the study. Deriving cost from AI can simply be achieved with the right funding, competencies and by developing a subculture that is open to innovation. Ultimately, innovation is about taking new risks and challenging conventions. To turn in sustainable audit satisfactorily and improve confidence inside the capital markets, for the benefit of all stakeholders, the focal point on AI and the audit will long keep.

5.1. Theoretical and Practical Contribution

AI in auditing is an emerging study area that has not been extensively researched as there are few prior studies available in this area. As theoretical contribution, this study contributes to knowledge in this emerging study area by filling the gap in literature on the research area. For the practical contribution, the study gives insights to auditors and corporate governors on the advantages the adoption of AI brings to each stage of audit process. By extensively exploring the implementation of AI in auditing and how the interaction of AI on audit process enhances effectiveness of the process. Giving detail information from the point of view of auditors that are already using the system. Which is hoped to spur more implementation of the technology in order to enhance the overall quality of audit for the benefits of all stakeholders.

5.2. Limitation of the study

Even though the primary aim of this study was fully achieved, there are challenges encountered during the study which add up to the limitations of the study. One of these limitations is the short timeframe of the study, this potentially gave the researchers a lot of rush in gathering data as thus enough time could not be given to the auditors that may have wanted to partake in the interview but could not because of their busy schedule within the time frame given in our interview request letter. Slow, no response and low responses to the request sent out is also another limiting factor to the study. This could be noted as part of the responsible factors for the small sample size the study had. Another limitation to the study is the ongoing situation of covid-19 pandemic around the world that warranted social distancing measures which ruled out conducting the interviews at the office premises of the auditors as is expected of a qualitative researcher. However, the study leveraged on IT tools and still got credible data through video interview sessions on various social media mediums which allowed for online face to face interactions for good rapport. Non-availability of adequate studies on AI in auditing to draw wider insights from is another limitation that gave a bit of a challenge during the study.

5.3. Future Research Agenda

The main aim of this study is to explore how AI enhances effectiveness in audit process. As suggestion for future research, further studies within the area of AI in auditing is essential to continuously research how accurate the AI algorithm becomes gradually as the software develops. This is essential in order to reduce the challenges associated with possible bias that may be lurking within the algorithm if gone undetected. Which could potentially reduce the professionalism and continual reliability of AI as unbiased.

Also, this same study could be conducted quantitatively within the same context or in another context to compare if the results will remain the same.

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APENDIX 1

REQUEST FOR INTERVIEW

I and my colleague (Salim) are graduate students of Auditing and Control at Kristianstad University, Kristianstad Sweden. Our research for master's thesis is based on Artificial intelligence in auditing. How AI is transforming auditing process. As it is well known that technology advancement has brought a lot of changes to the ways in which businesses record transactions, stores data and disclose financial information, this which gives audit profession the challenge to keep to the pace by adopting equally advanced technology-based tools like AI for ease of auditing and to stay abreast of this change. Our study is particularly examining how AI enhances effectiveness of each step of auditing process from pre-engagement to the reporting stage.

We hope to get a chance to interview auditors from prestigious firms like yours that has adopted the use of artificial intelligence tools in their internal auditing process, in order to gather necessary data for our study. As a result of the present situation of covid-19 pandemic and social distancing measures in place, we hope to conduct the interview online either via Zoom or Skype whichever channel is convenient for you (so, it is not location restricted. The context is Sweden as a whole). The interview is expected to last approximately 30mins - 45mins. It will be conducted in English Language.

We are quite aware of the busy schedule of auditors; however, we hope the interview can be scheduled within the 2nd week of May because of the time restriction for our thesis.
Ethical concerns: The interview will be audio recorded for ease of transcribing later for analysis and could be made available to our supervisor for the purpose of the study only. Participation is voluntary and anonymity of the interviewee and that of the firm will be maintained as required. Consent for participation can be withdrawn by email at any time and the decision will be respected. The interview guide questions will be sent some days ahead of the interview date as soon as we get a feedback on the scheduled date.

Your contribution to our research will be highly appreciated because not only will it help our thesis, but it will also advance knowledge on the transformational change AI brings to each phase of auditing process. We look forward to hearing from you. We can be reached for further clarification if there is any through our email addresses.
Thank you.

Warm regards,

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APPENDIX 2

Interview Guide Questions

1. **General Questions**
   What is your title/role at the firm?
   How many years of experience as an auditor do you have (as part of an audit team)?
   What is/are your responsibilities on the team during the audit process?
   What is your educational background? (is it in accounting, economics, business etc)
   Are you CPA certified?

2. **Competence in the use of IT tools**
   How tech savvy are you? (how well do you use Information technology tools)
   Are you familiar with software used for accounting processes?
   How comfortable are you with using technology tools either for personal purposes and/or for work?

3. **Personal views on importance of automation of auditing process for audit profession**
   What do you understand by automating audit process?
   Are you familiar with what artificial intelligence tools are?
   Do you use AI-based tool/tools at your firm for auditing process?
   How comfortable are you with the use of these tools for your work? if not comfortable, why?
   Will you say AI based tools are a threat to continuous availability of jobs for auditors? If yes, how is it so?

4. **Auditing Process**
   What role does AI based tools play in the planning stage of your audit process?
   System audit for internal auditing requires soliciting input (document) for the assignment, risk assessment and materiality determination, what role does AI play in this step of the process?
   With the internal control tests, substantive tests and other verifications required at the execution stage, how does AI tools transform this stage of the process from what it used to be?
   For the concluding stage, which is reporting, does the AI based tools have significance on this stage? How

   Overall, how does AI enable you to complete a high-quality audit?

5. **The role AI plays in the process**
   Before the adoption of AI tools, what method do you use for the auditing process? (is it manual or another expert tool)
   From your experience on the job, what role does AI play in each step of the process?
   What difference does the adoption of AI tools in auditing process make from the previous method used?
   Do you think adopting AI in auditing enhances effectiveness of the auditing process? In what ways
   How would you rate the effectiveness of auditing process with the adoption of AI tools on the scale of 1 to 10?

6. **Ethical concerns**
   From your professional opinion, what are the pro & cons of using AI in auditing process?
   What are the challenges encountered so far in the use of AI for auditing from your experience?
   Does AI functionality ensure compliance to required auditing Standards?
   Will you say the use of AI impairs or promotes professional judgement of auditors? If yes, in what ways