ARTIFICIAL INTELLIGENCE VS TRADITIONAL METHODS IN AUDITING: A COMPARATIVE ANALYSIS OF EFFICIENCY, ACCURACY, AND PRACTICAL RESTRICTIONS.

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ABSTRACT:

The incorporation of artificial intelligence (AI) into the auditing industry is the subject of this research project, which focuses on how AI will impact traditional auditing procedures, potential adoption difficulties, and how AI will eventually improve audit operations. Using a mixed-methods approach, the study investigates how AI is changing the auditing industry by using qualitative theme evaluation and quantitative survey analysis. Key findings show that by automating tedious procedures and analyzing big information, AI greatly increases audit efficiency and accuracy. Constraints are also identified by the report, including the requirement for a large financial commitment, the lack of qualified AI specialists, and worries about data confidentiality and safety. Notwithstanding these drawbacks, AI has the potential to revolutionize auditing procedures; several participants acknowledged that AI can improve fraud detection, anomaly identification, and real-time monitoring. The study concludes that, even if artificial intelligence (AI) is expected to dominate auditing in the future, human oversight and involvement are still necessary to guarantee accuracy, ethical concerns, and the overall quality of the audit. Strong data security standards, more funding for auditor AI training, and ongoing investigation into the moral consequences of using AI in auditing are among the recommendations. This study adds to the expanding literature of research on artificial intelligence in the auditing and accounting industries and provides useful information for regulators, auditors, and accounting companies. The results imply that the best strategy for negotiating the changing audit scenario may involve a hybrid paradigm in which AI augments human auditors.

INTRODUCTION

1.1 BACKGROUND:

Technological progress is altering every aspect of human existence at an exponential rate. Over the years, there have been various advancements in accounting; the most recent significant being the invention of bookkeeping with double entries more than 500 years ago. The fictional universe of science has already been acquainted with artificially intelligent robots by the end of the 20th century. Accounting is moving beyond manual input and book preparation methods toward automation. The twenty-first century is the automation era, and accounting is one of the leading sectors in this trend. Accounting automation handles all aspects of a business's lifecycle, not only the financial management department. This implies that the program helps record, alter, and interpret transactional data across the complete accounting process, with reduced dependence on human transaction entry (Chukwuani & Egiyi, 2020).

The 1980s were a time when advanced AI and expert systems could shine. Significant time and cost reductions were made possible by the introduction of electronic computers, which offered automated analyses and logical results (Carlson, 1957). Since then, a range of tools, computerization, and information technology have completely changed the way accountants gather, store, process, and distribute data. The effects of robotic process automation, according to Damasiotis et al. (2015), accounting departments were the first to widely use IT, and they were also the ones that spearheaded office computerization. Therefore, IT and accounting are now tightly connected. Bookkeeping and basic transaction processing were rapidly computerized. For automation to work, several programs had to be used, and programming and data entry took a lot of time and effort. ERPs made it possible to link specific assembly line workers or barcode scan events to specific accounting transactions. As a result, financial reports were produced instantly by encoding processes as opposed to being created by a group of accountants. Nevertheless, ERP systems continued to need connections to other programs, which contributed to the solution's high level of difficulty.

Accounting has always been known for its demanding requirements, which require a high degree of precision and focus on detail. With the advent of AI in auditing, traditional methods have been completely transformed. Technology has completely changed the internal oversight of financial reporting and accounting cycle, which has had an impact on the auditing procedures and technologies used by the auditor to collect audit evidence, obtain reasonable assurance, and complete the audit. Assuring the accuracy of the financial data and the type of audit report to be used was more challenging because the auditor's primary tool was a calculator, and the paper documents repeated the evidence (Shaikh, 2005). As per the reports made by ACCA (2018), software solutions that fully or partially automate repetitive, manual, and rule-driven human tasks are known as Robotic Process Automation. Developments in cutting-edge technologies such as blockchain and machine learning data analytics are expected to impact the accounting and auditing industry. Although the application of AI in auditing is not a new thing in this world, its influence is presently predicted to be stronger due to the availability of vast amounts of data and processing power.

1.2 PURPOSE OF THE STUDY:

This research aims to thoroughly assess the application of artificial intelligence in auditing compared to traditional auditing techniques. As technology is continuously changing many businesses, the auditing industry is no exception.

Firstly, this research helps to comprehend how AI may improve auditing process efficiency. Traditional auditing techniques need a great deal of manual data gathering, analysis, and verification, which may be labor-intensive and time-consuming. On the other hand, this study will examine if machine learning techniques may improve efficiency and expedite the auditing process, offering insightful information to businesses trying to maximize their operations (Munoko et al., 2020)

In addition, the research will compare the accuracy and dependability of audit findings obtained by AI with those produced by conventional methods. Artificial intelligence (AI) systems are capable of very accurate and consistent dataset analysis, whereas traditional approaches mostly depend on human expertise and are prone to mistakes. However, it's critical to evaluate how well AI can identify irregularities and guarantee compliance with auditing criteria without sacrificing the caliber of the audit results (Qayyum et al., 2020).

Lastly, it will investigate the wider range of analyses of data that AI may help with throughout the auditing procedure. Conventional approaches frequently use sampling strategies that might miss important trends in the data. Artificial Intelligence (AI) provides a more thorough analysis by processing large volumes of data, which may reveal insights that traditional approaches could overlook. This part of the research helps in knowing whether AI can give a more comprehensive audit regardless of its limitations and challenges, expanding the auditing process's total reach (Lehner, 2023).

Overall means, the goal of this study is to present a thorough comparison between AI and traditional auditing techniques, along with actionable advice for auditing companies thinking about incorporating AI into their operations. By focusing on these important topics, the study will add to the current conversation about the direction of auditing and how artificial intelligence might improve the breadth, accuracy, and efficiency of audits.

1.3 AIMS AND OBJECTIVES OF THE STUDY:

Objective 1: To carefully assess the effectiveness of AI-based and Conventional auditing methods regarding the amount of time needed to complete the audit tasks.

Like many corporate procedures in this era of information, accounting has been changing. While most firms have moved from paper-based to automated systems for collecting and storing information, the accounting industry continues to use manual recording tools for handling daily financial and transactional data. Using manual methods, such as spreadsheets, restricts access to current and real-time data and leaves no room for reporting until the end of the books and the beginning of a new month. During an economic shutdown, employees typically work long hours and rely more on detective human controls than defensive automated controls. Generally, spreadsheets increase the risk of mistakes and reduce efficiency. Eliminating the tools that cause uncertainty is the first step for any financial team to get it under control. As per Chukwuaini and Egiyi (2020), this strongly indicates the addition of more automation at each step. Therefore, accounting software may help employees become less erratic and more visionary by eliminating repetitive, manual, and boring operations.

Objective 2: To compare the accuracy and reliability of audit outcomes produced by AI-based techniques to Traditional approaches.

Traditional auditing makes extensive use of judgment from humans, which is prone to mistakes and discrepancies. Whereas the auditing procedure was carried out more accurately with reliable outcomes using AI technologies. Before reporting or utilizing the data further, robots can verify it. Therefore, Lacity & Willcocks (2016) have stated that the inaccuracy in data and the risks associated with quality are reduced, provided that the relevant rules and algorithms have been extensively verified in advance. Finance and accounting teams are working differently due to continuous accounting, which incorporates management, digitization, and period-end responsibilities into routine procedures. By providing accountants with the insight to provide accurate reports at any time of the month, this aids in the business's decision-making. Accuracy always increases and accountants use valuable staff more effectively when they don't expect to complete remote tasks or try to cram weeks of work into one. This helps to compare the mistake rates, anomaly detection, and general dependability of audit findings from AI and conventional techniques to make sure that the use of AI does not jeopardize the audit process's integrity.

Objective 3: To examine the constraints of artificial intelligence and the degree to which it may be applied instead of traditional techniques.

Audit work is becoming more and more vulnerable as real-time accounting and the importance of information become more widely recognized. According to Shaikh et al., (2018), the job of the auditors may be somewhat diminished by the implementation of programs that allow for instantaneous real-time modifications and the ongoing monitoring of IT systems. The lack of applicants with RPA expertise and experience is another factor. It is difficult to integrate AI with the current auditing system. This difficulty stems from the fact that it needs more money and training time. Another problem with AI use is data loss from different processes, as system inconsistencies can lead to a lot of private data being lost. In the words of Aitkazinov (2023), to prevent problems such as over-auditing or incorrectly interpreting data patterns, using AI in auditing necessitates a thorough examination of these constraints. This helps to examine the technological and practical limitations of artificial intelligence (AI) in auditing, offering a fair assessment of its suitability and pointing out areas in which supervision by humans is still essential. Making educated judgments regarding using AI in audit procedures will be made easier for businesses if they are aware of these constraints. The use of the conventional accounting method has significantly decreased, and the digitization of the accounting process has brought about many changes. However, are these changes advantageous to the accounting sector, and how auditors fit into this picture remains a question (Xing et al., 2023). Therefore, the necessity to investigate artificial intelligence's application in the auditing process despite these challenges and limitations is crucial.

1.4 RESEARCH QUESTION:

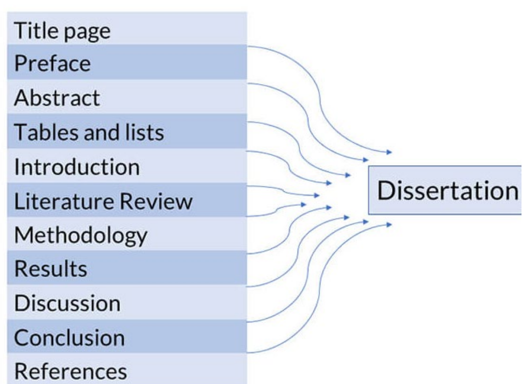
The topic of this research study, "How does the use of AI in the auditing process compare to conventional methods in terms of efficiency, accuracy, and scope?" intends to investigate and contrast the effects of traditional auditing procedures with AI-based methodologies. The research examines AI's potential uses and compares these novel approaches to more traditional, well-established ones. It makes it possible for the research to consider the differences in methodology, outcome, and professional influence, providing a thorough picture of the evolution of auditing procedures. Along with the three main objectives, it thoroughly assesses the possible advantages and disadvantages of incorporating AI into auditing procedures.

1.5 SCOPE OF DISSERTATION:

Comparing AI-based auditing and conventional auditing procedures is the focus of the research question in this study. Three crucial factors are being evaluated: scope, precision, and efficiency. Focusing on these fundamental aspects, the research seeks to offer a thorough comprehension of the efficiency and possible benefits or drawbacks of artificial intelligence in the auditing procedure (Al-Sayyed et al., 2021). Online questionnaire surveys are an efficient and useful method for gathering primary data for this study. A dissertation's scope describes the parameters and restrictions of the study. It outlines the scope of the investigation, including the topic of interest, the methodologies employed, and the duration of the study. The scope of this dissertation is the study of machine learning (AI) in auditing, including how it affects conventional auditing methods, what obstacles and limitations arise in putting it into practice, and what the auditing industry may see going forward. The study mainly focuses on the ramifications for auditors and the larger auditing industry, as well as the technological and practical hurdles associated with integrating AI into auditing operations (Bryman, 2016). With a focus on both the benefits and drawbacks, this in-depth examination seeks to shed light on the revolutionary potential of artificial intelligence (AI) in auditing and further our knowledge of how contemporary technologies are changing the way that auditing is done.

1.6 DISSERTATION STRUCTURE:

This dissertation's framework aims to investigate AI's application to auditing methodically. The research ideas are introduced in Chapter 1 with a summary of the study's history, objectives and targets, research question, and scope. In Chapter 2, the literature on artificial intelligence (AI) in auditing is reviewed with an emphasis on getting to know the role of AI in auditing, how AI reduces audit time, how accurate and reliable it is in comparison to conventional approaches, and the dangers and limits that come with it. In Chapter 3, the study design and methods are explained in depth. The research strategies and time horizon are covered, along with the research philosophy, strategy, research approach, techniques, and analytic procedures. The data analysis and discussion are presented in Chapter 4, which also provides insights into the main data gathered and looks at how it relates to or deviates from the study questions and hypotheses. The dissertation ends in Chapter 5, which summarizes the main conclusions, addresses the research topic, points out research gaps, suggests areas for more study, and provides helpful suggestions while outlining any limits. An appendix with supplemental material is included in Chapter 6, and an APA 7th edition style reference list is included in Chapter 7. This framework guarantees a thorough and well-organized analysis of the study issue, offering lucid insights into the efficacy and implications of artificial intelligence in auditing.



CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION:

There are significant changes brought about by artificial intelligence (AI) in several areas, including auditing. The primary issue faced by many businesses is how to interpret their data as they face greater pressure to gauge long-term value development. In the olden days, there was a time when a company's worth to its shareholders was once shown in an annual report by a robust order book, an appropriate balance sheet, and a track record of paying out attractive dividends. However, things have changed recently, and businesses now must articulate corporate value more broadly. Whether it is due to high-profile corporate failures or the pressure from the millennial generation to adopt a more responsible and socially conscious approach to business, the emphasis has shifted. Openness, long-term viability, and diversity are becoming more and more important components of the whole success metric as it is no longer only about optimizing profits (Boillet & Larkin, 2020). This study of literature review investigates how AI is changing auditing procedures with an emphasis on how it affects reliability, accuracy, and efficiency. Additionally, it looks at how much time is spent on AI-driven audit duties, assesses the precision and reliability of these audits, and pinpoints the dangers and restrictions related to AI in auditing. It also attempts to give a thorough grasp of how artificial intelligence (AI) is changing the auditing environment and the consequences for audit professionals through a detailed analysis of the available research.

2.2 ROLE OF AI IN AUDITING:

To begin with, the use of AI has drawn a lot of attention and investigation in the quickly changing fields of accounting and finance. RSM (2023) posted in their news and publications that (AI) has become a game-changer in the auditing industry, transforming conventional audit procedures and producing revolutionary results for auditors and organizations. Particularly as companies look to improve the effectiveness, precision, and openness of their financial reporting procedures, the role of AI in auditing has drawn a lot of interest (Kokina & Davenport, 2017). As per EY (2018) report, Artificial intelligence (AI) may be broadly described as a computing technology that demonstrates human intellect in some way. The goal of AI's auditing skills is to automate labor-intensive operations. These consist of scheduled and ongoing tasks for the duration of the audit. Therefore, Agnew (2016) has stated that the audit tasks that were previously conducted manually but are now made easier by technology stand to gain the most out of artificial intelligence tools.

Artificial intelligence, also known as machine intelligence, is defined by Ransbotham et al.. (2017) as the amalgamation of human-like intellect in machines. Understanding the context and using the available data to make informed judgments is the fundamental principle of artificial intelligence. On the other hand, O'Leary (1987) describes AI as a general word that encompasses a variety of activities such as expert systems, deep thinking and learning, pattern recognition, and the use of natural language by computers, among others. By contrast, Gunning & Aha (2019) describe artificial intelligence as a computer program that can decide what is best given according to the current situation. Well, Jackson (2019) adds that a lot of data and a high operating capacity are necessary for an AI system to function well. AI is expected to be included in practically all "new software products and related services by 2020," according to a 2017 report by Gartner (Alsheibani et al., 2018). Hence, it proves that most of the software has demonstrated this to date.

Although it was purely theoretical, Srinivasan (2016) suggested that automating the external audit process may result in the extinction of human auditors. Baldwin et al., (2006) outline the prior applications of AI that describe the use of artificial neural networks for risk estimation and analytical review procedures, as well as the use of genetic algorithms to help with the categorization of jobs like bad debt or receivable debt. Although there isn't an extensive framework that people are aware of, this list highlights particular audit duties appropriate for apps using AI-enabled technologies.

In one of the articles for the Harvard Commercial Review made by Davenport & Ronanki, Hasan (2022) pointed out their viewpoint that artificial intelligence should be approached by enterprises more from a commercial perspective than a technology standpoint. Businesses may utilize AI to accomplish three major objectives: automating business processes, interacting with clients and staff, and obtaining knowledge via data analysis. Chukwuani & Egiyi (2020) researched the impact of machine learning on the accounting industry. They did this to illustrate the extent of process automation advancements in the accounting industry. They believed that the accounting profession now focuses on software and computers instead of the paper and pencil period. The development of digital technology and the internet also accompanied the introduction of AI into finance. The rise of digital payment methods, algorithmic trading, and online banking has been made possible by this convergence, further altering the financial environment (Coeckelbergh, 2017). AI's capacity to handle and examine data from many digital sources has played a pivotal role in this shift.

While using AI in accounting and audits is not new (Keenoy 1958), current advancements in information and technology provide reason to believe that its influence on the profession will be greater in the years to come. Significant data and processing power, both readily available now in massive quantities, are necessary for artificial intelligence. Furthermore, artificial intelligence software has been more widely available in open-source and proprietary formats during the past few years. AI is a computer program that can simulate the "cognitive" function of the human mind, make balanced judgments, analyze its surroundings, and take activities that increase the likelihood that it will achieve a goal, according to Issa et al. (2016). This will help in facilitating the focus on tasks that will yield the highest benefit for the customers (Lu et al., 2017). If abnormalities and/or unlawful transactions are not found right away, it might be challenging for auditors to find them later (Shaikh, 2005). AI-based auditing solutions simplify the process of identifying these high-risk transactions.

According to a KPMG (2017) analysis, tech-powered and data-driven auditing is expected to take the spotlight in the future, with artificial intelligence (AI) becoming a significant driver of innovation and transformation in the auditing sector. There is a noticeable trend toward AI's increasing integration and utilization, even if there is still a large gap in its application to auditing processes.

Li (2023) stated that the creation of intelligent decision-making systems marked a significant turning point in the history of artificial intelligence in finance. These AI-powered financial decision-making systems base their choices on trends, data analysis, and predictive modeling. They are now necessary instruments for financial planning, asset allocation, and portfolio management. The financial audit is set for a significant and quick change because of the unparalleled speed at which technology is developing and the increased capacity for data collection and analysis that it affords enterprises. Technology and the knowledge of today's competent auditors work together to enable audit experts to go far deeper into an organization's financial aspects and give insights that help them make better judgments to facilitate a high-quality audit. AI technologies are predicted to play a bigger role in accounting as they develop, leading to further changes in the industry and the competencies needed by its practitioners.

2.3 ACCELERATING TIME EFFICIENCY:

As automation rises, so too will the focus on the auditing process and the roles and levels of involvement of auditors. The duties of auditors won't change despite these adjustments. Still, AI promises to provide real-time information evaluation and the assessment of unstructured content. (Samsonova-Taddei & Siddiqui, 2015).

The primary drawbacks of traditional auditing methods are their reliance on entering information manually, documentation on paper, and ledger maintenance. Despite their long history of success, these techniques are frequently labor-intensive. Since these procedures are manual, financial reporting cannot be completed as quickly or efficiently, which makes it difficult to handle massive amounts of data efficiently. Whereas the capacity of AI to deliver real-time data and analysis is one of its main advantages in auditing. AI-driven systems provide immediate analysis, in contrast to traditional approaches that frequently include a delay between data entry and report production. This facilitates more prompt and informed decision-making (Tandiono, 2023). In fast-paced corporate settings where financial information must be processed quickly, this capability is very helpful. AI has also improved the scope and complexity of financial analysis. It can forecast future developments and patterns, providing a more complete picture of a company's financial health than traditional accounting approaches, which are usually restricted to past data analysis (Meiryani et al., 2022). In terms of risk management and strategic planning, this predictive skill is priceless.

Effectiveness and Efficiency play an important role in determining the audit tasks. It refers to how well an audit activity produces the maximum value given a set amount of input. Company finances, managerial time, and training are a few examples of those inputs (Shamsuddin, 2018). Nowadays, auditors must quickly make sense of a vast amount of data while sifting through it. Omoteso (2012) argues that the removal of pointless activities is one of the ways AI is revolutionizing auditing. For example, the double-entry accounting system will be eliminated by blockchain technology, modernizing bookkeeping. Thus, this ability will enable the auditors to complete their duties quickly and efficiently. Through the studies of Craig (1994), it is understood that the implementation of AI expert systems has many benefits. Initially, auditors focused on past data confirming the manager’s declared financial performance. However, following the introduction of artificial intelligence globally, the focus of auditing systems shifted from historical data to real-time data analysis. Since then, investors have preferred to make investment decisions depending on real-time data analysis rather than historical company performance reports. Therefore, Van Liempd et al., (2019) have stated that continuous auditing is a better method to meet this need than auditing after a fiscal period. Companies should aim to give investors timely and pertinent information, as opposed to auditing them after certain financial reports are completed. This helps businesses to receive information from the AI systems as they record and carry out transactions.

AI is also revolutionizing the auditing industry by making it possible to gather audit evidence very quickly. Robotic Process Automation (RPA) is another area where AI is being used in accounting to automate normal and repetitive operations. Data input, reconciliation, and report production are among the chores that RPA in accounting may do, freeing up human accountants to work on more important projects. Manual collection of data is time-consuming and difficult, with a lot of human mistakes that can occasionally lead to less accurate findings. Mei et al., (2018) said that Intelligent Document Processing and other similar AI-based technologies have been developed throughout time as a solution to these restrictions. In earlier times, AI uses in banking were restricted to simple data processing and analysis. However, as technology advanced, these applications grew more complex and potent. The advent of algorithms for deep learning and machine learning marked a significant turning point by enabling financial institutions to analyze large datasets at a pace and precision never previously possible (Mihai & Duțescu, 2022). This technology has revolutionized risk assessment, identifying fraud, and financial forecasting.

AI's impact on business is clear from its capacity to provide useful insights, automate intricate procedures, and analyze enormous volumes of data. According to Wamba-Taguimdje et al., (2020), this skill has completely changed how firms approach strategy creation, operational efficiency, and decision-making. By automating routine tasks like data entry and transaction classification as well as more complex processes like audit and compliance, artificial intelligence has significantly decreased the time and resources required for accounting. According to Brennan et al., (2017), the use of AI in audits is now most noticeable when it comes to data collecting. This suggests that technology with AI capabilities may locate pertinent information, extract it from papers, and apply it, freeing up human auditors' time to focus on areas that call for more complex decision-making. AI, for instance, makes it possible to fully automate laborious processes like payment transaction testing, including extracting any supporting data for additional substantial testing.

Chui et al., (2016) say AI has the potential to shake up businesses that deal with mundane, repetitive operations. Since audits often include large numbers of repeat transactions, Baldwin et al., (2006) have stated that AI can change the way they are conducted. Based on Youyou et al., (2015) studies, AI-based judgments are more efficient than human ones. Therefore, it is argued that conventional manual audit methods are time-consuming and error-prone since people aren't good at gathering and evaluating massive amounts of transactional data. To reduce the amount of time spent analyzing the documents by half, Deloitte employs technology that uses natural language processing to extract information and data from populations or samples. This data is then transferred to a platform for automated contract information review (Eggers et al., 2019).

Artificial intelligence streamlines audits by enabling quick data collecting. A shorter period spent on data gathering enables the auditor to begin data analysis, improving the timeliness of outcomes. Thus, the auditing process can be completed more quickly when it is automated since auditors may work on it continuously. The typical auditing process will alter due to automation, including the time spent auditing. However, from Mohammed et al., (2018) research, it is understood that AI and auditors can work well together as a team. As auditors concentrate on data analysis and decision-making, artificial intelligence would be tasked with data extraction. Auditors may devote more time to client consultations, giving them greater value for their money and time.

Using artificial intelligence techniques to reduce the time required to complete audit tasks is in line with (**Objective 1**). The aim of this research is directly addressed by carefully comparing the shorter audit cycle times of AI vs conventional auditing techniques. This investigation not only shows how AI may simplify audit procedures but also emphasizes how crucial it is to evaluate these developments considering more established methods to increase time efficiency.

2.4 EVALUATING ACCURACY AND DEPENDABILITY:

Efforts to streamline accounting processes have their roots back in the 1950s when punch cards were used for data storage and retrieval as part of process mechanization (Keenoy, 1958). Further efficiency increases were made possible with the implementation of (ERP) systems, which allowed for better automation, centralized management of the system, and cross-functional integration. The notion of audit effectiveness varies across individuals. Some assess the success of an audit based on the outcome of an audit task, while others gauge it based on how they see the audit company. According to Bender (2006), the formal meaning is "the quality, competence, procedures, and independence of the audit firm."

The audit business must have competent personnel working for it and enough processes in place to do an efficient audit. Regardless of how, Dowling and Leech (2012) argue that to improve the effectiveness and productivity of audit operations, audit companies are progressively using complex, high-tech audit support systems, as opposed to the earlier electronic systems that took the place of paper-based systems in auditing. As businesses get bigger, there is an increase in the amount of data that must be inspected. Therefore, auditors need to keep giving investors accurate and reliable information. The data must continue to be provided in a way that satisfies the dependability criteria, which calls for auditors to carefully review the financial reports. It takes a lot of work to produce auditing reports that are both trustworthy and precise. Therefore, it is anticipated that AI systems will offer a tactical edge in achieving these goals. The examination of financial accounts from various places can be done remotely by AI. AI is also expected to help auditing firms in mitigating the consequences of the intricacy involved in managing financial data and reporting. Since the complexity of information has increased over the years, it has been challenging for consumers to obtain a high-value guarantee of the caliber of the accounting records they are viewing. As the chance of mistakes rises with the size of an organization, Artificial intelligence (AI) acts as a solution to simplify these operations. (Ghanoum & Alaba, 2020).

The availability of a large quantity of data and a reduced margin for mistakes would greatly improve the automated audit process's dependability. When conducting an audit, safety comes from delivering high-quality services and giving clients enough information. As generations pass by, it is believed that artificial intelligence improves efficiency and quality, which raises the level of reliability of consumer audit reports. Most auditors agree that using AI to automate auditing lowers the possibility of human mistakes, increasing the audit's appeal and security for customers (Omoteso, 2016). Using AI, auditors may make trustworthy deductions instead of speculating about potential problems, as they would with traditional audit techniques. Additionally, when it comes to data recovery, an automated audit method is more secure and efficient than a traditional audit procedure.

The integration of AI in accounting has sparked the creation of intelligent systems that can carry out difficult operations including risk assessment, fraud detection, and predictive analysis. These technologies have improved financial reporting accuracy while also offering deeper financial data insights that facilitate more strategic financial planning and decision-making (Smith, 2018). When it comes to auditing, artificial intelligence will allow auditors to obtain precise and current information at any time. The auditing industry is being revolutionized by making it possible to gather audit evidence more accurately. In the case of audit evidence, according to Cascarino (2012), it refers to the whole body of data that auditors gather to determine if the financial reports that a company presents are truthful representations of the firm's financial status. After the implementation of AI tools into auditing, auditors don't need to look at every transaction or activity. Rather, they must provide enough relevant evidence to support their audit conclusion. Using a variety of methods, including investigation, observation, interview, and testing, auditors get information they believe pertinent and helpful in developing an audit conclusion. Hence artificial intelligence helps in improving the gathering of auditing evidence.

To state it differently, auditing using artificial intelligence is a powerful strategy that fundamentally altered traditional management accounting thinking. This approach offers several benefits, including the ability to manage the financial operations of different banks and other financial-credit institutions, plan effectively, and make management decisions that are more accurate, precise, and productive. Furthermore, through the research made by Brenninkmeijer et al., (2018) about the auditing standards, it is evident that every company, regardless of its commercial setting, was established with a certain set of objectives in mind. According to this perspective, managerial expertise is a tool for effectively allocating the resources of AI expert systems already in place to meet predetermined organizational goals. A manager's duties include organizing, planning, and supervising organizational activities to maximize organizational interest. In the modern world, responsible and innovative managers constantly strive to receive ongoing feedback to stay strong and ready to handle organizational problems and issues. They do this by accurately monitoring and evaluating their performance. Consequently, one of the reliable indicators of an organization's ability to successfully meet its goals is the manager's ability to make the most use of the resources like artificial intelligence tools at hand.

As per Jedrzejka (2019), accounting personnel are required to oversee procedures in conventional accounting roles, which involve registering books of accounts, creating accounting vouchers, forming statements, and other tasks. This traditional method of accounting is too much work and requires a large amount of material, financial, and manpower resources. Although tasks may be finished on time, it leads to overtime labor, long workdays, weariness, and mistakes, all of which inevitably distort accounting information. On the other hand, reliability and productivity are increased when a business employs accounting software for all financial processes. Accounting staff just need to enter data; the auditing is left to the computer. Accounting staff members may input necessary data incorrectly, but the software system will quickly identify this and indicate the issue as an incorrect data entry, which can be corrected to improve the quality of the accounting data.

Evaluating Accuracy and Dependability is linked to **(Objective 2**). This literature review helps in demonstrating how artificial intelligence (AI) vs traditional methods in auditing may be used to provide trustworthy audit outcomes. To guarantee that the expected benefits are achieved without jeopardizing the reliability and integrity of audit results, it is also very crucial to carefully consider the consequences of integrating AI into auditing procedures.

2.5 RISKS AND LIMITATIONS:

Ghanoum & Alaba (2020) have stated that the job of auditors will evolve with time even if there hasn't been a significant shift yet. This is related to the technological side, where advancements are always happening. While AI-driven auditing methods have numerous advantages over traditional methods, including higher accuracy, efficiency, and analytical capabilities, they also bring with them new challenges that need to be overcome. The future of accounting hinges on striking a balance between minimizing AI's negative effects and taking advantage of its benefits. As the field advances, it is projected that AI will be used more frequently in accounting processes, altering the landscape for financial monitoring and evaluation. As Tandiono (2023) has mentioned, there are many additional challenges in implementing AI in auditing. The requirement for specific expertise and abilities to manage and comprehend AI systems is one major worry. Accounting experts will need to complete extra training and education because of this need, which is a deviation from standard accounting abilities. Notwithstanding all its advantages, Zhang et al., (2021) argue that concerns about data security, confidentiality, and ethics remain paramount. To properly utilize AI, businesses must carefully traverse these obstacles while upholding regulatory compliance and customer confidence. Safeguarding the privacy and integrity of financial data is crucial in this technology-based strategy. The likelihood of hacking and data breaches rises with reliance on digital technology.

AI has important consequences for the workforce as well. Since technology is changing so quickly, learning and adapting must be done constantly. Numerous regular tasks have been mechanized by AI, which has changed the skill sets needed in the workforce. Therefore, Harayama et al., (2021) said that professionals who can collaborate with AI, understand its results, and use its potential for strategic advantage are in greater demand. Considering this change, training, and development initiatives must be reevaluated to equip personnel for an AI-driven corporate environment. For certain businesses, particularly those that are small to medium-sized, the expense of integrating AI into accounting systems may be unaffordable. AI technology can come with a hefty upfront cost in addition to continuous maintenance, upgrades, and training expenses. The accounting industry's adoption of AI may be slowed down by this financial obstacle. Another problem that arises is that organizations encounter resistance to change when incorporating AI into accounting systems. Workers may be reluctant to embrace new technology because they don't know how AI may improve their jobs or because they fear losing their jobs. Strong change management techniques and transparent communication about the advantages of AI will be needed to overcome this opposition (Odonkor et al., 2024). Today's accountants need to be digital savvy in addition to having a solid foundation in accounting. The contemporary accountant's job now requires them to be proficient with AI tools.

There are plenty of risks along with benefits associated with AI in auditing. Compliance and commercial ethics provide the most danger. A company's reputation is largely determined by its adherence to established rules and business ethics. As to Alton's (2017) findings, corporate social responsibility endeavors now have a far greater effect on a company's capacity to boost sales than they did a decade ago. Problems might arise when artificial intelligence is used for work-related tasks. Because AI technologies can make conclusions, they are radically altering the structure of our commercial processes. If AI conclusions are not verified by a human mind, businesses may be forced to make poor judgments. The repercussions of a mistake this size might be disastrous if a malfunction in any area of the code leads to actions that are not morally right. Organizations may be in danger if programmers are not properly trained in controls when developing AI or if it is acquired from other sources. Aryal and Callahan (2022) point out that extremely sophisticated and complicated AI systems are capable of deviating from moral conduct if they are not under monitoring and control. While using AI in higher-stakes domains like risk or materiality evaluations has enormous promise, a company must consider how a hypothetical malfunction may damage its brand.

Given that AI technology is based on repetition, it may be more prone to errors or unreliability in complicated or unique situations. Like this, the broad use of AI compared to traditional methods in auditing may result in unanticipated events. While it is wonderful to have an AI that can operate without human oversight, the dangers involved would rise dramatically. As AI develops and permeates more areas of the workforce, the most significant hazards connected with it such as ethical concerns and dangers to human creativity will only become worse (Munoko et al., 2020). The expense of installing expert systems is yet another risk. It often comes with hefty installation expenses during the early phase. The cost of AI software is determined by several variables, such as whether a business needs a whole system or just a virtual assistant, as well as the functionality and management of the system (Malviya & Lal, 2021). Furthermore, integrating anything that is not completely established or understood comes with a higher price to pay.

Nickerson (2019) brings forth that there are still a lot of unaddressed limitations with AI, particularly when it comes to the financial outcomes of businesses of all shapes and sizes. Currently, available AI systems are still not particularly flexible, and before they can generate consistently correct answers, they must examine millions of data points. Unique accounting or organizational cases may not be able to offer accurate or meaningful data in the short term since the questions need to be repetitive for the machine to learn. Relying too soon on these findings might be quite troublesome. Furthermore, not all the issues that need to be looked at by interested parties regarding fiduciary duty and reasonable care are quantifiable or need the analysis of data. Zemankova (2019) says that despite the enormous advantages of artificial intelligence (AI), the hazards associated with it are so significant that businesses will only be able to utilize expert systems to support accountants rather than employing them to make decisions on their own. Businesses employ AI, but only insofar as it assists people and does not make judgments on its own since they are aware of this danger. Even under sufficient human oversight, artificial intelligence (AI) has limits despite its tremendous advantages to the accounting industry. However, Artificial Intelligence serves as a valuable tool to accountants, supplementing their work by doing mundane and basic chores that humans find unpleasant.

This concludes that, despite the obstacles and restrictions that have been shown linking to (**Objective 3**), artificial intelligence continues to be superior to conventional techniques in the field of auditing. The success or failure of the accounting profession in the future will depend on how well these problems are solved and have taken advantage of the possibilities.

2.6 CONCLUSION:

In contrast to conventional methodologies, the literature study demonstrates how artificial intelligence (AI) has the potential to greatly improve the time, accuracy, and reliability of audit operations. This shows the revolutionary role of AI in auditing. Artificial intelligence (AI) solutions have the potential to improve overall productivity and dependability by streamlining audit processes, lowering human error, and providing more thorough data analysis (Bumgarner & Vasarhelyi, 2018). Through automation, studies demonstrate that AI may shorten the time needed for audit duties; nevertheless, there are still obstacles to overcome, such as initial installation costs and the requirement for technical skills (Alaba, 2022). Even while artificial intelligence (AI) has many benefits, it is also important to address some of its drawbacks, including the possibility of excessive dependency on technology. (Seethamraju & Hecimovic, 2020). To guarantee the greatest levels of precision as well as reliability in the audit profession, this evaluation emphasizes the need for a balanced method that combines AI breakthroughs with conventional auditing ideas. The results of this assessment of the literature pave the way for more empirical research on the relative efficacy of conventional and AI-based auditing techniques.

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

3.1 INTRODUCTION:

The studies made by Saunders et al., (2019) have clearly stated that one must be explicit about what one is up to, the reason for doing it, and the consequences of findings for their research endeavor. Thereafter, they should ensure that the ideas are supported by prior research in the field, that the study design is clear, and have considered the methods for gathering and analyzing data. Globally, the creation and implementation of financial robots have been an expanding trend. Artificial intelligence falls under the technological science category. It is formed primarily by studying the intelligence of human simulation, extension, and development, leading to the formation of theories, techniques, technologies, and application systems. It may be defined as a computer system that uses technology to convert human knowledge into useful forces (Finio & Downie, 2023). Therefore, careful research is necessary to prove that the theory is practically true. In this chapter, the research strategy and technique used in the study comparing artificial intelligence and conventional auditing approaches are described. The goal of the study is to thoroughly evaluate how AI affects auditing processes by investigating important factors including audit work scope, quality, and duration efficiency. For the results to be reliable and valid, a strong research approach is essential. An introduction of the research philosophy opens this chapter, which is then followed by the research approach, methodology, and methods. Together with this, the study's time frame is also included. The chapter ends with the main methodological components. The study's ability to thoroughly evaluate the hypotheses and offer trustworthy insights on the application of AI in auditing is ensured by the thorough research design.

3.2 RESEARCH PHILOSOPHY:

The study's theoretical framework is supported by the research philosophy, which also has an impact on the techniques and methods selected. The quantitative character of this study, which entails applying statistical techniques to examine hypotheses drawn from theoretical frameworks, is in line with positivism (Mbanaso et al., 2023) The positive ideology used in this research depends on the idea that what exists is real and quantifiable using empirical evidence. A strong basis for contrasting AI-based and conventional auditing techniques is provided by positivist research, which aims to identify patterns and correlations that can be extrapolated across comparable settings (Creswell, J. W., & Creswell, J. D., 2018).

The researcher's questions and hypotheses help to concentrate and restrict the study's objectives. This formulation is a crucial milestone in every research and requires careful writing. As Tullie (2010) proposed, a primary tenet of this positivist paradigm is that science seeks to discover "the most objective methods possible to get the closest approximation of reality”. Since quantitative research focuses on researching things that can be seen and quantified in some manner, it mostly belongs to this school of thought. As per the research idea, the hypothesis would be that the efficiency, precision, and range of AI-driven auditing methodologies will either match or surpass those of conventional procedures. This method works well for this research because it gathers and analyzes quantitative data to evaluate theories about the effectiveness, precision, and range of traditional and AI-based auditing techniques. Therefore, to test theories and reach conclusions, positivism places a strong emphasis on making use of empirical evidence and statistical evaluation. This guarantees that the conclusions are supported by actual data, offering a thorough contrast between artificial intelligence and conventional auditing techniques. As clearly stated, the research project idea is committed to positivism to generate dependable, broadly applicable findings that advance the field of auditing and artificial intelligence.

3.3 RESEARCH APPROACH:

Planned and executed research processes and research methodologies include a range from general hypotheses to specific techniques for gathering, analyzing, and interpreting data. This strategy requires several decisions, which do not have to be made in the order that they make sense to us or in which they are presented. The ultimate choice is the method to be applied when studying a subject. The type of research topic or concern being researched also influences the choice of research technique (Mulisa,2022). Thus, this research paper is all about finding the difference between artificial intelligence and traditional methods in auditing in terms of certain aspects and comparing how far the changes have made the auditing industry a booming sector.

In this study, a deductive research methodology is used, which begins with the formulation of theories and literature-based hypotheses. After that, these theories are put to the test by gathering and examining actual data. Because it enables the methodical testing of predetermined assumptions about the effectiveness, precision, and range of using AI in auditing in comparison to conventional approaches. A quantitative research approach is used in terms of numbers rather than words. The method of assessing objective hypotheses by looking at the connection between variables is called quantitative research. In turn, these variables may be monitored, usually using devices, allowing for the statistical analysis of numerical data. Like qualitative, researchers using this method operate on the presumptions that hypotheses can be tested deductively, bias can be prevented, a substitute or hypothetical explanations can be controlled for, and the results can be generalized and replicated. This approach allows for systematic measurement of variables related to the engagement of artificial intelligence and traditional methods in auditing. By a predefined set of multiple-choice questions, the research collects quantitative information from participants via online platforms (Mkansi & Acheampong, 2012).

3.4 RESEARCH METHODOLOGY:

In the words of (Al-Ababneh, 2020), a methodology is a method of study that converts ontology and epistemological principles into rules outlining the proper way to do research as well as the guiding concepts, processes, and practices of the field. The foundation of the quantitative technique is the positivist research viewpoint. It moreover focuses on assessing variables and evaluating theories connected to broad causal explanations.

In this research, a quantitative technique is employed which is used to gather and examine numerical data. Quantitative approaches are appropriate for this study since they allow for the accurate and unbiased evaluation of factors including scope, accuracy, and time efficiency. To evaluate the hypotheses and provide conclusions on the relative effectiveness of artificial intelligence (AI) and conventional auditing techniques, the study makes use of organized questionnaires and statistical techniques (Mohajan, 2021). Primary data is the type of data that is used in this study. Primary data is research information that has been gathered straight from the source, without using middlemen. The data collection technique used in this project is a survey conducted online using Qualtrics. According to Engel et al., (2014), surveys are a useful tool for gathering an extensive range of respondents quickly and affordably. The survey aims to get opinions and experiences on AI-based and conventional auditing techniques from auditing experts. It also includes participation from those with less experience or no auditing background as well. Both closed-ended and open-ended questions are included in the questionnaire to collect both numerical data and qualitative opinions. Opinions from respondents served as the primary source of subject data. The perspectives and reactions of the respondents to the consequences of artificial intelligence's introduction into the auditing business comprise the study's core data.

The data collection was primarily administered in a way where the participants could engage from all over the world. Research indicated that the probability-stratified sampling strategy and simple random were appropriate for handling multiple data and estimating outcomes (Bauer et al., 2021). The population of interest for the survey in this research was utilized from any auditing or accounting firm including small, large, or medium-sized companies. Individual auditors with professionalism, specific industries that are undergoing auditing in their organization, and the regulations and recommendations of professional groups or regulatory bodies that supervise auditing standards and procedures that might impact the use of AI in auditing, and for generalized opinions participants with less experience are all included as the sources of data to the online survey. The research study concludes with an answer to the research question, which was determined by investigating and obtaining empirical data from auditors in auditing firms that have already incorporated artificial intelligence (AI) into their audit process. These auditors were able to provide a detailed analysis based on their experience and reality regarding the differences machine learning makes in the effectiveness of the audit process when compared to traditional auditing or other technologies they may have used in the past.

3.5 RESEARCH STRATEGIES:

To successfully structure the inquiry process and answer the research questions, research strategies are essential. Surveys are used in the research plan to collect data from the intended audience. Utilizing a predetermined, organized set of multiple-choice questions guarantees data collecting uniformity and makes statistical analysis easier (Nardi, 2018). With the use of surveys, which are useful instruments for acquiring quantitative data, a researcher may quickly and efficiently collect data from a sizable number of participants. A systematic set of questions with multiple options is used in the study to minimize biases and increase the objectivity of the findings by ensuring consistency and dependability in the data obtained. In addition to making comparison and analysis easier, this organized technique enables rigorous statistical analysis, an essential tool for spotting trends, patterns, and correlations. As a result, the survey approach is a suitable and successful method for this study since it is consistent with the positivist ideology of obtaining objective, quantifiable findings (Fowler Jr, 2013).

The primary variables of interest, such as scope, accuracy, and time efficiency, are intended to be measured by the survey questionnaire. To gather data on the respondents' origins and background checks, it includes demographic questions and Likert-scale questions to measure respondents' perceptions and experiences (South et al., 2022). Performance indicators of AI-based and conventional auditing techniques will be directly compared using a comparative analysis approach. The goal of the study is to present actual data on the efficacy of AI in auditing by comparing criteria such as the scope of audit outcomes, accuracy of results, and processing time. The hypotheses are then tested using R-studio to determine the impact of artificial intelligence on auditing. These tactics cover the whole schedule for gathering data, measuring, and evaluating it, guaranteeing a methodical approach to the research.

3.6 RESEARCH TIME HORIZON:

The research focuses on a cross-sectional time horizon. In this type of study, the variables are examined for connections by gathering data at a particular moment in time. This methodology makes sense for the study as it helps to compare the current state of traditional and AI-based auditing techniques. Abdelhakim & Badr (2021) suggests that through the collection of responses from individuals using online resources within a particular period, the study offers a glimpse into participants' opinions and perceptions. The data collection took place around a month after the necessary clearances were obtained from the supervisors. An approximate total of 100 responses was anticipated. It took around a week to complete the design work of the survey consisting of 15 total questions including open-ended and closed-ended. After that, the process of gathering data began, and it was completed quickly, gathering between 75 and 80 records within a month.

3.7 RESEARCH TECHNIQUES AND PROCEDURES:

The creation of a standardized survey questionnaire, data gathering, and statistical analysis are some of the research methodologies. There are several steps in the data-gathering process. To guarantee the level of accuracy and reliability, the survey questionnaire is first designed using the study goals as a guide, and it is then tested using statistical procedures. The sampling phase next entails employing stratified random sampling to choose a representative sample of auditing experts. After that, administering the survey comprises giving the online form to the chosen sample and gathering their answers within a predetermined window of time. To resolve any missing or inconsistent replies, the survey data is reviewed and cleaned as the last stage in the data cleaning process. Several statistical approaches are applied during the data assessment procedure to examine hypotheses and develop conclusions. Descriptive statistics are computed to summarize survey results, including metrics like the mean, median, and standard deviation. Regression analysis and correlation tests are examples of inferential statistics used to test hypotheses and find meaningful distinctions between AI-based and conventional auditing techniques (Field, 2013). Additionally, thematic analysis is used on open-ended survey responses to find recurring themes and insights on the application of AI in auditing (Clarke & Braun, 2006).

3.8 CONCLUSION:

In this chapter, it describes the overall concept of this research study. The research method and design including research approach, philosophy, methodology, strategies, time horizon, techniques, and procedures, are all included. This helps rigorously test its assumptions and results in trustworthy findings on the contrasting results of artificial intelligence and conventional auditing methods because of the quantitative methodology, positivist mindset, and deductive approach (Bryman, 2016). The data analysis findings will be presented in the upcoming chapter along with a discussion of how they relate to the goals and theories of the study.

CHAPTER 4: DATA ANALYSIS AND DISCUSSIONS

4.1 INTRODUCTION:

This chapter delves into the examination and conversation of the information gathered from our study about the relative effectiveness, precision, and range of AI-based auditing approaches in comparison to conventional auditing methodologies. The aim is to present a thorough assessment of the results, placing them in the context of our study hypothesis. To get insight into the possible advantages and disadvantages of using machine learning in auditing procedures by methodically analyzing the data. The chapter opens with a thorough examination of the primary information collected from auditing experts as well as from inexperienced participants via questionnaires. These questionnaires were made to gather a broad variety of viewpoints and experiences concerning traditional and AI-based auditing techniques. The study uses inferential statistics, such as correlation and regression evaluation, to test the research hypotheses and find statistically significant variance between the two auditing approaches, as well as descriptive statistics, like mean, median, and standard deviation, to summarize the survey responses (Gentle, 2020). It also includes a qualitative examination of the open-ended survey results in addition to the quantitative analysis. To provide a deeper, more complex comprehension of the data, this thematic analysis seeks to uncover recurrent themes and ideas on the application of Artificial Intelligence in auditing (Clarke & Braun, 2022). A comprehensive picture of the state of AI in auditing today is given by integrating both quantitative and qualitative analysis, which highlights the technology's potential and drawbacks.

The discussion part will evaluate whether the data confirms or refuses the hypothesis by interpreting the findings in the context of the body of current literature. It helps to evaluate the reliability of our conclusions and their significance for the auditing sector by contrasting our results with those of earlier research. The main conclusions of the chapter are summed up, the resulting consequences for policy and procedure are discussed, and recommendations for further study are made. This thorough investigation seeks to offer insightful information to scholars, policymakers, and auditors interested in artificial intelligence's changing role in auditing (Han et al., 2023).

4.2 PRIMARY DATA ANALYSIS:

The process of analyzing data involves gathering primary data, processing it, and drawing conclusions to aid in decision-making. A typical approach is descriptive analysis, which involves gathering data, putting it into words or layouts, and then describing it to give the analysis performed in this study a more realistic clarity. The RStudio statistics software is used to analyze the descriptive and inferential analysis of the data. A quantitative approach to data analysis was employed in this investigation (Meiryani et al., 2022). This study intends to ascertain whether the application of Artificial Intelligence in auditing influences the traditional methods in terms of time efficiency, accuracy, and scope. The research findings and analysis begin with descriptive statistics about the study's data. While objective 3 is established by thematic analysis, the findings of hypothesis testing and discussion of the hypothesis were assessed statistically using the R studio data processing tools concerning objectives 1 and 2. The core data for this study was obtained through a questionnaire given to staff members who have been working in the auditing sector, as well as staff members who are familiar with or utilize AI-based tools in auditing within their organizations. Participants with neutral or less experienced in the auditing field with or without the use of artificial intelligence in auditing were also involved. Therefore, the examination of answers from individuals with different degrees of expertise in artificial intelligence (AI) auditing yields important information on how AI affects auditing procedures. The goal of the data analysis is to find both the parallels and contrasts in these two groups' perspectives and experiences. By doing so, the analysis will shed light on AI's role and efficacy in the auditing industry. While less experienced individuals give theoretical or perceived viewpoints, seasoned auditors contribute practical observations. By pointing out discrepancies between perceptions and the truth, this dual analysis can assist in shaping future implementation and training plans for the auditing profession (Jamieson et al., 2023).

To summarize and comprehend the information gathered from survey participants, descriptive statistics are crucial. They offer a means of calculating the variation of the information using (standard deviation) as well as (mean and median) for the main trend (McClave et al., 2022). The following survey questions are used to analyze:

Survey questions:	**Variables:**	**Mean:**	**Median:**	**Standard deviation:**
How effective do you think AI is in detecting anomalies in financial data?	"Effectiveness"	1.608	2.000	0.608
Do you think AI will become the standard practice in auditing in the next 5-10 years?	"Future"	1.481	1.000	0.574
How does the integration of AI impact the roles and responsibilities of auditing professionals?	"Impact"	1.456	1.000	0.594

Table: 1 – *DESCRIPTIVE STATISTICS ANALYSIS*

According to the mean, median, and standard deviation values, in the case of AI detecting anomalies in financial data, the opinions seem to indicate that, with some variation, AI is useful for identifying abnormalities (Bleibaum et al., 2020). This indicates that while some respondents disagree, many believe AI to be a useful tool for spotting anomalies in financial data. There is a lot of hope that AI will eventually replace auditing as the norm. With very little disagreement, many respondents think AI will either certainly or probably be widespread in the next five to ten years. The duties and roles of auditing experts are expected to undergo major changes due to artificial intelligence. This suggests that someone is aware of how AI has the potential to revolutionize the industry (Lucky, n.d). The findings clearly show that people are generally in favor of using AI in auditing. As per the responses taken to analyze the data, people think AI will soon become prevalent, think it can identify abnormalities well, and expect big changes in professional duties and responsibilities because of AI integration. These observations are consistent with current studies indicating that artificial intelligence is transforming conventional auditing techniques by improving productivity, precision, and capacity to manage massive amounts of data. Since AI can eliminate mistakes and automate complicated operations, its acceptance in auditing is expected to increase as it continues to develop. Thus, it can be said that it is not only influencing the future of the auditing profession but also altering existing auditing techniques, highlighting the necessity for auditors to pick up new skills and adjust to the changing environment. These observations are consistent with recent research indicating that artificial intelligence (AI) is transforming conventional auditing techniques by improving productivity, precision, and capacity to manage massive amounts of data. Because AI can eliminate mistakes and automate complicated operations, its acceptance in auditing is expected to increase as it continues to develop (Luthfiani, 2024).

To interpret **objective 1**, the association between the participants' judgments of AI's effectiveness in auditing and their familiarity with it was investigated using Pearson's correlation test. The following survey questions were utilized for performing the analysis:

Questions:	Multiple choices:	Number of responses:
How familiar are you with the use of AI in auditing?	Very familiar Neutral Not familiar at all	10 37 29
Based on your understanding or experience, how effective do you think AI-based auditing is compared to conventional methods?	Much more efficient Slightly more efficient About the same Slightly less efficient	24 27 15 5

	Much less efficient	1

Table: 2 – *SURVEY RESPONSES FOR CORRELATION TEST ANALYSIS*

The estimated effectiveness of artificial intelligence auditing techniques is positively correlated with auditing familiarity, as indicated by the Pearson correlation coefficient (r) of 0.2792457. This positive association implies that the impression of AI's efficacy in auditing rises with increased experience with the technology. With 72 degrees of freedom (df), the t-value is 2.4676 and the p-value is 0.01598. If the P-value is below your threshold level of significance ($P<0.05$), then we can reject the null hypothesis (Di Leo & Sardanelli, 2020). Therefore, the results show that the observed correlation is statistically significant as the p-value of 0.01598 is smaller than the traditional significance level of 0.05. Thus, the null hypothesis stating that there is no correlation between perceived effectiveness and AI familiarity, can be rejected. The correlation coefficient's 95% confidence interval is between 0.05420572 and 0.47728990. The fact that there is no zero in this interval lends further support to the finding that the two variables have a strong positive correlation. The findings show that individuals who are more experienced with artificial intelligence (AI) in auditing generally believe it to be more successful than conventional techniques. This result is consistent with other studies that indicate a favorable correlation between one's comfort level with technology and their perception of its advantages (Vasarhelyi et al., 2022). Being familiar with AI technologies probably boosts one's confidence in using them and comprehension of their benefits, such as improved precision and quickness of data processing.

```
> cor.test(auditing1$effectiveness, auditing1$familiarity)

        Pearson's product-moment correlation

data:  auditing1$effectiveness and auditing1$familiarity
t = 2.4676, df = 72, p-value = 0.01598
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.05420572 0.47728990
sample estimates:
      cor
0.2792457
```

Figure: 1 - *CORRELATION TEST OUPUT USING R STUDIO*

The positive association has important ramifications for AI-based auditing's accuracy and efficiency. Gaining greater experience with AI technologies may help with their adoption and use, which helps speed up audit processes and produce more accurate findings. Research has demonstrated that AI can eliminate human error, automate repetitive operations, and use sophisticated data analysis to deliver more profound conclusions. Experts in artificial intelligence (AI) auditing, for example, may use these tools to do more thorough data analysis and spot trends and abnormalities that older approaches would overlook. This may result in audits that are more accurate and provide stakeholders with more comfort (Moffitt et al., 2018). Hence, the results of the survey's analysis show that as the knowledge and familiarity of AI-based auditing techniques increases, the effectiveness of the use of artificial intelligence also increases compared to traditional methods proving it is significantly positively correlated. This connection emphasizes how crucial expertise and familiarity are to optimizing AI's advantages for the auditing process. To fully grasp AI's promise in improving time efficiency, accuracy, and scope, auditors must continue their education and training. This is especially true as AI continues to advance.

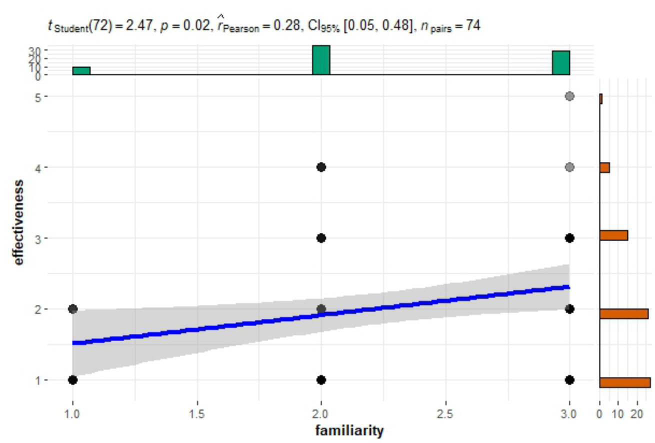


Figure: 2 – ***A PLOT THAT DEPICTS THE CORRELATION BETWEEN FAMILIARITY AND EFFECTIVENESS IN AUDITING***

The graph shows the relationship between the two variables. “Familiarity" with AI in auditing, which is represented by the x-axis, goes from 1(very familiar) to 3 (not familiar at all). The “Effectiveness” of AI in auditing compared with traditional methods is represented in the y-axis. The values range from 1 (much more efficient) to 5 (much less efficient). The blue line represents the regression line that shows a general trend of the data. There is a tendency for perceived efficacy to rise along with increased familiarity with AI. A relatively positive association is shown by the Pearson correlation coefficient (r = 0.28). Studies have demonstrated that a greater level of expertise with AI tools results in greater understanding and use of these technologies, which raises their claimed effectiveness (Davenport & Ronanki, 2018). Using AI in auditing can drastically cut down on the amount of time needed to finish audit activities which can also improve audit reliability and accuracy by decreasing human error and improving the capacity for thorough analysis of big datasets (Wang & Cuthbertson, 2015). This idea is supported by the graph's positive correlation, which indicates that auditors become more aware of these advantages as they work with AI technologies. This result corresponds with academic literature, which emphasizes the need for expertise and training to reap the rewards of artificial intelligence in auditing fully. Therefore, with increased familiarity with AI, auditors may better utilize its capabilities, resulting in more precise and efficient audits.

To investigate **objective 2**, the data is tested using regression analysis which is a tool for investigating the connections between different variables. The appropriate questions for this analysis are focused on how respondents perceive the length of time it takes to complete an audit and how that leads to higher accuracy in the audit outcomes. The following questions are utilized for this testing:

Questions:	**Multiple choices:**	**Number of responses:**
Which method do you think requires more time to complete an audit?	Conventional methods AI-based techniques	64 15

What role does accuracy play in the auditing process?	Extremely important Very important Moderately important Slightly important Not important	48 19 11 0 1

Table: 3 – *SURVEY RESPONSES FOR REGRESSION ANALYSIS*

Regression analysis-worthy questions should logically relate to one another and be able to affect one another (Montgomery et al., 2021). "Time" taken to complete an audit using artificial intelligence vs traditional methods is taken as the dependent variable whereas, "Accuracy" playing an important role in the auditing sector is taken as the independent variable for the analysis. When Accuracy is zero, the intercept (1.04702) shows the time variable's anticipated value. At $p < 2e\text{-}16$, this coefficient is very significant. As per the analysis, time and accuracy appear to be positively correlated, according to the accuracy coefficient (0.08817). The Time is predicted to rise by around 0.08817 units for every unit improvement in accuracy. This association is not exactly below the traditional significance level (0.05), but it is slightly significant ($p = 0.0723$).

```
> regression <-read.csv("regression.csv")
> Linear_model <-lm(Time ~ Accuracy, data = regression)
> summary(Linear_model)

Call:
lm(formula = Time ~ Accuracy, data = regression)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4879 -0.2233 -0.1352 -0.1352  0.8648

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.04702    0.08979  11.660   <2e-16 ***
Accuracy     0.08817    0.04839   1.822   0.0723 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.389 on 77 degrees of freedom
Multiple R-squared:  0.04133,	Adjusted R-squared:  0.02888
F-statistic: 3.319 on 1 and 77 DF,  p-value: 0.07235
```

Figure: 3 - *REGRESSION ANALYSIS OUTPUT USING R STUDIO*

Regression analysis is typically employed in predicting and foreseeing, where its use closely parallels the field of machine learning. Finding a linear relationship to explain the association between an independent and dependent variable is the goal of simple linear regression (Maulud & Abdulazeez, 2020). Therefore, the coefficients that are acquired by the result of the "lm" function in R can be used to generate the model's formula. $Y = \alpha + \beta 1x1 + \varepsilon$, where Y is the dependent variable, α is the intercept or constant, β1 is the slope, x1 is the independent variable and ε is known as epsilon or error term. As per the formula, Time acts as the dependent variable and Accuracy plays the role of independent variable. Therefore, Time = 1.04702 + 0.08817 * Accuracy, which gives the $R^2 = 1.12919$. This shows that 112% of the variation in the Y value is accounted for by the X value. Hence, it proves a positive relationship between the dependent and independent variables. While the accuracy is zero, the intercept shows the projected amount of time needed for the audit. The shift in the auditing time needed for an increase of one unit in accuracy is shown by the slope. More specifically, it is anticipated that the time needed would rise by around 0.08817 units for every extra unit of accuracy. This positive correlation implies that longer auditing periods are linked to greater accuracy. According to the positive slope, there is a tendency for the time needed for auditing to grow as accuracy does. This is because more accuracy calls for more assurances and checks, which could take longer to guarantee correctness (Frost. J, 2020). Nonetheless, it demonstrates that, even with longer turnaround times, artificial intelligence produces audits with greater accuracy than conventional approaches. Auditors and companies must weigh the trade-off between attaining high accuracy and sustaining efficiency if greater precision results in longer auditing time frames. A better understanding of this connection can aid in resource allocation and planning.

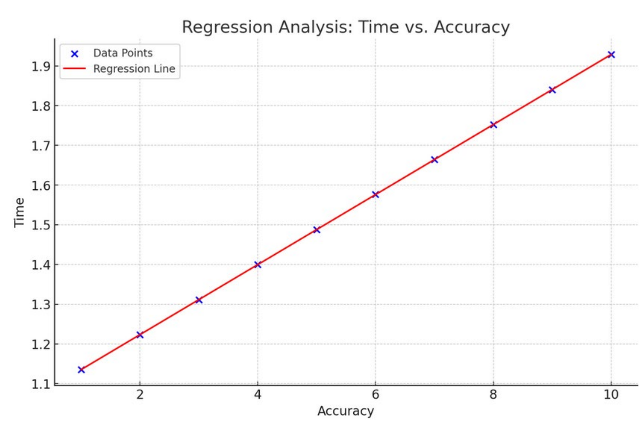


Figure: 4 - *PLOT OF SIMPLE LINEAR REGRESSION*

Plotting the independent variable (Accuracy) along the x-axis and the one that is dependent (Time) along the y-axis illustrates a basic linear regression analysis. The figure illustrates the relationship between the precision of the auditing procedure and the amount of time needed for auditing, with each of the points on the plot representing a result from the dataset.

In the case of **objective 3**, according to Cernasev & Axon (2023), thematic analysis is used to look at the data that offers comprehensive responses to the study's objectives and the research issue. Using strong inductive analysis to provide accurate and meaningful explanations of the message being given is the primary objective. The following survey question is employed:

Describe in a few words any additional thoughts or comments on using AI in auditing.

↓

PARTICIPANT RESPONSES:	TRENDS AND PATTERNS / INTERPRETATION:
"Using AI in auditing can significantly improve accuracy and efficiency." "AI can process large volumes of data much faster than humans, significantly reducing the time required for routine audit tasks." "AI in auditing increases accuracy and efficiency by automating repetitive processes and analyzing massive amounts of data."	Efficiency and Accuracy of AI: By automating processes, analyzing massive data sets rapidly, and lowering human error, artificial intelligence is thought to improve auditing efficiency and accuracy. This is in line with previous research that emphasizes the advantages of AI for data-intensive activities (Moffitt et al., 2018).

"AI can be hacked, errors can occur, and can also impact data privacy." "The use of AI can boost the process in many ways, but it can adversely affect the working professionals in auditing." "It raises concerns about data privacy, the need for human oversight, and the potential for algorithmic bias.	Risks and Limitations: Even though AI has many benefits, there are serious worries about data privacy, mistakes, and employment implications. To secure sensitive information, these difficulties require careful execution and strong security measures (Odonkor et al., 2024).
"AI will be the next lead auditor." "AI in Auditing would minimize human errors and speed up the process." "AI in auditing is highly effective, significantly increasing accuracy and efficiency."	AI's future in auditing: It's widely accepted that artificial intelligence will be very important to auditing in the future, improving audit speed as well as precision. This illustrates the continuous trend in financial procedures toward using cutting-edge technologies (Kokina & Davenport, 2017).
"AI in auditing will help in the efficient handling of data entry, validation, and pattern recognition tasks by AI algorithms." "Auditors can use AI to produce data-driven insights and visualizations for audit committee and board reporting." "With the use of AI in auditing, auditors become more relaxed in their workplace."	Effect on the Roles of Auditors: AI is expected to transform the roles of auditors, shifting their focus from routine tasks to more complex, judgment-based activities. This aligns with the notion that AI can augment human capabilities, allowing auditors to focus on strategic decision-making (Alles, 2015)

"AI in auditing holds promise for improving efficiency and effectiveness, but ethical considerations and human oversight remain crucial." "AI can be very useful in the future, but it can be tricky as well."	Security and moral issues: The ethical ramifications of AI-driven audits are acknowledged, as is the requirement to maintain human oversight. To preserve integrity and confidence in the auditing process, honesty and responsibility in AI algorithms are crucial (IEEE, 2019).

Table: 4 – *THEMATIC ANALYSIS FOR TRENDS AND PATTERNS*

Since artificial intelligence has the potential to improve accuracy and efficiency in auditing, a thematic analysis of survey responses indicates a significant endorsement for its inclusion (Santos, 2023). But obstacles including worries about data privacy, moral ramifications, and the effect on employment draw attention to the necessity of a methodical and deliberate approach. AI is predicted to be a key player in changing conventional auditing procedures as it develops, striking a balance between the advantages of automation and the need for human oversight.

4.3 CONCLUSION:

Survey data analysis shows a distinct trend toward the acceptance of AI as a game-changing instrument in the auditing industry. Most responders agree that AI has improved the effectiveness, precision, and capacity to manage massive data quantities and automate tedious operations. This is consistent with research that shows how artificial intelligence (AI) may transform auditing procedures by decreasing human error and expediting procedures (Brown Liburd et al., 2015). However, the research also highlights a few issues that need to be resolved if AI is to be used successfully. These worries align with previous research findings, which stress the need for strong data governance structures and ongoing professional development to handle AI technologies properly. Additionally, even though AI is viewed as a vital tool for auditors in the future, it should complement human auditors rather than completely replace them. Because human judgment is still crucial in complicated decision-making processes, a hybrid strategy that combines AI and human knowledge will likely be the most successful (Moffin et al., 2018). To conclude, the survey's findings along with the possibility of large operational gains, point to a strong preference for the application of AI in auditing.

CHAPTER 5: CONCLUSION

5.1 SUMMARY OF FINDINGS:

The research on machine learning in auditing sheds light on how technology affects the field. According to the results, AI significantly improves auditing procedures' speed and accuracy by quickly handling massive amounts of data and reducing human mistakes. Nonetheless, issues including data privacy, high upfront costs, implementation difficulty, and the requirement for highly qualified staff continue to be major problems. Respondents are hopeful that during the next five to ten years, AI will become prevalent despite these obstacles. Significantly, the report emphasizes that the expertise of human auditors will continue to be essential, particularly when making difficult decisions, upholding moral principles, and reducing dangers such as algorithmic bias. This methodical approach is in line with previous research that highlights the need for human supervision in the efficient and moral application of AI (Byrnes et al., 2018). According to Gepp et al., (2018), while integrating AI improves auditing procedures, to effectively reap the benefits of this approach, certain things must be carefully considered. Combining AI skills with human knowledge will be essential to improving audit effectiveness and standardization as the sector develops. The ability to adopt even more sophisticated technological solutions, particularly in the form of an ecosystem approach, has arisen from the replacement of these manual operations with technical solutions.

5.2 RESEARCH GAP:

Finding a gap in the current literature and creating a study to fill it is a popular strategy for creating and responding to quantitative research questions. Researchers can find valuable questions to analyze the data using helpful guiding concepts (Jamieson et al., 2023). Gray et al., (2014) looked at the output of research on expert systems and artificial intelligence in accounting and found that during the late 1990s, there was a decline in both practice and research in these areas. According to his reviews of other literature, publications on expert systems about accounting peaked between 1986 and 1998, declined in 1999, and have been comparatively low ever since. The findings indicate that throughout the previous 30 years, artificial intelligence research in auditing has increased significantly, despite a brief hiatus in the field in the late 1990s.

As a result of the continuous progress in computer technology, most sizable accounting firms have included artificial intelligence in their integrated audit systems for automation to make audit decisions. ICT tools like Electronic Data Interchange, Electronic File Transfer, and Image Processing are progressively replacing traditional audit trails, as previously estimated by Bell et al., 1998. This will drastically alter the audit process. Even with the encouraging developments regarding artificial intelligence in auditing, there are still large research gaps. A significant deficiency exists in the body of research on the long-term effects of machine learning on the field of auditing, specifically concerning the appropriate ratio of AI automation to human supervision. Most research so far has concentrated on short-term advantages and difficulties, such as improved data processing capacities and possible decreases in human mistakes. The use of artificial intelligence will get more and more sophisticated, which will save costs, produce better results, and enhance our quality of life. Numerous AI components will soon be operating on our behalf, frequently in the background (Brynolfsson & McAfee, 2014). However, there is no actual data about how AI will impact auditors' duties in the future, particularly how it will affect work in the industry and how requirements for skill will alter (Wu et al., 2020).

5.3 AREAS OF FURTHER RESEARCH:

Brynolfsson & McAfee (2014) have stated that more computing resources will be added to the earth in the next coming years than it has ever been in history. It seems anticipated that the rise will be more than a thousandfold during the next twenty-four years. Exabytes of data have already been digitized, but the rate at which this data is being digitized is increasing. From the usage of pencil and paper to typewriters, calculators, spreadsheets, and accounting software, accounting has changed along with technological advancements. Longitudinal studies that look at the long-term impacts of integrating AI in auditing are necessary, even though much current research has concentrated on the immediate impact of AI. These studies ought to look at how AI affects the auditing industry over time, especially in terms of job responsibilities, necessary competencies, and the general efficacy of audit procedures. Such studies may also look at how auditors adjust to artificial intelligence tools and if they enhance the quality of audits over time (Shazly et al., 2024). It is imperative to have strong ethical and legal frameworks as AI gets more integrated into audits. Future studies should concentrate on developing policies that guarantee accountability, impartiality, and openness in audits powered by AI. This entails investigating the ethical conundrums brought on by increasing machine learning in decision-making processes as well as how to avoid algorithmic biases that might jeopardize audit results (Raisch & Krakowski, 2020).

To fully understand how AI affects audit quality and efficiency, especially in complex auditing environments, more study is required. This entails assessing how well AI detects fraud, maintains compliance, and lowers audit risks. The increasing use of AI technologies in auditing necessitates a comprehension of the changing nature of human-AI partnerships. Research should examine the best ways for audits and AI systems to collaborate, determining which activities are most appropriate for AI automation and which call for human judgment and experience (Qader & Cek, 2024. Additional case studies tailored to individual industries are required to illustrate the usefulness of machine learning in auditing across various sectors.

5.4 RECOMMENDATIONS:

Technology is gradually taking over human talents and capabilities. Considering how many science-fictional technologies are becoming true daily, drastic measures might seem essential. Many recommendations can be made to improve the integration of artificial intelligence technologies' efficiency in the field of auditing. Investment in training programs that provide auditors with the abilities they need to collaborate with AI technologies efficiently should be an organization's top priority. This covers instruction in data analytics, comprehension of AI algorithms, and interpretation of insights produced by AI (Ungerer & Slade, 2022). According to Alles (2015), AI should be viewed as a tool for improving human auditors' abilities rather than as a substitute for them. More accurate and comprehensive audits may result from fostering cooperation between AI tools and auditors. Firms should carry out pilot studies to evaluate AI tools in various auditing scenarios. This research can assist in identifying possible obstacles and advantages unique to each business. On the other hand, Raisch & Krakowski (2020) have stated that organizations using AI for auditing should create and follow ethical standards and legal frameworks. These guidelines ought to guarantee the responsible use of AI technologies and the impartiality and fairness of their results. Companies should also set up measures to track how AI affects audit efficiency and quality over time. This involves monitoring mistake rates, audit completion times, and the precision of audit results (Bird et al., 2020). Organizations may better overcome the difficulties of incorporating machine learning into auditing and optimize AI's advantages to the audit process by putting these tips into practice.

5.5 LIMITATIONS OF THE STUDY:

It is important to recognize the many constraints that this study encountered. Due to the survey's narrow focus, results might be skewed and could not accurately reflect the auditing industry. The data's dependability was impacted by subjectivity caused by using Likert scale questions. Furthermore, the study's cross-sectional design makes it more difficult to forecast how opinions about AI in auditing would change. Another issue is self-reported information bias since respondents could have given responses that were accepted by society. The study's inability to offer specific proof of AI's influence on auditing is further hampered by its emphasis on opinions rather than scientific results. Furthermore, the ethical issues surrounding AI as well as the variations in its adoption between businesses and geographies were not thoroughly investigated. These restrictions draw attention to the necessity for more research to fill up these gaps, especially via ongoing research and empirical assessments that support or refute the views investigated in this work. The fact that several survey items were left blank, despite participants' ability to skip any question they chose, was another weakness of this study. Due to this, the data was not full, which could have had an impact on the final analysis and interpretation of the results. The absence of replies may add bias or diminish the study's statistical power, making it difficult to reach firm results in some areas. Future studies might address this problem by putting mechanisms in place to reduce the amount of missing data for example, by creating required questions for important survey sections or sending follow-up reminders (Schafer & Graham, 2002; Gani et al., 2023)

Appendix : SURVEY ONLINE QUESTIONNAIRE:

Survey – Online questionnaire samples:

[Artificial intelligence vs Traditional methods in Auditing]

1. Have you ever been involved in an audit process, either directly or indirectly?
   - Yes
   - No
2. How familiar are you with the use of AI in auditing?
   - Very familiar
   - Neutral
   - Not familiar at all
3. Based on your understanding or experience, how effective do you think AI-based auditing is compared to conventional methods?
   - Much more efficient
   - Slightly more efficient
   - About the same
   - Slightly less efficient
   - Much less efficient
4. What role does accuracy play in the auditing process?
   - Extremely important
   - Very important
   - Moderately important
   - Slightly important
   - Not important
5. In your opinion, what factors contribute to the efficiency of AI in auditing? [Select all that apply]
   - Speed of processing data
   - Accuracy of data analysis
   - Ability to handle large volumes of data
   - Automation of repetitive tasks
   - Real-time monitoring
   - Others [specify]
6. Do you believe AI can reduce errors in auditing compared to conventional methods?
   - Strongly agree
   - Somewhat agree
   - Neutral
   - Somewhat disagree
   - Strongly disagree
7. What are the common sources of errors in conventional auditing methods? [Select all that apply]
   - Human errors
   - Data entry mistakes
   - Misinterpretation of data
   - Lack of thoroughness
8. How effective do you think AI is in detecting anomalies in financial data?
   - Very effective
   - Effective
   - Ineffective
   - Very ineffective
9. Which method do you think is more reliable in terms of overall accuracy?
   - AI-based auditing
   - Conventional auditing
   - Both are equally reliable
10. What are the primary obstacles or limitations related to AI in auditing? [Select all that apply]
   - High initial cost
   - Complexity of implementation
   - Data privacy concerns
   - Resistance to changes
   - Lack of skilled personnel
   - All of the above
11. Do you think AI will become the standard practice in auditing in the next 5-10 years?
   - Definitely yes
   - Might or might not
   - Definitely no

12. How does the integration of AI impact the roles and responsibilities of auditing professionals?

    - Significantly changes roles
    - Somewhat changes roles
    - No change in roles

13. What additional skills will auditors require in the future with the rise of AI? [Select all that apply]

    - Data analysis skills
    - Understanding of machine learning
    - Strong IT skills
    - Critical thinking
    - Strong communication skills
    - All of the above

14. Which method do you think requires more time to complete an audit?

    - Conventional methods
    - AI-based techniques

15. Describe in a few words any additional thoughts or comments on using AI in auditing.

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