

Determinants of Artificial Intelligence Adoption in the Audit Profession in Saudi Arabia

MOHAMMAD ALASKAR

ID: 20200465

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Supervised by:

Dr. Ja Kim, Dr. Tam Nguyen, and Dr. Muhammad Rafique

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List of Abbreviations

GAAP	Generally Accepted Accounting Principles
IFRS	International Financial Reporting Standards
ISA	International Standards on Auditing
SAS	Statement On Auditing Standards
PCAOB	Public Company Accounting Oversight Board
IAASB	International Auditing and Assurance Standards Board
IFIAR	International Forum of Independent Audit Regulators
IFAC	International Federation of Accountants
ICAEW	Institute Of Chartered Accountants In England And Wales
CAI	Chartered Accountants Ireland
ICAS	Institute of Chartered Accountants of Scotland
RSBs	Recognised Supervisory Bodies
FRC	Financial Reporting Council
ACCA	Association Of Chartered Certified Accountants
AICPA	American Institute of Certified Public Accountants
SOCPA	Saudi Organisation for Chartered and Professional Accountants
SAA	Saudi Accounting Association
CPA	Certified Public Accountant
IIA	Institute Of Internal Auditors
SEC	Securities And Exchange Commission
CMA	Capital Market Authority
GAZT	General Authority of Zakat and Tax
KSA	Kingdom of Saudi Arabia
ERP	Enterprise Resource Planning
CAATs	Computerised Assisted Audit Tools
IT	Information Technology
ICT	Information And Communication Technology
GAS	Generalised Audit Software
ACL	Audit Command Language
VRT	Visual Recognition Technology

RPA	Robotic Process Automation
UTAUT	Unified Theory of Acceptance and Use of Technology
TAM	Technology Acceptance Model
TPB	Theory Of Planned Behaviour
C-TAM-TPB	Combining Technology Acceptance Model and Theory of Planned Behaviour
MPCU	Model of PC Utilisation
TRA	Theory of Reasoned Action
IDT	Innovation Diffusion Theory
MM	Motivational Model
SCT	Social Cognitive Theory
ILO	International Labour Organisation
WHO	World Health Organisation
SDAIA	Saudi Data and Artificial Intelligence Authority
GDPR	General Data Protection Regulation
EY	Ernst & Young
PWC	Pricewaterhousecoopers
KPMG	Klynveld Peat Marwick Goerdeler
IBM	International Business Machines

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Declaration

I hereby declare that the work presented in this thesis, entitled ‘Ethics and Technology Acceptance: Determinants of Artificial Intelligence Adoption in the Audit Profession in Saudi Arabia’, is entirely my own original work. This thesis has not been submitted for any other academic qualification or examination at any other institution.

All sources used in the research and writing of this thesis have been duly acknowledged and referenced according to the appropriate citation style. Any ideas or quotations from the works of other authors have been properly attributed and cited. I affirm that I have not used any unacknowledged sources in the preparation of this thesis.

Mohammad Alaskar

Abstract

Artificial intelligence is considered as the fourth industrial revolution and is having a profound impact on our lives. Amid the recent rapid development of artificial intelligence, the framework of determinants of the use of artificial intelligence in the business environment such as the audit profession is still far from the rapid development of artificial intelligence. This thesis provides a framework for the determinants that influence the decision of using artificial intelligence. It expands and modifies the Unified Theory of Technology Acceptance and Use to cover important aspects that auditors should consider when using artificial intelligence. The new framework of artificial intelligence acceptance was empirically tested via a questionnaire sent to 403 auditors working in Saudi Arabia. Moreover, to verify and obtain a profound understanding of the result of the questionnaire, it was followed by an interview with 26 external auditors.

Based on the questionnaire and interview, this thesis finds that ethical factor is considered by external auditors as one of the most important determinants of artificial intelligence technology adoption. The findings also indicate that auditors consider both facilitating conditions, performance expectancy, and effort expectancy when intending to implement artificial intelligence in audit engagements. Indeed, auditors consider facilitating conditions as the most influential factor when adopting artificial intelligence technology. This thesis contributes in framing the determinants of artificial intelligence acceptance and empirically tested these determinants. Also, it contributes to the existing literature by exploring the determinants influencing the acceptance of advanced technology within the audit profession in Middle East countries.

Moreover, the thesis contributes to the societal debate on artificial intelligence and ethics by providing empirical evidence of ethical concerns by the potential users of the artificial

intelligence technology. The thesis contributes to identifying six dimensions of ethical concerns regarding the acceptance of artificial intelligence in the audit profession. These dimensions are as follows: substitution of human labour, confidentiality and data protection, independence, auditability of audit processes, repurposing client data, and professional scepticism and judgment.

Chapter 1: Introduction

1.1 Research Background

Accounting and auditing are two fields in which artificial intelligence is making a strong impact, since they usually involve a wealth of data that require a large amount of time, money, and human resources to process. All auditing phases—from client acceptance to reporting the audit opinion—involve challenges, often owing to clients' volume of transactions and big data. To overcome these obstacles, according to Michael and Dixon (2019), the utilisation of big data analytics techniques can effectively manage this enormous volume of data and transactions.

Auditing firms have been encouraged to invest in smart technology, such as textual analysis technology, natural language processing technology, speech recognition, and visual recognition technology. Yoon et al. (2015) expect Big Data to enhance auditors' ability to gather adequate and appropriate audit evidence. Utilising artificial intelligence, auditors can scrutinize vast quantities of financial information, detect aberrations and irregularities, and generate reports that can aid in the identification and prevention of financial fraud. Moreover, Gepp et al. (2018) concluded that auditing would benefit tremendously from adopting artificial intelligence and big data techniques that combine numerous big data models to complement human experts.

The Big 4 accounting firms have invested large amounts of money in incorporating new technologies into audit procedures (Issa et al., 2016). Klynveld Peat Marwick Goerdeler (KPMG) declared its collaboration with International Business Machines Corporation (IBM), in which it will use IBM's Watson Artificial Intelligence suite to apply cognitive computing technology to the services offered by KPMG. Deloitte also cooperated with Kira Systems Inc to launch a cognitive system that assists in extracting and structuring textual information for

improved analysis, examination of massive volumes of complicated documents, and assisting auditors in reviewing the files (Deloitte, 2016).

In this thesis, we define artificial intelligence as the simulation of human intelligence in machines that are programmed to think, reason, and make decisions. It encompasses a broad range of techniques and methods that enable machines to perform tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, learning from experience, and solving complex problems. Throughout the thesis, we mention other terms that are somehow linked to Artificial Intelligence in the literature, such as Big Data Analytics, Machine Learning , and Robotic Process Automation (RPA). To avoid confusion between these terms, we will define each of them separately. Big Data Analytics involves the process of examining and analysing vast and complex datasets, often referred to as "big data." The objective is to uncover patterns, trends, correlations, and other valuable insights that can aid decision-making and improve business outcomes. Big Data Analytics encompasses various techniques, such as data mining, machine learning, and statistical analysis, to process and derive meaningful information from large datasets.

Machine Learning is a subset of artificial intelligence that focuses on developing algorithms and statistical models that enable computers to learn and improve their performance on a specific task based on data, without being explicitly programmed for that task. Instead of following predefined rules, Machine Learning systems learn from patterns in the data and make predictions or decisions accordingly. RPA is a technology that involves automating repetitive and rule-based tasks using software robots (bots). These bots mimic human actions on computer systems, interacting with applications to execute processes, manipulate data, trigger responses, and perform routine tasks without human intervention. RPA is not a form of artificial intelligence, as it doesn't possess intelligence or the ability to learn. However, it may be referred to as an artificial intelligence system if it were linked to a machine learning system.

Some audit processes, such as journal entry tests that can be conducted on 100% of the population by utilising computer-assisted auditing techniques (like Watson), have become fully automated. However, there are still evidence-collection domains that have not been automated. Appelbaum and Nehmer (2017) note that numerous areas of evidence collection in the field of auditing—such as interviews, counts of inventory, evaluation of assets, and observation—are still non-digital. These areas of evidence collection have the potential to be automated by applications that adopt machine learning, natural language processing, textual analysis, speech recognition, visual recognition, and cognitive technologies.

Researchers have discussed using natural language processing to conduct automatic contract analysis to support audits (Zhaokai and Moffitt, 2019). The usage of machine learning has been explored to predict bankruptcy (e.g., Gentry et al., 2002), fraud (e.g., Cecchini et al., 2010; Perols, 2011; Perols et al., 2017; Bao et al., 2020), restatement/misstatement (e.g., Bertomeu et al., 2021), and accounting estimates (e.g., Ding et al., 2020). Zhang (2019) suggests robotic process automation (RPA) and artificial intelligence-based technologies to create a smart audits environment. Moreover, in an audit brainstorming session, auditors can use a cognitive aid assisted by cognitive technologies to provide interactive decision help for information retrieval and risk assessment (Li and Vasarhelyi, 2018).

Furthermore, researchers have explored the usage of drones and visual recognition to conduct inventory counting in audits (Christ et al., 2021; Sun, 2019). Christ et al. (2021) show that the use of drones and automated counting technology might increase the speed, accuracy, and calibre of the documentation produced by audits of the inventory, enhancing asset measuring procedures as a consequence. Sun (2019) notes that, with visual recognition technology, auditors could take advantage of an enormous amount of formerly uninvestigated qualitative data extracted from non-traditional sources by transferring that data into a form of machine-readable quantitative data.

An example of a non-traditional source would be a video of a board of directors meeting. This video clip could be used to identify people in the meeting, analyse their facial expressions, and examine the words used in the meeting. Even though artificial intelligence technology can improve the efficiency and effectiveness of the audit process, not enough evidence is available on the use of artificial intelligence by individual auditors. Gepp et al. (2018) found that auditors lag behind the other service sectors in using valuable artificial intelligence and big data techniques. Indeed, in an empirical study, Austin et al. (2021) assert that artificial intelligence is not yet used within the entire auditing field. This creates an incentive to study the determinants that motivate or prevent auditors from adopting artificial intelligence technology. Furthermore, as artificial intelligence technology has ethical implications, the thesis aims to address the influence of ethical concerns when accepting and applying artificial intelligence technology in the audit profession.

1.2 Research Gap and Justification

The existing literature focuses on both the uses and benefits of artificial intelligence in the audit profession, while neglecting the empirical examination of the determinants that influence the individual auditors' decision to use artificial intelligence. Apart from the large investment in artificial intelligence technology by big audit firms, there is a need to study the behaviour of those individual auditors working within these audit firms towards artificial intelligence technologies. Scholars argue that the auditing industry should embrace the full potential of artificial intelligence technology to improve audit quality, efficiency, and effectiveness (Cao et al., 2015; Appelbaum et al., 2017; Sun and Vasarhelyi, 2018). Among artificial intelligence tools, robots can be used to enhance the automation of sending and receiving back audit inquiries (Raschke et al., 2018; Moffitt et al., 2018). Furthermore, drones and visual recognition software can be used to capture high-quality images and videos for assets and facilities measurements (Christ et al., 2021) and machine learning can help detect

and interpret patterns that are present in ongoing accounting misstatements (Bertomeu et al., 2021). Bao et al. (2020) develop a fraud prediction model using a machine-learning approach. They show that their model exceeds the performance of two benchmark models by a significant margin; namely, it improves on the logistic regression model of Dechow et al. and the support-vector-machine model of Cecchini et al.

Zhaokai and Moffitt (2019) proposes using natural language processing to conduct automatic contracts analysis. They introduced the contract analytics framework, which they claim provides guidance for incorporating textual analysis into audits of large numbers of contracts. Zhang (2019) provides, using the concept of audit workflow, a framework for implementing intelligent process automation in audit engagements. He states that the implementation of intelligent process automation positively impacts audit efficiency and effectiveness. Al-Sayyed et al. (2021) studied the effect of artificial intelligence technologies on audit evidence. Their results show increased interest in artificial intelligence technology by auditors due to its scientific importance in improving the collection of audit evidence.

Notwithstanding the significant effort employed by scholars in studying the benefits and uses of artificial intelligence in the audit profession, there remains a gap that needs to be filled. Since the implementation of artificial intelligence in the audit profession is voluntary, there is a need to explore implementation decision by auditors. We need to explore the determinants that influence the auditor's decision when accepting artificial intelligence for use during the audit process.

1.3 Research Motivations

Three reasons have motivated an investigation into this phenomenon. First, despite the many uses (Zhaokai and Moffitt, 2019; Bao et al., 2020; Bertomeu et al., 2021; Christ et al., 2021) and significant benefits (Cao et al., 2015; Appelbaum et al., 2017a; Raschke et al., 2018; Zhang, 2019) of artificial intelligence in the audit profession, the literature indicate that

advanced technology and artificial intelligence are still little utilised in an auditing profession (Curtis and Payne, 2014; Pedrosa et al., 2019 Austin et al., 2021). Consequently, to address this reluctant behaviour, the author is motivated to study the determinants that influence the adoption of artificial intelligence from the perspective of auditors. This step will help significantly in optimizing the objectives of the literature that discusses the uses and benefits of artificial intelligence in the audit profession.

The second motivation for this study is that audit firms, professional associations, regulators, clients, and researchers hold artificial intelligence technology in high regard. Big audit firms seem to have invested large amounts of money in advanced smart technology. Both KPMG, EY, Deloitte and PWC state on their official websites that they invest large amounts of money in developing artificial intelligence tools that help them in performing audit engagements. Also, although the regulatory bodies of the audit profession such as the Institute of Chartered Accountants in England and Wales (ICAEW), or international auditing standard boards, do not explicitly mandate that auditors use artificial intelligence techniques in their audits, they do suggest the use of advanced technology in performing audit engagements. For instance, the regulatory bodies for the external audit process suggest that external auditors use remote auditing tools, such as visual recognition technology, to overcome COVID-19 restrictions (ICAEW, 2020). Consequently, to contribute to the realisation of these great aspirations in artificial intelligence, the author is motivated to need to study the behaviour of those individual auditors working within these audit firms towards artificial intelligence technologies and, thus, optimise the results of these huge investments in technology. Studying the factors that influence the auditors' decision to accept artificial intelligence will significantly help in achieving the desired results for these great aspirations and large investments.

The third reason is that under the leadership of crown prince Mohammed Bin Salman, Kingdom of Saudi Arabia (KSA) has an ambitious vision (vision 2030) backed by huge

investments toward creating a digital transformation that include the application of artificial intelligence at all levels and sectors. One of these sectors is the service sector, including auditing. To help achieve part of the ambitious vision's goals, the author was motivated to study the determinants of artificial intelligence technology acceptance in audit industry in KSA. Investigating the determinants of artificial intelligence technology acceptance will significantly smoothen the journey of digital transformation called by Vision 2030. Also, studying the factors that affect the decision of the potential users of the artificial intelligence technology highlights the spillover effects of artificial intelligence technology acceptance on the whole society and economy.

1.4 The Research Objectives

This study aims to probe, in detail, the factors that play a role in influencing the decisions of individual auditors - auditors working in audit firms or an audit partner - in accepting artificial intelligence from their perspective. This probing will explore the impact of auditors' perceptions on the expected performance of artificial intelligence technology when auditing with respect to the acceptable uses of this technology in the audit profession. In addition, this study, aims to explore the influence of auditors' perceptions on the effort needed to use artificial intelligence technology in an auditing environment.

This research, also, investigates the impact of auditors' perceptions on the technical, organisational infrastructure of artificial intelligence technology in the auditing environment. Additionally, it examines the impact of ethical concerns, associated with the use of artificial intelligence technology in auditing, on the acceptance of this technology in the profession from the perspective of auditors. Moreover, this work explores the impact of the COVID-19 pandemic on the acceptance of artificial intelligence in the profession. Finally, it establishes an artificial intelligence adoption model for auditors, which is developed with reference to the literature on the acceptance of audit technologies as well as the results of this present study.

1.5 The Research Questions

This research attempts to answer a set of questions that will achieve the earlier-mentioned objectives of this thesis. The research questions are as follows:

Research question 1: What are the determinants that influence the auditors' decision when implementing artificial intelligence in the audit profession?

Research question 1 A: Does the size of the firm in which the auditor works play a role in influencing his/her decision when using artificial intelligence in the audit profession?

Research question 2: What are the ethical concerns associated with the use of artificial intelligence in the audit profession?

Research question 2 A: Do auditors take ethical concerns associated with the use of artificial intelligence into consideration when deciding to use artificial intelligence in the audit profession?

Research question 3: Has the COVID-19 pandemic affected the acceptance of artificial intelligence in the audit profession?

1.6 Research Approach and Methodology

This thesis answers the research questions and empirically validates the research model using an explanatory sequential mixed method. The object of using a mixed approach is to combine the benefits of both qualitative and quantitative research, which raises the internal validity of the study findings, and offsets the deficiencies of both qualitative and quantitative research methods while using their strengths. Bryman (2007) states that combining results from two approaches can provide information that could not otherwise be gathered. For this study, the quantitative data (i.e., from the questionnaire) is used to test the thesis model using one form of artificial intelligence technology, visual recognition. The reason for using only visual recognition in the questionnaire is discussed in detail in the Methodology chapter section 6.3.2, 6.3.7, and 6.5.3. On the other hand, the qualitative data helps to confirm the results of the

quantitative method and provides a deeper understanding of the ongoing study, including an additional explanation of the results of the quantitative data.

Firstly, the quantitative data is collected from auditors using a questionnaire. To ensure that a representative sample is withdrawn from the population in the first method, potential respondents were contacted randomly through their pages on social media (Twitter, LinkedIn, and WhatsApp) or their email addresses obtained from the website of their departments. The questionnaire was sent to 447 participants and a total of 403 responses were received, but 92 were incomplete and were not included in analysis. The final 311 respondents are auditors employed in national and international certified public accounting (CPA) firms in Saudi Arabia.

The qualitative data is collected by conducting semi-structured interviews. The objective of conducting semi-structured interviews is to obtain a comprehensive understanding of the factors leading to artificial intelligence acceptance and the extent of the researcher's understanding of the research problem. The author interviewed 26 auditors who work in local, national, and international CPA firms in Saudi Arabia. Participants were randomly selected from those who participated in the questionnaire; the author communicated with them through their emails. The interviews were conducted online using Microsoft Office Teams. To optimise the captured information, all the interviews were recorded (after obtaining permission from the participants) and transcribed. Each interview lasted approximately 1 hour (ranging from 48–65 minutes). 24 out of the 26 interviews were conducted in Arabic language because it was the mother tongue of the participants and they preferred to speak it; however, the interviews were later translated into English.

1.7 Research Contribution

This this has a significant practical contribution as it provides answers to the research question of which factor, among performance expectancy, effort expectancy, social influence,

facilitating conditions, and ethical concerns, is the most significant in the adoption of artificial intelligence technology. According to the results, auditors do not give much attention to social influence in their adoption journey, but they do consider effort expectancy. The fact that effort expectancy has some influence over auditors' decision of artificial intelligence acceptance underscores the importance of user experience and ease of use in the adoption of artificial intelligence. This is particularly relevant in the context of artificial intelligence, as it can be a complex and technical field that requires specialised knowledge. Making artificial intelligence user-friendly and accessible to a wider audience can lead to more widespread adoption and greater benefits for society.

In terms of performance expectancy and ethical concerns, the author finds that auditors regard them equally important, but facilitating conditions has been regarded the most critical factor in accepting and utilising artificial intelligence technology in audit engagements. These findings suggest that audit firms should focus on developing their IT infrastructure to facilitate the journey of artificial intelligence technology adoption. Furthermore, the regulatory bodies must keep up with the remarkable advancements in artificial intelligence by continuously updating auditing standards and providing guidelines for using this technology in the auditing profession. The lack of endorsement of audit standards can make auditors hesitant to use artificial intelligence in audit engagements.

The practical contribution of this thesis also sheds light on the potential danger of the unscrutinised development of artificial intelligence technology and the need for policymakers to swiftly establish ethical guidelines that can achieve a consensus and be acted upon. Artificial intelligence stands out from previous technological advancements due to its exceptional features, including its ability to learn, adapt, process complex information, interact with humans, and operate autonomously. The remarkable performance of ChatGPT exemplifies the distinctiveness of artificial intelligence from its predecessors. Nevertheless, the distinctive

characteristics of artificial intelligence can pose significant risks to society. Therefore, the author recognises that addressing the ethical concerns related to artificial intelligence is as crucial as government and regulatory agency efforts to mitigate the effects of climate change. The associations of accountants have to promote debates on ethical issues of artificial intelligence technology, as its implications, both benefits and costs, should be considered in the profession. Additionally, the thesis calls upon scholars to investigate how artificial intelligence technology interacts with cultures, which can enhance our comprehension of this crucial technology.

This thesis also theoretically contributes to the field of artificial intelligence adoption and ethical concerns. It provides empirical evidence of how auditors take ethical concerns into account while incorporating and utilising artificial intelligence. By extending the UTAUT model to include ethical concerns as a crucial factor in the adoption of new technology, this thesis bridges the gap between the ethical aspect of artificial intelligence and technology adoption theory, making a significant theoretical contribution. This contribution provides scholars with insights into integrating ethical concerns into technology acceptance models. This integration will assist in capturing the moral, social, and professional implications of artificial intelligence, making it imperative to consider ethical considerations when adopting new technology.

Finally, the thesis also offers a valuable contribution by delving into the perceptions of auditors and clients regarding the use of artificial intelligence in the audit profession, taking into account the effects of the Covid-19 pandemic. This crisis has had a far-reaching impact on society, particularly on the audit industry. As one of the first empirical investigations of its kind, this study assesses how the pandemic has influenced the adoption of technology in this sector. The findings indicate that auditors are now recognising the importance of utilising smart

audit tools to facilitate remote auditing. Furthermore, the research highlights that clients have become more adaptable when it comes to sharing data online.

1.8 The Thesis Chapters

This thesis consists of nine chapters as follows;

The first chapter has acted as an introduction to the thesis; it contains a description of the research background alongside an analysis of the research gaps and motivations. It also examines the research objectives, questions, and methodology, in addition to the research contributions. The introduction chapter ends with a summary of the thesis structure.

The second chapter introduces the environment from which the data is collected. This helps the reader to understand the legal, regulatory, and professional context that may impact the research results. Moreover, the second chapter provides a historical overview of technological developments, starting with the first industrial revolution and ending with the fourth industrial revolution. This historical view is included to enable the reader to become more familiar with the events that followed each industrial revolution and the effects of these transformations on society and professions.

In the third chapter, this thesis reviews the literature that discusses factors influencing auditors' decisions when using artificial intelligence. This discussion assists in the understanding of the factors that affect the behaviour of auditors towards the use of assistive technology systems during the auditing process. Also, the thesis discusses the ethical philosophies and ethical perspectives on the use of technology in auditing. This discussion helps the reader to understand the literary debate on the ethical concerns associated with the use of artificial intelligence in the audit profession, as the ethical concerns of artificial intelligence are an important part of the research contributions of this thesis. This examination also helps the thesis to fill in research gaps that have arisen in the literature.

The fourth chapter presents the theoretical framework for this thesis and the literature that helped to develop the hypotheses of this thesis. At the end of this chapter, the model for the thesis is shown.

The fifth chapter reviews the research philosophy used in this thesis and provides justifications for this particular type of philosophy. This chapter shows the research strategy and the approach employed in this thesis. Furthermore, it introduces data collection instruments and methods that are closely followed that improve the reliability and validity of these instruments.

The sixth chapter is devoted to displaying the quantitative data of this thesis. First, the results of the validations of the measurement scales are shown. Second, the study model test results are displayed. Lastly, the results of the quantitative part of the thesis, and the implementations of these results, are considered.

Chapter seventh is dedicated to the captured qualitative data. The results and discussion of qualitative data are introduced in this chapter. Finally, it shows the implementation of these results for the audit profession.

The final chapter concludes the thesis; it offers a summary and then examines the contribution of this thesis to the research topic. Moreover, it provides the limitations of the thesis and recommendations for future research.

Chapter 2: The Historical Development of Accounting and Auditing in Saudi Arabia and Historical Technology Development

2.1 Introduction

This chapter discusses the historical development of accounting and auditing in Saudi Arabia and the historical development of technology. Since all the research data has been collected from KSA, it is necessary to provide the readers with information about its accounting and auditing history. This will help familiarise readers with the changes that have taken place in the accounting and audit environment in the KSA and the effects resulting from these changes. Moreover, since this thesis explores the factors towards the acceptance of artificial intelligence in the audit profession, it is necessary to provide readers with the history of artificial intelligence development and make them aware of the consequences of the creative destruction of the industrial revolutions.

2.2 A Comprehensive View of The History of Accounting and Auditing in The Kingdom of Saudi Arabia

The history of accounting and auditing in the KSA is discussed through the use of the accounting history framework developed by (Carnegie and Napier, 2002). Carnegie and Napier (2002) propose a set of seven dimensions (7P) to explore the scope of international accounting history. The seven Ps proposed are periods, places, people, practices, propagation, products, and profession. The purpose of using this accounting history framework, 'the seven Ps,' is to illustrate the historical development of accounting and audit practices in Saudi Arabia. This framework will help readers comprehend the journey of audit development in the country, highlighting the potential significant role of technology in this evolution. Since the purpose of this study is not a complete survey on the development of accounting and auditing in Saudi Arabia, the seven Ps are discussed briefly.

2.2.1 Period

The first P represents period, which covers 1938 to 2023. These eight decades are divided into four fundamental stages for the history of Saudi accounting and auditing according to economic, political, social, and educational factors. Prior to 1938, the Saudi Arabian economy was based on primitiveness, and its income was derived from Hajj and Umrah to the holy cities of Mecca and Medina. For the majority of Saudi citizens, who were either nomads or lived in tiny towns and villages, agriculture and the herding of livestock represented their primary sources of income (Al-Rehaily, 1992). Therefore, before 1938, no systematic accounting system existed developed.

After the discovery of Saudi oil in 1938, the kingdom began its first stage (1938–1979) of accounting development, which lasted for four decades. Next, through The Saudi Organisation for Chartered and Professional Accountants (SOCPA) professionalisation initiative, the second stage of accounting development in Saudi Arabia (1979–1992) led to the creation of formal accounting regulations. The third stage (1992–2016) involved the approval of Saudi accounting standards, which were reviewed and developed by the SOCPA. It resulted in a transformation from Saudi's Generally Accepted Accounting Principles (GAAP) to the full adoption International Financial Reporting Standards (IFRS) and International Standards on Auditing (ISA). The current stage (2016–2023) is Vision 2030, which builds upon the previous stages by applying an interconnection between the systems of the regulatory bodies that regulate the work of all companies registered in the KSA.

2.2.2 Place

The KSA is the second-biggest sovereign state in the Arab world and the largest in the Middle East. The KSA covers more than two million square kilometres in total, or around 80% of the Arabian Peninsula. The geographic location of the KSA means that it plays a crucial role as a strategic link between Africa, Europe, and Asia. For instance, access to the European

markets is possible from the north and west of Saudi Arabia. In addition, Asian markets are accessible from the east side of Saudi Arabia, and emerging markets like Egypt and Sudan are reachable from the west and south sides of the country. The world's top oil exporter and second-largest oil producer, directly behind the USA, is the KSA. In addition, KSA is a participant of the G20 and has a significant economy on a global scale. According to Al-Filali and Gallarotti (2012), the Saudi stock market, known as the Tadawul, is among the biggest developing markets worldwide and is the most significant in the Middle East, as noted by Piesse et al. (2012).

2.2.3 People

All the people (both Saudi and non-Saudi) who have influenced the development of the accounting and auditing profession are represented in this group such as the government, accountants, professional bodies, and academics. The development of the accounting and audit profession has occurred gradually according to the four stages mentioned earlier. The oil economic revolution in the first stage (1938–1979) led to a high demand for specialists in the accounting and auditing profession. The development of the accounting and auditing profession in the first stage heavily relied on foreign accountants, who came with foreign experiences due to a shortage of Saudi accountants at that time. This, in turn, impacted the development of the accounting profession in the KSA (Shinawi, 1970; Al-Rumaihi, 1997).

In general, the accounting and auditing profession was directly affected by the Egyptian accounting and auditing culture. This is due to the large number of Egyptian accountants working in Saudi Arabia during the first stage. As a result, the British accounting and auditing culture had an indirect influence due to its strong connection to Egyptian accounting (Al-Faisal, 1992; Al-Rehaily, 1992; Al-Rumaihi, 1997).

In the second stage (1979–1992), the SOCPA was established. Significant credit for the idea of its establishment belongs to Abdulaziz Al-Rashed, who owned an audit firm called 'Al-

Rashed Consulting and Accounting’ (Mihret et al., 2017). The SOCPA project was approved by the Ministry of Commerce in 1980, after Al-Rashed Consulting and Audit Office submitted a detailed project report including the cost to the Minister of Commerce. The SOCPA project was divided into three tasks (displayed in Table 1), each with a team of two foreign experts and one Saudi expert to execute the tasks (Mihret et al., 2017).

Table 1. Three tasks of the SOCPA project and the members assigned to each task (Mihret et al., 2017)

Project teams and team members	Professional affiliation of team member	Role played in the project	Country of residence at the time of the project
a. Financial accounting framework and standards			
Sabry Heakel, PhD	AICPA	International technical expert	US, Professor of Accounting at the University of Minnesota
Mohamed E. Mustafa, PhD		International technical expert	US, Professor of accounting at California State University
Abdul-Rahman I. AL Humaid, PhD		Advisor	Saudi Arabia, Professor of Accounting at King Saud University
b. Auditing standards			
David Hatherly	ICAEW	International technical expert	Scotland, Head of the technical division of Accounting and Auditing research at the Institute of Chartered Accountants in Scotland.
Peter Skuze	ICAEW	International technical expert	England, Partner in Charge at a medium-sized accounting firm
Abdiullah Al-Faisal, PhD		Advisor	Saudi Arabia, Professor of Accounting at King Saud University
c. Internal organisation of the profession			
Ivan O. Bull	AICPA	International technical expert	US, held high positions in AICPA, including Chairman of the AICPA Board of Directors (1976)
Wallace E. Olson	Vice-chair of AICPA	International technical expert	US, held high positions in AICPA, including Deputy Chairman of the AICPA Board of Directors (1973–1973)
Abdullah Al-Moneef, PhD		Advisor	Saudi Arabia, Professor of Accounting at King Saud University

In the third stage (1992–2016), the government worked on improving several societal areas, including the accounting and auditing industry. The government influenced the latter by boosting the number of accounting programmes at public and private colleges to more than 30. In the fourth stage (2016–2023), the interconnection obligation compelled companies to link their procedures to the regulatory bodies' systems through platforms, such as FATOORAH, that connect companies' systems with the Zakat, Tax and Customs Authority (ZATCA).

2.2.4 Practices

Accounting and auditing practices in the KSA are discussed through the examination of the four stages mentioned earlier.

Stage 1. During the first ten years of oil discoveries, since most businesses were owned by individuals or were family businesses, the owner had complete control over the accounts and financial resources. During this stage, there was no interest in bookkeeping or documenting activities; instead, accounting procedures consisted of simple daily accounts (the day-to-day operations of the business) (Al-Rehaily, 1992, p. 149). In 1950, the Saudi government issued a royal decree for tax and zakat regulations (17/2/28/3322), which provided legitimacy to the accounting profession in Saudi Arabia. The decree obligated companies to maintain accounting records for tax purposes. In 1965, the Company Act was issued which recognised the accounting profession and included accounting and auditing guidelines, such as procedures for the appointment of an auditor and the rights and responsibilities of auditors (Al-Rehaily, 1992, p. 151).

Stage 2. Between 1972 and 1992, a mixture of US and British accounting standards emerged due to the lack of an accounting body to regulate accounting procedures in the KSA (Al-Rehaily, 1992; Mihret et al., 2017). The different standards used in this period are due to the various accounting cultures that operated at the time. Al-Rehaily (1992) surveyed the type of accounting standards widely practiced in the KSA. He found that the practitioners at that

time used the International Accounting Standards (44%), American Accounting Standards (30%), British Accounting Standards (19%), and other standards (7%).

Stage 3. At this stage, a major development occurred in the practice of accounting. This arose because a royal decree (No. M/12 dated 1992) was issued that assigned the SOCPA to review, develop, and approve accounting standards in the KSA. Following the procedures used for the preparation of USA, UK, and international standards, the SOCPA issued the accounting and auditing standards that meet KSA's GAAP. Companies continued to operate in accordance with the Saudi accounting standards between 1992 and 2016.

Stage 4. Due to the development of the IFRS and ISA, the KSA joined the G20. At this time, the SOCPA prepared a strategic plan to apply the IFRS and ISA. In 2017, all the companies of Saudi Arabia had to prepare their financial statements in accordance with IFRS and auditing firms aligned with ISA.

2.2.5 Propagation

The propagation arises from the Saudi accounting and auditing culture as a result of religious, economic, and political interactions. What makes the KSA different to other countries is that it is an absolute monarchy and an Islamic state. Below is a brief explanation of the KSA's legal system, religious system, and sources of legislation; how these factors affect the accounting profession is also discussed.

The KSA is a monarchy that derives its regulations and laws from religious sources, and since its establishment, until 1992, there was no written constitution. In 1992, a political reform resulted in the drafting of a constitution called the 'Basic Law of Governance'. The Saudi economy is classified as an economy that heavily depends on oil. It has benefited from oil booms that have financed the development of infrastructure and other sectors of the state (Alsultan, 2017). Due to its heavy dependence on oil and the decline in oil prices, the Saudi economy has shown its weakness. Thus, the KSA seeks to diversify its sources of income by

encouraging economic and investment activities, increasing non-oil trade between countries, raising the level of foreign investment, and investing in modern technologies such as artificial intelligence (Saudi Vision 2030).

After reviewing the political, economic, and social situation of the KSA, we can observe the direct and indirect impact of these aspects on the establishment or development of the accounting and auditing profession. In the propagation section, the interaction of accounting with the social, political, religious, and economic environment in the KSA will be briefly discussed for the four stages mentioned earlier.

2.2.5.1 Stage 1 (1938–1978): After The Discovery Of Oil

2.2.5.1.1 The Companies Act

In 1965, the Companies Law was issued. This law deals with the legal structure of Saudi companies and clarifies the processes involved in forming and dissolving businesses. Al-Ghamdi and Al-Angari (2005) state that the law established specifications for corporate financial reporting and served as legislation that controlled the accounting profession in Saudi Arabia.

2.2.5.1.2 Bank Control Law

The Central Bank of Saudi Arabia, in its capacity as the regulator of the operations of banks and financial institutions, issued the Banking Control Law in 1966, which includes accounting standards and the guidelines for regulating audit committees of financial institutions (Ramady, 2009).

The most crucial elements of an audit are covered in various articles of this law. For example, Article 14 states that ‘The Auditors shall submit a report on the balance sheet and profit and loss account. This report shall include whether, in the auditor’s opinion, the bank’s balance sheet duly and correctly represents its financial position and the extent of their satisfaction with any explanations or information they may have requested from the bank’s

managers or other staff’ and ‘every bank shall annually appoint two auditors from among the approved list of auditors registered with the Ministry of Commerce and Industry’ (Banking Control Law, 1966, p. 11).

2.2.5.1.3 Accounting Law

In response to the commercial and economic developments of the 1970s oil revolution, Royal Decree No. 422 issued the first accounting law in 1974. This law was a milestone in the development of the accounting profession; it established the Supreme Committee of Accountants, which operates as an advisory committee under the umbrella of the Ministry of Commerce (Al-Eissa, 2009). The task of this committee was to issue licenses for accountants and set a variety of modest requirements for these licenses, such as a bachelor’s degree in accounting, business administration, or economics, three years of experience in accounting, and Saudi nationality (Al-Rehaily, 1992, p. 152). Although the committee positively impacted the accounting and auditing profession in Saudi Arabia, its activities demonstrated that it was insufficient and ineffective in terms of granting the accounting profession the necessary developments. This was due to its administrative facilities, limited financial resources, and the part-time employment of committee members (Al-Eissa, 2009).

2.2.5.2 STAGE 2 (1979–1992): ACCOUNTING REGULATIONS

2.2.5.2.1 SAUDI ACCOUNTING ASSOCIATION

In the 1970s and 1980s, there was no independent professional accounting body, similar to ICAEW in the UK or AICPA in the USA, in the KSA (Al-Rehaily, 1992). In 1981, the King Saud University, represented by the Department of Accounting, established the Saudi Accounting Association (SAA) (Albader, 2015). The SAA is a non-profit academic body, operating under the supervision of the university, that develops the accounting profession in the KSA. Al-Rehaily (1992) listed four main objectives of the SAA, these are;

- To foster the development of accounting throughout Saudi Arabia.

- To encourage professional accountants to contribute to the advancement of accounting throughout Saudi Arabia.
- To facilitate the exchange of ideas between the association and other accounting-related organisations in Saudi Arabia and worldwide.
- To offer advice, and conduct the necessary research, to advance the accounting profession.

2.2.5.2.2 REGULATING ACCOUNTANTS AND AUDITORS

Between 1979 and 1992, work on a professional accounting project in Saudi Arabia began. The Ministry of Commerce, the Supreme Committee for Professional Accountants, and the SAA collaborated with Abdulaziz Al-Rashe to develop the Saudi accounting profession and its practices to cope with the country's rapid economic development (Al-Rehaily, 1992; Mihret et al., 2017). In 1980, the Ministry of Commerce approved a comprehensive report that contained the professional initiative for accounting (the SOCPA project) presented by Abdulaziz Al-Rashed's office (Al-Eissa, 2009). Al-Eissa (2009, p. 30) states that the SOCPA project was divided into three stages, these are;

- The first phase, lasting from 1980 to 1981, was a comparative study of the accounting profession in various countries.
- The second phase, from 1982 to 1986, involved the development of a conceptual framework for the accounting profession in the KSA.
- The third phase, which occurred in 1991 and 1992, was the establishment of SOCPA.

2.2.5.3 STAGE 3 (1992–2016): EVOLUTION OF SAUDI ACCOUNTING AND AUDITING STANDARDS

2.2.5.3.1 SAUDI ACCOUNTING AND AUDIT STANDARDS AND CODE OF ETHICAL CONDUCT

At the end of 1992, the SOCPA issued both the financial accounting framework and standards and the auditing standards. The US accounting system was chosen as the foundation for developing Saudi accounting and its auditing standards, as well as financial reporting standards (Mihret et al., 2017). In 1994, the Board of Directors of SOCPA issued the Code of Conduct and Ethics. This code, according to SOCPA, contains a set of principles representing ethical values that serve as the ideal measures of professional behavior, and the behavioral qualities that auditors should have when performing their work and dealing with colleagues.

2.2.5.3.2 THE G20 AND THE IMPLICATIONS FOR THE ADOPTION OF INTERNATIONAL FINANCIAL REPORTING STANDARDS

In 2011, according to the International Auditing and Assurance Standards Board (IAASB) website, all G20 countries except Saudi Arabia had either adopted IFRS or developed a road map for applying IFRS in the near future. The G20 countries have adopted IFRS to improve the disclosure quality and to standardise the categories used in the G20 countries (IFRS Foundation, 2020). The SOCPA technical committee decided to align the Saudi standards with IFRS utilising a methodology that ensures consideration of the Saudi environment, whether it is with regards to Sharia provisions, approved regulations, or the level of technical readiness of the parties (Albader, 2015).

To ensure work integration and participation of relevant authorities, the Board of Directors of SOCPA have established a steering committee comprised of representatives from the Ministry of Finance, the Saudi Central Bank, and the Capital Market Authority (CMA), as well as representatives from the Accounting and Auditing Standards Committees of SOCPA.

After their deliberations, the committee considered that the transition to IFRS should reflect local factors and be gradually conducted (i.e., in a five-year transformation project) to technically and professionally prepare the local environment for the transition and create optimal results (SOCPA, 2020). On 18 March 2012, the SOCPA approved the five-year transformation project.

2.2.5.4 STAGE 4 (2016–2023): THE ADOPTION OF IFRS AND ISA

The Board of Directors of SOCPA decided that the adoption of the full version of IFRS should be effective from the beginning of 2017 for all listed companies in the stock market (Tadawul) and the beginning of 2018 for non-listed companies. Moreover, the Board of Directors decided that all auditing firms are required to apply ISA to all their audit work (SOCPA, 2020).

2.2.6 Products

The products include regulation, objectives, results, and financial data provided to the public. Considering that the standards are accounting products, SOCPA has issued 22 accounting standards, 15 auditing standards, and a range of professional interpretations and opinions in many areas of accounting, as well as the adoption of the IFRS and the ISA (Bakr, 2020). While the accounting profession in the KSA is regulated by SOCPA, which acts as a professional accountancy sector under the Ministry of Commerce, it is subject to all Saudi government decisions. Government notices and instructions may be classified as a communication product because they provide information and compliance requirements to other accounting firms and organisations.

2.2.7 Profession

2.2.7.1 An Overview of The Audit

Before discussing the profession in the KSA, an overview of the audit and the importance of audit will be introduced. The audit is defined as a service with the highest level of assurance

that a certified public accountant performs; it is intended to provide user comfort with the accuracy of financial statements (AICPA, 2015). To have an improved understanding of audits, it is better to know the objectives of auditing accounts and records of an organisation, and the auditor's responsibility when auditing a client. The latest update of auditors' objectives which is applicable for audits of financial statements for periods commencing on or after 15th of December 2019, the Financial Reporting Council (FRC) states 'the auditor's objectives are to obtain reasonable assurance about whether the financial statements as a whole are free from material misstatement, whether due to fraud or error, and to issue an auditor's report that includes the auditor's opinion.' The public should notice that reasonable assurance does not ensure that the auditor will always detect a material misstatement when it exists, but the auditor provides a high level of assurance on the financial statements. Also, the RFC lists six responsibilities of the auditor as following:

- 'Identifies and assesses the risks of material misstatement of the entity's (or where relevant, the consolidated) financial statements, whether due to fraud or error, designs and performs audit procedures responsive to those risks, and obtains audit evidence that is sufficient and appropriate to provide a basis for the auditor's opinion. The risk of not detecting a material misstatement resulting from fraud is higher than for one resulting from error, as fraud may involve collusion, forgery, intentional omissions, misrepresentations, or the override of internal control. The auditor includes an explanation in the auditor's report of the extent to which the audit was capable of detecting irregularities, including fraud.
- Obtains an understanding of internal control relevant to the audit in order to design audit procedures that are appropriate in the circumstances, but not for the purpose of expressing an opinion on the effectiveness of the entity's (or where relevant, the group's) internal control.

- Evaluates the appropriateness of accounting policies used and the reasonableness of accounting estimates and related disclosures made by the directors.
- Concludes on the appropriateness of the directors' use of the going concern basis of accounting and, based on the audit evidence obtained, whether a material uncertainty exists related to events or conditions that may cast significant doubt on the entity's (or where relevant, the group's) ability to continue as a going concern. If the auditor concludes that the use of the going concern basis of accounting is appropriate and no material uncertainties have been identified, the auditor reports these conclusions in the auditor's report. If the auditor concludes that a material uncertainty exists, the auditor is required to draw attention in the auditor's report to the related disclosures in the financial statements or, if such disclosures are inadequate, to modify the auditor's opinion.
- Evaluates the overall presentation, structure and content of the financial statements, including the disclosures, and whether the financial statements represent the underlying transactions and events in a manner that achieves fair presentation.
- Where the auditor is required to report on consolidated financial statements, obtains sufficient appropriate audit evidence regarding the financial information of the entities or business activities within the group to express an opinion on the consolidated financial statements. The group auditor is responsible for the direction, supervision and performance of the group audit. The group auditor remains solely responsible for the audit opinion.'

The requirement for an external audit report for the company's financial statements differs according to the country's Company Act. For example, under the KSA companies Act, all companies are required to appoint an external auditor, except for small companies. The Act states a company is considered a small company if it meets these two requirements: 49

employees or less and annual turnover of 40 million Saudi riyal or less. In the United States, the Companies Act states that all public entities are required to have an external audit firm. Private entities, in general, are not required to have an external audit firm unless they seek funding through private placements of debt or equities securities.

2.2.7.2 The Importance of Audits

In most countries, having an external auditor for public companies is a legal requirement. The auditors' objective is to form an independent opinion on the financial statements of the audited entity. The opinion includes whether the financial statements show a true and fair view of the company finances and whether they have been properly prepared in accordance with accounting standards and comply with legal requirements. According to the IFRS, the management must comply with accounting IFRS during their operations and show this compliance in their financial statements. The ISA states that auditors are responsible for investigating the client's compliance with the accounting policies; they are also required to form an auditor opinion on the fairness and accuracy of the client's financial statements. Aside from conducting audits to meet the legal matters for a statutory audit, the audit processes provide substantial and invaluable insight of the financial statements into the users of the financial statements, including investors, and lenders.

Audit reports, and the quality of audit reports, are essential issues for the public. Once the auditors have issued their report, the public will have a more detailed picture of the financial and non-financial performance of the company, which cannot be seen except by an independent body that works without fear of repercussions in the workplace. According to ISA 265 'Communicating Deficiencies in Internal Control to Those Charged with Governance and Management', it is one of the external auditors' jobs to determine any deficiency in the internal control of the company where processes could be improved to minimise the chance of fraud and inefficiency. Thus, having an external body (the external audit firm) that highlights areas

of defect or weakness in the organisation's structure may help the managers to improve the financial and non-financial performance of the organisation.

The importance of an audit to the owners of companies appears in the form of judging the performance of the management. As owners of companies authorise the directors to manage the affairs of the company, the audits are a substantial mechanism that assists owners in evaluating the stewardship of the directors (ICAEW, 2006). Thus, the quality of the audit process is an essential issue for the stakeholders in general and the owners in particular. As the quality of the audit report is a substantial matter, Issa et al. (2016) state that audit activities completed with the aid of technology are more effective and efficient. Computer-assisted audit tools (CAATs) play a significant role in detecting fraudulent activities, which can result in improved audit quality.

2.2.7.3 The profession in the KSA

In KSA from 1938 to 1978, there were no professional accounting regulations, only primitive initiatives from small accounting firms. During this period, the Ministry of Finance was responsible for issuing licenses to chartered accountants and later, in 1957, it was transferred to the Ministry of Commerce and Industry (Al-Rehaily, 1992, p. 150). The first accounting firm established was 'Saba, Nawar, and Co', which was a foreign company. The number of accounting firms gradually increased to 20 by the end of the 1970s (Ba-Eissa, 1984, p. 301).

In the period 1979–1992, there was a partnership between the government and the private sector that established a professional accounting profession. During this time, the number of Saudi and foreign companies increased significantly to 175 (Al-Rumaihi 1997, p. 208). In 1981, King Saudi University began holding a series of seminars that assisted the development of accounting, discussed the state of the accounting and auditing profession, and identified the factors that limited the growth of the profession.

The period 1992–2016 was when SOCPA was founded. SOCPA has extensively helped spread the accounting profession by creating the necessary rules for the fellowship certificate examinations (i.e., the CPA exam), including the professional, practical, and scientific aspects of the auditing profession and the applicable regulations. According to Al-Rumaihi (1997) in 1995, the total number of licenced accountants was 324, including 261 Saudi accountants.

From 2016 to 2023, the number of professional members affiliated with SOCPA surpassed 18,000 for the first time. According to the SOCPA, at the date of writing this thesis, there are 196 chartered accounting firms licenced to practice in the KSA. At the audit firm level, the Big Four accounting firms (Ernst & Young (EY), Deloitte, PWC, and KPMG) are regarded as market leaders in Saudi Arabia's auditing and accounting profession. The majority of the technical committees of the SOCPA are composed of members from the Big Four audit firms. Zureigat (2015) says due to the high level of trust in their audits and the high quality of the audits they provide, the Big Four firms capture 80% of the market share in Saudi Arabia.

2.3 Conclusion Of The Historical Development of Accounting and Auditing in Saudi Arabia.

In the previous sections, the author discussed the history of accounting and auditing in KSA through the use of the accounting history framework developed by Carnegie and Napier. This discussion can help the reader of this thesis to understand the development of the accounting and auditing profession in the KSA through the seven dimensions (7Ps). Understanding the development of the accounting and auditing profession can help in understanding the writer's arguments and conclusions. In the next section, the author discusses the technology adoption history.

2.4 Technology Adoption in History

In this section, the author examines the stages of the industrial revolutions including the development of technology, and the effects associated with these stages. Discussing these

stages helps to understand the changes brought by the industrial revolutions and the spillover effects of these developments, which will help in achieving the objectives of the research and reach the desired results. Moreover, the author reviews the technological stages, starting from the first industrial revolution and ending with the fourth industrial revolution.

2.4.1 The First Industrial Revolution

The industrial revolutions describe the tremendous changes in how humans live, work, and interact. Throughout history, humans have witnessed four industrial revolutions. The first revolution started in the 18th century and involved the introduction of steam power and mechanical production facilities. The second revolution began in the late 19th century, establishing electrical appliances and labour division. The third revolution started in the 1970s, introducing programmable systems through the development of information technology (IT) and electronics to automate industrial processes. The fourth revolution, which is where we reside today, introduced smart technologies and the creation of cyber-physical systems.

Industrial revolutions are an ongoing phenomenon related to which is economic development theory, which discusses the gradual developments that are continuously occurring in economies. The first use of the term ‘industrial revolution’ dates from July 6th 1799, in a letter written by French envoy Louis-Guillaume Otto (Teich et al., 1996). The term industrial revolution did not become popular until the late 1830s (Blanqui, 1882). However, authors such as Sir John Harold Clapham in his book ‘An Economic History of Modern Britain: Machines and National Rivalries (1887–1914) with an Epilogue (1914–1929)’, and Nicholas Craftsere argued that the term industrial revolution is redundant because industrial changes are self-sustaining process of economic growth.

In contrast, others have argued that the radical changes that occurred over specific time periods in the industrial sector should be called industrial revolutions. Deane (2000) states that radical changes in the methods and characteristics of economic organisation ought to be

described as an industrial revolution. He also mentioned the seven identifiable changes in the methods and characteristics of an industrial economy that describe an industrial revolution. These changes must develop together, and to an adequate degree, to constitute an industrial revolution. The seven interrelated changes are: (i) the shift of labour from production related to primary commodities to production related to manufactured goods and services, (ii) directing economic efforts towards production directed to the national and international markets, rather than limiting it to family production, (iii) widespread and systematic application of modern sciences and applied sciences with the purpose of using them in the production process to cover market needs, (iv) the emergence of new social and professional classes determined by ownership of or relationship to the production's means other than the land, (v) intensive and comprehensive use of capital resources as a supplement or alternative to human efforts, (vi) depersonalizing the typical unit of production and expanding it to depend less on family and tribes and more on companies and public institutions, and (vii) population movement from small rural areas to large urban societies.

The first industrial revolution started in Great Britain and later spread to European countries and the United States (Carus-Wilson, 1941). Many manufacturing changes occurred during the first industrial revolution since its techniques evolved from hand production to machine production methods, alongside the introduction of mechanised factory systems and iron production processes. Furthermore, the first industrial revolution impacted the population growth rate in Great Britain, where population growth increased at an unprecedented rate (Goldstone, 1986). Ashton (1997) states that the first industrial revolution was the process of shifting from a handicraft and agrarian market to an economy dominated by industry and machine manufacturing. He also noted that the first industrial revolution started around 1760 and spanned to around 1840.

Before the first industrial revolution, handicrafts were the main driver of all industries. Many industries, such as the textile, clothing, and iron industries, were manufactured by hand. However, with the advent of the central water wheel and steam engine, the textile industry transformed into mechanised factories. Landes (2008) states that the textile industry was the pioneering sector for using modern production methods. As a result, the use of machines for manufacturing caused a major revolution in the textile industry.

Furthermore, one of the areas that flourished during the first industrial revolution was the iron industry. The major event that changed the iron industries in the first industrial revolution was the replacement of wood in the heating process with coal. The latter was more abundant than wood (Landes, 2008), and coal required less labour to mine compared to the same amount of heat provided by wood that required cutting and converting into charcoal (Gordon, 2001). Although coal was used in iron smelting before the Industrial Revolution, the first experiments were not successful enough to create industrial-scale production. The real beginning of the iron industry was in 1774 when John Wilkinson invented the high-precision boring machine for boring cylinders (T. and Roe, 1916). From this discussion, the societal and economic impact of the first industrial revolution appears through the creation of job opportunities and the demolition of another group of jobs.

2.4.2 The Second Industrial Revolution

The second industrial revolution, also known as the technological revolution (Atkeson and Kehoe, 2001), was a key stage in the historical development of the industrial economy, in which many innovations such as steel production, petroleum, and electricity were introduced. The concept of 'The 2nd Industrial Revolution' was introduced by Patrick Geddes in 1910 and used by economists such as Erick Zimmerman in 1951 (Jull, 1999). The second industrial revolution is generally between the period of 1870 to 1914 (Mokyr, 1998). Despite the great leap forward created by the first industrial revolution, it was limited to steam and waterpower.

The second industrial revolution witnessed the establishment of railroads, large-scale steel production, petroleum and telegraph use, and the beginning of electrification.

During this period, there was exceptional economic growth that did not occur in previous years. The second industrial revolution period (1859–1873) has been characterised as one of the most beneficial innovations in history (Mowery and Rosenberg, 1991). In industrialised countries, the standard of living improved considerably, as the prices of products and goods decreased dramatically due to the increase in production and the decrease in production costs. Wells (1899) states that the improvement in the efficiency of steam engines also allowed ships to carry more tonnage, which boosted the international trade volume.

The second industrial revolution caused unrest and unemployment in some sectors, such as the iron industry and shipping, due to the replacement of manpower with machines (Wells, 1899). However, simultaneously it created new markets such as oil, rubber, paper, fertiliser, bicycles, automobiles, and electrification that lowered the unemployment caused by this revolution. The petroleum industry began in Scotland in 1848 when chemist James Young established the first small oil refining business (Clerk, 1897). The discovery of petroleum and petroleum products had a significant impact on other industries, such as those related to rubber and electricity. In the electricity sector, the largest plant for generating and distributing electricity was inaugurated in London in 1882, followed soon after by the Pearl Street Station in New York; these two power stations were both totally dependent on oil.

Identical to the first industrial revolution, the second industrial revolution caused a significant growth in population and, at that time, it was apparent that governments had begun to protect their national economies with trade tariffs. Second, it directly affected wages and living standards, significantly improving from 1870 to 1914. During the second industrial revolution, the number of skilled and unskilled workers increased due to the raises in wages; in addition, engineering colleges and others were established to meet the great demands of the

labour market (Monsees, 1961). Third, it transformed the geographical leadership of the revolution away from solely Britain into a more dispersed position, despite this country remaining in the main leadership role for the industrialised Western nations. Finally, it changed the relationship between the knowledge of nature and its effect on technological practices. Kuznets (1965) argues that modern economic growth depends on the growth of useful knowledge over the last century.

2.4.3 The Third Industrial Revolution

The third industrial revolution (also known as the computer or digital revolution because of the development of semiconductors, computing, personal computing, and the internet (Schwab, 2016)) began in the 1960s. It involved a transfer from mechanical technology to digital electronics via the adoption and widespread use of digital record-keeping and digital computers (Dreyer et al., 2006). During the third industrial revolution, the use of computers and the Internet spread, and people became dependent on technology in all aspects of their lives, which created the so-called information age.

The roots of the digital revolution began in 1941 when John Bardeen and Walter Hauser discovered the first working transistor (Brinkman et al., 1997). This breakthrough paved the way for the development of more advanced computers. Later, companies, universities, and armies began to develop computer systems that automated calculations, which were previously conducted manually. In 1952, the LEO was the first commercially available general-purpose computer (Hendry, 1987). In the 1970s, the personal computer entered homes and video game use spread (Campbell-Kelly et al., 1997). Day et al. (2005) reported that in 1989 about 15% of US households had a personal computer, and by 2000 the percentage had risen to 51%.

The world was introduced to the concept of the Internet in 1961 when a message was sent through a network called ARPANET. In 1989, Tim Berners-Lee invented the world wide web (WWW), which was only available to governments and universities until 1991, when it

became publicly available (Adamic et al., 2000). In 2009, the internet user population reached 1.8 billion (26% of the world population at the time) (Buhalis and Jun, 2011). The services offered by the Internet made the world interconnected and facilitated the process of finding and sharing information. The WWW has had an enormous impact on the international economy. Without the WWW there will not be globalization and outsourcing.

The third industrial revolution has had a positive impact on socio-economic life in many aspects, including the creation of new jobs, the disclosure of information that previously could have been easily concealed by tyrannical regimes, the facilitation of rapid communication since sending a message could take days or weeks in the past, and a much greater interconnectedness. The third industrial revolution created jobs that were not present in previous revolutions. With the widespread use of digital technology in business, the shift from analog to digital record-keeping became a new standard within companies, which created a new type of job. The latter is the data entry clerk, who is responsible for converting invoices and customers' details into digital data. Moreover, the technologies of the third industrial revolution helped eliminate various tyrannical regimes. Kaku (2012) states that the failure of the Soviet coup in 1991 was because of the use of technologies, such as the fax machine and computer, that enabled classified information to be more easily disclosed. In addition, with regard to productivity and performance in the private sector, Brynjolfsson and Hitt (2003) studied the effect of computing on productivity and output growth; they found that computerisation is associated with a significant improvement in business productivity and performance.

Despite the many advantages of the third industrial revolution discussed above, there are also negative side effects including privacy concerns, information overload, internet predators, forms of social isolation, and media saturation. The storage and use of vast amounts of diverse information have created the possibility that companies can track the personal information of individuals and their activities and interests. Markoff (2002) states there will be organisations

that can control people through a central authority that monitors people in real-time and collect personal information about them and their activities such as the Office of Information Awareness at the Defence Advanced Research Projects Agency. Beniger (2009) states that advocates of labour and consumer rights are fighting against discrimination during hiring decisions, unwanted direct marketing to individuals, unfair employee behaviour such as communication outside of the work environment, and involuntarily sharing personal information. The Internet, especially since the advent of the world wide web, has launched new avenues for sharing information and communication, which has increased the potential opportunities for the immoral exploitation of personal information.

2.4.4 The Fourth Industrial Revolution

The fourth industrial revolution represents the changes to the lives and working environments of humans due to the development of artificial intelligence technology, the Internet of Systems, the Internet of Things, and cyber-physical systems. Kauffman (2019) states that the core idea of the fourth revolution is the integration of the Internet of Things and the Internet of Services into the manufacturing environment. The fourth industrial revolution focuses on converting factories into smart factories that are: capable of managing complexity, less prone to disruption, and manufacture goods more efficiently (Kagermann et al., 2013). Implementing smart new technologies in all aspects of life makes these technologies interact with each other more readily, have greater visualization of the procedures and surroundings, and autonomously produce critical decisions. While the fourth revolution is an extension of the third revolution (Digital Revolution), it is anticipated that the fourth revolution will affect all economies, disciplines, and industries.

Drath and Horch (2014) express that the industrial revolution can be associated with three essential aspects:

1. The great economic benefits brought about by the industrial revolution, at the level of operational effectiveness and the enabling and developing of new business models, products, and services (Telukdarie and Sishi, 2018; Lasi et al., 2014).
2. The disadvantages and concerns that the industrial revolutions may bring at the community and economic levels (Dimitrieska et al., 2018; Lin, 2016).
3. The argument that the industrial revolution needs to be experienced and anticipated before and during the event, rather than being observed post-revolution and developed over the years (Drath and Horch, 2014; Song, 2017).

These three aspects have allowed businesses, researchers, and academics to debate the fourth industrial revolution.

In the fourth economic revolution, companies and institutions compete to become market leaders in establishing cyber-physical systems that autonomously perform all the processes and procedures necessary in production or manufacturing processes. Cyber-physical systems are computerised schemes in which advanced algorithms control and monitor machines. For these types of systems, both software and hardware components are deeply interwoven, any interactions behave differently from each other if the context changes, various and distinct behavioural forms arise, and performance of more than one operation is possible for different time and spatial zones. Examples of cyber-physical systems include robotics, medical monitoring, automatic pilot avionics, autonomous vehicles, and industrial control systems (Bhrugubanda, 2015). With the rapid development of artificial intelligence and smart technologies that the world is currently witnessing, smart machines will soon play a vital role in shaping manufacturing and service economies. This will be achieved by building global databases that can be used to create advanced algorithms that assist in the creation of smart systems (Kagermann et al., 2013; Gilchrist, 2016; Kauffman, 2019).

Governments, businesses, and academia have high expectations for the fourth industrial revolution, which is seen as a pushing force towards significant changes in every form of industry. Integration at all levels will undoubtedly have a potentially positive impact on economic growth in both service and manufacturing economies. Simultaneously, it can reduce operating costs over the long term. According to Hermann et al. (2016):

‘The economic impact of this industrial revolution is supposed to be huge, as Industry 4.0 promises substantially increased operational effectiveness as well as the development of entirely new business models, services, and products’.

In the book ‘The Fourth Industrial Revolution’ (Schwab, 2016), the author is optimistic about the fourth industrial revolution; he makes two important points. First, the fourth industrial revolution has provided an opportunity for the world to meet the unmet needs of two billion people, which will lead to an increase in demand for existing products and services and, at the same time, will empower and connect people and societies worldwide. Second, the fourth industrial revolution will increase the ability to address the negative external factors, such as carbon emissions, through enormous investments in technological advances in renewable energy while concurrently boosting potential economic growth.

However, it is necessary to consider the potential negative impacts associated with these rapid industrial changes; such undesirable influences could be at any level. Artificial intelligence technologies rely heavily on the data collected from confidential individuals and organisational information, which makes such data vulnerable to breaches and leaks (Hernandez et al., 2014; Koscher et al., 2010). Jeon and Suh (2017) state that the protection of personal information has emerged, alongside the development of information and communication technology (ICT) and the spread of social networks, due to the occurrence of personal information leakage. Such a loss of individual and organisation confidential

information will certainly raise many concerns among users of these technologies; it may become a reason for rejecting these smart technologies.

Moreover, the fourth industrial revolution may have a negative impact due to the influence of smart technologies on the labour market. The implementation of smart technology may affect the labour market in two ways. First, it may replace the human workforce, especially those jobs that involve repetitive and precise manual labour. Schwab (2016) states that the fourth industrial revolution had created fewer job opportunities for the human workforce compared to previous industrial revolutions. Besides, Frey and Osborne (2017) quantified that 702 different professions may become fully automated via the use of artificial intelligence technologies. A report by the International Labour Organisation (ILO, 2016) states that workers with highly repeatable jobs, unskilled workers, and low-skilled employees would be at high risk of unemployment. This is because computational automation will exclude manual and cognitive-intensive skills. Furthermore, some researchers believe that highly skilled employees are immune to automation because they specialise in more complex tasks that require analytical skills, decision-making, problem-solving, or other soft skills. However, new forms of advanced artificial intelligence can fulfil several of these tasks, which were previously believed to require the indispensable intervention of humans. According to Acemoglu and Restrepo (2018), these automated tasks include financial planning, accounting, management consulting, and various specialties in the medical profession.

The second aspect that automation and smart technology may have an effect on is labour skills and experience. Many jobs no longer require human intervention, which leads to a lower amount of human experience in these jobs. For example, automated storytelling systems that can write any form of narration for an audience (Ammanabrolu et al., 2019) may lead to less experienced human writers. The replacement of humans with artificial intelligence in performing specific tasks will lead to a huge gap in the understanding of the nature of the tasks

that depend on experience and practice, such as writing, accounting, and finance. This gap is expected to increase with the passage of time and for future generations, meaning that the physical understanding of these operations will be lost.

2.4.4.1 ARTIFICIAL INTELLIGENCE FROM A MULTI-STAKEHOLDER PERSPECTIVE

The term ‘artificial intelligence’ has been defined in the literature in many ways. In one of the first research projects on artificial intelligence, McCarthy et al. (1955) define artificial intelligence as ‘the problem of making a machine behave in ways that would be called intelligent if a human were so behaving’. Moreover, Minsky (1982) defines artificial intelligence as ‘the science of making machines do things that would require intelligence if done by men’. In a recent paper, Visvikis et al. (2019) define artificial intelligence as ‘intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and other animals’. From the previous definitions, it has become clear that artificial intelligence is an attempt to exhibit or simulate human intelligence with a machine.

Evidence from literature demonstrates that interest in artificial intelligence is growing among stakeholders¹. A report by Stanford shows that, between 1998 and 20018, the number of peer-reviewed papers related to the topic of ‘artificial intelligence’ has increased by more than 300 percent (Stanford, 2019). The same report has shown that in the year 2019, a total of 58 percent of large firms have already employed artificial intelligence technologies in at least one function or business unit (Stanford, 2019), and most of the firms reported benefits from the use of artificial intelligence technologies (McKinsey Global, 2019). Despite this major trend towards artificial intelligence, the added benefit and problems remain undiscovered from a multi-stakeholder perspective.

¹ Throughout the thesis, the term ‘stakeholders’ refers to investors, lenders, managers, owners, employees, customers, suppliers, local communities, and society at large.

The European Commission (2020) emphasizes that the effects of artificial intelligence systems should be evaluated not only in terms of their impact on individuals, but also in terms of their impact on society as a whole. Companies are part of society, and all decisions they make have a direct or non-direct impact on society, if not in the short term over a longer period. Therefore, companies must consider the public interest in all their decisions, whether that judgment is to adopt a new strategy or new technologies. According to The World Economic Forum (2019), the objective of a company is to involve all its stakeholders in generating long-term value that is mutually beneficial. By generating this value, a company benefits not just its shareholders, but also all its stakeholders, such as employees, customers, suppliers, local communities, and society in general. The literature on artificial intelligence needs to include more research that discovers the added value and harm it may cause from a multi-stakeholder perspective. It is important for researchers to investigate whether the benefits derived from the adoption of artificial intelligence are equitably distributed among the stakeholders and whether there exists any potential conflict of interest between them.

Furthermore, those who have argued that artificial intelligence has more positive than negative impacts on stakeholders must examine whether the negative impact has been distributed fairly among the stakeholders. To study the main beneficiaries of artificial intelligence and which stakeholders are affected most by the adoption of artificial intelligence, we must explore the benefit drivers for each type of stakeholder. Moreover, it is necessary to know the effect of the adoption of artificial intelligence on these drivers.

Shareholders' benefits are focused on financial drivers (Bender, 2013) such as growth rate, cost reduction, and revenue increase, which leads to a return on their investments. Thus, to understand the potential impact of artificial intelligence on shareholders, the relationship between financial drivers and artificial intelligence needs to be investigated. A report written by Manyika and Sneider (2018) notes that artificial intelligence technologies are currently

generating high value. Moreover, companies are using these technologies in a range of operations to find anomalies in production, personalise product recommendations, and identify fraudulent transactions. The report indicates that artificial intelligence and automation could reverse the decline in labour productivity caused by the 2008 crisis, with the ability to reach two percent growth annually over the next decade plausible. Güngör (2020) states that many companies have successfully used artificial intelligence for cost-cutting purposes such as workforce optimization, supply chain management, and preventive maintenance. Moreover, artificial intelligence indirectly helps to add value to shareholders by improving some operational procedures and processes. Bredmar (2017) wrote that artificial intelligence and digitization had granted firms more control over the operational processes, which has led to increased operational effectiveness.

The customer value driver has the perception of value, quality, and accessibility of the product or service versus the price paid to obtain it (Mahajan, 2016). The added value to the customer through artificial intelligence is indirectly assumed, such as the significant role artificial intelligence plays in improving medical diagnostic accuracy, weather forecast accuracy, and financial transaction safety. Besides, many large brands are using artificial intelligence to enhance the customer experience in their physical stores. For example, Burberry introduced technologies such as large video projections, radio frequency identification, and smart tablets at the stores to display live videos showing how the products were created and how they can be worn (Marr, 2019). Furthermore, American Express has built artificial intelligence systems that rely on algorithms to monitor data from card transactions worldwide in real time, which means fraudulent characteristics can be detected instantly (Marr, 2019). These systems will enhance customer experience and increase security when they use their bank cards. On the other hand, artificial intelligence may negatively impact the clients' confidentiality and privacy (Reynolds, 2012; Jobin et al., 2019; Munoko et al., 2020). This

highlights an essential question: ‘Will customers outweigh the benefits of artificial intelligence over the negative aspects of it, or *vice versa*?’

An employee value driver is related to employee development, well-being, employee engagement with the company goals, and productivity (Güngör, 2020). According to Goswami (2015), employee value is achieved by achieving a balance between job satisfaction and performance within a particular work culture. Artificial intelligence systems play a crucial role in enhancing employee productivity. For example, intelligent knowledge management systems facilitate easy access to relevant information for employees, while augmented reality tools assist in visualizing problems and identifying solutions. However, there is a heated debate about the possible impact of artificial intelligence on job security across all sectors (Arthur and Owen, 2019; Leclercq-Vandelannoitte, 2019; Huang and Rust, 2018; Makridakis, 2017; Farisco et al., 2020). Reducing the number of employees in the company through smart technology may benefit the employers through reducing the production cost, but at the same time it has a significant negative impact on both employees due to the loss of their jobs and society due to the high unemployment rate.

The argument is that the implementation of artificial intelligence will eventually take over human workforce jobs. Manyika et al. (2017) report that until 2030, 400 million workers, 15 percent of the global workforce, could be replaced by artificial intelligence technologies. The impact of implementing artificial intelligence technologies will definitely differ across countries based on several factors, such as the cost of deployment and labour market dynamics. In economies where wage levels are high, such as France, Japan, and the United States, the impact will be greatest. This discussion highlights another essential question: ‘Will employees outweigh the benefits of artificial intelligence over the negative aspects of it, or *vice versa*?’

2.4.4.2 COVID-19, AUTOMATION, AND REMOTE WORKING

Social emergencies and economic crises play a significant role in reforming the economy and making managers rethink the way organisations are run. The precise impact of this role appears via the dismantling of certain main products or changing the mechanisms and procedures by which companies are run. Emergencies and crises harm companies' financial and operational performance and the economy in general and, simultaneously, have a positive effect in the long run. A crisis often sheds light on the deficiencies in the administrative and financial systems; for example, the early 2000s recession highlighted shortcomings in areas such as surveillance, information sharing, crisis management, and liquidity support (Claessens, 2011).

On March 11, 2020, the World Health Organisation (WHO) declared Covid-19 a global pandemic (WHO, 2020). This announcement prompted many governments to initiate precautionary measures such as a total curfew in the affected areas, a partial curfew, non-essential activities curfew, non-essential shop closure, or the closure of the unnecessary economic sector to eradicate the virus or at least contain it. Due to the increasing number of positive cases in the UK, on March 24th 2020, the British government began a lockdown suppression strategy in which all educational institutions and businesses, except healthcare and essential goods supplies, were closed (Burgess, 2020). On March 11, the Italian government prompted a national lockdown because of the rapid spread of the virus throughout Italy (Gatto et al., 2020). In the KSA, the Saudi government announced a 21-days lockdown strategy starting from the 16th of March 2020 to reduce the rapid spread of the virus throughout the country.

Although many voices were calling for an exploration of the potential harms of automation technologies (Huang and Rust, 2018; Leclercq-Vandelannoitte, 2019; Farisco et al., 2020; Munoko et al., 2020; Arthur and Owen, 2022;), the global pandemic provided the

tipping point that accelerated the widespread adoption of automation technology. The three main reasons that may have accelerated the adoption of artificial intelligence during the Covid-19 pandemic are given in the following. The first reason is the companies' increased confidence in artificial intelligence to fulfil human labour shortages due to government requirements to reduce workers' numbers at work sites. Smart technologies do not require social distancing as they are not at risk of catching the virus. The US retailer Walmart used robots to clean their stores' floors, and its rival Amazon used robots in its warehouses to aid packaging, storage, and shipping (Thomas, 2020). In response to the epidemic, Rwanda has expanded the use of robots that measure people's temperatures, identify people who are not wearing a mask, and deliver medicine to the infected (Tucker, 2020). Coombs (2020) states that the growth of demand faced by robot manufacturers shows the rapid transformation companies are heading towards, even after the pandemic, by transforming all their production or service processes to fully automated organisational implementations.

The second reason is the incremental familiarity with automation technologies by the public. The urgent need that pushed people to adopt digital technology, such as video conferencing, made them more familiar and at ease with the technology, creating opportunities for its long-term adoption. Abubakre et al. (2017) express that information system papers, which have explored the theory of culture, have introduced the concept of IT culture that explains individuals' social practices and preferences when interacting with technologies. These social practices and personal preferences are affected by humans' motivations and personal needs (Coombs, 2020). Thus, the need for remote work technologies and internal motivations to overcome the lack of physical attendance of human employees at their work sites made both people and companies more familiar with the adoption of artificial intelligence technologies.

The third reason for the increased adoption of artificial intelligence is the change in consumer preference in favour of automation technologies. The preference of humans before Covid-19 may not be to interact with smart machines entirely, but the situation has changed after the outbreak of the epidemic. In a BBC news article, Martin Ford, an author focusing on artificial intelligence and robotics, states that the coronavirus started to change consumers' preferences towards favouring artificial intelligence technologies due to the risk of interacting with humans (Thomas, 2020). Frey (2020) asserted that decreased trust among humans is a prominent feature that epidemics create on human behaviour, referring to the Spanish influenza pandemic in 1918.

Artificial intelligence and remote working technologies have received colossal attention to help alleviate the impact of the virus. Coombs (2020) expresses that many artificial intelligence applications – including natural language processing, computer vision, knowledge reasoning, machine learning, and robotics – were used during the coronavirus crisis. According to Howard and Borenstein (2020) due to the restrictions on the human workforce, artificial intelligence technology was used to monitor the content on YouTube, and automated response robots were used to reply to customer inquiries.

Furthermore, moving robots reminded people to adhere to the rules of social distancing in parks in Singapore, isolated students at graduation ceremonies in Japan, and delivered food to quarantined people in urban areas of the UK (Tucker, 2020). In healthcare, artificial intelligence techniques have been exploited to discover transmission methods, improve the infection detection rate, develop a vaccine against the virus, and assess the social impact of the epidemic (Bullock et al., 2020). Likewise, Zhao et al. (2022) state in Tokyo semi-autonomous robots helped to clean and sterilise hospitals and deliver equipment and medication.

In auditing, the emergence of Covid-19 has renewed the conversation and focus on finding alternatives to traditional auditing methods (Litzenberg, 2020). Appelbaum et al.

(2020) state that the existence of artificial intelligence technology such as video feeds, first-person view (FPV) cameras and drones, and artificial intelligence video assessment tools could assist auditors in conducting a remote audit examination. The regulatory bodies for the external audits suggested that external auditors use remote auditing tools, such as visual recognition technology, to overcome Covid-19 restrictions (ICAEW, 2020). Barac et al. (2021) asserted that many auditing firms have used remote work tools, such as video conferencing and remote interview technology, due to the worldwide travel restrictions and constraints on gatherings.

2.5 Conclusion

In this chapter, the author discussed the geographical context of the thesis. He examined the history and the development of the accounting and audit profession in the KSA. The discussion specifically covered period, place, people, practices, propagation, products, and profession. Next, the author briefly analysed the historical development of artificial intelligence by reviewing the industrial revolutions, starting with the first industrial revolution and ending with the fourth industrial revolution. The author provided a brief overview of each industrial revolution and its accompanying events, including its positive and negative effects.

At the end of the chapter, the author reviewed artificial intelligence from a multilateral perspective. He also looked at automation and remote work during the Covid-19 pandemic. In next chapter, the author reviews the audit literature on technology acceptance.

Chapter 3: Literature Review

3.1 Information Technology (IT) in Audits

The Concise Oxford Dictionary (1911, p. 698) defines IT as ‘the study or use of systems (especially computers, telecommunications, etc.) for storing, retrieving, and sending information’. IT is seen as a means by which the shortcomings of manual work can be overcome. The progress in advanced new technologies significantly impacts the audit community at all levels. From the perspective of the auditing field, technologies are simultaneously an opportunity and a challenge to be used to understand clients’ financial positions and improve the audit’s quality. Bierstaker et al. (2001) state that technology is an essential tool for auditors to comprehend their clients’ business processes and manage the shift to a paperless business setting.

The use of information systems and technologies by firms has led to several consequences, including the need for auditors to be equipped with technologies and more experienced teams to deal with IT-based systems (Banker et al., 2002; Brazel and Agoglia, 2007; Curtis et al., 2009; Yoon et al. 2015). Moreover, one of the reasons that drive audit firms to implement IT in every aspect of auditing is the high expectation of the public in terms of accuracy, validity, reliability, timeliness, relevance, and completeness of the information (Yoon et al. 2015). suggest that IT can be utilised by audit firms to enhance their work quality and increase the efficiency of their employees.

Moreover, the requirements stated by regulators push audit firms to exploit technologies to meet these requirements. For example, the PCAOB states that ‘while obtaining an understanding of the company’s information system related to financial reporting, the auditor should obtain an understanding of how the company uses information technology (‘IT’) and how IT affects the financial statements’ (PCAOB, AS 2110, B1, 2017). Although this requirement will be discussed more in detail in later chapters, this requirement of understanding

the IT system can be conflicted with the opaque nature of Artificial intelligence technology, creating dilemma for auditors between due diligence and efficiency. Furthermore, the PCAOB states that ‘the auditor also should understand how IT affects the company’s flow of transactions’ (PCAOB, AS 2201, Par 36, 2017). Thus, to meet these requirements, auditors need to use auditing technologies (Curtis and Payne, 2008).

Although this thesis discusses the implementation of artificial intelligence in audits, being knowledgeable about other technologies employed in the auditing environment is crucial. In a review of the literature, Greenstein-Prosch et al. (2008) identified and categorised 36 different types of technology that are employed in the auditing environment. (Table 3).

Table 2. Various types of technology used in the audit environment (Greenstein-Prosch et al., 2008).

	Technology	Definition
1	Word Processing	A computer program that facilitates the entry and preparation of documents such as letters or reports
2	Electronic Spreadsheets	This software allows the auditor to enter either alphanumeric or numeric data and manipulate it either via standard functions or auditor-programmed functions
3	E-mail	Exchange of mail messages via Intranets or the Internet
4	Electronic Working Papers	The software which generates a trial balance, lead schedules, and other schedules useful for the recording of evidence in an audit or assurance engagement
5	Internet Search & Retrieval	Permits a user to search text that is in electronic format and retrieve, view, and print the desired text
6	Image Processing	Conversion of paper documents into an electronic form through scanning and the subsequent storage and retrieval of the electronic image
7	Electronic Presentations	Software that facilitates the organization and use of text, voice, or images to communicate concepts
8	Generalized Audit Software	A computer program which helps the auditor access client computer data files, extract relevant data, and perform audit functions such as addition or comparison
9	Expert Systems	The computer software that provides relevant information and decision models to assist a human in making a decision or accomplishing some tasks
10	Embedded Audit Modules	Programmed routines incorporated into an application program that is designed to perform an audit function
11	Real-time Audit Module	Programmed routines incorporated into an application program that is designed to perform an audit function
12	Database Search & Retrieval	Software that uses relational structures between data files and facilitates varying data retrieval and use
13	Simulation Software	An abstraction of some aspect of the actual system via software. An auditor may use a model to evaluate the reliability of information from real-world sources. This may be thought of as a very high-level analytical review of a company’s data
14	Flowcharting/Data Modelling	Software using the source code version of programs to produce flowcharts of program logic

15	Computer-Aided Systems Engineering Tools	An integrated package of computer tools that automate important aspects of the software development process to increase software development effectiveness in terms of productivity of systems development and quality of developed systems
16	Encryption Software	Changing data using some types of encoding/decoding algorithm so that unauthorized persons who can access the encrypted data will not be able to read it or use it
17	Groupware	Software that permits auditors to categorize, store, and share data among themselves as well as communicate with each other about that data, preferably in a real-time mode
18	Cooperative Client/Server Environment	Distribution of processing functions between two or more computers as in a local area network. This also includes end-user computing, where users on the network also process and store data on their personal computers
19	Workflow Technology	Software and hardware that facilitates the capture of data in the workplace to improve the management of the business. For example, using an electronic scanner to record the movement of materials in a warehouse based on the barcodes on the materials
20	Database Design & Installation	Software that permits the creation and use of relational structures between data files
21	Time Management & Billing Systems	A computer program that assists in capturing, managing, billing, and reporting the time spent on professional activities
22	Test Data	A set of transactions processed by the auditor to test the programmed or procedural operations of a computer application
23	Small Business Accounting Software	The accounting software package used to record transactions, maintain general and subsidiary ledgers, and generate financial statements
24	Digital Communications	Bandwidth – telecommunications devices used to facilitate the rapid and unfettered transfer of data
25	Tax Return Preparation Software	Software, perhaps incorporating expert knowledge, which assists the accountant/auditor in identifying relevant information, capturing, and recording it in a manner that can be filed with tax authorities
26	Firewall Software/Hardware	Part of 'security technology' that enforces an access control policy between two networks
27	User Authentication Systems	Devices used to verify that a system user is who he or she claims to be
28	EDI-Traditional	Transfer of data or payments electronically between computers using software that may, or may not, require human intervention to affect the transfer
29	EDI-Web Based	The extension to XML-based EDI
30	Wireless Communications	The ability to transfer digital data without the use of cables, twisted-pair, or fiber optics
31	Agent Technologies	Programmed modules that are given certain levels of authority and autonomy to act on behalf of their 'supervisor', such as to decide whether to order more inventory and from which supplier
32	Intrusion Detection & Monitoring	Part of 'security technology' that identifies unauthorized requests for services
33	Internal Network Configurations	Linkage of individuals and data through hardware and software systems that permit the exchange of various types of data
34	External Network Configurations	Intranet, extranet, and Internet access devices that enable users physically separated from the server to access it
35	Enterprise Resource Planning	Business-wide information systems that cross boundaries
36	Application Service Providers	Companies which host (i.e., provide hardware, software, and connectivity) for specific business applications

The above-mentioned technologies may not be entirely different from each other since they may have the same functions and fundamentals (Greenstein-Prosch et al., 2008). For

instance, Computer-Aided Systems Engineering Tools perform client's data analysis in an identical manner to the Expert Systems.

3.1.1 Computerised Assisted Audit Tools

Aside from IT discussed in the previous section, the use of technology in the audit profession has been addressed in the literature under the term 'computerised assisted audit tools (CAATs)'. The term CAATs was first introduced in 1974 (Pedrosa, 2015).² Matthews (2006) articulates that, at the advent of computer production in the 1960s, the main argument for the society of auditors was whether to audit 'through' or 'around' the computer. Auditing around the computer approach means that the auditors verify input and output without being aware of the actual processes inside the computer (Matthews, 2006). In contrast, auditing through the computer approach means that the auditor is required to have adequate computing knowledge to be capable of realising the quality of processes undertaken by the computer (Matthews, 2006). The reason for having this argument was the fear of losing the audit trail. Most of the auditors at that time preferred auditing through the computer approach for two reasons: the advance in the capabilities of computers and the increase in the responsibility of auditors to detect internal control weaknesses and fraud (Matthews, 2006).

After the ascendancy of this type of approach to auditing via the computer, the idea of audit automation started to emerge. The term 'audit automation' increasingly began appearing in the auditing literature as a reference to the use of computers during auditing engagements and performing audits through computers (Vasarhelyi and Lin, 1985; Manson et al., 1998). Audit automation has been defined as 'The use of computers in the management, planning, performance, and completion of audits to eliminate or reduce time spent on computational or clerical tasks, to improve the quality of audit judgments, and to ensure consistent audit quality'

² The reason for introducing the term CAATs was due to the issuance of Auditing Standards No. 3 'The Effects of EDP on the Auditor's Study and Evaluation of Internal control' By AICPA.

(ICAEW, 1993, p.5). Due to the growth of the use of computing systems in the work environment, the AICPA in 1984 issued Statement on Auditing Standards (SAS) No. 48 'The effects of Computer Processing on the Examination of Financial Statements' (AICPA, 1984). SAS No. 48 insists that auditors must consider the whole picture of a firm when trying to audit its financial statements. In May 2001, AICPA issued a new standard (SAS 94) as an amendment to SAS 55, which guides auditors in relation to IT.

Vasarhelyi (1984) proposes the idea of directly computerising manual auditing tasks and called for auditing automation. He states that the changes in the accounting process are likely to occur due to five factors: (i) physical location of the auditor, (ii) audit timing, (iii) technological dependence, (iv) time required for data access, and (v) working paper treatment. Bierstaker et al. (2001) agree with the ideas of Vasarhelyi and state that accounting firms would no longer be able to use the traditional auditing method as audit clients continue to shift toward electronic data storage to improve efficiency. They argue that auditors who use new technology would observe a significant increase in audit efficiency and effectiveness.

In general, the auditing literature has defined CAATs as techniques that utilise a machine ('the computer') as an audit tool. Braun and Davis (2003) provide a broad definition of CAATs, which is the use of any technology to aid in audit engagements. Lin and Wang (2011) state that 'CAATs refer to various tools, technologies, and software that help auditors to conduct control and confirmation tests, analysis and verification of financial statement data, and continuous monitoring and auditing'. Rafeq (2004) defines CAATs as software that assists auditors in gaining access, analysing and assessing clients' data, and eventually performing an audit opinion. CAATs can be classified into six categories: data mining software, data analysis software, operating system and database management system, security evaluation software, network security evaluation software, and software and code testing tools.

3.1.2 Advantages and Disadvantages of Computerised Assisted Audit Tools in Auditing

3.1.3 Advantages

The operations that companies undertake have become more complex due to the significant advances in the information technologies used to manage daily operations. This complexity of day-to-day operations makes it difficult for auditors to do their job using traditional audit practices. This created a need for IT-driven audit techniques to assist auditors with the audit process (Lombardi et al., 2015; Pathak and Lind, 2010). IT-based audit techniques provide many advantages to the audit profession.

First, IT helps auditors effectively communicate with the auditing team. Chen et al. (2015) state that technologies such as group brainstorming have a vital influence on the firms' communication processes. The corporate audit process may not be in the vicinity of a specific city or country, but across many countries since some firms now have branches worldwide. Thus, having effective communication systems helps auditors to make correct and timely decisions. Moreover, these systems assist the auditors in exchanging documents at high speed and with a high standard of confidentiality.

Second, IT tools enhance a drilling into the objects under investigation, which assists auditors in finding more evidence to support the audit opinion on the client's financial statements. For example, Big Data analytics could help auditors find anomalies and exceptions for further audit investigation (Cao et al., 2015). Bertomeu et al. (2021) found that advanced technology, such as machine learning tools, has helped to detect and interpret patterns present in ongoing accounting misstatements. Furthermore, advanced data analysis techniques may assist in the assessing of the entire population of the element being examined rather than just sampling. Rozario and Thomas (2019) state that artificial intelligence not only speeds up auditors' work by enabling the automation of tasks, but also allows auditors to test the entire

population of transactions. Thus, IT-driven audit tools will assist auditors in making more accurate and effective decisions compared to traditional audit methods.

Third, IT-driven audit tools enable auditors to do continuous auditing for specific objectives. Vasarhelyi and Halper (1991) state that traditional auditing might not prevent economic losses because traditional audits are performed only once a year, and the audit data may be gathered long after the financial events are recorded. To solve these problems continuous auditing was introduced, in which IT tools play a significant role. Debreceeny et al. (2005) state that the monitoring and control layer might assist in providing continuous monitoring of accounting information systems. The monitoring and control layer continuously analyses and compares data obtained against fixed benchmarks and, when anomalies are spotted, it alerts auditors for further investigation (Byrnes et al., 2015). Moreover, Appelbaum and Nehmer (2017) suggest the use of a drone in the processes of continuous auditing.

Fourth, the implementation of IT influences the attitudes and behaviour of auditors, as well as audit processes. Using IT-driven audit tools lessens the time auditors spend on routine tasks, enabling them to devote more time to jobs requiring judgment and critical thinking (Lombardi et al., 2015). Moreover, Database Search & Retrieval allows auditors to search for specific information efficiently without browsing through many documents. Furthermore, Ghasemi et al. (2011) express that performing manual auditing functions costs auditors time but audit software packages, such as trial balance software, empower auditors to input the working trial balance and automatically compute the adjusted trial balance. IT-driven audit tools can facilitate access to information and reduce the time needed to search for information.

3.1.4 Disadvantages

Despite the many advantages that IT provides the auditing profession, some disadvantages should not be ignored in this context. First, IT-driven audit tools are associated

with high initial installation and maintenance costs. The high costs of IT create obstacles for audit firms, especially in small- and medium-sized firms, when taking advantage of this technology during the process of auditing (Janvrin, et al., 2008). Curtis and Payne (2008) state that auditing software typically requires a considerable investment due to the cost of installation, subscription fee, training cost, and time required to learn how to use it. These costs may have a major impact on audit companies, especially small companies, in the early years of implementation. Moreover, IT-driven audit tools are not like the traditional ones; they need to be regularly maintained and upgraded, which adds to the costs of adopting IT during auditing. Fischer (1996) states that the high risk of implementing technology is due to the failure to achieve improvements in efficiency and effectiveness, the lack of technical assistance when required, and the difficulties in training.

The second disadvantage of IT-driven audit technology is the complexity of implementation and usage associated with these technologies. Krieger et al. (2021) assert that the implementation of IT audit tools requires auditors to have an information science background. This means that the application of CAATs requires skills in both IT and auditing, which most auditors do not have. Alles (2015) states that reducing the skills needed for using IT audit tools is particularly important for enabling the widespread implementation of these tools. Thus, one obstacle that audit firms face when implementing IT-driven audit tools is their complexity of execution.

The third disadvantage of IT-driven audit technology is the need for frequent and up-to-date training courses because the advances in IT are rapid. Pennington et al. (2006) propose that auditors resist using IT audit tools when the tasks are complicated and adequate training courses are not provided. For audit firms to use IT audit tools effectively, they must offer their auditors adequate training courses for each tool. However, these training courses cost auditors the time that they might have spent on actual audits.

3.2 Factors Influencing Computerised Assisted Audit Tools Acceptance

Many factors influence the implementation of new technology in the external audit profession. The literature shows that researchers study the phenomenon of accepting technology in the audit profession from multiple perspectives. Reviewing these determinants in the literature contributes to answering the research questions and understanding this phenomenon.

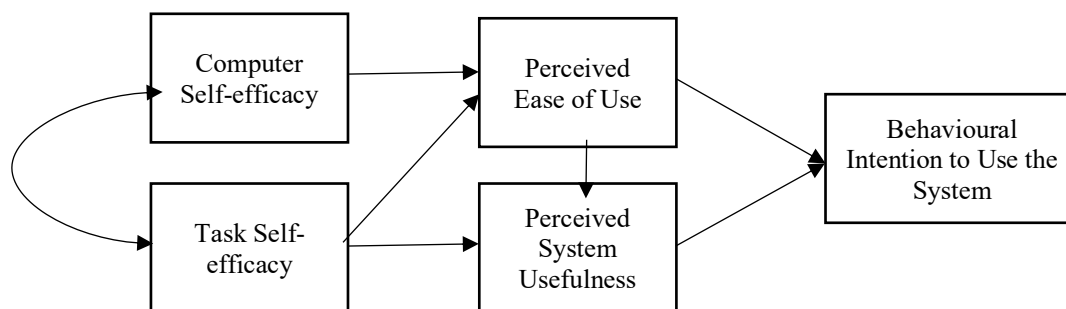
To explore this phenomenon in a deep and accurate scientific way, researchers used many theories and research methods. Schafer and Eining (2002) studied the factors that predict the auditors' decision to accept the use of technology in audit engagements. They use the theory of planned behaviour (TPB) to explore the auditors' behavioural intention. The data was collected through a survey of 26 questions sent to 34 auditors. The results show that the constructs of the TPB (i.e., attitude, subjective norm, and perceived behavioural control) predict an auditor's decision of technology acceptance. Moreover, the results show that the attitude could be decomposed into cognitive and emotional components. Although this study was one of the first attempts to study technology acceptance in the auditing profession, there is a lack of confidence when generalising its results for two reasons. First, the sample of the study is only 34 auditors, which is a small sample for obtaining any generalised results. Furthermore, the data was gathered from only one of the Big Four accountancy firms in the USA, making it difficult to generalise the results.

Bedard et al. (2003) explored the influence of intensive training of a system on the user's acceptance of that system during audit engagements. They adopted the technology acceptance model (TAM) with some modifications (Figure 1) to achieve the study's objectives. They collected the data of the study through a survey given to 289 senior/staff auditors (the first group) and 142 manager/partner auditors (the second group). They determined that training is associated with shifts in the first group's perceptions of their task and computer self-efficacy.

In contrast, the second group's self-perceptions did not change on average. They also found that the increment of computer self-efficacy for both groups is positively associated with shifts in system ease-of-use perceptions. The increment of task self-efficacy for the first group is positively related to shifts in the first group's ease-of-use perceptions. They concluded that training enhances the implementation of technology in the audit profession.

The two previous studies -Schafer and Eining (2002) and Bedard et al. (2003)- are considered among the first studies conducted in the field of adopting technology in the auditing profession, but it is difficult to claim that the results of these two studies can be applied to modern technologies used in the auditing profession. The reason why the results of these two studies cannot be applied to modern technologies is that this modern technology, such as artificial intelligence, is fundamentally different from its predecessors. For this reason, the author believes that there is a gap in the literature that needs to be filled regarding the factors that influence the auditor's decision to use artificial intelligence during the audit process.

Panel A. Model of self-efficacy perceptions, system perceptions, and behavioural intention.



Panel B. Model of the shifts in perceptions of the self and systems during training.

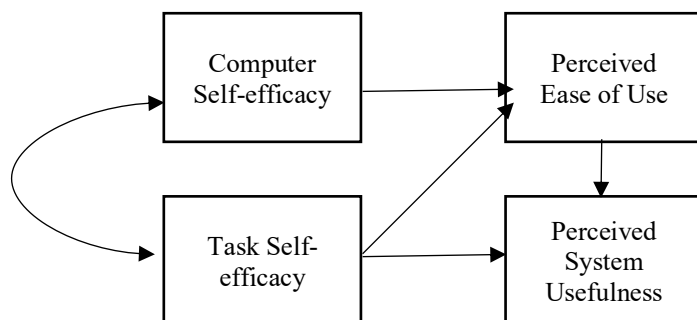


Figure 1. Modified technology acceptance model (Bedard et al., 2003).

Pennington et al. (2006) explored the effect of qualitative overload in mediating the relationship between perceived ease of use and the intention to use Audit Command Language (ACL). Qualitative overload was defined as the pressure an auditor feels when he perceives that the task at hand is too complex and insufficient training has been provided. They adopted a partial model of the TAM to test the proposed hypotheses (Figure 2). The data was collected from 43 master's students in accounting via a survey. The results showed that qualitative overload mediates the relationship between the perceived ease of ACL use and the intention to use ACL. They state that as the perceived ease of using ACL increased, the received qualitative overload stress decreased, which resulted in a positive relationship with the intention to use ACL.

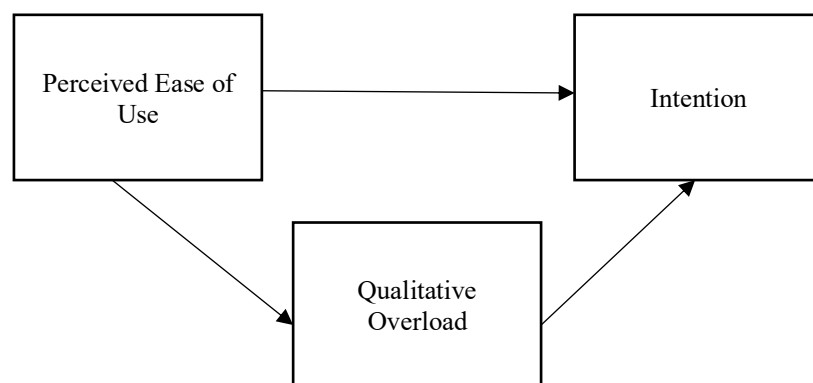


Figure 2. Partial TAM model (Pennington et al., 2006).

Ismail and Abidin (2009) conducted a study to explore the level of IT knowledge and the importance of IT among Malaysian auditors. Based on a questionnaire collected from 95 auditors, they found that technology adoption was in its early stages in Malaysia. They state that the level of auditors' IT knowledge is lower than the auditors' perception of the importance of technologies. The unfamiliarity with these technologies may affect their perceived usefulness, leading to a lower intention to adopt these tools (Greenstein-Prosch et al., 2008).

Ahmi (2012) states that most of the external auditors in the UK do not use Generalised Audit Software (GAS) due to the unawareness of its benefits for small audit firms.

It is noteworthy that realising the importance of IT in the audit profession is not the only factor that motivates auditors to use technology during the audit process. A study by Janvrin et al. (2008) found that auditors might understand the importance of technologies in the audit profession; however, they do not use auditing technology frequently. This indicates that being aware of the importance of technology is not the only factor that motivates auditors to adopt that technology. Indeed, Vasarhelyi and Romero (2014) showed that the implementation of technology in the audit processes is a complicated phenomenon. They interviewed ten individuals, including auditors and managers of the IT and forensic support groups and concluded that the characteristics of the audit team largely determine the levels of technology utilisation in the audit engagements. Vasarhelyi and Romero (2014) found that when the IT support team member had an accounting background, he collaborated using current practices and facilitated access to the available audit tools. Whereas if the IT support team member has only an information science background, the support team's participation was limited to testing the client's controls.

Curtis and Payne (2008) explored the factors and individual characteristics affecting technology implementation decisions in auditing. Their research scope covers three aspects: (i) the influence of budget and evaluation periods on technology acceptance, (ii) the influence of the managing partner on the behaviour of individuals within the firms, and (iii) the influence of individual characteristics on implementing technology in the audit processes. They adopted two constructs of the UTAUT that reflect the scope of the study: performance expectancy and social influence. The data their study was collected through an instrument given to 139 participants. The results show longer-term budget and evaluation periods motivated individual auditors to use technology during the audit processes. Moreover, the results indicate that the

encouragement of managing partners positively impacted the implementation of technology in the audit profession. Finally, the results suggest that, in the absence of external factors, risk-seeker auditors are more likely to use technology in audit engagement in contrast to risk-averse auditors.

Janvrin et al. (2008) explored whether the audit firm size influenced the IT perceived importance and auditing IT software used. They did not use a theory to test their assumptions but argued that before understanding why auditors and audit firms adopt a particular type of technology, it was necessary to identify and document auditor IT software use and its perceived importance. Their results were based on data collected through a questionnaire given to 181 auditors representing the Big Four, national, regional, and local firms. The results indicate that its perceived importance and the auditing software used varied with respect to the size of the audit firm. Furthermore, their results show that a wide range of audit applications – including analytical techniques, electronic work papers, Internet search tools, and sampling – are frequently used by auditors. Surprisingly, the results indicate that although auditors rarely use audit applications, they perceive these applications as important.

The fact that the audit company purchases an audit IT tool and the employees perceive the importance of the audit IT tool but do not use it (or even underuse it) shows a misalignment in the firms' and employees' goals. Due to this situation, Loraas and Diaz (2011) attempted to examine the influence of the perceived ease of learning the new technology on the decision to use it. To achieve the aim of their study, they adopted the theory of goal orientation. The study data was collected from a vignette-based experiment given to 106 auditor seniors. Their results indicate that the perceived ease of learning controls the level of knowledge processing undergone by the potential user; when using easy-to-use technology, the potential user relies on his situational learning dispositions. For technology that is difficult to use, the potential user depends on dispositional goal orientations.

Stoel et al. (2012) conducted a study to identify the determinants that impact the quality of IT audits from the perspective of auditors. They adopted a framework of logical factors related to IT audit quality developed by Havelka and Merhout (2009) to achieve the objectives of the study. The outcome of their research was deduced from data collected through a questionnaire given to 187 IT audit professionals, financial auditors, and other accounting professionals involved with IT audits. The results indicate that out of the 13 factors identified in the study framework, the five most influential factors for IT audit quality are independence, accounting knowledge and audit skills, business process knowledge, responsiveness, and fieldwork and audit procedures. One of the limitations that may impact the results of their study is the reliance on Information Systems Audit and Control Associations to distribute their online survey. Furthermore, the data was collected from the USA, and replicates that study to KSA participants might produce different results.

Ahmi and Kent (2012) explored IT audit quality model utilising of GAS in small- and medium-sized audit firms in the UK (Figure 3). They attempted to test the extent of the current usage of GAS in UK audit firms, the factors that motivate those who do use GAS, and the factors that prevent those who do not use GAS from employing it. To properly fulfil the objectives of the study, they modified the model for IT audit quality developed by Havelka and Merhout (2007). Ahmi and Kent's (2012) data was collected through a web-based survey sent to 205 statutory auditors across the UK. The results indicated that 73% of the external auditors in the UK do not use GAS in their audit engagements. The results show two main reasons for not using GAS: the perceived limited benefit of using GAS for auditing small clients and the high implementation costs. Interestingly, Debreceeny et al. (2005) conducted a study to evaluate the nature and extent of the utilisation of GAS by bank internal and external auditors. They found that external auditors make no use of GAS due to the inapplicability of GAS towards

testing the financial statement assertions or the extent (or quality) of computerised internal controls maintained by the bank.

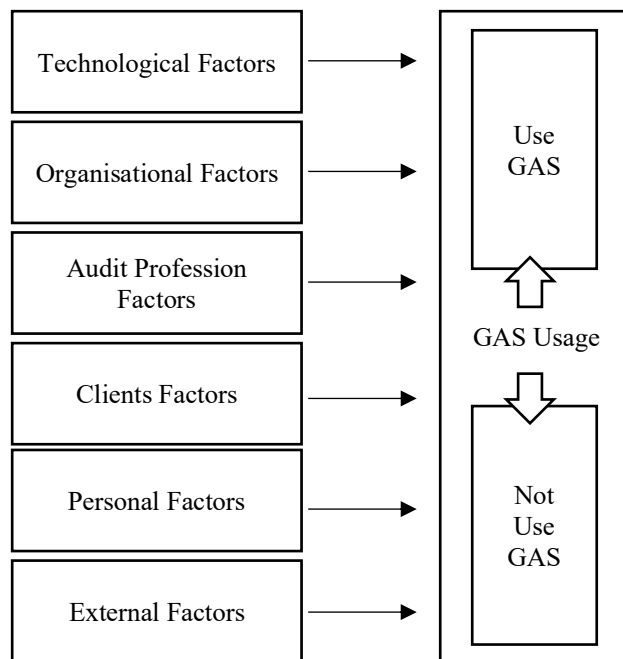


Figure 3. Factors of the IT audit quality model (Ahmi and Kent, 2012).

Curtis and Payne (2014) conducted a study to assess whether the UTAUT can properly fit technology acceptance into the external audit profession. The study data was collected through a survey sent to 75 in-charge auditors from one Big Four accounting firm. The results show a need to reshape the unified theory to fit technology acceptance into the external auditing context properly. The re-shape proposed was as follows. First, a direct association between performance expectancy and the voluntary intention to accept technology. Second, a direct relation between effort expectancy and performance expectancy, and performance expectancy mediates the relationship between effort expectancy and the voluntary intention to accept technology. Third, a direct association between facilitating conditions and effort expectancy, and effort expectancy mediate the relationship between facilitating conditions and performance expectancy. Fourth, a direct connection between social influence and the voluntary intention to accept technology. Lastly, a direct association between the budget period and the intention to accept technology (Figure 4).

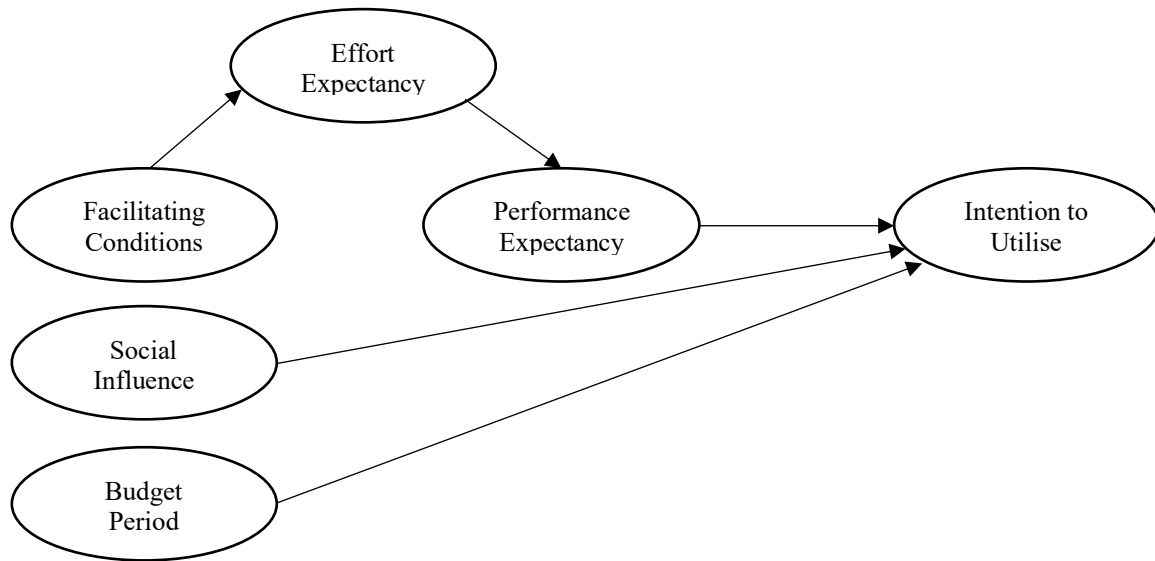


Figure 4. Reshaped unified theory for an external audit (Curtis and Payne, 2014).

Mahzan and Lymer (2014) attempted to identify the underlying factors that assist a successful adoption of CAATs in the functions of an internal audit. To obtain an improved understanding of the underlying factors, a research model was adopted based on the UTAUT (Figure 5). The study data was collected by interviewing 10 internal auditors, of which eight worked at UK companies and two worked for Malaysian firms. The results show that the performance expectancy and the facilitating conditions are the most influential factors when adopting technology in the internal audit profession. Moreover, the results indicate that both social influence and effort expectancy do not influence technology acceptance. Finally, the results show that the relation between the study constructs is moderated by both experience and voluntariness.

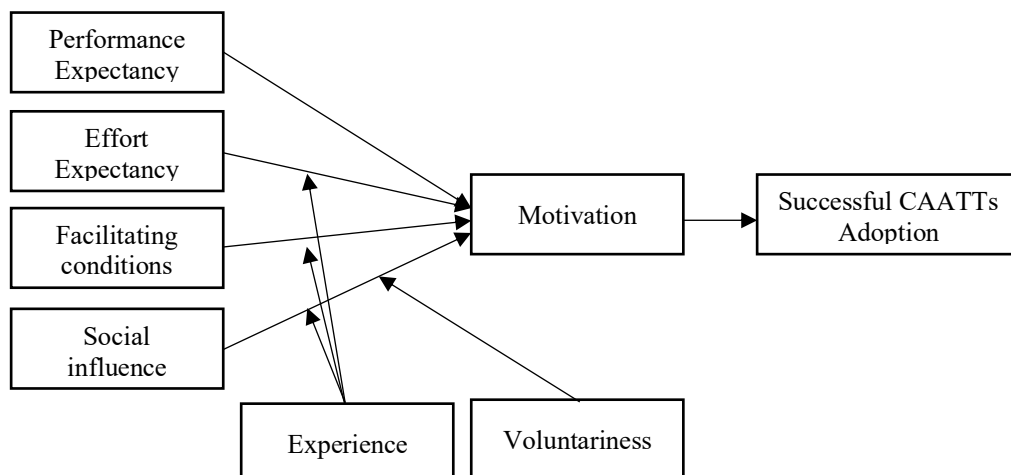


Figure 5. Modified unified theory of acceptance and use of technology (Mahzan and Lymer, 2014).

A recent study by Pedrosa et al. (2019) aims to present a theoretical background on the individual acceptance of CAATs in the audit profession of a European country. The authors built a study model based on the UTAUT; some of them also published literature in the field of technology acceptance (Figure 6). The study data was collected through a questionnaire distributed electronically to 100 statutory auditors from an unmentioned European country. The results indicate four constructs for the studied model: the main drivers of the adoption of CAATs (the perceived usefulness of CAATs), the effort expectancy, the facilitating conditions, and the number of auditors.

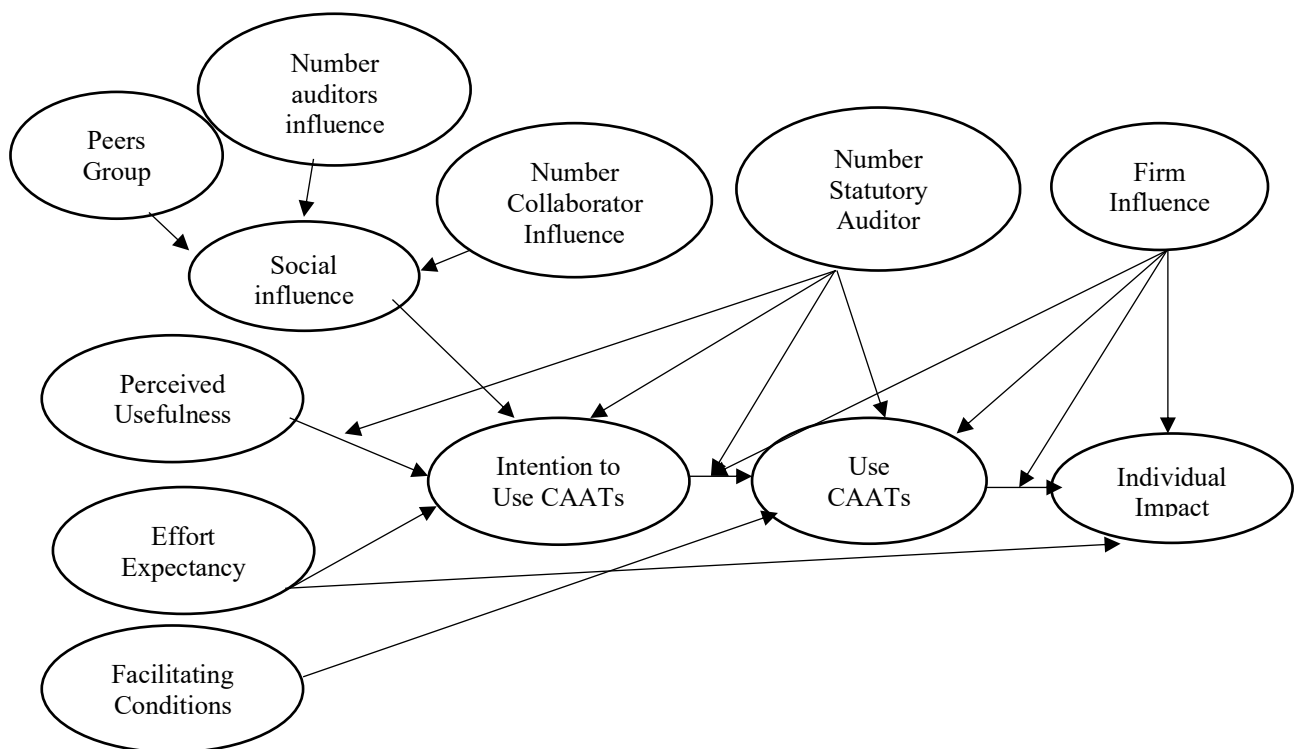


Figure 6. Factors that influence technology acceptance (Pedrosa et al., 2019).

Krieger et al. (2021) conducted a study that examines the process by which audit firms adopt advanced data analytics. The authors aimed to devise a framework for adopting advanced data analytics using grounded theory. The study data was collected through 15 semi-structured interviews with auditors and experts involved in the development and implementation of advanced data analytics in the audit profession. The results indicate that the technological capability of both the auditors and innovation teams at the audit firm plays a significant role in

the adoption of auditing technology. Moreover, the results reveal a need to bridge the gap between the audit domain and technology. To close the gap, the authors suggest that auditors need to be equipped with technological knowledge and that the innovation teams should have cross-disciplinary professionals.

Seethamraju and Hecimovic (2022) explored the factors that influence the adoption of artificial intelligence tools in the practice of auditing. To meet the study's objectives, the technology-organisations-environment framework was adopted (Figure 7). The study data was collected via 24 semi-structured interviews with a range of stakeholders included such as audit partners, managers from a standard setter body, managers from professional bodies, and IT specialists. The results of the study show the factors from three perspectives. First, from a technological perspective, the compatibility of the tools with the existing audit tools and client accounting systems, the perceived benefits, and the maturity of the tool are the key factors that affect artificial intelligence adoption in the auditing field. Second, from the organisational perspective, data quality and trust in the tools and organisational readiness are the two main factors affecting artificial intelligence acceptance. Third, from the environmental perspective, regulation readiness, auditing standards, and clients' readiness are the key aspects of artificial intelligence adoption.

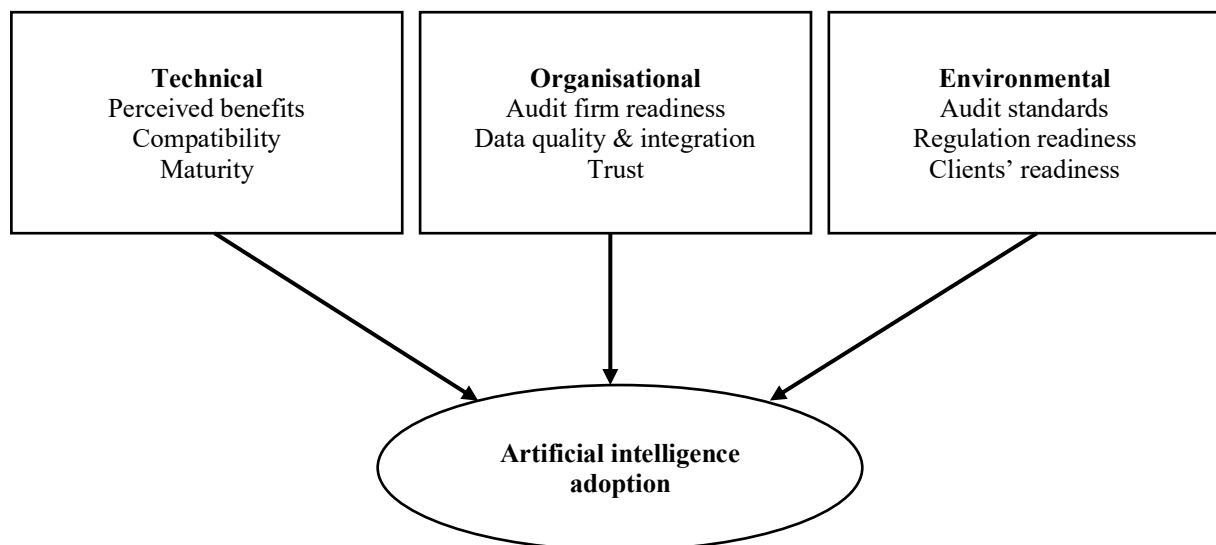


Figure 7. Technology-organisations-environment framework (Seethamraju and Hecimovic, 2022).

As discussed in the above section, the literature largely focuses on the acceptance of traditional technology in the audit profession (Schafer and Eining, 2002; Bedard et al., 2003; Pennington et al., 2006; Curtis and Payne, 2008) or utilizes theories that are not comprehensive in terms of the number of factors that may play a role in the acceptance of new technology in the audit profession. For example, TAM (Technology Acceptance Model) used by Pennington et al. (2006) and Bedard et al. (2003), and the theory of planned behaviour (TPB) used by Schafer and Eining (2002), failed to include the influence of facilitating conditions on the acceptance of new technology. Moreover, recent studies that are concerned with the factors affecting the acceptance of new technologies in audit engagements have neglected the impact of ethical considerations related to artificial intelligence on the technology acceptance journey (Pedrosa et al., 2019; Krieger et al., 2021; Seethamraju and Hecimovic, 2022). Therefore, the gap in the literature regarding the acceptance of new technology in the external audit environment is evident, and this study intends to address it by answering the research questions.

3.3 Artificial Intelligence Technology and The Audit Profession

This section discusses the artificial intelligence technology used in auditing. The author starts by defining artificial intelligence. Next, he examines what makes artificial intelligence technology different from previous technologies. Finally, he lists and considers the forms of artificial intelligence technology employed in the audit profession.

McCarthy et al. (1955) define artificial intelligence as ‘the problem of making a machine behave in ways that would be called intelligent if a human were so behaving’. This definition would be valid if it did not consider artificial intelligence a problem. McCarthy et al. may have perceived artificial intelligence as a problem due to its unavailability at the time. Minsky (1982) defines artificial intelligence as ‘the science of making machines do things that would require intelligence if done by men’. In a recent paper, Visvikis et al. (2019) define artificial

intelligence as ‘intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and other animals’. The United States Department of Defence defines artificial intelligence as ‘the ability of machines to perform tasks that normally require human intelligence’.

The optimal way to differentiate between artificial intelligence systems and other IT schemes is to contrast artificial intelligence with other forms of IT technology. IT systems involve rules-based software in which human experts codify subject matter and knowledge into a long series of programmes. For instance, human experts may codify into the system this rule: ‘If given X input, then provide Y output’. In rules-based software, human experts consider many potential inputs and reflect on the numerous rules for different inputs that attain a specific output.

In contrast, artificial intelligence and machine learning systems learn their knowledge from data (Kotsiantis, 2007). They use an extensive training database to produce artificial intelligence models. Mitchell (2006) states that machine learning focuses on the issue of how to make computers program themselves. It is noteworthy that the process of learning, in the form of artificial intelligence and machine learning, is still guided by humans. For instance, human experts may choose the data format, the algorithms, or the dataset learning parameters.

In general, the family of artificial intelligence systems can be broken down into four branches based on the form of data used in machine learning. First, supervised-learning artificial intelligence systems require data classified and organised by human experts, ‘the supervisors’, and need feedback on the accuracy of the system predictions during the training process (Saravanan and Sujatha, 2018). This type of artificial intelligence system has incredible performance; however, having sufficiently organised and classified data can be time-consuming, difficult, and expensive.

Second, unsupervised-learning artificial intelligence systems that, in contrast to the previous kind, do not require classified, organised, and labelled data (Saravanan and Sujatha, 2018). Unlike most other learning techniques, unsupervised systems can produce unexpected outcomes (Wang et al., 2019); they can be useful when looking for hidden patterns in raw data (Sitkrongwong et al., 2020).

Third, semi-supervised learning artificial intelligence systems combine both approaches. Zhu and Goldberg (2009) state that semi-supervised learning systems are based on extending either supervised or unsupervised learning systems to discover additional information typical of the other learning paradigms.

Last is reinforcement-learning artificial intelligence systems, which have autonomous artificial intelligence agents that collect data and develop it based on trial-and-error interactions with the world (Da Silva and Costa, 2019). The use of any of the discussed artificial intelligence types may have a different impact and results than the traditional technology used in auditing engagements. In addition to the types of learning models of artificial intelligence technology, there are also different types of applications of artificial intelligence.

3.3.1 IBM'S Watson

Watson is a cognitive computing technology that helps to integrate machine learning and other artificial intelligence technologies when assisting businesses in their decisions. In 2011, Watson competed on the television show 'Jeopardy' against champions Brad Rutter and Ken Jennings, where it won the top prize (Gabbatt, 2011). This was a significant victory for Watson since its ability to understand structured and unstructured data was clearly shown and it found solutions to questions posed in a natural language.

The method by which Watson operates involves IBM assembling data into a single warehouse called the Watson corpus; each corpus is created for each field in which Watson is utilised (Chen et al., 2016). Therefore, for medicine, finance, and accounting, a suited Watson

corpus could be established with content related to each of these fields. The content is formed into a formatted dataset that can be employed for analysis.

At the beginning of 2016, KPMG declared that it would collaborate with IBM Watson to add cognitive technology to its service offerings so that auditors can use Watson to analyse enormous amounts of financial data and detect anomalies (Issa et al., 2016). Steve Rainey, Chief Innovation Officer and National Leader for Data and Analytics, of KPMG in the USA proclaimed: ‘through our alliance with IBM, we are developing cognitive solutions with Watson that allow greater collaboration between humans and systems’. According to Issa et al. (2016), IBM Watson performs several artificial intelligence technologies, more precisely deep learning technologies, including textual analysis, natural language processing, audio processing, and visual recognition.

The objective of KPMG when applying Watson is to free its skilled workforce from wasting significant time on routine tasks, so that they can more fully use their qualifications and critical thinking skills on more complicated works (Lacity, 2017). Auditors can use their professional expertise on high-value tasks, such as professional judgments, instead of spending their time on routine manual tasks. Companies have a loan portfolio that usually ranges from 40 to 150 loans and, in a traditional audit, audit firms audit a sample of the commercial loans to evaluate the creditworthiness of each loan. However, Lacity (2017) says Watson has the potential to enable 100% of the population of loans to be read and assessed to determine the creditworthiness of each loan.

3.3.2 Machine Learning and Textual Analysis

Text analysis is the process of extracting insightful information, such as keywords, from textual documents (Sun and Vasarhelyi, 2018). During the audit engagements of a client, auditors have to traverse through countless textual documents when searching for evidence or checking for transactions. There are two common approaches are used by those who want to

analyse a pile of textual documents, which are essentially a bag-of-words, and machine learning. The bag-of-words approach is a very common procedure for extracting sentences and documents, in which analyst examines a graph of the words within the text (Goldberg, 2017). In this procedure, the document is treated as a bag full of words and, by calculating the frequency of specific terms using a specified lexicon, the properties of the text are obtained.

The other textual analysis approach involves analysing the documents using machine learning algorithms. Machine learning is a computing technique that can find hidden patterns in an enormous dataset and make predictions or classifications (Alpaydin, 2020; Mitchell, 2006). As stated earlier, there are four different types of machine learning algorithms: (i) supervised machine learning algorithms, which require the text to be labelled and classified by humans (Saravanan and Sujatha, 2018); (ii) unsupervised machine learning algorithms that use unlabelled and unclassified texts (Saravanan and Sujatha, 2018) and can produce unexpected outcomes (Wang et al., 2019), a useful tool when attempting to find hidden patterns in raw data (Sitkrongwong et al., 2020); (iii) semi-supervised machine learning algorithms that combine both approaches, which is based on extending either the supervised or unsupervised learning systems to enable additional information that is typical of the other learning paradigms (Zhu and Goldberg, 2009); (iv) reinforcement machine learning algorithms, in which autonomous artificial intelligence agents collect data and develops it based on trial-and-error interactions with the world (Da Silva and Costa 2019). Using these different types of artificial intelligence may help auditors to traverse through all the clients' documents either structured or unstructured data in a short time.

In recent years, machine learning applications in accounting and auditing have seen a growing trend (Dickey et al., 2019; Zhang et al., 2021; Perols, 2011; Ding et al., 2020; Bao et al., 2020; Bertomeu et al., 2021). Ding et al. (2020) studied the influence of machine learning in improving managerial estimates in the accounting and audit profession. Their findings imply

that machine learning approaches can be very beneficial to managers and auditors in enhancing accounting estimations; hence, they increase the value of financial information to investors. Bao et al. (2020) developed a fraud prediction model using a machine-learning approach. They show that their fraud prediction model exceeds the performance of two benchmark models, i.e., the Dechow et al. (2011) logistic regression model and the Cecchini et al. (2010) support-vector-machine model, by a large margin.

Bertomeu et al. (2021) find machine learning to help detect and interpret patterns present in ongoing accounting misstatements. Zhang et al. (2021) attempted to provide accounting researchers and regulators with a portfolio of informative audit quality indicators. Using machine learning algorithms, they identify 11 audit-related variables that reflect auditor competence, independence, effort, incentive, and the quality of the audited financial reports. Sun and Vasarhelyi (2018) state that KPMG is using Watson to analyse millions of textual interactions on social media such as Facebook, Amazon, Twitter, and YouTube and use it to deliver higher quality audits.

3.3.3 Natural Language Processing and Auditing

Liddy (2001) defines natural language processing as ‘a theoretically motivated range of computational techniques for analysing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications’. She states that natural language processing is a discipline within artificial intelligence that focuses on the interactions between computers and human language. She also attempts to solve the problem that computers require unambiguous and precise messages to permit interpretations. Yet, human interactions are frequently ambiguous and imprecise.

The utilisation of natural language processing in the accounting and auditing profession has been previously discussed in the literature (Goel et al., 2010; Chen et al., 2017; Craja et al.,

2020). Goel et al. (2010) argue that clues in the text could help determine the likelihood of fraud. Using natural language processing, they analysed the verbal content and presentation style of the qualitative section of the annual reports, and they investigated the linguistic traits that separate fraudulent from nonfraudulent annual reports. The results indicate that implementing natural language processing is an effective means for detecting fraudulent annual reports. Through natural language processing, they were able to improve the prediction accuracy from 56% to 89%. Natural language ability to raise the accuracy of predicting fraudulent annual reports by 30 percent gives it an advantage over the traditional methods used in prediction.

Humpherys et al. (2011) explored if natural language processing can help determine veracity by identifying textual cues that indicate the intent of the writers in an organisational report context. The results shows that natural language processing could assist the SEC and financial auditors detect fraud and protect the public's investments. Sun et al. (2016) state that auditors can employ this natural language processing to extract the required information from documents, such as management discussion and analysis sections of 10-K, conference call transcripts, and other forms of articles; the extracted data can assist in audit analytics.

3.3.4 Speech Recognition and Auditing

Speech recognition technology powered by artificial intelligence is now widely used in daily life. Speech recognition technology can distinguish between background noise and speech in a variety of accents with near-human accuracy. The well-known voice assistant, Amazon Echo Dot, can converse with people and perform activities such as playing music, creating to-do lists, and providing real-time weather updates. The usage of speech recognition technology in the audit profession has been discussed by several authors including (Issa et al., 2016; Sun and Vasarhelyi, 2017; Sun, 2019; Li and Liu, 2020).

Issa et al. (2016) state that speech recognition technology can bridge the gap between the spoken word and its written form. Sun and Vasarhelyi (2017) claim that speech recognition powered by deep learning could help auditors automate typical activities that would otherwise require massive labour hours. They argue that, when auditors perform interviews with internal auditors, management and employees to acquire background information about a client's business during the audit engagement, the language used in the interviews is as important as the answers. They suggest that auditors could use speech recognition technology to investigate for possible concealment or falsification via the detection of uncertainty terms such as kind of, maybe, or sort of, as well as response latency. Moreover, Sun (2019) states that speech recognition technology could solve the problem of taking advantage of voice data, such as conference call earnings, and the analysis of this voice data can extract keywords and topics discussed by management and other participants.

3.3.5 Visual Recognition and Auditing

In this thesis, the author discusses visual recognition technology in more detail since it is used as a specific case in the questionnaire for the quantitative data analysis.

3.3.5.1 History Of Visual Recognition

In identifying and recognising images, the human brain is trained unconsciously to observe, identify, and categorise different objects. When a person observes images of objects, his or her brain cumulatively stores these images to utilise them in future for distinguishing between objects. The abilities of the human mind develop cumulatively, unconsciously, and effortlessly. The subconscious mind accomplishes all the processes without any difficulties. Contradicting the process by which the human brain functions, computers have difficulty identifying and differentiating the features of objects. To accomplish image recognition, computers utilise various techniques, such as neural networks and learning algorithms, alongside artificial intelligence software and cameras. Low (1991) in his book 'Introductory

Computer Vision and Image Processing’ wrote: ‘Image recognition is the ability of a system or software to identify objects, people, places, writing and actions in images’. In the context of computing, recognition is a type of machine learning in which a computer has to examine images and structure mathematical models based on what it ‘sees’ (Dubey, 2005).

Visual recognition is part of the computer vision realm, so it is necessary to explore the history of this field. The early years of the 1970s marked the beginning of computer vision. From the early age of computer vision, it was regarded as the missing part of an ambitious plan to imitate humans’ visual capability and empower robots with this capability. At the time, some early robotics and artificial intelligence pioneers (at institutions like Massachusetts Institute of Technology, Stanford, and Carnegie Mellon University) thought that resolving the problem of visual input would be a simple first step toward unravelling more challenging issues such as higher-level thinking and planning (Szeliski, 2022). One of the main aspects that differentiated computer vision from the current area of digital photo processing was the willingness to retrieve the three-dimensional frame of the images from photos and employ this as a block to build an entire understanding of the scene.

In the 1980s, most scholars’ attention was concentrated on more advanced mathematical techniques for implementing quantitative images and sight analysis; for example, pyramid blending (Burt and Adelson, 1983), physically-based models (Terzopoulos and Witkin, 1988), and regularization-based surface reconstruction (Terzopoulos, 1988). In the 1990s, while the previously developed technologies were still being investigated, a sudden uptick in interest in employing projective invariants for recognition led to a concerted attempt to address the structure of a motion problem (Forsyth et al., 1991). Ultimately, the field of computer vision adopted full global optimization, which was later acknowledged to be identical to the bundle adjustment typically employed in photogrammetry (Szeliski, 2022). The adoption of full global

optimization opened the doors to the rapid and significant developments in the field of visual recognition.

In recent years, computer vision has sparkled with incredible works by the leading technology companies such as Google, IBM, and Apple. One of the most outstanding technologies developed in the last decade was the combination of learning and feature-based techniques for object recognition. Facebook combines machine learning, computer vision, and their vast database of photographs according to Khan et al. (2018) to accomplish a very accurate facial recognition system, which is utilised when the site suggests who to tag in a photograph.

The literature on visual recognition can be classified into object recognition or classification, identification, and detection. Object recognition means using visual data that an image has to classify objects (Is the object in the image of a building or a car?). Identification means using visual data in an image to identify an object, such as identifying a particular person through his appearance or recognising a specific car through its appearance. Finally, detection means scanning images or documents to extract desired information, such as scanning contracts to detect fraud or using images of carcinogenic cells to detect possible abnormal cells.

3.3.5.2 Functions of Visual Recognition in The Auditing Profession

The external audit profession is one of the professions that may benefit greatly from the advances in technologies. Yoon et al. (2015) expect that big data would enhance the efforts of auditors to gather adequate and appropriate audit evidence. Images and videos are one form of big data that is discussed in many recent audit literature such as Yoon et al.(2015), Appelbaum et al. (2017), Salijeni (2018), and Christ et al. (2021). Images and videos can be used as complementary evidence as Yoon et al. (2015) and Christ et al. (2021) discussed in their papers. According to Michael and Dixon (2019), utilising advanced technology and big data analytics in audit engagements to perform complementary voluntary disclosures can effectively narrow the gap between what is expected of an audit and what is actually delivered.

In terms of audit evidence, the audit standard (ISA 500: audit evidence) requires auditors to collect appropriate and sufficient audit evidence for which an appropriate measure of relevance and reliability of this audit evidence is needed. In addition, the measure of the quantity of the audit evidence that assists the auditor's opinion must be sufficient (FRC 2019). ISA No. 500 states that sufficiency depends on the appropriateness (i.e., the reliability and relevance) of the audit evidence collected for formulating the auditor's opinion. Visual recognition technology can assist in enhancing the sufficiency of audit evidence, in which it can collect more evidence when there are lower reliability and relevance for the audit evidence. Three elements, i.e., technology, cost/benefit constraints, and social interactions, affect the scope and quality of collected audit evidence (Louwers et al., 2007; Bradley and Hatfield, 2013). Visual recognition technology can play an essential role in these three elements since it can reduce face-to-face interaction with the audit client and lower the cost of collecting audit evidence; it is considered one of the technologies that may significantly change the audit environment.

Srivastava and Shafer (1992) state that the field of audit evidence could be classified into three categories: (i) individual accounts, (ii) audit objectives, and (iii) financial statements. Because auditors tend to gather excessive amounts of evidence at a detailed level, without thoroughly analysing the evidence provided at the financial statement level (Srivastava and Shafer, 1992), audit efficiency could be significantly increased if audit evidence from financial statements were supplemented by evidence collected and analysed by visual recognition technology. Analysing a large set of images of a client using visual recognition technology may raise some suspicions that may lead to further investigations. Yoon et al. (2015) assert that if the anticipated misstatement risk is large (small), the evidential framework and substantive procedures will be more (less) comprehensive.

For auditing individual accounts, visual recognition technology can reduce error rates and determine the more essential anomalies during additional inspections. Christ et al. (2021) found that automated counting software can assist auditors in decreasing error rates from 0.15% to 0.03%, while providing higher-quality audit documentation. Furthermore, during their fieldwork, the auditors faced many social predicaments, which overshadowed the auditing process. Bennett and Hatfield (2013) explored the influence of social interactions between staff-level auditors and client management on staff auditors' perceptions and their decisions regarding the collection of audit evidence. The findings indicate that staff-level auditors might reduce the amount of evidence they gather to prevent these unpleasant interactions. They suggest auditors might use remote means of communication, such as email, to obtain the needed audit evidence without involving in-person interactions. In such cases, visual recognition technology can help auditors to mitigate the negative impact of avoiding face-to-face communication on the quality of the audit process.

Some of the audit procedures have been fully automated, such as the audit tests that can be conducted on 100 percent of the population by utilising computer-assisted auditing techniques, like Watson. However, there are still domains during the evidence collection that have not been automated. Appelbaum and Nehmer (2017) state that areas of evidence collection in the field of auditing – for example, interviews, counts of inventory, evaluation of assets, and observation – are still non-digital. Issa et al. (2016) claim that auditing tasks that are usually performed manually and repetitively (for example, counting inventories) could be readily automated. Visual recognition technology can potentially assist in automating the repetitive audit tasks of evidence collection. Indeed, Sutton et al. (2016) state that a supplement to risk assessments, including systems using facial recognition and tone detection, could be used in auditing when electronically interviewing clients before the auditor arrives at the client's workplace. Moreover, Tysiac (2020) suggests that video-conferencing technology has

enabled new ways of remote auditing, such as holding live interviews with clients and watching for visual cues that would have been observed in a face-to-face interview.

Jeanne Boillet, EY global assurance innovation leader, proposed that artificial intelligence (in the form of visual recognition) can assist auditors during contract reviews. She said, by using pre-chosen standards, artificial intelligence techniques were better qualified to precisely extract information from lease contracts compared to the capabilities of the average auditor. The automation of auditing tasks could be achieved through machine learning and image recognition alongside reviewing source documents such as sales invoices, bank checks, and deposit slips, all of which may be supplementary evidence to be used in the traditional audit process (Ukpong et al., 2019). For example, when auditing invoices and bank statements, visual recognition techniques can identify the date of a particular transaction, the type of a particular transaction, the description of a particular transaction, and the balance of the account at a specific time.

Identifying the contents and scenes in a photograph or video, tagging human faces, and recognising objects can be easily achieved through visual recognition techniques. Such procedures can improve the efficiency of the auditors' work and add value to the evidence collection in the auditing procedures. According to Dickey et al. (2019), previous research suggests that artificial intelligence has the capability to accurately identify instances of lying in speech or indications of nervousness in facial expressions. Through visual recognition, auditors can take advantage of the enormous amount of formerly untapped qualitative data that can be extracted from non-traditional sources and transfer it into machine-readable quantitative data (Sun, 2019). An example of a non-traditional source is a video of the board of directors' meetings. This video clip can be used to identify people in the meeting, evaluate facial expressions, and analyse the words used in the meeting.

Ukpong et al. (2019) studied the nature of accounting and auditing problems and the need to apply artificial intelligence in Nigeria. Through a survey of 45 stakeholders, their findings indicate that visual recognition techniques would enable auditors to understand the contents of photographs captured by a drone, and automatically recognise the objects in these photos and classify them into a predefined logical class. Christ et al. (2021) attempted to answer the calls for evidence that support the argument that drones can improve audit quality. They use drones and automated counting software to conduct audits of cattle and sheep for livestock firms. The results indicate that automated counting software could decrease count time from 681 hours to 19 hours, as well as decrease error rates from 0.15% to 0.03%, while providing higher-quality audit documentation.

3.3.5.3 Visual Recognition Technology and Inventory Check

The external auditor is obligated, according to the auditing standards (ISA 501: Audit Evidence—Additional Considerations for Specific Items), to physically attend inventory counts unless it is impracticable (FRC, 2022b). However, there are situations in which it is impossible to attend physically. Paragraph A12 of ISA 501 provides examples of such a scenario, including the inventory residing in a location that could endanger the auditor.

In the case of epidemics and diseases, such as Covid-19, it might not be safe for the auditor to attend a physical observation of the inventory. Dohrer (2020) states that it is entirely rational to interpret paragraph A12 of ISA No. 501 in a way that Covid-19 places the auditor's safety in danger. The outbreak of Covid-19 made inventory testing an exceptional challenge for auditors, since audit firms requested that their staff work from home and clients were not allowing auditors to visit their sites. Moreover, when attempting to access certain places or countries, government restrictions may apply in certain circumstances. ICAEW (2020) reported that the UK government imposed restrictions on auditors due to the unprecedented situation of Covid-19, which made attending inventory counts unlikely.

Due to the pandemic, it has become necessary to search for techniques that enable auditors to audit their clients remotely. Tysiac (2020) states that technological advancements had enabled new forms of remote auditing, which are considered necessities for effective remote audit procedures. The use of visual recognition technology is one of the optional and available technologies that assist in the verification of the inventory's condition; it acts towards the audit's objective of asserting its valuation. ICAEW (2020) announced that when it is impractical to attend an entire stock take physically, auditors may use video technology with caution since they may not notice obsolete or damaged stock. Furthermore, ICAS (2020) states that auditors could use video-conferencing technologies or a 360-degree tour video of the premises on the day of the stock take. Video conferencing allows auditors to share documents on the screens for simultaneous checking (Tysiac, 2020). The video clips compensate exceptionally well for the lack of physical attendance during the inventory count. Dohrer (2020) shows that video observation is an excellent option for auditors during an inventory count since many warehouses have security cameras that can be controlled remotely.

When auditors use remote audit techniques, it does not mean they are less obligated to comply with standards. When auditors perform audits remotely, Tysiac (2020) urges that they still have the same obligations to comply with auditing standards. ICAEW (2020) insists that the auditor must take all precautions, even if it is not applicable to physically attend the premises, when confirming the inventory's existence and condition.

3.4 Factors Influencing the Acceptance of Artificial Intelligence

Since artificial intelligence can be considered as an extension of rules-based technology, the author now discusses factors that are likely to impact the acceptance of artificial intelligence based on the literature on the acceptance of technology in the audit profession. In the next section, factors that may have an influence on artificial intelligence acceptance have been

divided into five categories: (i) personal factors, (ii) organisational factors, (iii) client factors, (iv) technological factors, and (v) regulatory factors.

3.4.1 Personal Factors.

Personal factors are all aspects related to the auditor's personality. They will be further classified into seven categories: (i) auditor's age, (ii) gender, (iii) experience, (iv) beliefs, (v) responsibility, (vi) preferences, and (vii) knowledge of technology.

3.4.1.1 Auditor's Age

Several studies have discovered an association between a user's age and the willingness to make changes (Birren et al., 1980; Nickell and Pinto 1986; Morris and Venkatesh, 2000; Venkatesh et al., 2003). Birren et al. (1980) argue that the slowing of behaviour with age is visible not only in motor responses and sensory processes but also in the increasing complexity of behaviour. They argued that, as people get older, their willingness to change becomes less likely, especially when changes are complicated. Nickell and Pinto (1986) state that extensive evidence points to a negative relationship between tenure in the workforce (tenure represents aging) and the acceptance of the technological change. Furthermore, Forteza and Prieto (1994) found that older workers have more difficulty accepting new workplace changes.

Igbaria and Parasuraman (1989) found that the age of the manager is directly related to behaviour toward microcomputers. Venkatesh et al. (2003) state that users' age had an influence in moderating the relationship between the four determinants (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) of acceptance and actual use of technology in the workplace. Morris and Venkatesh (2000) found that the attitude towards using technology has more influence on younger workers' decisions to use technology compared with older workers' decisions. While subjective norms and perceived behavioural control influence older workers' decisions to use technology more than younger workers' choices.

In contrast to the studies mentioned earlier, Agarwal and Prasad (1999) could not find a significant relationship between age and the acceptance of new IT. They provided explanations for this their findings. The explanations are that the tenure on the work place, which was a surrogate for age in their study, is not adequately robust to show age considerations, or probably that age is not a significant influence on technology acceptance. Curtis and Payne (2008) and Janvrin et al. (2008) found that the auditors' age does not influence their technology adoption decisions. Moreover, Bierstaker et al. (2014) studied factors that influence CAATs acceptance in the audit profession. They also found that the auditors' age does not significantly impact the acceptance of technology in the audit profession.

3.4.1.2 Auditor's Gender

Gender differences have been extensively discussed in technology acceptance literature (Gefen and Straub, 1997; Vekiri and Chronaki, 2008; Curtis and Payne, 2008; Cai et al., 2017). Gefen and Straub (1997) found that women and men perceive technology differently but do not use it differently. They suggest that, in addition to other culture effects, researchers should include gender in the IT diffusion models. Around the same time, a meta-analysis of studies of gender differences in computer-related attitudes and behaviour by Whitley (1997) found that men showed a more positive attitude toward technology usage than women. A recent meta-analysis study of 50 articles from 1997 to 2014 on gender differences in technology by Cai et al. (2017) found that men still have more favourable attitudes toward the usage of technology; however, that difference is considered insignificant. Tsai and Lin (2004) state that with more women gaining more experiences related to the importance of technology, gender differences in the usage of technologies have narrowed down over the years.

In the field of auditing, Foster et al. (2003) claim that there are no considerable differences between males and females in the use of technology. Additionally, Payne and Curtis (2008) found that gender does not significantly impact the decision to adopt audit technology,

while Rahman (2008) determined that there is no difference in gender in terms of readiness to implement data mining technology. Furthermore, Bierstaker et al. (2014) studied factors that influence CAATs acceptance in the audit profession; they found that the auditor's gender does not significantly influence the acceptance of technology in the audit profession. The lack of an effect of gender on the use of technology in the auditing profession may be due to the similar educational background of both male and female auditors.

3.4.1.3 Auditor's Experience

Audit experience is the number of years an auditor has been engaging and performing audits. A considerable number of researchers have investigated the relationship between audit experience and acceptance of technology (Karahanna et al., 1999; Schafer and Eining, 2002; Wehner and Jessup, 2005; Payne and Curtis, 2008).

Karahanna et al. (1999) investigated IT adoption across time; they found that experience with a tool is an important moderator in understanding the usage of that tool. It is noteworthy that the experience discussed in the previous cited paper is the experience with the technology, not the experience in the field. Wehner and Jessup (2005) explored factors that affect GAS usage in the audit profession. They found that auditors with more experience are more likely to accept new technology that facilitates audit engagements. Indeed, Schafer and Eining (2002) discussed at length how experience affects technology acceptance decisions in the audit profession. They state that experience influences the decisions of the auditors in three ways: task-specific knowledge, a potential dilution effect, and auditor learning and task complexity. Rahman (2008) expresses that auditors' experience may impact their attitude toward technology; thus, it may influence the future use of technology.

Interestingly, Tumi (2013) found that experienced auditors have more capacity to cope with the lack of technology training courses compared to those less experienced auditors. As training technology courses are essential when adopting a technical tool in the audit profession

(Widuri et al., 2016), the results of Tumi (2013) may indicate that experienced auditors are more likely to use technology in audits. Surprisingly, Bierstaker et al. (2014) studied factors that influence CAATs acceptance in the audit profession. They state that the results did not show significant changes when including experience in the study's model. It may be the reason for the difference in Bierstaker et al's. (2014) results from the Tumi's (2013) results is that Bierstaker et al collected 60% of their data from auditors who attended the same training seminar.

3.4.1.4 Auditors' Responsibility

Auditors' responsibility is related to the efforts of the auditors to ensure public accountability, including the client's shareholders and the community as a whole. When auditors believe that artificial intelligence technology enhances audit quality, they should be responsible enough to take action to accept the technology. Moreover, when auditors believe that artificial intelligence technology negatively impacts stakeholders, they should take measures that prevent the adoption of the technology. According to Dipboye (1977) and Korman (1970), the feelings of responsibility are a result of psychological ownership and, as a consequence, the responsible person will take proactive steps to safeguard, take care of, and nurture the targets to which he or she belongs.

The literature on artificial intelligence application in audit practices has shown that artificial intelligence is associated with both advantages and disadvantages. Cao et al. (2015) argue that artificial intelligence and Big Data analytics could help auditors to discover anomalies and exceptions for further audit investigations. Moreover, Raschke et al. (2018) suggest that auditors could use artificial intelligence bots that generate continuous automatic audit inquiries, as well as evaluate client responses. Ding et al. (2020) studied the influence of machine learning in improving managerial estimates in the accounting and audit profession. Their findings imply that machine learning approaches can be beneficial to managers and

auditors in enhancing accounting estimations; hence, increasing the value of financial information to investors.

Bao et al. (2020) developed a fraud prediction model using a machine-learning approach. They proved that their model exceeds the performance of two benchmark models by a large margin; these models are the Dechow et al. logistic regression model and the Cecchini et al. support-vector-machine model. Furthermore, Christ et al. (2021) show that using drones and automated counting technology may increase the speed, accuracy, and calibre of the documentation produced by the audits of inventory, consequently enhancing asset measuring procedures.

In contrast, Duan et al. (2019) state that the ethical and legal issues associated with artificial intelligence applications have grown to be a significant challenge. Moreover, Munoko et al. (2020) have warned that assuming artificial intelligence is always precise and valid, always behaving within the required constraints, or its deviations from the required constraints are always visible and correctable, are not valid assumptions. They state that these assumptions might lead to severe consequences. Losbichler and Lehner (2021) inform society of three limits that stem from artificial intelligence-based controlling which are (i) the inherent biases in the complementary information processing between humans and machines, (ii) the issues with complex systems' partial detectability and controllability, and (iii) the Bremermann limit³. Since artificial intelligence is in its infancy and the overall picture is still blurry, the auditors' responsibility of those who believe in the ethical concerns associated with artificial intelligence may push them not to accept it.

³ The Bremermann limit refers to the fastest a self-contained system can compute in the physical universe. Bremermann's limit states that human knowledge has been placed at an absolute, insurmountable limit that can not be overcome even by all technological advancements.

3.4.1.5 Auditor's Preferences

Auditor's preferences refer to an individual's choices, whether to use manual traditional audits methodology or more advanced audit techniques. Ahmi (2012) surveyed 205 statutory auditors across the UK and, although auditors perceived the importance of technology in the audit profession, most preferred to use traditional auditing methodology. Similarly, Bierstaker et al. (2013) did not find any connection between auditor's preferences and intention to use technology and suggested that personal preferences are more relevant in contexts of individual technological options. In contrast, Lowe et al. (2018) state that they found evidence that suggests auditors might like to employ even more advanced IT in audits compared to what they presently use. This changes in the auditors' desire to use more advanced technologies might be a result of the technological complexities in the client's environment.

3.4.1.6 Auditors' Knowledge of Artificial Intelligence Technology

Knowing artificial intelligence technologies, including how to use them and their benefits, may impact the acceptance and adoption of artificial intelligence. Arguably, knowledgeable auditors (i.e., those who work without supervision) have more intention to use artificial intelligence tools in audit practices than those who do not have certain knowledge. Pennington et al. (2006) explored the effect of qualitative overload in mediating the relationship between perceived ease of use and the intention to use ACL. The results show that qualitative overload mediates the relationship between the perceived ease of use of ACL and the intention to use ACL due to a lack of knowledge of the technology. Alam and Mohammad (2009) state that understanding the benefits of IT, and having knowledge about IT, is important for adopting IT.

Ismail and Abidin (2009) claim that the level of auditors' IT knowledge is lower than the auditors' perception of the importance of technologies. This unfamiliarity with technologies may affect their perceived usefulness, leading to a lower intention to adopt these tools

(Greenstein-Proscha et al., 2008). When the auditor feels that he does not sufficiently know how to use artificial intelligence and how to deal with its complexities, this may cause him to refrain from using it in audit engagements.

3.4.2 Organisational Factors

Organisational factors are issues attached to the organisation where the auditor works. Schein (2017) state that culture is an institutional process that allows behaviour to change and improve over time. It is evident that each organisation will have a different artificial intelligence implementation experience. The majority of these variations are probably due to certain organisational traits including organisational culture, process, and size. Kim et al. (2009) state that organisational factors involve many aspects, such as training and management support. This thesis categorises organisational factors into four parts: (i) firm size, (ii) IT team, (iii) high-level management support, and (iv) training courses.

3.4.2.1 Firm Size

The literature has discussed the implications of the size of an audit firm on the acceptance of new technology (Zhu et al., 2003; Janvrin et al., 2008; Rosli et al., 2012). Based on the technology-organisation-environment theoretical framework, Zhu et al. (2003) explored the adoption of electronic business (also known as EB) at the firm level, encompassing six adoption enablers and inhibitors. Their results indicate that the firm size is a significant adoption driver. Moreover, Janvrin, Bierstaker et al. (2008) examined whether the perceived importance of IT and the use of auditing IT varies by audit firm size. They found that there was a connection.

Rosli et al. (2012) developed a new technology adoption framework to address factors that influence CAATs acceptance in public audit firms. In their framework, they included the size of the audit firm as one of the determinants that influence the decision of the audit firm to adopt a new audit tool. Ahmi and Kent (2012) investigated the utilisation of GAS by external auditors in the UK. Their results indicate that auditors in small audit firms felt it was not worth

implementing the GAS because the overhead of adoption outweighed the benefits. Arguably, artificial intelligence will elicit similar feelings from small audit firms' employees. Indeed, Appelbaum et al. (2017) comment on the use of automation and Big Data by saying that, in the audit market where prices are competitive, it leaves little room for more analytics, even if they provide a stronger guarantee of an accurate depiction. They also pondered whether the trade-off between cost and benefit plays a role in the adoption of automation and Big Data. Moreover, Chaney et al. (2004) state that large audit firms invest more money in IT including training and facilities, which grants them access to larger audits and more complicated clients. Therefore, it is likely that financial resources would enable the Big Four accountancy firms to implement technology that is superior to others and use specialist IT to a greater extent than others (Janvrin et al., 2008).

3.4.2.2 Information Technology Team

Historically, as part of the procedures to enable more accurate audit opinions, auditors have depended on experts from other fields to assist them (Salijeni et al., 2019). Having an IT team who is an expert on the subject in the audit firm may influence the auditor's decision to accept artificial intelligence technology. According to Curtis and Payne (2014), an experienced IT team can solve installing problems much more efficiently than a less experienced IT team.

The auditors may not be aware of the benefits created by a specific technology; thus, an IT team may guide and inform them about the benefits of the technology and how to use it. Recruiting IT specialists in the audit team is considered an important element in the acceptance of technology (Tumi, 2013). In fact, each of the Big Four accounting firms has created a team responsible for identifying new technologies that may help auditors during audit engagements (Damerji, 2020). Abou-El-Sood et al. (2015) explored the association between the perceived use and importance of the tools and the firm-specific/auditor-specific characteristics. The

results shows that the use of auditing technology in audit procedures is perceived to be significant when the level of IT expertise increases.

Furthermore, Axelsen et al. (2017) argue that financial auditors might need specialists to help them to understand the technology. Under the standard (ISA 220: Quality Management for an Audit of Financial Statements), the auditor is endorsed to have experts in other fields, such as IT (IAASB, 2009). Arguably, auditors who have an IT team or have easy access to technical experts may be more willing to use artificial intelligence than those who are not.

3.4.2.3 High-Level Management Support

High-level management support refers to the degree to which high-level management enables involvement and support of technology acceptance. Organisational culture varies since some organisations have supportive and encouraging high-level management that motivates employees to adopt most technologies, while others create barriers preventing it. The support of management is related to the culture of the organisation (Urbach et al., 2010). Curtis and Payne (2008) argue that an auditor is more likely to use technology or software when they receive encouragement from high-level management. By providing facilities and encouragement, partners and senior staff can support the auditors in their use of generalised audit systems (Widuri et al., 2016).

Studies on the acceptance of CAATs in the audit profession, such as (Mahzan and Lymer, 2009; Pedrosa et al., 2019; Rosli et al., 2012; Pedrosa, 2015) have found a relationship between the adoption of CAATs and the support of high-level management. Ahmi (2012) also examined this relationship and found that the lack of high-level management support was one of the reasons for auditors not adopting data mining technology.

3.4.2.4 Training Courses

Engaging in artificial intelligence training programmes and courses may influence the adoption of these techniques in the audit profession. Investing in technology training

programmes is crucial for the effective acceptance of new technologies (Compeau et al., 1999). Curtis and Payne (2008) argue that training courses are required for auditors who want to adopt new technologies and tools because it assists them in understanding these new technologies. In addition, Janvrin et al. (2008) state that audit firm management should provide IT training programmes to improve the auditors' perception of the benefits of CAATs.

Widuri et al. (2016) found that training programmes are essential when implementing GAS. These courses could be completed by sending auditors to a third-party training provider or arranging in-house training courses. Al-Ansi et al. (2013) investigated the level of IT usage and the factors that influence IT usage among audit practitioners in Yemen. Their results show that training programmes significantly influence the utilisation of IT in the external audit environment. Moreover, Perkhofer et al. (2019) explored the implementation of analysing and visualizing Big Data tools in the accounting field. Their findings show that the implementation of these tools needs sufficient training and support in the initial implementation phases. Indeed, Meredith et al. (2020) studied drivers of and barriers to decision-support technology used by financial report auditors. They suggest that accounting firms ought to prioritise providing training on decision-support technology to their employees, including those in management and upper-level position.

3.4.3 Client Factors

Client factors represent all the issues or concerns related to the client of the auditors. They demonstrate the impact of clients' readiness in the utilisation of advanced audit tools during audit engagements. These factors are categorised into three groups: (i) the client's internal control system, (ii) the nature of the client's environment, and (iii) the client's confidentiality.

3.4.3.1 Client's Internal Control System

The client's internal system may be a crucial factor in the implementation of visual recognition technologies. Alles (2015) claims that history shows that auditors were pushed to

use auditing methodology that fit enterprise resource planning (ERP) system clients use, since these systems dramatically influence how clients were managed and records were kept. Moreover, Debreceeny et al. (2005) emphasise this point by stating that external auditors have limited usage of their advanced audit software because of the limitations of the advanced internal controls system of their clients.

CCTV cameras distributed over large geographical areas are used to monitor activities in different facilities such as manufacturing centres, distribution centres and retail outlets (Trenciansky and Murdoch, 2012). A client with a CCTV system that controls the whole firm from different angles using high-resolution cameras may facilitate the audit work. Trenciansky and Murdoch (2012) argue that organisations are not employing the full potential advantages of the enormous investment in CCTV systems if it is purely for security. The development of CCTV systems has become more advanced as it moves to digital video and control signals. In addition, drones integrated with cameras, recording and playing back (at any time) features, and controlling distant cameras have all become more popular (Trenciansky and Murdoch, 2012).

3.4.3.2 Nature of The Client

The client's nature may influence the auditors' decision to use artificial intelligence technology. Large and complexed clients may need different and more advanced audit tools. Additionally, a client with a large open area of stocks or assets may need different audit tools. Christ et al. (2021) propose the idea of using drones and automated counting software to conduct audits of cattle and sheep for livestock firms. They showed that using drones and automated counting technology increases the speed, accuracy, and calibre of the documentation produced by audits of the inventory, consequently enhancing the asset measuring procedures.

Moreover, clients with inventories in an area where it is dangerous to reach, or come close to, may encourage auditors to use remote auditing tools. Appelbaum and Nehmer (2017)

state that a video clip or images of hard-to-approach asset items might help an auditor to verify their condition and support the affirmation of valuation in the audit objective. Indeed, Flowerday and Von Solms (2005) argue that the modern-day business changes in firms require auditors to develop new procedures and processes for auditing these firms.

3.4.3.3 Client Confidentiality

Auditors obtain a large amount of client information throughout the audit engagements that may affect the client's confidentiality if released to the public. The international code of ethics stipulates that auditors are obligated to adhere to the principles of confidentiality when it comes to information obtained during the audit process (IFAC, 2021). Moreover, ISA (250: Consideration of Laws and Regulations in an Audit of Financial Statements) says that an obligation that acts upon the audit firm's personnel is to observe, at all times, the confidentiality of information contained in engagement documentation unless under certain circumstances (FRC, 2017). Currently, the literature discussing the impact of confidentiality on the acceptance of artificial intelligence in the audit profession is limited. Wright and Xie (2019) and West (2019) state that confidentiality and data protection problems are the key challenges associated with accepting artificial intelligence-based decision-making in an accounting setting.

West (2019) proposes the term 'data capitalism' and defines it as 'a system in which the commoditization of our data enables an asymmetric redistribution of power that is weighted toward the actors who have access and the capability to make sense of information'. Data is the backbone of artificial intelligence, and the commodification of data makes it a target in legitimate or illegitimate ways for many parties. The notion that artificial intelligence technologies heavily rely on data collected from confidential individuals and organisation information makes these technologies vulnerable to breaches and leaks (Hernandez et al., 2014; Koscher et al., 2010). Moreover, Munoko et al. (2020) state that when audit firms upload clients' data into the artificial intelligence systems, this data has to be kept safe and protected

against security breaches and confidentiality hazards. Indeed, Lehner et al. (2022) warn that, when using artificial intelligence, the impact of leaked documents should not be underestimated to prevent fraudulent activities (e.g., Wikileaks).

The challenge of keeping clients' confidentiality may influence the decision to use artificial intelligence technology. Temesgen (2004) states that many clients had prevented auditors from using particular software because they were concerned about their confidentiality.

3.4.4 Technological Factors

Technological factors are issues that are attached to artificial intelligence itself and the developers of it. These factors will be categorised into compatibility and simplicity.

3.4.4.1 Compatibility

In innovation diffusion theory, Moore and Benbasat (1991) define compatibility as 'the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters'. In the case of artificial intelligence the idea is that, when auditors perceive that the artificial intelligence technology is compatible with the audit's existing systems and the client's existing systems, they might be more motivated to adopt artificial intelligence. Indeed, Alles (2015) states that history shows that auditors were pushed to use auditing methodology that fit the ERP system clients use since these systems dramatically influenced how clients were managed and records were kept.

Both Rahman (2008) and Ahmi (2012) investigated the factors influencing the adoption of CAATs in audit engagements. Their results indicate that one of the main issues raised by auditors when accepting new technology was the compatibility of the new system with the pre-existing operating systems. Moreover, Seethamraju and Hecimovic (2022) explored the factors that influence the adoption of artificial intelligence tools in the audit practice. They found that

the compatibility of the tools with the existing audit tools and client accounting systems is one of the key factors affecting artificial intelligence adoption in the audit practice.

3.4.4.2 Simplicity and Flexibility

The simplicity and flexibility of a system encourage and motivate users of the system to use it frequently. In the audit profession, audit engagements are complicated processes that require professional human judgement. Thus, having an artificial intelligence system that allows auditors to express their professional judgement and override some procedures (though adding a rational box) would make auditors more likely to adopt the system. Having auditors justify their rationale helps improve judgement accuracy (Ashton 1992). Dowling and Leech (2014) state that the audit system's flexibility encouraged auditors to apply and expand their knowledge because they had to take responsibility for how they used the system throughout their engagements.

The less complicated a system is to learn, the lower chance that the user of this system will fail when trying to learn it (Loraas and Diaz, 2011). Mustapha and Lai (2017) investigated factors that influence IT usage in audit firms in Malaysia. Their results indicate that around 35.7% of their respondents used Microsoft Excel as IT software during the audit process due to the simplicity of the software. Indeed, Venkatesh et al. (2003) state that the flexibility of the system positively influences the decision to adopt that system. Arguably, the case in artificial intelligence acceptance will be the same. If auditors perceive artificial intelligence as a simple and flexible system, they will be more likely to accept it in audit practices.

3.4.5 Regulatory Factors

Auditing profession is regulated by a combination of entities including government agencies (e.g., the Securities and Exchange Commission (SEC) in the United States, or the FRC in the UK), professional organisations (e.g., ICAEW and AICPA), international organisations (e.g., the IAASB). The auditors' decisions are directly or indirectly affected by

their perception of the requirements and regulations of the regulatory bodies. Regulatory factors are issues that are associated with auditing standards and regulatory bodies.

Kend and Nguyen (2020) highlight the importance of regulators when implementing new technology and the need for regulators to stay on track with the fast-paced IT market in the auditing field. If there is a gap between audit standards and technological development, it is difficult for audit firms to take advantage of this development as long as this advanced technology is not discussed in the audit standards. Issa et al. (2016) state that regulatory bodies and clients must collaborate to open doors for new advanced technology to be applied in the external audit environment. Moreover, in their work, Meredith et al. (2020) emphasise the importance of professional organisations taking a proactive role in fostering collaboration between technology specialists and audit professionals. They also add that professional bodies should provide auditors with guideline on how modern technologies can fit pre-existing audit methodologies.

Since the implementation of artificial intelligence in the audit profession is still in its infancy, and the procedure by which artificial intelligence algorithms work is complex for the human brain, this will impact the decisions of the regulatory bodies for the audit process. The implications of implementing artificial intelligence in the audit profession, such as the influence of artificial intelligence on auditors' independency and audit transparency, may make regulatory bodies more conservative in legislating the use of artificial intelligence in the audit profession. Lehner et al. (2022) state that AI-based decisions need accountable factors that influence the decisions and transparency that concern the inner workings of the algorithms behind the decisions.

Salijeni et al. (2019) claim that until standard setters remove what auditors perceive to be uncertainty around the use of big data and data analytics, auditors will not fully employ big data and data analytics in audit engagements. Moreover, Eilifsen et al. (2020) interviewed the

heads of professional practice of five international public accounting firms in Norway; they found that there is uncertainty about how the supervisory inspection authorities will evaluate and accept audit evidence generated by advanced technology. Indeed, Stoel et al. (2012) argue that two fundamental factors affect IT audit acceptance: (i) growth of reliance on IT for business operations and (ii) new requirements from regulatory and professional bodies set to audit these operations.

Meredith et al. (2020) argue that professional bodies should consider changes to audit methodology to enable the use of technological developments. They state that digitalisation highlights the need for changing audit functions to lay out a deeper and more robust analysis of clients. Hajek and Henriques (2017) offered an illustration of how audit methodology could be transformed by concentrating on identifying 'green flags,' for which fraud is likely absent, using machine learning techniques. According to them, the identification of 'green flags' is regarded as more precise than identifying 'red flags'.

3.5 Ethical Concerns

An important part of the research contribution of this thesis is the ethical concerns associated with the use of artificial intelligence in the audit profession from the perspective of auditors. These ethical considerations may impact auditors, clients, the audit profession, and/or society as a whole. But before the author dives into a discussion on the ethical concerns of artificial intelligence, it is necessary to introduce the philosophical schools of ethics and morals. In this part of the chapter, the author starts with ethics philosophies. Next, the author examines ethics in business and ethics in the audit profession. Lastly, he analyses ethical concerns associated with technology and artificial intelligence.

3.5.1 Ethics Philosophies

The philosophies related to ethics attempt to reach a systematic understanding of the nature of morality. Understanding the nature of morality helps answer the question: 'how we

ought to live and why?'. To understand the nature of morality, a comprehensive and uncontroversial definition of morality must be reached. However, it turns out that achieving such a definition of morality is an impossible mission. This is because each theory of ethics and morals expounds a different conception of what morality is. Therefore, a comprehensive and uncontroversial definition would not be aligned with all the theories in the field. Thus, the focus shifts towards determining a minimum conception of morality that every moral theory would accept, at least as a starting point. Rachels and Rachels (2019), in their book 'The Elements of Moral Philosophy', provide a minimum conception of morality which is 'morality is, at the very least, the effort to guide one's conduct by reason – that is, to do what there are the best reasons for doing – while giving equal weight to the interests of each individual who will be affected by what one does'. Through this minimum conception of morality, it is clear that the nature of morality rests on two important pillars.

First, moral judgments must be supported by good reasons. However, people's judgments of good reasons are sometimes irrational because their feelings guide them. For example, a person may feel he knows the truth about an issue without considering the arguments on the other side. Paul and Elder (2006) state that people's feelings are a product of cultural conditioning, prejudice, or selfishness. Thus, the judgments of good reasons must be peeled away, as much as possible, from feelings and should be guided by logic.

The second pillar of morality imposes impartial considerations for each person's interests. The idea is that, in the scale of morality, each party's or individual's interests are weighted the same with no privilege of one over the other. To achieve such impartiality, all parties affected by the moral judgment must be identified; they could be individuals or a group of people, such as a society. Furthermore, the degree of moral judgment that influences each party must be considered. Sometimes equality does not mean justice and discrimination does not mean racism. Rachels and Rachels (2019) provided an example to illustrate that discrimination is not

always racism. They say a film director is not racist when choosing a black person to do the role of the film hero, instead of a white person, in a movie about Fred Shuttlesworth, the heroic African American civil rights leader. In this case, the director would not be open to criticism because he had a good reason to prefer a black person over a white person.

3.5.1.1 Culture Relativism ‘Moral Relativism’

Moral relativism is a philosophical stance about the nature of morality. Cultural relativism philosophy connects cultures and ethics wherever moral codes are built based on cultural backgrounds. The sociologist Sumner (1906: 75) states:

‘The ‘right’ way is the way which the ancestors used and which has been handed down. The tradition is its own warrant. It is not held subject to verification by experience. The notion of right is in the folkways. It is not outside of them, of independent origin, and brought to test them. In the folkways, whatever is, is the right. This is because they are traditional, and therefore contain in themselves the authority of the ancestral ghosts. When we come to the folkways we are at the end of our analysis.’

Hence, it can be said that people judge whether this conduct is moral based on standards handed down from their ancestors. Park (2014) defines cultural relativism as a position which asserts that there are no universal standards of moral codes, since each culture has the right to hold its own standards of what is right and wrong. Supporters of moral relativism say that, although human cultures are different, this variation may be intrinsic since some cultures may agree on specific values and morals. For example, many cultures agree that lying and betrayal are immoral.

Rachels and Rachels (2019) summarised the claims made by moral relativists in five points: (i) moral codes fluctuate according to society, (ii) what is right within a society is determined by the moral code of the society, (iii) there is no objective standard by which one

society's code can be judged superior to another's, (iv) a society's moral code has no particular status; it is just one of many, (v) it is a sign of arrogance for us to pass judgement on the conduct of others. Instead, a tolerant attitude must be adopted towards other cultures' practices.

3.5.1.2 Criticisms of Moral Relativism

On its initial appearance, moral relativism is entirely rational. However, it faces many criticisms, which can be summarised in three points. The first point is that no one could claim that other societies' customs are morally inferior to his own (Wong, 1995). Eshetu (2017) states that moral relativism would forbid us from criticising other cultures that have less benign practices. For example, just because the X government has a lengthy history of suppressing political dissent within its boundaries, moral relativism precludes us from criticising that government's oppressive actions. Critics of moral relativism state that accepting this philosophy means agreeing that other cultures' social practices are immune from criticism.

The second point is that moral relativism casts doubt on the concept of moral progress since some social changes are considered adjustments for the better. Many people see the changes that have taken place in the social status of women, especially in western countries, as progress in women rights (Wellman, 2019). Based on moral relativism, these changes cannot be seen legitimately as progress since progress means substituting a method of performing tasks with a superior procedure. However, advocates of moral relativism say: How can the new method be judged as a better solution when the old method was in accordance with the social standards of that time? Therefore, based on moral relativism, it is immoral to judge conduct by the standards of another era.

The third point where moral relativism has been criticised relates to the method of deciding whether actions are right or wrong by just consulting the standards of the society. Moral relativism proposes a simple test for judging what is right and wrong, which involves

asking whether the action is consistent with the society's ethical code or not (Zechenter, 1997). This proposition assumes that this code is perfect, which forbids people from criticising it.

3.5.1.3 Ethical Subjectivism

The theory of ethical subjectivism was developed from a simple idea provided by David Hume. He (n.d.:255) says that 'morality is determined by sentiment. It defines virtue to be whatever mental action or quality gives to a spectator the pleasing sentiment of approbation; and vice the contrary'. In other words, when an individual expresses that an action is morally acceptable or unacceptable, it means that the individual approves of that action or disapproves of it and nothing beyond that. Rachels and Rachels (2019) claim that ethical subjectivism assigns moral judgment a meaning that will always be true as long as the speaker is sincere.

3.5.2 Ethics in The Business World

Ethics studies are an ancient tradition inspired by religious heritage, cultural heritage, and philosophical beliefs. At the early age of mankind, virtue and ethical principles were derived from religions, cultures and philosophical beliefs. However, with the emergence of businesses, a fundamental question began to be repeated in academic and practical environments. Would traditional ethics be enough for developing business life, or were new ethical approaches and formulations necessary to deal with the new era of business? In a business environment, business ethics topics have grown with the development of organisational work. According to Lewis, (1985), at that time, business ethics were found in undergraduate and graduate courses, public seminars, and sermons.

The Encyclopedia of Philosophy, Volume 3, states that the word 'ethics' is utilised in three different ways, either by referring to (i) a 'way of life', (ii) a 'moral code', i.e., an array of principles and rules of conduct, and (iii) inquiry about approaches of life and principles and rules of conduct. The first component revolves around the ethics of religions; the second component centres on professional ethics and unethical attitudes, while the last component

involves a philosophical viewpoint usually given a name that refers to metaethics (Abelson and Nielsen, 1967). Reynolds (2012) attempted to differentiate between morals, law, and ethics, providing an interesting definition of each. He states that morals ‘are one’s personal beliefs about right and wrong’, while ethics ‘describe standards or codes of behaviour expected of an individual by a group (nation, organisation, profession) to which an individual belongs’. To circumvent the confusion between law and ethics, he says that a law ‘is a system of rules that tells us what we can and cannot do’.

Taylor (1975) defines ethics as ‘inquiry into the nature and grounds of morality’, in which the word ‘morality’ refers to rules of conduct, principles, standards, and ethical judgments. Robin and Reidenbach (1987) define business ethics as ‘a request that the organisation or individual behave in accordance with the carefully thought-out rules of moral philosophy’. The problem with business ethics definitions in the literature is that there is no agreement on moral philosophy concepts. The reason for the disagreement on these concepts is that they differ among cultures and religions. Lewis (1985) reviewed 158 textbooks seeking common ground towards defining business ethics. After reviewing the literature to determine areas of agreement among the business ethics’ definitions, Lewis (1985) states that incorporating every concept mentioned about business ethics is like nailing jello to a wall. However, concentrating on the four most mentioned concepts, Lewis (1985) states the following: ‘business ethics is rules, standards, codes, or principles which provide guidelines for morally right behaviour and truthfulness in specific situations’.

Historically, business ethics can be both descriptive and normative (Werhane, 1994). Academic and research work commonly employ descriptive approaches (Tseng et al., 2010; Enderle, 2015) to describe people’s conduct and explain the moral standards they claim to follow when conducting such behaviours. Descriptive ethics mix research from different scientific fields – such as psychology, history, anthropology, and sociology – to understand

what people do and believe about ethical norms (Müller et al., 2014; Alzola, 2015; Enderle, 2015).

Normative ethics is the process of attempting to reach moral standards that determine right and wrong behaviour. Thus, normative ethics try to discover whether people's moral conduct is legitimate and how they should behave. The normative approach is primarily for corporate practice and career specialisation (Tseng et al., 2010). Organisations provide a document (or guidelines) with an ethics policy for their employees that defines acceptable conduct and develops higher standards. Moreover, regulatory bodies offer a code of ethics, or professional ethics protocols, for those who practice in the profession.

3.5.3 Ethics and The Auditing Profession

Society as a whole has formed a vital trust relationship with the independent auditor, which carries out a basic and substantial task to create an effective function for the financial market and the economic system in general (Duska, 2005). In return, the profession of auditing should fulfil the requirements of this trust relationship by creating a mechanism that enables auditors to take responsible action when performing their tasks (Jensen, 2006).

In every country or geographical area, the regulatory bodies for the audit profession issue a code of audit ethics to ensure the application of the highest standards of professional conduct that consider the public interest. In the UK, the ICAEW sets the Code of Ethics for professional accountants and states that the purpose of the code is to lay out the foundational ethical principles that professional accountants should follow, reflecting on the profession's understanding of its duty to serve the public interest (ICAEW, 2021). The foundation principles of ethics in the audit profession are independence, integrity, confidentiality, objectivity, professional behaviour, professional competence, and due care.

Generally, audit firms face three different types of responsibility through which ethical issues arise. The first type of responsibility is the audit firm's responsibility toward the client's

shareholders. They rely on audited financial statements when they make investment decisions and depend upon auditors to ratify the fairness and accuracy of financial information (Satava et al., 2006). Auditors are responsible for reporting issues that they think will affect the clients' financial stance (Guiral et al., 2010). Early alert signals in an audit report are crucial for the user of the financial report, since these alerts may influence the users' decisions (Guiral-Contreras et al., 2007; Ruiz-Barbadillo et al., 2004). Thus, ethically auditors should fulfil the full responsibility towards meeting the trust given to them by shareholders. Any breach of the audit responsibility towards stakeholders will raise ethical concerns for the audit profession.

The second type of responsibility is the audit firm's responsibility towards its clients. The clients trust the auditors and share company's private data with them. Auditors obtain a large amount of client information throughout the auditing process that may affect the client's confidentiality if released to the public. The international code of ethics states that auditors must comply with the confidentiality principles concerning information acquired through the audit process (IFAC, 2021). According to Munoko et al. (2020), auditors are responsible for safeguarding and protecting data against security breaches and the risks associated with breaches of confidentiality.

The third type of responsibility is the responsibility of the audit firm towards its employees and the community as a whole. An audit firm's decisions and actions should comply with the accepted ethics in society; the latter expects that companies will abide by the accounting rules in general. Within the community, breaches will raise ethical concerns for the audit profession. Jones (1980) states that corporate social responsibility imposes on companies their need to contribute to reducing unemployment and promoting society's financial stability. When the decisions of audit firms contribute to reducing reliance on the human workforce, these decisions may raise many ethical concerns because of their impact on the financial stability of society as a whole (Farisco et al., 2020). Decisions to shift to automation and the

use of artificial intelligence instead of human may be considered a breach of corporate social responsibility.

3.5.4 Ethical Concerns with Technology

The growth of complex IT, databases that store a large amount of important and personal information, and the increased dependence on information systems in all aspects of life has increased doubts among academics and non-academics about using these information systems or technology ethically. Sollie (2007) states that it is noteworthy that technology is becoming increasingly more complex and intrusive in all areas of life, which may lead to unforeseen consequences for both humanity and the environment. Technology can threaten people's autonomy, breach privacy rights (Laczniak and Murphy, 2006), and cause physical and financial harm to individuals (Martin et al., 2019). Furthermore, information systems can be ethically controversial, as they may influence societal norms and personal values (Cole and Banerjee, 2013). Information systems have embedded politics and values, as these systems can make actions easier or more difficult (Winner, 1980) and, moreover, they may act differently for various groups of individuals.

In addition, Reynolds (2012) emphasises that, due to IT breakthroughs in contemporary life, the significant value of ethics and human privacy has been underemphasised. He provided examples of ethical violations that may occur in contemporary information systems, such as ethical breaches of copyright through the internet, advertisements through spam email, hacking of financial and retail institutions' databases to steal customer information, and the planting of cookies on website visitors' hard drives to track their online purchases and activities.

Profitable companies may provide excellent services and assistance for the sake of advancing people and society as a whole. However, the competitive process between companies should be organised and codified because this competition may cause harm to the ethical principles in business, intentionally or unintentionally. Companies are using significant

resources to develop technology and apply it to the work environment; they are entrusted with the operational, administrative, and strategic decisions. Martin et al. (2019) claim that, despite companies' role in developing technology and creating valuable judgments about its use, we must understand what ethical values companies can offer society.

As profitable companies use new technologies and gain from technological developments, researchers interested in business ethics attempt to study the effects of profit-motives on the ethics of new information systems. The field of business ethics tries to stably align the potential divergence from profit-motives of firms with applying ethics to new technologies. Martin et al. (2019) argue that technology developers have a moral responsibility to proactively address the harmful presumptions and results of emerging digital technologies. They mentioned two reasons why this responsibility falls on the shoulders of technology developers before anyone else. First, in the emerging regulatory environment, other institutions cannot address the social costs and ethical issues created by new technology. No independent oversight agencies or third parties test new technologies and align them with societal values. Thus, in this non-ideal case, the responsibility for controlling ethical issues related to technology is internal, not external.

The second reason ethical obligations rest with the developer is that ethics must be considered while designing technologies, and developers largely control the design decisions. A technology's design anticipates how it will function; it requires presumptions about the type of users and how the technology will be used. Before beginning the technology design process, developers record insights and preferences about how the world works (Bijker and Law, 1994). During this process, ethical issues must be taken into consideration. Thus, design managers and engineers need to know how certain values – such as economic opportunity, justice, clearness, and transparency – are translated into design decisions.

Beginning in the early 1980s, the accounting and auditing profession has adopted and integrated various new technologies. During the initial phase of these technologies, they were much more straightforward and had less ambiguity behind their processes. The precursors of audit technology, such as generalised audit systems, aided auditors in decision-making. They consisted of substantial information based on rules and facts fed by professionals within the field. Experts could question these technologies and trace their processes, which provided instructions for certain scenarios (Vasarhelyi and Kogan, 1998). With the accelerated development in the use and application of technology, such as expert auditing systems, considerable and reasonable ethical questions began to emerge (Dillard and Yuthas, 2001). Small decisions made by technical systems are the intermediate elements for making significant and major decisions. Dillard and Yuthas (2001) state that auditors use decisions made by expert systems as inputs toward providing an audit opinion. This case raised the ethical issue of who is liable if the technology fails to influence a correct decision. Specht et al. (1991) argue that the failure of technical systems in their decision-making processes could expose auditors to high legal risks. Khalil (1993) warns that the legal responsibility of inaccurate judgements cannot be simply ejected from humans and transferred to computer systems.

3.5.5 Artificial Intelligence Ethics

Many people interested in technology count on the era of artificial intelligence to advance the business sector in the future. Smart machine and artificial intelligence technologies can outperform people in some activities, including implicit judgment and self-learning (Chui et al., 2016). Artificial intelligence and automation add many benefits to firms, such as lowering costs, increasing productivity, reducing waste, lessening the wasting of time, increasing safety, and raising quality. However, others warn that artificial intelligence and automation may cause disruptions to society and the economy (Leclercq-Vandelannoitte, 2019; Arthur and Owen,

2019; Kim and Scheller-Wolf, 2019). During the first few years of the application and use of artificial intelligence techniques, the negative effects may not appear clearly, as they may be less significant in the initial phases and grow cumulatively. Elliot et al. (1985) wrote that during the initial years of using technologies, the ethical issues of technologies in the audit environment were not evident. The euphoria of new inventions may obscure the negative aspects of the invention for some segments of society.

In the business environment, all aspects of emerging changes and innovations must be investigated, studied, and examined since these modifications may have long-term effects on businesses or society. One of the changes in the business environment is the use of smart technology or artificial intelligence. Munoko et al. (2020) brought attention to some of the ethical concerns with the application of artificial intelligence that should be evaluated from an ethical stance; however, they did not discuss the potential response of workers to any of these concerning areas. The article invited further research on how humans engage with intelligent technology and smart machines, as well as additional research into what relationships humans will have with smart machines. Stahl and Wright (2018) mention that artificial intelligence technologies are presently experiencing significant developments that will boost their social influence. Part of which is the ethical concerns that impact humans and the real-life environment, inherit with the implementation of technologies. These concerns have attracted the attention of researchers interested in ethical issues.

Evidently, there is an agreement in the literature that artificial intelligence has to be 'ethical'. However, discussions have appeared on what comprises 'ethical artificial intelligence' and the best applications, technological standards, and ethical exigencies required for its attainment. Srivastava and Rossi (2018) state that since human choices are expected to be ethical, decisions made by artificial intelligence have the same expectations and need to avoid accidental, perceived, and intended bias. Jobin et al. (2019) conducted a study on ethical

concerns in artificial intelligence implementation and found universal concurrence arising around five principles: (i) privacy, (ii) justice and fairness, (iii) responsibility, (iv) transparency, and (v) non-maleficence. They added that arguments have emerged on how these five principles are interpreted, how to implement them, what makes them considered substantial, and what domains they pertain to.

The objective of drawing attention towards the ethical implications of using artificial intelligence is to make the adopters aware of the potential ethical issues inherent in these technologies. Munoko et al. (2020) state three unethical assumptions some auditors make when using new artificial intelligence technologies: (i) that technologies are always precise and valid, (ii) they always behave within the required constraints, and (iii) deviations from the necessary constraints are always visible and correctable. These assumptions may make auditors develop their future decisions (the auditor's report) based on incorrect foundations. Just because algorithmic decisions are produced from complex processes does not mean they are automatically equitable, and the algorithm's operational consistency is not equivalent to objectivity. DeDeo (2014) explains this issue concisely: 'algorithms may be mathematically optimal but ethically problematic'.

Another ethical concern is the reflection of human biases on how artificial intelligence works and makes decisions (Char et al., 2018). The inheriting of human biases by artificial intelligence is very likely because artificial intelligence works according to pre-made algorithms. The developers working on developing algorithms may subconsciously reflect human biases in their algorithms. Moreover, human bias may be inherited by artificial intelligence systems through the type of data that these systems are fed. Ohm (2009) wrote that artificial intelligence biases accumulate as more data is added to the training set. Bad data employed to train artificial intelligence systems can implicitly include racial, gender, or

ideological biases (IBM, 2018). Therefore, the data that accumulates in artificial intelligent databases may become the source of bias.

The ability of machine learning and artificial intelligence to learn from data over time, without human intervention, makes artificial intelligence technologies distinct from other and previous technologies (Shaw, 2019); it is much more challenging to understand the processes behind their operations. These complex traits of artificial intelligence can have side effects in whatever field they are used. Osoba and Welser (2017) discussed ethical issues inherent in artificial intelligence systems. They state that, although artificial intelligence systems provide substantial aid to decision-makers, such as timely and effective decisions and freeing their cognitive capacity for other significant deliberations, it is hard to assess its fairness, estimate risk, and judge accuracy. They add that artificial intelligence could suppress the causal perception behind decisions. Therefore, at IBM, the company sought to mitigate the effect of this issue by providing clients and partners the ability to audit and understand how their artificial intelligence systems arrived at a given decision or recommendation (IBM, 2018).

Moreover, the objectives behind the design of artificial intelligence systems are required to be meditated upon. Artificial intelligence systems can be developed to perform in unethical manners. One example is a tool (i.e., Greyball) that Uber uses to allow the company to identify and circumvent local regulations by predicting which ride hailers may be undercover law-enforcement officers (Munoko et al., 2020). Char et al. (2018) state that the designers of the algorithm might aid companies in cheating; for example, the algorithm used by Volkswagen allowed the vehicles to pass emissions tests by decreasing cars' nitrogen oxide emissions when testing these cars.

An extensive effort has to be dedicated to studying the consequences of using artificial intelligence on the unemployment rate. Many researchers and ethicists expect that the accelerated development of automation and artificial intelligence technologies will

significantly impact the human workforce (Autor, 2015; Executive Office of the President of the United States of America, 2016; Shaw, 2019). Shaw (2019) states that artificial intelligence systems motivate anxiety about unemployment, as these technologies are expected to replace a myriad of truck drivers and make both Lyft and Uber obsolete. Frey and Osborne (2017) examined how susceptible current jobs are to artificial intelligence developments by implementing a novel methodology to estimate the probability of computerisation for 702 occupations. Their results indicated that the majority of employees with transportation and logistics jobs, as well as most office and administrative support workers and labour in production sectors, are at risk. Surprisingly, the occupations that their results indicate are at high risk due to the development of artificial intelligence are the most rapidly growing occupations in the USA during the past decades (David and Dorn, 2013). This makes artificial intelligence more concern-able since its impact might be on the sectors with the most growing occupations.

Many workers fear losing their jobs due to the usage of artificial intelligence and automation. Habakkuk and Postan (1966) state that technological advances in the industrial revolutions raised many ethical issues such as social disparity, labour rights, and working conditions. In front of the Amazon headquarters, more than 1,000 employees shouted: ‘We are people, not robots!’ (Wang, 2013). In Rome, riot police intervened to break up demonstrations by a group of taxi drivers against ridesharing apps (Wright and Schultz, 2018). Moreover, as a response to the increasing shift towards automation by companies, Honda employees have refrained from producing a sport utility vehicle known as ‘Kona’ (Jin, 2017).

There are attempts by all parties to limit the moral harm caused by the use of artificial intelligence. Addressing the ethical issues associated with the implementation of artificial intelligence should be an ongoing process that includes feedback loops to ensure that the process is continuously improved (Brey, 2012) in which cooperation between regulatory

bodies, artificial intelligence developers and adopters, and all other stakeholders are apparent (Munoko et al., 2020). Freeing artificial intelligence systems from ethical concerns requires deep collaboration across industries, specialties, and backgrounds (IBM, 2018). Regulatory bodies should create and update standards that keep pace with technological advances and govern the implementation of these technologies. Professional bodies should organise multi-disciplinary and multi-stakeholder conferences, such as the Artificial Intelligence, Ethics and Society (AIES), to transfer the dynamics of artificial intelligence ethics conversation into actions. Moreover, within the companies that implement artificial intelligence, there is a necessity for ethical governance of the implementation processes of artificial intelligence and the artificial intelligence itself.

The field of auditing is experiencing an incremental implementation of artificial intelligence. In 2015, World Economic Forum predicted that by 2025, one-third of corporate audits will be implemented by artificial intelligence (World Economic Forum, 2015). Furthermore, Munoko et al. (2020) state that one of the Big Four audit companies expects that continued corporations' investments in artificial intelligence will improve global productivity gains by \$6.6 trillion by 2030. Although the developers of artificial intelligence have promised to develop the quality of auditing, and many voices are encouraging firms to use artificial intelligence (Cao et al., 2015; Issa, et al., 2016; Appelbaum et al., 2017; Raschke et al., 2018; Zhang, 2019), there are essential points to be addressed relating to the ethical issues inherent in artificial intelligence technologies. A group of published scientific papers have called for more efforts to study the impact of ethical concerns rooted in artificial intelligence on the auditing and accounting profession (Martin, 2019; Munoko et al., 2020; Losbichler and Lehner, 2021; Lehner et al., 2022).

In part of this thesis, the author discusses the impact of ethical considerations associated with artificial intelligence on the adoption of artificial intelligence in the audit profession. The

thesis examines the ethical concerns of artificial intelligence from the perspective of auditors and how valid the concerns discussed in the literature are. This analysis is expected to contribute to reducing the negative effects of artificial intelligence on the audit profession and the process of adopting artificial intelligence in auditing.

3.6 Conclusion

In the business environment most companies, especially public companies, are required to have, at the end of each accounting cycle, financial statements audited by an independent external auditor. With outstanding technical progress, due to big data in the business environment and the extensive expansion of companies, firms perform thousands of complex electronic operations daily and store these operations in their accounting programmes or enormous databases. This fact makes it difficult for audit firms to audit their clients in the traditional way; as a result, much of the literature now suggests using advanced technology in audit engagements. For example, the literature recommends using machine learning and natural language processing to help auditors detect and interpret patterns present in ongoing accounting misstatements and to determine veracity by identifying textual cues that indicate the intent of the writers in an organisational reporting context.

Although the previous literature discussed the methods and uses of artificial intelligence in the audit profession, it does not discuss the determinants that influence the auditor's decision to use artificial intelligence. Artificial intelligence techniques have characteristics, such as the ability to make decisions independent of human intervention, that make them unique and distinct from traditional auditing methods. Also, from the perspective of the auditors, the impact of ethical concerns associated with the implementation of artificial intelligence in the audit profession has not been addressed in the literature. These points clarify the gap in the literature that this thesis intends to discuss and contribute to closing.

Chapter 4: Theoretical Framework

4.1 Introduction

From the discussions in the previous chapters, the author concluded that this research is multidisciplinary and there is a need for a theoretical framework that organises the research process properly. This chapter presents the theoretical framework for this thesis, including the theory used and the justifications for using it, and how the hypotheses of the thesis have been developed. The theoretical framework ensures that the researcher does not deviate from the boundaries of the deployed theories when making scholarly conclusions. The role of the theoretical framework when conducting research is as same as the role of a map when travelling (Sinclair, 2007; Krainovich-Miller, 2017).

The scientific papers published in the field of technology acceptance in the audit profession illustrate that the determinants of technology acceptance could be viewed from many perspectives. For example, these factors may be considered from the standpoint of the firm (i.e., the audit firms) or perceived from the perspective of the type of technology (for example, artificial intelligence). Since the study of the determinants of accepting artificial intelligence in the auditing profession may be conducted from many possible perspectives, the author uses the theoretical framework to assist in determining the boundaries of the research and to traverse through this journey to reach the desired research goals.

4.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

In this thesis, the UTAUT (Figure 8) is employed to investigate the main determinants influencing individual auditors when implementing artificial intelligence during audit engagements. The UTAUT was initially developed and tested by Venkatesh et al. (2003) in the field of management information systems.

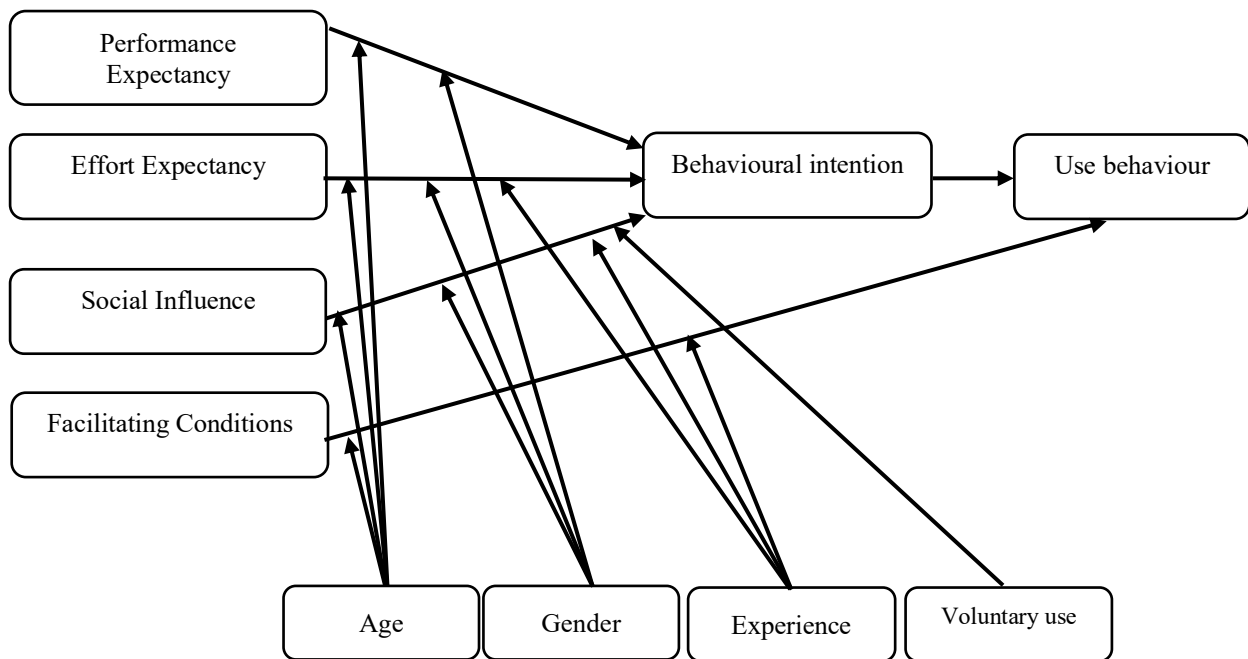


Figure 8. The UTAUT (Venkatesh et al., 2003).

The method used to formulate the UTAUT, involved empirically reviewing eight of the most well-known models used in the field of IT to study the factors that affect the acceptance of technology. The eight models are the theory of reasoned action (TRA), the TAM, the motivational model (MM), the TPB, a model combining the TAM and the TPB (C-TAM-TPB), the model of PC utilisation (MPCU), the innovation diffusion theory (IDT), and the social cognitive theory (SCT) (Figure 9). Venkatesh et al. (2003) discovered that there are four primary determinants that determine the willingness and actual usage of new technology. Additionally, they found that four moderators can affect the relationship between these determinants and the willingness to adopt new technology. The four determinants are performance expectancy, effort expectancy, social influence, and facilitating conditions, while the four moderators are gender, age, experience, and voluntary use (Figure 8).

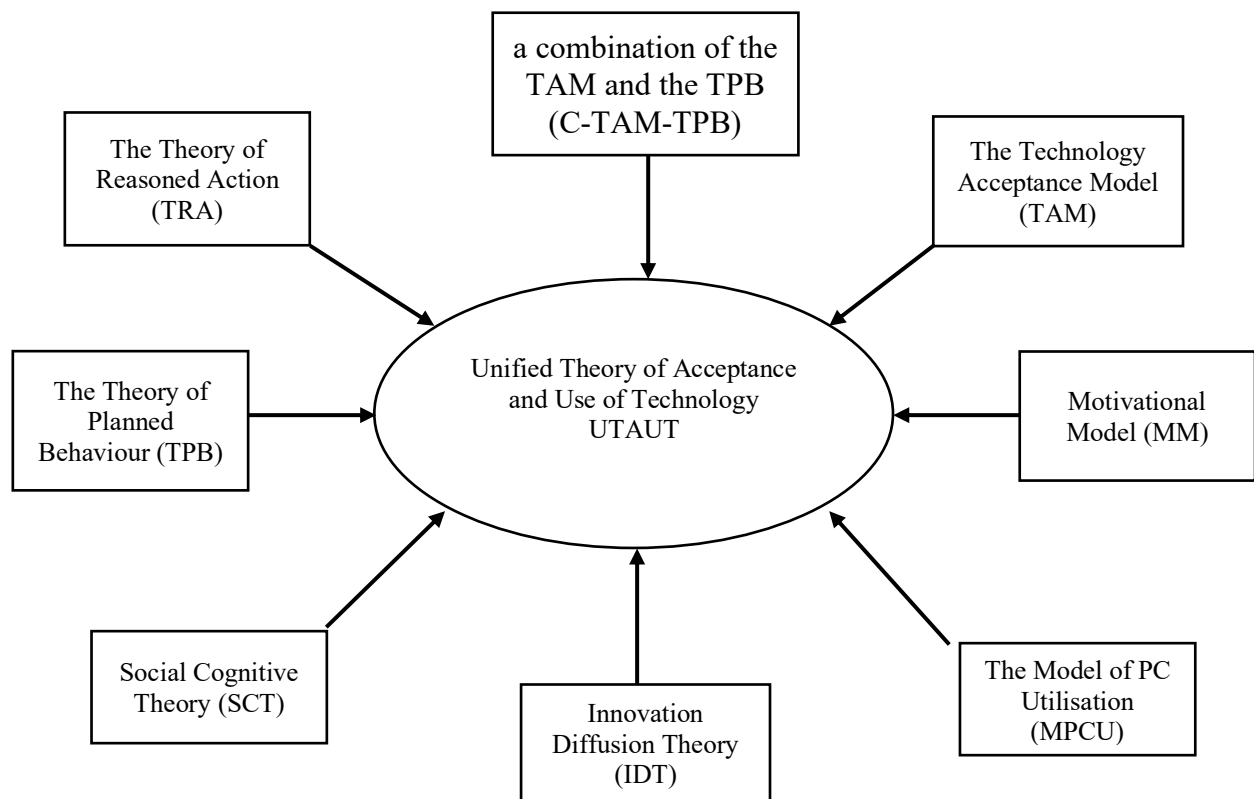


Figure 9. The Eight Models.

To empirically test the UTAUT in comparison to the eight models, Venkatesh et al. (2003) used data from four organisations over a six-month period with three measurement points. They discovered that the eight models demonstrated between 17 and 53 percent of the variance in user intentions to use IT, while the UTAUT outperformed the eight individual models (adjusted R^2 of 69 percent). To confirm their results, they used data from two new organisations (not the previous four organisations) and determined the UTAUT shows similar outcomes (adjusted R^2 of 70 percent).

The UTAUT indicates that the first three determinants (i.e., performance expectancy, effort expectancy, and social influence) determine the intention of the behaviour, which eventually establishes the usage behaviour. While the final determinant (i.e., facilitating conditions) is a direct determinant of usage behaviour. Venkatesh et al. (2003) define performance expectancy as ‘the degree to which an individual believes that using the system will help him or her to attain gains in job performance’. Performance expectancy can be

measured in several ways, such as improvement through the use of new technology, usefulness for the company and employees, enhancement of productivity, and positive impact on performance. Venkatesh et al. (2003) state that, from a theoretical point of view, gender and age would moderate the relationship between performance expectancy and intention.

The second determinant is effort expectancy, defined by Venkatesh et al. (2003) as ‘the degree of ease associated with the use of the system’. Effort expectancy can be evaluated by various measurements, such as ease of new technology usage, stress-free interaction with the new technology, and flexibility of the new technology. Venkatesh et al. (2003) propose that gender, age, and experience moderate the relationship between effort expectancy and behavioural intention.

The third determinant is social influence, defined by Venkatesh et al. (2003) as ‘the degree to which an individual perceives that important others believe he or she should use the new system’. Social influence can be measured by what important people (with respect to the user), senior management, and the organisation in general feel about the new technology. Venkatesh et al. (2003) clarified that these four moderators – i.e., age, gender, experience, and voluntariness – influence the relationship between social influence and behavioural intentions.

The last determinant is facilitating conditions, defined by Venkatesh et al. (2003) as ‘the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system’. Facilitating conditions can be measured by the availability of the new technology, knowledge to run the new technology, and placement of the new technology to fit into the culture of the corporation. Venkatesh et al. (2003) state that age and experience affect the relationship between facilitating conditions and behavioural usage.

4.2.1 Studies Employed The Unified Theory of Acceptance and Use of Technology

Many studies in different fields have applied the UTAUT when attempting to understand the motivations for adopting new technologies and the side effects of their adoption. The

UTAUT framework is progressively grabbing the researchers' attention in studying people's acceptance of using mobile technologies (Park et al., 2007; Min et al., 2008; Hu et al., 2020). Moreover, in the field of education, the UTAUT has been used to understand the factors that influence adopting technologies in education (Moran et al., 2010; Moran et al., 2010; Van Schaik, 2011; Thomas et al., 2013; Garone et al., 2019).

In the context of auditing, a considerable number of papers have utilised the UTAUT to understand the impacts of technologies in the field of auditing, especially CAATs (Janvrin et al., 2008; Curtis and Payne, 2008 and 2014; Mahzan and Lymer, 2014; Zainol et al., 2017; Handoko et al., 2018; Rawashdeh and Rawashdeh, 2021). The lack of use of CAATs in the audit profession encouraged Janvrin et al. (2008) to utilise the UTAUT model to investigate factors affecting auditors' acceptance of CAATs. They collected data from surveying 181 auditors who work at local, provincial, national, and the Big Four firms in the USA. Janvrin et al.'s. (2008) results show that performance expectancy, facilitating conditions, and effort expectancy enhance the possibility that auditors use CAATs. Furthermore, they found that auditors who work at Big Four companies have a higher rate of performance expectancy and facilitating conditions compared to those who work at smaller firms. They offer two reasons that explain this discovery: Big Four firms (i) are likely to audit clients that utilise a complicated system and (ii) have the capacity to respond to developments quicker than smaller firms.

Curtis and Payne (2008) explored the factors and individual characteristics that affect the technology implementation decisions in auditing. Their research scope covers three aspects: (i) the influence of budget and evaluation periods on technology acceptance, (ii) the influence of the managing partner on the behaviour of individuals within the firms, and (iii) the influence of individual characteristics on implementing technology in the audit processes. They adopted the two constructs of the UTAUT that reflect the scope of their study, which are performance expectancy and social influence. The data for this study was collected through an information-

gathering tool given to 139 participants. Curtis and Payne's (2008) results show that longer-term budget and evaluation periods motivate individual auditors to use technology during the audit processes. Moreover, the results indicate that the encouragement of managing partners positively impacted the implementation of technology in the audit profession. Finally, the results suggest that, in the absence of external factors, risk-seeker auditors are more likely to use technology in audit engagements compared to risk-averse auditors.

Gonzalez et al. (2012) questioned the reasons for the low growth of implementing continuous auditing tools. In their study, they employed the UTAUT with an alteration to three of the moderators applied (i.e., age, gender, and experience). Since their study is not investigating the impact of personal differences, they replaced age, gender, and experience with annual sales. They collected their data via a survey emailed to 9013 internal auditors worldwide. The results can be categorised into three groups (table 4): factors, moderators, and cultural differences. First, for factors, they found the significant factors that lead to the adoption of continuous auditing technologies correspond to effort expectancy and social influence. Second, for moderators, they discovered the volume of annual sales moderates the relationship between performance expectancy and intention to use continuous audit systems in which firms with high annual sales volume tend to use continuous audit technology without overly strict questioning the technology's performance expectancy. Also, voluntary adoption of the system moderates the impact of social influence on intention to use continuous audit systems in which a mandatory use of the systems carries heavier pressure of social influence than a voluntary use. Finally, for cultural differences, they determined that culture had a strong influence on continuous audit systems adoption. For example, internal auditors who work in North American companies are highly likely to adopt the system when they experience soft compulsion pressure created by positive social influence. In contrast, internal auditors who

work in Middle Eastern companies intend to adopt the new approach only if that system is made mandatory to use by higher authorities.

Table 3. The Results of Gonzalez et al. (2012)

Category	Results
Factors	The intention to use continuous auditing technology is influenced by two primary factors, namely, effort expectancy and social influence.
Moderators	The volume of annual sales moderates the relationship between performance expectancy and intention to use continuous audit systems as well as the voluntary use moderates the relationship between social influence and intention to use continuous audit systems
Cultural differences	The response of internal auditors in North America to adopt a new system is more inclined towards positive social influence from peers and higher authorities, while in the Middle East, internal auditors are more likely to adopt the system if it is made mandatory by the higher authorities.

4.2.2 Reasons For Employing The Unified Theory of Acceptance and Use of Technology

In the following section, the author will present justifications for his opinion that the UTAUT is the most appropriate theory for studying the determinants that affect the auditor's decision to use artificial intelligence in the audit profession. The justifications is presented by explaining how the constructs of the UTAUT can cover most of the concepts discussed in the literature on technology acceptance.

4.2.2.1 Performance Expectancy

The performance expectancy effect on the adoption of new technology has been expressed in the literature in several ways such as individual impact (DeLone and McLean, 1992; Sedera et al., 2004; Gable et al., 2008), perceived benefits or 'usefulness' (Iacovou et al., 1995; Davis, 1989), job fit (Thompson et al., 1991), relative advantages (Moore and Benbasat, 1991), and outcome expectations performance (Compeau and Higgins, 1995).

The individual impact is closely related to the performance in which an individual believes that an information system would improve his performance or his department's performance (DeLone and McLean, 1992). Sedera et al. (2004) state that individual impact refers to how the technology 'in their case enterprise system' has affected the performance of individual users. While Gable et al. (2008) indicate that individual impact is a measurement of

the degree to which the technology, in their case an ‘information system’, has affected the capabilities and effectiveness of the users. All these definitions somewhat refer to performance expectancy; this is one of the reasons why the UTAUT has been adopted in this thesis.

Perceived usefulness indicates the extent to which an individual believes that utilising a specific technical tool would improve his or her work performance (Davis, 1989). This definition of perceived usefulness is relatively similar to the description of performance expectancy given by Venkatesh et al. (2003). Iacovou et al. (1995) state that perceived benefits indicate the perception level of the pertinent advantages that a technical tool, in their case ‘Electronic Data Interchange’, can associate the organisation with.

In the technology acceptance literature, job fit has been used to refer to performance expectancy. Thompson et al. (1991) define job fit as ‘the extent to which an individual believes that using [a technology] can enhance the performance of his or her job’. This definition of job fit is relatively similar to the previously discussed definition of performance expectancy. Furthermore, the relative advantage has been utilised to refer to performance expectancy. Moore and Benbasat (1991) identify the relative advantage as ‘the degree to which an innovation is perceived as being better than its precursor’. An individual considers innovation to be an improvement compared to its precursor when the enhanced and improved performance of the individual has occurred.

Outcome expectations performance also refers to performance expectancy and is defined as the consequences related to behaviours due to ‘the adoption of new technology’ (Compeau and Higgins, 1995). Performance expectancy indicates any advantages that can be inherited from the adoption of new technologies. Davis (1989) states that performance expectancy refers to the advantages perceived by an individual, including the improved ability to accomplish assignments more quickly, which increases his or her productivity while working and makes the job easier.

A considerable number of papers (Ebimobowei et al. 2013; Handoko et al. 2018; Pedrosa et al. 2019) in audit literature show that perceiving and realising the benefits of new technologies by auditors has motivated them to utilise and exploit these technologies to improve the efficiency and effectiveness of audit procedures. Ebimobowei et al. (2013) studied factors that influence the adoption of CAATs in Nigeria. They sent a questionnaire to 202 auditors who practice in public accounting firms. They found that performance expectancy has the most influence on the adoption of technologies. Handoko et al. (2018) conducted a study based on 156 financial auditors who work at audit firms (including the Big Four companies) in Jakarta. Their results indicate that performance expectancy plays a significant role in the behavioural intention of auditors when adopting CAATs. Recently, Pedrosa et al. (2019) surveyed 100 statutory auditors to identify the adoption determinants of CAATs. Their findings reveal that the perceived usefulness (i.e., the performance expectancy) is one of the main drivers of the adoption and use of CAATs.

4.2.2.2 Effort Expectancy

In technology acceptance literature, the factor known as effort expectancy has been expressed in different ways such as perceived ease of use (Davis, 1989), complexity (Thompson et al., 1991), and ease of use (Moore and Benbasat, 1991). Davis (1989) used the factor in terms of the perceived ease of use and defined it as ‘the degree to which a person believes that using a system would be free of an effort’. This definition of perceived ease of use is relatively similar to the definition of effort expectancy given by Venkatesh et al. (2003). This indicates that when the term perceived ease of use is used in the literature as a factor that influences the adoption of technology, it refers to the term effort expectancy discussed in the UTAUT.

The term complexity, also, has been used in the literature to refer to the factor effort expectancy. When Thompson et al. (1991) utilised the term complexity, they defined it as ‘the

degree to which a system is perceived as relatively difficult to understand and use'. This definition is relatively similar to the description of effort expectancy given by Venkatesh et al. (2003), which is 'the degree of ease associated with the use of the system'. Thus, the term complexity in the literature refers to the concept of effort expectancy. The latter is the perceived effort a user needs to competently use the technology, including the time necessary to master the technology and the courses required to learn to use the technology.

Al-Gahtani et al. (2007) surveyed 722 workers who use desktop computer applications in Saudi Arabia to examine the acceptance and use of desktop computers application in the workplace. Their findings suggest a non-existent impact of effort expectancy on the acceptance and use of desktop computer applications in the workplace. Almutairi (2008) sent a questionnaire to 634 employees who work at Kuwaiti ministries to examine the adoption of information systems in these ministries. In contrast to Al-Gahtani et al. (2007), his results indicate that effort expectations impact the usage of information systems in Kuwaiti ministries.

In the context of an audit, recent studies have found that effort expectancy is one of the main drivers of the acceptance of technology (Ebimobowei et al., 2013; Pedrosa et al., 2019), while a study by Handoko et al. (2018) claims that effort expectancy does not have a significant influence on the intention of auditors to use technology. To explain these differences, Pedrosa et al. (2019) state that perceived ease of use had more influence on the adoption of technology when advanced technological features were exercised because they are more intricate than basic features.

4.2.2.3 Social Influence

The factor known as social influence has been expressed differently within models that intend to study the issues that influence the acceptance of new technology. In the TRA, Davis (1989) applied the term subjective norm; he defines it as a 'person's perception that most people who are important to him think he should or should not perform the behaviour in

question’. This definition is relatively similar to the one for social influence used in the UTAUT.

In the MPCU, Thompson et al. (1991) uses the term social factor. They define it as ‘the individual’s internalization of the reference group’s subjective culture, and specific interpersonal agreement that the individual has made with others, in a specific situation’. This definition of social factor is relatively similar to the definition of social influence employed in the UTAUT. Furthermore, Moore and Benbasat (1991), in their model ‘innovation diffusion theory’, utilise the term image and define it as ‘the degree to which use of an innovation is perceived to enhance one’s image or status in one’s social system’. The definition of image given by Moore and Benbasat (1991) is relatively similar to the one for social influence utilised in the UTAUT.

Using the UTAUT, Dulle and Minishi-Majanja (2011) examined the acceptance and usage of open access within public universities in Tanzania. They found that social influence significantly affects researchers’ actual use of open access. In contrast, Almutairi (2008), in his examination of the adoption of the information system in Kuwaiti ministries, found that social influence has no impact on information system usage. Similar to the previous study, Alshehri et al. (2012) studied the acceptance of e-government services in the KSA. They found that social influence has no significant impact on the user behavior of e-government services. The difference in the results in the first study and the two subsequent studies may be due to the difference in cultures, as it appears that the first study was conducted in an African country and the two subsequent studies were conducted in two countries of the Gulf Cooperation Council.

In the context of auditing, Ramen et al. (2015) found that social influence positively impacts the decision to adopt CAATs. Contrary to previous findings, some of the literature results signify that social influence has no significant impact on the acceptance of CAATs (Janvrin et al., 2008a; Handoko et al., 2018; Pedrosa et al., 2019). Pedrosa et al. (2019) argue

that social influence is not a direct determinant of the intention to use CAATs. The difference in the results in the first study and subsequent studies may be due to the extent to which auditors perceive the use of CAATs to be mandatory in Mauritius, where the first study was conducted. Also, the difference may be due to the different cultures in the geographical areas in which these studies were conducted.

4.2.2.4 Facilitating Conditions

The roots of the construct facilitation conditions used in the UTAUT originate from the perceived behavioural control (in Both the TPB, and the C-TAM-TPB), facilitating conditions (in the MPCU), and compatibility (in the IDT) (Venkatesh et al., 2003). Taylor and Todd (1995) state that ‘perceived behavioural control reflects perceptions of internal and external constraints on behaviour’. In their theory, known as the PC utilisation model, Thompson et al. (1991) claim that facilitating conditions are internal or external factors that observers may admit are factors that facilitate system utilisation. In the innovation diffusion theory, Moore and Benbasat (1991) defines compatibility as ‘the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters’.

In the context of an audit, Janvrin et al. (2008) determined that facilitating conditions, such as organisational and technical infrastructure support, positively impact the probability that auditors adopt CAATs. Consistent with a previous study (Janvrin et al., 2008), it was found that facilitating conditions were positively associated with the usage of CAATs by individual auditors (Ebimobowei et al., 2013; Ramen et al., 2015; Handoko et al., 2018; Pedrosa et al., 2019). These results indicate the importance of facilitating conditions in the adoption of technology in audit profession.

4.3 Theory of Acceptance and Use of Technology 2 (UTAUT2)

Venkatesh et al. (2012) state that the UTAUT had distilled the crucial factors relate to predicting behavioural intentions to primarily use technology in an organisational context.

Thus, there is a need for a systematic investigation and theorising of the salient factors that would apply to a consumer technology use context. To apply the UTAUT to a consumer technology use, they extended the theory by adding three new constructs, hedonic motivation, price value, and habit, to the four existing constructs. Their explanation for adding these new factors is as follows. Hedonic motivation predicts the impact of fun and pleasure on the behavioural intention of consumers to use technology. Price value differentiates between consumer and organisational use settings, in which the consumers and employers bear the monetary costs of use. Habit was added to study the effects of habit on the behavioural intention of consumers to use technology.

For further clarity, Venkatesh et al. (2012) define the three added constructs as follows: ‘hedonic motivation is the fun or pleasure derived from using a technology’, ‘price value is consumers’ cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them’, and ‘habit is a perceptual construct that reflects the results of prior experiences’. The purpose of including these three constructs was to extend the UTAUT to also cover a consumer technology use context. Therefore, the UTAUT2 is not a development of the UTAUT; instead, it acts as an expansion of the previous version that encompasses another context (i.e., consumer technology use).

Since this thesis aims to investigate the determinants that influence the intention to use artificial intelligence in an organisational context, the author perceived that the UTAUT2 does not fit the objectives of this study.

4.4 Hypotheses Development and Conceptual Framework

The UTAUT has been used to explain what motivates individuals (auditors in this study) to accept new technology. Auditors, as individuals, have motivations when deciding to adopt technology for audit engagements. However, institutional work organises their motivations, shaping them to align with the organisation’s objectives. There are some differences between studies that applied the UTAUT to analyse the implementation of technology in the field of

information management systems and those used to examine the application of technology in the field of audit, due to the nature of the audit profession (Curtis and Payne, 2014). In this thesis, the author modified UTAUT to make it commensurate with the study of the determinants that affect the acceptance of artificial intelligence in the audit profession, which accords with the discussions on artificial intelligence and audits in the literature.

The author expanded the UTAUT by adding a new construct (i.e., ethical concerns) to the main constructs of the UTAUT. The purpose of this step is to study the effects of artificial intelligence ethical concerns discussed in the literature (Martin, 2019; Munoko et al., 2020; Losbichler and Lehner, 2021; Tiron-Tudor and Deliu, 2021; Lehner et al., 2022) on the implementation of artificial intelligence in the audit profession. Artificial intelligence has unique features (as discussed in Section 3.5.5 of Chapter 3) that distinguish them from previous technologies used, result in new ethical issues not formerly encountered (Munoko et al., 2020).

In the UTAUT, age, gender, and experience works as a moderator. Since the application of artificial intelligence technology in auditing is new, it is expected that there will not be much variations in the artificial intelligence experience among auditors. Furthermore, since the auditors are likely much more homogenous than a user group in information management system research in terms of age, education, and work experience, it is expected that the effect of age and gender will not be significant in the audit setting (Curtis and Payne, 2014). Following Curtis and Payne (2014), age, gender, and experience are not included in the model of this thesis. However, the data related to these moderators (i.e., age, education, and work experience) will be collected and their effect on the constructs of the thesis's model will be statistically tested. If the results show that these mediators have an effect, they will be reintegrated into the thesis model (figure 10).

Moreover, Johns (2006) argues that researchers do not adequately recognise or appreciate the effect of context on organisational behaviour, which he defines as 'situational opportunities

and constraints that affect the occurrence and meaning of organisational behaviour as well as functional relationships between variables'. In addition, Ahmi and Kent (2012) state that auditors in small audit firms rarely implement the GAS because the overheads of its adoption outweighed the benefits. Thus, the author uses a latent variable *firm size* as a moderator for the main constructs of the UTAUT.

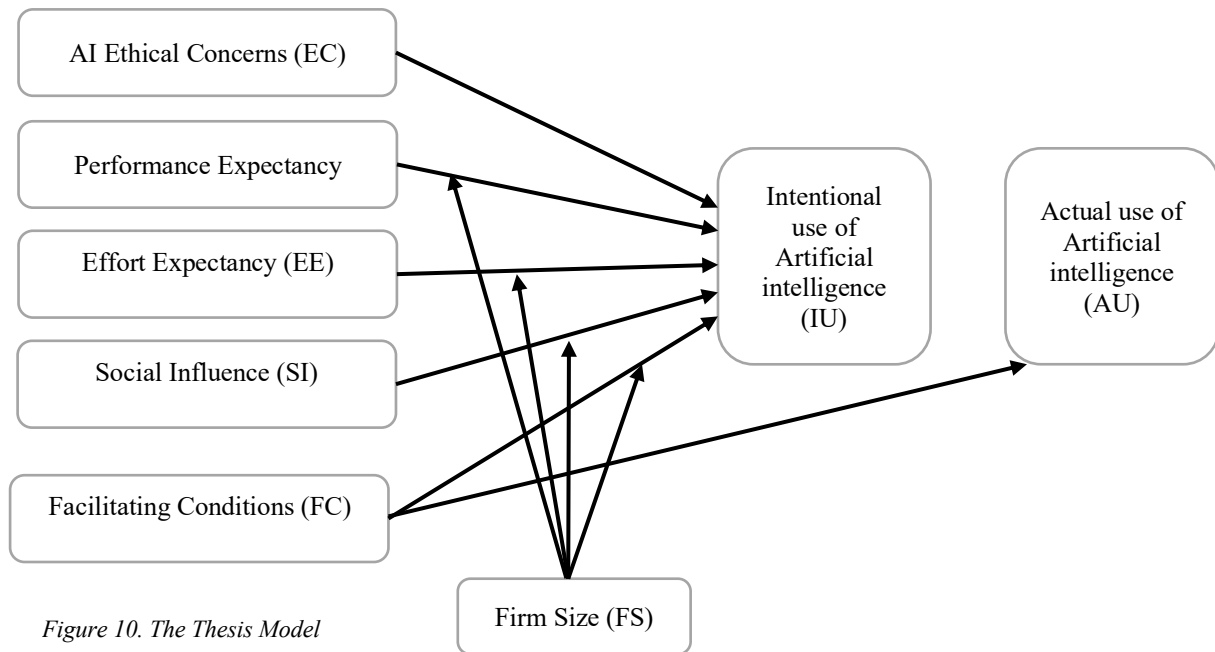


Figure 10. The Thesis Model

4.4.1 Performance Expectancy

The construct performance expectancy used in this thesis is defined as the degree to which an external auditor believes that using artificial intelligence will enhance audit job performance. This improvement refers to any advantages inherited from the acceptance of artificial intelligence, including the usefulness of artificial intelligence in the work of the external auditor, the effectiveness of artificial intelligence in accomplishing audit tasks, and the productivity boom as a result of artificial intelligence use. Ebimobowei et al. (2013) studied factors that influence the decision of auditors when implementing CAATs in audit engagements in Nigeria. They determined that performance expectancy has the most influence on the adoption of technologies. Handoko et al. (2018) examined factors that affect the acceptance of CAATs in the audit environment. Their results indicated that performance

expectancy plays a significant role in the behavioral intention of auditors when adopting CAATs. Recently, Pedrosa et al. (2019) surveyed 100 statutory auditors in a European Country to identify the adoption determinants of CAATs. Their findings signified that the perceived usefulness (i.e., the performance expectancy) is one of the main drivers of the adoption and use of CAATs. Therefore, the author states that an external auditor's intention to adopt artificial intelligence increases as his performance expectancy rises. It is expected that:

H_{1a}: External auditor's perceived performance expectancy positively affects intention to use artificial intelligence.

To increase an auditor's perceived performance expectancy, artificial intelligence has to be suitable for auditing tasks. Goodhue and Thompson (1995) state that technology is more likely to be employed if it performs all (or most) of its intended tasks. For example, when using visual recognition technology to count inventories, it must be able to differentiate between different objects. Moreover, when natural language processing is used to analyse annual reports, it has to separate fraudulent annual reports from nonfraudulent ones effectively.

Bertomeu et al. (2021) state that machine learning provides empirical techniques to audits via accounting datasets with numerous variables and scant prior knowledge of functional forms. Arguably, large corporations have more transitions and complicated data than relatively small corporations. Thus, it is valid to say auditors of large clients are more likely to perceive higher performance expectancy of artificial intelligence than those who audit relatively small clients.

Moreover, Issa et al. (2016) note that visual recognition technology enables auditors to recognise the contents of photographs automatically and to classify them into predefined logical classes. While visual recognition technology may perform efficiently for inventories that include large objects (such as cars), it might struggle to identify objects in more complicated cases, such as inventories that include small and precious objects. Hence, the

client's characteristics influence the application of artificial intelligence. For example, a large client with enormous warehouses, open-air inventories, hard-to-reach assets, or vast and sprawling farms may motivate auditors to use visual recognition technology. Curtis and Payne (2008) note that the size of the client plays a significant role in the auditors' decision to use new technology.

Larger clients tend to hire Big Four audit firms for their high level of expertise (Francis and Wilson, 1988; Mark and David, 1990). The nature of the large client's environment may require audit firms to develop or adopt new technology. Hence, it is expected that auditors who work at large audit firms perceive artificial intelligence tools to be more valuable than auditors at medium- and small-sized audit firms. Janvrin et al. (2008) state that auditors working at the Big Four auditing firms were more likely to utilise technology in audit testing compared to those working at other audit firms. Hence, this thesis hypothesises that:

H_{1b}: The size of the audit firm will moderate the influence of performance expectancy on the intention to use artificial intelligence, such that the effect will be stronger for auditors who work at large audit firms.

4.4.2 Effort Expectancy

The construct effort expectancy is defined in this thesis as the effort that an auditor perceives he or she will make in order to properly use artificial intelligence in audit engagements. Thus, this perceived effort will be affected by the requirements and complexities associated with the use of artificial intelligence, including the financial cost of using artificial intelligence, the clearness and understandability associated with the interaction with artificial intelligence, the time needed to become skilful at using artificial intelligence, the difficulty associated with the use of artificial intelligence, and the learning processes relating to operating artificial intelligence. To decrease effort expectancy, the accessibility of artificial intelligence and the interactions with it are required to be straightforward. Loraas and Diaz (2011) claim

that, since less complicated technologies are easier to learn, potential users have a lower chance of failure when trying to understand them. Moreover, Dowling and Leech (2014) state that the audit system's flexibility encouraged auditors to apply and expand their knowledge because they had to take responsibility for how they used the system throughout the audit engagements.

Al-Gahtani et al. (2007) examined the factors that influence the acceptance and use of desktop computers application in workplaces within Saudi Arabia. Their results do not suggest any impact made by effort expectancy on the acceptance and use of desktop computer applications in the workplace. In the context of an audit, Handoko et al. (2018) supported the results of Al-Gahtani et al. (2007); they state that effort expectancy does not significantly influence the intention of auditors to use technology. In contrast, recent study by Pedrosa et al. (2019) established that effort expectancy is one of the main drivers of the acceptance of the technology.

To explain these differences, Pedrosa et al. (2019) state that perceived ease of use had more influence on the adoption of technology when advanced technology features are exercised, since such features are more intricate than basic features. Indeed, Alles (2015) notes that the proper usage of artificial intelligence tools and Big Data involves more than just gathering and analysing vast amounts of data; it also requires a knowledge of when and how to use the data to inform critical decisions. Moreover, Shaikh (2016) states that the user of the advanced deep learning programmes must also be familiar with the fundamentals of math (particularly calculus, probability, and linear algebra), statistics, and machine learning. Moreover, the use of artificial intelligence might necessitate more advanced programming abilities, such as Python and C++.

Since artificial intelligence is a new smart technology in the audit profession, it is likely that an external auditor's intention to adopt artificial intelligence decreases if he or she

perceives increased difficulties when using artificial intelligence. Hence, this thesis hypothesises that:

H_{2a}: Auditor's effort expectancy negatively affects intention to use artificial intelligence.

Appelbaum et al. (2017) comment upon the use of automation with Big Data by claiming that in the audit market, where prices are competitive, it leaves little room for more analytics, even if they provide a stronger guarantee of accurate depiction. The high costs of advanced technology are a major obstacle to its use in the audit profession. Meredith et al. (2020) propose that addressing the issue of technology costs at the organisational level should involve incorporating IT specialists into audit teams, enhancing staff training on decision support technology, and extending the time frames for budget evaluation in audits to alleviate short-term concerns about the costs of new technology.

A report prepared by the Chartered Professional Accountants of Canada (CPA Canada) states that audit firms might need to make changes in their multidisciplinary teams to enable the inclusion of specialists with additional technical expertise that use advanced analytics, automation, and artificial intelligence tools (AICPA 2020). Moreover, training courses are effective tools for introducing new technology into the workplace, and a well-prepared course will undoubtedly assist auditors in the process of learning the new technology. Indeed, Curtis and Payne (2008) mention that training auditors to use new technology is one way to facilitate the process of accepting technology.

Chaney et al. (2004) note that larger audit firms are assisting their auditors by investing more money into IT, training, and facilities. Dagilienė and Klovienė (2019) state that, due to a lack of qualified staff and limited technology capabilities, small audit firms might be unable to use big data analytics for their clients. Thus, it is anticipated that large audit firms will have a

professional IT department specialised in modern technologies, which reduces auditors perceived difficulty in using artificial intelligence. Therefore, this thesis hypothesises that:

H_{2b}: Firm size will moderate the influence of effort expectancy on the intention to use artificial intelligence, such that the effect will be less for auditors who work at large audit firms.

4.4.3 Social Influence

For this thesis, the construct social influence is defined as the degree to which an external auditor perceives that important other people (for example, superiors in their audit firm) believe that he or she should use artificial intelligence. Social influence refers to any impact originating from society, including people who are important to the auditor, the senior management of the firm, colleagues who work with the auditor, and their clients. Almutairi (2008) examined factors that impact the employees' decision to use information system in Kuwaiti ministries. their results state that social influence did not impact information system usage. Alshehri et al. (2012) studied factors affecting the acceptance of e-government services in the KSA by employing the UTAUT and discovered that social influence had no significant impact on the user behaviour in accepting e-government services. Inconsistent with these studies, Dulle and Minishi-Majanja (2011) investigated the determinants of the acceptance and usage of open access within public universities in Tanzania and found that social influence significantly affected researchers' actual use of open access. The difference in the results of the first two studies from the latter study may indicate that people in Cooperation Council countries do not show influence of society on their decision to use technology.

In the context of auditing, previous research (Janvrin et al., 2008; Handoko et al., 2018; Pedrosa et al., 2019) found that social influence had no significant impact on the acceptance of CAATs. Pedrosa et al. (2019) express that social influence is not a direct determinant of the intention to use CAATs. In contrast to these previous studies, Ramen et al. (2015) determined

that the decision to adopt CAATs is positively impacted by social influence. When dealing with artificial intelligence, the author expects that society would influence the intention to use it. An external auditor's intention to use artificial intelligence escalates as the degree of social influence increases. The social influence that affects the auditors' decision may originate from an external environment (i.e., clients, competitors, and regulatory bodies) or the organisation (i.e., peers and high-level management).

Rosli et al. (2012) anticipate that both competitive pressure and encouragement from professional accounting bodies would motivate auditors to adopt new technology. High competitiveness in the audit profession may encourage auditors to use artificial intelligence because of its ability to increase competitive advantages by reducing costs, such as time wastage. Curtis and Payne (2008) state that there is a strong possibility that the auditors-in-charge would choose to use software, such as Excel, over manual approaches if their superior preferred technology. In highly hierarchical organisations such as audit firms, it is anticipated that individuals consider the attitudes of those who have evaluative authority concerning their decisions. Therefore, this thesis hypothesises that:

H_{3a}: Social influence positively impacts an external auditor's intention to use artificial intelligence.

Curtis and Payne (2008) state that the auditor's decision to adopt technology or software is influenced by encouragement from high-level management and co-workers. This assertion was verified by Pedrosa et al. (2019) in a recent study. Pedrosa et al. (2019) found that the number of auditors in a firm impacts social influence. An audit firm with more auditors will have a greater social influence than those with fewer auditors. It can be predicted that large audit firms have more auditors than medium- and small-sized audit firms. Therefore, this thesis hypothesises that:

H3b: The size of the audit firm will moderate the influence of social influence on the intention to use artificial intelligence, such that the effect of social influence will be stronger for auditors who work at large audit firms.

4.4.4 Facilitating Conditions

The construct facilitating conditions is defined in this thesis as the degree to which an external auditor believes that the regulatory and technical infrastructure of the audit firm, the clients, and the regulators exist to support his or her use of artificial intelligence. Facilitating conditions refer to all the circumstances required to facilitate the application of artificial intelligence, which includes the necessary resources and knowledge, the availability of the IT team for assistance with artificial intelligence, and the availability of audit standards and guidance that discuss the implementations of artificial intelligence.

Researchers in the acceptance of technologies area have found a significant impact of facilitating conditions in the acceptance of new technologies in the workplace. Facilitating conditions is one of the main drivers of the adoption of technology (Almutairi, 2008; Dulle and Minishi-Majanja, 2011; Alshehri et al., 2012). In the context of an audit, Janvrin et al. (2008) determined that facilitating conditions, such as organisational and technical infrastructure support, positively impact the probability that auditors will adopt CAATs. Consistent with earlier research (Janvrin et al., 2008), Ebimobowei et al. (2013), Ramen et al. (2015), Handoko et al. (2018), and Pedrosa et al. (2019) state that facilitating conditions were positively associated with the usage of computer-assisted audit tools and techniques by accounting firms.

Artificial intelligence, similar to any other technology, requires significant investments in technical infrastructure. Indeed, Issa et al. (2016) argue that the application of artificial intelligence in audits had been made possible by advancements in infrastructure speed, availability, and scale as well as by the creation of cloud computing and the advent of new data storage and processing technology, such as Apache Hadoop. Moreover, Dai and Vasarhelyi

(2017) state that blockchains may act as a basis for automatic assurance and could make the current auditing paradigm nimbler and more precise. When auditors perceive significant investments in artificial intelligence infrastructure, it will increase their motivation to accept artificial intelligence.

Moreover, the technology used by the clients and their technological infrastructure significantly affect the decisions of auditors to adopt artificial intelligence. Indeed, Alles (2015) claims that the auditors' actions are in step with the clients' movements in reality. He states that when Big Data becomes important to the operation of the businesses of the clients, auditors will have no choice but to also embrace Big Data.

Furthermore, auditors' perceptions of international auditing standards significantly influence their decisions. Salijeni et al. (2019) state that auditors would not become fully engaged with Big Data and data analytics in audits until standard setters remove what they perceive to be uncertainty around using these new tools. Indeed, Eilifsen et al. (2020) interviewed the heads of professional practice of five international public accounting firms in Norway and found that they do not use artificial intelligence. This is due to the uncertainty about how the supervisory inspection authorities evaluate and accept audit evidence generated by advanced technology. Kend and Nguyen (2020) highlight the importance of regulators in the implementation of new technology and the need for regulators to keep on track with fast-paced IT in the auditing field.

Thus, an auditor's intention to adopt artificial intelligence will grow as his or her belief that the regulatory and technical infrastructure of the audit firm, the clients, and the regulators increasingly support the use of artificial intelligence. Thus, this thesis hypothesises that:

H_{4a}: Facilitating conditions positively impact an external auditor's intention to use artificial intelligence.

Moreover, following Venkatesh et al. (2003), this thesis also has the postulate that:

H_{4b}: Facilitating conditions positively impact an external auditor's actual use of artificial intelligence.

Facilitating conditions comprise situations involving both the client and the organisation, including the resources, knowledge, training, management support, and client collaboration, that make it easier for auditors to use artificial intelligence. Munoko et al. (2020) state that the Big Four audit companies are investing considerable sums of money in developing artificial intelligence tools. Arguably, these investments will positively influence the facilitating conditions' perception of auditors who work at large audit firms. Moreover, Pedrosa (2015) states that large companies have more technical competencies that enable the efficient completion of complicated audits. Professional competence is essential for applying artificial intelligence because the system needs to be continually fed an extensive amount of data to improve its effectiveness.

Moreover, Alles (2015) highlights that if using Big Data is indeed a strategic necessity for clients, then auditors must perform the equivalent of 'auditing through' Big Data. Arguably, large clients will move towards using Big Data and artificial intelligence faster than smaller clients. Since larger clients tend to hire Big Four audit firms for their high level of expertise (Francis and Wilson, 1988; Mark and David, 1990), the perceptions of auditors working in large audit firms, regarding the suitability of the client's technology infrastructure for smart audit tools, will be higher than auditors working in smaller audit firms. Thus, this thesis hypothesis that:

H_{4c}: The size of the audit firm will moderate the influence of facilitating conditions on the intention to use artificial intelligence, such that the perception of facilitating conditions will be higher for auditors who work at large audit firms.

4.4.5 Artificial Intelligence Ethical Concerns

Artificial intelligence ethical concerns are defined as the degree to which an external auditor believes that artificial intelligence will violate the ethics of the audit profession, or the general moral principles accepted in society. Trustworthiness is an important factor in influencing human decisions in engaging with an agency or a third party. In the case of implementing artificial intelligence in audit engagements, the trust relationship between the auditors and the smart audit technology is crucial. Lehner et al. (2022) confirm the importance of this trust; they state that the decisions of artificial intelligence would not be taken seriously if humans do not trust the accounting artificial intelligence decision-making systems (i.e., a lack of institutional trust). They add that even if artificial intelligence is trusted to draw valid conclusions and take appropriate actions, distrust by humans based on rational reasons (such as the absence of ethical guidelines for artificial intelligence decisions) or irrational reasons (such as refusing to follow orders from the machine) could impair the execution of such decisions (i.e., there is a lack of organisational trust).

Auditors' perceptions of the trustworthiness of artificial intelligence may be affected by many considerations. Artificial intelligence systems are currently exhibiting a weak level of intelligence, whereby the system can execute (and probably surpass) a human in a specific task. However, these systems do not possess the fundamental traits of the human brain, such as self-awareness, self-control, self-motivation, and self-consciousness (Lu et al., 2018). In this thesis, artificial intelligence ethical concerns are added to the UTAUT to enable a study of the influence of ethical issues including the clients' confidentiality, auditors' professional scepticism, the auditability of the audit procedures, auditor independence, employment rate in the audit profession, and repurposing clients' data. These issues may play a significant role in the auditors' decision to accept artificial intelligence.

4.4.5.1 Client Confidentiality

Client confidentiality is an essential point of the audit profession. The international code of ethics states that auditors must comply with the confidentiality principles concerning information acquired during the audit process (IFAC, 2021). The literature discussing the impact of confidentiality on the acceptance of artificial intelligence in the audit profession is limited. Confidentiality and data protection problems are expected to be one of the key challenges associated with accepting artificial intelligence-based decision-making in an accounting setting (Wright and Xie, 2019; West, 2019).

When audit firms upload clients' data into artificial intelligence systems, this data needs to be protected against any security breaches and hazards of confidentiality. Lehner et al. (2022) argue that, when using artificial intelligence, the impact of leaked documents should not be underestimated when attempting to prevent fraudulent activities (e.g., Wikileaks). Thus, the author expects that the auditor's perception of the ability of artificial intelligence to preserve the confidentiality of clients will impact the decision to use artificial intelligence in the audit profession.

4.4.5.2 Auditors' Professional Scepticism

One of the fundamentals of the auditing profession is an individual auditor's professional scepticism (Hurt, 2010). The auditing profession emphasises the value of professional scepticism since the first professional standards were codified up until the present times. A statement, effective for audits of financial statements for periods ending on or after December 15, 1997, in auditing Standards No. 82, states 'due professional care requires the auditor to exercise professional scepticism (PCAOB, 1972). Despite the undoubted benefits of artificial intelligence in audits (Seethamraju and Hecimovic, 2022; Gepp et al., 2018), artificial intelligence may negatively affect the multiple characteristics of professional scepticism. Indeed, Westermann et al. (2015) conducted interviews with 30 audit partners and concluded

that although IT has enhanced the efficiency and effectiveness of audits, it may also impede auditors' capacity to develop critical thinking skills, problem-solving abilities, and professional scepticism.

As users become more accustomed to software, they become desensitised and fall into habitual patterns of behaviour, which could potentially cause them to override their natural instincts (Goddard et al., 2012; Lehner et al., 2022). Moreover, Seow (2011) states that long-term usage of decision aids could cause the auditor to primarily concentrate on problems identified by the system and ignore other aspects or issues not detected by the system. Thus, the author expects that the auditor's perception of the negative impact of artificial intelligence in his professional scepticism will have an impact on the decision to use artificial intelligence in the audit profession.

4.4.5.3 Auditability of The Audit Procedures

The audit process is overseen by professional regulatory bodies, as well as senior management of the audit firm. This oversight is stipulated by the auditing standards, which hold the auditor responsible for failures in the auditing process. This situation highlights the necessity for transparent, explainable artificial intelligence decision-making that enables algorithm auditability (Munoko et al., 2020). Auditor must be transparent with regard to the tools they use to reach the audit opinion and at the same time able to explain the logic behind the audit opinion.

Moreover, in the European Union, the General Data Protection Regulation (GDPR) regulates the use of artificial intelligence. This is because Article 22 of the GDPR grants individuals a right to ask the user of artificial intelligence decision aids to review the decision-making process to determine whether or not there are systematic errors. This places a legal obligation on firms to have the ability to explain the steps of decision-making, which requires the auditability of AI-based decisions (Lehner et al., 2022). Thus, the auditors' perception of

their ability to explain artificial intelligence-based decisions may play an important role in accepting artificial intelligence technology in the audit environment. Therefore, the author expects that the auditor's perception of traceability and auditability of artificial intelligence decisions will impact the decision to use artificial intelligence in the audit profession.

4.4.5.4 Auditor Independence

Maintaining independence is one of the most important elements in audits; it enables the opinions of external auditors to be free of impurities that may affect their credibility. Auditors are required, by the international code of ethics, to exhibit 'Independence in appearance – the avoidance of facts and circumstances that are so significant that a reasonable and informed third party would be likely to conclude that a firm's or an assurance team member's integrity, objectivity, or professional scepticism has been compromised' (IFAC, 2021). Even though artificial intelligence and big data analysis provide extensive opportunities for audit firms, the legislation and the rules of ethics that regulate how auditors exercise their profession in total independence must be considered (Manita et al., 2020). The use of advanced audit technology must not impair the auditors' feeling of independence.

Regulatory bodies have raised concerns about the possibility of external auditors violating independence requirements when utilising artificial intelligence in audit engagements. They caution that 'the external auditor would need to avoid taking management responsibility in these areas but maintain a strictly advisory role, providing advice or recommendations to the audit client' (ACCA, 2017). Thus, the author expects that auditors' perception of harm caused by artificial intelligence on auditors' independence will influence their acceptance of artificial intelligence.

4.4.5.5 Workforce Substitution

Business automation aligns with many benefits for institutions such as cost cutting, productivity boost, safety, and quality. However, automation and technological development

evoked several ethical issues, such as labour rights and social inequalities (Postan and Habakkuk, 1966). As firms in all industries become more reliant on machines, many predict that the evolution of artificial intelligence will dangerously affect workers, economies, and nations (Autor, 2015; Executive Office of the President of the United States of America, 2016). One ethical issue that arises from accepting artificial intelligence systems is the potential replacement of humans by artificial intelligence in the labour market (Farisco et al., 2020). Munoko et al. (2020) write that autonomous artificial intelligence affects the audit profession and society due to the loss of specific kinds of jobs. Frey and Osborne (2017) anticipate that, within two decades, 47% of jobs in the USA would be automated, meaning a high percentage of employees may lose their jobs. This high rate of substitution of human labour forces by machines may have a significant economic impact in the long run.

Munoko et al. (2020) state that self-governing artificial intelligence systems could be applied to supplant the human workforce in the audit environment, which may drive the audit industry into an ‘invisible workforce’. Artificial intelligence systems, at the first stage, substitute some employee tasks, but future technological advances mean that such systems may replace the entire human workforce and, thus, dominate all the required tasks (Huang and Rust, 2018). EY, one of the Big Four audit firms, published a report entitled ‘As we say robot, will our children say colleague?’ (Ernst & Young, 2016). Furthermore, The results of Fedyk et al. (2022) show that artificial intelligence ultimately displaces human auditors, although the effect on labour takes several years to materialise. Therefore, auditors’ perception of the negative impact of artificial intelligence on the workforce may cause objections among auditors about accepting and adopting artificial intelligence.

4.4.5.6 Retrieval and Repurposing of Client Data

When developing artificial intelligence systems for auditing, large datasets are required to train a more authentic, accurate, and effective artificial intelligence algorithm. However, this

may cause a violation of privacy, confidentiality, and data protection. The training process is performed continuously so that the ability and accuracy of the system's algorithms improve with an increase in the amount of data fed into the system. This situation creates a concern: is this client data repurposing, i.e., the utilisation of client data beyond what was intended when the data were generated (Munoko et al., 2020). Here an important question arises. Is using confidential clients' data to train artificial intelligence systems ethically acceptable in the auditing profession?

The collection of Big Data by artificial intelligence systems may be subject to retrieval and reused for purposes other than the purpose for which it was collected, such as for the purpose of consulting and financial services. The retrieval of the client data may be performed by the auditing company or by a third party if the data is stored in the databases of other companies. Thus, the author expects that the auditors' perception of the risk of reusing client data for other purposes may hinder the acceptance of artificial intelligence in the audit profession.

4.4.5.7 Computation Complexity

Nowadays, artificial intelligence systems are outstanding (Jung et al., 2021) because they can solve complex and compound decision problems faster than a human could possibly do. However, these artificial intelligence systems operate via algorithms that may develop and include highly sophisticated operations, which makes them difficult to understand even by the developers of these algorithms (Preece, 2018). The ambiguity in the processes of artificial intelligence renders it difficult to ascertain which inputs were beholden in the decision-making process and when the outputs are faulty (Association for Computing Machinery (ACM) US Public Policy Council, 2017). The lack of transparency in artificial intelligence may influence the relationship between audit firms and their clients; thus, it could push the auditors not to accept the technology. Munoko et al. (2020) write that the complexity of artificial intelligence

systems could lead to a deficiency of transparency, which is a ‘precondition for public trust and confidence’. The absence of transparency regarding technology can jeopardise the trust and interest in it (Wright, 2011).

As discussed previously, ethical concerns may affect the implementation of artificial intelligence systems. Thus, this thesis hypothesises that:

H₅: Ethical concerns negatively impact an external auditor’s intention to use artificial intelligence.

4.5 Conclusion

This chapter provided an insight into the theoretical framework for this thesis. In the first part of this chapter, the author presented the theory used in this thesis, UTAUT, and discussed the reasons that made him perceived that UTAUT is the most appropriate theory that answers the questions of the thesis and serves its objectives. Next, the author reviewed the studies that used UTAUT and explained the constructs of the theory, including the definition of each construct and the dimensions it covers.

This chapter, also, discussed the modification that the author made on UTAUT by adding a construct (i.e., ethical concerns) and a moderator (i.e., firm size). Finally, this chapter discussed the development of the thesis' hypotheses. In the next chapter, research design and methodology employed in this thesis is explained and justified.

Chapter 5: Research Design and Methodology

This chapter aims to explain the method and strategy for collecting and analysing the data necessary for arriving at the actual contribution that this thesis aims for and to answer the research questions and achieve its objectives. Moreover, this chapter presents the academic justification and viewpoint of the philosophy used to support and underpin the research. Also, the chapter explains the logic behind the instruments used to collect the thesis data, and it also addresses the reliability and validity of the study. Figure (11) shows the journey of the methodology chapter.

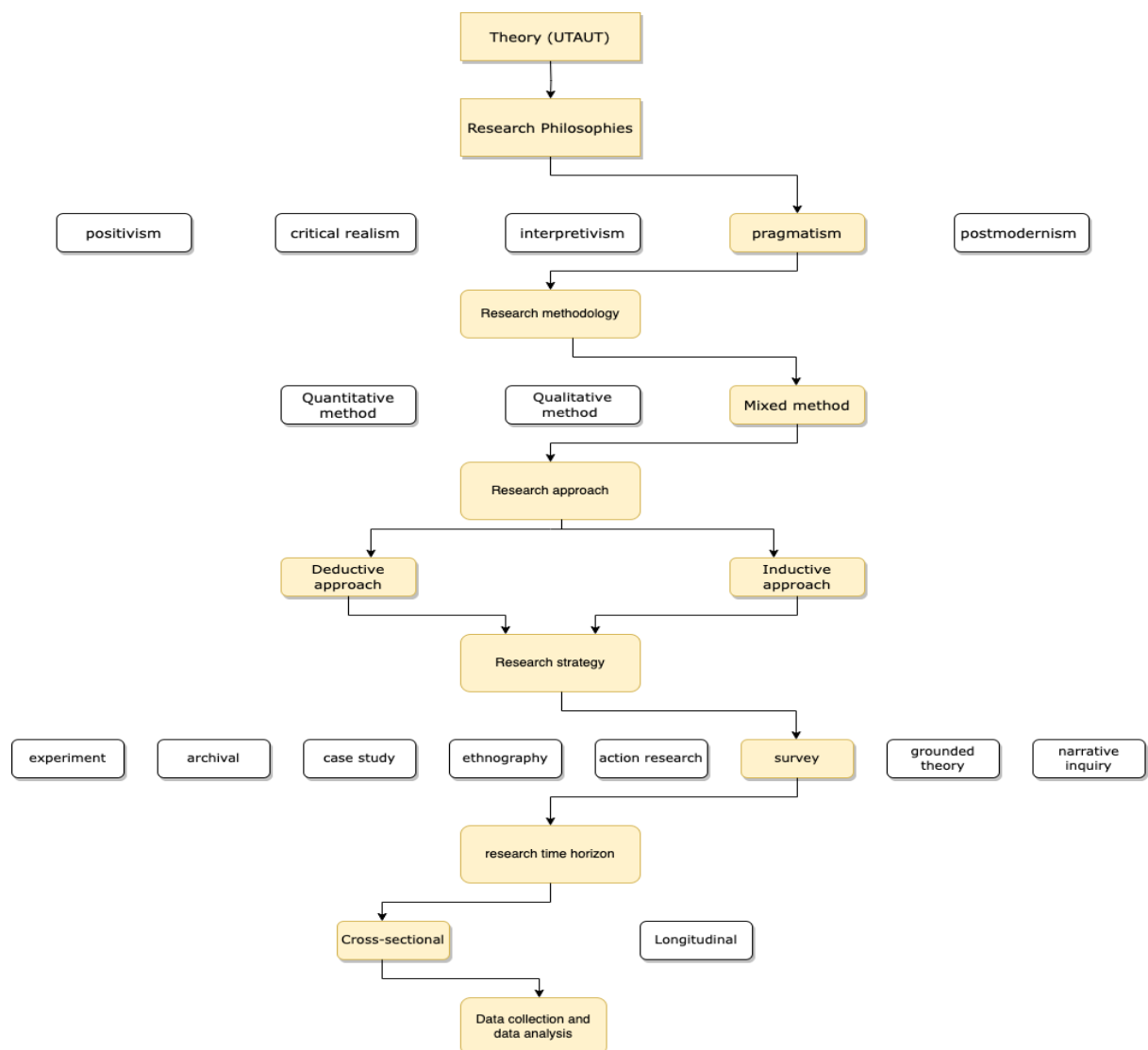


Figure 11. Flowchart for the research design and methodology.

5.1 Research Methodology and Methods

The research methodology is known to differ significantly from one discipline to another. In business and management research, the methodology has unique characteristics that may differ slightly from one specialty to another within the discipline of business and management. To unify and cohere the methodology chapter, the author intends to use what Saunders et al. (2019) call the 'research onion' (Figure 12) to determine the research philosophy, approach, strategy, choice, time horizons, and techniques and procedures.

Research methodology and research method are distinct and are not interchangeable. Ghauri et al. (2020) define research methodology as the overall strategy of selection that allows a researcher to address the research questions and achieve the research objectives most properly within given constraints. Therefore, the research methodology is not related to only one phase of the research rather it is related to the whole investigation. Creswell (2018) describes research methodology as the programme that directs the researchers through their research journey. On the other hand, research methods refer to all the tools and techniques used to perform research operations, whether it is data collection or data analysis (Kothari, 2004). In addition, Collis and Hussey (2013) state that methods refer to tools for collecting or analysing the data. Therefore, it can be said that the method concerns one phase of the research, and there may be more than one procedure in the form of a method for data analysis and one for collecting data. As for the methodology, the research has one such approach that systematically guides the researcher through the procedures of the research.

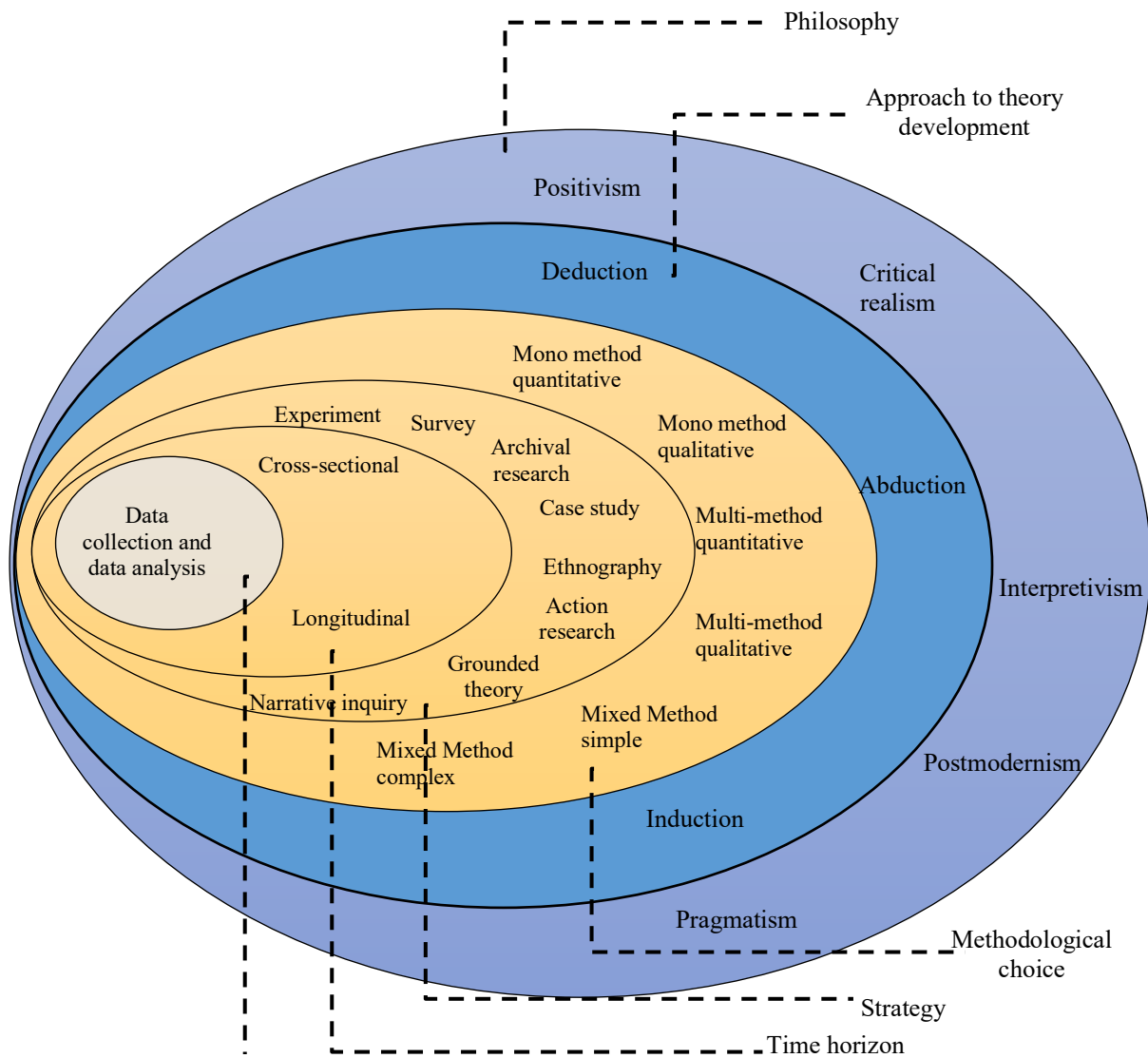


Figure 12. The 'research onion' (Saunders et al., 2019).

5.2 Research Philosophy

According to Saunders et al. (2019), research philosophy is a method of ideologies and assumptions about the evolution of knowledge. Every study has assumptions, which include the realities encountered by the research (i.e., the ontological assumptions), people's knowledge (epistemological assumptions), and the researcher's morals that shape the research (axiological assumptions). In business research, there many essential philosophies such as positivism, critical realism, interpretivism, postmodernism, and pragmatism. Each of these philosophies has a different way of approaching the realities that encounter the study and peoples' knowledge of the phenomena, alongside the researcher's morals that shape the study.

In this thesis, due to their relevance to the context of this study, the author will discuss only three philosophies that appear under the umbrella term research philosophy.

5.2.1 Positivism

Saunders et al. (2019, p. 144) define positivism as ‘the philosophical stance of the natural scientist and entails working with an observable social reality to produce law-like generalisations’. Moreover, Walliman (2011) states that positivism is an objective approach that tests theories and hypotheses to create causes and effects laws. In this case, the author examines a specific population sample using scientific instruments to study a problem or an idea under exploration and then generalises the results to the rest of the population. Thus, researchers who follow the positivist thought school start with theories and follow that with hypotheses. They then test the hypotheses on a representative population sample to generalise the results to the rest of the population. Orlikowski and Baroudi (1991) propose that a research paper can be categorized as positivist if it involves testing hypotheses, quantifying variables, providing formal assumptions, and drawing inferences about a phenomenon from a sample to a particular population.

5.2.2 Interpretivism

Saunders et al. (2019) define interpretivism as a philosophy that differentiates between physical phenomena and humans and their social world. Moreover, Matthews and Ross (2010, p. 28) define interpretivism as ‘an epistemological position that prioritises people’s subjective interpretations and understandings of social phenomena and their actions.’ Interpreters argue that there is a massive difference between studying physical phenomena and examining people and social phenomena.

Interpretivists have criticised positivists as trying to create definitive universal laws that fit everybody. The logic behind interpreters’ criticism of positivists is that people are not the same as physical phenomena because people have different cultural backgrounds, languages,

and histories that influence their reactions. Therefore, interpretive studies do not predetermine variables (i.e., dependent and independent ones). Instead, they concentrate on the complexity of the case and understand it from the research participants' point of view (Kaplan and Maxwell 2005); this is the challenge for interpretivists, as stated by Saunders et al. (2019). Hence, it can be said that the interpretivists do not start the research with a theory. Rather, they begin to study the case, deconstruct its complexity, and then provide a base theory for the studied situation.

5.2.3 Pragmatism

Saunders et al. (2019) define pragmatism as the philosophical approach that reconciles precise and rigid knowledge and various contextualised experience, positivism and interpretivism, and objectivism and subjectivism. Moreover, Kelemen and Rumens (2008, p. 41) state that 'pragmatism asserts that concepts are only relevant in as much as they are relevant for action'. Hence, it can be said that pragmatists consider that there is no single method or view that can interpret the world; rather, there are multiple methods that might explain numerous realities. It is the researcher's duty to combine these methods to serve the research's objectives. Indeed, Creswell (2018) states that pragmatic philosophy is applied when engaging both quantitative and qualitative methods in a single research procedure.

In this thesis, the author adopts the position of pragmatism. Namely, there is no single method used to probe and understand the aspects that influence auditors' intent when deciding to use artificial intelligence in audit engagements. The adoption of the pragmatists' point of view is not an escape from the challenge of understanding other philosophies, but rather its ability to explain the undertaken research.

5.3 Philosophical Perspective

5.3.1 Overview on Ontology

Ontology is one of the philosophical perspectives that relate to the research on artificial intelligence and auditing. For instance, the study likens humans to new technologies, such as

computers and robots, where both embody existence. Based on the concept of reality as explained in metaphysics, artificial intelligence is somewhat similar to the human mind because machines that apply the phenomenon can feed themselves via an extensive database, and sophisticated algorithms can perform functions based on need without human intervention. For instance, in Tesla cars, self-driving algorithms can recognise shapes or objects through cameras and sensors, enabling machines through deep learning to resemble and sometimes surpass human brain functioning.

Ding et al. (2016) describe ontology as the prescribed idea of creating knowledge in a particular field. This research seeks to identify determinants that influence enabling artificial intelligence to engage in daunting accounting and auditing tasks through the use of unstructured data, as opposed to previous technologies where information had to be organised in a particular way to facilitate its use. A good example is how the standard Structured Query Language (SQL) databases and datasheets in Microsoft Excel operate compared to contemporary systems such as IBM WATSON. The use of ontology helps to understand aspects related to human behaviour and perception toward smart machines and the impact of these machines on people in the future.

The use of ontology in this research also helps to illustrate machines as conscious beings, with the ability to perform analytics tasks that equate to the functioning of a human brain. Incorporating ontological concepts in the research is vital because it helps to acknowledge the significance of philosophy in understanding scientific formulations. Therefore, the phenomenon helps to understand artificial intelligence as a reality, as well as the determinants that influence the intention to use artificial intelligence in auditing engagements.

5.3.2 Pragmatist Research Philosophy and Ontology

While ontology explains the existence of artificial intelligence technologies that help in accounting and auditing processes, pragmatist philosophy underpins several research methods to answer study questions. The role of ontology in the study is to aid in comprehending the

artificial intelligence reality, as argued by Raddon (2010), which facilitates and coordinates the processes of applying new technologies in an audit. On the other hand, pragmatism justifies using two methods since they make it possible to understand the aspects of artificial intelligence acceptance in the audit profession. This includes the degree of difficulty in dealing with artificial intelligence in audit engagements, the influence of the surrounding environment on the use of artificial intelligence, the effect of facilitating conditions on the use of artificial intelligence, and the impact of ethical concerns related to the use of artificial intelligence in auditing. Moon et al. (2016) argue that a researcher's philosophical position facilitates the acquisition of knowledge and the comprehension of reality.

The research combines both questionnaires and interviews to understand the determinants that influence the intention to enable artificial intelligence machine use in auditing procedures, with the latter providing a glimpse into the explanation of the impact of the determinants and how to mitigate this impact. The philosophy is demonstrated in the study through the distribution of questionnaires to a large group of audit firms' members, with the aim to cover all sizes of audit firms. Collecting a large group of respondents helps generalise the results of the study; it enables the making of reliable inferences since the size of the firm may influence the behaviour of the auditors. However, in the questionnaire, it is impossible to test the thesis model constructs using the term artificial intelligence since there is more than one type of artificial intelligence technology. This will lead to confusion and misunderstanding among the questionnaire participants. The questions of the questionnaire must be interpreted in the same way by all the respondents (Robson and McCartan, 2016). Thus, in the questionnaire, the author will use one form of artificial intelligence known as visual recognition technology to test the study model. This increases the confidence that all respondents have the same understanding of the items and the questions posed in the questionnaire.

Moreover, the interview of several auditors enriches the questionnaire results by providing more explanations and allows for deep diggings that discover more details; it ensures that the research questions are answered only after exploring several ideas regarding the topic. The data collected for the interview is not restricted to visual recognition technology because the questions posed in the interview were about artificial intelligence implementation in the audit profession in general, which includes deep and machine learning and semantics alongside various automation thresholds and artificial intelligence systems. Hence, choosing pragmatist philosophy and the ontological method that pragmatists use to observe the world is meant to recognise the existence of artificial intelligence and justify applying multiple research methods to facilitate a more reliable study outcome.

5.3.3 Pros of The Ontological Pragmatist Philosophy

Integrating the ontological pragmatist philosophy has several advantages for the research on artificial intelligence and auditing. Firstly, ontology encourages the recognition of artificial intelligence and its various guises, together with its support for machine and deep learning that can be equated to human conscience. Tsang (2017) posits that ontology categorises and associates the aspects that makeup reality, which helps in the artificial intelligence study by acknowledging the ability of computers to reason and take instructions. Similarly, the pragmatist philosophy supports the attainment of dependable deductions concerning the research question by encouraging the scrutiny of what determinants influence the intention to implement artificial intelligence works for an auditing context. This is achieved by analysing surveys collected from interviewing people in the auditing and accounting realm.

Tsang (2017) argues that pragmatism focuses on ‘objective reality, stressing the influence of the inner world of human experience in action.’ The statement shows the significance of involving auditing firms and employees in the study as they are better

positioned to explain the determinants of artificial intelligence acceptance. Simultaneously, the sample of interviews provides a pack of scholarly ideas and explanations on the subject.

5.3.4 Limitations of The Ontological Pragmatist Philosophy

One of the limitations of the ontological pragmatist philosophy in this thesis is that it recognises the determinants of intention to implement artificial intelligence in the auditing processes but mostly focuses on the views of auditors. For instance, the approach emphasises human experience towards artificial intelligence in auditing rather than the artificial intelligence process itself, which can provide an understanding of the various components of the technology that could revolutionise financial accounting. Thus, there is a need for research that shows how artificial intelligence procedures are structured to provide machines with the ability to perceive commands like humans and process data in multiple formats to perform audit roles.

5.3.5 Overview on Epistemology

Epistemology emphasises the aspect of knowledge, which in this case helps to understand artificial intelligence in context, together with its components, and its significance in the auditing process. Johnson and Duberley (2013) describe epistemology as the ‘study of the criteria by which we can know what does and does not constitute warranted or scientific knowledge.’ Furthermore, Al-Saadi (2014) notes that epistemology helps people to observe the world and draw logic from it. The philosophy helps in this research by providing a deeper understanding of artificial intelligence acceptance, how it operates, as well as the implementation of artificial intelligence in the auditing process (Pollock, 2017).

The study’s focus on the behaviour of auditors during the use of artificial intelligence is motivated by the perceived lack of use of this technology, which may reformulate the process of detecting misstatements and fraud in the financial statements by auditors. The approach helps to breakdown determinants that may influence the intention to implement artificial

intelligence in the audit profession, which contributes to answering the research questions. For example, epistemology applies in the decision to poll the opinions of people who work in the field of auditing, whether through interviews or questionnaires, to provide a glimpse of what elements affect the intention to use artificial intelligence in audit procedures.

This philosophical model also assists in understanding how people in the auditing field perceive artificial intelligence technologies and how it works. Moreover, it seeks to establish whether their knowledge about the phenomenon is learned or assumed. The development of the Likert scale is also based on epistemological grounds, since it is correlated to the different categories of artificial intelligence acceptance factors established from the literature review of various studies on the technology's use in an audit. Furthermore, epistemology ensures that the conclusions made from the study employ valid conceptions that answer the research questions comprehensively.

5.3.6 Pragmatist Research Philosophy and Epistemology

In this research, pragmatism underpins epistemology by ensuring that the inference regarding artificial intelligence knowledge, process, and applicability in auditing and other accounting fields is more valid after utilising more than one method to collect data. First, the research is only feasible after the research's hypotheses are not only tested by one research method, such as a questionnaire, but also the results of the first method need to be analysed and explained by another method, such as an interview. The questionnaire is completed after a careful selection, where all participants must have worked in the field of auditing and understand audit processes. Secondly, interviewing experts in auditing, after analysing the results of the questionnaires, will give the results of the first method another dimension by providing a deep explanation and interpretation of the results. The interview participants must again have adequate experience in the field of audit.

Using the two research methodologies, which include questionnaires and interviews, provides different avenues through which knowledge may be attained from a pragmatic outlook (Morgan, 2014). Rysiew (2016) claims that epistemology requires some input, such as an exploration effort, to actualise it. Consequently, it is difficult to attain the facts needed to justify a phenomenon, such as determinants influencing the implementation of artificial intelligence in the auditing profession, without considering conceptions from different sources. This implies that the pragmatist research philosophy forms the basis for the study about artificial intelligence in auditing, from an epistemological perspective.

The data collected for the interview is not restricted to the visual recognition technology since the questions posed in the interview were about the artificial intelligence implementation in the audit profession, which include deep and machine learning and semantics, as well as various automation thresholds and artificial intelligence systems. Thrall et al. (2018) argue that artificial intelligence technologies have enhanced computing capabilities and entail deep-learning algorithms. All these aspects provide a platform for the acquisition of viable knowledge of artificial intelligence's applicability in auditing and financial accounting in general. Therefore, it would be difficult to validate the facts where the intention to use artificial intelligence in the audit procedures is influenced by specific determinants, which would be challenging without considering the pragmatist research philosophy.

5.3.7 Pros of The Epistemological Pragmatist Research Philosophy

The epistemological pragmatist research philosophy is beneficial because it supports the use of different data sources to assemble facts that validate knowledge in various aspects. For instance, it would be impractical to examine the research model using the visual recognition technology questionnaire and disregard the other forms of artificial intelligence. Moreover, pragmatism underpins the use of several research methods and sources to provide

comprehensive data (Martela, 2015), while epistemology emphasises the use of facts to validate knowledge.

Epistemology also facilitates the formulation of proper inferences because it upholds a resolute claim on the importance of effective analysis of the collected data to provide useful answers to the research questions (Grimm et al., 2016). It implies that the breakdown of the artificial intelligence study results should be careful to avoid the prospect of distorting facts to make unreliable conclusions. Thus, an epistemological pragmatist research philosophy would help to improve the investigation of artificial intelligence acceptance in auditing by testing the study model using the visual recognition technology questionnaire, then conducting a detailed interview with a group of respondents to enrich the questionnaire results by providing more explanation and digging deeper to obtain additional details about artificial intelligence acceptance.

5.3.8 Limitations of The Epistemological Pragmatist Research Philosophy

This approach emphasises collecting data through multiple research methods to improve the prospect of obtaining accurate information for the analysis. However, it is usually challenging to validate people's knowledge about abstract issues, such as the ability of artificial intelligence-powered machines to perform auditing processes, because it depends on perceptions and beliefs. Therefore, the deductions drawn from the research may provide conflicting answers to the research questions because there are numerous ways of knowing determinants that affect the intention to use artificial intelligence, and the model only relies on individuals' ability to justify what they know.

5.4 Research Approach

5.4.1 Deductive Research

Walliman (2011) defines deductive research as a research approach that starts with general statements and, through logical arguments, ends with a particular conclusion. The

deductive research approach is typically associated with the quantitative research methodology. The process of the deductive approach is linear, in which one step follows the other (Bell et al., 2018). Deductive research begins with a theory, or more than one theory, which is followed by developing hypotheses and eventually testing these hypotheses through observation and experiment.

In the case of this thesis, the hypotheses have been developed through the guidance of the UTAUT theory, and later these hypotheses will be tested by a survey (i.e., visual recognition technology questioners). The findings will help to conduct the new survey (i.e., semi-structured interviews) to improve the theories through an inductive research approach. Mixed methods research involves two phases of data collection, in which quantitative data is collected and analysed in the first phase, and the results are then used to build upon the second phase, the quantitative phase (Creswell, 2018). Bell et al. (2018) state that the last step of deductive research might involve induction, as one of the purposes of research is to develop a theoretical framework. The use of theory in research does not mean the perfection of the theory rather it is a general orientation to guide the researcher (Bell et al., 2018). In this thesis, the author uses the theory to guide the flow of the research and to set the boundaries of it.

5.4.2 Inductive Research

Walliman (2011) defines inductive research as an approach that begins with specific observations and ends with general conclusions. Inductive research uses observations to draw generalisable inferences and construct a theory. The inductive research approach is typically associated with a qualitative approach. The use of grounded theory in an inductive paper is often to analyse data and generate a theory (Bell et al., 2018). This thesis started with the deductive approach, where a theory was borrowed from the information management system to develop the thesis hypotheses and then tested these hypotheses using a questionnaire. Next,

this thesis used the inductive approach to obtain insights and more clarification about the deductive results.

5.5 Methodological Choice

The methodological choice is whether a researcher follows a qualitative, quantitative, or mixed methods research design. One way of distinguishing between these three methods is through data analysis. Saunders et al. (2019, p. 175) state that ‘quantitative is often used as a synonym for any data collection technique (such as a questionnaire) or data analysis procedure (such as graphs or statistics) that generates or uses numerical data, while, qualitative is often used as a synonym for any data collection technique (such as an interview) or data analysis procedure (such as categorising data) that generates or uses non-numerical data’. The mixed method is a combination of both the qualitative and quantitative design. Since the mixed method is the one used in this thesis, the author will elaborate on this method in more detail.

5.5.1 Mixed Methods Research

A mixed-methods study means integrating or incorporating both quantitative and qualitative methods into one research. Saunders et al. (2019, p. 181) define mixed methods research as ‘the branch of multiple methods research that integrates the use of quantitative and qualitative data collection techniques and analytical procedures in the same research project’. In other words, a mixed-methods study is a collection of quantitative and qualitative approaches in its most basic form, with the ambition of gaining a deeper and broader understanding of social phenomena that can be accomplished using either a quantitative or qualitative approach alone. Bryman (2007) argues that, through mix-methods, it is possible to obtain quantitative and qualitative results together to offer insights that could not otherwise be gathered.

Mixed-methods research is classified in terms of fitting decisions into a fixed mixed method and an emergent mixed method. A fixed design of mixed methods is a study in which

the decision to use qualitative and quantitative methods for the procedures of the study is planned and predetermined. In contrast, an emergent design of mixed methods is refined during the investigation (when mixed methods are required) due to problems that occur within different procedures. An emergent mixed-methods approach arises when a researcher determines that only one methodology, either quantitative or qualitative, in an ongoing study is insufficient to contribute to satisfying the findings (Creswell and Clark, 2017). In the current thesis, qualitative and quantitative approaches are planned and predetermined. The author realises that it is not practical to use the term artificial intelligence in the questionnaire since there are many forms of artificial intelligence. Therefore, he uses a visual recognition technology questionnaire to test the study model. In the second method, the term artificial intelligence is employed in a semi-structured interview to obtain in-depth results from the questionnaire.

Previous studies, such as Morgan (1998, 2013), have differentiated various types of mixed methods in terms of two issues: priority decisions and sequence decisions. The priority decision means the technique (either qualitative or quantitative) that weighs more in the principal data-gathering tool and the sequence decision means the method that exceeds the other.

Regarding the sequence decision, there are four basic mixed-methods designs, each of which serves a particular purpose (Bell et al., 2018). The first one is the convergent parallel design (Figure 13), in which investigators simultaneously collect both quantitative and qualitative data. This method enables the investigators to compare the findings of the quantitative data with the conclusions of the qualitative data (Creswell, 2018). Despite the many benefits that this method provides to the researcher, in terms of comparing the results of two different methods on one research question, it may not be accurate for some research questions to compare findings that originate from different methods. This inaccuracy happens

because of many factors, such as the variation in sample size, the difference in the type of sample, and the variation in ambient conditions.

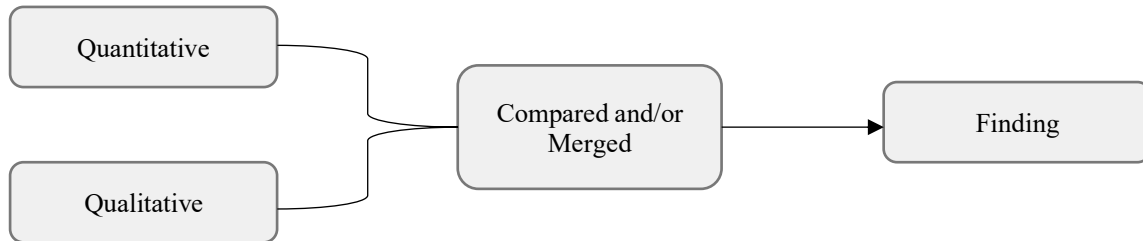


Figure 13. Representation of convergent parallel design.

The second one is exploratory sequential design (Figure 14). Unlike convergent parallel design, qualitative data in this form is collected before quantitative data. In other words, the researcher collects and analyses data that leads him or her to another stage, which is the stage of quantitative data collection. This method serves two purposes: the preparation of hypotheses (or hunches) to be tested by a quantitative method and the generalisation of qualitative findings through quantitative research (Creswell, 2018). In this type of framework, the researcher cannot prepare a quantitative data collection instrument before completing the collection and analysis of qualitative data because the instrument is entirely dependent on the results of qualitative data.

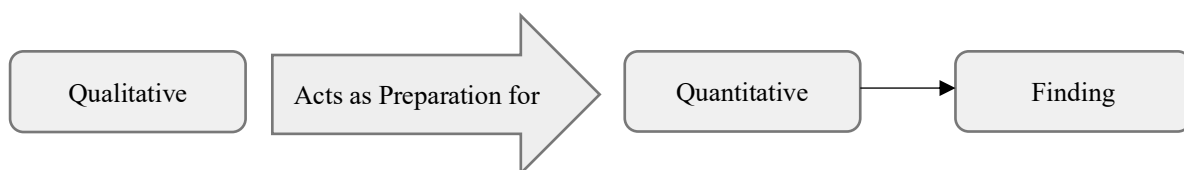


Figure 14. Representation of exploratory sequential design.

The third design is the explanatory sequential design (Figure 15). As opposed to the exploratory sequential design, quantitative data in this form is collected before the qualitative data. This design serves the purpose of explaining or elaborating the quantitative findings. The researcher initially performs quantitative research and then analyses the results. Next, through qualitative research, he builds on the findings to describe the results in more detail (Creswell,

2018). The researcher who uses this method does not aim in the second phase (i.e., the qualitative data) to collect additional data that answers his research question. Instead, he seeks to collect additional data that explains, in depth, the results he reached from the data collected in the first phase (i.e., the quantitative data).

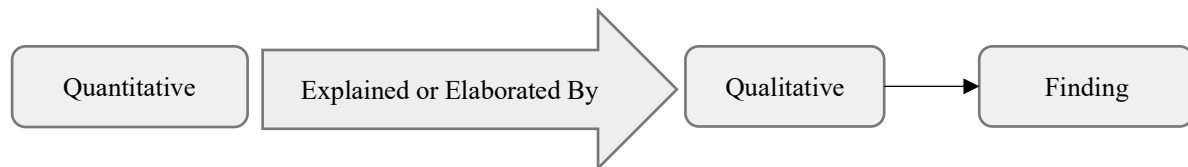


Figure 15. Representation of exploratory sequential design.

The final design is the embedded design (Figure 16). Some textbooks, such as Creswell (2018), do not mention this form of mixed methods. However, Bell, Bryman and Harley (2018) have considered this form. Unlike the previous three forms, in this case one method is embedded within the other during data collection. For example, a researcher may include some quantitative questions when conducting the interviews. The purpose of using this design is to enhance either method (either quantitative or qualitative) with the other approach.

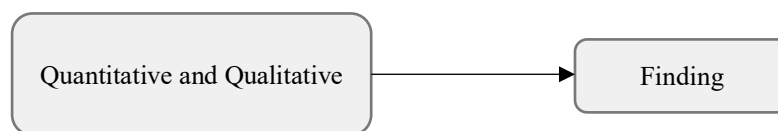


Figure 16. Representation of embedded design.

The present research adopts the mix-methods research approach and the explanatory sequential design. The author collects the quantitative data and analyses it in the first stage. In the second stage, he gathers qualitative data. The purpose of using this approach is to obtain further explanations and analyse the quantitative findings through the qualitative method.

5.5.1.1 Advantages of Using Mixed-Methods Research

Each scientific research approach (quantitative and qualitative) has its strengths and weaknesses (Saunders et al., 2019; Bell et al., 2018; Creswell, 2018). Combining the two approaches can, therefore, be a fruitful choice. For the current research, this combination may enable the author to offset the deficiencies of both methods and, at the same time, make the

areas of strength in both methods more robust. An additional benefit of mixing the two approaches, as argued by Bryman (2007), is that the combined results of the two methodologies can provide information that could not be gathered otherwise. For the current research, the author uses a questionnaire based on one form of artificial intelligence (i.e., visual recognition technology) to collect quantitative data. The purpose of the quantitative data collection is to examine the hypotheses. Next, the author uses a semi-structured interview with expert auditors to delve into the determinants that influence artificial intelligence acceptance.

When exploring a research problem, combining quantitative and qualitative approaches may enable a researcher to collect various types of data relating to different cultural components, from ideals to material objects; this is where cultural researchers have found difficulties. Hence, instead of being restricted to one form of data collection, i.e., precisely quantitative or qualitative, researchers may collect a wide variety of data using all available resources (Creswell and Clark, 2017). Indeed, Denscombe (2008) acknowledges that the application of mixed-methods research could increase data accuracy; researchers can also use the original data to improve their analysis and construction.

Mixing two research approaches (i.e., qualitative and quantitative) can improve the study's validity. Saunders et al. (2019) highlight that triangulation could help establish the quality of the research. Indeed, Scandura and Williams (2000) reviewed all the papers published over the two periods 1985-7 and 1995-7 in three top-tier American journals: the Academy of Management Journal, the Administrative Science Quarterly, and the Journal of Management. They were especially interested in tracing changing practices in the triangulation process and the use of various validity steps. The research showed that researchers are increasingly using research methods and methodological techniques that compromise triangulation in order to publish in these three top-tier general management journals.

5.5.1.2 The Rationale For The Mixed-Methods Design

The main reason for using the mixed approach is that, through the quantitative method, the author can collect quantitative data from a large, representative sample of the audit community. However, it is impractical to survey a large sample in general on artificial intelligence, as this may make the respondents' interpretations of the questions vary. For example, suppose a question in the questionnaire asked: 'I think artificial intelligence will be useful in the field of external audit'. Here, the respondents' interpretations will differ depending on which form of artificial intelligence technology the question means. Therefore, the author surveys the participants on only one form of artificial intelligence, which is visual recognition technology.

The quantitative data will be collected at the first stage and will assess the determinants that affect the individual auditors' intention when using visual recognition technology in audit engagements. In the second stage, qualitative data will be collected by interviewing a small group of the sample that participated in the questionnaire, followed by delving into the results of the questionnaire and the determinants that influence the decision of the external auditor when using artificial intelligence during audit engagements. In particular, while the questionnaire contributes solid data for the study questions, interviews help explain how the determinants influence the behavioural intention of auditors.

It can be argued that collecting quantitative data seems adequate to address the study questions. However, the nature of the questions necessitates the researcher to collect additional and more precise details that do not entirely rely on quantitative data to provide a broad overview of research questions. Furthermore, combining two research approaches may lead to an improvement in the research validity. Validity is one of the essential elements that ensure good-quality research and, thus, increase the impact of its results.

5.6 Research Strategy

Research strategy, which some authors such as Bell et al. (2018) and Creswell (2018) call research design, is the strategy that provides a framework that indicates the most appropriate method for collecting and analysing the research data. Saunders et al. (2019) clarify that there is no one research strategy inherently superior to others; rather, there is a strategy that properly enables the researcher to achieve the research objectives and answer the research questions. There are several possible research strategies to achieve the research objectives such as experiments, surveys, narrative inquiries, grounded theories, and case studies. Since survey is the optimal strategy that fits the current research's objectives and answers its questions, the author explains this strategy in more detail.

5.6.1 Survey

Bell et al. (2018, p. 59) define a survey as 'a cross-sectional design to which data collected predominantly by questionnaire or by a structured interview on more than one case (usually quite a lot more than one) and at a single point in time to collect a body of quantitative or quantifiable data in connection with two or more variables (usually many more than two), which are then examined to detect patterns of association.' Surveying is a strategy commonly used in research that attempts to study human behaviours. Due to the survey's features and ability to measure people's behaviour through certain types of questions, it is the most frequently used strategy for research studies on adopting technology.

Creswell (2018) states that survey research answers three types of questions: (i) descriptive questions, (ii) questions about the relationship between variables, and (iii) questions about the predictive relationship between variables over a period of time. Indeed, Saunders et al. (2019) state that a survey strategy answers who, what, where, how much, and how many questions. Thus, a survey is an effective strategy when gathering data about individual

preferences, private behaviours, and expectations through which the researcher seeks written or verbal responses to particular questions (Straub et al., 2004).

Since this thesis attempts to study the behaviours of a group of people towards accepting the use of artificial intelligence, the survey strategy is the most appropriate to serve the objectives of this thesis and answer its questions. Initially, the author designs the thesis questionnaire, which contains all the variables this study intends to measure, to answer the research questions of this thesis. Then, the designed questionnaire was electronically distributed to auditors working in large, medium, and small audit firms to investigate their intentional behaviours towards artificial intelligence adoption. After collecting the questionnaires, the author analysed them using SPSS and then discussed the results. After analysing and discussing the questionnaire results, the results were employed to design the semi-structured interview instruments. Such interviews explain and elaborate on the results from the questionnaires (Figure 17).

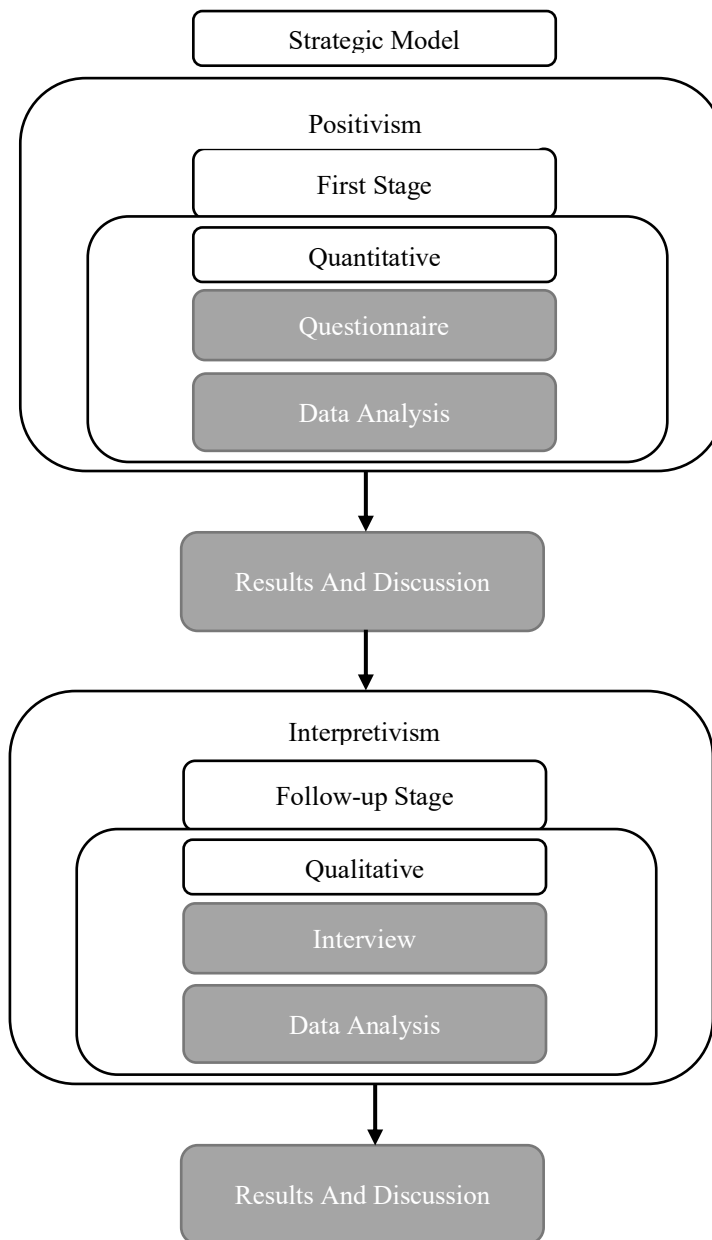


Figure 17. Strategy of this thesis based on surveys.

5.7 Research Time Horizon

During research, data collection can occur at a specific point in time (cross-sectional) or over an extended period, akin to keeping a diary (longitudinal). A cross-sectional method is often associated with surveys as it studies a particular subject at a specific time (Bell et al., 2018). Most business research uses the cross-sectional method because of the nature of business research. Moreover, more researchers are employing the cross-sectional method because of the limitation of their time. This thesis is considered a cross-sectional study.

5.8 Research Quality and Robustness

To ensure that the research is conducted at a high level of accuracy, the researcher must follow specific criteria that guarantee the quality of the study. These criteria ensure (to the reader) that the research results and the conclusion are based on a disciplined methodology. There are two prominent criteria to evaluate the quality of business and management research: reliability and validity. Since this study uses a mix-method approach for data collection, there will be a focus on the reliability and validity of both the questionnaire (quantitative) and the interview (qualitative).

Issues affecting the quality of qualitative data may originate from a lack of standardisation in processing the data (i.e., from the interviews). Saunders et al. (2019) state that the issues that affect the quality of qualitative data originate from three types of potential bias: interviewer bias, response bias, and participation bias. The concerns that influence the quality of the qualitative and quantitative data of this thesis are discussed in the following sections.

5.8.1 Reliability/Dependability

Reliability is a key characteristic of research quality in management and business research. Saunders et al. (2019) refer to reliability as the ability to replicate the study and its consistency. Bell et al. (2018, p. 46) state that ‘reliability is concerned with the question of whether the results of a study are repeatable’. Thus, for a study to be seen as reliable, the replication of the study design under the same conditions should lead to the same findings and conclusions.

When reliability is considered, a distinction must be made between two types of reliability: internal reliability and external reliability. Internal reliability refers to consistency throughout the research stages (Saunders et al., 2019). In research that uses a questionnaire to collect data, there are a variety of methods to measure internal reliability, including Cronbach’s

alpha. The latter is a measure that ensures that a subgroup of the questions in the questionnaire measures the same concept or construct for which they are intended (Tavakol and Dennick, 2011). Hence, this alpha is applied to measure the consistency of responses across a subset of the questions that are combined as a scale to measure a specified construct. Lee Cronbach developed his alpha in 1951, the most frequently used method to calculate internal consistency (Saunders et al., 2019).

Since this thesis has two data collection instruments, Cronbach's alpha is used to examine the internal consistency of the questionnaire items. However, for the qualitative part (i.e., the interview), the notion of internal reliability is not relevant in the same way as quantitative research (Bell et al., 2018). Saunders et al. (2019) state that the findings derived from qualitative data are not intended to be repeatable since they reflect reality only at the time they were collected. They mention that the increasingly robust dependability of qualitative study is possible through the use of more than one interviewer, observer, and data analyst. In the case of this thesis, it is impractical to seek help from another interviewer, observer, and data analyst. However, after coding the interviews, the coding was sent to two academic experts to measure the degree of agreement over the coding of the interviews. This step of measuring the coding of the interviews serves the notion of internal reliability (Bell et al., 2018).

External reliability refers to the possibility of obtaining the same results if the data were re-collected using the same instrument from the same researcher, or another under as near equivalent conditions as possible (Saunders et al., 2019). There are some methods to measure external reliability, including the test re-test reliability. Saunders et al. (2019, p. 518) state that 'test re-test reliability estimates of reliability are obtained by correlating data collected with those from the same questionnaire collected under as near equivalent conditions as possible'. Thus, to measure the external consistency, the data collection instrument needs to be sent to the participants twice under the same conditions (or as close as possible) to ensure that the

same answers are obtained. However, it is challenging to measure the external reliability since it is difficult to obtain respondents from the same sample twice.

5.8.2 Validity

Although reliability is an extremely important element in determining research quality, it is insufficient by itself to ensure good-quality research. There is another element that assists in determining the quality of research, which is validity. In general, validity in research refers to three essential aspects: the appropriateness of the measures utilised, the accuracy of the analysis of the results, and the generalisability of the findings (Saunders et al., 2019). When considering validity, a distinction must be made between two types of validity, which are external validity and internal validity. It is noteworthy that, by using validity, it is convenient to assess quantitative research; however, it is considered philosophically inappropriate to evaluate qualitative research based on interpretive assumptions (Bell et al., 2018). Lincoln and Guba (1985) and Guba and Lincoln (1994) propose a criterion to ensure the quality of qualitative research: credibility and transferability.

Since this thesis employs both qualitative and quantitative data, the author has attempted to ensure that both external and internal validity are met for the quantitative data and credibility and transferability are met for the qualitative data.

5.8.2.1 External Validity

External validity considers the generalisability of the study's findings and conclusions to other relevant contexts (Saunders et al., 2019). Generalisation takes many forms, including the possibility of generalising the results of a study for one of the departments in a particular company to formulate policies and practices for another department. Generalisation is a legacy of quantitative research that attempts to imitate the natural sciences and develop law-like generalisations about the social world (Bell et al., 2018). Studies performed using a questionnaire sent to a number of people usually claim that the findings can apply to individuals

other than those who participated in the study. This assertion is proven true when the research uses a representative sample (Bell et al., 2018).

In this thesis, for the quantitative part, a probability sample is used to ensure external validity. The participants in the questionnaire were contacted randomly without prior selection to people working in a specific geographical area in Saudi Arabia, a specific audit firm, or a specific age and gender. Bell et al. (2018, p. 188) define a probability sample as ‘a sample that has been selected using random selection so that each unit in the population has a known chance of being selected’. A probability sample enables the researcher to make inferences about the entire population based on information from a random sample of that population. Saunders et al. (2019) claim that the use of a probability sample is commonly associated with survey research strategies because it helps to make statistical inferences from a sample about a whole population.

5.8.2.2 Internal Validity

In general, internal validity refers to the extent that the research findings can be attributed to the intervention that the researcher is researching rather than to flaws in his or her research design (Saunders et al., 2019). In the case of questionnaires, internal validity refers to the ability of the instrument (the questionnaire) to measure what the researcher intends it to measure (Saunders et al., 2019). Internal validity has several types, which include content validity, criterion-related validity, and construct validity.

Some textbooks refer to content validity as face validity (e.g., Bell et al., 2018). Content validity concerns the extent to which the questions or statements in the questionnaire provide adequate coverage of the phenomenon being studied (Saunders et al., 2019). From the definition, it is clear that the validity of the content is connected to a judgment of adequate coverage. To reach the most appropriate judgment of adequate coverage, Bell et al. (2018) have

suggested two ways: carefully reviewing the relevant literature to observe the prior discussion of adequate coverage and asking a panel of individuals who are experts in the field.

In the current thesis, the questionnaire design was primarily based on previous research in technology acceptance (Davis, 1989; Moore and Benbasat, 1991; Thompson et al., 1991; Compeau and Higgins, 1995; Venkatesh et al., 2003). Furthermore, to meet content validity, the questionnaire was sent to five academics and experts (excluding the supervisors) in the field of technology application to assess the coverage of the questionnaire and to evaluate whether each item in the questionnaire is essential and useful.

The criterion-related validity, known as predictive validity, is the ability of the questions in the questionnaire to make accurate predictions (Saunders et al., 2019). Predictive validity in the present study means data collected by questions within the questionnaire that accurately predict the behavioural intention of auditors to accept artificial intelligence. Measuring the accuracy of predicting questions in a questionnaire requires knowing the future behaviour of the survey participants. However, this method is impractical, especially in the present research due to the limitation of time and frequency of access to the participants. Saunders et al. (2019) suggest that the correlation between the multiple-item scales for each construct would help to determine the predictive validity of each question. In this thesis, each construct is measured by four or more items, which allows for a correlation between them and determines each item's predictivity.

The final type of internal validity is construct validity, which is concerned with the extent to which a set of questions or statements actually measures the presence of the construct the researcher intended them to measure (Saunders et al., 2019). Construct validity is one of the most valuable measures of validity (Bolarinwa, 2015). It is established through two steps: verification of convergent validity and verification of discriminant validity.

When using various scales to measure the same construct, the overlap between these scales is known as convergent validity (Saunders et al., 2019). On the other hand, discriminant validity entails ensuring scales used for one construct are different (in terms of the content) from scales used to measure another construct (Bell et al., 2018). Saunders et al. (2019) state that, in a questionnaire, the most appropriate method to test construct validity is through data analysis software, such as SPSS, because of the difficulties in testing it against existing data. In this thesis, the validity of the constructs is tested using the data analysis software SPSS; the results are displayed in the next chapter.

5.8.2.3 Credibility

Bell et al. (2018) state that establishing the credibility of qualitative data findings requires both making sure that research is conducted in accordance with good practice standards and sending research findings to the participants to validate that the investigator has accurately grasped that social reality. Credibility is the parallel criterion to internal validity (Saunders et al., 2019).

The literature has suggested a range of techniques that may help achieve credibility for qualitative data (Amankwaa, 2016; Saunders et al., 2019; Bell et al., 2018). First, the researcher should have long-term research involvement to create rapport and confidence and gather enough data. For this thesis, the author spent more than three years creating awareness and understanding of the phenomenon. Second, the researcher should use a different person to discuss ideas and test findings. In this thesis, since most of the interviews were conducted in Arabic and then translated into English by a certified translation provider, the author sought help from an academic who knows both languages to ascertain the accuracy of the translation of the Arabic transcripts to English.

Third, the researcher should check the data analysis and interpretations with the participants. In this thesis, the author shared the results of the qualitative data with three

randomly selected participants to confirm that he correctly understood the participants' intended meaning. Apparently, the author did not share the entire interview of the selected participants since this would be inefficient, but he shared the points that he used to reach the results of the thesis. Fourth, the researcher must ensure that his preconceived notions about what the research will reveal do not take precedence over the participant's social constructions. This point is especially essential for this thesis, since the results from quantitative data (i.e., the questionnaire) may affect the coding process during the qualitative data analysis. To ensure the preconceived expectations did not influence the coding processes, the interview codes were shared with two academic experts who verified the accuracy of the coding.

5.8.2.4 Transferability

Transferability is defined as the necessity to fully describe the study questions, design, context, findings, and resulting interpretations in the project report (Saunders et al., 2019). Transferability is the parallel criterion to external validity or generalisability (Bell et al., 2018). In this thesis, knowing that the qualitative data collected cannot make statistical generalisations about the entire population of auditors is important. However, in the methodology chapter, the author attempted to elaborate when explaining the processes of qualitative data collection and analysis. He tried to produce what Geertz (2008) calls the thick description that enriches the qualitative data findings. Guba and Lincoln (1994) argue that the thick description works as a database that allows others to judge the potential transferability of results to other contexts.

5.9 Participants in The Study

The participants of the study consist of two groups. The first group is the auditors who work in the field of external audit in the KSA. The purpose of the study is to measure an individual auditor's intent to accept artificial intelligence in audit engagements. To ensure that a representative sample is taken from the population, the potential respondents of this group were randomly contacted through their social media pages or the official websites of audit firms

operating in the KSA. For example, the author used the filter feature on LinkedIn to select the required sample ‘External Auditors’ and the geographical location ‘KSA’.

This group of participants was used to collect quantitative data by their participation in an online questionnaire (Qualtrics). Each participant received an electronic questionnaire and was required to fill in all the mandatory sections in the questionnaire. In this group, the author was able to obtain 403 questionnaires. Not all of the questionnaires collected were used in the analysis process, as a small percentage of the questionnaires were excluded due to incompleteness or wrong entries. These problems are discussed in Chapter 7 (Empirical Qualitative Study).

The second group was randomly selected from the participants in the first group. In this group, the author excluded participants with less than five years of experience. The author assumes that auditors with less than four years of experience may not be involved heavily in audit engagements. The aim of this second group is to collect qualitative data (via interviews) to delve into the results of the quantitative data from the questionnaires. Hence, the author intends to benefit from those participants with long audit experience, since they will be more likely to elaborate deeply on the use of artificial intelligence in the audit profession.

5.10 Data Collection Instruments Design

This thesis designs two data collection instruments. The first instrument, the questionnaire, was designed to collect quantitative data from the potential respondents. The section provided below introduces the details of the questionnaire. The second instrument, the semi-structured interview, was designed to collect qualitative data for the thesis; a section below (6.10.2) introduces the details of such interviews.

5.10.1 Questionnaire Design

For the quantitative part, an online self-completed questionnaire was adopted. The self-completed questionnaire, as defined by Saunders et al. (2019), is a questionnaire specifically

designed to be completed by a participant without the intervention of the interviewer (i.e., a researcher). In general, there are three ways to distribute a self-completed questionnaire: internet questionnaire, in which a potential participant accesses the questionnaire through his or her web browser using a hyperlink; QR code questionnaire, in which a potential participant accesses the questionnaire by scanning the code with a smartphone; posted (postal or mail) questionnaire, in which the questionnaire is posted or handed to a potential participant and collected later.

This thesis uses an internet questionnaire that is designed through qualtrics.com. Qualtrics is an online questionnaire tool for creating, distributing, and analysing questionnaire results (Smith and Albaum, 2010). Since qualtrics.com offers many features that enable the researcher to design the questionnaire that suits his or her research, as well as its partnership with the University of Nottingham, it has been utilised to design the thesis questionnaire. The Arabic version of the questionnaire was presented to an academic researcher fluent in both Arabic and English to ensure the accuracy of the translation. In Qualtrics, both the English and Arabic versions of the questionnaire are available, and the potential participant selects their preferred language.

An important point when designing a questionnaire is to develop one that accurately fits the research objectives, yet ideally avoids asking too many questions. Nardi (2018) states that no single agreed-upon method of writing questionnaires exists. However, the questionnaire's developer should avoid being too wordy and having a poor design because it may result in frustration, biases, and non-compliance. Although self-completed questionnaires have the advantage since a potential participant may fill it out in his or her free time, a questionnaire with too many questions consumes the participant's time and affects the quality of answers. The participants (in this case, the auditors) are busy with many auditing tasks, especially the data collection that occurs during the hectic season (January to April).

Most of the items utilised in the questionnaire were adopted from the literature on technology acceptance, due to the high validity and reliability they have shown (Table 5). The ethical concerns items were added specifically to accommodate the objectives of the research. The ethical concerns items were adopted in the questionnaire based on ethical issues raised in the literature. The latent variables items are closed-ended items using a five-point Likert-type scale. Such scales are generally utilised to measure attitude, providing a range of responses to a given statement (Jamieson, 2004). The Likert scales neatly fit this study since the research aims to investigate factors influencing auditors' decision attitude when accepting artificial intelligence.

The independent constructs (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, and ethical concerns) and the dependent construct (behavioural intention) were scored on a five-point scale (strongly agree, agree, neutral, disagree, and strongly disagree). The dependent construct (actual use) was scored on a Yes or No scale. The model's moderator (audit firm size) was measured using tick boxes with four options (Big Four firms, international audit firms but not Big Four, regional audit firms, and others). Here, each participant has to select one of the four options. The option 'other' includes a writing box that allows the participants to categorise their audit firm.

The questionnaire be divided into three parts. The first part is the cover page which contains a statement that explains the purpose of the research, introduces visual recognition technology (VRT) to the participants, and explains the usage of visual recognition technology in audit engagements. This section aims to introduce the participants to the study and provide a general idea of visual recognition technology since many auditors may not fully understand this new technology. In addition, a statement that explains the participant's privacy and anonymity is included.

The second section contains demographic questions such as gender, age, education, qualifications, position, experience, and audit firm size. The demographic data is collected to test the potential influence of the demographic factors on the thesis' model. This data is included in the analysis, and their significant influence on the results is reported later. The third section contains 25 close-ended items.

Table 4. Latent variables on artificial intelligence acceptance for this thesis.

Latent Variables	Items	Roots
Performance expectancy	I believe VRT will be useful in the field of external auditing.	(Venkatesh et al., 2003; Davis, 1989; Moore and Benbasat, 1991; Compeau and Higgins, 1995)
	Using VRT will enable me to accomplish tasks more efficiently.	(Venkatesh et al., 2003; Davis, 1989; Compeau and Higgins, 1995)
	Using VRT will increase the quality of the output of the audit.	(Moore and Benbasat, 1991; Compeau and Higgins, 1995)
	If I use the VRT, I will spend less time on routine job tasks.	(Moore and Benbasat, 1991; Thompson et al., 1991)
Effort expectancy	Learning and understanding how to work with VRT will be complicated.	(Venkatesh et al., 2003; Davis, 1989; Thompson et al., 1991; Compeau and Higgins, 1995)
	VRT will not be flexible to work with.	(Davis, 1989)
	It will be difficult to make VRT do what I want it to do.	(Davis, 1989; Compeau and Higgins, 1995)
	It will be difficult for me to become skilled at using VRT.	(Venkatesh et al., 2003; Davis, 1989)
Social influence	The expectation from peers is an important factor for me to use VRT.	(Venkatesh et al., 2003; Davis, 1989; Thompson et al., 1991)
	Clients think that I should use VRT.	(Venkatesh et al., 2003; Davis, 1989)
	The senior management of my organisation will be supportive of the use of VRT.	(Venkatesh et al., 2003; Thompson et al., 1991)
	People using VRT will have more prestige than those who do not.	(Compeau and Higgins, 1995)
Facilitating conditions	I have the resources necessary to use VRT.	(Venkatesh et al., 2003; Davis, 1989)
	I have the knowledge necessary to use VRT.	(Venkatesh et al., 2003; Davis, 1989; Thompson et al., 1991)
	Using VRT is compatible with other systems I use.	(Venkatesh et al., 2003; Davis, 1989; Compeau and Higgins, 1995)
	A specific person (or group) is available to assist me to use VRT.	(Venkatesh et al., 2003; Thompson et al., 1991)
Ethical concerns	VRT will substitute my role in the future.	(Munoko et al., 2020; Farisco et al., 2020; Huang and Rust, 2018)
	Using VRT will result in a client's confidential information being leaked.	(Wright and Xie, 2019; West, 2019; Lehner et al., 2022)
	VRT will hinder the auditability of the audit process.	(Munoko et al., 2020; Lehner et al., 2022)
	It will be difficult to control data when using VRT.	(Munoko et al., 2020; Lehner et al., 2022)
	The automatic performance of routine audit tasks by VRT will negatively affect my professional scepticism and judgement.	(Westermann et al., 2015; Goddard et al., 2012; Lehner et al., 2022)
	VRT will impair auditor independence.	(Manita et al., 2020)

Intentional use	I intend to use VRT in the near future.	(Venkatesh et al., 2003)
	I will recommend using VRT to others.	(Venkatesh et al., 2003)
Actual use	Do you use VRT?	(Venkatesh et al., 2003; Davis, 1989; Compeau and Higgins, 1995)

5.10.1.1 The Questionnaire

5.10.1.1.1 Coverage

The cover page contains three statements. The first statement explains the purpose of the research and the researcher to the participants. The statement is:

‘This questionnaire is a part of a research project to study factors influencing external auditors’ intention to adopt visual recognition technology, which is one of the artificial intelligence technologies that are currently used and has potential in the field of external audits. The questionnaire will be used as a data collection instrument for my Doctoral degree in accounting at the University of Nottingham. As a questionnaire participant, you will receive the results of this study after I analyse and discuss the data. Your thoughts and valuable answers will be highly helpful for the research to obtain an understanding of this topic. The questionnaire should take around ten minutes to complete. If you wish to add further comments, please feel free to do so at the end of the questionnaire.’

The second statement introduces and explains visual recognition technology. The latter is a new smart technology that has recently been developed. Thus, there is a chance some of the auditors may not understand or be aware of the new technologies used in the field of external audit. The statement is:

‘Visual recognition technology (VRT) is one of the artificial intelligence technologies that can identify objects, people, places, writing, and actions in images. It can autonomously extract data from images and analyse the data to perform some audit functions. Functions of VRT include assets assessment,

identification of people, and data extraction from files without the intervention of auditors.

Visual recognition technology can assist auditors in performing an audit in many cases. During the Covid-19 period, when physical inventory checking is difficult, auditors can use VRT built-in CCTV system to verify the inventory condition. VRT can also be used to identify people in a conference, analyse facial expressions, and analyse words that were used in the conference. In addition, visual recognition cameras built into drones can assist auditors to verify the condition of hard-to-approach items of assets.'

The third statement explains that the privacy of the survey participants is maintained and that they will remain anonymous. The statement is:

'This questionnaire has been approved by the Ethics Committee at the University of Nottingham. All information will be treated in the strictest confidence and only be used for this research purpose. Your identity will not be identified. Results will be combined with other participants' results and analysed as a group.'

5.10.1.1.2 Demographic Questions

The questionnaire has eight demographic questions, which are based on gender, age, education, years of experience, accounting qualification, IT audit qualification, position, and firm size. Gender information was attained via the question 'What is your gender?', which has three possible answers: male, female, and prefer not to say. Age was found by asking 'How old are you?' and the answer is based on age ranges. The age ranges start from below 21 to 53+, and each age range is ten years. The question on education was: 'What is the highest level of education you have completed?'. This question has four possible answers: Bachelor's degree, Master's degree, Doctoral degree, and other. The option 'other' was used to adjust between the

various names of education levels between countries. If a participant ticks ‘other’, he or she is required to write down their level of education.

The professional accounting qualification was asked for by using two stages: ‘Do you have a professional accounting qualification?’ and ‘If yes, what is the qualification?’. The reason that the author asked for this moderator in two stages is to avoid wasting the time of those who do not have a professional accounting qualification. Namely, they will not see the second question if their answer to the first question is ‘no’. The IT audit qualification was also asked for in two stages. In the first stage, the participants were asked: ‘Do you have an IT audit qualification?’. If their answer is ‘Yes’, the second stage question will appear that states: ‘What is your IT audit qualification?’.

The experience of the auditor was discovered via the question: ‘How long have you been working in the field of external audit?’. Same as for determining age, the answer to this question is based on year ranges. The first option is less than a year. Subsequently, the year ranges are five years (e.g., 1-5 and 6-10). The final demographic question concerns the size of the audit firm where the participant works. The audit firm size was attained by asking: ‘What is the size of the firm where you work?’. This question has four boxes in which the participant had to tick a box that indicates the firm size where he or she works. The four boxes are Big Four, international audit firm (but not Big Four), regional audit firm, and other.

5.10.1.1.3 Independent Constructs

The questionnaire was designed to fit the study model. This thesis assumes that five constructs (latent variables) influence the intention of auditors’ discussion when accepting artificial intelligence. The constructs are performance expectancy, effort expectancy, social influence, facilitating conditions, and ethical concerns. Table 6 shows the questionnaire’s latent variables and the items for each latent variable.

Table 5. Variables of the questionnaire.

Questionnaire’s variables and the variables' questions			
Independent Constructs			
Category	Latent Variables	Items	Dimension
1	Performance expectancy	I believe VRT will be useful in the field of external auditing.	Effectiveness
		Using VRT will enable me to accomplish tasks more efficiently.	Efficiency
		Using VRT will increase the quality of the output of the audit.	Quality
		If I use the VRT, I will spend less time on routine job tasks.	Timesaving
2	Effort expectancy	Learning and understanding how to work with VRT will be complicated.	Difficulty of understanding
		VRT will not be flexible to work with.	Flexibility
		It will be difficult to make VRT do what I want it to do.	Difficulty of use
		It will be difficult for me to become skilled at using VRT.	Mastering
3	Social influence	The expectation from peers is an important factor for me to use VRT.	Expectation of peers
		Clients think that I should use VRT.	Expectation of clients
		The senior management of my organisation will be supportive of the use of VRT.	Expectation of managers
		People using VRT will have more prestige than those who do not.	Prestige in general
4	Facilitating conditions	I have the resources necessary to use VRT.	Resources
		I have the knowledge necessary to use VRT.	Knowledge
		Using VRT is compatible with other systems I use.	Compatibility
		A specific person (or group) is available to assist me to use VRT.	External resource
5	Ethical concerns	VRT will substitute my role in the future.	Substitution
		Using VRT will result in a client’s confidential information being leaked.	Confidentiality
		VRT will hinder the auditability of the audit process.	Auditability
		It will be difficult to control data when using VRT.	Data protection
		The automatic performance of routine audit tasks by VRT will negatively affect my professional scepticism and judgement.	Professional scepticism and judgment.
		VRT will impair auditor independence.	Auditor independence
Dependent Construct			
Category	Variables	Items	Dimension
1	Intentional use	I intend to use VRT in the near future.	Future use
		I will recommend others to use VRT.	Recommendation of use
2	Actual use	Do you use VRT?	Actual use

- The first category is performance expectancy. This category has four closed-end items.

Each item measures one dimension of performance expectancy, including the expected

effectiveness of visual recognition technology in audit engagements, the expected impact of visual recognition technology on the efficiency of audit assignments, the expected impact of visual recognition technology on audit quality, and the expected impact of visual recognition technology on timesaving.

- The second category is effort expectancy. This category has four closed-end items. Each of the four items measures a dimension of effort expectancy, including the expected difficulty of understanding visual recognition technology, the expected difficulty of using visual recognition technology, the expected flexibility of visual recognition technology, and the expected effort to master using visual recognition technology.
- The third category is social influence. This is measured from four dimensions: the social impact of peers, the social impact of clients, the social impact of managers, and the overall social impact. Each of these four dimensions is tested using a closed-end item.
- The fourth category is the facilitating conditions. This category has four closed-end items. Each of the four items measures one dimension of facilitating conditions, including the necessary resources needed when implementing artificial intelligence, the necessary knowledge needed when using artificial intelligence, the compatibility of artificial intelligence with other systems, and the availability of the IT team for assistance with artificial intelligence.
- The fifth category is ethical concerns. These are the ethical issues that an external auditor may perceive when using visual recognition technology. This category has six closed-end items. Each item measures one dimension of ethical concerns, including the impact of the visual recognition technology on employment rate, the impact of visual recognition technology on the client's confidential information, the impact of visual recognition technology on auditability, the impact of visual recognition technology on

the ability to protect data, the impact of visual recognition technology on the auditor's professional scepticism and judgment, and the impact of visual recognition technology on the auditor independence.

5.10.1.1.4 Dependent Constructs

This thesis has two dependent constructs: the intention to use visual recognition technology and the actual use of visual recognition technology. The intention to use visual recognition technology refers to the degree to which an external auditor intends to use visual recognition technology; it is measured using two closed-end items. These two items attempt to measure two dimensions: the intention of an auditor to use visual recognition technology in the future and the intention to recommend the use of visual recognition technology to others. The second dependent construct is the actual use of visual recognition technology, which is measured using Yes or No answers.

5.10.1.2 Coding of The Constructs and Constructs' Items.

Coding for constructs and constructs' items was also developed (Table 7). The purpose of coding the constructs and their items was to facilitate the data analysis process. There are seven constructs and 22 constructs' items in the questionnaire. The constructs were coded based on each word's first letter (e.g., performance expectancy is denoted by PE). The constructs' items were coded based on the constructs coding plus a numeric arrangement.

Table 6. Coding of the constructs and constructs' items.

Construct	Code	Constructs' items	Code
Performance expectancy	PE	I believe VRT will be useful in the field of external auditing.	PE1
		Using VRT will enable me to accomplish tasks more efficiently.	PE2
		Using VRT will increase the quality of the output of the audit.	PE3
		If I use the VRT, I will spend less time on routine job tasks.	PE4
Effort expectancy	EE	Learning and understanding how to work with VRT will be complicated.	EE1
		VRT will not be flexible to work with.	EE2
		It will be difficult to make VRT do what I want it to do.	EE3
		It will be difficult for me to become skilled at using VRT.	EE4
Social influence	SI	The expectation from peers is an important factor for me to use VRT.	SI1
		Clients think that I should use VRT.	SI2

		The senior management of my organisation will be supportive of the use of VRT.	SI3
		People using VRT will have more prestige than those who do not.	SI4
Facilitating conditions	FC	I have the resources necessary to use VRT.	FC1
		I have the knowledge necessary to use VRT.	FC2
		Using VRT is compatible with other systems I use.	FC3
		A specific person (or group) is available to assist me to use VRT.	FC4
Ethical concerns	EC	VRT will substitute my role in the future.	EC1
		Using VRT will result in a client's confidential information being leaked.	EC2
		VRT will hinder the auditability of the audit process.	EC3
		It will be difficult to control data when using VRT.	EC4
		The automatic performance of routine audit tasks by VRT will negatively affect my professional scepticism and judgement.	EC5
		VRT will impair auditor independence.	EC6
Intentional use	IU	I intend to use VRT in the near future.	IU1
		I will recommend others to use VRT.	IU2
Actual use	AU	Do you use VRT?	AU
Firm size	FS	■ Big four ■ International audit firm (not Big Four) ■ Regional audit firm ■ Other.	FS

5.10.1.3 Pre-Test and Pilot Test

The way people think varies from person to person, which makes it inappropriate to rely on one person when designing a tool to collect data from people. From this standpoint, the need to test the data collection instrument before starting the actual process arises. Backstrom and Hursh (1963) note 'No amount of intellectual exercise can substitute for testing an instrument designed to communicate with ordinary people'. Therefore, for this thesis, a pre-test and a pilot test were conducted for the questionnaire before commencing the actual data-gathering phase.

5.10.1.3.1 Pre-Test

The purpose of pretesting is to determine any deficiencies with the data-collecting instruments (Hunt et al., 1982; Saunders et al., 2019). Kumar et al. (2013) list three reasons for conducting a pre-test: to ensure that the wording of the questions is correct, to guarantee that the sequence of the questions is accurate, and to certify that the respondents have clearly understood all the questions. A pre-test is completed to determine: if there is room for developing the data collection instrument by changing the wording or the presentation, the

relevance of the questions used in the questionnaire to the research questions and research objectives, the clarity of the questions, and whether the questions convey the intended meaning.

A form for the pre-test was emailed to five academics who are auditing and IT experts. Feedback and suggestions were received and used to improve the content and layout of the instrument, such as modifying the wording of some questions and adjusting the font size for some paragraphs.

5.10.1.3.2 Pilot Test

To identify the reliability and validity of the instrument and save time and resources, a pilot test was conducted in advance of the data collection phase. A group of prospective respondents (external auditors) were invited to participate in the pilot test. The size of the pilot sample is not specified in the literature, however, a range of 10 to 30 participants is proposed by Isaac and Michael (1995).

Due to the difficulty of accessing a large sample in the current study and the fact that the sample used in the pilot test cannot be combined with the main sample, the pilot test population was 20 external auditors. This group was given a month to return the questionnaires. The collected questionnaires were analysed through Cronbach's alpha to evaluate the reliability of the multi-item measurement scale. Cronbach's alpha is the most regularly utilised and widely accepted method to evaluate the reliability of a multi-item measurement scale (Hair et al., 2019).

The reliability and validity were tested only for the constructs that directly influenced the decision to adopt visual recognition technology such as performance expectancy, effort expectancy, social influence, facilitating conditions, and ethical concerns. The reliability and validity test resulted in the omission of one of the items pre-determined for ethical considerations. The deleted item was intended to measure the impact of using visual

recognition technology on the auditors' responsibility. The item was as follows: 'I will be held responsible if VRT fails during an audit'.

5.10.2 Interview Design

A semi-structured interview was designed to collect qualitative data for the research. The purpose of this interview design is to enable the researcher to obtain an improved understanding of the research problem, as well as to dig deeper into the results obtained from the quantitative data. The broad interview questions were planned in advance (Table 8), and the interviewer always attempted to take a neutral stance. Bell et al. (2018) state the importance of the interviewer being neutral during the interview and not affecting the thoughts of the interviewee. An interview guide ensured that all the posed questions had the same wording. All the participants received the same main questions, although the questions may not be in the same order.

During the interview, the interviewer used follow-up questions to help the participants to elaborate on their answers. Examples of the follow-up questions used during the interview are 'could you give an example?', 'what do you mean by such and such?', and 'could you tell me more about such and such?'. Furthermore, the interviewer posed probing questions to increase the engagement of the participants in the interview. Examples of these probing questions are: 'why do you think this is the case?', 'how do you conclude such and such?', and 'what is the connection between x and y?'. Saunders et al. (2019) claim that follow-up and probing questions help the interviewer explore under-researched phenomena and produce a fuller account without affecting the thoughts of the interviewee.

Table 7. Questions used in the interview phase.

General information	Could you introduce yourself (your age, your experience, your position, your qualifications, and your auditing firm)?
Main questions	Please tell me about the factors that influence your artificial intelligence use decisions?
	In your opinion, what are the ethical issues that may arise from implementing artificial intelligence in the audit profession?

	Do you think using artificial intelligence in the audit profession will serve broad community goals and values?
	Are you worried about the usage of data collected by artificial intelligence? (e.g., in terms of retrieval, longevity, and third-party usage)?
	Do you agree with those who say long-term use of artificial intelligence will lead the auditors to focus only on the issues that are identified by the system and not consider other unidentified issues?
	In your opinion, will artificial intelligence impact external auditors' independence?
	In your opinion, what are the limitations of artificial intelligence in the audit profession?

5.11 Rules on Ethics and Confidentiality

The University of Nottingham requires that all studies involving human participants be subject to ethical scrutiny and approval before the data collection process. Therefore, before sending the questionnaire, the approval of the ethics committee of the University of Nottingham was obtained. A statement written on the cover page of the questionnaire explains the purpose of the research and the ethical rules. In addition, a privacy note is given in the questionnaire that mentions that the survey is anonymous.

5.12 Conclusion

This chapter provided an insight into the methodological philosophy employed in this thesis, and the strategy used in collecting relevant data that produces valuable findings and insightful conclusions. This thesis adopts pragmatism philosophy as it aims to investigate the research questions by using qualitative and quantitative data. Initially, the researcher collected quantitative data via a questionnaire to test the hypotheses. Subsequently, semi-structured interviews were conducted to delve deeper into the results from the quantitative data and provide an improved understanding of the research problem.

Moreover, this chapter sheds light on the procedures that were followed to develop the data collection instruments. The author designed a questionnaire to collect the quantitative data, as well as a semi-structured interview to gather the qualitative data. Additionally, this chapter discusses the methods and procedures used to ensure the reliability and validity of data

collection instruments. Finally, the author examines the tests performed on the data collection instruments to ensure their suitability for answering the thesis questions. In the next chapter, the author displays the empirical quantitative results and discusses these results.

Chapter 6: Empirical Quantitative Results

6.1 Introduction

This chapter is devoted to examining the influence of the independent factors in the study model on the dependent factors through the analysis of the data collected through the questionnaire. Here, the author presents both the descriptive statistics and factor analysis results, as well as the results of the tests of the thesis hypotheses. The author used SPSS analysis software to analyse and test the accuracy of the quantitative data collected.

The qualitative results of the data collected from the participants are presented in the next section including the justification for excluding a small percentage of the participants. In the second part of this chapter, the author subjects the data to a set of data quality tests and a set of tests that ensures the reliability and validity of the data collection questionnaire. The author examines the data through a Kaiser-Meyer-Olkin (KMO) test to ensure the quality of the data. Moreover, the author runs the eigenvalues to ascertain the number of latent variables that can be extracted from the questionnaire. Additionally, the author tests the data using Cronbach's alpha and composite reliability to ensure the reliability of the data, as well as the average variance extracted and the Fornell-Larcker criterion that ensures convergent validity and discriminant validity.

The next part of this chapter presents the results of the influence of the independent factors on dependent ones; it also introduces the effects of the impact of the moderators on the independent variables. Finally, the chapter discusses the results and links them to the literature, while also providing a discussion on the implementations of the results.

6.2 Descriptive Statistics Results

This thesis adopts a mixed-method approach to empirically validate the research model (Figure 10). The author collected study data using two different methods. In the first method, the author obtained questionnaire responses from 403 auditors working in national and international certified public accounting (CPA) firms. The participants were randomly selected by communicating with them through their social media pages or emails. Out of the 403 participants, only 311 participants were included in the data analysis. The ninety-two excluded questionnaires were due to one of the following issues. Either the participant did not complete the questionnaire, the participant chose the same option to answer all the questions of the questionnaire, or the participant entered the wrong entries. The goal of excluding this small set of questionnaires is to raise the quality of the data used to test the thesis hypotheses.

The first instrument used for the data collection was developed to examine the study's proposed structural model (Figure 10). The author relied on questionnaires used in the literature to design the instrument (Venkatesh et al., 2003; Davis, 1989; Moore and Benbasat, 1991; Compeau and Higgins, 1995; Thompson et al., 1991) with some modifications to appropriately fit the proposed structural model (Appendix 1). The modifications, also based on the literature (Goddard et al., 2012; Westermann et al., 2015; Munoko et al., 2020; Lehner et al., 2022), were conducted to capture the influence of ethical concerns.

The first part of the instrument introduced visual recognition technology to test the proposed structural model. The second part of the instrument contained questions on participants' characteristics and the firms they worked for. The final part of the instrument contained questions on the proposed structural model's latent variables. Each item was measured using a 5-point Likert scale, with a score of 1 indicating 'strongly agree' and 5 specifying 'strongly disagree'.

As shown in Table 9, the questionnaire respondents were a total of 311 auditors from regional, national, and international firms from geographically different regions of the KSA. The questionnaire respondents' mean age was 27 years old, with a mean audit experience of 3.25 years. The participants worked in audit firms of different sizes with 50.2% employed by Big Four firms, 24.7% by international audit firms (not Big Four), 21.8% by regional firms, and 3.3% by local audit firms. Of the questionnaire respondents, 95% and 5% held audit staff- and managerial-level positions, respectively. The highest educational level attained by the significant majority (85.5%) was a bachelor's degree, followed by a master's degree (14%) and a doctoral degree (0.5%). Of the participants, 28.6% had CPA certificates, and most (N = 209) were male.

Table 8. Descriptive statistics for the questionnaire.

Descriptive Statistics for the questionnaire				
		N	Percentage	Average
Gender	Male	209	67%	
	Female	102	33%	
Age				27
Experience				3.25
Education	Bachelor's degree	266	85.5%	
	Master's degree	43	14%	
	Doctoral degree	2	0.5%	
Holding CPA	Yes	89	28.6%	
	No	222	71.4%	
Position	Staff	294	95%	
	Senior manager	17	5%	
Firm Size (FS)	Big Four	156	50.2 %	
	International firm (not big four)	77	24.7%	
	Regional firm	68	21.8%	
	Local firm	10	3.3%	

Table 10 shows the descriptive statistics (sample number, mean, standard deviation, and variance) for the 24 variables. The table shows that the highest mean was for variable EE1 and the smallest was for variable PE1.

Table 9. Descriptive statistics for the 24 variables.

		N	Mean	Std. Deviation	Variance
I believe VRT will be useful in the field of external auditing.	PE1	311	2.00	.740	.547
Using VRT will enable me to accomplish tasks more efficiently.	PE2	311	2.06	.748	.559
Using VRT will increase the quality of the output of the audit.	PE3	311	2.15	.788	.621
If I use VRT, I will spend less time on routine job tasks.	PE4	311	1.95	.784	.615
Learning and understanding how to work with VRT will be complicated.	EE1	311	3.15	.925	.855
VRT will not be flexible to work with.	EE2	311	2.99	.905	.820
It will be difficult to make VRT do what I want it to do.	EE3	311	3.04	.882	.778
It will be difficult for me to become skilled at using VRT.	EE4	311	2.65	.940	.884
The expectation from peers is an important factor for me to use VRT.	SI1	311	2.49	.758	.575
Clients think that I should use VRT.	SI2	311	2.71	.803	.645
The senior management of my organisation will be supportive of the use of VRT.	SI3	311	2.32	.789	.623
People using VRT will have more prestige than those who do not.	SI4	311	2.30	.865	.748
I have the resources necessary to use VRT.	FC1	311	2.91	.967	.936
I have the knowledge necessary to use VRT.	FC2	311	3.12	1.038	1.078
Using VRT is compatible with other systems I use.	FC3	311	2.75	.794	.630
A specific person (or group) is available to assist me to use VRT.	FC4	311	2.84	.985	.970
VRT will substitute my role in the future.	EC1	311	2.75	.976	.953
Using VRT will result in a client's confidential information being leaked.	EC2	311	2.75	1.030	1.061
VRT will hinder the auditability of the audit process.	EC3	311	2.76	.943	.888
It will be difficult to control data when using VRT.	EC4	311	2.70	.878	.772
The automatic performance of routine audit tasks by VRT will negatively affect my professional scepticism and judgement.	EC5	311	2.79	.923	.852
VRT will impair my independence.	EC6	311	2.50	.986	.972
I intend to use VRT in the near future.	IU1	311	2.40	.840	.705
I will recommend using VRT to others.	IU2	311	2.39	.805	.648
Valid N (listwise)		311			

6.3 Instrument Validation.

To increase construct validity (Hunt et al., 1982; Shadish et al., 2002; Saunders et al., 2019), the author conducted two rounds of pilot testing. First, the instruments were sent to five

academics who were auditing and IT experts. On the basis of their feedback, the instruments were revised. Second, the revised questionnaire was sent to 20 external auditors. This group was given a month to return the questionnaires. Finally, the questionnaire was revised based on their feedback and Cronbach's alpha test results.

6.3.1 Validation of The Measurement Scales

The Kaiser-Meyer-Olkin (KMO) test is a statistical measure used in the context of factor analysis and structural equation modelling to assess the adequacy of data for factor analysis. The KMO test is particularly useful for determining if the variables in a dataset are appropriate for factor analysis. It assesses the degree of common variance among variables and examines whether there is enough shared variance to justify the use of factor analysis. Table 11 shows the results of the Kaiser-Meyer-Olkin (KMO) quality assurance test, which revealed a test score of 0.837; this is an acceptable value based on the minimum acceptable value of 0.6. This means the measurement was of high quality, at a significance of 0.001 (Kaiser, 1970; Dziuban and Shirkey, 1974; Cerny and Kaiser, 1977).

Table 10. Results of the Kaiser-Meyer-Olkin and Bartlett Test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.837
	Approx. Chi-Square	3299.215
Bartlett's Test of Sphericity	df	276
	Sig.	0.000

6.3.2 Eigenvalues For Variables

Eigenvalues are the sum of squared component loadings across all the items for each component, representing the amount of variance in each item that can be explained by the principal component. Table 12 shows the analysis results for the six extracted factors (latent variables) with values >1. The interpretation ratios of the variances were reached from the total

variance for each factor separately, and the six factors revealed a total variance of 66.9%, which is a high percentage. Moreover, this indicates that more factors could influence the intention to use (IU) when more items are generated on the basis of expert opinions.

Table 11. Analysis results for the six extracted factors.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings ^a
	Total	% Of Variance	Cumulative %	Total	% Of Variance	Cumulative %	Total
1	5.414	22.558	22.558	5.414	22.558	22.558	4.185
2	3.880	16.166	38.724	3.880	16.166	38.724	3.420
3	2.286	9.526	48.249	2.286	9.526	48.249	3.637
4	1.941	8.087	56.337	1.941	8.087	56.337	3.061
5	1.505	6.271	62.607	1.505	6.271	62.607	3.283
6	1.025	4.272	66.880	1.025	4.272	66.880	3.163
7	0.778	3.240	70.119				
8	0.713	2.971	73.091				
9	0.615	2.563	75.653				
10	0.598	2.494	78.147				
11	0.542	2.257	80.404				
12	0.519	2.161	82.566				
13	0.506	2.106	84.672				
14	0.450	1.875	86.547				
15	0.430	1.792	88.339				
16	0.422	1.758	90.097				
17	0.386	1.610	91.707				
18	0.359	1.496	93.202				
19	0.340	1.416	94.619				
20	0.303	1.262	95.881				
21	0.286	1.190	97.071				
22	0.262	1.092	98.163				
23	0.245	1.019	99.182				
24	0.196	0.818	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

6.3.3 Reliability and Validity

In the measurement model evaluation, all 24 items were included in the analysis because their factor loadings were greater than 0.6 (Tabachnick et al., 2007). To test the reliability of

the constructs, the study used Cronbach's alpha and composite reliability (CR). Cronbach's alpha assumes that all items of a latent variable are equally reliable, which means that they all produce a consistent outcome under consistent conditions (Diamantopoulos et al., 2012). All CR values were higher than the recommended value of 0.7 (Hair Jr et al., 2017). The Cronbach's alpha value of each construct exceeded the 0.70 threshold, which indicates good reliability for the constructs. The convergent validity was acceptable, as the average variance extracted (AVE) for all constructs was greater than 0.5. The results for reliability and validity, alongside the factor loadings for the items, are presented in Table 13. The reason the author used Promax was that the correlation between two of the factors (PE and IU) acceded at 0.32. Tabachnick et al. (2007, p. 646) argued that:

‘perhaps the best way to decide between orthogonal and oblique rotation is to request oblique rotation [e.g., direct Oblimin or Promax] with the desired number of factors and look at the correlations among factors... if factor correlations are not driven by the data, the solution remains nearly orthogonal. Look at the factor correlation matrix for correlations around 0.32 and above. If correlations exceed 0.32, then there is 10% (or more) overlap in variance among factors, enough variance to warrant oblique rotation unless there are compelling reasons for orthogonal rotation’.

Table 12. Reliability and validity results.

Latent variable	Indicators	Loading	AVE	Composite Reliability	Cronbach's alpha
PE	PE1	0.846	0.641	0.876	0.809
	PE2	0.855			
	PE3	0.785			
	PE4	0.707			
EE	EE1	0.792	0.638	0.876	0.811
	EE2	0.788			
	EE3	0.786			

	EE4	0.828			
SI	SI1	0.754	0.636	0.875	0.809
	SI2	0.795			
	SI3	0.837			
	SI4	0.803			
FC	FC1	0.820	0.675	0.893	0.838
	FC2	0.874			
	FC3	0.754			
	FC4	0.803			
EC	EC1	0.809	0.605	0.902	0.868
	EC2	0.858			
	EC3	0.776			
	EC4	0.728			
	EC5	0.778			
	EC6	0.703			
IU	IU1	0.935	0.874	0.933	0.855
	IU2	0.935			

Principal component analysis was used as the extraction method, and Promax with Kaiser normalization was used as the rotation method.

Discriminant validity was assessed using the Fornell-Larcker criterion. Table 14 shows that the square root of the AVE for each construct was greater than its correlation with other constructs, which indicates that discriminant validity was established (Fornell and Larcker, 1981).

Table 13. Parameters for discriminant validity.

Discriminant validity								
		AVE	PE	EE	SI	FC	EC	IU
Correlation	PE	0.641	<i>0.800</i>					
	EE	0.638	0.180	<i>0.799</i>				
	SI	0.636	0.373	-0.068	<i>0.798</i>			
	FC	0.675	0.210	-0.102	0.277	<i>0.822</i>		
	EC	0.605	0.256	0.272	0.162	-0.050	<i>0.778</i>	
	IU	0.874	0.410	0.195	0.244	0.369	0.288	<i>0.935</i>

Note: Values in italics represent the square root of AVE.

6.3.4 Results of The Thesis Model

This study was conducted to determine if a group of variables can influence an individual's intention to adopt a form of artificial intelligence technology, which is visual recognition technology. It was hypothesised that performance expectancy (PE), social influence (SI), and facilitating conditions (FC) could positively predict the intention to adopt visual recognition technology (IU). Moreover, it was hypothesised that facilitating conditions could positively predict the actual use of visual recognition technology (AU). Additionally, it was theorised that effort expectancy (EE) and ethical concerns (EC) could negatively predict the intention to adopt visual recognition technology.

Multiple regression and logistic regression analyses were performed to test these hypotheses. Results of the multiple regression show that 31% of the variance in the dependent variable (IU) can be explained by the independent variables (PE, EE, SI, FC, and EC); collectively, $F(5, 305) = 31.8$ and $p < 0.001$. Moreover, the value of the variance inflation factor (VIF) shows that there is no issue with multi-collinearity between the variables since the value is less than 3.

The logistic regression, which studies the relationship between both the independent variables (IU and FC) and the dependent variable (AU), was able to correctly classify 84.2% of the actual use of visual recognition technology cases (Table 15). The author uses logistic regression as the actual use of visual recognition technology is dichotomous (2 categories: Yes and No).

Table 14. Logistic regression of the results.

			Predicted		Percentage Correct
			AU		
Observed			0	1	
Step 1		0	255	8	97.0
	AU	1	41	7	14.6
Overall Percentage					84.2

Table 16 shows the standard and non-standard regression coefficients, the standard error, the value of t with the value of P , the value of the variance inflation factor (VIF) and the tolerance coefficients. The VIF shows that it is unlikely that there is a problem with multicollinearity between the variables, as it was less than 3. The regression equations can be written as follows:

$$IU = 0.222*PE - 0.103*EE + 0.084*SI + 0.352*FC - 0.199*EC + \text{Error term (main equation),}$$

$$\text{Log}(p/1-p) = -2.050 + 1.057*FC + 0.047 *IU \text{ (secondary equation),}$$

where p is the probability of actual use of visual recognition technology.

Looking at the unique individual contributions of the predictors, the results show the performance expectancy ($\beta = 0.222$, $t = 3.37$, and $p = 0.001$), effort expectancy ($\beta = -0.103$, $t = -1.84$, and $p = 0.042$), facilitating conditions ($\beta = 0.352$, $t = 6.81$, and $p = 0.001$), and ethical concerns ($\beta = -0.199$, $t = -3.75$, and $p = 0.001$). Furthermore, the results reveal that social influence does not significantly influence the intention to use visual recognition technology ($\beta = 0.048$, $t = 0.78$, $p = 0.433$). Moreover, the secondary model shows that facilitating conditions significantly affect the actual use of visual recognition technology ($\beta = 1.077$, $t = 5.5$, $p = 0.001$). In addition, the intention to use visual recognition technology does not significantly influence the actual use of visual recognition technology ($\beta = -0.047$, $t = -0.2$, $p = 0.783$). Results of the logistic regression indicate that, with a 95% degree of confidence, a 1% increase for the FC determines growth in the odds ratio for an auditor to actually use visual recognition technology with 194%. The results presented in Table 16 demonstrate a relationship between

the independent and dependent variables as postulated in the hypotheses of this research. The independent and dependent variables analysis results are presented in Table 16 and Figure 18.

Moreover, Table 16 shows the Pearson correlation coefficient between the dependent and independent variables in the first equation. The R -value was 0.55, with an R^2 value of 0.317 and an adjusted R^2 value of 0.310, which indicates that the model explains 31% of the variance in the IU visual recognition technology.

Table 15. Results of the independent and dependent variables analysis.

Dependent Variable	Independent Variables	R	Adj R^2	F	P	Std. Error		t	P	95% conf	interval	Collinearity Statistics	
						B	r					Tolera	VIF
IU	(Constant)					0.000	.047	.000	1.000	-.092	.092		
	PE					.222	.066	3.37	.001	.093	.352	.78	1.28
	EE	.55	.310	31.8	.00	-.103	.056	-1.84	.042	-.214	.006	.88	1.13
	SI					.048	.061	.78	.433	-.073	.170	.79	1.26
	FC					.352	.051	6.81	.000	.251	.454	.89	1.13
	EC					-.199	.053	-3.75	.000	-.304	-.095	.86	1.16
Dependent Variable	Independent Variables					B	S.E.	Wald	t	p	95% conf	Interval	Exp(B)
AU	(Constant)					-2.05	.198	103	-10.3	0.000	-2.44	-1.66	.129
	FC	.	.	.	.	1.077	.195	29.2	5.50	0.000	.693	1.46	2.94
	IU					-.047	.170	.066	-0.2	0.783	-.380	.286	.95

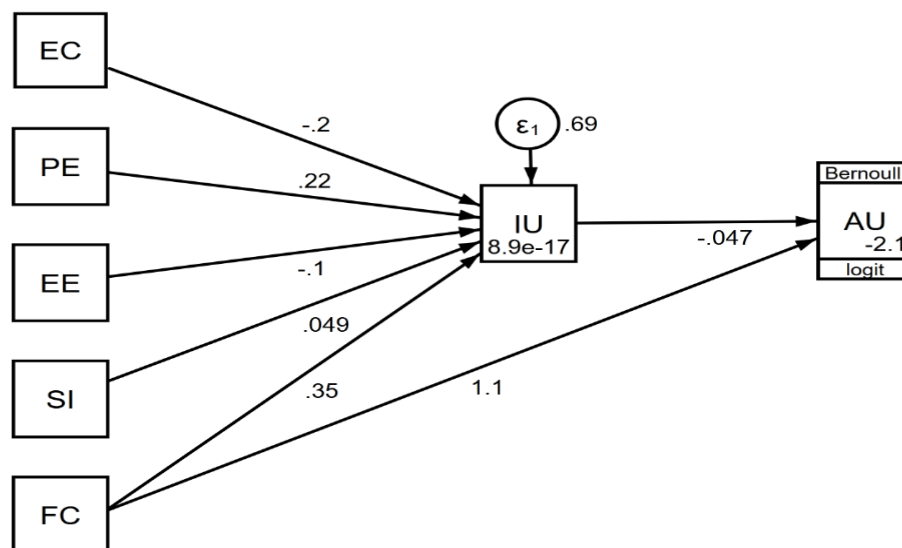


Figure 18. Relationship between the independent and dependent variables.

Table 17 shows the dependent (IU) and independent variables (PE, EE, SI, FC, and ECs) in the first model and the dependent (AU) and independent variables (IU and FC) in the second model, which are included in the regression equations. The analysis did not exclude any variables. The method used for both models involve all the variables in a block being entered in a single step.

Table 16. Dependent and independent variables in the first and second models.

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	EC, FC, EE, SI, PE ^b	.	Enter
2	FC, IU	.	Enter

a. Dependent Variable: 1-IU, 2-AU

b. All requested variables entered.

In the main regression equation, the dependent variable IU was regressed on the predicting variables PE, EE, SI, FC, and EC. Significantly, the overall model predicted the dependent variable IU, with $F_{(5,305)} = 31.8$, $p < 0.001$ (Table 18), which indicates that the independent variables might have played a significant role in shaping the dependent variable (IU).

Table 17. Statistical parameters for model 1.

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	96.212	5	20.705	31.8	0.000 ^b
	Residual	213.788	305	0.694		
	Total	310.000	310			

a. Dependent Variable: IU

b. Predictors: (Constant), EC, FC, EE, SI, PE

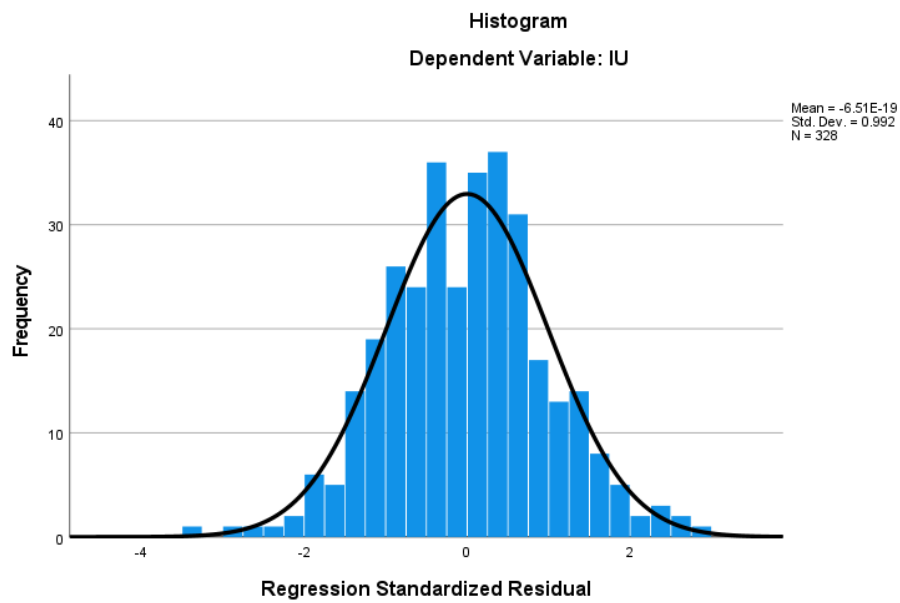


Figure 19. Histogram of regression standardised residual.

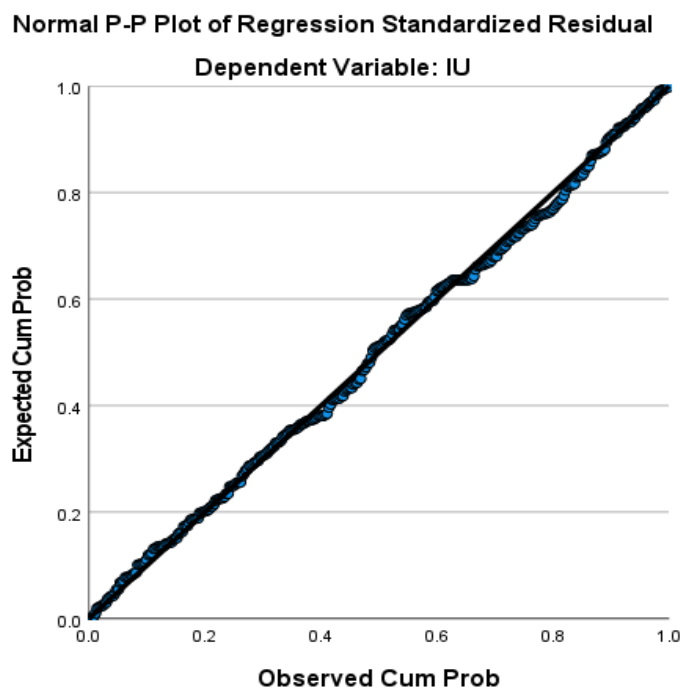


Figure 20. Normal P-P plot of regression standardised residual

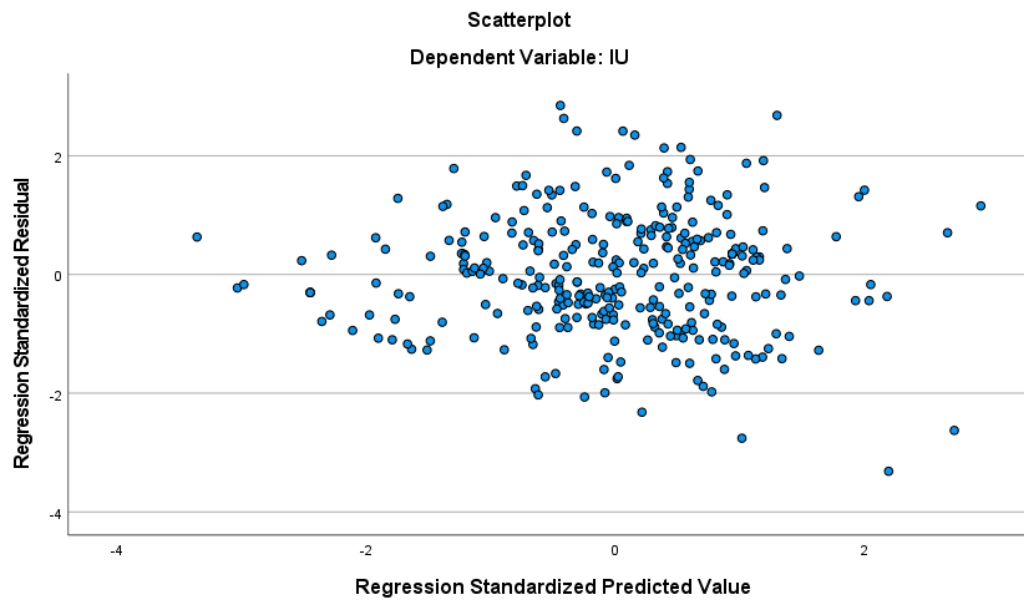


Figure 21. Scatterpot.

Figures 19, 20, and 21 show the moderation of the regression standardised residuals and the data gathered around the straight line. Therefore, the residuals follow a normal distribution, which is a condition for the validity of the regression analysis.

6.3.5 Moderator Factor Results

6.3.5.1 Firm Size

This study also investigated audit firm size (FS), which acts as a moderating variable in the relationship between the dependent variable (IU) and the independent variables (PE, EE, IS, FC, and ECs). It was hypothesised that audit FS enhances the relationship between the IU VRT and the independent variables. A multiple regression analysis was performed to test this hypothesis. The results depict that audit FS was not a predictor ($\beta = -0.06$, $t = -1.18$, and $p < 0.238$). Furthermore, the interaction variable FS and the other independent variables (PE, EE, SI, and FC) did not predict the IU visual recognition technology ($\beta = -0.077$, $t = -1.05$, $p < 0.296$; $\beta = -0.033$, $t = -0.57$, $p < 0.57$; $\beta = -0.101$, $t = -1.5$, $p < 0.135$; and $\beta = 0.33$, $t = -0.64$, $p < 0.522$, respectively). Thus, it can be concluded that FS does not moderate the relationship

between the dependent and independent variables. The results of the moderator analysis are presented in Table 19.

Table 18. Moderator analysis for the independent and dependent variables.

Dependent Variable	Independent Variables	R	Adj R ²	F	P	β	t	p	VIF
IU	Constant	0.571	0.303	13.9	0.000	0.010	0.204	0.839	
	PE					0.510	2.11	0.036	1.368
	EE					-0.052	-0.26	0.791	1.178
	SI					0.395	1.76	0.079	1.286
	FC					0.22	1.28	0.200	1.156
	FS					-0.060	-1.18	0.238	1.065
	PE * FS					-0.077	-1.05	0.296	1.495
	EE * FS					-0.033	-.57	0.57	1.204
	SI * FS					-0.101	-1.5	0.135	1.390
	FC * FS					0.033	0.64	0.522	1.162

6.4 Discussion And Implications

Despite the rapid development in artificial intelligence techniques in the last decade and the events that have pushed companies to accept new technologies due to the intensity of competition and the crisis caused by the coronavirus disease pandemic, prior literature indicated that the adoption of artificial intelligence techniques in the field of auditing is relatively low (Omoteso, 2012; Issa et al., 2016; Kokina and Davenport, 2017; Sun and Vasarhelyi, 2018; Sun, 2019; Austin et al., 2021). Artificial intelligence technology is important because it may increase audit quality, effectiveness, and efficiency (Appelbaum and Nehmer, 2017; Sun and Vasarhelyi, 2018; Sun, 2019; Ukpogon et al., 2019). To obtain a clear understanding of the determinants that may influence auditors' decisions to adopt artificial intelligence technology, the author applied a commonly accepted theory of technology acceptance from the management information system literature (Venkatesh et al., 2003). The

auditing context differs in many determinants from the typical management information system context, including the influence of audit firm size on auditors' behaviours. Furthermore, the artificial intelligence technology context varies from a typical technology context, including the ethical concerns associated with the application of artificial intelligence technology. Owing to these distinctions, the author re-shared the theoretical model to capture the influences of ethical concerns and audit firm size on the intention to accept artificial intelligence technology. The author then tested this model in the auditing context with participants from auditing firms of different sizes.

The results obtained from 311 auditors working in Big Four, national, and local firms indicated that facilitating conditions, performance expectancy, ethical concerns, and effort expectancy directly influenced the auditors' intention to accept artificial intelligence technology. Moreover, the results suggest that facilitating conditions directly influence the actual use of artificial intelligence. Additionally, the outcomes indicate that social influence did not play an essential role in the influence on auditors' decision to accept artificial intelligence technology and that audit firm size did not moderate the relationship between the five determinants and the intentional use of artificial intelligence technology.

This study and previous ones show the evident influence of facilitating conditions on auditors' intentional use of a new form of technology (Ebimobowei et al., 2013; Mahzan and Lymer, 2014; Curtis and Payne, 2014; Bierstaker et al., 2014; Pedrosa et al., 2019). The results of this analysis differ from those of other studies in that the results suggest that facilitating conditions had the most influence on the auditors' intentional use of artificial intelligence technology.

This study discloses the auditors' intentional use of artificial intelligence in the field of auditing. The analysis defined ten hypotheses, of which five were supported and five were not. The supported hypotheses were the influences of performance expectancy, effort expectancy,

facilitating conditions, and ethical concerns on auditors' intentions and the influence of facilitating conditions on artificial intelligence's actual use. The hypotheses that were not supported were the influence of social influence on auditors' intentions and the four hypotheses that audit firm size moderates the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions and auditors' intentions.

Hypothesis 1 explores the effect of performance expectancy on auditors' intention to use artificial intelligence. The performance expectancy effect on the adoption of new technology, mentioned by Venkatesh et al. (2003), has been expressed in the literature in several ways, such as individual impact (DeLone and McLean, 1992; Sedera et al., 2004; Gable et al., 2008), perceived benefits of 'usefulness' (Davis, 1989; Iacovou et al., 1995), job fit (Thompson et al., 1991), relative advantage (Moore and Benbasat, 1991), and outcome expectation performance (Compeau and Higgins, 1995). All these studies showed the effects of users' personal beliefs about the impact of this new technology on their job performance. The results of this study indicate that performance expectancy influenced the auditors' intentional use of artificial intelligence ($\beta = 0.222$), which is consistent with studies conducted in the field of auditing by Mahzan and Lymer (2014), Ebimobowei et al. (2013), Bierstaker et al. (2014), Pedrosa et al. (2019), Curtis and Payne (2014), and Handoko et al. (2018). This analysis is slightly different from the aforementioned ones in that it does not indicate performance expectancy as the most influential determinant of the intention of the external auditor to use artificial intelligence, but it is the second most influential determinant after facilitating conditions. Thus, the results encourage audit firm management, when intending to adopt artificial intelligence, to invest in explaining and clarifying to the auditors the possible benefits to their audit performance, such as raising efficiency and effectiveness, as well as quality and reducing time (Chen et al., 2009; Omoteso, 2012).

The second hypothesis indicates that the size of the audit firm in which the auditor works moderates the relationship between performance expectancy and auditors' intentional use of artificial intelligence. This hypothesis was proposed in response to the result of Abou-El-Sood et al. (2015), who indicate that the perceived importance and benefits of audit technology are relatively higher for those in Big Four firms, and to the results of Janvrin et al. (2008), who propose that auditors working at Big Four companies are more likely to utilise technology in audit testing compared to those working at other audit firms. The results of this study show that firm size did not moderate the relationship between performance expectancy and the auditors' intentional use of artificial intelligence ($\beta = -0.060$) and that the interaction variable of firm size and performance did not predict the intentional use of artificial intelligence ($\beta = -0.077$). The thesis results may support the results of Pedrosa et al. (2019), who indicate that the number of statutory auditors does not moderate the effector of the perceived usefulness on auditors' intentional use of computer-assisted audit techniques, where a large number of statutory auditors refers to large audit firm size. The thesis did not hypothesise that the audit firm size moderates the relationship between auditors' intentional use of artificial intelligence and the actual use of artificial intelligence. Thus, all auditors working in large and small auditing companies could have had their intentional use of artificial intelligence inflated, but the actual use might have occurred in large companies because of their capabilities other than financial or technical capabilities.

Hypothesis 3 explored the effect of effort expectancy on auditors' intentional use of artificial intelligence. The effort expectancy effect on the adoption of new technology, mentioned by Venkatesh et al. (2003), has been expressed in several ways in the literature, such as perceived ease of use (Davis, 1989), complexity (Thompson et al., 1991), and ease of use (Moore and Benbasat, 1991). These studies showed the influence of users' personal beliefs about the effort needed to use this new technology on their intentional use of the new

technology. The results of this study indicate that effort expectancy influences auditors' intentional use of artificial intelligence ($\beta = -0.103$), which is similar to the results of the studies conducted in the field of auditing (Ebimobowei et al., 2013; Curtis and Payne, 2014; Pedrosa et al., 2019). They also show that effort expectancy is the third most influential determinant of auditors' intentional use of artificial intelligence. Thus, it urges the developers of artificial intelligence to make these systems flexible so that they can be compatible with various systems used by clients. The clients of audit firms are of different sizes and sectors; thus, it is normal that the auditors' clients use various ERP systems.

Furthermore, when intending to adopt artificial intelligence, it is an encouragement for audit firm management to invest in training and educating their auditors on how to use this new technology. Training should involve how to use the new technology and how to synchronise it with different ERP systems used by their clients, since each client may have different ERP systems. The results of the study are supported by the research conducted by Bedard et al. (2003), which show an enhancement of training on technology implementation through the training's impact on users' perceptions of their tasks and computer self-efficacy. Furthermore, the study upholds the research of Perkhofer et al. (2019), who state the necessity of offering sufficient training to boost perceived ease of use and then increasing technology usage in the accounting profession. It is certain that these training courses require vast budgets (Widuri et al., 2016); their costs must be considered before deciding to use artificial intelligence.

The fourth hypothesis represents the effect of audit firm size, in which the auditor works in moderating the relationship between effort expectancy and auditors' intentional use of artificial intelligence. This hypothesis was proposed in response to the results of Chaney et al. (2004) and Janvrin et al. (2009), who suggest that the Big Four audit firms provide more training programmes in IT for their auditors, which enables them to audit large and more complicated accounts. The study results do not support this hypothesis ($\beta = -0.060$), and the

interaction variable of firm size and effort expectancy does not predict the intentional use of artificial intelligence ($\beta = -0.033$). This could be a result of the lack of artificial intelligence specialised training programmes in large audit firms. It is noteworthy that the results of this thesis do not indicate that small audit firms offer the same number and size of training programmes in IT, but rather that audit firm size does not moderate the relationship between effort expectancy and auditors' intentional use of artificial intelligence. Furthermore, this can be a result of the modernity of artificial intelligence in the field of auditing (Sun and Vasarhelyi, 2018; Austin et al., 2021); the Big Four firms are still in the early stages of studying the feasibility of using artificial intelligence in auditing.

Hypothesis 5 explores the effect of social influence on auditors' intentional use of artificial intelligence. The term 'social influence' used in the UTAUT has been expressed in different ways such as 'subjective norm' (Davis, 1989), 'social factor' (Thompson et al., 1991), and 'image' (Moore and Benbasat, 1991). These studies show the influence of the community on potential users' intentional use of new technology. However, the analysis does not reveal a significant influence of social influence on auditors' intentional use of artificial intelligence ($\beta = 0.048$). These outcomes are similar to those of the studies conducted in the field of auditing by Bierstaker et al. (2014), Mahzan and Lymer (2014), Curtis and Payne (2014), and Pedrosa et al. (2019). The reason why the results of this study contradict earlier ones (Venkatesh et al., 2003) may be that, in an audit context, auditors give personal preferences less weight than decisions to use artificial intelligence for personal purposes because they have a responsibility to collect adequate audit evidence (Bierstaker et al., 2014). This may also result from their belief that clients care much more about the cost of the audit process, not the tools used in the audit process. For example, auditors may imagine that clients are not interested in conducting audits using artificial intelligence (or the traditional method) as much as they are interested in issuing an audit opinion at a cost that suits them.

Hypothesis 6 represents the effect of audit firm size, in which the auditor works in moderating the relationship between social influence and the auditors' intentional use of artificial intelligence. This hypothesis was proposed in response to the results of Ahmi and Kent (2012) and Curtis and Payne (2008), which show a notable effect of encouragement from senior management on the auditors' intentional use of new technology. Moreover, it was proposed in response to the results of Pedrosa et al. (2019), who argue that the number of auditors in a firm has an impact on social influence, and due to the fact that large audit firms have more auditors than small ones. The study results do not support this hypothesis ($\beta = -0.060$), and the interaction variables of firm size and social influence do not predict the intentional use of artificial intelligence ($\beta = -0.101$). This could result from the difficulty of generalising the effect of SI across hierarchical levels within firms, in which the effect will be diminished at higher levels (Meredith et al., 2020).

Hypothesis 7 explores the effect of facilitating conditions on auditors' intentional use of artificial intelligence. The roots of the term 'facilitating conditions' used in the UTAUT originates from the term 'perceived behavioural control' used by Taylor and Todd (1995) and the term 'compatibility' employed by Moore and Benbasat (1991). The aforementioned studies show the effects of the auditors' perception that the organisational and technical infrastructures exist to support their intentional use of artificial intelligence. The results of this study indicate that facilitating conditions had an influence on the auditors' intentional use of artificial intelligence ($\beta = 0.352$), which is consistent with studies conducted in the field of auditing by Ebimobowei et al. (2013), Mahzan and Lymer (2014), Curtis and Payne (2014), Bierstaker et al. (2014), and Pedrosa et al. (2019). The results of this analysis differ from those of the aforementioned studies in that the results propose that facilitating conditions have the most influence on the auditors' intentional use of artificial intelligence. Thus, when intending to adopt artificial intelligence, the results encourage audit firms' management to increase

auditors' perceptions that the resources, knowledge, and IT support exist to help them through their adoption journey. Moreover, the management of audit firms must operate the technical team's work in close proximity to the audit team. Audit firms should integrate IT teams into the audit teams and increase audit technology training programmes for staff at all levels (Meredith et al., 2020). Moreover, Curtis and Payne (2014) encouraged audit firms to provide the resources and structural support necessary to facilitate both the intentional use of new technology and the actual implementation of the new technology.

Hypothesis 8 explores the effect of facilitating conditions on auditors' actual use of artificial intelligence. The roots of the term 'actual use of artificial intelligence' used in this thesis originate from the term 'use' used by DeLone and McLean (1992), the term 'usage behaviour' employed by Taylor and Todd (1995), the term 'usage' utilised by Compeau and Higgins (1995), and the term 'use behaviour' used by Venkatesh et al. (2003). The aforementioned studies showed the effects of the auditors' perception that the organisational and technical infrastructures exist to support their actual use of artificial intelligence. The results of this thesis indicate that facilitating conditions have a strong influence on the auditors' AU of artificial intelligence ($\beta = 1.077$). The result suggests that, with a 95% degree of confidence, a 1% increase of facilitating conditions determines a growth of the odds ratio for an auditor to actually use visual recognition technology with 194%. The finding is similar to the results of previous studies conducted in the field of auditing (Bierstaker et al., 2014; Handoko et al., 2018; Pedrosa et al., 2019). The result encourages audit firms to boost auditors' perception that infrastructure and technology are always available to help them use artificial intelligence.

Hypothesis 9 represents the effect of audit firm size, in which the auditor works in moderating the relationship between facilitating conditions and auditors' intentional use of artificial intelligence. This hypothesis was proposed in response to the results of Rosli et al.

(2013) and Bierstaker et al. (2014), who describe how the limitations of resources and specialised IT teams in smaller audit firms affect auditors' use of new technology. The thesis results do not support this hypothesis ($\beta = -0.060$), and the interaction variable of firm size and facilitating conditions does not predict the intentional use of artificial intelligence ($\beta = 0.033$). This could be a result of the modernity of artificial intelligence in the field of auditing (Sun and Vasarhelyi, 2018; Austin et al., 2021), which means that the differences between small and large audit firms are insignificant for this issue. Moreover, the reason for the lack of influence of audit firm size might be that large firms do not have technical teams specialised in artificial intelligence, owing to the limited use of artificial intelligence in audits at present.

The final hypothesis addresses the effect of the ethical concerns associated with the use of artificial intelligence in the field of auditing on auditors' intention to employ artificial intelligence. This hypothesis aims to study the impact of the ethical considerations that the auditor believes are implicit in the use of artificial intelligence in the field of auditing. The potential ethical considerations that are inherent in the use of artificial intelligence are discussed in the literature, such as data and retrieval, due professional care, confidentiality, data security, de-professionalisation (Gepp et al., 2018; Munoko et al., 2020; Lehner et al., 2022), and bias within professional judgements (Meredith et al., 2020). The results of this thesis indicate that ethical concerns influence auditors' intentional use of artificial intelligence ($\beta = -0.199$). This finding shows that the technology that auditors believe is more ethical is the technology that is more likely to be used in the field of auditing. Thus, developers of artificial intelligence are encouraged to address issues related to the confidentiality of information and data security in their technology. The nature of auditors' work means that client confidentiality is an essential matter, which cannot be traded off regardless of whether auditors use artificial intelligence or traditional auditing methods (Munoko et al., 2020).

Furthermore, when intending to adopt artificial intelligence, it is an encouragement for audit firm management to have a non-disclosure agreement with developers or those who store data (a third party). The audit firms must also explicitly discuss with artificial intelligence developers the factors behind who should be held accountable for artificial intelligence's decisions in the case of litigation (Munoko et al., 2020). Moreover, the audit firms' management should explain to the auditors that artificial intelligence will help them make more accurate decisions, but will not replace them. On the legislative side, standard setters should reformulate the ethics code to include ethical issues that may arise from the use of augmented and autonomous artificial intelligence.

6.5 Conclusion

This chapter has discussed the quantitative data that was collected using the questionnaire. Overall, this chapter has three main sections. The first section presented the results of the reliability and validity of the questionnaire, as well as the descriptive statistic results. The second section introduced the effects of the main constructs of the thesis model, as well as the results of the thesis model moderator. The final section discussed the quantitative data results and the implementations of the results.

The first section of this chapter highlighted the descriptive results of the data collected from the participants. The data was collected from participants' answers to the demographic questions in the questionnaire. Descriptive results showed the ratios of male to female participants as well as the ages, experience, qualifications, and the size of the companies in which the participants worked. Moreover, this section showed the results of the tests that the author used to examine the reliability and validity of the thesis data. The outcome of the Kaiser-Meyer-Olkin (KMO) test revealed a score of 0.837, which is an acceptable value based on the minimum acceptable value of 0.6. This means that the measurement is of high quality. The Cronbach's alpha test revealed that each of the constructs exceeded the 0.70 threshold, which

indicates good reliability for the constructs. The discriminant validity test showed that the square root of the AVE of each construct is greater than its correlation with other constructs, which indicates that discriminant validity is established.

The second section of this chapter showed the results of the thesis model. These findings demonstrated that the main predictors of auditors' intention to use artificial intelligence are performance expectancy, effort expectancy, facilitating conditions, and ethical concerns. Furthermore, the results revealed that social influence does not significantly impact the intention to use visual recognition technology. Additionally, the results uncovered that facilitating conditions significantly influence the actual use of artificial intelligence, and the intention to use artificial intelligence does not significantly influence the actual use of artificial intelligence. In addition, the results depicted that audit firm size does not moderate the relationship between the intention to use artificial intelligence and the other independent variables (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions).

The final section of this chapter discussed the quantitative data results and highlighted the implementations of the results. This chapter examined the effects from the perspective of the literature on technology acceptance and, moreover, discussed the reasons behind these results. Additionally, in light of these results, this chapter provided recommendations for the audit firms that invest vast amounts of money in artificial intelligence, the technology companies that develop artificial intelligence systems, and the regulatory bodies that impose audit standards and ethical codes.

Chapter 7: Empirical Qualitative Results

7.1 Introduction

This chapter is dedicated to delving deeper into the findings discussed in the previous chapter by conducting a comprehensive series of interviews with professionals actively engaged in the external audit profession. These interviews will provide valuable insights and perspectives, allowing us to gain a more nuanced understanding of the intricate dynamics and challenges inherent in artificial intelligence technology acceptance. Through candid conversations with seasoned practitioners, we aim to shed light on key aspects of accepting artificial intelligence technology in audit engagements, such as regulatory compliance, risk of artificial intelligence implementation in the audit profession, industry best practices, and emerging trends, which will significantly enrich our analysis and contribute to a more holistic view of this critical area of study.

In the first part of this chapter, the descriptive results of the qualitative data are examined and in the second part, the implementation of these results are discussed. The thesis presents the descriptive results of the interview participants. These results are the age and gender of the participants, the firms they work in, their experience, and their professional certificates. The second part of this chapter provides the thematic results of the interviews and considers these results from the literature perspective.

7.2 Descriptive Results

As stated in the methodology chapter, the thesis has adopted a mixed-method approach to empirically validate the research model (Figure 10). The data was collected using two different methods. The quantitative method, and the results from it, were discussed in chapter seven. In the qualitative method, the author interviewed 26 auditors who worked in local,

national, and international CPA firms based in Saudi Arabia for more than 3 years. These participants were randomly selected from those who contributed to the questionnaires. The objective of conducting semi-structured interviews is to obtain a comprehensive understanding of artificial intelligence acceptance determinants and to learn the extent of the researcher's understanding of the research problem. The interviews were conducted online using Microsoft Office Teams. To optimise information capture, all the interviews were recorded (after obtaining permission from the participants) and transcribed. Each interview lasted approximately 1 hour (in the range of 48–65 minutes). Most interviews were conducted in Arabic because it was the participants' mother tongue, and they preferred to speak it. However, these interviews were translated into English afterwards by a certified translation provider. Table 20 shows the data of the participants such as age, gender, and experience. Participants were encoded with codes, such as participant 1, to protect their anonymity.

Table 19. Information on the participants.

Participant number	Age	Gender	Experience	Position	Certificates	Firm size
Participant 1	51 years	Male	26 years	Head of the firm	SOCPA ⁴	Local firm
Participant 2	34 years	Male	11 years	-	SOCPA	Medium firm
Participant 3	53 years	Male	25 years	A director of the firm	CPA ⁵	Local firm
Participant 4	36 years	Male	13 years	Senior auditor	CPA	Medium firm
Participant 5	36 years	Male	12 years	Senior auditor	CPA	Big Four firm
Participant 6	31 years	Male	5 years	An auditor		Big Four firm
Participant 7	37 years	Male	14 years	A manager	CPA	Big Four firm
Participant 8	42 years	Male	18 years	Senior auditor	CPA	Big Four firm
Participant 9	33 years	Male	33 years	Senior auditor		Big Four firm
Participant 10	29 years	Male	7 years	Head of the firm	SOCPA	Local firm
Participant 11	35 years	Male	10 years	An audit manager	ACCA ⁶	Big Four firm
Participant 12	32 years	Female	7 years	An assistant manager	ACCA	Big Four firm
Participant 13	38 years	Male	18 years	An audit manager	ACCA	Medium firm
Participant 14	29 years	Female	6 years	An auditor	CPA-SOCPA	Big Four firm
Participant 15	29 years	Female	5 years	An auditor	SOCPA	Big Four firm
Participant 16	58 years	Male	24 years	An audit manager	CPA	Medium firm
Participant 17	31 years	Female	8 years	An auditor	CPA	Big Four firm
Participant 18	33 years	Male	10 years	A partner	SOCPA	Medium firm

⁴ SOCPA is a designation provided to licensed accounting professionals by the Saudi Organisation for Chartered and Professional Accountant.

⁵ CPA is a designation provided to licensed accounting professionals by AICPA.

⁶ ACCA is a global professional accounting qualification offered by the Association of Chartered Certified Accountants.

Participant 19	44 years	Male	13 years	An audit manager	ACCA-CPA-CFA ⁷	Medium firm
Participant 20	38 years	Male	18 years	Senior auditor	ACCA	Medium firm
Participant 21	30 years	Female	7 years	Senior auditor	SOCPA	Big Four firm
Participant 22	27 years	Male	5 years	An auditor		Big Four firm
Participant 23	25 years	Male	5 years	An auditor		Local firm
Participant 24	27 years	Female	4 years	An auditor		Big Four firms
Participant 25	37 years	Male	14 years	An audit manager	SOCPA - ACCA	Big Four firms
Participant 26	28 years	Female	6 years	An auditor		Medium firm

To increase construct validity (Hunt et al., 1982; Shadish et al., 2002; Saunders et al., 2019), the author conducted a pre-test for the data collection instrument. The latter was sent to five academics, who are experts in the field of auditing and IT and, based on their feedback, the instrument was revised.

The data collected was analysed using a pattern-matching technique. Pattern matching compares a theoretically predicted pattern to an empirically observed pattern (Sinkovics, 2018). The basic idea is that people can make sense of the world by comparing what they observe outside with their internal mental models (Hammond, 1966). Pattern-matching techniques can be used effectively in qualitative data analysis when the research questions are supported by a theoretical assumption (Yin, 2009), which is the case in this study.

The author used NVivo 12 (the software used to evaluate qualitative data) to code and analyse the transcripts. First, the transcripts were uploaded to NVivo. Next, the data was arranged into different codes. These codes were then linked to the most relevant pre-identified construct in the research model. For example, when a participant says: ‘Artificial intelligence helps me complete audit work faster than the traditional audit method,’ the author creates a code called ‘timesaving’ and links it to the pre-identified construct ‘performance expectancy’.

Table 21 shows the descriptive analysis of the interview participants, which included 26 auditors from regional, national, and international firms in geographically different regions of the KSA. The interview respondents’ mean age was 35.5 years, and the mean audit experience

⁷ CFA is a globally recognised professional designation given by the chartered financial analyst Institute.

was 12.3 years. They work in audit firms of different sizes, with 60% employed by Big Four firms, 25% by international audit firms (not Big Four), and 15% by local audit firms. Of the participants, 90% had CPA certificates and most (N = 19) were male.

Table 20. Descriptive statistics for interview.

Descriptive statistics for interview		
Gender	Male	19
	Female	7
Age		35.5 years
Experience		12.3 years
Accounting qualification	YES	81%
	NO	19%
Firm size	Big Four	54%
	International firm (not big four)	31%
	Local firm	15%

7.3 Results and Discussion of Qualitative Data (Interviews)

7.3.1 Performance Expectancy

Performance expectancy was one of the pre-identified constructs. The goal is to explore the influence of auditors' perception of the expected performance of artificial intelligence technology on the intention to use artificial intelligence. In general, the participants showed a clear and direct impact of performance expectancy on the intention to use artificial intelligence techniques. The talks of the participants revolved around four main and essential themes: (i) the effectiveness of artificial intelligence technology in performing audit tasks, (ii) the efficiency of artificial intelligence technology in performing audit tasks, (iii) the influence of artificial intelligence technology on the quality of external auditors' outcomes, and (iv) artificial intelligence technology capability in saving auditors' time. These four dimensions of performance expectancy were examined by a number of participants in several scenarios. In the following section, each of these four themes are discussed in more detail.

7.3.1.1 Effectiveness of Artificial Intelligence Technology in Performing Audit Tasks

The effectiveness of artificial intelligence in the audit profession is defined as the ability of artificial intelligence to produce new ways of gathering evidence, opening channels to communicate with clients, and handling big data; all of which add more value to the auditor report in the end. A large part of the literature has examined the added value that artificial intelligence technology can create in the field of auditing. Raschke et al. (2018) discuss the possibility of using artificial intelligence bots that generate continuous automatic audit inquiries, as well as evaluate client responses. This is consistent with the comment of one of the interviewees who says: *'we rely on the documents received from our clients.....we have to run several tests to ensure the validity of these documents and some of these tests are conducted using RPA [Robotic Process Automation], which autonomously generates confirmation requests, sending confirmation requests, receiving requests, and informs the auditor when we received them'* (P17). Another interviewee said: *'we use RPA because it helps with the clerical work... so, a lot of confirmation processes are done by artificial intelligence... cash and bank information, confirmation of accounts receivable, and confirmation of accounts payables, which we used to collect as samples and send each client or bank an individual email, but it is now being done based on the parameters which we set... all of these communications are sent by the system itself'* (P12). These comments show that auditors perceive the effectiveness of artificial intelligence in the process of data collection and clients' document validations.

Revolutionary artificial intelligence techniques are rapidly emerging in the global markets. For example, visual recognition techniques can understand the content of an image or a clip and identify the object and subject (including human faces) in the image (Rosenberg, 2013). This can be utilised in the audit process to facilitate the automation of fraud detection and assets and inventory checks (Issa et al., 2016). An interviewee comments that: *'in my personal experience, I have noticed that more than one employee uses the same ERP account,*

which goes against the principle of the segregation of duties... If the ERP system requires a video record of those who perform entries and there is a smart audit system that could match employee ID with the recorded video, I would personally love to use it' (P9). The participant shows his desire to use a smart verification tool to identify the person who performs entries in the client's ERP system. If a smart tool is available to the auditor that does this task, it is more likely the auditor will use it.

It should be noted that participant 9 referred to the importance of the availability of advanced internal control systems (e.g., ERP) for the clients in the implementation of artificial intelligence. Debreceeny et al. (2005) emphasise this point by stating that external auditors have limited usage of their advanced audit software because of the limitation of their clients' advanced internal controls system. The client's use of advanced technology will increase the effectiveness of the artificial intelligence systems used by the auditor.

Another participant says: *'I remember when I went to check a client's stock and they had a huge pile of pipes... It was impossible to do a traditional inventory check, so we had to use an artificial intelligence application on the phone to check the number of pipes'* (P16). This comment indicates that the nature of the client plays a role in influencing the perception of auditors towards the effectiveness of artificial intelligence in the audit profession. Clients who have large warehouses or open-air inventories, assets that are difficult to reach, and enormous and sprawling farms may encourage auditors to take advantage of smart audit tools, like visual recognition technology.

It is inferred from the above discussion that, when an external auditor perceives that the use of artificial intelligence will benefit his work by confirming customer data's credibility, it is more likely that the auditor is willing to use this technology. This inference is consistent with Pedrosa et al. (2019) findings, which indicate that the more an auditor perceives the effectiveness of a tool in performing audit tasks, the greater intention he or she reveals to use

it. Moreover, this result is consistent with Ahmi and Kent (2012), who find that auditors with relatively small and uncomplicated clients do not use GAS because they do not perceive the usefulness of such complicated advanced audit systems to them.

7.3.1.2 Efficiency of Artificial Intelligence Technology in Performing Audit Tasks

The efficiency of artificial intelligence refers to the ability of artificial intelligence to accomplish audit tasks with the least amount of money. Since many of the auditing tasks are structured and repetitive (Kokina and Davenport, 2017; Issa et al., 2016), auditors are motivated to use artificial intelligence to save money by reducing human labour (Raschke et al., 2018). This is consistent with a comment of an interviewee who works at one of the Big Four audit firms: *'using artificial intelligence, the audit company can reduce the number of auditors it has... I mean, instead of six or seven auditors going to one client, now only two, or even one, can go down because the system helps him analyse the client's data'* (P15). Another participant said: *'our behaviour as auditors is profit-driven behaviour...we are motivated to use artificial intelligence and automation technology because these technologies reduce costs and the number of employees by half or more'* (P5). These comments from the participants indicates that they wish to use artificial intelligence because it may lead to higher efficiency in performing audit tasks.

Thus, it can be understood from what the interviewees claim that, when the auditor perceives that artificial intelligence technology leads to greater efficiency when performing audit tasks (whether by reducing cost or conserving resources), they will be more likely to accept or use artificial intelligence technology. This result is validated by Greenstein-Prosch et al. (2008), who emphasise that, in order to increase the adoption of a specific system, the impact of that system on work efficiency needs to be made clear. This indicates that if an audit firm plans to successfully implement artificial intelligence technology, the impact of this technology on performance efficiency should be understood and evident to the members of the firm.

7.3.1.3 Perceived Impact of Artificial Intelligence on Audit Quality

There is a growing appreciation among audit researchers (Fischer, 1996; Holm and Zaman, 2012), as well as regulatory bodies such as FRC, that: ‘there is no single agreed definition of audit quality that can be used as a “standard” against which actual performance can be assessed’ (FRC 2006, p. 7). For clarification, the author states that audit quality refers to: ‘(a) achieving the fundamental objective of obtaining reasonable assurance that the financial statements as a whole are free of material misstatement, and (b) ensuring material deficiencies detected are addressed or communicated through the audit report’. This research does not investigate whether artificial intelligence will raise auditing quality. Yet, it does discuss the sequence of perceiving that the use of artificial intelligence leads to improved audit quality.

Recent reports by International Forum of Independent Audit Regulators (IFIAR) have revealed significant issues regarding the quality of financial report audits on a global scale, particularly the inadequacy of quality control procedures used by corporations (IFIAR, 2018; IFIAR, 2017). Adequate audit quality is crucial for investor confidence; without it, they cannot properly assess the value of investments (Meredith et al., 2020). Part of the responsibility for developing the quality of audits lies with the audit firms, whether by changing the strategies of the audit process or by developing advanced techniques that promote a better understanding of clients and more comprehensive documentation of procedures.

Previous studies indicate that advanced audit technologies are generally seen as having a positive impact on audit quality (Salijeni et al., 2019; Abou-El-Sood et al., 2015; Alon and Dwyer, 2010). Decision support technology offers a means for auditors to enhance audit quality (Meredith et al., 2020) by improving their decision-making, particularly through mitigating decision-making biases (Song et al., 2017; Abdolmohammadi and Usoff, 2001). An interviewee states that: *‘I would like to use artificial intelligence because the use of artificial intelligence techniques will benefit us in terms of consistency... what I meant by consistency is,*

instead of relying on the judgment of different auditors in the audit team or in the audit firm, artificial intelligence will treat all of the accounts by the same standards and the same consistency, which will lead to a high-quality audit opinion' (P19). This comment indicates that the participant believes that artificial intelligence will have a significant role in procedural consistency in decision-making. This belief makes him motivated to use artificial intelligence.

Moreover, another interviewee states: *'at our firm, we want to use artificial intelligence because it excludes the human element in terms of mistakes, personal inclinations, and biases'* (P4). This participant intends to use artificial intelligence because he perceives that the use of artificial intelligence will lead to a reduction of human bias. His point of view is consistent with previous results (Song et al., 2017; Abdolmohammadi and Usoff, 2001) that indicate the use of decision-making systems improves auditors' decision-making, particularly by minimising decision-making biases. On the other hand, some of the interviewees claim that the use of artificial intelligence techniques will negatively impact audit quality due to the ineffectiveness of this technology in making professional audit judgments. A participant expressed that: *'we don't use artificial intelligence to make audit judgments because it is not possible for it to surpass the professional judgments of the auditors... a human mind's ideas are not limited... unlike artificial intelligence, which is limited by algorithms, even if it sometimes seems well developed'* (P9). The participant's perception that artificial intelligence is not adequately configured to perform judgment in the audit profession distances him from using artificial intelligence. The participant's comment confirms what Castelo et al. (2019) state that artificial intelligence aversion possibly due to beliefs that algorithms lack the necessary capabilities to perform subjective tasks effectively.

Another interviewee agreed with P9 and states that: *'we assume that artificial intelligence will not perform all of the audit procedures... I think there will be problems and shortcomings in many aspects, especially the aspects that depend on personal observation and professional*

judgment' (P26). Some of the literature examines the view of the previous participants that any modern technology cannot compensate for human professional judgment. Meredith et al. (2020) note that the less use of human professional judgements in audits might potentially decrease the quality of audits. Moreover, according to Dowling and Leech (2007), a decision aid is not adequate for forming an audit opinion as the audit opinion necessitates the exercise of professional judgement by the auditor. The concerns of implementing artificial intelligence technology in forming audit judgments are discussed in section 8.3.4.2.

After the above discussion, the author concludes that both negative and positive perceptions of the impact of artificial intelligence on audit quality will affect the acceptance of artificial intelligence in the audit profession. The more an external auditor believes that the use of artificial intelligence technology will increase the audit quality, the more likely he accepts the use of artificial intelligence techniques and vice-versa. This conclusion aligns with the results of Curtis and Payne (2014), who state that CAATs utilisation decisions depend on the perceived outcome quality of using these tools. This means that, to have successful and smooth artificial intelligence acceptance, external auditors need to understand the impact of artificial intelligence technology on the quality of their statutory audit opinion.

It is particularly noteworthy that external auditors should consider the new types of evidence collected by artificial intelligence as supplemental evidence. This is not an attempt to provide a higher audit quality by replacing the financial information with a new type of evidence (Issa et al., 2016). An interviewee says: '*international auditing standards obligate us to largely base our opinion on financial statements and financial data and we use artificial intelligence to have a clear vision and make us more confident when issuing a legal opinion of our client's financial statements*' (P25). This comment may indicate that the auditor perceives that evidence collected by artificial intelligence will not replace traditional financial evidence. Rather, it will provide them with more evidence that adds value to the decision-making process.

7.3.1.4 Perceived Impact of Artificial Intelligence on Time-Saving

Technology in general, and artificial intelligence techniques in particular, have the potential to shorten the time auditors need to complete audit tasks. Elliott and Kielich (1985) report that an expert system reduces the time taken to complete audit tasks. Moreover, the same is found for the application of artificial intelligence, since it can significantly assist auditors by enabling them to examine a complete population of transactions quickly (Issa et al., 2016). Fisher et al. (2016) found that the integration of linguistic analysis and deep learning applications can automatically analyse a vast file of audit evidence in a short time without human intervention.

When an auditor feels that artificial intelligence techniques decrease the time pressures required for the audit process, his desire to use this technology increases. Payne and Curtis (2017) state that during the hectic audit season, auditors experience high levels of workload and time pressures. Auditor's workload, particularly during the busy audit season, can compel them to work during their personal time. Nehme et al. (2022) state that performing work tasks during personal time is considered a dysfunctional auditing behaviour, as it may result in insufficient time for auditor to complete professional requirements and attending training workshops aimed at enhancing their auditing skills. An interviewee comments that: *'honestly, for women, auditing work is a hard job. I mean, there are times when I had to sit and do auditing work for a very long time. Especially, when I've been to a large client for the first time and asked for the trial balance to arrange the auditing work... I would appreciate being able to use a smart tool that helps to identify the nature of each account... assets or liabilities... and helps in the mapping process... that could save me time'* (P14). This auditor reveals that the catalyst for her to use artificial intelligence is its ability to save time. If a smart tool could help or autonomously perform process mapping accounts for all the client's activities, she will accept the use of the tool.

Another participant adds that: *‘a lot of confirmation processes are done by artificial intelligence... cash and bank information, confirmation of accounts receivable, and confirmation of accounts payables, which we used to collect as samples and send each client or bank an individual email, but it is now being done based on the parameters which we set... all of these communications are sent by the system itself... If these processes were done manually, it would take hours of our auditing time’* (P12). The participant’s comment may indicate that the reason for performing the clerical work through the RPA is to save time.

It may be inferred from the previous discussion that, when the auditor perceives that artificial intelligence helps mitigate audit time pressure, they will be more motivated to accept or use this technology. This result is validated by Bierstaker et al. (2014), who found that time-saving plays a vital role in audit aid decision tool acceptance. This indicates that if an audit firm plans to implement artificial intelligence technology successfully, the positive impact of this technology on timesaving should be understood and evident to every member of the firm.

7.3.2 Effort Expectancy

Effort expectancy was one of the pre-identified constructs. Its goal is to explore the influence of auditors’ perception of the expected effort of using artificial intelligence on the intention to use it. In general, the interviewees showed a clear and direct impact of effort expectancy on the intention to use artificial intelligence techniques. The participants’ talks revolved around four main essential themes: (i) the cost of implementing artificial intelligence technology, (ii) the difficulty of understanding artificial intelligence technology, (iii) the difficulty of using artificial intelligence technology, and (iv) the flexibility of artificial intelligence technology. These four dimensions of effort expectancy were examined by a number of participants in several scenarios. In the following sections, each of these four themes will be discussed in more detail.

7.3.2.1 Cost of Implementing Artificial Intelligence Technology

Most of audit firms are profit-driven firms, meaning that the cost/benefits are one of the key principles they depend on when making decisions. Thus, it can be said that the cost of the technology that could be used in the audit process may play an important role in the decision to use them or not. Even though audit software would be categorised as a fixed cost by its nature and included in the fixed-fee audit contract (Palmrose, 1989), audit firms should consider the variable costs associated with maintaining software and auditor training. The initial financial outlays and continuing maintenance costs related to the acquisition of decision support technology are considered significant (Pedrosa et al., 2015; Ahmi and Kent, 2012).

Appelbaum et al. (2017) comment on the use of Big Data automation by saying that in the audit market, where prices are competitive, it leaves little room for more analytics, even if they provide a stronger guarantee of accurate depiction. They further wondered about the cost versus benefit trade-off with the use of automation and big data. An interviewee comments on this point by saying: *‘The cost of this smart technology is an essential point... I mean the cost versus the benefit.... sometimes it is one of the reasons for not using artificial intelligence because we are working in a market and there are many competitors... If we charge more for our audit fees because we use smart technology, well, the clients don’t care about what technology we use for the audits... they just want an auditor’s report to be submitted to the regulatory authorities’* (P13). This participant perceives that the cost of artificial intelligence is an obstacle to its application in the audit profession; this is because it will raise audit fees and, thus, make it difficult for audit firms to compete in the market.

Another participant, a director of a local audit firm, adds: *‘we must study the financial cost of artificial intelligence and the benefits of using it... audit systems are expensive in the early years of their application, due to high production costs such as research and development... later their prices decrease...in our firm we periodically evaluate the cost of the*

system versus the future benefit of it... If the benefits exceed the cost, we adopt it' (P3). The participant's comment shows that he believes that the current cost of artificial intelligence is high. However, they are periodically evaluating this technology in the hope that the costs will fall and they will be able to adopt it in future. Moreover, it can be inferred that the obstacle to the adoption of current artificial intelligence is its high cost. Mahzan and Lymer (2009) assert that the emergence of less expensive variants of audit systems means the price of audit systems may no longer be a concern.

Furthermore, a head of a small audit firm states: *'we have the ambition to be one of the leading companies in the use of advanced technology such as artificial intelligence applications in auditing... but I think firms that are taking the initiative in artificial intelligence application are certainly the big four firms, followed by the big ten, and so on, because the technology is very costly... small companies can't afford these costs, even if we assume that this technology is useful for small companies'* (P10). This is consistent with what Lovata (1988) says in that one of the essential barriers to implementing technology in the auditing field is the initial cost of the technology. In addition, this point was verified by previous results (Ahmi and Kent 2012), which show that high costs are believed to be the main constraint in the adoption of general audit software.

It can be understood from the above discussions that the perception of the artificial intelligence technology installation and maintenance cost versus the obtained benefits from using artificial intelligence technology is one of the stumbling blocks in the way of accepting artificial intelligence in the audit profession. These results are consistent with prior literature, which indicates that the use of technology in audits may depend on predictable cost trade-offs (Bierstaker et al., 2014; Niemi, 2004; Ahmi and Kent, 2012; Lovata, 1988). Meredith et al. (2020) propose that addressing the issue of technology costs at the organisational level should involve incorporating IT specialists into audit teams, enhancing staff training on decision

support technology, and extending the time frames for budget evaluation in audits to alleviate short-term concerns about the costs of new technology.

7.3.2.2 Difficulty in Understanding Artificial Intelligence Technology

Understanding artificial intelligence in the audit profession is the ability of an individual auditor to perceive the following: how algorithms work, the logic by which artificial intelligence systems make decisions, and how to integrate smart technology, which has the capability to make a decision, in professional judgments. Alles (2015) notes that the proper usage of artificial intelligence tools and Big Data involves more than just gathering and analysing vast amounts of data. It also requires knowing when and how to use the data to inform important decisions. The use of artificial intelligence might necessitate more advanced programming abilities, such as Python and C++. Furthermore, the user of advanced Deep Learning programmes must also be familiar with the fundamentals of math (particularly calculus, probability, and linear algebra), statistics, and machine learning (Shaikh, 2016). Thus, the mainstream use of artificial intelligence technology could be curbed due to the steep learning curve.

The ambiguity surrounding the way artificial intelligence performs audit tasks may impact the auditor's acceptance of the use of artificial intelligence. A participant, who is the head of an audit firm, comments that: *'I was in a meeting with a group of decision makers from audit firms in Riyadh, and one of the points on the meeting agenda was to discuss the use of artificial intelligence... during the discussion, it seemed to me that there is a lack of understanding about artificial intelligence and the ways artificial intelligence is used in auditing'* (P1). Moreover, an audit manager states that: *'audits need an element of personal judgment...I do not understand how artificial intelligence is going to make personal judgment by using algorithms and to what extent theses judgments are going to be accurate'* (P16). The participants' feedback may denote that, at the managerial level, there is no clear understating

of artificial intelligence technology, as well as the use of artificial intelligence. The misunderstandings on how algorithms and artificial intelligence work may reduce the passion and enthusiasm to accept this new technology in the audit profession.

Another comment by an audit manager emphasises the impact of understanding technology on its use when he says: *'I personally believe in the maturity model in human development, where an individual goes through six stages to reach the desired results... now we are in the reluctance stage due to a lack of understanding about artificial intelligence and the way the algorithms work... the need to learn makes us reluctant to use these tools...when these tools become popular in the field of auditing, we will move onto the next stage in the maturity model'* (P19). Furthermore, participant 2 emphasises that the use of artificial intelligence requires auditors to break out of their comfort zone and learn new skills. He argues that auditors who do traditional audits for a long time might face a larger problem because of their routines. The comments from previous participants show that understanding how artificial intelligence works in the audit profession requires the auditor to make some effort. This effort may differ from one auditor to another according to the extent of his knowledge of contemporary technology.

Thus, it could be concluded from the above discussion that the perception of how difficult it is to understand intelligence technology installation, and how artificial intelligence can perform audit tasks, play an important role in accepting artificial intelligence in the audit profession. When an auditor perceives that he knows the nature of the work of algorithms in artificial intelligence and the integration of this technology into the audit, they will be more motivated to accept artificial intelligence. This result is consistent with Pedrosa et al. (2019), who underline the importance of understanding the interactions with computer-assisted audit tools in accepting these tools. Moreover, this result is aligned with the conclusions of Curtis and Payne (2014), who indicate the need to understand the ways of interacting with audit

software in the audit process in order to adopt the software. Therefore, it can be said that if an audit firm wants a smooth acceptance of artificial intelligence technology, managers should help their auditors understand how artificial intelligence technology works and how to integrate it with the audit processes.

7.3.2.3 Difficulty in Using Artificial Intelligence Technology

Like any other tool, the use of artificial intelligence technology needs effort. This effort is a subjective norm, and individuals vary in estimating the effort required to use a particular technology. Alles (2015) says that some advanced audit programmes are challenging to use and are operated by IT specialists rather than general auditors. A report prepared by the Chartered Professional Accountants of Canada (CPA Canada) states that audit firms may need to make more changes to their multidisciplinary teams, which should include specialists with additional technical expertise in the use of advanced analytics, automation, and artificial intelligence tools (AICPA 2020). Auditors who do not have a technical background, or do not hold IT audit certifications, will perceive that using artificial intelligence techniques in the audit profession is highly demanding. These perceptions will impact the acceptance of artificial intelligence.

An auditor with experience in a medium size audit firm, but is now in one of the Big Four audit firms, says: *'most of the client data does not allow us to use artificial intelligence technology because the data is unstructured... so we need to make a huge effort to address it and make some adjustments...also, some clients especially small clients use accounting software that is not suitable for synchronising with new advanced audit technology... these obstacles make using artificial intelligence for auditing hard'* (P16). This auditor talks about the problem of dealing with unstructured client data and the ways and difficulties of feeding artificial intelligence systems with this type of data. He perceives that feeding artificial intelligence with unstructured data is difficult.

Another participant comments about the difficulty of making amendments to client data after it has been fed into the system. He says that: *'we use a smart audit system... the problem is that if one step is missing, the system cannot perform the analysis process... it just shows an error signal, so I follow the entries step by step to find where the error is... frankly, this takes time and effort... sometimes I prefer to perform the audits in the traditional way... it's faster, instead of spending two or three days trying to find the error in the system... and sometimes the amendments are not accepted, and instead it asks me to enter the data again from the beginning'* (P15). The interviewee's comment shows that some auditors face problems when interacting with smart audit tools, whether in the entry process or modifying the previous inputs. These problems make them prefer the traditional auditing method over the use of smart audit tools. Moreover, this comment denotes that the ease of interaction with artificial intelligence, whether through amendments to the entered data or other operations, is essential for artificial intelligence acceptance.

From the interviews, it was found that the auditors may encounter obstacles in obtaining client data, which is necessary to properly operate the artificial intelligence. Alles (2015) says that integrating more advanced analytics and artificial intelligence into audit engagements requires electronic data and Big Data about the clients. The data sources on which the auditor relies when issuing his or her professional opinion may be from within the client organisation or outside it, such as banks and suppliers.

One of the difficulties that the auditor may face in obtaining the data needed for artificial intelligence is the lack of cooperation from the client. An interviewee states that: *'client cooperation is very important as the main object of auditing is to provide a reliable confirmation of the validity of the client's financial statements. Some clients do not want to give us full access to all their data, instead they push us to use the second auditing approach, which is the traditional one'* (P23). Ahmi and Kent (2012) found that clients' support, when

obtaining the correct data in a timely manner, is important when implementing new advanced audit technology. One of the participants excused his client's actions, when they refused to cooperate with the auditor in using artificial intelligence, by saying: *'clients may refuse to give our artificial intelligence system full access... they don't want an opinion on their financial statements from a machine... they want to discuss it in person and provide justifications or clarify unclear points... maybe some data is not ready yet... it has happened many times that the client's justifications have been correct... at the same time, the audit software has made mistakes many times, too'* (P18). The participants' comments show that the perceptions of difficulty may not only be the problem of using artificial intelligence, but also the difficulty in obtaining permission from the client to provide data in a form that the auditor requires or the delivery of access to the client's system in the way the auditor wants.

Furthermore, the difficulty of using artificial intelligence may not be due to the lack of cooperation of the clients, but rather because of the limitation of the client's accounting systems. A senior auditor, who works at a Big Four firm, says: *'we are obligated, according to auditing standards, to check daily entries, check transactions and check the TB [trial balance] of clients... some of the clients, even large clients, use ERP systems that do not issue GL [general ledger] compatible with our analytic tools... thus we cannot use our advanced auditing tools... instead we perform traditional audits'* (P8). The point raised by the participant is consistent with those by Alles (2015), who says history shows that auditors were pushed to use auditing methodology that fit ERP systems used by clients since these systems dramatically influence how clients were managed and records were kept. This leads the author to state that clients may want to cooperate with the external auditor and know that the evaluation of the firm's performance from an outside point of view is very useful, but the problem is the incompatibility of the advanced analysis tools used by auditors with the ERP systems their clients employ.

Thus, it can be understood from the above discussion that when an auditor perceives that artificial intelligence technology will be difficult to use in audits, he will be less likely to accept or use this technology. This result is validated by Janvrin et al. (2009), who points out that, to increase CAATs usage, audit firm should enhance their IT team to improve the auditor's degree of ease associated with using the CAATs. Moreover, this result is consistent with the results of Ahmi and Kent (2012), which confirm that the advantages of the GAS are hindered by what auditors believed to be high implementation costs and the lack of ease of use. Thus, it is recommended that if an audit firm plans to implement artificial intelligence technology successfully, the managers should facilitate the use of artificial intelligence by providing IT specialists and training courses. The author also encourages audit firms to discuss with clients, in the engagement phase, the audit methodology they are adopting, the tools used in the audit process, the data that the auditor needs, and the proper form of data the auditor requires. The results of which are an improved understanding of the process by the client and sufficient cooperation between the auditors and clients.

7.3.2.4 Perceived Flexibility of Artificial Intelligence Technology

The perceived flexibility of artificial intelligence means the ability of artificial intelligence systems to comply with different clients' ERP systems, since clients may be from the same or different sectors. An audit firm usually interacts with various ERP systems. Large clients use complex ERP systems that enable them to deal with an enormous volume of transactions, operations, and tasks. On the other hand, small clients may use limited ERP systems due to financial constraints and the lesser number of transactions and operations that they produce. Furthermore, an audit firm may have clients from different sectors such as the financial, construction, and IT sectors. Due to the considerable diversity of client types, auditors prefer to use flexible auditing tools that have the ability to align with this diversity.

Dowling and Leech (2014) state that the flexibility of the audit system encouraged auditors to apply and expand their knowledge because they had to take responsibility for how they used it throughout audit engagements. Auditors want to encounter the flexibility of the audit system to develop his or her experience. A senior auditor comments that: *'The nature of our work requires us to be flexible and use a flexible methodology, as well as flexible tools... if the processes of feeding the artificial intelligence system are not flexible, it won't suit our work'* (P20). Moreover, an audit manager says that: *'the current audit systems are not flexible and do not have prescribed substantive procedures to help the audit team... artificial intelligence has to be flexible... it has to empower IT specialists in the audit team to amend the options of how we use the system'* (P7). These comments from the participants confirm the importance of conceiving flexibility in smart audit systems. This is because flexibility provides the auditors with confidence in their ability to use these systems for all the circumstances they face during the audits.

Thus, it could be concluded from the above discussion that the perception of the flexibility of artificial intelligence (when interacting with it) plays a vital role in the acceptance of artificial intelligence in the audit profession. When an auditor perceives that the system is flexible, for rational amendments relevant to the audit engagement, they will be more motivated to accept artificial intelligence. This result is consistent with the research of Venkatesh et al. (2003), who states that a flexible system positively influences the decision to adopt that system. Hence, this encourages artificial intelligence developers, and audit firms that build artificial intelligence systems in-house, to provide auditors with flexible tools that enable them to override some of the procedures by adding a rationale box. Auditors are required to provide a written explanation and justifications in a rationale box whenever they perceive the need to override some of the procedures. Having auditors justify their rationale helps improve judgement accuracy (Ashton, 1992). Moreover, Dowling and Leech (2014) claim that enabling

auditors to question the applicability of a system's procedures is crucial because it reduces the risk of an overreliance on the system. Giving the auditor the ability to express his opinion makes him feel the importance of evoking consciousness during the use of these systems in the audit engagements.

7.3.3 Facilitating Conditions

Facilitating conditions was one of the pre-identified constructs. The goal is to explore the influence of auditors' perception that facilitating conditions exist to support his or her intention to use artificial intelligence. In general, the interviewees showed a clear and direct impact of facilitating conditions on the intention to use artificial intelligence techniques. The statements of the participants revolved around three main and essential themes: (i) IT infrastructure, (ii) audit standards, and (iii) professional regulatory bodies. These three dimensions of facilitating conditions were examined by a number of participants in several scenarios. The following sections will discuss each of these themes in more detail.

7.3.3.1 It Infrastructure and Artificial Intelligence Application

IT infrastructure refers to the existence of hardware, software, networks, information system, and ICT. This section discusses the influence of the perceived support of IT infrastructure in both the audit firm and the clients on artificial intelligence acceptance. First, the author will discuss the IT infrastructure of the audit firm, which includes the audit firm providing appropriate artificial intelligence resources and support to their employees such as a support centre, artificial intelligence user guidelines, and a hotline.

Abd Rahman (2008) states that good technical infrastructure and workshops would ensure the successful implementation of new technology, including data mining auditing tools. An interviewee supports this statement by saying: *'most of the big four firms have adopted some kind of artificial intelligence, since they have IT departments filled with a lot of people with an IT background and versed in the subject... small audit firms often don't have the many*

resources needed to install such a system' (P12). Moreover, another participant adds: *'I do think firms that have an advanced information technology team are in an advantage... It helps them in the process of implementing these technologies...the more advanced a firm's infrastructure, the more it helps the firm to adopt artificial intelligence technology'* (P2). The interviewees' comments suggest that the perception of the quality of the infrastructure of an audit firm has a motivational effect on auditors to accept artificial intelligence technology. When the auditor perceives that there is a team in the company that supports him or her in the use of artificial intelligence, their desire to use artificial intelligence is greater.

Issa et al. (2016) argue that the application of artificial intelligence in audits has been made possible by the advancements in infrastructure speed, availability, and scale as well as by the creation of cloud computing and the advent of new data storage and processing technology such as Apache Hadoop. Moreover, Dai and Vasarhelyi (2017) state that a blockchain can act as a basis to enable automatic assurance and makes the current auditing paradigm more nimble and precise. An audit manager in one of the Big Four audit firms comments that: *'I would imagine that, in the coming years, as clients rely on blockchain technology in their operations and transactions, audit firms will have to develop the technical infrastructure to enable them to use significant artificial intelligence and big data analytics techniques'* (P25). The participant advises audit firms to be fully prepared, in terms of the audit firm technical infrastructure, for the fourth industrial revolution which will have a significant impact on the way companies manage their day-to-day business activities. Alles (2015) highlights that if using Big Data is truly a strategic necessity for firms, then auditors must be performing the equivalent of 'auditing through' Big Data.

Second, the author discusses the IT infrastructure of the clients, which includes the ICT used by clients. The auditor's perception of the client's systems is an essential element since auditors are compelled to rely on clients' IT infrastructure when data is obtained and controls

verified (Alles, 2015). An audit partner confirms this point by stating: *‘the client’s technical infrastructure and the way the client record the accounting information is an essential factor... the client is the one who the audit process is carried out on...our small clients still rely on traditional accounting... thus, if the technical infrastructure is not ready, it is logical that we cannot apply artificial intelligence technology’* (P18). Moreover, an audit manager states that: *‘the current technical structure of clients may not be ready for the implementation of artificial intelligence tools for auditing... but I hope our clients’ move toward digitalisation accelerates in the future’* (P7). The auditors’ comments show that their perceptions of the client’s technical infrastructure significantly influence their acceptance of artificial intelligence. Auditors believe that if the client’s technical infrastructure is well-developed, it will enable them to use smart audit tools.

It can be understood from the above discussion that, when an auditor perceives the existence of quality IT infrastructure of both the audit firm and clients, they will be more likely to accept or use artificial intelligence technology. This result is validated by the results of Janvrin et al. (2009), who indicate that the probability of auditors utilising CAATs is influenced by both organisational and technical infrastructure support. Furthermore, this result is consistent with the results of Abd Rahman (2008), which show that 80% of the respondents agreed that technical support, compatibility of software, and a department with an appropriate ICT infrastructure are likely to be influential in any decision to employ data mining.

Thus, the author recommends the management of audit firms to have a strategic investment plan in technical infrastructure to cope with upcoming artificial intelligence technology. This encouragement is congruent with Bierstaker et al. (2014), who urge audit firm management to make further technological infrastructure investments to support the CAATs, especially for auditors who are less likely to adopt new technologies. They state auditors may feel more comfortable utilising the CAATs if, for instance, the audit team

includes a member who is solely responsible for IT support. The author also encourages medium and small companies to have a strategic investment plan for their technical infrastructure, not only so that the auditors can use smart audit tools but also the company can keep pace with future technological developments. Ghobakhloo et al. (2012) say quality IT infrastructure can significantly assist SMEs by providing relevant and high-quality data in a timely manner.

7.3.3.2 Perceived Audit Standards' Obligations and Artificial Intelligence Application

Auditing is a profession regulated by regulatory bodies that issue auditing standards and professional ethics protocols; the auditor must adhere to them while performing audits. This section discusses the influence of the perceived audit standards' obligations on artificial intelligence acceptance.

Under auditing standards, the use of professional judgement is mandatory (FRC, 2022) and widely acknowledged as one of the essential principles of an audit (Gay and Simnett, 2012). Dowling and Leech (2007) argue that decision support technologies cannot be used to generate the audit opinion, because it is a task that needs the application of an auditor's professional judgement. A senior auditor agreed with Dowling and Leech's arguments and says: *'we do not use artificial intelligence when generating professional judgments because it is not possible for it to surpass professional human judgments... A human mind's ideas are not limited, unlike artificial intelligence, which is limited by algorithms, even if it sometimes seems well developed'* (P9). The participant believes that the professional judgment that the auditing standards require must be performed through the human mind, which smart machines cannot do.

On the other hand, Meredith et al. (2020) argue that the statement that human judgement must be employed while performing audit opinion is used as a defence against the use of decision support technology, notably since it is believed that the two practices are at odds. In

an interesting study, Wahdan and Eddy Vaassen (2009) compared the audit opinions given by a system, called the Auditor's Report Expert, to audit opinions provided by auditors. They investigated views in which this system disagreed with the auditors. In one of these instances, the auditor stated that the system was accurate; the auditor offered a less harsh assessment merely to keep the client. In addition, Meredith et al. (2020) state that if decision-support technology prevents auditors from expressing the audit opinion they genuinely want to provide, they may not wish to use this technology.

The author is not discussing here the necessity of using artificial intelligence techniques to form an audit opinion, nor using artificial intelligence indicates unethical audit behaviour. This discussion, however, suggests that the way an auditor perceives the obligations of audit standards could impact his or her decision to use artificial intelligence.

Moreover, the participants in the study highlighted the lack of explanation in auditing standards of how modern smart tools would fit with pre-existing audit methodology. Auditors see the lack of details on artificial intelligence usage in auditing standards as a chance to innovate without worrying about potentially onerous regulatory constraints (P24). In contrast, some interviewees require more guidance in the auditing standards to alleviate this confusion. An audit partner states that: *'auditing standards need to address how to use these new technologies in auditing... the process of auditing clients has become complicated due to the increase in client operations and data, which, in turn, has made it difficult to rely on traditional auditing'* (P18).

Another interviewee adds: *'The audit standards may have touched upon the use of analytical tools and sampling tools... but frankly... I find that audit standards do not address the uses of artificial intelligence technology in auditing clients'* (P23). Indeed, Eilifsen et al. (2020) interviewed the heads of professional practice of five international public accounting firms in Norway. They found that they are uncertain about how the supervisory inspection

authorities will evaluate and accept audit evidence generated by advanced technology. This shows that the blurred guideline of the use of artificial intelligence in auditing standards puts auditors at a loss when aligning with the rapid technical flow, meaning that auditors often wait until sufficient details are issued before employing artificial intelligence.

This result is consistent with the conclusions of Salijeni et al. (2019), who states that auditor will not fully engage with big data and data analytics in their audits until standard setters remove what they perceive to be uncertainty around the use of new tools. Similarly, Kuruppu et al. (2012) note that auditors who participated in their questionnaire felt auditing standards need to provide additional details regarding the usage of corporate failure models, when conducting going concern evaluations.

Thus, it could be concluded from the above discussion that the auditors' perception of audit standards' obligations plays an important role in accepting artificial intelligence in the audit context. When an auditor perceives that the audit standards are clearly evident in terms of using artificial intelligence technology, they will be more motivated to accept artificial intelligence. Interestingly, in their study, Salijeni et al. (2019) report on the feedback provided by some members of the IAASB regarding the necessity of updating audit standards to address both Big Data and data analytics usage. The members contend that the existing auditing standards are sufficiently adaptable to allow for the integration of these technologies in the audit process, and therefore see no reason to consider any revisions at this time.

However, this argument of not needing to change audit standards does not seem logical. It does not support what the Chair of IAASB and Staff Fellow claims, which is that the IAASB is committed to ensuring that standard-setting keeps up with emerging technology; it needs to be flexible enough to adapt to disruptive technologies (Seidenstein and Davies, 2022). The literature suggests that the current auditing standards do not provide sufficient opportunity for modern technology to be fully exploited in the conduct of an audit (Cao et al., 2015; Salijeni

et al., 2019). The author encourages audit standard setters to keep the standards updated to meet the digital transformations that many sectors have already experienced. To encourage businesses and accounting firms to use artificial intelligence in their audit operations, existing auditing standards that call for particular labour-intensive procedures will need to be revised (Issa et al., 2016). When audit standard setters maintain a lookout for disruptive technologies and keep the standards up-to-date without losing focus on setting high-quality standards, it will help auditors use new technologies to fulfil audit and assurance requirements.

7.3.3.3 Perceived Behaviour of Regulatory Bodies

This section discusses the impact of professional and governmental regulatory bodies that regulate audit firms and clients alike. Before discussing the impact of regulatory bodies, the author will introduce the regulatory bodies in Saudi Arabia (the country where the data was collected). In Saudi Arabia, governmental regulatory bodies impose government requirements on companies; they also oversee the implementation of these requirements (i.e., the Ministry of Commerce and the GAZT). On the other hand, there are professional regulatory bodies that impose the requirements of the profession and oversee the implementation of these requirements (i.e., the Saudi Organisation for Auditors and Accountants (SOCPA) and Capital Market Authority).

In general, SOCPA is the setter of accounting standards, auditing standards, and ethical codes; it is the body that oversees the compliance of all firms registered in Saudi Arabia with these standards. In addition to SOCPA, the CMA oversees companies that are listed on the Saudi capital market, as well as auditing firms that perform audits on companies listed on this stock market. For an accounting firm (or a certified public accountant) to be able to perform audit engagements for listed companies, they have to be registered with the Capital Market Authority.

The qualitative data shows the considerable impact of regulators on the application of artificial intelligence technologies in the audit environment. An audit manager working at one of the Big Four firms says: *‘the quick response of regulators affects the implementation of newly emerging technologies...for example, the e-signing of contracts was illegal before the Coronavirus crisis...but SOCPA legalised e-signing in response to the lockdown imposed by the Saudi government during the Coronavirus crisis...this quick response by the SOCPA to the lockdown was followed by a quick response from the company by approving e-signing’* (P11). In addition, a director of a local audit firm commented on the e-signing. He says: *‘SOCPA does not allow auditors to sign their document with an electronic signature.... meaning that the signature of the certified accountant must be a real signature.... however, it issued interim approval for the electronic signature to be used during the days of the Coronavirus crisis, so we could complete the audit without the need to go to the workplace’* (P3). The participants’ comment shows the importance of a rapid response by the regulatory bodies and, beyond that, they should provide initiatives in technical solutions that enable auditors to keep pace with the rapid developments in the business environment. The study by Meredith et al. (2020) highlights the need for professional bodies to be proactive in facilitating the collaboration between technology specialists and audit professionals. Moreover, they add that professional bodies should provide auditors with suggestions on how modern technologies fit pre-existing audit methodology.

Some participants also mention that the new regulatory laws imposed on clients provide auditors with an opportunity to use modern technology during audits. A senior auditor says: *‘In the next few years, all clients’ transactions will be automated... all data will be uploaded onto databases... all clients’ invoices will be linked directly to ZATCA, due to electronic connection and electronic bills... at the same time, accounts receivable will be linked to banks... most of the clients’ transactions will be electronically linked to outside sources... in*

this case, auditing will be based on big data which will require the use of artificial intelligence to analyse these data'(P20). The previous participant indicates a new act issued by ZATCA that requires all companies operating in Saudi Arabia to integrate their system with the system of ZATCA through a platform called FATOORAH (ZATCA, 2019).

Moreover, an audit manager commented on the obligation of ZATCA in issuing e-invoices by saying: *'The pace of the transition to the digital environment in Saudi Arabia is going very quickly... now, the ZATCA has an e-invoicing plan, which stated that all companies were obliged to have an electronic invoicing system by the beginning of 2021 and, by the beginning of 2023, the companies must integrate their invoicing systems with the ZATCA system... the auditors must change from the ways in which they carry out audits, moving from the traditional audit to the smart audit, and this is a matter of time'* (P7). Auditors' perceptions of regulators' view of digital transformation are important in the transformation journey towards smart audit. When auditors perceive that the regulatory bodies are pushing clients toward digitalisation, they will feel the need to adopt new modern technologies so that they do not lag behind their clients' digitalisation movement.

This result agrees with Alles (2015), who says that the auditors' movements in reality are a sequence of the clients' movements. He states that when Big Data becomes important to the operation of the businesses of the clients, auditors will feel that they have no choice but to embrace Big Data.

Moreover, one of the aspects that the participants discuss is the responsibility of regulatory bodies to engage with audit firms in the process of transition to smart auditing by modifying the audit methodology. An interviewee argues that: *'the current way in which audits are conducted may not be suitable for the use of artificial intelligence ... the audit profession may need complete reforming, so that continuous auditing and real time audits are integrated with artificial intelligence technologies'* (P22). In fact, voices calling for a reconsideration of

the audit methodology are beginning to increase. Meredith et al. (2020) claim that, at the profession level, professional bodies should consider changes to audit methodology to make use of technological development. In addition, Manita et al. (2020) state that digitalisation highlights the need for changing audit functions to lay out a deeper and more robust analysis of clients. Hajek and Henriques (2017) offered an illustration of how audit methodology could be transformed by concentrating on identifying 'green flags,' for which fraud is likely absent, using machine learning techniques. According to them, the identification of 'green flags' is regarded as more precise than identifying 'red flags'.

It can be understood from the above discussion that, when an auditor perceives that the regulatory bodies exist to help them throughout the movement from traditional audits to smart audits using artificial intelligence technology, they will be more likely to accept artificial intelligence technology. These results align with the findings of Kend and Nguyen (2020), who highlight the importance of regulators in the implementation of new technology and the need for regulators to keep on track with fast-paced IT in the auditing field. As a result, the author encourages regulatory and professional bodies to become involved in the process of adopting artificial intelligence in the audit field through funding research in this field, conducting training courses, and providing consultations to auditing firms. Moreover, Meredith et al. (2020) suggest professional bodies should take a proactive approach to encourage cooperation between specialists in decision support systems and professionals in auditing.

7.3.4 Ethical Concerns

Ethical concerns are one of the pre-identified constructs. The goal is to explore the influence of ethical concerns on implementing artificial intelligence technology. Ethical concerns refer to the degree an auditor perceives that the implementation of artificial intelligence in audits will have unethical side effects for the profession. The participants elaborated on artificial intelligence ethical concerns that may influence the journey of artificial

intelligence acceptance. The ethical concerns that the participants spoke about were divided into six themes: (i) the impact of artificial intelligence technology on client confidentiality and data protection, (ii) the impact of artificial intelligence technology on professional scepticism, (iii) the impact of artificial intelligence on the auditability of the audit procedures, (iv) the impact of artificial intelligence usage on auditor independence, (v) the impact of audit automation on the labour displacement in the audit profession, and (vi) artificial intelligence and repurposing client data. The following sections will discuss each of these themes in more detail.

7.3.4.1 Impact of Artificial Intelligence Technology on Client Confidentiality and Data

Protection

This section discusses the impact of the perceived influence of artificial intelligence technology on client confidentiality and data protection. The literature regarding the impact of confidentiality on the acceptance of artificial intelligence in the audit profession is limited. Confidentiality and data protection problems are some of the key challenges associated with accepting artificial intelligence-based decision-making in an accounting setting (Wright and Xie, 2019; West, 2019). The international code of ethics states that auditors must comply with the confidentiality principles concerning information required through the audit process (IFAC, 2021). When audit firms upload client data into systems that use artificial intelligence, this data has to be kept safe and protected against security breaches and hazards of confidentiality (Munoko et al., 2020). The auditor's perception of the ability of the intelligence systems to secure clients' data plays a pivotal role in the decision to use artificial intelligence.

Some auditors expressed their concern that clients will not allow them to use artificial intelligence techniques during the audit process due to fear of breaches that might expose their confidentiality (P4, P6, P12, P13, P15, and P16). An audit manager who works at a medium-sized audit firm says: *'there are some items such as wages and compensation for employees*

that are highly confidential for clients... some clients require that the person who audits these items is at the highest level in the audit team and require that the auditor does not take any document related to these items away, but rather takes notes' (P16). Moreover, participants 6 and 15 confirm that clients do not always allow them to keep or save their data in online forms of storage due to the sensitivity of the data. These comments manifest the auditors' concerns about the client's reaction to the use of artificial intelligence technology in the audit engagement. Auditors perceive that clients will prevent them from using artificial intelligence because of their fear that the confidentiality of their information will be compromised.

Moreover, a head of a local audit firm expresses his concerns about audits that can be exposed to cyber criminals. He states that: *'Artificial intelligence has in-built databases that are used to train machine learning models... these databases are vulnerable to hacking...leaking information to people who are not authorised to obtain this information is a very big problem in the field of auditing...there is the risk of a leak when analysing financial data, as well as many other legal documents'* (P1). Moreover, a senior auditor has the same concerns since he says: *'In the engagement of their services, auditors and clients sign a non-disclosure agreement.... when using artificial intelligence will auditors be able to keep this agreement? Keeping clients' confidential information in databases is different from keeping this information safe in the traditional way such as storing files in a locker... this concern needs to be addressed well when designing artificial intelligence'* (P20). This feedback from the participants illustrates the extent to which auditors are concerned about client confidentiality when using artificial intelligence, and the need for guarantees by the developers of artificial intelligence that this data will be safe against breaches. Lehner et al. (2022) say that, when using artificial intelligence, the impact of leaked documents should not be underestimated to prevent fraudulent activities (e.g., Wikileaks).

In contrast, some participants perceive that exposing client data to online storage is nothing new to the audit profession. A head of a local audit firm states that: *'I think client confidentiality is already exposed to hacking... for example, emails... the emails between the client and the auditor exchanging information or files are in fact stored online by a third party.... this danger existed in the past...but whenever an auditor sees a risk with respect to a client's confidentiality, it is the auditor's duty to reduce the level of risk to the lowest level possible'* (P10). Another participant agrees when he says: *'I don't think there should be any issue with client confidentiality, since even if artificial intelligence stores some of the clients' information online, there are strict controls to mitigate issues for the confidentiality'* (P12). The argument that online data storage existed before the use of artificial intelligence may be partially valid. However, this thesis cannot overlook the significant impact of artificial intelligence on the amount of data required and the way it is stored. The fourth industrial revolution has created a fundamental shift in the importance of data within businesses.

West (2019) proposes the term 'data capitalism' and defines it as 'a system in which the commoditization of our data enables an asymmetric redistribution of power that is weighted toward the actors who have access and the capability to make sense of information'. Data is the backbone of artificial intelligence; the commodification of data makes it a target for legitimate or illegitimate practices by many parties. Thus, the challenge of keeping clients' confidentiality will be greater compared to the auditor's experiences when using non-advanced technology.

Furthermore, another concern in regard to client confidentiality arises when using artificial intelligence in the presence of a third party. Munoko et al. (2020) raised the question of how would audit firms, which use third-party artificial intelligence platforms, be sure that confidential information is not in a position where it is not adequately protected? Some of the participants spoke about the same concern in the interviews. For example, an audit manager

comments: *‘The audit firm must have control over artificial intelligence whether it is a database or a tool... If a third-party has access to client data, the auditors must sign a non-disclosure agreement and an access agreement that limits people who have the right to access the data... otherwise, clients will not give auditors access to information that may cause a risk to them in terms of competition or information related to the confidentiality of the clients’* (P19). This participant shows his concerns about the potential negative impact of third parties on clients’ confidentiality. He believes that the problem of the third party must be addressed before starting to use artificial intelligence in the audit profession, and its treatment should be through a non-disclosure agreement.

Thus, it may be inferred from the above discussion that the auditors’ perception of the influence of artificial intelligence technology on client confidentiality plays an important role in accepting artificial intelligence in the audit context. When an auditor perceives that the use of artificial intelligence technology will negatively impact clients’ confidentiality, they will be more likely to resist the acceptance of artificial intelligence. Due to the increasing introduction of Big Data into auditing (Gepp et al., 2018; Seethamraju and Hecimovic, 2022), it is necessary to study auditors’ perceptions towards the implication of artificial intelligence on clients’ confidentiality. The author recommends audit firms and artificial intelligence developers to address client confidentiality concerns associated with implementing artificial intelligence.

7.3.4.2 Impact of Artificial Intelligence Technology on Professional Scepticism

One of the fundamentals of the auditing profession is an individual auditor’s professional scepticism (Hurt, 2010). The auditing profession emphasises the value of professional scepticism since the first professional standards were codified. A statement, effective for audits of financial statements for periods ending on or after December 15, 1997, in auditing Standards No. 82, states ‘due professional care requires the auditor to exercise professional scepticism’ (PCAOB, 1972). Hurt (2010) states that carefully reviewing auditing standards exhibit that the

standards can implicitly reveal multiple characteristics of professional scepticism. An example of the multiple characteristics from AS 1015 (due professional care in the performance of work) paragraph 07: ‘Professional scepticism is an attitude that includes a questioning mind and a critical assessment of audit evidence’ (PCAOB, 2018). Despite the undoubted benefits of artificial intelligence in auditing (Seethamraju and Hecimovic, 2022; Gepp et al., 2018), artificial intelligence may have negative consequences on the multiple characteristics of professional scepticism. Indeed, Westermann et al. (2015) conducted interviews with 30 audit partners and concluded that although IT has enhanced the efficiency and effectiveness of audits, it may also impede auditors' capacity to develop critical thinking skills, problem-solving abilities, and professional scepticism.

An audit partner draws attention to the point discussed in the above paragraph and says: *‘Directing the auditors’ attention to the points raised by artificial intelligence is one of the risks... because, in the long run, auditing will be a routine task... and the auditor will assume that the smart system does not make mistakes...in the case of human auditing, the situation is different because the auditor uses his analytical skills and professional judgment...so it is not just focusing on red flags’* (P18). Indeed, prior studies suggest that as users become more familiar with a software package, they may become desensitised and exhibit habitual behaviours that could potentially cause them to act against their natural instincts (e.g., Goddard et al., 2012; Lehner et al., 2022). Moreover, Seow (2011) argues that the prolonged use of decision aids could result in auditors focusing primarily on the issues identified by the tool, while neglecting other important aspects or problems that may not have been detected by the system.

An auditor who works at one of the Big Four firms adds that: *‘once we’ve been using artificial intelligence frequently for a long time, we will start to gain trust in the system and just assume the output is always correct....so audit tasks will become just part of the daily*

routine' (P15). Although trust in artificial intelligence is essential for its successful implementation in the workplace (Jarrahi, 2018), having professional scepticism is a requirement in an auditing environment. Auditors, through their experience in audits, develop the skill of professional scepticism, which help them discover the risk areas of the clients and then develop an appropriate approach to obtain reasonable assurance about whether the financial statements are free of material misstatement. Thus, reducing reliance on the human mind in decision-making processes, through decision aids, may negatively affect the experience of novice auditors in the decision-making process. Indeed, an auditor wonders: *'If artificial intelligence collects, extracts, and analyses client data, how can we learn the necessary audit skills?'* (P24). Arnold and Sutton (1998) refer to this as 'deskilling', such that the auditing abilities of an auditor may not be as refined as those of their peers who did not rely on cutting-edge technological tools.

A senior auditor argues that artificial intelligence will not entirely perform audit tasks; it will instead work as an assistant to the human auditor and the auditors would be able to develop the professional scepticism skills needed in the audit profession (P5). However, despite the belief of auditors that the artificial intelligence they employ may not be fully autonomous, their over-reliance on the technology could ultimately result in the system becoming autonomous (Munoko et al., 2020). For instance, artificial intelligence should be regarded as autonomous if auditors never object to the decisions provided by the algorithms for complex audit tasks.

It can be understood from the above discussion that, when an auditor perceives that the use of artificial intelligence technology may impair his professional scepticism skills, they will unlikely accept artificial intelligence technology. Professional audit bodies and audit firms should reflect on the impact of artificial intelligence on the professional scepticism skills of auditors in general and novice auditors in particular. It is crucial to ensure that novice auditors are technically proficient and adequately trained to use artificial intelligence correctly, while

also retaining their professional judgment (Munoko et al., 2020). Research conducted by Plumlee et al. (2015) has demonstrated that training auditors on how to approach and think about problems can enhance their performance on tasks that require illogical reasoning, mental representations, and sceptical thinking. The author recommends audit firms to counter the shortfalls that may arise due to the use of artificial intelligence by training auditors on tasks that develop their professional scepticism skills.

7.3.4.3 Impact of Artificial Intelligence on The Auditability of The Audit Procedures

The audit process is overseen by professional regulatory bodies, as well as senior management of the audit firm. This oversight is stipulated by the auditing standards, which state that the auditor holds the responsibility in the event of a failure in the audit process. This situation highlights the necessity for transparent, explainable artificial intelligence decision-making that enables algorithm auditability (Munoko et al., 2020). Moreover, in the European Union, the GDPR regulates the use of artificial intelligence in article 22 of the GDPR. This is because it grants individuals a right to ask the user of artificial intelligence decisions aids to review the decision-making process to determine whether or not the system had made a mistake. In KSA, the Saudi Data and Artificial Intelligence Authority (SDAIA) has set some obligations on the users of artificial intelligence such as sustainable development and well-being, human values and justice, transparency and interpretability, safety and security, and responsibility and accountability. This places a legal obligation on firms to have the ability to explain the steps of decision-making, which requires the auditability of AI-based decisions (Lehner et al., 2022). Thus, the auditors' perception of their ability to explain artificial intelligence-based decisions may play an important role in accepting artificial intelligence technology in the audit environment.

A head of a local audit firm commented on the problem of not being able to explain the steps taken to reach the audit opinion. He states: *'It will be hard for us to explain the logic used*

by artificial intelligence, especially when clients do not like our auditing opinion.... or our audit team must be specialised in artificial intelligence' (P10). This comment manifests the importance of the ability of the audit team to explain the underlying logic behind an artificial intelligence decision. Lehner et al. (2022) say that AI-based decisions need auditability of the factors that influence the findings and transparency concerning the inner workings of the algorithms behind the decisions. Moreover, a head of a local audit firm says: *'If SOCPA does not have specialists who can examine the tools used in audits... we will not use artificial intelligence because they oversee the auditors' work'* (P1). This comment shows the importance of artificial intelligence auditability, not only by the audit firm but also by regulatory bodies. Losbichler and Lehner (2021) state that there will certainly be a difference from the perspectives of regulatory requirements, when audit firms use artificial intelligence, regarding auditability and transparency.

Furthermore, an audit manager showed an auditability concern when assessing auditors. He expresses that: *'From time to time, we need to assess auditors' performance... how can we assess auditors' performance if they use artificial intelligence tools?... I personally do not know how to follow the decisions made by artificial intelligence tools at the same time our IT team does not know the proper audit processes'* (P25). This comment shows a gap between audit specialists and artificial intelligence specialists. This disparity needs to be addressed by finding specialists in both auditing and artificial intelligence concurrently, so that they can audit the decisions taken by artificial intelligence through an auditor's eyes. For audit partners, the artificial intelligence tool's auditability is crucial since it enables them to comprehend and assess the efficiency of the artificial intelligence tool used in audit engagements (Appelbaum et al., 2020).

Thus, it could be concluded from the above discussion that the auditors' perception of artificial intelligence auditability plays an important role in accepting artificial intelligence

tools in the audit context. When an auditor believes that the decisions of the artificial intelligence tools will not be auditable and traceable, they will be less likely to accept the artificial intelligence tools. Lehner et al. (2022) state that the knowledge of the underlying concepts of artificial intelligence algorithms must be understandable by most professionals (including auditors); otherwise, it would limit the use of artificial intelligence. They add that, when allowing for subsequent explainability and auditability, an ethical AI-based decision-making process must begin in the development phases of its underlying algorithms. This requires developers' moral awareness in the design phase. Thus, the author recommends artificial intelligence developers, and audit firms who develop their artificial intelligence tools in-house, to address auditability concerns.

7.3.4.4 Impact of Artificial Intelligence Use on Auditor Independence

Maintaining independence is one of the critical elements that make the opinion of the external auditors free of impurities that may affect its credibility. Auditors are required, by the international code of ethics, to exhibit: 'Independence in appearance – the avoidance of facts and circumstances that are so significant that a reasonable and informed third party would be likely to conclude that a firm's or an assurance team member's integrity, objectivity or professional scepticism has been compromised' (IFAC, 2021). Even though artificial intelligence and big data analysis provide enormous opportunities for audit firms, the legislation and the rules of ethics that regulate how auditors exercise their profession in terms of their independence must be considered (Manita et al., 2020). The perception that the use of artificial intelligence harms the auditor's sense of independence may play a role in the acceptance of artificial intelligence. Some of the interviewees in this study showed concern about artificial intelligence affecting their independence in two scenarios.

The first scenario was predicted by Issa et al. (2016) as one of the disadvantages of using artificial intelligence in an audit context. They explain this scenario in terms of a client running

a continuous control monitoring system, for which external auditors will have two choices. One is to connect their artificial intelligence systems with the clients' continuous control monitoring systems, possibly compromising their independence. The other is to maintain the use of sample techniques and risk the dangers of becoming behind the times compared to their client from an information perspective. A senior auditor says that: *'the use of artificial intelligence must not have a negative impact on the independence of the audit process by entirely relying on client systems to feed databases, there must be ways to ensure the correctness and accuracy of the information provided by the client system'* (P21). The involvement of clients in feeding the artificial intelligence databases creates concerns for auditors regarding the impairment of their independence. Vasarhelyi and Romero (2014) express reservations regarding the independence of the data extraction process when decision support technology is employed, as it is anticipated that client involvement in providing and collecting data will become more prevalent.

Moreover, when asked about the possibility of synchronising the artificial intelligence system of the audit firm with the client's systems to allow for real-time audits, another auditor answered: *'I would not say it is not possible... but there may be a breach of auditors' independence... relying on clients for evidence collection could pose a threat to our independence'* (P6). Interestingly, Austin et al. (2021) interviewed various stakeholders (i.e., client management, audit partners, technologists, and standard setters) and found that, while some clients' managers think auditors should rely on the data analytics tools of their clients to obtain improved insight in the company's operations, auditors report concerns about abiding by professional requirements, especially the rules involving independence.

The second scenario that may harm the independence of the auditor is that artificial intelligence may cause the auditor to be portrayed as an assistant to the clients rather than as a watchdog over their financial reporting. An auditor who worked at a Big Four audit firm states

that: *‘our analysis tools provide an amazing report... and provide the client with a different, and advanced analytical view of the company... there are clients who ask us for a monthly generated report for an extra fee’* (P17). The tremendous power of artificial intelligence systems, Big Data analytics tools, and the potential insights that these tools offer may impact auditors’ way of thinking, possibly unconsciously, with respect to their consultancy views. Also, the potential insights that these tools offer may be used by auditors to justify their high audit fees.

Salijeni et al. (2019) conducted 22 interviews with people who had substantial experience creating, putting into practice, or evaluating the effects of Big Data and Data Analytics in auditing. One of the partner auditors they interviewed states: *‘they [clients] can see this is really beneficial for them and we’ve got clients who ask us, “Can we buy your software?”, and the answer is, “No”, because this will have an impact on our audit work and independence’*. They concluded that the use of advances in Big Data and Data Analytics in auditing could affect the ‘mindset’ of the auditor. The use of artificial intelligence by external auditors in audit engagements has been flagged by regulatory bodies as potentially breaching independence rules. These bodies have issued a warning that: *‘the external auditor would need to avoid taking management responsibility in these areas but maintain a strictly advisory role, providing advice or recommendations to the audit client’* (ACCA, 2017).

It can be understood from the above discussion that, when an auditor perceives that the use of artificial intelligence technology may impair his independence, they is likely not to accept artificial intelligence technology. The tensions corresponding to auditors’ independence have become increasingly exacerbated with the use of artificial intelligence (Munoko et al., 2020); more practical guidance is thus warranted. Austin et al. (2021) state that standard setters should elaborate on their guidance regarding the concerns of the cognitive bias that could affect auditors’ assessment of independence when providing analytics-based insights to clients. The

author recommends standard setters to test if less independence can lead to improved assurance. Is it possible to compromise part of the auditors' independence in exchange for improved assurance for the public?

7.3.4.5 Impact of Audit Automation on The Labour Displacement in The Audit Profession

The rapid progress in artificial intelligence technology may impact society as a whole by replacing the human labour force with machines; thus, a high unemployment rate may arise. Since accounting historically depends on the contribution of human resources, Munoko et al. (2020) call for the exploration of the impact of artificial intelligence on recruitment in the audit profession and, indirectly, its effect on the number of students who choose to major in accounting if traditional accounting and auditing jobs significantly decline. The results of Fedyk et al. (2022) show that Artificial intelligence ultimately displaces human auditors, although the effect on labour takes several years to materialise. This study explores the impact of auditors' perception of being replaced by artificial intelligence on the decision to implement artificial intelligence in the audit profession.

Many participants believe that artificial intelligence cannot perform all audit tasks and, thus, cannot fully replace the human workforce in the audit profession. Participants 1, 4, 7, 11, 12, 17, and 19 mention that there are tasks in auditing that require human intervention, such as professional judgment, which make it impossible for artificial intelligence to complete all the work of human auditors. They mention that artificial intelligence may reduce the number of auditors in the audit team but, simultaneously, it increases diversity in the audit team since it requires the presence of people specialised in artificial intelligence in the team so that they can deal with these new systems.

The participant's perception is consistent with Issa et al. (2016), who state that automating cognitive non-routine tasks, which need quick adaptation, is currently exceedingly challenging. They conclude that artificial intelligence can only aid the auditor by making the

task easier to complete, while leaving the final decision to the auditor. Indeed, an interviewee says: *‘artificial intelligence is taking over routine tasks.... auditors who carry out routine work are at risk, and this pushes them to develop, and I personally think that this is a positive thing because it will motivate them to develop and, thus, have a positive impact on society’* (P10). This participant indicates that artificial intelligence will positively impact society in the long run by motivating the human workforce to develop their capabilities to keep pace with the advances in the field of artificial intelligence.

Issa et al. (2016) ask whether the automation of specific audit procedures, through the applications of artificial intelligence, will create or destroy more jobs. An audit manager who works at a Big Four audit firm states: *‘I do not agree with those who say artificial intelligence will replace humans... It may reduce the number of auditors in the audit team, but at the same time it will increase the audit firm capacity to accept more clients, and this will create new jobs’* (P7). He adds: *‘this topic was discussed in one of the meetings with the EY CEO... the CEO said artificial intelligence will create more than 100,000 jobs because it forces companies to hire experts in the new technology’* (P7). The notion that artificial intelligence will create jobs in some sectors, such as the technology sector and data analysis, is clear. However, the job safety of auditors employed in specific environments, especially those who perform routine work, is unclear.

Some participants expressed concerns about audit firms replacing humans with artificial intelligence. A female auditor who works at a Big Four audit firm states: *‘I do not want a technology that dispenses with me... if I knew a tool would one day make the audit sector dispense with me... no, sorry, I will not accept the use of this technology and I don’t mind spending a lot of time doing audits as a result’* (P14). Another interviewee expresses her opinion saying: *‘in the past, we had a larger audit team performing the audit process, now the situation is different, due to the use of smart tools, so what will be the result if our firm uses*

artificial intelligence at higher levels?... I agree we should develop our skills, but the problem is that the jobs at the higher levels of companies are limited, so it is difficult to compete for these jobs... I have been doing audits for nine years... it is not possible to start again and learn about another field... I have financial obligations' (P26). These perceptions may be an obstacle to the use of artificial intelligence in the audit profession because the catalyst behind these perceptions is the fear of losing job security.

Thus, it could be concluded from the above discussion that the perception that artificial intelligence will cause an increase in the unemployment rate in the auditor community will play a role in the acceptance of artificial intelligence. When an auditor believes that the artificial intelligence tools will take his or her job, they will be less likely to accept the artificial intelligence tools. Munoko et al. (2020) anticipate that autonomous artificial intelligence will have an effect on the audit profession (and society as a whole) through the loss of specific kinds of jobs. Moreover, Frey and Osborne (2017) expect that within two decades, 47% of jobs in the USA will be automated, which means that a high percentage of employees will lose their jobs. The substitution of human labour is an ethical issue arising from the acceptance of artificial intelligence (Farisco et al., 2020). Audit firms are encouraged to assist auditors in learning new skills, such as data analysis skills and artificial intelligence systems feeding skills, especially those auditors who perform routine tasks in audits.

7.3.4.6 Artificial Intelligence and Repurposing Client Data

The development of artificial intelligence systems requires an enormous amount of data for training purposes to raise the accuracy of artificial intelligence algorithms. This training process is performed continuously so that the ability and accuracy of the system's algorithms increase with a growth in the amount of data fed into the system. This situation creates concerns about client data repurposing (i.e., client data may be utilised beyond its initial intention when the data was first generated) (Munoko et al., 2020). This study explores the perceived impact

of artificial intelligence leading to the repurposing of client data on the implementation of artificial intelligence.

Participants expressed their opinion on the reuse of client data in the form of three aspects. The first aspect is the use of client data to feed and develop the quality and accuracy of the work of artificial intelligence systems. A head of a local audit firm states: *'We always have a clause in the engagement letter stating that we will use client data for general purposes such as writing reports on a specific sector and so on... using client data to train and develop the system and increase the efficiency and accuracy of the system, I see it as legitimate because this situation is like a human learning curve... just as auditors learn from their previous experiences, artificial intelligence learns from the huge data it runs through it'* (P10). The participant does not see ethical concerns when reusing client data for the purpose of developing the artificial intelligence systems that the company uses in the audit process, as long as there is no direct harm to the clients. Based on the argument that learning by people is based on their previous experiences, he assumed that the use of client data to train artificial intelligence systems is ethical.

The second aspect is the reuse of client data to provide non-audit services. An audit manager mentions that: *'It is expected that if audit firms collect data about a certain sector they'll use these data.... auditing firms write reports on certain sectors based on the data they've collected during the audit process, and they sell these reports in the form of consultations to parties they do not audit... speaking from an ethical preceptive... I think this is a matter that should be carefully reconsidered. I had a discussion with a colleague, and he said this was normal practice for him... he takes data from clients and sells it in the form of advisory reports to other clients'* (P13). The participant's concern is that audit firms may benefit from big data collected through artificial intelligence systems via non-audit services they deliver. The use of client data to provide non-audit services may result in client data

reaching competing companies, which directly harms the client. Moreover, competitors may deliberately request non-audit services from audit firms only to access client data. Indeed, a senior auditor who works at a Big Four audit firm says: *‘the client data collected by the auditor is not at the absolute disposal of the audit firm. There are restrictions and conditions and, ethically, the audit firm is not allowed to use this information to harm the clients and benefit competitors’* (P5).

The third aspect is the reuse of client data by a third party, such as those who develop artificial intelligence systems or those who own Big Data databases. A director of a local audit firm says: *‘the audit firm must check with the artificial intelligence developer or the owner of the databases to make sure that he is not using client data for other purposes... the audit firm can also ask the IT auditors to audit the third party to ensure that he is not using the data for other purposes. This process is a type of risk reduction process’* (P3). Miller and Anderson (2004) confirm that audit firms must be satisfied that sufficient procedures are in place to ensure the security of the client’s interests. This means that it is the auditor’s responsibility to confirm to clients that other parties will not use their data for other purposes. Moreover, a senior audit states: *‘If there is a third party, there should be an agreement that the client data is not seen by anyone and is not used for anything other than the purpose for which it was collected for’* (P8). Participants confirm that ensuring that the third party does not use client data for other purposes is one of the ways to reduce risks and maintain client confidentiality.

It may be inferred from the above discussion that the repurposing of client data may influence the acceptance of artificial intelligence. When an auditor perceives the usage of artificial intelligence technology may lead to a repurposing of client data for non-audit services, they are more likely not to accept artificial intelligence technology. Repurposing client data was first discussed, by Munoko et al. (2020), as an artificial intelligence-related ethical issue. This thesis recommends standard setters and regulatory bodies to address the issue of

repurposing client data collected by artificial intelligence. Moreover, this research encourages audit firms to have clear and explicit agreements with artificial intelligence developers regarding the repurposing of client data for other purposes, to limit this behaviour.

7.3.5 COVID-19

The interviews reveal unexpected results which is the impact of Covid-19 on the acceptance of artificial intelligence in the audit profession. The reason why these results are surprising, which have not been thoroughly and deeply discussed in the literature, is that the Covid-19 pandemic is a sudden and unprecedented phenomenon. Some participants talked about the need to use artificial intelligence to overcome the obstacles that the auditor may face during crises, such as the use of artificial intelligence in remote audits. Some participants also spoke about the impact of Covid-19 in changing the mindset of clients regarding sharing data online and allowing the auditor to access the client's system remotely.

One of the participants mentions that: *'The past two years have shown the technical shortcomings that exist in the auditing profession and the need for advances in artificial intelligence... during the pandemic many companies got a qualified opinion or a disclaimer of opinion instead of getting an unqualified opinion ... because the auditor contacted the clients' banks to send an endorsement or confirmation of the balances, but many banks were unable to issue these endorsements because their employees were not able to go to their workplace, due to the lockdown... these uncontrolled circumstances affected the auditors and clients received an unfavourable audit opinion'* (P1). From the participant's perspective, artificial intelligence could be a useful tool that can assist auditors in overcoming unexpected obstacles. The participant's point of view is consistent with the findings of Farahani and Esfahani (2022), who state that artificial intelligence can be a powerful tool in detecting fraud during the Covid-19 outbreak and can also decrease the harmful effects of Covid-19. Thus, timely actions can be taken.

The participant's statement shows that unprecedented crises make the auditors doubt the usefulness of traditional audit methods, and the need for new and modern audit methodology becomes apparent. In fact, Muslihatun et al. (2021) note that the Covid-19 pandemic is increasing the reliance on advanced technological tools, and these tools provide a new perspective on audits in the future. Moreover, The Chartered Professional Accountants of Canada has shown future interest in using emerging technologies such as automation, analytics, and artificial intelligence in the future (AICPA, 2020).

Moreover, qualitative data has shown that the impact of the Covid-19 pandemic has affected the clients' mindset. Some participants mentioned that clients have become more open to the notion of sharing data with the auditors via internet channels, and they are more accepting the idea of accessing their systems remotely. An audit manager says: *'the coronavirus pandemic sped up the pace of digitalisation and smart transformation in the field of auditing.... in the past, we used to ask clients to send us data via electronic channels to reduce transportation costs, but the clients refused... maybe because of data confidentiality.... but the coronavirus pandemic and lockdown made these clients resort to sending data digitally and it has broken down the barrier of fear audit firms had in place'* (P16). Furthermore, an audit manager who works at a Big Four audit firm confirms this point by stating: *'many clients accepted the need to share data remotely during the crisis and some of them now request this option "can we share the data with you remotely... do you have the ability to perform the audit remotely"... clients have become open to this option'* (P7). This change in clients' mindset may be a catalyst for auditors to use artificial intelligence because client collaboration is essential when collecting the extensive amount of data that the artificial intelligence system requires.

Ahmi and Kent (2012) found that clients' collaboration with auditors to obtain the correct data in a timely manner is an important issue when discussing the implementation of new advanced audit technology. Thus, it can be said that the Covid-19 pandemic paved the way and

created the proper environment towards a shift to smart auditing. This occurred by attracting the attention of auditors and regulatory bodies to the importance of using modern technologies in the audit profession and making clients more open to sharing their data remotely with the auditors.

7.4 Conclusion

This chapter has discussed the qualitative data that was collected during the interviews. Overall, this chapter has two main sections. The first section presented the descriptive results of the qualitative data. The second part provided the thematic results and discussed the qualitative data findings from the literature perspective.

The descriptive results are the ages of the participants, the participant's gender, the firms they work in, their experience, and the professional certificates they hold. The interview respondents' mean age was 35.5 years and the mean audit experience was 12.3 years. They worked in audit firms of different sizes with 60% employed by Big Four firms, 25% by international audit firms (not Big Four), and 15% by local audit firms. Of the participants, 90% had CPA certificates and most respondents (N = 19) were male.

In the second section of this chapter, the author has thematised the qualitative data into five themes. In the first theme, the author discussed the influence of performance expectancy from the interviewees' perspective as well as examined the interviewee's perspective with respect to the literature. In the second theme, the author addressed the influence of effort expectancy from the interviewee's perspective as well as compared what the interviewees said with what is stated in the literature. In the third theme, the author discussed the impact of facilitating conditions on artificial intelligence acceptance from the perspective of the interviewees. In this theme, the author highlighted the importance of audit standards and regulatory bodies in the journey of artificial intelligence acceptance.

In the fourth theme, the author discussed the ethical concerns associated with the implementation of artificial intelligence in the audit profession. The data collected from the interviewees showed that artificial intelligence is associated with six ethical concerns that require investigation before implementing artificial intelligence. In the last theme, the author touched upon the impact of the Covid-19 pandemic on the use of artificial intelligence in the auditing profession. Additionally, the author examined the impact of the pandemic on clients' acceptance of sharing their confidential data with auditors via online channels.

Chapter 8: Conclusion

8.1 Introduction

In this chapter the significance and contribution of this thesis, along with some recommendations and ideas for future research are discussed. Auditing phases—from client acceptance to reporting the audit opinion—involve tough challenges, often owing to clients' volume of transactions and big data. To overcome these obstacles, auditing firms have been encouraged by researchers to invest in smart technology, such as textual analysis technology, natural language processing technology, speech recognition, and VRT. Smart technology can provide several benefits to the audit environment including enhancing audit quality, improving auditors' decision-making, reducing audit costs, and speeding up audit processes. Yoon et al. (2015) expect that big data will enhance the efforts of auditors when gathering adequate and appropriate audit evidence. Indeed, some audit processes, such as journal entry tests, can be conducted on 100% of the population via the utilisation of computer-assisted auditing techniques (like Watson) that are fully automated. Moreover, Issa et al. (2016) suggest that auditing tasks that are usually performed in a manual, repetitive way – such as counting inventories – could be readily automated. The areas of evidence collection in the auditing field – such as interviews, counts of inventory, evaluation of assets, and observation – have the potential to be automated by visual recognition technology.

Three reasons have motivated the study of the reluctance of auditors to use artificial intelligence in the audit environment. First, despite the many uses of artificial intelligence in the audit profession, as previously discussed in the literature (Zhaokai and Moffitt, 2019; Bao et al., 2020; Bertomeu et al., 2021; Christ et al., 2021), and the great benefits of artificial intelligence to the audit profession (Cao et al., 2015; Appelbaum et al., 2017a; Raschke et al., 2018; Zhang, 2019), the literature indicates that the actual use of advanced technology by auditors remains small in the audit environment (Curtis and Payne, 2014; Pedrosa et al., 2019).

Seethamraju and Hecimovic (2022) state that despite of the excellent potential benefits that artificial intelligence possesses, empirical studies show that its application is limited in the audit profession. Consequently, to address this reluctant behaviour, the author is motivated to study the determinants that have influenced the adoption of artificial intelligence from the perspective of auditors.

The second motivation for conducting this study is that both the auditing profession (i.e., audit firms and professional associations) and stakeholders (i.e., regulators, clients, and researchers) hold artificial intelligence technology in high regard. Although the regulatory bodies of the audit profession, as well as international auditing standards, do not explicitly mandate auditors to use artificial intelligence techniques in their audits, they implicitly suggest the use of advanced technology for auditing. For instance, the regulatory bodies for the external audit process suggest that external auditors use remote auditing tools, such as visual recognition technology, to overcome Covid-19 restrictions (ICAEW, 2020).

Moreover, audit firms have made significant investment in advanced smart technology. Klynveld Peat Marwick Goerdeler (KPMG) declared its collaboration with IBM, for which it uses IBM's Watson Artificial Intelligence suite to apply cognitive computing technology to services offered by KPMG. Deloitte co-operated with Kira Systems Inc. to launch a cognitive system that assists in extracting and structuring textual information for improved analysis, examination of massive volumes of complicated documents, and helping auditors to review documents (Deloitte, 2016). These vast investments in artificial intelligence can only achieve the desired results when the auditor accepts the use of this new technology in their profession. Consequently, the author is motivated to study the determinants that influence the auditors' decision to accept artificial intelligence to optimise the results of these colossal investments.

Lastly, the KSA (where the research data was collected) has an ambitious vision (known as Vision 2030), which is backed by immense investments in digital transformation and artificial

intelligence at all levels and sectors. One of these sectors is the service sector, including auditing. Studying the determinants that affect the auditor's decision to accept artificial intelligence in the audit profession will assist in achieving the goals of this ambitious vision and reduce the negative effects of this transformation.

Hence, this thesis has attempted to explore the determinants that influence the voluntary decision of auditors to accept artificial intelligence techniques in the audit profession. This exploration process was made by answering four research questions:

Research question 1: What are the determinants that influence the intention of external auditors when adopting artificial intelligence technology?

Research question 2: Do auditors address artificial intelligence ethical concerns when adopting artificial intelligence technology?

Research question 3: Does the auditing firm size influence an auditor's decision when adopting artificial intelligence technology?

Research question 4: Did the Covid-19 crisis have an impact on changing the perception of both auditors and clients of the importance of using artificial intelligence technology in audits?

8.2 An Overview of The Research

In the literature, researchers discuss a set of determinants that play a significant role in the acceptance of technology in general. These determinants were classified into five groups: personal factors, organisational factors, client factors, technological factors, and regulatory factors. Personal factors include auditor's age, auditor's gender, auditor's experience, auditor's responsibility, and auditor's knowledge of technology. Indeed, Forteza and Prieto (1994) express that older workers have more difficulty accepting new changes in workplace environments, including technology. Moreover, Whitley (1997) found that men show a more positive attitude toward the use of technology compared to women. However, in a recent meta-analysis study of gender differences in technology, Cai et al. (2017) found that the differences

between men's and women's attitudes toward the use of technology can be considered insignificant.

Furthermore, personal factors include the auditor's experience; Wehner and Jessup (2005) state that those with more experience have more confidence to accept new technology that facilitates the audit procedures. Regarding the auditor's responsibility, it means the auditor's efforts to ensure public accountability. It has been stated in the literature that public accountability is one of the factors that drive an accountant to adopt the technology (Rahman, 2008; Ang et al., 2001). Moreover, Alam and Noor (2009) claim that understanding the benefits of IT and having knowledge about IT is important for adopting IT.

The second classified group is organisational factors, which include audit firm size, quality of the IT team, high-level management support, budgeting, and training and courses. Janvrin et al. (2008) mention that the audit firm size plays a significant role in accepting new technology. They argue that a lack of financial capabilities prevents small audit firms from adopting advanced IT. Indeed, Chaney et al. (2004) assert that large audit firms invest more money into IT, including training and facilities that grant them the ability to audit larger and more complicated clients. Moreover, in regard to having access to an expert IT team, Salijeni et al. (2019) express that the automated procedures that create a more efficient and effective audit process require that auditors are more dependent on the assistance of experts from other fields. Having an IT team in the audit firm, who are experts in the required technology, may influence the auditor's decision to accept and adopt artificial intelligence. An experienced IT team can solve installation problems more efficiently than a less experienced one (Curtis and Payne, 2014).

Furthermore, one of the other organisational factors is high-level management support. Curtis and Payne (2008) argue that an auditor is likelier to use technology or software when he or she notices encouragement from high-level management. Indeed, Pedrosa et al. (2019) found

a positive impact on the adoption of the CAATs due to the support of high-level management. Moreover, the extensive initial costs of advanced technology, such as artificial intelligence, make spreading the costs of the technology over an extended period an important element of the adoption journey. Curtis and Payne (2008) found that employing a longer-term budget plan strongly influences the decision to accept new technology. Regarding training courses, Widuri et al. (2016) discovered that such programmes are essential when implementing the GAS; they are completed by either sending auditors to an external training provider or arranging in-house training.

The third classified group is client factors, including the client's internal control system, the nature of the client's activities, and client confidentiality. The literature draws attention to the importance of clients' advanced internal control systems in the implementation of new technology. Debreceeny et al. (2005) emphasise this point when they state that external auditors have limited use for their advanced audit software because of the limitations of their clients' advanced internal controls system. Moreover, a client with a CCTV system with high-resolution cameras that controls the whole firm from different angles may facilitate the audit work. Auditors can take advantage of such cameras to collect more supportive evidence. In addition, the literature emphasises the influence of the nature of the client's activities on the implementation of technology. Clients who have large warehouses or open-air inventories, assets that are difficult to reach, and vast and sprawling farms may encourage auditors to take advantage of visual recognition technologies. A video clip or images of hard-to-approach asset items may help an auditor to verify their condition and support the affirmation of valuation in the audit objective (Appelbaum and Nehmer, 2017).

Regarding the impact of client confidentiality in new technology implementation, the literature emphasises that confidentiality and data protection problems are one of the key challenges associated with accepting artificial intelligence-based decision-making in an

accounting setting (Wright and Xie, 2019; West, 2019). According to Temesgen (2004), several clients have prevented auditors from using particular software because they were concerned about their confidentiality. Indeed, regulatory bodies and clients must collaborate to open doors to applying new advanced technology in the external audit environment (Issa et al., 2016).

The fourth classified group is technological factors, which include the compatibility of the new technology, simplicity of the new technology, and the availability of regular maintenance and upgrade of the new technology. The literature has discussed the impact of the compatibility of the new technology with the pre-existence systems, in both the audit firm and the clients. Both Rahman (2008) and Ahmi (2012) found that one of the main issues raised by auditors when accepting new technology was the compatibility of the new system with the pre-existing operating systems. The literature, furthermore, mentions that the difficulty and ease of use of new technology play a significant role in accepting this technology. Mustapha and Lai (2017) state that around 35.7% of their respondents use Microsoft Excel during the audit process due to the simplicity of the software. Lastly, because of the rapid changes in the business environment as well as new legislation issued by regulatory bodies, the literature has discussed the need for audit tools, including technical systems, to be flexible and continuously scalable. Indeed, Ahmi (2012) claims that to prevent issues of compatibility, audit technology has to be regularly upgraded to cope with changes in the audit environment.

The fifth classified group is the regulatory factor, which means the perceived obligations from regulatory bodies regarding the use of new technology. The literature states that international auditing standards have a lot of ambiguity regarding the possibility of using advanced technologies, including artificial intelligence, as well as a lack of detail in the standards on how to use these advanced systems. Salijeni et al. (2019) state that, until standard setters remove what they perceive to be uncertainty around the use of big data and data

analytics, they will compromise full engagement with their use. Moreover, Eilifsen et al. (2020) interviewed the heads of professional practice of five international public accounting firms in Norway and found that they are uncertain about how the supervisory inspection authorities will evaluate and accept audit evidence generated by advanced technology. Indeed, Stoel et al. (2012) argue that two fundamental factors affect IT audit acceptance: (1) growth of reliance on IT for business operations and (2) new requirements from regulatory and professional bodies set to audit these operations. These two factors are substantial for the mandatory adoption of artificial intelligence; however, in the case of voluntary adoption, the situation is much more complicated.

8.3 Research Theoretical Framework

As the literature that discusses the determinants of accepting the new technology is sprawling a theoretical framework was necessitated to comprehend the boundaries of this study. After reviewing a number of studies in the external audit literature, the UTAUT seems to be the most appropriate theory for this study. The UTAUT (Figure 8) was developed and tested by Venkatesh et al. (2003) in the field of management information systems. The model was formulated by reviewing eight existing models: the TRA, the TAM, the MM, the TPB, a model combining the technology acceptance model and the theory of planned behaviour, the MPCU, the IDT, and the SCT. The UTAUT identified four main determinants (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderators (i.e., gender, age, experience, and voluntary use), all of which play a significant role in determining the intention and use of new technology.

In this thesis, the UTAUT is modified to fit the most significant factors that may influence the implementation of artificial intelligence in the external audit environment. This study expanded the UTAUT by adding a new construct, i.e., ethical concerns of artificial intelligence, to the four constructs of the UTAUT. The purpose of adding this new construct

was to study the effects of artificial intelligence ethical concerns on the implementation of artificial intelligence technologies. Artificial intelligence technologies have unique features that distinguish them from previous technologies used in the field of accounting and auditing and, as such, create new ethical issues not previously encountered (Munoko et al., 2020).

In the UTAUT, each age, gender, and work experience act as a moderator. Since the new technology will be applied for the first time, experience cannot be tested. Furthermore, since auditors are likely to be much more homogenous compared to the user group in normal information management system research in terms of age, education, and work experience, the effect of age and gender will not be as significant in the audit setting (Curtis and Payne, 2014). Following Curtis and Payne's causation, the age and gender moderators will be tested separately, but the predictions will not be made for them.

Johns (2006) argues that researchers do not adequately recognise or appreciate the effects of context on organisational behaviour, which he defined as 'situational opportunities and constraints that affect the occurrence and meaning of organisational behaviour as well as functional relationships between variables.' Thus, the author used the factor 'firm size' as a moderator for all the constructs, excluding ethical concerns of artificial intelligence.

8.4 Research Contribution

Artificial intelligence enables auditors to take advantage of an enormous amount of formerly uninvestigated qualitative data, which can be extracted from non-traditional sources and converted into machine-readable quantitative data. Michael and Dixon (2019) assert that the integration of big data analytics in auditing means a shift from conventional financial accounting data to unstructured non-financial data. The inclusion of big data in audits opens up new avenues for auditors to extract insights from a broader range of sources, including social media, videos, and other unstructured data.

The involvement of machine learning and artificial intelligence systems may help the audit profession to deliver a higher quality of audit evidence and more relevant business insights. For example, the application of artificial intelligence can enable auditors to examine 100% of the population of transactions in a short time. Munoko et al. (2020) and Rozario and Thomas (2019) state that artificial intelligence may not only speed up auditors' work by enabling the automation of tasks such as risk evaluation and 100% population testing, but also enhance judgement on audits. Despite the positive potential benefits that artificial intelligence possesses, the literature shows that its application is limited in the audit profession.

This thesis makes a significant contribution to the field of artificial intelligence technology adoption and ethical concerns. Theoretically, it provides empirical evidence of how auditors consider ethical concerns when adopting and utilising artificial intelligence technology, which is one of the few empirical studies on artificial intelligence ethics. This research adds value to the existing literature, which mainly comprises theoretical and methodological papers. By extending the UTAUT model to include ethical concerns as a crucial determinant of new technology adoption behaviour, this thesis makes a theoretical contribution by bridging the gap between the ethical aspect of artificial intelligence and technology adoption theory. Additionally, this thesis is one of the pioneering studies to link the fields of artificial intelligence and accounting, which is crucial as artificial intelligence technology is expected to revolutionise accounting and auditing practices. This contribution also provides insights for scholars to integrate ethical concerns into technology acceptance models. Integrating ethical concerns to technology acceptance models will help to capture the moral, social and professional implications of artificial intelligence.

The theoretical contribution of this thesis is of paramount importance not only for academia but also for the society as a whole, considering the rapid proliferation of artificial intelligence in various sectors. As artificial intelligence technology is becoming more

ubiquitous, it is crucial to ensure that its adoption and usage are in line with ethical norms and values. The ethical concerns discussed in this thesis can help policymakers, organisations, and individuals make informed decisions about the ethical implications of artificial intelligence technology. Moreover, by adding ethical concerns as a determinant of technology adoption behaviour, this thesis contributes to the growing body of literature that recognises the importance of ethical concerns in technology development and use in diverse domains, including finance, healthcare, education, and beyond.

The practical contribution of this thesis is also significant as it provides answers to the research question of which factor, among performance expectancy, effort expectancy, social influence, facilitating conditions, and ethical concerns, is the most significant in the adoption of artificial intelligence technology. According to the results, auditors do not give much attention to social influence in their adoption journey, but they do consider effort expectancy. The fact that effort expectancy has some influence over auditors' decision of artificial intelligence acceptance underscores the importance of user experience and ease of use in the adoption of artificial intelligence. This is particularly relevant in the context of artificial intelligence, as it can be a complex and technical field that requires specialised knowledge. Making artificial intelligence user-friendly and accessible to a wider audience can lead to more widespread adoption and greater benefits for society.

In terms of performance expectancy and ethical concerns, the author finds that auditors regard them equally important, but facilitating conditions has been regarded the most critical factor in accepting and utilising artificial intelligence technology in audit engagements. These findings suggest that audit firms should focus on developing their IT infrastructure to facilitate the journey of artificial intelligence technology adoption. Furthermore, the regulatory bodies must keep up with the remarkable advancements in artificial intelligence by continuously updating auditing standards and providing guidelines for using this technology in the auditing

profession. The lack of endorsement of audit standards can make auditors hesitant to use artificial intelligence in audit engagements.

The practical contribution of this thesis also sheds light on the potential danger of the unscrutinised development of artificial intelligence technology and the need for policymakers to swiftly establish ethical guidelines that can achieve a consensus and be acted upon. Artificial intelligence stands out from previous technological advancements due to its exceptional features, including its ability to learn, adapt, process complex information, interact with humans, and operate autonomously. The remarkable performance of ChatGPT exemplifies the distinctiveness of artificial intelligence from its predecessors. Nevertheless, the distinctive characteristics of artificial intelligence can pose significant risks to society. Therefore, the author states that addressing the ethical concerns related to artificial intelligence is as crucial as government and regulatory agency efforts to mitigate the effects of climate change. The associations of accountants have to promote debates on ethical issues of artificial intelligence technology, as its implications, both benefits and costs, should be considered in the profession. Additionally, the thesis calls upon scholars to investigate how artificial intelligence technology interacts with cultures, which can enhance our comprehension of this crucial technology.

The thesis also offers a valuable contribution by delving into the perceptions of auditors and clients regarding the use of artificial intelligence in the audit profession, taking into account the effects of the Covid-19 pandemic. This crisis has had a far-reaching impact on society, particularly on the audit industry. As one of the first empirical investigations of its kind, this study assesses how the pandemic has influenced the adoption of technology in this sector. The findings indicate that auditors are now recognising the importance of utilising smart audit tools to facilitate remote auditing. Furthermore, the research highlights that clients have become more adaptable when it comes to sharing data online. Overall, this study provides valuable

insights into the changes brought about by the pandemic and the potential for artificial intelligence advancements to transform the audit profession.

8.5 Implication of The Findings

The results of this thesis have significant implications for future practical applications. Aligned with previous literature in the field of auditing, this thesis suggests that auditors exhibit a more favourable attitude towards the implementation of artificial intelligence when they perceive higher performance in their auditing duty as a result of its use. Therefore, the author recommends that artificial intelligence developers, as well as audit firm management, work towards increasing auditors' perception of the performance expectancy from the use of artificial intelligence. This can be achieved by clearly outlining the positive impact of artificial intelligence on improving auditor efficiency and effectiveness, enhancing the quality of audit outputs, and saving time in the audit process.

Aligned with previous studies in the field of auditing, this thesis shows that when auditors perceive using artificial intelligence in their audit duties as easy, they exhibit a more positive attitude towards its implementation. Thus, the author urges artificial intelligence developers to create more flexible systems that can be compatible with various systems used by audit firm clients. Since clients of audit firms come in different sizes and sectors, it is expected that they use various forms of ERP systems. The author also recommends that audit firm management invest in training and educating their auditors on how to use this new technology. The training should cover how to feed data into artificial intelligence systems and how to synchronise them with different ERP systems used by clients, as each client may have different systems. The author also advises novice auditors to develop their skills in using artificial intelligence along with their professional auditing skills.

This thesis demonstrates that when auditors perceive that there are audit standards, organisational support, and technical infrastructure in place to facilitate the adoption of

artificial intelligence, they show a more positive attitude towards its implementation. Therefore, the author recommends that audit firm management, when considering the adoption of artificial intelligence, focus on increasing auditors' perceptions that the necessary resources, knowledge, and IT support are available to guide them through the adoption process. Additionally, audit firm management should integrate IT teams with audit teams and provide audit technology training to staff at all levels. The author also suggests that regulatory and professional bodies play a more active role in the adoption process by funding research, offering training courses and consultations to auditing firms.

This study has discussed the ethical concerns of artificial intelligence via six aspects and presented evidence that these matters play a significant role in the decision to use artificial intelligence. The first aspect is the potential impact of the vast amount of data collected by artificial intelligence on client confidentiality. Artificial intelligence in auditing requires access to vast amounts of sensitive clients' financial and non-financial data. Ensuring the privacy and security of this data is crucial to maintain ethical standards. Data breaches or unauthorized access to confidential information can have severe consequences and erode trust in the auditing process.

This study concluded that the auditors' perception of the negative impact of artificial intelligence on client confidentiality plays an important role in accepting artificial intelligence in auditing. When an auditor perceives that the use of artificial intelligence technology negatively impacts client confidentiality, he or she will refuse to accept artificial intelligence. Thus, the author recommends audit firms and artificial intelligence developers to address client confidentiality concerns associated with the implementation of artificial intelligence. Addressing this problem may be through non-disclosure agreements or by limiting access to the vast amount of collected data to certain people.

The second ethical aspect discussed in this thesis is the possible negative impact of artificial intelligence on the professional scepticism skills of auditors. Overreliance on artificial intelligence technology in the audit process can diminish the role of professional judgment and critical thinking, which are essential aspects of ethical auditing. Auditors may become overly dependent on AI outputs without thoroughly understanding the underlying assumptions and limitations.

This thesis concludes that when an auditor perceives that the use of artificial intelligence technology might impair their professional scepticism skills, they are unlikely to accept artificial intelligence technology. Professional audit bodies and audit firms should reflect on the impact of artificial intelligence on the professional scepticism skills of auditors, particularly novice auditors. This is a critical step to ensure that novice auditors are technically qualified and can use artificial intelligence correctly without losing their ability to exercise professional judgment. The author recommends that audit firms counter any shortcomings that may arise from the use of artificial intelligence by training auditors on tasks that develop their professional scepticism skills. By training auditors on how to "think about problems," they can improve their performance on complicated tasks and develop a more sceptical approach.

The third ethical aspect discussed in this study is the negative impact of artificial intelligence on the auditability and traceability of auditors' decisions. The argument is that the reliance on an audit artificial intelligence system is like reliance on Black-Box Systems. Some artificial intelligence algorithms are considered "black-box" systems, meaning that they make decisions without providing clear explanations for how those decisions were reached. This lack of transparency and traceability can create ethical dilemmas for auditors who need to justify their findings and conclusions to stakeholders.

The study concluded that the auditors' perception of artificial intelligence auditability plays an important role in accepting artificial intelligence tools in the audit context. When an

auditor believes that the decisions of the artificial intelligence tools will not be auditable and traceable, he will be less likely to accept the artificial intelligence tools. Lehner et al. (2022) state that the knowledge of the underlying concepts of artificial intelligence algorithms must be understandable by most professionals (including auditors), otherwise the use of artificial intelligence will be limited. They add that in order to allow for subsequent explainability and auditability, an ethical AI-based decision-making process must start in the development phases of its underlying algorithms. This requires developers' moral awareness in the design phase. Thus, the author encourages artificial intelligence developers, and audit firms who develop their artificial intelligence tools in-house, to address auditability concerns. Delivering auditability and traceability may be made possible by having the artificial intelligence make decisions in short, traceable phases. It may also be achieved by providing a box at each decision-making stage, in which the procedures followed by the system for issuing the decision are explained.

The fourth ethical aspect discussed in this study is the negative impact of artificial intelligence on auditors' independence. The use of artificial intelligence tools provided by audit firms or third-party vendors can raise questions about auditor independence. The study concluded that when an auditor perceived the use of artificial intelligence technology might impair his or her independence, they are likely not to accept artificial intelligence technology. The tensions about auditors' independence have become increasingly exacerbated with the use of artificial intelligence; thus, more practical guidance is warranted. Austin et al. (2021) state that standard setters should elaborate on their guidance regarding the concerns of the cognitive bias that could affect auditors' assessment of independence when providing analytics-based insights to clients. The study results urge standard setters and audit firms to address the possible negative impact of artificial intelligence on auditors' independence. Moreover, the author recommends standard setters to test if less independence can lead to improved assurance. If it

can lead to this outcome, is it possible to compromise part of the auditors' independence in exchange for improved assurance for the public?

The fifth ethical aspect discussed in this study is the negative impact of artificial intelligence on society by raising the unemployment rate in the auditors' community. As artificial intelligence and automation technologies continue to advance, there is concern about job displacement for auditors. If routine tasks are automated, auditors may face ethical dilemmas related to job loss and the potential for biased decision-making when relying solely on artificial intelligence-generated insights.

This study concluded that auditors' perception of being replaced by artificial intelligence would play a significant role in the acceptance of artificial intelligence. When an auditor believes that the artificial intelligence tools will take his or her job, they will be less likely to accept artificial intelligence. The study results encourage audit firms to help auditors learn new skills, such as data analysis skills and artificial intelligence systems feeding skills, especially those auditors who perform routine tasks in audits and, thus, are at more risk of being replaced.

The final ethical aspect discussed in this study is the possibility of repurposing client data collected by artificial intelligence for non-audit services. The study concluded that if an auditor perceives that the use of artificial intelligence technology might lead to the repurposing of client data for non-audit services, they are unlikely to accept artificial intelligence technology. Repurposing client data was first identified by Munoko et al. (2020) as an ethical issue related to artificial intelligence. The author recommends that standard setters address cases related to the repurposing of client data collected by artificial intelligence. Standard setters should discuss the repurposing of clients' data by audit firms in terms of providing consultation and audit services. The author also recommends that audit firms have clear and

explicit agreements with artificial intelligence developers regarding the repurposing of client data for other purposes.

8.6 Limitations and Future Research

Due to time and cost restraints, the characteristics of this study as a doctoral research project have limited the study's breadth and coverage. Additionally, it is crucial to evaluate the findings of the analysis in light of the following limitations when evaluating the results.

In the first part of the data collection stage, the quantitative data (i.e., the questionnaire) was dedicated only to one of the tools of artificial intelligence: visual recognition technology. This occurred because this study is based on examining the determinants that affect the auditors' decision to use artificial intelligence tools and, since many of these tools have not yet been used, the participants are unlikely to have much idea of how these tools operate in the audit profession. Therefore, researchers must explain in the questionnaire how the tools work for auditors, so that the participants can understand the context in which the researcher is working. Explanation of all the artificial intelligence tools used in the auditing profession, and the inclusion of all these tools in the questionnaire, will affect the length of the questionnaire. This may subsequently negatively impact the participation rate since the questionnaire will take longer to complete and, thus, may not attract the interest of the desired participants.

This study could not examine the longitudinal relationship between the intention to use artificial intelligence and the actual use of artificial intelligence, analogous to the work by Venkatesh et al. (2003) for the UTAUT. The reason for this oversight is that the researcher could not create a longitudinal data collection process over a certain time period (this was six months for the UTAUT), due to time limitations and the difficulties of accessing the same participants over a certain period of time. Another note about the results generalisation is that the data for this study, both the quantitative and qualitative parts, was collected in a developing country (i.e., Saudi Arabia). Although the Saudi Arabian government invests vast sums in

technical advancements and artificial intelligence, it is difficult to know for sure if the results of this study can be applied to a completely different society, such as a developed country.

In addition, one of the points that this thesis does not discuss is the extent to which the size of the audit firm affects the actual use of artificial intelligence. However, via the interviews, the participants provided some expressions that show the possibility that the impact of the size of the audit firm does affect the actual use (not the intention to use); this point should be the subject of future studies that aim to investigate the existence of this relationship empirically. The study also showed the viewpoint of auditors towards the lack of audit standards for guidance and instructions related to the use of artificial intelligence in the audit profession. Future studies can address further how to remedy this shortcoming in auditing standards and how the standards can be updated to enable the auditor to remain in lockstep with the rapid developments in artificial intelligence.

Finally, this study discussed the impact of ethical concerns on auditors' decision to use artificial intelligence; this analysis was conducted with respect to six aspects. Future studies could focus on addressing each of these concerns and how audit firms and regulators can minimise the negative impact of these concerns. For example, future research could discuss methods by which decisions made by artificial intelligence are auditable, or consider ways to maintain client confidentiality in the environment of artificial intelligence and big data. The results of qualitative data (i.e., the interviews) also showed that the Covid-19 crisis significantly impacted the mentality of auditors and clients. The crisis has promoted the need to use artificial intelligence to solve some difficulties, such as remote auditing. Here, future studies could measure the magnitude of this impact, including an analysis on the extent of the use of artificial intelligence before and after the Covid-19 crisis. The author believes this thesis provides a ground for future debate about the implementation of artificial intelligence technology in the auditing industry and, more generally, business.

Reference List

- Abdolmohammadi, M. and Usoff, C. (2001). A longitudinal study of applicable decision aids for detailed tasks in a financial audit. *Intelligent Systems in Accounting, Finance & Management*, 10(3), pp.139–154.
- Abelson, R. and Nielsen, K. (1967). History of ethics. In Paul Edwards (ed.), *The Encyclopedia of Philosophy*. New York: Macmillan. pp. 3--81.
- Abou-El-Sood, H., Kotb, A. and Allam, A. (2015). Exploring Auditors' Perceptions of the Usage and Importance of Audit Information Technology. *International Journal of Auditing*, 19(3), pp.252–266.
- Abubakre, M., Ravishankar, M.N. and Coombs, C. (2017). Revisiting the trajectory of IT implementation in organisations: an IT culture perspective. *Information Technology & People*, 30(3), pp.562–579.
- ACCA. (2017). *Ethics and trust in a digital age*. [online]. Available from: <https://www.accaglobal.com/gb/en/technical-activities/technical-resources-search/2017/august/ethics-and-trust-in-a-digital-age.html>. (Accessed 13 May. 2020).
- Acemoglu, D. and Restrepo, P. (2018). Low-Skill and High-Skill Automation. *Journal of Human Capital*, 12(2), pp.204–232.
- Adamic, L.A. and Huberman, B.A. (2000).
- Adom, D., Hussein, E.K. and Agyem, J.A. (2018). Theoretical and conceptual framework: Mandatory ingredients of a quality research. *International journal of scientific research*, 7(1), pp.438-441.
- Agarwal, R. and Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? *Decision sciences*, 30(2), pp.361–391.
- Ahmi, A. (2012). *the Use of Generalised Audit Software (Gas) By External Auditor in the Uk*. PhD. Brunel University.
- Ahmi, A. and Kent, S. (2012). The utilisation of generalized audit software (GAS) by external auditors. *Managerial Auditing Journal*, 113.
- AICPA. (2015). *CPA FINANCIAL SERVICES: Audits*. [online]. Available from: <https://us.aicpa.org/content/dam/aicpa/advocacy/state/downloadabledocuments/what-is-an-audit.pdf> (Accessed 21 Nov. 2019).
- AICPA. (1984). *Statement on Auditing Standards No. 48 - The Effects of Computer Processing On the Examination of Financial Statements*. [online]. Available from: https://egrove.olemiss.edu/cgi/viewcontent.cgi?article=1047&context=aicpa_sas (Accessed 05 Jan. 2021).
- AICPA. (2020). *The Data-Driven Audit: How Automation and AI are Changing the Audit and the Role of the*

Auditor. [online]. Available from:

<https://us.aicpa.org/content/dam/aicpa/interestareas/frc/assuranceadvisoryservices/downloadabledocuments/the-data-driven-audit.pdf> (Accessed 21 Sep. 2022).

Al-Ansi, A.A., Ismail, N.A. Bin and Al-Swidi, A.K. (2013). The effect of IT knowledge and IT training on the IT Utilization among external auditors: evidence from Yemen. *Asian Social Science*, 9(10), p.307.

Al-Eissa, A.I. (2009). *Non-audit services and auditor independence: the case of Saudi Arabia*. PhD. Victoria University.

AL-FAISAL, A.M. (1992). The accounting profession in Saudi Arabia. In *International handbook of accounting education and certification* (pp. 127-140). Pergamon.

Al-Filali, I.Y. and Gallarotti, G.M. (2012). Smart development: Saudi Arabia's quest for a knowledge economy. *International Studies*, 49(1-2), pp.47-76.

Al-Gahtani, S.S., Hubona, G.S. and Wang, J. (2007). Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT. *Information & management*, 44(8), pp.681-691.

AL-Ghamdi, S. and AL-Angari, H. (2005).

Al-Rehaily, A.S.F. (1992). *The evolution of accounting in Saudi Arabia: A study of its relevance to the social and economic environment*. PhD. University Of Hull.

Al-Rumaihi, J.S.H. (1997). *Setting accounting standards in a non-Western environment: with special reference to the Kingdom of Saudi Arabia*. PhD. University of Dundee.

Al-Saadi, H. (2014). Demystifying Ontology and Epistemology in research methods. *Research gate*, 1(1), pp.1-10.

Al-Sayyed, S., Al-Aroud, S. and Zayed, L. (2021). The effect of artificial intelligence technologies on audit evidence. *Accounting*, 7(2), pp.281-288.

Alam, S.S. and Noor, M.K.M. (2009). ICT adoption in small and medium enterprises: An empirical evidence of service sectors in Malaysia. *International Journal of Business and management*, 4(2), pp.112-125.

Albader, M. (2015). *Transition to IFRS and its implications for accounting education in Saudi Arabia*. PhD. Victoria University.

Alles, M.G. (2015). 449.

Almutairi, H. (2008). Validating the unified theory of acceptance and use of technology in Kuwaiti ministries: a structural equation modelling approach. *International Journal of Information Systems and Change Management*, 3(3), pp.191-219.

Alon, A. and Dwyer, P. (2010). The impact of groups and decision aid reliance on fraud risk

- assessment. *Management Research Review*, 33(3), pp.240-256.
- Alpaydin, E. (2020). *Introduction to machine learning*. Cambridge, Massachusetts: The MIT Press.
- Alshehri, M., Drew, S., Alhussain, T. and Alghamdi, R. (2012). The Effects of Website Quality on Adoption of E-Government Service: An empirical Study Applying UTAUT Model Using SEM. *arxiv preprint arxiv:1211.2410*.
- Alsultan, A.S. (2017). *Audit quality, IPOs and earnings management: evidence from Saudi Arabia*. PhD. University of Portsmouth
- Alzola, M. (2015). Virtuous persons and virtuous actions in business ethics and organizational research. *Business Ethics Quarterly*, 25(3), pp.287–318.
- Amankwaa, L. (2016). Creating protocols for trustworthiness in qualitative research. *Journal of Cultural Diversity*, 23(3), pp.121–127.
- Ammanabrolu, P., Tien, E., Cheung, W., Luo, Z., Ma, W., Martin, L. and Riedl, M. (2019). Guided neural language generation for automated storytelling. In *Proceedings of the Second Workshop on Storytelling*, pp. 46-55.
- Ang, C.L., Davies, M.A. and Finlay, P.N. (2001). An empirical model of IT usage in the Malaysian public sector. *The Journal of Strategic Information Systems*, 10(2), pp.159-174.
- Appelbaum, Deniz, Budnik, S. and Vasarhelyi, M. (2020). Auditing and Accounting During and After the COVID-19 Crisis. *The CPA Journal*, 90(6), pp.14–19.
- Appelbaum, D, Issa, H. and Strauss, R. (2020). *A reasonable assurance framework for ethical AI systems*. Working paper, Montclair University.
- Appelbaum, D., Kogan, A. and Vasarhelyi, M.A. (2017). Big data and analytics in the modern audit engagement: Research needs. *Auditing*, 36(4), pp.1–27.
- Appelbaum, D. and Nehmer, R.A. (2017). Using drones in internal and external audits: An exploratory framework. *Journal of Emerging Technologies in Accounting*, 14(1), pp.99–113.
- Arnold, V. and Sutton, S.G. (1998). The theory of technology dominance: Understanding the impact of intelligent decision aids on decision maker's judgments. *Advances in accounting behavioral research*, 1(3), pp.175–194.
- Arthur, K.N.A. and Owen, R. (2019). A Micro-ethnographic Study of Big Data-Based Innovation in the Financial Services Sector: Governance, Ethics and Organisational Practices. *Journal of Business Ethics*, 160(2), pp.363–375.
- Ashton, R.H. (1992). Effects of justification and a mechanical aid on judgment performance. *Organizational Behavior and Human Decision Processes*, 52(2), pp.292–306.

- Ashton, T.S. (1997). *The Industrial Revolution : 1760-1830*. London: Oxford University Press.
- ACMU.S. Public Policy Council and ACM Europe Policy Committee. 2017. Statement on Algorithmic Transparency and Accountability. (2017). Council, U.P.P., 2017. Statement on algorithmic transparency and accountability. *Commun. ACM*. [Online]. Available: <https://www.acm.org/binaries/content/assets/public-policy/acm-pres-ltr-un-reweapons-systems.pdf> (Accessed 13 May. 2020)
- Atkeson, A. and Kehoe, P.J. (2001). The Transition to a New Economy After the Second Industrial Revolution. *National Bureau of Economic Research Working Paper Series*. No. 8676.
- Austin, A.A., Carpenter, T.D., Christ, M.H. and Nielson, C.S. (2021). The data analytics journey: Interactions among auditors, managers, regulation, and technology. *Contemporary Accounting Research*, 38(3), pp.1888-1924.
- Autor, D.H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3), pp.3–30.
- Axelsen, M., Green, P. and Ridley, G. (2017). Explaining the information systems auditor role in the public sector financial audit. *International Journal of Accounting Information Systems*, 24, pp.15-31.
- Ba-Eissa, M.O. (1984). *The professionalisation of accounting: a study of the development of the accountancy profession with a special reference to Great Britain, the United States and Saudi Arabia*. PhD. Univesrity of Kent.
- Backstrom, C.H. and Hursh, G.D. (1963). *Survey Research*. Chicago: Northwestern University Press.
- Bakr, S.A. (2020). *The adoption of the international financial reporting standard for small and medium-sized entities (IFRS for SMEs) in the kingdom of Saudi Arabia*. PhD. Royal Holloway, University of London.
- Banker, R.D., Chang, H. and Kao, Y.C. (2002). Impact of information technology on public accounting firm productivity. *Journal of information systems*, 16(2), pp.209-222.
- Bao, Y., Ke, B., Li, B., Yu, Y.J. and Zhang, J. (2020). Detecting accounting fraud in publicly traded US firms using a machine learning approach. *Journal of Accounting Research*, 58(1), pp.199-235.
- Barac, K., Plant, K., Kunz, R. and Kirstein, M. (2021). Audit practice: A straightforward trade or a complex system?. *International Journal of Auditing*, 25(3), pp.797-812.
- Bedard, J.C., Jackson, C., Ettredge, M.L. and Johnstone, K.M. (2003). The effect of training on auditors' acceptance of an electronic work system. *International Journal of Accounting Information Systems*, 4(4), pp.227-250.
- Bell, E., Bryman, A. and Harley, B. (2018). *Business research methods*. 5th ed. Oxford: Oxford University Press.
- Bender, R. (2013). *Corporate financial strategy*. 4th ed. London: Routledge.
- Beniger, J. (2009). *The control revolution: Technological and economic origins of the information society*. Harvard

university press.

- Bennett, G.B. and Hatfield, R.C. (2013). The effect of the social mismatch between staff auditors and client management on the collection of audit evidence. *The Accounting Review*, 88(1), pp.31-5
- Bertomeu, J., Cheynel, E., Floyd, E. and Pan, W. (2021). Using machine learning to detect misstatements. *Review of Accounting Studies*, 26, pp.468-519.
- Bhrugubanda, M. (2015). A review on applications of cyber physical systems. *International Journal of Innovative Science, Engineering and Technology*, 2(6), pp.728–730.
- Bierstaker, J., Janvrin, D. and Lowe, D.J., 2014. What factors influence auditors' use of computer-assisted audit techniques?. *Advances in Accounting*, 30(1), pp.67-74.
- Bierstaker, J.L., Burnaby, P. and Thibodeau, J. (2001). The impact of information technology on the audit process: An assessment of the state of the art and implications for the future. *Managerial Auditing Journal*, 16 (3), pp. 159-164.
- Bijker, W.E. and Law, J. (1994). *Shaping technology/building society: Studies in sociotechnical change*. MIT press.
- Birren, J.E., Woods, A.M. and Williams, M.V. (1980). Behavioral slowing with age: Causes, organization, and consequences. In *Aging in the 1980s: Psychological issues*. Washington, DC, US: American Psychological Association, pp. 293–308.
- Blanqui, A.J. (1882). *Histoire de l'économie politique en Europe depuis les anciens jusqu'à nos jours*. Librairie Guillaumin.
- Bolarinwa, O.A. (2015). Principles and methods of validity and reliability testing of questionnaires used in social and health science researches. *Nigerian Postgraduate Medical Journal*, 22(4), pp.195–201.
- Braun, R.L. and Davis, H.E. (2003). Computer-assisted audit tools and techniques: analysis and perspectives. *Managerial Auditing Journal*, 18(9), pp.725–731.
- Brazel, J.F. and Agoglia, C.P. (2007). An examination of auditor planning judgements in a complex accounting information system environment. *Contemporary Accounting Research*, 24(4), pp.1059-1083.
- Bredmar, K. (2017). Digitalisation of enterprises brings new opportunities to traditional management control. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy*, 8(2), pp.115-125.
- Brey, P.A. (2012). Anticipating ethical issues in emerging IT. *Ethics and Information Technology*, 14, pp.305-317.
- Brinkman, W.F., Haggan, D.E. and Troutman, W.W. (1997). A history of the invention of the transistor and where it will lead us. *IEEE journal of solid-state circuits*, 32(12), pp.1858-1865.

- Brown-Liburd, H. and Vasarhelyi, M.A. (2015). Big Data and audit evidence. *Journal of Emerging Technologies in Accounting*, 12(1), pp.1-16.
- Bryman, A. (2007). Barriers to integrating quantitative and qualitative research. *Journal of mixed methods research*, 1(1), pp.8-22.
- Bryman, A. (2012). Social research methods Bryman. *OXFORD University Press*.
- Brynjolfsson, E. and Hitt, L.M. (2003). Computing productivity: Firm-level evidence. *Review of economics and statistics*, 85(4), pp.793–808.
- Buhalis, D. and Jun, S.H. (2011). E-tourism. *Contemporary tourism reviews*, 1, pp.2–38.
- Bullock, J., Luccioni, A., Pham, K.H., Lam, C.S.N. and Luengo-Oroz, M. (2020). Mapping the landscape of artificial intelligence applications against COVID-19. *Journal of Artificial Intelligence Research*, 69, pp.807-845.
- Burgess, M. (2020). The UK's lockdown rules, explained. [online]. Available from: <https://www.wired.co.uk/article/uk-lockdown> (Accessed 12 Nov, 2020).
- Burt, P.J. and Adelson, E.H. (1983). A multiresolution spline with application to image mosaics. *ACM Transactions on Graphics (TOG)*, 2(4), pp.217–236.
- Byrnes, P.E., Ames, B., Vasarhelyi, M.A. and Warren, D. (2015). The current state of continuous auditing and continuous monitoring. *AICPA (Ed.), Audit Analytics and Continuous Audit: Looking Towards the Future, American Institute of Certified Accountants, New York*, pp.53-70.
- Cai, Z., Fan, X. and Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education*, 105, pp.1-13.
- Campbell-Kelly, M., Aspray, W., Snowman, D.P., McKay, S.R. and Christian, W. (1997). Computer A history of the information machine. *Computers in Physics*, 11(3), pp.256-257.
- Cao, M., Chychyla, R. and Stewart, T. (2015). Big data analytics in financial statement audits. *Accounting Horizons*, 29(2), pp.423-429.
- Carnegie, G.D. and Napier, C.J. (2002). Exploring comparative international accounting history. *Accounting, Auditing & Accountability Journal*, 15(5), pp.689–718.
- Carus-Wilson, E.M. (1941). An industrial revolution of the thirteenth century. *The Economic History Review*, 11(1), pp.39–60.
- Castelo, N., Bos, M.W. and Lehmann, D.R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, 56(5), pp.809–825.
- Cecchini, M., Aytug, H., Koehler, G.J. and Pathak, P. (2010). Detecting management fraud in public

- companies. *Management Science*, 56(7), pp.1146-1160.
- Cerny, B.A. and Kaiser, H.F. (1977). A study of a measure of sampling adequacy for factor-analytic correlation matrices. *Multivariate behavioral research*, 12(1), pp.43–47.
- Chaney, P.K., Jeter, D.C. and Shivakumar, L. (2004). Self-selection of auditors and audit pricing in private firms. *The accounting review*, 79(1), pp.51-72.
- Char, D.S., Shah, N.H. and Magnus, D. (2018). Implementing Machine Learning in Health Care — Addressing Ethical Challenges. *New England Journal of Medicine*, 378(11), pp.981–983.
- Chen, C.X., Trotman, K.T. and Zhou, F. (2015). Nominal versus interacting electronic fraud brainstorming in hierarchical audit teams. *The Accounting Review*, 90(1), pp.175-198.
- Chen, H.J., Huang, S.Y. and Kuo, C.L. (2009). Using the artificial neural network to predict fraud litigation: Some empirical evidence from emerging markets. *Expert Systems with Applications*, 36(2 PART 1), pp.1478–1484.
- Chen, Y.J., Wu, C.H., Chen, Y.M., Li, H.Y. and Chen, H.K. (2017). Enhancement of fraud detection for narratives in annual reports. *International Journal of Accounting Information Systems*, 26, pp.32-45.
- Chen, Y., Argentinis, J.E. and Weber, G. (2016). IBM Watson: how cognitive computing can be applied to big data challenges in life sciences research. *Clinical therapeutics*, 38(4), pp.688-701.
- Christ, M.H., Emett, S.A., Summers, S.L. and Wood, D.A. (2021). Prepare for takeoff: Improving asset measurement and audit quality with drone-enabled inventory audit procedures. *Review of accounting studies*, pp.1-21.
- Chui, M., Manyika, J. and Miremadi, M. (2016). Where machines could replace humans-and where they can't (yet). *McKinsey Q.*, 3 (2016), pp. 58-69.
- Claessens, S. (2011). Lessons from the Recent Financial Crisis for Reforming National and International Financial Systems: The Road Ahead to a Sustainable Global Economic System. *ABCDE*, p.241.
- Clerk, D. (1897). *The gas and oil engine*. 7th ed. New York: Longmans.
- Cole, B.M. and Banerjee, P.M. (2013). Morally contentious technology-field intersections: The case of biotechnology in the United States. *Journal of business ethics*, 115, pp.555-574.
- Collis, J. and Hussey, R. (2013). *Business Research Practical Guide for Undergraduate and Postgraduate Students*. 4th ed. Basingstoke: Hampshire.
- Compeau, D., Higgins, C.A. and Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS quarterly*, pp.145-158.
- Compeau, D.R. and Higgins, C.A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, pp.189-211.

- Shadish, W.R., Cook, T.D. and Campbell, D.T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Belmont, Ca: Wadsworth Cengage Learning.
- Coombs, C. (2020). Will COVID-19 be the tipping point for the intelligent automation of work? A review of the debate and implications for research. *International journal of information management*, 55, p.102182.
- Craja, P., Kim, A. and Lessmann, S. (2020). Deep learning for detecting financial statement fraud. *Decision Support Systems*, 139, p.113421.
- Creswell, J.W. (2018). *Research design : qualitative, quantitative, and mixed methods approaches*. 5th ed., I. J. D. Creswell, ed. Thousand Oaks, Calif. ; London: Sage Publications.
- Creswell, J.W. and Plano Clark, V.L. (2017). *Designing and Conducting Mixed Methods Research*. 3rd ed. Los Angeles: Sage.
- Curtis, M.B., Jenkins, J.G., Bedard, J.C. and Deis, D.R. (2009). Auditors' training and proficiency in information systems: A research synthesis. *Journal of information systems*, 23(1), pp.79-96.
- Curtis, M.B. and Payne, E.A. (2008). An examination of contextual factors and individual characteristics affecting technology implementation decisions in auditing. *International Journal of Accounting Information Systems*, 9(2), pp.104-121.
- Curtis, M.B. and A. Payne, E. (2014). Modeling voluntary CAAT utilization decisions in auditing. *Managerial Auditing Journal*, 29(4), pp.304-326.
- Motivation to use big data and big data analytics in external auditing. *Managerial Auditing Journal*.
- Dagilienė, L. and Kloviėnė, L. (2019). Motivation to use big data and big data analytics in external auditing. *Managerial Auditing Journal*, 34(7), pp.750–782.
- Dai, J. and Vasarhelyi, M.A. (2017). Toward blockchain-based accounting and assurance. *Journal of Information Systems*, 31(3), pp.5–21.
- Damerji, H. (2020). *Technology Readiness Impact on Artificial Intelligence Technology Adoption by Accounting Students*. PhD. Universtiy of La Verne.
- David, H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American economic review*, 103(5), pp.1553–1597.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, pp.319-340.
- Davis, G.B. and Weber, R. (1986). The Impact of Advanced Computer Systems on Controls and Audit Procedures: A Theory and an Empirical Test. *Auditing: A Journal of Practice & Theory*, 5(2), pp.35-49.

- Day, J.C., Janus, A. and Davis, J. (2005). *Computer and Internet Use in the United States: 2003 Special Studies Helping You Make Informed Decisions Current Population Reports*.
- Day, J.C., Janus, A., & Davis, J. (2005). *Computer and Internet use in the United States: 2003*. Washington, DC: U.S. Department of Commerce
- Deane, P. (2000). *The first industrial revolution*. London: Cambridge Univ. Press.
- Debreceeny, R., Lee, S.L., Neo, W. and Shuling Toh, J. (2005). Employing generalized audit software in the financial services sector: Challenges and opportunities. *Managerial Auditing Journal*, 20(6), pp.605-618.
- Debreceeny, R.S., Gray, G.L., Ng, J.J.J., Lee, K.S.P. and Yau, W.F. (2005). Embedded audit modules in enterprise resource planning systems: Implementation and functionality. *Journal of Information Systems*, 19(2), pp.7-27.
- DeDeo, S. (2014). Wrong side of the tracks: Big data and protected categories. *arXiv preprint arXiv:1412.4643*.
- Deloitte. (2016). *Deloitte Forms Alliance with Kira Systems to Drive the Adoption of Artificial Intelligence in the Workplace*. [online]. Available from: <https://www2.deloitte.com/us/en/pages/about-deloitte/articles/press-releases/deloitte-forms-alliance-with-kira-systems-to-drive-the-%0Aadoption-of-artificial-intelligence-in-the-workplace.html> (Accessed 21 Sep. 2020).
- DeLone, W.H. and McLean, E.R. (1992). Information systems success: The quest for the dependent variable. *Information systems research*, 3(1), pp.60-95.
- Denscombe, M. (2008). Communities of practice: A research paradigm for the mixed methods approach. *Journal of mixed methods research*, 2(3), pp.270–283.
- Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P. and Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: a predictive validity perspective. *Journal of the Academy of Marketing Science*, 40, pp.434-449.
- Dickey, G., Blanke, S. and Seaton, L. (2019). Machine Learning in Auditing. *The CPA Journal*, pp.16–21.
- Dillard, J.F. and Yuthas, K. (2001). A responsibility ethics for audit expert systems. *Journal of Business Ethics*, 30, pp.337-359.
- Dimitrieska, S., Stankovska, A. and Efremova, T. (2018). The Fourth Industrial Revolution –“Advantages And Disadvantages. *Economics and Management*, 14(2), pp.182–187.
- Ding, K., Lev, B., Peng, X., Sun, T. and Vasarhelyi, M.A. (2020). Machine learning improves accounting estimates: Evidence from insurance payments. *Review of accounting studies*, 25, pp.1098-1134.
- Ding, L.Y., Zhong, B.T., Wu, S. and Luo, H.B. (2016). Construction risk knowledge management in BIM using ontology and semantic web technology. *Safety science*, 87, pp.202-213.

- Dipboye, R.L. (1977). A critical review of Korman's self-consistency theory of work motivation and occupational choice. *Organizational behavior and human performance*, 18(1), pp.108–126.
- Dohrer, B. (2020). How auditors can test inventory without a site visit. [online]. Available from: <https://www.journalofaccountancy.com/news/2020/mar/auditing-how-to-observe-inventory-during-coronavirus-pandemic.html> (Accessed 12 May. 2022).
- Dowling, C. and Leech, S. (2007). Audit support systems and decision aids: Current practice and opportunities for future research. *International Journal of Accounting Information Systems*, 8(2), pp.92-116.
- Dowling, C. and Leech, S.A. (2014). A Big 4 firm's use of information technology to control the audit process: How an audit support system is changing auditor behavior. *Contemporary accounting research*, 31(1), pp.230–252.
- Drath, R. and Horch, A. (2014). Industrie 4.0: Hit or hype?[industry forum]. *IEEE industrial electronics magazine*, 8(2), pp.56-58.
- Dreyer, K.J., Hirschhorn, D.S., Thrall, J.H. and PACS, M. (2006). *A guide to the digital revolution*. New York: Springer.
- Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019). Artificial intelligence for decision making in the era of Big Data– evolution, challenges and research agenda. *International journal of information management*, 48, pp.63–71.
- Dubey, P. (2005). Recognition, mining and synthesis moves computers to the era of tera. *Technology@ Intel Magazine*, 9(2), pp.1–10.
- Dubois, A. and Gadde, L.E. (2002). Systematic combining: an abductive approach to case research. *Journal of business research*, 55(7), pp.553-560.
- Dulle, F.W. and Minishi-Majanja, M.K. (2011). The suitability of the Unified Theory of Acceptance and Use of Technology (UTAUT) model in open access adoption studies. *Information development*, 27(1), pp.32-45.
- Duska, R. (2005). The good auditor–Skeptic or Wealth accumulator? Ethical lessons learned from the Arthur Andersen debacle. *Journal of Business Ethics*, 57, pp.17-29.
- Dziuban, C.D. and Shirkey, E.C. (1974). When is a correlation matrix appropriate for factor analysis? Some decision rules. *Psychological bulletin*, 81(6), p.358.
- Easterby-Smith, M., Thorpe, R. and Jackson, P. (2012). *Management research*. Los Angeles; London: Sage.
- Ebimobowei, A., Ogbonna, G.N. and Enebraye, Z.P. (2013). Auditors' usage of computer assisted audit tools and techniques: Empirical evidence from Nigeria. *Research Journal of Applied sciences, Engineering and technology*, 6(2), pp.187-195.
- Eilifsen, A., Kinserdal, F., Messier Jr, W.F. and McKee, T.E. (2020). An exploratory study into the use of audit data

- analytics on audit engagements. *Accounting Horizons*, 34(4), pp.75-103.
- Eilifsen, A. (2014). *Auditing and assurance services*. Maidenhead: McGraw-Hill Education.
- Elliot, R.K. and Kielich, J.A. (1985). Expert systems for accountants. *Journal of Accountancy (pre-1986)*, 160(000003), p.126.
- Enderle, G. (2015). Exploring and conceptualizing international business ethics. *Journal of Business Ethics*, 127, pp.723-735.
- Ernst & Young. (2016). *As we say robot, will our children say colleague?* [online]. Available from: [https://www.ey.com/Publication/vwLUAssets/As_we_say_robot,_will_our_children_say_colleague/\\$File/ey-as-we-say-robot-will-our-children-say-colleague.pdf](https://www.ey.com/Publication/vwLUAssets/As_we_say_robot,_will_our_children_say_colleague/$File/ey-as-we-say-robot-will-our-children-say-colleague.pdf) (Accessed 17 Oct. 2022).
- Ertenlice, O. and Kalayci, C.B. (2018). A survey of swarm intelligence for portfolio optimization: Algorithms and applications. *Swarm and evolutionary computation*, 39, pp.36–52.
- Eshetu, Y. (2017). Understanding Cultural Relativism: a critical appraisal of the theory. *International Journal of Multicultural and Multireligious Understanding*, 4(6), pp.24-30.
- Executive Office of the President of the United States of America. (2016). Artificial Intelligence, Automation, and the Economy. *WhiteHouse*. [online]. Available from: <https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/Artificial-Intelligence-Automation-Economy.PDF> (Accessed 03 Aug. 2022).
- Farahani, M.S. and Esfahani, A. (2022). Opportunities and Challenges of Applying Artificial Intelligence in the Financial Sectors and Startups during the Coronavirus Outbreak. *International Journal of Innovation in Management, Economics and Social Sciences*, 2(4), pp.33–55.
- Farisco, M., Evers, K. and Salles, A. (2020). Towards establishing criteria for the ethical analysis of artificial intelligence. *Science and Engineering Ethics*, 26, pp.2413-2425.
- Fedyk, A., Hodson, J., Khimich, N. and Fedyk, T. (2022). Is artificial intelligence improving the audit process?. *Review of Accounting Studies*, 27(3), pp.938-985.
- Fischer, M.J. (1996). “Real-izing” the benefits of new technologies as a source of audit evidence: An interpretive field study. *Accounting, Organizations and Society*, 21(2-3), pp.219-242.
- Fisher, I.E., Garnsey, M.R. and Hughes, M.E. (2016). Natural language processing in accounting, auditing and finance: A synthesis of the literature with a roadmap for future research. *Intelligent Systems in Accounting, Finance and Management*, 23(3), pp.157–214.
- Flowerday, S. and Von Solms, R. (2005). Continuous auditing: verifying information integrity and providing

- assurances for financial reports. *Computer Fraud & Security*, 2005(7), pp.12-16.
- Flyvbjerg, B. (2011). Case Study. In *The Sage Handbook of Qualitative Research*. Thousand Oaks: Sage, pp. 301–316. [online]. Available from: <https://ssrn.com/abstract=2278194> (Accessed 09 Apr. 2021).
- Fornell, C. and Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), pp.39–50.
- Forsyth, D., Mundy, J.L., Zisserman, A., Coelho, C., Heller, A. and Rothwell, C. (1991). Invariant descriptors for 3 d object recognition and pose. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13(10), pp.971-991.
- Forteza, J.A. and Prieto, J.M. (1994). Aging and work behavior. In *Handbook of industrial and organizational psychology, Vol. 4, 2nd ed.* Palo Alto, CA, US: Consulting Psychologists Press, pp. 446–483.
- Foster, B.P., Karcher, J.N. and Levitan, A.S. (2003). Gender and accountants' use of technology. *The CPA Journal*, 73(2), p.68.
- Francis, J.R. and Wilson, E.R. (1988). Auditor changes: A joint test of theories relating to agency costs and auditor differentiation. *Accounting review*, pp.663-682.
- FRC. (2006). *Discussion Paper Promoting Audit Quality*. London. [online]. Available from: <https://www.frc.org.uk/getattachment/8f9c7425-e898-4749-b255-3f9ca93e6865/Feedback-Paper-Promoting-Audit-Quality-Oct-2007.pdf>.
- FRC. (2022). INTERNATIONAL STANDARD ON AUDITING (UK) 200 (REVISED JUNE 2016) Overall Objectives of the Independent Auditor and the Conduct of an Audit in Accordance with International Standards on Auditing (UK). [online]. Available from: [https://www.frc.org.uk/getattachment/aa24dd60-5ca4-4cec-8c67-ac470b82f931/ISA-\(UK\)-200_Revised-June-2016.pdf](https://www.frc.org.uk/getattachment/aa24dd60-5ca4-4cec-8c67-ac470b82f931/ISA-(UK)-200_Revised-June-2016.pdf)(Accessed 03 Aug. 2022)..
- FRC. (2019). *INTERNATIONAL STANDARD ON AUDITING (UK) 500: Audit Evidence*.
- FRC. (2004). *International standard on auditing (uk and ireland) 501 audit evidence—specific considerations for selected items*. [online]. Available from: [https://www.frc.org.uk/getattachment/75e03edb-2692-443d-99d3-3cca2763477b/ISA-\(UK\)-501.pdf](https://www.frc.org.uk/getattachment/75e03edb-2692-443d-99d3-3cca2763477b/ISA-(UK)-501.pdf) (Accessed 13 Dec. 2020).
- FRC. (2017). *International Standard On Auditing 250*. [online]. Available from: [https://www.frc.org.uk/getattachment/dce50b77-37d0-4148-b3e6-aec9d00e882d/ISA-\(UK\)-250A-Revised-July-2017_final.pdf](https://www.frc.org.uk/getattachment/dce50b77-37d0-4148-b3e6-aec9d00e882d/ISA-(UK)-250A-Revised-July-2017_final.pdf) (Accessed 26 May. 2021).
- Frey, C. (2020). Covid-19 will only increase automation anxiety. *Financial times*. [online]. Available from: <https://www.ft.com/content/817228a2-82e1-11ea-b6e9-a94cffd1d9bf> (Accessed 16 Nov. 2020).

- Frey, C.B. and Osborne, M.A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change*, 114, pp.254-280.
- Gabbatt, A. (2011). IBM computer Watson wins Jeopardy clash. *The Guardian*, 17.
- Gable, G., Sedera, D. and Chan, T. (2008). Re-conceptualizing Information System Success: The IS-Impact Measurement Model. *Journal of the Association for Information Systems*, 9(7), pp.377-408.
- Intelligence reframed: multiple intelligences for the 21st century*. New York: Basic Books.
- Garone, A., Pynoo, B., Tondeur, J., Cocquyt, C., Vanslambrouck, S., Bruggeman, B. and Struyven, K. (2019). Clustering university teaching staff through UTAUT: Implications for the acceptance of a new learning management system. *British Journal of Educational Technology*, 50(5), pp.2466-2483.
- Gatto, M., Bertuzzo, E., Mari, L., Miccoli, S., Carraro, L., Casagrandi, R. and Rinaldo, A. (2020). Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures. *Proceedings of the National Academy of Sciences*, 117(19), pp.10484-10491.
- Gay, G.E. and Simnett, R. (2012). *Auditing and assurance services in Australia*. North Ryde, N.S.W.: McGraw-Hill Education
- Geertz, C. (2008). Thick description: Toward an interpretive theory of culture. In *The cultural geography reader* (pp. 41-51). Routledge.
- Gefen, D. and Straub, D.W. (1997). Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS quarterly*, pp.389-400.
- Gentry, J.A., Shaw, M.J., Tessmer, A.C. and Whitford, D.T. (2002). Using inductive learning to predict bankruptcy. *Journal of Organizational Computing and Electronic Commerce*, 12(1), pp.39-57.
- Gepp, A., Linnenluecke, M.K., O'Neill, T.J. and Smith, T. (2018). Big data techniques in auditing research and practice: Current trends and future opportunities. *Journal of Accounting Literature*, 40, pp.102-115.
- Ghasemi, M., Shafeiepour, V., Aslani, M. and Barvayeh, E. (2011). The impact of Information Technology (IT) on modern accounting systems. *Procedia-Social and Behavioral Sciences*, 28, pp.112-116.
- Ghauri, P.N., Kjell Grønhaug and Strange, R. (2020). *Research methods in business studies*. New York: Cambridge University Press.
- Ghobakhloo, M., Hong, T.S., Sabouri, M.S. and Zulkifli, N. (2012). Strategies for successful information technology adoption in small and medium-sized enterprises. *Information*, 3(1), pp.36-67.
- Gilchrist, A. (2016). Introducing Industry 4.0. *Industry 4.0: The Industrial Internet of Things*, pp.195-215.
- Goddard, K., Roudsari, A. and Wyatt, J.C. (2012). Automation bias: a systematic review of frequency, effect

- mediators, and mitigators. *Journal of the American Medical Informatics Association*, 19(1), pp.121–127.
- Goel, S., Gangolly, J., Faerman, S.R. and Uzuner, O. (2010). Can linguistic predictors detect fraudulent financial filings?. *Journal of Emerging Technologies in Accounting*, 7(1), pp.25-46.
- Goldberg, Y. (2017). Neural Network Methods for Natural Language Processing.
- Goldstone, J.A. (1986). The demographic revolution in England: a re-examination. *Population studies*, 40(1), pp.5-33.
- Gonzalez, G.C., Sharma, P.N. and Galletta, D.F. (2012). The antecedents of the use of continuous auditing in the internal auditing context. *International Journal of Accounting Information Systems*, 13(3), pp.248-262.
- Goodhue, D.L. and Thompson, R.L. (1995). Task-technology fit and individual performance. *MIS quarterly*, pp.213-236.
- Gordon, R.B. (2001). *American Iron, 1607-1900* (Vol. 19). JHU Press.
- Goswami, P., 2015. Employee value proposition: a tool for employment branding. *International Journal of Scientific and Research Publications*, 5(12), pp.263-264.
- Greenawalt, M.B. (1995). Operationalizing the operational audit course. *Managerial Auditing Journal*, 10(3), pp.26-30.
- Greenstein-Prosche, M., McKee, T.E. and Quick, R. (2008). A comparison of the information technology knowledge of United States and German auditors. *The International Journal of Digital Accounting Research*, 8(14), pp.45-79.
- Grimm, S.R., Baumberger, C. and Ammon, S. (2017).
- Guba, E.G. and Lincoln, Y.S. (1994). Competing paradigms in qualitative research. *Handbook of qualitative research*, 2(163–194), p.105.
- Guiral-Contreras, A., Gonzalo-Angulo, J.A. and Rodgers, W. (2007). Information content and recency effect of the audit report in loan rating decisions. *Accounting & Finance*, 47(2), pp.285-304.
- Guiral, A., Rodgers, W., Ruiz, E. and Gonzalo, J.A. (2010). Ethical dilemmas in auditing: Dishonesty or unintentional bias? *Journal of business ethics*, 91, pp.151-166.
- Güngör, H. (2020). Creating value with artificial intelligence: A multi-stakeholder perspective. *Journal of Creating Value*, 6(1), pp.72-85.
- H.W. and Fowler, F.G. (1911). 'The concise Oxford dictionary.' *Notes and Queries*.
- Hair, J.F., Black, W.C. and Babin, B.J. (2019). *Multivariate data analysis*. Andover, Hampshire, United Kingdom: Cengage Learning Emea. Copyright.

- Hair Jr, J.F., Sarstedt, M., Ringle, C.M. and Gudergan, S.P. (2017). *Advanced issues in partial least squares structural equation modeling*. Los Angeles: Sage publications.
- Hajek, P. and Henriques, R. (2017). Mining corporate annual reports for intelligent detection of financial statement fraud—A comparative study of machine learning methods. *Knowledge-Based Systems*, 128, pp.139–152.
- Hammond, K.R. (1966). Probabilistic functionalism: Egon Brunswik's integration of the history, theory, and method of psychology. *The psychology of egon brunswik*, 15, p.80.
- Handoko, B.L., Ariyanto, S. and Warganegara, D.L. (2018). Perception of financial auditor on usage of computer assisted audit techniques. In *2018 3rd International Conference on Computational Intelligence and Applications (ICCIA)* (pp. 235-239).
- Havelka, D. and Merhout, J. (2007). Development of an information technology audit process quality framework. *AMCIS 2007 Proceedings*, p.61.
- Havelka, D. and Merhout, J.A. (2009). Grounded theory of the information technology audit process by external auditors: using group data for grounded theory development. In *1st Annual Pre-ICIS Workshop on Accounting Information Systems*. Phoenix, AZ.
- Hendry, J. (1987). The teashop computer manufacturer: J. Lyons, LEO and the potential and limits of high-tech diversification. *Business History*, 29(1), pp.73-102.
- Hermann, M., Pentek, T. and Otto, B. (2016). Design principles for industrie 4.0 scenarios. In *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE, pp. 3928–3937.
- Hernandez, G. Arias, O. Buentello, D. and Jin, Y. (2014). “Smart nest thermostat: A smart spy in your home,” presented at the Black Hat USA Conf. [Online]. Available: <https://www.blackhat.com/docs/us-14/materials/us-14-Jin-Smart-NestThermostat-A-Smart-Spy-In-Your-Home-WP.pdf> (Accessed: 13 Dec. 2019).
- Hill, R. (1998). What sample size is “enough” in internet survey research. *Interpersonal Computing and Technology: An electronic journal for the 21st century*, 6(3–4), pp.1–12.
- Holm, C. and Zaman, M. (2012). Regulating audit quality: Restoring trust and legitimacy. In *Accounting forum*. Elsevier, pp. 51–61.
- Howard, A. and Borenstein, J. (2020). AI, Robots, and Ethics in the Age of COVID-19. *mitsloan management review*. [online]. Available from: <https://sloanreview.mit.edu/article/ai-robots-and-ethics-in-the-age-of-covid-19/> (Accessed 11 Nov. 2020).
- Hu, S., Laxman, K. and Lee, K. (2020). Exploring factors affecting academics' adoption of emerging mobile technologies-an extended UTAUT perspective. *Education and Information Technologies*, 25(5), pp.4615–4635.

- Huang, M.H. and Rust, R.T. (2018). Artificial intelligence in service. *Journal of service research*, 21(2), pp.155-172.
- Hume, D. (2006). *An enquiry concerning the principles of morals*. Oxford: Clarendon Press.
- Humpherys, S.L., Moffitt, K.C., Burns, M.B., Burgoon, J.K. and Felix, W.F. (2011). Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems*, 50(3), pp.585-594.
- Hunt, S.D., Sparkman Jr, R.D. and Wilcox, J.B. (1982). The pretest in survey research: Issues and preliminary findings. *Journal of marketing research*, 19(2), pp.269-273.
- Hurt, R.K. (2010). Development of a scale to measure professional skepticism. *Auditing: A Journal of Practice & Theory*, 29(1), pp.149–171.
- Iacovou, C.L., Benbasat, I. and Dexter, A.S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS quarterly*, pp.465-485.
- IBM. (2018). *Bias in AI: How we Build Fair AI Systems and Less-Biased Humans*. [online] Available at: <https://www.ibm.com/policy/bias-in-ai/#:~:text=Bias%20in%20AI%3A%20How%20we> (Accessed 17 Feb. 2020).
- ICAEW. (1993). audit automation, IT briefing number 4. london, (chartech books).
- ICAEW. (2006). *Audit quality fundamentals - Audit purpose*. Audit and Assurance Faculty. [online] Available at: <https://www.icaew.com/-/media/corporate/files/technical/audit-and-assurance/audit-quality/audit-quality-forum-fundamentals/fundamentals-audit-purpose.ashx#:~:text=Its%20purpose%20is%20to%20encourage,confidence%20in%20the%20independent%20audit> (Accessed 07 Jul. 2022).
- ICAEW. (2020). *Coronavirus, stocktake attendance and the auditor's report*. [online]. Available from: <https://www.icaew.com/insights/viewpoints-on-the-news/2020/mar-2020/coronavirus-stocktake-attendance-and-the-auditors-report> (Accessed 03 Aug. 2022).
- ICAS. (2020). *Implications for Attendance at Stocktakes for Financial Years ending on or after 31 March 2020*. [online]. Available from: https://www.icas.com/__data/assets/pdf_file/0010/535852/Audit-Evidence-Non-Attendance-at-Stocktake-200325_FINAL.pdf. (Accessed 018 Jan. 2023).
- IFAC. (2021). *International Ethics Standards Board for Accountants - Handbook of the International Code of Ethics for Professional Accountants*. [online]. Available from: https://www.ifac.org/system/files/publications/files/IESBA-English-2021-IESBA-Handbook_Web.pdf (Accessed 18 Feb. 2022).
- IFAC (2012), “The auditor’s responsibilities relating to fraud in an audit of financial statements”, International

- Standard on Auditing 240: IFAC Handbook of International Quality Control, Auditing, Review, Other Assurance, IAASB, New York.
- IFIAR. (2018). *International Forum of Independent Audit Regulators, Survey of inspection findings 2017*. [online]. Available from: <https://www.ifiar.org/?wpdmdl=7970> (Accessed 01 Jun. 2022).
- IFIAR. (2017). *International Forum of Independent Audit Regulators Report on 2016 Survey of Inspection Findings March 2017*. [online]. Available from: <https://www.ifiar.org/?wpdmdl=2055> (Accessed 17 Aug. 2021).
- Igbaria, M. and Parasuraman, S., 1989. A path analytic study of individual characteristics, computer anxiety and attitudes toward microcomputers. *Journal of Management*, 15(3), pp.373-388.
- International Labour Organization (ILO). (2016). *World Employment And Social Outlook*. [online]. Available from: https://www.ilo.org/global/research/global-reports/weso/2016/WCMS_443480/lang--en/index.htm (Accessed 03 Dec. 2019).
- Isaac, S. and Michael, W.B. (1995). *Handbook in research and evaluation: a collection of principles, methods, and strategies useful in the planning, design, and evaluation of studies in education and the behavioral sciences*. San Diego, Ca: Edits, © Printing.
- Ismail, N.A. and Abidin, A.Z. (2009). Perception towards the importance and knowledge of information technology among auditors in Malaysia. *Journal of Accounting and Taxation*, 1(4), p.61.
- Issa, H., Sun, T. and Vasarhelyi, M.A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *Journal of Emerging Technologies in Accounting*, 13(2), pp.1–20.
- Jamieson, S. (2004). Likert scales: How to (ab) use them? *Medical education*, 38(12), pp.1217-1218.
- Janvrin, D., Bierstaker, J. and Lowe, D.J. (2009). An investigation of factors influencing the use of computer-related audit procedures. *Journal of Information Systems*, 23(1), pp.97-118.
- Janvrin, D., Bierstaker, J. and Lowe, D.J. (2008). An examination of audit information technology use and perceived importance. *Accounting horizons*, 22(1), pp.1-21.
- Jarrahi, M.H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons*, 61(4), pp.577–586.
- Jensen, M. (2006). Should we stay or should we go? Accountability, status anxiety, and client defections. *Administrative Science Quarterly*, 51(1), pp.97-128.
- Jeon, J. and Suh, Y. (2017). Analyzing the major issues of the 4th industrial revolution. *Asian Journal of Innovation and Policy*, 6(3), pp.262–273.
- Jobin, A., Ienca, M. and Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine*

- Intelligence*, 1(9), pp.389-399.
- Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of management review*, 31(2), pp.386-408.
- Johnson, P. and Duberley, J. (2000). *Understanding management research*. London; Thousands Oaks; New Delhi: Sage Publications, Cop.
- Jones, T.M. (1980). Corporate social responsibility revisited, redefined. *California management review*, 22(3), pp.59–67.
- Jull, J. (1999). The second industrial revolution. The history of a concept. *Rivista internazionale di storia della storiografia*, (36), pp.81–90.
- Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A. and Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. *Current Opinion in Biotechnology*, 70, pp.15-22.
- Kagermann, H., Wahlster, W. and Helbig, J. (2013). Recommendations for implementing the strategic initiative Industrie 4.0: Final report of the Industrie 4.0 Working Group. *Forschungsunion: Berlin, Germany*.
- Kaiser, H.F. (1970). A second generation little jiffy. *Psychometrika*, 35(4), pp.401–415.
- Kaku, M. (2012). *Physics of the future: how science will shape human destiny and our daily lives by the year 2100*. New York: Anchor Books.
- Kaplan, B. and Maxwell, J.A. (2005). Qualitative research methods for evaluating computer information systems. *Evaluating the organizational impact of healthcare information systems*, pp.30-55.
- Karahanna, E., Straub, D.W. and Chervany, N.L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS quarterly*, pp.183–213.
- Kauffman, M. (2019). *Industry 4.0: The Impact of Horizontal Integration on Manufacturing Business Models and Intellectual Property Strategies*. PhD. Coventry University.
- Kelemen, M. and Rumens, N. (2011). *An Introduction to Critical Management Research*. London: Sage.
- Kend, M. and Nguyen, L.A. (2020). Big data analytics and other emerging technologies: the impact on the Australian audit and assurance profession. *Australian Accounting Review*, 30(4), pp.269–282.
- Khalil, O.E. (1993). Artificial decision-making and artificial ethics: A management concern. *Journal of Business Ethics*, 12, pp.313-321.
- Khan, S., Rahmani, H., Shah, S.A.A. and Bennamoun, M. (2018). A guide to convolutional neural networks for computer vision. *Synthesis lectures on computer vision*, 8(1), pp.1-207.

- Kim, H.J., Mannino, M. and Nieschwietz, R.J. (2009). Information technology acceptance in the internal audit profession: Impact of technology features and complexity. *International Journal of Accounting Information Systems*, 10(4), pp.214-228.
- Kim, T.W. and Scheller-Wolf, A. (2019). Technological Unemployment, Meaning in Life, Purpose of Business, and the Future of Stakeholders. *Journal of Business Ethics*, 160, pp. 319–337.
- Kokina, J. and Davenport, T.H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*, 14(1), pp.115–122.
- Korman, A.K. (1970). Toward an hypothesis of work behavior. *Journal of Applied psychology*, 54(1p1), p.31.
- Koscher, K., Czeskis, A., Roesner, F., Patel, S., Kohno, T., Checkoway, S., McCoy, D., Kantor, B., Anderson, D., Shacham, H. and Savage, S. (2010). Experimental security analysis of a modern automobile. In *2010 IEEE symposium on security and privacy*, pp. 447-462.
- Kothari, C.R. (2004). *Research methodology: methods and techniques*. 2nd ed. New Delhi: New Age International (P) Limited, Publishers.
- Kotsiantis, S.B., Zaharakis, I. and Pintelas, P. (2007). Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160(1), pp.3-24.
- KPMG. (2016). *Creating innovative solutions through the power of digital collaboration*. [online]. Available from: <https://home.kpmg/xx/en/home/about/alliances/ibm.html> (Accessed 24 Jun. 2022).
- Krainovich-Miller, B. (2017). Gathering and appraising the literature. *Nursing research: methods and critical appraisal for evidence-based practice*, 9th edn. Elsevier, Mosby, St. Louis, MO, pp.45–65.
- Krieger, F., Drews, P. and Velte, P. (2021). Explaining the (non-) adoption of advanced data analytics in auditing: A process theory. *International journal of accounting information systems*, 41, p.100511.
- Kumar, M., Talib, S.A. and Ramayah, T. (2013). *Business research methods*. Oxford Fajar/Oxford University Press.
- Kuruppu, N., Laswad, F. and Oyelere, P. (2012). Assessing going concern. *Pacific Accounting Review*, 24(1), pp.33–50.
- Kuznets, S. (1965). *Towards a Theory of Economic Growth “in Economic Growth and Structure*. New York: WW Norton & Co.
- Lacity, M. (2017). Reimagining Professional Services with Cognitive Technologies at KPMG. *UMSL Business*, pp.1-21.
- Laczniak, G.R. and Murphy, P.E. (2006). Marketing, consumers and technology: Perspectives for enhancing ethical transactions. *Business Ethics Quarterly*, 16(3), pp.313-321.

- Landes, D.S. (2008). *The unbound Prometheus: technical change and industrial development in Western Europe from 1750 to the present*. Cambridge: Cambridge University Press.
- Lasi, H., Fettke, P., Kemper, H.G., Feld, T. and Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, 6 (4), pp.239–242.
- Leclercq-Vandelannoitte, A. (2019). Is Employee Technological “Ill-Being” Missing from Corporate Responsibility? The Foucauldian Ethics of Ubiquitous IT Uses in Organizations. *Journal of Business Ethics*, 160, pp 339–361.
- Lehner, O.M., Ittonen, K., Silvola, H., Ström, E. and Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking. *Accounting, Auditing & Accountability Journal*, 35(9), pp.109-135.
- Lewis, P. V. (1985). Defining ‘business ethics’: Like nailing jello to a wall. *Journal of Business ethics*, 4(5), pp.377–383.
- Li, Q. and Liu, J. (2020). Development of an intelligent NLP-based audit plan knowledge discovery system. *Journal of Emerging Technologies in Accounting*, 17(1), pp.89–97.
- Li, Q. and Vasarhelyi, M. (2018). Developing a cognitive assistant for the audit plan brainstorming session. *The International Journal of Digital Accounting Research*, 18, pp.119–140.
- Liddy, E. D. (2001). Natural language processing. In *Encyclopedia of library and information science* (2 nd ed.). New York, NY: CRC Press Marcel Dekker.
- Lin, C. and Wang, C. (2011). A selection model for auditing software. *Industrial Management & Data Systems*, 111(5), pp.776–790.
- Lin, J.Y. (2016). The latecomer advantages and disadvantages. *Diverse development paths and structural transformation in the escape from poverty*, p.43.
- Lincoln, Y.S. and Guba, E.G. (1985). *Naturalistic inquiry*. Newbury Park, CA: Sage.
- Litzenberg, R. (2020). *Remote Auditing For Covid-19 And Beyond*. [online]. Available from: <https://na.theiia.org/periodicals/Public Documents/EHSKB-Remote-Auditing-for-COVID-19-and-Beyond.pdf> (Accessed 03 Sep. 2022).
- Lombardi, D.R., Bloch, R. and Vasarhelyi, M.A. (2015). The current state and future of the audit profession. *Current Issues in Auditing*, 9(1), pp. P10-P16.
- Loraas, T.M. and Diaz, M.C., 2011. Learning new technologies: the effect of ease of learning. *Journal of Information Systems*, 25(2), pp.171-194.
- Losbichler, H. and Lehner, O.M. (2021). Limits of artificial intelligence in controlling and the ways forward: a call

- for future accounting research. *Journal of Applied Accounting Research*, 22(2), pp.365–382.
- Louwers, T.J., Sinason, D.H., Strawser, J.R., Thibodeau, J.C. and Blay, A.D. (2007). *Auditing & Assurance Services*. 8th ed. New York: McGraw-Hill, Inc.
- Lovata, L.M. (1988). The utilization of generalized audit software. *Auditing: A Journal Of Practice & Theory*, 8(1), pp.72-86.
- Lowe, D.J., Bierstaker, J.L., Janvrin, D.J. and Jenkins, J.G. (2018). Information technology in an audit context: Have the Big 4 lost their advantage? *Journal of information systems*, 32(1), pp.87-107.
- Lu, H., Li, Y., Chen, M., Kim, H. and Serikawa, S. (2018). Brain intelligence: go beyond artificial intelligence. *Mobile Networks and Applications*, 23, pp.368-375.
- Mahajan, G. (2016). *Value creation: The definitive guide for business leaders*. New Delhi: SAGE Publications.
- Mahzan, N. and Lymer, A. (2009). Examining motivations to adopt computer assisted audit tools and techniques (CAATTs): Cases of UK internal auditors. In *Creating Global Economies through Innovation and Knowledge Management Theory and Practice - Proceedings of the 12th International Business Information Management Association Conference, IBIMA 2009*.
- Mahzan, N. and Lymer, A. (2014). Examining the adoption of computer-assisted audit tools and techniques. *Managerial Auditing Journal*, 29(4), pp.327–349.
- Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, 90, pp.46-60.
- Manita, R., Elommal, N., Baudier, P. and Hikkerova, L. (2020). The digital transformation of external audit and its impact on corporate governance. *Technological Forecasting and Social Change*, 150, p.119751.
- Manson, S., McCartney, S., Sherer, M. and Wallace, W.A. (1998). Audit automation in the UK and the US: A comparative study. *International Journal of Auditing*, 2(3), pp.233-246.
- Manson, S., McCartney, S. and Sherer, M. (2001). Audit automation as control within audit firms. *Accounting, Auditing & Accountability Journal*, 14(1), pp.109-130.
- Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R. and Sanghvi, S. (2017). *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*, No. December, McKinsey Global Institute, pp. 1-160.
- Manyika, J., & Sneider, K. (2018). AI, automation, and the future of work: Ten things to solve for. McKinsey Global Institute. [online]. <https://www.mckinsey.com/featured-insights/future-of-work/ai-automation-and-the-future-of-work-ten-things-to-solve-for> (Accessed 01 Jul 2022).
- Mark, E.H. and David, D.W. (1990). A Contingent Model of Intra-Big Eight Auditor Changes. *Auditing: A Journal of*

Practice & Theory, 9, pp.55-74.

- Markoff, J. (2002). Pentagon plans a computer system that would peek at personal data of Americans. *New York Times*, 9. [online]. Available from: <https://www.nytimes.com/2002/11/09/us/threats-responses-intelligence-pentagon-plans-computer-system-that-would-peek.html>. (Accessed 23 Oct. 2022).
- Marr, B. (2019). *Artificial intelligence in practice: how 50 successful companies used artificial intelligence to solve problems*. Chichester, West Sussex, United Kingdom: John Wiley & Sons Ltd.
- Martela, F. (2015). Fallible inquiry with ethical ends-in-view: A pragmatist philosophy of science for organizational research. *Organization Studies*, 36(4), pp.537-563.
- Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*, 160(4), pp.835–850.
- Martin, K., Shilton, K. and Smith, J. (2019). Business and the Ethical Implications of Technology: Introduction to the Symposium. *Journal of Business Ethics*, 160(2), pp.307–317.
- Matthews, B. and Ross, L. (2010). *Research methods: a practical guide for the social sciences*. 1st ed. Harlow: Pearson Longman.
- Matthews, D. (2006). *A history of auditing: the changing audit process in Britain from the nineteenth century to the present day*. ; New York: Routledge.
- McCarthy, J., Minsky, M.L., Rochester, N. and Shannon, C.E. (2018). A proposal for the Dartmouth summer research project on artificial intelligence (1955). *Reprinted online at <http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html>*.
- McCarthy, J., Minsky, M.L., Rochester, N., Shannon, C.E. (1955). *A proposal for the dartmouth summer research project on artificial intelligence*. [online]. Available from <http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html> (Accessed 15 Nov 2019).
- McKinsey Global Institute. (2019). Global AI Survey: AI proves its worth, but few scale impact. [online]. Available from <https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact> (Accessed 21 Jan. 2022).
- Meredith, K., Blake, J., Baxter, P. and Kerr, D. (2020). Drivers of and barriers to decision support technology use by financial report auditors. *Decision Support Systems*, 139, p.113402.
- Michael, A. and Dixon, R. (2019). Audit data analytics of unregulated voluntary disclosures and auditing expectations gap. *International Journal of Disclosure and Governance*, 16, pp.188-205.
- Mihret, D.G., Alshareef, M.N. and Bazhair, A. (2017). Accounting professionalization and the state: The case of

- Saudi Arabia. *Critical Perspectives on Accounting*, 45, pp.29–47.
- Miller, R.I. and Anderson, A.W. (2004). Legal and ethical considerations regarding outsourcing. *Journal of Accountancy*, 197(3), p.31.
- Min, Q., Ji, S. and Qu, G., 2008. Mobile commerce user acceptance study in China: a revised UTAUT model. *Tsinghua Science and Technology*, 13(3), pp.257-264.
- Minsky, M. L. (1968). *Semantic information processing*. Cambridge, MA: MIT Press
- Mitchell, T.M. (2006). *The discipline of machine learning*. Pittsburgh: Carnegie Mellon University, School of Computer Science, Machine Learning Department.
- Moffitt, K.C., Rozario, A.M. and Vasarhelyi, M.A. (2018). Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting*, 15(1), pp.1–10.
- Mokyr, J. (1998) The Second Industrial Revolution, 1870–1914. In *Storia dell'economia Mondiale*; Valerio, C., Ed.; Laterza: Rome, Italy.
- Monsees, M. E. The American Civil Engineer: Origins and Conflicts. By Daniel H. Calhoua. Cambridge, Harvard University Press, 1960. Pp. xii 295. *Business History Review*. Cambridge University Press, 35(1), pp. 142–145.
- Moon, K., Brewer, T.D., Januchowski-Hartley, S.R., Adams, V.M. and Blackman, D.A. (2016). A guideline to improve qualitative social science publishing in ecology and conservation journals. *Ecology and Society*, 21(3).
- Moore, G.C. and Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, 2(3), pp.192-222.
- Moran, M., Hawkes, M. and Gayar, O.E. (2010). Tablet personal computer integration in higher education: Applying the unified theory of acceptance and use technology model to understand supporting factors. *Journal of educational computing research*, 42(1), pp.79-101.
- Morgan, D.L. (2013). *Integrating qualitative and quantitative methods: a pragmatic approach*. Thousand Oaks, California: Sage Publications, Inc.
- Morgan, D.L. (1998). Practical strategies for combining qualitative and quantitative methods: Applications to health research. *Qualitative health research*, 8(3), pp.362-376.
- Morgan, D.L. (2014). Pragmatism as a paradigm for social research. *Qualitative inquiry*, 20(8), pp.1045-1053.
- Morris, M.G. and Venkatesh, V. (2000). Age Differences In Technology Adoption Decisions: Implications For A Changing Work Force. *Personnel Psychology*, 53(2), pp.375–403.
- Mowery, D.C. and Rosenberg, N. (1991). *Technology and the pursuit of economic growth*. Cambridge; New York; Port Chester: Cambridge University Press.

- Müller, R., Turner, R., Andersen, E.S., Shao, J. and Kvalnes, Ø. (2014). Ethics, trust, and governance in temporary organizations. *Project Management Journal*, 45(4), pp.39-54.
- Munoko, I., Brown-Liburd, H.L. and Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics*, 167, pp.209-234.
- Muslihatun, F.A.N., Hantono, B.S. and Fauziati, S. (2021). Using Artificial Intelligence Technology for Decision Support System in Audit Risk Assessment: A Review Paper. In *2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*. IEEE, pp. 326–331.
- Mustapha, M. and Lai, S.J. (2017). Information Technology in Audit Processes: An Empirical Evidence from Malaysian Audit Firms. *International Review of Management and Marketing*, 7(2), pp.53–59.
- Nardi, P.M. (2018). The Taylor & Francis Group.
- Nehme, R., Michael, A. and Haslam, J. (2022). The impact of time budget and time deadline pressures on audit behaviour: UK evidence. *Meditari Accountancy Research*, 30(2), pp.245-266.
- Neuman, W.L. (2020). *Social research methods: Qualitative and quantitative approaches*. 7th ed. Harlow, Essex: Pearson.
- Nickell, G.S. and Pinto, J.N. (1986). The computer attitude scale. *Computers in human behavior*, 2(4), pp.301–306.
- Niemi, L. (2004). Auditor size and audit pricing: evidence from small audit firms. *European accounting review*, 13(3), pp.541–560.
- O’Leary, D.E. and O’Keefe, R.M. (1997). The impact of artificial intelligence in accounting work: Expert systems use in auditing and tax. *AI & Society*, 11(1–2), pp.36–47.
- Ohm, P. (2009). Broken promises of privacy: Responding to the surprising failure of anonymization. *UCLA L. Rev.*, 57, p.1701.
- Omoteso, K. (2012). The application of artificial intelligence in auditing: Looking back to the future. *Expert Systems with Applications*, 39(9), pp.8490–8495.
- Orlikowski, W.J. and Baroudi, J.J. (1991). Studying information technology in organizations: Research approaches and assumptions. *Information systems research*, 2(1), pp.1-28.
- Osoba, O. and Welser, W. (2017). *An intelligence in our image : the risks of bias and errors in artificial intelligence*. Santa Monica, Calif.: Rand Corporation.
- Palmrose, Z.-V. (1989). The relation of audit contract type to audit fees and hours. *Accounting Review*, pp.488–499.
- Park, J., Yang, S. and Lehto, X. (2007). Adoption of Mobile Technologies for Chinese Consumers. *Journal of Electronic Commerce Research*. 8(3), 196–206.

- Park, S. (2014). Cultural relativism and the theory of relativity. *FilosoFija. sociologija*, (1), pp.44–51.
- Pathak, J. and Lind, M.R. (2010). An e-business audit service model in the B2B context. *Information Systems Management*, 27(2), pp.146-155.
- Paul, R., & Elder, L. (2006). *The thinker's guide to understanding the foundations of ethical reasoning*. Dillon Beach: Foundation for Critical Thinking.
- Payne, E.A. and Curtis, M.B. (2008). Can the unified theory of acceptance and use of technology help us understand the adoption of computer-aided audit techniques by auditors? In *American Accounting Association Auditing Section Midyear Conference, St. Petersburg, FL, January* (pp. 15-17).
- Payne, E.A. and Curtis, M.B. (2017). Factors associated with auditors' intention to train on optional technology. *Current Issues in Auditing*, 11(1), pp.A1-A21.
- PCAOB. (2018). *Amendments To Auditing Standards For Auditor's Use Of The Work Of Specialists*. [online]. Available from: https://pcaob-assets.azureedge.net/pcaob-dev/docs/default-source/rulemaking/docket044/2018-006-specialists-final-rule.pdf?sfvrsn=322a6948_0 (Accessed 25 Jul. 2020).
- PCAOB. (2017). PCAOB Auditing Standards No. 3. , (202), pp.1–725. [online]. Available from: https://pcaobus.org/Standards/Auditing/Documents/PCAOB_Auditing_Standards_as_of_December_15_2017.pdf (Accessed 11 Dec. 2022).
- PCAOB. (1972). Pre-Reorganized Auditing Standards and Interpretations. [online]. Available from: <https://pcaobus.org/oversight/standards/archived-standards/pre-reorganized-auditing-standards-interpretations/details/AU230#:~:text=Due professional care requires the,critical assessment of audit evidence> (Accessed 04 Aug. 2022).
- Pedrosa, I., Costa, C.J. and Aparicio, M. (2019). Determinants adoption of computer-assisted auditing tools (CAATs). *Cognition, Technology and Work*, 22(3), pp.565–583.
- Pedrosa, I., Costa, C.J. and Laureano, R.M.S. (2015). Motivations and limitations on the use of information technology on statutory auditors' work: An exploratory study. In *2015 10th Iberian Conference on Information Systems and Technologies (CISTI)*. IEEE, pp. 1–6.
- Pedrosa, I.M.M. (2015). *Computer-Assisted Audit Tools and Techniques Use: Determinants for Individual Acceptance*. PhD. ISCTE-Instituto Universitario de Lisboa.
- Pennington, R.R., Kelton, A.S. and DeVries, D.D. (2006). The effects of qualitative overload on technology acceptance. *Journal of Information Systems*, 20(2), pp.25-36.
- Perkhofer, L.M., Hofer, P., Walchshofer, C., Plank, T. and Jetter, H.C. (2019). Interactive visualization of big data in

- the field of accounting: A survey of current practice and potential barriers for adoption. *Journal of Applied Accounting Research*, 20(4), pp.497-525.
- Perols, J. (2011). Financial statement fraud detection: An analysis of statistical and machine learning algorithms. *Auditing: A Journal of Practice & Theory*, 30(2), pp.19–50.
- Perols, J.L., Bowen, R.M., Zimmermann, C. and Samba, B. (2017). Finding needles in a haystack: Using data analytics to improve fraud prediction. *The Accounting Review*, 92(2), pp.221-245.
- Piesse, J., Strange, R. and Toonsi, F. (2012). Is there a distinctive MENA model of corporate governance? *Journal of Management & Governance*, 16(4), pp.645–681.
- Plumlee, R.D., Rixom, B.A. and Rosman, A.J. (2015). Training auditors to perform analytical procedures using metacognitive skills. *The Accounting Review*, 90(1), pp.351–369.
- Pollock, J.L. (2017). Procedural epistemology—at the interface of philosophy and AI. *The Blackwell guide to epistemology*, pp.383-414.
- Pongpatrachai, D., Cragg, P. and Fisher, R. (2014). IT infusion within the audit process: Spreadsheet use in small audit firms. *International Journal of Accounting Information Systems*, 15(1), pp.26-46.
- Postan, M.M. and Habakkuk, H.J. (1966). *The Cambridge Economic History of Europe*. Cambridge: Cambridge University Press.
- Preece, A. (2018). Asking ‘Why’ in AI: Explainability of intelligent systems—perspectives and challenges. *Intelligent Systems in Accounting, Finance and Management*, 25(2), pp.63-72.
- Rachels, S. and Rachels, J. (2019). *The elements of moral philosophy*. 9th ed. New York, Ny: McGraw-Hill Education.
- Rahman, A. (2008). *Utilisation of data mining technology within the accounting information system in the public sector: A country study-Malaysia*. PhD. University of Tasmania
- Ramady, M.A. (2009). Evolving banking regulation and supervision: A case study of the Saudi Arabian Monetary Agency (SAMA). *International Journal of Islamic and Middle Eastern Finance and Management*, 2(3), pp.235–250.
- Ramen, M., Jugurnath, B. and Ramhit, P. (2015). UTR-CTOE: a new paradigm explaining CAATs adoption. *Journal of Modern Accounting and Auditing*, 11(12), pp.615-631.
- Raschke, R.L., Saiewitz, A., Kachroo, P. and Lennard, J.B. (2018). AI-enhanced audit inquiry: A research note. *Journal of Emerging Technologies in Accounting*, 15(2), pp.111-116.
- Rawashdeh, B. and Rawashdeh, A. (2021). Factors influencing the usage of XBRL tools. *Management Science*

- Letters*, 11(4), pp.1345–1356.
- Ray, C.M., Sormunen, C. and Harris, T.M. (1999). Men's and women's attitudes toward computer technology: A comparison. *Office Systems Research Journal*, 17, pp.1-8.
- Reynolds, G. (2012). *Ethics in information technology*. New York: Cengage Learning.
- Robin, D.P. and Reidenbach, R.E. (1987). Social responsibility, ethics, and marketing strategy: Closing the gap between concept and application. *Journal of marketing*, 51(1), pp.44-58.
- Robson, C. and McCartan, K. (2016). *Real World Research: A Resource for Users of Social Research Methods in Applied Settings*. 4th ed. Chichester: John Wiley & Sons Ltd.
- Rosenberg, C. (2013). *Improving Photo Search: A Step Across the Semantic Gap*. [online]. Available from: <https://ai.googleblog.com/2013/06/improving-photo-search-step-across.html> (Accessed 16 Jun. 2022).
- Rosli, K., Yeow, P. and Eu-Gene, S. (2013). Adoption of audit technology in audit firms. In *ACIS 2013: Information systems: Transforming the Future: Proceedings of the 24th Australasian Conference on Information Systems* (pp. 1-12).
- Rosli, K., Yeow, P.H.P. and Siew, E.G. (2012). Computer-assisted auditing tools acceptance using I-TOE: A new paradigm. In *Proceedings - Pacific Asia Conference on Information Systems, PACIS 2012*. Paper 195.
- Rozario, A.M. and Thomas, C. (2019). Reengineering the audit with blockchain and smart contracts. *Journal of emerging technologies in accounting*, 16(1), pp.21–35.
- Ruiz-Barbadillo, E., Gómez-Aguilar, N., De Fuentes-Barberá, C. and García-Benau, M.A. (2004). Audit quality and the going-concern decision-making process: Spanish evidence. *European Accounting Review*, 13(4), pp.597-620.
- Rysiew, P. (2016). Naturalism in epistemology. In E. N. Zalta (Ed.), *The Stanford encyclopedia of philosophy*. [online]. Available from <http://plato.stanford.edu/archives/spr2016/entries/epistemology-naturalized/> (Accessed 11 Feb. 2022).
- Salijeni, G., Samsonova-Taddei, A. and Turley, S. (2019). Big Data and changes in audit technology: contemplating a research agenda. *Accounting and Business Research*, 49(1), pp.95–119.
- Salijeni, G.M. (2018). *Big Data Analytics And The Social Relevance Of Auditing : An Exploratory Study*. PhD. Manchester Business School.
- Saravanan, R. and Sujatha, P. (2018). A state of art techniques on machine learning algorithms: a perspective of supervised learning approaches in data classification. In *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*. IEEE, pp. 945–949.

- Satava, D., Caldwell, C. and Richards, L. (2006). Ethics and the auditing culture: Rethinking the foundation of accounting and auditing. *Journal of Business Ethics*, 64, pp.271-284.
- Saunders, M., Lewis, P. and Thornhill, A. (2019). *Research Methods for Business Students*. 8th ed. Harlow: Pearson.
- Scandura, T.A. and Williams, E.A. (2000). Research methodology in management: Current practices, trends, and implications for future research. *Academy of Management journal*, 43(6), pp.1248–1264.
- Schafer, B.A. and Eining, M.M. (2002), “Auditor’s adoption of technology: a study of domain experts”, *paper presented at American Accounting Association 2002 Meeting*, in San Diego.
- Van Schaik, P. (2011). Unified theory of acceptance and use for Web sites used by students in higher education. In *Technology acceptance in education*, pp. 159-181.
- Schein, E.H. (2017). *Organizational Culture and Leadership*. 5th ed. Hoboken, New Jersey Wiley.
- Schwab, K. (2016). *The Fourth Industrial Revolution*. London: Penguin Random House.
- Sedera, D., Gable, G. and Chan, T. (2004). Measuring enterprise systems success: the importance of a multiple stakeholder perspective. In *Proceedings of the 12th European Conference on Information Systems: The European IS profession in the global networking environment*, pp. 1-14.
- Seethamraju, R. and Hecimovic, A. (2022). Adoption of artificial intelligence in auditing: An exploratory study. *Australian Journal of Management*, p.03128962221108440.
- Seidenstein, T. and Davies, D. (2022). Assurance in the Digital Age. , (IFAC). [online]. Available from: <https://www.ifac.org/knowledge-gateway/supporting-international-standards/discussion/assurance-digital-age> (Accessed 21 July. 2022).
- Seow, P.-S. (2011). The effects of decision aid structural restrictiveness on decision-making outcomes. *International Journal of Accounting Information Systems*, 12(1), pp.40–56.
- Shaikh, J. (2016). A Complete Guide on Getting Started with Deep Learning in Python. *International Journal of Digital Accounting Research*, 18, pp.413–435.
- Shaw, J. (2019). Artificial Intelligence and Ethics, Ethics and the dawn of decision-making machines. *harvard magazine*. [online]. Available from: <https://harvardmagazine.com/2019/01/artificial-intelligence-limitations> (Accessed 17 Jan. 2023).
- Shinawi, A.A.K. (1970). *The role of accounting and accountants in the developing economy of Saudi Arabia*. PhD. University of Southern California.
- Da Silva, F.L. and Costa, A.H.R. (2019). A survey on transfer learning for multiagent reinforcement learning systems. *Journal of Artificial Intelligence Research*, 64, pp.645–703.

- Simkin, M.G., Norman, C.A. and Rose, J. (2018). *Core concepts of accounting information systems*. United Kingdom: Wiley.
- Sinclair, M. (2007.) A guide to understanding theoretical and conceptual frameworks. *Evidence-Based Midwifery*, 5(2), pp.39-40.
- Sinkovics, N. (2018). Pattern matching in qualitative analysis. In C. Cassel, A. Cunliffe, & G. Grandy (Eds.). *The sage handbook of qualitative business and management research methods* (pp. 468–485). Thousand Oaks: Sage Publications.
- Sitkrongwong, P., Takasu, A. and Maneeroj, S. (2020). Context-aware user and item representations based on unsupervised context extraction from reviews. *IEEE Access*, 8, pp.87094-87114.
- Smith, S. M & Albaum G. S (2010) *An Introduction to Marketing Research*, NY: Sage Publishers, P 129.
- Sollie, P. (2007). Ethics, technology development and uncertainty: an outline for any future ethics of technology. *Journal of Information, Communication and Ethics in Society*, 5(4), pp.293–306.
- Song, Q., Chan, S.H. and Wright, A.M. (2017). The efficacy of a decision support system in enhancing risk assessment performance. *Decision Sciences*, 48(2), pp.307–335.
- Song, S. (2017). Historical Development of Industrial Revolutions and the Place of So called 'the Fourth Industrial Revolution'. *Journal of Science and Technology Studies*, 17(2), pp.5–40.
- Specht, L.B., Trotter, R.C., Young, R.M. and Sutton, S.G. (1991). The public accounting litigation wars: will expert systems lead the next assault?. *Jurimetrics*, 31(2), pp.247-257.
- Srivastava, B. and Rossi, F. (2018). Towards composable bias rating of AI services. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 284-289.
- Srivastava, R.P. and Shafer, G.R. (1992). Belief-function formulas for audit risk. *Accounting Review*, pp.249–283.
- Stahl, B.C. and Wright, D. (2018). Ethics and privacy in AI and big data: Implementing responsible research and innovation. *IEEE Security & Privacy*, 16(3), pp.26–33.
- Stake, R.E. (1995). *The Art of Case Study Research*. London: Sage.
- Stanford (2019). Artificial Intelligence Index Report 2019. *Steering Committee*. Available at: https://hai.stanford.edu/sites/default/files/ai_index_2019_report.pdf (Accessed 12 Jan. 2022).
- Stoel, D., Havelka, D. and Merhout, J.W. (2012). An analysis of attributes that impact information technology audit quality: A study of IT and financial audit practitioners. *International Journal of Accounting Information Systems*, 13(1), pp.60-79.
- Straub, D., Boudreau, M.-C. and Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications*

- of the Association for Information systems*, 13(1), p.24.
- Suddaby, R. (2006). From the editors: What grounded theory is not. *Academy of management journal*, 49(4), pp.633-642.
- Sumner, W.G. (1906). *Folkways: Sociological importance of usages, manners, customs, mores and morals*. 1959 Reprint.
- Sun, T., Liu, Y. and Vasarhelyi, M. (2016). The Performance of Sentiment Features of MD&As for Financial Misstatement Prediction: A Comparison of Deep Learning and “Bag of Words” Approach. Working paper, Rutgers, The State University of New Jersey.
- Sun, T. and Vasarhelyi, M. (2017). Deep Learning and the Future of Auditing: How an Evolving Technology Could Transform Analysis and Improve Judgment. *CPA Journal*, 87(6), pp. 24–29.
- Sun, T. and Vasarhelyi, M. (2018). Embracing Textual Data Analytics in Auditing with Deep Learning. *The International Journal of Digital Accounting Research*, pp.49–67.
- Sun, T.S. (2019). Applying deep learning to audit procedures: An illustrative framework. *Accounting Horizons*, 33(3), pp.89–109.
- Sutton, S.G., Holt, M. and Arnold, V. (2016). “The reports of my death are greatly exaggerated”—Artificial intelligence research in accounting. *International Journal of Accounting Information Systems*, 22, pp.60–73.
- Szeliski, R. (2020). *COMPUTER VISION: algorithms and applications*. S.L.: Springer Nature.
- T., C.M. and Roe, J.W. (1916). *English and American Tool Builders*. London, England: McGraw-Hill.
- Tabachnick, B.G., Fidell, L.S. and Ullman, J.B. (2013). *Using multivariate statistics* (Vol. 6, pp. 497-516). Boston, MA: pearson.
- Tavakol, M. and Dennick, R. (2011). Making sense of Cronbach's alpha. *International journal of medical education*, 2, p.53.
- Taylor, P.W. (1975). *Principles of ethics* Belmont, Calif.: Wadsworth Pub. Co.
- Taylor, S. and Todd, P.A. (1995). Understanding information technology usage: A test of competing models. *Information systems research*, 6(2), pp.144-176.
- Teich, M. and Porter, R. and Gustafsson, B. (1996). *The industrial revolution in national context: Europe and the USA / The industrial revolution in national context : Europe and the USA*. Cambridge England; New York: Cambridge University Press.
- Telukdarie, A. and Sishi, M.N. (2018). Enterprise Definition for Industry 4.0. In *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE, pp. 849–853.

- Temesgen, Z.B. (2004). *Determinants for Effective Application of Software in Computer Assisted Auditing Techniques (CAATs)*. Dissertation. School of Management Ronneby Sweden.
- Terzopoulos, D. (1988). The computation of visible-surface representations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 10(4), pp.417–438.
- Terzopoulos, D. and Witkin, A. (1988). Physically based models with rigid and deformable components. *IEEE Computer Graphics and Applications*, 8(6), pp.41–51.
- The European Commission. (2020). *White Paper on AI - A European Approach to Excellence and Trust*. [online]. Available from: https://ec.europa.eu/info/files/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en (accessed 07 Mar. 2021).
- The World Economic Forum. (2019). Davos Manifesto 2020: The Universal Purpose of a Company in the Fourth Industrial Revolution. [online]. Available from: <https://www.weforum.org/agenda/2019/12/davos-manifesto-2020-the-universal-purpose-of-a-company-in-the-fourth-industrial-revolution/> (Accessed 17 Nov. 2020).
- Thomas, T., Singh, L. and Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development using ICT*, 9 (3), pp.71–85.
- Thomas, Z. (2020). Coronavirus: Will Covid-19 speed up the use of robots to replace human workers? [online]. Available from: <https://www.bbc.co.uk/news/technology-52340651> (Accessed 19 May 2022).
- Thompson, R.L., Higgins, C.A. and Howell, J.M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS quarterly*, pp.125-143.
- Thrall, J.H., Li, X., Li, Q., Cruz, C., Do, S., Dreyer, K. and Brink, J. (2018). Artificial intelligence and machine learning in radiology: opportunities, challenges, pitfalls, and criteria for success. *Journal of the American College of Radiology*, 15(3), pp.504-508.
- Tiron-Tudor, A. and Deliu, D. (2022). Reflections on the human-algorithm complex duality perspectives in the auditing process. *Qualitative Research in Accounting & Management*, 19(3), pp.255-285.
- Trenciansky, P. and Murdoch, P.L., Sentry Technology Corp (2012). *Enterprise management system and auditing method employed thereby*. U.S. Patent Application 13/512,412.
- Tsai, C.C. and Lin, C.C. (2004). Taiwanese adolescents' perceptions and attitudes regarding the internet: Exploring gender differences. *Adolescence*. 39, pp.725–734.
- Tsang, E.W.K. (2017). *The philosophy of management research*. London; New York: Routledge.
- Tseng, H.C., Duan, C.H., Tung, H.L. and Kung, H.J. (2010). Retracted article: Modern business ethics research: Concepts, theories, and relationships. *Journal of business ethics*, 91, pp.587-597.

- Tucker, I. (2020). The Five: Robots Helping to Tackle Coronavirus. *The guardian*. [online]. Available from: <https://www.theguardian.com/technology/2020/may/31/the-five-robots-helping-to-tackle-coronavirus> (Accessed 11 Nov. 2020).
- Tumi, A. (2013). *An investigative study into the influence of information technology on the audit processes in Libya*. PhD. Glasgow Caledonian University.
- Tysiac, K. (2020). Remote auditing comes to forefront during pandemic. [online]. Available from: <https://www.journalofaccountancy.com/news/2020/mar/remote-auditing-during-coronavirus-pandemic.html> (Accessed 23 Sep. 2022).
- Ukpong, E.G., Udoh, I.I. and Essien, I.T. (2019). Artificial Intelligence: Opportunities, Issues and Applications in Banking, Accounting, and Auditing in Nigeria. *Asian Journal of Economics, Business and Accounting*, 10(1), pp.1–6.
- Urbach, N., Smolnik, S. and Riempp, G. (2010). An empirical investigation of employee portal success. *The Journal of Strategic Information Systems*, 19(3), pp.184-206.
- Vasarhelyi, M.A. (1984). Automation and Changes in the Audit Process (Practice Note). *Auditing: A Journal of Practice & Theory* 4 (1), pp.100–106.
- Vasarhelyi, M.A. and Halper, F.B. (1991). The continuous audit of online systems. In *Auditing: A Journal of Practice and Theory*. pp.87–104.
- Vasarhelyi, M.A. and Kogan, A. (1997). Artificial Intelligence in Accounting and Auditing: *Artificial Intelligence In Accounting and Auditing*.
- Vasarhelyi, M.A. and Kogan, A. (1998). *Artificial Intelligence in Accounting and Auditing: Towards New Paradigms*, Vol. 1. Princeton, NJ: Markus Wiener Publishers.
- Vasarhelyi, M.A., Kogan, A. and Tuttle, B.M. (2015). Big data in accounting: An overview. *Accounting Horizons*, 29(2), pp.381-396.
- Vasarhelyi, M.A. and Lin, W.T. (1985). EDP auditing instruction using an interactive generalized audit software. *Journal of Accounting Education*, 3(2), pp.79-89.
- Vasarhelyi, M. and Romero, S. (2014). Technology in audit engagements: A case study. *Managerial Auditing Journal*, 29(4), pp.350-365.
- Vekiri, I. and Chronaki, A. (2008). Gender issues in technology use: Perceived social support, computer self-efficacy and value beliefs, and computer use beyond school. *Computers & education*, 51(3), pp.1392-1404.
- Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003). User acceptance of information technology:

- Toward a unified view. *MIS quarterly*, pp.425-478.
- Venkatesh, V. and Morris, M.G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS quarterly*, pp.115-139.
- Venkatesh, V., Thong, J.Y. and Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, pp.157-178.
- Visvikis, D., Cheze Le Rest, C., Jaouen, V. and Hatt, M. (2019). Artificial intelligence, machine (deep) learning and radio (geno) mics: definitions and nuclear medicine imaging applications. *European journal of nuclear medicine and molecular imaging*, 46(13), pp.2630-2637.
- Wahdan, M.A. and Eddy Vaassen, A.I.M. (2009). Computer Producing a" Fair" Auditor's Report. In *The Proceeding of the Congress 18th IMDA*. Tbilisi, Georgia, pp. 293–300.
- Walliman, N. (2011). *Social Research Methods*. London; Sage Publications, Ltd.
- Wang, D. (2013). German employees rally outside Amazon headquarters: 'We're People, Not Robots'.' *kuow*. [online]. Available from: <https://kuow.org/stories/german-employees-rally-outside-amazon-headquarters-were-people-not-robots/> (Accessed 16 Jan 2020).
- Wang, S., Cai, J., Lin, Q. and Guo, W. (2019). An overview of unsupervised deep feature representation for text categorization. *IEEE Transactions on Computational Social Systems*, 6(3), pp.504-517.
- Weber, R. (1998). *Information Systems Control and Audit*. 1 edition. Upper Saddle River, NJ, United States, NJ, United States: Pearson Education (US).
- Wehner, D. and Jessup, C.M. (2005). Factors affecting generalized audit software usage. In *AAA Midwest Accounting Meeting*.
- Wellman, C. (2019). *Proliferation Of Rights: moral progress or empty rhetoric?* S.L.: Routledge.
- Wells, D.A. (1899). *Recent economic changes: and their effect on the production and distribution of wealth and the well-being of society*. New York: D. Appleton and Company.
- Werhane, P.H. (1994). The Normative/Descriptive Distinction in Methodologies of Business Ethics. *Business ethics quarterly*, 4(2), pp.175–180.
- West, S.M. (2019). Data capitalism: Redefining the logics of surveillance and privacy. *Business & society*, 58(1), pp.20–41.
- Westermann, K.D., Bedard, J.C. and Earley, C.E. (2015). Learning the “craft” of auditing: A dynamic view of auditors' on-the-job learning. *Contemporary Accounting Research*, 32(3), pp.864–896.
- Whitley Jr, B.E. (1997). Gender differences in computer-related attitudes and behavior: A meta-analysis. *Computers*

in human behavior, 13(1), pp.1-22.

- Widuri, R., O'Connell, B. and Yapa, P.W.S. (2016). Adopting generalized audit software: an Indonesian perspective. *Managerial Auditing Journal*, 31(8/9), pp.821–847.
- Wong, D.B. (1995). Pluralistic relativism. *Midwest Studies in Philosophy*, 20, pp.378–399.
- World Economic Forum. (2015). *Deep shift technology tipping points and societal impact*. [online]. Available at: https://www3.weforum.org/docs/WEF_GAC15_Technological_Tipping_Points_report_2015.pdf (Accessed 26 May 2021).
- World Health Organization (WHO). (2020). Novel Coronavirus—China. [online]. Available from: <https://www.who.int/csr/don/12-january-2020-novel-coronavirus-china/en/> (Accessed 12 Nov. 2020).
- Wright, S.A. and Schultz, A.E. (2018). The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, 61(6), pp.823-832.
- Wright, S.A. and Xie, G.-X. (2019). Perceived privacy violation: Exploring the malleability of privacy expectations. *Journal of Business Ethics*, 156(1), pp.123–140.
- Yin, R.K. (2014). *Case study research: Design and methods*. 5th ed. Los Angeles: Sage.
- Yoon, K., Hoogduin, L. and Zhang, L. (2015). Big data as complementary audit evidence. *Accounting Horizons*, 29(2), pp.431-438.
- Zager, L., Malis, S.S. and Novak, A. (2016). The role and responsibility of auditors in prevention and detection of fraudulent financial reporting. *Procedia Economics and Finance*, 39, pp.693-700.
- Zainol, S.S., Samsuri, A.S., Tunku Arifin, T.R., Hussin, S., Othman, M.S. and Jie, S.J. (2017). Determinants of computer assisted audit techniques (Caats) adoption. A study in small and medium practices in Malaysia. *European Journal of Business and Social Sciences*, 6(2), pp.135-150.
- ZATCA. (2019). E-Invoicing (Fatoorah) Implementation In Ksa. [online]. Available from: <https://zatca.gov.sa/en/E-Invoicing/Introduction/Pages/Roll-out-phases.aspx> (Accessed 11 Oct. 2022).
- Zechenter, E.M. (1997). In the name of culture: Cultural relativism and the abuse of the individual. *Journal of anthropological research*, 53(3), pp.319-347.
- Zhang, C. (2019). Intelligent process automation in audit. *Journal of emerging technologies in accounting*, 16(2), pp.69–88.
- Zhang, C.A., Vasarhelyi, M. and Cho, S. (2021). Identifying Informative Audit Quality Indicators (IAQI) Using Machine Learning. *Miklos and Cho, Soohyun, Identifying Informative Audit Quality Indicators (IAQI) Using Machine Learning (Feb 2021)*.

- Zhang, J., Yang, X. and Appelbaum, D., 2015. Toward effective big data analysis in continuous auditing. *Accounting Horizons*, 29(2), pp.469-476.
- Zhao, Z., Ma, Y., Mushtaq, A., Rajper, A.M.A., Shehab, M., Heybourne, A., Song, W., Ren, H. and Tse, Z.T.H. (2022). Applications of robotics, artificial intelligence, and digital technologies during COVID-19: a review. *Disaster Medicine and Public Health Preparedness*, 16(4), pp.1634-1644.
- Zhaokai, Y. and Moffitt, K.C. (2019). Contract analytics in auditing. *Accounting Horizons*, 33(3), pp.111–126.
- Zhou, T., Lu, Y. and Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in human behavior*, 26(4), pp.760-767.
- Zhu, K., Kraemer, K. and Xu, S. (2003). Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors. *European journal of information systems*, 12, pp.251-268.
- Zhu, X. and Goldberg, A.B. (2009). Introduction to semi-supervised learning. *Synthesis lectures on artificial intelligence and machine learning*, 3(1), pp.1–130.

Appendices

Appendix 1. The questionnaire.

English ▼

Introduction

The Determinants of the Intention to Use Visual Recognition Technology in the External Audit Environment.

The purpose of the questionnaire:

This questionnaire is a part of a research project to study the factors influencing external auditors' intention to adopt visual recognition technology, which is one form of artificial intelligence technologies that are currently used and has untapped potential in the field of external audits. The questionnaire will be used as a data collection instrument for my Doctoral degree in accounting at the University of Nottingham. As a questionnaire participant, you will receive the results of this study after I analyse and discuss the data.

Your thoughts and answers will be extremely helpful and valuable for the researcher, in order to obtain a deeper understanding of this topic. The questionnaire should take around ten minutes to complete. If you wish to add further comments, please feel free to do so at the end of the questionnaire.

Statement of privacy and security:

This questionnaire has been approved by the Ethics Committee at the University of Nottingham. All information will be treated in the strictest confidence and will only be used for this research purpose. Your identity will remain anonymous. The results will be combined with other participants' results and analysed as a group.

If you have any queries or feedback, please do not hesitate to email me.

Mohammad Alaskar

Mohammad.alaskar@nottingham.ac.uk

Business School, University of Nottingham

Visual recognition technology definition:

Visual recognition technology (VRT) is one form of artificial intelligence technologies that is used to identify objects, people, places, writing, and actions in images. It can autonomously extract data from images and analyse the data, in order to perform a number of audit functions. Functions of VRT include asset assessment, the identification of people, and data extraction from files without the intervention of auditors.

Visual recognition technology can assist auditors in performing an audit in many cases. During the COVID-

19 period, when physical inventory checking has been difficult, auditors have been able to use a VRT built-in CCTV system to verify inventory conditions. VRT can also be used to identify people at a conference, analyse facial expressions, and analyse words used during a conference. In addition, drones with built-in visual recognition cameras can assist auditors to verify the conditions of hard-to-approach asset items.

What is your gender?

Male Female

☐☐

Prefer not to say

☐

How old are you?

Under 21 years
old

☐

21-30years old

☐

31-40 years old

☐

41-50 years old

☐

over 50 years
old

☐

What is the highest level of education you have completed?

Bachelor's degree

☐

Master's degree

☐

Doctoral degree

☐

Other

☐

Do you have a professional accounting qualification?

Yes No

☐
☐

What is your professional accounting qualification?

Do you have an IT audit qualification?

Yes No

☐
☐

What is your IT audit qualification?

How long have you been working in the field of an external audit?

Less than a
year

☐

1-5 years

☐

6-10 years

☐

11-15 years

☐

16-20 years

☐

Over 20
years

☐

What is your position?

Staff Senior manager

☐
☐

What category does your organisation belong to?

Big Four

☐

International audit
firm (not one of the
Big Four)

☐

Regional audit firm

☐

Other

☐

Using the scale given, please indicate to what extent you agree with the given statements by choosing the most appropriate answer.

I believe VRT will be useful in the field of external audit.

Strongly agree

☐

Agree Neutral

☐
☐

Disagree



Strongly
disagree



Using VRT will enable me to accomplish tasks more efficiently.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



Using VRT will increase the quality of output of the audit.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



If I use VRT, I will spend less time on routine job tasks.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



Learning and understanding how to work with VRT will be complicated

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



VRT will not be flexible to work with.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



It will be difficult to make VRT do what I want it to do.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



It will be difficult for me to become skilled at using VRT.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



The expectation from peers is an important factor for me to use VRT.

Strongly agree



Agree Neutral



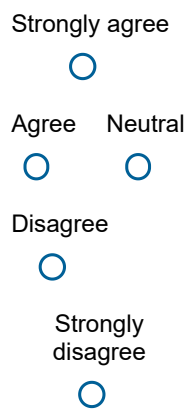
Disagree



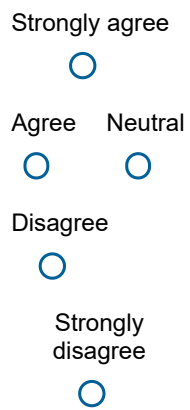
Strongly
disagree



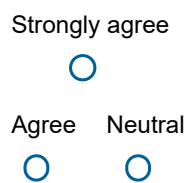
Clients think that I should use VRT.



The senior management of my organisation will be supportive of the use of VRT.



People using VRT will have more prestige than those who do not.



Disagree



Strongly
disagree



I have the resources necessary to use VRT.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



I have the knowledge necessary to use VRT.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



Using VRT is compatible with other systems I use.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



A specific person (or group) is available to assist me to use VRT.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



VRT will substitute my role in the future.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



Using VRT will result in a client's confidential information being leaked.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



VRT will hinder the auditability of the audit process.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



It will be difficult to control data when using VRT.

Strongly agree



Agree Neutral



Disagree



Strongly
disagree



The automatic performance of routine audit tasks by VRT will negatively affect my professional scepticism and judgement.

Strongly agree

☐

Agree Neutral

☐
☐

Disagree

☐

Strongly
disagree

☐

VRT will impair my independence.

Strongly agree

☐

Agree Neutral

☐
☐

Disagree

☐

Strongly
disagree

☐

Do you use VRT to perform audits?

Yes No

☐
☐

List the types of VRT you use in your organization

I intend to use VRT in the near future.

Strongly agree

☐

Agree Neutral

☐
☐

Disagree

☐

Strongly
disagree

☐

I will recommend using VRT to others.

Strongly agree

☐

Agree Neutral

☐
☐

Disagree

☐

Strongly
disagree

☐

List some audit tasks that can be performed by VRT

Any other thoughts about VRT:

If you would like to receive a copy of the study's results, please provide your email address.

Block 1

**This is the end of this survey
Thank you for participating in this survey.**

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Appendix 2. The interview guideline.

General information	Could you introduce yourself (your age, your experience, your position, your qualifications, and your auditing firm)?
	بعد إذنك، ممكن نتكلم عن نفسك بما في ذلك العمر، الخبرة، المستوى الوظيفي، الشهادات المهنية و الشركة التي تعمل فيها؟
Main questions	Please tell me about the factors that influence your artificial intelligence use decisions?
	لو سمحت، في اعتقادك ماهي العوامل التي تأثر على قرارك في استخدام الذكاء الاصطناعي خلال عملية التدقيق؟
	In your opinion, what are the ethical issues that may arise from implementing artificial intelligence in the audit profession?
	هل تعتقد أن هناك مخاوف اخلاقية مرتبطة باستخدام الذكاء الاصطناعي في مهنة التدقيق؟
	Do you think using artificial intelligence in the audit profession will serve broad community goals and values?
	هل تعتقد أن استخدام الذكاء الاصطناعي في مهنة التدقيق سوف يخدم اهداف المجتمع ويحفظ قيمه كذلك؟
	Are you worried about the usage of data collected by artificial intelligence? (e.g., in terms of retrieval, longevity, and third-party usage)?
	هل أنت قلق بشأن البيانات الضخمة التي يجمعها الذكاء الاصطناعي فيما يتعلق باسترجاع هذه البيانات واستخدامها لأغراض غير أغراض التدقيق سوا كان ذلك من قبل شركة التدقيق أو من قبل طرف ثالث؟
	Do you agree with those who say long-term use of artificial intelligence will lead the auditors to focus only on the issues that are identified by the system and not consider other unidentified issues?
	برأيك هل تتفق مع من يقول أن استخدام الذكاء الاصطناعي لفترة طويلة سوف يجعل المدققين يركزون فقط على النقاط التي يبرزها الذكاء الاصطناعي ويتجاهلون المواضيع الأخرى خلال عملية التدقيق؟
	In your opinion, will artificial intelligence impact external auditors' independence?
	برأيك هل سوف يآثر استخدام الذكاء الاصطناعي على استقلالية المدققين؟
	In your opinion, what are the limitations of artificial intelligence in the audit profession?
	برأيك ماهي قصور التي يمكن أن تكون في أنظمة الذكاء الاصطناعي حينما تستخدم في مهنة التدقيق؟

Follow-up questions:

What do you mean by?

Could you give an example of?

Could you tell me more about?

Probing Questions:

Why do you think is the ,case?

How do you conclude.....?

What is the connection between and?