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Assessing factors influencing adoption of Artificial Intelligence in audit of public entities in Kenya.

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ASSESSING FACTORS INFLUENCING ADOPTION OF ARTIFICIAL INTELLIGENCE IN AUDIT OF PUBLIC ENTITIES IN KENYA

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DECLARATION AND APPROVAL

I declare that this dissertation has not been previously submitted and approved for an award of any degree by this or any other university. To the best of my knowledge and belief, this dissertation contains no materials previously published or written by another person except where due reference is made in the research report itself:

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ABSTRACT

The current digital era, industrial 4.0 and surge of financial transactions leading to a deluge of data has complicated the work of contemporary auditor rendering traditional auditing methodologies inadequate. This has birthed Artificial Intelligence (AI) with capacity to match the transmuting nature of fraud. As other professions rush to benefit from AI, auditing has lagged behind with low levels among the big four that includes Deloitte, PricewaterhouseCoopers, Ernst & Young and Klynveld Peat Marwick Goerdeler. Key stakeholders such as professional bodies and Supreme Audit Institutions are under pressure to include risk in audit an arduous task for auditors using traditional methodologies compelling exploration of robotic auditors born from AI. However, the desire to espousal remains low with several factors considered as encouraging or stifling the process. The purpose of this study was to assess factors influencing the adoption of AI in audit of public entities in Kenya. The specific objectives were to determine the influence of technological, organizational and environmental factors guided by Technology Organization Environment (TOE) framework and Diffusion of Innovation (DOI) theory. It targeted all the active audit personnel in the Office of Auditor General (OAG) who is the principal government auditor in Kenya. Simple random sampling was used to select 333 auditors to participate in the study with structured questionnaire to collect data. Validity and reliability of the research instrument was ascertained in a trial study. Data was analysed using both the descriptive and inferential statistics riding on Statistical Package of Social Sciences (SPSS). Descriptive statistics included percentages, means and standard deviations, while the inferential included the multinomial logistic regression, spearman rank correlation and factor analysis. Tables and figures were used in data presentation. The results revealed that technological, organizational and environmental factors positively influence the low adoption of AI in audit of public entities in Kenya with odds ratios that are higher than 1. Organizational factors showed a slight edge over technology, which came second with environmental factors scoring least. However, they collectively accounted for 86.170% of factors that influence adoption of AI in audit of public service entities. To overcome the limitation in smart auditing, the study recommends stakeholders to focus on addressing the factors associated with adoption to match the emerging challenges in the wake of torrential flow of transactional data.

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OPERATIONAL DEFINITION OF KEY TERMS

Technological factors: The technology factors refer to both the internal and external technologies available in the unit of analysis, (Hmoud & Várallyai, 2020). In this study technological factors were conceptualized in terms of knowledge on data analytics, capital/investment required, precision, data security and anomaly detection.

Organizational factors: These refer to the characteristics and attributes of the organizations such as organizational structure, size and linkages among employees, (Tullo, 2019). In the study, organizational factors included **e**fficiency and effectiveness, management of online transactions, audit continuity, audit performance, and management support.

Environmental factors: These refer to the external forces such as competitors, industry and regulations that operate outside the organization but influences its decisions, (Alsheibani, 2018). In the study, environmental factors included auditing standards, legislative bodies, professional bodies, competition, and public pressure.

AI Adoption: This refers to willingness of an organization to implement AI technology in the management of its business transactions, (Radhakrishnan & Chattopadhyay, 2020). In the study AI, adoption was conceptualized in terms of beginner, intermediate and advanced.

Artificial Intelligence: Refers to the technologies that allow machines to imitate human intellect and to behave with human capacities for decision-making, thought, and intention, (Noordin, 2022).

Auditing: This is the financial review and appraisal of an organization's financial statements

Public entities: These are the portion of an economic system, funded and controlled by government to provide basic goods, services, or works, sensitive to be provided by private players in the economy, (Haberberg and Rieple, 2019).

LIST OF ABBREVIATIONS

AI:	Artificial Intelligence
DOI:	Diffusion of Innovation Theory (DOI)
NACOSTI:	National Commission of Science, Technology, and Innovation
OAG:	Office of Auditor General
SPSS:	Statistical Package for Social Sciences
TOE:	Technological Organizational Environmental
VIF:	Variance of Inflation Factor (VIF)

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The digital era popularly referred as Industrial 4.0 has complicated decision-making process by availing ocean of data. The steady increase results from the torrential flow of data from array of tools and applications rendering traditional methodologies inadequate across specialities. The complication of syntheisizing data has led to the birth of Artificial intelligence (AI) that enables interrogation of database going beyond what sampling provides. This ensures precision enhancing quality in decision making causing a seismic shift across fields.

However as found out by Gepp et al. (2018) the usage of AI is relatively more entrenched in other fields compared to audit, which has been slow to exploit its meticulous benefits. Pereira et al. (2022), argues that though entire humanity has been compelled to accept this digital transformation, audit profession still lags behind. The delayed adoption is similarly true in accounting going by the findings of Mehta et al. (2022) who highlighted the opportunity missed from use of AI such as improvement on asset valuation, decision making, risk management, internal and external auditing.

According to Noordin (2022) AI is a type of computer discipline that focuses on developing intelligent computer systems with ability to reason, learn and act autonomously. Fedyk (2022) defines it as machine-based technology that is capable of representing, structuring and modelling data to allow precise estimates and interpretation. On his part, (Tullo, 2019) conceptualized AI as the study of how to make computers understand verbal communication, learn, recognize images and solve problems and learn

There are several economic benefits and possibilities associated with AI. According to Raji and Buolamwini (2019) AI can scrutinise the entire population of data (big data), run various checks and compose reports. AI can also automate manual tasks including walking through high number of documents to make analysis that would be impossible with the human mind. The importance of AI was emphasized by Maragno (2023) for its ability to improve efficiency in administration of entities operations and quality service delivery. Nevertheless, understanding this benefit pegged on the appropriate execution of the AI, defined by exceptional factors that support or stifle its use. However, to realize the benefits associated with AI, massive investment is necessary for a robust technological infrastructure alongside building the capacity of staff. This has remained a limiting factor to many public entities across the globe forming the basis of this study aimed at assessing factors influencing the adoption of AI in public entities.

Even though AI has immense benefits, there is standing clash between the expectations and outcome of its adoption (Brynjolfsson, 2017). Among the contentious issues, there is inadequate knowledge in change management, restricted access to data, lack of regulations and ethical guideline, data protection issues, lack of technical competence among others affecting the adoption process (Eckemo, 2020). Shulembeva (2023) also noted that the absence of auxiliary audit standards has undermined the smooth adoption process of AI in audit.

PWC et al (2019) noted that the responsibility of approving new auditing procedures rests with standards setting bodies that has to undergo an elaborate process. Hussein et al, (2016) also acknowledged the complex process in updating prevailing auditing standards to accommodate such disruptive technology.

The nature of these challenges and their categorical overlap with organizational capability suggests a possible source of lag in adoption of AI by governmental auditors. For governments that have adopted AI, there is perceived struggle to comprehend the principles, ethical and the technical procedures that are created to govern the use of AI (Cath 2018).

1.1.1 Adoption of Artificial Intelligence in Auditing

The explosive growth of financial transactions has influenced the development of AI in auditing (Shulembeva, 2023). AI has ushered in smart auditing which facilitates flexible, real-time, and efficient data collection and analysis (Rawashdeh & Bakhit, 2023). According to Oluoch (2022), AI has the potential to strengthen audit integrity by cutting on costs and time for internal audit. Rathor (2024) acknowledged the powerful role played by AI in the detection fraud. This is supported by Dayyabu (2023) who also argued that with AI, auditors can easily detect outliers and recognize fraudulent financial transactions.

According to Nwakaego and Ikechukwu (2015) AI has power to transform auditing process by facilitating sophisticated audits much more efficiently and accurately.

Through AI, quality of audits can be obtained rapidly by the application of smart tools that are beyond the ability of the traditional data-processing applications. Seethamraju and Hecimovic (2023) enumerated the number of ventures undertaken by AI to support audit processes. The auditing profession is thus set for a paradigm shift in which the traditional audit methods will systematically be replaced with AI (Agnew, 2016). Gentner (2018) noted the ability of AI in helping auditors to efficiently find errors in figures and pick forms that can help in analysis. According to Cordery and Hay (2019) the transmuting nature of financial crimes have triggered auditors to yield to pressure to generate credible and impactful audits as clients demand for greater transparency in financial management (Morin, 2019).

Major organizations including IBM, Deloitte, Amazon, PricewaterhouseCoopers (PwC) and Ernst & Young (EY) have already embraced AI to audit their financial transactions. IBM utilizes AI-powered real-time auditing to monitor its global financial transactions. Deloitte employs AI for real-time auditing processes to enhance audit efficiency and effectiveness (Lukong, 2022). Amazon on the other hand utilizes real time auditing with AI to monitor its vast e-commerce transactions, identify potential fraud, and provide dynamic insights into sales performance (Kunene et al., 2022). PwC has also deployed machine learning algorithms for fraud detection in financial audits. Ernst & Young (EY) incorporated Natural Language Processing (NLP) in its financial statement analysis to process textual information from financial reports, contracts, and regulatory filings (Leitner-Hanetseder & Lehner, 2022). Locally Safaricom Company has deployed AI to help it in profiling million of its customers to a rating that facilitates their loan products.

Although AI enables auditors to review financial transactions within a shorter time using less effort, the larger audit profession including SAI have lagged behind adopting it (Pereira, 2022; Gepp, 2018). Afrosai, (2020) review revealed that the much focus on digitization by many countries in Africa has not translated to adoption of AI in audit. However, Shulembeva (2023) noted that 74% of audit executives globally are keen on adopting AI to keep pace with the dynamic presented by the continued heavy flow of transaction data.

To monitor financial activities of the public entities, the SAIs have the responsibility to direct audits of all government entities. Muzurura (2022) pointed that in their role, SAIs has the duty to independently check and advise on corporate governance and integrity of the financial parameters. The public audit role is emphasized as one that reinforces the governance of these entities and to draw benefits of this technology, they have to navigate through factors that affect the process adoption of AI (Ferry & Midgley, 2022).

1.1.2 Factors Influencing Adoption of AI Adoption

As postulated by the TOE theory, some of the factors that could influence adoption of AI comprises technological, organizational and environmental factors (Radhakrishnan & Chattopadhyay, 2020). The technological influences that affect the operations and governance of organizations include the usefulness of the technology, ease of use, trust and security among others (Hmoud & Várallyai, 2020). These factors are perceived to greatly influence adoption of AI in public entities as they determine the competitive advantage and leverage on the organizational processes (Chen, 2019). In this study, the technological factors investigated were knowledge/training on data analytics, capital required, precision concerns, data security and improved anomaly detection.

Organizational factors are considered as the processes within an organization that influence its operations and existence (Tullo, 2019). These factors are characteristics within the organization's internal environment. Organizational factors include business culture, finances, objectives, leadership styles and strategic direction. According to Weber and Schütte (2019), organizational factors determining the adoption of AI are concerned with the need to automate the systems and reduce direct human engagement. In this study, the organizational factors that were considered to play a role in determining the adoption of AI included efficiency and effectiveness, management of online transaction, audit continuity, audit performance and management Support.

Environmental factors are forces operating outside an organization, but affect the decisions made in the organization (Alsheibani, 2018). Environmental factors such as government laws and policies, competitive pressure, economic and social policies, and technological innovations can determine AI adoption in an organization. In this study, the environmental factors considered were auditing standards, legislative bodies, professional bodies, competition and public pressure.

Globally, the adoption of AI in audit of public entities is markedly different across nations and regions (Kar & Spanjer, 2015). In the USA, the government is continuously funding research on AI to determine ways of adopting AI in various fields and the adoption has improved tremendously over the years (Weber & Schütte, 2019). Generally, the US government is committed to seeing a change in the approaches used in minimizing financial misstatement in the state agencies. In Brazil, Velasco (2021) noted that AI has been adopted to expose various fraud and irregularities in public entities.

In Africa, many governments are yet to embrace AI especially in auditing public entities. Research indicates that out of the 55 countries, only three have fully embraced AI (Gries & Naudé, 2021). Hence, the adoption of AI remains at its infancy in audit of public entities with survey index ranking Mauritius, Egypt and South Africa at the top of the list (Noordin, 2022). In Nigeria, weaknesses of internal and external auditing have resulted into serious reports of fraud by civil servants thus calling for the adoption of AI to fight the menace.

1.1.3 Public Entities in Kenya

Public entities can be described as organizations anchored in law in which the state has full or partial control (OECD, 2015). Haberberg and Rieple (2019) consider public entities as the portion of the economic system, funded and controlled by government to provide basic goods, services or works, sensitive to be provided by private players in the economy. In Kenya, the State Corporation Act Cap 446 (1987) of the laws of Kenya defines a public entity as a government entities established via an Act of Parliament or by the order of the president to perform the functions specified in the order. The public entities are created to carry out important role in the provision of public service delivery. The public entities have fostered broader development goals since pre-independence. These entities span through various sectors, including education, healthcare, agriculture, infrastructure, energy, environmental management and finance. There are a host of public entities, each playing a unique role in the country's development. Prominent among them are the Kerio Valley Development Authority (KVDA), National Cereals and Produce Board, the Water Resources Management Authority, the Anti-Counterfeit Authority, Public Universities, National Hospitals, The Kenya Pipeline Corporation, Kenya Cooperative Creameries, Kenyatta National Hospital, The National Hospital Insurance Fund and the Kenya Medical Training Institute. The country also hosts state agencies such as KENHA, KURA, NCA, KERRA, The Kenya Power and Lighting Company, Kenya Railways Authority, National Environment and Management Authority, Kenya Wildlife Service and Kenya Forest Service, KEBS, and the National Bank of Kenya amongst other public entities.

This dynamic array of public entities in Kenya not only provides essential services to the citizens but also offers a spectrum of opportunities for research, innovation, and improvement in public service delivery. The management of these public entities determines the extent to which they may fulfil their mandate. Consequently, measures have been taken to enhance their capacity to help realize socioeconomic development goals. However, majority of the public entities are characterized by inefficiency and mismanagement of resources (Mati, 2020) yet the expectations for improved efficiency and effectiveness remain high. In addition, the public entities are constrained by inability to adapt to the rapidly changing technological landscapes especially with regard to the auditing functions (Chege, 2020). To ensure effective financial management of the resources The Office of Auditor General (OAG) is tasked with auditing their financial transactions (Nyongesa, 2020). However, there are gaps in adopting AI in audit of public entities. For instance, Amitebi (2017) examined AI adoption and found that users' knowledge and abilities were critical in its adoption. Oyanda (2016) failed to associate any specific factors to AI adoption. Nevertheless, adopting AI in audit of public entities may be the greatest technological achievement in Kenya (Oyanda, 2016).

1.1.2 Public service audit

A study by Velasco et al. (2021) established that investigators in Brazil have been uncovering numerous corruption and money laundering schemes at all levels of government and in country's largest corporations. Stanley and Nkiruka, (2020) also stated that despite the continuous auditing by both Internal and External auditors in the private and public organizations in Nigeria, there are still serious reports of fraud raising the question on whether auditing of Government entities is effective. Effort by government and various accounting bodies in Nigeria to manage fraud has not yielded the desired result, as fraud and corruption allegations against managers of government climb steadily.

The unending cases of fraud has been a drawback of Public Services globally leading to loss of state resources. Weeks Brown (2018) estimated between 2% to 5% of the global GDP being lost through corruption and money laundering negatively impacting both to public and private sector's development and on the negative strengthening organized crime. They acknowledged the inability of law enforcement agencies lacking capacity to carry out systematic risk assessment for timely intervention due to the traditional methods.

Stanley and Nkiruka (2020) acknowledge the inadequacy of the traditional approaches to detect and prevent fraud modern fraud tactics. They stated that the regular annual auditing is not sufficiently effective aiding fraud picked months after the date of the transactions, if ever. Such belated discovery of fraud would then only have recourse on punishment, which demonstrates a reactive approach instead of a proactive approach in management of fraud

Locally, the retired president of Kenya out of frustration lamented of how the country was losing approximately 2 Billion Kenya shillings on daily basis through corruption. It is worth noting that a number of former County Chiefs are either in court or are under active investigation for fraud related charges. All this points out to a grave weakness in the public service audit calling for departure of traditional audit methods and adoption of special skills to keep pace with advancement of voluminous transactions.

The office of Auditor general becomes the critical player in the war of fraud prevention in the public service. The big question remains; with the agitation to increase more funds to the devolved units, how much more will be lost. Why has the public watchdog not been able to stop the systematic loss of public funds. Could it be a case of their methodology or capacity to keep pace with fraud riding on the volumes of transaction data? Possible reason lay in the traditional audit methodologies coupled with annual rather than continuous audit in public entities.

A solution has been prescribed in the work of Scholl and Alawadhi (2016) who advocated use of big data an element of AI that has the capacity for continuous auditing. Such methodology would provide auditor a chance to express opinion on a process before commitment or release of public funds.

Alles et al. (2006) also suggested use of continuous audit for control, monitoring and data assurance. Besides, firms' automated internal audit procedures enables them to save cost, conduct more frequent audits and minimise audit staff involvement (Alles et al., 2006); Balios, 2021). Public service may also explore the findings of Warren et al. (2015) that suggested big data analytics for use in elimination of disparities between different accounting and reporting standards. This would accelerate the movement toward a global accounting regime with fair value accounting as a key cornerstone.

1.2 Statement of the Problem

It is estimated that between 2% to 5% of the global GDP vanishes yearly through fraud denying development as well as strengthening organized crimes (Dhone & Nitya, 2023). This has influenced a number of governments to prioritize fraud detection and prevention by exploring usage of AI. Although they consider AI as a source of digital transformation and decisive tool for accountability, there exits obstacles slowing full adoption especially in Africa (Afrosai, 2020). In addition, most managers of public entities have not been enthusiastic about adopting AI despite the governments' efforts to promote digitization (Bănărescu, 2015). A long side this, the rising cases of fraud have influenced a strong expectation by stakeholders for auditors to prevent and detect statutory fraud. This has led to an increase in amount spent on auditing more than what was previously projected. With the rapid advances in technology, AI is touted to fundamentally transform auditing methodologies. However, extant studies have not adequately interrogated the factors persuading its adoption in audit of public entities. For example, Maragno (2023) examined the unique factors constraining the adoption of AI without showing the specific factors constraining its adoption in audit of public entities. Kokina (2017) expressed reservations about the adoption of AI in audit of public entities due to lack of transparency and ability to comprehend AI algorithms. Brennan (2017) also questioned whether AI can be trusted both on the scientific and practical fronts.

In Kenya, OAG presence in public entities is felt once a year, which makes it difficult to adequately provide assurance with the delay facilitating the concealment of irregularities. This means that factors that are critical for implementation of AI in audit, which includes technological, organizational, and environmental, have not been properly understood. In the context of the study, adoption of AI in audit of public entities was operationalized by three levels namely beginners, intermediate and advanced (Ittner & Larcker, 2012). It is on this foundation that the study examined the factors affecting the adoption of AI in audit of public entities in Kenya.

1.3 Research Objectives

1.3.1 General Objective

The general objective of the study was to assess the factors influencing the adoption of Artificial Intelligence in audit of public entities in Kenya

1.3.2 Specific Objectives

i. To determine technological factors influencing the adoption of Artificial Intelligence in audit of public entities in Kenya.
ii. To evaluate organizational factors that influence the adoption of Artificial Intelligence in audit of public entities in Kenya
iii. To assess environmental factors that influence the adoption of Artificial Intelligence to audit public entities in Kenya

1.4 Research Questions

i. What are the technological factors that influence the adoption of Artificial Intelligence in audit of public entities in Kenya?
ii. What are the organizational factors that influence the adoption of Artificial Intelligence in audit of public entities in Kenya?
iii. What are the environmental factors that influence the adoption of Artificial Intelligence in audit of public entities in Kenya?

1.5 Scope of the Study

This study was limited to the adoption of AI in audit of public entities in Kenya. The unit of analysis was public entities and information about adoption of AI in audit of public entities was gathered from the auditors working at the OAG. This was because OAG is the principle institution mandated to scrutinize the books of accounts of the public entities in Kenya. Although there are many factors that may influence the adoption of AI in audit of public entities, the study focused on technological, organizational and environmental factors in accordance with the TOE framework and the DOI theory. Information was collected using structured questionnaires and analysed using both descriptive and inferential statistics. The ordered logistic regression model, Spearman rank correlation analysis and factor analysis were deployed in data analysis. The study was carried out between January 2024 and February 2024.

1.6 Significance of the Study

1.6.1 The Government of Kenya

The government is the greatest loser when it comes to financial irregularities since its capability to efficiently deliver services citizens. The study may inform the government on the need to invest in AI in order to minimize financial losses in the public entities. Thus, the government can structure policies through legislation that enhance the use of AI in auditing public entities.

1.6.2 Auditors

The outcome of the study may enable the auditors to appreciate the underlying power of AI in auditing. As financial experts, the finding of the study may inform the auditors on the role of AI in enhancing audit deliverables. Auditing deals with complex tasks and AI can be embraced to reduce labour costs and increase accuracy and efficiency of delivery quality audit reports.

1.6.3 Public entities

The findings of the study may enable the public entities to appreciate the use of AI to enhance the integrity of audit information. This may motivate them to build a credible database that may allow application of AI to provide critical insights for quality decision-making. Public entities can be able to employ professionals equipped with the relevant skills and competencies to support the adoption of AI.

1.6.4 Theoretical Contribution

The study may help in the refinement of theories used to guide the study in understanding the emerging technologies such as AI to match the ever-evolving dynamics of fraud. It will also contribute towards understanding the factors that underlie their deployment across government entities.

1.6.5 Practical Contribution:

Because of the dire consequences of audit errors, it is important to prevent and detect in its infancy so that the arising damages can be mitigated if not eliminated.

1.6.6 Regulators or Professional Bodies

The study may be considered by the audit regulators and professional bodies to sensitize their members on the important aspects and use of AI in audits. This can help to enhance accountability and transparency among auditors.

1.6.7 Researchers and Academicians

For future researchers and academics, the study is significant since it creates a platform for future research and provide background information on emerging technologies in auditing public entities. The findings can help enrichment of the curriculum to help address the acute shortage of professionals in the field of AI. The study has also highlighted areas in technological innovations in other sectors of the economy that may be pursued by other scholars.

1.7 Chapter Summary

This chapter has explained the background of the study, problem statement, research questions and objectives and the scope and significance of the study along with operational definitions. The background of the study has laid foundation for examining the factors influencing the adoption of AI in audit of public entities in Kenya. The next chapter has presented the review of literature as guided by the study objectives.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

The chapter has reviewed literature that informed AI adoption in audit of public entities. The chapter also discusses the theoretical framework and empirical review of the study. It has also presented the conceptual framework and research gap.

2.2 Theoretical Framework

The theoretical framework is useful in showing the relationships among study variables. It is also used to define the research scope and boundaries (Adom, 2018). This study was guided by two theories: Technological Organizational Environmental (TOE) theory and the diffusion of Innovation (DOI) theory. The tenets of the theories are first discussed, followed by their applicability and relevance to the current study.

2.2.1 Technological Organizational Environmental (TOE)

The study was anchored on the Technological Organizational Environmental (TOE) theory advanced by Tornatzky and Fleischer in 1990. TOE is concerned with the characteristics and capabilities that enable an organization to implement new technologies (Alsheibani, 2018). In this regard, the theory explains how adoption of new technologies is determined by organizational, environmental, and technological factors. The strength of the framework lies in its capacity to compact numerous variables to a holistic model enabling evaluation of their effects on technological adoption. TOE has been used as a framework in multiple studies with a range of different factors being identified and verified. These factors are considered significant in the analysis of readiness of an organization on technological adoption and innovation deployment (Hoti, 2015). The domains including use in e-Business, eCommerce, e-Government, Enterprise Resource Planning, Cloud Computing and Big Data (Sila, 2013).

According to Alsheibani (2018) espousing new innovations is a strategy for business success and the TOE paradigm describes how technical, environmental, and institutional fundamentals influence decisions regarding innovation adoption. The analysis of application of the framework shows that specific factors such as firm size, scope, organizational preparedness and top management support as important consideration to reviewing the adoption of new technologies. However, the choice of factors heavily depends on the nature of the organization but general factors include market uncertainty, competitive pressure and regulatory environment. Applying TOE in the domain of AI, Sun (2018) observed that other factors such as security, privacy and ethical concerns have also been discussed. The choice of the framework is often informed by its capability to extend outside the innovation paradigm to explore the influential factors for adopting new technologies. As a theoretical framework, TOE enables application of both the qualitative and quantitative research approaches. However, the current study used the framework due to its ability to facilitate the examination of the adoption of AI in audit of public entities.

2.2.2 Diffusion of Innovation Theory (DOI)

The study was also guided by Everett Rogers' diffusion framework of innovations. It is a broadly used theory to observe the trend in acceptance of fresh ideas in different fields especially in the field of innovation. The theory postulates that adoption of new technologies flows from four categories namely innovators, early adopters, early majority, late majority and laggards. The innovators and early adopters are usually fast to try out new things and take on the possibility of risks for the innovations or ideas. On the other hand, laggards are risk averse and drag their feet towards adoption of new things unless they are forced by circumstances. According to Rogers (2003), DOI framework explains the way in which innovations can help to spread awareness about the innovations through communication channels. The theory provides justification for technological acceptance by both individuals and entities (Rogers, 2003).

DOI theory conceptualizes innovation acceptance as a five-step process, which are gaining familiarity of an innovation, secondly persuasion, third use of data collected at the initial stage and then the boldness during the second stage to make a decision on the technological acceptance or rejection. The other stages rely on the affirmative conclusion made in the third stage. Acceptance of innovation is in the fourth step and the last one is the use of the innovation by the adopter. In this study, the focus was on the adoption phase in which different factors are considered to distinguish groups of adoption predictors. Consequently, resource, management support, entities’ structure, complexity and effective communication are critical factors influencing AI adoption. However, some factors including entity’s size, ease of the innovation, organizational slack, and structure also influence AI adoption. Thus, DOI theory was found relevant in this study and was considered as a basis for conceptualizing the adoption of AI in audit of public entities.

2.3 Artificial Intelligence in Audit of Public Service

Artificial intelligence has been applied in businesses to generate near-real-time information (Sun, Lin, Qiu & Rimba, 2020). AI can be integrated into an auditing system to drastically reduce human labour requirements in the process (Sun, et al, 2020). This means that AI was not developed to replace human intellect but was designed to assist auditors in delivering vital financial insights to public entities. With AI, auditors can have increased access to near-real-time data from a broader range of sources (Gulin, Hladika & Valenta, 2019). However, the auditors must learn the new technology to gain further understanding regarding AI applications (Krumwiede, 2017). According to Ferry (2022), audits of public entities entrench accountability with audit areas of considerable focus such as financial, compliance and performance audits (Hay & Cordery, 2021). Financial audits proclaim themselves on the reliability of the financial reports. Compliance audits ensure that auditing is carried out within the laws and regulations while performance audits examine economy, efficiency, and effectiveness of the financial transaction in the public entities.

However, the adoption of AI in audit of public entities have been found to lag (Desouza, 2020). Tangi (2023) contends that public entities need to adopt AI to fulfil the challenge of ensuring accountability and responsibility to the public. According to Maragno (2023) AI has great capacity to impact the management of the public entities but achieving these goals rest on the appropriate execution of the technology, which is defined by distinctive factors that afford or limits its use. Correspondingly, the governments should be alive of the factors influencing the adoption of AI in audit of public entities.

2.4 Factors Influencing adoption of AI in audit of public entities

As the quantity of financial data steadily surges, the more problematic it has become for traditional expert systems to detect irregularities (Baratzadeh & Hasheminejad, 2022). However, the volumes of data handled by auditors require innovation to make it easy to discover the hidden patterns that cannot be seen from the usual limited sampled data. According to Handoko (2020) at least 75% of organizations have expressed intention to adopt AI but the increased need for AI adoption has been influenced by the technological factors, organizational factors, and environmental factors.

2.4.1 Technology Factors and Adoption of Artificial Intelligence

From a technological viewpoint, innovation validates the important components in AI adoption. Numerous studies have examined the effect of innovative traits on the innovation process, although compatibility, comparative benefit, complexity, trial ability, and observability have been associated with AI adoption (Chau & Tam, 2017; Wu, 2007). Technical compatibility is a critical feature in determining whether an innovation is accepted (Azadegan & Teich, 2010). For instance, if AI innovation is compatible with the prevailing IT set up; its implementation is likely be less costly and within reasonable time. The comparative benefit of technology is the point to which it is viewed as greater to the strategy it is replacing (du Plessis & Smuts, 2021), emphasizing an organization's propensity to adopt new technologies that are perceived to bring competitive advantage. In this regard, AI is likely to result to explicit benefits in terms of strategic and working effectiveness (Greenhalgh, 2004) and the applications can help organizations to cut down on operational costs, advance quality, clientele experiences, and efficiency. In addition, technical complexity of innovation influences its ability to comprehend and use it (Yang, 2013). According to Attewell (2024) AI is fairly new and many entities lack good grasp of benefits may be slow to adopt it.

The influence of technological factors has been examined in the past studies. In these studies, it is evident that AI adoption is the new technological frontier that most countries are pursuing in relation to audit of public entities (Bhatti, 2019). A rapidly changing technological landscape has had a significant impact on the production, distribution and communication of government entities and these entities must recognize the potential for AI adoption to gain a competitive advantage (Pan, & Zhang, 2021). The role of AI is essential and it recognizes the improvements in field of auditing. Siau and Wang (2018) examined both the extent and nature of AI adoption on institutional performance in Norway. The study employed the cross sectional survey design and based on a sample size of 350 audit teams. By using the regression analysis, the study established that technological factors were positively associated with institutional performance. However, the study was not based on public entities and the results could not apply in the present study.

According to Kuo-Chen (2019) AI adoption depends on various factors, including usefulness, ease of use, cost, and security. Based on comparative studies AI adoption presents a better way compared to the use of computer systems and manual auditing processes. Although familiarity with the AI takes time, public entities are sure that their operations will improve rapidly (Mvurya, 2020). This is because AI uses simple algorithms that enable users to navigate the systems and establish an operational module that fits production needs. The effectiveness of AI technologies is one of the driving forces behind its adoption in public entities (Nyongesa, 2020).

Developers of AI technologies believe that the system can overshadow human brains and perform better at specific tasks such as auditing. Benke and Benke (2018) attribute the usefulness of AI to product marketing, product diversity, and supply replenishment. AI approaches are effective in reducing wastages and risks in public entities. System security is a priority of any business that wants to transit from one system to another. The new system must guarantee the safety of the current data held by the public entities.

In auditing, it might be challenging to determine the trustworthiness of the auditors since they will have little control over their activities. Ngumuta (2018) scrutinized the purported link between the trustworthiness of the auditors and their effectiveness in auditing state owned parastatals in Kenya. The study adopted a sample of 208 study participants who were randomly selected from 10 counties in Kenya as moderated by technological factors. With the adoption of Pearson's correlation and multiple regression analysis to analyze the data, the results evidently illustrated a significant association between trustworthiness and effectiveness ($r=0.6710$; $p=0.001$). In the study technological factors served as moderating variable while in the current study technological factors were taken as independent variable. However, the study emphasized that the public entities need to work on various modalities to ensure AI adoption is safe and not a threat to their current data. Therefore, in this study knowledge on data analytics, capital required, precision concerns, data security and improved anomaly detection as they pertained to the adoption of AI to audit public entities.

2.4.2 Organizational Factors and Adoption of Artificial Intelligence

Organizational competencies extend beyond leadership, management support and resources available to facilitate AI adoption. These abilities are very specific, non-sharable and exist in an organization. For instance, management backing is critical for any serious organizational change because in their role they direct division of resources and service integration. Theorists concluded that managerial backing as key in both the execution of a new innovation (Müller & Jugdev, 2012) and deployment of technology (Kim, 2015). As a result, an organization may fats rack adoption of AI to increase its performance and gain an advantage when supported by the management. According to Lin and Lin (2008), the size of an entity has a considerable role in its capacity to accept technology. It is evident that large entities are more likely to invest in AI earlier at a larger scale than smalls ones. However, organizational preparedness is also critical on acceptance of AI in auditing. According to King and He (2018) AI acceptance is defined by the entities' readiness, the existing internal knowledge, and resources within the organization.

Past studies have examined how quality strategies can contribute to the performance of organizations. However, the outcomes of these studies are inconsistent and inconclusive. For instance, Seethamraju and Hecimovic (2023) studied the role of the organizational factors on the technological adoption in public institutions in Iran. It deployed self-generated questionnaires to collect data under the descriptive design. Primary data was collected from 101 selected licensed auditors. Using structural equation model, the empirical results postulated that organizational factors constrained the introduction of new technologies. However, the study did not specify the kinds of organizational factors as was highlighted in the current study. Nevertheless, Seethamraju and Hecimovic (2023) clarified the organizational context as the topographies and capitals of an entity, such as networking among employees, intra-firm corporations' and firm size. Organizational structure has been studied to appreciate its association to the technological acceptance (Zaltman, 2020). Previous literature on innovation postulates that backing from top management is a critical signal of technology acceptance (Martins, 2019). Top management support is derived from creating a culture that inspires change towards the mission and vision (Tushman & Nadler, 1986). This would include describing the role of technology within the organization's global policy. Scholars such as Scherer (1980) contend that larger organizations are likely to embrace technology though this has been challenged on the grounds that size is often a rudimentary proxy for fundamental organizational factors such as access to particular resources (Kimberly, 2023).

One of the major strategic management decision adopted by organizations today is technological changes that will stir growth and development (Wallace & Townsend, 2020). The adoption of AI requires the consideration of the advantages or functions, as compared to the existing technology. In this regard, the introduction of AI in audit of public entities should coincide with the associated values, the demand for it and the experience of potential users (Rodgers, 2020). However, AI is the new wave of technological development that most public entities are trying to adopt (Thangiri, 2018). Some of the vital organizational factors that drive technological changes within the auditing function include efficiency and effectiveness, management of online transactions, Audit continuity, audit performance and Management Support (Thangiri, 2018). These factors are strategic in determining whether an organization can adopt AI or not.

Generally, organizational factors play an essential role in determining the adoption of AI. Every organization operates within the confine of a specific mission and vision to help it achieve its overall objectives. Strategic direction means a plan that needs implementation to realize its mission and vision (Asango & Odhiambo, 2020). Most organizations have the strategic direction to realize their overall objectives. Organizations that are IT-oriented usually set up their strategic direction towards implementing technological changes relevant to their mission (Calitz, 2017). In the case of public entities, the technical changes have to be aligned to the organizational strategy (Ngumuta, 2018) and the need to ensure that the organization's data is not put at risk (Mailu, 2018). Therefore, a thorough analysis is needed to anticipate and solve any threats that the organization will face.

AI adoption involves complex data management that require a well-versed management team (Kagumba & Wausi, 2018). Therefore, the government must consider efficiency and effectiveness, management of online transactions, Audit continuity, audit performance and reduction of audit risk need to be considered when establishing a strategic direction for adopting AI in auditing public entities. This study explored how these considerations influenced AI adoption in audit of public entities in Kenya.

2.4.3 Environmental Factors and Adoption of Artificial Intelligence

Organizations are affected by the external environmental factors (Hutajulu, 2021). The factors range from external isomorphic pressures from the government, competitors to customers (Gibbs & Kraemer, 2004). For example, the government is key in helping IT innovation (Wang, 2022) and could formulate and implement policies to inspire the commercialization of new innovations. According to Al-Hawamdeh and Alshaer (2022) acceptance of AI is an elaborate process that will work better through the guidelines outlined by the government. Market dynamics such product demand, competition and consumer loyalty falls outside the jurisdiction of organizational but can affect the adoption of AI (Hao, 2018). However, competition has been a motivator for innovation and acceptance of new technologies which if often seen as a strategic venture (Dutton, 2018). In the context of auditing public entities, external factors such as auditing standards and professional and regulatory policies have a considerable influence on the adoption of AI.

Past studies have examined the environmental factors likely to influence AI adoption in audit of public entities. For example, Sonam (2017) analyzed the correlation between environmental factors and technological advancement. Relevant information was reviewed on whether they relate to technological advancement. Mixed research was used to inform data collection process with a sample size of thirty auditors. The analysis showed that organizational flexibility to environment was highly associated with technological adoption in the auditing department. Also, the conservative nature of the audit entities and lack of capacity within those organizations were found to constrain the adoption of new technology in the auditing department. From this study it can be construed that adoption of AI should be backed up by the auditor’s judgement alongside the external factors that have been described in this study.

Moreover, studies on technology acceptance concur that AI adoption is informed by efficiency or acceptability motives and less by external pressures (Asare, 2021; Duho, 2022). Legislation can also positively or negatively influence the adoption of AI in audit of public entities. For instance, new legislations focusing on privacy requirements can alter how public entities handle account information (Duho, 2022). However, political, legal, social-cultural, environmental, ecological and economic reasons are examples of external factors (Wang, 2019) with adverse influence on AI adoption. According to Wang (2019) sensitivity to these factors may be the difference between success and failure of AI adoption.

In Kenya, public entities are influenced by internal and external circumstances that directly or indirectly affect the business performance (Kimeu & Okello, 2018). However, the decision to adopt AI is driven by the need to remain relevant in the global market and to meet the customers' needs in the changing world (Reuben & Ajowi, 2019). The external factors with the potential to influence AI adoption in Kenya include competitive pressure, public demands, and government laws and policies. The focus of this study was on the competitive pressure, public demands, and government regulations as proposed by Kimeu and Okello (2018). The result points that these factors favour AI adoption and has widened market competition (Thangiri, 2018). It also revealed that public entities have strived to learn from other organizations that have successfully adopted AI. Therefore, the study explored how public demands influence the adoption of AI.

Although ideologies guide business operations, adopting technologies such as AI requires government goodwill through ICT policies that support its implementation in public entities (Calitz, 2017). AI adoption requires government's support through policy frameworks that create favourable environments conducive for AI adoption (Thangiri, 2018). From the perspective of AI adoption to audit public entities, government laws and policies can either be a driving force or an obstacle to its adoption.

2.7 Research Gap

AI is an active research topic with several studies seeking to understand and evaluate the uses of AI in fields across professionals (Alsamhi, 2018; Wan, 2016). Some of the concluded work documented the empirical work associated with AI most of which are descriptive (Zou, 2015) as well their applications (Xu & Jia, 2021). However, few studies have focused on the adoption of AI, particularly in the audit of public service entities. For instance, Alsheibani (2018) presented a framework for AI adoption, but failed to examine the factors affecting its adoption in audit. As a result, the study was required to examine the factors that influenced the proclivity to AI adoption in audit of public entities leading to considerable changes in the accounting procedures and practices.

These changes have transformed the auditors' role of providing assurance on the voluminous data. It is evident that the auditors are alive to the need to adoption of AI technology and the necessary organizational and technological support required. However, most of the literature reviewed was descriptive and stressed more on the potential of AI as opposed to disclosing the antecedent factors influencing its adoption.

Issa (2016) is vindictive that the literature is fragmented and not adequate to support the adoption of AI in audit of public entities. Similarly, past studies revealed some variations on data sources, measures used as well as the conceptual and theoretical considerations.

This makes the subject inconclusive in espousing the effect of technological, organizational and environmental factors influencing adoption of AI in audit of public entities constituting the research gap which this study sort to fill.

2.5 Conceptual Framework

A conceptual framework is a representation of the anticipated relationship between variables (Gartner, 2021). A conceptual framework is based on the researcher's reasoning and literature reviews. The conceptual framework consists of the independent variables and the dependent variables.

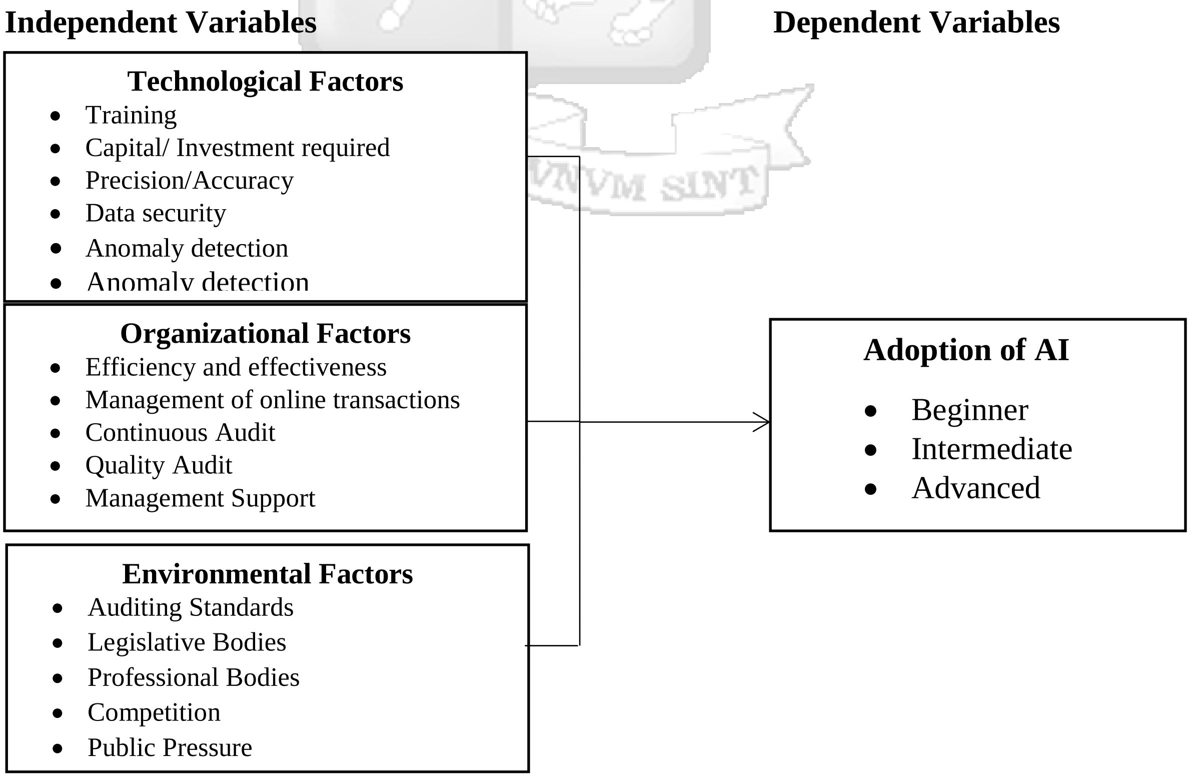

Figure 2.1: Conceptual Framework
Source: Researcher (2024)

The adoption of AI in audit of public entities was measured by three indicators, which are beginner, intermediate and advanced as captured on the conceptual framework.

2.6 Operationalization of Variables

Table 2.1 shows how the variables in this study were operationalized.

Table 2.1: Operationalization of Study Variables

Variable	Indicators	Measure	Data analysis method
Technological factors	• Knowledge on data analytics • Capital required • Precision • Data security • Anomaly detection	Likert scale, close-ended questions	Descriptive and inferential analysis; Factor analysis, logistical regression Analysis, Spearman Rank Correlation analysis
Organizational factors	• Efficiency and effectiveness • Management of online transactions • Audit continuity • Audit Quality • Management Support	Likert scale, close-ended questions	Descriptive and inferential analysis; Factor analysis, logistical regression Analysis, Spearman Rank Correlation analysis
Environmental factors	• Auditing Standards • Legislative bodies • Professional bodies • Competition • Public pressure	Likert scale, close-ended questions	Descriptive and inferential analysis; Factor analysis, logistical regression Analysis, Spearman Rank Correlation analysis
AI Adoption	• Beginner • Intermediate • Advanced	Likert scale, close-ended questions	Descriptive and inferential analysis; Factor analysis, logistical regression Analysis, Spearman Rank Correlation analysis

2.8 Chapter Summary

This chapter has presented a review of literature review for the study. It has described the theory that informed the study and presented an empirical analysis of the empirical studies done on the factors influencing the adoption of AI in audit of public entities. Based on the literature review, the chapter has presented the conceptual framework showing the nature of the relationship between technological, organizational and environmental factors and AI adoption in audit of public entities. The chapter further operationalized the variables for measurement in the data collection.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This chapter covers the research philosophy, design, population, sampling, data collection methods, data analysis, research quality and ethical considerations.

3.2 Research Philosophy

Research philosophy refers to the set of beliefs, principles and assumptions that guide a researcher in conducting research, and which determine the methodologies to be utilised (Saunders, Lewis & Thornhill, 2016). Collins and Hussey (2014) defined the research philosophy as a framework that shapes the ideas about reality and nature of knowledge. Research philosophies offer distinctive ways that scientists use to make logic from the world around them.

There are many research philosophies, but this study was guided by positivism that points that all authentic facts can be verified through systematic and scientific approaches such as observation, tests, and arithmetic proof. Park (2020) defines positivism as a hypothetical deductive approach that allows the measure of priori hypotheses often stated quantitatively, with functional relationships between independent and dependent variables. Positivism cogitates social sciences to be as scientific as natural science and believes in observable and measurable facts as a basis, (Junjie & Yingxin, 2022). It also employs quantitative methods such as structured official statistics, structured questionnaires and social surveys, which the study has deployed. The opinion of the professional auditors working for the OAG will be used to draw an understanding of the factors influencing the adoption of AI in audit of public entities. The main benefit of using the positivism is that it enables generating of scientific theories and testing them enabling achieve generalization of results.

3.3 Research Design

A research design basically the outline of the plan for collection and analysis of data in a way that combines research significance and purpose with economy and procedure. A research design presents the plan detailing what research instruments to be used, how data is to be gathered and possibly how the study provide logical answers and solutions to the research problem. The study adopted the descriptive design together with inferential analysis. A descriptive design aims to systematically obtain information to describe a phenomenon, situation, or population (Creswell, 2014). To realise the study objectives, quantitative techniques were adopted, and this resulted into a clearer description of the trends and relationships among the study variables.

3.4 Target Population of the Study

The population is a collection of events, objects or individuals with common characteristics of which the researcher is willing to study (Cooper & Schindler, 2014). It also refers to the entire group of individuals that the researcher is interested in studying (Bryman & Bell, 2007). According to Kothari (2004) a well-defined population guides the sampling process. The population of the study comprised of qualified public auditors in Kenya. The study concentrated on the auditors working for OAG with the assumption that they had the necessary academic credentials and professional experience in auditing public entities with the possibility of utilizing AI during the audit. The target population was made up of 1,247 active audit personnel at the AOG (OAG, 2021).

3.5 Sampling Procedure and Sample Size

The study employed two sampling techniques namely purposive and simple random sampling. Purposive sampling was used to select the auditors working for OAG charged with responsivity of auditing public entities. The study employed the formula by Yamane (1967) to calculate the sample size:

$$N=\frac{N}{1+N(e)^2}$$

Where n was the sample size, N was the population size, and *e* was the level of precision required. The formula was applied to realize the target sample as follows;

$$n = \frac{1,249}{1+1,249(0.05)^2}$$

$$= 302.97$$

From this computation, the number of respondents was 303 with an additional 10% to compensate for the possible non-response.

303+ (303*10%) = 333.3

Therefore, the target sample size was 333 respondents.

3.6 Data Collection

The researcher adopted a structured questionnaire to collect data from the sampled respondents. The questionnaires were considered ideal because they ensured anonymity of the responses, permitted the use of standardized questions, and were less expensive to administer while also eliminating uncertainties during administration (Creswell, 2014). The questionnaire was structured to capture all the research questions under investigation. It also provided for sections that focused on the general information about the respondents.

The responses to the questions were ranked using a 5-point Likert scale to determine the respondents' level of agreement with the concerned variable parameters. The responses were ranked based on a 5-point Likert scale with values ranging from 1 to 5(1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree). The questionnaires were administered through the assistance of google forms. The interface enabled by the google forms was user friendly, intuitive and simple to operate. It was also easy to share the questionnaires with the respondents through a shared questionnaire link.

3.7 Research Quality

Research quality was determined through instrument validity and piloting to test instrument reliability.

3.7.1 Validity

According to McMillan (2012) validity is concerned with whether the research instrument measures what it is intended to measure. In this study, content validity was used to ascertain the completeness, comprehensiveness, and relevance of the questionnaire items and to determine whether the items addressed the research objectives. Professional accountants rated the questionnaire items with regard to the level of accuracy. From the expert ratings, I-SDI tools was computed the ratings.

3.7.2 Reliability

Reliability refers to the degree at which the research instrument yields consistent findings (Leavy, 2017). To ensure that the questionnaire was reliable, the researcher carried out a pilot test. According to Creswell (2014) a pilot study is carried out using population with similar characteristics to the target population. In this study, the researcher conducted a pilot test using 6 respondents who were not part of the final study sample. The researcher employed the Cronbach's alpha to determine the reliability of the research instrument. Cronbach's alpha reliability coefficient threshold was set at 0.70.

3.8 Data Analysis

Data analysis is the inspecting, cleaning, transforming, and modelling data with the goal of appreciating useful information to inform and decision making (Cooper & Schindler, 2014). After collecting the requisite data, the returned questionnaires were scrutinized to ensure completeness and coded to facilitate analysis. The analysis of data was guided by the study objective with descriptive and inferential statistics. The quantitative data was guided by descriptive statistics such as frequency counts, means, percentages and standard deviations. However, before inferential analysis, diagnostic tests were carried out to test the assumptions of normality.

Spearman rank correlation was adopted to determine the strength and relationship between the independent (technological, organizational, and environmental factors) and the dependent variable (adoption of AI).

Factor analysis with fundamental assumption that some underlying factors, which are smaller than the number of observed variables, are responsible for the co-variation among the observed variances. The advantages of factor analysis is its ability to provide a meaningful interpretation useful in achieving parsimonious explanation of the variables. In this study, the principal components analysis was adopted to reduce large number of variables to a smaller set of components that account for a large amount of observed variance. The orthogonal rotations were adopted based on the assumption that the generated factors were independent.

The study finally applied the multinomial logistic regression model to determine how relevant the independent variables (technological, organizational and environmental factors) influencing the adoption of AI in audit of public entities. The logistic regression was modelled as described below.

Let Y be an ordinal outcome with J categories. The logit was given by;

$$log\frac{P(Y \leq j)}{P(Y > j)} = logit\big(P(Y \leq j)\big) \dots i$$

The multinomial logistic regression was redefined as;

$$logit\big(P(Y \leq j)\big) = \beta_{j0} + \beta_{1x1} + \beta_{2x2} \dots + \beta_{pxp} \dots ii$$

Where;

$$\hat{p}(s) = \beta_{j0} + \beta_{1x1} + \beta_{2x2} \dots + \beta_{pxp} \dots iii$$

Where; $s - multinominal\ dependent\ variable$ (The adoption of AI in audit of public entities)

$\hat{p}(s)$- Estimated probability that there is the adoption of AI in audit of public entities.

$x_1, x_2 \dots x_p$- Independent variables/predictor variables (technological, organizational, environmental factors)

β_{j0}- Constant

$\beta_1 \dots + \beta_p$ Are model coefficient parameters (intercept and slopes) with p predictor variables (technological, organizational, environmental factors) for the ordinal outcomes: $j = 1, \dots, J - 1$.

The entire model being tested was such that the natural log odds of adoption of AI= intercept + technological (predictor) + organizational (predictor) + environmental factors (predictor). The logit model summary is presented in table 3.4.

Variable	**Type**	**Description**
AI adoption	Ordinal	Beginner, Intermediate, Advanced)
Technological factors	Ordinal	
Environmental factors	Ordinal	
Organizational factors	Ordinal	

Table 3.2: Logit model Variable Description

As shown in table 3.4, the significance of the independent variables was assessed once the suitability of the model was realized. When the *i*th independent variable changed by a unit, the logistic regression coefficient for that variable indicated the change in the expected log odds of having an outcome, assuming all other factors remained constant. That is, log probabilities of outcome are anticipated to vary by *i* units if the *i*th independent variable is modified one unit while all other predictors are kept constant. The Wald statistic and the likelihood ratio test are two distinct tests used in logistic regression to determine the significance of an independent variable (Menard, 2023). To ensure validity of the model, the study assumed that there was no high inter-correlations among predictor variables (multicollinearity), no influential value (extreme values or outliers) in the continuous predictor variables, and the model did not favour sparse data (data consisted a lot of zero values). Contrasted with the linear regression, logistic regression model is a classification model. The analysis was aided by Statistical Package for Social Sciences (SPSS) version 25. The results were presented in tables and figures to facilitate interpretation.

3.9 Ethical Considerations

The researcher obtained the ethical approval from Strathmore University's Institutional Ethics Review Committee and a research permit from the National Commission of Science, Technology, and Innovation (NACOSTI). The researcher also obtained an introductory letter from Strathmore University to introduce the researcher to the respondents. Participation in the study was voluntary as no participant was coerced to be involved in the study and as well anonymity preserved as advocated by (Zhang, 2016).

Anonymity of respondents as well as the organization was ensured by sharing questionnaire anonymously. In this regard, the information gathered was declared solely for the purpose intended herein. The researcher ensured that the final report was original and where information was borrowed from other authors, acknowledgement was properly done and an approved anti plagiarism test was used to test the originality of the report.

3.10 Chapter Summary

The chapter has presented the research design and the methodology that was followed. The chapter has also identified the population of interest, explained the sampling procedure employed and the data collection approach. The data collection instruments and procedures, including ethical considerations have been described. The quality of the research was equally explained.

CHAPTER FOUR

RESEARCH FINDINGS AND PRESENTATION

4.1 Introduction

This chapter presents the findings of the study. The chapter covers the validity and reliability, response rate, the results on the demographic characteristics of the respondents and the descriptive and inferential analysis. The chapter presents the interpretation of results.

4.2 Validity Test Results

As shown in table 4.1, I-SDI for each of the variable was greater than 0.78, which indicated that the questionnaire adopted in data collection generated valid responses. It also suggested that the questionnaire met the content validity and was suitable to be used for further data collection.

Variable	Number of items	I-SDI
Technological factors	5	0.873
Organizational factors	5	0.911
Environmental factors	5	0.899
Adoption of AI	3	0.981

Table; 4.1 Validity Test Results

4.3 Reliability test results

From the summary presented in Table 4.2 technological factors had an alpha value of 0.952 while organizational factors had alpha value of 0.897. It is also evident that environmental factors had an alpha of 0.799 and the adoption of AI had a value of 0.885. All these values were greater than 0.70. This showed that all the items in the questionnaire met the set reliability criteria of Cronbach alpha 0.70 ($\alpha>0.70$). This allowed the researcher to use the questionnaire in the main study for data collection.

Variable	Cronbach's Alpha	Number of items
Technological factors	0.952	5
Organizational factors	0.897	5
Environmental factors	0.799	5
Adoption of AI	0.885	3

Table 4.2: Reliability test results

4.4 Response Rate

The study set to get data from 333 auditors working for the OAG on their perception of the factors influencing the adoption of AI in audit of public entities through a shared google link. The number of questionnaires distributed was 333. As shown in Table 4.3, a total of 220 questionnaires were completed and returned. This accounted for 66% of the total number of questionnaires distributed.

Sample Size	No. of Questionnaires Returned	Response Rate (%)
333	**220**	66%

Table 4.3: Response Rate *Source: Survey Data (2024)*

This response rate was considered sufficient for adoption in analysis. Mugenda and Mugenda (2003) and Kothari (2004) averred that a response rate above 50% was adequate for a descriptive study. Hennink, Hutter and Bailey (2020) also concurred that a response rate exceeding 30% of the number of online-shared questionnaires provided enough data that can be used to generalize the characteristics of a study sample to the rest of the target population. Based on these assertions the response rate of 66% was considered to be adequate to provide data for analysis.

4.5 Demographic Characteristics of the Respondents

This section discusses the demographic profile of the respondents. It presents the results on the demographic characteristics of the respondents. The findings are presented in table 4.4.

Characteristics	Parameters	Frequency	Percent (%)
Gender	Male	125	56.67%
	Female	95	43.33%
	Total	**220**	**100%**
Age Bracket	20-30	86	39.17%
	31-40	81	36.67%
	41-50	42	19.17%
	51-60	11	5.00%
	Total	**220**	**100%**
Education level	Certificate	15	6.67%
	Diploma	50	22.50%
	Undergraduate	125	56.67%
	Postgraduate	32	14.41%
	Total	**220**	**100%**
Registered	Registered	163	74.17%
	Not registered	57	25.83%
	Total	**220**	**100%**
Using AI	Yes	123	55.83%
	No	97	44.17%
	Total	**220**	**100%**
Operation Level	Entry level	48	21.67%
	Middle level	130	59.17%
	Senior level	42	19.17%
	Total	**220**	**100%**
Auditing Years	0-5 years	134	60.83%
	6-10 years	39	17.50%
	11-15 years	24	10.83%
	16-20 years	17	7.50%
	21 and above	7	3.33%
	Total	**220**	**100%**

Table 4.4: Demographic Characteristics of the Respondents *Source: Survey Data (2024)*

As shown in table 4.4, 43% of the respondents were female and 57% were male. This is a balanced gender distribution in the institution. There are more of the young professionals in the audit aged between 20-40 years providing a combination of 39% compared to the rest. Since technology is permeating institutions at fast rate, the young professional is deemed to have the enthusiasm to learn and adopt AI relatively faster. This gives advantage to the organization to plan in the near future by building capacity of the young professionals. Most of the respondents have first degree as well as a good number with postgraduate qualification making a combination of 68%. This give credence to the data collected as having been filled by experts in the field of audit. It was also established that 74% of the respondents are also professionals registered with their respective bodies. The professional institutions were acknowledged to have prescribed how data should be handled considering privacy and confidentiality at 55%. Majority of the participants are of middle level category in management at 59%. The analysis also showed that the level of access given to auditors to audit public entities falls between 44% as perceived by 41%-60% of the respondents.

4.6 Descriptive Statistical Findings

This section presents the descriptive results based on the parameters for both the dependent and the independent variables. Descriptive analysis included measure of central tendency (mean) and measure of dispersion (standard deviation). The descriptive statistics were obtained by keying in and running the parameters for each variable in the SPSS. The results are discussed in the subsequent sections.

4.6.1 Descriptive Results for Technological Factors

The study generated descriptive results from the questionnaires to determine the influence of technological factors. The respondents were required to rate their level of agreement with parameters for technological factors based on a scale ranging from 1 to 5, with 1 being Strongly Disagree, 2 Disagree, 3 being Undecided, 4 being agree, and 5 being strongly agree. Table 4.7 summarizes the respondents' level of agreement with the various parameters.

Parameters	**N**	**Mean**	**Std. Dev**
Knowledge on data analytics	220	4.61	1.42
Capital required	220	3.83	1.45
Precision concerns	220	3.43	1.07
Data security	220	4.44	1.26
Improve anomaly detection	220	3.98	1.56

Table 4.5: Descriptive Results for Technological Factors *Source: Survey Data (2024)*

From Table 4.5 it is evident that a high number of respondents indicated that knowledge on data analytics and data security had the greatest influence on the adoption of AI in audit of public entities as depicted by mean scores of 4.61(SD=1.42) and 4.44 (SD=1.26) respectively. The respondents placed precision conserns as a least influencial factor to the adoption of AI in audit of public service entities, however it was also above avarage (M=3.43; SD=1.07).

4.6.2 Descriptive Results for Organizational Factors

The researcher sought to establish the respondents' views concerning organizational factors. Five parameters of organizational factors were presented to the respondents and the results obtained are presented in Table 4.8.

Parameters	**N**	**Mean**	**Std. Dev**
Efficiency and effectiveness	220	4.38	1.43
Management Support	220	4.58	1.17
Audit continuity	220	3.32	1.10
Audit performance	220	3.63	1.23
Management of online transactions	220	4.32	1.66

Table 4.6: Descriptive Results for Organizational Factors *Source: Survey Data (2024)*

The findings presented in Table 4.6 demonstrated that management support was observed to have the greatest influence in the adoption of AI in audit of public entities (M=4.58; SD=1.17) as well as efficiency and effectiveness persuasions (M=4.38; SD=1.43). It is also evident that the management of online transactions with (M=4.32; SD=1.66) was equally influential than he rest of the organizational factors. However, the analysis showed that audit on continuous basis at (M=3.32; SD=1.10) was perceived to be a relatively less influential organizational factor.

4.6.3 Descriptive Results for Environmental Factors

The study participants were to rate various parameters relating to environmental factors. The researcher used a combination of indicators of environmental factors and presented them to the respondents and the results are presented in table 4.7.

Parameters	N	Mean	Std. Dev
Auditing standards	220	4.68	1.39
Legislative bodies	220	4.27	1.16
Professional bodies	220	4.49	1.18
Competition	220	3.40	1.21
Public pressure	220	3.38	1.55

Table 4.7: Descriptive Results for Environmental Factors *Source: Survey Data (2024)*

The results presented in table 4.7 postulated that auditing standards (M=4.68; SD=1.39), professional bodies (M=4.49; SD=1.18) and legislative bodies (M=4.27; SD=1.16) were the key environmental factors associated with the adoption of AI in audit of public entities. The results also pointed that majority of the respondents were noncommittal about competition (M=3.40; SD=1.21) and public pressure (M=3.38; SD=1.55) as being key environmental factors associated with the adoption of AI.

4.6.4 Descriptive Results for the adoption of AI in Audit

The participants were asked to show their level of agreement with aspects of the adoption of AI in audit of public entities. Table 4.8 summarizes the participants' responses with the parameters of the adoption of AI as described in terms of the mean and standard deviation.

Adoption of AI	N	Mean	Std. Deviation
Beginner	**220**	4.1684	.74551
Intermediate	**220**	4.0974	.73066
Advanced	**220**	3.9053	.84977
Valid N (listwise)	**220**		

Table 4.8: The Adoption of AI in Audit of Public Entities *Source: Survey Data, 2024*

The results presented in table 4.8 show higher responses regarding the attributes of the adoption of AI in audit of public entities. For instance, the response for beginners' adoption revealed a mean score of 4.1684 and a standard deviation of 0.74551. A relatively good number of respondents also strongly agreed with intermediate adoption as revealed by a mean response of 4.0974 with a corresponding standard deviation of 0.73066. Lastly, the respondents also concurred that AI adoption was advanced as revealed by a mean response of 3.9053 with a standard deviation of 0.84977.

4.6.5 Factor Analysis

The factor analysis was applied to determine the factors among the observed variables that strongly determined the adoption of AI in audit of public entities. The factor analysis considered factors representing the technological factors, organizational factors and environmental factors. For analysis and interpretation purposes the focus was on Initial Eigenvalues and Extracted Sums of Squared Loadings. The initial step in carrying out factor analysis was to determine if the study variables were related and if they were, to which extent. Most of the correlations exceeded 0.30 thus making the use of factor analysis appropriate. The correlation matrix produced a substantial number of large correlations indicating that factor analysis was an appropriate statistical methodology. The principal components analysis was utilized to extract the communalities as shown in Table 4.9.

Factors	Initial	Extraction
Knowledge on data analytics	1.000	.834
Capital required	1.000	.719
Precision concerns	1.000	.870
Data security	1.000	.692
Improve anomaly detection	1.000	.586
Efficiency and effectiveness	1.000	.687
Management Support	1.000	.957
Audit continuity	1.000	.954
Audit Performance	1.000	.967
Management of online transactions	1.000	.965
Auditing standards	1.000	.480
Legislative bodies	1.000	.953
Professional bodies	1.000	.891
Competition	1.000	.956
Public Pressure	1.000	.909
Beginner	1.000	.935
Intermediate	1.000	.938
Advanced	1.000	.927

Extraction Method: Principal Component Analysis.

Table 4.9: Communalities *Source: Survey Data, 2024*

The communality for a variable is the variance accounted for by all the extracted factors. The higher the communality, the more reliable it is an indicator. It is desirable for the mean level of communality to be at least .70 and for communalities not to vary over a wide range. The mean communality for the 18 variables in this study was .81. Table 4.10 shows the total variance explained by each of the extracted components.

	Initial Eigenvalues		
Component	Total	% of Variance	Cumulative %
1	5.431	18.728	18.728
2	4.270	14.725	33.453
3	3.545	12.223	45.676
4	3.104	10.705	56.381
5	2.742	9.457	65.838
6	2.006	6.916	72.754
7	1.349	4.651	77.404
8	1.074	3.704	81.108
9	.881	3.039	84.147
10	.849	2.929	87.076
11	.770	2.657	89.733
12	.572	1.974	91.707
13	.553	1.906	93.612
14	.446	1.539	95.151
15	.342	1.179	96.330
16	.270	.929	97.260
17	.221	.763	98.022
18	.192	.663	98.686

Table 4.10 Total Variance explained by each of the Extracted Components

Source: Survey Data, 2024

Each variable is standardized with the maximum variance for each as 1.0. An eigenvalue reflects the proportion of variance explained by each component. The general rule is that only components with an eigenvalue of 1.0 or greater should be retained for analysis. The results show that eight components with an eigenvalue of 1.0 or greater explained almost 81.108% of the total variance. The eight components with eigenvalues greater than 1.0 were rotated using Varimax software to generate an orthogonal solution as shown in Table 4.11.

Factors	Component							
	1	2	3	4	5	6	7	8
Knowledge on data analytics					.735			
Capital required		.582	-.508					
Precision concerns		.526	.554					
Data security	-.572							
Improve anomaly detection								
Efficiency and effectiveness		.601	-.513					
Management Support		.605	.581					
Audit continuity	-.757							
Audit performance				.833				
Management of online transactions	.802					.525		
Auditing standards							.532	
Legislative bodies				-.518	.726			
Professional bodies		.712						
Competition		.581	.619					
Public pressure	-.741							
Beginner				.836				
Intermediate	.2206					.548		
Advanced				-.550	.680			
Extraction Method: Principal Component Analysis.								
a. 8 components extracted.								

Table 4.3 Component Matrix[a] *Source: Survey Data, 2024*

As shown in table 4.11, Varimax software was utilized to produce an orthogonally rotated matrix. It is generally accepted that loadings should be .30 or greater to provide any interpretive value. The higher the loading, the greater confidence the researcher can have that a strong relationship exists. The guideline for interpreting loadings is as follows: .71=excellent, .63=very good, .55=good, .45=fair and .32=poor. Several variables had loadings in the very good to excellent range, which provided a basis for the researcher to make more definitive conclusions about the components. All loadings less than .30 were eliminated from the rotated component matrix as shown in Table 4.12.

Variables	Component							
	1	2	3	4	5	6	7	8
Knowledge on data analytics						.812		
Capital required			.823					
Precision concerns	.911							
Data security		.757						
Improve anomaly detection						.531		
Efficiency and effectiveness			.799					
Management Support	.964							
Audit continuity		.954						
Audit performance					.981			
Managing online transactions				.926				
Auditing standards							.591	
Legislative bodies						.966		
Professional bodies			.926					
Competition	.968							
Public pressure		.931						
Beginner					.956			
Intermediate				.928				
Advanced						.948		
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.								
a. Rotation converged in 6 iterations.								

Table 4.42: Rotated Component Matrix[a] *Source: Survey Data, 2024*

As shown in table 4.12, component one contains three variables or 16.6% of the total variables included in the study. All the three variables (precision concerns, Management Support, and competition) loaded in the excellent range. Another set of three variables, representing 16.6% of the total variables, loaded in the good to excellent range. In component three, there were three loadings representing 16.6% of the total variables all of which their loadings were in the excellent ranges. According to Stevens (2009) components with at least four loadings greater than .60 or at least three loadings greater than .80 are considered reliable. Applying these guidelines, components 4-8 were also deemed reliable as most of the loadings in the components met the prescribed threshold. Examining all the loadings for all the variables, it was only the variables related to auditing standards and improves anomaly detection that had almost no relational link to the other variables in the study. In other words, their inclusion in the study was not related to the adoption of AI in audit of public entities. These variables were eliminated, and the remaining variables were rotated again using Varimax and the results presented in table 4.13.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	4.980	20.749	20.749	4.980	20.749	20.749
2	4.049	16.870	37.619	4.049	16.870	37.619
3	3.340	13.918	51.537	3.340	13.918	51.537
4	2.944	12.268	63.805	2.944	12.268	63.805
5	2.550	10.625	74.430	2.550	10.625	74.430
6	1.789	7.455	81.885	1.789	7.455	81.885
7	1.029	4.286	86.170	1.029	4.286	86.170
8	.856	3.565	89.736			
9	.742	3.091	92.827			
10	.526	2.191	95.017			
11	.279	1.162	96.179			
12	.252	1.051	97.231			
13	.211	.880	98.111			
14	.148	.617	98.727			
15	.078	.324	99.051			
16	.048	.199	99.250			
17	.045	.186	99.436			
18	.040	.165	99.601			

Extraction Method: Principal Component Analysis

Table 4.5: Total Variance Explained Excluding some Variables *Source: Survey Data, 2024*

The result yielded seven components with eigenvalues of 1.0 or higher as shown in table 4.13. It is evident that over 86.170% of the total variance was explained by the seven components. Each component has a number of variables with high loadings and also other variables with very low loadings as shown in table 4.14.

Variables	Components						
	1	2	3	4	5	6	7
Knowledge on data analytics	.140	-.361	-.245	-.201	.778	.020	-.041
Capital required	-.278	.549	.552	.009	.155	.023	-.042
Precision concerns	.582	.536	-.383	.247	.104	-.110	.078
Data security	-.136	.563	.581	-.055	.142	.074	.039
Improve anomaly detection	.564	.621	-.427	.164	.138	-.158	.040
Efficiency and effectiveness	-.648	.194	-.447	.230	.125	.507	.040
Management Support	.153	-.271	.372	.785	.353	.036	-.041
Audit continuity	.830	-.018	.147	-.124	-.098	.472	-.090
Audit performance	.017	-.354	-.113	-.451	.783	-.027	.048
Manage online transactions	-.301	.702	.477	-.063	.248	.021	.114
Auditing standards	.518	.609	-.472	.166	.218	-.145	.021
Legislative bodies	-.640	.154	-.462	.227	.117	.007	.693
Professional bodies	.172	-.283	.440	.752	.253	-.049	.004
Competition	.789	-.048	.168	-.130	-.092	.493	-.112
Public pressure	.007	-.367	-.102	-.490	.745	-.011	.037
Beginner	-.305	.694	.491	-.058	.230	.052	.106
Intermediate	.514	.605	-.443	.194	.200	-.182	.074
Advanced	.134	-.302	.378	.753	.383	.051	-.053
Extraction Method: Principal Component Analysis.							
a. 7 components extracted.							

Table 4.6: Component Matrix[a] with high and low Loadings *Source: Survey Data, 2024*

By eliminating loadings less than .40, table 4.15 provided a clearer way to focus on the strongest relationships among the study variables.

1	2	3	4	5	6	7
.582Precision concerns	.549 Capital required	.552 Data security	.785 Management Support	.778 data analytics knowledge	.507 Efficiency & effectiveness	.693 Legislative bodies
.564 Improve anomaly detection	.536 Precision concerns	.581 Capital required	.752 Professional bodies	.783 Audit performance		
.830Audit continuity	.563 Data security		.753 Advanced	.745 Public pressure		
.518Auditing standards	.621 Improve anomaly detection					
.789 Competition	.702 Manage online transactions					
.514 Intermediate	.609 Auditing standards					
	.694Beginner					
	.605Intermediate					

Table 4.7: Component Loadings >.40 *Source: Survey Data, 2024*

As shown in table 4.15, knowledge on data analytics (.778), improve anomaly detection (.621), data security (.563), capital required (.581) and precision concerns (.582) which represented technological factors loaded excellently and moderately and independent of each other. The sub variables for organizational factors loaded strongly in components 1, 4, 5 and 2 (.830 for Audit continuity, .785 for Management Support, 783 audit performance and .702 for manage online transactions) and moderately in the other components (.507 for effectiveness and efficiency. Turning to environmental factors variables, the highest loads were .789 for competition, .752 for professional bodies, .745 for public pressure, .693 for legislative bodies and .609 for auditing standards. Lastly, advanced (.753), beginner (.694) and intermediate (.605) loaded highly with respect to the adoption of AI in audit of public entities. Hence, it is observed that by eliminating the unrelated variables, 86.170% of the variance in the adoption of AI in audit of public entities was explained by technological, organizational, and environmental factors.

4.7 Diagnostic Tests of Statistical Assumptions

The diagnostic tests are required for most of the statistical procedures based on the assumption that the population from which samples are taken should be normally distributed (Singh & Masuku, 2014). The diagnostic tests help to draw accurate conclusions about reality (Ghasemi, & Zahedias, 2012). If the assumptions of the diagnostic tests are not met, the statistical analysis may yield inappropriate results, and this may lead to overestimation or underestimation of the statistical significance (Osborne & Waters, 2002). However, when normality tests assumptions are violated, non-parametric tests may be used especially when the sample size is large (Gibson, & Gebken, 2022). In this study, the diagnostic tests used were multi collinearity test and Kolmogorov-Smirnov-Shapiro-Wilk test.

4.7.1 Multi collinearity Test

The study adopted the Variance of Inflation Factor (VIF) to check for multi collinearity. According to Kothari (2004) multi collinearity test estimates the level of correlation of the independent variables. The threshold for VIF value is 10 with the VIF values greater than 10 indicating the presence of multi collinearity. As a rule of thumb, if any of the VIF is greater than 10, multi collinearity is significantly large and poorly estimated and the variable concerned should be dropped. A VIF value less than ten with a tolerance value greater than 0.1 are recommended. However, if the VIF value is greater than 4, further investigation is warranted, Moreover, if there is more than one variable having a VIF value exceeding five, one of them ought to be dropped. The results are shown in table 4.18.

Model	**Collinearity Statistics**	
	Tolerance	**VIF**
(Constant)		
AI adoption	0.19	3.26
Technological factors	0.39	1.01
Organizational Factors	0.33	3.01
Environmental Factors	0.36	2.78

Table 4.8: Multi collinearity Test Statistics

From the findings presented in Table 4.16, the VIF values for all the variables was less than 10, a clear indication that multi-collinearity did not exist among the study variables. Therefore, the results indicated that the values for tolerance and VIF were within the acceptable range. This suggested that there was no threat of multi collinearity problem and therefore, all the independent variables could be used for further analysis using the regression model.

4.7.2 Kolmogorov-Smirnov-Shapiro-Wilk Test

Normality is used to determine if the data set is well modelled by a normal distribution. The assumption of normality is a prerequisite for inferential analysis (Singh & Kultar, 2007). With a small sample size, most parametric tests require normal data to avoid distorting the results of any further analysis. In this study, the Kolmogorov-Smirnov test was adopted to test normality as the data set was above 100. Ghasemi and Zahedias (2012) posited that the Kolmogorov-Smirnov (K-S) test is the most popular test for normality. Generally, the null hypothesis is often based on the normal distribution of data with the researcher’s interest is to have the Kolmogorov-Smirnov (K-S) test results turn out to be statistically insignificant as the evidence of the normality of the distribution of the data. The rule to be observed is the rejection of the null hypothesis when the *p*-value is greater than 0.05 paving way to infer that the data was normally distributed. However, a further analysis may be required if the p=values are less than 0.05. The results of the Kolmogorov-Smirnov-Shapiro-Wilk Test of normality are presented in table 4.17.

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**Df**	**Sig.**	**Statistic**	**Df**	**Sig.**
AI adoption	.079	220	.000	.982	220	.001
Technological factors	.114	220	.000	.978	220	.000
Organizational Factors	.127	220	.000	.955	220	.000
Environmental Factors	.111	220	.000	.974	220	.000

a. Lilliefors Significance Correction

Table 4.9: Kolmogorov-Smirnov-Shapiro-Wilk Test

From the findings in table 4.19, focusing on Kolmogorov-Smirnov test, the results showed that technological factors, organizational factors, environmental factors and AI adoption had p-values of less than 0.05 implying that the gathered data statistically significant and therefore was not normally distributed. The data for each variable were logged in a bid to ascertain whether they were normally distributed after logging and the results of the logged variables are captured in table 4.18.

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**Df**	**Sig.**	**Statistic**	**Df**	**Sig.**
log_AI adoption	.080	220	.000	.983	220	.002
log_Technological factors	.102	220	.000	.979	220	.000
log_Organizational Factors	.126	220	.000	.955	220	.008
log_Environmental Factors	.108	220	.000	.974	220	.000

a. Lilliefors Significance Correction

Table 4.18: Kolmogorov-Smirnov-Shapiro-Wilk test for Logged Variables

From table 4.18 it is evident that the log transformed variables were statistically significant and therefore not normally distributed. Given that the transformed variables were not normally distributed after logging them, the study adopted the spearman rank correlation analysis and the ordinal regression analysis for further analysis.

4.8 Inferential Statistics

This section presents the inferential analysis. The analysis was carried out in light of the objectives of the study. The inferential analysis involved Spearman rank correlation analysis and the ordinal regression analysis.

4.8.1 Spearman Rank Correlation Analysis

The relationship between the independent variables and the dependent variable was investigated using Spearman Rank correlation analysis. This enabled the researcher to ascertain whether the three factors (technological, organizational, and environmental factors) covaried with the adoption of AI in audit of public entities. The results are presented in Table 4.19.

			AI Adoption	Technological factors	Organizational Factors	Environmental Factors
Spearman's Rho	**AI Adoption**	Coefficient	1.000	.436**	.496**	.553**
		Sig. (2-tailed)	.	.000	.000	.000
		N	220	220	220	220
	Technological factors	Coefficient	.436**	1.000	.653**	.711**
		Sig. (2-tailed)	.000	.	.000	.000
		N	220	220	220	220
	Organizational Factors	Coefficient	.496**	.653**	1.000	.793**
		Sig. (2-tailed)	.000	.000	.	.000
		N	220	220	220	220
	Environmental Factors	Coefficient	.553**	.711**	.793**	1.000
		Sig. (2-tailed)	.000	.000	.000	.
		N	220	220	220	220

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.19: Spearman Rank Correlation Analysis Results Source: **Survey Data (2024)**

Table 4.19 shows that the results of the Spearman Rank Correlation Analysis coefficients between technological factors, organizational factors and environmental factors and AI adoption were all positive, with p-values of less than 0.05. The analysis further revealed that there was a positive relationship (r=0.436, p=0.000) between technological factors, and AI adoption. There was also a positive and statistically significant relationship (r=0.496; p=0.000) between organizational factors and AI adoption. The results also reveal that there was a positive and statistically significant relationship (r=0.553; p=0.000) between and environmental factors and AI adoption in audit of public entities. It is evident from these results that a consideration of technological, organizational, and environmental factors would enhance the adoption of AI as all the relationships were statistically significant.

4.8.2 Multinomial Logistic Regression

The multinomial logistical regression model was applied to determine the influence of technological, organizational, and environmental factors on AI adoption. The results for the ordinal logistic regression analysis are presented in table 4.20.

Term	Estimate (Log odds ratio)	Std. Error	Statistic (t-value)
Advance/Beginner	-2.55	0.32	-7.96
Beginner/Intermediate	0.92	0.282	3.26
Organizational factors	0.05	0.06	0.840
Technological factors	0.04	0.06	0.716
Environmental factors	0.02	0.06	0.474

Table 4.20: Log Odd Ratio of the Coefficients to the Standard Error *Source: Survey Data, 2024*

The results in table 4.20 represent the multinomial logistic regression output coefficients indicating the log odd ratio of the coefficients to the standard error. Organizational factors are noted to have relatively higher influence on the adoption of AI in audit of public entities as compared to the technological and environmental factors. The results, however, do not reveal any significant test by default. This was, however, achieved through further analysis of the estimated values of the intercepts. The results table too presented the estimates for the two intercepts that indicated where the latent variable was cut to make the three groups entailed in the data set (Advanced-Beginner intercept and Beginner-Intermediate intercept). The estimated models can be written as;

$$logit(\hat{p} \leq 1) = -2.55 - 0.05 * organizational_{factors} * -0.04 technological_{factors} - 0.02 enviromental_{factors \ldots\ldots\ldots (i)}$$

$$logit(\hat{p} \leq 2) = 0.92 - 0.05 * organizational_{factors} * -0.04 technological_{factors} - 0.02 enviromental_{factors \ldots\ldots\ldots (ii)}$$

-2.55 and 0.92 represents $\boldsymbol{\beta_{j0}}$- Constant with the model coefficients' parameters of 0.05, 0.04 and 0.02 (intercept and slopes) with p predictor variables (technological factors, organizational factors, environmental factors) for the ordinal outcomes $j = 1, \ldots, J-1$.

Since the coefficients of the predictors are the log odds ratio, the estimates have to be transformed (exponentiated) to odds ratio in order to interpret the ordinal logistic regression results. The results of the transformed coefficient estimates are presented in table 4.21.

Term	Estimate (Odds ratio)	Std. Error	Statistic (t-value)	p-value
Advance/Beginner	0.08	0.32	-7.96	0.00
Beginner/Intermediate	2.51	0.282	0.282	0.00
Organizational factors	1.05	0.06	0.840	0.00
Technological factors	1.04	0.06	0.716	0.00
Environmental factors	1.03	0.06	0.474	0.00

Table 4.10: Transformed Coefficient Estimates *Source: Survey Data, 2024*

The results presented in table 4.21 show the exponentiated coefficients (odds ratio) and where the odds ratios are interpreted (1.04, 1.05 and 1.03). It is evident that the exponential values are significant in providing the exact influence of the three factors influencing the adoption of AI in audit of public entities. The exponential coefficient (the odds ratio) related to technological factors was 1.04 which was higher than 1. This is an indication that technological factors had the odds ratio of 1.04 times influence on the adoption of AI in audit of public entities to a higher level (either from beginner level to intermediate level of from the intermediate level to advance level). Similarly, the exponential coefficient (the odds ratio) related to organizational factors was 1.05, which was higher than 1. This is an indication that organizational factors had the odds ratio of 1.05 times in influencing the adoption of AI in audit of public entities to a higher level (either from beginner level to intermediate level of from intermediate level to advance level). Lastly, the exponential coefficient (the odds ratio) related to environmental factors was 1.03 which was higher than 1. This suggested that the environmental factors had the odds ratio of 1.03 times of influencing the adoption of AI in audit of public entities to a higher level (either from beginner level to intermediate level of from intermediate level to advance level).

It is important to note that all the P-value for the predictor variables in Table 4.21 were all <0.05 implying that there was a significant difference between the three factors that influenced the adoption of AI in audit of public entities. However, the actual values indicated a very low influence of adoption, which could be attributed to the perceived low level of AI applications by the government auditors.

4.9 Chapter Summary

The chapter has presented analysis of the results. Descriptive analysis was used to profile the demographic characteristics of the respondents and the descriptive findings. The multinomial logistic regression showed that there was a significant difference between the three factors that influenced the adoption of AI in audit of public entities. Spearman rank correlation analysis was used to examine the relationship between the study variables. Factor analysis was employed to ascertain the factors that correlated with each other in determining the adoption of AI in audit of public entities in Kenya.

CHAPTER FIVE

DISCUSSIONS, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary of the study findings. The chapter also discusses findings based on the objectives. It also presents the conclusions and recommendations of the study. The chapter also presents the suggestions for further research and highlights the limitations that the study encountered.

5.2 Summary of Major Findings

It is evident that 333 questionnaires were distributed but a total of 220 questionnaires were completed and returned accounting for 66% response rate. This response rate was considered sufficient. Carvajal and Hardigan (2016) observe that a return rate greater than 60% was sufficient for adoption in analysis while Mugenda and Mugenda (2003) contended that 50% response rate is adequate for analysis. Majority of respondents were male as represented by 57% while the females were 43%. This is a fairly balanced gender distribution in the institution. There is more opportunity for the professional auditors to adopt AI in audit as majority of the respondents were relatively young more likely be enthusiastic about new technology as it continues permeating institutions. According to Agnew (2016) this puts the organization in strategic position to build the capacity of the young professionals.

The results pertaining to ordinal logistic regression, postulated that the odds ratio related to the technological, organizational, and environmental factors were more than 1 which suggested that the factors had the odds ratio of influencing the adoption of AI. However, there exist significant difference between the three factors that influenced the adoption of AI in audit of public entities. Also, the actual values indicated a very low influence which was attributed to the low levels of adoption or rather AI being at infancy in audit of public entities.

With regard to factor analysis, data analytics (.778), improve anomaly detection (.621), data security (.563), capital required (.581) and precision concerns (.582) represented the technological factors that loaded excellently and moderately to influence the adoption of AI. The sub-variables for organizational factors that loaded strongly were Audit continuity (.830), Management Support (.785), audit performance (.783) and the management of online transactions (.702). The environmental factors with the highest loads were competition (.789), professional bodies (.752) and public pressure (.745). Based on the factor analysis, 86.170% of the variance in the adoption of AI in audit of public entities was explained by technological, organizational, and environmental factors. The Spearman rank correlation coefficients for technological factors (r=0.436, p=0.000) organizational factors (r=0.496; p=0.000) and environmental factors (r=0.553; p=0.000) and the adoption of AI in audit of public entities were shown to be positive, with p-values of less than 0.05.

5.3 Discussions of the Research Findings

The general objective of the study was to assess the factors influencing AI adoption in audit of public entities in Kenya. This section presents a discussion of the findings as guided by the specific objectives.

5.3.1 Technological Factors and Adoption of AI in Audit of Public Entities

The results show that technological factors positively influenced the adoption of AI in audit of public entities in Kenya. Among the technological factors enhancing the adoption of AI included knowledge on data analytics, capital required or investment, precision concerns, data security and anomaly detection. These results are consistent with Bochco (2020) who proved that technological factors have a great influence on the adoption of a new technology like AI. This provides the justification to improve technological infrastructure of the AOG.

According to Kuo-Chen (2019) the advancement of technology such as AI in the auditing procedures can realize economic growth by inhibiting pilferages to ensure value for money. As depicted by Vadlamudi (2019) the adoption of AI can open new frontiers for the auditors to explore other areas of operations enhancing their skills. The findings are also supported by Chege (2020) who found that public entities have a duty mitigate and eliminate financial leakages associated with fraud. However, Ngumuta (2018) warned that the adoption of the new technology should have a backup for data security purposes. Similarly, Al-Okaily, Alqudah, Al-Qudah and Alkhwaldi (2022) expressed fears that technological factors can compromise the adoption of AI if compatibility concerns are not addressed from the onset. In this regard, the findings suggest that data security was one of the preferred technological factors consistent with Oakley (2014) who recommended adequate resources to take care of the new technology. Levin (2019) and Gordon (2017) also averred that technological factors should be legally backed in the advent of cybercrime and related security concerns.

5.3.2 Organizational Factors and Adoption of AI in Audit of Public Entities

For organizational factors, a number of factors have been associated with the adoption of AI. Among those evaluated, management support, efficiency and effectiveness and management of online transaction were found to be the main influencers. While continuous audit and quality ranked lower as factors influencing adoption of AI for public entities.

The results pertaining to the organizational factors are consistent with Meyer (2011) who demonstrated that organizational readiness was positively related to the probable adoption of AI. Angelini (2023) postulated that audit task complexity tended to influence the adoption of AI. This is in congruent with Heimans (2019) who pointed out that the auditors' information technology competency tended to influence the adoption of AI. Keshine (2018) agrees that government support can easily influences AI adoption. Horváth and Partners (2020) study also revealed that the adoption of AI is a long process and the auditors need to time embrace the new technology.

Thangiri (2018) claimed that organizational factors have a great influence on the adoption of AI especially when the need to adopt the emerging technologies is associated with efficiency and economic gains. Kagumba and Wausi (2018) agreed that public entities should consider the short-term and long-term benefits of adopting AI to guide the auditing activities. As hypothesized by Ngumuta (2018) AI involves complex data management that must factor in continuos training for the implementers of the new technology. The findings are supported by Asango and Odhiambo (2020) whose work noted that management support greatly influence the strategic direction especially with regard to adopting and aligning AI with the organizational strategy.

5.3.3 Environmental Factors and Adoption of AI in Audit of Public Entities

It is evident that the environmental factors greatly influenced the adoption of AI. This is consistent with Trump (2019) who observed that business objectives, finances, organizational structures, technology, and human resources are associated with technological adoption. This is in harmony with the study outcomes where auditing standards, legislative bodies, professional bodies, competition, and public pressure were associated with the AI adoption. It is apparent that most of these factors are outside the control of the public entities. The results of this study relates to the findings of Kimeu and Okello (2018) where it emerged that environmental factors played a significant role in assessing the opportunities and threats for adopting AI. Compared to the present study, Kimeu and Okello (2018) contended that competitive pressure, public demands, and government regulation were major environmental factors. However, it is apparent that environmental factors are also driven by global technological trends.

In their analysis, Reuben and Ajowi (2019) observed the need to comply with the public pressure often motivated organizations to adopt new technologies. Spagnoletti (2021) suggested that public demands greatly affect the government's priority in adopting significant technologies. Another important revelation was by Nyanga'nga (2015) who noted that external factors such as auditing standard setting bodies, professional and regulatory entities have a considerable effect on the adoption of AI in audit of public entities similar to the results presented in this study.

5.4 Conclusion

The purpose of the study was to assess the factors influencing the adoption of AI in audit of public entities in Kenya. Based on the study findings, it is evident that technological factors, organizational factors, and environmental factors influenced the adoption of AI in audit of public entities. The study concluded that there was a positive relationship ($r=0.436$, $p=0.000$) between technological factors and the adoption of AI in audit of public entities. A positive and statistically significant relationship ($r=0.496$; $p=0.000$) between organizational factors and the adoption of AI in audit of public entities. Lastly a positive and statistically significant relationship ($r=0.553$; $p=0.000$) between environmental factors and the adoption of AI in audit of public entities. Based on factor analysis, 86.170% of the variance in the adoption of AI in audit of public entities was explained by technological factors, organizational factors, and environmental factors. Hence, the study concludes that the public entities must consider the technological, organizational, and environmental factors when planning to adopt AI in audit of public entities.

5.5 Recommendations

This section presents the recommendations for the managers, private sector and policy makers, practitioners, theory, and knowledge. The recommendations were proposed in relation to the study objectives.

5.5.1 Recommendations for the Management of the Public Entities

The study recommends that government entities should work together with the OAG on implementing policies such as increasing investment in AI development, building capacity of stakeholders such as auditors, ICT experts, accountants, and managers on the potential benefits of AI. It is also important for the management to address the ethical and social dilemmas that may arise from the AI adoption.

Based on the conclusions drawn, the study recommends that managers of the public entities should consider the factors influencing the adoption of AI in auditing process. A strategy to address issues that emerged such as privacy of confidential data, fear of job losses that can cause resistance, legislative, ethical issues among other factors along the lens of the TOE framework and Diffusion of Innovation Theory would ensure successful implementation. The public entities should have data backup options to ensure smooth transition to the new systems of auditing.

5.5.2 Recommendations for the Private Sector

The outcome of the study has provided impetus for developing a strong Public Private Partnership (PPP) through auditing to leverage on the potency of financial transparency engendered by AI. Through PPP, the technological, organizational, and environmental factors can jointly be addressed during the acquisition, adoption and execution of AI in the auditing process considering the infrastructure has been a barrier to embracing technology.

5.5.3 Recommendations for Policy Makers

The findings have presented insights to guide policy formulation pertaining to the technological, organizational, and environmental factors influencing the adoption of AI in audit of public entities. Hence, the government should adopt the findings to guide in the review of policies pertaining to the paradigm shift from manual auditing to the use of AI in auditing. The government should also involve all the auditors with the aim of promoting acceptance of AI as a new way of auditing public entities. In this regard, policy interventions are recommended to engage the public entities to accelerate policy awareness so that auditors can operate within the confines of the law in light of data protection provisions.

5.5.4 Recommendation for Theory

This study has highlighted the significance of TOE framework and DOI theory as adopted to guide the study. These theories are relevant due to their emphasis on the distinguishing features of technological adoption. As postulated by TOE model and the DOI theory, the results have confirmed that the consideration of the technological, organizational, and environmental factors is important when adopting AI in audit of public entities. Supporting auditing can also be perceived as a sign of strong resolve to promote accuracy and privacy in the process of auditing public entities and rather be a laggard, the government should be proactive to embrace AI and experience the quality offered by smart audit earlier in the process than later. To achieve this it requires a strategy that may place a design that can address the underlying factors as postulated in the TOE framework and Diffusion of Innovation Theory.

5.5.5 Recommendations for Knowledge

Given that many public entities fail to reach their objectives, studies that consider the adoption of AI in audit of public entities from the perspective of the technological, organizational, and environmental factors are bound to make positive contributions both to literature and knowledge. Therefore, this study has presented empirical evidence that should be embraced by scholars pursuing professional courses in public policy and corporate governance and related study areas. This study should be taken as a foundation for building further arguments in the academia and in ascertaining the determinants of adoption of AI in audit of public entities in Kenya and beyond. The findings anticipated contribute to the build-up of empirical knowledge of the research community regarding factors associated with the adoption of AI in the auditing profession and the auditors should benefit from the results by gaining additional knowledge on AI adoption in the auditing practice.

5.6 Suggestions for Further Studies

The study assessed the factors influencing the adoption of AI in audit of public entities. However, it only considered three factors (technological factors, organizational factors and environmental factors) which accounted for 86.170% of the variance in the adoption of AI in audit of public entities. The study recommends a further work to establish the contribution of other factors including influence of AI in other organizations such as business and private entities in Kenya. Alongside this, a holistic study to include accountants, ICT, managers among others will help expand knowledge and enrich the subject.

The perceptions of the taxpayers on the adoption of AI in auditing public entities can also be an area for further exploration by researchers.

5.7 Limitations of the Study

The study limitations can be described as errors in the methodology used that compromise accurate discussion of the research findings. The study was limited to the adoption of AI in audit of public entities. This gave the researcher an opportunity to undertake an in-depth assessment of the factors influencing the adoption of AI. However, the researcher focused on the auditors who are mainly involved in auditing public institutions. This might make it implausible to generalize the study to a wider population including those auditors working in the private sector.

The study also only focused on three factors, that is, technological factors, organizational factors, and environmental factors in relation to the adoption of AI in audit of public entities. This implies that other factors were excluded. Methodologically, the study was limited to the descriptive design with a bias on the use of self-administered questionnaire; this further limit it from generalizing the findings to all organizations.

The use of online method of administering the questionnaires was a limitation because it was not easy to determine whether the respondents expressed their true opinion on the level of the adoption of AI in auditing public entities. However, this was addressed through the instrument's reliability and validity tests to ensure the questions attained the thresh hold of the measurement. The willingness of respondents to provide reliable information was enhanced by assuring the respondents anonymity throughout the data collection study, which served to win their confidence. The researcher also sought research permit from NACOSTI and the ethical committee of Strathmore University for permission to collect data.

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APPENDICES

Appendix I: Questionaire to the Auditors

I am **Andrew Muga Apondi**, a postgraduate student at Strathmore University undertaking a master's degree in commerce. I am carrying out a study on ***ASSESSING FACTORS INFLUENCING ADOPTION OF ARTIFICIAL INTELIGENCE IN AUDIT OF PUBLIC ENTITIES IN KENYA.*** Through purposive and random sampling, you have been selected to participate in the study as a research respondent. Your honest responses will be treated with utmost confidentiality and used for the purpose of the study only. Kindly complete the questionnaire by filling it in as instructed.

SECTION A: DEMOGRAPHIC INFORMATION

1. What is your gender? Male [ ] Female [ ]
2. What is your age bracket? 20-30 [ ] 31-40 [ ] 41-50 [ ] 51-60 [ ]
3. Which is your highest academic qualification? Certificate [ ] Diploma [ ] Undergraduate [ ] Graduate [ ] Post Graduate [ ]
4. Are you registered with a professional body? Registered [ ] Not Registered [ ]
5. Is there any documented guideline by OAG on how to handle client's data in light of privacy and confidentiality requirements? Yes [ ] No [ ]
6. Is there any documented guideline by professional body on how to handle client's data in light of privacy and confidentiality? Yes [ ] No [ ] N/A [ ]
7. Does either OAG or the professional body prescribe on how you can use Artificial Intelligence in execution of your work? Yes [ ] No [ ] N/A [ ]
8. Which is your level of operation in the department? Entry [ ] Middle Level [ ] Senior Level [ ]
9. How many years have you worked for the Office of Auditor General?

0-5 years [ ] 6-10 years [ ] 11-15years [ ] 16-20years [ ] 21-and above

Section II: Adoption of artificial intelligence

10. Are you aware of the applications of AI in audit No [ ] Yes [ ]
11. Have you ever attended a course on Artificial Intelligence to assist you in auditing? No [ ] Yes [ ]
13. Are your using knowledge gained through training to use AI in carrying out audit? Yes [ ] No [ ] N/A [ ]
14. Without formal training on AI, are you in a position to use such self-developed skills when carrying out in audit? Yes [ ] No [ ]

15. Is Artificial intelligence relevant in audit of public entities? Yes   [ ] No [ ]

16. By use of percentage, what category of score do you perceive the normal/traditional sampling methods of auditing can pick irregularities in public service processes? 1-20% [ ] 21-40% [ ] 41-60% [ ] 61-80% [ ] 81-100% [ ]

17. By use of percentage, what category of score do you perceive Artificial intelligence can identify irregularities in public service processes? 1-20% [ ] 21-40% [ ] 41-60% [ ] 61-80% [ ] 81-100% [ ]

18. By use of percentage, what category of score can you assign the level of access given by the public entities to its database in the course of OAG work?

1-20% [ ] 21-40% [ ] 41-60% [ ] 61-80% [ ] 81-100% [ ]

19. To what extent do think OAG has adopted AI in audit of public entities.

Beginner [ ] Intermediate [ ] Advanced [ ]

SECTION B: Technological Factors

20. Please indicate the extent to which you agree with the following technological factors associated with the adoption of AI to audit public entities with 1=Strongly Disagree, 2= Disagree, 3=Neutral, 4=Agree and 5=Strongly Agree.

RANKING	1	2	3	4	5
Knowledge on data analytics					
Capital required					
Precision concerns					
Data security					
Improve anomaly detection					

SECTION C: Organizational Factors

21. Specify the extent to which you agree with the following organizational factors associated with the adoption of AI to audit public entities using the given key: 1=Strongly Disagree, 2= Disagree, 3=Neutral, 4=Agree and 5=Strongly Agree.

RANKING	1	2	3	4	5
Efficiency and effectiveness					
Management Support					
Audit continuity					
Audit Performance					
Management of online transactions					

SECTION E: Environmental Factors

22. Show your level of agreement with the following environmental factors associated with the adoption of AI in auditing public entities using the given key: 1=Strongly Disagree, 2= Disagree, 3=Neutral, 4=Agree and 5=Strongly Agree.

RANKING	1	2	3	4	5
Auditing Standards					
Legislative Bodies					
Professional Bodies					
Competition					
Public Pressure					

Appendix II: Request Letter to AOG

OFFICE OF THE AUDITOR GENERAL
P. O. Box 30084 - 00100, NAIROBI
REGISTRY
25 JAN 2024
RECEIVED

25th January 2024

The Auditor General
Office of the Auditor General
P O Box 30084-00100
NAIROBI

Dear Madam,

RE: REQUEST TO CARRY OUT A STUDY AT THE OAG

I am a Master of Commerce Student at Strathmore University intending to carry a study titled "***Factors Affecting the Adoption of Artificial Intelligence in Audit of Public Service Entities in Kenya***".

I am also an active employee of Kenya Agricultural Research Institute (KALRO) based at Dairy Research Institute in Naivasha. I humbly request your permission to carry out the study, which will entail a questionnaire administered through a shared google link on the audit personnel who have had experience carrying out audit activities on Public entities in Kenya.

I will gladly shared the results of the study upon request with hope that it can add value to your highly esteemed Institution.

Attached is an Introduction letter from the School and the Questionnaire for the study.

Thank you in anticipation.

Andrew M Apondi
ID 21985338....PHONE-0721788352

Encl.

Appendix III: Research Permit from NACOSTI

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

Ref No: **974962**

Date of Issue: **02/February/2024**

RESEARCH LICENSE

This is to Certify that Mr.. ANDREW MUGA APONDI of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: ASSESS FACTORS AFFECTING ADOPTION OF ARTIFICIAL INTELIGENCE IN AUDIT OF PUBLIC SERVICE ENTITIES IN KENYA for the period ending : 02/February/2025.

License No: **NACOSTI/P/24/32789**

974962

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

Appendix IV: Ethical Approval

Strathmore
UNIVERSITY

24th January 2024

Mr Apondi Andrew,
Andrew.Apondi@strathmore.edu

Dear Mr Apondi,

RE: Assess Factors Affecting Adoption of Artificial Intelligence in Audit of Public Service Entities in Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC1958/23.** The approval period is from **24th January 2024 to 23rd January 2025.**
This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
24-Jan-2024
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
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